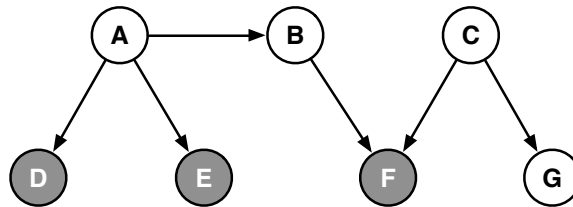


**Out:** Tue Jul 12**Due:** Fri Jul 15 (outside CSE 3214, by 2 pm)**5.1 Inference in a polytree**

For the belief network shown below, consider how to *efficiently* compute the posterior probability  $P(G|D, E, F)$ . This can be done in five consecutive steps in which the later steps rely on the results from earlier ones.



Complete the procedure below for this inference; in particular, show how to compute the necessary result, *as efficiently as possible*, at each step. *Show your work and justify your reasoning* for full credit. Your answers should be expressed in terms of the CPTs of the belief network and the results of previous steps.

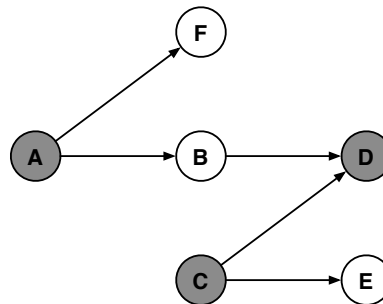
- (a)  $P(A = a|D, E)$
- (b)  $P(B = b|D, E)$
- (c)  $P(F|C = c, D, E)$
- (d)  $P(C = c|D, E, F)$
- (e)  $P(G|D, E, F)$

**Hint:** at each step, you'll want to exploit what you just computed in the last one.

**5.2 More inference**

For the belief network shown below, consider how to *efficiently* compute the following probabilities. Express your answers in terms of the CPTs of the belief network; also, in parts (b,c), you may re-use your answer from (a). *Justify briefly each step in your calculations.*

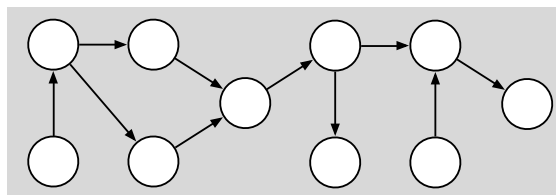
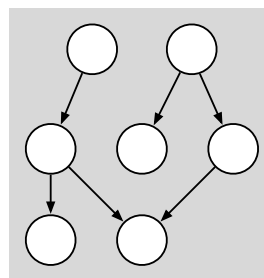
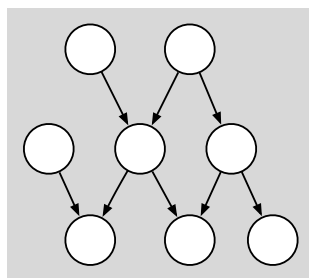
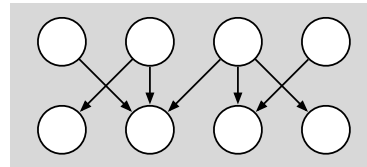
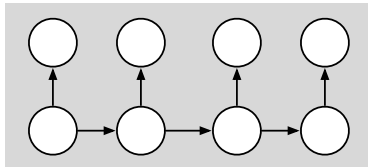
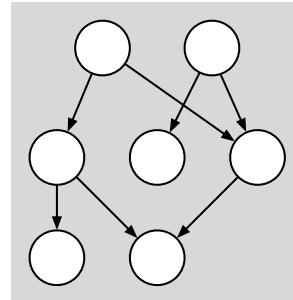
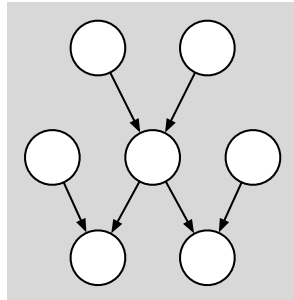
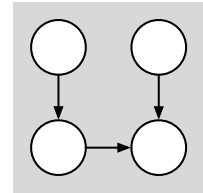
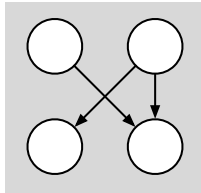
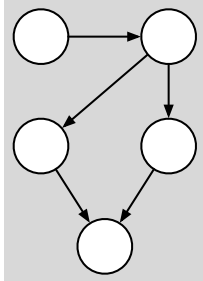
- (a)  $P(B|A, C, D)$
- (b)  $P(B|A, C, D, E, F)$
- (c)  $P(B, E, F|A, C, D)$



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### 5.3 To be, or not to be, a polytree: that is the question.

Circle the DAGs shown below that are polytrees. In the other DAGs, shade **two** nodes that could be *clustered* so that the resulting DAG is a polytree.



## 5.4 Markov modeling

In this problem, you will construct and compare unigram and bigram models defined over the four-letter alphabet  $\mathcal{A} = \{a, b, c, d\}$ . Consider the following 16-token sequence  $\mathcal{S}$ :

$$\mathcal{S} = \text{"a a c c b b d d d d b b c c a a"}$$

### (a) Unigram model

Let  $\tau_\ell$  denote the  $\ell$ th token of this sequence, and let  $L = 16$  denote the total sequence length. The overall likelihood of this sequence under a unigram model is given by:

$$P_U(\mathcal{S}) = \prod_{\ell=1}^L P_1(\tau_\ell),$$

where  $P_1(\tau)$  is the unigram probability for the token  $\tau \in \mathcal{A}$ . Compute the maximum likelihood estimates of these unigram probabilities on the training sequence  $\mathcal{S}$ . Complete the table with your answers.

$\tau$	a	b	c	d
$P_1(\tau)$				

### (b) Bigram model

The overall likelihood of the sequence  $\mathcal{S}$  under a bigram model is given by:

$$P_B(\mathcal{S}) = P_1(\tau_1) \prod_{\ell=2}^L P_2(\tau_\ell | \tau_{\ell-1}),$$

where  $P_2(\tau' | \tau)$  is the bigram probability that token  $\tau \in \mathcal{A}$  is followed by token  $\tau' \in \mathcal{A}$ . Compute the maximum likelihood estimates of these bigram probabilities on the training sequence  $\mathcal{S}$ . Complete the table with your answers.

	$\tau'$				
	$P_2(\tau'   \tau)$	a	b	c	d
	a	$\frac{2}{3}$	0	$\frac{1}{3}$	0
$\tau$	b				
	c				
	d				

(c) **Likelihoods**

Consider again the training sequence  $\mathcal{S}$ , as well as three test sequences  $\mathcal{T}_1$ ,  $\mathcal{T}_2$ , and  $\mathcal{T}_3$  of the same length, shown below. Note that  $\mathcal{T}_2$  and  $\mathcal{T}_3$  contain bigrams (underlined) that are not in the training sequence  $\mathcal{S}$ .

$\mathcal{S} = \text{"a a c c b b d d d d b b c c a a"}$   
 $\mathcal{T}_1 = \text{"b d b d b d b d b d b d b d b d"}$   
 $\mathcal{T}_2 = \text{"a a a a d d d d b b b b c c c c"}$   
 $\mathcal{T}_3 = \text{"a d a d a d a d a d a d a d a d"}$

Consider the probabilities of these sequences under the unigram and bigram models from parts (a) and (b) of this problem (i.e., the models that you estimated from the training sequence  $\mathcal{S}$ ). For each of the following, indicate whether the probability on the left is equal ( $=$ ), greater ( $>$ ), or less ( $<$ ) than the probability on the right.

Note: you can (and should) answer these questions without explicitly computing the numerical values of the expressions on the left and right hand sides.

$P_U(\mathcal{S})$    $P_U(\mathcal{T}_1)$

$P_U(\mathcal{S})$    $P_U(\mathcal{T}_2)$

$P_U(\mathcal{S})$    $P_U(\mathcal{T}_3)$

$P_B(\mathcal{S})$    $P_B(\mathcal{T}_1)$

$P_B(\mathcal{S})$    $P_B(\mathcal{T}_2)$

$P_B(\mathcal{T}_2)$    $P_B(\mathcal{T}_3)$

$P_U(\mathcal{S})$    $P_B(\mathcal{S})$

$P_U(\mathcal{T}_1)$    $P_B(\mathcal{T}_1)$

$P_U(\mathcal{T}_2)$    $P_B(\mathcal{T}_2)$

$P_U(\mathcal{T}_3)$    $P_B(\mathcal{T}_3)$

(d) **Likelihoods**

Consider the model obtained by linear interpolation (or mixing) of the unigram and bigram models estimated in part (a) of this problem:

$$P_M(\tau'|\tau) = (1 - \lambda)P_1(\tau') + \lambda P_2(\tau'|\tau),$$

with mixing coefficient  $\lambda \in [0, 1]$ . For a sequence of tokens of length  $L$ , the mixture model computes the log-likelihood as:

$$\mathcal{L} = \log P_1(\tau_1) + \sum_{\ell=2}^L \log P_M(\tau_\ell|\tau_{\ell-1}).$$

Naturally, this value varies as a function of the coefficient  $\lambda$ . For  $\lambda$  near zero, it is close to the log-likelihood of the unigram model; for  $\lambda$  near one, it is close to that of the bigram model. This last part of this problem asks you to consider, for each of the sequences below, the *qualitative* behavior of the mixture model's log-likelihood as a function of  $\lambda \in [0, 1]$ . (For instance, is this function constant, or if not, where do its maximum and minimum occur?)

The plots below illustrate four possible behaviors of the mixture model's log-likelihood as a function of  $\lambda \in [0, 1]$ . For each sequence below, indicate the one plot (either A, B, C, or D) that sketches the correct qualitative behavior.

$\mathcal{S} = \text{"a a c c b b d d d d b b c c a a"}$

☐

$\mathcal{T}_1 = \text{"b d b d b d b d b d b d b d b d"}$

☐

$\mathcal{T}_2 = \text{"a a a a d d d d b b b b c c c c"}$

☐

$\mathcal{T}_3 = \text{"a d a d a d a d a d a d a d a d a d"}$

☐
