

9.3 Forward Chaining

- As before, let us consider knowledge bases in Horn normal form
- A definite clause either is atomic or is an implication whose body is a conjunction of positive literals and whose head is a single positive literal

$\text{Student}(\text{John})$
 $\text{EagerToLearn}(x)$
 $\text{Student}(y) \wedge \text{EagerToLearn}(y) \Rightarrow \text{Thesis_2011}(y)$

- Unlike propositional literals, first-order literals can include variables
- The variables are assumed to be universally quantified



- As in propositional logic we start from facts, and by applying Generalized Modus Ponens are able to do forward chaining inference
- One needs to take care that a "new" fact is not just a renaming of a known fact

$\text{Likes}(x, \text{Candy})$
 $\text{Likes}(y, \text{Candy})$

- Since every inference is just an application of Generalized Modus Ponens, forward chaining is a sound inference algorithm
- It is also complete in the sense that it answers every query whose answers are entailed by any knowledge base of definite clauses



Datalog

- In a Datalog knowledge base the definite clauses contain no function symbols at all
- In this case we can easily prove the completeness of inference
- Let in the knowledge base
 - p be the number of predicates,
 - k be the maximum arity of predicates (= the number of arguments), and
 - n the number of constants
- There can be no more than pn^k distinct ground facts
- So after this many iterations the algorithm must have reached a *fixed point*, where new inferences are not possible



- In Datalog a polynomial number of steps is enough to generate all entailments
- For general definite clauses we have to appeal to Herbrand's theorem to establish that the algorithm will find a proof
- If the query has no answer (is not entailed by the KB), forward chaining may fail to terminate in some cases
- E.g., if the KB includes the Peano axioms, then forward chaining adds facts

$\text{NatNum}(S(0)).$
 $\text{NatNum}(S(S(0))).$
 $\text{NatNum}(S(S(S(0)))).$

...

- Entailment with definite clauses is semidecidable



9.4 Backward Chaining

- In predicate logic backward chaining explores the bodies of those rules whose head unifies with the goal
- Each conjunct in the body recursively becomes a goal
- When the goal unifies with a known fact – a clause with a head but no body – no new (sub)goals are added to the stack and the goal is solved
- Depth-first search algorithm
- The returned substitution is composed from the substitutions needed to solve all intermediate stages (subgoals)
- Inference in Prolog is based on backward chaining



9.4.2 Logic programming

- Prolog, Alain Colmerauer 1972
- Program = a knowledge base expressed as definite clauses
- Queries to the knowledge base
- **Closed world assumption**: we assume $\neg\phi$ to be true if sentence ϕ is not entailed by the knowledge base
- Syntax:
 - Capital characters denote variables,
 - Small character stand for constants,
 - The head of the rule precedes the body,
 - Instead of implication use `:-`,
 - Comma stand for conjunction,
 - Period ends a sentence
- `thesis_2011(X) :- student(X), eager_to_learn(X).`
- Prolog has a lot of syntactic sugar, e.g., for lists and arithmetics



- Prolog program `append(X, Y, Z)` succeeds if list `Z` is the result of appending (catenating) lists `X` and `Y`

```
append([ ], Y, Y) .
append([A|X], Y, [A|Z]) :- append(X, Y, Z) .
```

- Query: `append([1], [2], Z) ?`

```
Z=[1,2]
```

- We can also ask the query

```
append(A, B, [1,2]) ?:
```

Appending what two lists gives the list `[1,2]`?

- As the answer we get back all possible substitutions

```
A=[ ]      B=[1,2]
A=[1]      B=[2]
A=[1,2]    B=[ ]
```



- The clauses in a Prolog program are tried in the order in which they are written in the knowledge base
- Also the conjuncts in the body of the clause are examined in order (from left to right)
- There is a set of built-in functions for arithmetic, which need not be inferred further
 - E.g., `X is 4+3 → X=7`
- For instance I/O is taken care of using built-in predicates that have side effect when executed
- Negation as failure

```
alive(X) :- not dead(X) .
```

"Everybody is alive if not provably dead"



- The negation in Prolog does not correspond to the negation of logic (using the closed world assumption)

```
single_student(X) :-
    not married(X), student(X).
student(peter).
married(john).
```

- By the closed world assumption, $X=peter$ is a solution to the program
- The execution of the program, however, fails because when $X=john$ the first predicate of the body fails
- If the conjuncts in the body were inverted, it would succeed



- An equality goal succeeds if the two terms are unifiable
 - E.g., $X+Y=2+3 \rightarrow X=2, Y=3$
- Prolog omits some necessary checks in connection of variable bindings \rightarrow Inference is not sound
- These are seldom a problem
- Depth-first search can lead to infinite loops (= incomplete)

```
path(X,Z) :- path(X,Y), link(Y,Z).
path(X,Z) :- link(X,Z).
```

- Careful programming, however, lets us escape such problems

```
path(X,Z) :- link(X,Z).
path(X,Z) :- path(X,Y), link(Y,Z).
```



- Anonymous variable `_`

```
member(X, [X|_]) .
member(X, [_|Y]) :- member(X, Y) .
```
- Works just fine

```
member(d, [a,b,c,d,e,f,g])?
yes
member(2, [3,a,4,f])?
no
```
- But queries

```
member(a, X)?
member(a, [a,b,r,a,c,a,d,a,b,r,a])?
```

do not necessarily give the intended answers



- We can explicitly prune the execution of Prolog programs by *cutting*
- Negation using cut

```
not X:- X, !, fail.
not X.
```
- `fail` causes the program to fail
- At the point of a cut all bindings that have been made since starting to examine the rule are fixed
- For the conjuncts in the body preceding the cut, no new solutions are searched for
- Neither does one examine other rules having the same head



- Prolog may come up with the same answer through several inference paths
- Then the same answer is returned more than once


```
minimum(X,Y,X) :- X<=Y.
minimum(X,Y,Y) :- X>=Y.
```
- Both rules yield the same answer for the query `minimum(2,2,M)?`
- One must be careful in using cut for optimizing inference


```
minimum(X,Y,X) :- X<=Y, !.
minimum(X,Y,Y).
```
- This program is erroneous, for instance `minimum(2,8,8)` holds according to it



- The key question of Prolog and logic programming obviously is efficiency of execution
- Prolog implementations use a wide variety of enhancement techniques
- For example, instead of generating all possible solutions for a subgoal before examining the next subgoal, a Prolog interpreter is content (so far) with just one
- Similarly variable binding is at each instant unique; only when the search runs into a dead end, can *backing up* to a choice point lead to unbinding of variables
- A stack of history, called the *trail*, needs to be maintained to keep track of all variable bindings



9.5 Resolution



180

- Kurt Gödel's **completeness theorem** (1930) for first-order logic: any entailed sentence has a finite proof
$$\vdash \phi \Leftrightarrow \vdash \phi$$
- It was not until Robinson's (1965) resolution algorithm that a practical proof procedure was found
- Gödel's more famous result is the **incompleteness theorem**: a logical system that includes the principle of induction, is necessary incomplete
- There are sentences that are entailed, but have no finite proof
- This holds in particular for number theory, which thus cannot be axiomatized



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- For resolution, we need to convert the sentences to CNF
- E.g., "Everyone who loves all animals is loved by someone"

$$\forall x: [\forall y: \text{Animal}(y) \Rightarrow \text{Loves}(x, y)] \Rightarrow [\exists y: \text{Loves}(y, x)].$$

- **Eliminate implications**
$$\forall x: [\neg \forall y: \neg \text{Animal}(y) \vee \text{Loves}(x, y)] \vee [\exists y: \text{Loves}(y, x)].$$
- **Move negation inwards**
$$\forall x: [\exists y: \text{Animal}(y) \wedge \neg \text{Loves}(x, y)] \vee [\exists y: \text{Loves}(y, x)].$$
- **Standardize variables**
$$\forall x: [\exists y: \text{Animal}(y) \wedge \neg \text{Loves}(x, y)] \vee [\exists z: \text{Loves}(z, x)].$$



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- **Skolemization**

$$\forall x: [\text{Animal}(F(x)) \wedge \neg \text{Loves}(x, F(x))] \vee \text{Loves}(G(z), x).$$

- **Drop universal quantifiers**

$$[\text{Animal}(F(x)) \wedge \neg \text{Loves}(x, F(x))] \vee \text{Loves}(G(z), x).$$

- **Distribute \vee over \wedge**

$$[\text{Animal}(F(x)) \vee \text{Loves}(G(z), x)] \wedge [\neg \text{Loves}(x, F(x)) \vee \text{Loves}(G(z), x)].$$

- The end result is quite hard to comprehend, but it doesn't matter, because the translation procedure is easily automated



- First-order literals are complementary if one unifies with the negation of the other

- Thus the binary resolution rule is

$$\frac{\ell_1 \vee \dots \vee \ell_k, m}{(\ell_1 \vee \dots \vee \ell_{i-1} \vee \ell_{i+1} \vee \dots \vee \ell_k)(\theta)}$$

where $\text{Unify}(\ell_i, \neg m) = \theta$

- For example, we can resolve

$[\text{Animal}(F(x)) \vee \text{Loves}(G(x), x)]$ and $[\neg \text{Loves}(u, v) \vee \neg \text{Kills}(u, v)]$
by eliminating the complementary literals $\text{Loves}(G(x), x)$ and $\neg \text{Loves}(u, v)$ with unifier $\theta = \{ u/G(x), v/x \}$ to produce the **resolvent** clause $[\text{Animal}(F(x)) \vee \neg \text{Kills}(u, v)]$

- Resolution is a complete inference rule also for predicate logic in the sense that we can check (not generate) all logical consequences of the knowledge base
- $\text{KB} \models \alpha$ is proved by showing that $\text{KB} \wedge \neg \alpha$ is unsatisfiable through a proof by refutation





- *Theorem provers (automated reasoners)* accept full first-order logic, whereas most logic programming languages handle only Horn clauses
- For example Prolog intertwines logic and control
- In most theorem provers, the syntactic form chosen for the sentences does not affect the result
- Application areas: verification of software and hardware
- In mathematics theorem provers have a high standing nowadays: they have come up with novel mathematical results
- For instance, in 1996 a version of well-known Otter was the first to prove (eight days of computation) that the axioms proposed by Herbert Robbins in 1933 really define Boolean algebra



13 QUANTIFYING UNCERTAINTY

- In practice agents almost never have full access to the whole truth of their environment and, therefore, must act under *uncertainty*
- A logical agent may fail to acquire certain knowledge that it would require
- If the agent cannot conclude that any particular course of action achieves its goal, then it will be unable to act
- Conditional planning can overcome uncertainty to some extent, but it does not resolve it
- An agent based solely on logics cannot choose rational actions in an uncertain environment





- Logical knowledge representation requires rules without exceptions
- In practice, we can typically at best provide some *degree of belief* for a proposition
- In dealing with degrees of belief we will use *probability theory*
- Probability 0 corresponds to an unequivocal belief that the sentence is false and, respectively, 1 to an unequivocal belief that the sentence is true
- Probabilities in between correspond to intermediate degrees of belief in the truth of the sentence, not on its relative truth
- Utilities that have been weighted with probabilities give the agent a chance of acting rationally by preferring the action that yields the highest expected utility
- Principle of *Maximum Expected Utility* (MEU)



13.2 Basic Probability Notation

- A **random variable** refers to a part of the world, whose status is initially unknown
- Random variables play a role similar to proposition symbols in propositional logic
- E.g., **Cavity** might refer whether the lower left wisdom tooth has a cavity
- The *domain* of a random variable may be of type
 - *Boolean*:
we write $Cavity = true \Rightarrow cavity$ and
 $Cavity = false \Rightarrow \neg cavity$;
 - *discrete*: e.g., **Weather** might have the domain
{ sunny, rainy, cloudy, snow };
 - *continuous*: then one usually examines the cumulative distribution function; e.g., $X \leq 4.02$



- Elementary propositions can be combined to form complex propositions using all the standard connectives:

$$\text{cavity} \wedge \neg \text{toothache}$$
- An atomic event is a complete specification of the world, i.e., an assignment of values to all the variables
- Properties of atomic events:
 - They are mutually exclusive
 - The set of all atomic events is exhaustive — at least one must be the case
 - Any particular atomic event entails the truth or falsehood of every proposition
 - Any proposition is logically equivalent to the disjunction of all atomic events that entail the truth of the proposition

$$\text{cavity} \equiv (\text{cavity} \wedge \text{toothache}) \vee (\text{cavity} \wedge \neg \text{toothache})$$



Prior probability

- Degrees of belief are always applied to propositions
- Prior probability $P(a)$ is the degree of belief accorded to proposition a in the absence of any other information

$$P(\text{cavity}) = 0.1$$
- In particular, prior probability is the agent's initial belief before it receives any percepts
- The probability distribution $P(X)$ of a random variable X is a vector of values for probabilities of the elements in its (ordered) domain
- E.g., when $P(\text{sunny}) = 0.02$, $P(\text{rainy}) = 0.2$, $P(\text{cloudy}) = 0.7$, and $P(\text{snow}) = 0.08$, then

$$P(\text{Weather}) = [0.02, 0.2, 0.7, 0.08]$$





- The **joint probability distribution** of two random variables is the product of their domains
- E.g., $P(\text{Weather}, \text{Cavity})$ is a 4×2 table of probabilities
- Full joint probability distribution covers the complete set of random variables used to describe the world
- For continuous variables it is not possible to write out the entire distribution as a table, one has to examine *probability density functions* instead
- Rather than examine point probabilities (that have value 0), we examine probabilities of value ranges
- We will concentrate mostly on discrete-valued random variables

