CSE 575: Statistical Machine Learning

Mid-Term 1

Instructor: Prof. Hanghang Tong September 12th, 2017

First Name:							
Last Name:							
Email:							
ASU ID:							
Q	Topic	Max Score	Score				
1	MLE	20					
2	Continuous Bayes Classifier	20					
3	Discrete Bayes Classifier	20					
4	Naive Bayes Classifier	30					
5	Bayes Classier vs. Naive Bayes Classier	10					
Total:		100					

- This exam book has 11 pages, including this cover page and a blank page at the end.
- Good luck!

1 Maximum Likelihood Estimation (20 points)

Suppose we have a 1-dimensional random variable X, and its pdf f(X) (probability density function) is defined as $f(X) = \frac{1}{b-a-4}$ for $a \le X \le 6$ or $10 \le X \le b$ and f(X) = 0 otherwise, where a and b two unknown parameters.

If we draw five data points x_1 , x_2 , x_3 , x_4 and x_5 independently from this distribution, and we observe that $x_1 = 1$, $x_2 = 5$, $x_3 = 10$, $x_4 = 15$ and $x_5 = 12$.

1. [5 pts.] What is the likelihood L of observing $\{x_1, x_2, x_3, x_4, x_5\}$? (Hints: the likelihood L is function of the two parameters a and b.)

Solutions: $L = (\frac{1}{b-a-4})^5$ if $a \le 1$ and $b \ge 15$. Otherwise L = 0 (lose two points if not specifying when L is zero; lose two points if the condition for a non-zero L is wrong).

2. [10 pts.] What is the maximum likelihood estimation of a (5 points)? What is the maximum likelihood estimation of b (5 points)? Justify your answer.

Solutions: a=1 and b=15 (we want a as large as possible and b as small as possible, in order to maximize L. in the meanwhile, $a \le 1$ and $b \ge 15$ in order to have a non-zero L.

3. [5 pts.] What is the likelihood of $\{x_1, x_2, x_3, x_4, x_5\}$ given your MLE estimation of a and b?

Solutions: $L = (0.1)^5$.

2 Continuous Bayes Classifier (20 points)

We want to build a Bayes Classifier for a binary classification task (y=1 or y=2) with a 1-dimensional input feature (x). We know the following quantities: (1) P(y=1)=0.8; (2) P(x|y=1)=0.5 for $1 \le x \le 2$, P(x|y=1)=0.25 for $2 < x \le 4$ and P(x|y=1)=0 otherwise; and (3) P(x|y=2)=0.5 for $3 \le x \le 5$ and P(x|y=2)=0 otherwise.

• [2pts]. What is the prior of the class label y = 2?

Solutions: P(y = 2) = 0.2

• [3pts]. What is P(y = 1|x)?

Solutions: $P(y = 1|x) = 1 \ (1 \le x < 3), P(y = 1|x) = 2/3 \ (3 \le x \le 4)$ and 0 otherwise (1 pt for each case)

• [3pts]. What is P(y = 2|x)?

Solutions: P(y = 2|x) = 1/3 $(3 \le x \le 4), P(y = 2|x) = 1$ $(4 < x \le 5)$ and 0 otherwise

• [4pts]. For x = 1, what is class label your classifier will assign? What is the risk of this decision?

Solutions: y = 1, risk is 0 (2 pts for each)

• [4pts]. For x = 3.5, what is class label your classifier will assign? What is the risk of this decision?

Solutions: y = 1, risk is 1/3 (2 pts for each)

• [2pts]. What is the decision boundary of your Bayes classifier?

Solutions: [1,4]: y=1; (4,5]: y=2; tie/unknown otherwise. (1 pt for each segment. lose 0.5pt if mistaken on the boundary)

• [2pts]. What is the Bayes error of your Bayes classifier?

Solutions: 0.1

3 Discrete Bayes Classifier (20 points)

We want to build a Bayes Classifier for a binary classification task (y = 1 or y = 2) with one discrate feature x, where $x \in \{1, 2, 3, 4, 5, 6\}$. We know the following quantities: (1) P(y = 1) = 0.5; (2) P(x = 1|y = 1) = 0, P(x = 2|y = 1) = 0.1, P(x = 3|y = 1) = 0.5, P(x = 4|y = 1) = 0.2, P(x = 5|y = 1) = 0.1, P(x = 6|y = 1) = 0.1; and (3) P(x = 1|y = 2) = 0.1, P(x = 2|y = 2) = 0.2, P(x = 3|y = 2) = 0.2, P(x = 6|y = 2) = 0.2.

- [2pts]. What is the prior of the class label y = 2? Solutions: P(y = 2) = 0.5
- [4pts]. Put all the P(x|y=1) and P(x|y=2) numbers into a 6×2 table, whose rows correspond to six different values of x (i.e., x=1,2,...,6), and two columns correspond to two different values of y (i.e., y=1 and y=2).

Solution:

0	0.1
0.1	0.2
0.5	0.2
0.2	0.3
0.1	0.2
0.1	0

- [4pts]. What is P(y = 1|x = 3)? What is P(y = 2|x = 3)? Solutions: 5/7 and 2/7 (2 pts each).
- [2pts]. For an example with the following feature x = 6, what is class label your classifier will assign? What is the risk of this decision?

Solutions: y = 1, risk is 0 (1 pt for each)

• [2pts]. For an example with the following feature x = 1, what is class label your classifier will assign? What is the risk of this decision?

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Solutions: y = 2, risk is 0 (1 pt for each)

• [3pts]. What is the decision boundary of your Bayes classifier?

Solutions: x = 3, 6, y = 1, otherwise y = 2 (each wrong decision for one x value, lose half a point).

• [3pts]. What is the Bayes error of your Bayes classifier?

Solutions: 0.3

4 Naive Bayes Classifier (30 points)

Given the training data set in the following Table, we want to train a binary classifier, with (1) the last column being the class label y (i.e., y = 1 or y = 0); (2) x_1 , x_2 and x_3 being three binary features; and (3) each row being a training data point.

Data	x_1	x_2	x_3	y
1	0	0	0	1
2	0	0	1	0
3	0	1	1	0
4	0	1	1	0
5	0	0	1	1
6	1	0	1	1
7	1	0	1	0
8	1	0	1	0
9	1	1	1	1
10	1	0	1	1

1. [9 pts.] How many independent parameters are there in your Naive Bayes classifier? What are they? Justifiy your answer.

Solutions: (1) P(y = 1), (2) $P(x_1 = 1|y = i)$ (i = 1, 0), (3) $P(x_2 = 1|y = i)$ (i = 1, 0), (4) $P(x_3 = 1|y = i)$ (i = 1, 0) (2 pts for correctly naming 1 parameter). 7 independent parameters in total (1 pt for each).

2. **[9 pts.]** What are your estimations for these parameters? (say using standard MLE).

Solutions: (1) P(y = 1) = 0.5,

(2)
$$P(x_1 = 1|y = 1) = 0.6$$
 and $P(x_1 = 1|y = 0) = 0.4$,

(3)
$$P(x_2 = 1|y = 1) = 0.2$$
 and $P(x_2 = 1|y = 0) = 0.4$,

(4)
$$P(x_3 = 1|y = 1) = 0.8$$
 and $P(x_3 = 1|y = 0) = 1$.

(3 pts for the prior and 1 pt for each of the rest estimation)

3. **[6 pts.]** Now, given a new (test) example x = (0, 1, 0), what is P(y = 1|x)? Which class label will the naive Bayes classier assign to this example? Justify your answer.

Solutions:
$$P(x|y=1)P(y=1) = P(x_1=0|y=1)P(x_2=1|y=1)P(x_3=0|y=1)P(y=1) = 0.4 \times 0.2 \times 0.2 \times 0.5 = 0.008$$
. $P(x|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|y=1)P(x_3=0|$

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- $0)P(y=0) = P(x_1=0|y=0)P(x_2=1|y=0)P(x_3=0|y=0)P(y=0) = 0.6 \times 0.4 \times 0 \times 0.5 = 0$. Therefore, $P(y=1|x) = \frac{P(x|y=1)P(y=1)}{P(x|y=1)P(y=1)+P(x|y=0)P(y=0)} = 1$. The assigned label will be y=1. (3pt for the correct p(y=1|x), 3 pts for the correct label prediction)
- 4. **[6 pts.]** Now, given a new (test) example x = (1, 0, 1), what is P(y = 1|x)? Which class label will the naive Bayes classier assign to this example? Justify your answer.

Solutions: $P(x|y=1)P(y=1) = P(x_1=1|y=1)P(x_2=0|y=1)P(x_3=1|y=1)P(y=1) = 0.6 \times 0.8 \times 0.8 \times 0.5 = 0.192.$ $P(x|y=0)P(y=0) = P(x_1=1|y=0)P(x_2=0|y=0)P(x_3=1|y=0)P(y=0) = 0.4 \times 0.6 \times 1 \times 0.5 = 0.12.$ Therefore, $P(y=1|x) = \frac{P(x|y=1)P(y=1)}{P(x|y=1)P(y=1)+P(x|y=0)P(y=0)} = \frac{0.192}{0.192+0.12} = 8/13 > 0.5.$ The assigned label will be y=1. (3pt for the correct p(y=1|x), 3 pts for the correct label prediction)

5 Gaussian Bayes Classifier and Naive Gaussian Bayes Classifier (10 points)

Consider a binary classification task, where the feature vector X has d dimensions and the class label y is either 1 or 0. We consider two types of classifiers, i.e., (1) Gaussian Bayes Classifier and (2) Gaussian Naive Bayes Classifier. In Gaussian Bayes Classifier, we assume P(X|y) follows a multi-variate Gaussian distribution for each class label (y=0 and y=1). In Gaussian Naive Bayes Classifier, we assume that for each class label (y=0 and y=1), different dimensions of the feature vector X are conditionally independent with each other, each following a single variate Gaussian distribution.

1. **[5 pts.]** How many independent parameters are there in your Gaussian Bayes Classifier?

Solutions: $(d+(1+2+...+d)) \times 2+1 = d^2+3d+1$ (1 for class prior. for each class label, we have d for mean vector of Gaussian and (1+2+...+d) for the co-variance matrix. lose two points if treating d^2 parameters for the co-variance matrix. lose 1 point if missing the parameter for the class prior or treating 2 parameters for the class prior.)

2. **[5 pts.]** How many independent parameters are there in your Naive Gaussian Bayes Classifier?

Solutions: $(1+1) \times d \times 2 + 1 = 4d + 1$ (1 for class prior. for each class label, for each dimension of the feature, we have 1 for mean of Gaussian and (1) for the variance. lose 1 point if missing the parameter for the class prior or treating 2 parameters for the class prior.)

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