

# CS 540 Introduction to Artificial Intelligence Logic

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#### Announcements

#### • Homeworks:

HW2 due Tuesday before class

#### • Roadmap

Date	Торіс	<b>Reading materials</b>	Assignments
Thursday, Sept 9	Welcome and Course Overview	Slides	
Tuesday, Sept 14	Probability	Slides	HW 1 Released
Thursday, Sept 16	Linear Algebra and PCA	Slides	
Tuesday, Sept 21	Statistics and Math Review	Slides	HW 1 Due, HW 2 Released
Thursday, Sept 23	Introduction to Logic	Slides	
Tuesday, Sept 28	Natural Language Processing		HW 2 Due, HW 3 Released
Thursday, Sept 30	Machine Learning: Introduction		

#### Homework Review: Classification

• Expression

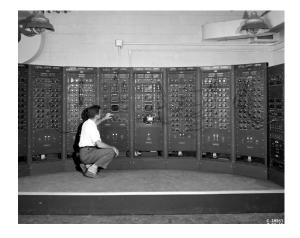
 $P(H|E_1, E_2, \dots, E_n) = \frac{P(E_1|H)P(E_2|H)\cdots, P(E_n|H)P(H)}{P(E_1, E_2, \dots, E_n)}$ 

- *H*: some class we'd like to infer from evidence
  - Estimate prior P(H)
  - \_ Estimate  $P(E_i|H)$  from data!
  - Empirical count-based estimates

# Logic & Al

Why are we studying logic?

- Traditional approach to AI ('50s-'80s)
  - "Symbolic AI"
  - The Logic Theorist 1956
    - Proved a bunch of theorems!
- Logic also the language of:
  - Knowledge rep., databases, etc.



## Symbolic Techniques in Al

Lots of systems based on symbolic approach:

- Ex: expert systems, planning, more
- Playing great chess

- Less popular recently!
- "Good old fashioned AI"





J. Gardner

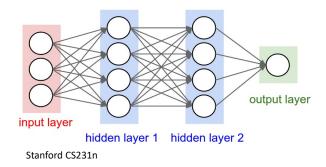
## Symbolic vs Subsymbolic

Rival approach: subsymbolic

- Probabilistic models
- Neural networks

years

• Extremely popular last 20

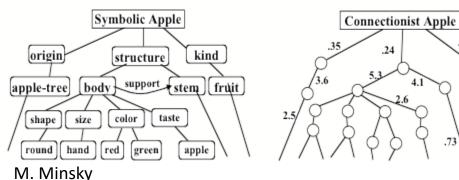


.24

.63

.73





# Symbolic vs Subsymbolic

- Easier to debug
- Easier to explain
- No need for big data
- Better for abstract problems
  - Symbol grounding problem

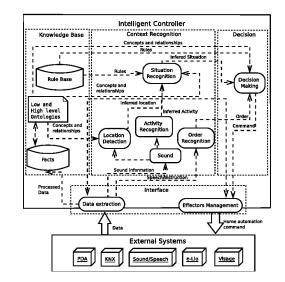
Credit: Henry Lieberman

- Robust to noise
- Less built-in knowledge
- Easier to scale
- Better for perceptual problems

## Symbolic vs Subsymbolic

Analogy: Logic versus probability

- Which is better?
- Future: combination; best-of-bothworlds
  - Actually been worked on:
  - Example: Markov Logic Networks



### Symbolic and Connectionist



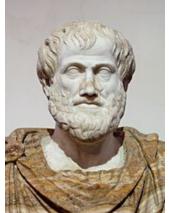
# Outline

- Introduction to logic
  - Arguments, validity, soundness
- Propositional logic
  - Sentences, semantics, inference
- First order logic (FOL)
  - Predicates, objects, formulas, quantifiers



# Basic Logic

- Arguments, premises, conclusions
  - Argument: a set of sentences (premises) + a sentence (a conclusion)
  - Validity: argument is valid iff it's necessary that if all premises are true, the conclusion is true
  - Soundness: argument is sound iff valid & premises true
  - Entailment: when valid arg., premises entail conclusion



#### **Propositional Logic Basics**

Logic Vocabulary:

- Sentences, symbols, connectives, parentheses
  - Symbols: P, Q, R, ... (atomic sentences)
  - Connectives:

∧ and
∨ or
⇒ implies
⇔ is equivalent
¬ not

[conjunction] [disjunction] [implication] [biconditional] [negation]

- Literal: P or negation  $\neg$  P

#### **Propositional Logic Basics**

Examples:

- $(P \lor Q) \Rightarrow S$ 
  - "If it is cold or it is raining, then I need a jacket"
- $Q \Rightarrow P$ 
  - "If it is raining, then it is cold"
- ¬R
  - "It is not hot"



#### **Propositional Logic Basics**

Several rules in place

- Precedence:  $\neg$ ,  $\land$ ,  $\lor$ ,  $\Rightarrow$ ,  $\Leftrightarrow$
- Use parentheses when needed
- Sentences: well-formed or not well-formed:

#### Sentences & Semantics

- Think of symbols as defined by user
- Sentences: built up from symbols with connectives
  - Interpretation: assigning True / False to symbols
  - Semantics: interpretations for which sentence evaluates to True
  - Model: (of a set of sentences)
     interpretation for which all sentences
     are True



#### **Evaluating a Sentence**

#### • Example:

P	Q	$\neg P$	$P \wedge Q$	$P \lor Q$	$P \Rightarrow Q$	$P \Leftrightarrow Q$
false	false	true	false	false	true	true
false	true	true	false	true	true	false
true	false	false	false	true	false	false
true	true	false	true	true	true	true

- Note:
  - If P is false, P⇒Q is true regardless of Q ("5 is even implies 6 is odd" is True!)
  - Causality unneeded: "5 is odd implies the Sun is a star" is True!)

#### Evaluating a Sentence: Truth Table

• Ex:

Р	Q	R	¬ P	Q∧R	¬P∨Q∧R	¬P∨Q∧R⇒Q
0	0	0	1	0	1	0
0	0	1	1	0	1	0
0	1	0	1	0	1	1
0	1	1	1	1	1	1
1	0	0	0	0	0	1
1	0	1	0	0	0	1
1	1	0	0	0	0	1
1	1	1	0	1	1	1

#### • Satisfiable

There exists some interpretation where sentence true

**Q 1.1**: Suppose P is false, Q is true, and R is true. Does this assignment satisfy (i)  $\neg(\neg p \rightarrow \neg q) \land r$ (ii)  $(\neg p \lor \neg q) \rightarrow (p \lor \neg r)$ 

- A. Both
- B. Neither
- C. Just (i)
- D. Just (ii)

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**Q 1.2**: Let A = "Aldo is Italian" and B = "Bob is English". Formalize "Aldo is Italian or if Aldo isn't Italian then Bob is English".

- a.  $A \lor (\neg A \rightarrow B)$
- b.  $A \lor B$
- c.  $A \lor (A \rightarrow B)$
- d. A  $\rightarrow$  B

**Q 1.2**: Let A = "Aldo is Italian" and B = "Bob is English". Formalize "Aldo is Italian or if Aldo isn't Italian then Bob is English".

- a. A ∨ (¬A → B)
- b. A ∨ B (equivalent!)
- c.  $A \lor (A \rightarrow B)$
- d. A  $\rightarrow$  B

# **Q 1.3**: How many different assignments can there be to $(x_1 \land y_1) \lor (x_2 \land y_2) \lor ... \lor (x_n \land y_n)$

- A. 2
- B. 2<sup>n</sup>
- C. 2<sup>2n</sup>
- D. 2n

# **Q 1.3**: How many different assignments can there be to $(x_1 \land y_1) \lor (x_2 \land y_2) \lor ... \lor (x_n \land y_n)$

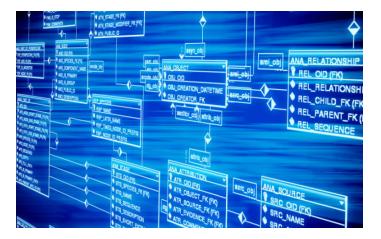
- A. 2
- B. 2<sup>n</sup>
- C. 2<sup>2n</sup>
- D. 2n

#### **Knowledge Bases**

- Knowledge Base (KB): A set of sentences
  - Like a long sentence, connect with conjunction

**Model of a KB**: interpretations where all sentences are True

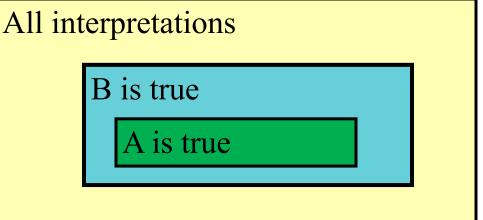
**Goal:** inference to discover new sentences



### Entailment

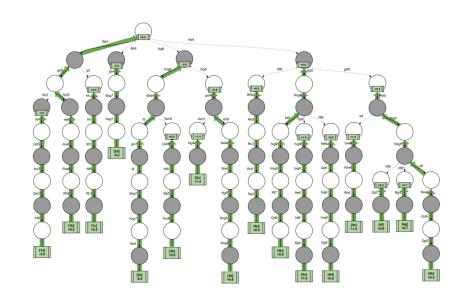
**Entailment**: a sentence logically follows from others

- Like from a KB. Write  $A \models B$
- A ⊨ B iff in every interpretation where A is true, B is also true
   All interpretations



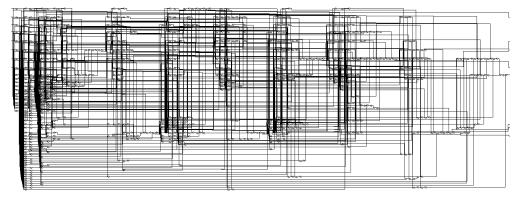
#### Inference

- Given a set of sentences (a KB), **logical inference** creates new sentences
  - Compare to prob. inference!
- Challenges:
  - Soundness
  - Completeness
  - Efficiency



### Methods of Inference: 1. Enumeration

- Enumerate all interpretations; look at the truth table
  - "Model checking"
- Downside: 2<sup>n</sup> interpretations for n symbols



S. Leadley

### Methods of Inference: 2. Using Rules

- *Modus Ponens*:  $(A \Rightarrow B, A) \vDash B$
- And-elimination
- Many other rules
  - Commutativity, associativity, de Morgan's laws, distribution for conjunction/disjunction



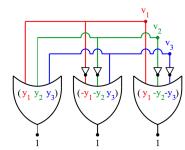
#### Methods of Inference: 3. Resolution

- Convert to special form and use a single rule
- **Conjunctive Normal Form** (CNF)

$$(\neg A \lor B \lor C) \land (\neg B \lor A) \land (\neg C \lor A)$$
  
a clause

Conjunction of clauses; each clause disjunction of literals

• Simple rules for converting to CNF



#### Methods of Inference: 3. Resolution

Start with our KB and query B

- Add  $\neg B$
- Show that this leads to a contradiction
- Take clauses with a symbol and its complement
  - Merge, throw away symbol: PvQvR, ¬QvSvT: PvRvSvT
  - If no symbol left, KB entails B
  - No new clauses, KB does not entail B

**Q 2.1**: What is the CNF for  $(\neg p \land \neg (p \Rightarrow q))$ 

- A.  $(\neg p \land \neg (p \Rightarrow q))$
- B. (¬p) ∧ (¬p ∨ ¬q)
- C.  $(\neg p \lor q) \land (p \lor \neg q) \land (p \lor q)$
- D.  $(\neg p \lor \neg q) \land (\neg p \lor q) \land (p \lor \neg q) \land (p \lor q)$

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- B. (¬p) ∧ (¬p ∨ ¬q)
- C.  $(\neg p \lor q) \land (p \lor \neg q) \land (p \lor q)$
- D. (¬p ∨ ¬q) ∧ (¬p ∨ q) ∧ (p ∨ ¬q) ∧ (p ∨ q)

**Q 2.2**: Which has more rows: a truth table on *n* symbols, or a joint distribution table on *n* binary random variables?

- A. Truth table
- B. Distribution
- C. Same size
- D. It depends

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# Finding CNFs

• CNF:

#### $(\neg A \lor B \lor C) \land (\neg B \lor A) \land (\neg C \lor A)$

- Automating transformation
  - Use equivalences for connectives we don't use (i.e.,  $\Rightarrow$ )
  - Move negatives inside (DeMorgan's laws)
  - Push v inside  $\land$  by distributing
- Not guaranteed to be satisfiable

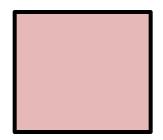
# First Order Logic (FOL)

Propositional logic has some limitations

- Ex: how to say "all squares have four sides"
- No context, hard to generalize; express facts

**FOL** is a more expressive logic; works over

• Facts, Objects, Relations, Functions



# First Order Logic (FOL)

#### **Basics:**

- Constants: "16", "Green", "Bob"
- Functions: map objects to objects
- Predicates: map objects to T/F:
  - \_ Greater(5,3)
  - Color(grass, green)



## First Order Logic (FOL)

#### **Basics:**

- Variables: x, y, z
- Connectives: Same as propositional logic
- Quantifiers:
  - $\forall$  universal quantifier:  $\forall x$  human(x)  $\Rightarrow$  mammal(x)
  - ∃ existential quantifier