CS561 Artificial Intelligence - Spring 2010 Midterm 2 Solutions

1. (25 points) First-order Logic / Knowledge Representation [Graded by Rohan]

Part a:

 $\forall pPerson(p) \land Person(Raymond) \Rightarrow Loves(p,Raymond)$ $\forall pPerson(p) \Rightarrow Loves(p,Raymond)$ $\forall pLoves(p,Raymond)$

Part b:

 $\forall \ c,dCat(c) \land \ Dog(d) \land \ Day(Tuesday) \Rightarrow Rains(c,Tuesday) \land \ Rains(d,Tuesday) \\ \forall \ c,dCat(c) \land \ Dog(d) \Rightarrow Rains(c,Tuesday) \land \ Rains(d,Tuesday)$

Part c:

 $\exists \, d, oDog(d) \land \, Owner(o,d) \Rightarrow \forall \, cCat(c) \land \, Likes(o,c) \\ \exists \, d, o \, \forall \, cDog(d) \land \, Owner(o,d) \Rightarrow Cat(c) \land \, Likes(o,c)$

Part d:

 $\exists x Person(x) \Rightarrow Human(x) \equiv \exists x \neg Person(x) \lor Human(x)$ but what we want is $\exists x Person(x) \land Human(x)$

Hence, using implication and existential quantification may yield incorrect results.

Part e:

 $\forall x Person(x) \Rightarrow Human(x) \equiv \forall x \neg Person(x) \lor Human(x)$

This means that if Person(x) is true, then Human(x) must be true. However $\forall x Person(x) \land Human(x)$ does not mean that if Person(x) is true that Human(x) must be true, therefore using and with universal quantification may yield incorrect results.

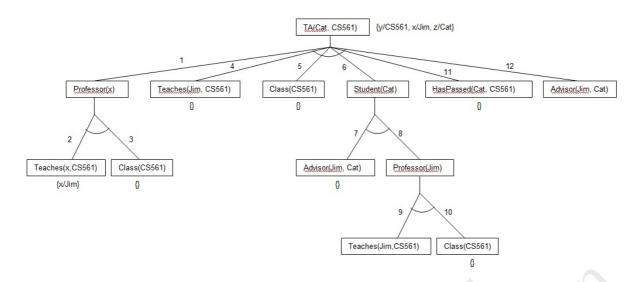
OR The key is using universal identifier, the predicate has to be universal truth. Forall x Person(x) ^ Human(x) . Since all objects in the universe are not necessarily human/person, therefore this predicate cannot represent the correct semantics.

Part f:

Yes, but it may require a large number of literals making it far less efficient, but easier to evaluate.

2. (40 points) First-order Inference [Solution by Nadeesha, Part a. graded by William, Part b. graded by Nadeesha]

Part a:



Grading key:

3 points: Show proof that backward chaining was attempted

1 point: Numbering the edges

1 point: Unifications

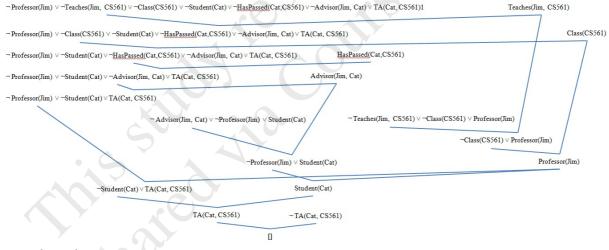
9 points: Clauses to imply TA(z,y) (1 point for each clause and 0.5 point for each edge) 3 points: Clauses to imply Professor(x) (1 point for each clause and 0.5 point for each

edge)

3 points: Clauses to imply Student(y) (1 point for each clause and 0.5 point for each

edge)

Part b:

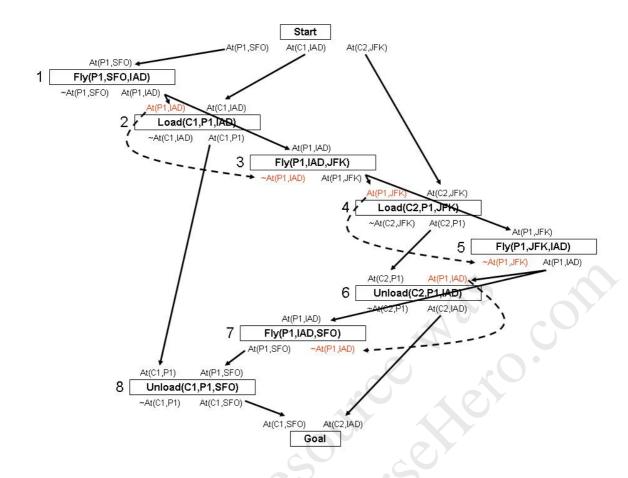


Grading key:

-1 for each missing step towards the empty clause or each major error

3. (25 points) Planning (STRIPS) [Solution by William, Graded by Guan]

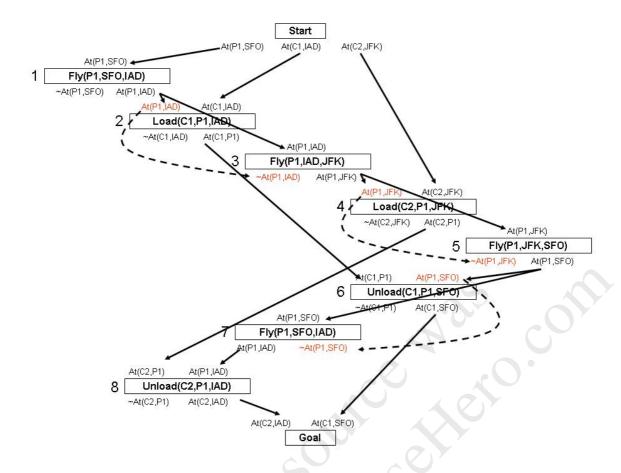
Solution 1
Part a:



1 possible linear solution.

Solution: Fly(P1,SFO,IAD) -> Load(C1,P1,IAD) -> Fly(P1,IAD,JFK) -> Load(C2,P1,JFK) -> Fly(P1,JFK,IAD) -> Unload(C2,P1,IAD) -> Fly(P1,IAD,SFO) -> Unload(C1,P1,SFO)

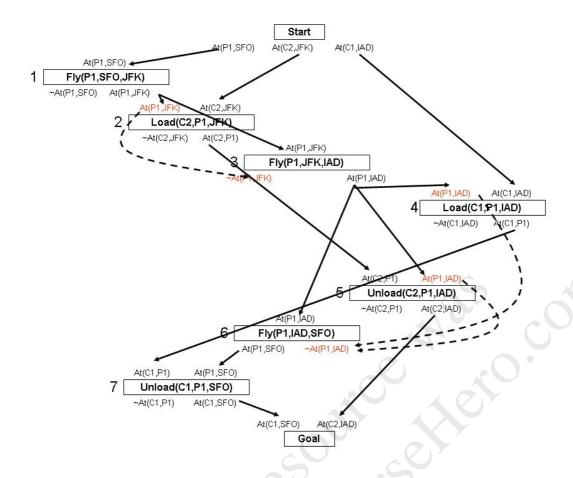
Solution 2 Part a:



1 possible linear solution.

Solution: Fly(P1,SFO,IAD) -> Load(C1,P1,IAD) -> Fly(P1,IAD,JFK) -> Load(C2,P1,JFK) -> Fly(P1,JFK,SFO) -> Unload(C1,P1,SFO) -> Fly(P1,SFO,IAD) -> Unload(C2,P1,IAD)

Solution 3 Part a:



2 possible linear solutions.

Solution: Fly(P1,SFO,JFK) -> Load(C2,P1,JFK) -> Fly(P1,JFK,IAD) ->

Load(C1,P1,ÎAD) -> Unload(C2,P1,ÎAD) -> Fly(P1,ÎAD,SFO) ->

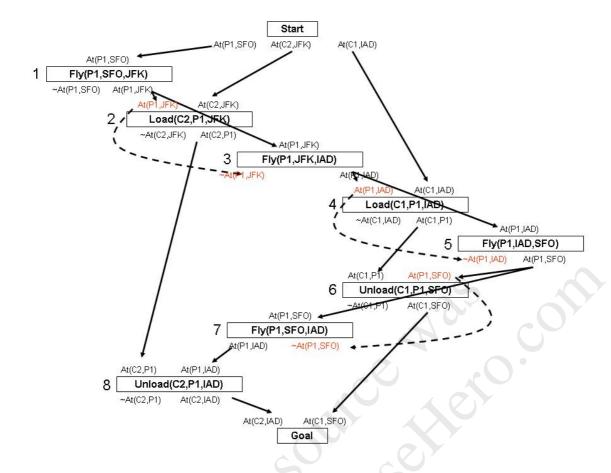
Unload(C1,P1,SFO)

Solution: Fly(P1,SFO,JFK) -> Load(C2,P1,JFK) -> Fly(P1,JFK,IAD) ->

Unload(C2,P1,IAD) -> Load(C1,P1,IAD) -> Fly(P1,IAD,SFO) ->

Unload(C1,P1,SF0)

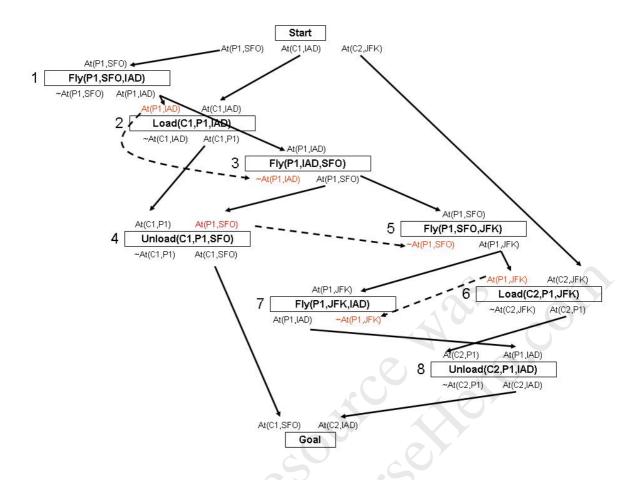
Solution 4 Part a:



1 possible linear solutions.

Solution: Fly(P1,SFO,JFK) -> Load(C2,P1,JFK) -> Fly(P1,JFK,IAD) -> Load(C1,P1,IAD) -> Fly(P1,IAD,SFO) -> Unload(C1,P1,SFO) -> Fly(P1,SFO,IAD) -> Unload(C2,P1,IAD)

Solution 5 Part a:



1 possible linear solutions.

Solution: $Fly(P1,SFO,IAD) \rightarrow Load(C1,P1,IAD) \rightarrow Fly(P1,IAD,SFO) \rightarrow Unload(C1,P1,SFO) \rightarrow Fly(P1,SFO,JFK) \rightarrow Load(C2,P1,JFK) \rightarrow Fly(P1,JFK,IAD) \rightarrow Unload(C2,P1,IAD)$

Grading Key:

a)

write something 5 points

understanding of planning 5 points if answer contains states and links

or 3 points

correct 2 points if answer is correct

finish 2 points if answer has a finish state

numbering actions 1 point

causal link 3 points if the line starts from the effect and

ends at another precondition

or 1 point if there's a line

clobbers 2 points if all the clobbers are correct

or 1 point if the clobber are partially correct

b)

number of solutions 1 point

solution 4 points if correct

or 1 or 2 or 3 points based on solution

4. (15 points) Probability [Solution by William, Graded by Rohan]

By definition, the variables are independent. Only give partial credit for people who decides they are not dependent, unless they explicitly state their dependence assumptions.

Part a:

If you assume that the variables are independent, then P(x1=true,x2=true,x3=true,x4=true) = $P(x1=true) \times P(x2=true) \times P(x3=true) \times P(x4=true)$ = $0.75 \times 0.75 \times 0.25 \times 0.25$

Otherwise,

P(x1=true,x2=true,x3=true,x4=true)
= P(x1=true|x2=true,x3=true,x4=true) x P(x2=true|x3=true,x4=true) x P(x3=true|x4=true) x P(x4=true)
or some other combination of conditional probabilities

Part b:

If you assume that the variables are independent, then P(x1=false,x2=false,x3=false,x4=false) = $P(x1=false) \times P(x2=false) \times P(x3=false) \times P(x4=false)$ = $(1-0.75) \times (1-0.75) \times (1-0.25) \times (1-0.25)$ = $0.25 \times 0.25 \times 0.75 \times 0.75$

Otherwise,

P(x1=false,x2=false,x3=false,x4=false) = P(x1=false|x2=false,x3=false,x4=false) x P(x2=false|x3=false,x4=false) x P(x3=false|x4=false) x P(x4=false) or some other combination of conditional probabilities

Part c:

If you assume that the variables are independent, then yes. Otherwise, no.

5. (45 points) Probabilistic Inference [Solution by Harris, Graded by Harris]

Part a:

 $P(A \land B \land C \land D \land E) = P(F|E,B)P(E|C,D)P(C|A)P(D|B)P(B|A)P(A)$

Part b:

As we know the truth value of A,B,C,E,F and according to the Bayesian Network, the probability of D depends on truth value of B. Therefore, we only have to get the answer straight from the network P(D|B) for B is true and $P(D|\sim B)$ for B is not true.

Part c:

Since D is independent of C, the observation of C will not affect the prob(D).

We can infer $P(D|A) = P(D|B)P(B|A) + P(D|\sim B)P(\sim B|A)$ $P(D|\sim A) = P(D|B)P(B|\sim A) + P(D|\sim B)P(\sim B|\sim A)$

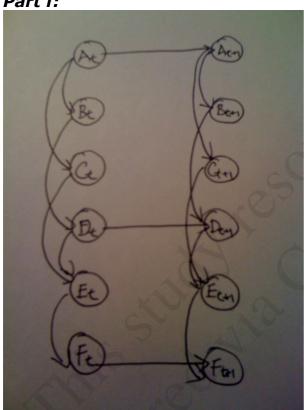
Part d:

It includes its parent (B), its child (E) and its child's parent (C).

Part e:

For direct inference of E, we need the observations of C and D only.





For this, it is enough if they just add the three temporal nodes (A_t, D_t and F_t).