

PDEEC MACHINE LEARNING | 2017/2018 - 1st SEMESTER 15-782 CMU | Portugal Programme

| | Duration: 2h45min |
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| Name: | |

Exam: 23 January 2018

- 1. Indicate whether each of the following assertions is true or false. Give a **very short explanation**.
- a) The optimal value of the objective function for the estimation of a probability density through the EM algorithm, using a mixture of p+1 Gaussians, cannot be higher than the objective function for the same estimation, using a mixture of p Gaussians.
- b) The naive Bayes classifier is a special case of the Bayes classifier.
- 2. Consider the dataset D described in the Table. The set D is to be used as training data for a binary classifier to identify whether a point $(x_1; x_2)$ falls inside some given target shape or not. Positive class labels (+) correspond to data-points falling inside the target shape, while negative class labels (-) correspond to data-points not falling inside the target shape.

Table: Training dataset containing 20 data-points pertaining to two different classes.

| X_1 | -2.4 | -2.1 | -1.7 | -1.6 | -1.5 | -1.2 | -1.1 | -0.5 | 0.0 | 0.0 |
|-------|------|------|------|------|------|------|------|------|------|-----|
| X_2 | 0.4 | -0.3 | -1.6 | -1.3 | 1.5 | 1.9 | -2.0 | 0.1 | 0.4 | 2.0 |
| Class | _ | _ | _ | _ | _ | _ | _ | + | + | _ |
| X_1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0.4 | 0.8 | 1.0 | 1.7 | 2.0 |
| X_2 | -0.7 | -0.6 | 0.0 | -0.5 | -0.5 | 0.9 | 0.2 | 0.1 | -1.0 | 0.4 |
| Class | + | + | + | + | + | + | + | + | _ | _ |

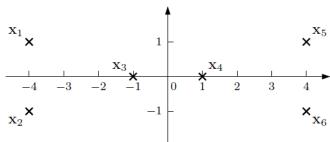
- (A) Given a data-point $p = (x_1; x_2)$, consider the two binary attributes, A_1 and A_2 , where attribute $A_i(p)$ is 1 if $|x_i| > 1$ and 0 otherwise, i = 1; 2. Using these attributes to represent each of the data-points in D, compute the parameters of a Naïve Bayes classifier for the dataset D. Using this classifier, compute the class label for the point (0.9; 0.9).
- (B) Suppose that you want to use a perceptron to classify the points in D. Indicate any pre-processing steps necessary for the perceptron to perfectly classify all points in the data-set D. Note: You don't actually need to perform these steps, just explain what they would consist of.

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3. Consider the following dataset.

| X ₁ | X 2 | y 1 | y 2 |
|----------------|------------|------------|------------|
| -1.5 | -2 | -5.1 | 2.7 |
| -1 | -0.5 | -2.5 | -1.05 |
| 0 | 0 | 0.05 | 0.01 |
| +1 | +1 | 3.2 | 3.9 |
| +1.5 | +2 | 4.9 | 8.7 |

- a) Consider that $y_1 = w_{11}x_1 + w_{21}x_2$. Estimate w_{11} and w_{21} by linear regression.
- b) assume now that $y_2 = w_{12}x_1x_2 + w_{22}x_2$. Estimate w_{11} and w_{21} by linear regression.
- c) Field knowledge tells us that $w_{11} = w_{12}$. Simultaneously estimate the four parameters imposing this constraint.
- 4. Consider an ensemble learning algorithm that uses simple majority voting among K learned hypotheses. Suppose that each hypothesis has an error ϵ and that the errors made by each hypothesis are independent of the others'. Calculate a formula for the error of the ensemble algorithm in terms of K and ϵ , and evaluate it for the cases where K=5 and 20, and ϵ = 0.1 and 0.4. If the independence assumption is removed, is it possible for the ensemble error to be worse than ϵ ?
- 5. Consider a classification support vector machine (SVM) that uses a second-degree polynomial kernel, i.e., a kernel of the form $K(\bar{x},\bar{y})=(\bar{x}\cdot\bar{y}+a)^2$, where a is a scalar. Show that the classification boundary of the SVM in the input space is described by an equation of the form $\bar{x}^TA\bar{x}+\bar{v}^T\bar{x}+c=0$, in which A is a matrix, \bar{v} is a vector, and c is a scalar.
- 6. Consider the 6-point data-set D = $\{x_1,..., x_6\}$, depicted in Figure, where the data-points are marked with an "x".

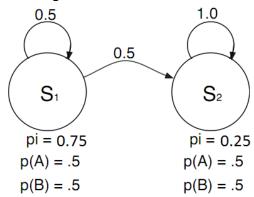


Suppose now that we wish to partition the dataset D into three clusters. Manually run K-means on this data-set, indicating the cluster associations and prototype vectors after each iteration.

Initialize your vector prototypes to $\mu_1 = [-2.5, 0]^T$, $\mu_2 = [0, 0]^T$ and $\mu_3 = [2.5, 0]^T$.

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7. Use the HMM depicted in the Figure to work out the following questions (A and B).



- (A) In the given HMM, what is the probability that an observation sequence {AAB} was generated?
- (B) Given the observed sequence $\{AAB\}$, what's the most likely (to be observed) value for t=5?

Solve one of the following:

- (C) In the HMM described in the classes, observations are generated for all time steps. If we only observe the outputs x_{t1} , ..., x_{tk} at the time steps t_1 , ..., t_k , how could you modify the forward algorithm to calculate P(x)?
- (C) Show that a stochastic matrix P always has the value $\lambda = 1$ as its eigenvalue.

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