

UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN  
CS440/ECE448 Artificial Intelligence

**Exam 1**  
Spring 2026

February 16, 2026

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**Your Name:** \_\_\_\_\_

**Your NetID:** \_\_\_\_\_

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**Instructions**

- Please write your name on the top of every page.
- Have your ID ready; you will need to show it when you turn in your exam.
- This will be a **CLOSED BOOK, CLOSED NOTES** exam. You are permitted to bring and use only one 8.5x11 page of notes, front and back, handwritten or typed in a font size comparable to handwriting.
- No electronic devices (phones, tablets, calculators, computers etc.) are allowed.
- Make sure that your answer includes only the variables that it should include, but **DO NOT** simplify explicit numerical expressions. For example, the answer  $x = \frac{1}{1+\exp(-0.1)}$  is **MUCH** preferred (much easier for us to grade) than the answer  $x = 0.524979$ .

**Possibly Useful Formulas**

$$P(X = x|Y = y)P(Y = y) = P(Y = y|X = x)P(X = x)$$

$$P(X = x) = \sum_y P(X = x, Y = y)$$

$$E[f(X, Y)] = \sum_{x,y} f(x, y)P(X = x, Y = y)$$

$$\text{Precision, Recall} = \frac{TP}{TP + FP}, \frac{TP}{TP + FN}$$

$$\text{MPE=MAP: } f(x) = \arg \max (\log P(Y = y) + \log P(X = x|Y = y))$$

$$\text{Naive Bayes: } P(X = x|Y = y) \approx \prod_{i=1}^n P(W = w_i|Y = y)$$

$$\text{Laplace Smoothing w/OOV: } P(W = w_i) = \frac{k + \text{Count}(W = w_i)}{k + \sum_v (k + \text{Count}(W = v))}$$

$$\text{Fairness: } P(Y|A) = \frac{P(Y|f(X), A)P(f(X)|A)}{P(f(X)|Y, A)}$$

$$\text{Score: } v_{t+1}(j) = \max_i v_t(i) + \log a_{ij} + \log b_j(x_{t+1})$$

$$\text{Backpointer: } \psi_{t+1}(j) = \arg \max_i v_t(i) + \log a_{ij} + \log b_j(x_{t+1})$$

$$\text{Linear Regression: } \mathcal{L} = \frac{1}{n} \sum_{i=1}^n (\mathbf{w}^T \mathbf{x}_i - y_i)^2$$

**Question 1 (26 points)**

Valentine's baskets and Easter baskets differ in the candies that they contain. Let  $P(E = \top)$  be the probability that you have received an Easter basket, and let  $P(E = \perp) = 1 - P(E = \top)$  be the probability of receiving a Valentine's basket. Let  $P(M = m|E = e)P(C = c|E = e)$  be the probability that you receive  $m$  marshmallow candies and  $c$  caramel candies given  $E = e$ .

- (a) (13 points) A Bayes classifier observes  $m$  and  $c$ , then chooses the value of  $E$  with the highest *a posteriori* probability. In terms of the distributions  $P(E)$ ,  $P(M|E)$ , and  $P(C|E)$ , what is the error rate of the Bayes classifier? Your answer may contain explicit summations, minimizations, and/or maximizations; please specify the variable(s) over which you are summing, maximizing, and/or minimizing.

**Solution:**

$$\begin{aligned} P(\text{Error}) &= \sum_c \sum_m \min_e P(E = e)P(M = m|E = e)P(C = c|E = e) \\ &= 1 - \sum_c \sum_m \max_e P(E = e)P(M = m|E = e)P(C = c|E = e) \end{aligned}$$

- (b) (13 points) You are currently five years old; you have received five Easter baskets and five Valentine's baskets. The contents of the Easter baskets, written as  $(c, m)$  tuples, were

$$\mathcal{D}_{\text{Easter}} = \{(3, 3), (4, 4), (5, 5), (3, 5), (4, 5)\}$$

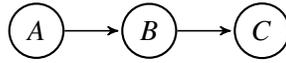
In terms of a Laplacian smoothing parameter  $k$ , estimate  $P(C = c|E = \top)$  and  $P(M = m|E = \top)$  for  $c, m \in \{3, 4, 5, \text{other}\}$ .

**Solution:**

$$P(C = c|E = \top) = \begin{cases} \frac{2+k}{5+4k} & c \in \{3, 4\} \\ \frac{1+k}{5+4k} & c = 5 \\ \frac{k}{5+4k} & c = \text{other} \end{cases}, \quad P(M = m|E = \top) = \begin{cases} \frac{3+k}{5+4k} & m = 5 \\ \frac{1+k}{5+4k} & m \in \{3, 4\} \\ \frac{k}{5+4k} & m = \text{other} \end{cases},$$

**Question 2 (30 points)**

Consider three binary events  $A$ ,  $B$ , and  $C$ , related by the Bayes network shown here:



The parameters of this Bayes network are given by the unknown constants  $v$  through  $z$ , as follows:

$$\begin{aligned}
 P(A) &= v \\
 P(B|A) &= w, \quad P(B|\neg A) = x \\
 P(C|B) &= y, \quad P(C|\neg B) = z
 \end{aligned}$$

- (a) (10 points) Are events  $A$  and  $B$  independent, conditionally independent given knowledge of  $C$ , both, or neither? Explain your answer.

**Solution:** They are neither independent nor conditionally independent. **Acceptable explanation #1:** there is an arrow connecting  $A$  to  $B$ , so  $B$  always depends on  $A$  regardless of the rest of the graph. **Acceptable explanation #2:** They are not independent because they have an unknown common ancestor ( $A$ ). They are not conditionally independent given  $C$  because then they would have a known common descendant ( $C$ ).

- (b) (10 points) Suppose  $C$  is unknown. Find the four probabilities  $P(A, B)$ ,  $P(A, \neg B)$ ,  $P(\neg A, B)$ , and  $P(\neg A, \neg B)$ .

**Solution:**

$$\begin{aligned}
 P(A, B) &= vw \\
 P(A, \neg B) &= v(1 - w) \\
 P(\neg A, B) &= (1 - v)x \\
 P(\neg A, \neg B) &= (1 - v)(1 - x)
 \end{aligned}$$

- (c) (10 points) Suppose  $C$  is known to be true. Find  $P(C)$ , and in terms of  $P(C)$  find  $P(A, B|C)$ ,  $P(A, \neg B|C)$ ,  $P(\neg A, B|C)$ , and  $P(\neg A, \neg B|C)$ .

**Solution:**

$$P(C) = vwy + v(1-w)z + (1-v)xy + (1-v)(1-x)z$$
$$P(A, B|C) = \frac{vwy}{P(C)}$$
$$P(A, \neg B|C) = \frac{v(1-w)z}{P(C)}$$
$$P(\neg A, B|C) = \frac{(1-v)xy}{P(C)}$$
$$P(\neg A, \neg B|C) = \frac{(1-v)(1-x)z}{P(C)}$$

**Question 3 (20 points)**

$Y_t = 1$  means that your office is being robbed at time  $t$ , otherwise  $Y_t = 0$ . Suppose you know that  $Y_0 = 0$ .  $X_t = 1$  means that the security system sends a notification to your phone at time  $t$ , otherwise  $X_t = 0$ . Define  $a_{ij} = P(Y_{t+1} = j | Y_t = i)$ , and  $b_{ij} = P(X_t = j | Y_t = i)$ . Suppose there is some normalizer,  $z$ , and base,  $c$ , such that  $\log_c(a_{ij}/z) = \log_c(b_{ij}/z) = 0$  for  $i = j$ , but for  $i \neq j$ ,  $\log_c(a_{ij}/z) = -3$  and  $\log_c(b_{ij}/z) = -2$ . Suppose that  $\{X_1, \dots, X_9\} = \{1, 0, 1, 1, 1, 1, 0, 0, 1\}$ . Draw a trellis specifying the numerical values of  $v_t(i) = \max_{Y_{\tau}, \tau < t} \log_c P(Y_1, \dots, Y_t = i | X_1, \dots, X_t)/z$  for  $i \in \{0, 1\}$  and  $1 \leq t \leq 9$ , and specify a sequence of state variables  $\{Y_1, \dots, Y_9\}$  that maximizes the score. If there are more than one state sequences with the same maximum score, you only need to provide one of them.

**Solution:** A correct answer needs to show the following numerical values. The arrows need not be shown, but may be helpful to you in solving the second part of the question:

$t$	1	2	3	4	5	6	7	8	9
$X_t$	1	0	1	1	1	1	0	0	1
$v_t(0)$	$\leftarrow -2$	$\leftarrow -2$	$\leftarrow -4$	$\leftarrow -6$	$\leftarrow -8$	$-10$	$\swarrow -8$	$\leftarrow -8$	$\leftarrow -10$
$v_t(1)$	$\swarrow -3$	$-5$	$-5$	$\leftarrow -5$	$\leftarrow -5$	$\leftarrow -5$	$\leftarrow -7$	$\leftarrow -9$	$\leftarrow -9$

There are three maximum-likelihood state sequences, any of which is a correct answer:  $\{0, 0, 1, 1, 1, 1, 1, 1, 1\}$ ,  $\{0, 1, 1, 1, 1, 1, 1, 1, 1\}$ , or  $\{1, 1, 1, 1, 1, 1, 1, 1, 1\}$ .

**Question 4 (24 points)**

Consider a linear regression model  $f(\mathbf{x}_i) = \mathbf{w}^T \mathbf{x}_i$  where  $\mathbf{x}_i$  is an  $m$ -dimensional vector drawn from a size- $n$  training corpus,  $1 \leq i \leq n$ . Suppose you want to choose the vector  $\mathbf{w}$  to minimize  $\mathcal{L}_{\text{train}}$ , defined as

$$\mathcal{L}_{\text{train}} = \frac{1}{n} \sum_{i=1}^n |f(\mathbf{x}_i) - y_i|^3,$$

where  $y_i$  is a real-valued scalar for  $1 \leq i \leq n$ .

- (a) (12 points) Find the gradient  $\frac{\partial \mathcal{L}_{\text{train}}}{\partial \mathbf{w}}$ .

**Solution:**

$$\frac{\partial \mathcal{L}_{\text{train}}}{\partial \mathbf{w}} = \frac{1}{n} \sum_{i=1}^n 3\mathbf{x}_i |f(\mathbf{x}_i) - y_i|^2 \text{sign}(f(\mathbf{x}_i) - y_i)$$

- (b) (12 points) Suppose you also have a development corpus, with tokens numbered  $n+1 \leq i \leq n+j$ , and a test corpus, with tokens numbered  $n+j+1 \leq i \leq n+j+k$ . The losses in these corpora are

$$\mathcal{L}_{\text{dev}} = \frac{1}{j} \sum_{i=n+1}^{n+j} |f(\mathbf{x}_i) - y_i|^3,$$

$$\mathcal{L}_{\text{test}} = \frac{1}{k} \sum_{i=n+j+1}^{n+j+k} |f(\mathbf{x}_i) - y_i|^3.$$

Your client, a hardware manufacturer, is very clever about finding things to measure. They propose the following experiment: (1) increase  $m$  by finding something else to measure about each product, (2) re-train the new  $\mathbf{w}$ , finding the value that minimizes  $\mathcal{L}_{\text{train}}$ , (3) measure  $\mathcal{L}_{\text{dev}}$  and  $\mathcal{L}_{\text{test}}$ , (4) repeat.

Do you expect  $\mathcal{L}_{\text{dev}}$  to be smallest when  $m = 1$ , when  $m = \frac{n}{2}$ , or when  $m = \frac{3n}{2}$ ? Why?

**Solution:**  $\mathcal{L}_{\text{dev}}$  is the sum of optimization error plus generalization error. Optimization error gets smaller as  $m$  increases, but generalization error gets larger as  $m$  increases, therefore I would expect  $m = \frac{n}{2}$  to have the smallest  $\mathcal{L}_{\text{dev}}$ .

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