

Final Exam - Moed Bet
 Total time for the exam: 3 hours!

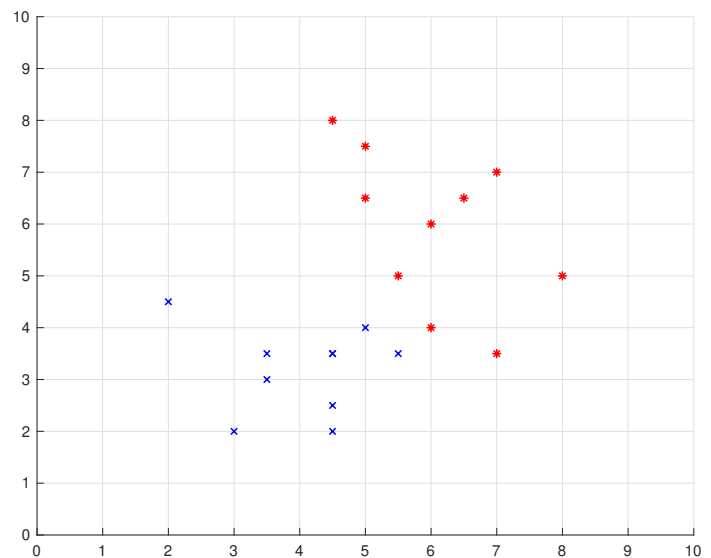
Important: Please copy the following sentence and sign it: “ I am respecting the rules of the exam: Signature:_____ ”

1) **Supervised and unsupervised learning (36 pt)**

You are given a training set of 19 samples in Fig 1. 10 red samples marked as red asterisks (*) and the rest are marked as blue Xs i.e., X. Each sample is given by a 2D feature vector. Create a unique test set by using the first 8 digits of your ID number, i.e. for ID number 123456789 the test set is $[(1, 2), (3, 4), (5, 6), (7, 8)]$

Feature 1	Feature 2	Label
2	4.5	Blue
3	2	
3.5	3	
3.5	3.5	
4.5	2	
4.5	2.5	
4.5	3.5	
5	4	
5.5	3.5	
4.5	8	Red
5	6.5	
5	7.5	
5.5	5	
6	4	
6	6	
6.5	7.5	
7	3.5	
7	7	
8	5	

Table form



2D Map form

Fig. 1: Training set

Supervised

- Use the training dataset to classify your test set using KNN for $K = 1, 3$.
- Fit a single Gaussian to each class
 - Assume full covariance matrix and draw Gaussians' contour lines and the decision line.
 - Assume diagonal covariance matrices and draw the Gaussians' contour lines and decision line.

Unsupervised

Use (4, 4) and (7, 4) as the initial points for the following.

- Fit a unsupervised GMM, assume diagonal covariance matrices. Draw the Gaussians' contour lines and decision line.
- Fit a K-means to the data and draw the outcome centroids and decision line.

Ranking the models

- Rank the supervised models according to the complexity of the inference. Explain your answer.
- Rank the unsupervised models according to the complexity of the inference. Explain your answer.

Solution:

- Your may verify your answers for your unique test set using the region-divided figures on Fig2.
- See Fig 3.
- See Fig4.
- See Fig 5
- Inference complexity from small to large, Assuming the data set is sufficiently large:
 GMM-diagonal \rightarrow GMM-full \rightarrow 1NN \rightarrow 3NN.
 This is because per sample GMM need to calculate the probability for each class while KNN need to run over all samples.
- Inference complexity: Kmeans \rightarrow GMM-diagonal.
 Kmeans needs to find the closest centroid while GMM calculates probability (exponentiation, matrix inverse, etc.). When the covariance matrix is αI_n , where α is constant and I_n is identity matrix of size n, then the complexity of Kmeans and GMM is the same (and will yield similar predictions).

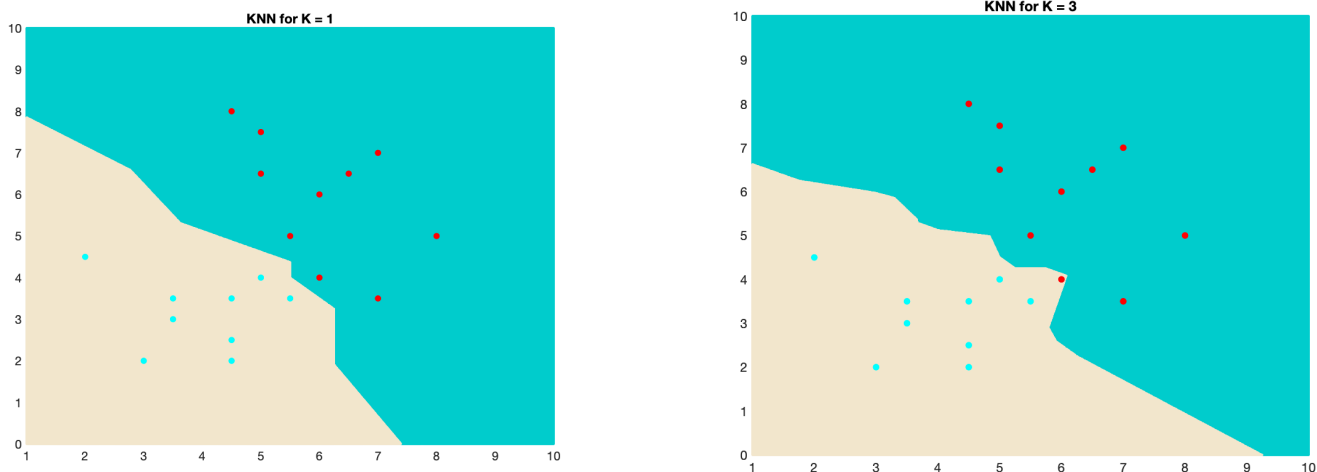


Fig. 2: KNN classification regions for K=1,3

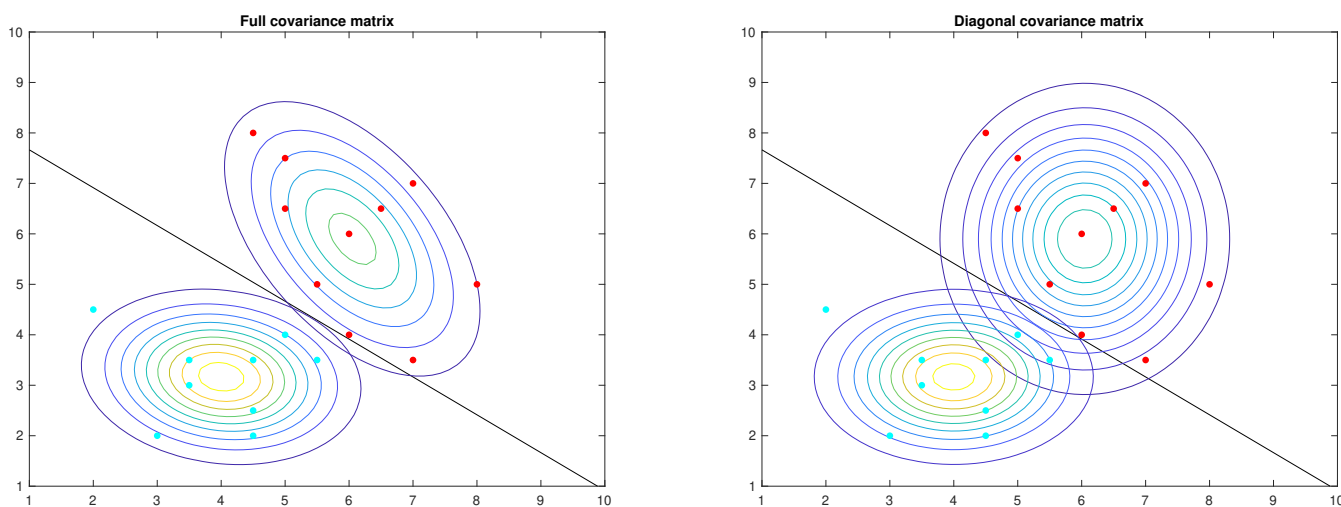


Fig. 3: Supervised GMM using diagonal/full covariance matrices

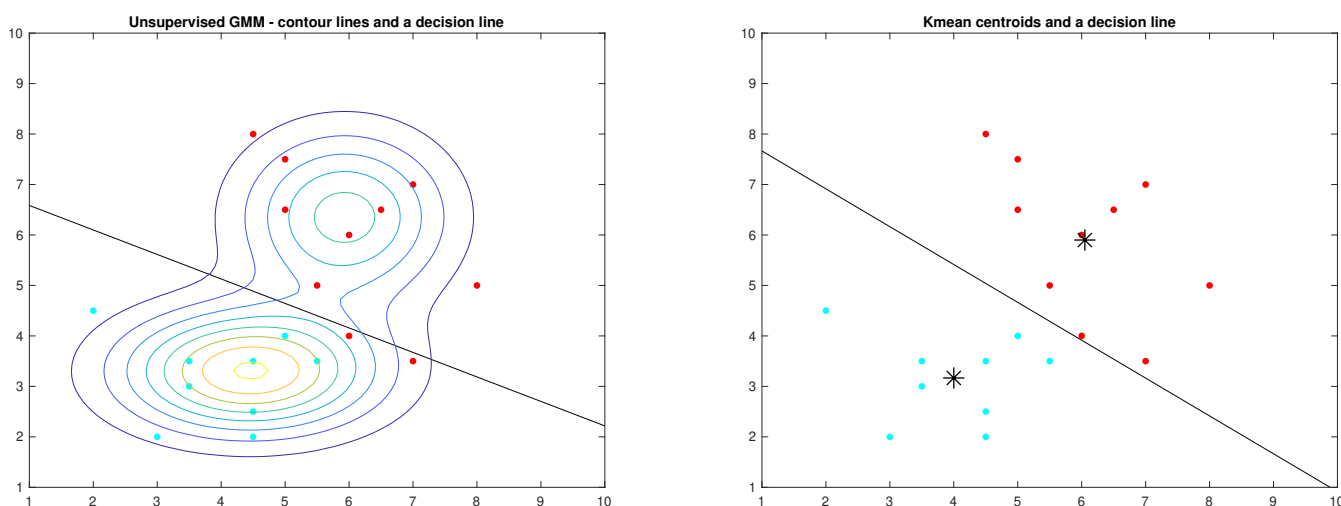


Fig. 4: GMM with 2 classes and diagonal matrices

Fig. 5: K-means

Fig. 4-5: Unsupervised models initiated from (4,4) and (4,7)

2) MINE (23 points)

- a) (10 points) Suppose we are given with a set of i.i.d. samples from two random variables, $\{(x_i, y_i)\}_{i=1}^n$, where $(x_i, y_i) \sim P_{X,Y}$, $x_i, y_i \in \mathbb{R}$ and we attempt to estimate $I(X;Y)$. The method is based on MINE $I_n(X, Y)$ as taught in class.

Which of the following experiment graphs is a possible description of the estimated MI during training (Figure 6)? Write the indices of the correct graphs in your solution and explain your choice.

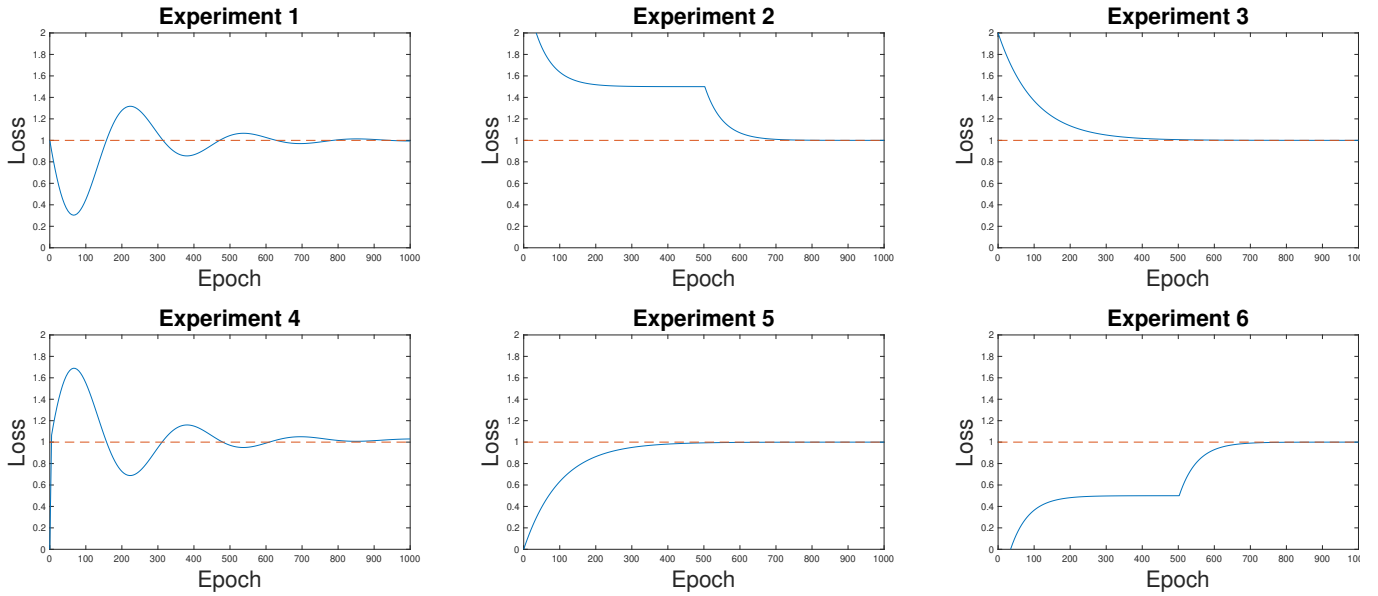


Fig. 6: Experiments - filled line represents the model's loss and dashed line represents the true value.

Solution: As learned in class, the objective of MINE is a lower bound on the mutual information, due to the supremum. Therefore, only graphs 5 and 6 are valid. The answer of choosing graphs 3 and 2 instead was also accepted, but note that this answer is not completely valid, because implementation of this optimization with a minus sign might lead to descending cost, but then we would expect the limit to be $-I(X; Y)$.

- b) Now, we wish to estimate the multivariate mutual information between the d -dimensional random vectors, (X^d, Y^d) , based on the algorithm and 1-dimensional samples presented in (2a), .
- (8 points) What criteria should the elements of $X^d, Y^d \in \mathbb{R}^d$ satisfy if we want to use the dataset given in question (2a)?
 - (5 points) What is the relation between the output of MINE and $I(X^d; Y^d)$ under this criteria and $n \rightarrow \infty$?

Solution We need to find a way to express $I(X^d, Y^d)$ with $I(X; Y)$, the limit of a trained MINE model with the sample set of subsection (a). We can use the chain rule and result with

$$\begin{aligned} I(X^d; Y^d) &= \sum_{j=1}^d I(X^d; Y_j | Y^{j-1}) \\ &= \sum_{j=1}^d \sum_{k=1}^d I(X_k; Y_j | X^{k-1} Y^{j-1}). \end{aligned}$$

Therefore, we need to demand

$$I(X_k; Y_j | X^{k-1} Y^{j-1}) = I(X_1; Y_1) \quad j, k = 1, \dots, d. \quad (1)$$

Which happens iff the components of (X^d, Y^d) are iid. Under this criteria we could use MINE $I_n(X, Y)$, the estimator of $I(X; Y)$ to calculate the d -dimensional mutual information, and the relation is given by:

$$I(X^d; Y^d) = dI_n(X, Y) \quad (2)$$

3) Bound on the binomial coefficient and types. (51 points)

Let $k, n \in \mathbb{N}$ such that $k \leq n$. Let $q := \frac{k}{n}$. **Reminder:** The binomial expression is given by

$$(a + b)^n = \sum_{k=0}^n \binom{n}{k} a^k b^{n-k} \quad (3)$$

Furthermore the number of sequences of length n with k ones is $\binom{n}{k}$.

In this question we prove the following inequality:

$$\frac{1}{n+1} 2^{nH_b(q)} \leq \binom{n}{k} \leq 2^{nH_b(q)} \quad (4)$$

where, $H_b(p) = -p \log p - (1-p) \log(1-p)$ is the binary entropy function.
Steps:

a) (3 points) Show that:

$$1 = \sum_{i=0}^n \binom{n}{i} q^i (1-q)^{n-i} \quad (5)$$

Solution:

From the binomial expression:

$$\sum_{i=0}^n \binom{n}{i} q^i (1-q)^{n-i} = (q + (1-q))^n = 1 \quad (6)$$

b) (5 points) Deduce that for every $i = 0, \dots, n$:

$$\binom{n}{i} \leq \frac{1}{q^i (1-q)^{n-i}} \quad (7)$$

Solution:

We note that every argument of the sum $\sum_{i=0}^n \binom{n}{i} q^i (1-q)^{n-i}$ is **non-negative** (since for every i : $\binom{n}{i}, q, (1-q) \geq 0$), and according to b) the sum is equal to 1. Hence, any argument by itself $\binom{n}{i} q^i (1-q)^{n-i} \leq 1$.

c) (5 points) Using the above inequality show that the right hand side of inequality (4) holds.

Solution:

After simplification using log rules and $q := \frac{k}{n}$ we have:

$$2^{nH_b(q)} = \frac{1}{q^k (1-q)^{n-k}}. \quad (8)$$

Hence, the right hand side of inequality (4) holds according to (7) because $k \in \{0, 1, \dots, n\}$.

d) (8 points) Assume the following:

$$\operatorname{argmax}_{i=0, \dots, n} \binom{n}{i} p^i (1-p)^{n-i} = np, \quad np \in \mathbb{Z} \quad (9)$$

prove the following inequality:

$$\binom{n}{k} \geq \frac{1}{n+1} 2^{nH_b(q)} \quad (10)$$

Solution:

In our case, $\operatorname{argmax}_{i=0, \dots, n} \binom{n}{i} q^i (1-q)^{n-i} = nq = k$, hence

$$1 = \sum_{i=0}^n \binom{n}{i} q^i (1-q)^{n-i} \leq \sum_{i=0}^n \binom{n}{k} q^k (1-q)^{n-k} = (n+1) \binom{n}{k} q^k (1-q)^{n-k} = (n+1) \binom{n}{k} 2^{-nH_b(q)}, \quad (11)$$

where the last equality follows from (8). From the positivity of the arguments we can divide and get (10).

e) (8 points) The type of a Binary sequence of length n with k ones is $\frac{k}{n}$. Provide a lower and upper bound on the number of sequences of length n of a specific type $\frac{k}{n}$.

Solution:

As it can be deduced from c) and d), (4) holds.

f) (3 points) Is the number of sequences with a fixed type exponential or polynomial?

Solution:

Exponential. We test the lower and upper bounds of (4) when $n \rightarrow \infty$ while q is fixed (consequently $H_b(q)$ is fixed). $2^{nH_b(q)}$ is exponential, while for the lower bound the denominator $n+1$ is only polynomial, hence both bounds are exponential, then $\binom{n}{k}$ is exponential.

g) (8 points) How many different types there exists if the sequence is Binary and has length n .

Solution:

Summing all possible types $\frac{k}{n}$ of length n with $k \in \{0, 1, \dots, n\}$ ones, we have $n+1$ different types.

h) (3 points) Is the number of different types that you calculated in the previous sub-question exponential or polynomial?

Solution:

Polynomial.

i) (8 points) For a binary sequence of length n with a type p we actually consider the ratio $\frac{k}{n}$ of such that $\frac{k}{n}$ is the closest number to p . For instance if $p = 0.5$ and $n = 100$ or $n = 101$ then $k = 50$. How many sequences of a fixed type p there exists asymptotically, namely, calculate

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log(\text{number of sequences of type } p).$$

Solution:

We examine this limit for both the lower and upper bounds. We note that $\lim_{n \rightarrow \infty} q(n, p) = \lim_{n \rightarrow \infty} \frac{k(n, p)}{n} = p$. Then,⁵

$$\begin{aligned} \lim_{n \rightarrow \infty} \frac{1}{n} \log\left(\frac{1}{n+1} 2^{nH_b(q(n, p))}\right) &= \lim_{n \rightarrow \infty} \frac{1}{n} \log\left(\frac{1}{n+1}\right) + \frac{1}{n} \log(2^{nH_b(q(n, p))}) \\ &= \lim_{n \rightarrow \infty} \frac{1}{n} \log(2^{nH_b(q(n, p))}) \\ &= \lim_{n \rightarrow \infty} H_b(q(n, p)) \\ &= H_b(p), \end{aligned} \tag{12}$$

and this is the limit for **both** bounds. Finally, from the sandwich theorem we have that the limit in the question equals $H_b(p)$.

Intuition: In this question you have developed an analysis of the number of sequences with a fixed ratio of the alphabet. Note, that you have obtained the entropy expression as a result of a basic combinatorical question. This result is very fundamental and requires only basic knowledge. Hence, we could actually start the course and define the entropy using this fundamental result.

Good Luck!