

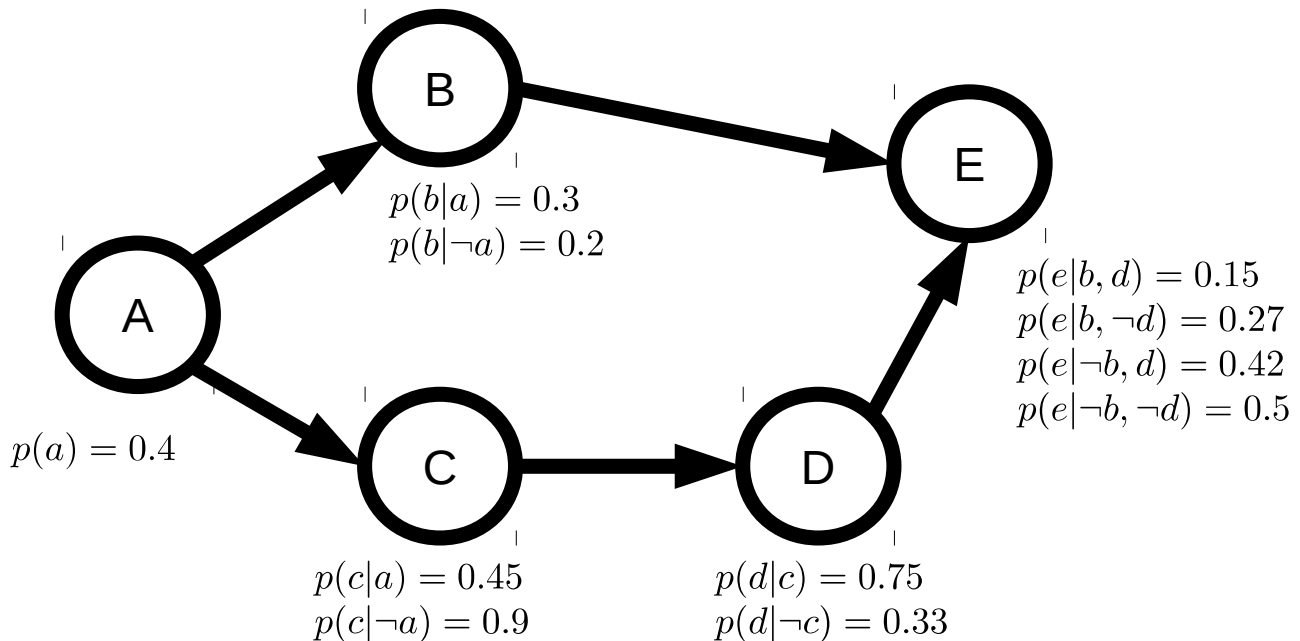
CSci5512, Fall-2021

ASSIGNMENT 1 :

Assigned: 09/30/21 Due: 10/14/21 at 11:55 PM (submit via Canvas, you may scan or take a picture of your paper answers) Please organize your work before submitting.

On all problems you must show work to receive full credit; all answers done individually

Problem 1 & 2 use the following Bayesian Network:



Problem 1. (points)

Write two different ways to find the probability of $p(d|b, \neg e)$. using the chain rule and pushing the sums as far right as possible. You may keep your answers in terms of $p(\text{variables})$ rather than putting in numerical values. Which one of these ways is more efficient?

Problem 2. (points)

Use Variable elimination to find $p(d|b, \neg e)$ in the above BayesNet (you might want to refer to your answer in problem 1, but it is not necessary).

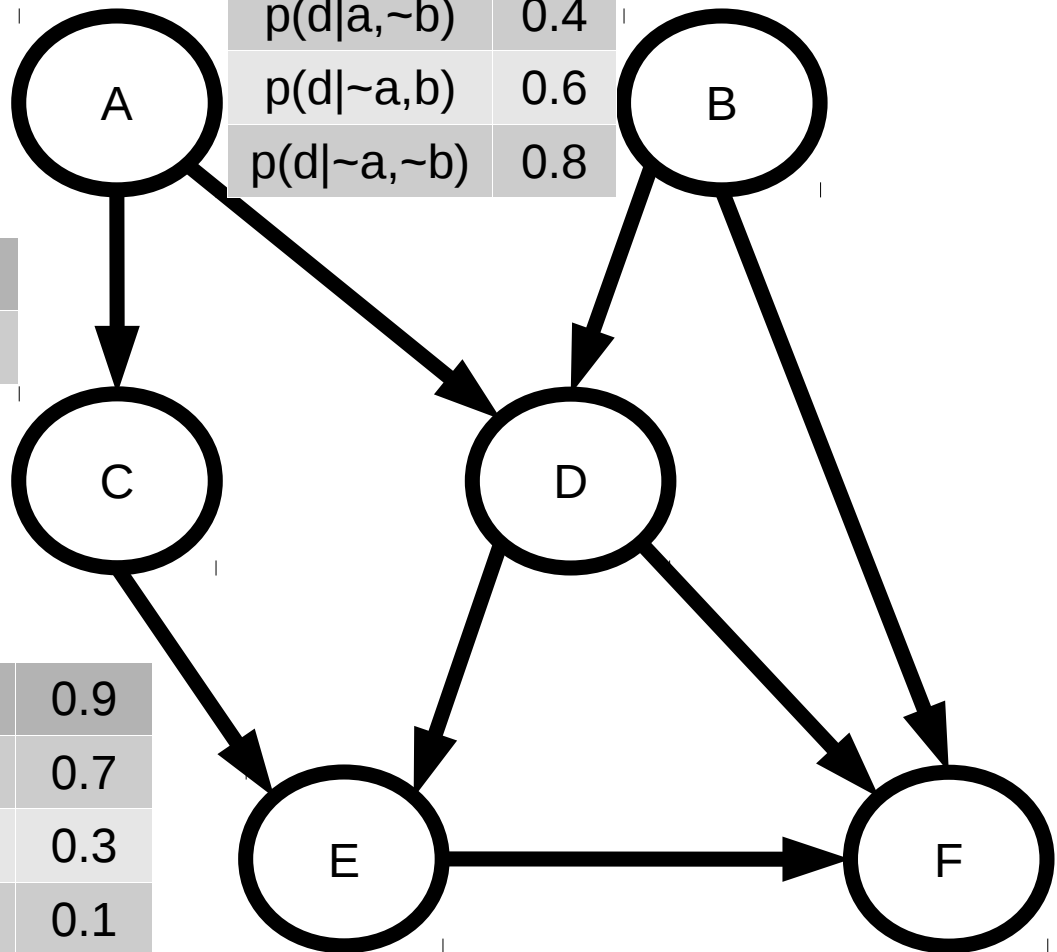
Problems 3, 4 and 5 refer to this Bayesian Network:

$p(a)$	0.4	$p(d a,b)$	0.2	$p(b)$	0.7
		$p(d a,\sim b)$	0.4		
		$p(d \sim a,b)$	0.6		
		$p(d \sim a,\sim b)$	0.8		

$p(c a)$	0.9
$p(c \sim a)$	0.3

$p(e c,d)$	0.9
$p(e c,\sim d)$	0.7
$p(e \sim c,d)$	0.3
$p(e \sim c,\sim d)$	0.1

$p(f b,d,e)$	0.2
$p(f b,d,\sim e)$	0.1
$p(f b,\sim d,e)$	0.4
$p(f b,\sim d,\sim e)$	0.3
$p(f \sim b,d,e)$	0.6
$p(f \sim b,d,\sim e)$	0.7
$p(f \sim b,\sim d,e)$	0.8
$p(f \sim b,\sim d,\sim e)$	0.5



Problem 3. (15 points)

(Part 1) Use rejection sampling to estimate $p(d|\neg b,e,f)$. You should write your own code to solve this problem (not find an already implemented version). You may use some code existing code (such as a “Node” class or something), but the main algorithm should be coded on your own. Submit both your final answer to this part, and your source code as a supplementary file. A list of languages we will accept are: C++, Java, Python, OCaml, and Matlab. If you want to use a language that is not on this list, please email me (jparker@cs.umn.edu) and we can see if it is possible.

(Part 2) Approximately how many samples do you need to use in order to find $p(d|\neg b,e,f)$ accurate within 2 significant figures/digits after rounding? (This approximation can either be derived mathematically or empirically.)

Problem 4. (15 points)

(Part 1) Again estimate $p(d|\neg b,e,f)$, but using likelihood weighting this time. (Same rules as previous problem.)

(Part 2) Approximately how many samples do you need to use in order to find $p(d|\neg b,e,f)$ accurate within 2 significant figures/digits after rounding?

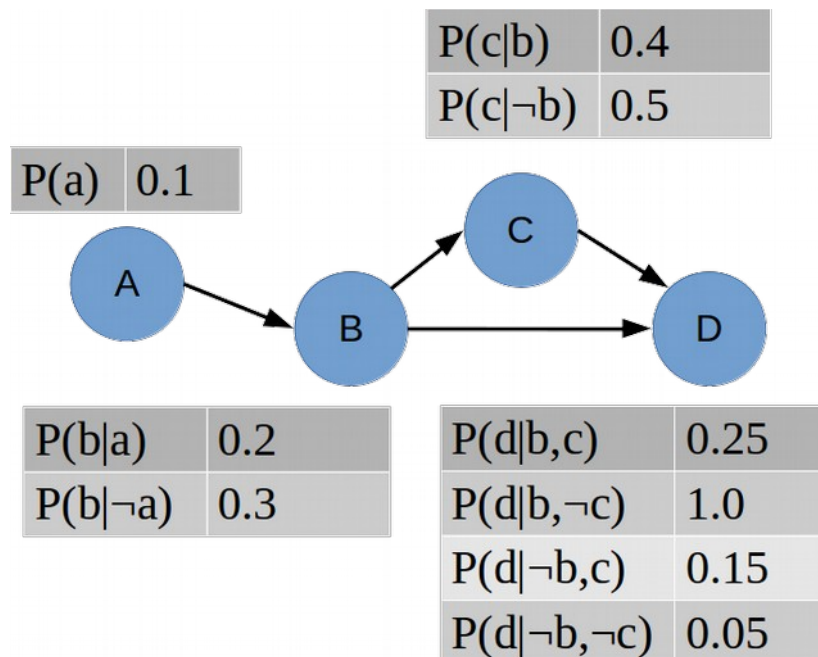
Problem 5. (15 points)

(Part 1) Again estimate $p(d|\neg b,e,f)$, but using Gibbs sampling. (Same rules as previous problem.)

(Part 2) Approximately how many samples do you need to use in order to find $p(d|\neg b,e,f)$ accurate within 2 significant figures/digits after rounding?

Problem 6. (10 points)

Consider the network below (should be familiar). Assuming we want to find $p(\neg a,\neg b,\neg d|c)$ using Gibbs sampling. In-class we discussed how you can treat Gibbs sampling as walking around a graph as a Markov chain.

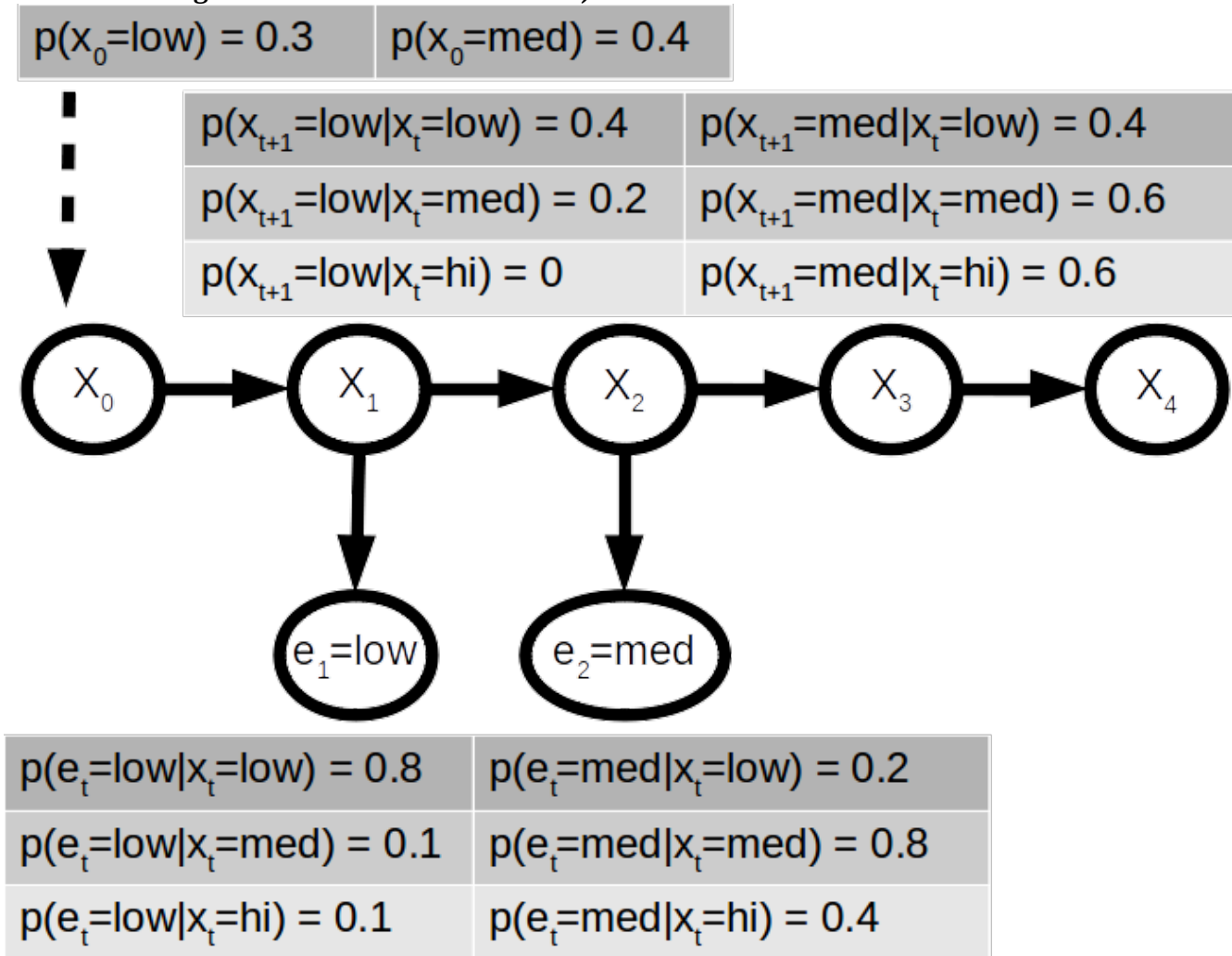


(1) Specifically write out all 8 states and the transition probabilities between them (i.e. edge

probabilities) for this problem. Assume that each “free” variable (a,b,d) are picked equally at random to have a chance to change (1/3 prob).

(2) Assume $p(a,b,d|c) \approx 0.00424$ (approximation), use our stationary distribution property (“flow across both directions is the same”) to solve for $p(\neg a, \neg b, \neg d|c)$. (Do not solve or approximate this probability from scratch. Use the stationary distribution property specific to Gibbs sampling.)

Problems 7 & 8 deal with this HMM: (note: the variables have 3 possible values of low/medium/high rather than our normal T/F)



Problem 7. (15 points)

Use filtering to estimate $p(x_2=\text{high} \mid e_1 = \text{low}, e_2 = \text{medium})$.

Problem 8. (5 points)

Use prediction to estimate $p(x_4=\text{low} \mid e_1 = \text{low}, e_2 = \text{medium})$.