

Artificial Intelligent

Sem. Ganjil 2023/2024

09. Logical Agent

Lionov



Overview

- Knowledge-Based Agent
- The Wumpus World
- Propositional Logic
- Method Checking
- Theorem Proving
- Intro. to First Order Logic











Problems with Problem-Solving Agent:



Problems with Problem-Solving Agent: "know" very limited thing







Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment





Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:





Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:

• combine raw knowledge and experience





Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:

- combine raw knowledge and experience
- using reasoning







Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:

- combine raw knowledge and experience
- using reasoning

example: playing minesweeper





Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:

- combine raw knowledge and experience
- using reasoning

example: playing minesweeper





Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:

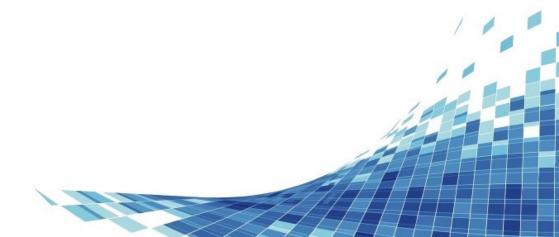
- combine raw knowledge and experience
- using reasoning

example: playing minesweeper

Knowledge-Based Agent takes actions that

• use a process of reasoning: needs knowledge to choose actions





Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:

- combine raw knowledge and experience
- using reasoning

example: playing minesweeper

- use a process of reasoning: needs knowledge to choose actions
- represent its internal representation of knowledge





Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:

- combine raw knowledge and experience
- using reasoning

example: playing minesweeper

- use a process of reasoning: needs knowledge to choose actions
- represent its internal representation of knowledge
- knowledge = sentences in a knowledge representation language (formal language).





Problems with Problem-Solving Agent:

- "know" very limited thing
- requires fully observability and static environment

Human can acquire new information:

- combine raw knowledge and experience
- using reasoning

example: playing minesweeper

- use a process of reasoning: needs knowledge to choose actions
- represent its internal representation of knowledge
- knowledge = sentences in a knowledge representation language (formal language).
- · A sentence is an assertion about the world.



Logical Agent

Logical AI

"The idea is that an agent can represent knowledge of its world, its goals and the current situation by sentences in logic and decide what to do by inferring that a certain action or course of action is appropriate to achieve its goals."

John McCarthy

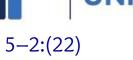












Knowledge-Based Agent is composed of:

• Knowledge base or KB (domain-specific content):





- Knowledge base or KB (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)





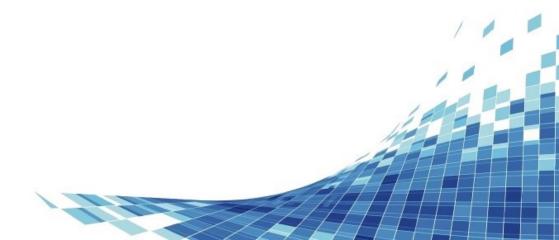
- Knowledge base or KB (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)
 - expressed in a knowledge representation language





- Knowledge base or KB (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)
 - expressed in a knowledge representation language
 - initially contains some background knowledge





- Knowledge base or \mathfrak{KB} (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)
 - expressed in a knowledge representation language
 - initially contains some background knowledge
- Inference mechanism (domain-independent algorithm):





- Knowledge base or \mathfrak{KB} (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)
 - expressed in a knowledge representation language
 - initially contains some background knowledge
- Inference mechanism (domain-independent algorithm):
 - deriving new sentences from old





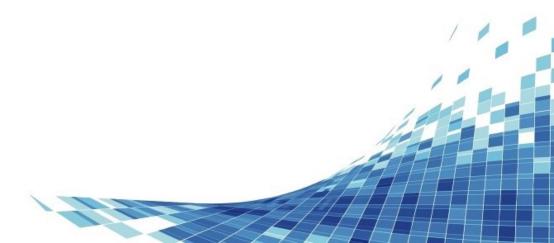
- Knowledge base or KB (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)
 - expressed in a knowledge representation language
 - initially contains some background knowledge
- Inference mechanism (domain-independent algorithm):
 - deriving new sentences from old
 - use declarative approach (instead of procedural)





- Knowledge base or KB (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)
 - expressed in a knowledge representation language
 - initially contains some background knowledge
- Inference mechanism (domain-independent algorithm):
 - deriving new sentences from old
 - use declarative approach (instead of procedural)
 - add new sentences (TELL)





- Knowledge base or KB (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)
 - expressed in a knowledge representation language
 - initially contains some background knowledge
- Inference mechanism (domain-independent algorithm):
 - deriving new sentences from old
 - use declarative approach (instead of procedural)
 - add new sentences (Tell)
 - query what is known (Ask)





Knowledge-Based Agent is composed of:

- Knowledge base or KB (domain-specific content):
 - set of senteces (that represent facts/belief about the environment)
 - expressed in a knowledge representation language
 - initially contains some background knowledge
- Inference mechanism (domain-independent algorithm):
 - deriving new sentences from old
 - use declarative approach (instead of procedural)
 - add new sentences (Tell)
 - query what is known (Asκ)

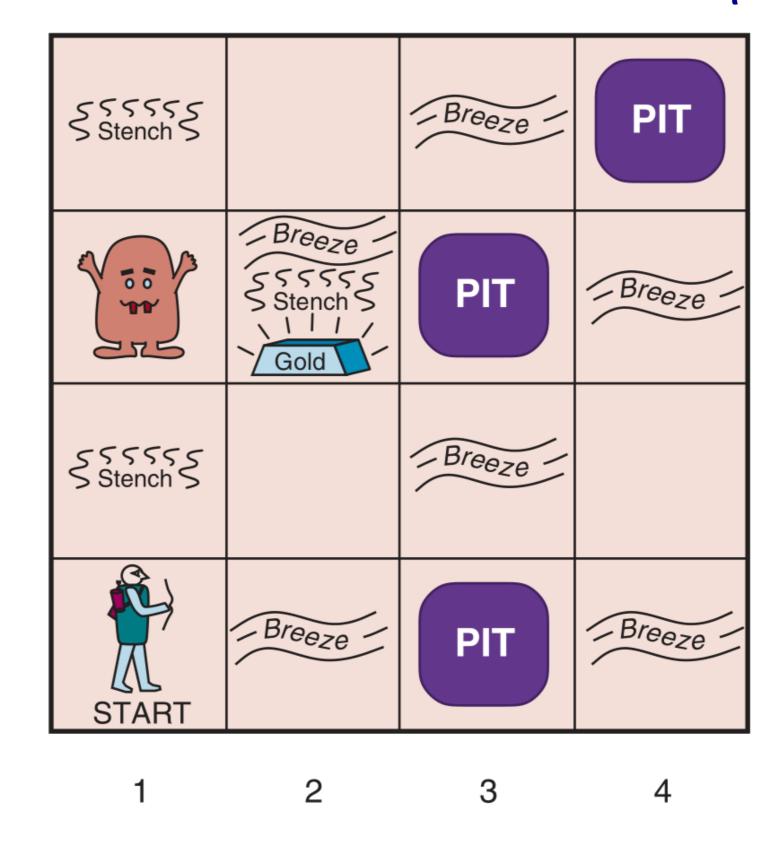
function KB-AGENT(percept) returns an action persistent: KB, a knowledge base t, a counter, initially 0, indicating time

Tell(KB, Make-Percept-Sentence(percept, t)) $action \leftarrow \text{Ask}(KB, \text{Make-Action-Query}(t))$ Tell(KB, Make-Action-Sentence(action, t)) $t \leftarrow t + 1$

return action



The Wumpus World









Performance: +1000 take the gold and climb out the cave. -1000 for falling into a pit or being eaten by the wumpus. -10 for using the arrow and -1 for each action taken. The game ends either when the agent dies or when the agent climbs out of the cave.





Performance: +1000 take the gold and climb out the cave. -1000 for falling into a pit or being eaten by the wumpus. -10 for using the arrow and -1 for each action taken. The game ends either when the agent dies or when the agent climbs out of the cave.

Environment: 4x4 grid rooms (walls surrounding the grid), Start in [1,1], facing east. The locations of the gold and the Wumpus are chosen randomly (not at [1,1]) with a uniform distribution. Each square (not at [1,1]) can be a pit with probability 0.2.





Performance: +1000 take the gold and climb out the cave. -1000 for falling into a pit or being eaten by the wumpus. -10 for using the arrow and -1 for each action taken. The game ends either when the agent dies or when the agent climbs out of the cave.

Environment: 4x4 grid rooms (walls surrounding the grid), Start in [1,1], facing east. The locations of the gold and the Wumpus are chosen randomly (not at [1,1]) with a uniform distribution. Each square (not at [1,1]) can be a pit with probability 0.2.

Sensors: Stench and Breeze: adjacent to the wumpus and a pit, respectively. Glitter: square with gold. Bump: walks into a wall. Scream: the wumpus is killed. Given to the agent as a list of five symbols, ex.: [Stench, Breeze, None, None, None].





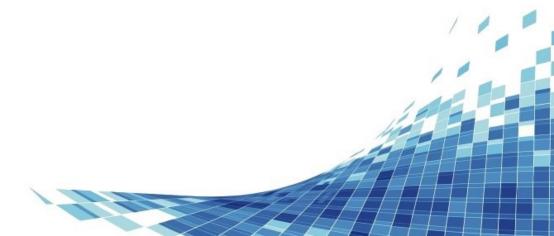
Performance: +1000 take the gold and climb out the cave. -1000 for falling into a pit or being eaten by the wumpus. -10 for using the arrow and -1 for each action taken. The game ends either when the agent dies or when the agent climbs out of the cave.

Environment: 4x4 grid rooms (walls surrounding the grid), Start in [1,1], facing east. The locations of the gold and the Wumpus are chosen randomly (not at [1,1]) with a uniform distribution. Each square (not at [1,1]) can be a pit with probability 0.2.

Sensors: Stench and Breeze: adjacent to the wumpus and a pit, respectively. Glitter: square with gold. Bump: walks into a wall. Scream: the wumpus is killed. Given to the agent as a list of five symbols, ex.: [Stench, Breeze, None, None, None].

Actuators: Forward, TurnLeft or TurnRight (both 90°), Grab, Shoot (used only once), Climb (only from [1,1]).





Performance: +1000 take the gold and climb out the cave. -1000 for falling into a pit or being eaten by the wumpus. -10 for using the arrow and -1 for each action taken. The game ends either when the agent dies or when the agent climbs out of the cave.

Environment: 4x4 grid rooms (walls surrounding the grid), Start in [1,1], facing east. The locations of the gold and the Wumpus are chosen randomly (not at [1,1]) with a uniform distribution. Each square (not at [1,1]) can be a pit with probability 0.2.

Sensors: Stench and Breeze: adjacent to the wumpus and a pit, respectively. Glitter: square with gold. Bump: walks into a wall. Scream: the wumpus is killed. Given to the agent as a list of five symbols, ex.: [Stench, Breeze, None, None, None].

Actuators: Forward, TurnLeft or TurnRight (both 90°), Grab, Shoot (used only once), Climb (only from [1,1]).

Properties: Partially Observable, Static, Discrete, Single-agent, Deterministic, Sequential



Exploring the Wumpus world

SSSSS Stench		Breeze -	PIT
100	SSSSS Stench S	PIT	-Breeze
SSSSS Stench		Breeze -	
START	-Breeze	PIT	-Breeze





ŀ				
	1,4	2,4	3,4	4,4
	1,3	2,3	3,3	4,3
	1,2 OK	2,2	3,2	4,2
	1,1 A OK	2,1 OK	3,1	4,1

 $\mathbf{A} = Agent$

 $\mathbf{B} = Breeze$

G = Glitter, Gold

OK = Safe square

P = Pit

S = Stench

V = Visited

W = Wumpus

The initial situation: after percept [None, None, None, None, None]





ā				
	1,4	2,4	3,4	4,4
	1,3	2,3	3,3	4,3
	1,2 OK	2,2	3,2	4,2
	1,1 A OK	2,1 OK	3,1	4,1

\mathbf{A}	= Agent
В	= Breeze
G	= Glitter, Gold
OK	= Safe square
P	= Pit
\mathbf{S}	= Stench
\mathbf{V}	= Visited
XX7	- Wumpus

1,4	2,4	3,4	4,4
1,3	2,3	3,3	4,3
1,2 OK	2,2 P?	3,2	4,2
1,1 V OK	2,1 A B OK	3,1 P?	4,1

After moving to [2,1] and perceiving [None, Breeze, None, None, None]





k				
	1,4	2,4	3,4	4,4
	^{1,3} w!	2,3	3,3	4,3
	1,2A S OK	2,2 OK	3,2	4,2
	1,1 V OK	2,1 B V OK	3,1 P!	4,1

A = Agent

B = Breeze

G = Glitter, Gold

OK = Safe square

 $\mathbf{P} = Pit$

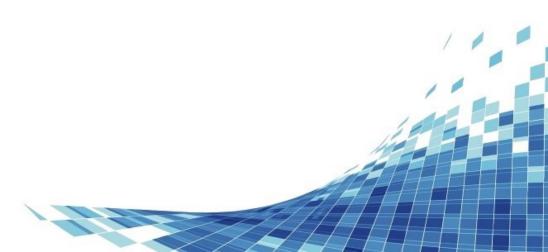
S = Stench

V = Visited

W = Wumpus

After moving to [1,1] and then [1,2], and perceiving [Stench, None, None, None, None]





1,4	2,4	3,4	4,4
1,3 W!	2,3	3,3	4,3
1,2A S OK	2,2 OK	3,2	4,2
1,1 V OK	2,1 B V OK	3,1 P!	4,1

A	= Agent
В	= Breeze
\mathbf{G}	= Glitter, Gold
OK	= Safe square
P	= Pit
\mathbf{S}	= Stench
\mathbf{V}	= Visited
\mathbf{W}	= Wumpus

1,4	2,4 P?	3,4	4,4
1,3 W!	2,3 A S G B	3,3 _{P?}	4,3
1,2 V OK	2,2 V OK	3,2	4,2
1,1 V OK	2,1 B V OK	3,1 P!	4,1

After moving to [2,2] and then [2,3], and perceiving [Stench, Breeze, Glitter, None, None]





Logics are formal languages for representing knowledge



Logics are formal languages for representing knowledge

• Syntax: defines a well-formed sentence in the language



Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence





Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences



Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

$$\mathfrak{KB} \models \boldsymbol{\alpha}$$

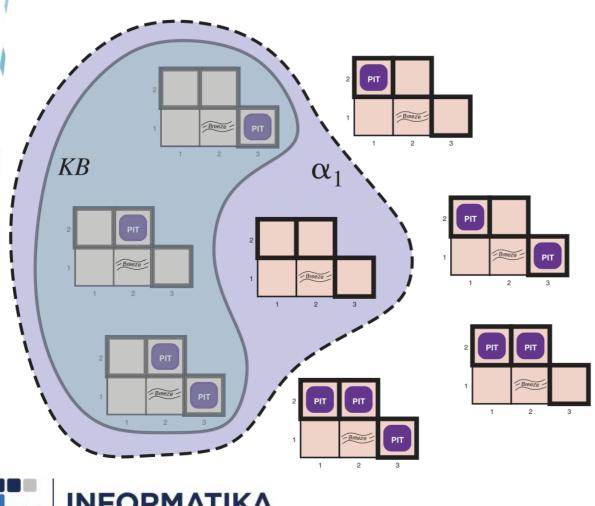




Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

$$\mathfrak{KB} \models \boldsymbol{\alpha}$$

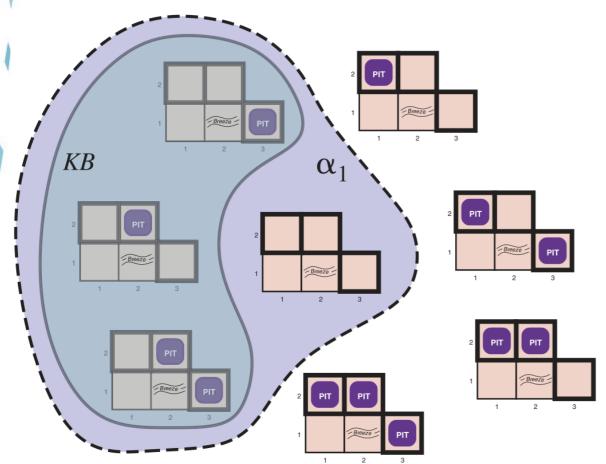


Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

Logical entailment: a sentence follows logically from another sentence

$$\mathcal{KB} \models \alpha$$

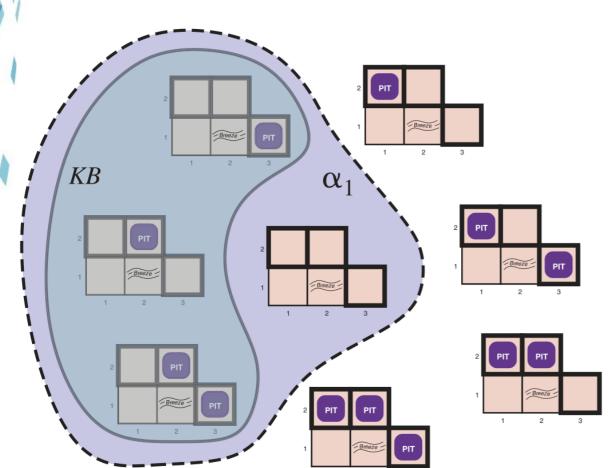


• XB: nothing in [1,1] and a breeze in [2,1] (from agent's percept)

Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

$$\mathcal{KB} \models \alpha$$

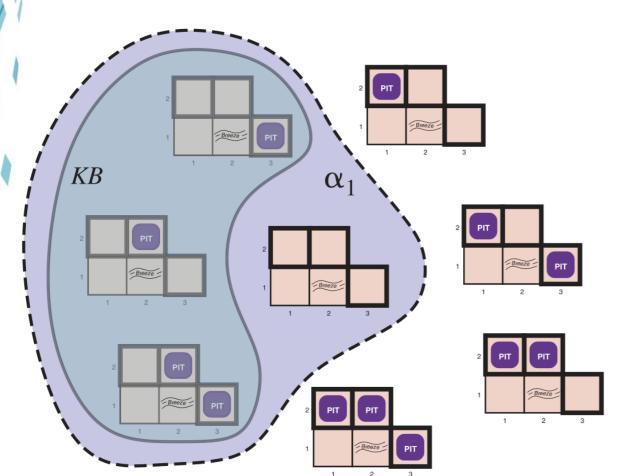


- XB: nothing in [1,1] and a breeze in [2,1] (from agent's percept)
- \mathfrak{KB} is false where [1,2] contains a pit. There is no breeze in [1,1].

Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

$$\mathfrak{KB} \models \boldsymbol{\alpha}$$

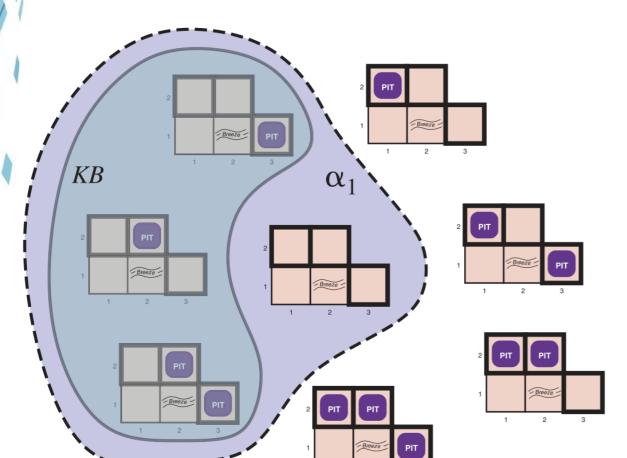


- XB: nothing in [1,1] and a breeze in [2,1] (from agent's percept)
- \mathfrak{KB} is false where [1,2] contains a pit. There is no breeze in [1,1].
- α_1 = "There is no pit in [1,2]"

Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

$$\mathcal{KB} \models \alpha$$



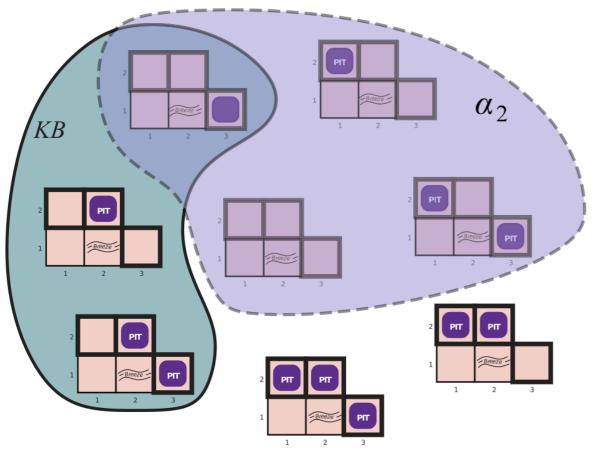
- XB: nothing in [1,1] and a breeze in [2,1] (from agent's percept)
- \mathfrak{XB} is false where [1,2] contains a pit. There is no breeze in [1,1].
- α_1 = "There is no pit in [1,2]"
- in every model in which \mathfrak{KB} is true, so does α_1
- hence, $\mathcal{KB} \models \alpha_1$



Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

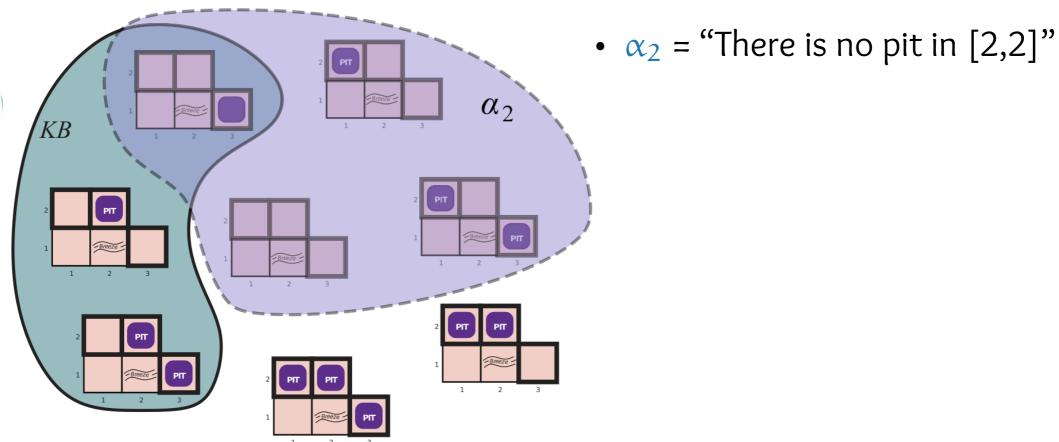
$$\mathfrak{KB} \models \boldsymbol{\alpha}$$



Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

$$\mathcal{KB} \models \alpha$$

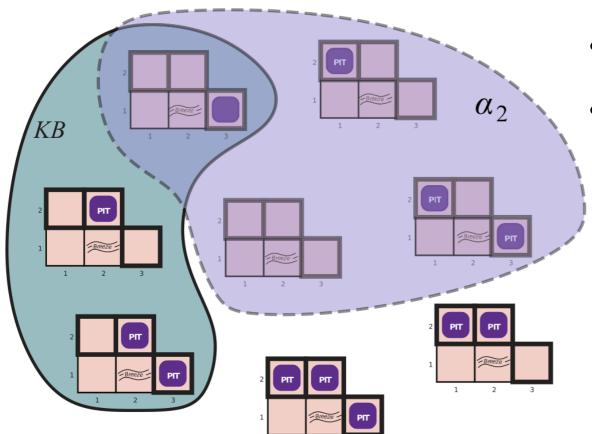




Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

$$\mathcal{KB} \models \alpha$$

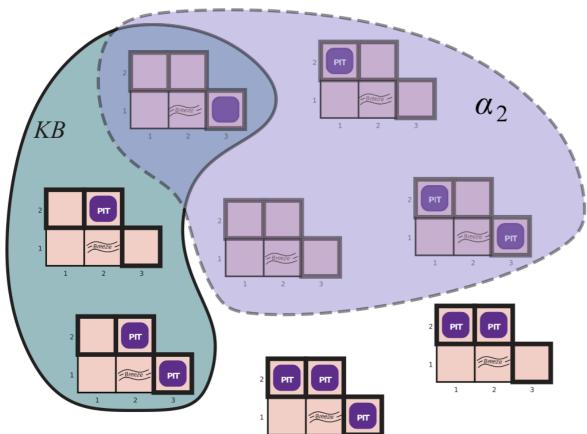


- α_2 = "There is no pit in [2,2]"
- in some model in which \mathfrak{KB} is true, α_2 is false

Logics are formal languages for representing knowledge

- Syntax: defines a well-formed sentence in the language
- Semantic: defines the meaning of a sentence
- Inference: rules to derive a new sentence from other sentences

$$\mathcal{KB} \models \alpha$$



- α_2 = "There is no pit in [2,2]"
- in some model in which \mathfrak{KB} is true, α_2 is false
- hence, \mathfrak{KB} does not entail α_2

Logical inference is performed using





Logical inference is performed using

• Model Checking: entailment through semantics, enumerate all models and show that the sentence α must hold in all models, $\mathcal{KB} \models \alpha$; or





Logical inference is performed using

- Model Checking: entailment through semantics, enumerate all models and show that the sentence α must hold in all models, $\mathcal{KB} \models \alpha$; or
- Theorem Proving: entailment through syntax, apply rules of inference to \mathcal{KB} to build a proof of α without enumerating and checking all models; $\mathcal{KB} \vdash \alpha$ $\mathcal{KB} \vdash_{i} \alpha$ denotes inference algorithm i derives α from \mathcal{KB}



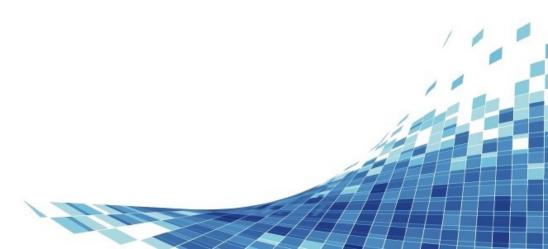


Logical inference is performed using

- Model Checking: entailment through semantics, enumerate all models and show that the sentence α must hold in all models, $\mathcal{KB} \models \alpha$; or
- Theorem Proving: entailment through syntax, apply rules of inference to \mathcal{KB} to build a proof of α without enumerating and checking all models; $\mathcal{KB} \vdash \alpha$ $\mathcal{KB} \vdash_{i} \alpha$ denotes inference algorithm i derives α from \mathcal{KB}

Inference algorithms should hold these two properties:





Logical inference is performed using

- Model Checking: entailment through semantics, enumerate all models and show that the sentence α must hold in all models, $\mathcal{KB} \models \alpha$; or
- Theorem Proving: entailment through syntax, apply rules of inference to \mathcal{KB} to build a proof of α without enumerating and checking all models; $\mathcal{KB} \vdash \alpha$ $\mathcal{KB} \vdash_{i} \alpha$ denotes inference algorithm i derives α from \mathcal{KB}

Inference algorithms should hold these two properties:

• Sound(logically valid): derives only entailed sentences, does not infer false formula

$$\{\alpha | \mathcal{KB} \vdash \alpha\} \subseteq \{\mathcal{KB} \models \alpha\}$$





Logical inference is performed using

- Model Checking: entailment through semantics, enumerate all models and show that the sentence α must hold in all models, $\mathcal{KB} \models \alpha$; or
- Theorem Proving: entailment through syntax, apply rules of inference to \mathfrak{KB} to build a proof of α without enumerating and checking all models; $\mathfrak{KB} \vdash \alpha$ $\mathfrak{KB} \vdash_{\mathfrak{i}} \alpha$ denotes inference algorithm \mathfrak{i} derives α from \mathfrak{KB}

Inference algorithms should hold these two properties:

• Sound(logically valid): derives only entailed sentences, does not infer false formula

$$\{\alpha | \mathcal{KB} \vdash \alpha\} \subseteq \{\mathcal{KB} \models \alpha\}$$

• Complete: derives all entailed sentences

$$\{\alpha | \mathcal{KB} \vdash \alpha\} \supseteq \{\mathcal{KB} \models \alpha\}$$





Logical inference is performed using

- Model Checking: entailment through semantics, enumerate all models and show that the sentence α must hold in all models, $\mathcal{KB} \models \alpha$; or
- **Theorem Proving:** entailment through syntax, apply rules of inference to \mathcal{KB} to build a proof of α without enumerating and checking all models; $\mathcal{KB} \vdash \alpha$ $\mathfrak{KB} \vdash_{i} \alpha$ denotes inference algorithm i derives α from \mathfrak{KB}

Inference algorithms should hold these two properties:

• Sound(logically valid): derives only entailed sentences, does not infer false formula

$$\{\alpha | \mathcal{KB} \vdash \alpha\} \subseteq \{\mathcal{KB} \models \alpha\}$$

• Complete: derives all entailed sentences

$$\{\alpha | \mathcal{KB} \vdash \alpha\} \supseteq \{\mathcal{KB} \models \alpha\}$$

The basic rules (background knowledge) can be produced from learning











..... is the simplest logic

Propositional Logic





.... is the simplest logic

Syntax of PL: defines the allowable sentences or propositions





.... is the simplest logic

Syntax of PL: defines the allowable sentences or propositions

Sentence/Definition/Proposition: a declarative statement, either TRUE OR FALSE





.... is the simplest logic

Syntax of PL: defines the allowable sentences or propositions

Sentence/Definition/Proposition: a declarative statement, either TRUE OR FALSE

Atomic sentence: a single sentence symbol





.... is the simplest logic

Syntax of PL: defines the allowable sentences or propositions

Sentence/Definition/Proposition: a declarative statement, either TRUE OR FALSE

Atomic sentence: a single sentence symbol

Compound sentence: formed from atomic sentence, parentheses, & logical connectives





.... is the simplest logic

Syntax of PL: defines the allowable sentences or propositions

Sentence/Definition/Proposition: a declarative statement, either TRUE OR FALSE

Atomic sentence: a single sentence symbol

Compound sentence: formed from atomic sentence, parentheses, & logical connectives

A BNF (Backus-Naur Form) grammar of sentences in propositional logic:

```
Sentence \rightarrow AtomicSentence \mid ComplexSentence
```

$$AtomicSentence \rightarrow True \mid False \mid P \mid Q \mid R \mid \dots$$

$$ComplexSentence \rightarrow (Sentence)$$

$$\neg$$
 Sentence

$$Sentence \wedge Sentence$$

$$Sentence \lor Sentence$$

$$Sentence \Rightarrow Sentence$$

$$Sentence \Leftrightarrow Sentence$$

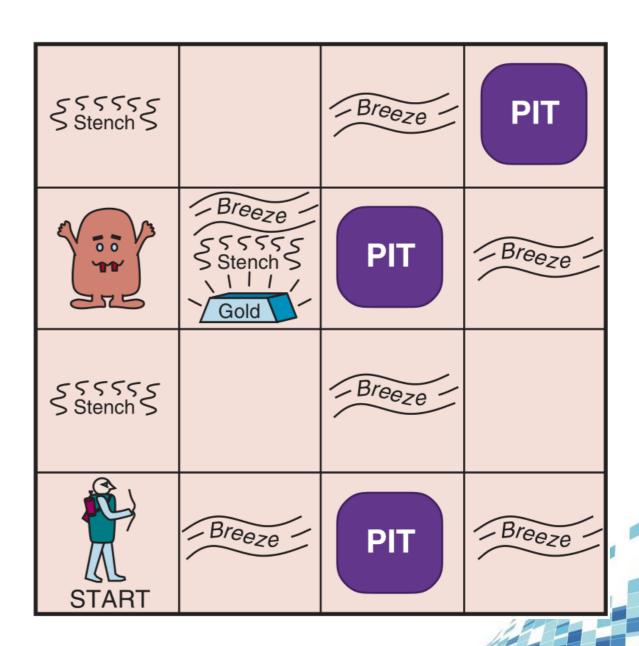
Operator Precedence : $\neg, \land, \lor, \Rightarrow, \Leftrightarrow$







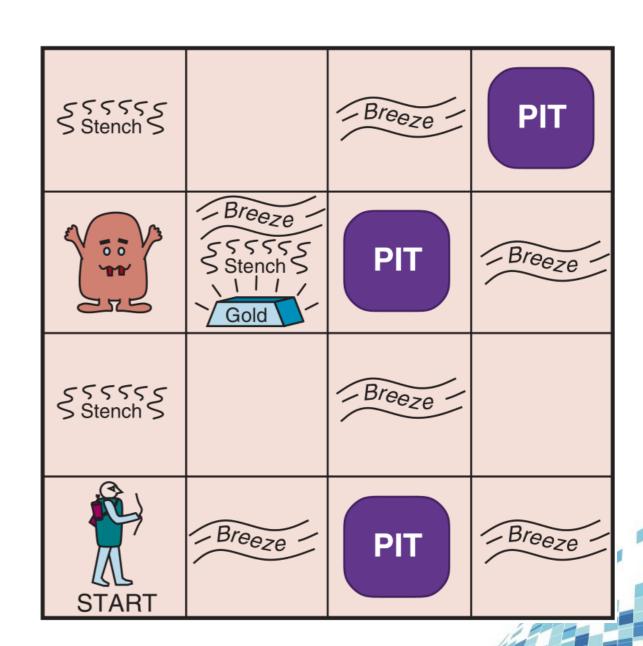
The Wumpus world KB





The Wumpus world KB

Symbols for each [x, y]:



The Wumpus world \mathcal{KB}

Symbols for each [x, y]:

• $P_{i,j}$ is true if there is a pit in [i, j]

SSSSS Stench S		Breeze	PIT
	S S S S S S S S S S S S S S S S S S S	PIT	Breeze
SSSSS Stench		Breeze	
START	-Breeze	PIT	_Breeze _



The Wumpus world XB

Symbols for each [x, y]:

- $P_{i,j}$ is true if there is a pit in [i, j]
- $B_{i,j}$ is true if there is a breeze in [i,j]

SSSSS Stench		Breeze	PIT
100	SSSSS Stench S	PIT	-Breeze
SSSSS Stench		Breeze	
START	Breeze	PIT	Breeze



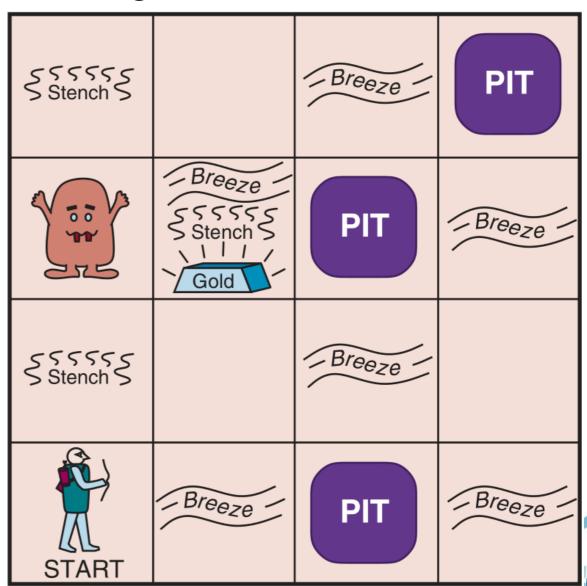
Symbols for each [x, y]:

- $P_{i,j}$ is true if there is a pit in [i,j]
- $B_{i,j}$ is true if there is a breeze in [i,j]
- and the same for W (wumpus), S (stench), and L (agent's location)

SSSSS Stench		Breeze	PIT
	SSSSS Stench S	PIT	Breeze
SSSSS Stench		Breeze	
START	-Breeze	PIT	Breeze

Symbols for each [x, y]:

- $P_{i,j}$ is true if there is a pit in [i,j]
- $B_{i,j}$ is true if there is a breeze in [i,j]
- and the same for W (wumpus), S (stench), and L (agent's location)





Symbols for each [x, y]:

- $P_{i,j}$ is true if there is a pit in [i,j]
- $B_{i,j}$ is true if there is a breeze in [i,j]
- and the same for W (wumpus), S (stench), and L (agent's location)

XB for the reduced Wumpus world:

• $R_1 : \neg P_{1,1}$

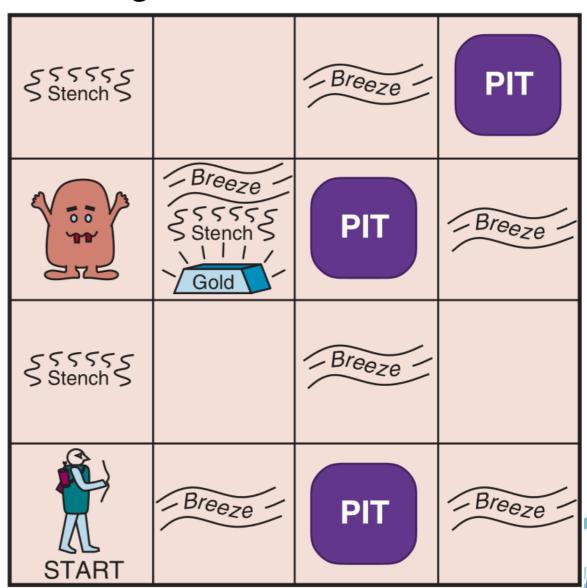
SSSSS Stench		Breeze	PIT
500	SSSSS Stench S	PIT	Breeze
SSSSS Stench		Breeze	
START	-Breeze	PIT	Breeze



Symbols for each [x, y]:

- $P_{i,j}$ is true if there is a pit in [i,j]
- $B_{i,j}$ is true if there is a breeze in [i,j]
- and the same for W (wumpus), S (stench), and L (agent's location)

- $R_1 : \neg P_{1,1}$
- $R_2: B_{1,1} \iff P_{1,2} \vee P_{2,1}$

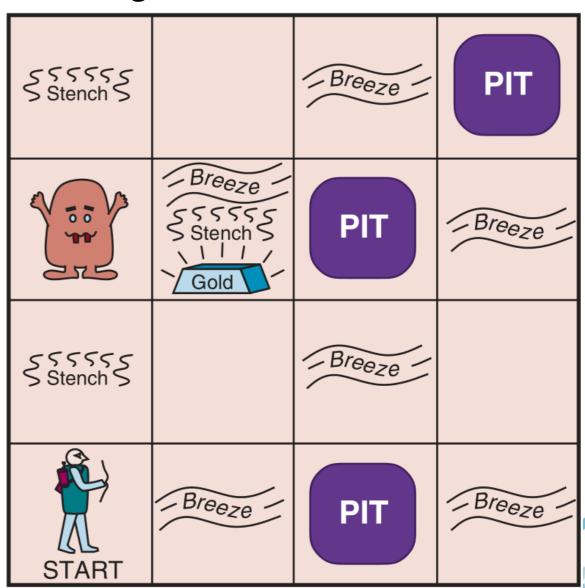




Symbols for each [x, y]:

- $P_{i,j}$ is true if there is a pit in [i,j]
- $B_{i,j}$ is true if there is a breeze in [i,j]
- and the same for W (wumpus), S (stench), and L (agent's location)

- $R_1 : \neg P_{1,1}$
- $R_2: B_{1,1} \iff P_{1,2} \vee P_{2,1}$
- $R_3: B_{2,1} \iff P_{1,1} \vee P_{2,2} \vee P_{3,1}$

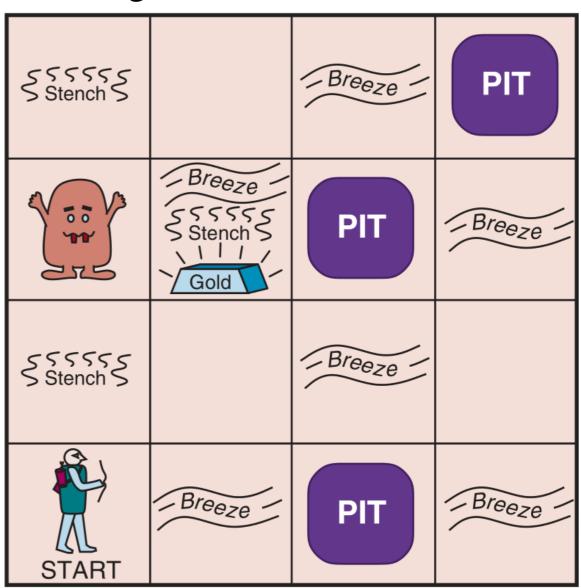




Symbols for each [x, y]:

- $P_{i,j}$ is true if there is a pit in [i,j]
- $B_{i,j}$ is true if there is a breeze in [i,j]
- and the same for W (wumpus), S (stench), and L (agent's location)

- $R_1 : \neg P_{1,1}$
- $R_2: B_{1,1} \iff P_{1,2} \vee P_{2,1}$
- $R_3: B_{2,1} \iff P_{1,1} \vee P_{2,2} \vee P_{3,1}$
- $R_4 : \neg B_{1,1}$

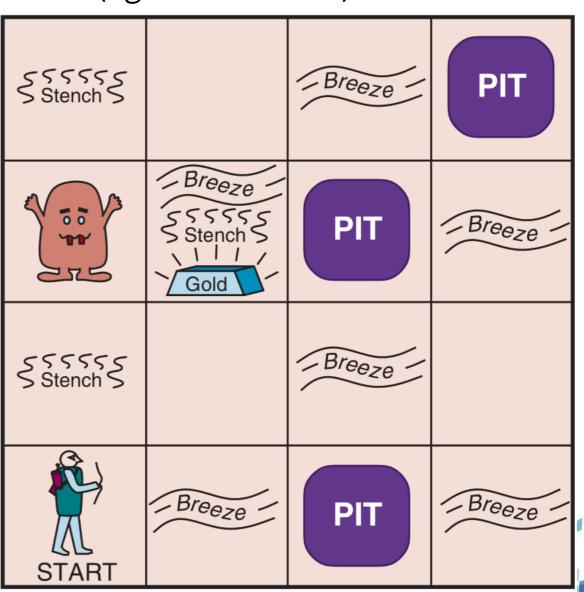




Symbols for each [x, y]:

- $P_{i,j}$ is true if there is a pit in [i,j]
- $B_{i,j}$ is true if there is a breeze in [i,j]
- and the same for W (wumpus), S (stench), and L (agent's location)

- $R_1 : \neg P_{1,1}$
- $R_2: B_{1,1} \iff P_{1,2} \vee P_{2,1}$
- $R_3: B_{2,1} \iff P_{1,1} \vee P_{2,2} \vee P_{3,1}$
- $R_4 : \neg B_{1,1}$
- $R_5: B_{2,1}$





Symbols for each [x, y]:

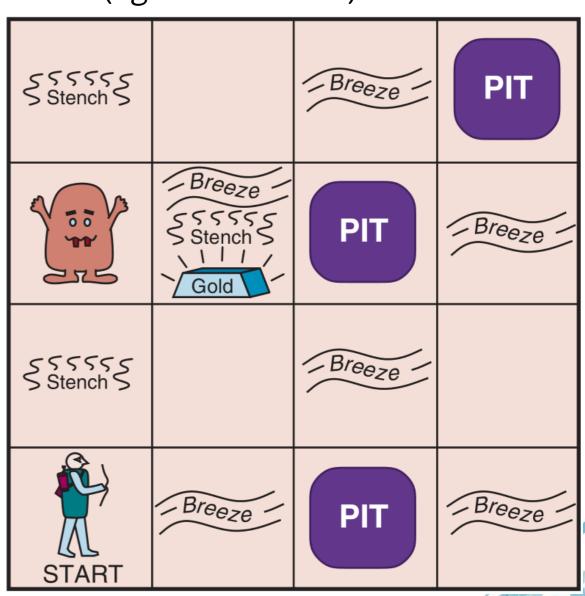
- $P_{i,j}$ is true if there is a pit in [i,j]
- $B_{i,j}$ is true if there is a breeze in [i,j]
- and the same for W (wumpus), S (stench), and L (agent's location)

XB for the reduced Wumpus world:

- $R_1 : \neg P_{1,1}$
- $R_2: B_{1,1} \iff P_{1,2} \vee P_{2,1}$
- $R_3: B_{2,1} \iff P_{1,1} \vee P_{2,2} \vee P_{3,1}$
- $R_4 : \neg B_{1,1}$
- $R_5 : B_{2,1}$

Questions (based on above \mathfrak{KB}):

- $\mathfrak{KB} \models : P_{1,2}$
- $\mathfrak{KB} \models : P_{2,2}$











Based on truth table enumeration





Based on truth table enumeration

Models: assignments of TRUE or FALSE to every proposition symbol.



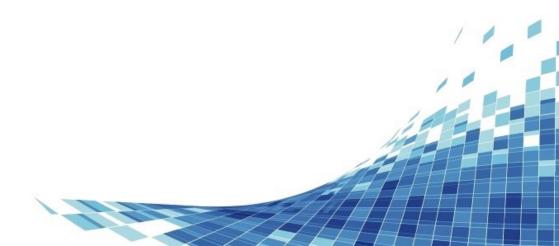


Based on truth table enumeration

Models: assignments of TRUE or FALSE to every proposition symbol.

$B_{1,1}$	$B_{2,1}$	$P_{1,1}$	$P_{1,2}$	$P_{2,1}$	$P_{2,2}$	$P_{3,1}$	R_1	R_2	R_3	R_4	R_5	KB
$false \\ false$	$false \\ false$	$false \\ false$	$false \\ false$	$false \\ false$	$false \\ false$	$false \ true$	$true \ true$	$true \ true$	$true \\ false$	$true \ true$	$false \\ false$	$false \\ false$
$\vdots \\ false$	$\vdots \\ true$	$\vdots \\ false$	$\vdots \\ true$	$\vdots \\ true$	$\vdots \\ false$	$\vdots \\ true$	$\vdots \\ true$	$\vdots \\ false$				
false false false	true true true	$false \\ false \\ false$	$false \\ false \\ false$	$false \\ false \\ false$	$false \ true \ true$	$true \\ false \\ true$	$true \ true \ true$	true true true	true true true	true true true	$true \ true \ true$	$\frac{true}{true}$ $\frac{true}{true}$
$false$ \vdots $true$	$true \\ \vdots \\ true$	$false \\ \vdots \\ true$	$false \\ \vdots \\ true$	$true$ \vdots $true$	$false \\ \vdots \\ true$	$false \\ \vdots \\ true$	$true$ \vdots $false$	$false \\ \vdots \\ true$	$false \\ \vdots \\ true$	$true$ \vdots $false$	$true \\ \vdots \\ true$	$false$ \vdots $false$





Based on truth table enumeration

Models: assignments of TRUE or FALSE to every proposition symbol.

$B_{1,1}$	$B_{2,1}$	$P_{1,1}$	$P_{1,2}$	$P_{2,1}$	$P_{2,2}$	$P_{3,1}$	R_1	R_2	R_3	R_4	R_5	KB
$false \\ false$	$false \\ false$	$false \\ false$	$false \\ false$	$false \\ false$	$false \\ false$	$false \ true$	$true \ true$	$true \ true$	$true \\ false$	$true \ true$	$false \\ false$	$false \\ false$
$\vdots \\ false$	$\vdots \\ true$	$\vdots \\ false$	$\vdots \\ true$	$\vdots \\ true$	$\vdots \\ false$	$\vdots \\ true$	$\vdots \\ true$	$\vdots \\ false$				
false false false	true true true	$false \\ false \\ false$	$false \\ false \\ false$	$false \\ false \\ false$	$false \ true \ true$	$true \\ false \\ true$	$true \ true \ true$	true true true	true true true	true true true	$true \ true \ true$	$\frac{true}{true}$ $\frac{true}{true}$
$false$ \vdots $true$	$true \\ \vdots \\ true$	$false \\ \vdots \\ true$	$false \\ \vdots \\ true$	$true$ \vdots $true$	$false \\ \vdots \\ true$	$false \\ \vdots \\ true$	$true$ \vdots $false$	$false \\ \vdots \\ true$	$false \\ \vdots \\ true$	$true$ \vdots $false$	$true \\ \vdots \\ true$	$false$ \vdots $false$

If \mathfrak{KB} and α contain n symbols, then there are 2^n models and the complexity of the enumeration (algorithm) is $O(2^n)$











Method checking is inefficient: truth tables might have an exponential number of models

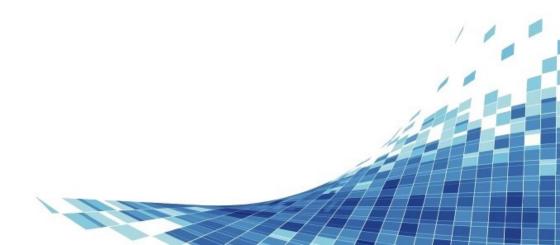




Method checking is inefficient: truth tables might have an exponential number of models

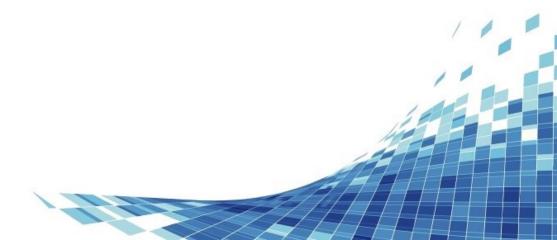
Search for proofs is a more efficient because we can ignore irrelevant information





Method checking is inefficient: truth tables might have an exponential number of models Search for proofs is a more efficient because we can ignore irrelevant information Apply inference rules directly to the \mathfrak{KB} without consulting the model. It is **sound**.





Method checking is inefficient: truth tables might have an exponential number of models

Search for proofs is a more efficient because we can ignore irrelevant information

Apply inference rules directly to the \mathfrak{KB} without consulting the model. It is **sound**.

- Modus Ponens
- And-Elimination
- standard logical equivalences: biconditional elimination, De Morgan rule, etc





Method checking is inefficient: truth tables might have an exponential number of models

Search for proofs is a more efficient because we can ignore irrelevant information

Apply inference rules directly to the \mathfrak{KB} without consulting the model. It is **sound**.

- Modus Ponens
- And-Elimination
- standard logical equivalences: biconditional elimination, De Morgan rule, etc

Inference as a search problem!





Method checking is inefficient: truth tables might have an exponential number of models

Search for proofs is a more efficient because we can ignore irrelevant information

Apply inference rules directly to the \mathfrak{KB} without consulting the model. It is **sound**.

- Modus Ponens
- And-Elimination
- standard logical equivalences: biconditional elimination, De Morgan rule, etc

Inference as a search problem!

Ways to ensure completeness:





Method checking is inefficient: truth tables might have an exponential number of models

Search for proofs is a more efficient because we can ignore irrelevant information

Apply inference rules directly to the \mathfrak{KB} without consulting the model. It is **sound**.

- Modus Ponens
- And-Elimination
- standard logical equivalences: biconditional elimination, De Morgan rule, etc

Inference as a search problem!

Ways to ensure completeness:

• Proof by resolution: use powerful inference rules (resolution rules)





Method checking is inefficient: truth tables might have an exponential number of models

Search for proofs is a more efficient because we can ignore irrelevant information

Apply inference rules directly to the \mathfrak{KB} without consulting the model. It is **sound**.

- Modus Ponens
- And-Elimination
- standard logical equivalences: biconditional elimination, De Morgan rule, etc

Inference as a search problem!

Ways to ensure completeness:

- Proof by resolution: use powerful inference rules (resolution rules)
- Forward or Backward chaining: use of modus ponens on a restricted form of propositions (Horn clauses)





Resolution: a single inference rule





Resolution: a single inference rule

Resolution yields a complete (and sound) inference algorithm when coupled with any complete search algorithm





Resolution: a single inference rule

Resolution yields a complete (and sound) inference algorithm when coupled with any complete search algorithm

Unit resolution rule:

$$\frac{\ell_1 \vee \ldots \vee \ell_i \vee \ldots \vee \ell_k, \quad m}{\ell_1 \vee \ldots \vee \ell_{i-1} \vee \ell_{i+1} \vee \ldots \vee \ell_k}$$

where ℓ_i and m are complementary literals





Resolution: a single inference rule

Resolution yields a complete (and sound) inference algorithm when coupled with any complete search algorithm

Unit resolution rule:

$$\frac{\ell_1 \vee \ldots \vee \ell_i \vee \ldots \vee \ell_k, \quad m}{\ell_1 \vee \ldots \vee \ell_{i-1} \vee \ell_{i+1} \vee \ldots \vee \ell_k}$$

where ℓ_i and m are complementary literals

Resolution inference rule

$$\frac{\ell_1 \vee \ldots \vee \ell_i \vee \ldots \vee \ell_k, \quad m_1 \vee \ldots \vee m_j \vee \ldots \vee m_n}{\ell_1 \vee \ldots \vee \ell_{i-1} \vee \ell_{i+1} \vee \ldots \vee \ell_k \vee m_1 \vee \ldots \vee m_{j-1} \vee m_{j+1} \vee \ldots \vee}$$

where ℓ_i and m_j are complementary literals





Resolution: a single inference rule

Resolution yields a complete (and sound) inference algorithm when coupled with any complete search algorithm

Unit resolution rule:

$$\frac{\ell_1 \vee \ldots \vee \ell_i \vee \ldots \vee \ell_k, \quad m}{\ell_1 \vee \ldots \vee \ell_{i-1} \vee \ell_{i+1} \vee \ldots \vee \ell_k}$$

where ℓ_i and m are complementary literals

Resolution inference rule

$$\frac{\ell_1 \vee \ldots \vee \ell_i \vee \ldots \vee \ell_k, \quad m_1 \vee \ldots \vee m_j \vee \ldots \vee m_n}{\ell_1 \vee \ldots \vee \ell_{i-1} \vee \ell_{i+1} \vee \ldots \vee \ell_k \vee m_1 \vee \ldots \vee m_{j-1} \vee m_{j+1} \vee \ldots \vee}$$

where ℓ_i and m_j are complementary literals

The \mathfrak{KB} must be transformed to CNF (Conjunctive Normal Form): Conjunction of disjunction of literals. Example: $(A \lor B \lor \neg C) \land (C \lor \neg D)$





Wumpus: there is no breeze at [1,1], so there can be no pits in neighboring squares





Wumpus: there is no breeze at [1,1], so there can be no pits in neighboring squares

$$\mathfrak{KB} = R_2 \wedge R_4 = (B_{1,1} \iff (P_{1,2} \vee P_{2,1})) \wedge \neg B_{1,1}$$





Wumpus: there is no breeze at [1,1], so there can be no pits in neighboring squares

$$\mathfrak{KB} = R_2 \wedge R_4 = (B_{1,1} \iff (P_{1,2} \vee P_{2,1})) \wedge \neg B_{1,1}$$

We want to prove that there is no pits at [1,2]

$$\alpha = \neg P_{1,2}$$





Wumpus: there is no breeze at [1,1], so there can be no pits in neighboring squares

$$\mathfrak{KB} = R_2 \wedge R_4 = (B_{1,1} \iff (P_{1,2} \vee P_{2,1})) \wedge \neg B_{1,1}$$

We want to prove that there is no pits at [1,2]

$$\alpha = \neg P_{1,2}$$

Answer:

• To show $KB \models \alpha$ we show that $(KB \land \neg \alpha)$ is unsatisfiable





Wumpus: there is no breeze at [1,1], so there can be no pits in neighboring squares

$$\mathfrak{KB} = R_2 \wedge R_4 = (B_{1,1} \iff (P_{1,2} \vee P_{2,1})) \wedge \neg B_{1,1}$$

We want to prove that there is no pits at [1,2]

$$\alpha = \neg P_{1,2}$$

Answer:

- To show $KB \models \alpha$ we show that $(KB \land \neg \alpha)$ is unsatisfiable
- Convert $(KB \land \neg \alpha)$ into CNF





Wumpus: there is no breeze at [1,1], so there can be no pits in neighboring squares

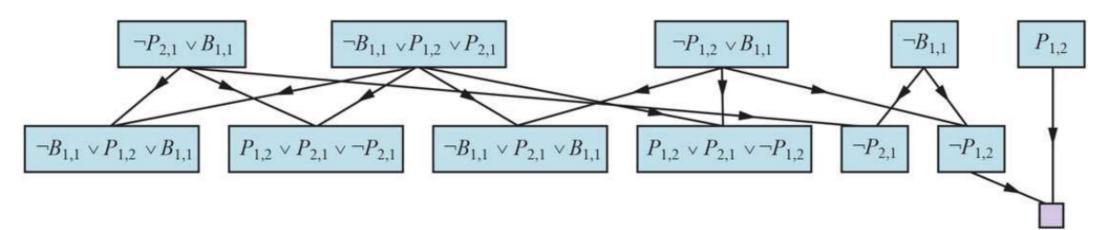
$$\mathfrak{KB} = R_2 \wedge R_4 = (B_{1,1} \iff (P_{1,2} \vee P_{2,1})) \wedge \neg B_{1,1}$$

We want to prove that there is no pits at [1,2]

$$\alpha = \neg P_{1,2}$$

Answer:

- To show $KB \models \alpha$ we show that $(KB \land \neg \alpha)$ is unsatisfiable
- Convert (KB $\wedge \neg \alpha$) into CNF





Wumpus: there is no breeze at [1,1], so there can be no pits in neighboring squares

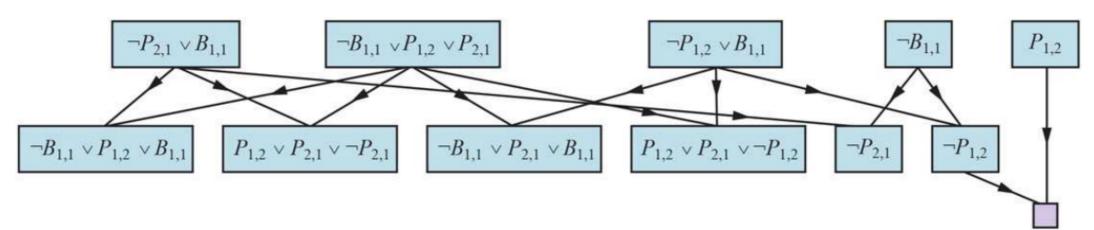
$$\mathfrak{KB} = R_2 \wedge R_4 = (B_{1,1} \iff (P_{1,2} \vee P_{2,1})) \wedge \neg B_{1,1}$$

We want to prove that there is no pits at [1,2]

$$\alpha = \neg P_{1,2}$$

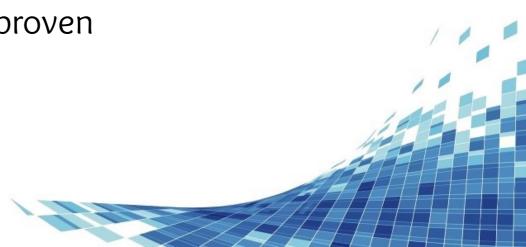
Answer:

- To show $KB \models \alpha$ we show that $(KB \land \neg \alpha)$ is unsatisfiable
- Convert (KB $\wedge \neg \alpha$) into CNF



· An empty clause is yielded, meaning the query is proven







Chaining



Chaining

 \mathfrak{KB} = conjunction of Horn clauses



Chaining

 \mathfrak{KB} = conjunction of Horn clauses

Horn clause is a disjunction of literals of which at most one is positive

$$\neg \ell_1 \vee \neg \ell_2 \vee \ldots \vee \neg \ell_n \vee \ell_{n+1} \equiv \ell_1 \wedge \ell_2 \wedge \ldots \wedge \ell_n \implies \ell_{n+1}$$





Chaining

 \mathfrak{KB} = conjunction of Horn clauses

Horn clause is a disjunction of literals of which at most one is positive

$$\neg \ell_1 \vee \neg \ell_2 \vee \ldots \vee \neg \ell_n \vee \ell_{n+1} \equiv \ell_1 \wedge \ell_2 \wedge \ldots \wedge \ell_n \implies \ell_{n+1}$$

Inference with Horn clauses can be done through the forward-chaining and backward-chaining algorithms that run in linear time





Chaining

 \mathfrak{KB} = conjunction of Horn clauses

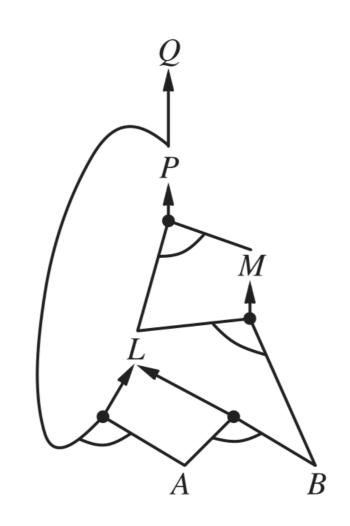
Horn clause is a disjunction of literals of which at most one is positive

$$\neg \ell_1 \vee \neg \ell_2 \vee \ldots \vee \neg \ell_n \vee \ell_{n+1} \equiv \ell_1 \wedge \ell_2 \wedge \ldots \wedge \ell_n \implies \ell_{n+1}$$

Inference with Horn clauses can be done through the forward-chaining and backward-chaining algorithms that run in linear time

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



Propositional Logic for KB has limitations

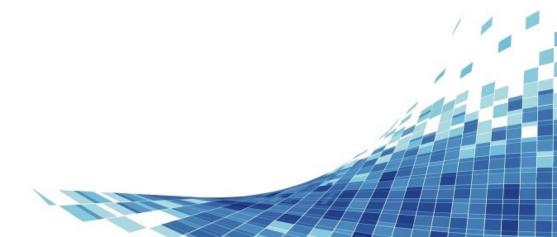




Propositional Logic for XB has limitations

unable to express information about different objects and their relations





Propositional Logic for KB has limitations

- unable to express information about different objects and their relations
- unable to express a fact for a set of objects without enumerating all of them





Propositional Logic for KB has limitations

- unable to express information about different objects and their relations
- unable to express a fact for a set of objects without enumerating all of them

Why don't we use other languages?





Propositional Logic for KB has limitations

- unable to express information about different objects and their relations
- unable to express a fact for a set of objects without enumerating all of them

Why don't we use other languages?

• natural language: use for communication, ambiguity





Propositional Logic for XB has limitations

- unable to express information about different objects and their relations
- unable to express a fact for a set of objects without enumerating all of them

Why don't we use other languages?

- natural language: use for communication, ambiguity
- programming language: no mechanism for deriving facts from other facts, lack the expressiveness required to directly handle partial information





Propositional Logic for KB has limitations

- unable to express information about different objects and their relations
- unable to express a fact for a set of objects without enumerating all of them

Why don't we use other languages?

- natural language: use for communication, ambiguity
- programming language: no mechanism for deriving facts from other facts, lack the expressiveness required to directly handle partial information

Combining the best of formal and natural languages





Propositional Logic for KB has limitations

- unable to express information about different objects and their relations
- unable to express a fact for a set of objects without enumerating all of them

Why don't we use other languages?

- natural language: use for communication, ambiguity
- programming language: no mechanism for deriving facts from other facts, lack the expressiveness required to directly handle partial information

Combining the best of formal and natural languages

• Propositional logic: declarative, context-independet, unambigous,





Propositional Logic for KB has limitations

- unable to express information about different objects and their relations
- unable to express a fact for a set of objects without enumerating all of them

Why don't we use other languages?

- natural language: use for communication, ambiguity
- programming language: no mechanism for deriving facts from other facts, lack the expressiveness required to directly handle partial information

Combining the best of formal and natural languages

- Propositional logic: declarative, context-independet, unambigous,
- natural language: representational ideas











Declarative language that can also recognize:





Declarative language that can also recognize:

Objects: all nouns and noun phrases





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects

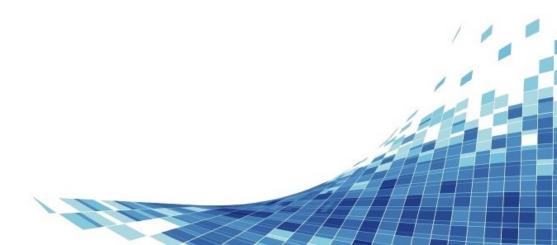




Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input

Syntax of FOL:





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input

Syntax of FOL:

• Terms are either: constant symbols (e.g. 13), variables, or functions (e.g. sqrt(x))





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input

Syntax of FOL:

- Terms are either: constant symbols (e.g. 13), variables, or functions (e.g. sqrt(x))
- Atomic formulas are predicates applied to terms (e.g., sister(a,b))





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input

Syntax of FOL:

- Terms are either: constant symbols (e.g. 13), variables, or functions (e.g. sqrt(x))
- Atomic formulas are predicates applied to terms (e.g., sister(a,b))
- Connectives $(\lor, \land, \neg, \Longrightarrow, \Longleftrightarrow)$, equality (=), and quatifiers (\forall, \exists)





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input

Syntax of FOL:

- Terms are either: constant symbols (e.g. 13), variables, or functions (e.g. sqrt(x))
- Atomic formulas are predicates applied to terms (e.g., sister(a,b))
- Connectives(\vee , \wedge , \neg , \Longrightarrow , \Longleftrightarrow), equality(=), and quatifiers (\forall , \exists)

Sentences can be created by applying connectives, equality, and/or quantifiers to atomic formulas





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input

Syntax of FOL:

- Terms are either: constant symbols (e.g. 13), variables, or functions (e.g. sqrt(x))
- Atomic formulas are predicates applied to terms (e.g., sister(a,b))
- Connectives(\vee , \wedge , \neg , \Longrightarrow , \Longleftrightarrow), equality(=), and quatifiers (\forall , \exists)

Sentences can be created by applying connectives, equality, and/or quantifiers to atomic formulas

Examples:





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input

Syntax of FOL:

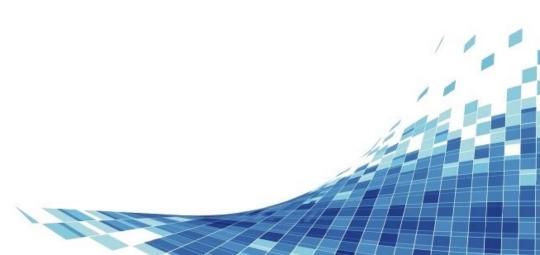
- Terms are either: constant symbols (e.g. 13), variables, or functions (e.g. sqrt(x))
- Atomic formulas are predicates applied to terms (e.g., sister(a,b))
- Connectives(\vee , \wedge , \neg , \Longrightarrow , \Longleftrightarrow), equality(=), and quatifiers (\forall , \exists)

Sentences can be created by applying connectives, equality, and/or quantifiers to atomic formulas

Examples:

• All birds except dodo fly: $\forall x \operatorname{bird}(x) \land \neg \operatorname{dodo}(x) \implies \operatorname{fly}(x)$





Declarative language that can also recognize:

- Objects: all nouns and noun phrases
- Relations: either unary or n-ary relations between objects
- Functions: relations that only have one value for a given input

Syntax of FOL:

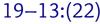
- Terms are either: constant symbols (e.g. 13), variables, or functions (e.g. sqrt(x))
- Atomic formulas are predicates applied to terms (e.g., sister(a,b))
- Connectives(\vee , \wedge , \neg , \Longrightarrow , \Longleftrightarrow), equality(=), and quatifiers (\forall , \exists)

Sentences can be created by applying connectives, equality, and/or quantifiers to atomic formulas

Examples:

- All birds except dodo fly: $\forall x \operatorname{bird}(x) \land \neg \operatorname{dodo}(x) \implies \operatorname{fly}(x)$
- Some wombat like ice-cream: $\exists x \ wombat(x) \land likes(x, ice cream)$





Inference for FOL

There are procedures to do inference with a knowledge base of FOL formulas:



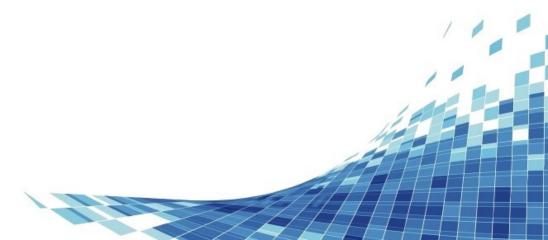


Inference for FOL

There are procedures to do inference with a knowledge base of FOL formulas:

- Universal Instantiation and Existential Instantiation with Unification
- Forward chaining: used in deductive databases. It can be combined with relational database operations
- Backward chaining: used in logic programming that provide very fast inference





Inference for FOL

There are procedures to do inference with a knowledge base of FOL formulas:

- Universal Instantiation and Existential Instantiation with Unification
- Forward chaining: used in deductive databases. It can be combined with relational database operations
- Backward chaining: used in logic programming that provide very fast inference

Note on natural language:

Conversion between natural language and logical expressions is possible due to the expressiveness of FOL. This is very valuable in many areas, such as development of virtual assitants like Alexa, Cortana, Siri, and many more.





Logic is used to represent the environment of the agent and reason about that env.





Logic is used to represent the environment of the agent and reason about that env.

While models are encoded explicitly, there are some limitations:





Logic is used to represent the environment of the agent and reason about that env.

While models are encoded explicitly, there are some limitations:

· It is difficult to model every aspect of the world





Logic is used to represent the environment of the agent and reason about that env.

While models are encoded explicitly, there are some limitations:

- · It is difficult to model every aspect of the world
- rule-based and do not use data like machine learning





Logic is used to represent the environment of the agent and reason about that env.

While models are encoded explicitly, there are some limitations:

- · It is difficult to model every aspect of the world
- rule-based and do not use data like machine learning
- do not handle uncertainty like probability, although fuzzy logic allows for degree of truth







