

CS 1571 Introduction to AI
Lecture 13

Propositional logic

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Midterm

- **The midterm** for the course will be held on
 - October 28, 2014
 - In class exam
 - Closed book
 - Material covered by October 23, 2014

Logical inference problem

Logical inference problem:

- **Given:**
 - a knowledge base KB (a set of sentences) and
 - a sentence α (called **a theorem**),
- **Does a KB semantically entail α ?** $KB \models \alpha$?

In other words:

- In all interpretations in which sentences in the KB are true, is α also true?

Logical inference problem

Logical inference problem:

- **Given:**
 - a knowledge base KB (a set of sentences) and
 - a sentence α (called **a theorem**),
- **Does a KB semantically entail α ?** $KB \models \alpha$

Approaches to solve the logical inference problem:

- **Truth-table approach**
- **Inference rules**
- **Conversion to SAT**
 - **Resolution refutation**

Properties of inference solutions

- **Truth-table approach**
 - **Blind**
 - **Exponential in the number of variables**
- **Inference rules**
 - **More efficient**
 - **Many inference rules to cover logic**
- **Conversion to SAT - Resolution refutation**
 - **More efficient**
 - **Sentences must be converted into CNF**
 - **One rule – the resolution rule - is sufficient to perform all inferences**

KB in restricted forms

If the sentences in the KB are restricted to some special forms
some of the sound inference rules may become complete

Example:

- **Horn form (Horn normal form)**
 - a clause with **at most one positive literal**

$$(A \vee \neg B) \wedge (\neg A \vee \neg C \vee D)$$

Can be written also as:

$$(B \Rightarrow A) \wedge ((A \wedge C) \Rightarrow D)$$

- **Two inference rules that are sound and complete for KBs in the Horn normal form:**
 - **Resolution**
 - **Modus ponens**

KB in Horn form

- **Horn form:** a clause with **at most one positive literal**
 $(A \vee \neg B) \wedge (\neg A \vee \neg C \vee D)$
- **Not all sentences in propositional logic can be converted into the Horn form**
- **KB in Horn normal form:**
 - Two types of propositional statements:
 - **Rules** $(\neg B_1 \vee \neg B_2 \vee \dots \neg B_k \vee A)$
 \equiv
 $(\neg(B_1 \wedge B_2 \wedge \dots B_k) \vee A)$
 \equiv
 $(B_1 \wedge B_2 \wedge \dots B_k \Rightarrow A)$
 - Propositional symbols: **facts** B

Why KB in Horn form is useful?

KB in Horn normal form:

- **Rules (in implicative form):** If then statements known to be true

$$(B_1 \wedge B_2 \wedge \dots B_k \Rightarrow A)$$

- If**
1. The stain of the organism is gram-positive, and
 2. The morphology of the organism is coccus, and
 3. The growth conformation of the organism is chains
- Then** the identity of the organism is streptococcus

- **Facts = propositions known to be true**

Examples: B_1 or

The stain of the organism is gram-positive

Inferences: let us infer new true propositions, such as A , or the identity of the organism is streptococcus in the rule conclusion

These are referred as inferences on propositional symbols

KB in Horn form

- **Application of the resolution rule:**

- Infers new facts from previous facts

$$\frac{(A \vee \neg B), B}{A} \qquad \frac{(A \vee \neg B), (B \vee \neg C)}{(A \vee C)}$$

- Resolution is **sound and complete** for inferences on propositional symbols for KB in the Horn normal form (clausal form)

- Similarly, **modus ponens is sound and complete** when the HNF is written in the implicative form

Complexity of inferences for KBs in HNF

Question:

How efficient the inferences in the HNF can be?

Answer:

Inference on propositional symbols →

Procedures linear in the size of the KB in the Horn form exist.

- Size of a clause: the number of literals it contains.
- Size of the KB in the HNF: the sum of the sizes of its elements.

Example:

$A, B, (A \wedge B \Rightarrow C), (C \Rightarrow D), (C \Rightarrow E), (E \wedge F \Rightarrow G)$

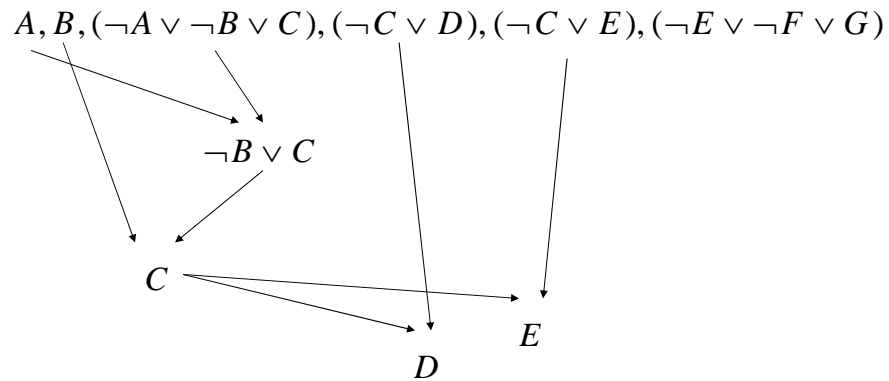
or

$A, B, (\neg A \vee \neg B \vee C), (\neg C \vee D), (\neg C \vee E), (\neg E \vee \neg F \vee G)$

The size is: 12

Complexity of inferences for KBs in HNF

How to do the inference on propositional symbols? If the HNF (is in the clausal form) we can apply resolution.

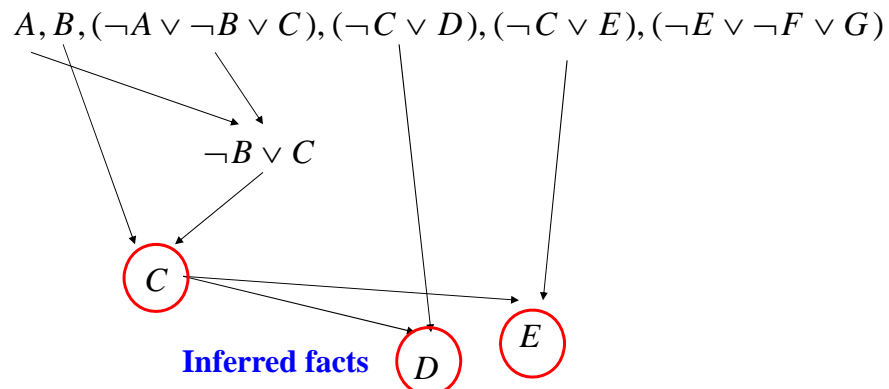


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Complexity of inferences for KBs in HNF

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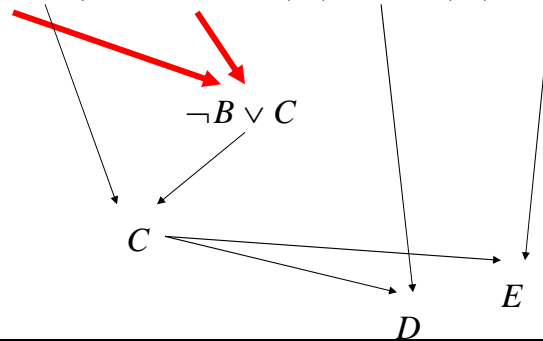
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Complexity of inferences for KBs in HNF

Features:

- Every resolution is a **positive unit resolution**; that is, a resolution in which **one clause is a positive unit clause** (i.e., a proposition symbol).

$A, B, (\neg A \vee \neg B \vee C), (\neg C \vee D), (\neg C \vee E), (\neg E \vee \neg F \vee G)$



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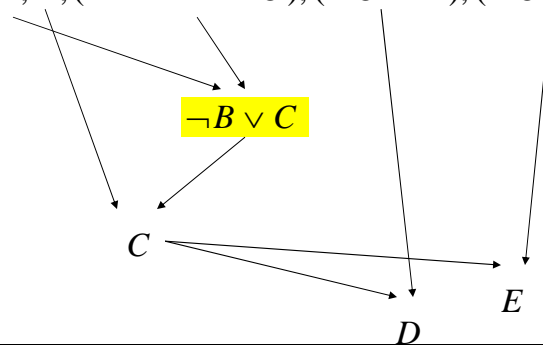
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Complexity of inferences for KBs in HNF

Features:

- At each resolution, the input clause which is not a unit clause is a logical consequence of the result of the resolution. (Thus, the input clause may be deleted upon completion of the resolution operation.)

$A, B, (\neg A \vee \neg B \vee C), (\neg C \vee D), (\neg C \vee E), (\neg E \vee \neg F \vee G)$



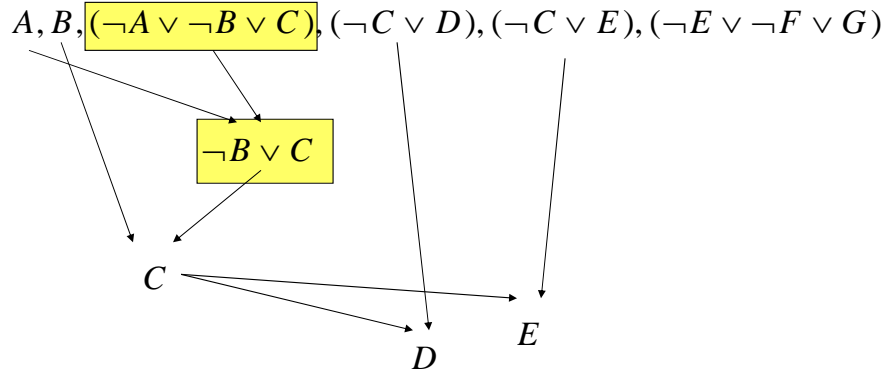
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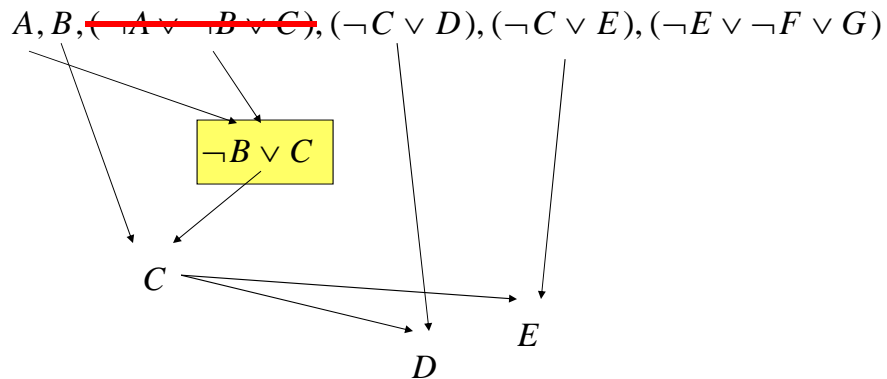
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Complexity of inferences for KBs in HNF

Features:

- Following this deletion, the size of the KB (the sum of the lengths of the remaining clauses) is one less than it was before the operation.)



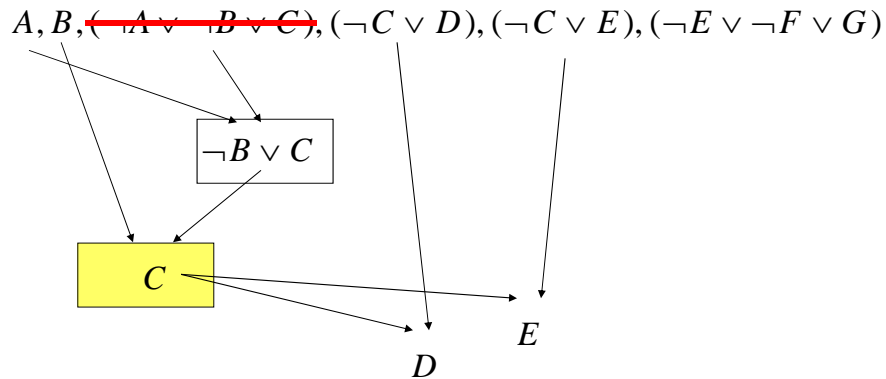
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Complexity of inferences for KBs in HNF

Features:

- Following the deletion, the size of the KB (the sum of the lengths of the remaining clauses) is one less than it was before the operation.) **Now let us see one more step ...**



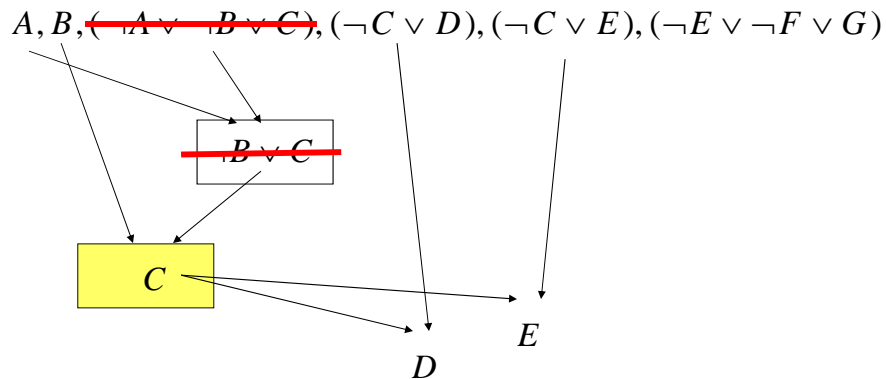
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Complexity of inferences for KBs in HNF

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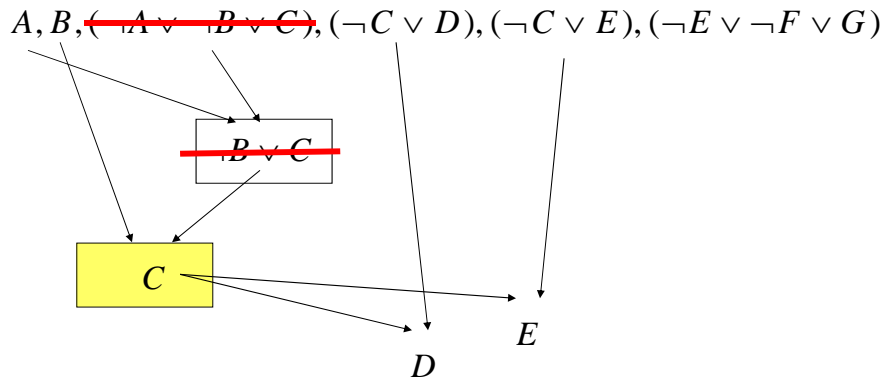
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Complexity of inferences for KBs in HNF

Features:

- If n is the size of the KB, then at most n positive unit resolutions may be performed on it.



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Complexity of inferences for KBs in HNF

A linear time resolution algorithm:

- The number of positive unit resolutions is limited to the size of the formula (n)
- But to assure overall linear time we need to access each proposition in a constant time:
- Data structures indexed by proposition names may be accessed in constant time. (This is possible if the proposition names are number in a range (e.g., 1..n), so that array lookup is the access operation.
- If propositions are accessed by name, then a symbol table is necessary, and the algorithm will run in time $O(n \cdot \log(n))$.

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Forward and backward chaining

Two inference procedures based on **modus ponens** for **Horn KBs**:

- **Forward chaining**

Idea: Whenever the premises of a rule are satisfied, infer the conclusion. Continue with rules that became satisfied.

- **Backward chaining (goal reduction)**

Idea: To prove the fact that appears in the conclusion of a rule prove the premises of the rule. Continue recursively.

Both procedures are **complete for KBs in the Horn form !!!**

Forward chaining example

- **Forward chaining**

Idea: Whenever the premises of a rule are satisfied, infer the conclusion. Continue with rules that became satisfied.

Assume the KB with the following rules and facts:

KB: R1: $A \wedge B \Rightarrow C$

R2: $C \wedge D \Rightarrow E$

R3: $C \wedge F \Rightarrow G$

F1: A

F2: B

F3: D

Theorem: E ?

Forward chaining example

Theorem: E

KB: R1: $A \wedge B \Rightarrow C$

R2: $C \wedge D \Rightarrow E$

R3: $C \wedge F \Rightarrow G$

F1: A

F2: B

F3: D

Forward chaining example

Theorem: E

KB: R1: $A \wedge B \Rightarrow C$

R2: $C \wedge D \Rightarrow E$

R3: $C \wedge F \Rightarrow G$

F1: A

F2: B

F3: D

Rule R1 is satisfied.

F4: C

Forward chaining example

Theorem: E

KB: R1: $A \wedge B \Rightarrow C$

R2: $C \wedge D \Rightarrow E$

R3: $C \wedge F \Rightarrow G$

F1: A

F2: B

F3: D

Rule R1 is satisfied.

F4: C

Rule R2 is satisfied.

F5: E ✓

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Forward chaining

- Efficient implementation: linear in the size of the KB
- **Example:**

$P \Rightarrow Q$

$L \wedge M \Rightarrow P$

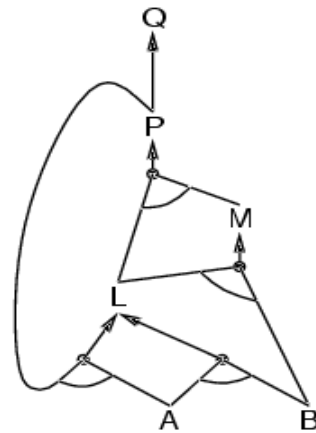
$B \wedge L \Rightarrow M$

$A \wedge P \Rightarrow L$

$A \wedge B \Rightarrow L$

A

B



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Forward chaining

- Count the number of facts in the antecedent of the rule

$P \Rightarrow Q$

$L \wedge M \Rightarrow P$

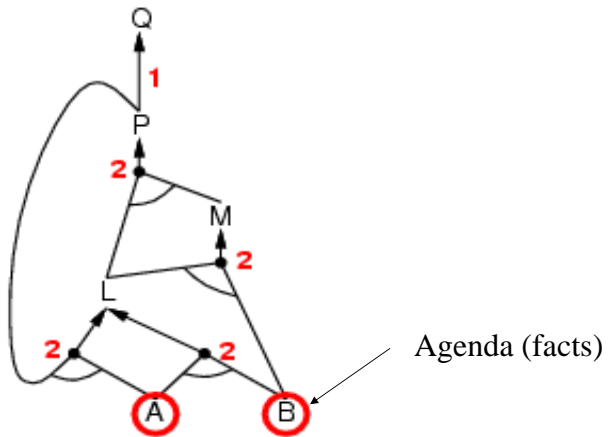
$B \wedge L \Rightarrow M$

$A \wedge P \Rightarrow L$

$A \wedge B \Rightarrow L$

A

B



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Forward chaining

- Inferred facts decrease the count

$P \Rightarrow Q$

$L \wedge M \Rightarrow P$

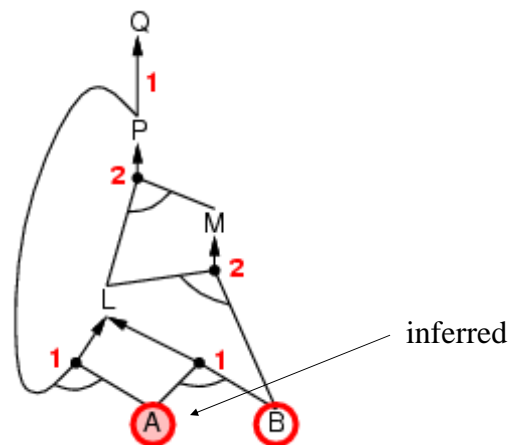
$B \wedge L \Rightarrow M$

$A \wedge P \Rightarrow L$

$A \wedge B \Rightarrow L$

A

B



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Forward chaining

- New facts can be inferred when the count associated with a rule becomes 0

$$P \Rightarrow Q$$

$$L \wedge M \Rightarrow P$$

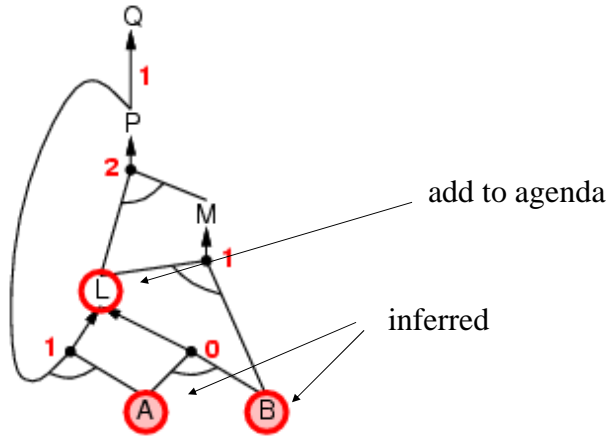
$$B \wedge L \Rightarrow M$$

$$A \wedge P \Rightarrow L$$

$$A \wedge B \Rightarrow L$$

A

B



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Forward chaining

-

$$P \Rightarrow Q$$

$$L \wedge M \Rightarrow P$$

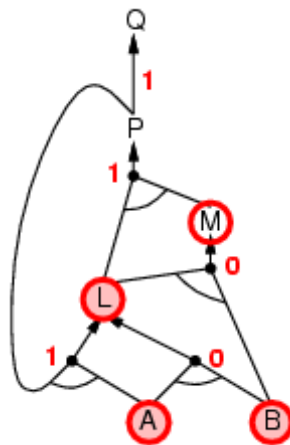
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A

B



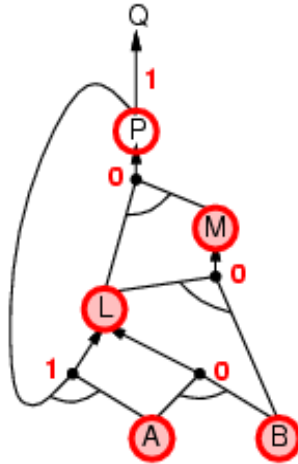
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Forward chaining

•

$P \Rightarrow Q$
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 $A \wedge P \Rightarrow L$
 $A \wedge B \Rightarrow L$
 A
 B



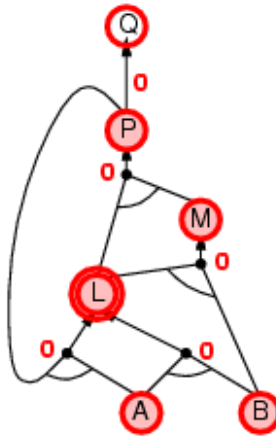
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 A
 B



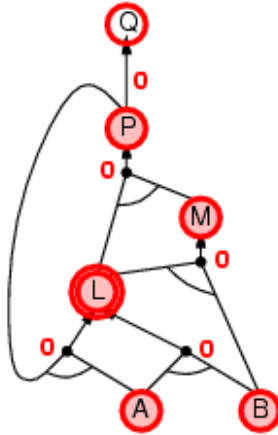
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Forward chaining

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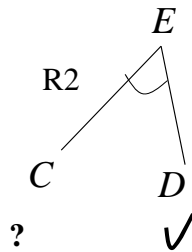
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 A
 B



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Backward chaining example



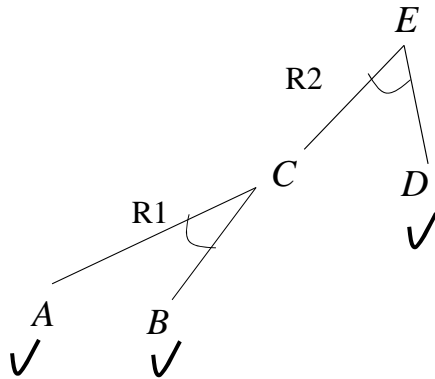
KB: R1: $A \wedge B \Rightarrow C$
 R2: $C \wedge D \Rightarrow E$
 R3: $C \wedge F \Rightarrow G$
 F1: A
 F2: B
 F3: D

- Backward chaining is more focused:
 - tries to prove the theorem only

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Backward chaining example



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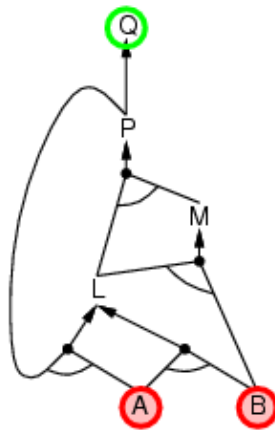
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Backward chaining

- Efficient implementation

$P \Rightarrow Q$ ←
 $L \wedge M \Rightarrow P$
 $B \wedge L \Rightarrow M$
 $A \wedge P \Rightarrow L$
 $A \wedge B \Rightarrow L$
 A ←
 B ←

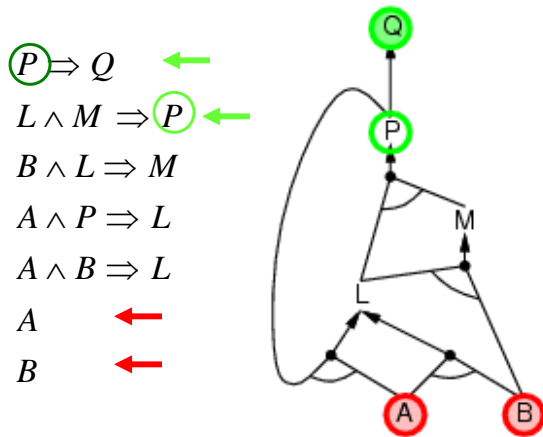


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Backward chaining

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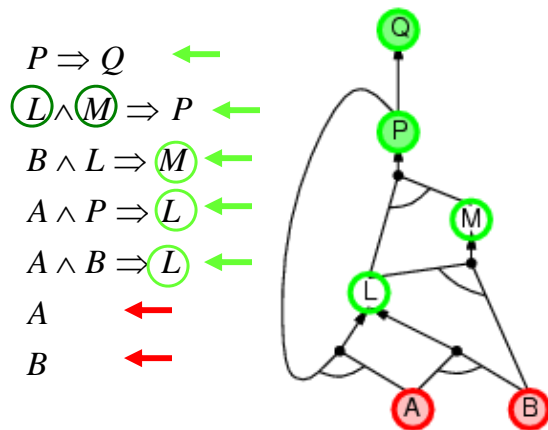


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Backward chaining

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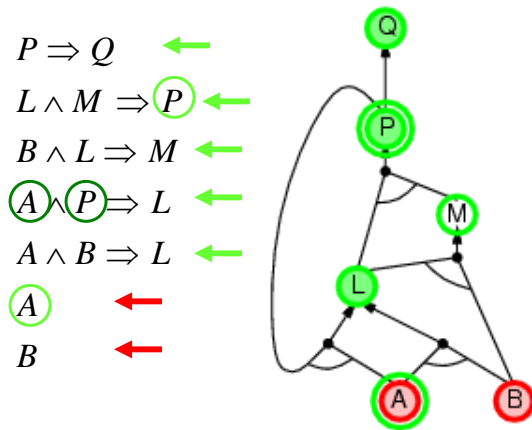


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Backward chaining

- Efficient implementation

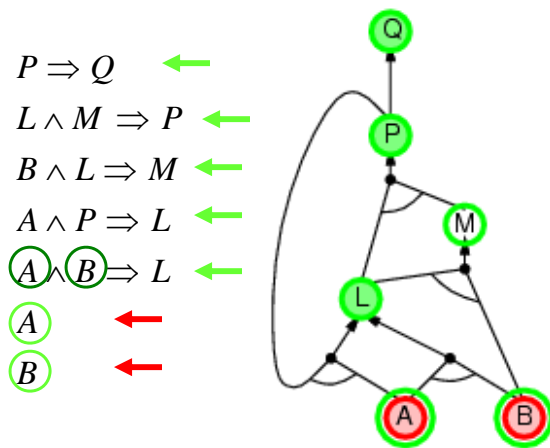


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Backward chaining

- Efficient implementation

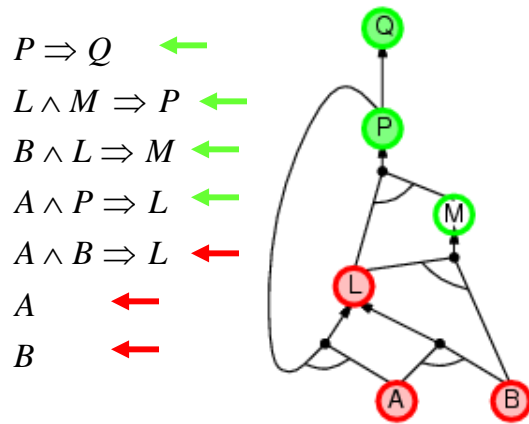


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Backward chaining

- Efficient implementation

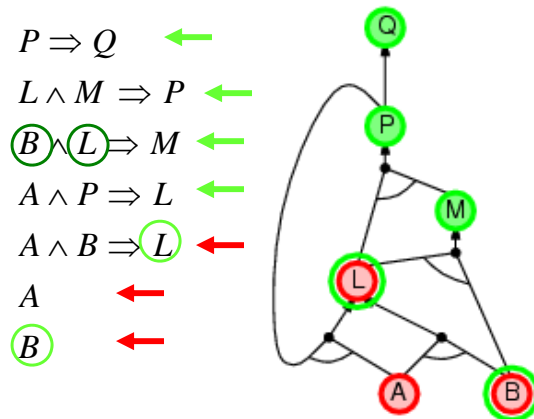


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Backward chaining

- Efficient implementation

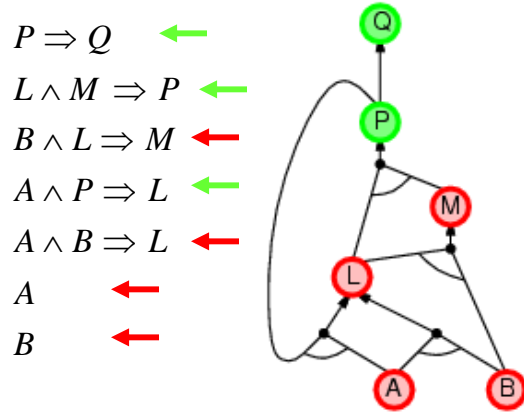


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Backward chaining

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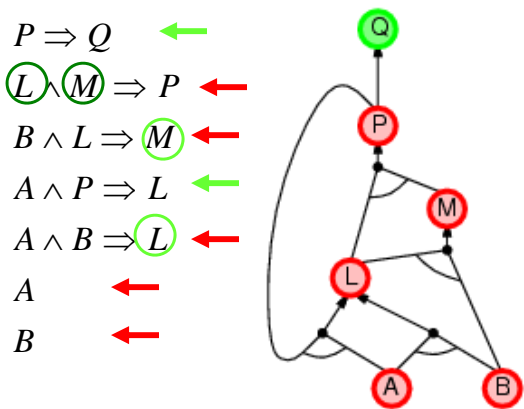


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Backward chaining

- Efficient implementation

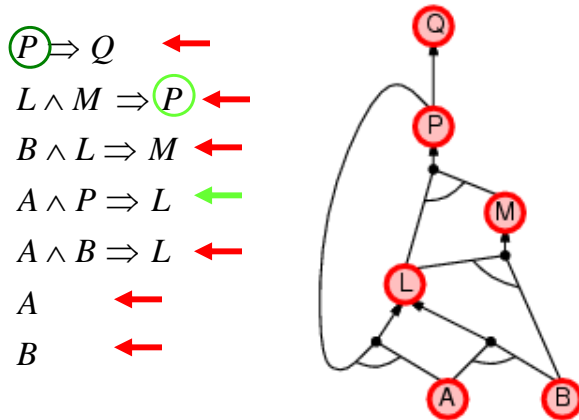


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Backward chaining

- **Efficient implementation**



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Forward vs Backward chaining

- **FC is data-driven**, automatic, unconscious processing,
 - e.g., object recognition, routine decisions
- May do lots of work that is irrelevant to the goal
- **BC is goal-driven**, appropriate for problem-solving,
 - e.g., Where are my keys? How do I get into a PhD program?
- Complexity of BC can be **much less** than **linear in size of KB**

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KB agents based on propositional logic

- Propositional logic allows us to build **knowledge-based agents** capable of answering queries about the world by inferring new facts from the known ones
- **Example:** an agent for diagnosis of a bacterial disease

Facts: The stain of the organism is gram-positive
The growth conformation of the organism is chains

Rules: (If) The stain of the organism is gram-positive \wedge
 The morphology of the organism is coccus \wedge
 The growth conformation of the organism is chains
(Then) \Rightarrow The identity of the organism is streptococcus