

**Course:** CSC591/791, Graph Data Mining: Theory, Algorithms, and Applications

**Final Exam:** Comprehensive, home-take exam.

**STUDENT's ID:** \_\_\_\_\_

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This exam is intended to be an **individual** effort. You are allowed to use and reference the materials posted on Moodle, cited in the exam, your homework assignments, your notes, the class slides, and the lecture assignments. You are **NOT** allowed to use the other sources, such as your classmates and the internet at large.

1. Good luck!
  2. You get BONUS 5 points if your solution is in LaTeX (both source and PDF)
  3. Otherwise, a PDF (even a scanned hand-written solution) must be uploaded into Moodle
  4. The Total Exam Score by the TA: \_\_\_\_\_ out of **(100 points)**
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  - obtains assistance in any academic work from another individual in a situation in which the student is expected to perform independently;
  - gives assistance to another individual in a situation in which that individual is expected to perform independently;
  - offers false data in support of laboratory or field work.

3. The act of submitting work for evaluation or to meet a requirement is regarded as assurance that the work is the result of the student's own thought and study, produced without assistance, and stated in that student's own words, except as quotation marks, references, or footnotes acknowledge the use of other sources. Submission of work used previously must first be approved by the instructor.
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By signing this exam, the student acknowledges the above terms and agrees to abide by NCSU policies on academic integrity.

Agreed \_\_\_\_\_ (specify your ID)

Date \_\_\_\_\_

1. \_\_\_\_\_ out of **(15 points)**: Given an infectious disease following the SIS virus propagation model with transmission probability  $\beta = 0.3$  and healing probability  $\delta = 0.5$ , in a contact network with 10 nodes and the following edges:  $\{(0, 1), (0, 3), (1, 4), (2, 3), (2, 6), (5, 6), (5, 7), (6, 7), (7, 9), (8, 9)\}$ , answer:
  - (a) \_\_\_\_\_ out of **(1 point)**: What is the spectral radius of the network?
  - (b) \_\_\_\_\_ out of **(1 point)**: What is the effective strength of the virus?
  - (c) \_\_\_\_\_ out of **(1 point)**: According to the theorem studied in class [1], can the infection result in an epidemic?
  - (d) \_\_\_\_\_ out of **(9 points)**: Using the NetShield algorithm [2], which 3 nodes should be immunized to minimize the spread of the infection?
  - (e) \_\_\_\_\_ out of **(3 points)**: After immunizing the 3 nodes selected in (4), can the infection result in an epidemic?

**References:**

- 1 B. A. Prakash, D. Chakrabarti, M. Faloutsos, N. Valler, C. Faloutsos. Got the Flu (or Mumps)? Check the Eigenvalue! arXiv:1004.0060 [physics.soc-ph], 2010.
- 2 H. Tong, B. A. Prakash, C. Tsourakakis, T. Eliassi-Rad, C. Faloutsos, D. H. Chau. On the Vulnerability of Large Graphs. In ICDM, 2010.

**Answers:**

- (a) The spectral radius (i.e., the largest eigenvalue of the adjacency matrix) of the network is  $\lambda_1 = 2.3728$ .
- (b) The effective strength of the virus is  $s = \lambda_1 * \frac{\beta}{\delta} = 2.2143 * \frac{0.3}{0.5} = 1.4237$ .
- (c)  $s > 1$ . Therefore, the infection can result in an epidemic.
- (d) The 3 nodes selected for immunization by the NetShield algorithm are  $\{6, 7, 3\}$ .
- (e) The effective strength of the virus after immunizing the nodes is  $s' = \lambda'_1 * \frac{\beta}{\delta} = 1.4142 * \frac{0.3}{0.5} = 0.8485$ . Since  $s' < 1$  after immunizing the nodes, the infection cannot result in an epidemic.

2. \_\_\_\_\_ out of **(15 points)**: Given random variables  $x, y, w, z$ , **prove or disprove** the following statements about their conditional independence ( $\perp$ ) relationships (see the lecture on  $D$ -separation and example below; if you decide to disprove the stmt, then a counter-example of a DAG will suffice):

- (a) \_\_\_\_\_ out of **(0 points)**: Example:  $(x \perp y, w | z) \implies (x \perp y | z)$

**Proof:**

$$\begin{aligned}
 p(x, y | z) &= \sum_w p(x, y, w | z) = \sum_w p(x | z) p(y, w | z) = \\
 &= p(x | z) \sum_w p(y, w | z) = p(x | z) p(y | z)
 \end{aligned}$$

- (b) \_\_\_\_\_ out of **(6 points)**:  $(x \perp y, z) \& (x, y \perp w | z) \implies (x \perp w | z)$

**Proof:**

$$\begin{aligned} p(x, w | z) &= \sum_y p(x, y, w | z) = \sum_y p(x, y | z) p(w | z) = \\ p(x | z) p(w | z) \sum_y p(y | z) &= p(x | z) p(w | z) \end{aligned}$$

- (c) \_\_\_\_\_ out of **(9 points)**:  $(x \perp y, z) \& (x \perp y | w) \implies (x \perp y | z, w)$

**Proof by counter-example:** Consider the DAG,  $x \rightarrow z \leftarrow u \rightarrow w \leftarrow y$ . Using  $D$ -deparation,

$$\begin{aligned} &(x \perp y | z) \\ &(x \perp y | w) \\ &\neg(x \perp y | z, w) \end{aligned}$$

since the path between  $x$  and  $y$  is activated when both  $z$  and  $w$  are observed.

3. \_\_\_\_\_ out of **(15 points)**: Suppose you need to design an efficient algorithm for analyzing random walks of an undirected simple graph  $G$ . Let  $A$  be its adjacency matrix with Singular Value Decomposition (SVD)  $A = U\Lambda U^t$ .

- (a) \_\_\_\_\_ out of **(5 points)**: Prove that the power matrix  $A^k = U\Lambda^k U^t$ .

**Proof:** To compute  $A^k$ , we observe that

$$\begin{aligned} A^k &= \underbrace{(U\Lambda U^t)(U\Lambda U^t) \dots (U\Lambda U^t)}_{k \text{ times}} \\ U^t U &= I \\ A^k &= U\Lambda^k U^t \end{aligned}$$

- (b) \_\_\_\_\_ out of **(10 points)**: Devise an efficient algorithm to compute  $A^k$  for different values of  $k$ . What is its Big-O complexity?

**Answer:** An efficient algorithm to compute  $A^k$ :

- i. Do SVD for  $A$ :  $A = U\Lambda U^T$ .  
SVD has time complexity  $O(\min\{m^2 n, m n^2\})$ .
- ii. Calculate  $\Lambda^k$ : for each diagonal element  $\lambda_i$  in  $\Lambda$ , calculate  $\lambda_i^k$ .  
This step takes  $O(n \log_2(k))$  by using exponentiating by squaring:  $\lambda_i^k = \begin{cases} \lambda_i * (\lambda_i^2)^{\frac{k-1}{2}}, & \text{if } k \text{ is odd} \\ (\lambda_i^2)^{\frac{k}{2}}, & \text{if } k \text{ is even.} \end{cases}$
- iii. Do the matrix multiplication  $A^k = U\Lambda^k U^T$ .  
This last step takes  $O(n^3)$  with a naive approach, but can be further reduced using other matrix multiplication algorithms like Strassen in  $O(n^{\log_2 7}) \approx O(n^{2.807})$ .

Thus, the Big-O complexity is  $O(\min\{m^2 n, m n^2\} + n \log_2(k) + n^{2.807})$ .

4. \_\_\_\_\_ out of **(10 points)**: Let  $G$  be an undirected complete bi-partite graph. Prove that if  $\lambda$  is an eigenvalue of its adjacency matrix then  $-\lambda$  is also its eigenvalue. Hint: Assume that after the permutation of rows and columns, the adjacency matrix is of the form:

$$A = \begin{pmatrix} 0 & B \\ B^t & 0 \end{pmatrix}$$

**Proof:** If  $G$  is a bi-partite graph, then we can permute the rows and columns of its adjacency matrix  $A$  to obtain its block-diagonal form:

$$A = \begin{pmatrix} 0 & B \\ B^t & 0 \end{pmatrix}$$

Suppose that  $u$  is an eigenvector  $u$  of  $A$  with eigenvalue  $\lambda$ :

$$u = \begin{pmatrix} x \\ y \end{pmatrix}$$

Then

$$\begin{pmatrix} 0 & B \\ B^t & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \lambda \begin{pmatrix} x \\ y \end{pmatrix}$$

This implies that  $B^t x = \lambda y$  and  $By = \lambda x$ . This implies that

$$\begin{pmatrix} 0 & B \\ B^t & 0 \end{pmatrix} \begin{pmatrix} x \\ -y \end{pmatrix} = \begin{pmatrix} -By \\ B^t x \end{pmatrix} = -\lambda \begin{pmatrix} x \\ -y \end{pmatrix}$$

Therefore,  $\begin{pmatrix} x \\ -y \end{pmatrix}$  is an eigenvector of  $A$  with eigenvalue  $-\lambda$ .

5. \_\_\_\_\_ out of **(20 points)**: Consider the following training examples:

Instance	$x_1$	$x_2$	$x_3$	class, $y$
1	T	T	T	+
2	T	T	T	+
3	F	F	T	+
4	F	T	F	-
5	T	F	T	-
6	T	F	F	-
7	F	F	F	-
8	F	T	F	-

- (a) \_\_\_\_\_ out of **(10 points)**: You will be using a naïve Bayes classifier for this question. Given a test example with attributes  $x_1 = T$ ,  $x_2 = T$ , and  $x_3 = F$ , which class will be assigned to this test example? Show your work clearly.

**Answer:**

$$\begin{aligned} p_+ &= p(y = + | x_1 = T, x_2 = T, x_3 = F) = \frac{p(x_1 = T, x_2 = T, x_3 = F, y = +)}{p(x_1 = T, x_2 = T, x_3 = F)} \\ &= \frac{p(x_1 = T, x_2 = T, x_3 = F | y = +) p(y = +)}{p(x_1 = T, x_2 = T, x_3 = F)} \end{aligned}$$

$$p_- = p(y = - | x_1 = T, x_2 = T, x_3 = F) = \frac{p(x_1 = T, x_2 = T, x_3 = F | y = -) p(y = -)}{p(x_1 = T, x_2 = T, x_3 = F)}$$

Note that the denominator in both formulas above has the same constant value.

$$\begin{aligned} & p(x_1 = T, x_2 = T, x_3 = F | y = +) p(y = +) \\ &= p(x_1 = T | y = +) p(x_2 = T | y = +) p(x_3 = F | y = +) p(y = +) \\ &= \frac{2}{3} * \frac{2}{3} * \frac{0}{3} * \frac{3}{8} \\ &= 0 \\ p_+ &= 0 / \underbrace{p(x_1 = T, x_2 = T, x_3 = F)}_{\text{constant}} = 0 \end{aligned}$$

$$\begin{aligned} & p(x_1 = T, x_2 = T, x_3 = F | y = -) p(y = -) \\ &= p(x_1 = T | y = -) p(x_2 = T | y = -) p(x_3 = F | y = -) p(y = -) \\ &= \frac{2}{5} * \frac{2}{5} * \frac{4}{5} * \frac{5}{8} \\ &= \frac{2}{25} \\ &= 0.08 \\ p_- &= 0.08 / \underbrace{p(x_1 = T, x_2 = T, x_3 = F)}_{\text{constant}} > 0 \end{aligned}$$

Since  $p_+ < p_-$ , we should assign class "-" to this test example.

- (b) \_\_\_\_\_ out of **(10 points)**: Repeat the question in part (a) using the following Bayesian Belief network as the classifier:

$$x_3 \rightarrow x_2 \rightarrow y \rightarrow x_1$$

**Answer:**

$$x_3 \rightarrow x_2 \rightarrow y \rightarrow x_1$$

↓

$$p(x_1, x_2, x_3, y) = p(x_1 | y) p(x_2 | x_3) p(x_3) p(y | x_2)$$

Using conditional probability, we get

$$\begin{aligned}
p_+ &= p(y = + | x_1 = T, x_2 = T, x_3 = F) = \frac{p(x_1 = T, x_2 = T, x_3 = F, y = +)}{p(x_1 = T, x_2 = T, x_3 = F)} \\
&= \frac{p(x_1 = T | y = +) p(x_2 = T | x_3 = F) p(x_3 = F) p(y = + | x_2 = T)}{p(x_1 = T, x_2 = T, x_3 = F)} \\
p_- &= p(y = - | x_1 = T, x_2 = T, x_3 = F) = \frac{p(x_1 = T, x_2 = T, x_3 = F, y = -)}{p(x_1 = T, x_2 = T, x_3 = F)} \\
&= \frac{p(x_1 = T | y = -) p(x_2 = T | x_3 = F) p(x_3 = F) p(y = - | x_2 = T)}{p(x_1 = T, x_2 = T, x_3 = F)}
\end{aligned}$$

Note that the denominator in both formulas above has the same constant value.

$$\begin{aligned}
p(x_1 = T, x_2 = T, x_3 = F, y = +) &= \\
&= p(x_1 = T | y = +) p(x_2 = T | x_3 = F) p(x_3 = F) p(y = + | x_2 = T) \\
&= (2/3) * (1/2) * (1/2) * (1/2) = \frac{1}{12} = 0.083 \dots \\
p_+ &= \frac{1}{12} / \underbrace{p(x_1 = T, x_2 = T, x_3 = F)}_{\text{constant}} \\
p(x_1 = T, x_2 = T, x_3 = F, y = -) &= (2/5) * (1/2) * (1/2) * (1/2) = \frac{1}{20} = 0.05 \\
p_- &= \frac{1}{20} / \underbrace{p(x_1 = T, x_2 = T, x_3 = F)}_{\text{constant}}
\end{aligned}$$

Since  $p_+ > p_-$ , we should assign class "+" to this test example.

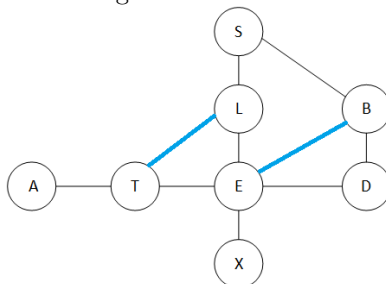
6. \_\_\_\_\_ out of (10 points): Show the key steps of the Junction Tree algorithm for the following DAG (Note: No need to show the details of the last step, i.e., the Belief Propagation inference step):

$$A \rightarrow T \rightarrow E \rightarrow D; S \rightarrow L \rightarrow E \rightarrow X; S \rightarrow B \rightarrow D$$

**Answers:**

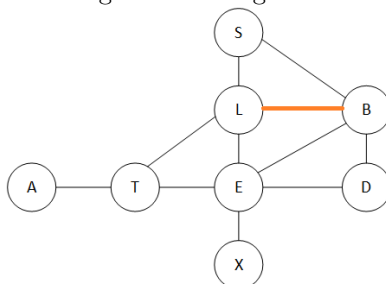
- 1.) Start with a DAG.
- 2.) Moralize: marry parents of each node (add edges  $L - T$  and  $B - E$ ) and remove edge directions.

Figure 1: Moralize



- 3.) Triangulate: if there is loops of length  $> 3$ , split it into triangles (add edge  $L - B$  to triangulate).

Figure 2: Triangulate



- 4.) Find cliques: there are 6 cliques  $AT, ELT, SLB, BLE, BDE, EX$ .
- 5.) Form a junction tree of cliques (3 possibilities for a minimum spanning tree).

Figure 3: Junction tree (possibility 1)

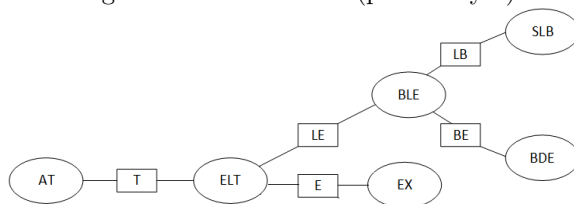




Figure 4: Junction tree (possibility 2)

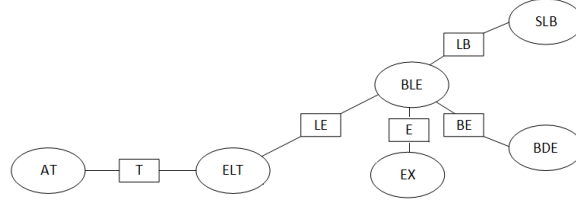
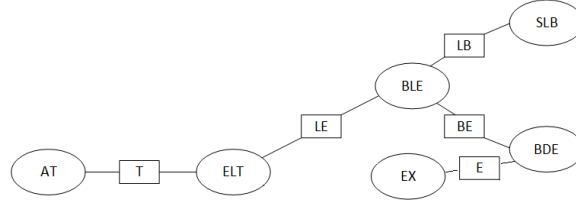


Figure 5: Junction tree (possibility 3)



6.) Do belief propagation in junction tree.

7. \_\_\_\_\_ out of **(15 points)**: Using the Maximum Likelihood estimation, find the parameters for the following Bernoulli Trials problem (show all the derivations):

INPUT:

- $M$  iid coin flips:  $D = H, H, T, H, \dots$
- Model:  $p(H) = \theta$  and  $p(T) = 1 - \theta$

OUTPUT:  $\theta_{ML}^*$

- (a) \_\_\_\_\_ out of **(10 points)**: What is the likelihood function  $l(\theta; D) = \log p(D|\theta)$ ? (Hint: Introduce a random variable  $x$  that is equal to 1 if the trial is a Head and it is equal to zero if the trial is a Tail.)

**Answer:**

$$\begin{aligned}
 l(\theta; D) &= \log p(D|\theta) \\
 &= \log \left( \prod_{m=1}^M \theta^{x^m} (1-\theta)^{1-x^m} \right) \\
 &= \sum_{m=1}^M \log(\theta^{x^m} (1-\theta)^{1-x^m}) \\
 &= \log(\theta) \sum_{m=1}^M x^m + \log(1-\theta) \sum_{m=1}^M (1-x^m) \\
 &= \log(\theta) N_H + \log(1-\theta) N_T
 \end{aligned}$$

- (b) \_\_\_\_\_ out of **(5 points)**: What is  $\theta_{ML}^*$ ?

**Answer:**

$$\begin{aligned}
 \frac{\partial l}{\partial \theta} &= \frac{N_H}{\theta} - \frac{N_T}{1-\theta} \\
 \Rightarrow \theta_{ML}^* &= \frac{N_H}{N_H + N_T}
 \end{aligned}$$