

CPSC 322

Introduction to Artificial Intelligence

November 29, 2004

Things...



There will be a practice homework assignment coming.



Using plans in language understanding

Knowledge of goals and plans is useful in block-stacking and route-finding, but it's also essential in understanding stories that describe unusual events.

That means we use goals and plans all the time when reading or listening, because it's usually the unusual events that motivate telling the story in the first place.

Using plans in language understanding

For example, this story isn't all that unusual. It's also the kind of story that people don't really tell. Why would they? It happens all the time...it's not worth telling.

John and Mary went to McDonald's.
John ordered a Big Mac and fries.
Mary had a Quarter Pounder.
John put the trash in the wastebasket.
They went home.

Using plans in language understanding

On the other hand, this is the kind of story that people would find to be much more interesting and therefore worth telling:

John and Mary went to McDonald's.

John ordered a Big Mac and fries.

Suddenly, Mary's husband Lenny burst through the door with a shotgun.

John hid under a table.

Using plans in language understanding

Is Lenny going duck hunting?

Is he going to ask if anyone lost a shotgun outside?

Will he try to trade the shotgun for some McNuggets?

John and Mary went to McDonald's.

John ordered a Big Mac and fries.

Suddenly, Mary's husband Lenny burst through the door with a shotgun.

John hid under a table.

How do you know?

Using plans in language understanding

What are the goals that drive John, Mary, and Lenny?
What plans are they executing to fulfill those goals?

John and Mary went to McDonald's.

John ordered a Big Mac and fries.

Suddenly, Mary's husband Lenny burst through the
door with a shotgun.

John hid under a table.

How do you know?

Using plans in language understanding

Here is a simpler example (maybe):

John needed money for a down payment on a new house.
He got his gun and went to the 7-Eleven store on the corner.

As with any story, understanding involves making the inferences that connect one sentence to another.

In this case, we're given John's goals in the first sentence, and we have John's actions in the next sentence. We assume that the two sentences are related because they come one after the other. How can we do this?

Using plans in language understanding

John needed money for a down payment on a new house.
He got his gun and went to the 7-Eleven store on the corner.

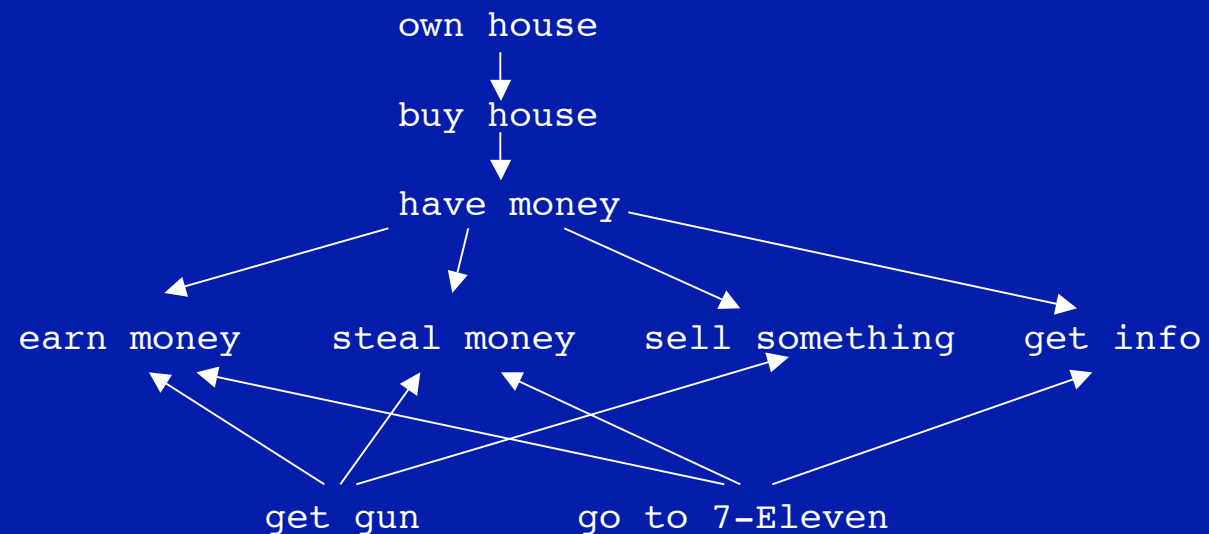
goal:

plan:

precond/subgoal:

possible plans:

actions:



How do you figure out which plan is the connection?

Using plans in language understanding

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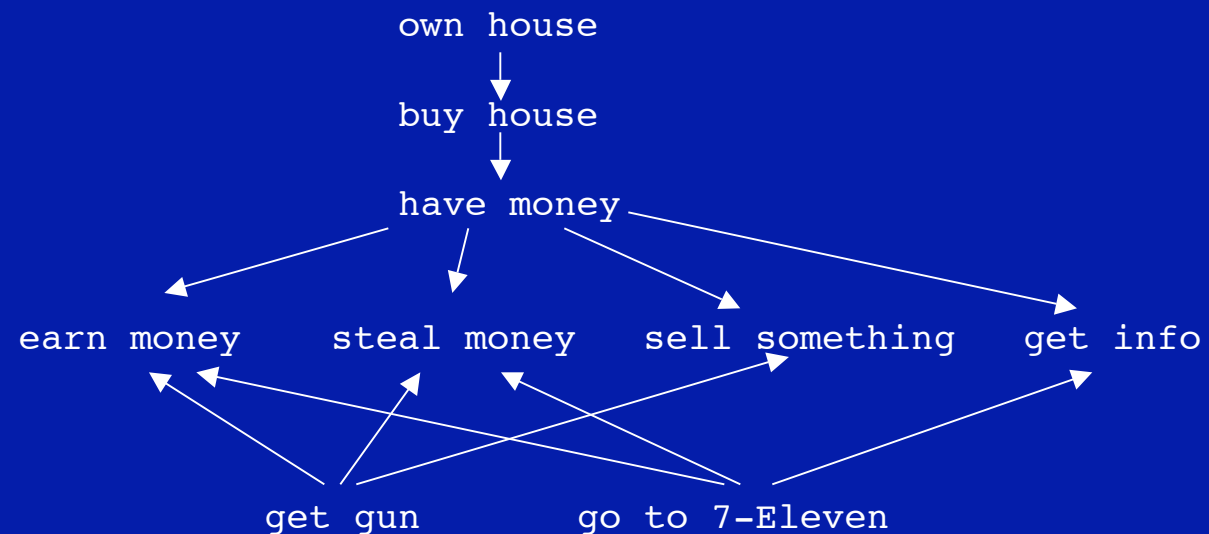
goal:

plan:

precond/subgoal:

possible plans:

actions:



How do you figure out which plan is the connection?
The get info plan doesn't easily explain the gun.

Using plans in language understanding

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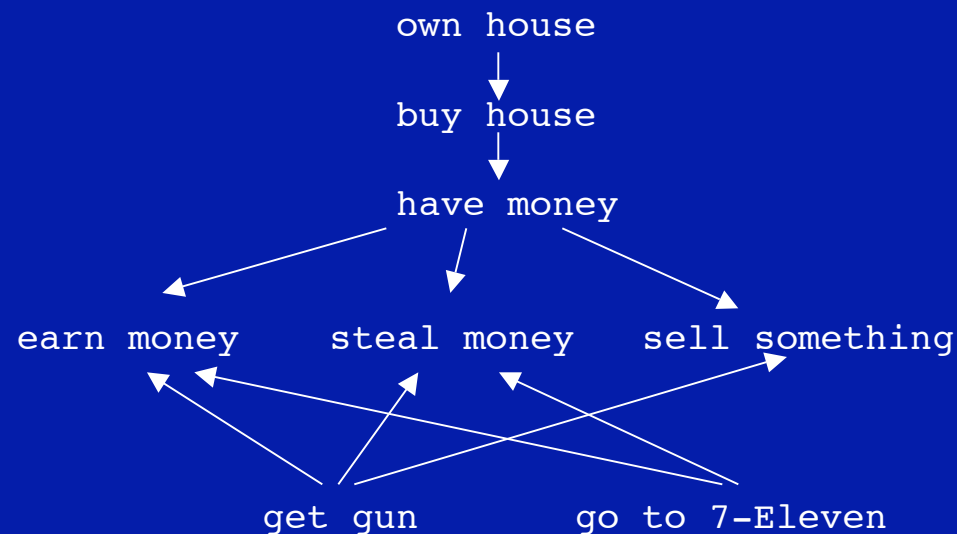
goal:

plan:

precond/subgoal:

possible plans:

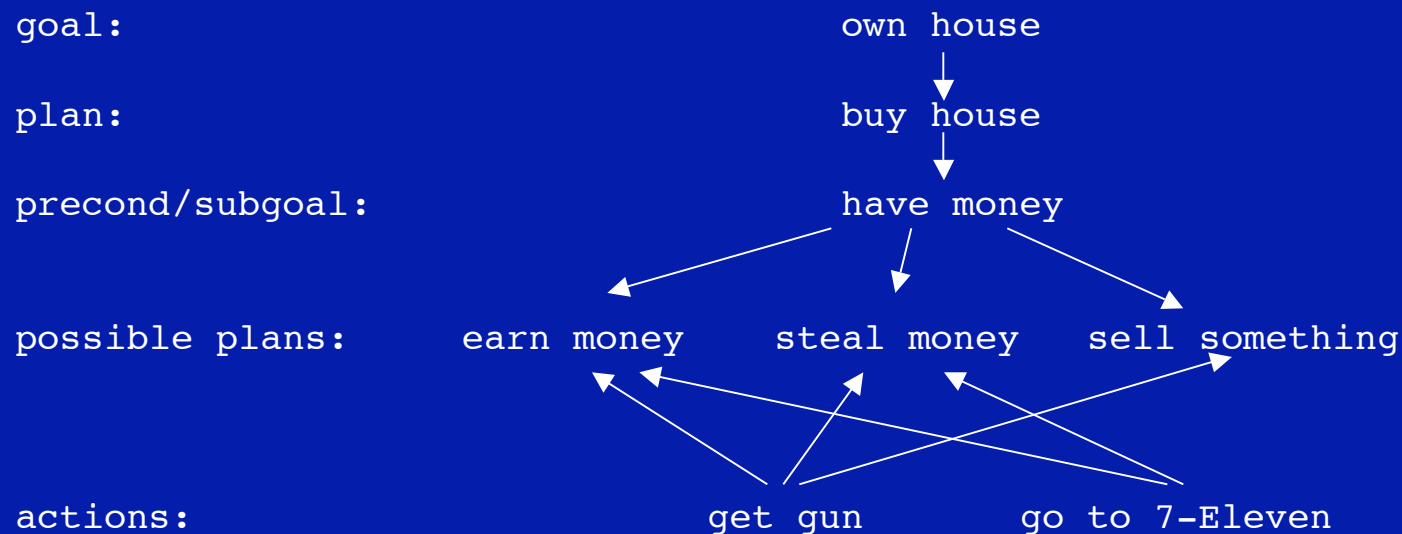
actions:



How do you figure out which plan is the connection?
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Using plans in language understanding

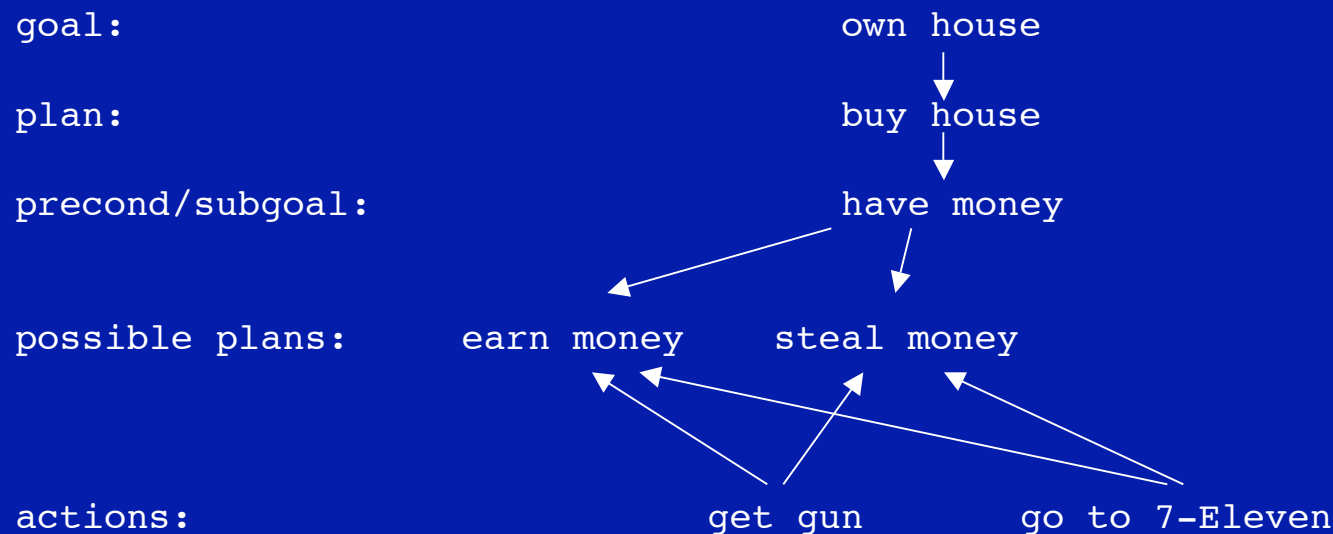
John needed money for a down payment on a new house.
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How do you figure out which plan is the connection?
The sell something plan may not explain the 7-Eleven.

Using plans in language understanding

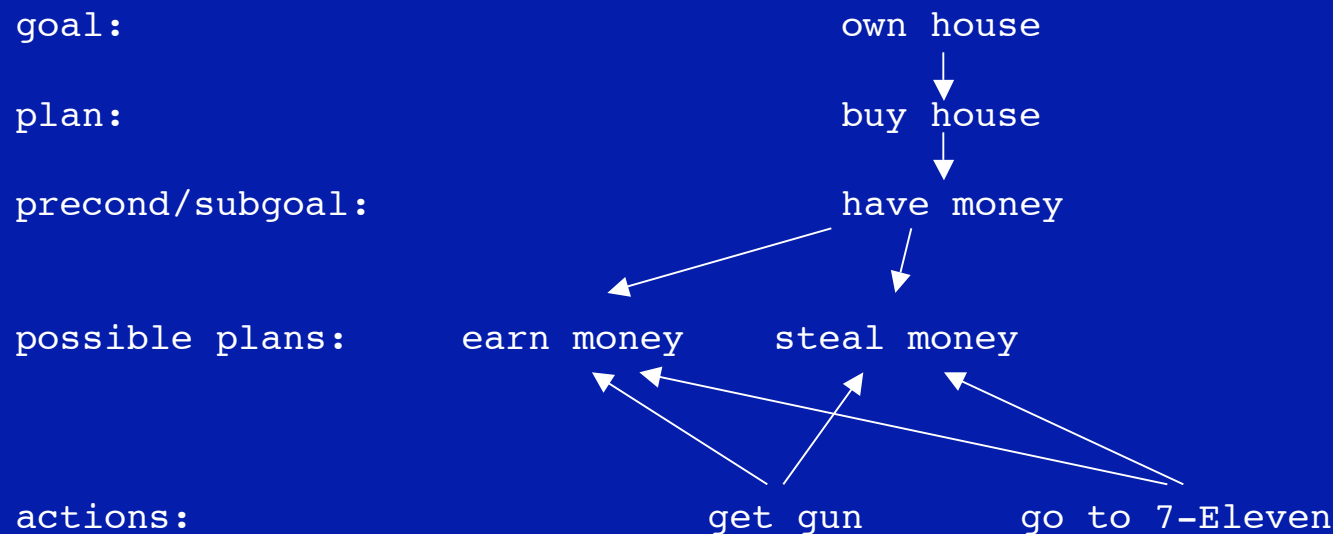
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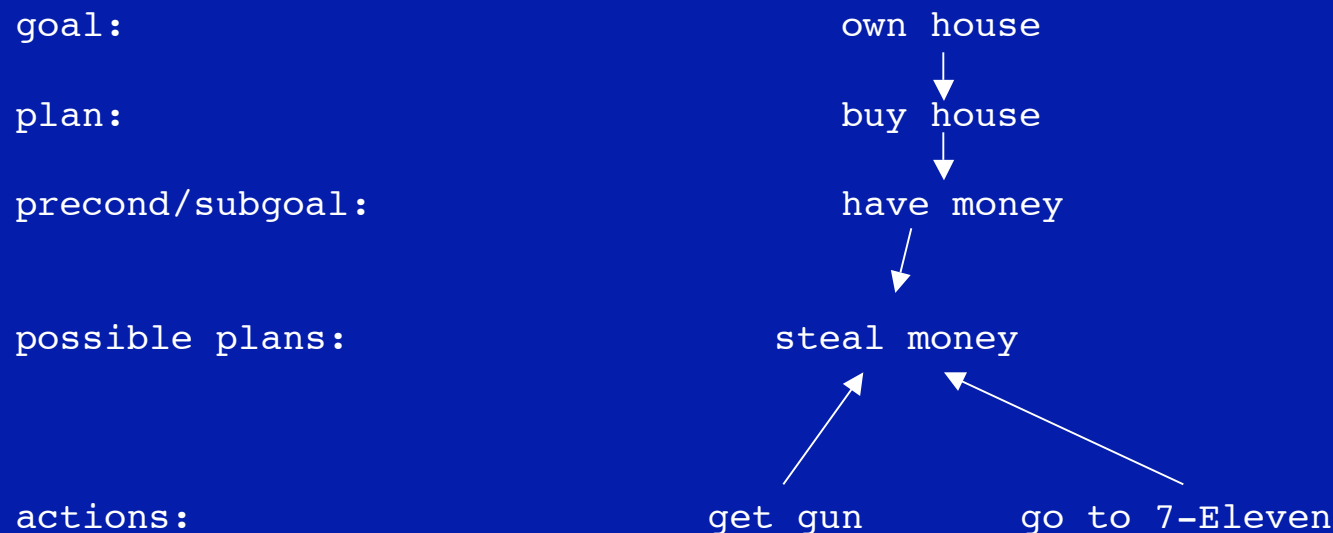
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He got his gun and went to the 7-Eleven store on the corner.



How do you figure out which plan is the connection?
We've learned to think that guns are tools for overpowering people (precondition to stealing), not for earning a living.

Using plans in language understanding

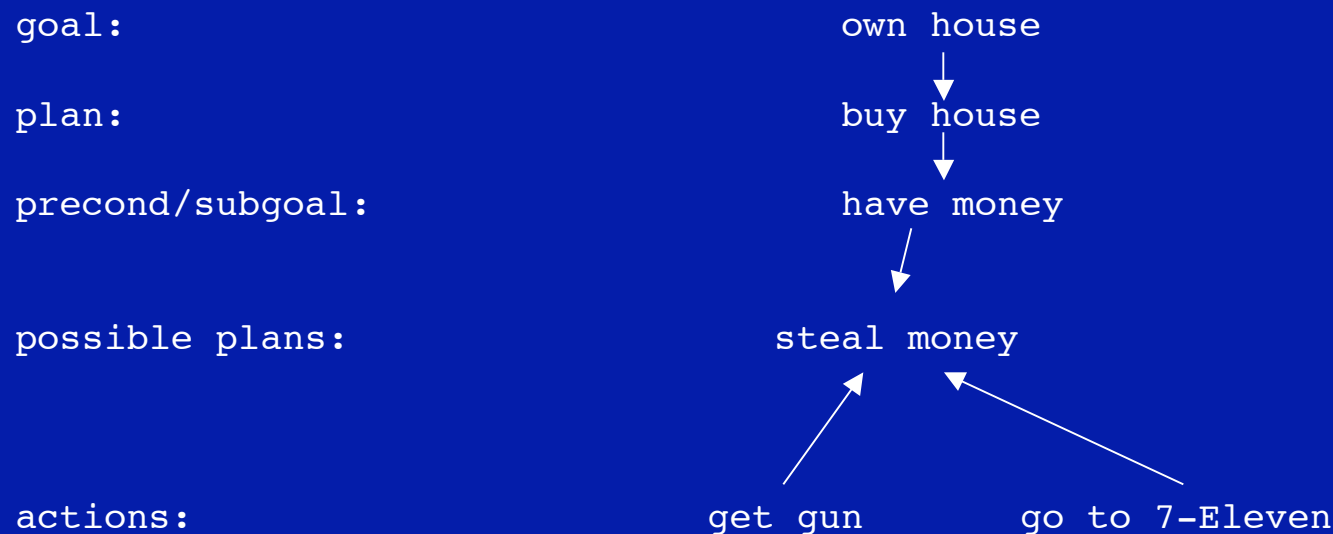
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Using plans in language understanding

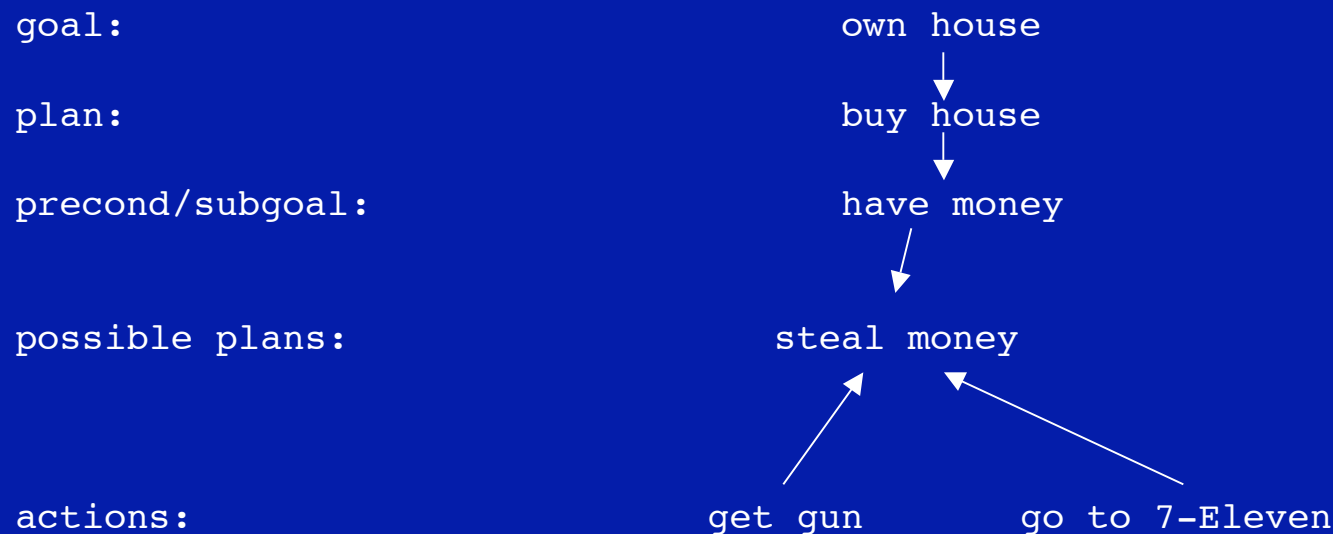
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That plan of stealing money becomes the context for understanding these two sentences as well as those that follow.

Using plans in language understanding

John needed money for a down payment on a new house.
He got his gun and went to the 7-Eleven store on the corner.



Where does that knowledge about an actor's goals and plans come from? Are we born with it? No, it comes from...

Learning (chapter 11)

Learning is the “holy grail” of artificial intelligence because it is the essential element in intelligence -- both natural and artificial. Why?

Learning

Learning is the “holy grail” of artificial intelligence because it is the essential element in intelligence -- both natural and artificial. Why?

People change as a result of their experiences. We adapt to new situations and learn from our experiences. If machines are going to be intelligent, they must be able to do the same.

Learning

Learning is the “holy grail” of artificial intelligence because it is the essential element in intelligence -- both natural and artificial. Why?

It's probably impossible to build in the large amount of knowledge required for any realistic domain by hand.

Learning

Learning is the “holy grail” of artificial intelligence because it is the essential element in intelligence -- both natural and artificial. Why?

Dealing with novel input inherently requires adaptation and learning (otherwise the system will only be able to deal with situations for which it was designed).

Learning

Learning is the “holy grail” of artificial intelligence because it is the essential element in intelligence -- both natural and artificial. Why?

Dealing with changing environments requires learning (since the knowledge base may otherwise become obsolete).

Learning

Learning is the “holy grail” of artificial intelligence because it is the essential element in intelligence -- both natural and artificial. Why?

It's the only way that artificially intelligent systems will seem really intelligent to people.

Learning

Definition: learning is the adaptive changes that occur in a system which enable that system to perform the same task or similar tasks more efficiently or more effectively over time.

This could mean:

- The range of behaviors is expanded: the agent can do more
- The accuracy on tasks is improved: the agent can do things better
- The speed is improved: the agent can do things faster

What kinds of learning do we do?

Here are some examples of the kinds of learning that people do. This is not an exhaustive list...

What kinds of learning do we do?

Rote learning

“1 times 3 is 3, 2 times 3 is 6, 3 times 3 is 9,...”

Taking advice from others

“If you have one piece close to the other end of the Oska board, try sacrificing some of your other pieces”

Learning from problem solving experiences

“I have to stack these blocks again...what do I know from last time that'll make this time easier so I don't have to do the planning thing again?”

Learning from examples

“Hmmm, last time at the watering hole, Og was eaten. The time before that, Zorg was eaten. I'm getting kind of thirsty....”

Learning by experimentation and discovery

“I wonder what will happen if I move this piece to that space?”

What kinds of learning do AI folks study?

supervised learning: given a set of pre-classified examples, learn to classify a new instance into its appropriate class

unsupervised learning: learning classifications when the examples are not already classified

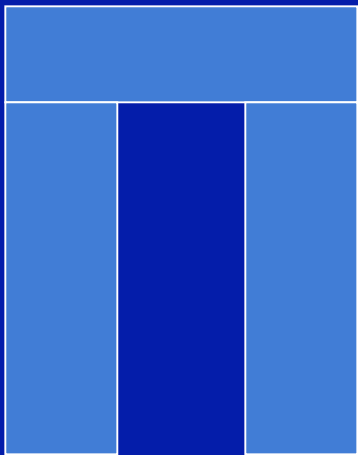
reinforcement learning: learning what to do based on rewards and punishments

analytic learning: learning to reason faster

(again, this is not an exhaustive list)

Example: Supervised learning of concept

Say it's important for your system to know what an arch is, in a structural sense. You want to teach the program by a series of examples. You tell your system that this is an arch:

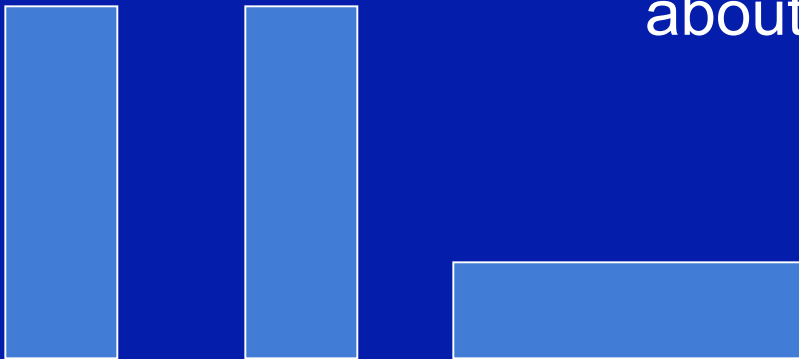


What does your system know about “archness” now?

Example: Supervised learning of concept

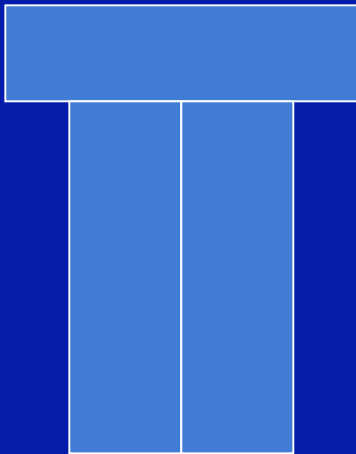
Now you tell it that this isn't an arch:

What does your system know
about "archness" now?



Example: Supervised learning of concept

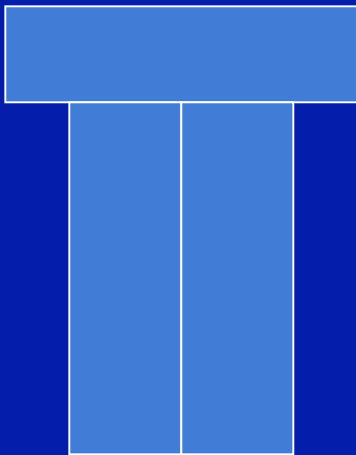
And then you tell it that this isn't an arch:



What does your system know about “archness” now?

Example: Supervised learning of concept

This may not seem all that exciting, but consider the same sort of task in a different domain....



What does your system know about “archness” now?

Example: Supervised learning of concept

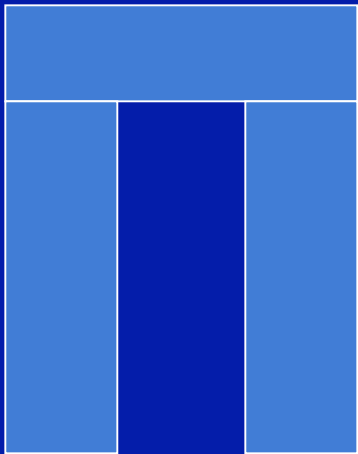
1 Gulfstream Park		Alw 36000N2X		1 MILE 70 YDS	
1 MILE 70 YARDS (1:39) ALLOWANCE. Purse \$36,000 FOR THREE YEAR OLDS WHICH HAVE NEVER WON TWO RACES OTHER THAN MAIDEN, CLAIMING OR STARTER OR WHICH HAVE NEVER WON THREE RACES. Weight, 122 lbs. Non-winners Of A Race Other Than Maiden, Claiming Or Starter At A Mile Or Over Since January 1 Allowed 2 lbs. Such A Race Since December 1 Allowed 4 lbs.				START & FINISH	
1 Smoocher Own: Franks Farms Red Green Orange, Jf On White Ball, White & SANTOS J A (135 23 11 10.17) 2003: (1157 176.15)		B. c. 3 (Feb) Sire: Kissin Kris (Kris S.) \$7,500 Dam: Alta's Princess (Screen King) Br: John Franks (Fia) Tr: Bert David R (4 0 1.00) 2003: (298 38.13)		Life 5 2 1 0 \$234,653 90 D.Fst 5 2 1 0 \$234,653 90 2004 1 0 0 0 \$3,000 77 Wet(324) 0 0 0 0 \$0 - 2003 4 2 1 0 \$231,653 90 Turf(233) 0 0 0 0 \$0 - GP 1 0 0 0 \$3,000 77 Dst(326) 3 1 1 0 \$196,475 90	
17Jan04-10GP fst 1 1/4 :24 :481 1:12:41.43 Holy Bull-G3 77 9 74 54 74 59 510 Santos J A L122 9.40 76-24 Second of June 1224 Silver Wagon 12010 Friends Lake 122 4 wide, tired 9 15Nov03-8W0 fst 1 1/4 :224 :463 1:11:41.432 Display 135k 86 2 35 39 32 20 210 McAleney J S L122 *1.35 79-25 Judiths Wild Rsn 1510 Smoocher 1221 Bgharround 1170 Inside, advance 4w 5 5Oct03-9W0 fst 1 1/4 :241 :474 1:12:41.463 Grey C-C-62 90 9 95 74 43 12 124 McAleney J S L113 6.35 73-30 Smoocher 134 Organ Grinder 184 Niggon 1143 Rail rly, jump tracks 9 31Aug03-5W0 fst 7/8 :224 :462 1:11:41.249 Md Sp Wt 60k 88 6 4 51 41 24 1m McAleney J S L120 *1.50 61-27 Smoocher 120 Picadilly Bay 1154 Campo Lago 1203 Duel outside, got nod 8 9Aug03-3W0 fst 5/8 :223 :463 1:12 1.182 Md Sp Wt 60k 62 2 6 49 4 52 5/4 McAleney J S L120 10.65 78-16 Wint'ry Wisky 117 Wily Not Gold 151 Gokky Go 1204 Broke in air Sw, turn 6 WORKS: Feb7 GP 5f fst 1:00 B 3/25 Jan11 GP 5f fst 1:00 H 2/17 Jan5 GP 4f fst :49 B 4/24 Dec28 GP 5f fst 1:00 H 2/24 Dec21 PmM 5f fst 1:01 B 3/23 Dec19 Tam 4f fst :50 B 1/31 TRAINER: 20H45-180/121 10 \$1.62 Dir(124.14 \$1.84) Routes(164.12 \$1.64) Alw(91.13 \$2.37)					
2 Caiman Own: Victor Achar White Red, Gold & Blue Chevrons, White BOULANGER G (102 6 7 10.06) 2003: (1254 183.15)		B. c. 3 (Feb) KEE NOV1 \$3,000 Sire: Malibu Moon (A.P. Indy) \$10,000 Dam: Storming Up (Storm Bird) Br: John T.L. Jones Jr (Kj) Tr: Medina Angel M(11 1 0 1.09) 2003: (107 9.08)		Life 4 2 1 0 \$4,032 68 D.Fst 4 2 1 0 \$4,032 68 2004 1 0 0 0 \$0 68 Wet(359) 0 0 0 0 \$0 - 2003 3 2 1 0 \$4,032 - Turf(236) 0 0 0 0 \$0 - GP 1 0 0 0 \$0 68 Dst(375) 1 0 0 0 \$0 68	
17Jan04-10GP fst 1 1/4 :24 :481 1:12:41.43 Holy Bull-G3 68 8 84 98 91 91 824 Boulanger G 116 75.70 71-24 Second of June 1224 Silver Wagon 12010 Friends Lake 122 Through after 1/2 9 17Oct03-Mexico City (Mex) ft 1 LH 1:404 Conditions Race Alw 3200 18 Contreras L A 109 3.00 Caiman 1099 First 1144 Parducci 1141 Tracked leader, led 1-1/2 out, easily 8 21Sep03-Mexico City (Mex) ft 7/8 LH 1:26 Conditions Race Alw 3200 21 Contreras L A 109 4.50 Lososki 1171 Caiman 1099 Chentex 1176 Tracked in St, gained 2nd 120 out 6 30Aug03-Mexico City (Mex) ft 6/8 LH 1:14 Maiden Claimer Md dn Clm 2000 11 Lara R A 110 4.40 Caiman 1101 Quien Cobra 114 Qui Woker 1105 Handily placed, led over 1f out, driving 7 WORKS: Feb8 GP 5f fst 1:03 B 5/24 Jan28 Crc 3f fst :35 H 9/15 Jan13 Crc 3f fst :49 B 3/28 Dec19 Crc 4f fst :50 B 10/23 TRAINER: 20H45-180/111 27 \$3.75 1stLax(8.10 \$0.80) Dir(18.89 \$1.26) Routes(48.04 \$0.58) Alw(10.10 \$0.00)					
11Jly03-4Crc fst 5f :224 :471 1:004 Md 40000(0-35) 60 1 4 54 56 31 1 Boulanger G L118 9.10 64-17 All True 1181 Grand Red 1181 Superstar Prospect 1182 Sdy bkstr, rail rally 8 WORKS: Jan27 Crc 1 fst :49 B 3/3 Jan20 Crc 5f fst 1:02 B 9/15 Jan3 Crc 3f fst :37 B 3/15 Dec15 Crc 5f fst 1:04 H 4/10 Dec Crc 4f fst :40 H 9/24 Nov29 Crc 4f fst :50 B 2/25 TRAINER: Sprint/Route(44.05 \$0.48) Dir(130.12 \$1.37) Routes(265.10 \$1.08) Alw(100.10 \$1.36)					
4 Capejinsky Own: John D Murphy Sr Yellow Green, Pink Diamond Belt, Pink Sleeves BRAVO J (151 12 22 27.08) 2003: (590 128.22)		B. c. 3 (May) KEE SEP02 \$120,000 Sire: Cape Town (Seeking the Gold) \$25,000 Dam: Gwenjinsky (Seattle Dancer) Br: Cabotela Partnership (Ky) Tr: Gorham Michael E(30 2 4 4.87) 2003: (388 64.16)		Life 6 2 3 0 \$110,740 83 D.Fst 5 2 2 0 \$99,000 82 2003 6 2 3 0 \$110,740 83 Wet(343) 1 0 1 0 \$11,740 83 L 118 2002 0 M 0 0 \$0 - Turf(294) 0 0 0 0 \$0 - GP 0 0 0 0 \$0 - Dst(328) 1 0 0 0 \$3,000 82	
15Nov03-6Lr fst 1 1/4 :24 :481 1:12:41.434 Lr fst-G3 82 5 77 79 79 69 59 Valdes R A L122 7.10 61-15 Tapit 1224 Polish Rifle 1221 Ghost Mountain 1221 Wide trip, no response 7 11Oct03-7Dl fst 1 1/4 :244 :489 1:14:13.392 Dover 100k 82 1 32 53 41 1 14 Valdes R A L116 2.60 87-22 Capejinsky 1164 Tsuzommi 1161 Hurricane Shocky 1161 Boxed, much the best 8 13Sep03-8Dl sly 1 :239 :472 1:12:13.379 Whirlig Ash 58k 83 5 54 51 24 24 26 Valdes R A L118 5.60 91-18 Paddington 118 Capejinsky 1189 Venizia 1181 Circled, second best 7 26Jly03-3Dl fst 5f :222 :461 59.1059 Md Sp Wt 36k 71 7 3 43 34 31 15 Black A S L118 *50 90-07 Capejinsky 1189 WanaKa 184 Atticus Kristy 183 Bid 4w, drew off late 7 6Jly03-6Dl fst 6f :222 :463 58:11.111 Md Sp Wt 36k 72 3 3 43 31 21 21 Black A S L118 *2.10 87-10 P. Kerney 1181 Capejinsky 1189 Musical Vision 1181 Gradually closed gap 8 15Jun03-6Dl fst 5f :222 :464 58:11.111 Md Sp Wt 36k 61 5 1 24 24 26 24 Black A S L118 2.20 91-10 Stored 189 Capejinsky 1181 Heworth 1184 No match, easily 2nd 5 WORKS: Feb7 GP 4f fst :49 B 2/62 Jan26 GP 5f fst 1:00 H 3/13 Jan14 GP 5f fst 1:03 B 2/26 Jan4 GP 5f fst 1:00 H 1/22 Dec19 GP 4f fst :51 B 18/22 TRAINER: 61-180Days(40.15 \$1.37) Dir(136.16 \$1.73) Routes(178.11 \$2.11) Alw(93.14 \$1.12)					
5 Farnum Alley Own: Laura & Eugene Meloy Dark Navy Blue, Gold Chevrons, Navy Blue DAY P (20 4 13.20) 2003: (905 215.22)		B. c. 3 (May) KEE SEP02 \$150,000 Sire: Distorted Humor (Forty Niner) \$50,000 Dam: Falon (Cox's Ridge) Br: WinStar Farm LLC (Ky) Tr: Reinster Anthony(12 2 3 1.17) 2003: (190 34.18)		Life 3 2 0 0 \$47,855 80 D.Fst 2 1 0 0 \$20,400 79 2004 1 1 0 0 \$20,400 79 Wet(395) 1 1 0 0 \$27,455 80 L 122 2003 2 1 0 0 \$27,455 80 Turf(270) 0 0 0 0 \$0 - GP 1 1 0 0 \$20,400 79 Dst(355) 1 1 0 0 \$20,400 79	
15Jan04-5GP fst 1 1/4 :24 :483 1:13:1.45 Alw 34000w1k 79 1 79 79 99 31 1m Peck B D L120b 16.60 64-15 Farnum Alley 120 Tiger Heart 1181 Speedjama 1181 Angled out, just up 10 19Nov03-5CD gd 1 @ 23 :464 1:12:13.384 Md Sp Wt 43k 80 5 43 34 41 21 1k Martinez J R Jr L122b 5.50 73-24 Farnum Alley 120 Shots 1221 Crson Unleashed 1221 Angled Sw lane, driving 10 1Nov03-5CD fst 6f :223 :46 1:12 1.184 Md Sp Wt 42k 53 6 9 111 912 99 79 Martinez J R Jr L122b 18.40 71-14 Exploit Storm 122 Pure 122 Go Now 1221 Duck out hit, foe start 12 WORKS: Feb6 PmM 5f my 1:04 B 18/21 Jan7 PmM 4f fst :51 B 3/40 Jan10 PmM 5f fst 1:02 B 3/37 Dec28 PmM 4f fst :50 B 2/46 Dec22 PmM 4f fst :49 B 9/27 Dec15 PmM 4f fst :50 B 17/20 TRAINER: 20H45-180/128 18 \$1.27 Dir(119.13 \$1.61) Routes(172.18 \$1.87) Alw(75.21 \$2.32)					
6 Birdstone Own: Marylou Whitney Stables Red Elton Blue, Brown Belt, Brown Cap BAILY J D (73 13 13.18) 2003: (776 206.27)		B. c. 3 (May) Sire: Grindstone (Unbridled) \$5,000 Dam: Dear Birdie (Storm Bird) Br: Marylou Whitney Stables (Ky) Tr: Zito Nicholas P(42 5 6 6.12) 2003: (507 77.15)		Life 3 2 0 0 \$339,000 99 D.Fst 2 1 0 0 \$312,000 94 L 118 2003 3 2 0 0 \$339,000 99 Wet(333) 1 1 0 0 \$27,000 94 2002 0 M 0 0 \$0 - Turf(195) 0 0 0 0 \$0 - GP 0 0 0 0 \$0 - Dst(337) 1 1 0 0 \$300,000 94	
4Oct03-76L fst 1 1/4 :234 :481 1:13:1.44 Champagne-G1 94 3 43 31 21 1m Bailey J D L122 2.25 80-26 Birdstone 1223 Chpel Roy 1122 Dshbord Drumm 122 3 wide, going away 7 30Aug03-8Sar fst 7f :222 :464 1:10:1.232 Hopeful-G1 70 6 1 61 51 31 46 Prado E S L122 2.30 83-11 Silver Wagon 124 Chpl Roy 1221 Notorious Rogu 1221 Hit gate start, 5 wide 7 2Aug03-4Sar my 6f :214 :464 58 1:101 Md Sp Wt 45k 99 4 5 34 13 18 112 Prado E S L119 3.85 91-12 Birdstone 1191 Bold Loy 1194 Hornshope 1191 When ready, drew off 9 WORKS: Feb10 PmM 4f fst :50 B 2/47 Feb4 PmM 6f fst 1:15 B 6/7 Jan24 PmM 5f fst 1:02 B 1/39 Jan7 PmM 5f fst 1:02 B 1/38 Jan10 PmM 4f fst :40 B 1/31 Dec30 PmM 3f fst :37 B 1/3 TRAINER: 61-180Days(66.09 \$0.54) Dir(159.15 \$1.98) Routes(322.14 \$1.55) Alw(187.12 \$1.22)					

What does your system know about “winning horses” now?

But I digress....

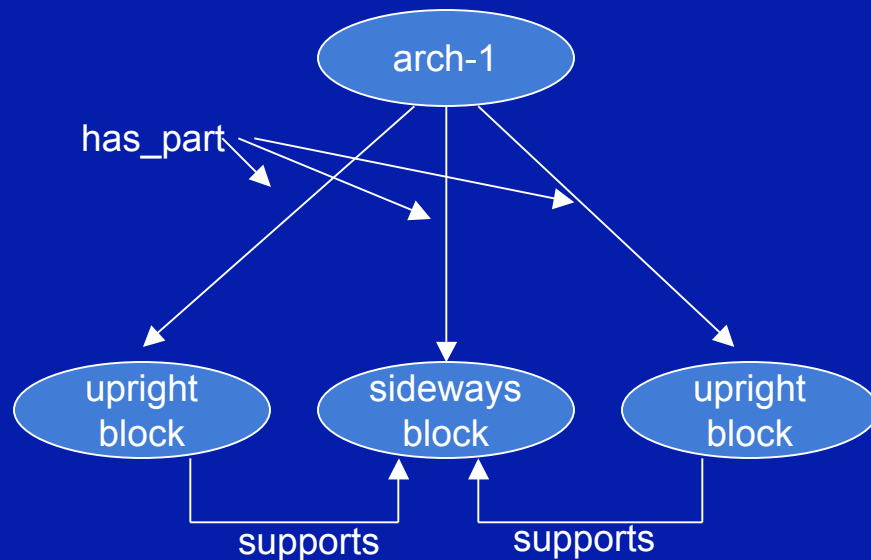
Example: Supervised learning of concept

Let's go back to the simpler arch problem and see how a computer program could learn the concept



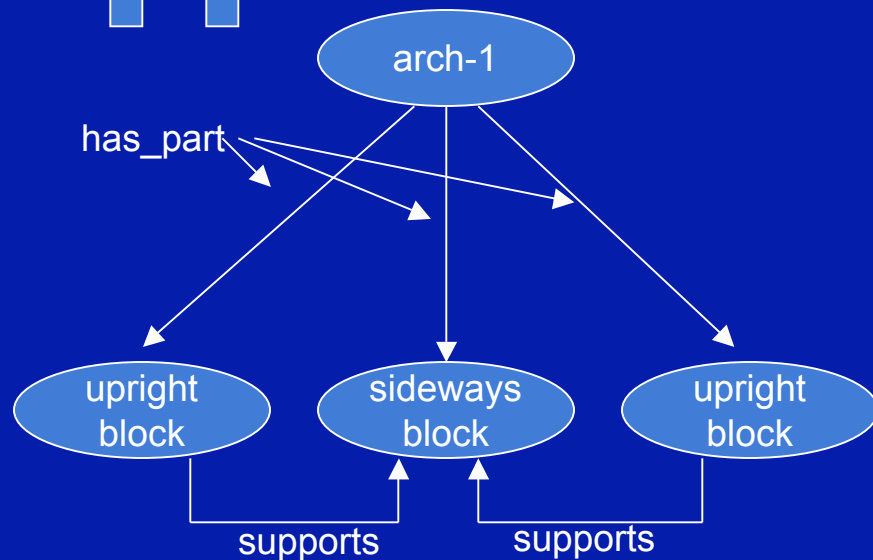
Example: Supervised learning of concept

We need to provide a representation language for these arch examples. A semantic network with nodes like “upright block” and “sideways block” and relations like “supports” and “has_part” works:



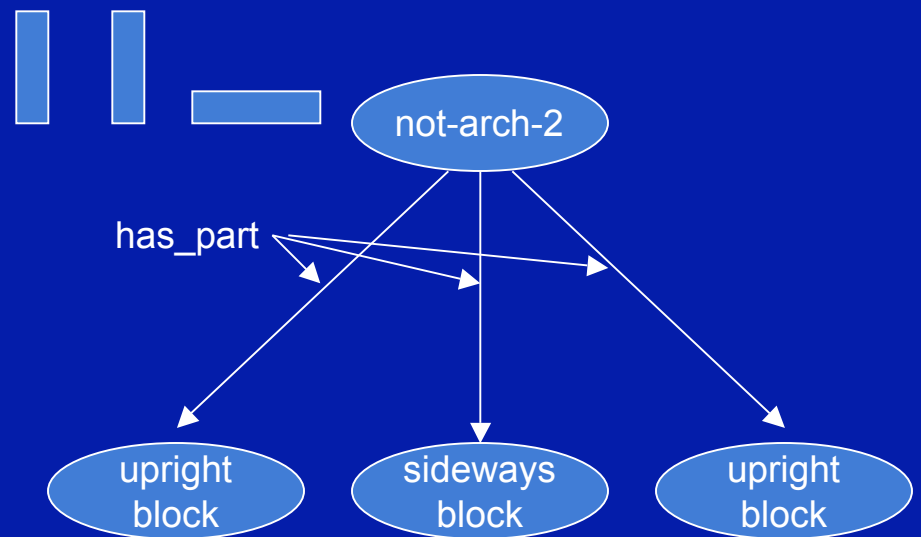
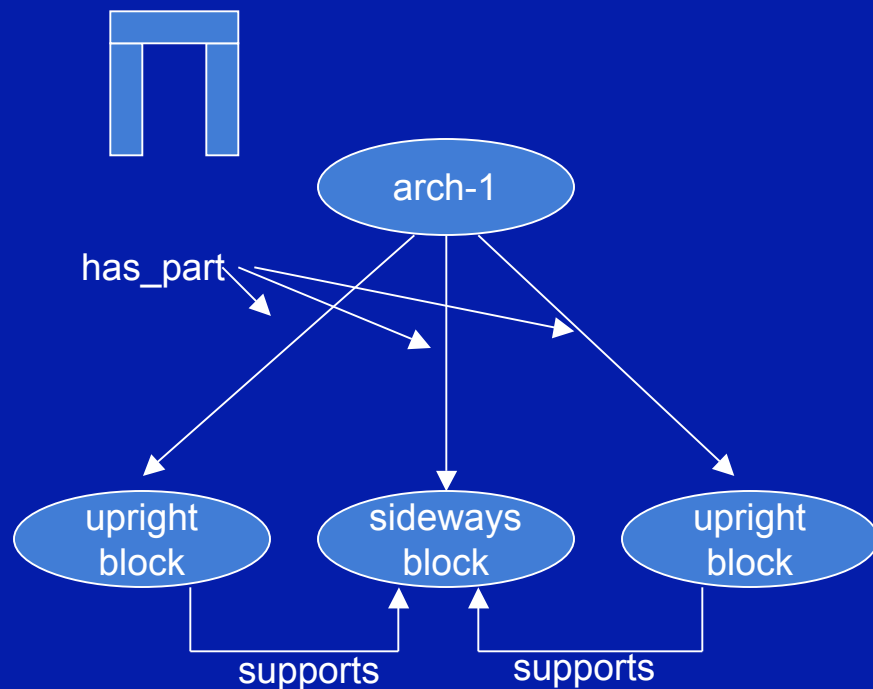
Example: Supervised learning of concept

So let's say our arch-learning program doesn't yet have a concept for arch. We start it off with this semantic net as a positive training example. This is now what it knows about "archness"...its internalized arch concept.



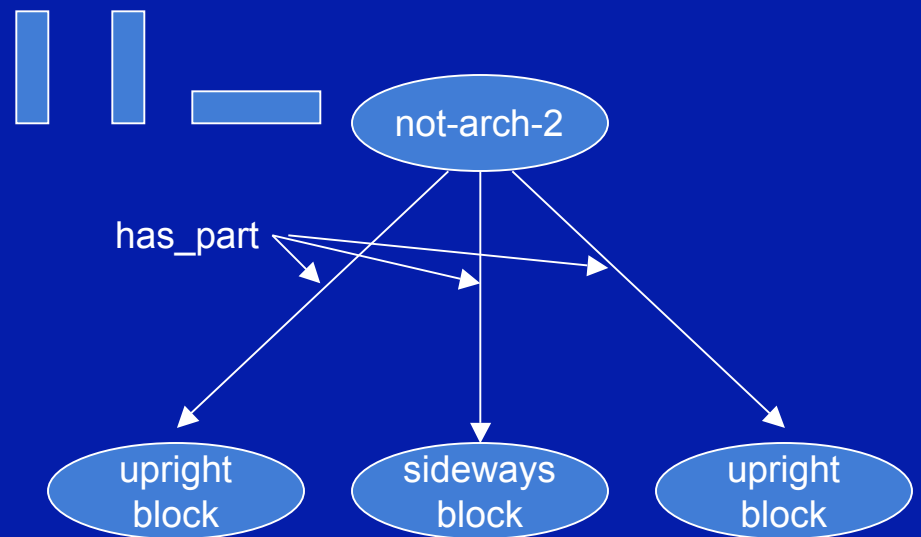
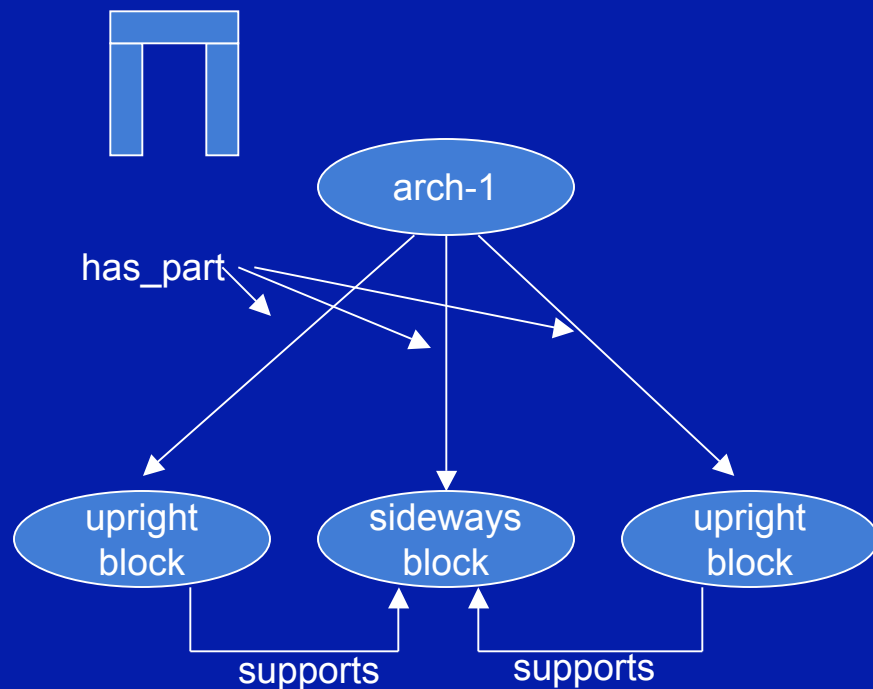
Example: Supervised learning of concept

Now we present the program with a negative example or “near miss” ...almost an arch, but not quite:



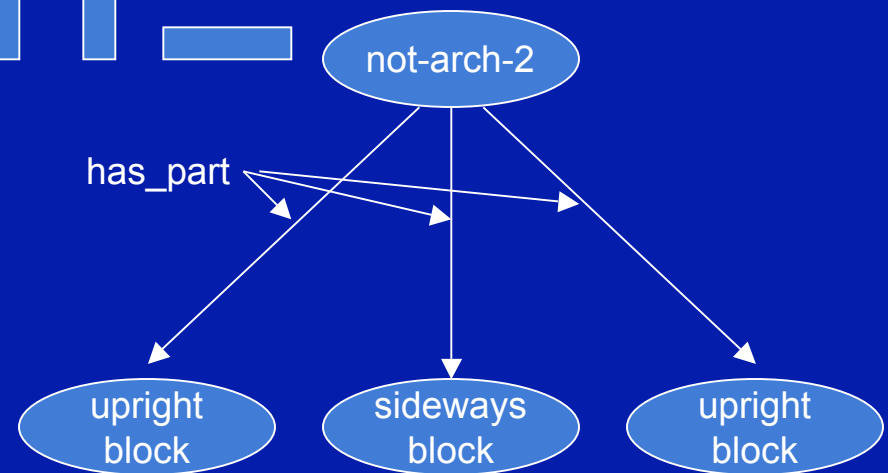
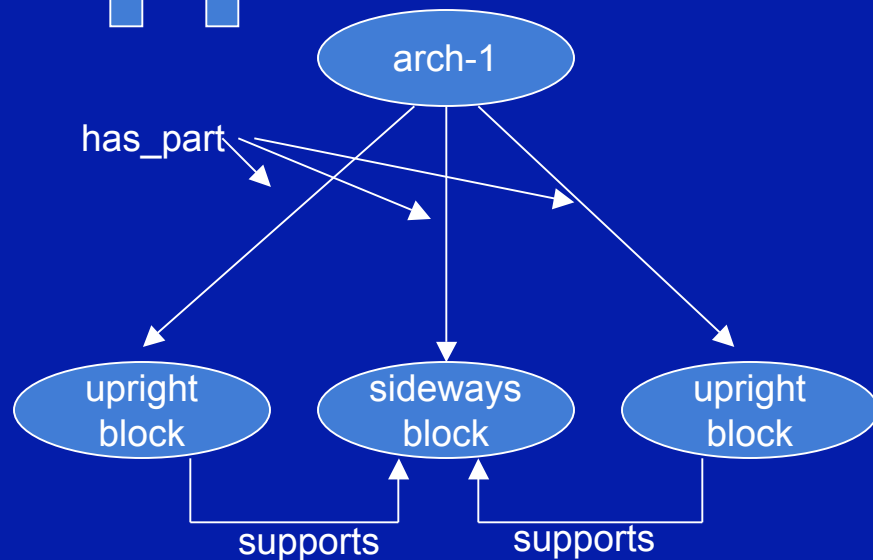
Example: Supervised learning of concept

The program must now figure out what the difference is between its arch concept and the near miss. What is it?



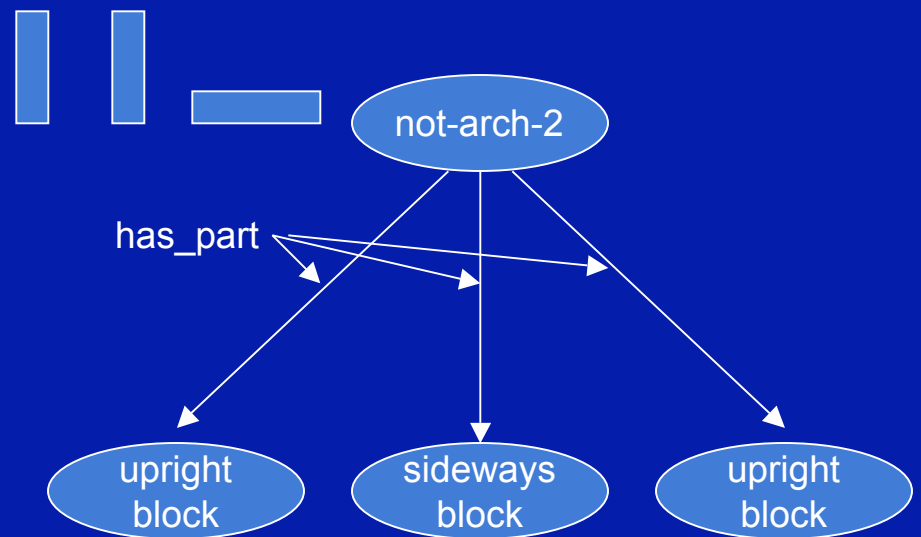
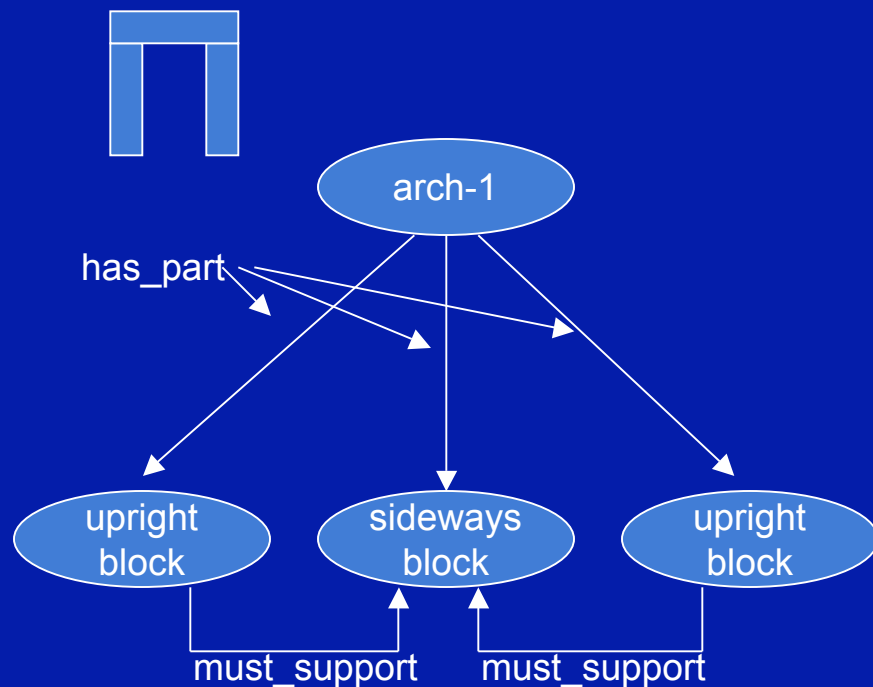
Example: Supervised learning of concept

The difference is that the support links are missing in the negative example. Since that's the only difference, the support links must be required. That is, the upright blocks must support the sideways block.



Example: Supervised learning of concept

The program revises its concept of the arch accordingly.



Example: Supervised learning of concept

Negative examples help the learning procedure specialize. If the model of an arch is too general (too inclusive), the negative examples will tell the procedure in what ways to make the model more specific.

