

**CS 559: Midterm**  
**Duration: 2:00**

**Answer all problems. Show all calculations and provide sufficient explanation. If in doubt, explain more.**

**Write your name on this page and additional pages (if necessary)**

**NAME:**

**Problem 1. (10 Points)** In the context of Fisher's Linear Discriminant Analysis, explain why maximizing the distance between the projected class means is not sufficient for obtaining well-separated data after the projection. A simple sketch may be helpful for your answer.

**Problem 2. (15 Points)**

(1) Maximum Likelihood Estimation (MLE) techniques assume a certain parametric form for the class-conditional probability density functions. This implies that (select one only) (5 pt):

- a. The form of the decision boundaries is also determined in some cases.
- b. The form of the decision boundaries is always unpredictable.

(2) Linear Discriminant Analysis techniques assume a certain parametric form for the decision boundaries. This implies that (select one only) (5 pt):

- a. The form of the class-conditional densities is also determined in some cases.
- b. The form of the class-conditional densities remains unknown in general.

(3) Briefly explain your above-two answers. (5 pts)

**Problem 3. (15 points)** Let  $D$  denote the data samples and  $H$  denote hypothesis. Provide the relationship between the following probability pairs, using one of the following operators:

(1)  $=$ , (2)  $\leq$ , (3)  $\geq$ , and (4) (depends)

Explain your answers briefly.

(a)  $\sum_h P(H = h|D = d)$  and 1 (3 pts)

(b)  $\sum_h P(D = d|H = h)$  and 1 (3 pts)

(c)  $\sum_h P(D = d|H = h)P(H = h)$  and 1 (3 pts)

(d)  $P(H = h|D = d)$  and  $P(H = h)$  (3 pts)

(e)  $P(H = h|D = d)$  and  $P(D = d|H = h)P(H = h)$  (3 pts)

**Problem 4. (20 points)** Let  $x$  be a one-dimensional binary (0 or 1) variable following a Bernoulli distribution:

$$P(x|\theta) = \theta^x(1 - \theta)^{1-x},$$

where  $\theta$ , the probability that  $x = 1$ , is the unknown parameter to be estimated. Show that the maximum-likelihood estimate for  $\theta$  is

$$\hat{\theta} = \frac{1}{n} \sum_{k=1}^n x_k$$

**Problem 5. True or False. No explanation needed. (20 points)**

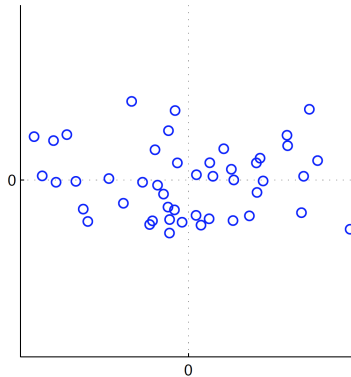
- (1) MLE and MAP never produce the same result.
- (2) Posterior is always higher than prior.
- (3) One can find a closed-form solution for any optimization problem.
- (4) When applying generative models, we usually assume that the parameter estimation for each class is independent.
- (5) K-NN is a parameteric approach.
- (6) Histogram estimation is a parametric approach.
- (6) A belief network is a directed acyclic graph.
- (7) PCA can be solved using SVD.
- (8) PCA can be applied for face detection.
- (9) Covariance matrix captures the shape of a distribution.
- (10) A subspace must pass through the origin.

**Problem 6. (20 points)** Assume we are given a set of  $D$  dimensional data samples.

PCA: Principal Component Analysis LDA: Fisher Linear Discriminant Analysis

- (a) Which quantity does PCA maximize in order to obtain the first projection direction? (3 pts)
- (b) Which quantity does PCA minimize in order to obtain the first projection direction? (3 pts)
- (c) Which quantity does LDA maximize in order to obtain the first projection direction? (3 pts)
- (d) Consider a data set with two data points:  $(2, 2), (-2, -2)$ . Compute the covariance matrix (3 pts)

Suppose the covariance matrix of the two-dimensional data set plotted below is  $\begin{bmatrix} \alpha & 0 \\ 0 & \beta \end{bmatrix}$ . We assume the horizontal axis corresponds to the first dimension and the vertical one corresponds to the second.



- (e) Draw the first principal direction estimated from the data. (4 pts)
- (f) How large is the variance of the data projected on the first principal component? (4 pts)