Artificial Intelligence 1 Winter Semester 2024/25

– Lecture Notes – Part III: Knowledge and Inference

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This document contains Part III of the course notes for the course "Artificial Intelligence 1" held at FAU Erlangen-Nürnberg in the Winter Semesters 2016/17 ff. A Video Nugget covering this document can be found at https://fau.tv/clip/id/22466.

This part of the course introduces representation languages and inference methods for structured state representations for agents: In contrast to the atomic and factored state representations from ??, we look at state representations where the relations between objects are not determined by the problem statement, but can be determined by inference-based methods, where the knowledge about the environment is represented in a formal language and new knowledge is derived by transforming expressions of this language.

We look at propositional logic – a rather weak representation langauge – and first-order logic – a much stronger one – and study the respective inference procedures. In the end we show that computation in Prolog is just an inference process as well. Other parts of the lecture notes can be found at http://kwarc.info/teaching/AI/notes-*.pdf.

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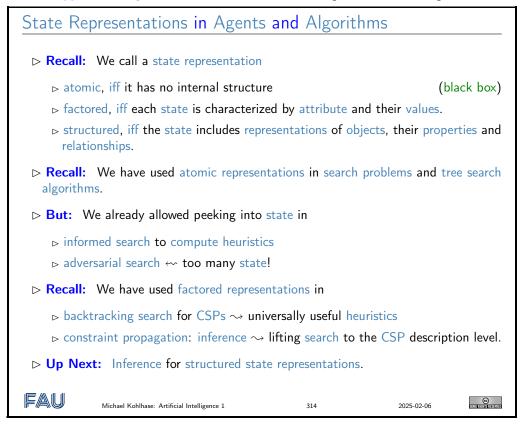
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Chapter 10

Propositional Logic & Reasoning, Part I: Principles

10.1 Introduction: Inference with Structured State Representations

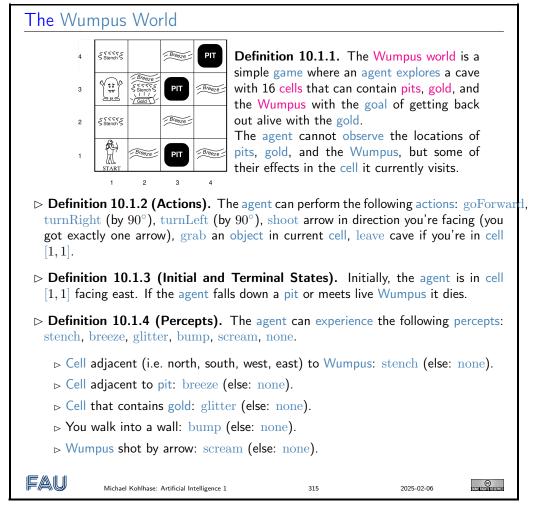
A Video Nugget covering this section can be found at https://fau.tv/clip/id/22455.



10.1.1 A Running Example: The Wumpus World

To clarify the concepts and methods for inference with structured state representations, we now introduce an extended example (the Wumpus world) and the agent model (logic-based agents) that use them. We will refer back to both from time to time below.

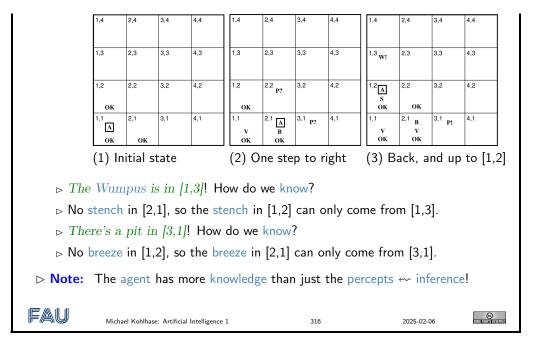
The Wumpus world is a very simple game modeled after the early text adventure games of the 1960 and 70ies, where the player entered a world and was provided with textual information about percepts and could explore the world via actions. The main difference is that we use it as an agent environment in this course.



The game is complex enough to warrant structured state representations and can easily be extended to include uncertainty and non-determinism later.

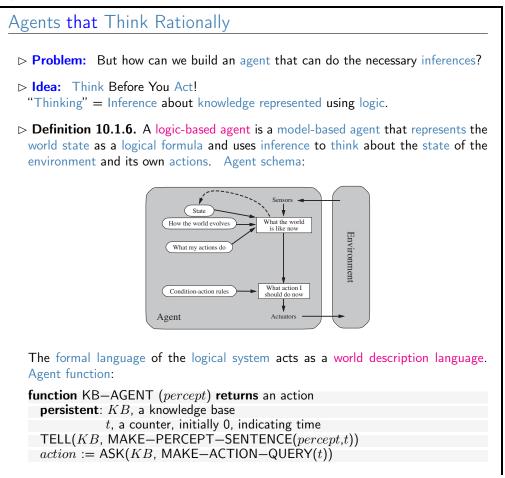
As our focus is on inference processes here, let us see how a human player would reason when entering the Wumpus world. This can serve as a model for designing our artificial agents.

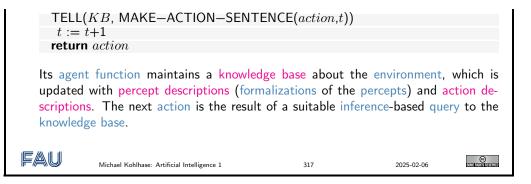
Reasoning in the Wumpus World
Example 10.1.5 (Reasoning in the Wumpus World).
As humans we mark cells with the knowledge inferred so far: A: agent, V: visited, OK: safe, P: pit, W: Wumpus, B: breeze, S: stench, G: gold.



10.1. INTRODUCTION: INFERENCE WITH STRUCTURED STATE REPRESENTATIONS7

Let us now look into what kind of agent we would need to be successful in the Wumpus world: it seems reasonable that we should build on a model-based agent and specialize it to structured state representations and inference.



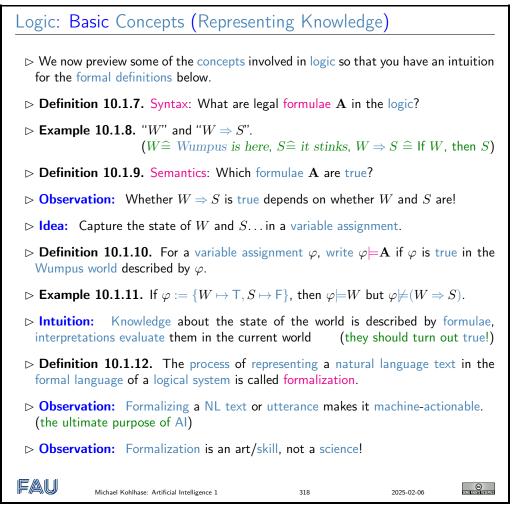


10.1.2 Propositional Logic: Preview

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We will now give a preview of the concepts and methods in propositional logic based on the Wumpus world before we formally define them below. The focus here is on the use of PL^0 as a world description language and understanding how inference might work.

We will start off with our preview by looking into the use of PL^0 as a world description language for the Wumpus world. For that we need to fix the language itself (its syntax) and the meaning of expressions in PL^0 (its semantics).



It is critical to understand that while PL^0 as a logical system is given once and for all, the agent designer still has to formalize the situation (here the Wumpus world) in the world description

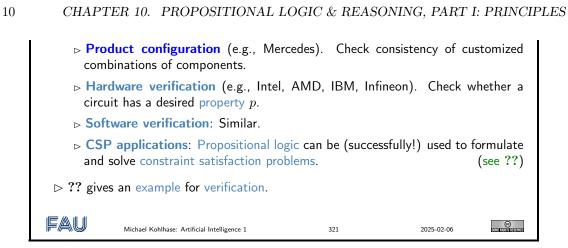
language (here PL⁰; but we will look at more expressive logical systems below). This formalization is the seed of the knowledge base, the logic-based agent can then add to via its percepts and action descriptions, and that also forms the basis of its inferences. We will look at this aspect now.

Logic: Basic Concepts (Reasoning about Knowledge) \triangleright Definition 10.1.13. Entailment: Which B follow from A, written A \models B, meaning that, for all φ with $\varphi \models \mathbf{A}$, we have $\varphi \models \mathbf{B}$? E.g., $P \land (P \Rightarrow Q) \models Q$. \triangleright Intuition: Entailment $\hat{=}$ ideal outcome of reasoning, everything that we can possibly conclude. e.g. determine Wumpus position as soon as we have enough information \triangleright Definition 10.1.14. Deduction: Which formulas B can be derived from A using a set C of inference rules (a calculus), written $\mathbf{A}\vdash_{\mathcal{C}} \mathbf{B}$? $\succ \text{ Example 10.1.15. If } \mathcal{C} \text{ contains } \frac{\mathbf{A} \ \mathbf{A} \Rightarrow \mathbf{B}}{\mathbf{B}} \text{ then } P, P \Rightarrow Q \vdash_{\mathcal{C}} Q$ \triangleright Intuition: Deduction $\hat{=}$ process in an actual computer trying to reason about entailment. E.g. a mechanical process attempting to determine Wumpus position. > Critical Insight: Entailment is purely semantical and gives a mathematical foundation of reasoning in PL^0 , while Deduction is purely syntactic and can be implemented well. (but this only helps if they are related) \triangleright Definition 10.1.16. Soundness: whenever $\mathbf{A}\vdash_{\mathcal{C}} \mathbf{B}$, we also have $\mathbf{A}\models\mathbf{B}$. \triangleright Definition 10.1.17. Completeness: whenever $\mathbf{A} \models \mathbf{B}$, we also have $\mathbf{A} \vdash_{\mathcal{C}} \mathbf{B}$. Fau Michael Kohlhase: Artificial Intelligence 1 319 2025-02-06

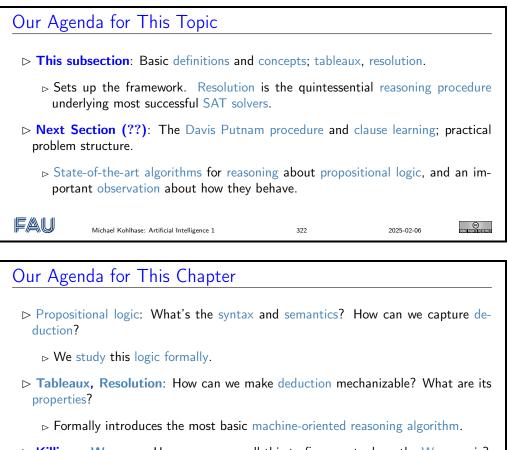
General	Problem Solving <mark>using</mark> L	ogic		
	Any problem that can be form helf reasoning tool.	ulated as reason	ning about logic.	ightarrow use
-	ccessful using propositional logic ility testing; ??)	and modern SA	T solvers! (Propc	ositional
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Propositional Logic and Its Applications

- \triangleright Propositional logic = canonical form of knowledge + reasoning.
 - \triangleright Syntax: Atomic propositions that can be either true or false, connected by "and, or, and not".
 - ▷ Semantics: Assign value to every proposition, evaluate connectives.
- > Applications: Despite its simplicity, widely applied!



10.1.3 Propositional Logic: Agenda



▷ Killing a Wumpus: How can we use all this to figure out where the Wumpus is?

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▷ Coming back to our introductory example.

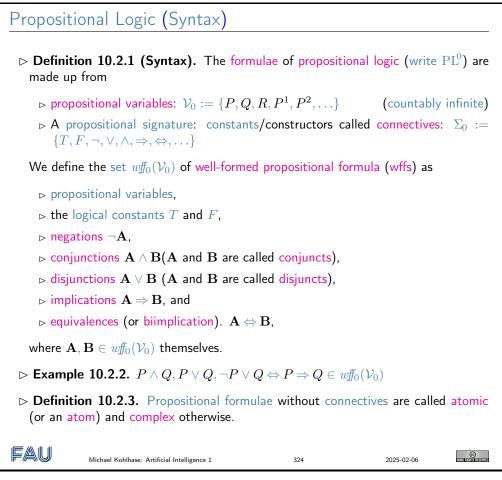
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10.2 Propositional Logic (Syntax/Semantics)

Video Nuggets covering this section can be found at https://fau.tv/clip/id/22457 and https://fau.tv/clip/id/22458.

We will now develop the formal theory behind the ideas previewed in the last section and use that as a prototype for the theory of the more expressive logical systems still to come in AI-1. As PL^0 is a very simple logical system, we could cut some corners in the exposition but we will stick closer to a generalizable theory.



We can also express the formal language introduced by ?? as a context-free grammar.

Proposit	ional Logic Gra	amm	nar (Overview		
⊳ Gramm	nar for Proposition	al Lo	gic:			
	positional variables positional formulae			$\mathcal{V}_{0} = \{P, Q, R, \dots, \dots\}$ X $T F$ $\neg A$ $A_{1} \land A_{2}$ $A_{1} \lor A_{2}$ $A_{1} \Rightarrow A_{2}$ $A_{1} \Leftrightarrow A_{2}$	variable variable truth val negation conjunct disjunct implicat equivale	lues 1 tion ion ion
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Propositional logic is a very old and widely used logical system. So it should not be surprising that there are other notations for the connectives than the ones we are using in AI-1. We list the

<u>Alternati</u>	ve Notations for	Connec	tives			
	Here	Elsewhe	re			
	$\neg \mathbf{A}$	$\sim \mathbf{A} \overline{\mathbf{A}}$	_		-	
	$\mathbf{A}\wedge \mathbf{B}$	$\mathbf{A} \& \mathbf{B}$	A • B	\mathbf{A}, \mathbf{B}		
	$\mathbf{A} \lor \mathbf{B}$	$\mathbf{A} + \mathbf{B}$	$\mathbf{A} \mid \mathbf{B}$	$\mathbf{A};\mathbf{B}$		
	$\mathbf{A} \Rightarrow \mathbf{B}$	$\mathbf{A} \to \mathbf{B}$	$\mathbf{A} \supset \mathbf{B}$			
	$\mathbf{A} \Leftrightarrow \mathbf{B}$	$\mathbf{A}\leftrightarrow \mathbf{B}$	$\mathbf{A}\equiv\mathbf{B}$			
	F	\perp 0				
	T	\top 1				
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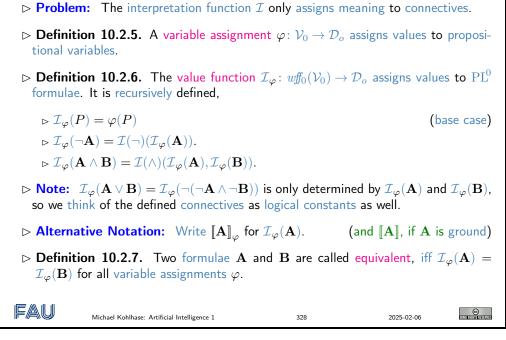
most important ones here for completeness.

These notations will not be used in AI-1, but sometimes appear in the literature. The semantics of PL^0 is defined relative to a model, which consists of a universe of discourse and an interpretation function that we specify now.

Semantics of PL^0 (Models)
▷ Warning: For the official semantics of PL ⁰ we will separate the tasks of giving meaning to connectives and propositional variables to different mappings.
\triangleright This will generalize better to other logical systems. (and thus applications)
$ ightarrow$ Definition 10.2.4. A model $\mathcal{M}:=\langle \mathcal{D}_o,\mathcal{I} angle$ for propositional logic consists of
▷ the universe $\mathcal{D}_o = \{T,F\}$ ▷ the interpretation \mathcal{I} that assigns values to essential connectives. ▷ $\mathcal{I}(\neg): \mathcal{D}_o \to \mathcal{D}_o; T \mapsto F, F \mapsto T$ ▷ $\mathcal{I}(\wedge): \mathcal{D}_o \times \mathcal{D}_o \to \mathcal{D}_o; \langle \alpha, \beta \rangle \mapsto T, \text{ iff } \alpha = \beta = T$
We call a constant a logical constant, iff its value is fixed by the interpretation.
$\succ \text{ Treat the other connectives as abbreviations, e.g. } \mathbf{A} \lor \mathbf{B} \widehat{=} \neg (\neg \mathbf{A} \land \neg \mathbf{B}) \text{ and } \mathbf{A} \Rightarrow \mathbf{B} \widehat{=} \neg \mathbf{A} \lor \mathbf{B}, \text{ and } T \widehat{=} P \lor \neg P \qquad \text{(only need to treat } \neg, \land \text{ directly})$
\triangleright Note: PL^0 is a single-model logical system with canonical model $\langle \mathcal{D}_o, \mathcal{I} \rangle$.
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We have a problem in the exposition of the theory here: As PL^0 semantics only has a single, canonical model, we could simplify the exposition by just not mentioning the universe and interpretation function. But we choose to expose both of them in the construction, since other versions of propositional logic – in particular the system PL^{eq} below – that have a choice of models as they use a different distribution of the representation among constants and variables.

Semantics of PL^0 (Evaluation)

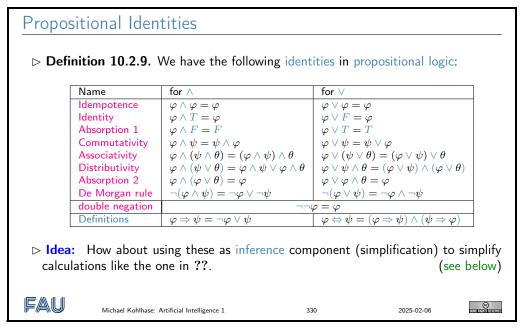


In particular in a interpretation-less exposition of propositional logic would have elided the homomorphic construction of the value function and could have simplified the recursive cases in ?? to $\mathcal{I}_{\varphi}(\mathbf{A} \wedge \mathbf{B}) = \mathsf{T}$, iff $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{T} = \mathcal{I}_{\varphi}(\mathbf{B})$.

But the homomorphic construction via $\mathcal{I}(\wedge)$ is standard to definitions in other logical systems and thus generalizes better.

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Computing Semantics
  \triangleright Example 10.2.8. Let \varphi := [T/P_1], [F/P_2], [T/P_3], [F/P_4], \dots then
                         \mathcal{I}_{\omega}(P_1 \vee P_2 \vee \neg (\neg P_1 \wedge P_2) \vee P_3 \wedge P_4)
                = \mathcal{I}(\vee)(\mathcal{I}_{\varphi}(P_1 \vee P_2), \mathcal{I}_{\varphi}(\neg(\neg P_1 \wedge P_2) \vee P_3 \wedge P_4))
                = \mathcal{I}(\vee)(\mathcal{I}(\vee)(\mathcal{I}_{\varphi}(P_1),\mathcal{I}_{\varphi}(P_2)),\mathcal{I}(\vee)(\mathcal{I}_{\varphi}(\neg(\neg P_1 \land P_2)),\mathcal{I}_{\varphi}(P_3 \land P_4)))
                = \mathcal{I}(\vee)(\mathcal{I}(\vee)(\varphi(P_1),\varphi(P_2)),\mathcal{I}(\vee)(\mathcal{I}(\neg)(\mathcal{I}_{\varphi}(\neg P_1 \land P_2)),\mathcal{I}(\wedge)(\mathcal{I}_{\varphi}(P_3),\mathcal{I}_{\varphi}(P_4))))
                      \mathcal{I}(\vee)(\mathcal{I}(\vee)(\mathsf{T},\mathsf{F}),\mathcal{I}(\vee)(\mathcal{I}(\neg)(\mathcal{I}(\wedge)(\mathcal{I}_{\varphi}(\neg P_{1}),\mathcal{I}_{\varphi}(P_{2}))),\mathcal{I}(\wedge)(\varphi(P_{3}),\varphi(P_{4}))))
                      \mathcal{I}(\vee)(\mathsf{T},\mathcal{I}(\vee)(\mathcal{I}(\neg)(\mathcal{I}(\wedge)(\mathcal{I}(\neg)(\mathcal{I}_{\varphi}(P_{1})),\varphi(P_{2}))),\mathcal{I}(\wedge)(\mathsf{T},\mathsf{F})))
                      \mathcal{I}(\vee)(\mathsf{T},\mathcal{I}(\vee)(\mathcal{I}(\neg)(\mathcal{I}(\wedge)(\mathcal{I}(\neg)(\varphi(P_1)),\mathsf{F})),\mathsf{F})))
                = \mathcal{I}(\vee)(\mathsf{T}, \mathcal{I}(\vee)(\mathcal{I}(\neg)(\mathcal{I}(\wedge)(\mathcal{I}(\neg)(\mathsf{T}), \mathsf{F})), \mathsf{F}))
                = \mathcal{I}(\vee)(\mathsf{T},\mathcal{I}(\vee)(\mathcal{I}(\neg)(\mathcal{I}(\wedge)(\mathsf{F},\mathsf{F})),\mathsf{F}))
                      \mathcal{I}(\vee)(\mathsf{T},\mathcal{I}(\vee)(\mathcal{I}(\neg)(\mathsf{F}),\mathsf{F}))
                = \mathcal{I}(\vee)(\mathsf{T}, \mathcal{I}(\vee)(\mathsf{T}, \mathsf{F}))
                         \mathcal{I}(\vee)(\mathsf{T},\mathsf{T})
                         Т
  \triangleright What a mess!
                                                                                                                                                                                                                   0
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Now we will also review some propositional identities that will be useful later on. Some of them we have already seen, and some are new. All of them can be proven by simple truth table arguments.



We will now use the distribution of values of a propositional formula under all variable assignments to characterize them semantically. The intuition here is that we want to understand theorems, examples, counterexamples, and inconsistencies in mathematics and everyday reasoning¹.

The idea is to use the formal language of propositional formulae as a model for mathematical language. Of course, we cannot express all of mathematics as propositional formulae, but we can at least study the interplay of mathematical statements (which can be true or false) with the copula "and", "or" and "not".

Semantic Properties of Propositional Formulae \triangleright Definition 10.2.10. Let $\mathcal{M} := \langle \mathcal{U}, \mathcal{I} \rangle$ be our model, then we call A \triangleright true under φ (φ satisfies **A**) in \mathcal{M} , iff $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{T}$, (write $\mathcal{M}\models^{\varphi}\mathbf{A}$) (write $\mathcal{M} \not\models^{\varphi} \mathbf{A}$) \triangleright false under φ (φ falsifies **A**) in \mathcal{M} , iff $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{F}$, \triangleright satisfiable in \mathcal{M} , iff $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{T}$ for some assignment φ , \triangleright valid in \mathcal{M} , iff $\mathcal{M} \models^{\varphi} \mathbf{A}$ for all variable assignments φ , \triangleright falsifiable in \mathcal{M} , iff $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{F}$ for some assignments φ , and \triangleright unsatisfiable in \mathcal{M} , iff $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{F}$ for all assignments φ . \triangleright **Example 10.2.11.** $x \lor x$ is satisfiable and falsifiable. \triangleright Example 10.2.12. $x \lor \neg x$ is valid and $x \land \neg x$ is unsatisfiable. \triangleright **Note:** As PL^0 is a single-model logical system, we can elide the reference to the model and regain the notation $\varphi \models \mathbf{A}$ from the preview for $\mathcal{M} \models^{\varphi} \mathbf{A}$. ▷ Definition 10.2.13 (Entailment). (aka. logical consequence) We say that A entails B (write $A \models B$), iff $\mathcal{I}_{\varphi}(B) = T$ for all φ with $\mathcal{I}_{\varphi}(A) = T$ (i.e. all assignments that make A true also make B true)

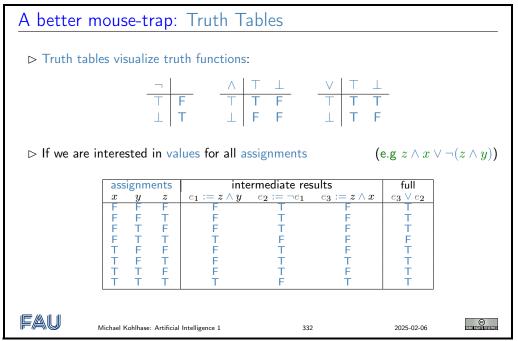
¹Here (and elsewhere) we will use mathematics (and the language of mathematics) as a test tube for understanding reasoning, since mathematics has a long history of studying its own reasoning processes and assumptions.

10.2. PROPOSITIONAL LOGIC (SYNTAX/SEMANTICS)

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Let us now see how these semantic properties model mathematical practice.

In mathematics we are interested in assertions that are true in all circumstances. In our model of mathematics, we use variable assignments to stand for "circumstances". So we are interested in propositional formulae which are true under all variable assignments; we call them valid. We often give examples (or show situations) which make a conjectured formula false; we call such examples counterexamples, and such assertions falsifiable. We also often give examples for certain formulae to show that they can indeed be made true (which is not the same as being valid yet); such assertions we call satisfiable. Finally, if a formula cannot be made true in any circumstances we call it unsatisfiable; such assertions naturally arise in mathematical practice in the form of refutation proofs, where we show that an assertion (usually the negation of the theorem we want to prove) leads to an obviously unsatisfiable conclusion, showing that the negation of the theorem is unsatisfiable, and thus the theorem valid.



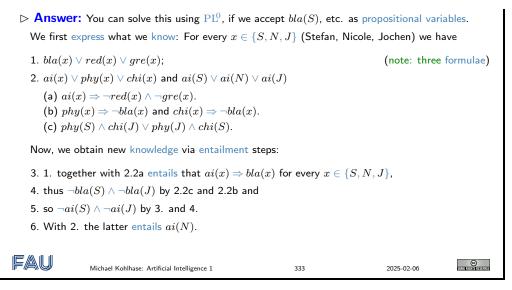
Let us finally test our intuitions about propositional logic with a "real-world example": a logic puzzle, as you could find it in a Sunday edition of the local newspaper.

Hair Color in Propositional Logic
▷ There are three persons, Stefan, Nicole, and Jochen.
1. Their hair colors are black, red, or green.
2. Their study subjects are AI, Physics, or Chinese at least one studies AI.

(a) Persons with red or green hair do not study AI.
(b) Neither the Physics nor the Chinese students have black hair.
(c) Of the two male persons, one studies Physics, and the other studies Chinese.

▷ Question: Who studies AI?

(A) Stefan
(B) Nicole
(C) Jochen
(D) Nobody



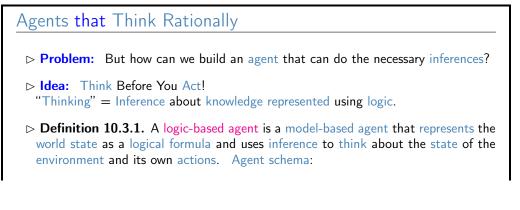
The example shows that puzzles like that are a bit difficult to solve without writing things down. But if we formalize the situation in PL^0 , then we can solve the puzzle quite handily with inference. Note that we have been a bit generous with the names of propositional variables; e.g. bla(x), where $x \in \{S, N, J\}$, to keep the representation small enough to fit on the slide. This does not hinder the method in any way.

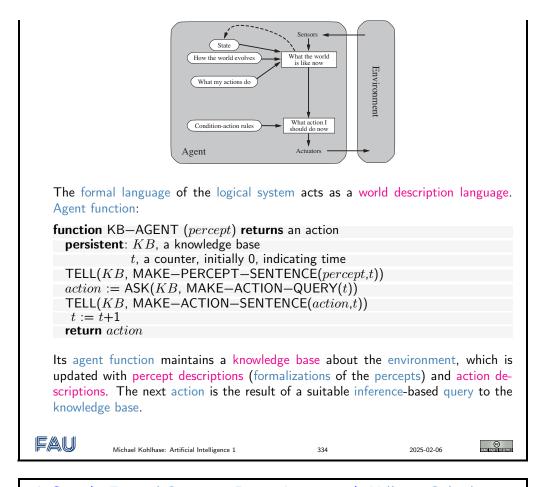
10.3 Inference in Propositional Logics

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We have now defined syntax (the language agents can use to represent knowledge) and its semantics (how expressions of this language relate to agent's environment). Theoretically, an agent could use the entailment relation to derive new knowledge from percepts and the existing state representation – in the MAKE–PERCEPT–SENTENCE and MAKE–ACTION–SENTENCE subroutines below. But as we have seen in above, this is very tedious. A much better way would be to have a set of rules that directly act on the state representations.

Let us now look into what kind of agent we would need to be successful in the Wumpus world: it seems reasonable that we should build on a model-based agent and specialize it to structured state representations and inference.





A Simple Formal System: Prop. Logic with Hilbert-Calculus

 $\triangleright \text{ Formulae: Built from propositional variables: } P, Q, R... \text{ and implication: } \Rightarrow$ $\triangleright \text{ Semantics: } \mathcal{I}_{\varphi}(P) = \varphi(P) \text{ and } \mathcal{I}_{\varphi}(\mathbf{A} \Rightarrow \mathbf{B}) = \mathsf{T}, \text{ iff } \mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{F} \text{ or } \mathcal{I}_{\varphi}(\mathbf{B}) = \mathsf{T}.$ $\triangleright \text{ Definition 10.3.2. The Hilbert calculus } \mathcal{H}^{0} \text{ consists of the inference rules:}$ $\overline{P \Rightarrow Q \Rightarrow P} \text{ K} \qquad \overline{(P \Rightarrow Q \Rightarrow R) \Rightarrow (P \Rightarrow Q) \Rightarrow P \Rightarrow R} \text{ S}$ $\frac{\mathbf{A} \Rightarrow \mathbf{B} \text{ A}}{\mathbf{B}} \text{ MP} \qquad \frac{\mathbf{A}}{[\mathbf{B}/X](\mathbf{A})} \text{ Subst}$ $\triangleright \text{ Example 10.3.3. A } \mathcal{H}^{0} \text{ theorem } \mathbf{C} \Rightarrow \mathbf{C} \text{ and its proof}$ $Proof: \text{ We show that } \emptyset \vdash_{\mathcal{H}^{0}} \mathbf{C} \Rightarrow \mathbf{C}$ $1. (\mathbf{C} \Rightarrow (\mathbf{C} \Rightarrow \mathbf{C}) \Rightarrow \mathbf{C}) \Rightarrow (\mathbf{C} \Rightarrow \mathbf{C} \Rightarrow \mathbf{C}) \Rightarrow \mathbf{C} \Rightarrow \mathbf{C} \qquad (S \text{ with } [\mathbf{C}/P], [\mathbf{C} \Rightarrow \mathbf{C}/Q], [\mathbf{C}/R])$

2. $C \Rightarrow (C \Rightarrow C) \Rightarrow C$ (K with $[C/P], [C \Rightarrow C/Q]$)3. $(C \Rightarrow C \Rightarrow C) \Rightarrow C \Rightarrow C$ (MP on P.1 and P.2)4. $C \Rightarrow C \Rightarrow C$ (K with [C/P], [C/Q])5. $C \Rightarrow C$ (MP on P.3 and P.4)

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This is indeed a very simple formal system, but it has all the required parts:

- A formal language: expressions built up from variables and implications.
- A semantics: given by the obvious interpretation function
- A calculus: given by the two axioms and the two inference rules.

The calculus gives us a set of rules with which we can derive new formulae from old ones. The axioms are very simple rules, they allow us to derive these two formulae in any situation. The proper inference rules are slightly more complicated: we read the formulae above the horizontal line as assumptions and the (single) formula below as the conclusion. An inference rule allows us to derive the conclusion, if we have already derived the assumptions.

Now, we can use these inference rules to perform a proof - a sequence of formulae that can be derived from each other. The representation of the proof in the slide is slightly compactified to fit onto the slide: We will make it more explicit here. We first start out by deriving the formula

$$(P \Rightarrow Q \Rightarrow R) \Rightarrow (P \Rightarrow Q) \Rightarrow P \Rightarrow R \tag{10.1}$$

which we can always do, since we have an axiom for this formula, then we apply the rule Subst, where **A** is this result, **B** is **C**, and X is the variable P to obtain

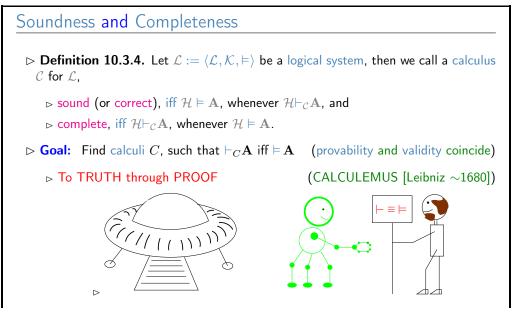
$$(\mathbf{C} \Rightarrow Q \Rightarrow R) \Rightarrow (\mathbf{C} \Rightarrow Q) \Rightarrow \mathbf{C} \Rightarrow R \tag{10.2}$$

Next we apply the rule Subst to this where **B** is $\mathbf{C} \Rightarrow \mathbf{C}$ and X is the variable Q this time to obtain

$$(\mathbf{C} \Rightarrow (\mathbf{C} \Rightarrow \mathbf{C}) \Rightarrow R) \Rightarrow (\mathbf{C} \Rightarrow \mathbf{C} \Rightarrow \mathbf{C}) \Rightarrow \mathbf{C} \Rightarrow R$$
(10.3)

And again, we apply the rule Subst this time, **B** is **C** and X is the variable R yielding the first formula in our proof on the slide. To conserve space, we have combined these three steps into one in the slide. The next steps are done in exactly the same way.

In general, formulae can be used to represent facts about the world as propositions; they have a semantics that is a mapping of formulae into the real world (propositions are mapped to truth values.) We have seen two relations on formulae: the entailment relation and the derivation relation. The first one is defined purely in terms of the semantics, the second one is given by a calculus, i.e. purely syntactically. Is there any relation between these relations?



10.4. PROPOSITIONAL NATURAL DEDUCTION CALCULUS

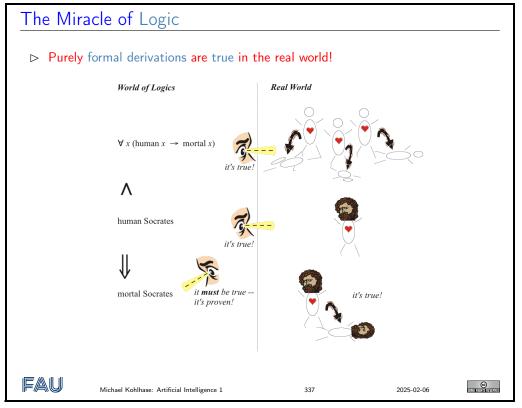
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Ideally, both relations would be the same, then the calculus would allow us to infer all facts that can be represented in the given formal language and that are true in the real world, and only those. In other words, our representation and inference is faithful to the world.

A consequence of this is that we can rely on purely syntactical means to make predictions about the world. Computers rely on formal representations of the world; if we want to solve a problem on our computer, we first represent it in the computer (as data structures, which can be seen as a formal language) and do syntactic manipulations on these structures (a form of calculus). Now, if the provability relation induced by the calculus and the validity relation coincide (this will be quite difficult to establish in general), then the solutions of the program will be correct, and we will find all possible ones. Of course, the logics we have studied so far are very simple, and not able to express interesting facts about the world, but we will study them as a simple example of the fundamental problem of computer science: How do the formal representations correlate with the real world.

Within the world of logics, one can derive new propositions (the *conclusions*, here: *Socrates is mortal*) from given ones (the *premises*, here: *Every human is mortal* and *Sokrates is human*). Such derivations are *proofs*.

In particular, logics can describe the internal structure of real-life facts; e.g. individual things, actions, properties. A famous example, which is in fact as old as it appears, is illustrated in the slide below.



If a formal system is correct, the conclusions one can prove are true (= hold in the real world) whenever the premises are true. This is a miraculous fact (think about it!)

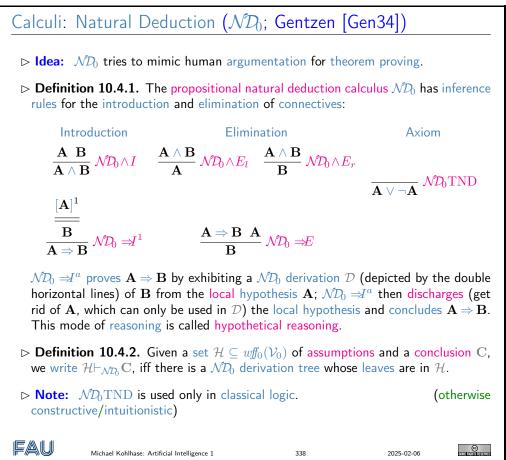
10.4 Propositional Natural Deduction Calculus

Video Nuggets covering this section can be found at https://fau.tv/clip/id/22520 and https://fau.tv/clip/id/22525.

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We will now introduce the "natural deduction" calculus for propositional logic. The calculus was created to model the natural mode of reasoning e.g. in everyday mathematical practice. In particular, it was intended as a counter-approach to the well-known Hilbert style calculi, which were mainly used as theoretical devices for studying reasoning in principle, not for modeling particular reasoning styles. We will introduce natural deduction in two styles/notations, both were invented by Gerhard Gentzen in the 1930's and are very much related. The Natural Deduction style (ND) uses local hypotheses in proofs for hypothetical reasoning, while the "sequent style" is a rationalized version and extension of the ND calculus that makes certain meta-proofs simpler to push through by making the context of local hypotheses explicit in the notation. The sequent notation also constitutes a more adequate data struture for implementations, and user interfaces.

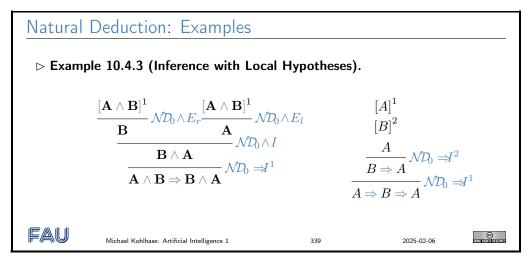
Rather than using a minimal set of inference rules, we introduce a natural deduction calculus that provides two/three inference rules for every logical constant, one "introduction rule" (an inference rule that derives a formula with that logical constant at the head) and one "elimination rule" (an inference rule that acts on a formula with this head and derives a set of subformulae).



The most characteristic rule in the natural deduction calculus is the $\mathcal{ND}_0 \Rightarrow I^a$ rule and the hypothetical reasoning it introduce. $\mathcal{ND}_0 \Rightarrow I^a$ corresponds to the mathematical way of proving an implication $\mathbf{A} \Rightarrow \mathbf{B}$: We assume that \mathbf{A} is true and show \mathbf{B} from this local hypothesis. When we can do this we discharge the assumption and conclude $\mathbf{A} \Rightarrow \mathbf{B}$.

Note that the local hypothesis is discharged by the rule $\mathcal{ND}_0 \Rightarrow I^a$, i.e. it cannot be used in any other part of the proof. As the $\mathcal{ND}_0 \Rightarrow I^a$ rules may be nested, we decorate both the rule and the corresponding local hypothesis with a marker (here the number 1).

Let us now consider an example of hypothetical reasoning in action.

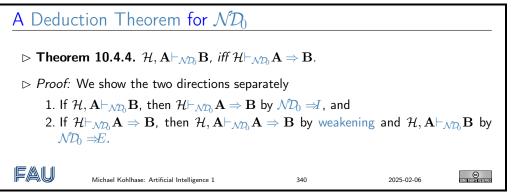


Here we see hypothetical reasoning with local local hypotheses at work. In the left example, we assume the formula $\mathbf{A} \wedge \mathbf{B}$ and can use it in the proof until it is discharged by the rule $\mathcal{ND}_0 \wedge E_l$ on the bottom – therefore we decorate the hypothesis and the rule by corresponding numbers (here the label "1"). Note the local assumption $\mathbf{A} \wedge \mathbf{B}$ is *local to the proof fragment* delineated by the corresponding (local) hypothesis and the discharging rule, i.e. even if this derivation is only a fragment of a larger proof, then we cannot use its (local) hypothesis anywhere else.

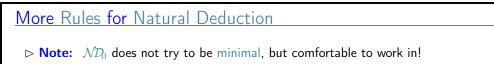
Note also that we can use as many copies of the local hypothesis as we need; they are all discharged at the same time.

In the right example we see that local hypotheses can be nested as long as they are kept local. In particular, we may not use the hypothesis **B** after the $\mathcal{ND}_0 \Rightarrow I^2$, e.g. to continue with a $\mathcal{ND}_0 \Rightarrow E$.

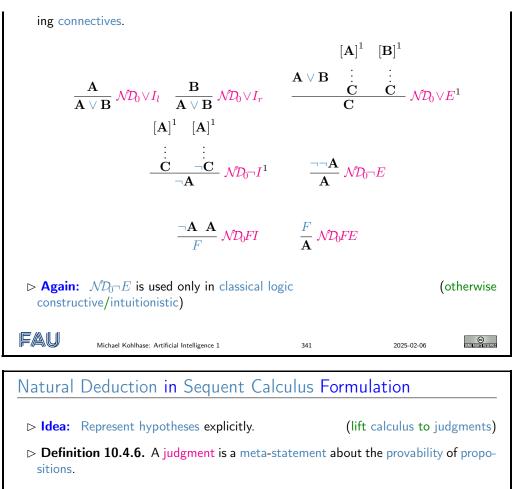
One of the nice things about the natural deduction calculus is that the deduction theorem is almost trivial to prove. In a sense, the triviality of the deduction theorem is the central idea of the calculus and the feature that makes it so natural.



Another characteristic of the natural deduction calculus is that it has inference rules (introduction and elimination rules) for all connectives. So we extend the set of rules from ?? for disjunction, negation and falsity.



 \triangleright Definition 10.4.5. \mathcal{ND}_0 has the following additional inference rules for the remain-



 \triangleright **Definition 10.4.7.** A sequent is a judgment of the form $\mathcal{H}\vdash \mathbf{A}$ about the provability of the formula \mathbf{A} from the set \mathcal{H} of hypotheses. We write $\vdash \mathbf{A}$ for $\emptyset \vdash \mathbf{A}$.

 \triangleright Idea: Reformulate \mathcal{ND}_0 inference rules so that they act on sequents.

▷ **Example 10.4.8**.We give the sequent style version of ??:

$$\frac{\overline{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A} \wedge \mathbf{B}}}{\frac{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{B}}{\mathcal{A} \wedge \mathbf{B} \vdash \mathbf{A} \wedge \mathbf{B}}} \underbrace{\mathcal{ND}_{\vdash}^{0} \wedge \mathbf{E}_{l}}{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A}} \underbrace{\mathcal{ND}_{\vdash}^{0} \wedge E_{l}}{\mathcal{ND}_{\vdash}^{0} \wedge I} = \frac{\overline{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A} \wedge \mathbf{B}}}{\frac{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{B} \wedge \mathbf{A}}{\mathbf{H} \wedge \mathbf{B} \Rightarrow \mathbf{B} \wedge \mathbf{A}}} \underbrace{\mathcal{ND}_{\vdash}^{0} \wedge I}_{\vdash \mathbf{A} \wedge \mathbf{B} \Rightarrow \mathbf{B} \wedge \mathbf{A}} \underbrace{\mathcal{ND}_{\vdash}^{0} \wedge I}_{\vdash \mathbf{A} \Rightarrow \mathbf{B} \Rightarrow \mathbf{A}} \underbrace{\mathcal{ND}_{\vdash}^{0} \Rightarrow I}_{\vdash \mathbf{A} \Rightarrow \mathbf{B} \Rightarrow \mathbf{A}} \underbrace{\mathcal{ND}_{\vdash}^{0} \Rightarrow I}_{\vdash \mathbf{A} \Rightarrow \mathbf{B} \Rightarrow \mathbf{A}}$$

▷ Note: Even though the antecedent of a sequent is written like a sequences, it is actually a set. In particular, we can permute and duplicate members at will.

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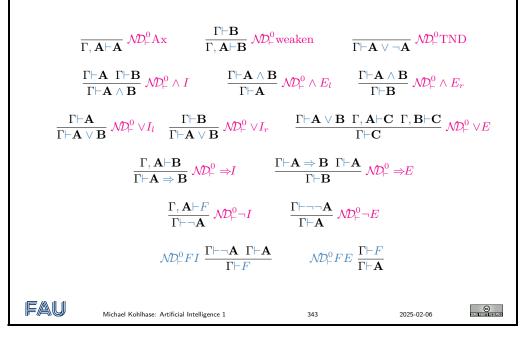
Sequent-Style Rules for Natural Deduction

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 \triangleright **Definition 10.4.9.** The following inference rules make up the propositional sequent style natural deduction calculus \mathcal{ND}^{0}_{-} :

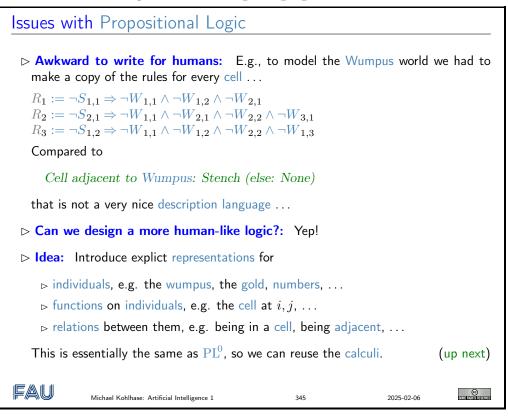


Linearized Notation for (Sequent-Style) ND Proofs ▷ Definition 10.4.10. Linearized notation for sequent-style ND proofs 1. $\mathcal{H}_1 \vdash \mathbf{A}_1 \quad (\mathcal{J}_1)$ 2. $\mathcal{H}_2 \vdash \mathbf{A}_2 \quad (\mathcal{J}_2)$ 3. $\mathcal{H}_3 \vdash \mathbf{A}_3 \quad (\mathcal{J}_3\mathbf{1}, \mathbf{2})$ $\frac{\mathcal{H}_1 \vdash \mathbf{A}_1 \quad \mathcal{H}_2 \vdash \mathbf{A}_2}{\mathcal{H}_3 \vdash \mathbf{A}_3} \mathcal{R}$ corresponds to \triangleright Example 10.4.11. We show a linearized version of the \mathcal{ND}_0 examples ?? $\underbrace{ \frac{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A} \wedge \mathbf{B}}_{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A} \wedge \mathbf{B}} \mathcal{N} \mathcal{D}_{\vdash}^{0} A_{\mathbf{X}}}_{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A} \wedge \mathbf{B}} \mathcal{N} \mathcal{D}_{\vdash}^{0} \wedge E_{l}}_{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A}} \underbrace{\mathcal{N} \mathcal{D}_{\vdash}^{0} \wedge E_{l}}_{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A}} \mathcal{N} \mathcal{D}_{\vdash}^{0} \wedge I}_{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{A}} \mathcal{N} \mathcal{D}_{\vdash}^{0} \wedge I$ $\frac{1}{\mathbf{A},\mathbf{B}\vdash\mathbf{A}}\mathcal{N}\mathcal{D}_{\vdash}^{0}$ $\frac{\mathbf{A} \wedge \mathbf{B} \vdash \mathbf{B} \wedge \mathbf{A}}{\vdash \mathbf{A} \wedge \mathbf{B} \Rightarrow \mathbf{B} \wedge \mathbf{A}} \mathcal{N} \mathcal{D}^0_{\vdash} \Rightarrow I$ $\begin{array}{rrrr} hyp & \vdash & formula \\ 1 & \vdash & \mathbf{A} \land \mathbf{B} \end{array}$ 1. $\vdash \mathbf{B}$ 2. 1 $\vdash \mathbf{A}$ 3. 1 \mathcal{ND}^{0}_{L} weaken 1,2 4. 1 $\vdash \mathbf{B} \wedge \mathbf{A}$ FAU Michael Kohlhase: Artificial Intelligence 1 344 2025-02-06

Each row in the table represents one inference step in the proof. It consists of line number (for referencing), a formula for the statement, a justification via a ND inference rule (and the rows this one is derived from), and finally a sequence of row numbers of proof steps that are local hypotheses in effect for the current row.

10.5 Predicate Logic Without Quantifiers

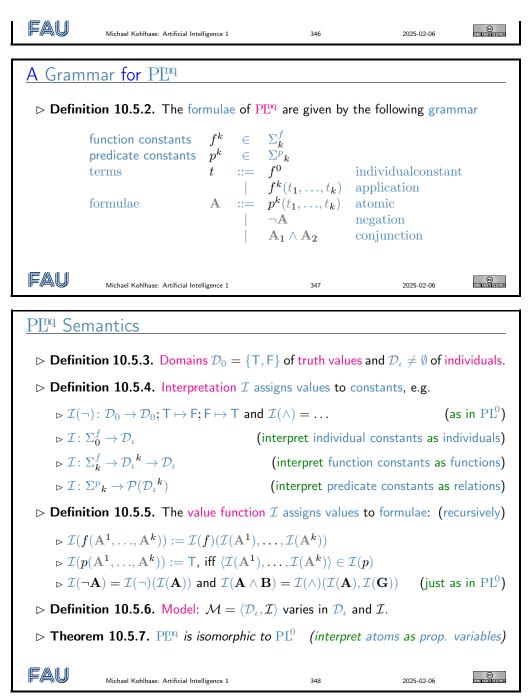
In the hair-color example we have seen that we are able to model complex situations in PL⁰. The trick of using variables with fancy names like bla(N) is a bit dubious, and we can already imagine that it will be difficult to support programmatically unless we make names like bla(N) into first-class citizens i.e. expressions of the logic language themselves.



Individuals and their Properties/Relationships

- Observation: We want to talk about individuals like Stefan, Nicole, and Jochen and their properties, e.g. being blond, or studying Al and relationships, e.g. that Stefan loves Nicole.
- Idea: Re-use PL⁰, but replace propositional variables with something more expressive! (instead of fancy variable name trick)
- \triangleright Definition 10.5.1. A first-order signature $\langle \Sigma^f, \Sigma^p \rangle$ consists of
 - $\succ \Sigma^f := \bigcup_{k \in \mathbb{N}} \Sigma^f_k$ of function constants, where members of Σ^f_k denote k-ary functions on individuals,
 - $\triangleright \Sigma^p := \bigcup_{k \in \mathbb{N}} \Sigma^p{}_k \text{ of predicate constants, where members of } \Sigma^p{}_k \text{ denote } k\text{-ary relations among individuals,}$

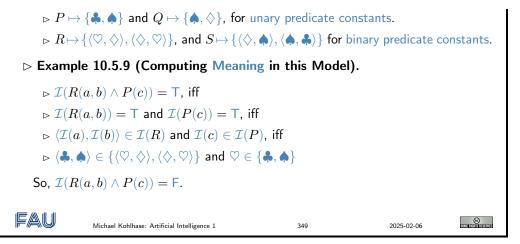
where Σ_k^f and Σ_k^p are pairwise disjoint, countable sets of symbols for each $k \in \mathbb{N}$. A 0-ary function constant refers to a single individual, therefore we call it a individual constant.



All of the definitions above are quite abstract, we now look at them again using a very concrete – if somewhat contrived – example: The relevant parts are a universe \mathcal{D} with four elements, and an interpretation that maps the signature into individuals, functions, and predicates over \mathcal{D} , which are given as concrete sets.

<u>A Model for PLnq</u>

- \triangleright **Example 10.5.8.** Let $L := \{a, b, c, d, e, P, Q, R, S\}$, we set the universe $\mathcal{D} := \{\clubsuit, \diamondsuit, \heartsuit, \diamondsuit\}$, and specify the interpretation function \mathcal{I} by setting
 - $\triangleright a \mapsto \clubsuit, b \mapsto \blacklozenge, c \mapsto \heartsuit, d \mapsto \diamondsuit$, and $e \mapsto \diamondsuit$ for constants,



The example above also shows how we can compute of meaning by in a concrete model: we just follow the evaluation rules to the letter.

We now come to the central technical result about PE^{q} : it is essentially the same as propositional logic (PL⁰). We say that the two logic are isomorphic. Technically, this means that the formulae of PE^{q} can be translated to PL^{0} and there is a corresponding model translation from the models of PL^{0} to those of PE^{q} such that the respective notions of evaluation are assigned to each other.

 PL^{nq} and PL^{0} are Isomorphic \triangleright **Observation:** For every choice of Σ of signature, the set \mathcal{A}_{Σ} of atomic $\mathbb{P}\mathbb{P}^{q}$ formulae is countable, so there is a $\mathcal{V}_{\Sigma} \subseteq \mathcal{V}_0$ and a bijection $\theta_{\Sigma} \colon \mathcal{A}_{\Sigma} \to \mathcal{V}_{\Sigma}$. θ_{Σ} can be extended to formulae as PI^{nq} and PL^{0} share connectives. \triangleright Lemma 10.5.10. For every model $\mathcal{M} = \langle \mathcal{D}_{\iota}, \mathcal{I} \rangle$, there is a variable assignment $\varphi_{\mathcal{M}}$, such that $\mathcal{I}_{\varphi_{\mathcal{M}}}(\mathbf{A}) = \mathcal{I}(\mathbf{A})$. \triangleright *Proof sketch:* We just define $\varphi_{\mathcal{M}}(X) := \mathcal{I}(\theta_{\Sigma}^{-1}(X))$ \triangleright Lemma 10.5.11. For every variable assignment $\psi \colon \mathcal{V}_{\Sigma} \to \{\mathsf{T},\mathsf{F}\}$ there is a model $\mathcal{M}^{\psi} = \langle \mathcal{D}^{\psi}, \mathcal{I}^{\psi} \rangle$, such that $\mathcal{I}_{\psi}(\mathbf{A}) = \mathcal{I}^{\psi}(\mathbf{A})$. > Proof sketch: see next slide \triangleright Corollary 10.5.12. PEq is isomorphic to PL⁰, i.e. the following diagram commutes: ▷ **Note:** This constellation with a language isomorphism and a corresponding model isomorphism (in converse direction) is typical for a logic isomorphism. FAU e Michael Kohlhase: Artificial Intelligence 1 2025-02-06 350

The practical upshot of the commutative diagram from ?? is that if we have a way of computing evaluation (or entailment for that matter) in PL⁰, then we can "borrow" it for PL^q by composing it with the language and model translations. In other words, we can reuse calculi and automated

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10.6. CONCLUSION

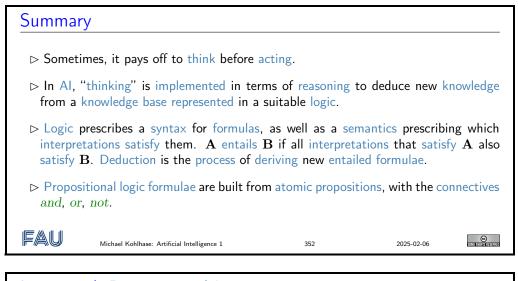
theorem provers from PL^0 for PL^{nq} .

But we still have to provide the proof for ??, which we do now.

Valuation and Satisfiability \triangleright Lemma 10.5.13. For every variable assignment $\psi: \mathcal{V}_{\Sigma} \to \{\mathsf{T},\mathsf{F}\}$ there is a model $\mathcal{M}^{\psi} = \langle \mathcal{D}^{\psi}, \mathcal{I}^{\psi} \rangle$, such that $\mathcal{I}_{\psi}(\mathbf{A}) = \mathcal{I}^{\psi}(\mathbf{A})$. \triangleright *Proof:* We construct $\mathcal{M}^{\psi} = \langle \mathcal{D}^{\psi}, \mathcal{I}^{\psi} \rangle$ and show that it works as desired. 1. Let \mathcal{D}^{ψ} be the set of $\operatorname{PL^{q}}$ terms over Σ , and $\triangleright \mathcal{I}^{\psi}(f): \mathcal{D}_{\iota}^{k} \to \mathcal{D}^{\psi^{k}}; \langle \mathbf{A}_{1}, \dots, \mathbf{A}_{k} \rangle \mapsto f(\mathbf{A}_{1}, \dots, \mathbf{A}_{k}) \text{ for } f \in \Sigma_{k}^{f}$ $\triangleright \ \mathcal{I}^{\psi}(p) := \{ \langle \mathbf{A}_1, \dots, \mathbf{A}_k \rangle \, | \, \psi(\theta_{\psi}^{-1} p(\mathbf{A}_1, \dots, \mathbf{A}_k)) = \mathsf{T} \} \text{ for } p \in \Sigma^p.$ 2. We show $\mathcal{I}^{\psi}(\mathbf{A}) = \mathbf{A}$ for terms \mathbf{A} by induction on \mathbf{A} 2.1. If $\mathbf{A} = c$, then $\mathcal{I}^{\psi}(\mathbf{A}) = \mathcal{I}^{\psi}(c) = c = \mathbf{A}$ 2.2. If $\mathbf{A} = f(\mathbf{A}_1, \dots, \mathbf{A}_n)$ then $\mathcal{I}^{\psi}(\mathbf{A}) = \mathcal{I}^{\psi}(f)(\mathcal{I}(\mathbf{A}_1), \dots, \mathcal{I}(\mathbf{A}_n)) = \mathcal{I}^{\psi}(f)(\mathbf{A}_1, \dots, \mathbf{A}_k) = \mathbf{A}.$ 3. For a PL^{q} formula **A** we show that $\mathcal{I}^{\psi}(\mathbf{A}) = \mathcal{I}_{\psi}(\mathbf{A})$ by induction on **A**. 3.1. If $\mathbf{A} = p(\mathbf{A}_1, \dots, \mathbf{A}_k)$, then $\mathcal{I}^{\psi}(\mathbf{A}) = \mathcal{I}^{\psi}(p)(\mathcal{I}(\mathbf{A}_1), \dots, \mathcal{I}(\mathbf{A}_n)) = \mathsf{T}$, iff $\langle \mathbf{A}_1, \dots, \mathbf{A}_k \rangle \in \mathcal{I}^{\psi}(p)$, iff $\psi(\theta_{\psi}^{-1}\mathbf{A}) = \mathsf{T}$, so $\mathcal{I}^{\psi}(\mathbf{A}) = \mathcal{I}_{\psi}(\mathbf{A})$ as desired. 3.2. If $\mathbf{A} = \neg \mathbf{B}$, then $\mathcal{I}^{\psi}(\mathbf{A}) = \mathsf{T}$, iff $\mathcal{I}^{\psi}(\mathbf{B}) = \mathsf{F}$, iff $\mathcal{I}^{\psi}(\mathbf{B}) = \mathcal{I}_{\psi}(\mathbf{B})$, iff $\mathcal{I}^{\psi}(\mathbf{A}) = \mathcal{I}_{\psi}(\mathbf{A}).$ 3.3. If $\mathbf{A} = \mathbf{B} \wedge \mathbf{C}$ then we argue similarly 4. Hence $\mathcal{I}^{\psi}(\mathbf{A}) = \mathcal{I}_{\psi}(\mathbf{A})$ for all PI^{rq} formulae and we have concluded the proof. Fau Michael Kohlhase: Artificial Intelligence 1 2025-02-06 351

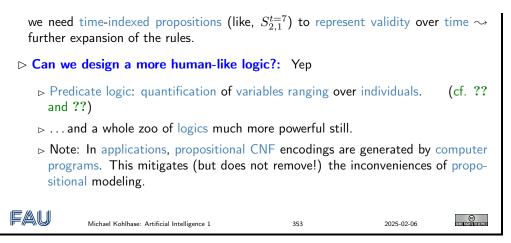
10.6 Conclusion

A Video Nugget covering this section can be found at https://fau.tv/clip/id/25027.



Issues with Propositional Logic

Time: For things that change (e.g., Wumpus moving according to certain rules),



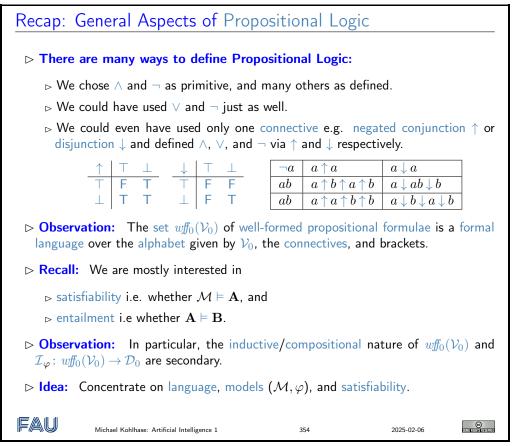
Suggested Reading:

- Chapter 7: Logical Agents, Sections 7.1 7.5 [RN09].
 - Sections 7.1 and 7.2 roughly correspond to my "Introduction", Section 7.3 roughly corresponds to my "Logic (in AI)", Section 7.4 roughly corresponds to my "Propositional Logic", Section 7.5 roughly corresponds to my "Resolution" and "Killing a Wumpus".
 - Overall, the content is quite similar. I have tried to add some additional clarifying illustrations. RN gives many complementary explanations, nice as additional background reading.
 - I would note that RN's presentation of resolution seems a bit awkward, and Section 7.5 contains some additional material that is imbo not interesting (alternate inference rules, forward and backward chaining). Horn clauses and unit resolution (also in Section 7.5), on the other hand, are quite relevant.

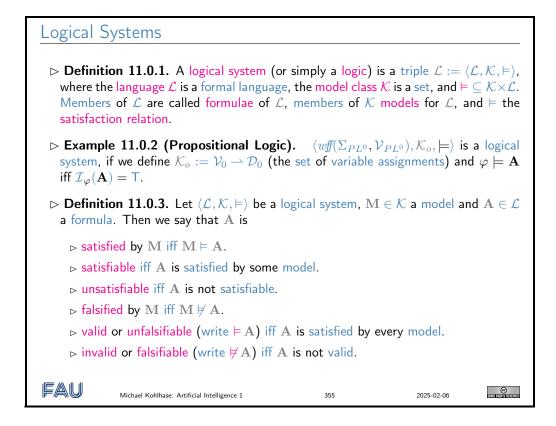
Chapter 11

Formal Systems: Syntax, Semantics, Entailment, and Derivation in General

We will now take a more abstract view and introduce the necessary prerequisites of abstract rule systems. We will also take the opportunity to discuss the quality criteria for calculi.



The notion of a logical system is at the basis of the field of logic. In its most abstract form, a logical system consists of a formal language, a class of models, and a satisfaction relation between models and expressions of the formal language. The satisfaction relation tells us when an expression is deemed true in this model.

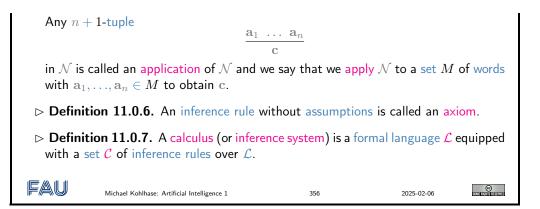


Let us now turn to the syntactical counterpart of the entailment relation: derivability in a calculus. Again, we take care to define the concepts at the general level of logical systems.

The intuition of a calculus is that it provides a set of syntactic rules that allow to reason by considering the form of propositions alone. Such rules are called inference rules, and they can be strung together to derivations — which can alternatively be viewed either as sequences of formulae where all formulae are justified by prior formulae or as trees of inference rule applications. But we can also define a calculus in the more general setting of logical systems as an arbitrary relation on formulae with some general properties. That allows us to abstract away from the homomorphic setup of logics and calculi and concentrate on the basics.

Derivation Relations and Inference Rules $\triangleright \text{ Definition 11.0.4. Let } \mathcal{L} \text{ be a formal language, then we call a relation } \vdash \subseteq \mathcal{P}(\mathcal{L}) \times \mathcal{L} \text{ a derivation relation for } \mathcal{L}, \text{ if}$ $\models \mathcal{H} \vdash \mathbf{A}, \text{ if } \mathbf{A} \in \mathcal{H} (\vdash \text{ is proof reflexive}),$ $\models \mathcal{H} \vdash \mathbf{A} \text{ and } (\mathcal{H}' \cup \{\mathbf{A}\}) \vdash \mathbf{B} \text{ imply } (\mathcal{H} \cup \mathcal{H}') \vdash \mathbf{B} (\vdash \text{ is proof transitive}),$ $\models \mathcal{H} \vdash \mathbf{A} \text{ and } \mathcal{H} \subseteq \mathcal{H}' \text{ imply } \mathcal{H}' \vdash \mathbf{A} (\vdash \text{ is monotonic or admits weakening}).$ $\triangleright \text{ Definition 11.0.5. Let } \mathcal{L} \text{ be a formal language, then an inference rule over } \mathcal{L} \text{ is a decidable } n + 1 \text{ ary relation on } \mathcal{L}. \text{ Inference rules are traditionally written as}$ $\frac{\mathbf{A}_1 \dots \mathbf{A}_n}{\mathbf{C}} \mathcal{N}$ where \mathbf{A}_1 and \mathcal{L} are schemata for words in \mathcal{L} and \mathcal{N} is a name. The \mathbf{A}_1

where A_1, \ldots, A_n and C are schemata for words in \mathcal{L} and \mathcal{N} is a name. The A_i are called assumptions of \mathcal{N} , and C is called its conclusion.



With formula schemata we mean representations of sets of formulae, we use boldface uppercase letters as (meta)-variables for formulae, for instance the formula schema $\mathbf{A} \Rightarrow \mathbf{B}$ represents the set of formulae whose head is \Rightarrow .

Derivations \triangleright **Definition 11.0.8.**Let $\mathcal{L} := \langle \mathcal{L}, \mathcal{K}, \vDash \rangle$ be a logical system and \mathcal{C} a calculus for \mathcal{L} , then a C-derivation of a formula $\mathbf{C} \in \mathcal{L}$ from a set $\mathcal{H} \subseteq \mathcal{L}$ of hypotheses (write $\mathcal{H}\vdash_{\mathcal{C}}\mathbf{C}$) is a sequence A_1, \ldots, A_m of \mathcal{L} -formulae, such that $\triangleright \mathbf{A}_m = \mathbf{C},$ (derivation culminates in C) \triangleright for all $1 \leq i \leq m$, either $\mathbf{A}_i \in \mathcal{H}$, or (hypothesis) $\triangleright \text{ there is an inference rule } \frac{\mathbf{A}_{l_1} \ \ldots \ \mathbf{A}_{l_k}}{\mathbf{A}_i} \text{ in } \mathcal{C} \text{ with } l_j < i \text{ for all } j \leq k.$ (rule application) We can also see a derivation as a derivation tree, where the A_{l_i} are the children of the node A_i . ⊳ Example 11.0.9. In the propositional Hilbert calculus \mathcal{H}^0 we have the derivation $P \vdash_{\mathcal{H}^0} Q \Rightarrow P$: the sequence is $P \Rightarrow Q \Rightarrow \overline{P}$ $P, P, Q \Rightarrow P$ and the corresponding tree on the right. $\overline{Q \Rightarrow P}$ FAU e Michael Kohlhase: Artificial Intelligence 1 357 2025-02-06

Inference rules are relations on formulae represented by formula schemata (where boldface, uppercase letters are used as metavariables for formulae). For instance, in ?? the inference rule $\frac{\mathbf{A} \Rightarrow \mathbf{B} \ \mathbf{A}}{\mathbf{B}}$ was applied in a situation, where the metavariables **A** and **B** were instantiated by the formulae *P* and $Q \Rightarrow P$.

As axioms do not have assumptions, they can be added to a derivation at any time. This is just what we did with the axioms in ??.

Formal Systems

- $\succ \mathsf{Let} \ \langle \mathcal{L}, \mathcal{K}, \vDash \rangle \text{ be a logical system and } \mathcal{C} \text{ a calculus, then } \vdash_{\mathcal{C}} \mathsf{is a derivation relation} \\ \mathsf{and thus} \ \langle \mathcal{L}, \mathcal{K}, \vDash, \vdash_{\mathcal{C}} \rangle \text{ a derivation system.}$
- $\vartriangleright \ \ \, \mathsf{Therefore} \ \ \, \mathsf{we} \ \, \mathsf{will} \ \, \mathsf{sometimes} \ \, \mathsf{also} \ \, \mathsf{call} \ \, \langle \mathcal{L}, \mathcal{C}, \mathcal{K}, \vDash \rangle \ \, \mathsf{a} \ \, \mathsf{formal} \ \, \mathsf{system}, \ \, \mathsf{iff} \ \, \mathcal{L} \ :=$

 $\langle \mathcal{L}, \mathcal{K}, \vDash \rangle$ is a logical system, and \mathcal{C} a calculus for \mathcal{L} .

▷ **Definition 11.0.10.** Let C be a calculus, then a C-derivation $\emptyset \vdash_C \mathbf{A}$ is called a proof of \mathbf{A} and if one exists (write $\vdash_C \mathbf{A}$) then \mathbf{A} is called a C-theorem.

Definition 11.0.11. The act of finding a proof for A is called proving A.

- \triangleright **Definition 11.0.12.** An inference rule \mathcal{I} is called admissible in a calculus C, if the extension of C by \mathcal{I} does not yield new theorems.
- ▷ Definition 11.0.13. An inference rule

$$\frac{\mathbf{A}_1 \ \dots \ \mathbf{A}_n}{\mathbf{C}}$$

is called derivable (or a derived rule) in a calculus C, if there is a C-derivation $A_1, \ldots, A_n \vdash_C C$.

▷ **Observation 11.0.14.** Derivable inference rules are admissible, but not the other way around.

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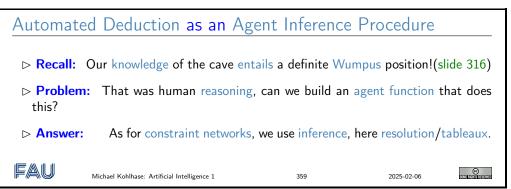
The notion of a formal system encapsulates the most general way we can conceptualize a logical system with a calculus, i.e. a system in which we can do "formal reasoning".

Chapter 12

Machine-Oriented Calculi for Propositional Logic

A Video Nugget covering this chapter can be found at https://fau.tv/clip/id/22531.

12.1 Test Calculi



The following theorem is simple, but will be crucial later on.

Unsatisfiability Theorem

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- $\succ \text{ Theorem 12.1.1 (Unsatisfiability Theorem). } \mathcal{H} \vDash \mathbf{A} \text{ iff } \mathcal{H} \cup \{\neg \mathbf{A}\} \text{ is unsatisfiable.}$
- ▷ *Proof:* We prove both directions separately
 - 1. " \Rightarrow ": Say $\mathcal{H} \models \mathbf{A}$ 1.1. For any φ with $\varphi \models \mathcal{H}$ we have $\varphi \models \mathbf{A}$ and thus $\varphi \not\models (\neg \mathbf{A})$.
 - 2. " \Leftarrow ": Say $\mathcal{H} \cup \{\neg \mathbf{A}\}$ is unsatisfiable.

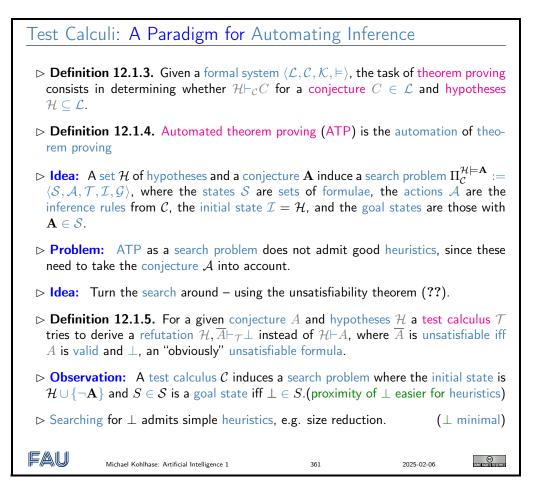
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2.1. For any φ with $\varphi \models \mathcal{H}$ we have $\varphi \not\models (\neg \mathbf{A})$ and thus $\varphi \models \mathbf{A}$.

▷ **Observation 12.1.2.** *Entailment can be tested via satisfiability.*

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12.1.1 Normal Forms

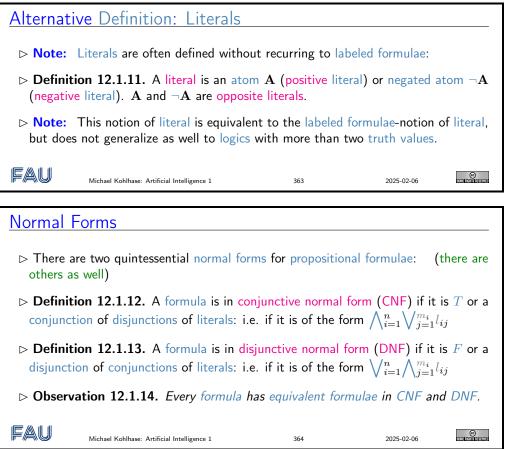
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Before we can start, we will need to recap some nomenclature on formulae.

Recap: Atoms and Literals
Definition 12.1.6. A formula is called atomic (or an atom) if it does not contain logical constants, else it is called complex.
$\triangleright \text{ Definition 12.1.7. Let } \langle \mathcal{L}, \mathcal{K}, \vDash \rangle \text{ be a logical system and } \mathbf{A} \in \mathcal{L}, \text{ then we call a pair } \mathbf{A}^{\alpha} \text{ of a formula and a truth value } \alpha \in \{T,F\} \text{ a labeled formula. For a set } \Phi \text{ of formulae we use } \Phi^{\alpha} := \{\mathbf{A}^{\alpha} \mid \mathbf{A} \in \Phi\}.$
We call a labeled formula \mathbf{A}^{T} positive and \mathbf{A}^{F} negative.
Definition 12.1.8. Let $\langle \mathcal{L}, \mathcal{K}, \vDash \rangle$ be a logical system and \mathbf{A}^{α} a labeled formula. Then we say that $\mathcal{M} \in \mathcal{K}$ satisfies \mathbf{A}^{α} (written $\mathcal{M} \models \mathbf{A}$), iff $\alpha = T$ and $\mathcal{M} \models \mathbf{A}$ or $\alpha = F$ and $\mathcal{M} \not\models \mathbf{A}$.
\triangleright Definition 12.1.9. Let $\langle \mathcal{L}, \mathcal{K}, \vDash \rangle$ be a logical system, $\mathbf{A} \in \mathcal{L}$ atomic, and $\alpha \in \{T,F\}$, then we call a \mathbf{A}^{α} a literal.
\triangleright Intuition: To satisfy a formula, we make it "true". To satisfy a labeled formula \mathbf{A}^{α} , it must have the truth value α .

▷ **Definition 12.1.10.** For a literal \mathbf{A}^{α} , we call the literal \mathbf{A}^{β} with $\alpha \neq \beta$ the opposite literal (or partner literal).

The idea about literals is that they are atoms (the simplest formulae) that carry around their intended truth value.



Video Nuggets covering this chapter can be found at https://fau.tv/clip/id/23705 and https://fau.tv/clip/id/23708.

12.2 Analytical Tableaux

Video Nuggets covering this section can be found at https://fau.tv/clip/id/23705 and https://fau.tv/clip/id/23708.

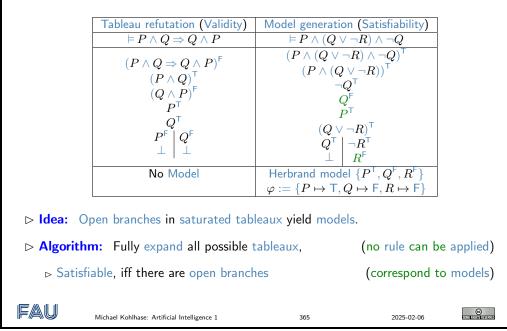
12.2.1 Analytical Tableaux

 Test Calculi: Tableaux and Model Generation

 ▷ Idea: A tableau calculus is a test calculus that

 ▷ analyzes a labeled formulae in a tree to determine satisfiability,

 ▷ its branches correspond to valuations (~> models).



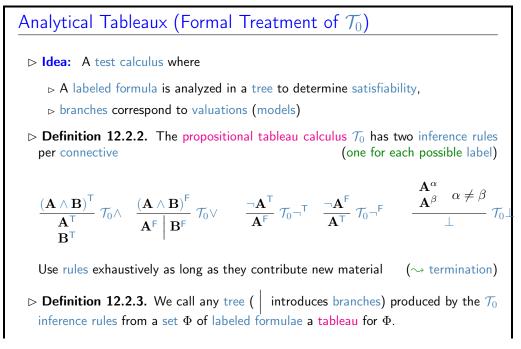
Example 12.2.1. Tableau calculi try to construct models for labeled formulae:

Tableau calculi develop a formula in a tree-shaped arrangement that represents a case analysis on when a formula can be made true (or false). Therefore the formulae are decorated with upper indices that hold the intended truth value.

On the left we have a refutation tableau that analyzes a negated formula (it is decorated with the intended truth value F). Both branches contain an elementary contradiction \perp .

On the right we have a model generation tableau, which analyzes a positive formula (it is decorated with the intended truth value T). This tableau uses the same rules as the refutation tableau, but makes a case analysis of when this formula can be satisfied. In this case we have a closed branch and an open one. The latter corresponds a model.

Now that we have seen the examples, we can write down the tableau rules formally.



12.2. ANALYTICAL TABLEAUX

▷ Definition 12.2.4. Call a tableau saturated, iff no rule adds new material and a branch closed, iff it ends in ⊥, else open. A tableau is closed, iff all of its branches are.

In analogy to the \bot at the end of closed branches, we sometimes decorate open branches with a \Box symbol.

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These inference rules act on tableaux have to be read as follows: if the formulae over the line appear in a tableau branch, then the branch can be extended by the formulae or branches below the line. There are two rules for each primary connective, and a branch closing rule that adds the special symbol \perp (for unsatisfiability) to a branch.

We use the tableau rules with the convention that they are only applied, if they contribute new material to the branch. This ensures termination of the tableau procedure for propositional logic (every rule eliminates one primary connective).

Definition 12.2.5. We will call a closed tableau with the labeled formula \mathbf{A}^{α} at the root a tableau refutation for \mathcal{A}^{α} .

The saturated tableau represents a full case analysis of what is necessary to give \mathbf{A} the truth value α ; since all branches are closed (contain contradictions) this is impossible.

 Analytical Tableaux (\mathcal{T}_0 continued)

 > Definition 12.2.6 (\mathcal{T}_0 -Theorem/Derivability). A is a \mathcal{T}_0 -theorem ($\vdash_{\mathcal{T}_0} A$), iff there is a closed tableau with A^F at the root.

 $\Phi \subseteq wf_0(\mathcal{V}_0)$ derives A in \mathcal{T}_0 ($\Phi \vdash_{\mathcal{T}_0} A$), iff there is a closed tableau starting with A^F and Φ^T . The tableau with only a branch of A^F and Φ^T is called initial for $\Phi \vdash_{\mathcal{T}_0} A$.

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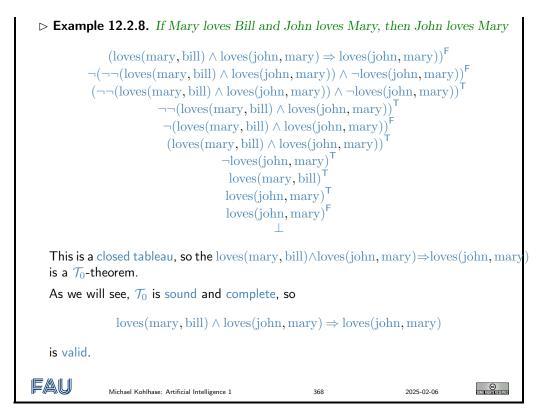
Definition 12.2.7. We will call a tableau refutation for \mathbf{A}^{F} a tableau proof for \mathbf{A} , since it refutes the possibility of finding a model where \mathbf{A} evaluates to F . Thus \mathbf{A} must evaluate to T in all models, which is just our definition of validity.

Thus the tableau procedure can be used as a calculus for propositional logic. In contrast to the propositional Hilbert calculus it does not prove a theorem \mathbf{A} by deriving it from a set of axioms, but it proves it by refuting its negation. Such calculi are called negative or test calculi. Generally negative calculi have computational advantages over positive ones, since they have a built-in sense of direction.

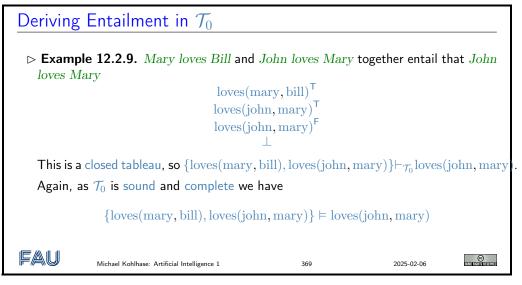
We have rules for all the necessary connectives (we restrict ourselves to \wedge and \neg , since the others can be expressed in terms of these two via the propositional identities above. For instance, we can write $\mathbf{A} \vee \mathbf{B}$ as $\neg(\neg \mathbf{A} \wedge \neg \mathbf{B})$, and $\mathbf{A} \Rightarrow \mathbf{B}$ as $\neg \mathbf{A} \vee \mathbf{B}$,....)

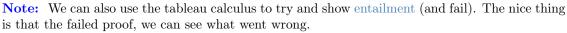
We now look at a formulation of propositional logic with fancy variable names. Note that loves(mary, bill) is just a variable name like P or X, which we have used earlier.

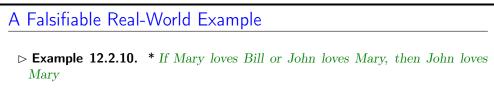
A Valid Real-World Example



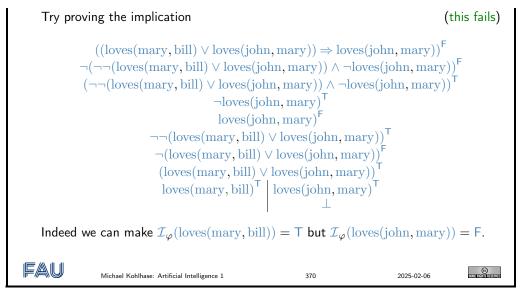
We could have used the unsatisfiability theorem (??) here to show that If Mary loves Bill and John loves Mary entails John loves Mary. But there is a better way to show entailment: we directly use derivability in T_0 .





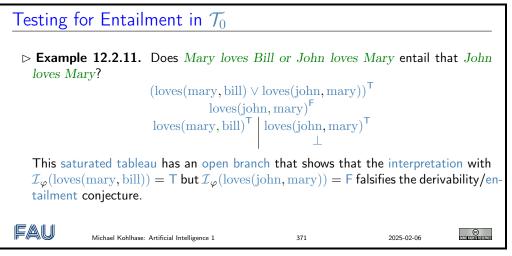


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Obviously, the tableau above is saturated, but not closed, so it is not a tableau proof for our initial entailment conjecture. We have marked the literal on the open branch green, since they allow us to read of the conditions of the situation, in which the entailment fails to hold. As we intuitively argued above, this is the situation, where *Mary loves Bill*. In particular, the open branch gives us a variable assignment (marked in green) that satisfies the initial formula. In this case, *Mary loves Bill*, which is a situation, where the entailment fails.

Again, the derivability version is much simpler:

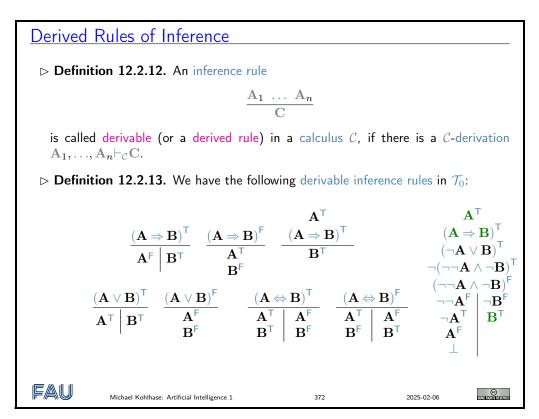


We have seen in the examples above that while it is possible to get by with only the connectives \lor and \neg , it is a bit unnatural and tedious, since we need to eliminate the other connectives first. In this section, we will make the calculus less frugal by adding rules for the other connectives, without losing the advantage of dealing with a small calculus, which is good making statements about the calculus itself.

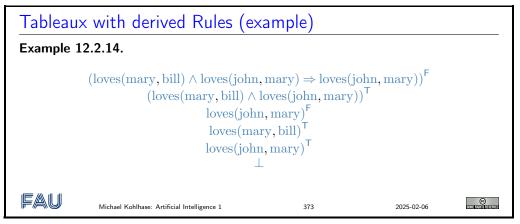
12.2.2 Practical Enhancements for Tableaux

The main idea here is to add the new rules as derivable inference rules, i.e. rules that only abbreviate derivations in the original calculus. Generally, adding derivable inference rules does not change the derivation relation of the calculus, and is therefore a safe thing to do. In particular, we will add the following rules to our tableau calculus.

We will convince ourselves that the first rule is derivable, and leave the other ones as an exercise.



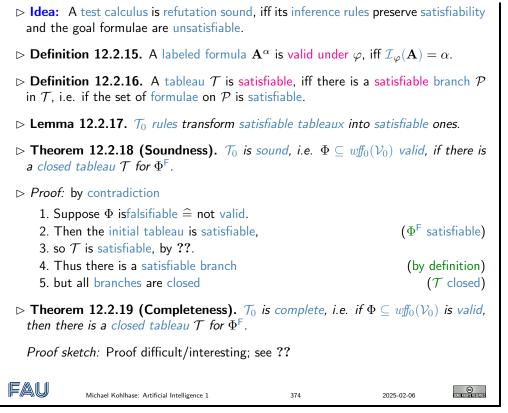
With these derived rules, theorem proving becomes quite efficient. With these rules, the tableau (??) would have the following simpler form:



12.2.3 Soundness and Termination of Tableaux

As always we need to convince ourselves that the calculus is sound, otherwise, tableau proofs do not guarantee validity, which we are after. Since we are now in a refutation setting we cannot just show that the inference rules preserve validity: we care about unsatisfiability (which is the dual notion to validity), as we want to show the initial labeled formula to be unsatisfiable. Before we can do this, we have to ask ourselves, what it means to be (un)-satisfiable for a labeled formula or a tableau.

```
Soundness (Tableau)
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Thus we only have to prove ??, this is relatively easy to do. For instance for the first rule: if we have a tableau that contains $(\mathbf{A} \wedge \mathbf{B})^{\mathsf{T}}$ and is satisfiable, then it must have a satisfiable branch. If $(\mathbf{A} \wedge \mathbf{B})^{\mathsf{T}}$ is not on this branch, the tableau extension will not change satisfiability, so we can assume that it is on the satisfiable branch and thus $\mathcal{I}_{\varphi}(\mathbf{A} \wedge \mathbf{B}) = \mathsf{T}$ for some variable assignment φ . Thus $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{T}$ and $\mathcal{I}_{\varphi}(\mathbf{B}) = \mathsf{T}$, so after the extension (which adds the formulae \mathbf{A}^{T} and \mathbf{B}^{T} to the branch), the branch is still satisfiable. The cases for the other rules are similar.

The next result is a very important one, it shows that there is a procedure (the tableau procedure) that will always terminate and answer the question whether a given propositional formula is valid or not. This is very important, since other logics (like the often-studied first-order logic) does not enjoy this property.

Termination for Tableaux \triangleright Lemma 12.2.20. T_0 terminates, i.e. every T_0 tableau becomes saturated after finitely many rule applications. \triangleright *Proof:* By examining the rules wrt. a measure μ 1. Let us call a labeled formulae \mathbf{A}^{α} worked off in a tableau \mathcal{T} , if a \mathcal{T}_0 rule has already been applied to it. 2. It is easy to see that applying rules to worked off formulae will only add formulae that are already present in its branch. 3. Let $\mu(\mathcal{T})$ be the number of connectives in labeled formulae in \mathcal{T} that are not worked off. 4. Then each rule application to a labeled formula in \mathcal{T} that is not worked off reduces $\mu(\mathcal{T})$ by at least one. (inspect the rules) 5. At some point the tableau only contains worked off formulae and literals. 6. Since there are only finitely many literals in \mathcal{T} , so we can only apply $\mathcal{T}_0 \perp$ a finite number of times.

\triangleright Corollary 12.2.21. \mathcal{T}_0 induces a decision procedure for validity in PL^0 .					
<i>Proof:</i> We combine the results so far					
 ▷ 1. By ?? it is decidable whether ⊢_{T₀}A 2. By soundness (??) and completeness (??), ⊢_{T₀}A iff A is valid. 					
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Note: The proof above only works for the "base \mathcal{T}_0 " because (only) there the rules do not "copy". A rule like

$$\begin{array}{c|c} (\mathbf{A} \Leftrightarrow \mathbf{B})^{\mathsf{T}} \\ \hline \mathbf{A}^{\mathsf{T}} & \mathbf{A}^{\mathsf{F}} \\ \mathbf{B}^{\mathsf{T}} & \mathbf{B}^{\mathsf{F}} \end{array}$$

does, and in particular the number of non-worked-off variables below the line is larger than above the line. For such rules, we would have a more intricate version of μ which – instead of returning a natural number – returns a more complex object; a multiset of numbers. would work here. In our proof we are just assuming that the defined connectives have already eliminated. The tableau calculus basically computes the disjunctive normal form: every branch is a disjunct that is a conjunction of literals. The method relies on the fact that a DNF is unsatisfiable, iff each literal is, i.e. iff each branch contains a contradiction in form of a pair of opposite literals.

12.3 Resolution for Propositional Logic

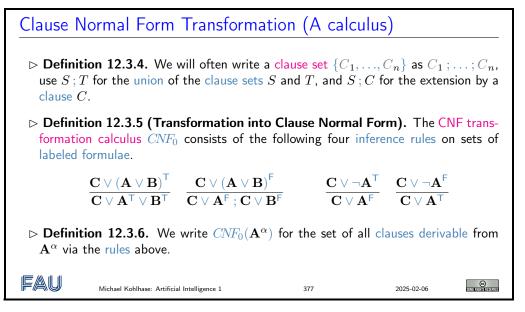
12.3.1 Resolution for Propositional Logic

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A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/23712. The next calculus is a test calculus based on the conjunctive normal form: the resolution calculus. In contrast to the tableau method, it does not compute the normal form as it goes along, but has a pre-processing step that does this and a single inference rule that maintains the normal form. The goal of this calculus is to derive the empty clause, which is unsatisfiable.

Another Test Calculus: Resolution
 Definition 12.3.1. A clause is a disjunction l₁^{α₁} ∨ ... ∨ l_n^{α_n} of literals. We will use
 for the "empty" disjunction (no disjuncts) and call it the empty clause. A clause with exactly one literal is called a unit clause.
 Definition 12.3.2 (Resolution Calculus). The resolution calculus R₀ operates a clause sets via a single inference rule:

$$\frac{P^{T} \lor A}{A \lor B} P^{F} \lor B}{A \lor B} R$$
 This rule allows to add the resolvent (the clause below the line) to a clause set which contains the two clauses above. The literals P^T and P^F are called cut literals.
 Definition 12.3.3 (Resolution Refutation). Let S be a clause set, then we call an R₀-derivation of from S R₀-refutation and write D: S⊢_{R₀}.



that the **C**-terms in the definition of the inference rules are necessary, since we assumed that the assumptions of the inference rule must match full clauses. The **C** terms are used with the convention that they are optional. So that we can also simplify $(\mathbf{A} \vee \mathbf{B})^{\mathsf{T}}$ to $\mathbf{A}^{\mathsf{T}} \vee \mathbf{B}^{\mathsf{T}}$.

Background: The background behind this notation is that **A** and $T \vee \mathbf{A}$ are equivalent for any **A**. That allows us to interpret the **C**-terms in the assumptions as T and thus leave them out.

The clause normal form translation as we have formulated it here is quite frugal; we have left out rules for the connectives \lor , \Rightarrow , and \Leftrightarrow , relying on the fact that formulae containing these connectives can be translated into ones without before CNF transformation. The advantage of having a calculus with few inference rules is that we can prove meta properties like soundness and completeness with less effort (these proofs usually require one case per inference rule). On the other hand, adding specialized inference rules makes proofs shorter and more readable.

Fortunately, there is a way to have your cake and eat it. Derivable inference rules have the property that they are formally redundant, since they do not change the expressive power of the calculus. Therefore we can leave them out when proving meta-properties, but include them when actually using the calculus.

Derived Rules of Inference

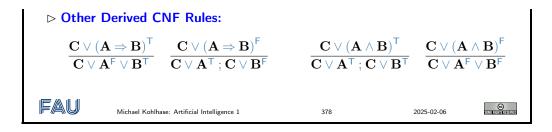
▷ Definition 12.3.7. An inference rule

$$\frac{\mathbf{A}_1 \ \dots \ \mathbf{A}_n}{\mathbf{C}}$$

is called derivable (or a derived rule) in a calculus C, if there is a C-derivation $A_1, \ldots, A_n \vdash_C C$.

▷ Idea: Derived rules make derivations shorter.

$$\triangleright \text{ Example 12.3.8.} \quad \frac{\frac{\mathbf{C} \vee (\mathbf{A} \Rightarrow \mathbf{B})^{\mathsf{T}}}{\mathbf{C} \vee (\neg \mathbf{A} \vee \mathbf{B})^{\mathsf{T}}}}{\frac{\mathbf{C} \vee (\neg \mathbf{A} \vee \mathbf{B})^{\mathsf{T}}}{\mathbf{C} \vee \mathbf{A}^{\mathsf{T}} \vee \mathbf{B}^{\mathsf{T}}}} \quad \rightsquigarrow \quad \frac{\mathbf{C} \vee (\mathbf{A} \Rightarrow \mathbf{B})^{\mathsf{T}}}{\mathbf{C} \vee \mathbf{A}^{\mathsf{F}} \vee \mathbf{B}^{\mathsf{T}}}$$



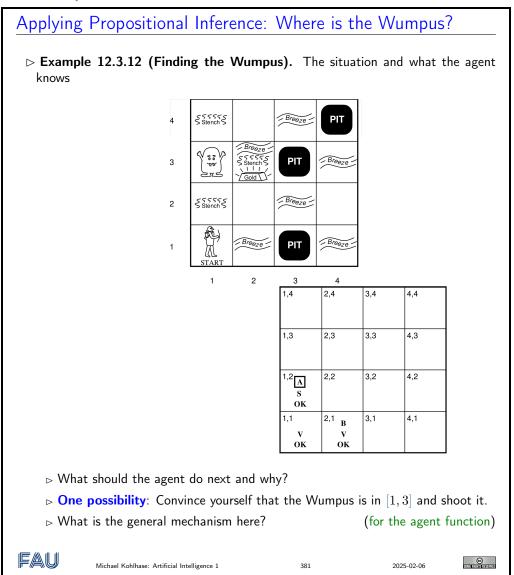
With these derivable rules, theorem proving becomes quite efficient. To get a better understanding of the calculus, we look at an example: we prove an axiom of the Hilbert Calculus we have studied above.

Example: Proving Axiom ${ m S}$ with Resolution						
⊳ Example 12.3.9. Claus	▷ Example 12.3.9. Clause Normal Form transformation					
$ \begin{array}{c} ((P \Rightarrow Q \Rightarrow R) \Rightarrow (P \Rightarrow Q) \Rightarrow P \Rightarrow R)^{F} \\ \hline (P \Rightarrow Q \Rightarrow R)^{T}; ((P \Rightarrow Q) \Rightarrow P \Rightarrow R)^{F} \\ \hline P^{F} \lor (Q \Rightarrow R)^{T}; (P \Rightarrow Q)^{T}; (P \Rightarrow R)^{F} \\ \hline P^{F} \lor Q^{F} \lor R^{T}; P^{F} \lor Q^{T}; P^{T}; R^{F} \end{array} $						
$Result\ \{P^F \lor Q^F \lor R^T,$	$Result \ \{ P^{F} \lor Q^{F} \lor R^{T} \ , \ P^{F} \lor Q^{T} \ , \ P^{T} \ , \ R^{F} \}$					
▷ Example 12.3.10. Reso	olution Proof					
1 2 3 4 5 6 7 8	$\begin{array}{c} P^{F} \lor Q^{F} \lor R^{T} \\ P^{F} \lor Q^{T} \\ P^{T} \\ R^{F} \\ P^{F} \lor Q^{F} \\ Q^{F} \\ P^{F} \\ \Box \end{array}$	initial initial initial resolve 1.3 with 4.1 resolve 5.1 with 3.1 resolve 2.2 with 6.1 resolve 7.1 with 3.1				
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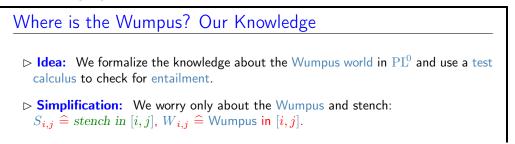
Clause Set Simplification				
\triangleright Observation: Let Δ be a clause set, l a literal with $l \in \Delta$ (unit clause), and Δ' be Δ where				
$ ightarrow$ all clauses $l \lor C$ have been removed and				
\triangleright and all clauses $\overline{l} \lor C$ have been shortened to C .				
Then Δ is satisfiable, iff Δ' is. We call Δ' the clause set simplification of Δ wrt. l .				
\triangleright Corollary 12.3.11. Adding clause set simplification wrt. unit clauses to \mathcal{R}_0 does not affect soundness and completeness.				
▷ This is almost always a good idea! (clause set simplification is cheap)				
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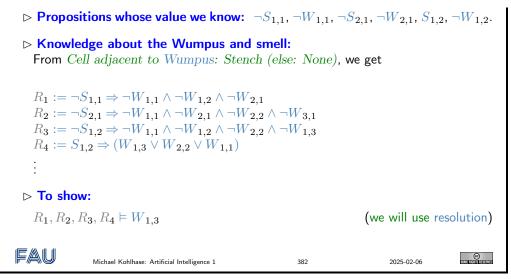
12.3.2 Killing a Wumpus with Propositional Inference

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/23713. Let us now consider an extended example, where we also address the question how inference in PL^0 – here resolution is embedded into the rational agent metaphor we use in AI-1: we come back to the Wumpus world.



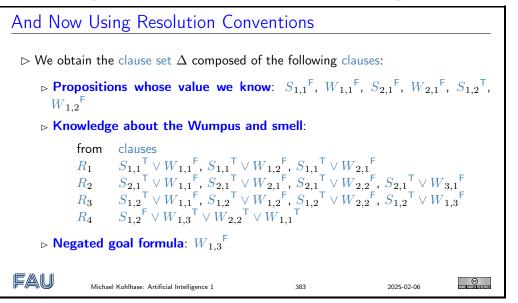
Before we come to the general mechanism, we will go into how we would "convince ourselves that the Wumpus is in [1, 3].





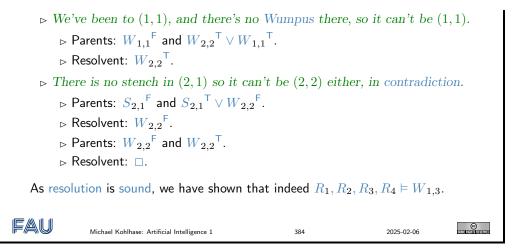
The first in is to compute the clause normal form of the relevant knowledge.

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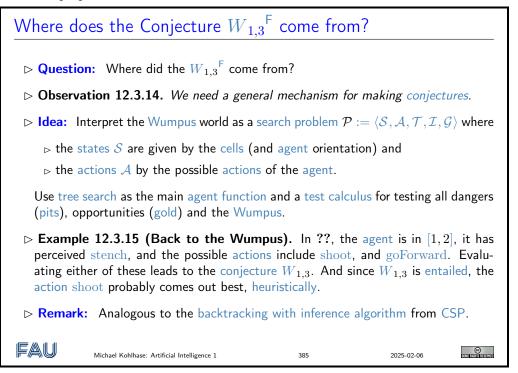


Given this clause normal form, we only need to find generate empty clause via repeated applications of the resolution rule.

Resolution Proof Killing the Wumpus!▷ Example 12.3.13 (Where is the Wumpus). We show a derivation that proves
that he is in (1,3).▷ Assume the Wumpus is not in (1,3). Then either there's no stench in (1,2),
or the Wumpus is in some other neigbor cell of (1,2).
▷ Parents: $W_{1,3}^{\mathsf{F}}$ and $S_{1,2}^{\mathsf{F}} \lor W_{1,3}^{\mathsf{T}} \lor W_{2,2}^{\mathsf{T}} \lor W_{1,1}^{\mathsf{T}}$.
▷ Resolvent: $S_{1,2}^{\mathsf{F}} \lor W_{2,2}^{\mathsf{T}} \lor W_{1,1}^{\mathsf{T}}$.
▷ There's a stench in (1,2), so it must be another neighbor.
▷ Parents: $S_{1,2}^{\mathsf{T}}$ and $S_{1,2}^{\mathsf{F}} \lor W_{2,2}^{\mathsf{T}} \lor W_{1,1}^{\mathsf{T}}$.
▷ Resolvent: $W_{2,2}^{\mathsf{T}} \lor W_{2,2}^{\mathsf{T}} \lor W_{1,1}^{\mathsf{T}}$.



Now that we have seen how we can use propositional inference to derive consequences of the percepts and world knowledge, let us come back to the question of a general mechanism for agent functions with propositional inference.



Admittedly, the search framework from ?? does not quite cover the agent function we have here, since that assumes that the world is fully observable, which the Wumpus world is emphatically not. But it already gives us a good impression of what would be needed for the "general mechanism".

12.4 Conclusion

Summary

▷ Every propositional formula can be brought into conjunctive normal form (CNF), which can be identified with a set of clauses.

 $\succ \text{ The tableau and resolution calculi are deduction procedures based on trying to derive a contradiction from the negated theorem (a closed tableau or the empty clause). They are refutation complete, and can be used to prove <math>\text{KB} \models \mathbf{A}$ by showing that $\text{KB} \cup \{\neg \mathbf{A}\}$ is unsatisfiable.

Excursion: A full analysis of any calculus needs a completeness proof. We will not cover this in AI-1, but provide one for the calculi introduced so far in??.

Chapter 13

Propositional Reasoning: SAT Solvers

13.1 Introduction

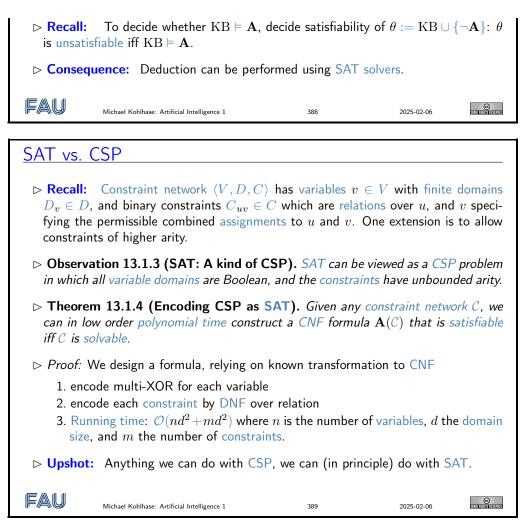
A Video Nugget covering this section can be found at https://fau.tv/clip/id/25019.

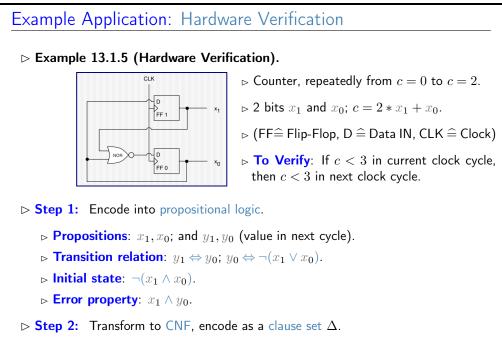
Reminde	r: Our Agenda for Prop	ositional Log	gic	
⊳ ?? : Bas	ic definitions and concepts; mad	chine-oriented cal	culi	
	up the framework. Tableaux and edures underlying most successfi		e quintessential r	easoning
⊳ This ch	apter: The Davis Putnam proc	edure and clause	learning.	
State-of-the-art algorithms for reasoning about propositional logic, and an im- portant observation about how they behave.				
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SAT: The Propositional Satisfiability Problem

- ▷ Definition 13.1.1. The SAT problem (SAT): Given a propositional formula A, decide whether or not A is satisfiable. We denote the class of all SAT problems with SAT
- \triangleright The SAT problem was the first problem proved to be NP-complete!
- \triangleright A is commonly assumed to be in CNF. This is without loss of generality, because any A can be transformed into a satisfiability-equivalent CNF formula (cf. ??) in polynomial time.
- \rhd Active research area, annual SAT conference, lots of tools etc. available: http://www.satlive.org/
- ▷ **Definition 13.1.2.** Tools addressing SAT are commonly referred to as SAT solvers.

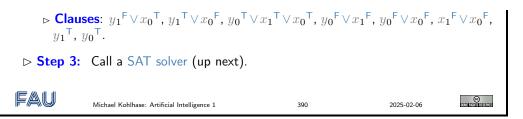
CHAPTER 13. PROPOSITIONAL REASONING: SAT SOLVERS





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13.2. DAVIS-PUTNAM



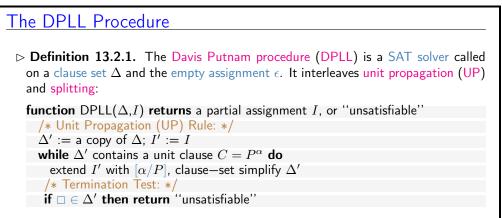
Our Agenda for This Chapter

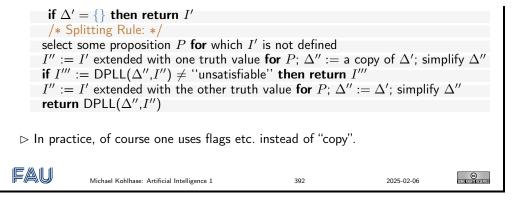
- The Davis-Putnam (Logemann-Loveland) Procedure: How to systematically test satisfiability?
 - ▷ The quintessential SAT solving procedure, DPLL.
- DPLL is (A Restricted Form of) Resolution: How does this relate to what we did in the last chapter?
 - ▷ mathematical understanding of DPLL.
- ▷ Why Did Unit Propagation Yield a Conflict?: How can we analyze which mistakes were made in "dead" search branches?
 - \triangleright Knowledge is power, see next.
- > Clause Learning: How can we learn from our mistakes?
 - \triangleright One of the key concepts, perhaps *the* key concept, underlying the success of SAT.
- ▷ Phase Transitions Where the Really Hard Problems Are: Are all formulas "hard" to solve?
 - \triangleright The answer is "no". And in some cases we can figure out exactly when they are/aren't hard to solve.

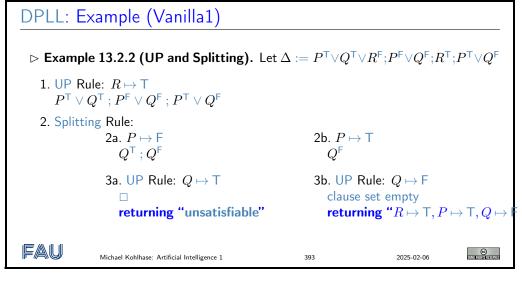
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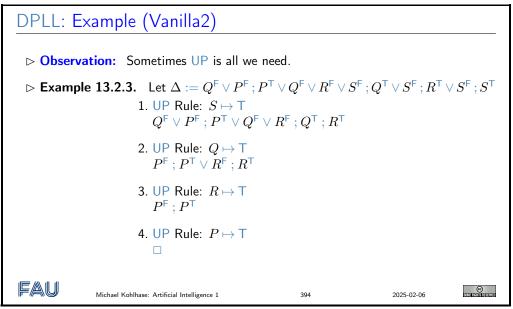
13.2 The Davis-Putnam (Logemann-Loveland) Procedure

A Video Nugget covering this section can be found at https://fau.tv/clip/id/25026.





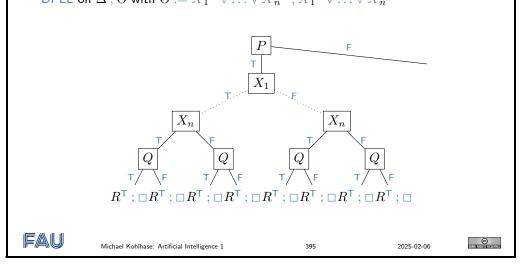




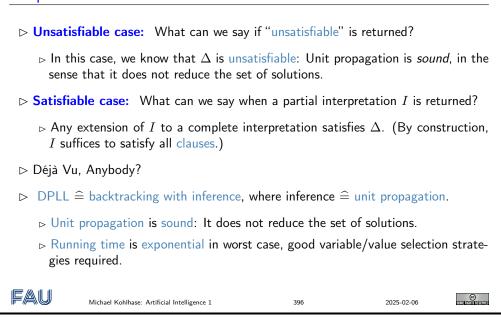
DPLL: Example (Redundance1)

13.3. DPLL $\hat{=}$ (A RESTRICTED FORM OF) RESOLUTION

 $\triangleright \text{ Example 13.2.4. We introduce some nasty redundance to make DPLL slow.} \Delta := P^{\mathsf{F}} \lor Q^{\mathsf{F}} \lor R^{\mathsf{T}} ; P^{\mathsf{F}} \lor Q^{\mathsf{F}} \lor R^{\mathsf{F}} ; P^{\mathsf{F}} \lor Q^{\mathsf{T}} \lor R^{\mathsf{T}} ; P^{\mathsf{F}} \lor Q^{\mathsf{T}} \lor R^{\mathsf{F}} \\ \mathsf{DPLL} \text{ on } \Delta ; \Theta \text{ with } \Theta := X_1^{\mathsf{T}} \lor \ldots \lor X_n^{\mathsf{T}} ; X_1^{\mathsf{F}} \lor \ldots \lor X_n^{\mathsf{F}}$



Properties of DPLL

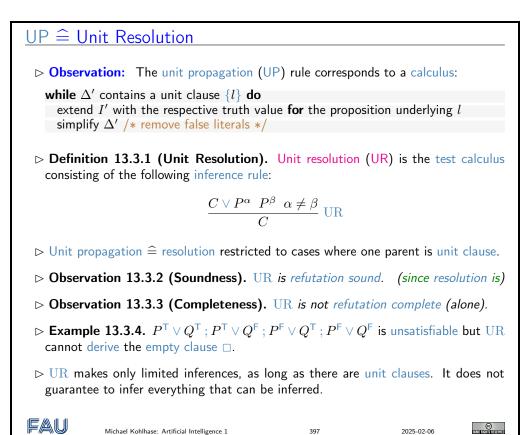


13.3 DPLL $\hat{=}$ (A Restricted Form of) Resolution

A Video Nugget covering this section can be found at https://fau.tv/clip/id/27022.

In the last slide we have discussed the semantic properties of the DPLL procedure: DPLL is (refutation) sound and complete. Note that this is a theoretical result the sense that the algorithm is, but that does not mean that a particular implementation of DPLL might not contain bugs that affect sounds and completeness.

In the satisfiable case, DPLL returns a satisfying variable assignment, which we can check (in low-order polynomial time) but in the unsatisfiable case, it just reports on the fact that it has tried all branches and found nothing. This is clearly unsatisfactory, and we will address this situation now by presenting a way that DPLL can output a resolution proof in the unsatisfiable case.



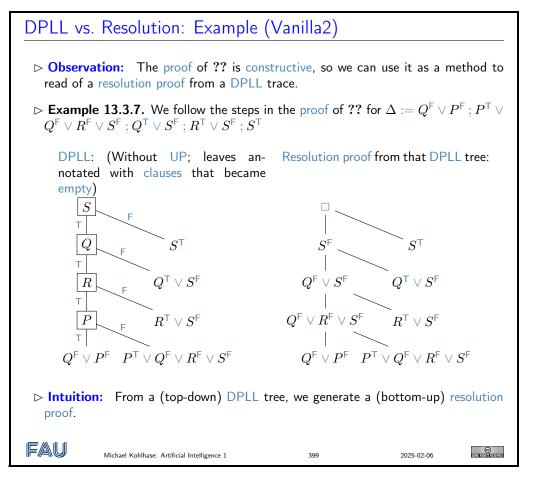
DPLL vs. Resolution

- ▷ Definition 13.3.5. We define the number of decisions of a DPLL run as the total number of times a truth value was set by either unit propagation or splitting.
- \triangleright **Theorem 13.3.6.** If DPLL returns "unsatisfiable" on Δ , then $\Delta \vdash_{\mathcal{R}_0} \Box$ with a resolution proof whose length is at most the number of decisions.
- ▷ Proof: Consider first DPLL without UP
 - 1. Consider any leaf node N, for proposition X, both of whose truth values directly result in a clause C that has become empty.
 - 2. Then for $X = \mathsf{F}$ the respective clause C must contain X^{T} ; and for $X = \mathsf{T}$ the respective clause C must contain X^{F} . Thus we can resolve these two clauses to a clause C(N) that does not contain X.
 - 3. C(N) can contain only the negations of the decision literals l_1, \ldots, l_k above N. Remove N from the tree, then iterate the argument. Once the tree is empty, we have derived the empty clause.
 - 4. Unit propagation can be simulated via applications of the splitting rule, choosing a proposition that is constrained by a unit clause: One of the two truth values then immediately yields an empty clause.

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For reference, we give the full proof here.

Theorem 13.3.8. If DPLL returns "unsatisfiable" on a clause set Δ , then $\Delta \vdash_{\mathcal{R}_0} \Box$ with a \mathcal{R}_0 -derivation whose length is at most the number of decisions.

Proof: Consider first DPLL with no unit propagation.

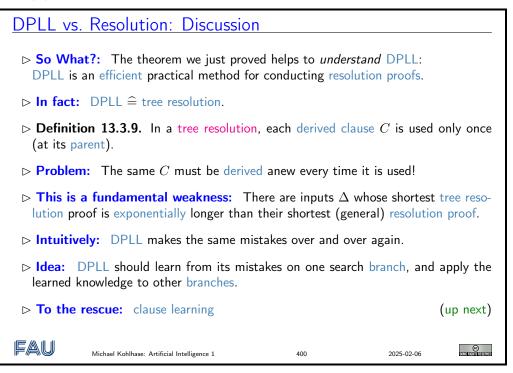
- 1. If the search tree is not empty, then there exists a leaf node N, i.e., a node associated to proposition X so that, for each value of X, the partial assignment directly results in an empty clause.
- 2. Denote the parent decisions of N by L_1, \ldots, L_k , where L_i is a literal for proposition X_i and the search node containing X_i is N_i .
- 3. Denote the empty clause for X by C(N, X), and denote the empty clause for X^{F} by $C(N, X^{\mathsf{F}})$.
- 4. For each $x \in \{X^{\mathsf{T}}, X^{\mathsf{F}}\}$ we have the following properties:
 - 1. $x^{\mathsf{F}} \in C(N, x)$; and
 - 2. $C(N,x) \subseteq \{x^{\mathsf{F}}, \overline{L_1}, \dots, \overline{L_k}\}.$

Due to , we can resolve C(N, X) with $C(N, X^{\mathsf{F}})$; denote the outcome clause by C(N).

- 5. We obviously have that (1) $C(N) \subseteq \{\overline{L_1}, \ldots, \overline{L_k}\}.$
- 6. The proof now proceeds by removing N from the search tree and attaching C(N) at the L_k branch of N_k , in the role of $C(N_k, L_k)$ as above. Then we select the next leaf node N' and iterate the argument; once the tree is empty, by (1) we have derived the empty clause. What we need to show is that, in each step of this iteration, we preserve the properties (a) and (b) for all leaf nodes. Since we did not change anything in other parts of the tree, the only node we need to show this for is $N' := N_k$.
- 7. Due to (1), we have (b) for N_k . But we do not necessarily have (a): $C(N) \subseteq \{\overline{L_1}, \ldots, \overline{L_k}\}$, but there are cases where $\overline{L_k} \notin C(N)$ (e.g., if X_k is not contained in any clause and thus

branching over it was completely unnecessary). If so, however, we can simply remove N_k and all its descendants from the tree as well. We attach C(N) at the $L_{(k-1)}$ branch of $N_{(k-1)}|$, in the role of $C(N_{(k-1)}, L_{(k-1)})$. If $\overline{L_{(k-1)}} \in C(N)$ then we have (a) for $N' := N_{(k-1)}$ and can stop. If $L_{(k-1)} \stackrel{\mathsf{F}}{\notin} C(N)$, then we remove $N_{(k-1)}$ and so forth, until either we stop with (a), or have removed N_1 and thus must already have derived the empty clause (because $C(N) \subseteq \{\overline{L_1}, \ldots, \overline{L_k}\} \setminus \{\overline{L_1}, \ldots, \overline{L_k}\}$).

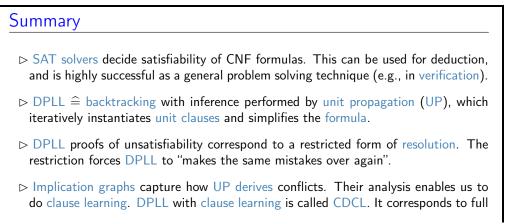
8. Unit propagation can be simulated via applications of the splitting rule, choosing a proposition that is constrained by a unit clause: One of the two truth values then immediately yields an empty clause.



Excursion: Practical SAT solvers use a technique called CDCL that analyzes failure and learns from that in terms of inferred clauses. Unfortunately, we cannot cover this in AI-1.??.

13.4 Conclusion

A Video Nugget covering this section can be found at https://fau.tv/clip/id/25090.

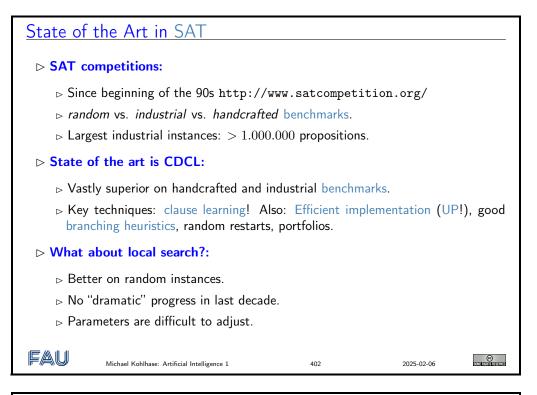


13.4. CONCLUSION

resolution, not "making the same mistakes over again".

- CDCL is state of the art in applications, routinely solving formulas with millions of propositions.
- \rhd In particular random formula distributions, typical problem hardness is characterized by phase transitions.

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But – What About Local Search for SAT?				
> There's a wealth of research on local search for SAT, e.g.:				
▷ Definition 13.4.1. The GSAT algorithm OUTPUT: a satisfying truth assignment of Δ, if found				
function GSAT (Δ , MaxFlips MaxTries				
for $i := 1$ to $MaxTries$				
I := a randomly-generated truth assignment				
for $j := 1$ to $MaxFlips$				
if I satisfies Δ then return I				
X := a proposition reversing whose truth assignment gives				
the largest increase in the number of satisfied clauses				
I := I with the truth assignment of X reversed				
end for				
end for				
return "no satisfying assignment found"				

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CHAPTER 13. PROPOSITIONAL REASONING: SAT SOLVERS

	s not as successful in SAT those presented in ??	applications, and	the underlying (Not cover)	
FAU Micha	el Kohlhase: Artificial Intelligence 1	403	2025-02-06	CO Stime fighting reserved
Topics We D	idn't Cover Here			
⊳ Variable/val	ue selection heuristics: A	whole zoo is out	there.	
•	tion techniques : One of the distribution of the distributication of the distribution of the distribution			ects. Fa-
impact at the	: In space of all truth value time (1992), caused huge ce clause learning hit the se	amount of follow	-up work. Less	-
⊳ Portfolios: ⊢	low to combine several SA	Γ solvers efficient	ly?	
⊳ Random res	t <mark>arts</mark> : Tackling heavy-tailed	d runtime distribu	itions.	
Tractable SAT: Polynomial-time sub-classes (most prominent: 2-SAT, Horn for- mulas).				
	sign weight to each clause rersion of SAT).	e, maximize weigl	nt of satisfied cla	auses (=
	pecial cases : There's a un de off inference vs. search.	niverse in betwee	n unit resolution	and full
polynomially?	lexity : Can one resolution Or is there an exponentia less efficient than Y)?	•		
	el Kohlhase: Artificial Intelligence 1	404	2025-02-06	COME FIGHTIS RESERVED

Suggested Reading:

- Chapter 7: Logical Agents, Section 7.6.1 [RN09].
 - Here, RN describe DPLL, i.e., basically what I cover under "The Davis-Putnam (Logemann-Loveland) Procedure".
 - That's the only thing they cover of this Chapter's material. (And they even mark it as "can be skimmed on first reading".)
 - This does not do the state of the art in SAT any justice.
- Chapter 7: Logical Agents, Sections 7.6.2, 7.6.3, and 7.7 [RN09].
 - Sections 7.6.2 and 7.6.3 say a few words on local search for SAT, which I recommend as additional background reading. Section 7.7 describes in quite some detail how to build an agent using propositional logic to take decisions; nice background reading as well.

Chapter 14

First-Order Predicate Logic

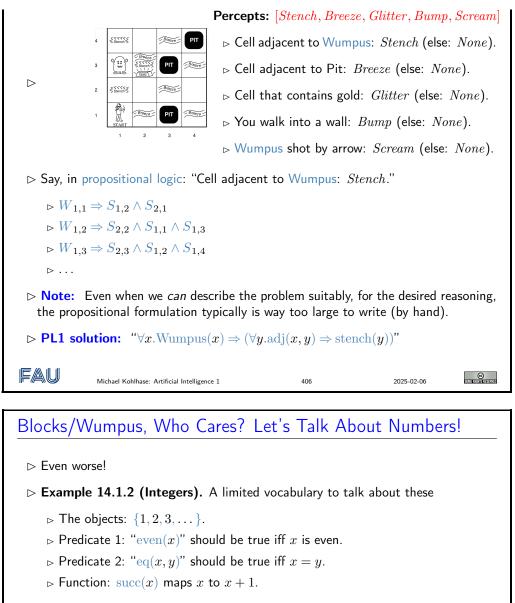
14.1 Motivation: A more Expressive Language

A Video Nugget covering this section can be found at https://fau.tv/clip/id/25091.

Let's Talk About Blocks, Baby
▷ Question: What do you see here?
ADBEC
▷ You say: "All blocks are red"; "All blocks are on the table"; "A is a block".
▷ And now: Say it in propositional logic!
ho Answer: "isRedA", "isRedB",, "onTableA", "onTableB",, "isBlockA",
▷ Wait a sec!: Why don't we just say, e.g., "AllBlocksAreRed" and "isBlockA"?
 Problem: Could we conclude that A is red? (No) These statements are atomic (just strings); their inner structure ("all blocks", "is a block") is not captured.
▷ Idea: Predicate Logic (PL ¹) extends propositional logic with the ability to explicitly speak about objects and their properties.
\triangleright How?: Variables ranging over objects, predicates describing object properties,
$ ightarrow \operatorname{Example 14.1.1.}$ " $\forall x.\operatorname{block}(x) \Rightarrow \operatorname{red}(x)$ "; "block(A)"
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Let's Talk About the Wumpus Instead?

CHAPTER 14. FIRST-ORDER PREDICATE LOGIC



 \triangleright **Old problem:** Say, in propositional logic, that "1 + 1 = 2".

▷ Inner structure of vocabulary is ignored (cf. "AllBlocksAreRed").

```
\triangleright PL1 solution: "eq(succ(1), 2)".
```

 \triangleright **New Problem:** Say, in propositional logic, "if x is even, so is x + 2".

- ▷ It is impossible to speak about infinite sets of objects!
- \triangleright PL1 solution: " $\forall x.even(x) \Rightarrow even(succ(succ(x)))$ ".

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Now We're Talking

14.1. MOTIVATION: A MORE EXPRESSIVE LANGUAGE

⊳ Example 14.1.3.

```
\forall n.gt(n,2) \Rightarrow \neg(\exists a, b, c.eq(plus(pow(a, n), pow(b, n)), pow(c, n)))
```

Read: Forall n > 2, there are no a, b, c, such that $a^n + b^n = c^n$ (Fermat's last theorem)

- ▷ **Theorem proving in PL1:** Arbitrary theorems, in principle.
 - ▷ Fermat's last theorem is of course infeasible, but interesting theorems can and have been proved automatically.
 - ▷ See http://en.wikipedia.org/wiki/Automated_theorem_proving.
 - Note: Need to axiomatize "Plus", "PowerOf", "Equals". See http://en.wikipedia. org/wiki/Peano_axioms

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FAU

What Are the Practical Relevance/Applications?

 \triangleright ... even asking this question is a sacrilege:

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- ▷ (Quotes from Wikipedia)
 - ▷ "In Europe, logic was first developed by Aristotle. Aristotelian logic became widely accepted in science and mathematics."
 - "The development of logic since Frege, Russell, and Wittgenstein had a profound influence on the practice of philosophy and the perceived nature of philosophical problems, and Philosophy of mathematics."
 - ▷ "During the later medieval period, major efforts were made to show that Aristotle's ideas were compatible with Christian faith."
 - ▷ (In other words: the church issued for a long time that Aristotle's ideas were incompatible with Christian faith.)

FAU

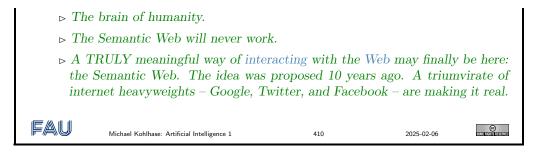
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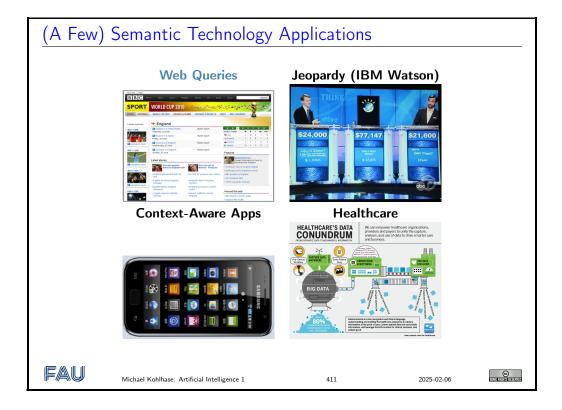
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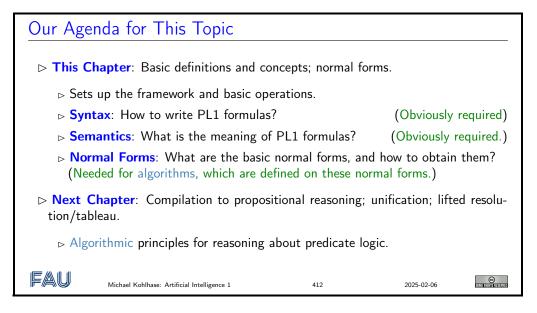
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What Are the Practical Relevance/Applications? You're asking it anyhow: Logic programming. Prolog et al. Databases. Deductive databases where elements of logic allow to conclude additional facts. Logic is tied deeply with database theory. Semantic technology. Mega-trend since > a decade. Use PL1 fragments to annotate data sets, facilitating their use and analysis. Prominent PL1 fragment: Web Ontology Language OWL. Prominent data set: The WWW. (semantic web) Assorted quotes on Semantic Web and OWL:







14.2 First-Order Logic

A Video Nugget covering this section can be found at https://fau.tv/clip/id/25093. First-order logic is the most widely used formal systems for modelling knowledge and inference processes. It strikes a very good bargain in the trade-off between expressivity and conceptual and computational complexity. To many people first-order logic is "the logic", i.e. the only logic worth considering, its applications range from the foundations of mathematics to natural language semantics.

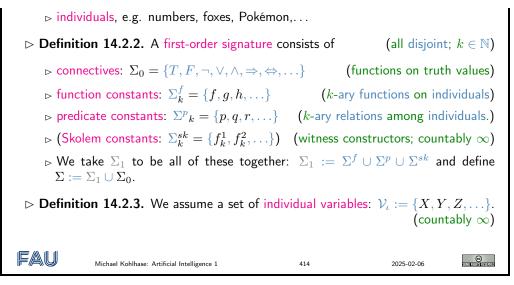
First-Order Predicate Logic (PL^1)				
▷ Coverage: We can talk about	(All humans are mortal)			
▷ individual things and denote them by varial	oles or constants			
▷ properties of individuals,	(e.g. being human or mortal)			
▷ relations of individuals,	(e.g. <i>sibling_of</i> relationship)			
▷ functions on individuals,	(e.g. the <i>father_of</i> function)			
We can also state the existence of an individual with a certain property, or the universality of a property.				
▷ But we cannot state assertions like				
\triangleright There is a surjective function from the natural numbers into the reals.				
First-Order Predicate Logic has many good properties (complete calculi, compactness, unitary, linear unification,)				
\triangleright But too weak for formalizing: (at least directly)				
▷ natural numbers, torsion groups, calculus,				
▷ generalized quantifiers (most, few,)				
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14.2.1 First-Order Logic: Syntax and Semantics

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/25094. The syntax and semantics of first-order logic is systematically organized in two distinct layers: one for truth values (like in propositional logic) and one for individuals (the new, distinctive feature of first-order logic).

The first step of defining a formal language is to specify the alphabet, here the first-order signatures and their components.

PL^1 Syntax (Signature and Variables)				
▷ Definition 14.2.1. First-order logic (PL ¹), is a formal system extensively used in mathematics, philosophy, linguistics, and computer science. It combines propositional logic with the ability to quantify over individuals.				
$\triangleright \ PL^1$ talks about two kinds of objects:	(so we have two kinds of symbols)			
\triangleright truth values by reusing PL^0				



We make the deliberate, but non-standard design choice here to include Skolem constants into the signature from the start. These are used in inference systems to give names to objects and construct witnesses. Other than the fact that they are usually introduced by need, they work exactly like regular constants, which makes the inclusion rather painless. As we can never predict how many Skolem constants we are going to need, we give ourselves countably infinitely many for every arity. Our supply of individual variables is countably infinite for the same reason.

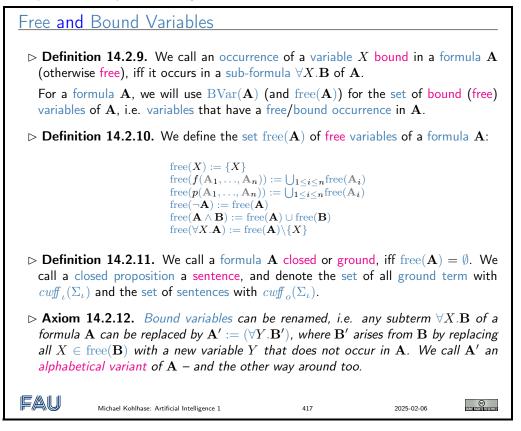
The formulae of first-order logic are built up from the signature and variables as terms (to represent individuals) and proposition (to represent proposition). The latter include the connectives from PL^0 , but also quantifiers.

PL^1 Syntax (Formulae)				
$ ho$ Definition 14.2.4. Terms: $\mathbf{A} \in wf_{\iota}(\Sigma_1, \mathcal{V}_1)$	\mathcal{V}_{ι}) (c	denote individuals)		
$\succ \mathcal{V}_{\iota} \subseteq \textit{wff}_{\iota}(\Sigma_1, \mathcal{V}_{\iota}),$ $\succ \text{ if } f \in \Sigma^f_k \text{ and } \mathbf{A}^i \in \textit{wff}_{\iota}(\Sigma_1, \mathcal{V}_{\iota}) \text{ for } i \leq$	$\leq k$, then $f(\mathbf{A}^1,\ldots,\mathbf{A}^n)$	$(k^{k}) \in wff_{\iota}(\Sigma_{1}, \mathcal{V}_{\iota}).$		
Definition 14.2.5. First-order propositions values)	s: $\mathbf{A} \in wff_o(\Sigma_1, \mathcal{V}_\iota)$:	(denote truth		
$\succ \text{ if } p \in \Sigma^{p}{}_{k} \text{ and } \mathbf{A}^{i} \in wf\!\!f_{\iota}(\Sigma_{1}, \mathcal{V}_{\iota}) \text{ for } i \leq k, \text{ then } p(\mathbf{A}^{1}, \dots, \mathbf{A}^{k}) \in wf\!\!f_{o}(\Sigma_{1}, \mathcal{V}_{\iota}),$ $\succ \text{ if } \mathbf{A}, \mathbf{B} \in wf\!\!f_{o}(\Sigma_{1}, \mathcal{V}_{\iota}) \text{ and } X \in \mathcal{V}_{\iota}, \text{ then } T, \mathbf{A} \wedge \mathbf{B}, \neg \mathbf{A}, \forall X.\mathbf{A} \in wf\!\!f_{o}(\Sigma_{1}, \mathcal{V}_{\iota}).$ $\forall \text{ is a binding operator called the universal quantifier.}$				
▷ Definition 14.2.6. We define the connect $\mathbf{A} \lor \mathbf{B} := \neg (\neg \mathbf{A} \land \neg \mathbf{B}), \ \mathbf{A} \Rightarrow \mathbf{B} := \neg \mathbf{A} \lor \mathbf{B}$ $F := \neg T$. We will use them like the primar	, $\mathbf{A} \Leftrightarrow \mathbf{B} := (\mathbf{A} \Rightarrow \mathbf{B})$	$\wedge ({f B} \Rightarrow {f A})$, and		
▷ Definition 14.2.7. We use $\exists X. \mathbf{A}$ as an abbreviation for $\neg(\forall X. \neg \mathbf{A})$. \exists is a binding operator called the existential quantifier.				
Definition 14.2.8. Call formulae without complex.	connectives or quan	tifiers atomic else		
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cal constants can be defined from them (as we will see when we have fixed their interpretations).

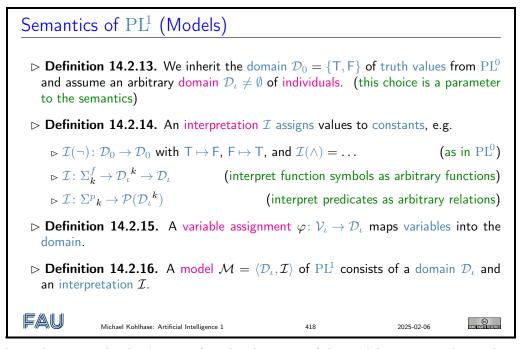
Alternative Notations for Quantifiers					
	Here	Elsewhere			
	$\forall x.\mathbf{A}$	$\bigwedge x.\mathbf{A}$ (x)A			
	$\exists x.\mathbf{A}$	$ \begin{array}{c} \bigwedge x.\mathbf{A} (x)\mathbf{A} \\ \bigvee x.\mathbf{A} \end{array} $			
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The introduction of quantifiers to first-order logic brings a new phenomenon: variables that are under the scope of a quantifiers will behave very differently from the ones that are not. Therefore we build up a vocabulary that distinguishes the two.



We will be mainly interested in (sets of) sentences – i.e. closed propositions – as the representations of meaningful statements about individuals. Indeed, we will see below that free variables do not gives us expressivity, since they behave like constants and could be replaced by them in all situations, except the recursive definition of quantified formulae. Indeed in all situations where variables occur freely, they have the character of metavariables, i.e. syntactic placeholders that can be instantiated with terms when needed in a calculus.

The semantics of first-order logic is a Tarski-style set-theoretic semantics where the atomic syntactic entities are interpreted by mapping them into a well-understood structure, a first-order universe that is just an arbitrary set.



We do not have to make the domain of truth values part of the model, since it is always the same; we determine the model by choosing a domain and an interpretation functiong.

Given a first-order model, we can define the evaluation function as a homomorphism over the construction of formulae.

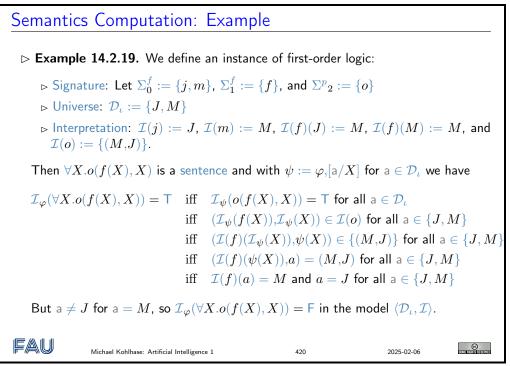
Semantics of PL^1 (Evaluation) \triangleright Definition 14.2.17. Given a model $\langle D, \mathcal{I} \rangle$, the value function \mathcal{I}_{φ} is recursively defined: (two parts: terms & propositions) $\triangleright \mathcal{I}_{\omega} \colon wff_{\iota}(\Sigma_1, \mathcal{V}_{\iota}) \to \mathcal{D}_{\iota}$ assigns values to terms. $\triangleright \mathcal{I}_{\varphi}(X) := \varphi(X)$ and $\triangleright \mathcal{I}_{\varphi}(f(\mathbf{A}_1,\ldots,\mathbf{A}_k)) := \mathcal{I}(f)(\mathcal{I}_{\varphi}(\mathbf{A}_1),\ldots,\mathcal{I}_{\varphi}(\mathbf{A}_k))$ $\triangleright \mathcal{I}_{\varphi} \colon wff_{\rho}(\Sigma_1, \mathcal{V}_{\iota}) \to \mathcal{D}_0$ assigns values to formulae: $\triangleright \mathcal{I}_{\omega}(T) = \mathcal{I}(T) = \mathsf{T},$ $\triangleright \mathcal{I}_{\varphi}(\neg \mathbf{A}) = \mathcal{I}(\neg)(\mathcal{I}_{\varphi}(\mathbf{A}))$ $\triangleright \mathcal{I}_{\varphi}(\mathbf{A} \wedge \mathbf{B}) = \mathcal{I}(\wedge)(\mathcal{I}_{\varphi}(\mathbf{A}), \mathcal{I}_{\varphi}(\mathbf{B}))$ (just as in PL^0) $\triangleright \mathcal{I}_{\varphi}(p(\mathbf{A}_1, \dots, \mathbf{A}_k)) := \mathsf{T}, \text{ iff } \langle \mathcal{I}_{\varphi}(\mathbf{A}_1), \dots, \mathcal{I}_{\varphi}(\mathbf{A}_k) \rangle \in \mathcal{I}(p)$ $\triangleright \mathcal{I}_{\varphi}(\forall X.\mathbf{A}) := \mathsf{T}, \text{ iff } \mathcal{I}_{\varphi,[\mathsf{a}/X]}(\mathbf{A}) = \mathsf{T} \text{ for all } \mathsf{a} \in \mathcal{D}_{\iota}.$ \triangleright Definition 14.2.18 (Assignment Extension). Let φ be a variable assignment into D and $a \in D$, then $\varphi_{\gamma}[a/X]$ is called the extension of φ with [a/X] and is defined as $\{(Y,a) \in \varphi \mid Y \neq X\} \cup \{(X,a)\}$: $\varphi, [a/X]$ coincides with φ off X, and gives the result a there. FAU Michael Kohlhase: Artificial Intelligence 1 419 2025-02-06

The only new (and interesting) case in this definition is the quantifier case, there we define the value of a quantified formula by the value of its scope – but with an extension of the incoming variable assignment. Note that by passing to the scope \mathbf{A} of $\forall x. \mathbf{A}$, the occurrences of the variable x in \mathbf{A} that were bound in $\forall x. \mathbf{A}$ become free and are amenable to evaluation by the variable

14.2. FIRST-ORDER LOGIC

assignment $\psi := \varphi, [a/X]$. Note that as an extension of φ , the assignment ψ supplies exactly the right value for x in **A**. This variability of the variable assignment in the definition of the value function justifies the somewhat complex setup of first-order evaluation, where we have the (static) interpretation function for the symbols from the signature and the (dynamic) variable assignment for the variables.

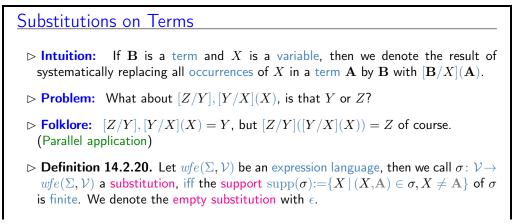
Note furthermore, that the value $\mathcal{I}_{\varphi}(\exists x.\mathbf{A})$ of $\exists x.\mathbf{A}$, which we have defined to be $\neg(\forall x.\neg \mathbf{A})$ is true, iff it is not the case that $\mathcal{I}_{\varphi}(\forall x.\neg \mathbf{A}) = \mathcal{I}_{\psi}(\neg \mathbf{A}) = \mathsf{F}$ for all $a \in \mathcal{D}_{\iota}$ and $\psi := \varphi, [a/X]$. This is the case, iff $\mathcal{I}_{\psi}(\mathbf{A}) = \mathsf{T}$ for some $a \in \mathcal{D}_{\iota}$. So our definition of the existential quantifier yields the appropriate semantics.

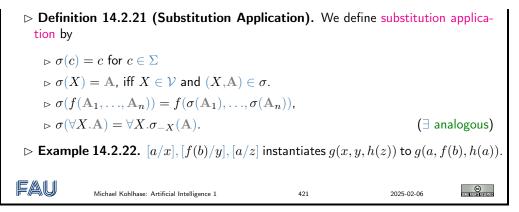


14.2.2 First-Order Substitutions

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/25156. We will now turn our attention to substitutions, special formula-to-formula mappings that

operationalize the intuition that (individual) variables stand for arbitrary terms.





The extension of a substitution is an important operation, which you will run into from time to time. Given a substitution σ , a variable x, and an expression \mathbf{A} , σ , $[\mathbf{A}/x]$ extends σ with a new value for x. The intuition is that the values right of the comma overwrite the pairs in the substitution on the left, which already has a value for x, even though the representation of σ may not show it.

Substitution Extension
Definition 14.2.23 (Substitution Extension). Let σ be a substitution, then we denote the extension of σ with [A/X] by σ,[A/X] and define it as {(Y,B) ∈ σ | Y ≠ X} ∪ {(X,A)}: σ,[A/X] coincides with σ off X, and gives the result A there.
Note: If σ is a substitution, then σ,[A/X] is also a substitution.
We also need the dual operation: removing a variable from the support:
Definition 14.2.24. We can discharge a variable X from a substitution σ by setting σ_{-X}:=σ,[X/X].

Note that the use of the comma notation for substitutions defined in ?? is consistent with substitution extension. We can view a substitution [a/x], [f(b)/y] as the extension of the empty substitution (the identity function on variables) by [f(b)/y] and then by [a/x]. Note furthermore, that substitution extension is not commutative in general.

For first-order substitutions we need to extend the substitutions defined on terms to act on propositions. This is technically more involved, since we have to take care of bound variables.

Substitutions on Propositions \triangleright Problem: We want to extend substitutions to propositions, in particular to quantified formulae: What is $\sigma(\forall X.\mathbf{A})$? \triangleright Idea: σ should not instantiate bound variables. $([\mathbf{A}/X](\forall X.\mathbf{B}) = \forall \mathbf{A}.\mathbf{B}'$ ill-formed) \triangleright Definition 14.2.25. $\sigma(\forall X.\mathbf{A}) := (\forall X.\sigma_{-X}(\mathbf{A})).$ \triangleright Problem: This can lead to variable capture: $[f(X)/Y](\forall X.p(X,Y))$ would evaluate to $\forall X.p(X, f(X))$, where the second occurrence of X is bound after instanti-

ation, whereas it was free before. Solution: Rename away the bound variable Xin $\forall X.p(X,Y)$ before applying the substitution.

 \triangleright Definition 14.2.26 (Capture-Avoiding Substitution Application). Let σ be a substitution, A a formula, and A' an alphabetic variant of A, such that $intro(\sigma) \cap$ $BVar(\mathbf{A}) = \emptyset$. Then we define capture-avoiding substitution application via $\sigma(\mathbf{A}) := \sigma(\mathbf{A}').$ Fau e

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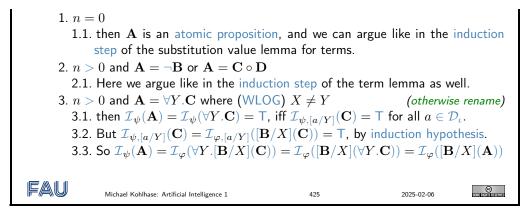
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We now introduce a central tool for reasoning about the semantics of substitutions: the "substitution value Lemma", which relates the process of instantiation to (semantic) evaluation. This result will be the motor of all soundness proofs on axioms and inference rules acting on variables via substitutions. In fact, any logic with variables and substitutions will have (to have) some form of a substitution value Lemma to get the meta-theory going, so it is usually the first target in any development of such a logic. We establish the substitution-value Lemma for first-order logic in two steps, first on terms, where it is very simple, and then on propositions.

Substitution Value Lemma for Terms \triangleright Lemma 14.2.27. Let A and B be terms, then $\mathcal{I}_{\omega}([\mathbf{B}/X]\mathbf{A}) = \mathcal{I}_{\psi}(\mathbf{A})$, where $\psi = \varphi, [\mathcal{I}_{\varphi}(\mathbf{B})/X].$ \triangleright *Proof:* by induction on the depth of **A**: 1. depth=0 Then A is a variable (say Y), or constant, so we have three cases 1.1. A = Y = X1.1.1. then $\mathcal{I}_{\varphi}([\mathbf{B}/X](\mathbf{A})) = \mathcal{I}_{\varphi}([\mathbf{B}/X](X)) = \mathcal{I}_{\varphi}(\mathbf{B}) = \psi(X) = \mathcal{I}_{\psi}(X) = \mathcal{I}_{\psi}(X)$ $\mathcal{I}_{\psi}(\mathbf{A}).$ 1.2. $\mathbf{A} = Y \neq X$ 1.2.1. then $\mathcal{I}_{\varphi}([\mathbf{B}/X](\mathbf{A})) = \mathcal{I}_{\varphi}([\mathbf{B}/X](Y)) = \mathcal{I}_{\varphi}(Y) = \varphi(Y) = \psi(Y) = \psi(Y) = \psi(Y)$ $\mathcal{I}_{\psi}(Y) = \mathcal{I}_{\psi}(\mathbf{A}).$ 1.3. \mathbf{A} is a constant 1.3.1. Analogous to the preceding case $(Y \neq X)$. 1.4. This completes the base case (depth = 0). 2. depth > 02.1. then $\mathbf{A} = f(\mathbf{A}_1, \dots, \mathbf{A}_n)$ and we have $\mathcal{I}_{\varphi}([\mathbf{B}/X](\mathbf{A})) = \mathcal{I}(f)(\mathcal{I}_{\varphi}([\mathbf{B}/X](\mathbf{A}_{1})), \dots, \mathcal{I}_{\varphi}([\mathbf{B}/X](\mathbf{A}_{n})))$ $= \mathcal{I}(f)(\mathcal{I}_{\psi}(\mathbf{A}_1),\ldots,\mathcal{I}_{\psi}(\mathbf{A}_n))$ $= \mathcal{I}_{\psi}(\mathbf{A}).$ by induction hypothesis 2.2. This completes the induction step, and we have proven the assertion. FAU e Michael Kohlhase: Artificial Intelligence 1 424 2025-02-06 Substitution Value Lemma for Propositions

 \triangleright Lemma 14.2.28. $\mathcal{I}_{\varphi}([\mathbf{B}/X](\mathbf{A})) = \mathcal{I}_{\psi}(\mathbf{A})$, where $\psi = \varphi, [\mathcal{I}_{\varphi}(\mathbf{B})/X]$.

 \triangleright *Proof:* by induction on the number *n* of connectives and quantifiers in **A**:



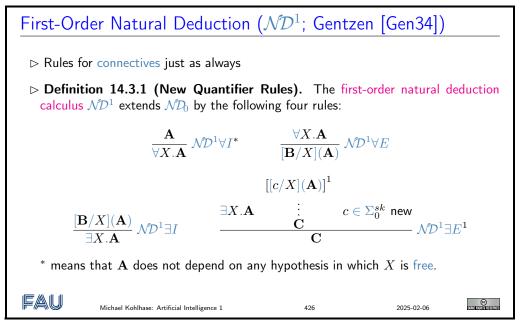
To understand the proof fully, you should think about where the WLOG – it stands for without loss of generality comes from.

14.3 First-Order Natural Deduction

A Video Nugget covering this section can be found at https://fau.tv/clip/id/25157. In this section, we will introduce the first-order natural deduction calculus. Recall from ?? that natural deduction calculus have introduction and elimination for every logical constant (the connectives in PL^0). Recall furthermore that we had two styles/notations for the calculus, the classical ND calculus and the sequent-style notation. These principles will be carried over to natural deduction in PL^1 .

This allows us to introduce the calculi in two stages, first for the (propositional) connectives and then extend this to a calculus for first-order logic by adding rules for the quantifiers. In particular, we can define the first-order calculi simply by adding (introduction and elimination) rules for the (universal and existential) quantifiers to the calculus \mathcal{ND}_0 defined in ??.

To obtain a first-order calculus, we have to extend \mathcal{ND}_0 with (introduction and elimination) rules for the quantifiers.

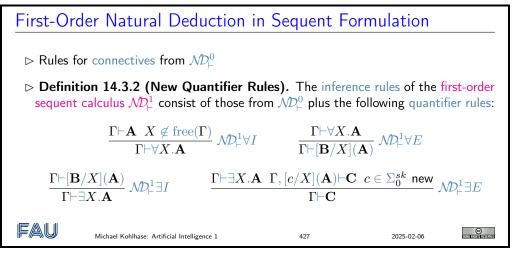


The intuition behind the rule $\mathcal{ND}^1 \forall I$ is that a formula **A** with a (free) variable X can be generalized to $\forall X.\mathbf{A}$, if X stands for an arbitrary object, i.e. there are no restricting assumptions about X. The $\mathcal{ND}^1 \forall E$ rule is just a substitution rule that allows to instantiate arbitrary terms **B** for X

14.3. FIRST-ORDER NATURAL DEDUCTION

in **A**. The $\mathcal{ND}^1 \exists I$ rule says if we have a witness **B** for X in **A** (i.e. a concrete term **B** that makes **A** true), then we can existentially close **A**. The $\mathcal{ND}^1 \exists E$ rule corresponds to the common mathematical practice, where we give objects we know exist a new name c and continue the proof by reasoning about this concrete object c. Anything we can prove from the assumption $[c/X](\mathbf{A})$ we can prove outright if $\exists X.\mathbf{A}$ is known.

Now we reformulate the classical formulation of the calculus of natural deduction as a sequent calculus by lifting it to the "judgments level" as we did for propositional logic. We only need provide new quantifier rules.



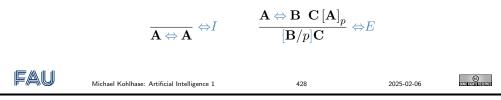
Natural Deduction with Equality

- ▷ Definition 14.3.3 (First-Order Logic with Equality). We extend PL¹ with a new logical constant for equality $= \in \Sigma^p_2$ and fix its interpretation to $\mathcal{I}(=) := \{(x,x) | x \in \mathcal{D}_\iota\}$. We call the extended logic first-order logic with equality (PL¹₌)
- \triangleright We now extend natural deduction as well.
- \triangleright **Definition 14.3.4.** For the calculus of natural deduction with equality $(\mathcal{ND}_{=}^{1})$ we add the following two rules to \mathcal{ND}^{1} to deal with equality:

$$\frac{\mathbf{A} = \mathbf{B} \ \mathbf{C} \left[\mathbf{A}\right]_p}{[\mathbf{B}/p]\mathbf{C}} = E$$

where $\mathbf{C}[\mathbf{A}]_p$ if the formula \mathbf{C} has a subterm \mathbf{A} at position p and $[\mathbf{B}/p]\mathbf{C}$ is the result of replacing that subterm with \mathbf{B} .

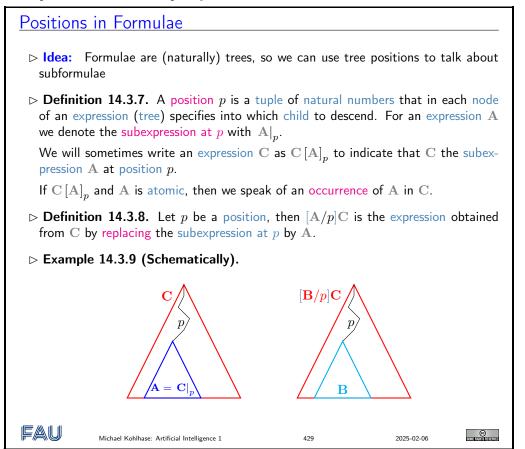
- \rhd In many ways equivalence behaves like equality, we will use the following rules in \mathcal{ND}^1
- \triangleright **Definition 14.3.5.** \Leftrightarrow *I* is derivable and \Leftrightarrow *E* is admissible in \mathcal{ND}^1 :



calculi.

Definition 14.3.6. We have the canonical sequent rules that correspond to them: $=I, =E, \Leftrightarrow I$, and $\Leftrightarrow E$

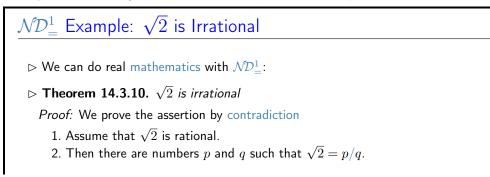
To make sure that we understand the constructions here, let us get back to the "replacement at position" operation used in the equality rules.



The operation of replacing a subformula at position p is quite different from e.g. (first-order) substitutions:

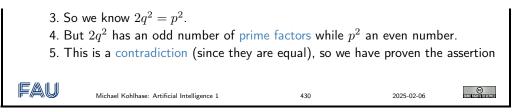
- We are replacing subformulae with subformulae instead of instantiating variables with terms.
- Substitutions replace all occurrences of a variable in a formula, whereas formula replacement only affects the (one) subformula at position p.

We conclude this section with an extended example: the proof of a classical mathematical result in the natural deduction calculus with equality. This shows us that we can derive strong properties about complex situations (here the real numbers; an uncountably infinite set of numbers).

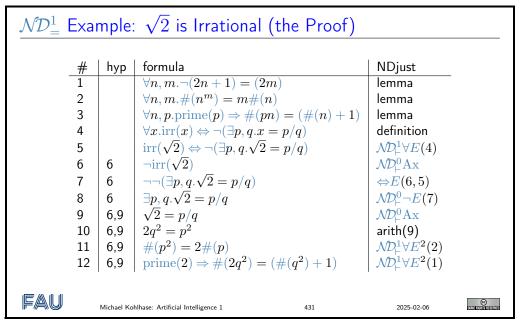


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If we want to formalize this into \mathcal{ND}^1 , we have to write down all the assertions in the proof steps in PL¹ syntax and come up with justifications for them in terms of \mathcal{ND}^1 inference rules. The next two slides show such a proof, where we write n to denote that n is prime, use #(n) for the number of prime factors of a number n, and write $\operatorname{irr}(r)$ if r is irrational.



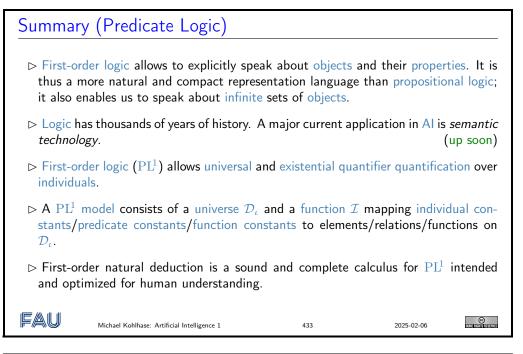
Lines 6 and 9 are local hypotheses for the proof (they only have an implicit counterpart in the inference rules as defined above). Finally we have abbreviated the arithmetic simplification of line 9 with the justification "arith" to avoid having to formalize elementary arithmetic.

$\mathcal{ND}^1_=$ Example: $\sqrt{2}$ is Irrational (the Proof continued)			
13		$\operatorname{prime}(2)$	lemma
14	6,9	$\#(2q^2) = \#(q^2) + 1$	$\mathcal{ND}_0 \Rightarrow E(13, 12)$
15	6,9	$\#(q^2) = 2\#(q)$	$\mathcal{ND}^1 \forall E^2(2)$
16	6,9	$\#(2q^2) = 2\#(q) + 1$	=E(14,15)
17		$\#(p^2) = \#(p^2)$	=I
18	6,9	$\#(2q^2) = \#(q^2)$	=E(17,10)
19	6.9	$2\#(q) + 1 = \#(p^2)$	=E(18,16)
20	6.9	2#(q) + 1 = 2#(p)	=E(19,11)
21	6.9	$\neg(2\#(q)+1) = (2\#(p))$	$\mathcal{ND}^1 \forall E^2(1)$
22	6,9	F	$\mathcal{ND}_{0}FI(20,21)$
23	6	F	$\mathcal{ND}^1 \exists E^6(22)$
24		$\neg\neg\operatorname{irr}(\sqrt{2})$	$\mathcal{ND}_0 \neg I^6(23)$
25		$\operatorname{irr}(\sqrt{2})$	$\mathcal{ND}_0 \neg E^2(23)$

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We observe that the \mathcal{ND}^1 proof is much more detailed, and needs quite a few Lemmata about # to go through. Furthermore, we have added a definition of irrationality (and treat definitional equality via the equality rules). Apart from these artefacts of formalization, the two representations of proofs correspond to each other very directly.

14.4 Conclusion



Applications for \mathcal{ND}^1 (and extensions)

- \triangleright **Recap:** We can express mathematical theorems in PL¹ and prove them in \mathcal{ND}^1 .
- ▷ **Problem:** These proofs can be huge (giga-steps), how can we trust them?
- \triangleright **Definition 14.4.1.** A proof checker for a calculus C is a program that reads (a formal representation) of a C-proof \mathcal{P} and performs proof-checking, i.e. it checks whether all rule applications in \mathcal{P} are (syntactically) correct.
- \triangleright **Remark:** Proof-checking goes step-by-step \sim proof checkers run in linear time.
- \triangleright Idea: If the logic can express (safety)-properties of programs, we can use proof checkers for formal program verification. (there are extensions of PL^1 that can)
- ▷ **Problem:** These proofs can be humongous, how can humans write them?
- ▷ Idea: Automate proof construction via
 - > lemma/theorem libraries that collect useful intermediate results
 - $_{\vartriangleright}$ tactics $\widehat{=}$ subroutines that construct recurring sub-proofs
 - ▷ calls to automated theorem prover (ATP)

(next chapter)

14.4. CONCLUSION

Proof checkers that do any/all of these are called proof assistants.

- Definition 14.4.2. Formal methods are logic-based techniques for the specification, development, analysis, and verification of software and hardware.
- \triangleright Formal methods is a major (industrial) application of AI/logic technology.

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Suggested Reading:

- Chapter 8: First-Order Logic, Sections 8.1 and 8.2 in [RN09]
 - A less formal account of what I cover in "Syntax" and "Semantics". Contains different examples, and complementary explanations. Nice as additional background reading.
- Sections 8.3 and 8.4 provide additional material on using PL1, and on modeling in PL1, that I don't cover in this lecture. Nice reading, not required for exam.
- Chapter 9: Inference in First-Order Logic, Section 9.5.1 in [RN09]
 - A very brief (2 pages) description of what I cover in "Normal Forms". Much less formal; I couldn't find where (if at all) RN cover transformation into prenex normal form. Can serve as additional reading, can't replace the lecture.
- **Excursion:** A full analysis of any calculus needs a completeness proof. We will not cover this in AI-1, but provide one for the calculi introduced so far in??.

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Chapter 15

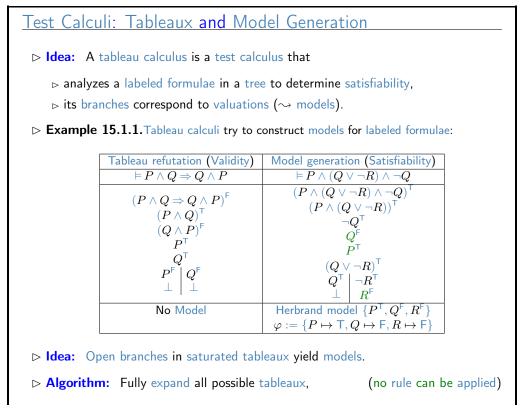
Automated Theorem Proving in First-Order Logic

In this chapter, we take up the machine-oriented calculi for propositional logic from ?? and extend them to the first-order case. While this has been relatively easy for the natural deduction calculus – we only had to introduce the notion of substitutions for the elimination rule for the universal quantifier we have to work much more here to make the calculi effective for implementation.

15.1 First-Order Inference with Tableaux

15.1.1 First-Order Tableau Calculi

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/25156.



▷ Satisfiable, iff there are open branches		25	(correspond to	models)
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Tableau calculi develop a formula in a tree-shaped arrangement that represents a case analysis on when a formula can be made true (or false). Therefore the formulae are decorated with upper indices that hold the intended truth value.

On the left we have a refutation tableau that analyzes a negated formula (it is decorated with the intended truth value F). Both branches contain an elementary contradiction \perp .

On the right we have a model generation tableau, which analyzes a positive formula (it is decorated with the intended truth value T). This tableau uses the same rules as the refutation tableau, but makes a case analysis of when this formula can be satisfied. In this case we have a closed branch and an open one. The latter corresponds a model.

Now that we have seen the examples, we can write down the tableau rules formally.

Analytical Tableaux (Formal Treatment of \mathcal{T}_0)			
▷ Idea: A test calculus where			
 A labeled formula is analyzed in a tree to determine satisfiability, branches correspond to valuations (models) 			
▷ Definition 15.1.2. The propositional tableau calculus \mathcal{T}_0 has two inference rules per connective (one for each possible label)			
$\frac{\mathbf{(\mathbf{A} \wedge \mathbf{B})}^{T}}{\mathbf{A}_{B}^{T}} \mathcal{T}_{0} \wedge \frac{\mathbf{(\mathbf{A} \wedge \mathbf{B})}^{F}}{\mathbf{A}_{F}^{F} \mathbf{B}_{F}^{F}} \mathcal{T}_{0} \vee \qquad \frac{\neg \mathbf{A}_{F}^{T}}{\mathbf{A}_{F}^{F}} \mathcal{T}_{0} \neg^{F} \qquad \frac{\mathbf{A}_{A}^{\alpha}}{\mathbf{A}_{A}^{F}} \alpha \neq \beta}{1} \mathcal{T}_{0} \mathcal{T}$			
Use rules exhaustively as long as they contribute new material $(\sim termination)$			
▷ Definition 15.1.3. We call any tree (introduces branches) produced by the \mathcal{T}_0 inference rules from a set Φ of labeled formulae a tableau for Φ .			
▷ Definition 15.1.4. Call a tableau saturated, iff no rule adds new material and a branch closed, iff it ends in ⊥, else open. A tableau is closed, iff all of its branches are.			
In analogy to the \perp at the end of closed branches, we sometimes decorate open branches with a \square symbol.			
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These inference rules act on tableaux have to be read as follows: if the formulae over the line appear in a tableau branch, then the branch can be extended by the formulae or branches below the line. There are two rules for each primary connective, and a branch closing rule that adds the special symbol \perp (for unsatisfiability) to a branch.

We use the tableau rules with the convention that they are only applied, if they contribute new material to the branch. This ensures termination of the tableau procedure for propositional logic (every rule eliminates one primary connective).

Definition 15.1.5. We will call a closed tableau with the labeled formula \mathbf{A}^{α} at the root a tableau refutation for \mathcal{A}^{α} .

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The saturated tableau represents a full case analysis of what is necessary to give \mathbf{A} the truth value α ; since all branches are closed (contain contradictions) this is impossible.

Analytic	al Tableaux (\mathcal{T}_0 continu	ed)		
	tion 15.1.6 ($\mathcal{T}_0 extsf{-}$ Theorem/Deri a closed tableau with \mathbf{A}^{F} at the		a \mathcal{T}_0 -theorem (H	$_{\mathcal{T}_0}\mathbf{A}$), iff
	$\mathcal{F}_0(\mathcal{V}_0)$ derives $\mathbf A$ in \mathcal{T}_0 ($\Phidash_{\mathcal{T}_0}\mathbf A$), is . The tableau with only a branch			
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Definition 15.1.7. We will call a tableau refutation for \mathbf{A}^{F} a tableau proof for \mathbf{A} , since it refutes the possibility of finding a model where \mathbf{A} evaluates to F . Thus \mathbf{A} must evaluate to T in all models, which is just our definition of validity.

Thus the tableau procedure can be used as a calculus for propositional logic. In contrast to the propositional Hilbert calculus it does not prove a theorem \mathbf{A} by deriving it from a set of axioms, but it proves it by refuting its negation. Such calculi are called negative or test calculi. Generally negative calculi have computational advantages over positive ones, since they have a built-in sense of direction.

We have rules for all the necessary connectives (we restrict ourselves to \land and \neg , since the others can be expressed in terms of these two via the propositional identities above. For instance, we can write $\mathbf{A} \lor \mathbf{B}$ as $\neg(\neg \mathbf{A} \land \neg \mathbf{B})$, and $\mathbf{A} \Rightarrow \mathbf{B}$ as $\neg \mathbf{A} \lor \mathbf{B}, \ldots$.)

We will now extend the propositional tableau techniques to first-order logic. We only have to add two new rules for the universal quantifier (in positive and negative polarity).

First-Order Standard Tableaux (\mathcal{T}_{1}) \triangleright Definition 15.1.8. The standard tableau calculus (\mathcal{T}_{1}) extends \mathcal{T}_{0} (propositional tableau calculus) with the following quantifier rules: $\frac{(\forall X.\mathbf{A})^{\mathsf{T}} \ \mathbf{C} \in cwff_{\iota}(\Sigma_{\iota})}{([\mathbf{C}/X](\mathbf{A}))^{\mathsf{T}}} \mathcal{T}_{1} \forall \qquad \frac{(\forall X.\mathbf{A})^{\mathsf{F}} \ c \in \Sigma_{0}^{sk} \text{ new}}{([c/X](\mathbf{A}))^{\mathsf{F}}} \mathcal{T}_{1} \exists$ \triangleright Problem: The rule $\mathcal{T}_{1} \forall$ displays a case of "don't know indeterminism": to find a refutation we have to guess a formula C from the (usually infinite) set $cwff_{\iota}(\Sigma_{\iota})$. For proof search, this means that we have to systematically try all, so $\mathcal{T}_{1} \forall$ is infinitely branching in general.

The rule $\mathcal{T}_1 \forall$ operationalizes the intuition that a universally quantified formula is true, iff all of the instances of the scope are. To understand the $\mathcal{T}_1 \exists$ rule, we have to keep in mind that $\exists X.\mathbf{A}$ abbreviates $\neg(\forall X.\neg \mathbf{A})$, so that we have to read $(\forall X.\mathbf{A})^{\mathsf{F}}$ existentially — i.e. as $(\exists X.\neg \mathbf{A})^{\mathsf{T}}$, stating that there is an object with property $\neg \mathbf{A}$. In this situation, we can simply give this object a name: c, which we take from our (infinite) set of witness constants Σ_0^{sk} , which we have given ourselves expressly for this purpose when we defined first-order syntax. In other words $([c/X](\neg \mathbf{A}))^{\mathsf{T}} = ([c/X](\mathbf{A}))^{\mathsf{F}}$ holds, and this is just the conclusion of the $\mathcal{T}_1 \exists$ rule.

Note that the $\mathcal{T}_1 \forall$ rule is computationally extremely inefficient: we have to guess an (i.e. in a search setting to systematically consider all) instance $\mathbf{C} \in wff_{\iota}(\Sigma_{\iota}, \mathcal{V}_{\iota})$ for X. This makes the rule infinitely branching.

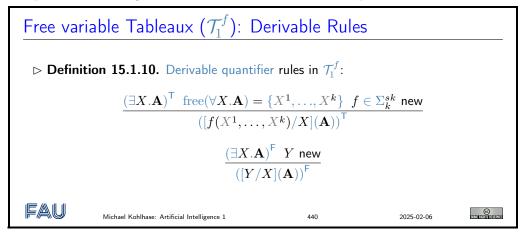
In the next calculus we will try to remedy the computational inefficiency of the $\mathcal{T}_1 \forall$ rule. We do this by delaying the choice in the universal rule.

Free variable Table	aux (\mathcal{T}_1^f)	
\triangleright Definition 15.1.9. The free variable tableau calculus (\mathcal{T}_1^f) extends \mathcal{T}_0 (propositional tableau calculus) with the quantifier rules:		
$\frac{\left(\forall X.\mathbf{A}\right)^{T} \ Y \text{ new }}{\left([Y/X](\mathbf{A})\right)^{T}} \ \mathcal{T}_{1}^{f} \forall$	$\frac{(\forall X.\mathbf{A})^{F} \operatorname{free}(\forall X.\mathbf{A}) = \{X^{1}, \dots, X^{k}\} f}{([f(X^{1}, \dots, X^{k})/X](\mathbf{A}))^{F}}$	${\displaystyle \in \Sigma_k^{sk}}$ new $\mathcal{T}_1^f \exists$
and generalizes its cu	t rule $\mathcal{T}_0 ot$ to:	
	$\begin{array}{cc} \mathbf{A}^{\alpha} & \\ \mathbf{B}^{\beta} & \alpha \neq \beta \ \ \sigma(\mathbf{A}) = \sigma(\mathbf{B}) \\ \hline & \\ \hline & \\ \bot: \sigma \end{array} \mathcal{T}_{1}^{f} \bot$	
$\mathcal{T}_1^f\!\!\perp$ instantiates the v	vhole tableau by $\sigma.$	
Advantage: No gue	ssing necessary in $\mathcal{T}_1^f orall$ -rule!	
⊳ New Problem: find	suitable substitution (most general unifier)	(later)
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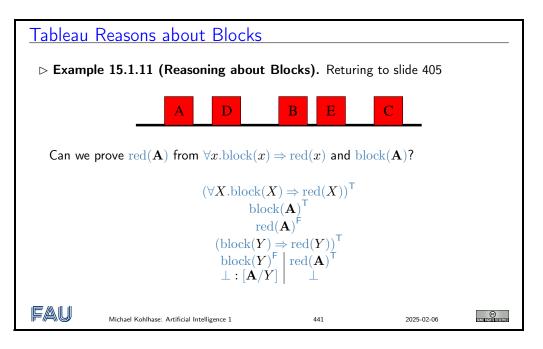
Metavariables: Instead of guessing a concrete instance for the universally quantified variable as in the $\mathcal{T}_1 \forall$ rule, $\mathcal{T}_1^f \forall$ instantiates it with a new metavariable Y, which will be instantiated by need in the course of the derivation.

Skolem terms as witnesses: The introduction of metavariables makes is necessary to extend the treatment of witnesses in the existential rule. Intuitively, we cannot simply invent a new name, since the meaning of the body **A** may contain metavariables introduced by the $\mathcal{T}_1^f \forall$ rule. As we do not know their values yet, the witness for the existential statement in the antecedent of the $\mathcal{T}_1^f \exists$ rule needs to depend on that. So witness it using a witness term, concretely by applying a Skolem function to the metavariables in **A**.

Instantiating Metavariables: Finally, the $\mathcal{T}_1^f \perp$ rule completes the treatment of metavariables, it allows to instantiate the whole tableau in a way that the current branch closes. This leaves us with the problem of finding substitutions that make two terms equal.



15.1. FIRST-ORDER INFERENCE WITH TABLEAUX



15.1.2 First-Order Unification

Video Nuggets covering this subsection can be found at https://fau.tv/clip/id/26810 and https://fau.tv/clip/id/26811.

We will now look into the problem of finding a substitution σ that make two terms equal (we say it unifies them) in more detail. The presentation of the unification algorithm we give here "transformation-based" this has been a very influential way to treat certain algorithms in theoretical computer science.

A transformation-based view of algorithms: The "transformation-based" view of algorithms divides two concerns in presenting and reasoning about algorithms according to Kowalski's slogan [Kow97]

algorithm = logic + control

The computational paradigm highlighted by this quote is that (many) algorithms can be thought of as manipulating representations of the problem at hand and transforming them into a form that makes it simple to read off solutions. Given this, we can simplify thinking and reasoning about such algorithms by separating out their "logical" part, which deals with is concerned with how the problem representations can be manipulated in principle from the "control" part, which is concerned with questions about when to apply which transformations.

It turns out that many questions about the algorithms can already be answered on the "logic" level, and that the "logical" analysis of the algorithm can already give strong hints as to how to optimize control.

In fact we will only concern ourselves with the "logical" analysis of unification here.

The first step towards a theory of unification is to take a closer look at the problem itself. A first set of examples show that we have multiple solutions to the problem of finding substitutions that make two terms equal. But we also see that these are related in a systematic way.

Unification (Definitions)

- \triangleright **Definition 15.1.12.** For given terms **A** and **B**, unification is the problem of finding a substitution σ , such that $\sigma(\mathbf{A}) = \sigma(\mathbf{B})$.
- \triangleright Notation: We write term pairs as $A = {}^{?}B$ e.g. $f(X) = {}^{?}f(g(Y))$.

- \triangleright Definition 15.1.13. Solutions (e.g. [g(a)/X], [a/Y], [g(g(a))/X], [g(a)/Y], or [g(Z)/X], [Z/Y]) are called unifiers, $U(\mathbf{A}=^{?}\mathbf{B}) := \{\sigma \mid \sigma(\mathbf{A}) = \sigma(\mathbf{B})\}.$
- \triangleright Idea: Find representatives in U(A=?B), that generate the set of solutions.
- \triangleright **Definition 15.1.14.** Let σ and θ be substitutions and $W \subseteq \mathcal{V}_{\iota}$, we say that a substitution σ is more general than θ (on W; write $\sigma \leq \theta[W]$), iff there is a substitution ρ , such that $\theta = \rho \circ \sigma[W]$, where $\sigma = \rho[W]$, iff $\sigma(X) = \rho(X)$ for all $X \in W$.
- ▷ **Definition 15.1.15.** σ is called a most general unifier (mgu) of **A** and **B**, iff it is minimal in U(**A**=[?]**B**) wrt. \leq [(free(**A**) \cup free(**B**))].

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The idea behind a most general unifier is that all other unifiers can be obtained from it by (further) instantiation. In an automated theorem proving setting, this means that using most general unifiers is the least committed choice — any other choice of unifiers (that would be necessary for completeness) can later be obtained by other substitutions.

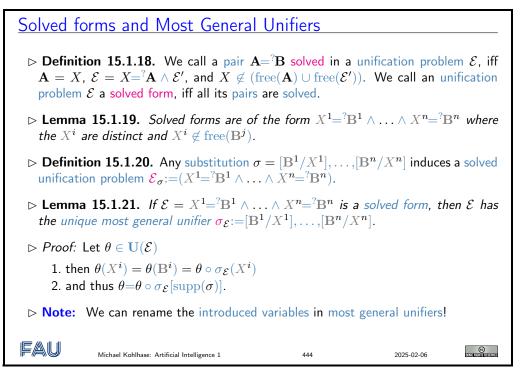
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Note that there is a subtlety in the definition of the ordering on substitutions: we only compare on a subset of the variables. The reason for this is that we have defined substitutions to be total on (the infinite set of) variables for flexibility, but in the applications (see the definition of most general unifiers), we are only interested in a subset of variables: the ones that occur in the initial problem formulation. Intuitively, we do not care what the unifiers do off that set. If we did not have the restriction to the set W of variables, the ordering relation on substitutions would become much too fine-grained to be useful (i.e. to guarantee unique most general unifiers in our case).

Now that we have defined the problem, we can turn to the unification algorithm itself. We will define it in a way that is very similar to logic programming: we first define a calculus that generates "solved forms" (formulae from which we can read off the solution) and reason about control later. In this case we will reason that control does not matter.

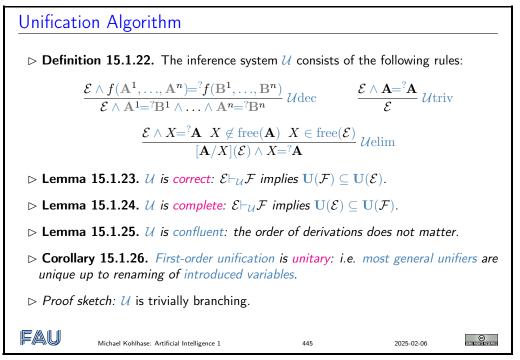
Unification Problems (Ê Equational Systems)
▷ Idea: Unification is equation solving.
▷ Definition 15.1.16. We call a formula A¹=?B¹ ∧ ... ∧ Aⁿ=?Bⁿ an unification problem iff Aⁱ, Bⁱ ∈ uff_ℓ(Σ_ℓ, V_ℓ).
▷ Note: We consider unification problems as sets of equations (∧ is ACI), and equations as two-element multisets (=? is C).
▷ Definition 15.1.17. A substitution is called a unifier for a unification problem *E* (and thus D unifiable), iff it is a (simultaneous) unifier for all pairs in E.

In principle, unification problems are sets of equations, which we write as conjunctions, since all of them have to be solved for finding a unifier. Note that it is not a problem for the "logical view" that the representation as conjunctions induces an order, since we know that conjunction is associative, commutative and idempotent, i.e. that conjuncts do not have an intrinsic order or multiplicity, if we consider two equational problems as equal, if they are equivalent as propositional formulae. In the same way, we will abstract from the order in equations, since we know that the equality relation is symmetric. Of course we would have to deal with this somehow in the implementation (typically, we would implement equational problems as lists of pairs), but that belongs into the "control" aspect of the algorithm, which we are abstracting from at the moment.



It is essential to our "logical" analysis of the unification algorithm that we arrive at unification problems whose unifiers we can read off easily. Solved forms serve that need perfectly as ?? shows.

Given the idea that unification problems can be expressed as formulae, we can express the algorithm in three simple rules that transform unification problems into solved forms (or unsolvable ones).



The decomposition rule \mathcal{U} dec is completely straightforward, but note that it transforms one unification pair into multiple argument pairs; this is the reason, why we have to directly use unification problems with multiple pairs in \mathcal{U} .

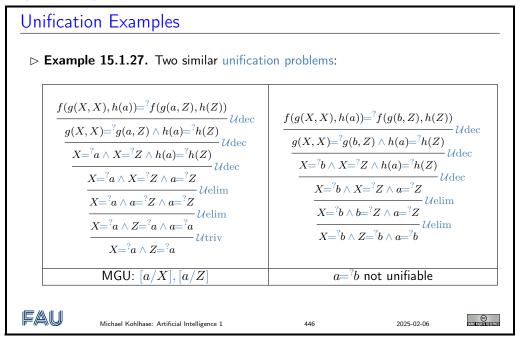
Note furthermore, that we could have restricted the \mathcal{U} triv rule to variable-variable pairs, since for any other pair, we can decompose until only variables are left. Here we observe, that constantconstant pairs can be decomposed with the \mathcal{U} dec rule in the somewhat degenerate case without arguments.

Finally, we observe that the first of the two variable conditions in \mathcal{U} elim (the "occurs-in-check") makes sure that we only apply the transformation to unifiable unification problems, whereas the second one is a termination condition that prevents the rule to be applied twice.

The notion of completeness and correctness is a bit different than that for calculi that we compare to the entailment relation. We can think of the "logical system of unifiability" with the model class of sets of substitutions, where a set satisfies an equational problem \mathcal{E} , iff all of its members are unifiers. This view induces the soundness and completeness notions presented above.

The three meta-properties above are relatively trivial, but somewhat tedious to prove, so we leave the proofs as an exercise to the reader.

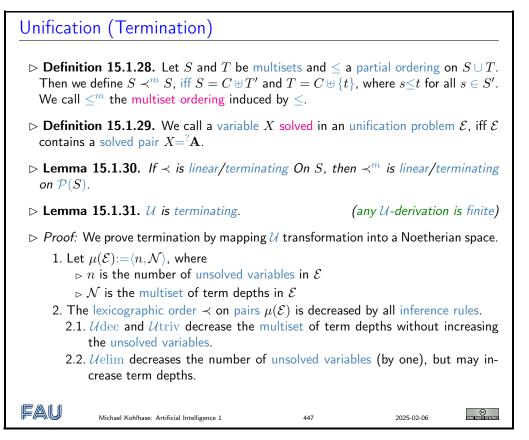
We now fortify our intuition about the unification calculus by two examples. Note that we only need to pursue one possible \mathcal{U} derivation since we have confluence.



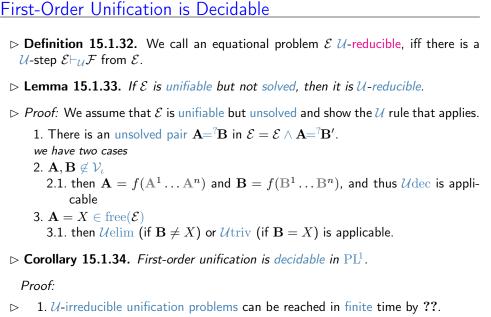
We will now convince ourselves that there cannot be any infinite sequences of transformations in \mathcal{U} . Termination is an important property for an algorithm.

The proof we present here is very typical for termination proofs. We map unification problems into a partially ordered set $\langle S, \prec \rangle$ where we know that there cannot be any infinitely descending sequences (we think of this as measuring the unification problems). Then we show that all transformations in \mathcal{U} strictly decrease the measure of the unification problems and argue that if there were an infinite transformation in \mathcal{U} , then there would be an infinite descending chain in S, which contradicts our choice of $\langle S, \prec \rangle$.

The crucial step in coming up with such proofs is finding the right partially ordered set. Fortunately, there are some tools we can make use of. We know that $\langle \mathbb{N}, \langle \rangle$ is terminating, and there are some ways of lifting component orderings to complex structures. For instance it is well-known that the lexicographic ordering lifts a terminating ordering to a terminating ordering on finite dimensional Cartesian spaces. We show a similar, but less known construction with multisets for our proof.



But it is very simple to create terminating calculi, e.g. by having no inference rules. So there is one more step to go to turn the termination result into a decidability result: we must make sure that we have enough inference rules so that any unification problem is transformed into solved form if it is unifiable.



2. They are either solved or unsolvable by ??, so they provide the answer.

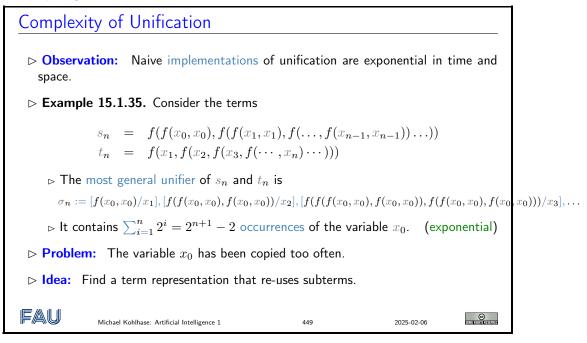
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15.1.3 Efficient Unification

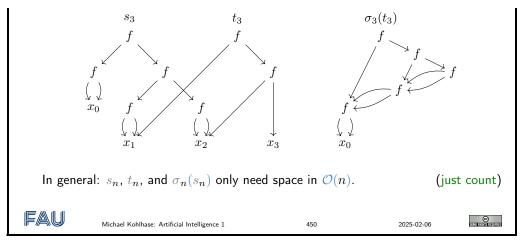
Now that we have seen the basic ingredients of an unification algorithm, let us as always consider complexity and efficiency issues.

We start with a look at the complexity of unification and – somewhat surprisingly – find exponential time/space complexity based simply on the fact that the results – the unifiers – can be exponentially large.



Indeed, the only way to escape this combinatorial explosion is to find representations of substitutions that are more space efficient.

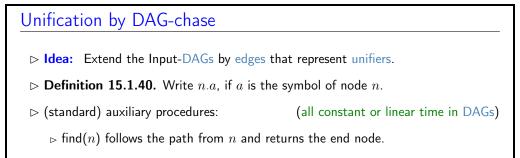
Directed Acyclic Graphs (DAGs) for Terms		
▷ Recall: Terms in first-order logic are essentially trees.		
recail. Terms in inst-order logic are essentially trees.		
▷ Concrete Idea: Use directed acyclic graphs for representing terms:		
\triangleright variables my only occur once in the DAG.		
▷ subterms can be referenced multiply.	(subterm sharing)	
\triangleright we can even represent multiple terms in a common DAG		
> Observation 15.1.36. <i>Terms can be transformed into DAGs in linear time.</i>		
\vartriangleright Example 15.1.37. Continuing from \ref{stress} s_3 , t_3 , and $\sigma_3(s_3)$	as DAGs:	

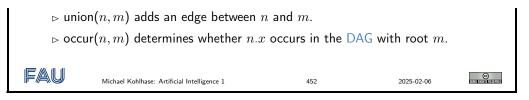


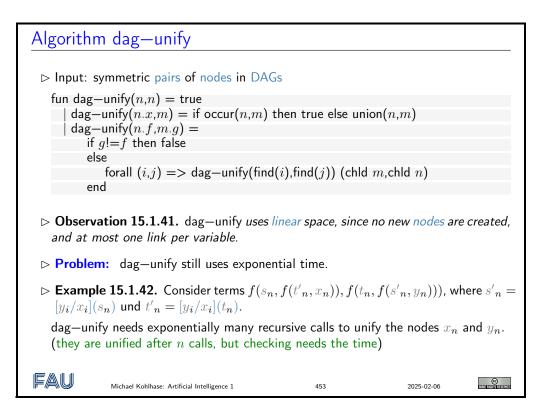
If we look at the unification algorithm from ?? and the considerations in the termination proof (??) with a particular focus on the role of copying, we easily find the culprit for the exponential blowup: \mathcal{U} elim, which applies solved pairs as substitutions.

DAG Unification Algorithm \triangleright **Observation:** In \mathcal{U} , the \mathcal{U} elim rule applies solved pairs \rightarrow subterm duplication. \triangleright Idea: Replace \mathcal{U} elim the notion of solved forms by something better. \triangleright Definition 15.1.38. We say that $X^1 = {}^2B^1 \land \ldots \land X^n = {}^2B^n$ is a DAG solved form, iff the X^i are distinct and $X^i \notin \text{free}(\mathbf{B}^j)$ for $i \leq j$. \triangleright **Definition 15.1.39.** The inference system \mathcal{DU} contains rules \mathcal{U} dec and \mathcal{U} triv from \mathcal{U} plus the following: $\frac{\mathcal{E} \wedge X = {}^{?}\mathbf{A} \wedge X = {}^{?}\mathbf{B} \ \mathbf{A}, \mathbf{B} \notin \mathcal{V}_{\iota} \ |\mathbf{A}| \leq |\mathbf{B}|}{\mathcal{E} \wedge X = {}^{?}\mathbf{A} \wedge \mathbf{A} = {}^{?}\mathbf{B}} \ \mathcal{D}\mathcal{U}merge$ $\frac{\mathcal{E} \land X = {}^{?}Y \ X \neq Y \ X, Y \in \operatorname{free}(\mathcal{E})}{[Y/X](\mathcal{E}) \land X = {}^{?}Y} \ \mathcal{D} \mathcal{U} \operatorname{evar}$ where $|\mathbf{A}|$ is the number of symbols in \mathbf{A} . \triangleright The analysis for \mathcal{U} applies mutatis mutandis. FAU 0 Michael Kohlhase: Artificial Intelligence 1 451 2025-02-06

We will now turn the ideas we have developed in the last couple of slides into a usable functional algorithm. The starting point is treating terms as DAGs. Then we try to conduct the transformation into solved form without adding new nodes.







Algorithm uf-unify

▷ **Recall:** dag—unify still uses exponential time. ▷ Idea: Also bind the function nodes, if the arguments are unified. uf-unify(n.f,m.g) =if g!=f then false else union(n,m); forall (i,j) => uf-unify(find(i),find(j)) (chld m,chld n) end > This only needs linearly many recursive calls as it directly returns with true or makes a node inaccessible for find. \triangleright Linearly many calls to linear procedures give quadratic running time. ▷ **Remark:** There are versions of uf—unify that are linear in time and space, but for most purposes, our algorithm suffices. Fau C Michael Kohlhase: Artificial Intelligence 1 454 2025-02-06

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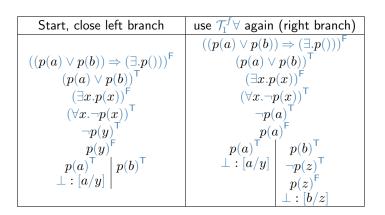
15.1.4Implementing First-Order Tableaux

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/26797. We now come to some issues (and clarifications) pertaining to implementing proof search for free variable tableaux. They all have to do with the – often overlooked – fact that $\mathcal{T}_1^{f} \perp$ instantiates the whole tableau.

The first question one may ask for implementation is whether we expect a terminating proof search; after all, \mathcal{T}_0 terminated. We will see that the situation for \mathcal{T}_1^f is different.

Termination and Multiplicity in Tableaux

- \triangleright **Observation 15.1.43.** All \mathcal{T}_1^f rules except $\mathcal{T}_1^f \forall$ only need to be applied once.
- \triangleright Example 15.1.44. A tableau proof for $(p(a) \lor p(b)) \Rightarrow (\exists .p())$.



After we have used up ${p(y)}^{\sf F}$ by applying [a/y] in $\mathcal{T}_1^f \bot$, we have to get a new instance $p(z)^{\mathsf{F}}$ via $\mathcal{T}_1^f \forall$.

- \triangleright **Definition 15.1.45.** Let \mathcal{T} be a tableau for **A**, and a positive occurrence of $\forall x.\mathbf{B}$ in A, then we call the number of applications of $\mathcal{T}_1^f orall$ to $orall x.\mathbf{B}$ its multiplicity.
- \triangleright **Observation 15.1.46.** Given a prescribed multiplicity for each positive \forall , saturation with \mathcal{T}_1^f terminates.
- ightarrow *Proof sketch:* All \mathcal{T}_1^f rules reduce the number of connectives and negative orall or the multiplicity of positive \forall .
- \triangleright **Theorem 15.1.47.** \mathcal{T}_1^f is only complete with unbounded multiplicities.
- \triangleright Proof sketch: Replace $p(a) \lor p(b)$ with $p(a_1) \lor \ldots \lor p(a_n)$ in ??
- \triangleright **Remark:** Otherwise validity in PL¹ would be decidable.

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▷ Implementation: We need an iterative multiplicity deepening process.

The other thing we need to realize is that there may be multiple ways we can use $\mathcal{T}_1^f \perp$ to close a branch in a tableau, and – as $\mathcal{T}_1^f \perp$ instantiates the whole tableau and not just the branch itself –

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this choice matters.

 Treating $T_1^{f_1} ⊥$

 ▷ Recall: The $T_1^{f_1} ⊥$ rule instantiates the whole tableau.

 ▷ Problem: There may be more than one $T_1^{f_1} ⊥$ opportunity on a branch.

 ▷ Example 15.1.48. Choosing which matters – this tableau does not close!

 $(\exists x.(p(a) \land p(b) \Rightarrow p()) \land (q(b) \Rightarrow q(x)))^{F}$ $(p(a) \land p(b) \Rightarrow p()) \land (q(b) \Rightarrow q(y)))^{F}$ $p(a)^{T}$ $p(b)^{T}$ $p(b)^{$

The method of spanning matings follows the intuition that if we do not have good information on how to decide for a pair of opposite literals on a branch to use in $\mathcal{T}_1^f \perp$, we delay the choice by initially disregarding the rule altogether during saturation and then – in a later phase– looking for a configuration of cuts that have a joint overall unifier. The big advantage of this is that we only need to know that one exists, we do not need to compute or apply it, which would lead to exponential blow-up as we have seen above.



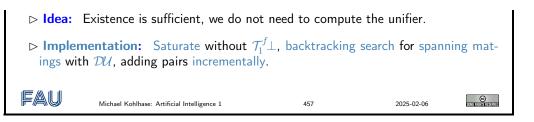
- \triangleright **Observation 15.1.49.** \mathcal{T}_1^f without $\mathcal{T}_1^f \perp$ is terminating and confluent for given multiplicities.
- \triangleright Idea: Saturate without $\mathcal{T}_1^f \perp$ and treat all cuts at the same time (later).
- ⊳ Definition 15.1.50.

Let \mathcal{T} be a \mathcal{T}_1^f tableau, then we call a unification problem $\mathcal{E} := \mathbf{A}_1 = {}^{?}\mathbf{B}_1 \land \ldots \land \mathbf{A}_n = {}^{?}\mathbf{B}_n$ a mating for \mathcal{T} , iff $\mathbf{A}_i^{\mathsf{T}}$ and $\mathbf{B}_i^{\mathsf{F}}$ occur in the same branch in \mathcal{T} .

We say that \mathcal{E} is a spanning mating, if \mathcal{E} is unifiable and every branch \mathcal{B} of \mathcal{T} contains $\mathbf{A}_i^{\mathsf{T}}$ and $\mathbf{B}_i^{\mathsf{F}}$ for some *i*.

 \triangleright **Theorem 15.1.51.** A T_1^f -tableau with a spanning mating induces a closed T_1 tableau.

▷ Proof sketch: Just apply the unifier of the spanning mating.



Excursion: Now that we understand basic unification theory, we can come to the meta-theoretical properties of the tableau calculus. We delegate this discussion to??.

15.2 First-Order Resolution

A Video Nugget covering this section can be found at https://fau.tv/clip/id/26817.

First-Order Resolution (and CNF) \triangleright Definition 15.2.1. The first-order CNF calculus CNF_1 is given by the inference rules of CNF_0 extended by the following quantifier rules: $\frac{\left(\forall X.\mathbf{A}\right)^{\mathsf{T}} \lor \mathbf{C} \ Z \not\in (\operatorname{free}(\mathbf{A}) \cup \operatorname{free}(\mathbf{C}))}{\left([Z/X](\mathbf{A})\right)^{\mathsf{T}} \lor \mathbf{C}}$ $\frac{(\forall X.\mathbf{A})^{\mathsf{F}} \vee \mathbf{C} \ \{X_1, \dots, X_k\} = \operatorname{free}(\forall X.\mathbf{A}) \ f \in \Sigma_k^{sk} \text{ new}}{([f(X_1, \dots, X_k)/X](\mathbf{A}))^{\mathsf{F}} \vee \mathbf{C}}$ the first-order CNF $CNF_1(\Phi)$ of Φ is the set of all clauses that can be derived from Φ. ▷ Definition 15.2.2 (First-Order Resolution Calculus). The First-order resolution calculus (\mathcal{R}_1) is a test calculus that manipulates formulae in conjunctive normal form. \mathcal{R}_1 has two inference rules: $\frac{\mathbf{A}^{\mathsf{T}} \lor \mathbf{C} \ \mathbf{B}^{\mathsf{F}} \lor \mathbf{D} \ \sigma = \mathbf{mgu}(\mathbf{A}, \mathbf{B})}{(\sigma(\mathbf{C})) \lor (\sigma(\mathbf{D}))} \qquad \qquad \frac{\mathbf{A}^{\alpha} \lor \mathbf{B}^{\alpha} \lor \mathbf{C} \ \sigma = \mathbf{mgu}(\mathbf{A}, \mathbf{B})}{(\sigma(\mathbf{A})) \lor (\sigma(\mathbf{C}))}$ FAU Michael Kohlhase: Artificial Intelligence 1 458 2025-02-06

 First-Order CNF – Derived Rules

 ▷ Definition 15.2.3. The following inference rules are derivable from the ones above via $(\exists X.\mathbf{A}) = \neg(\forall X.\neg \mathbf{A})$:

 $(\exists X.\mathbf{A})^T \lor \mathbf{C} \ \{X_1, \dots, X_k\} = \text{free}(\forall X.\mathbf{A}) \ f \in \Sigma_k^{sk} \text{ new}$
 $(\exists X.\mathbf{A})^T \lor \mathbf{C} \ \{X_1, \dots, X_k\} = \text{free}(\forall X.\mathbf{A}) \ f \in \Sigma_k^{sk} \text{ new}$
 $(\exists X.\mathbf{A})^T \lor \mathbf{C} \ \{X_1, \dots, X_k\} / X](\mathbf{A}))^T \lor \mathbf{C}$
 $(\exists X.\mathbf{A})^F \lor \mathbf{C} \ Z \notin (\text{free}(\mathbf{A}) \cup \text{free}(\mathbf{C}))$
 $(\exists Z.\mathbf{A})^F \lor \mathbf{C} \ Z \notin (\text{free}(\mathbf{A}) \cup \text{free}(\mathbf{C}))$

Excursion: Again, we relegate the meta-theoretical properties of the first-order resolution calculus to??.

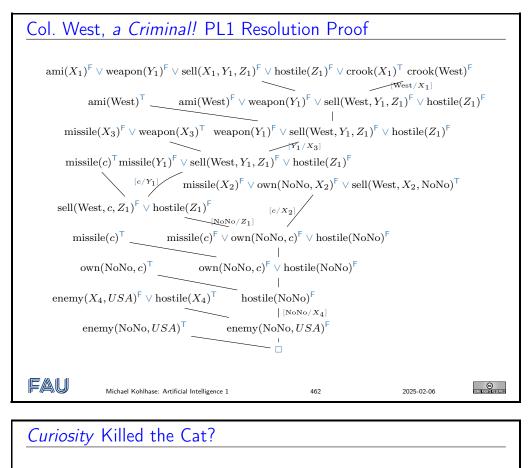
15.2.1 Resolution Examples

Col. West, a Criminal?
▷ Example 15.2.4. From [RN09]
The law says it is a crime for an American to sell weapons to hostile nations. The country Nono, an enemy of America, has some missiles, and all of its missiles were sold to it by Colonel West, who is American.
Prove that Col. West is a criminal.
\triangleright Remark: Modern resolution theorem provers prove this in less than 50ms.
▷ Problem: That is only true, if we only give the theorem prover exactly the right laws and background knowledge. If we give it all of them, it drowns in the combi- natorial explosion.
\triangleright Let us build a resolution proof for the claim above.
▷ But first we must translate the situation into first-order logic clauses.
\triangleright Convention: In what follows, for better readability we will sometimes write implications $P \land Q \land R \Rightarrow S$ instead of clauses $P^{F} \lor Q^{F} \lor R^{F} \lor S^{T}$.
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Col. West, a Criminal?

\triangleright It is a crime for an American to sell weapons to hostile Clause: $\operatorname{ami}(X_1) \wedge \operatorname{weap}(Y_1) \wedge \operatorname{sell}(X_1, Y_1, Z_1) \wedge \operatorname{host}(Z_1)$	
▷ Nono has some missiles: $\exists X.own(NN, X) \land mle(X)$ Clauses: $own(NN, c)^{T}$ and $mle(c)$	(c is Skolem constant)
▷ All of Nono's missiles were sold to it by Colonel West. Clause : $mle(X_2) \land own(NN, X_2) \Rightarrow sell(West, X_2, NN)$	
▷ Missiles are weapons: Clause : $mle(X_3) \Rightarrow weap(X_3)$	
▷ An enemy of America counts as "hostile": Clause: $enmy(X_4, USA) \Rightarrow host(X_4)$	
▷ West is an American: Clause: ami(West)	
▷ The country Nono is an enemy of America: enmy(NN, USA)	
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▷ **Example 15.2.5.** From [RN09]

Everyone who loves all animals is loved by someone. Anyone who kills an animal is loved by noone. Jack loves all animals. Cats are animals. Either Jack or curiosity killed the cat (whose name is "Garfield"). Prove that curiosity killed the cat. FAU

Curiosity Killed the Cat? Clauses

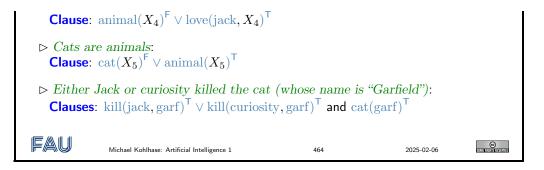
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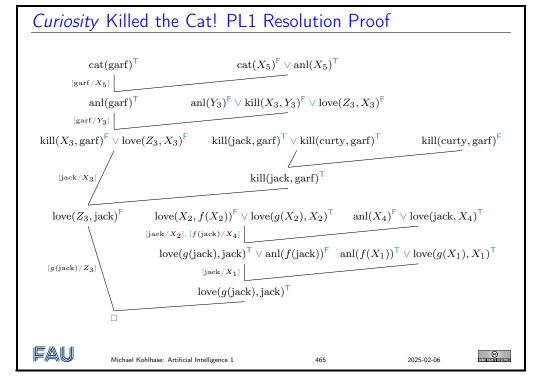
 \triangleright Everyone who loves all animals is loved by someone: $\forall X.(\forall Y.animal(Y) \Rightarrow love(X,Y)) \Rightarrow (\exists .love(Z,X))$ **Clauses:** animal $(g(X_1))^{\mathsf{T}} \lor \operatorname{love}(g(X_1), X_1)^{\mathsf{T}}$ and $\operatorname{love}(X_2, f(X_2))^{\mathsf{F}} \lor \operatorname{love}(g(X_2), X_2)$

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- ▷ Anyone who kills an animal is loved by noone: $\forall X.\exists Y.\text{animal}(Y) \land \text{kill}(X,Y) \Rightarrow (\forall.\neg\text{love}(Z,X))$ **Clause:** animal $(Y_3)^{\mathsf{F}} \lor \operatorname{kill}(X_3, Y_3)^{\mathsf{F}} \lor \operatorname{love}(Z_3, X_3)^{\mathsf{F}}$
- \triangleright Jack loves all animals:

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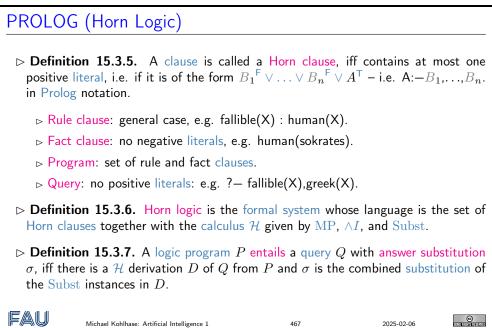
Excursion: A full analysis of any calculus needs a completeness proof. We will not cover this in the course, but provide one for the calculi introduced so far in??.

15.3 Logic Programming as Resolution Theorem Proving

A Video Nugget covering this section can be found at https://fau.tv/clip/id/26820. To understand Prolog better, we can interpret the language of Prolog as resolution in PL¹.

We know all this already \triangleright Goals, goal sets, rules, and facts are just clauses. (called Horn clauses) \triangleright Observation 15.3.1 (Rule). $H:=B_1,\ldots,B_n$. corresponds to $H^{\mathsf{T}} \lor B_1^{\mathsf{F}} \lor \ldots \lor B_n^{\mathsf{F}}$ (head the only positive literal) \triangleright Observation 15.3.2 (Goal set). $?=G_1,\ldots,G_n$. corresponds to $G_1^{\mathsf{F}} \lor \ldots \lor G_n^{\mathsf{F}}$ \triangleright Observation 15.3.3 (Fact). F. corresponds to the unit clause F^{T} . ▷ Definition 15.3.4. A Horn clause is a clause with at most one positive literal. ▷ Recall: Backchaining as search: ▷ state = tuple of goals; goal state = empty list (of goals). ▷ $next(\langle G, R_1, ..., R_l \rangle) := \langle \sigma(B_1), ..., \sigma(B_m), \sigma(R_1), ..., \sigma(R_l) \rangle$ if there is a rule $H:-B_1, ..., B_m$. and a substitution σ with $\sigma(H) = \sigma(G)$. ▷ Note: Backchaining becomes resolution $\frac{P^{\mathsf{T}} \lor \mathbf{A} \ P^{\mathsf{F}} \lor \mathbf{B}}{\mathbf{A} \lor \mathbf{B}}$ positive, unit-resulting hyperresolution (PURR)

This observation helps us understand Prolog better, and use implementation techniques from automated theorem proving.



PROLOG: Our Example

▷ **Program**:

human(leibniz). human(sokrates). greek(sokrates). fallible(X):—human(X).

- ▷ Example 15.3.8 (Query). ?- fallible(X),greek(X).
- \triangleright Answer substitution: [sokrates/X]

CHAPTER 15. AUTOMATED THEOREM PROVING IN FIRST-ORDER LOGIC

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To gain an intuition for this quite abstract definition let us consider a concrete knowledge base about cars. Instead of writing down everything we know about cars, we only write down that cars are motor vehicles with four wheels and that a particular object c has a motor and four wheels. We can see that the fact that c is a car can be derived from this. Given our definition of a knowledge base as the deductive closure of the facts and rule explicitly written down, the assertion that c is a car is in the induced knowledge base, which is what we are after.

 Knowledge Base (Example)

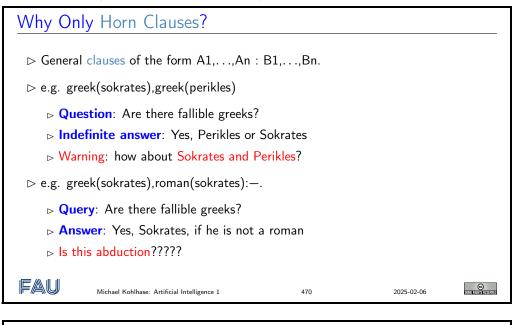
 Example 15.3.9. car(c). is in the knowlege base generated by
 has_motor(c).
 has_wheels(c,4).
 car(X):- has_motor(X),has_wheels(X,4).

 $\frac{m(c) \quad w(c,4)}{m(c) \land w(c,4)} \land I \quad \frac{m(x) \land w(x,4) \Rightarrow car()}{m(c) \land w(c,4) \Rightarrow car()} \quad \text{MP}$

 Final Weels(C,A)

 $\frac{m(c) \land w(c,4)}{m(c) \land w(c,4) \Rightarrow car()} \quad \text{MP}$
 $\frac{m(c) \land w(c,4)}{m(c) \land w(c,4) \Rightarrow car()} \quad \text{MP}$

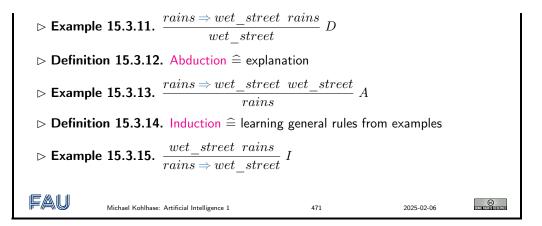
In this very simple example car(c) is about the only fact we can derive, but in general, knowledge bases can be infinite (we will see examples below).



Three Principal Modes of Inference

 \triangleright **Definition 15.3.10.** Deduction $\widehat{=}$ knowledge extension

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15.4 Summary: ATP in First-Order Logic

Summary: ATP in First-Order Logic
> The propositional calculi for ATP can be extended to first-order logic by adding quantifier rules.
The rule for the universal quantifier can be made efficient by introducing metavariables that postpone the decision for instances.
We have to extend the witness constants in the rules for existential quantifiers to Skolem functions.
\triangleright The cut rules can used to instantiate the metavariables by unification.
These ideas are enough to build a tableau calculus for first-order logic.
 Unification is an efficient decision procdure for finding substitutions that make first- order terms (syntactically) equal.
▷ In prenex normal form, all quantifiers are up front. In Skolem normal form, addi- tionally there are no existential quantifiers. In claus normal form, additionally the formula is in CNF.
\rhd Any PL^1 formula can efficiently be brought into a satisfiability-equivalent clause normal form.
\triangleright This allows first-order resolution.
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Chapter 16

Knowledge Representation and the Semantic Web

The field of "Knowledge Representation" is usually taken to be an area in Artificial Intelligence that studies the representation of knowledge in formal systems and how to leverage inference techniques to generate new knowledge items from existing ones. Note that this definition coincides with what we know as logical systems in this course. This is the view taken by the subfield of "description logics", but restricted to the case, where the logical systems have an entailment relation to ensure applicability. This chapter is organized as follows. We will first give a general introduction to the concepts of knowledge representation using semantic networks - an early and very intuitive approach to knowledge representation - as an object-to-think-with. In ?? we introduce the principles and services of logic-based knowledge-representation using a non-standard interpretation of propositional logic as the basis, this gives us a formal account of the taxonomic part of semantic networks. In $\ref{eq:matrix}$ we introduce the logic \mathcal{AC} that adds relations (called "roles") and restricted quantification and thus gives us the full expressive power of semantic networks. Thus \mathcal{AC} can be seen as a prototype description logic. In ?? we show how description logics are applied as the basis of the "semantic web".

16.1Introduction to Knowledge Representation

A Video Nugget covering the introduction to knowledge representation can be found at https: //fau.tv/clip/id/27279.

Before we start into the development of description logics, we set the stage by looking into alternatives for knowledge representation.

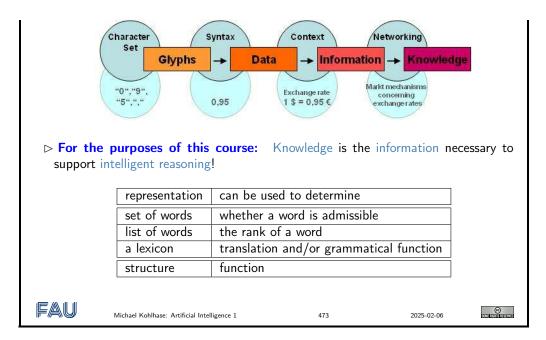
16.1.1Knowledge & Representation

To approach the question of knowledge representation, we first have to ask ourselves, what knowledge might be. This is a difficult question that has kept philosophers occupied for millennia. We will not answer this question in this course, but only allude to and discuss some aspects that are relevant to our cause of knowledge representation.

What is knowledge? Why Representation?

▷ Lots/all of (academic) disciplines deal with knowledge!

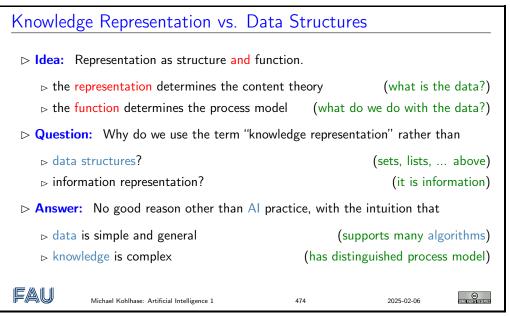
▷ According to Probst/Raub/Romhardt [PRR97]



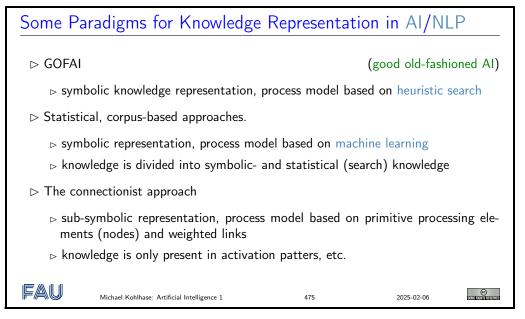
According to an influential view of [PRR97], knowledge appears in layers. Staring with a character set that defines a set of glyphs, we can add syntax that turns mere strings into data. Adding context information gives information, and finally, by relating the information to other information allows to draw conclusions, turning information into knowledge.

Note that we already have aspects of representation and function in the diagram at the top of the slide. In this, the additional functionality added in the successive layers gives the representations more and more functions, until we reach the knowledge level, where the function is given by inferencing. In the second example, we can see that representations determine possible functions.

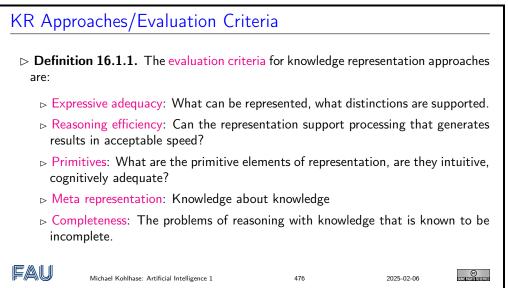
Let us now strengthen our intuition about knowledge by contrasting knowledge representations from "regular" data structures in computation.



As knowledge is such a central notion in artificial intelligence, it is not surprising that there are multiple approaches to dealing with it. We will only deal with the first one and leave the others to self-study.



When assessing the relative strengths of the respective approaches, we should evaluate them with respect to a pre-determined set of criteria.

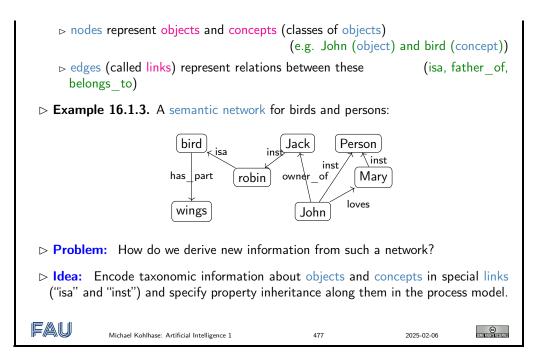


16.1.2 Semantic Networks

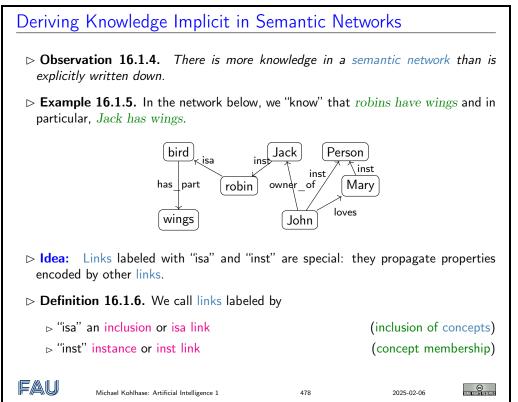
A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/27280. To get a feeling for early knowledge representation approaches from which description logics developed, we take a look at "semantic networks" and contrast them to logical approaches. Semantic networks are a very simple way of arranging knowledge about objects and concepts and their relationships in a graph.



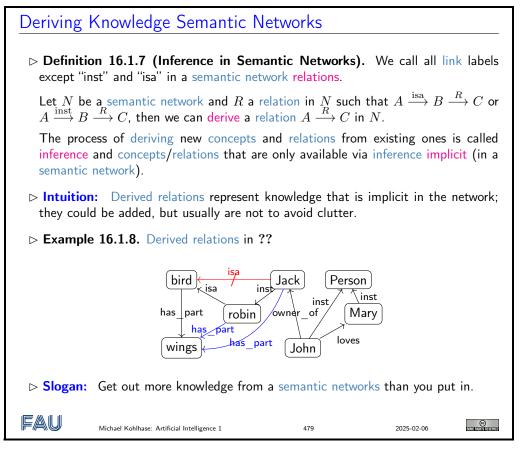
▷ Definition 16.1.2. A semantic network is a directed graph for representing knowledge: 102



Even though the network in ?? is very intuitive (we immediately understand the concepts depicted), it is unclear how we (and more importantly a machine that does not associate meaning with the labels of the nodes and edges) can draw inferences from the "knowledge" represented.



We now make the idea of "propagating properties" rigorous by defining the notion of derived relations, i.e. the relations that are left implicit in the network, but can be added without changing its meaning.



Note that ?? does not quite allow to derive that *Jack is a bird* (did you spot that "isa" is not a relation that can be inferred?), even though we know it is true in the world. This shows us that inference in semantic networks has be to very carefully defined and may not be "complete", i.e. there are things that are true in the real world that our inference procedure does not capture.

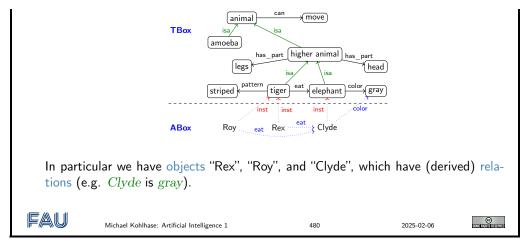
Dually, if we are not careful, then the inference procedure might derive properties that are not true in the real world even if all the properties explicitly put into the network are. We call such an inference procedure unsound or incorrect.

These are two general phenomena we have to keep an eye on.

Another problem is that semantic networks (e.g. in ??) confuse two kinds of concepts: individuals (represented by proper names like *John* and *Jack*) and concepts (nouns like *robin* and *bird*). Even though the isa and inst link already acknowledge this distinction, the "has_part" and "loves" relations are at different levels entirely, but not distinguished in the networks.

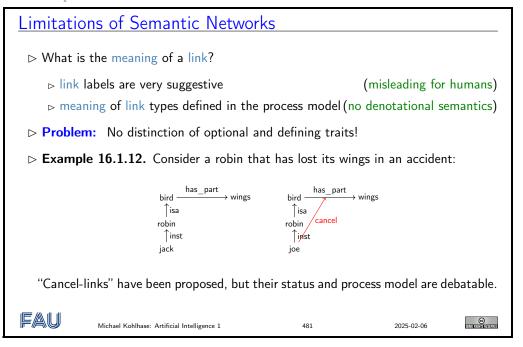
Terminologies and Assertions

- ▷ Remark 16.1.9. We should distinguish concepts from objects.
- \triangleright **Definition 16.1.10.** We call the subgraph of a semantic network N spanned by the isa links and relations between concepts the terminology (or TBox, or the famous Isa Hierarchy) and the subgraph spanned by the inst links and relations between objects, the assertions (together the ABox) of N.
- Example 16.1.11. In this semantic network we keep objects concept apart notationally:



But there are severe shortcomings of semantic networks: the suggestive shape and node names give (humans) a false sense of meaning, and the inference rules are only given in the process model (the implementation of the semantic network processing system).

This makes it very difficult to assess the strength of the inference system and make assertions e.g. about completeness.



To alleviate the perceived drawbacks of semantic networks, we can contemplate another notation that is more linear and thus more easily implemented: function/argument notation.

 Another Notation for Semantic Networks

 ▷ Definition 16.1.13. Function/argument notation for semantic networks

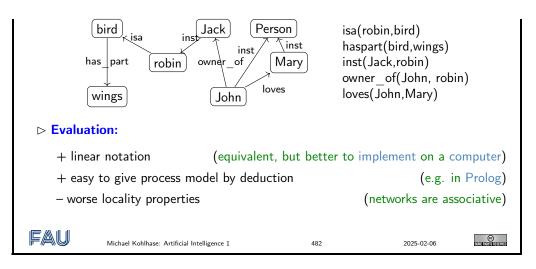
 ▷ interprets nodes as arguments
 (reification to individuals)

 ▷ interprets links as functions
 (predicates actually)

 ▷ Example 16.1.14.

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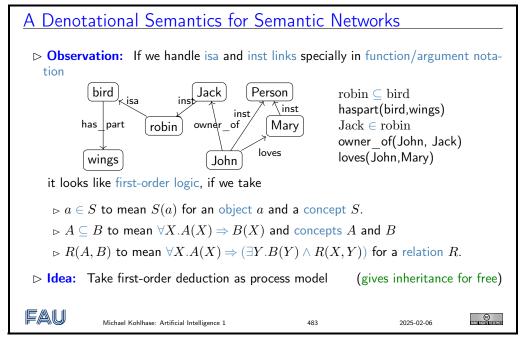
16.1. INTRODUCTION TO KNOWLEDGE REPRESENTATION



Indeed the function/argument notation is the immediate idea how one would naturally represent semantic networks for implementation.

This notation has been also characterized as subject/predicate/object triples, alluding to simple (English) sentences. This will play a role in the "semantic web" later.

Building on the function/argument notation from above, we can now give a formal semantics for semantic network: we translate them into first-order logic and use the semantics of that.



Indeed, the semantics induced by the translation to first-order logic, gives the intuitive meaning to the semantic networks. Note that this only holds only for the features of semantic networks that are representable in this way, e.g. the "cancel links" shown above are not (and that is a feature, not a bug).

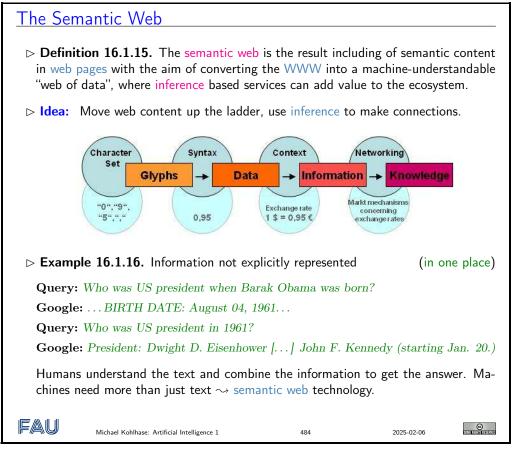
But even more importantly, the translation to first-order logic gives a first process model: we can use first-order inference to compute the set of inferences that can be drawn from a semantic network.

Before we go on, let us have a look at an important application of knowledge representation technologies: the semantic web.

16.1.3 The Semantic Web

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/27281. We will now define the term semantic web and discuss the pertinent ideas involved. There are two central ones, we will cover here:

- Information and data come in different levels of explicitness; this is usually visualized by a "ladder" of information.
- if information is sufficiently machine-understandable, then we can automate drawing conclusions.

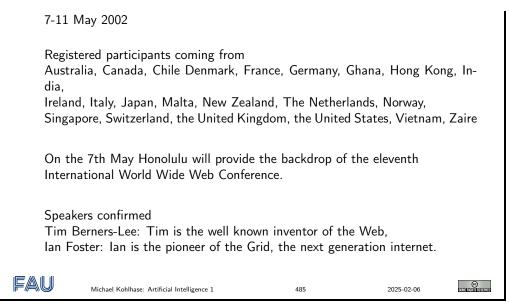


The term "semantic web" was coined by Tim Berners Lee in analogy to semantic networks, only applied to the world wide web. And as for semantic networks, where we have inference processes that allow us the recover information that is not explicitly represented from the network (here the world-wide-web).

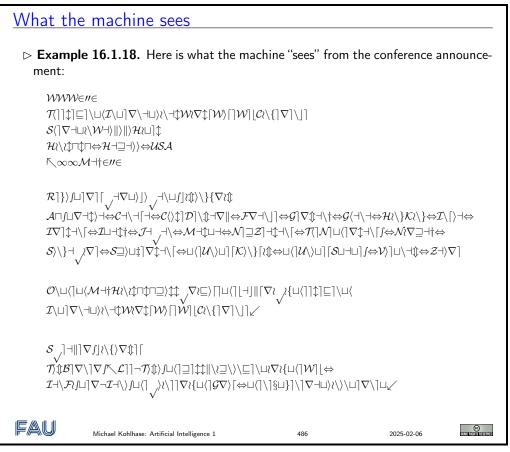
To see that problems have to be solved, to arrive at the semantic web, we will now look at a concrete example about the "semantics" in web pages. Here is one that looks typical enough.

What is the Information a User sees?
▷ Example 16.1.17. Take the following web-site with a conference announcement
WWW2002
The eleventh International World Wide Web Conference
Sheraton Waikiki Hotel
Honolulu, Hawaii, USA

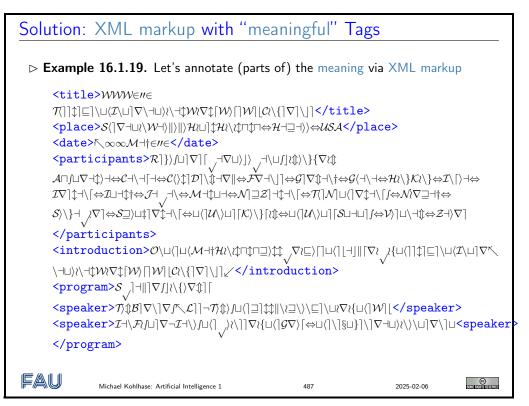
16.1. INTRODUCTION TO KNOWLEDGE REPRESENTATION



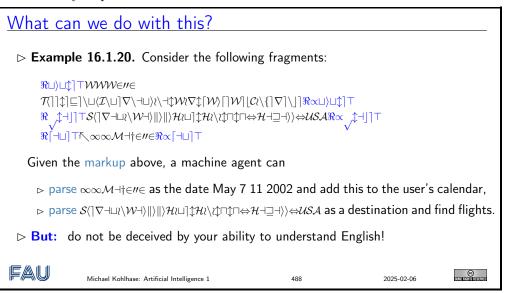
But as for semantic networks, what you as a human can see ("understand" really) is deceptive, so let us obfuscate the document to confuse your "semantic processor". This gives an impression of what the computer "sees".



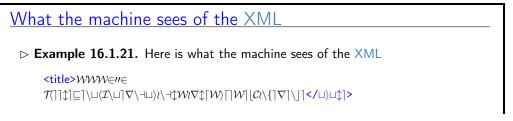
Obviously, there is not much the computer understands, and as a consequence, there is not a lot the computer can support the reader with. So we have to "help" the computer by providing some meaning. Conventional wisdom is that we add some semantic/functional markup. Here we pick XML without loss of generality, and characterize some fragments of text e.g. as dates.



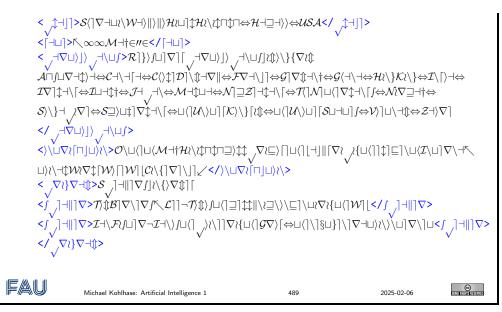
But does this really help? Is conventional wisdom correct?



To understand what a machine can understand we have to obfuscate the markup as well, since it does not carry any intrinsic meaning to the machine either.

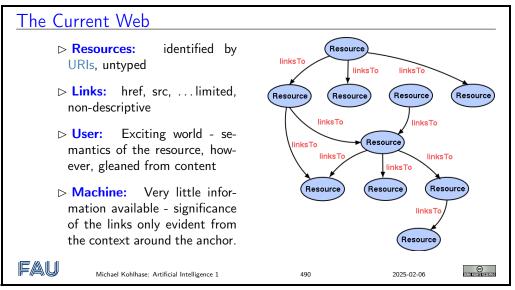


16.1. INTRODUCTION TO KNOWLEDGE REPRESENTATION



So we have not really gained much either with the markup, we really have to give meaning to the markup as well, this is where techniques from semenatic web come into play.

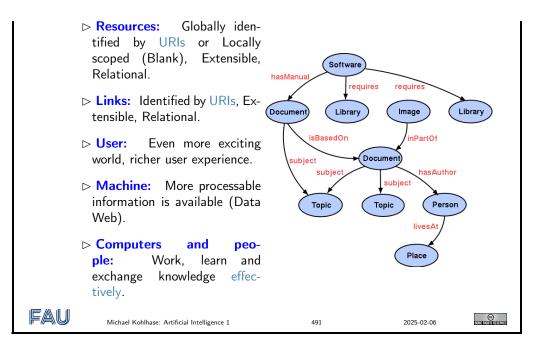
To understand how we can make the web more semantic, let us first take stock of the current status of (markup on) the web. It is well-known that world-wide-web is a hypertext, where multimedia documents (text, images, videos, etc. and their fragments) are connected by hyperlinks. As we have seen, all of these are largely opaque (non-understandable), so we end up with the following situation (from the viewpoint of a machine).



Let us now contrast this with the envisioned semantic web.

The Semantic Web

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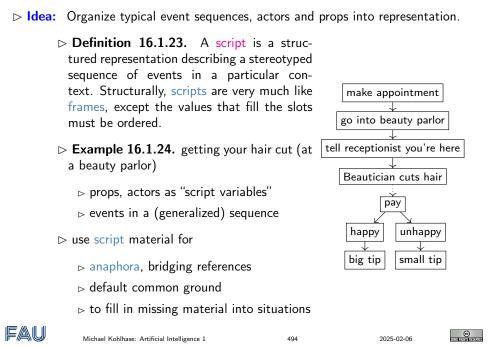
Essentially, to make the web more machine-processable, we need to classify the resources by the concepts they represent and give the links a meaning in a way, that we can do inference with that. The ideas presented here gave rise to a set of technologies jointly called the "semantic web", which we will now summarize before we return to our logical investigations of knowledge representation techniques.

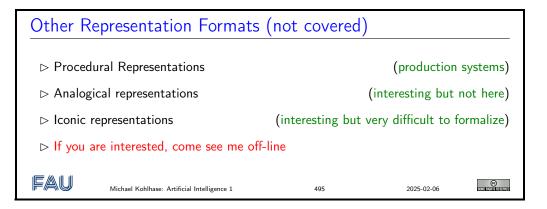
Towards a "Machine-Actionable Web"				
▷ Recall: We need external agreement on meaning of annotation tags.				
▷ Idea: standardize them in a community process (e.g. DIN or ISO)				
> Problem: Inflexible, Limited number of things can be expressed				
Better: Use ontologies to specify meaning of annotations				
 Ontologies provide a vocabulary of terms New terms can be formed by combining existing ones Meaning (semantics) of such terms is formally specified Can also specify relationships between terms in multiple ontologies 				
▷ Inference with annotations and ontologies (get out more than you put in!)				
▷ Standardize annotations in RDF [KC04] or RDFa [Her+13b] and ontologies on OWL [OWL09]				
\triangleright Harvest RDF and RDFa in to a triplestore or OWL reasoner.				
▷ Query that for implied knowledge (e.g. chaining multiple facts from Wikipedia)				
SPARQL: Who was US President when Barack Obama was Born?				
DBPedia: John F. Kennedy (was president in August 1961)				
Michael Kohlhase: Artificial Intelligence 1 492 2025-02-06				

16.1.4 Other Knowledge Representation Approaches

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/27282. Now that we know what semantic networks mean, let us look at a couple of other approaches that were influential for the development of knowledge representation. We will just mention them for reference here, but not cover them in any depth.

Frame Notation as Logic with Locality			
$catcher(catch_22, jack_2)$ Jack die	(where is the locality?) s an instance of catching d the catching ght a certain ball		
▷ Definition 16.1.22. Frames	(group everything around the object)		
(catch_object catch_22			
(catcher jack_2)			
(caught ball_5))			
 + Once you have decided on a frame, + easy to define schemes for concept - how to determine frame, when to ch 	(aka. types in feature structures)		
FAU Michael Kohlhase: Artificial Intelligence 1	493 2025-02-06 CONTRACTOR		
KR involving Time (Scripts [Sha	ank '77])		
▷ Idea: Organize typical event sequences	s, actors and props into representation.		
Definition 16.1.23. A script is a struc- tured representation describing a stereotyped sequence of events in a particular con-			





16.2 Logic-Based Knowledge Representation

A Video Nugget covering this section can be found at https://fau.tv/clip/id/27297. We now turn to knowledge representation approaches that are based on some kind of logical system. These have the advantage that we know exactly what we are doing: as they are based on symbolic representations and declaratively given inference calculi as process models, we can inspect them thoroughly and even prove facts about them.

Logic-Based Knowledge Representation				
▷ Logic (and related formalisms) have a well-defined semantics				
▷ explicitly (gives more underst	anding than statistical/neural methods)			
▷ transparently	(symbolic methods are monotonic)			
▷ systematically (we can prove theorems about our systems)				
\triangleright Problems with logic-based approaches				
\triangleright Where does the world knowledge come	from? (Ontology problem)			
▷ How to guide search induced by logical calculi (combinatorial explosion)				
▷ One possible answer: description logics. (next couple of times)				
Michael Kohlhase: Artificial Intelligence 1	496 2025-02-06 EUGENER			

But of course logic-based approaches have big drawbacks as well. The first is that we have to obtain the symbolic representations of knowledge to do anything – a non-trivial challenge, since most knowledge does not exist in this form in the wild, to obtain it, some agent has to experience the word, pass it through its cognitive apparatus, conceptualize the phenomena involved, systematize them sufficiently to form symbols, and then represent those in the respective formalism at hand.

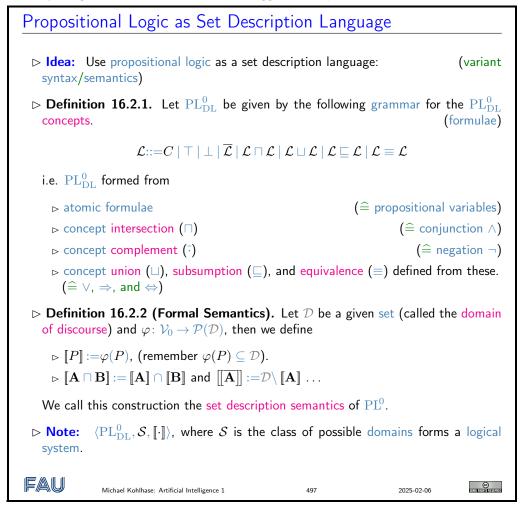
The second drawback is that the process models induced by logic-based approaches (inference with calculi) are quite intractable. We will see that all inferences can be played back to satisfiability tests in the underlying logical system, which are exponential at best, and undecidable or even incomplete at worst.

Therefore a major thrust in logic-based knowledge representation is to investigate logical systems that are expressive enough to be able to represent most knowledge, but still have a decidable – and maybe even tractable in practice – satisfiability problem. Such logics are called "description logics". We will study the basics of such logical systems and their inference procedures in the following.

16.2.1 Propositional Logic as a Set Description Language

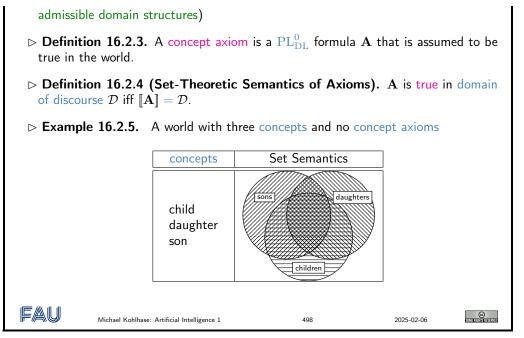
Before we look at "real" description logics in ??, we will make a "dry run" with a logic we already understand: propositional logic, which we will re-interpret the system as a set description language by giving a new, non-standard semantics. This allows us to already preview most of the inference procedures and knowledge services of knowledge representation systems in the next subsection.

To establish propositional logic as a set description language, we use a different interpretation than usual. We interpret propositional variables as names of sets and the connectives as set operations, which is why we give them a different – more suggestive – syntax.



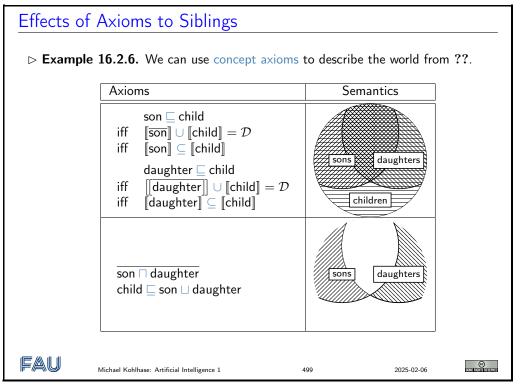
The main use of the set-theoretic semantics for PL^0 is that we can use it to give meaning to concept axioms, which we use to describe the "world".

Concept Axioms	
$\triangleright \text{ Observation: Set-theoretic semantics of 'true' an} \\ \bot := \varphi \sqcap \overline{\varphi})$	d 'false' $(\top:=arphi\sqcup\overline{arphi})$
$\llbracket op rbracket = \llbracket p rbracket \cup \llbracket ar p rbracket = \llbracket p rbracket \cup \mathcal{D} ar \llbracket p rbracket = \mathcal{D}$	Analogously: $\llbracket \bot \rrbracket = \emptyset$
\triangleright Idea: Use logical axioms to describe the world	(Axioms restrict the class of



Concept axioms are used to restrict the set of admissible domains to the intended ones. In our situation, we require them to be true – as usual – which here means that they denote the whole domain \mathcal{D} .

Let us fortify our intuition about concept axioms with a simple example about the sibling relation. We give four concept axioms and study their effect on the admissible models by looking at the respective Venn diagrams. In the end we see that in all admissible models, the denotations of the concepts son and daughter are disjoint, and child is the union of the two – just as intended.



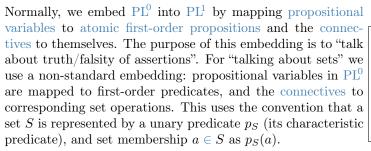
The set-theoretic semantics introduced above is compatible with the regular semantics of propositional logic, therefore we have the same propositional identities. Their validity can be established

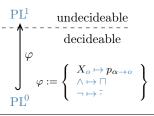
Propositional Identities					
	Name	for		for	
	Idempot.	$\varphi \sqcap \varphi = \varphi$		$\varphi \sqcup \varphi =$	φ
	Identity	$\varphi \sqcap \top = \varphi$		$\varphi \sqcup \bot =$	φ
	Absorpt.	$\varphi \sqcup \top = \top$		$\varphi \sqcap \bot =$	_
	Commut.	$\varphi \sqcap \psi = \psi \sqcap \varphi$		$\varphi \sqcup \psi = \psi \sqcup$	φ
	Assoc.	$\varphi \sqcap (\psi \sqcap \theta) = (\varphi \sqcap \psi) \sqcap \theta$	$\varphi \sqcup (\psi \sqcup \theta)$	$\varphi = (\varphi \sqcup \psi) \sqcup$	θ
	Distrib.	$\varphi \sqcap (\psi \sqcup \theta) = (\varphi \sqcap \psi) \sqcup (\varphi \sqcap \theta)$	$\varphi \sqcup (\psi \sqcap \theta) = (\varphi$	$(\varphi \sqcup \psi) \sqcap (\varphi \sqcup \psi)$	θ)
	Absorpt.	$\varphi \sqcap (\varphi \sqcup \theta) = \varphi$	φ	$\sqcup \varphi \sqcap \theta = \varphi \sqcap$	θ
	Morgan	$\overline{arphi \sqcap \psi} = \overline{arphi} \sqcup \overline{\psi}$		$\overline{\varphi \sqcup \psi} = \overline{\varphi} \sqcap$	$\overline{\psi}$
	dneg	$\overline{\overline{\varphi}}$ =	= φ		
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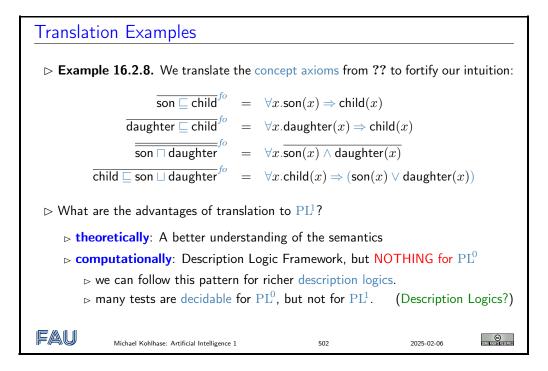
directly from the settings in ??.

There is another way we can approach the set description interpretation of propositional logic: by translation into a logic that can express knowledge about sets – first-order logic.

Set-Theoretic Semantics and Predicate Logic \triangleright **Definition 16.2.7.** Translation into PL¹ (borrow semantics from that) \triangleright recursively add argument variable x \triangleright change back $\sqcap, \sqcup, \sqsubseteq, \equiv$ to $\land, \lor, \Rightarrow, \Leftrightarrow$ \triangleright universal closure for x at formula level. Definition Comment $\overline{p}^{fo(x)} := p(x)$ $\frac{\overline{\mathbf{A}}}{\overline{\mathbf{A}}} \stackrel{fo(x)}{:=} \neg \overline{\mathbf{A}}^{fo(x)} \\
\overline{\mathbf{A}} \sqcap \overline{\mathbf{B}}^{fo(x)} := \overline{\mathbf{A}}^{fo(x)} \land \overline{\mathbf{B}}^{fo(x)} \\$ ∧ vs. □ $\begin{array}{l}
 \mathbf{A} \sqcap \mathbf{B} & := \mathbf{A} \land \mathbf{B} \\
 \overline{\mathbf{A}} \sqcup \overline{\mathbf{B}}^{fo(x)} := \overline{\mathbf{A}}^{fo(x)} \lor \overline{\mathbf{B}}^{fo(x)} \\
 \overline{\mathbf{A}} \sqsubseteq \overline{\mathbf{B}}^{fo(x)} := \overline{\mathbf{A}}^{fo(x)} \Rightarrow \overline{\mathbf{B}}^{fo(x)} \\
 \overline{\mathbf{A}} = \overline{\mathbf{B}}^{fo(x)} := \overline{\mathbf{A}}^{fo(x)} \Leftrightarrow \overline{\mathbf{B}}^{fo(x)}
 \end{array}$ ∨ vs. ⊔ \Rightarrow vs. \Leftrightarrow vs. = $:= \overline{(\forall x. \overline{\mathbf{A}}^{fo(x)})}$ for formulae FAU Michael Kohlhase: Artificial Intelligence 1 501 2025-02-06



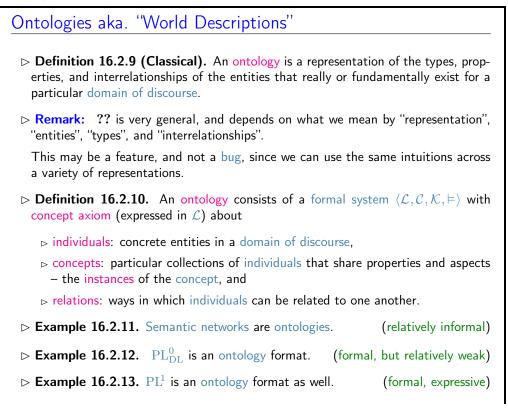




16.2.2 Ontologies and Description Logics

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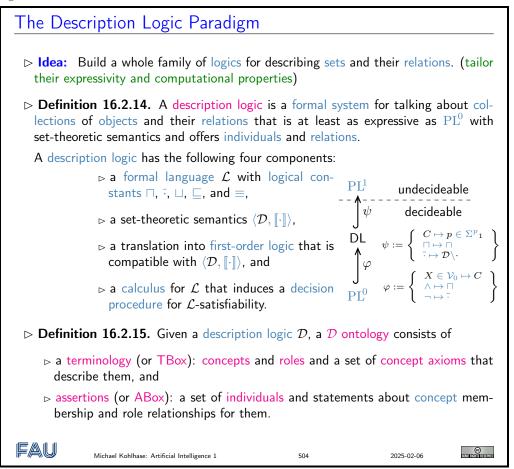
A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/27298. We have seen how sets of concept axioms can be used to describe the "world" by restricting the set of admissible models. We want to call such concept descriptions "ontologies" – formal descriptions of (classes of) objects and their relations.



16.2. LOGIC-BASED KNOWLEDGE REPRESENTATION

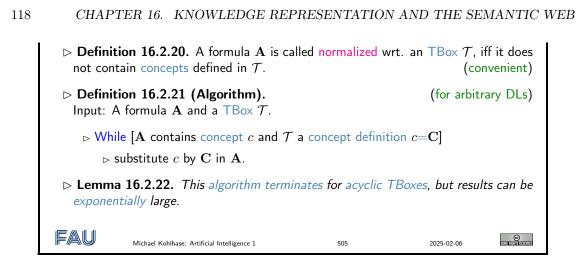
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As we will see, the situation for PL_{DL}^{0} is typical for formal ontologies (even though it only offers concepts), so we state the general description logic paradigm for ontologies. The important idea is that having a formal system as an ontology format allows us to capture, study, and implement ontological inference.



For convenience we add concept definitions as a mechanism for defining new concepts from old ones. The so-defined concepts inherit the properties from the concepts they are defined from.

► Let D be a description logic with concepts C.
► Definition 16.2.16. A concept definition is a pair c=C, where c is a new concept name and C ∈ C is a D-formula.
► Example 16.2.17. We can define mother=woman ¬ has_child.
► Definition 16.2.18. A concept definition c=C is called recursive, iff c occurs in C.
► Definition 16.2.19. An TBox is a finite set of concept definitions and concept axioms. It is called acyclic, iff it does not contain recursive definitions.

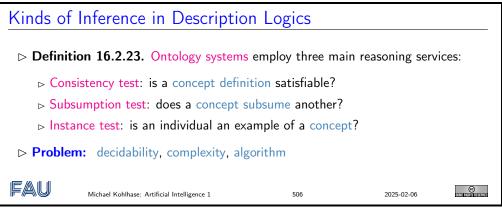


As PL_{DL}^0 does not offer any guidance on this, we will leave the discussion of ABoxes to ?? when we have introduced our first proper description logic ACC.

16.2.3 Description Logics and Inference

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/27299. Now that we have established the description logic paradigm, we will have a look at the inference services that can be offered on this basis.

Before we go into details of particular description logics, we must ask ourselves what kind of inference support we would want for building systems that support knowledge workers in building, maintaining and using ontologies. An example of such a system is the Protégé system [Pro], which can serve for guiding our intuition.



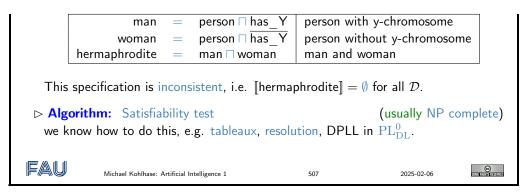
We will now through these inference-based tests separately.

The consistency test checks for concepts that do not/cannot have instances. We want to avoid such concepts in our ontologies, since they clutter the namespace and do not contribute any meaningful contribution.

Consistency Test

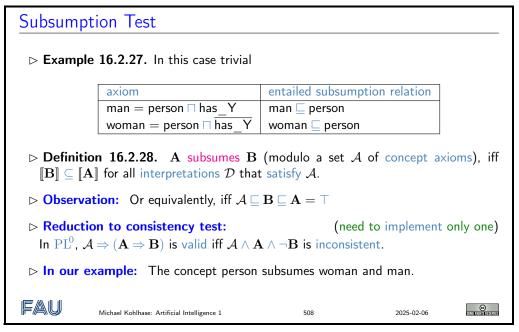
- \triangleright **Definition 16.2.24.** We call a concept *C* consistent, iff there is no concept *A*, with both $C \sqsubseteq A$ and $C \sqsubseteq \overline{A}$.
- \triangleright Or equivalently:
- \triangleright Definition 16.2.25. A concept C is called inconsistent, iff $\llbracket C \rrbracket = \emptyset$ for all \mathcal{D} .
- \triangleright Example 16.2.26 (T-Box in PL_{DL}^0).

16.2. LOGIC-BASED KNOWLEDGE REPRESENTATION



Even though consistency in our example seems trivial, large ontologies can make machine support necessary. This is even more true for ontologies that change over time. Say that an ontology initially has the concept definitions woman=person long_hair and man=person bearded, and then is modernized to a more biologically correct state. In the initial version the concept hermaphrodite is consistent, but becomes inconsistent after the renovation; the authors of the renovation should be made aware of this by the system.

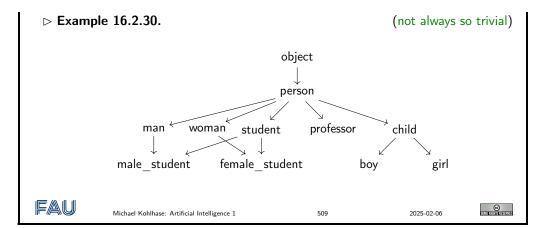
The subsumption test determines whether the sets denoted by two concepts are in a subset relation. The main justification for this is that humans tend to be aware of concept subsumption, and tend to think in taxonomic hierarchies. To cater to this, the subsumption test is useful.

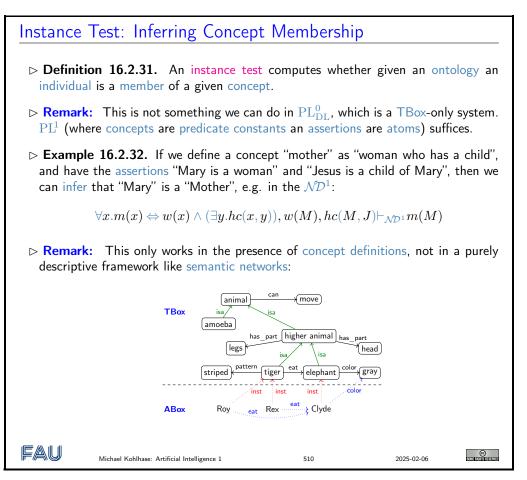


The good news is that we can reduce the subsumption test to the consistency test, so we can re-use our existing implementation.

The main user-visible service of the subsumption test is to compute the actual taxonomy induced by an ontology.

Classification			
▷ The subsumption relation among all concepts	(subsumption graph)		
\triangleright Visualization of the subsumption graph for inspection	(plausibility)		
▷ Definition 16.2.29. Classification is the computation of the subsumption graph.			





If we take stock of what we have developed so far, then we can see PL_{DL}^{0} as a rational reconstruction of semantic networks restricted to the "isa" relation. We relegate the "instance" relation to ??. This reconstruction can now be used as a basis on which we can extend the expressivity and inference procedures without running into problems.

16.3 A simple Description Logic: ALC

In this section, we instantiate the description-logic paradigm further with the prototypical logic \mathcal{ACC} , which we will introduce now.

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16.3.1 Basic ALC: Concepts, Roles, and Quantification

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/27300. In this subsection, we instantiate the description-logic paradigm with the prototypical logic ACC, which we will develop now.

Motivation for \mathcal{AC} (Prototype Description Logic)				
ho Propositional logic (PL ⁰) is not expressive enough!				
▷ Example 16.3.1. "mothers are women that have a child"				
\triangleright Reason: There are no quantifiers in PL^0 (existential (\exists) and universal (\forall))				
\triangleright Idea: Use first-order predicate logic (PL ¹)				
$orall x.mother(x) \Leftrightarrow woman(x) \wedge (\exists y.has_child(x,y))$				
\triangleright Problem: Complex algorithms, non-termination (PL ¹ is too expressive)				
\triangleright Idea: Try to travel the middle ground				
More expressive than PL^0 (quantifiers) but weaker than $\mathrm{PL}^1.$ (still tractable)				
▷ Technique: Allow only "restricted quantification", where quantified variables only range over values that can be reached via a binary relation like <i>has_child</i> .				
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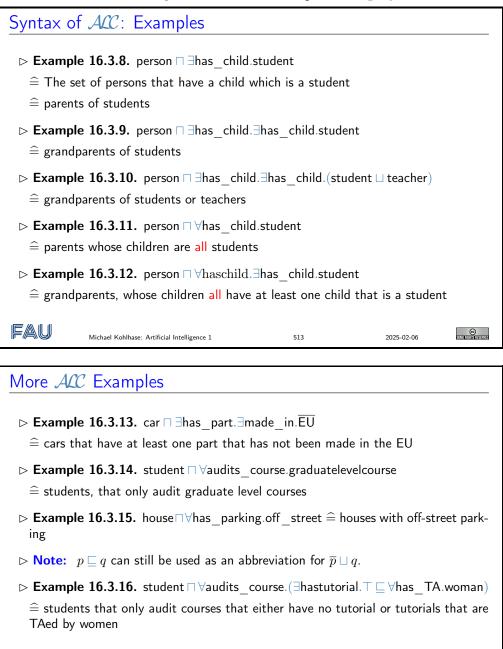
 \mathcal{AC} extends the concept operators of $\mathrm{PL}_{\mathrm{DL}}^{0}$ with binary relations (called "roles" in \mathcal{AC}). This gives \mathcal{AC} the expressive power we had for the basic semantic networks from ??.

Syntax of ACC

\triangleright Definition 16.3.2 (Concepts). variables" in PL_{DL}^{0})	(aka. "predicates" in PL^1 or "propositional
Concepts in DLs represent collections of	of objects.
ightarrow like classes in OOP.	
▷ Definition 16.3.3 (Special Concept and the bottom concept ⊥ (for "false"	ts). The top concept \top (for "true" or "all") or "none").
	nan, mother, professor, student, car, BMW, tack risk, furniture, table, leg of a chair,
▷ Definition 16.3.5. Roles represent bir	nary relations (like in PL^1)
	n, has_daughter, loves, hates, gives_course, g_of_table, has_wheel, has_motor,
	formulae of \mathcal{ACC} are given by the following $\mathcal{ACC} \sqcap F_{\mathcal{ACC}} \mid \mathcal{F}_{\mathcal{ACC}} \mid \exists \mathbb{R}.F_{\mathcal{ACC}} \mid \forall \mathbb{R}.F_{\mathcal{ACC}}$
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 $\mathcal{A\!C}$ restricts the quantification to range all individuals reachable as role successor. The distinction

between universal and existential quantifiers clarifies an implicit ambiguity in semantic networks.



As before we allow concept definitions so that we can express new concepts from old ones, and obtain more concise descriptions.

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ACC Concep	t Definitions
⊳ Idea: Defin	e new concepts from known ones.
	16.3.17. A concept definition is a pair consisting of a new concept finiendum) and an \mathcal{AC} formula (the definiens). Concepts that are not

definienda are called primitive.

 \triangleright We extend the $\mathcal{A\!C}$ grammar from $\ref{eq:main_started}$ by the production

$$CD_{ACC} ::= C = F_{ACC}$$

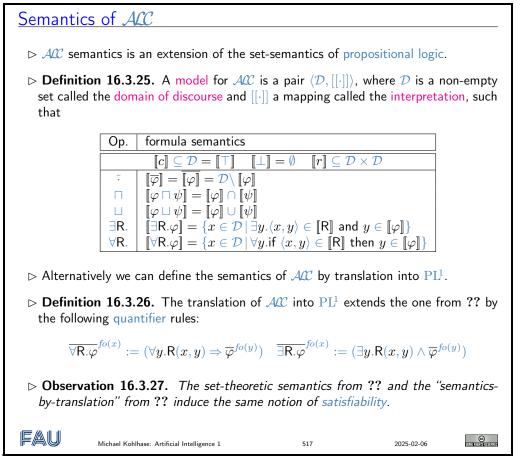
▷ Example 16.3.18.

[Definition	rec?
	$man = person \sqcap \exists has_chrom.Y_chrom$	-
	woman = person $\sqcap \forall has chrom Y chrom$	-
	mother = woman $\sqcap \exists has_child.person$	-
	$father = man \sqcap \exists has_child.person$	-
	$grandparent = person \sqcap \exists has_child.(mother \sqcup father)$	-
	german = person □ ∃has_parents.german	+
	$number_list = empty_list \sqcup \exists is_first.number \sqcap \exists is_rest.number_list$	+
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As before, we can normalize a TBox by definition expansion if it is acyclic. With the introduction of roles and quantification, concept definitions in ACC have a more "interesting" way to be cyclic as ?? shows.

```
TBox Normalization in ALC
  \triangleright Definition 16.3.19. We call an \mathcal{AC} formula \varphi normalized wrt. a set of concept
    definitions, iff all concepts occurring in \varphi are primitive.
  \triangleright Definition 16.3.20. Given a set \mathcal{D} of concept definitions, normalization is the
     process of replacing in an \mathcal{A}\mathcal{L} formula \varphi all occurrences of definienda in \mathcal{D} with
    their definientia.
  ▷ Example 16.3.21 (Normalizing grandparent).
              grandparent
              \mathsf{person} \ \sqcap \ \exists \mathsf{has\_child.} (\mathsf{mother} \ \sqcup \ \mathsf{father})
             person □ ∃has child. (woman □ ∃has child. person □ man □ ∃has child. person)
        \mapsto
              \mathsf{person} ~\sqcap~ \exists \mathsf{has\_child}. (\mathsf{person} ~\sqcap~ \exists \mathsf{has\_chird}. \mathsf{Y\_chrom} ~\sqcap~ \exists \mathsf{has\_child}. \mathsf{person} ~\sqcap~ \exists \mathsf{has\_chrom}. \mathsf{Y\_chrom} ~\sqcap~ \exists \mathsf{has\_child}. \mathsf{person})
  ▷ Observation 16.3.22. Normalization results can be exponential.
                                                                                                                   (contain
     redundancies)
  ▷ Observation 16.3.23. Normalization need not terminate on cyclic TBoxes.
  ▷ Example 16.3.24.
                                  person □ ∃has parents.german
             german
                           \mapsto
                                  person \Box \existshas parents.(person \Box \existshas parents.german)
                           \mapsto
                           \mapsto
                                  . . .
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Now that we have motivated and fixed the syntax of \mathcal{AC} , we will give it a formal semantics. The semantics of \mathcal{AC} is an extension of the set-theoretic semantics for PL^0 , thus the interpretation $[[\cdot]]$ assigns subsets of the domain of discourse to concepts and binary relations over the domain of discourse to roles.



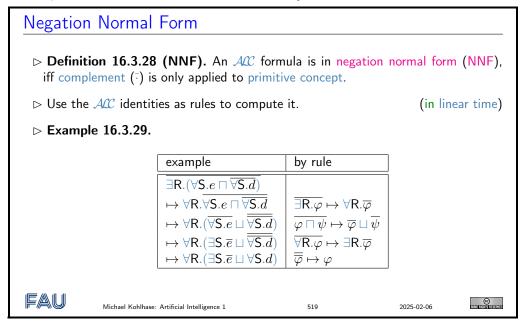
We can now use the \mathcal{AC} identities above to establish a useful normal form for \mathcal{AC} . This will play a role in the inference procedures we study next.

The following identities will be useful later on. They can be proven directly with the settings from ??; we carry this out for one of them below.

ACC Identities				
$\triangleright \boxed{\begin{array}{c c}1\\2\end{array}} \exists R.\varphi = \forall R.\overline{\varphi} & 3\\\forall R.(\varphi \sqcap \psi) = \forall R.\varphi \sqcap \forall R.\psi & 4\\ \triangleright \text{ Proof of } 1\end{array}}$, ,]		
$\begin{split} \begin{bmatrix} \exists R.\varphi \end{bmatrix} &= \mathcal{D} \setminus \llbracket \exists R.\varphi \rrbracket &= \mathcal{D} \setminus \{x \in \mathcal{D} \mid \exists y.(\langle x, y \rangle \in \llbracket R \rrbracket) \text{ and } (y \in \llbracket \varphi \rrbracket) \} \\ &= \{x \in \mathcal{D} \mid not \exists y.(\langle x, y \rangle \in \llbracket R \rrbracket) \text{ and } (y \in \llbracket \varphi \rrbracket) \} \\ &= \{x \in \mathcal{D} \mid \forall y.if (\langle x, y \rangle \in \llbracket R \rrbracket) \text{ then } (y \notin \llbracket \varphi \rrbracket) \} \\ &= \{x \in \mathcal{D} \mid \forall y.if (\langle x, y \rangle \in \llbracket R \rrbracket) \text{ then } (y \notin \llbracket \varphi \rrbracket) \} \\ &= \{x \in \mathcal{D} \mid \forall y.if (\langle x, y \rangle \in \llbracket R \rrbracket) \text{ then } (y \in (\mathcal{D} \setminus \llbracket \varphi \rrbracket)) \} \end{split}$				
$ = \{x \in \mathcal{D} \forall y. if (\langle x, y \rangle \in \llbracket R \rrbracket) then (y \in \llbracket \overline{\varphi} \rrbracket) \} \\ = \llbracket \forall R. \overline{\varphi} \rrbracket $				
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The form of the identities (interchanging quantification with connectives) is reminiscient of iden-

tities	in	\mathbf{PI}^1	this	is no	coin	cidence	as	the	"semantics	hv	translation"	of	??	shows
010100	111	т г ,	, unio	10 110	com	ciacinee	as	one	Somanuco	D.y	u ansia u on	or	•••	SHOWS.



Finally, we extend \mathcal{AC} with an ABox component. This mainly means that we define two new assertions in \mathcal{AC} and specify their semantics and PL¹ translation.

ACC with Assertions about Individuals \triangleright Definition 16.3.30. We define the ABox assertions for ACC: $(a \text{ is a } \varphi)$ \triangleright Role assertions $a:\varphi$ $\triangleright a \mathsf{R} b$ (a stands in relation R to b) assertions make up the ABox in \mathcal{ACC} . \triangleright **Definition 16.3.31.** Let $\langle \mathcal{D}, [[\cdot]] \rangle$ be a model for \mathcal{AC} , then we define $\triangleright \llbracket a : \varphi \rrbracket = \mathsf{T}$, iff $\llbracket a \rrbracket \in \llbracket \varphi \rrbracket$, and $\triangleright \llbracket a \ \mathsf{R} \ b \rrbracket = \mathsf{T}, \text{ iff } (\llbracket a \rrbracket, \llbracket b \rrbracket) \in \llbracket \mathsf{R} \rrbracket.$ \triangleright Definition 16.3.32. We extend the PL¹ translation of ACC to ACC assertions: $\triangleright \overline{a:\varphi}^{fo} := \overline{\varphi}^{fo(a)}$, and $\triangleright \overline{a \mathsf{R} b}^{fo} := \mathsf{R}(a, b).$ Fau © Michael Kohlhase: Artificial Intelligence 1 520 2025-02-06

If we take stock of what we have developed so far, then we see that ACC as a rational reconstruction of semantic networks restricted to the "isa" and "instance" relations – which are the only ones that can really be given a denotational and operational semantics.

16.3.2 Inference for ALC

Video Nuggets covering this subsection can be found at https://fau.tv/clip/id/27301 and https://fau.tv/clip/id/27302.

In this subsection we make good on the motivation from ?? that description logics enjoy tractable inference procedures: We present a tableau calculus for \mathcal{ACC} , show that it is a decision procedure, and study its complexity.

\mathcal{T}_{ACC} : A Tableau-Calculus for ACC						
Recap Tableaux: A tableau calculus develops an initial tableau in a tree-formed scheme using tableau extension rules.						
A saturated tableau (no rules applicable) constitutes a refutation, if all branches are closed (end in \perp).						
\triangleright Definition 16.3.33. The $\mathcal{A\!C\!C}$ tableau c	alculus $\mathcal{T}_{\!\!\mathcal{A}\!\mathcal{C}\!\!\mathcal{C}}$ acts on assertions:					
ightarrow x: arphi	(x inhabits concept φ)					
$\triangleright x R y \qquad \qquad (x \text{ and } y \text{ are in relation})$						
where φ is a normalized \mathcal{AC} concept in negation normal form with the following rules:						
$\frac{\frac{x:c}{x:\overline{c}}}{\perp} \mathcal{T}_{\perp} \qquad \frac{x:\varphi \sqcap \psi}{x:\varphi} \mathcal{T}_{\sqcap} \qquad \frac{x:\varphi \sqcup \psi}{x:\psi} $	$\frac{\psi}{\psi} \mathcal{T}_{\sqcup} \qquad \frac{x : \forall R.\varphi}{y : \varphi} \mathcal{T}_{\forall} \qquad \frac{x : \exists R.\varphi}{x \; R.y} \; \mathcal{T}_{\exists} \\ \frac{y : \varphi}{y : \varphi} \mathcal{T}_{\forall} \qquad \frac{y : \exists R.\varphi}{y : \varphi} \mathcal{T}_{\exists}$					
$\succ \text{ To test consistency of a concept } \varphi, \text{ normalize } \varphi \text{ to } \psi, \text{ initialize the tableau with} \\ x:\psi, \text{ saturate. Open branches } \sim \text{ consistent.} $ (x arbitrary)						
Michael Kohlhase: Artificial Intelligence 1	521 2025-02-06 CONTRACTOR					

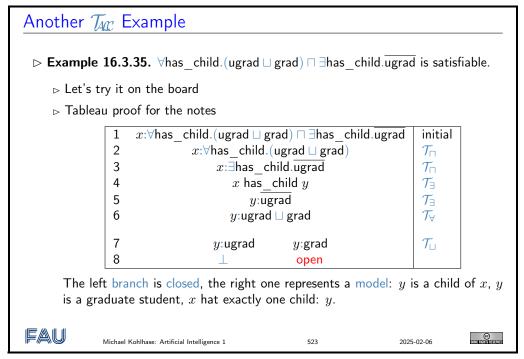
In contrast to the tableau tableau calculi for theorem proving we have studied earlier, \mathcal{T}_{AC} is run in "model generation mode". Instead of initializing the tableau with the axioms and the negated conjecture and hope that all branches will close, we initialize the \mathcal{T}_{AC} tableau with axioms and the "membership-conjecture" that a given concept φ is satisfiable – i.e. φ h as a member x, and hope for branches that are open, i.e. that make the conjecture true (and at the same time give a model).

Let us now work through two very simple examples; one unsatisfiable, and a satisfiable one.

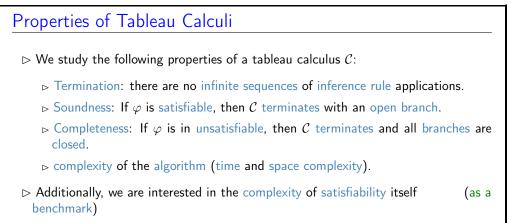
$\mathcal{T}_{\!\!\mathcal{A}\!\mathcal{C}}$ Examples						
Example 16.3.34 (Tableau Proofs). We have two similar conjectures about children.						
$\triangleright x:\forall has_child.m$	$> x: \forall has_child.man \sqcap \exists has_child.man \qquad (all sons, but a daughter)$					
	$x: \forall has_child.man \sqcap \exists has_child.man \\ x: \forall has child.man$	initial \mathcal{T}_{\Box}				
	$x:\exists$ has_child.man	\mathcal{T}_{\Box}				
	x has_child y	\mathcal{T}_{\exists}				
	y:man	\mathcal{T}_{\exists}				
		\mathcal{T}_{\perp}				
	inconsistent					
$> x: \forall has_child.man \sqcap \exists has_child.man \qquad (only sons, and at least one)$						

	$x:\forall has_child.man \sqcap \exists$	has_child.man	initial			
	<i>x</i> :∀has_child		\mathcal{T}_{\sqcap}			
	x:∃has_child		\mathcal{T}_{\sqcap}			
	x has_chil	d y	\mathcal{T}_{\exists} \mathcal{T}_{\exists}			
	y:man		\mathcal{T}_{\exists}			
	open					
This tableau shows a model: there are two persons, x and y . y is the only child of x , y is a man.						
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Another example: this one is more complex, but the concept is satisfiable.



After we got an intuition about \mathcal{T}_{AC} , we can now study the properties of the calculus to determine that it is a decision procedure for AC.



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The soundness result for \mathcal{T}_{AC} is as usual: we start with a model of $x:\varphi$ and show that an \mathcal{T}_{AC} tableau must have an open branch.

Correctness \triangleright Lemma 16.3.36. If φ satisfiable, then \mathcal{T}_{AC} terminates on $x:\varphi$ with open branch. \triangleright *Proof:* Let $\mathcal{M} := \langle \mathcal{D}, \llbracket \cdot \rrbracket \rangle$ be a model for φ and $w \in \llbracket \varphi \rrbracket$. $\mathcal{M} \models (x:\psi) \quad \text{iff} \quad \llbracket x \rrbracket \in \llbracket \psi \rrbracket$ 1. We define $\llbracket x \rrbracket := w$ and $\mathcal{M} \models x \mathsf{R} y$ iff $\langle x, y \rangle \in \llbracket \mathsf{R} \rrbracket$ $\mathcal{M} \models S$ iff $\mathcal{I} \models c$ for all $c \in S$ 2. This gives us $\mathcal{M} \models (x:\varphi)$ (base case) 3. If the branch is satisfiable, then either \triangleright no rule applicable to leaf, (open branch) (inductive case: next) \triangleright or rule applicable and one new branch satisfiable. 4. There must be an open branch. (by termination) FAU Michael Kohlhase: Artificial Intelligence 1 525 2025-02-06

We complete the proof by looking at all the \mathcal{T}_{AC} inference rules in turn.

 $\mathcal{C} ase analysis on the rules$ $\mathcal{T}_{\sqcap} applies then \mathcal{M}\models(x:\varphi \sqcap \psi), i.e. [x] \in [\varphi \sqcap \psi]$ so $[x] \in [\varphi]$ and $[x] \in [\psi]$, thus $\mathcal{M}\models(x:\varphi)$ and $\mathcal{M}\models(x:\psi)$. $\mathcal{T}_{\sqcup} applies then \mathcal{M}\models(x:\varphi \sqcup \psi), i.e. [x] \in [\varphi \sqcup \psi]$ so $[x] \in [\varphi]$ or $[x] \in [\psi]$, thus $\mathcal{M}\models(x:\varphi)$ or $\mathcal{M}\models(x:\psi)$,
wlog. $\mathcal{M}\models(x:\varphi)$. $\mathcal{T}_{\forall} applies then \mathcal{M}\models(x:\forall R.\varphi) and \mathcal{M}\models x R y, i.e. [x] \in [\forall R.\varphi] and \langle x, y \rangle \in [R], so$ $[y] \in [\varphi]$ $\mathcal{T}_{\exists} applies then \mathcal{M}\models(x:\exists R.\varphi), i.e. [x] \in [\exists R.\varphi],$ so there is a $v \in D$ with $\langle [x], v \rangle \in [R]$ and $v \in [\varphi]$.
We define [y] := v, then $\mathcal{M}\models x R y$ and $\mathcal{M}\models(y:\varphi)$

For the completeness result for \mathcal{T}_{AC} we have to start with an open tableau branch and construct a model that satisfies all judgments in the branch. We proceed by building a Herbrand model, whose domain consists of all the individuals mentioned in the branch and which interprets all concepts and roles as specified in the branch. Not surprisingly, the model thus constructed satisfies (all judgments on) the branch.

Completeness of the Tableau Calculus
▷ Lemma 16.3.37. Open saturated tableau branches for φ induce models for φ.
▷ Proof: construct a model for the branch and verify for φ
1. Let B be an open, saturated branch

C	> we define			
	$[\![c]\!]$: = {	$egin{array}{lll} x \mid x{:}\psi \in \mathcal{B} ext{ or } z \ x \mid x{:}c \in \mathcal{B} \ \langle x,y angle \mid x ext{ R } y \in \mathcal{B} \end{array}$,	
ء 2. <i>ا</i>	> well-defined since never $x:c, x:c$ > \mathcal{M} satisfies all assertions $x:c, x:c$ $\mathcal{A} \models (y:\psi)$, for all $y:\psi \in \mathcal{B}$ $\mathcal{A} \models (x:\varphi)$.	$x:\overline{c} ext{ and } x extsf{ R} y$,	(otherwise \mathcal{T}_\perp (by cons on $k=size(\psi)$ no	truction)
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We complete the proof by looking at all the \mathcal{T}_{AC} inference rules in turn.

Case Ana	lysis for Induction			
case $y:\psi = 1$	$y:\psi_1 \sqcap \psi_2$ Then $\{y:\psi_1, y:\psi_2\} \subseteq$	B	$(\mathcal{T}_{\Box}$ -rule, sa	turation)
so $\mathcal{M}{\models}(y$	$:\psi_1)$ and $\mathcal{M}{\models}(y{:}\psi_2)$ and $\mathcal{M}{\models}(y$	$:\psi_1 \sqcap \psi_2)$	(IH, De	efinition)
case $y:\psi = 1$	$y{:}\psi_1 \sqcup \psi_2$ Then $y{:}\psi_1 \in {f B}$ or $y{:}\psi_1$	$\psi_2 \in \mathbf{B}$	$(\mathcal{T}_{\sqcup}, sat)$	turation)
so $\mathcal{M}{\models}(y$	$:\psi_1)$ or $\mathcal{M}{\models}(y{:}\psi_2)$ and $\mathcal{M}{\models}(y{:}\psi_2)$	$\psi_1 \sqcup \psi_2)$	(IH, De	efinition)
case $y:\psi = 0$	$y{:}\exists {\sf R}. heta$ then $\{y \; {\sf R} \; z, z{:} heta\} \subseteq {f B}$ (z	new variable)	(\mathcal{T}_{\exists} -rules, sa	turation)
so $\mathcal{M} \models (z)$	$(heta)$ and $\mathcal{M}{\models}y \ R \ z$, thus $\mathcal{M}{\models}(y)$	R. heta).	(IH, De	efinition)
case $y:\psi = 0$	$y{:}orall {f R}. heta$ Let $\langle \llbracket y rbracket, v angle \in \llbracket {f R} rbracket$ for sol	me $r\in \mathcal{D}$		
then $v = z$	z for some variable z with $y \; R \; z \in$	B	(construction	n of [[R]])
So $z{:} heta\in \mathcal{B}$	\mathcal{B} and $\mathcal{M}\models(z{:} heta).$		(\mathcal{T}_{\forall} -rule, saturat	on, Def)
As v was a	arbitrary we have $\mathcal{M}\models(y{:}\forallR. heta).$			
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Termination

- \rhd Theorem 16.3.38. $\mathcal{T}_{\!\!A\!C\!C}$ terminates.
- \triangleright To prove termination of a tableau algorithm, find a well-founded measure (function) that is decreased by all rules

$$\frac{x:c}{\bot} \mathcal{T}_{\bot} \qquad \frac{x:\varphi \sqcap \psi}{x:\varphi} \mathcal{T}_{\sqcap} \qquad \frac{x:\varphi \sqcup \psi}{x:\varphi} \mathcal{T}_{\sqcup} \qquad \frac{x:\varphi \sqcup \psi}{x:\varphi} \mathcal{T}_{\sqcup} \qquad \frac{x:\forall \mathsf{R}.\varphi}{y:\varphi} \mathcal{T}_{\forall} \qquad \frac{x:\exists \mathsf{R}.\varphi}{x:\forall \mathsf{R}.\varphi} \mathcal{T}_{\exists} \qquad \frac{x:\forall \mathsf{R}.\varphi}{y:\varphi} \mathcal{T}_{\exists}$$

> *Proof:* Sketch (full proof very technical)

- 1. Any rule except \mathcal{T}_{\forall} can only be applied once to $x:\psi$.
- 2. Rule \mathcal{T}_{\forall} applicable to $x:\forall \mathbb{R}.\psi$ at most as the number of R-successors of x. (those y with $x \in y$ above)

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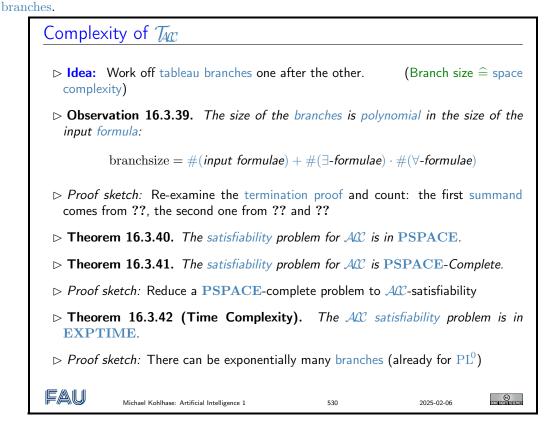
- 3. The R-successors are generated by $x:\exists R.\theta$ above, (number bounded by size of input formula)
- 4. Every rule application to $x:\psi$ generates constraints $z:\psi'$, where ψ' a proper sub-formula of ψ .

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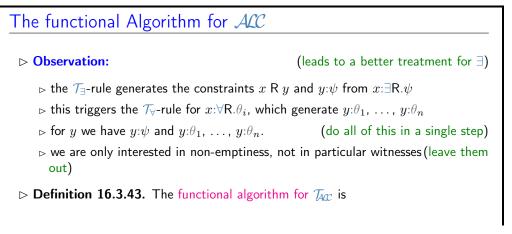
We can turn the termination result into a worst-case complexity result by examining the sizes of

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In summary, the theoretical complexity of \mathcal{AC} is the same as that for PL^0 , but in practice \mathcal{AC} is much more expressive. So this is a clear win.

But the description of the tableau algorithm \mathcal{T}_{AC} is still quite abstract, so we look at an exemplary implementation in a functional programming language.



```
consistent(S) =
        if \{c, \overline{c}\} \subseteq S then false
        elif '\varphi \sqcap \psi' \in S and ('\varphi' \notin S or '\psi' \notin S)
           then consistent(S \cup \{\varphi, \psi\})
        elif '\varphi \sqcup \psi' \in S and \{\varphi, \psi\} \notin S
             then consistent(S \cup \{\varphi\}) or consistent(S \cup \{\psi\})
        elif forall '\exists \mathsf{R}.\psi' \in S
         consistent({\psi} \cup {\theta \in \theta \mid \forall \mathsf{R}. \theta' \in S})
        else true
  \triangleright Relatively simple to implement.
                                                                              (good implementations optimized)
  \triangleright But: This is restricted to \mathcal{ACC}.
                                                                                  (extension to other DL difficult)
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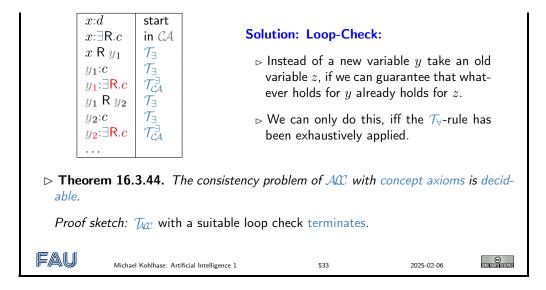
Note that we have (so far) only considered an empty TBox: we have initialized the tableau with a normalized concept; so we did not need to include the concept definitions. To cover "real" ontologies, we need to consider the case of concept axioms as well.

We now extend \mathcal{T}_{AC} with concept axioms. The key idea here is to realize that the concept axioms apply to all individuals. As the individuals are generated by the \mathcal{T}_{\exists} rule, we can simply extend that rule to apply all the concept axioms to the newly introduced individual.

Extending the Tableau Algorithm by Concept Axioms \triangleright concept axioms, e.g. child \sqsubseteq son \sqcup daughter cannot be handled in \mathcal{T}_{AC} yet. \triangleright Idea: Whenever a new variable y is introduced (by \mathcal{T}_{\exists} -rule) add the information that axioms hold for y. \triangleright Initialize tableau with $\{x:\varphi\} \cup CA$ (CA: = set of concept axioms) $\triangleright \text{ New rule for } \exists: \ \frac{x{:}\exists \mathsf{R}.\varphi \ \ \mathcal{CA} = \{\alpha_1, \ldots, \alpha_n\}}{y{:}\varphi} \ \mathcal{T}_{\mathcal{CA}}^\exists$ (instead of \mathcal{T}_{\exists}) $x \mathsf{R} u$ $y:\alpha_1$ $y:\alpha_n$ \triangleright **Problem:** $CA := \{\exists R.c\}$ and start tableau with x:d(non-termination) EAU Michael Kohlhase: Artificial Intelligence 1 532 2025-02-06

The problem of this approach is that it spoils termination, since we cannot control the number of rule applications by (fixed) properties of the input formulae. The example shows this very nicely. We only sketch a path towards a solution.

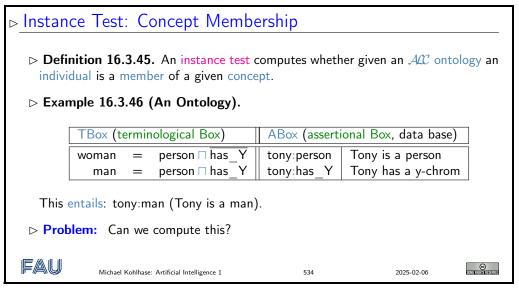
Non-Termination of \mathcal{T}_{AC} with Concept Axioms \triangleright **Problem:** $CA := \{\exists R.c\}$ and start tableau with x:d. (non-ter



16.3.3 ABoxes, Instance Testing, and ALC

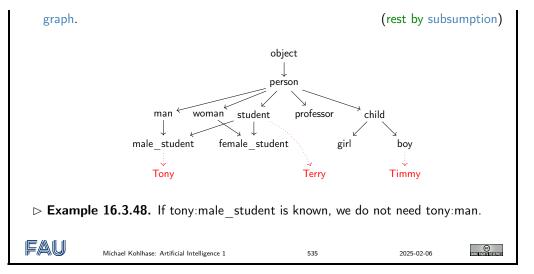
A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/27303. Now that we have a decision problem for \mathcal{AC} with concept axioms, we can go the final step to the general case of inference in description logics: we add an ABox with assertional axioms that describe the individuals.

We will now extend the description logic \mathcal{AC} with assertions that can express concept membership.



If we combine classification with the instance test, then we get the full picture of how concepts and individuals relate to each other. We see that we get the full expressivity of semantic networks in ACC.

▶ Definition 16.3.47. Realization is the computation of all instance relations between ABox objects and TBox concepts. ▶ Observation: It is sufficient to remember the lowest concepts in the subsumption



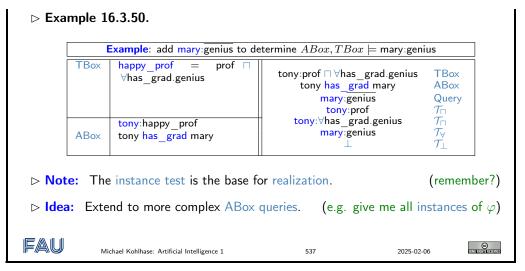
Let us now get an intuition on what kinds of interactions between the various parts of an ontology.

ABox Inference ▷ There are difference description logics ▷ Example 16.3.4	nt kinds of interac in general.	omena ions between TBox and ABox in $\mathcal{A}\mathcal{C}$ and in
property	exai	nple
internally inconsi	stent tony	:student, tony:student
inconsistent with	a I Box	Box: student □ prof Box: tony:student, tony:prof
implicit info that		Box: tony:∀has_grad.genius tony has_grad mary ⊨ mary:genius
information that bined with TBox	can be com-	Box: happy_prof = prof □ ∀has_grad.genius Box: tony:happy_prof, tony has_grad mary ⊨ mary:genius
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Again, we ask ourselves whether all of these are computable.

Fortunately, it is very simple to add assertions to \mathcal{T}_{AC} . In fact, we do not have to change anything, as the judgments used in the tableau are already of the form of ABox assertion.

Tableau-based Instance Test and Realization					
\triangleright Query: Do the ABox and TBox together entail $a:\varphi$?	$(a\in \varphi ?)$				
\triangleright Algorithm: Test $a:\overline{\varphi}$ for consistency with ABox and TBox. algorithm)	(use our tableau				
▷ Necessary changes:	(no big deal)				
⊳ Normalize ABox wrt. TBox.	(definition expansion)				
▷ Initialize the tableau with ABox in NNF.	(so it can be used)				



This completes our investigation of inference for ACC. We summarize that ACC is a logic-based ontology language where the inference problems are all decidable/computable via \mathcal{T}_{ACC} . But of course, while we have reached the expressivity of basic semantic networks, there are still things that we cannot express in ACC, so we will try to extend ACC without losing decidability/computability.

16.4 Description Logics and the Semantic Web

A Video Nugget covering this section can be found at https://fau.tv/clip/id/27289. In this section we discuss how we can apply description logics in the real world, in particular, as a conceptual and algorithmic basis of the semantic web. That tries to transform the World Wide Web from a human-understandable web of multimedia documents into a "web of machine-understandable data". In this context, "machine-understandable" means that machines can draw inferences from data they have access to. Note that the discussion in this digression is not a full-blown introduction to RDF and OWL, we leave that to [SR14; Her+13a; Hit+12] and the respective W3C recommendations. Instead we introduce the ideas behind the mappings from a perspective of the description logics we have discussed above.

The most important component of the <u>semantic</u> web is a standardized language that can represent "data" about information on the Web in a machine-oriented way.

Resource Description Framework						
Definition 16.4.1. The Resource Description Framework (RDF) is a framework for describing resources on the web. It is an XML vocabulary developed by the W3C.						
▷ Note: RDF is designed to be read and understood by computers, not to be displayed to people. (it shows)						
▷ Example 16.4.2. RDF can be used for describing (all "objects on the WWW")						
 properties for shopping items, such as price and availability time schedules for web events 						
\triangleright information about web pages (content, author, created and modified date)						
content and rating for web pictures						
\triangleright content for search engines						
▷ electronic libraries						

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Note that all these examples have in common that they are about "objects on the Web", which is an aspect we will come to now.

"Objects on the Web" are traditionally called "resources", rather than defining them by their intrinsic properties – which would be ambitious and prone to change – we take an external property to define them: everything that has a URI is a web resource. This has repercussions on the design of RDF.

Resources and URIs

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- \triangleright RDF describes resources with properties and property values.
- \triangleright RDF uses Web identifiers (URIs) to identify resources.

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- \triangleright **Definition 16.4.3.** A resource is anything that can have a URI, such as http: //www.fau.de.
- ▷ **Definition 16.4.4.** A property is a resource that has a name, such as *author* or *homepage*, and a property value is the value of a property, such as *Michael Kohlhase* or http://kwarc.info/kohlhase. (a property value can be another resource)
- Definition 16.4.5. A RDF statement s (also known as a triple) consists of a resource (the subject of s), a property (the predicate of s), and a property value (the object of s). A set of RDF triples is called an RDF graph.
- ▷ Example 16.4.6. Statements: [This slide]^{subj} has been [author]^{pred}ed by [Michael Kohlhase]^{obj}

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The crucial observation here is that if we map "subjects" and "objects" to "individuals", and "predicates" to "relations", the RDF triples are just relational ABox statements of description logics. As a consequence, the techniques we developed apply.

Note: Actually, a RDF graph is technically a labeled multigraph, which allows multiple edges between any two nodes (the resources) and where nodes and edges are labeled by URIs.

We now come to the concrete syntax of RDF. This is a relatively conventional XML syntax that combines RDF statements with a common subject into a single "description" of that resource.

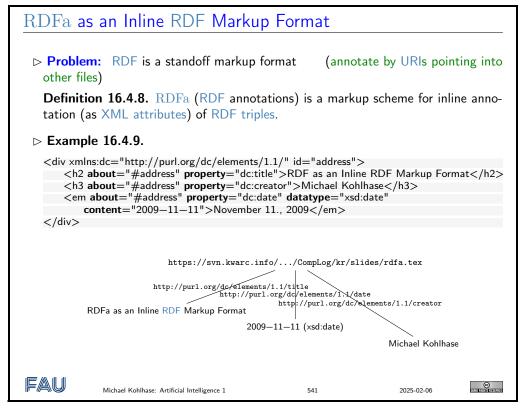
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This RDF document makes two statements:
The subject of both is given in the about attribute of the rdf:Description element
The predicates are given by the element names of its children
The objects are given in the elements as URIs or literal content.
Intuitively: RDF is a web-scalable way to write down ABox information.

Note that XML namespaces play a crucial role in using element to encode the predicate URIs. Recall that an element name is a qualified name that consists of a namespace URI and a proper element name (without a colon character). Concatenating them gives a URI in our example the predicate URI induced by the dc:creator element is http://purl.org/dc/elements/1.1/creator. Note that as URIs go RDF URIs do not have to be URLs, but this one is and it references (is redirected to) the relevant part of the Dublin Core elements specification [DCM12].

RDF was deliberately designed as a standoff markup format, where URIs are used to annotate web resources by pointing to them, so that it can be used to give information about web resources without having to change them. But this also creates maintenance problems, since web resources may change or be deleted without warning.

RDFa gives authors a way to embed RDF triples into web resources and make keeping RDF statements about them more in sync.



In the example above, the about and property attributes are reserved by RDFa and specify the subject and predicate of the RDF statement. The object consists of the body of the element, unless otherwise specified e.g. by the content and datatype attributes for literals content. Let us now come back to the fact that RDF is just an XML syntax for ABox statements.

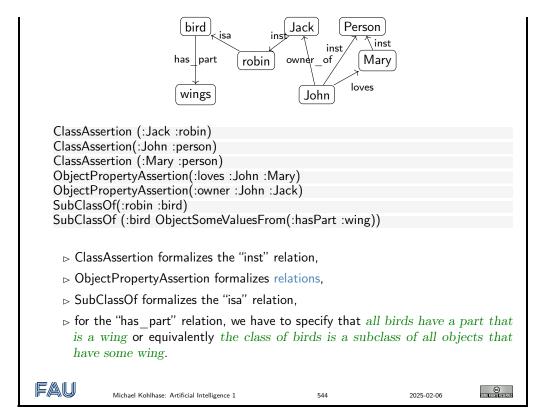
RDF as an ABox Language for the Semantic Web							
\triangleright Idea: RDF triples are ABox entries $h \ R \ s$ or $h:\varphi$.							
\triangleright Example 16.4.10. <i>h</i> is the resource for Ian Horrocks, <i>s</i> is the resource for Ulrike Sattler, R is the relation "hasColleague", and φ is the class foaf:Person							
<rdf:description about="some.uri/person/ian_horrocks"> <rdf:type rdf:resource="http://xmlns.com/foaf/0.1/Person"></rdf:type> <hascolleague resource="some.uri/person/uli_sattler"></hascolleague> </rdf:description>							
\triangleright Idea: Now, we need an similar language for TBoxes (based on \mathcal{AC})							
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In this situation, we want a standardized representation language for TBox information; OWL does just that: it standardizes a set of knowledge representation primitives and specifies a variety of concrete syntaxes for them. OWL is designed to be compatible with RDF, so that the two together can form an ontology language for the web.

OWL as an Ontology Language for the Semantic Web \triangleright Task: Complement RDF (ABox) with a TBox language. \triangleright **Idea:** Make use of resources that are values in rdf:type. (called Classes) ▷ **Definition 16.4.11.** OWL (the ontology web language) is a language for encoding TBox information about RDF classes. ▷ Example 16.4.12 (A concept definition for "Mother"). Mother=Woman □ Parent is represented as XML Syntax Functional Syntax <EquivalentClasses> EquivalentClasses(<Class IRI="Mother"/> :Mother <ObjectIntersectionOf> ObjectIntersectionOf(:Woman <Class IRI="Woman"/> <Class IRI="Parent"/> :Parent </ObjectIntersectionOf> </EquivalentClasses> FAU Michael Kohlhase: Artificial Intelligence 1 543 2025-02-06

But there are also other syntaxes in regular use. We show the functional syntax which is inspired by the mathematical notation of relations.

Extended OWL Example in Functional Syntax
Example 16.4.13. The semantic network from ?? can be expressed in OWL (in functional syntax)



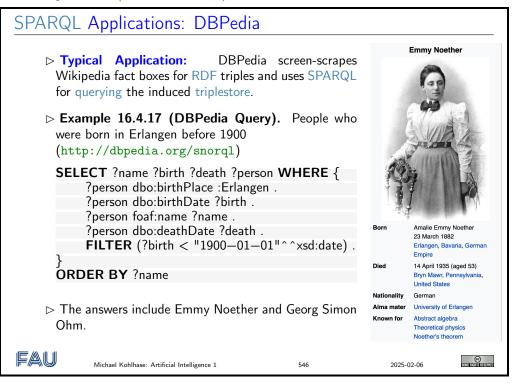
We have introduced the ideas behind using description logics as the basis of a "machine-oriented web of data". While the first OWL specification (2004) had three sublanguages "OWL Lite", "OWL DL" and "OWL Full", of which only the middle was based on description logics, with the OWL2 Recommendation from 2009, the foundation in description logics was nearly universally accepted.

The semantic web hype is by now nearly over, the technology has reached the "plateau of productivity" with many applications being pursued in academia and industry. We will not go into these, but briefly instroduce one of the tools that make this work.

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SPARQL end-points can be used to build interesting applications, if fed with the appropriate data. An interesting – and by now paradigmatic – example is the DBPedia project, which builds a large ontology by analyzing Wikipedia fact boxes. These are in a standard HTML form which can be analyzed e.g. by regular expressions, and their entries are essentially already in triple form: The subject is the Wikipedia page they are on, the predicate is the key, and the object is either the URI on the object value (if it carries a link) or the value itself.



A more complex DBPedia Query

Demo: DBPedia http://dbpedia.org/snorql/ Query: Soccer players born in a country with more than 10 M inhabitants, who play as goalie in a club that has a stadium with more than 30.000 seats. Answer: computed by DBPedia from a SPARQL query

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} order by ?soccerplaye:	y > 30000) 0000000) r			
Results: Browse ᅌ Go	! Reset			
SPARQL results:				
soccerplayer	countryOfBirth	team	countryOfTeam	stadiumcapad
:Abdesslam_Benabdellah 🗗	:Algeria 🚱	:Wydad_Casablanca 🚱	:Morocco 🚱	67000
:Airton_Moraes_Michellon	:Brazil 🕾	:FC_Red_Bull_Salzburg	:Austria 🗗	31000
:Alain_Gouaméné 🗗	:lvory_Coast @	:Raja_Casablanca	:Morocco 🗗	67000
:Allan_McGregor	:United_Kingdom	:Beşiktaş_J.K. @	:Turkey 🗗	41903
:Anthony_Scribe	:France @	:FC_Dinamo_Tbilisi	:Georgia_(country) 🗗	54549
:Brahim_Zaari 🖗	:Netherlands 🛃	:Raja_Casablanca 🗗	:Morocco 🗗	67000
:Bréiner_Castillo	:Colombia 🚱	:Deportivo_Táchira	:Venezuela 🚱	38755
:Carlos_Luis_Morales 🗗	:Ecuador 🕼	:Club_Atlético_Independiente	:Argentina 🚱	48069
:Carlos_Navarro_Montoya 🗗	:Colombia 🗗	:Club_Atlético_Independiente	:Argentina 🗗	48069
:Cristián_Muñoz 🗗	:Argentina 🕼	:Colo-Colo 🗗	:Chile 🚱	47000
:Daniel_Ferreyra	:Argentina 🗗	:FBC_Melgar	:Peru 🖉	60000
:David_Bičík 🕼	:Czech_Republic 🕼	:Karşıyaka_S.K. 🗗	:Turkey 🚱	51295
:David_Loria 🚱	:Kazakhstan 🚱	:Karşıyaka_S.K.	:Turkey 🗗	51295
:Denys_Boyko 嘧	:Ukraine 🛃	:Beşiktaş_J.K. 🗗	:Turkey 🚱	41903
:Eddie_Gustafsson	:United_States 🚱	:FC_Red_Bull_Salzburg	:Austria 🚱	31000
:Emilian_Dolha 🖗	:Romania 🚱	:Lech_Poznań 🖗	:Poland 🕼	43269
:Eusebio_Acasuzo 🕼	:Peru 🕼	:Club_Bolívar 🗗	:Bolivia 🗗	42000
:Faryd_Mondragón 🗗	:Colombia 🕼	:Real_Zaragoza 🚱	:Spain 🗗	34596
:Faryd_Mondragón 🗗	:Colombia 🚱	:Club_Atlético_Independiente 🗗	:Argentina 🗗	48069
:Federico_Vilar	:Argentina 🕼	:Club_Atlas 🗗	:Mexico 🗗	54500
:Fernando_Martinuzzi 🖗	:Argentina 🚱	:Real_Garcilaso &	:Peru 🗗	45000
:Fábio_André_da_Silva 🗗	:Portugal 🚱	:Servette_FC 🗗	:Switzerland 🕼	30084
:Gerhard_Tremmel 🗗	:Germany 🚱	:FC_Red_Bull_Salzburg	:Austria 🚱	31000
:Gift_Muzadzi 🗗	:United_Kingdom	:Lech_Poznań 🖉	:Poland 🚱	43269
:Günay_Güvenç 🗗	:Germany 🗗	:Beşiktaş_J.K. 🗗	:Turkey 🗗	41903
distant Manager of	:Portugal 🚱	:C.DPrimeiro_de_Agosto	:Angola 🚱	48500
:Hugo_Marques 🗗				

We conclude our survey of the semantic web technology stack with the notion of a triplestore, which refers to the database component, which stores vast collections of ABox triples.

Triple Stores: the Semantic Web Databases > Definition 16.4.18. A triplestore or RDF store is a purpose-built database for the storage RDF graphs and retrieval of RDF triples usually through variants of SPARQL. ▷ Common triplestores include > Virtuoso: https://virtuoso.openlinksw.com/ (used in DBpedia) > GraphDB: http://graphdb.ontotext.com/ (often used in WissKI) > blazegraph: https://blazegraph.com/ (open source; used in WikiData) > Definition 16.4.19. A description logic reasoner implements of reaonsing services based on a satisfiability test for description logics. ▷ Common description logic reasoners include > FACT++: http://owl.man.ac.uk/factplusplus/ ▷ HermiT: http://www.hermit-reasoner.com/ ▷ Intuition: Triplestores concentrate on querying very large ABoxes with partial consideration of the TBox, while DL reasoners concentrate on the full set of ontology

inference services, but fail on large ABoxes.

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16.4. DESCRIPTION LOGICS AND THE SEMANTIC WEB

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Appendix A

Excursions

As this course is predominantly an overview over the topics of Artificial Intelligence, and not about the theoretical underpinnings, we give the discussion about these as a "suggested readings" chapter here.

A.1 Completeness of Calculi for Propositional Logic

The next step is to analyze the two calculi for completeness. For that we will first give ourselves a very powerful tool: the "model existence theorem" (??), which encapsulates the model-theoretic part of completeness theorems. With that, completeness proofs – which are quite tedious otherwise – become a breeze.

A.1.1 Abstract Consistency and Model Existence

We will now come to an important tool in the theoretical study of reasoning calculi: the "abstract consistency"/"model existence" method. This method for analyzing calculi was developed by Jaako Hintikka, Raymond Smullyan, and Peter Andrews in 1950-1970 as an encapsulation of similar constructions that were used in completeness arguments in the decades before. The basis for this method is Smullyan's Observation [Smu63] that completeness proofs based on Hintikka sets only certain properties of consistency and that with little effort one can obtain a generalization "Smullyan's Unifying Principle".

The basic intuition for this method is the following: typically, a logical system $\mathcal{L} := \langle \mathcal{L}, \mathcal{K}, \vDash \rangle$ has multiple calculi, human-oriented ones like the natural deduction calculi and machine-oriented ones like the automated theorem proving calculi. All of these need to be analyzed for completeness (as a basic quality assurance measure).

A completeness proof for a calculus C for S typically comes in two parts: one analyzes Cconsistency (sets that cannot be refuted in C), and the other construct K-models for C-consistent
sets.

In this situation the "abstract consistency"/"model existence" method encapsulates the model construction process into a meta-theorem: the "model existence" theorem. This provides a set of syntactic ("abstract consistency") conditions for calculi that are sufficient to construct models.

With the model existence theorem it suffices to show that C-consistency is an abstract consistency property (a purely syntactic task that can be done by a C-proof transformation argument) to obtain a completeness result for C.

 Model Existence (Overview)

 ▷ Definition: Abstract consistency

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Definition: Hintikka set (maximally abstract consistent)
Theorem: Hintikka sets are satisfiable
Theorem: If Φ is abstract consistent, then Φ can be extended to a Hintikka set.
Corollary: If Φ is abstract consistent, then Φ is satisfiable.
Application: Let C be a calculus, if Φ is C-consistent, then Φ is abstract consistent.
Corollary: C is complete.

The proof of the model existence theorem goes via the notion of a Hintikka set, a set of formulae with very strong syntactic closure properties, which allow to read off models. Jaako Hintikka's original idea for completeness proofs was that for every complete calculus C and every C-consistent set one can induce a Hintikka set, from which a model can be constructed. This can be considered as a first model existence theorem. However, the process of obtaining a Hintikka set for a C-consistent set Φ of sentences usually involves complicated calculus dependent constructions.

In this situation, Raymond Smullyan was able to formulate the sufficient conditions for the existence of Hintikka sets in the form of "abstract consistency properties" by isolating the calculus independent parts of the Hintikka set construction. His technique allows to reformulate Hintikka sets as maximal elements of abstract consistency classes and interpret the Hintikka set construction as a maximizing limit process.

To carry out the "model-existence"/"abstract consistency" method, we will first have to look at the notion of consistency.

Consistency and refutability are very important notions when studying the completeness for calculi; they form syntactic counterparts of satisfiability.

Consistency

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 \triangleright Let C be a calculus,...

- \triangleright **Definition A.1.1.** Let C be a calculus, then a formula set Φ is called C-refutable, if there is a refutation, i.e. a derivation of a contradiction from Φ . The act of finding a refutation for Φ is called refuting Φ .
- \triangleright Definition A.1.2. We call a pair of formulae A and $\neg A$ a contradiction.
- \triangleright So a set Φ is *C*-refutable, if *C* canderive a contradiction from it.

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- \triangleright **Definition A.1.3.** Let C be a calculus, then a formula set Φ is called C-consistent, iff there is a formula B, that is not derivable from Φ in C.
- \triangleright **Definition A.1.4.** We call a calculus C reasonable, iff implication elimination and conjunction introduction are admissible in C and $A \land \neg A \Rightarrow B$ is a C-theorem.

▷ **Theorem A.1.5.** *C*-inconsistency and *C*-refutability coincide for reasonable calculi.

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It is very important to distinguish the syntactic C-refutability and C-consistency from satisfiability, which is a property of formulae that is at the heart of semantics. Note that the former have the calculus (a syntactic device) as a parameter, while the latter does not. In fact we should actually say S-satisfiability, where $\langle \mathcal{L}, \mathcal{K}, \vDash \rangle$ is the current logical system.

Even the word "contradiction" has a syntactical flavor to it, it translates to "saying against each other" from its Latin root.

Abstract Consistency \triangleright Definition A.1.6. Let ∇ be a collection of sets. We call ∇ closed under subsets. iff for each $\Phi \in \nabla$, all subsets $\Psi \subseteq \Phi$ are elements of ∇ . \triangleright Definition A.1.7 (Notation). We will use $\Phi * \mathbf{A}$ for $\Phi \cup \{\mathbf{A}\}$. \triangleright Definition A.1.8. A collection ∇ of sets of propositional formulae is called an abstract consistency class, iff it is closed under subsets, and for each $\Phi \in \nabla$ ∇_c) $P \notin \Phi$ or $\neg P \notin \Phi$ for $P \in \mathcal{V}_0$ ∇_{\neg}) $\neg \neg \mathbf{A} \in \Phi$ implies $\Phi * \mathbf{A} \in \nabla$ $\nabla_{\!\!\vee}$) $\mathbf{A} \lor \mathbf{B} \in \Phi$ implies $\Phi * \mathbf{A} \in \nabla$ or $\Phi * \mathbf{B} \in \nabla$ ∇_{\wedge}) \neg (**A** \lor **B**) $\in \Phi$ implies $\Phi \cup \{\neg$ **A**, \neg **B** $\} \in \nabla$ ▷ Example A.1.9. The empty set is an abstract consistency class. \triangleright Example A.1.10. The set $\{\emptyset, \{Q\}, \{P \lor Q\}, \{P \lor Q, Q\}\}$ is an abstract consistency class. **Example A.1.11.** The family of satisfiable sets is an abstract consistency class. FAU e Michael Kohlhase: Artificial Intelligence 1 551 2025-02-06

So a family of sets (we call it a family, so that we do not have to say "set of sets" and we can distinguish the levels) is an abstract consistency class, iff it fulfills five simple conditions, of which the last three are closure conditions.

Think of an abstract consistency class as a family of "consistent" sets (e.g. C-consistent for some calculus C), then the properties make perfect sense: They are naturally closed under subsets — if we cannot derive a contradiction from a large set, we certainly cannot from a subset, furthermore,

- ∇_c) If both $P \in \Phi$ and $\neg P \in \Phi$, then Φ cannot be "consistent".
- ∇_{\neg}) If we cannot derive a contradiction from Φ with $\neg \neg \mathbf{A} \in \Phi$ then we cannot from $\Phi * \mathbf{A}$, since they are logically equivalent.

The other two conditions are motivated similarly. We will carry out the proof here, since it gives us practice in dealing with the abstract consistency properties.

The main result here is that abstract consistency classes can be extended to compact ones. The proof is quite tedious, but relatively straightforward. It allows us to assume that all abstract consistency classes are compact in the first place (otherwise we pass to the compact extension).

Actually we are after abstract consistency classes that have an even stronger property than just being closed under subsets. This will allow us to carry out a limit construction in the Hintikka set extension argument later.

Compact Collections

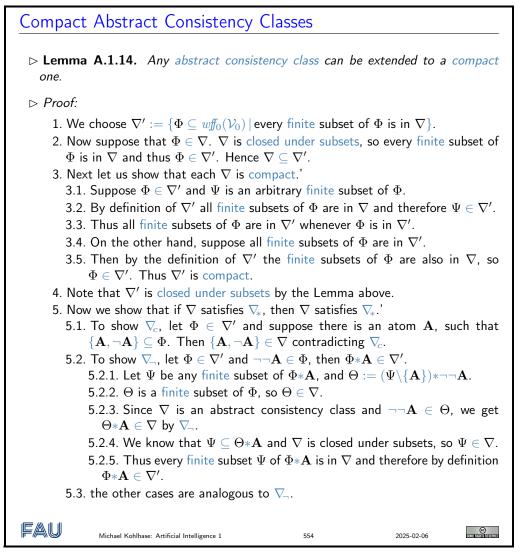
 \triangleright **Definition A.1.12.** We call a collection ∇ of sets compact, iff for any set Φ we have

 $\Phi \in \nabla$, iff $\Psi \in \nabla$ for every finite subset Ψ of Φ .

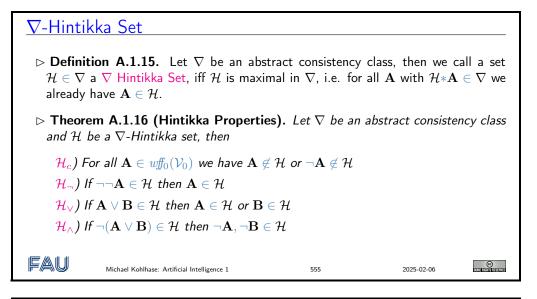
 \triangleright Lemma A.1.13. If ∇ is compact, then ∇ is closed under subsets.

⊳ Proof:				
 Suppose S ⊆ T and T ∈ ∇. Every finite subset A of S is a finite subset of T. As ∇ is compact, we know that A ∈ ∇. Thus S ∈ ∇. 				
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The property of being closed under subsets is a "downwards-oriented" property: We go from large sets to small sets, compactness (the interesting direction anyways) is also an "upwards-oriented" property. We can go from small (finite) sets to large (infinite) sets. The main application for the compactness condition will be to show that infinite sets of formulae are in a collection ∇ by testing all their finite subsets (which is much simpler).



Hintikka sets are sets of sentences with very strong analytic closure conditions. These are motivated as maximally consistent sets i.e. sets that already contain everything that can be consistently added to them.



∇ -Hintikka Set

 \triangleright *Proof:* We prove the properties in turn 1. \mathcal{H}_c by induction on the structure of A 1.1. $\mathbf{A} \in \mathcal{V}_0$ Then $\mathbf{A} \notin \mathcal{H}$ or $\neg \mathbf{A} \notin \mathcal{H}$ by ∇_c . 1.2. $A = \neg B$ 1.2.1. Let us assume that $\neg \mathbf{B} \in \mathcal{H}$ and $\neg \neg \mathbf{B} \in \mathcal{H}$, 1.2.2. then $\mathcal{H}*\mathbf{B}\in\nabla$ by ∇_{\neg} , and therefore $\mathbf{B}\in\mathcal{H}$ by maximality. 1.2.3. So both B and $\neg B$ are in \mathcal{H} , which contradicts the induction hypothesis. 1.3. $\mathbf{A} = \mathbf{B} \lor \mathbf{C}$ similar to the previous case 2. We prove \mathcal{H}_{\neg} by maximality of \mathcal{H} in ∇ . 2.1. If $\neg \neg \mathbf{A} \in \mathcal{H}$, then $\mathcal{H} \ast \mathbf{A} \in \nabla$ by ∇_{\neg} . 2.2. The maximality of \mathcal{H} now gives us that $\mathbf{A} \in \mathcal{H}$. Proof sketch: other \mathcal{H}_* are similar FAU C Michael Kohlhase: Artificial Intelligence 1 556 2025-02-06

The following theorem is one of the main results in the "abstract consistency"/"model existence" method. For any abstract consistent set Φ it allows us to construct a Hintikka set \mathcal{H} with $\Phi \in \mathcal{H}$.

Extension Theorem
► Theorem A.1.17. If ∇ is an abstract consistency class and Φ ∈ ∇, then there is a ∇-Hintikka set H with Φ ⊆ H.
▷ Proof:

Wlog. we assume that ∇ is compact (otherwise pass to compact extension)
We choose an enumeration A₁,... of the set wff₀(V₀)

3. and construct a sequence of sets \mathbf{H}_i with $\mathbf{H}_0 := \Phi$ and

$$\mathbf{H}_{n+1} := \left\{egin{array}{cc} \mathbf{H}_n & ext{if } \mathbf{H}_n st \mathbf{A}_n
ot\in
abla \ \mathbf{H}_n st \mathbf{A}_n & ext{if } \mathbf{H}_n st \mathbf{A}_n \in
abla \end{array}
ight.$$

4. Note that all H_i ∈ ∇, choose H := U_{i∈N}H_i
5. Ψ ⊆ H finite implies there is a j ∈ N such that Ψ ⊆ H_j,
6. so Ψ ∈ ∇ as ∇ is closed under subsets and H ∈ ∇ as ∇ is compact.
7. Let H*B ∈ ∇, then there is a j ∈ N with B = A_j, so that B ∈ H_{j+1} and H_{j+1} ⊆ H
8. Thus H is ∇-maximal

Note that the construction in the proof above is non-trivial in two respects. First, the limit construction for \mathcal{H} is not executed in our original abstract consistency class ∇ , but in a suitably extended one to make it compact — the original would not have contained \mathcal{H} in general. Second, the set \mathcal{H} is not unique for Φ , but depends on the choice of the enumeration of $wf_0(\mathcal{V}_0)$. If we pick a different enumeration, we will end up with a different \mathcal{H} . Say if \mathbf{A} and $\neg \mathbf{A}$ are both ∇ -consistent¹ with Φ , then depending on which one is first in the enumeration \mathcal{H} , will contain that one; with all the consequences for subsequent choices in the construction process.

Valuation $\triangleright \text{ Definition A.1.18. A function } \nu \colon wf_0(\mathcal{V}_0) \to \mathcal{D}_o \text{ is called a (propositional) valuation, iff}$ $<math display="block"> \models \nu(\neg \mathbf{A}) = \mathsf{T}, \text{ iff } \nu(\mathbf{A}) = \mathsf{F} \\
 \models \nu(\mathbf{A} \land \mathbf{B}) = \mathsf{T}, \text{ iff } \nu(\mathbf{A}) = \mathsf{T} \text{ and } \nu(\mathbf{B}) = \mathsf{T} \\ \triangleright \text{ Lemma A.1.19. If } \nu \colon wf_0(\mathcal{V}_0) \to \mathcal{D}_o \text{ is a valuation and } \Phi \subseteq wf_0(\mathcal{V}_0) \text{ with } \nu(\Phi) = \\ \{\mathsf{T}\}, \text{ then } \Phi \text{ is satisfiable.} \\ \triangleright \text{ Proof sketch: } \nu|_{\mathcal{V}_0} : \mathcal{V}_0 \to \mathcal{D}_o \text{ is a satisfying variable assignment.} \\ \triangleright \text{ Lemma A.1.20. If } \varphi \colon \mathcal{V}_0 \to \mathcal{D}_o \text{ is a variable assignment, then } \mathcal{I}_{\varphi} \colon wf_0(\mathcal{V}_0) \to \mathcal{D}_o \text{ is a valuation.} \\ \end{cases}$

Now, we only have to put the pieces together to obtain the model existence theorem we are after.

Model Existence
▷ Lemma A.1.21 (Hintikka-Lemma). If ∇ is an abstract consistency class and H a ∇-Hintikka set, then H is satisfiable.
▷ Proof:

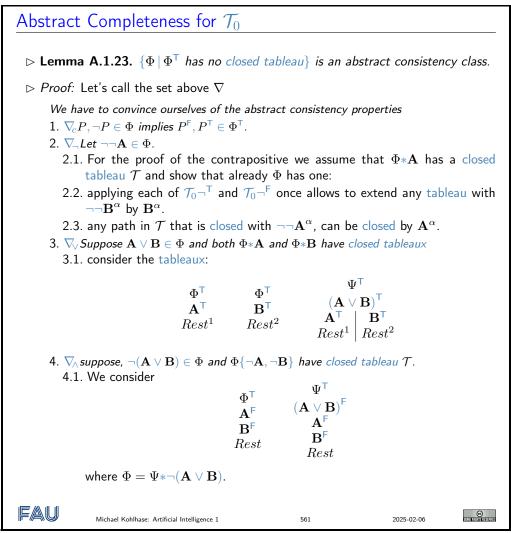
We define ν(A) := T, iff A ∈ H
then ν is a valuation by the Hintikka properties
and thus ν|_{ν₀} is a satisfying assignment.

	em A.1.22 (Model Existence). then Φ is satisfiable.	If $ abla$ is an abs	stract consistency c	lass and
Proof:				
2. W	here is a ∇ -Hintikka set $\mathcal H$ with Φ e know that $\mathcal H$ is satisfiable. particular, $\Phi \subseteq \mathcal H$ is satisfiable.	$\mathbb{P}\subseteq\mathcal{H}$	(Extension T (Hintikka-I	
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A.1.2 A Completeness Proof for Propositional Tableaux

With the model existence proof we have introduced in the last section, the completeness proof for first-order natural deduction is rather simple, we only have to check that Tableaux-consistency is an abstract consistency property.

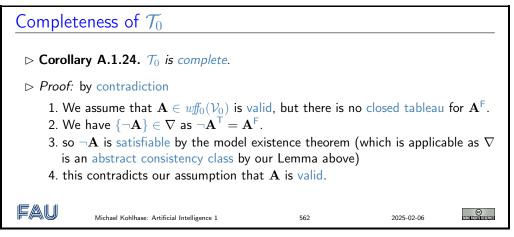
We encapsulate all of the technical difficulties of the problem in a technical Lemma. From that, the completeness proof is just an application of the high-level theorems we have just proven.



Observation: If we look at the completeness proof below, we see that the Lemma above is the only place where we had to deal with specific properties of the \mathcal{T}_0 .

So if we want to prove completeness of any other calculus with respect to propositional logic, then we only need to prove an analogon to this lemma and can use the rest of the machinery we have already established "off the shelf".

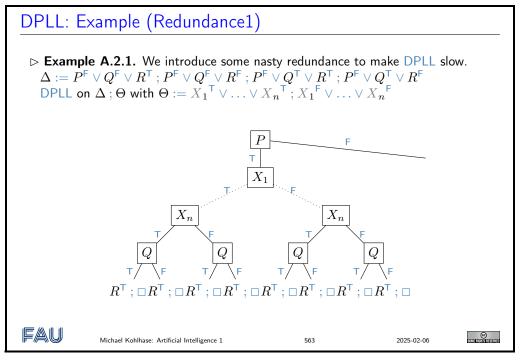
This is one great advantage of the "abstract consistency method"; the other is that the method can be extended transparently to other logics.



A.2 Conflict Driven Clause Learning

A.2.1 Why Did Unit Propagation Yield a Conflict?

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/27026.



How To Not Make the Same Mistakes Over Again?

▷ It's not that difficult, really:

A.2. CONFLICT DRIVEN CLAUSE LEARNING

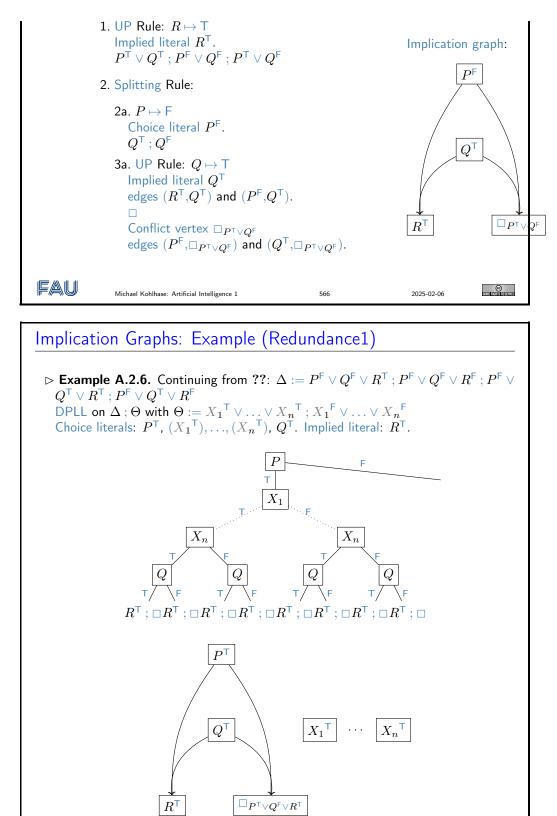
(A) Figure out what went wrong.
(B) Learn to not do that again in the future.
▷ And now for DPLL:
(A) Why did unit propagation yield a Conflict?
▷ This Section. We will capture the "what went wrong" in terms of graphs over literals set during the search, and their dependencies.
▷ What can we learn from that information?:
▷ A new clause! Next section.

Implication Graphs for DPLL \triangleright **Definition A.2.2.** Let β be a branch in a DPLL derivation and P a variable on β then we call $\triangleright P^{\alpha}$ a choice literal if its value is set to α by the splitting rule. $\triangleright P^{\alpha}$ an implied literal, if the value of P is set to α by the UP rule. $> P^{\alpha}$ a conflict literal, if it contributes to a derivation of the empty clause. ▷ Definition A.2.3 (Implication Graph). Let Δ be a clause set, β a DPLL search branch on Δ . The implication graph G_{β}^{impl} is the directed graph whose vertices are labeled with the choice and implied literals along β , as well as a separate conflict vertex \Box_C for every clause C that became empty on β . Whereever a clause $l_1, \ldots, l_k \vee l' \in \Delta$ became unit with implied literal l', G_{β}^{impl} includes the edges $(\overline{l_i}, l')$. Where $C = l_1 \vee \ldots \vee l_k \in \Delta$ became empty, G_{β}^{impl} includes the edges $(\overline{l_i}, \Box_C)$. \triangleright Question: How do we know that $\overline{l_i}$ are vertices in G_{β}^{impl} ? \triangleright Answer: Because $l_1 \lor \ldots \lor l_k \lor l'$ became unit/empty. \triangleright Observation A.2.4. G_{β}^{impl} is acyclic. \triangleright *Proof sketch:* UP can't derive l' whose value was already set beforehand. \triangleright **Intuition:** The initial vertices are the choice literals and unit clauses of Δ . FAU Michael Kohlhase: Artificial Intelligence 1 565 2025-02-06

Implication Graphs: Example (Vanilla1) in Detail

▷ **Example A.2.5.** Let $\Delta := P^{\mathsf{T}} \vee Q^{\mathsf{T}} \vee R^{\mathsf{F}}$; $P^{\mathsf{F}} \vee Q^{\mathsf{F}}$; R^{T} ; $P^{\mathsf{T}} \vee Q^{\mathsf{F}}$. We look at the left branch of the derivation from ??:

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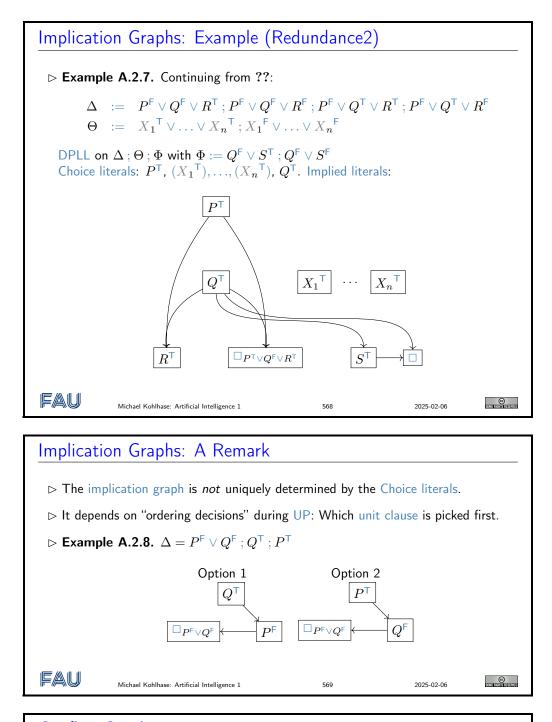


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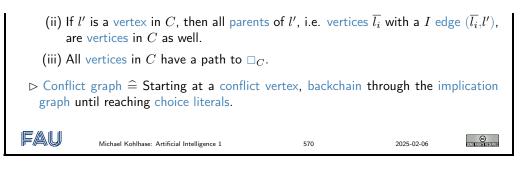
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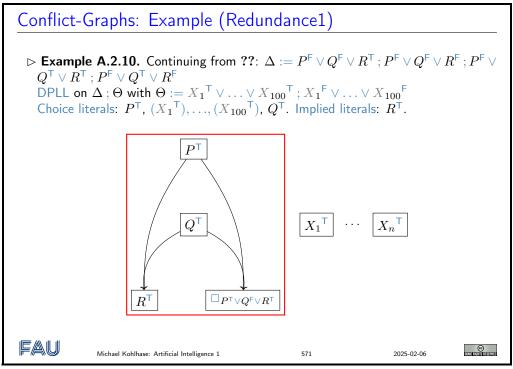
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Conflict Graphs

- \triangleright A conflict graph captures "what went wrong" in a failed node.
- \triangleright **Definition A.2.9 (Conflict Graph).** Let Δ be a clause set, and let G_{β}^{impl} be the implication graph for some search branch β of DPLL on Δ . A subgraph *C* of G_{β}^{impl} is a conflict graph if:
 - (i) C contains exactly one conflict vertex \Box_C .



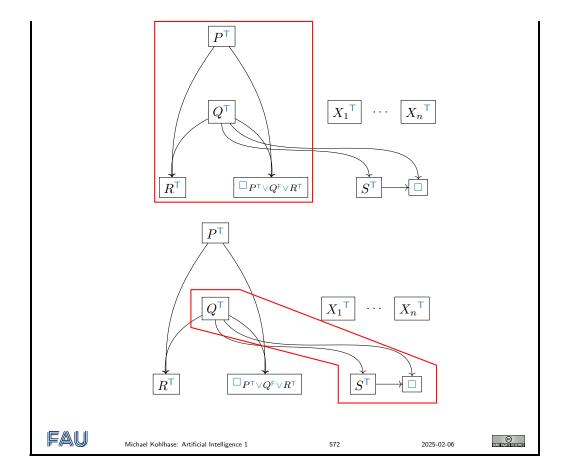


Conflict Graphs: Example (Redundance2)

▷ **Example A.2.11.** Continuing from ?? and ??:

 $\begin{array}{lll} \Delta & := & P^{\mathsf{F}} \lor Q^{\mathsf{F}} \lor R^{\mathsf{T}} ; P^{\mathsf{F}} \lor Q^{\mathsf{F}} \lor R^{\mathsf{F}} ; P^{\mathsf{F}} \lor Q^{\mathsf{T}} \lor R^{\mathsf{T}} ; P^{\mathsf{F}} \lor Q^{\mathsf{T}} \lor R^{\mathsf{F}} \\ \Theta & := & X_1^{\mathsf{T}} \lor \ldots \lor X_n^{\mathsf{T}} ; X_1^{\mathsf{F}} \lor \ldots \lor X_n^{\mathsf{F}} \end{array}$

 $\begin{array}{l} \mathsf{DPLL} \text{ on } \Delta \ ; \Theta \ ; \Phi \ \text{with } \Phi := Q^\mathsf{F} \lor S^\mathsf{T} \ ; Q^\mathsf{F} \lor S^\mathsf{F} \\ \mathsf{Choice \ literals:} \ P^\mathsf{T} \text{, } (X_1^\mathsf{T}), \dots, (X_n^\mathsf{T}) \text{, } Q^\mathsf{T} \text{. Implied \ literals:} \ R^\mathsf{T}. \end{array}$

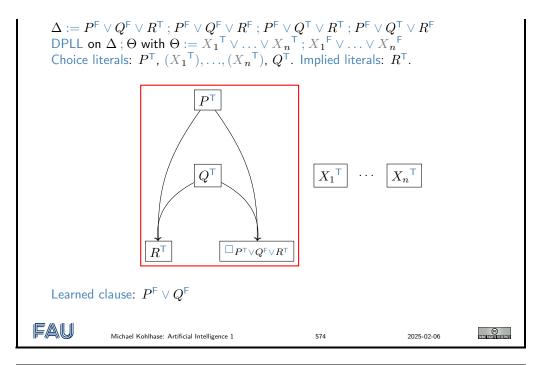


A.2.2 Clause Learning

Clause Learning ▷ **Observation:** Conflict graphs encode the entailment relation. \triangleright **Definition A.2.12.** Let Δ be a clause set, C be a conflict graph at some time point during a run of DPLL on Δ , and L be the choice literals in C, then we call $c := \bigvee_{l \in L} \overline{l}$ the learned clause for C. \triangleright **Theorem A.2.13.** Let Δ , C, and c as in ??, then $\Delta \models c$. ▷ Idea: We can add learned clauses to DPLL derivations at any time without losing (maybe this helps, if we have a good notion of learned clauses) soundness. > Definition A.2.14. Clause learning is the process of adding learned clauses to DPLL clause sets at specific points. (details coming up) FAU 2025-02-06 Michael Kohlhase: Artificial Intelligence 1 573

Clause Learning: Example (Redundance1)

▷ Example A.2.15. Continuing from ??:



The Effect of Learned Clauses

(in Redundance1)

- \triangleright What happens after we learned a new clause C?
- 1. We add C into Δ . e.g. $C = P^{\mathsf{F}} \vee Q^{\mathsf{F}}$.
- 2. We retract the last choice l'. e.g. the choice l' = Q.
- \triangleright **Observation:** Let C be a learned clause, i.e. $C = \bigvee_{l \in L} \overline{l}$, where L is the set of conflict literals in a conflict graph G.

Before we learn C, G must contain the most recent choice l': otherwise, the conflict would have occured earlier on.

So $C = l_1^{\mathsf{T}} \vee \ldots \vee l_k^{\mathsf{T}} \vee \overline{l'}$ where l_1, \ldots, l_k are earlier choices.

- \triangleright Example A.2.16. $l_1 = P$, $C = P^{\mathsf{F}} \lor Q^{\mathsf{F}}$, l' = Q.
- \triangleright **Observation:** Given the earlier choices l_1, \ldots, l_k , after we learned the new clause $C = \overline{l_1} \lor \ldots \lor \overline{l_k} \lor \overline{l'}$, the value of $\overline{l'}$ is now set by UP!

 \triangleright So we can continue:

We set the opposite choice *l*ⁱ as an implied literal.
 e.g. Q^F as an implied literal.

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4. We run UP and analyze conflicts. Learned clause: earlier choices only! e.g. $C = P^{\mathsf{F}}$, see next slide.

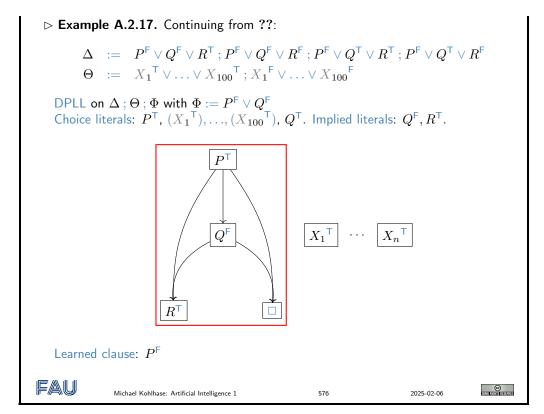
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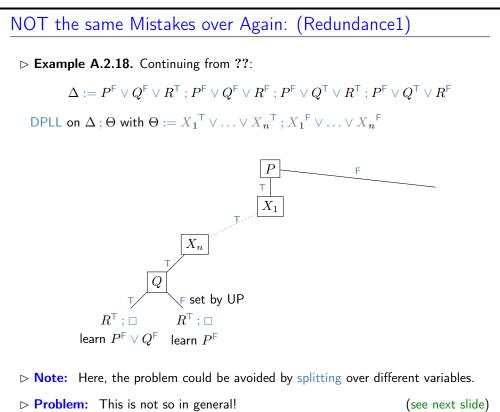
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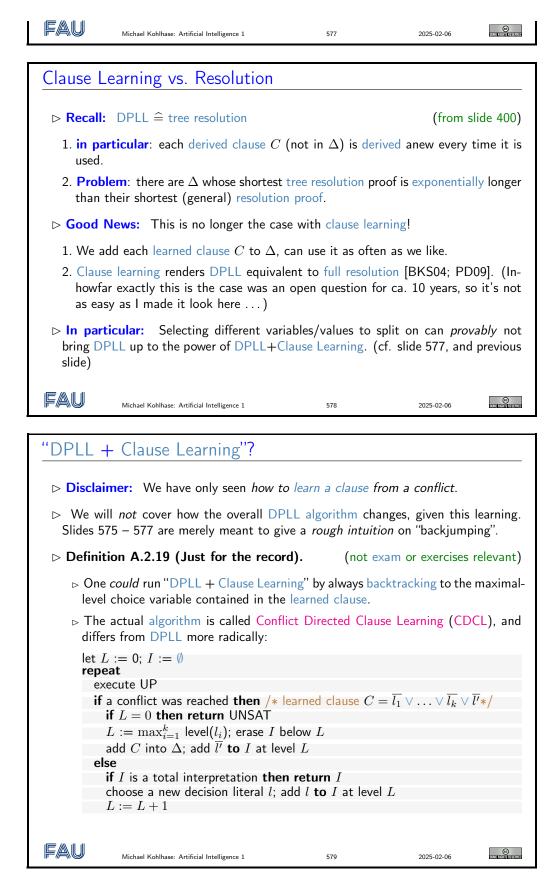
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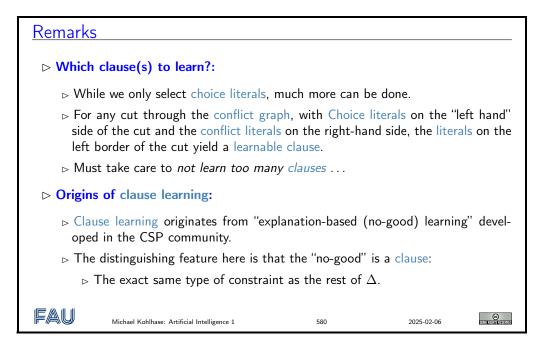
The Effect of Learned Clauses: Example (Redundance1)

A.2. CONFLICT DRIVEN CLAUSE LEARNING









A.2.3 Phase Transitions: Where the *Really* Hard Problems Are

A Video Nugget covering this subsection can be found at https://fau.tv/clip/id/25088.

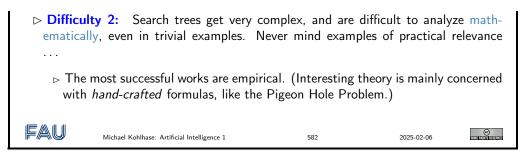
Where Are the Hard Problems?
SAT is NP hard. Worst case for DPLL is O(2ⁿ), with n propositions.
Imagine I gave you as homework to make a formula family {φ} where DPLL running time necessarily is in the order of O(2ⁿ).
I promise you're not gonna find this easy ... (although it is of course possible: e.g., the "Pigeon Hole Problem").
People noticed by the early 90s that, in practice, the DPLL worst case does not tend to happen.
Modern SAT solvers successfully tackle practical instances where n > 1.000.000.

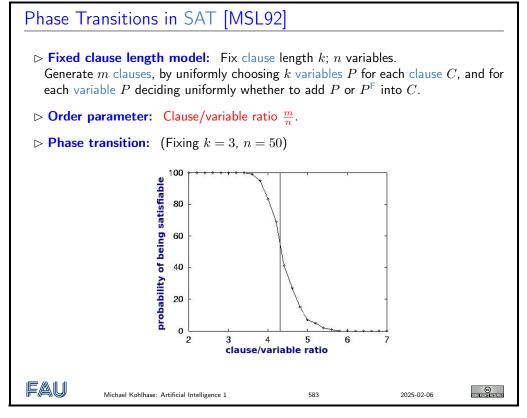
Where Are the Hard Problems?

▷ **So, what's the problem:** Science is about *understanding the world*.

▷ Are "hard cases" just pathological outliers?

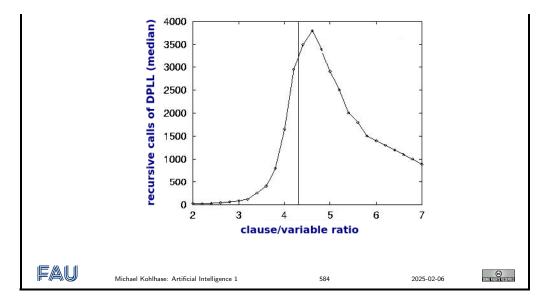
- ▷ Can we say something about the *typical case*?
- ▷ Difficulty 1: What is the "typical case" in applications? E.g., what is the "average" hardware verification instance?
 - \triangleright Consider precisely defined random distributions instead.





Does DPLL Care?

▷ **Oh yes, it does:** Extreme running time peak at the phase transition!



Why Does DPLL Care?

⊳ Intuition:

- **Under-Constrained:** Satisfiability likelihood close to 1. Many solutions, first DPLL search path usually successful. ("Deep but narrow")
- **Over-Constrained:** Satisfiability likelihood close to 0. Most DPLL search paths short, conflict reached after few applications of splitting rule. ("Broad but shallow")
- Critically Constrained: At the phase transition, many *almost-successful* DPLL search paths. ("Close, but no cigar")

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The Phase Transition Conjecture

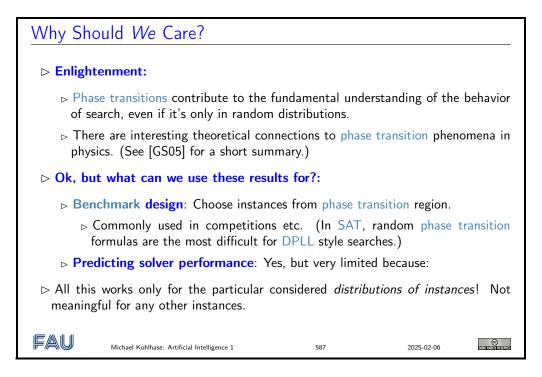
- \triangleright **Definition A.2.20.** We say that a class *P* of problems exhibits a phase transition, if there is an order parameter *o*, i.e. a structural parameter of *P*, so that almost all the hard problems of *P* cluster around a critical value *c* of *o* and *c* separates one region of the problem space from another, e.g. over-constrained and under-constrained regions.
- \triangleright All NP-complete problems exhibit at least one phase transition.
- \triangleright [CKT91] confirmed this for Graph Coloring and Hamiltonian Circuits. Later work confirmed it for SAT (see previous slides), and for numerous other NP-complete problems.

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A.3 Completeness of Calculi for First-Order Logic

We will now analyze the first-order calculi for completeness. Just as in the case of the propositional calculi, we prove a model existence theorem for the first-order model theory and then use that for the completeness proofs². The proof of the first-order model existence theorem is completely analogous to the propositional one; indeed, apart from the model construction itself, it is just an extension by a treatment for the first-order quantifiers.³

A.3.1 Abstract Consistency and Model Existence

We will now come to an important tool in the theoretical study of reasoning calculi: the "abstract consistency"/"model existence" method. This method for analyzing calculi was developed by Jaako Hintikka, Raymond Smullyan, and Peter Andrews in 1950-1970 as an encapsulation of similar constructions that were used in completeness arguments in the decades before. The basis for this method is Smullyan's Observation [Smu63] that completeness proofs based on Hintikka sets only certain properties of consistency and that with little effort one can obtain a generalization "Smullyan's Unifying Principle".

The basic intuition for this method is the following: typically, a logical system $\mathcal{L} := \langle \mathcal{L}, \mathcal{K}, \vDash \rangle$ has multiple calculi, human-oriented ones like the natural deduction calculi and machine-oriented ones like the automated theorem proving calculi. All of these need to be analyzed for completeness (as a basic quality assurance measure).

A completeness proof for a calculus C for S typically comes in two parts: one analyzes Cconsistency (sets that cannot be refuted in C), and the other construct K-models for C-consistent
sets.

In this situation the "abstract consistency"/"model existence" method encapsulates the model construction process into a meta-theorem: the "model existence" theorem. This provides a set of syntactic ("abstract consistency") conditions for calculi that are sufficient to construct models.

With the model existence theorem it suffices to show that C-consistency is an abstract consistency property (a purely syntactic task that can be done by a C-proof transformation argument)

EdN:2

EdN:3

 $^{^{2}\}mathrm{EdNote}$: reference the theorems

³EdNote: MK: what about equality?

to obtain a completeness result for \mathcal{C} .

Model Existence (Overview)			
▷ Definition: Abstract consistency			
Demitton. Abstract consistency			
Definition: Hintikka set (maximally abstract consistent)			
Theorem: Hintikka sets are satisfiable			
\triangleright Theorem: If Φ is abstract consistent, then Φ can be extended to a Hintikka set.			
\triangleright Corollary: If Φ is abstract consistent, then Φ is satisfiable.			
\triangleright Application: Let C be a calculus, if Φ is C -consistent, then Φ is abstract consistent.			
\triangleright Corollary: C is complete.			
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The proof of the model existence theorem goes via the notion of a Hintikka set, a set of formulae with very strong syntactic closure properties, which allow to read off models. Jaako Hintikka's original idea for completeness proofs was that for every complete calculus C and every C-consistent set one can induce a Hintikka set, from which a model can be constructed. This can be considered as a first model existence theorem. However, the process of obtaining a Hintikka set for a C-consistent set Φ of sentences usually involves complicated calculus dependent constructions.

In this situation, Raymond Smullyan was able to formulate the sufficient conditions for the existence of Hintikka sets in the form of "abstract consistency properties" by isolating the calculus independent parts of the Hintikka set construction. His technique allows to reformulate Hintikka sets as maximal elements of abstract consistency classes and interpret the Hintikka set construction as a maximizing limit process.

To carry out the "model-existence"/"abstract consistency" method, we will first have to look at the notion of consistency.

Consistency and refutability are very important notions when studying the completeness for calculi; they form syntactic counterparts of satisfiability.

Consistency

- \triangleright Let C be a calculus,...
- \triangleright **Definition A.3.1.** Let C be a calculus, then a formula set Φ is called C-refutable, if there is a refutation, i.e. a derivation of a contradiction from Φ . The act of finding a refutation for Φ is called refuting Φ .
- \triangleright Definition A.3.2. We call a pair of formulae A and $\neg A$ a contradiction.
- \triangleright So a set Φ is *C*-refutable, if *C* canderive a contradiction from it.
- \triangleright **Definition A.3.3.** Let C be a calculus, then a formula set Φ is called C-consistent, iff there is a formula B, that is not derivable from Φ in C.
- ▷ **Definition A.3.4.** We call a calculus C reasonable, iff implication elimination and conjunction introduction are admissible in C and $A \land \neg A \Rightarrow B$ is a C-theorem.
- ▷ **Theorem A.3.5.** *C*-inconsistency and *C*-refutability coincide for reasonable calculi.

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It is very important to distinguish the syntactic C-refutability and C-consistency from satisfiability, which is a property of formulae that is at the heart of semantics. Note that the former have the calculus (a syntactic device) as a parameter, while the latter does not. In fact we should actually say S-satisfiability, where $\langle \mathcal{L}, \mathcal{K}, \vDash \rangle$ is the current logical system.

Even the word "contradiction" has a syntactical flavor to it, it translates to "saying against each other" from its Latin root.

The notion of an "abstract consistency class" provides the a calculus-independent notion of consistency: A set Φ of sentences is considered "consistent in an abstract sense", iff it is a member of an abstract consistency class ∇ .

Abstract Consistency

- \triangleright **Definition A.3.6.** Let ∇ be a collection of sets. We call ∇ closed under subsets, iff for each $\Phi \in \nabla$, all subsets $\Psi \subseteq \Phi$ are elements of ∇ .
- \triangleright Notation: We will use $\Phi * \mathbf{A}$ for $\Phi \cup \{\mathbf{A}\}$.
- ▷ **Definition A.3.7.** A family $\nabla \subseteq wf_{o}(\Sigma_{\iota}, \mathcal{V}_{\iota})$ of sets of formulae is called a (firstorder) abstract consistency class, iff it is closed under subsets, and for each $\Phi \in \nabla$
 - $\nabla_{\!c}$) $\mathbf{A} \notin \Phi$ or $\neg \mathbf{A} \notin \Phi$ for atomic $\mathbf{A} \in wf\!\!f_o(\Sigma_\iota, \mathcal{V}_\iota)$.
 - $abla_{\neg}$) $\neg \neg \mathbf{A} \in \Phi$ implies $\Phi * \mathbf{A} \in \nabla$
 - $abla_{\wedge}$) $\mathbf{A} \wedge \mathbf{B} \in \Phi$ implies $\Phi \cup \{\mathbf{A}, \mathbf{B}\} \in \nabla$

 - $\nabla_{\!\!\forall}$) If $\forall X.\mathbf{A} \in \Phi$, then $\Phi * ([\mathbf{B}/X](\mathbf{A})) \in \nabla$ for each closed term \mathbf{B} .
 - ∇∃) If $\neg(\forall X.\mathbf{A}) \in \Phi$ and c is an individual constant that does not occur in Φ , then $\Phi * \neg([c/X](\mathbf{A})) \in \nabla$

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The conditions are very natural: Take for instance ∇_c , it would be foolish to call a set Φ of sentences "consistent under a complete calculus", if it contains an elementary contradiction. The next condition ∇_{\neg} says that if a set Φ that contains a sentence $\neg \neg \mathbf{A}$ is "consistent", then we should be able to extend it by \mathbf{A} without losing this property; in other words, a complete calculus should be able to recognize \mathbf{A} and $\neg \neg \mathbf{A}$ to be equivalent. We will carry out the proof here, since it gives us practice in dealing with the abstract consistency properties.

The main result here is that abstract consistency classes can be extended to compact ones. The proof is quite tedious, but relatively straightforward. It allows us to assume that all abstract consistency classes are compact in the first place (otherwise we pass to the compact extension).

Actually we are after abstract consistency classes that have an even stronger property than just being closed under subsets. This will allow us to carry out a limit construction in the Hintikka set extension argument later.

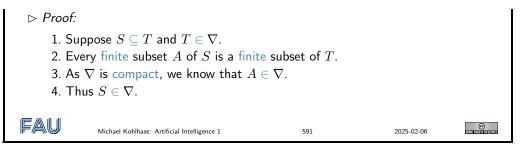
Compact Collections

 \rhd Definition A.3.8. We call a collection ∇ of sets compact, iff for any set Φ we have

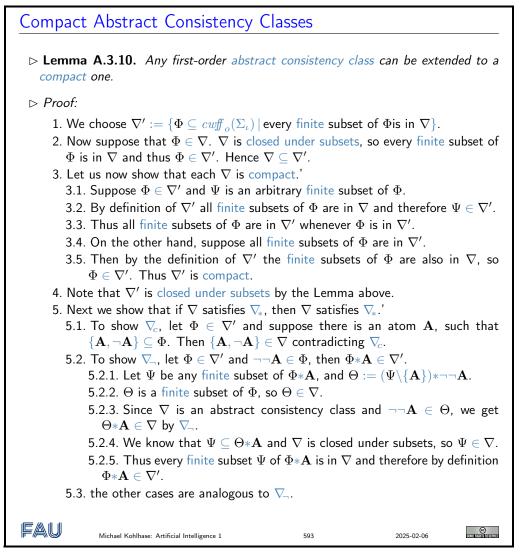
 $\Phi \in \nabla$, iff $\Psi \in \nabla$ for every finite subset Ψ of Φ .

 \triangleright Lemma A.3.9. If ∇ is compact, then ∇ is closed under subsets.

A.3. COMPLETENESS OF CALCULI FOR FIRST-ORDER LOGIC

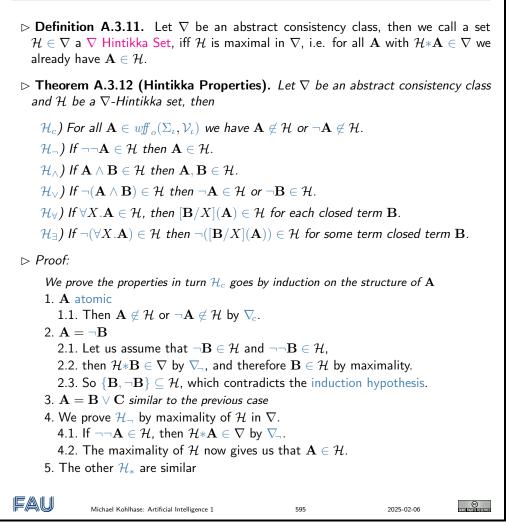


The property of being closed under subsets is a "downwards-oriented" property: We go from large sets to small sets, compactness (the interesting direction anyways) is also an "upwards-oriented" property. We can go from small (finite) sets to large (infinite) sets. The main application for the compactness condition will be to show that infinite sets of formulae are in a collection ∇ by testing all their finite subsets (which is much simpler).



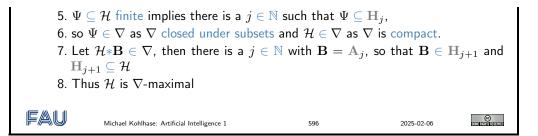
Hintikka sets are sets of sentences with very strong analytic closure conditions. These are motivated as maximally consistent sets i.e. sets that already contain everything that can be consistently added to them.

<u>∇-Hintikka Set</u>



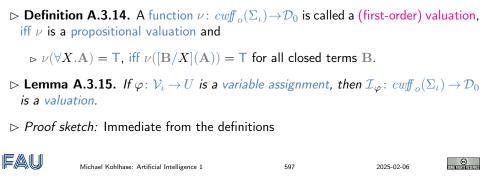
The following theorem is one of the main results in the "abstract consistency"/"model existence" method. For any abstract consistent set Φ it allows us to construct a Hintikka set \mathcal{H} with $\Phi \in \mathcal{H}$.

Extension Theorem $\triangleright \text{ Theorem A.3.13. If } \nabla \text{ is an abstract consistency class and } \Phi \in \nabla \text{ finite, then there is a } \nabla \text{-Hintikka set } \mathcal{H} \text{ with } \Phi \subseteq \mathcal{H}. \\ \triangleright \text{ Proof:} \\ 1. \text{ Wlog. assume that } \nabla \text{ compact } (else \text{ use compact extension}) \\ 2. \text{ Choose an enumeration } \mathbf{A}_1, \dots \text{ of } cuff_o(\Sigma_t) \text{ and } c_1, \dots \text{ of } \Sigma_0^{sk}. \\ 3. \text{ and construct a sequence of sets } \mathbf{H}_i \text{ with } \mathbf{H}_0 := \Phi \text{ and} \\ \mathbf{H}_{n+1} := \begin{cases} \mathbf{H}_n \cup \{\mathbf{A}_n, \neg([c_n/X](\mathbf{B}))\} & \text{ if } \mathbf{H}_n * \mathbf{A}_n \in \nabla \text{ and } \mathbf{A}_n = \neg(\forall X.\mathbf{B}) \\ \mathbf{H}_n * \mathbf{A}_n & \text{ else} \end{cases} \\ 4. \text{ Note that all } \mathbf{H}_i \in \nabla, \text{ choose } \mathcal{H} := \bigcup_{i \in \mathbb{N}} \mathbf{H}_i \end{cases}$



Note that the construction in the proof above is non-trivial in two respects. First, the limit construction for \mathcal{H} is not executed in our original abstract consistency class ∇ , but in a suitably extended one to make it compact — the original would not have contained \mathcal{H} in general. Second, the set \mathcal{H} is not unique for Φ , but depends on the choice of the enumeration of $cuff_o(\Sigma_{\iota})$. If we pick a different enumeration, we will end up with a different \mathcal{H} . Say if \mathbf{A} and $\neg \mathbf{A}$ are both ∇ -consistent⁴ with Φ , then depending on which one is first in the enumeration \mathcal{H} , will contain that one; with all the consequences for subsequent choices in the construction process.

Valuations



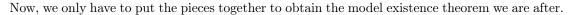
Thus a valuation is a weaker notion of evaluation in first-order logic; the other direction is also true, even though the proof of this result is much more involved: The existence of a first-order valuation that makes a set of sentences true entails the existence of a model that satisfies it.⁵

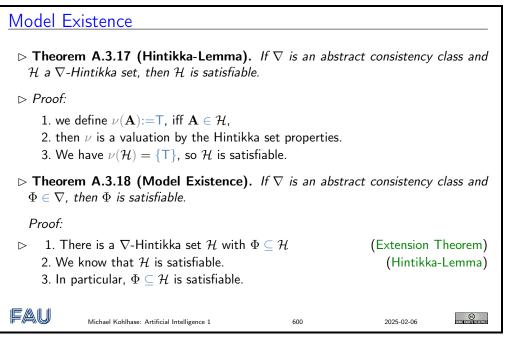
Valuation and Satisfiability $\triangleright \text{ Lemma A.3.16. If } \nu : cwff_o(\Sigma_{\iota}) \to \mathcal{D}_0 \text{ is a valuation and } \Phi \subseteq cwff_o(\Sigma_{\iota}) \text{ with}$ $\nu(\Phi) = \{\mathsf{T}\}, \text{ then } \Phi \text{ is satisfiable.}$ $\triangleright \text{ Proof: We construct a model for } \Phi.$ 1. Let $\mathcal{D}_{\iota} := cwff_{\iota}(\Sigma_{\iota}), \text{ and}$ $\triangleright \mathcal{I}(f) : \mathcal{D}_{\iota}^k \to \mathcal{D}_{\iota}; \langle \mathsf{A}_1, \dots, \mathsf{A}_k \rangle \mapsto f(\mathsf{A}_1, \dots, \mathsf{A}_k) \text{ for } f \in \Sigma^f$ $\triangleright \mathcal{I}(p) : \mathcal{D}_{\iota}^k \to \mathcal{D}_0; \langle \mathsf{A}_1, \dots, \mathsf{A}_k \rangle \mapsto \nu(p(\mathsf{A}_1, \dots, \mathsf{A}_k)) \text{ for } p \in \Sigma^p.$ 2. Then variable assignments into \mathcal{D}_{ι} are ground substitutions. 3. We show $\mathcal{I}_{\varphi}(\mathsf{A}) = \varphi(\mathsf{A}) \text{ for } \mathsf{A} \in wff_{\iota}(\Sigma_{\iota}, \mathcal{V}_{\iota}) \text{ by induction on } \mathsf{A}:$ 3.1.1. then $\mathcal{I}_{\varphi}(\mathsf{A}) = \varphi(X)$ by definition. 3.2. $\mathsf{A} = f(\mathsf{A}_1, \dots, \mathsf{A}_k)$ 3.2.1. then $\mathcal{I}_{\varphi}(\mathsf{A}) = \mathcal{I}(f)(\mathcal{I}_{\varphi}(\mathsf{A}_1), \dots, \mathcal{I}_{\varphi}(\mathsf{A}_n)) = \mathcal{I}(f)(\varphi(\mathsf{A}_1), \dots, \varphi(\mathsf{A}_n)) = f(\varphi(\mathsf{A}_1), \dots, \varphi(\mathsf{A}_n)) = \varphi(f(\mathsf{A}_1, \dots, \mathsf{A}_k)) = \varphi(\mathsf{A})$

⁴EDNOTE: introduce this above

 $^{^{5}\}mathrm{EdNote}$: I think that we only get a semivaluation, look it up in Andrews.

We show
$$\mathcal{I}_{\varphi}(\mathbf{A}) = \nu(\varphi(\mathbf{A}))$$
 for $\mathbf{A} \in uff_{o}(\Sigma_{\iota}, \mathcal{V}_{\iota})$ by induction on \mathbf{A} .
3.3. $\mathbf{A} = p(\mathbf{A}_{1}, \dots, \mathbf{A}_{k})$
3.3.1. then $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathcal{I}(p)(\mathcal{I}_{\varphi}(\mathbf{A}_{1}), \dots, \mathcal{I}_{\varphi}(\mathbf{A}_{n})) = \mathcal{I}(p)(\varphi(\mathbf{A}_{1}), \dots, \varphi(\mathbf{A}_{n})) = \nu(p(\varphi(\mathbf{A}_{1}), \dots, \varphi(\mathbf{A}_{n}))) = \nu(p(\varphi(\mathbf{A}_{1}), \dots, \varphi(\mathbf{A}_{n}))) = \nu(\varphi(\mathbf{A}_{1}))$
3.4. $\mathbf{A} = \neg \mathbf{B}$
3.4.1. then $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{T}$, iff $\mathcal{I}_{\varphi}(\mathbf{B}) = \nu(\varphi(\mathbf{B})) = \mathsf{F}$, iff $\nu(\varphi(\mathbf{A})) = \mathsf{T}$.
3.5. $\mathbf{A} = \mathbf{B} \wedge \mathbf{C}$
3.5.1. similar
3.6. $\mathbf{A} = \forall X \cdot \mathbf{B}$
3.6.1. then $\mathcal{I}_{\varphi}(\mathbf{A}) = \mathsf{T}$, iff $\mathcal{I}_{\psi}(\mathbf{B}) = \nu(\psi(\mathbf{B})) = \mathsf{T}$, for all $\mathbf{C} \in \mathcal{D}_{\iota}$, where $\psi = \varphi, [\mathbf{C}/X]$. This is the case, iff $\nu(\varphi(\mathbf{A})) = \mathsf{T}$.
4. Thus $\mathcal{I}_{\varphi}(\mathbf{A})\nu(\varphi(\mathbf{A})) = \nu(\mathbf{A}) = \mathsf{T}$ for all $\mathbf{A} \in \Phi$.
5. Hence $\mathcal{M} \models \mathbf{A}$ for $\mathcal{M} := \langle \mathcal{D}_{\iota}, \mathcal{I} \rangle$.





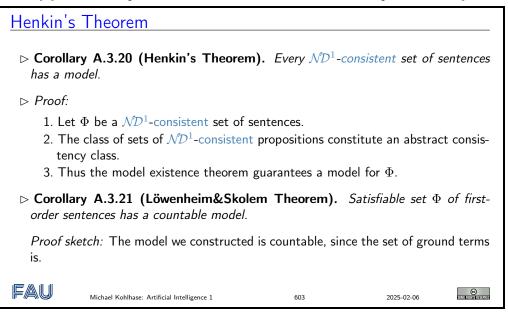
A.3.2 A Completeness Proof for First-Order ND

With the model existence proof we have introduced in the last section, the completeness proof for first-order natural deduction is rather simple, we only have to check that ND-consistency is an abstract consistency property.

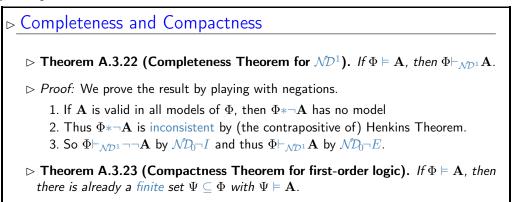
 Consistency, Refutability and Abstract Consistency
 ► Theorem A.3.19 (Non-Refutability is an Abstract Consistency Property). Γ := {Φ ⊆ cwff_o(Σ_ι) | Φ not ND¹−refutable} is an abstract consistency class.
 ► Proof: We check the properties of an ACC
 1. If Φ is non-refutable, then any subset is as well, so Γ is closed under subsets.

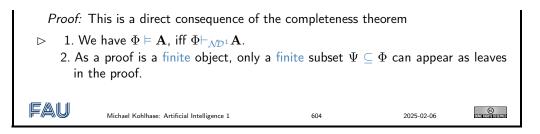
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We show the abstract consistency conditions \nabla_* for \Phi \in \Gamma.
         2. \nabla_c
             2.1. We have to show that \mathbf{A} \notin \Phi or \neg \mathbf{A} \notin \Phi for atomic \mathbf{A} \in wff_o(\Sigma_t, \mathcal{V}_t).
             2.2. Equivalently, we show the contrapositive: If \{\mathbf{A}, \neg \mathbf{A}\} \subseteq \Phi, then \Phi \notin \Gamma.
             2.3. So let \{\mathbf{A}, \neg \mathbf{A}\} \subseteq \Phi, then \Phi is \mathcal{ND}^1-refutable by construction.
             2.4. So \Phi \notin \Gamma.
         3. \nabla_{\neg} We show the contrapositive again
             3.1. Let \neg \neg \mathbf{A} \in \Phi and \Phi * \mathbf{A} \notin \Gamma
             3.2. Then we have a refutation \mathcal{D}: \Phi * \mathbf{A} \vdash_{\mathcal{ND}^1} F
             3.3. By prepending an application of \mathcal{ND}_0 \neg E for \neg \neg \mathbf{A} to \mathcal{D}, we obtain a refu-
                   tation \mathcal{D}: \Phi \vdash_{\mathcal{ND}^1} F'.
             3.4. Thus \Phi \notin \Gamma.
         Proof sketch: other \nabla_* similar
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This directly yields two important results that we will use for the completeness analysis.



Now, the completeness result for first-order natural deduction is just a simple argument away. We also get a compactness theorem (almost) for free: logical systems with a complete calculus are always compact.





A.3.3 Soundness and Completeness of First-Order Tableaux

The soundness of the first-order free-variable tableaux calculus can be established a simple induction over the size of the tableau.

Soundness of \mathcal{T}_1^f			
⊳ Lemma A.3.24. Tableau rules transfor	m satisfiable table	aux into satisfia	ble ones.
⊳ Proof:			
we examine the tableau rules in turn			
1. propositional rules as in propositiona	l tableaux		
2. $\mathcal{T}_1^f \exists by ??$			
3. $\mathcal{T}_1^f ot$ by $\ref{eq: substitution value lemma}$)		
4. $\mathcal{T}_{1}^{f} \forall$			
4.1. $\mathcal{I}_{\varphi}(\forall X.\mathbf{A}) = T$, iff $\mathcal{I}_{\psi}(\mathbf{A}) = T$	F for all $a \in \mathcal{D}_\iota$		
4.2. so in particular for some $a\in\mathcal{D}$	$\iota \neq \emptyset$.		
\triangleright Corollary A.3.25. \mathcal{T}_1^f is correct.			
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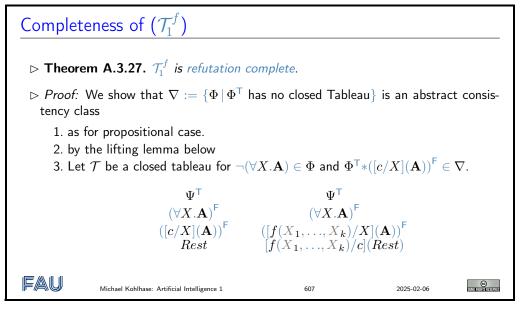
The only interesting steps are the cut rule, which can be directly handled by the substitution value lemma, and the rule for the existential quantifier, which we do in a separate lemma.

Soundness of $\mathcal{T}_{1}^{f} \exists$ \triangleright Lemma A.3.26. $\mathcal{T}_{1}^{f} \exists$ transforms satisfiable tableaux into satisfiable ones. \triangleright Proof: Let \mathcal{T}' be obtained by applying $\mathcal{T}_{1}^{f} \exists$ to $(\forall X.\mathbf{A})^{\mathsf{F}}$ in \mathcal{T} , extending it with $([f(X^{1},...,X^{k})/X](\mathbf{A}))^{\mathsf{F}}$, where $W := \text{free}(\forall X.\mathbf{A}) = \{X^{1},...,X^{k}\}$ 1. Let \mathcal{T} be satisfiable in $\mathcal{M} := \langle \mathcal{D}, \mathcal{I} \rangle$, then $\mathcal{I}_{\varphi}(\forall X.\mathbf{A}) = \mathsf{F}$. We need to find a model \mathcal{M}' that satisfies \mathcal{T}' (find interpretation for f) 2. By definition $\mathcal{I}_{\varphi,[a/X]}(\mathbf{A}) = \mathsf{F}$ for some $a \in \mathcal{D}$ (depends on $\varphi|_{W}$) 3. Let $g: \mathcal{D}^{k} \to \mathcal{D}$ be defined by $g(a_{1},...,a_{k}):=a$, if $\varphi(X^{i}) = a_{i}$ 4. choose $\mathcal{M} = \langle \mathcal{D}, \mathcal{I}' \rangle'$ with $\mathcal{I}' := \mathcal{I},[g/f]$, then by subst. value lemma $\mathcal{I}'_{\varphi}([f(X^{1},...,X^{k})/X](\mathbf{A})) = \mathcal{I}'_{\varphi,[\mathcal{I}'_{\varphi}(f(X^{1},...,X^{k}))/X]}(\mathbf{A}))$ $= \mathcal{I}'_{\varphi,[a/X]}(\mathbf{A}) = \mathsf{F}$ 5. So $([f(X^{1},...,X^{k})/X](\mathbf{A}))^{\mathsf{F}}$ satisfiable in \mathcal{M}'

A.3. COMPLETENESS OF CALCULI FOR FIRST-ORDER LOGIC

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This proof is paradigmatic for soundness proofs for calculi with Skolemization. We use the axiom of choice at the meta-level to choose a meaning for the Skolem constant. Armed with the Model Existence Theorem for first-order logic (??), the completeness of first-order tableaux is similarly straightforward. We just have to show that the collection of tableau-irrefutable sentences is an abstract consistency class, which is a simple proof-transformation exercise in all but the universal quantifier case, which we postpone to its own Lemma (??).



So we only have to treat the case for the universal quantifier. This is what we usually call a "lifting argument", since we have to transform ("lift") a proof for a formula $\theta(\mathbf{A})$ to one for \mathbf{A} . In the case of tableaux we do that by an induction on the tableau refutation for $\theta(\mathbf{A})$ which creates a tableau-isomorphism to a tableau refutation for A.

Tableau-Lifting

- \triangleright Theorem A.3.28. If \mathcal{T}_{θ} is a closed tableau for a set $\theta(\Phi)$ of formulae, then there is a closed tableau \mathcal{T} for Φ .
- \triangleright *Proof:* by induction over the structure of \mathcal{T}_{θ} we build an isomorphic tableau \mathcal{T} , and a tableau-isomorphism $\omega \colon \mathcal{T} \to \mathcal{T}_{\theta}$, such that $\omega(\mathbf{A}) = \theta(\mathbf{A})$.

only the tableau-substitution rule is interesting.

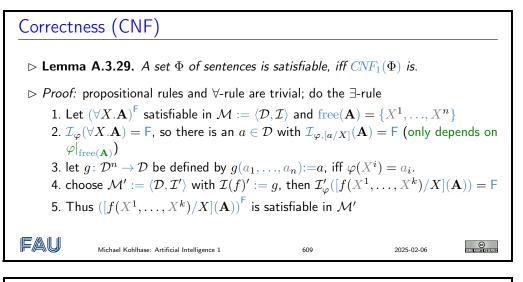
- 1. Let $(\theta(\mathbf{A}_i))^{\mathsf{T}}$ and $(\theta(\mathbf{B}_i))^{\mathsf{F}}$ cut formulae in the branch Θ^i_{θ} of \mathcal{T}_{θ}
- 2. there is a joint unifier σ of $(\theta(\mathbf{A}_1)) = ?(\theta(\mathbf{B}_1)) \land \ldots \land (\theta(\mathbf{A}_n)) = ?(\theta(\mathbf{B}_n))$
- 3. thus $\sigma \circ \theta$ is a unifier of **A** and **B**
- 4. hence there is a most general unifier ρ of $A_1 = {}^{?}B_1 \land \ldots \land A_n = {}^{?}B_n$
- 5. so Θ is closed.

calculi.

FAU Michael Kohlhase: Artificial Intelligence 1 608 2025-02-06 Again, the "lifting lemma for tableaux" is paradigmatic for lifting lemmata for other refutation

Soundness and Completeness of First-Order Resolution A.3.4

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Resolution (Correctness)

▷ Definition A.3.30. A clause is called satisfiable, iff I_φ(A) = α for one of its literals A^α.
 ▷ Lemma A.3.31. □ is unsatisfiable
 ▷ Lemma A.3.32. CNF transformations preserve satisfiability (see above)

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▷ Lemma A.3.33. *Resolution and factorization too!*

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Completeness (\mathcal{R}_1) \triangleright Theorem A.3.34. \mathcal{R}_1 is refutation complete. \triangleright Proof: $\nabla := \{\Phi \mid \Phi^T \text{ has no closed tableau}\} \text{ is an abstract consistency class}$ 1. as for propositional case. 2. by the lifting lemma below 3. Let \mathcal{T} be a closed tableau for $\neg(\forall X.\mathbf{A}) \in \Phi$ and $\Phi^T * ([c/X](\mathbf{A}))^F \in \nabla$. 4. $CNF_1(\Phi^T) = CNF_1(\Psi^T) \cup CNF_1(([f(X_1, \dots, X_k)/X](\mathbf{A}))^F))$ 5. $([f(X_1, \dots, X_k)/c](CNF_1(\Phi^T))) * ([c/X](\mathbf{A}))^F = CNF_1(\Phi^T))$ 6. so $\mathcal{R}_1 : CNF_1(\Phi^T) \vdash_{\mathcal{D}'} \Box$, where $\mathcal{D} = [f(X'_1, \dots, X'_k)/c](\mathcal{D})$.

Clause Set Isomorphism

 \triangleright Definition A.3.35. Let B and C be clauses, then a clause isomorphism $\omega \colon C \to D$ is a bijection of the literals of C and D, such that $\omega(L)^{\alpha} = M^{\alpha}$ (conserves labels) We call $\omega \theta$ compatible, iff $\omega(L^{\alpha}) = (\theta(L))^{\alpha}$

- \triangleright Definition A.3.36. Let Φ and Ψ be clause sets, then we call a bijection $\Omega: \Phi \to \Psi$ a clause set isomorphism, iff there is a clause isomorphism $\omega: \mathbf{C} \to \Omega(\mathbf{C})$ for each $\mathbf{C} \in \Phi$.
- \triangleright Lemma A.3.37. If $\theta(\Phi)$ is set of formulae, then there is a θ -compatible clause set isomorphism Ω : $CNF_1(\Phi) \rightarrow CNF_1(\theta(\Phi))$.

 \triangleright *Proof sketch:* by induction on the CNF derivation of $CNF_1(\Phi)$.

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