Introduction to Artificial Intelligence COMP 3501 / COMP 4704-4 Lecture 7

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Class Overview

- Review from Wednesday
- Inference in propositional logic
- Propositional logic agents
- First-Order Logic (Ch 8)

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Entailment

- α entails β or $\alpha \models \beta$
 - β follows logically from α
 - In every model in which α is true, β is also true
 - $M(\alpha) \subseteq M(\beta)$



Entailment examples?

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Propositional Logic Syntax

- Sentence → AtomicSentence | ComplexSentence
- AtomicSentence \rightarrow True | False | P | Q | R | ...
- Complex Sentence → (Sentence) | [Sentence]
 - | ¬ Sentence | Sentence ∧ Sentence
 - | Sentence ∨ Sentence | Sentence ⇒ Sentence
 - | Sentence ⇔ Sentence
- Operator precedence: ¬, ∧, ∨, ⇒, ⇔

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Model checking

- How does it work?
- What is the running time?
- What is the space required?



Example statements

- There is no pit in [1, 1]
- A square is breezy iff there is a pit in a neighboring square
- If there is no smell in [1, 1], there can't be a wumpus in [1, 2]

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Theorem proving [7.5]

- No longer consult models
 - Derive inferences (entailment) directly from KB
- In some ways this mimics algebraic theorem proving
 - Start with the known
 - Apply rules/transformations
 - Reach the desired result (if possible)

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Logical equivalence

- Two statements are logically equivalent if they are true in the same set of models
 - $\alpha = \beta$
 - $\alpha = \beta$ iff $\alpha \models \beta$ and $\beta \models \alpha$

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Standard logical equivalences

- $(\alpha \wedge \beta) = (\beta \wedge \alpha)$
- $(\alpha \vee \beta) \equiv (\beta \vee \alpha)$
- $((\alpha \land \beta) \land \gamma) = (a \land (\beta \land \gamma))$
- $((\alpha \lor \beta) \lor \gamma) = (a \lor (\beta \lor \gamma))$
- $\bullet \neg (\neg \alpha) \equiv \alpha$

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Standard logical equivalences

•
$$(\alpha \Rightarrow \beta) \equiv (\neg \beta \Rightarrow \neg \alpha)$$

•
$$(\alpha \Rightarrow \beta) = (\neg \alpha \lor \beta)$$

•
$$(\alpha \Leftrightarrow \beta) \equiv ((\alpha \Rightarrow \beta) \land (\beta \Rightarrow \alpha))$$

•
$$\neg(\alpha \lor \beta) \equiv (\neg \alpha \land \neg \beta)$$

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Standard logical equivalences

•
$$(\alpha \land (\beta \lor \gamma)) = ((\alpha \land \beta) \lor (\alpha \land \gamma))$$

•
$$(\alpha \vee (\beta \wedge \gamma)) = ((\alpha \vee \beta) \wedge (\alpha \vee \gamma))$$

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Validity

- A sentence is valid if it is true in all models
 - $\bullet P \lor \neg P$
 - $\bullet Q \Rightarrow Q$
- Valid sentences are tautologies
- Deduction theorem
 - For any sentences α and β , $\alpha \models \beta$ iff $(\alpha \Rightarrow \beta)$ is valid
 - Essence of model checking algorithm

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Validity and Satisfiability

- α is satisfiable iff $\neg \alpha$ is not valid
- $\alpha \models \beta$ iff $(\alpha \land \neg \beta)$ is unsatisfiable
 - Proof? [Hint: $\alpha \models \beta$ iff $(a \Rightarrow \beta)$ is valid]
- This is the logical basis of proof by contradiction



Satisfiability

- A sentence is satisfiable if it is true in some model
 - Abbreviated as SAT
 - Can we find a variable assignment that makes some statement true

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Validity and Satisfiability (Proof)

- α is satisfiable iff $\neg \alpha$ is not valid
 - if α is unsatisfiable, $\neg \alpha$ is valid
 - if $\neg \alpha$ is unsatisfiable, α is valid
- $\alpha \models \beta$ iff $(\alpha \land \neg \beta)$ is unsatisfiable
 - $\alpha \models \beta$ iff $(\alpha \Rightarrow \beta)$ is valid
 - $\alpha \models \beta$ iff $\neg(\alpha \Rightarrow \beta)$ is unsatisfiable
 - $\alpha \models \beta$ iff $\neg(\neg \alpha \lor \beta)$ is unsatisfiable
 - $\alpha \models \beta$ iff $(\alpha \land \neg \beta)$ is unsatisfiable

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Inference & Proofs

New notation for inference rules

$$\frac{given 1, \quad given 2}{conclusion}$$

• We supply the items on the top and conclude what is on the bottom

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Modus Ponens

• Latin for mode that affirms

$$\frac{\alpha \Rightarrow \beta, \quad \alpha}{\beta}$$

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And-Elimination

$$\frac{\alpha \wedge \beta}{\alpha}$$

Biconditional elimination

$$\frac{\alpha \Leftrightarrow \beta}{(\alpha \Rightarrow \beta) \land (\beta \Rightarrow \alpha)}$$
$$\frac{(\alpha \Rightarrow \beta) \land (\beta \Rightarrow \alpha)}{\alpha \Leftrightarrow \beta}$$

$$\frac{(\alpha \Rightarrow \beta) \land (\beta \Rightarrow \alpha)}{\alpha \Leftrightarrow \beta}$$



Wumpus World Example

• Previous definitions

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• Initial state: KB

Actions: all inference rules that apply (top of rule)

• Result: inference in bottom of rule added to KB

• Goal: sentence we want to prove

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Monotonicity

- The set of entailed sentences can only *increase* as information is added to the KB
 - if $KB \models \alpha$ then $KB \land \beta \models \alpha$
 - Adding β to our KB will not decrease what we can entail from the KB



Inference: sound & complete

- The previous inference rules were all sound
 - Derive entailed sentences
- Are they complete? No
 - There are some things they can't derive
 - (Example?)

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Unit Resolution

$$\frac{\ell_1 \vee \ell_2, \quad \neg \ell_2}{\ell_1}$$

• Can be generalized to more clauses (see book)

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Resolution

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Generalized resolution can handle more clauses

$$\frac{\ell_1 \vee \ell_2, \quad \neg \ell_2 \vee \ell_3}{\ell_1 \vee \ell_3}$$

• Completely general form in the book

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Examples

Conjunctive Normal Form (CNF)



 All propositional logic can be reduce to clauses or conjunctive normal form (CNF)

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Example

- $\bullet \; B_{1,1} \Leftrightarrow \left(P_{1,2} \vee P_{2,1}\right)$
- $B_{1,1} \Rightarrow (P_{1,2} \vee P_{2,1}) \wedge (P_{1,2} \vee P_{2,1}) \Rightarrow B_{1,1}$
- $(\neg B_{1,1} \lor (P_{1,2} \lor P_{2,1})) \land (\neg (P_{1,2} \lor P_{2,1}) \lor B_{1,1})$
- $(\neg B_{1,1} \lor P_{1,2} \lor P_{2,1}) \land (\neg (P_{1,2} \lor P_{2,1}) \lor B_{1,1})$
 - $(\neg P_{1,2} \land \neg P_{2,1}) \lor B_{1,1}$
 - $\bullet \; (\!(B_{1,1} \vee \neg P_{1,2}\!) \wedge (B_{1,1} \vee \neg P_{2,1}\!)\!)$
- $\bullet \; (\neg B_{1,1} \, \vee \, P_{1,2} \, \vee \, P_{2,1}) \, \wedge \, (B_{1,1} \, \vee \, \neg P_{1,2}) \, \wedge \, (B_{1,1} \, \vee \, \neg P_{2,1})$

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Example

- R1: dog_{fred} ⇒ likesbones_{fred}; R2: dog_{fred}
- R3: ¬dog_{fred} ∨ likesbones_{fred}
- Prove: likesbones_{fred}
- Add R4: ¬likesbones_{fred} to KB
- Resolve R4 and R3: R5: ¬dog_{fred}
- Resolve R5 and R2: (null)
 - Contradiction!



Using resolution

- Proofs using resolution are proofs by contradiction
 - $\alpha \models \beta$ iff $(\alpha \land \neg \beta)$ is unsatisfiable
- Assume we want to prove $\alpha \models \beta$
 - Add ¬ ß to KB
 - If we can infer false, we have a contradiction
 - If we can't, then $\alpha \not = \beta$

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Special Case: Horn & definite Clauses

- A Horn clause is a disjunction of literals of which at most one is positive
 - $\bullet \neg A \lor \neg B \lor C$
 - In Definite clause exactly one is positive
- Definite clauses correspond to implications
 - \bullet A \wedge B \Rightarrow C
- Modus Ponens is sound and complete with Horn clauses

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Building Logic Agents

- Can we now build propositional logic agents?
 - There are a few important details!
- All percepts depend on the current time/location of the agent
 - Frame problem: need to reason about what does/ does not change as time goes forward
 - This tremendously complicates writing proper logical descriptions of the world

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First-Order Logic: Motivation

- Returning to fred likes bones:
 - Expensive to have to specify if everyone likes bones
 - Works in wumpus world, but can be computationally infeasable
 - Cannot make statements like:
 - "All dogs like bones"



Building Logic Agents

- Can now build an agent
 - Use A* to plan movement
 - Use logical inference to decide where to go
- Caveat: planning gets more expensive as more time passes, even if the agent just moves around the know part of the state space
- Harder to build an agent that generates a full plan

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First-Order Logic

- Propositional logic only has variables
 - These are true or false
- First-order logic adds objects, functions and relations
- Also adds quantifiers:
 - ∃: There exists
 - ∀: For all

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First-Order Logic Examples

- Occupation(p, o); Boss(p1, p2); Customer(p1, p2)
- Emily; Doctor, Surgeon, Lawyer
- Emily is either a surgeon or a lawyer.
- All surgeons are doctors.
- Emily has a boss who is a lawyer.
- Every surgeon has a lawyer.

Homework: 7.14

-or-

Show a problem that resolution can solve and other rules cannot. (2 HW's -- do not use the internet.)

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