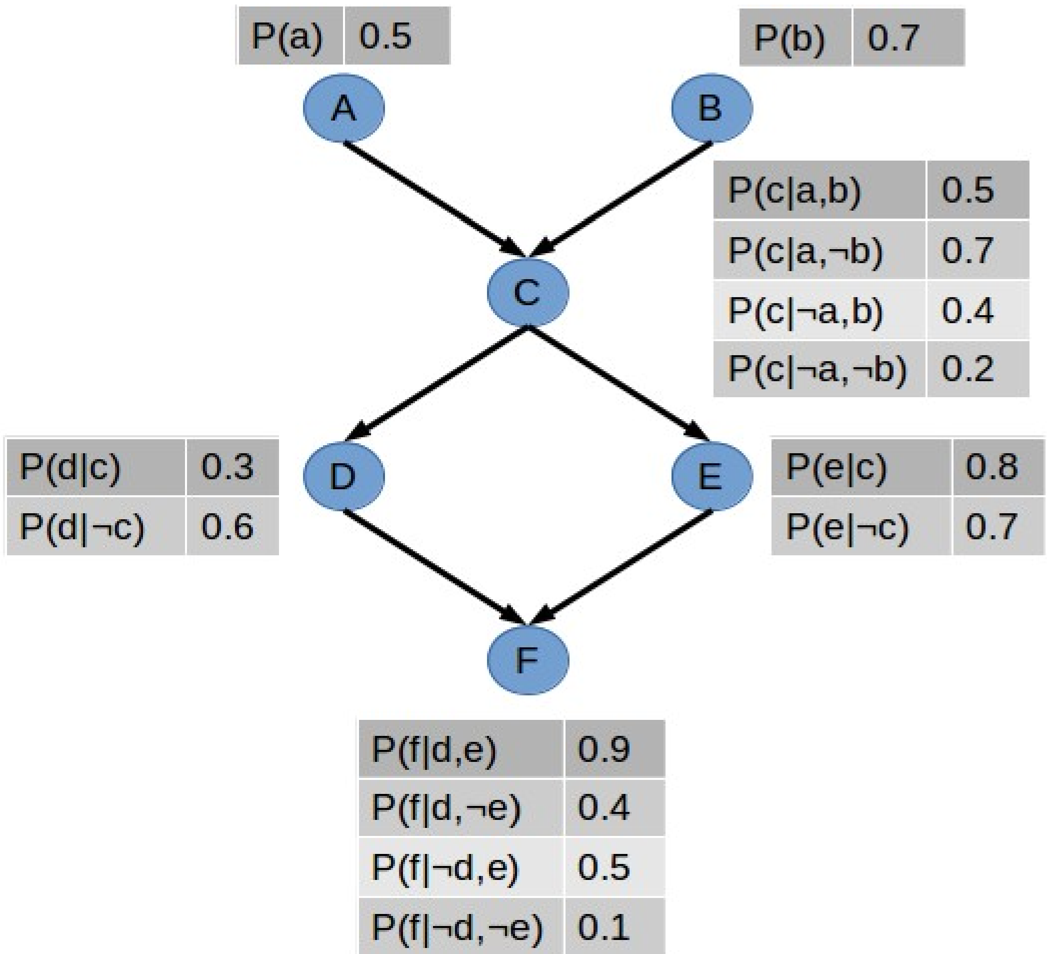
5512, Spring-2019
ASSIGNMENT 2:
Assigned: 02/19/19 Due: 03/03/19 at 11:55 PM (submit via Canvas, you may scan or take a picture of your paper answers) Submit only pdf or txt files (for non-code part), separate submission for code files
Show as much work as possible for all problems!

Problem 1. (20 points)
Use variable elimination on the Bayesian network below to find: P(d|¬b)

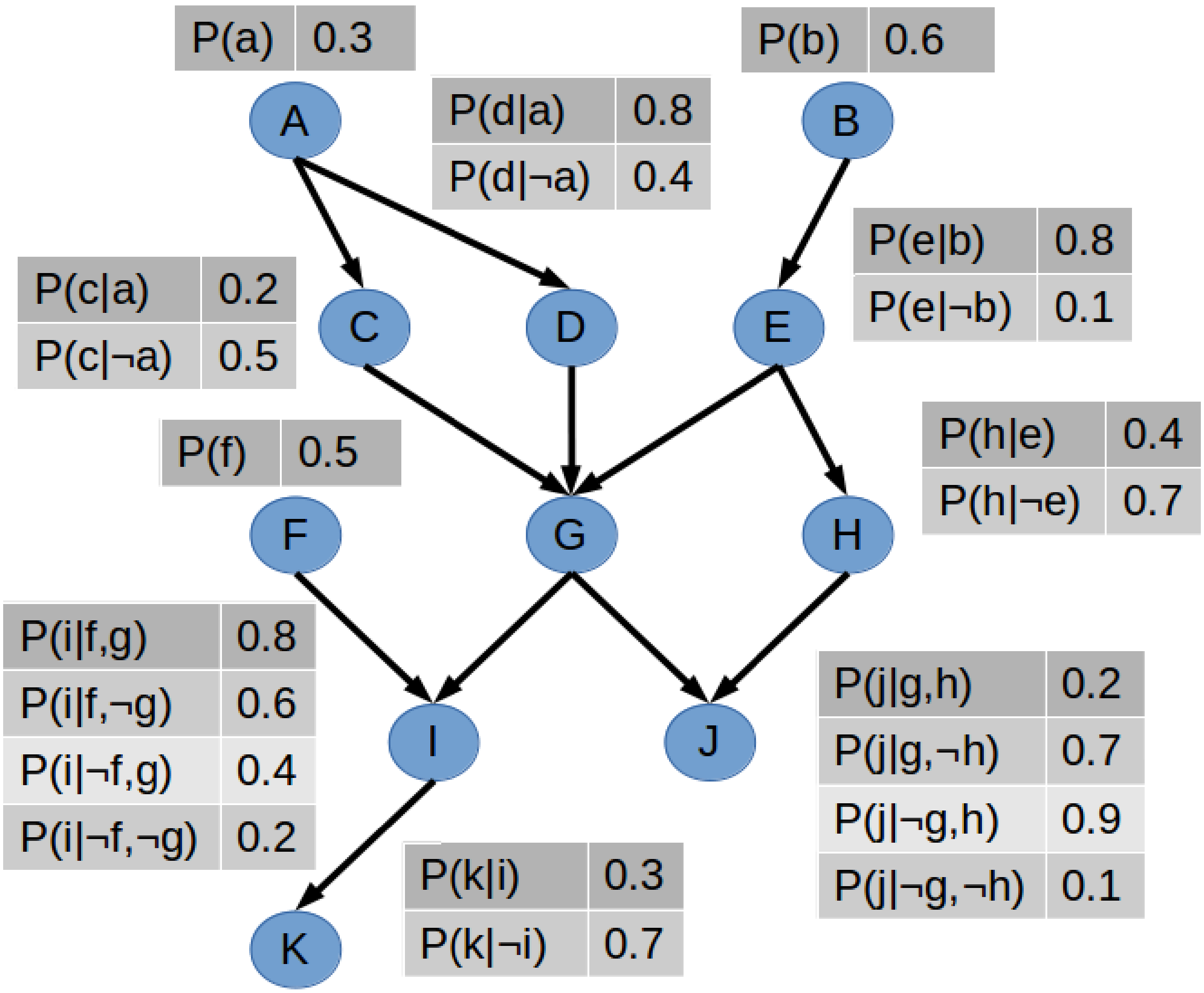


Problem 2. (10 points)
While I said the accuracy of likelihood weighting increases as 1/sqrt(N) if N samples are taken, (Dagum, Karp, Luby, Ross) show that a better bound is (μ is the actual probability):

$$P\Big((1-\epsilon)\mu \leq LikelihoodEstimate \leq (1+\epsilon)\mu\Big) > 1-\delta$$
$$N \geq \frac{4}{\mu\epsilon^2}\ln\frac{2}{\delta}$$

Using this information, determine how many samples you would need to have a 95% confidence that you are within 1% of the actual answer? (Hint: what assumptions can you make to make sure you are not underestimating?)

Problems 3, 4 and 5 will use the following Bayesian network:



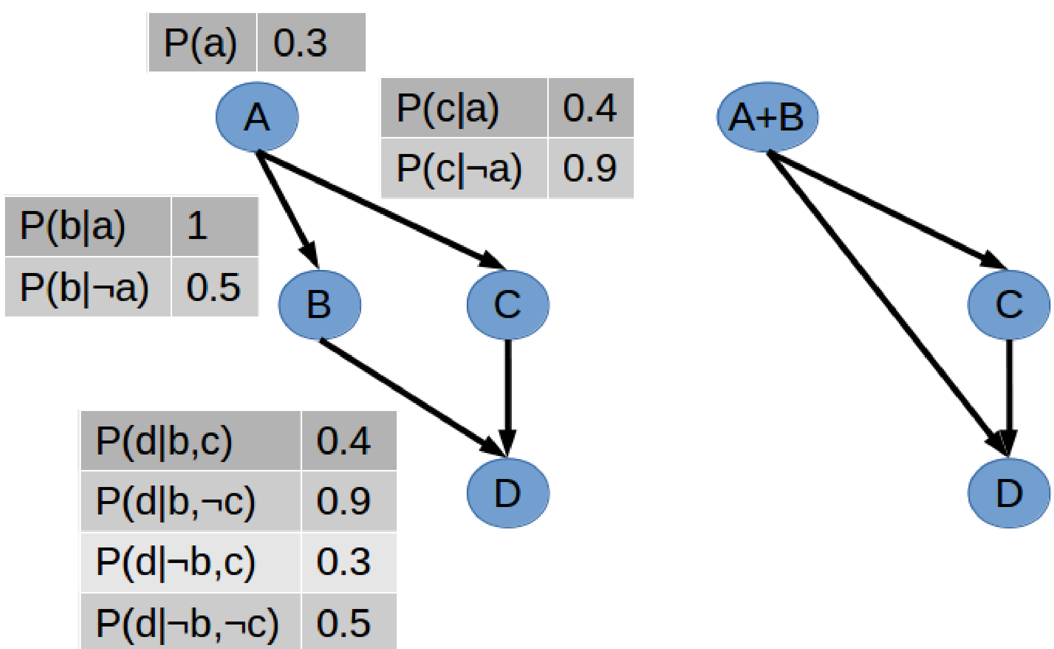
P(g|c,d,e)	0.1
P(g|c,d,¬e)	0.2
P(g|c,¬d,e)	0.3
P(g|c,¬d,¬e)	0.4
P(g|¬c,d,e)	0.5
P(g|¬c,d,¬e)	0.6
P(g|¬c,¬d,e)	0.7
P(g|¬c,¬d,¬e)	0.8

Problem 3. (25 points)
Use likelihood weighting to estimate P(g|k,¬b,c). Use an appropriate amount of samples, which will require you to write code. Submit your your code as a supplement. You have the options of Python (preferred), Matlab or Java.

Problem 4. (25 points)
Use Gibbs sampling to re-estimate P(g|k,¬b,c). Again you have to use sufficient samples to be close enough to the correct answer (you will lose points if you are too far away). Submit your code as a supplement. You have the options of Python (preferred), Matlab or Java.

Problem 5. (25 points)
For problem 5, you can use whatever method you want to find probabilities (though do say how you get them briefly).
(5.1) What is the Markov blanket of G?
(5.2) What is P(g| MarkovBlanket(G))? Assume all parts of the Markov Blanket are true (i.e. positive x, not ¬x).
(5.3) Find P(g|c,d,e,f). Then find P(g|c,d,e). Explain the relationship between these probabilities.
(5.4) Find P(g). Find P(g|f). Explain the relationship between these probabilities.
(5.5) What is the minimal set of given information (evidence) to make G conditionally independent from A?
(5.6) What is the minimal set of information (evidence) to make G conditionally independent from J?

Problem 6. (10 points)
Consider the Bayesian network below on the left. Suppose we want to merge/cluster variables/nodes A and B into the graph on the right. Provide probability tables for the three nodes on the right that will keep the probabilities of C and D the same as in the original Bayesian network. Then describe how you can deduce the values of A and B in the original Bayesian network from the value of A+B in the new Bayesian network.



P(a)	0.3

P(c|a)	0.4
P(c|¬a)	0.9

P(b|a)	1
P(b|¬a)	0.5

P(d|b,c)	0.4
P(d|b,¬c)	0.9
P(d|¬b,c)	0.3
P(d|¬b,¬c)	0.5