

I will not use a source other than my brain on this exam (not neighbors, not notes, not books, etc):

\_\_\_\_\_ (please sign)

1. Consider the data set

<u>V1</u>	<u>V2</u>	<u>V3</u>	<u>V4</u>	<u>C(class)</u>
1	-1	-1	1	-1
1	1	1	-1	-1
1	-1	-1	-1	-1
1	1	1	1	-1
-1	-1	1	1	1
-1	1	-1	1	1
-1	1	-1	-1	1
-1	-1	1	-1	1

**a) (2 pts)** Which variable,  $V_i$ , would be selected by a decision tree learner of the type described in the lecture as the root of the decision tree? Explain.

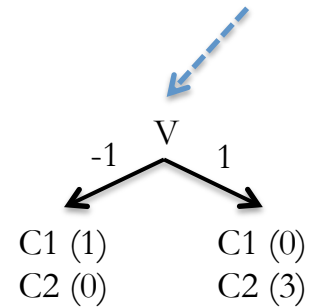
**b) (2 pts)** Give the value of  $P(C=1 | V2=1)$  as computed from the data table above (i.e., as a fraction or a floating point number; do not use pseudo-counts):

**c) (2 pts)** Give the value of  $P(C=1 | V2=1, V3=1)$  as computed from the table above (as a fraction or a floating point number; do not use pseudo-counts):

2. Assume that a decision tree has been constructed from training data, and it includes a node that tests on  $V$  at the frontier of the tree, with its left child yielding a prediction of class  $C1$  (because the only training datum there is  $C1$ ), and the right child predicting  $C2$  (because the only training data there are  $C2$ ). The situation is illustrated here:

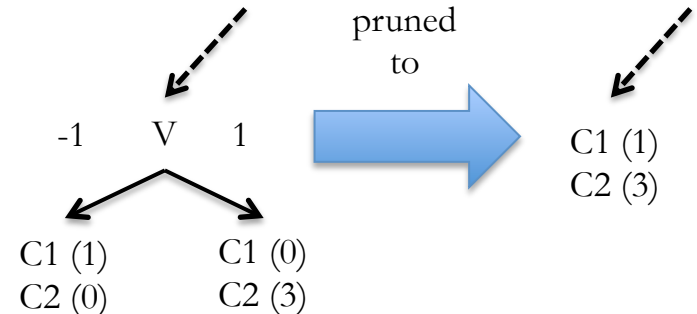
Suppose that during subsequent use, it is found that

- i) a large # of items ( $N > 1000$ ) are classified to the node with the test on  $V$  to the right
- ii) 50% of these have  $V = -1$  and 50% of these have  $V = 1$
- iii) post classification analysis shows that of the  $N$  items reaching the node during usage, 25% were  $C1$  and 75% were  $C2$
- iv) of the  $0.5 * N$  items that went to the left leaf during usage, 25% were  $C1$  and 75% were  $C2$
- v) of the  $0.5 * N$  items that went to the right leaf during usage, 25% were also  $C1$  and 75% were  $C2$

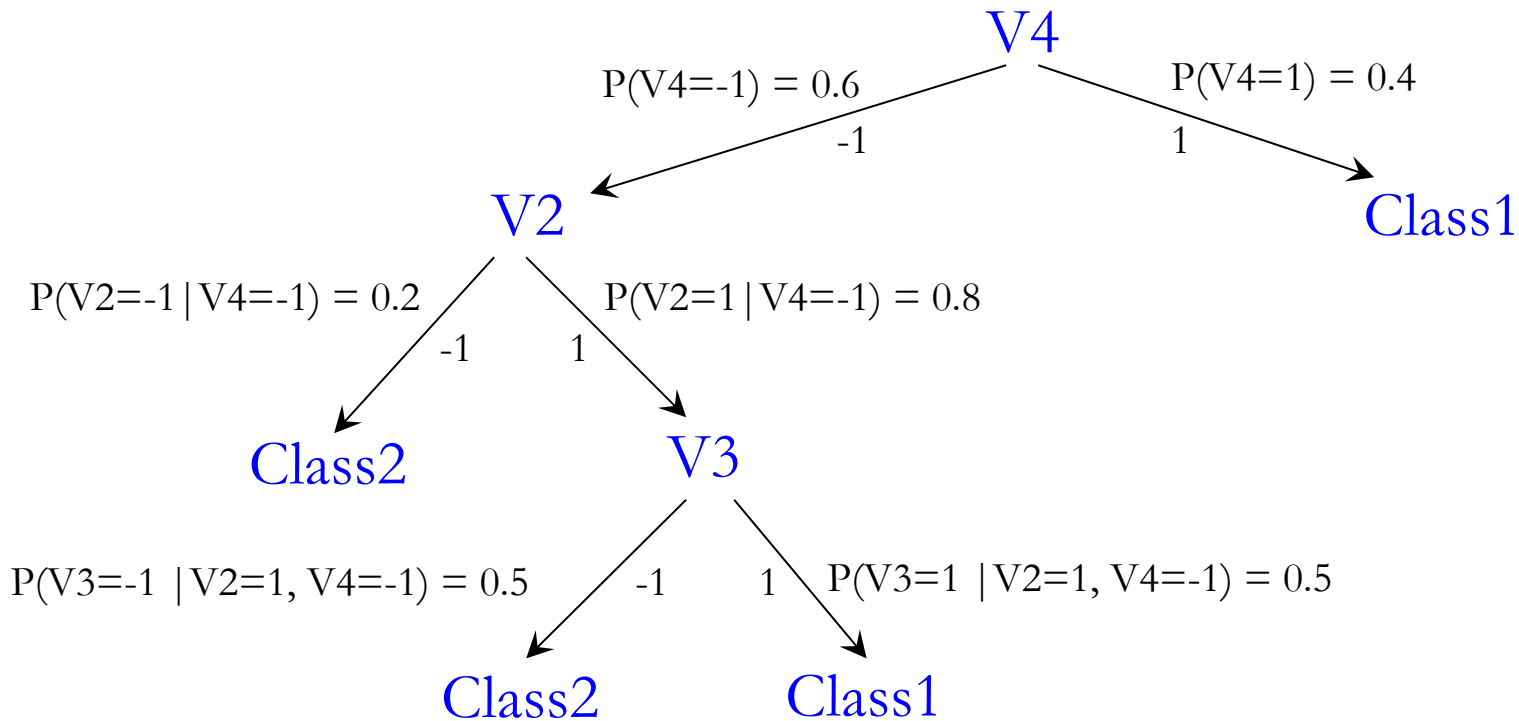


a) (2 pts) What was the error rate on the sample of  $N$  items that went to the sub-tree shown above?

b) (2 pts) What would the error rate on the same sample of  $N$  items have been if the sub-tree on previous page (and reproduced here) had been pruned to not include the final test on  $V$ , but to rather be a leaf that predicted  $C2$ ?



3. (4 pts) Consider the following decision tree, where each variable (including the Class variable) is binary valued. Along each Branch is the probability the branch will be taken if classification reaches the node from which the branch emanates.

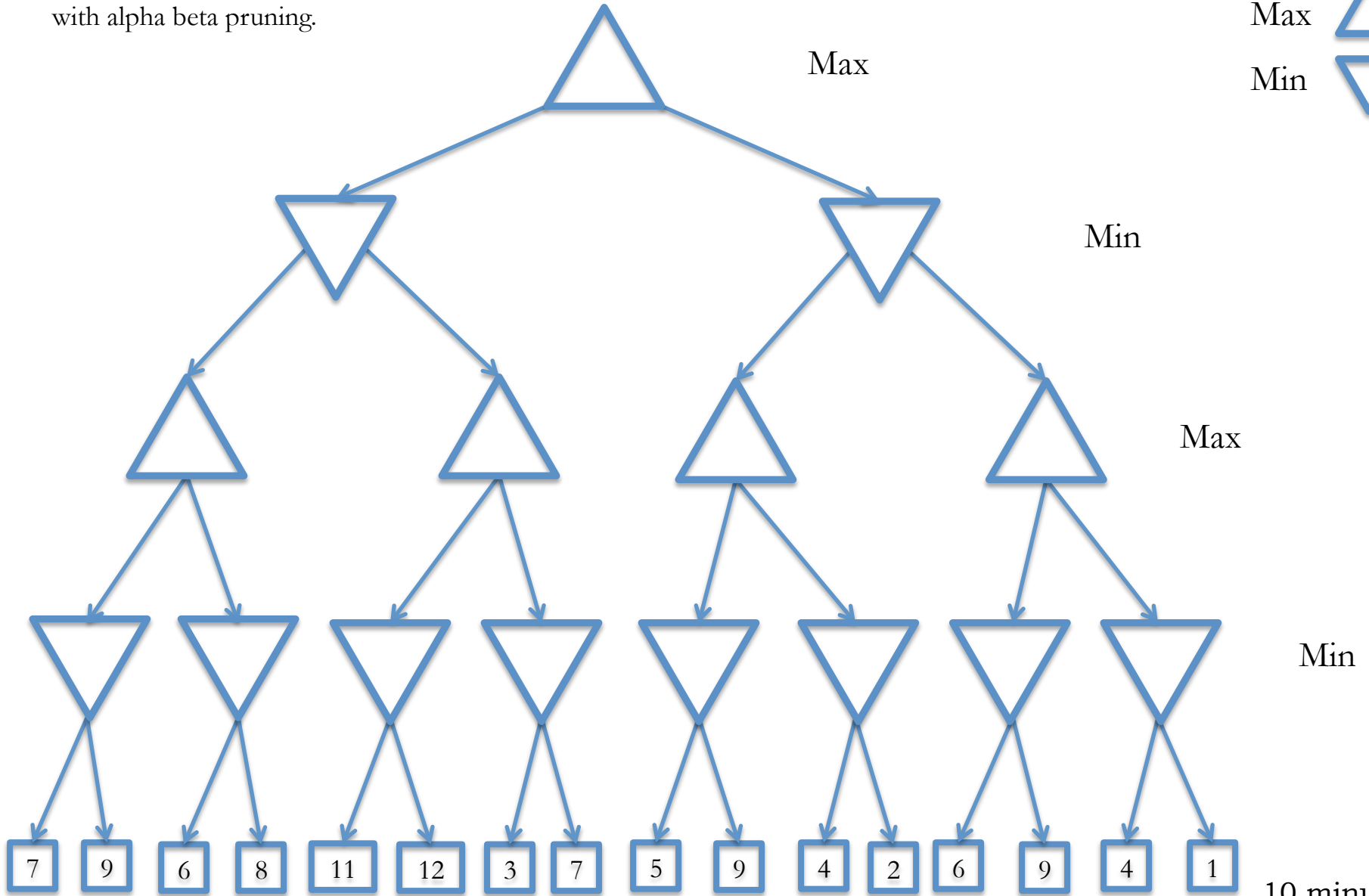
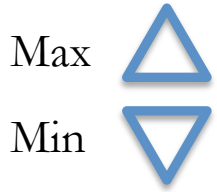


Give the expected number of internal nodes visited (i.e., the expected number of variable tests carried out) when classifying an arbitrary datum. **Give the answer as a real number**, or as an un-simplified arithmetic expression involving real numbers.

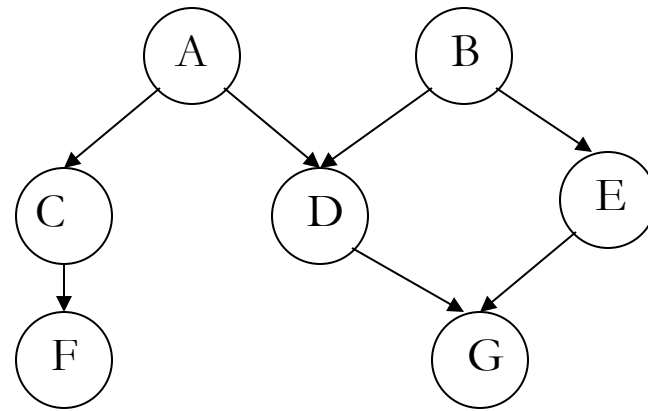
4 a) (3 pts) Leaves of this game tree give the values of those positions.

Give the value for the root node obtained through minimax search: \_\_\_\_\_

b) (5 pts) Put an 'X' through any arc into a subtree that can be pruned when using minimax search with alpha beta pruning.



5. Consider the following belief network:



Each variable is a binary-valued variable (e.g., A has values  $a$  and  $\sim a$ , B has values  $b$  and  $\sim b$ , etc). Probability tables are stored at each node. **For purposes of expressing your answers, you can assume that  $P(\sim x | \dots)$  is explicitly stored, as well as  $P(x | \dots)$  (i.e., you don't have to compute  $P(\sim x | \dots)$  as  $1 - P(x | \dots)$ ).**

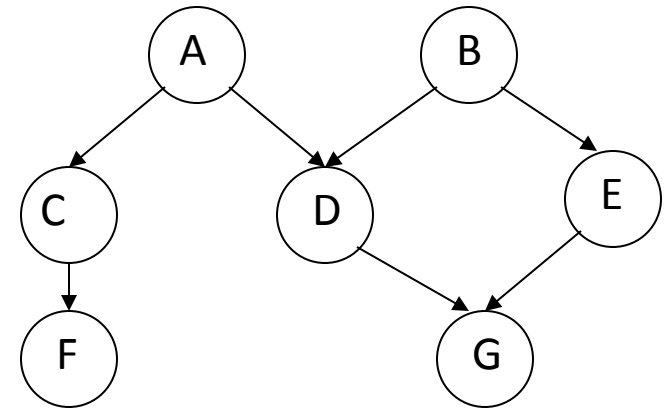
For each of the following, *involve the minimal number of variables necessary*.

**a) (2 pts)** Express  $P(a, \sim b, \sim c, d, e, f, \sim g)$  only in terms of probabilities found in the probability tables of the network.

**b) (2 pts)** Express  $P(\sim e | b, \sim c)$  only in terms of probabilities found in the probability tables of the network.

5. continued

c) (2 pts) Express  $P(f \mid \sim a)$  only in terms of probabilities found in the probability tables of the network.



d) (2 pts) Express  $P(b, \sim d, e)$  only in terms of probabilities found in the probability tables of the network.

e) (2 pts) Express  $P(b \mid e)$  only in terms of probabilities found in the probability tables of the network.

6. From Poole and Mackworth

Answer the following questions about how knowledge of the values of some variables would affect the probability of another variable.

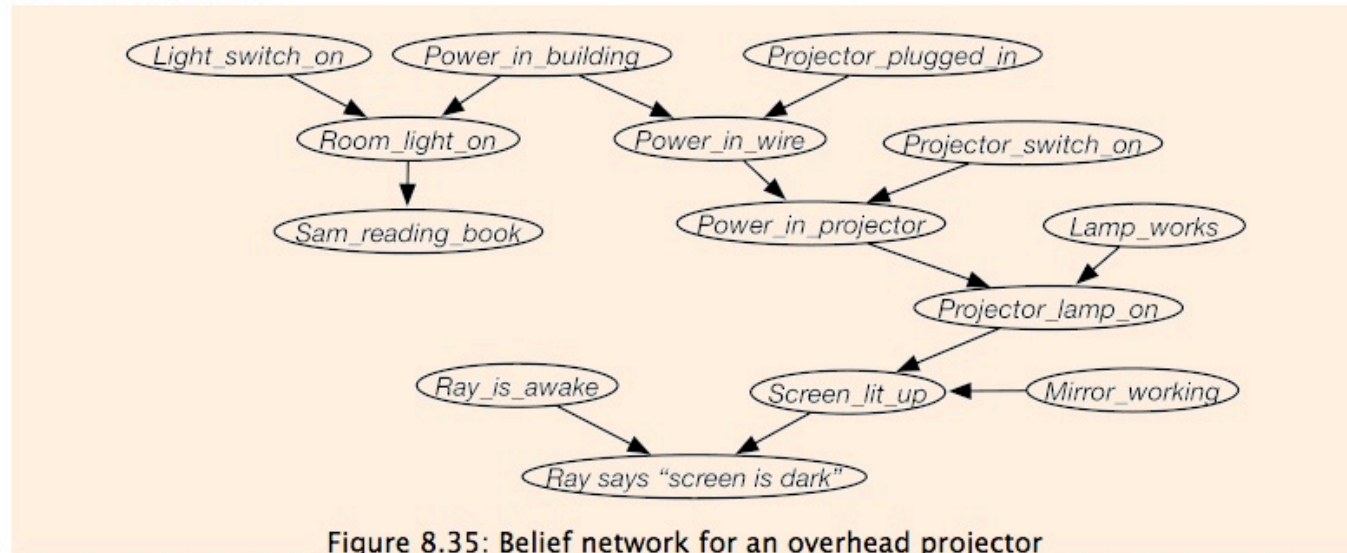


Figure 8.35: Belief network for an overhead projector

a) (2 pts) Can knowledge of the value of Projector\_plugged\_in affect your belief in the value of Sam\_reading\_book? Explain

b) (2 pts) Can knowledge of the value of Screen\_lit\_up affect your belief in the value of Sam\_reading\_book? Explain

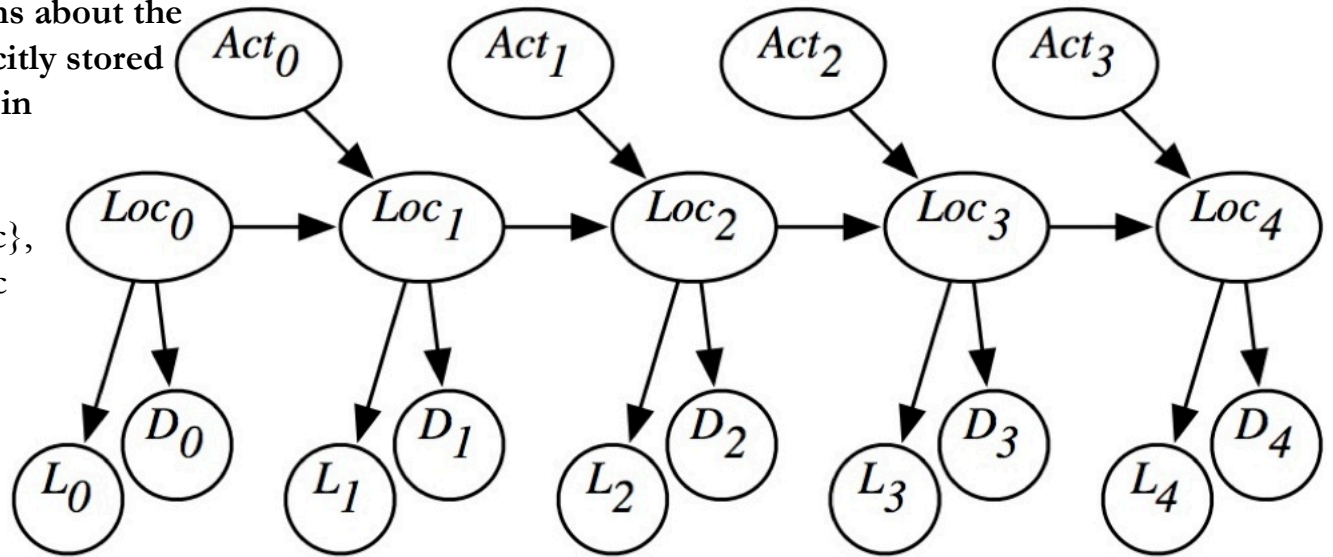
c) (2 pts) If Lamp\_works was observed, then belief in some variables might be changed. List those affected variables.

7. Consider this hidden Markov model. Assume all variables are binary valued.

Figure from Poole and Mackworth

Make the same assumptions about the probabilities that are explicitly stored in the probability tables as in Question 5.

The domain of  $Loc_k$  is  $\{c, \sim c\}$ ,  
 $L_i$  is  $\{l, \sim l\}$ ,  $D_j$  is  $\{d, \sim d\}$ , etc



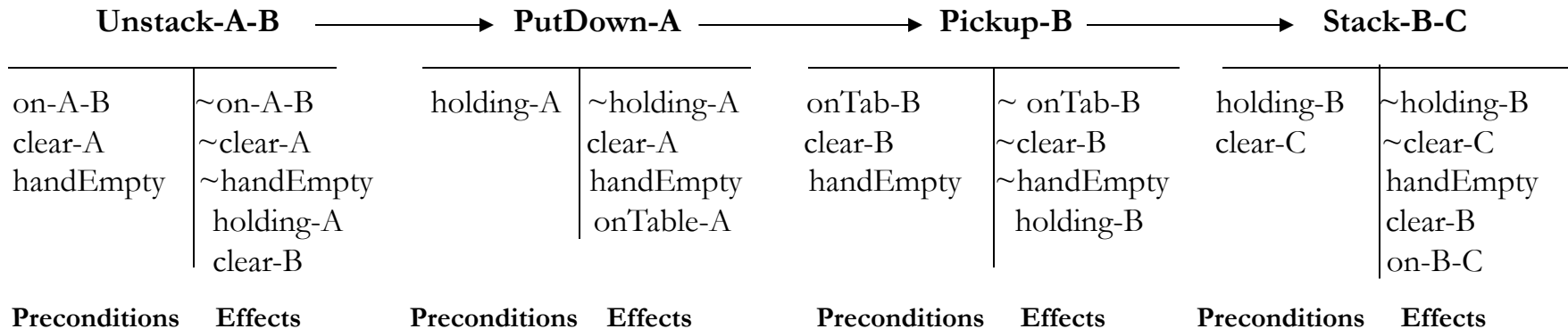
Assume that the following are observed:  $L_0 = \sim l$ ,  $D_0 = d$ ,  $Act_0 = a$ ,  $L_1 = \sim l$ ,  $D_1 = \sim d$

a) (2 pts) What two *joint* probabilities would have to be compared to determine which was more probable,  $Loc_1 = c$  or  $Loc_1 = \sim c$ , given the observations above.

b) (2 pts) Write those two joint probabilities only in terms of probabilities found in the network's probability tables.



8. Consider the following macro/composite operator in STRIPS notation – this is a block stacking application of the type seen in lecture.



The basic operators making up the composite operator are labeled along the top (Unstack-A-B, PutDown-A, Pickup-B, Stack-B-C), with preconditions of each given below the operator name and to the left; effects to the right.

a) (2 pts) Give the preconditions of this macro/composite operator

b) (2 pts) Give the effects of this macro/composite operator. You need only list un-negated effects (because we can build in a KB that allows reason from un-negated propositions to obtain the relevant negated propositions. For example,  $\text{handEmpty} \rightarrow \sim\text{holding-A}$ ;  $\text{handEmpty} \rightarrow \sim\text{holding-B}$ ; ...;  $\text{on-A-B} \rightarrow \sim\text{clear-B}$ ;  $\text{on-B-C} \rightarrow \sim\text{clear-C}$ , ...)