

# EE902 Final Exam 2023-24 Q3

Venkateswar Reddy Melachervu | 10 Mar 2024



**IIT KANPUR**  
Indian Institute of Technology Kanpur

Overall Status: Completed Detailed Status: Test-taker Completed

Test Finish Time: March 10, 2024 11:33:00 AM IST

VR

Venkateswar Reddy Melachervu

vmela23@iitk.ac.in

Test-Taker ID: - 130025089

Credibility Index: **LOW** ⓘ

Profile Picture Snapshot



Identity Card Snapshot



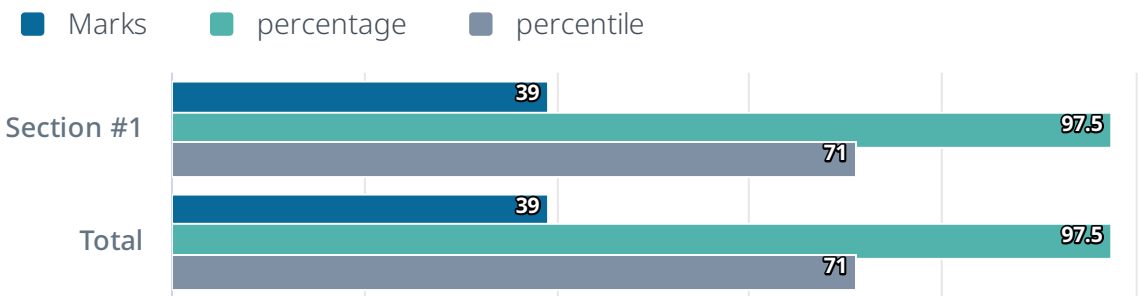
Overall Summary

39 Marks Scored  
out of 40

97.5 % 71.43 percentile  
out of 14 Test Takers

2h 31m 8s Time taken  
of 3hr

Marks Scored



Attempt Summary

Distribution of questions attempted in a total of 40 question(s).



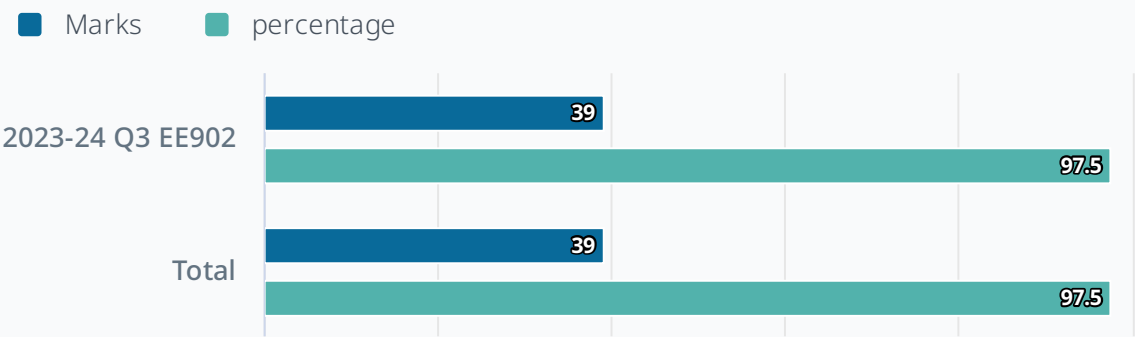
This shows the correctness of questions attempted by the test taker

Correct	39 Ques	39/39 Marks
Incorrect	1 Ques	0/1 Marks
Partially Correct	0 Ques	0/0 Marks
Not Attempted	0 Ques	0/0 Marks

Section-Wise Details

▼ Section 1 Section #1	question(s) 40 Q.	Time taken 2h 31m 8s (Untimed)	Marks Scored 39 / 40
---------------------------	----------------------	--------------------------------------	-------------------------

Marks Scored



Attempt Summary

Distribution of questions attempted in a total of 40 question(s).



This shows the correctness of questions attempted by the test taker

■ Correct	39 Ques	39/39 Marks
■ Incorrect	1 Ques	0/1 Marks

Q.

1

▼ Question 1

⌚ Time taken: 1m 55s

The Gaussian kernel is defined as

Response:

OPTIONS	RESPONSE	ANSWER
$\exp\left(\frac{\ \bar{\mathbf{x}}_i - \bar{\mathbf{x}}_j\ ^2}{2\sigma^2}\right)$		
$\exp\left(-\frac{\ \bar{\mathbf{x}}_i - \bar{\mathbf{x}}_j\ }{2\sigma^2}\right)$		
$\exp\left(-\frac{\ \bar{\mathbf{x}}_i - \bar{\mathbf{x}}_j\ ^2}{2\sigma^2}\right)$	✓	✓
$\ \bar{\mathbf{x}}_i - \bar{\mathbf{x}}_j\  \exp\left(-\frac{\ \bar{\mathbf{x}}_i - \bar{\mathbf{x}}_j\ }{2\sigma^2}\right)$		

Q.

2

▼ Question 2

⌚ Time taken: 54s

Logistic regression can be used in which of the following applications

Response:

OPTIONS	RESPONSE	ANSWER
Stock price forecasting		
Disease detection	✓	✓
Predicting the price of a home		
Clustering of users based on shopping information		

▼ Question 3

The learning model for the linear regression problem described in class is

Response:

OPTIONS	RESPONSE	ANSWER
$\underbrace{\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(M) \end{bmatrix}}_{\bar{\mathbf{y}}} = \underbrace{\begin{bmatrix} \bar{\mathbf{x}}(1) \\ \bar{\mathbf{x}}(2) \\ \vdots \\ \bar{\mathbf{x}}(M) \end{bmatrix}}_{\bar{\mathbf{X}}} \bar{\mathbf{h}} + \underbrace{\begin{bmatrix} \epsilon(1) \\ \epsilon(2) \\ \vdots \\ \epsilon(M) \end{bmatrix}}_{\bar{\boldsymbol{\epsilon}}}$		
$\underbrace{\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(M) \end{bmatrix}}_{\bar{\mathbf{y}}} = \underbrace{\begin{bmatrix} \bar{\mathbf{x}}^T(1) \\ \bar{\mathbf{x}}^T(2) \\ \vdots \\ \bar{\mathbf{x}}^T(M) \end{bmatrix}}_{\bar{\mathbf{X}}} \bar{\mathbf{h}} + \underbrace{\begin{bmatrix} \epsilon(1) \\ \epsilon(2) \\ \vdots \\ \epsilon(M) \end{bmatrix}}_{\bar{\boldsymbol{\epsilon}}}$	✔	✔
$\underbrace{\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(M) \end{bmatrix}}_{\bar{\mathbf{y}}} = \underbrace{\begin{bmatrix} \bar{\mathbf{x}}(1) \\ \bar{\mathbf{x}}(2) \\ \vdots \\ \bar{\mathbf{x}}(M) \end{bmatrix}}_{\bar{\mathbf{X}}} \bar{\mathbf{h}}^T + \underbrace{\begin{bmatrix} \epsilon(1) \\ \epsilon(2) \\ \vdots \\ \epsilon(M) \end{bmatrix}}_{\bar{\boldsymbol{\epsilon}}}$		
$\underbrace{\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(M) \end{bmatrix}}_{\bar{\mathbf{y}}} = \underbrace{\begin{bmatrix} \bar{\mathbf{x}}^T(1) \\ \bar{\mathbf{x}}^T(2) \\ \vdots \\ \bar{\mathbf{x}}^T(M) \end{bmatrix}}_{\bar{\mathbf{X}}} \bar{\mathbf{h}}^T + \underbrace{\begin{bmatrix} \epsilon(1) \\ \epsilon(2) \\ \vdots \\ \epsilon(M) \end{bmatrix}}_{\bar{\boldsymbol{\epsilon}}}$		

Consider the table below

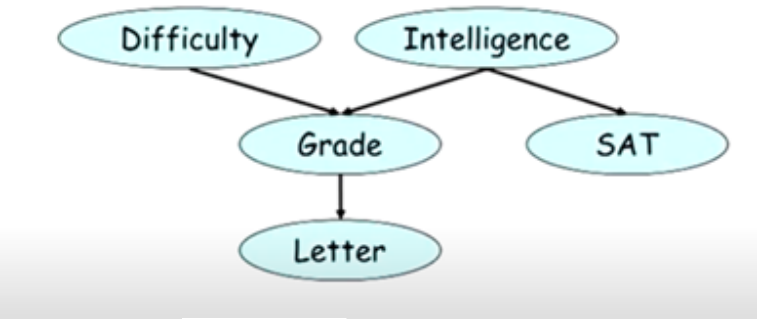
	$x_2 = 0$	$x_2 = 1$
$y = 0$	3	9
$y = 1$	6	12

The quantity  $p(y = 1)$  is given as

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{3}{4}$		
$\frac{3}{5}$	✔	✔
$\frac{1}{3}$		
$\frac{2}{5}$		

Consider the model



The quantity  $p(l^1|i^0, d^0)$  is an example of

Response:

OPTIONS	RESPONSE	ANSWER
Causal reasoning	✔	✔
Evidential Reasoning		
Intercausal Reasoning		
Not possible to evaluate		

Consider the linear regression problem with the design matrix  $X$  and response vector  $\bar{\mathbf{y}}$  given below  $X = \begin{bmatrix} -1 & 1 \\ -1 & -1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix}, \bar{\mathbf{y}} = \begin{bmatrix} 2 \\ -2 \\ 4 \\ -2 \end{bmatrix}$

The vector of regression coefficients is

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{1}{2} \begin{bmatrix} 3 \\ -2 \end{bmatrix}$		
$\frac{1}{2} \begin{bmatrix} -2 \\ 3 \end{bmatrix}$		
$\begin{bmatrix} -1 \\ 1 \end{bmatrix}$		
$\frac{1}{2} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$	✔	✔

What is the **margin** between two hyperplanes?

$\bar{\mathbf{a}}^T \bar{\mathbf{x}} = c_1$   
 $\bar{\mathbf{a}}^T \bar{\mathbf{x}} = c_2$

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{\ \bar{\mathbf{a}}\ }{ c_1 - c_2 }$		
$\frac{ c_1^2 - c_2^2 }{\ \bar{\mathbf{a}}\ }$		
$\frac{ c_1 - c_2 }{\ \bar{\mathbf{a}}\ ^2}$		
$\frac{ c_1 - c_2 }{\ \bar{\mathbf{a}}\ }$	✔	✔



The posterior probability  $p(y = 1|\bar{x} = \bar{v})$  is given as

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{p(\bar{x}=\bar{v} y=1)}{p(\bar{x}=\bar{v})}$		
$\frac{p(\bar{x}=\bar{v} y=1)\times p(y=1)+p(\bar{x}=\bar{v} y=0)\times p(y=0)}{p(\bar{x}=\bar{v})}$		
$\frac{p(\bar{x}=\bar{v} y=1)\times p(y=1)}{p(\bar{x}=\bar{v})}$	✔	✔
$\frac{p(\bar{x}=\bar{v})}{p(\bar{x}=\bar{v} y=1)\times p(y=1)}$		

The K - means **cost-function** to minimize is given as

Response:

OPTIONS	RESPONSE	ANSWER
$\min \sum_{i=1}^K \sum_{j=1}^M \alpha_i(j) \ \bar{x}(j) - \bar{\mu}_i\ $		
$\min \sum_{i=1}^K \sum_{j=1}^M \alpha_i(j) (\bar{x}(j) - \bar{\mu}_i)(\bar{x}(j) - \bar{\mu}_i)^T$		
$\min \sum_{i=1}^K \sum_{j=1}^M \alpha_i(j) \ \bar{x}(j) - \bar{\mu}_i\ ^2$	✔	✔
$\min \sum_{i=1}^K \alpha_i(j) \ \bar{x}(j) - \bar{\mu}_i\ ^2$		

The **entropy**  $H(X)$  of this source is

Response:

OPTIONS	RESPONSE	ANSWER
$-\sum_{i=1}^n p(x_i) \log_2 p(x_i)$	✔	✔
$\sum_{i=1}^n \frac{1}{p(x_i)} \log_2 \frac{1}{p(x_i)}$		
$-\sum_{i=1}^n p(x_i) \log_2 \frac{1}{p(x_i)}$		
$\sum_{i=1}^n \log_2 \frac{1}{p(x_i)}$		

What is the distance between the two hyperplanes given below

$$\begin{aligned}x_1 + \sqrt{2}x_2 + \sqrt{3}x_3 + \cdots + \sqrt{N}x_N &= 2\sqrt{2} \\ x_1 + \sqrt{2}x_2 + \sqrt{3}x_3 + \cdots + \sqrt{N}x_N &= -2\sqrt{2}\end{aligned}$$

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{8}{\sqrt{N(N+1)}}$	✔	✔
$\frac{2\sqrt{2}}{\sqrt{N(N+1)}}$		
$\frac{2}{\sqrt{\frac{N(N+1)(2N+1)}{6}}}$		
$\frac{1}{2\sqrt{\frac{N(N+1)(2N+1)}{6}}}$		

Consider the linear regression model below  
 $y(k) = h_0 + h_1x_1(k) + \cdots + h_nx_n(k) + \epsilon(k)$   
The quantities  $x_i(k)$  are

Response:

OPTIONS	RESPONSE	ANSWER
Response		
Regression coefficient		
Regressor	✔	✔
Model error		

The probability  $p(x_j = 1|y = 0)$  can be evaluated using the formula

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{\sum_{j=1}^N \mathbf{1}(x_j(i)=1,y(i)=0)}{N}$		
$1 - p(x_j = 1 y = 1)$		
$\frac{\sum_{i=1}^M \mathbf{1}(x_j(i)=1,y(i)=0)}{M}$		
$\frac{\sum_{i=1}^M \mathbf{1}(x_j(i)=1,y(i)=0)}{\sum_{i=1}^M \mathbf{1}(y(i)=0)}$	✔	✔

To determine the cluster in iteration  $l$ , we assign  $\bar{\mathbf{x}}(j)$  to cluster  $\tilde{i}$  with centroid  $\bar{\boldsymbol{\mu}}_i^{(l-1)}$  that satisfies

Response:

OPTIONS	RESPONSE	ANSWER
$\tilde{i} = \arg \max_i \bar{\mathbf{x}}^T(j) \bar{\boldsymbol{\mu}}_i^{(l-1)} - \left(\bar{\boldsymbol{\mu}}_i^{(l-1)}\right)^T \bar{\boldsymbol{\mu}}_i^{(l-1)}$	✔	✔
$\tilde{i} = \arg \max_i 2 \bar{\mathbf{x}}^T(j) \bar{\boldsymbol{\mu}}_i^{(l-1)} + \left(\bar{\boldsymbol{\mu}}_i^{(l-1)}\right)^T \bar{\boldsymbol{\mu}}_i^{(l-1)}$		
$\tilde{i} = \arg \max_i \bar{\mathbf{x}}^T(j) \bar{\boldsymbol{\mu}}_i^{(l-1)} + \left(\bar{\boldsymbol{\mu}}_i^{(l-1)}\right)^T \bar{\boldsymbol{\mu}}_i^{(l-1)}$		

The multivariate Gaussian PDF for parameters below is

$$\bar{\boldsymbol{\mu}} = \begin{bmatrix} -1 \\ 1 \end{bmatrix}, \mathbf{R} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{1}{\sqrt{12\pi}} e^{-\frac{1}{3}(x_1^2+x_2^2+3x_1+3x_2-x_1x_2+3)}$		
$\frac{1}{\sqrt{12\pi}} e^{-\frac{1}{3}(x_1^2+x_2^2+3x_1-3x_2+x_1x_2+3)}$		
$\frac{1}{\sqrt{12\pi}} e^{-\frac{1}{3}(x_1^2+x_2^2+3x_1-3x_2-x_1x_2+3)}$	✔	✔
$\frac{1}{\sqrt{12\pi}} e^{-\frac{1}{3}(x_1^2+x_2^2-3x_1-3x_2+x_1x_2+3)}$		

In the example considered in lectures, the size of the feature vector equals

Response:

OPTIONS	RESPONSE	ANSWER
Number of emails in the set		
Number of words in the dictionary	✔	✔
2		
Number of words in an e-mail		

Consider the ML example below for prediction of sales based on advertising

Year	Sales (Million Euro)	Advertising (Million Euro)
1	651	23
2	762	26
3	856	30
4	1,063	34
5	1,190	43
6	1,298	48
7	1,421	52
8	1,440	57
9	1,518	58

In this example, Advertising is the

Response:

OPTIONS	RESPONSE	ANSWER
Response		
Regression coefficient		
Model error		
Regressor	✔	✔

The **kernel SVM** problem can be defined as

Response:

OPTIONS	RESPONSE	ANSWER
$\max \sum_{i=1}^{2M} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j \bar{\mathbf{x}}_i^T \bar{\mathbf{x}}_j$ <p>subject to <math>\lambda_i \geq 0</math></p> $\sum_{i=1}^{2M} \lambda_i y_i = 0$		
$\max \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j K(\bar{\mathbf{x}}_i, \bar{\mathbf{x}}_j)$ <p>subject to <math>\lambda_i \geq 0</math></p> $\sum_{i=1}^{2M} \lambda_i y_i = 0$		
$\max \sum_{i=1}^{2M} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j K(\bar{\mathbf{x}}_i, \bar{\mathbf{x}}_j)$ <p>subject to <math>\lambda_i \geq 0</math></p> $\sum_{i=1}^{2M} \lambda_i y_i = 0$	✔	✔
$\max \sum_{i=1}^{2M} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j K(\bar{\mathbf{x}}_i, \bar{\mathbf{x}}_j)$ <p>subject to <math>\lambda_i \leq 0</math></p> $\sum_{i=1}^{2M} \lambda_i y_i \geq 0$		

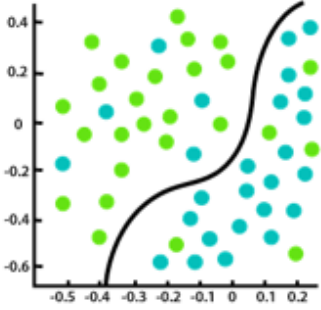
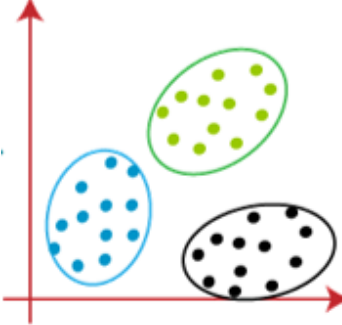
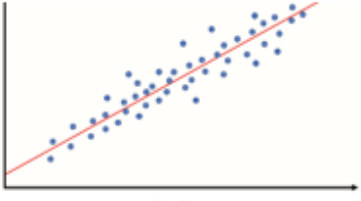

The regression coefficient vector from the training data is determined as

Response:

OPTIONS	RESPONSE	ANSWER
$\bar{\mathbf{h}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \bar{\mathbf{y}}$	✔	✔
$\bar{\mathbf{h}} = \mathbf{X}^T (\mathbf{X}^T \mathbf{X})^{-1} \bar{\mathbf{y}}$		
$\bar{\mathbf{h}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X} \bar{\mathbf{y}}$		
$\bar{\mathbf{h}} = (\mathbf{X} \mathbf{X}^T)^{-1} \mathbf{X}^T \bar{\mathbf{y}}$		

Which figure below represents linear regression

Response:

OPTIONS	RESPONSE	ANSWER
		
		
	✓	✓
		

1. The log-likelihood of the regression parameter  $\bar{\mathbf{h}}$  in logistic regression can be written as

Response:

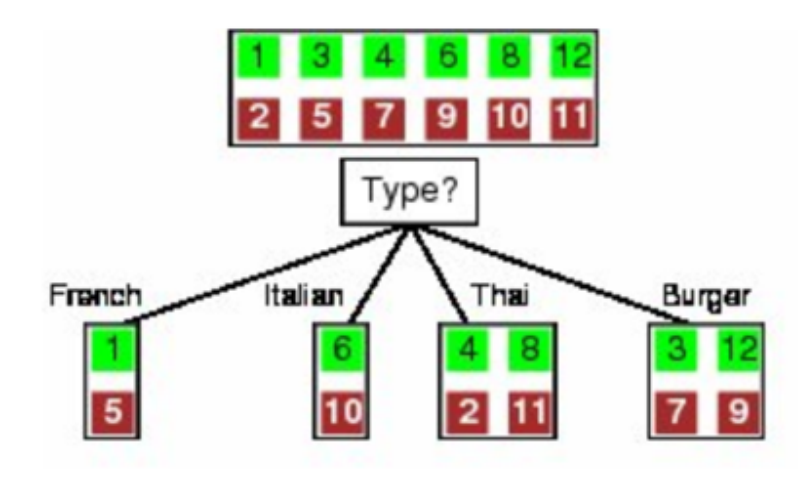
OPTIONS	RESPONSE	ANSWER
$\sum_{k=1}^M (1 - y(k)) \ln g(\bar{\mathbf{x}}(k)) + y(k) \ln (1 - g(\bar{\mathbf{x}}(k)))$		
$\sum_{k=1}^M y(k) \ln g(\bar{\mathbf{x}}(k)) + (1 - y(k)) \ln (1 - g(\bar{\mathbf{x}}(k)))$	✓	✓
$\prod_{k=1}^M (g(\bar{\mathbf{x}}(k)))^{y(k)} (1 - g(\bar{\mathbf{x}}(k)))^{1-y(k)}$		
$\prod_{k=1}^M (g(\bar{\mathbf{x}}(k)))^{1-y(k)} (1 - g(\bar{\mathbf{x}}(k)))^{y(k)}$		

The probability  $p(x_j = 1|y = 1)$  can be evaluated using Laplace smoothing as

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{\sum_{j=1}^N 1(x_j(i)=1,y(i)=1)+1}{\sum_{i=1}^M 1(y(i)=1)+2}$		
$\frac{\sum_{i=1}^M 1(x_j(i)=1,y(i)=1)+1}{\sum_{i=1}^M 1(y(i)=1)+2}$	✔	✔
$\frac{\sum_{i=1}^M 1(x_j(i)=1,y(i)=1)+1}{\sum_{i=1}^M 1(y(i)=1)+1}$		
$\frac{\sum_{i=1}^M 1(x_j(i)=1,y(i)=1)}{\sum_{i=1}^M 1(y(i)=1)}$		

What is the quantity  $H(X | \text{Type})$  for the type feature depicted in the figure below, where X is the final decision?



Response:

OPTIONS	RESPONSE	ANSWER
1	✔	✔
0.36		
0		
0.54		



The **conditional entropy**  $H(X|Y)$  is defined as

Response:

OPTIONS	RESPONSE	ANSWER
$\sum_{j=1}^m p(y_j)H(Y = y_j X)$		
$\sum_{j=1}^m p(y_j)H(X Y = y_j)$	✔	✔
$\sum_{j=1}^m H(X Y = y_j)$		
$\sum_{i=1}^n p(x_i)H(Y X = x_i)$		

The Gaussian discriminant classifier for both classes with identical covariances is

Response:

OPTIONS	RESPONSE	ANSWER
Ellipsoidal		
Spherical		
Conical		
Linear	✔	✔

The cluster assignment indicator  $\alpha_2(3)$

Response:

OPTIONS	RESPONSE	ANSWER
Equals 1 when $\bar{\mathbf{x}}(3)$ belongs to $\mathcal{C}_2$ and 0 otherwise	✔	✔
Equals 0 when $\bar{\mathbf{x}}(3)$ belongs to $\mathcal{C}_2$ and 1 otherwise		
Equals 1 when $\bar{\mathbf{x}}(2)$ belongs to $\mathcal{C}_3$ and 0 otherwise		
Equals 0 when $\bar{\mathbf{x}}(2)$ belongs to $\mathcal{C}_3$ and 1 otherwise		

Consider the two classes  $\mathcal{C}_0, \mathcal{C}_1$  distributed as below and determine when the classifier chooses  $\mathcal{H}_0$

$$\mathcal{C}_0 \sim N\left(\begin{bmatrix} 2 \\ -2 \end{bmatrix}, \begin{bmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{4} \end{bmatrix}\right), \mathcal{C}_1 \sim N\left(\begin{bmatrix} 4 \\ -4 \end{bmatrix}, \begin{bmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{4} \end{bmatrix}\right)$$

Response:

OPTIONS	RESPONSE	ANSWER
$x_1 + 4x_2 \geq -1$		
$x_1 + 2x_2 \leq 5$		
$4x_1 - x_2 \leq 3$		
$2x_1 - x_2 \leq 9$	✔	✔

The k - means algorithm is a/an

Response:

OPTIONS	RESPONSE	ANSWER
Supervised learning algorithm		
Reinforcement learning algorithm		
Deep learning algorithm		
Unsupervised learning algorithm	✔	✔

The *mean* and *covariance matrix* of the multivariate Guassian are defined as

Response:

OPTIONS	RESPONSE	ANSWER
$E\{\bar{\mathbf{x}}\} = \bar{\boldsymbol{\mu}}, E\{(\bar{\mathbf{x}} - \bar{\boldsymbol{\mu}})^2\} = \mathbf{R}$		
$E\{\bar{\mathbf{x}}\} = \bar{\boldsymbol{\mu}}, E\{(\bar{\mathbf{x}} - \bar{\boldsymbol{\mu}})(\bar{\mathbf{x}} - \bar{\boldsymbol{\mu}})^T\} = \mathbf{R}$	✔	✔
$E\{\bar{\mathbf{x}}\} = \mu, E\{(\bar{\mathbf{x}} - \bar{\boldsymbol{\mu}})^T(\bar{\mathbf{x}} - \bar{\boldsymbol{\mu}})\} = \mathbf{R}$		
$E\{\bar{\mathbf{x}}\} = \mu, E\{\bar{\mathbf{x}}\bar{\mathbf{x}}^T\} = \mathbf{R}$		

The optimization problem to determine the soft classifier is given as

Response:

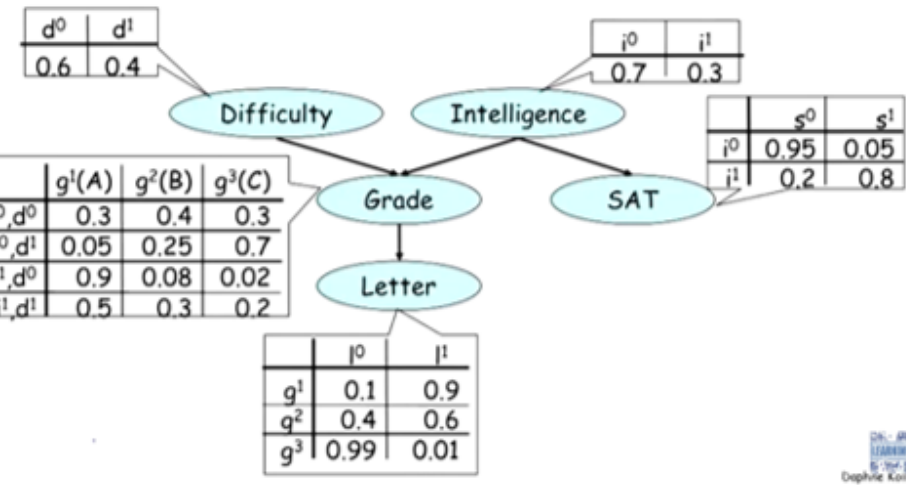
OPTIONS	RESPONSE	ANSWER
$\begin{aligned} \min \sum_{i=1}^N u_i + \sum_{i=1}^N v_i \\ \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq 1 - u_i, 1 \leq i \leq M \\ \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq -1 + v_i, M + 1 \leq i \leq 2M \\ u_i < 0, v_i < 0 \end{aligned}$		
$\begin{aligned} \min \ \bar{\mathbf{a}}\  \\ \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq 1 - u_i, 1 \leq i \leq M \\ \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq -1 + v_i, M + 1 \leq i \leq 2M \\ u_i \geq 0, v_i \geq 0 \end{aligned}$		
$\begin{aligned} \min \sum_{i=1}^N u_i + \sum_{i=1}^N v_i \\ \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq 1 - u_i, 1 \leq i \leq M \\ \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq -1 + v_i, M + 1 \leq i \leq 2M \\ u_i \geq 0, v_i \geq 0 \end{aligned}$	✔	✔
$\begin{aligned} \max \sum_{i=1}^N u_i + \sum_{i=1}^N v_i \\ \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq 1 - u_i, 1 \leq i \leq M \\ \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq -1 + v_i, M + 1 \leq i \leq 2M \\ u_i \geq 0, v_i \geq 0 \end{aligned}$		

Given a new observation  $\bar{x} = \bar{v}$ , it can be labeled as belonging to the class  $y = 1$  if

Response:

OPTIONS	RESPONSE	ANSWER
$\frac{\prod_{j=1}^N p(x_j=v_j y=1)}{p(y=0)} > \frac{\prod_{j=1}^N p(x_j=v_j y=0)}{p(y=1)}$		✓
$\frac{p(y=0)}{\prod_{j=1}^N p(x_j=v_j y=1)} > \frac{p(y=1)}{\prod_{j=1}^N p(x_j=v_j y=0)}$		
$\frac{\prod_{j=1}^N p(x_j=v_j y=1)}{p(y=1)} > \frac{\prod_{j=1}^N p(x_j=v_j y=0)}{p(y=0)}$	✓	
$\frac{p(y=1)}{\prod_{j=1}^N p(x_j=v_j y=1)} > \frac{p(y=0)}{\prod_{j=1}^N p(x_j=v_j y=0)}$		

Consider the model below



$p(d^0, i^1, g^1, s^1)$  can be evaluated as approximately

Response:

OPTIONS	RESPONSE	ANSWER
0.05871		
0.12960	✓	✓
0.11664		
0.45332		

In Gaussian discriminant analysis, we **choose**  $\mathcal{C}_0$  if

Response:

OPTIONS	RESPONSE	ANSWER
$p(\bar{\mathbf{x}}; \mathcal{C}_0) < p(\bar{\mathbf{x}}; \mathcal{C}_1)$		
$p(\bar{\mathbf{x}}; \mathcal{C}_0) = p(\bar{\mathbf{x}}; \mathcal{C}_1)$		
$p(\bar{\mathbf{x}}; \mathcal{C}_0) > 0$		
$p(\bar{\mathbf{x}}; \mathcal{C}_0) > p(\bar{\mathbf{x}}; \mathcal{C}_1)$	✔	✔

The dual problem for the SVM can be formulated as

Response:

OPTIONS	RESPONSE	ANSWER
$\max \sum_{i=1}^{2M} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j \bar{\mathbf{x}}_i^T \bar{\mathbf{x}}_j$ subject to $\lambda_i \leq 0$		
$\max \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j \bar{\mathbf{x}}_i^T \bar{\mathbf{x}}_j$ subject to $\lambda_i \leq 0$ $\sum_{i=1}^{2M} \lambda_i y_i \geq 0$		
$\max \sum_{i=1}^{2M} \lambda_i + \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j \bar{\mathbf{x}}_i^T \bar{\mathbf{x}}_j$ subject to $\lambda_i = 0$ $\sum_{i=1}^{2M} \lambda_i y_i = 0$		
$\max \sum_{i=1}^{2M} \lambda_i - \frac{1}{2} \sum_{i,j=1}^{2M} \lambda_i \lambda_j y_i y_j \bar{\mathbf{x}}_i^T \bar{\mathbf{x}}_j$ subject to $\lambda_i \geq 0$ $\sum_{i=1}^{2M} \lambda_i y_i = 0$	✔	✔

The optimization problem to determine the support vector classifier is

Response:

OPTIONS	RESPONSE	ANSWER
$\min \ \bar{\mathbf{a}}\ _2$ $\mathcal{C}_0: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq 1, \ 1 \leq i \leq M$ $\mathcal{C}_1: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq -1, \ M + 1 \leq i \leq 2M$		
$\min \frac{1}{\ \bar{\mathbf{a}}\ _2}$ $\mathcal{C}_0: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq 1, \ 1 \leq i \leq M$ $\mathcal{C}_1: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq -1, \ M + 1 \leq i \leq 2M$		
$\min \ \bar{\mathbf{a}}\ _2$ $\mathcal{C}_0: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq 1, \ 1 \leq i \leq M$ $\mathcal{C}_1: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq -1, \ M + 1 \leq i \leq 2M$		
$\min \frac{1}{\ \bar{\mathbf{a}}\ _2}$ $\mathcal{C}_0: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \leq 1, \ 1 \leq i \leq M$ $\mathcal{C}_1: \bar{\mathbf{a}}^T \bar{\mathbf{x}}_i + b \geq -1, \ M + 1 \leq i \leq 2M$		

The PDF of the Gaussian mixture is given as

Response:

OPTIONS	RESPONSE	ANSWER
$\sum_{i=1}^K \left( \left( \frac{1}{2\pi\sigma^2} \right)^{\frac{N}{2}} e^{-\frac{1}{2\sigma^2} \ \bar{\mathbf{x}} - \bar{\boldsymbol{\mu}}_i\ ^2} \right)^{p_i}$ <p>..</p>		
$\sum_{i=1}^K p_i \times \left( \frac{1}{2\pi\sigma^2} \right)^{\frac{N}{2}} e^{-\frac{1}{2\sigma^2} \ \bar{\mathbf{x}} - \bar{\boldsymbol{\mu}}_i\ ^2}$		
$\prod_{i=1}^K p_i \times \left( \frac{1}{2\pi\sigma^2} \right)^{\frac{N}{2}} e^{-\frac{1}{2\sigma^2} \ \bar{\mathbf{x}} - \bar{\boldsymbol{\mu}}_i\ ^2}$		
$\prod_{i=1}^K \left( \left( \frac{1}{2\pi\sigma^2} \right)^{\frac{N}{2}} e^{-\frac{1}{2\sigma^2} \ \bar{\mathbf{x}} - \bar{\boldsymbol{\mu}}_i\ ^2} \right)^{p_i}$		

The update rule in logistic regression is

Response:

OPTIONS	RESPONSE	ANSWER
$\bar{\mathbf{h}}(k+1) = \bar{\mathbf{h}}(k) + \eta \left( y(k+1) - g(\bar{\mathbf{x}}(k+1)) \right) \bar{\mathbf{x}}(k+1)$	✔	✔
$\bar{\mathbf{h}}(k+1) = \bar{\mathbf{h}}(k) - \eta \left( y(k+1) - g(\bar{\mathbf{x}}(k+1)) \right) \bar{\mathbf{x}}(k+1)$		
$\bar{\mathbf{h}}(k+1) = \bar{\mathbf{h}}(k) + \eta \left( y(k+1) - \bar{\mathbf{h}}^T(k) \bar{\mathbf{x}}(k+1) \right) \bar{\mathbf{x}}(k+1)$		
$\bar{\mathbf{h}}(k+1) = \bar{\mathbf{h}}(k) - \eta \left( y(k+1) - \bar{\mathbf{h}}^T(k) \bar{\mathbf{x}}(k+1) \right) \bar{\mathbf{x}}(k+1)$		

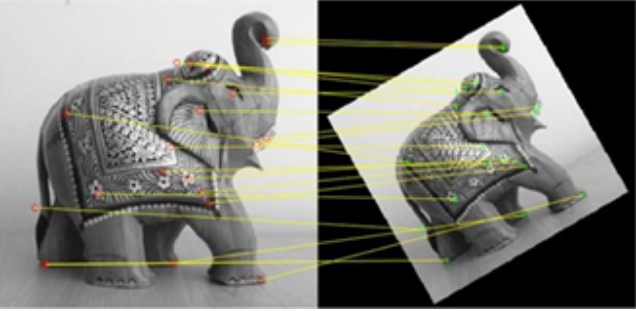
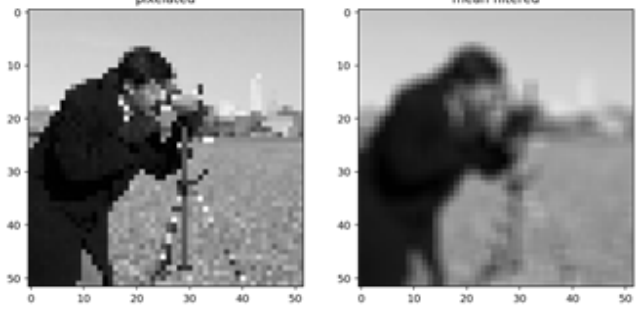
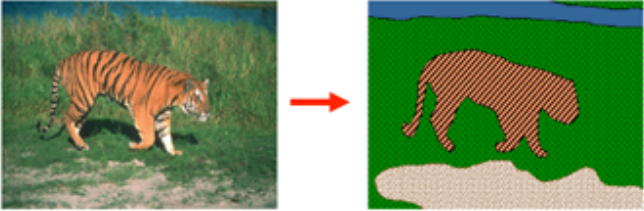
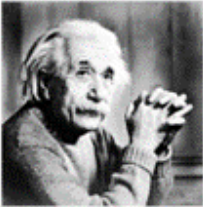
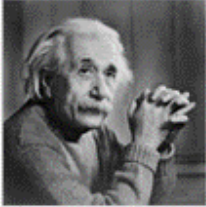
The expected value of the log-likelihood in iteration  $l$  is

Response:

OPTIONS	RESPONSE	ANSWER
$\prod_{j=1}^M \sum_{i=1}^N \left( \alpha_i^{(l)}(j) \ln p_i - \frac{N}{2} \ln 2\pi\sigma^2 - \frac{1}{2\sigma^2} \ \bar{\mathbf{x}}(j) - \bar{\boldsymbol{\mu}}_i\ ^2 \right)$		
$\prod_{j=1}^M \prod_{i=1}^N \left( \alpha_i^{(l)}(j) \ln p_i - \frac{N}{2} \ln 2\pi\sigma^2 - \frac{1}{2\sigma^2} \ \bar{\mathbf{x}}(j) - \bar{\boldsymbol{\mu}}_i\ ^2 \right)$		
$\sum_{j=1}^M \sum_{i=1}^N \alpha_i^{(l)}(j) \left( \ln p_i - \frac{N}{2} \ln 2\pi\sigma^2 - \frac{1}{2\sigma^2} \ \bar{\mathbf{x}}(j) - \bar{\boldsymbol{\mu}}_i\ ^2 \right)$	✔	✔
$\sum_{j=1}^M \prod_{i=1}^N \left( \ln p_i - \frac{N}{2} \ln 2\pi\sigma^2 - \frac{1}{2\sigma^2} \ \bar{\mathbf{x}}(j) - \bar{\boldsymbol{\mu}}_i\ ^2 \right)^{\alpha_i^{(l)}(j)}$		

Which for the following shows image segmentation

Response:

OPTIONS	RESPONSE	ANSWER
 The image shows a 3D model of an elephant on the left and its segmented version on the right. Yellow lines connect corresponding body parts (like the trunk, legs, and head) between the two images, illustrating the process of identifying and separating different regions of the image.		
 Two side-by-side grayscale images of a person. The left image is labeled 'pixelated' and shows a jagged, low-resolution version of the person. The right image is labeled 'mean filtered' and shows a smoother, blurred version of the same person, where individual pixel boundaries are softened.		
 A color image of a tiger in a grassy field on the left. A red arrow points to the right, where the same image is shown with segmentation. The tiger is highlighted with a red diagonal-hatch pattern, the grass is green, and the ground is tan.	✓	✓
<div><div>New Image</div></div> <div><div>Old image</div></div>		

As  $z \rightarrow \infty$ ,  $z \rightarrow -\infty$ , the logistic function approaches the limits


































Response:

OPTIONS	RESPONSE	ANSWER
0,1		
$\infty, 0$		
0, $\infty$		
1,0	✓	✓



Test Log

10th Mar 2024

09:01 AM		Started the test with Section #1
09:01 AM		Candidate gave us right to the following feeds - camera : HP TrueVision FHD RGB-IR (064e:3401) - microphone : Default - Microphone Array (Realtek High Definition Audio(SST))
09:01 AM		Candidate Looking Away from Screen
09:02 AM		Candidate Looking Away from Screen
09:03 AM		Away from test window
09:04 AM		Candidate Looking Away from Screen
09:05 AM		Away from test window
09:05 AM		Candidate Looking Away from Screen
09:07 AM		Candidate Looking Away from Screen for 02 mins
09:13 AM		Away from test window
09:14 AM		Candidate Looking Away from Screen
09:15 AM		Candidate Looking Away from Screen
09:15 AM		Candidate Looking Away from Screen
09:16 AM		Away from test window for 01 min
09:16 AM		Away from test window
09:16 AM		Candidate Looking Away from Screen
09:18 AM		Candidate Looking Away from Screen
09:18 AM		Away from test window for 01 min
09:19 AM		Candidate Looking Away from Screen
09:20 AM		Away from test window
09:21 AM		Away from test window
09:22 AM		Candidate Looking Away from Screen
09:22 AM		Away from test window
09:23 AM		Away from test window
09:26 AM		Candidate Looking Away from Screen
09:27 AM		Away from test window for 02 mins
09:29 AM		Candidate Looking Away from Screen
09:29 AM		Candidate Looking Away from Screen
09:30 AM		Candidate Looking Away from Screen for 01 min
09:32 AM		Candidate Looking Away from Screen for 06 mins
09:40 AM		Candidate Looking Away from Screen
09:43 AM		Candidate Looking Away from Screen for 03 mins
09:47 AM		Candidate Looking Away from Screen

09:48 AM	●	Candidate Face not Visible
09:48 AM	●	Away from test window for 18 mins
09:50 AM	●	Away from test window
09:54 AM	●	Away from test window
09:54 AM	●	Away from test window
09:57 AM	●	Away from test window for 02 mins
10:00 AM	●	Away from test window
10:00 AM	●	Candidate Looking Away from Screen
10:02 AM	●	Candidate Looking Away from Screen
10:03 AM	●	Candidate Looking Away from Screen
10:04 AM	●	Candidate Looking Away from Screen for 02 mins
10:06 AM	●	Away from test window for 05 mins
10:08 AM	●	Away from test window
10:08 AM	●	Away from test window
10:10 AM	●	Candidate Looking Away from Screen
10:11 AM	●	Away from test window
10:11 AM	●	Away from test window
10:12 AM	●	Candidate Looking Away from Screen
10:13 AM	●	Candidate Looking Away from Screen
10:15 AM	●	Away from test window for 02 mins
10:16 AM	●	Candidate Looking Away from Screen
10:17 AM	●	Candidate Looking Away from Screen
10:18 AM	●	Away from test window
10:18 AM	●	Candidate Looking Away from Screen
10:19 AM	●	Candidate Looking Away from Screen for 01 min
10:20 AM	●	Away from test window
10:21 AM	●	Away from test window
10:21 AM	●	Away from test window
10:22 AM	●	Away from test window
10:24 AM	●	Away from test window
10:24 AM	●	Away from test window
10:24 AM	●	Candidate Looking Away from Screen
10:25 AM	●	Away from test window
10:25 AM	●	Candidate Looking Away from Screen
10:26 AM	●	Away from test window
10:28 AM	●	Away from test window
10:28 AM	●	Candidate Looking Away from Screen
10:28 AM	●	Away from test window

10:29 AM	●	Candidate Looking Away from Screen
10:31 AM	●	Away from test window for 03 mins
10:32 AM	●	Candidate Looking Away from Screen
10:33 AM	●	Away from test window
10:33 AM	●	Away from test window
10:34 AM	●	Candidate Looking Away from Screen
10:35 AM	●	Candidate Looking Away from Screen
10:35 AM	●	Candidate Looking Away from Screen
10:36 AM	●	Candidate Looking Away from Screen
10:38 AM	●	Candidate Looking Away from Screen
10:42 AM	●	Candidate Looking Away from Screen
10:43 AM	●	Candidate Looking Away from Screen
10:45 AM	●	Candidate Looking Away from Screen
10:47 AM	●	Candidate Looking Away from Screen for 02 mins
10:51 AM	●	Additional person there
10:53 AM	●	Candidate Looking Away from Screen
10:54 AM	●	Away from test window for 10 mins
10:55 AM	●	Candidate Looking Away from Screen
10:56 AM	●	Away from test window
10:56 AM	●	Candidate Looking Away from Screen
10:57 AM	●	Away from test window
10:58 AM	●	Away from test window
10:58 AM	●	Away from test window
11:00 AM	●	Candidate Looking Away from Screen
11:01 AM	●	Candidate Looking Away from Screen
11:05 AM	●	Candidate Looking Away from Screen
11:06 AM	●	Candidate Looking Away from Screen
11:06 AM	●	Candidate Looking Away from Screen
11:07 AM	●	Candidate Looking Away from Screen
11:08 AM	●	Candidate Looking Away from Screen for 02 mins
11:11 AM	●	Candidate Looking Away from Screen
11:12 AM	●	Candidate Looking Away from Screen
11:13 AM	●	Candidate Looking Away from Screen
11:14 AM	●	Candidate Looking Away from Screen
11:15 AM	●	Candidate Looking Away from Screen for 01 min
11:17 AM	●	Candidate Looking Away from Screen
11:18 AM	●	Away from test window for 18 mins
11:18 AM	●	Candidate Looking Away from Screen

11:19 AM	●	Away from test window for 01 min
11:20 AM	●	Away from test window
11:20 AM	●	Away from test window
11:21 AM	●	Candidate Looking Away from Screen
11:23 AM	●	Away from test window for 01 min
11:23 AM	●	Candidate Looking Away from Screen
11:26 AM	●	Candidate Looking Away from Screen for 01 min
11:28 AM	●	Away from test window
11:28 AM	●	Candidate Looking Away from Screen
11:29 AM	●	Away from test window
11:31 AM	●	Away from test window
11:33 AM	●	Finished the test

Credibility Index: **LOW**

Profile Picture Snapshot

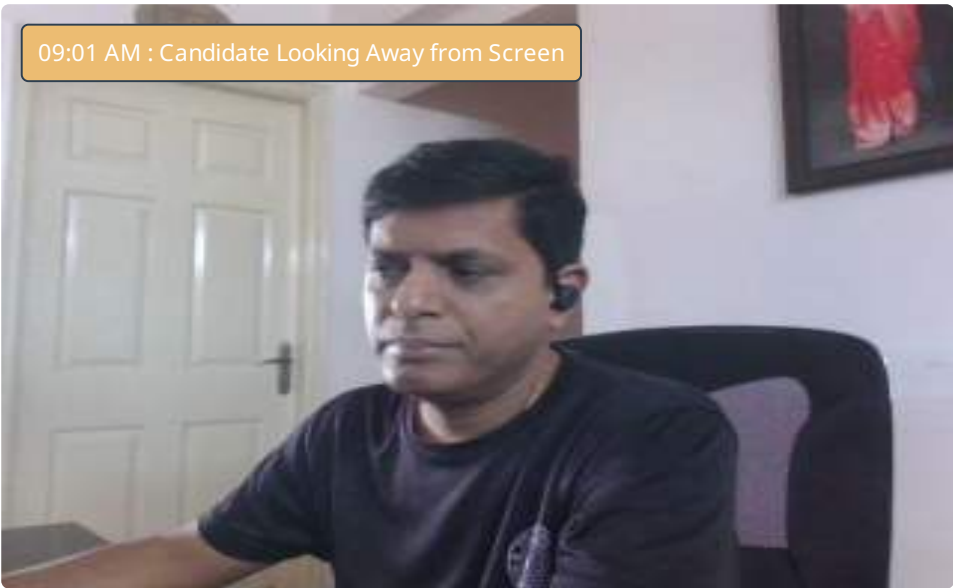


Identity Card Snapshot

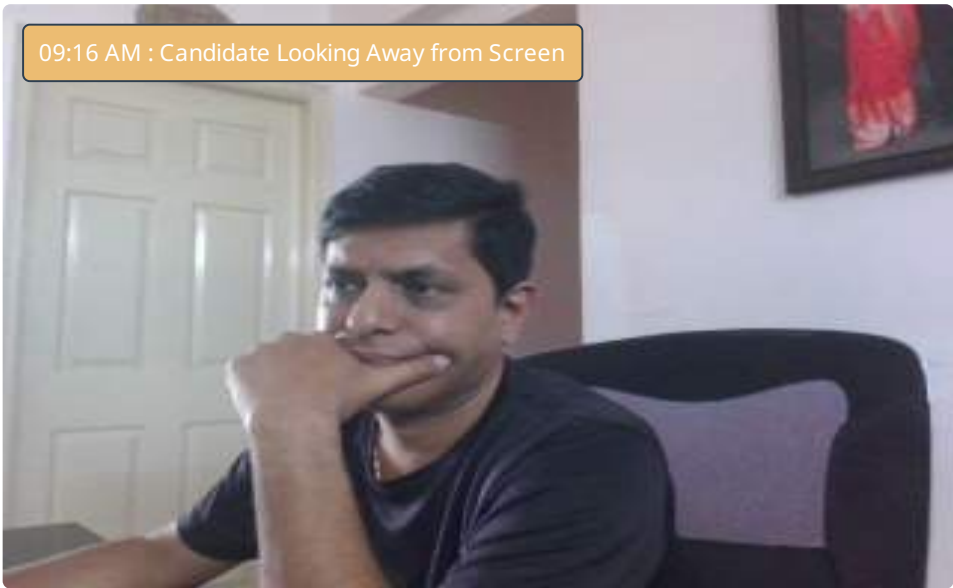


Images of Test-Taker

09:01 AM : Candidate Looking Away from Screen

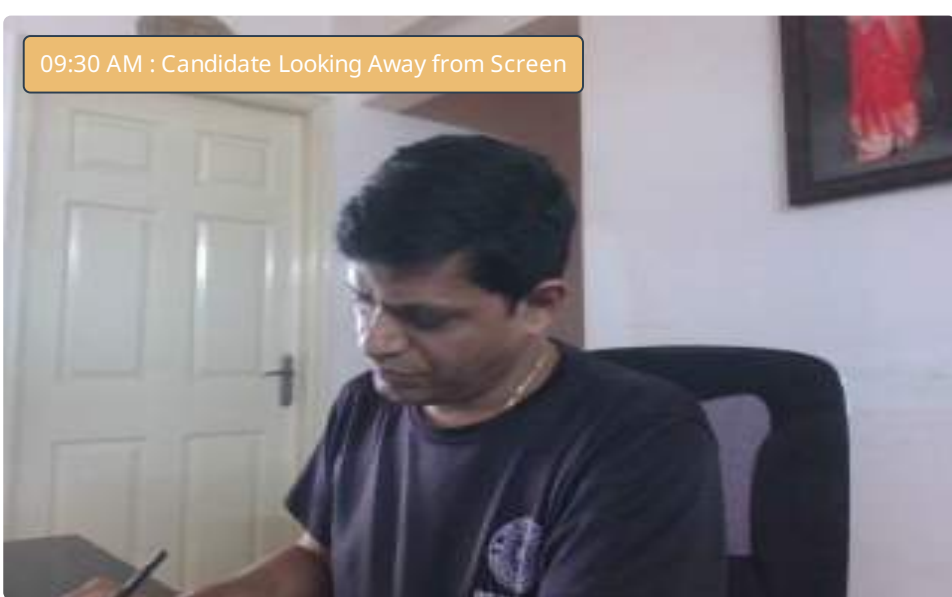


09:16 AM : Candidate Looking Away from Screen

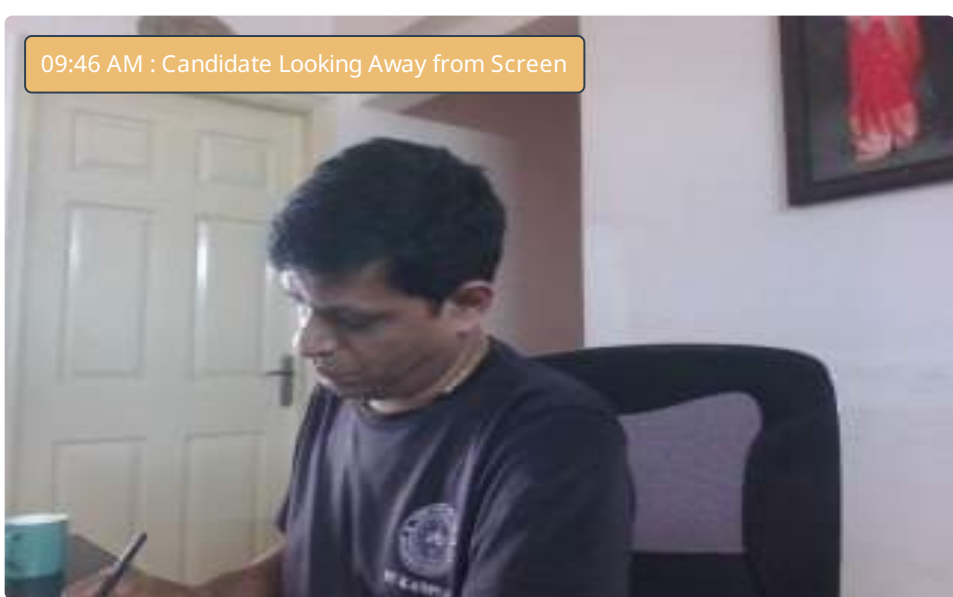




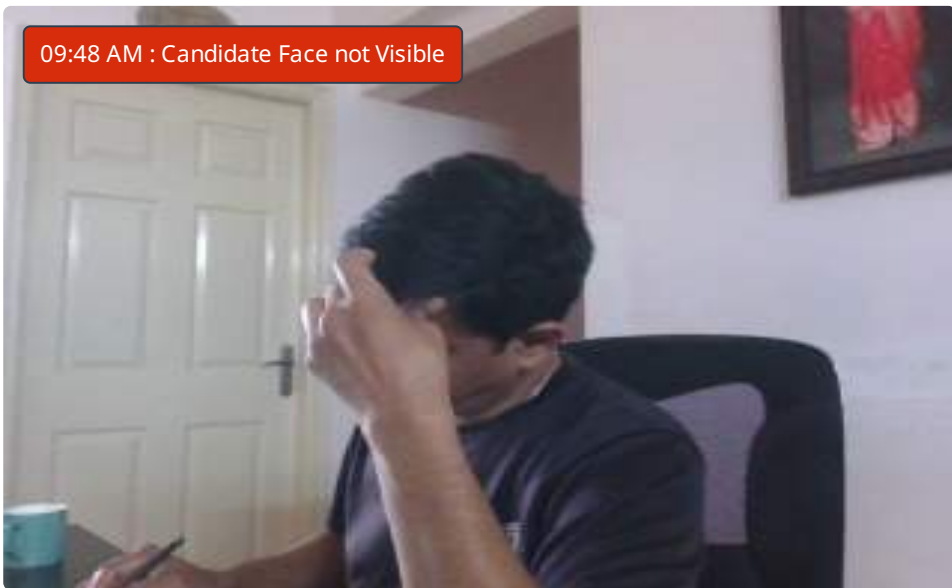
09:30 AM : Candidate Looking Away from Screen



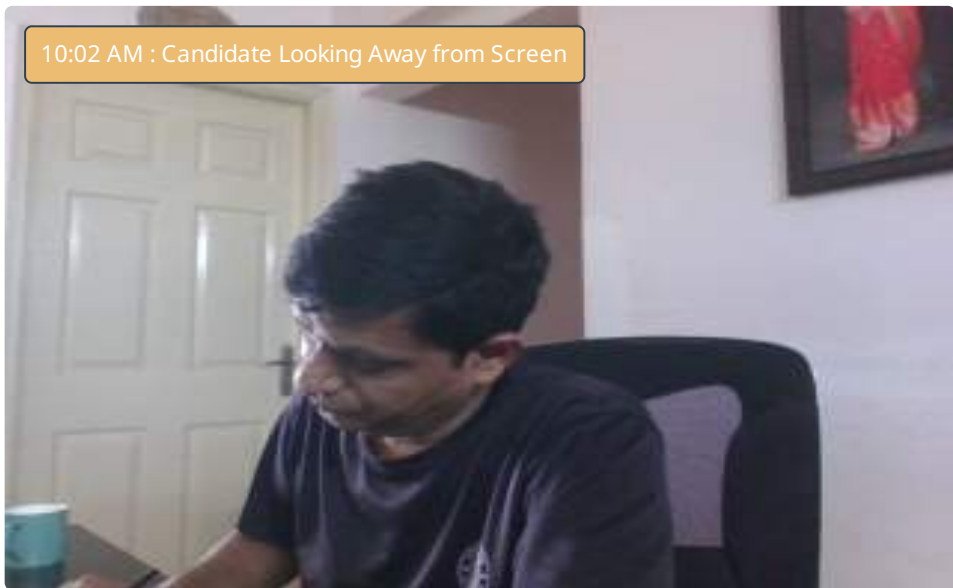
09:46 AM : Candidate Looking Away from Screen



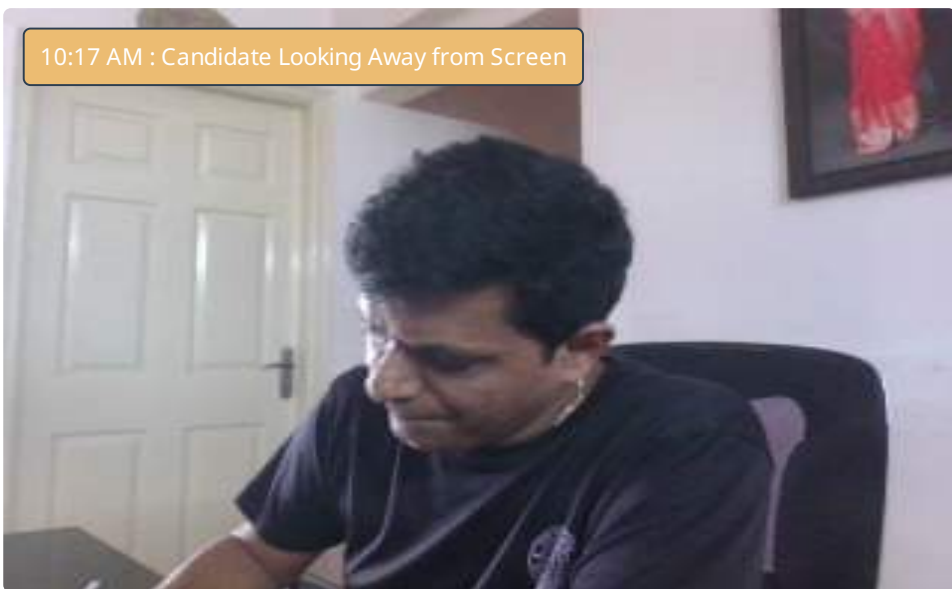
09:48 AM : Candidate Face not Visible



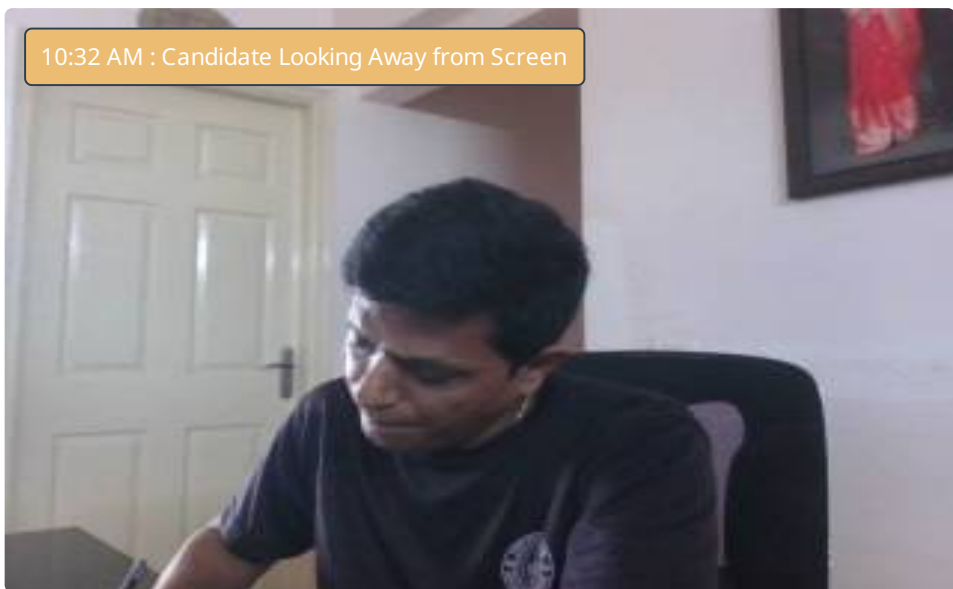
10:02 AM : Candidate Looking Away from Screen



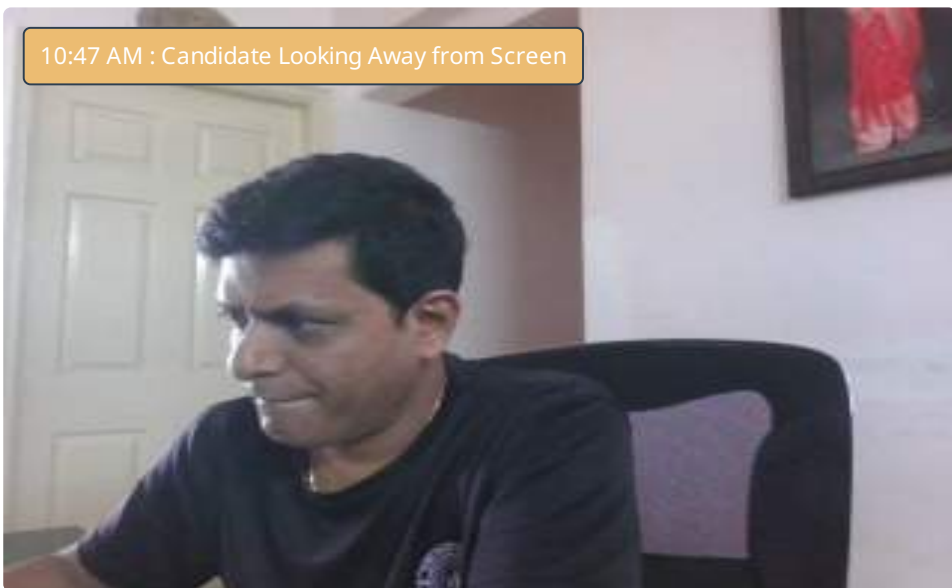
10:17 AM : Candidate Looking Away from Screen



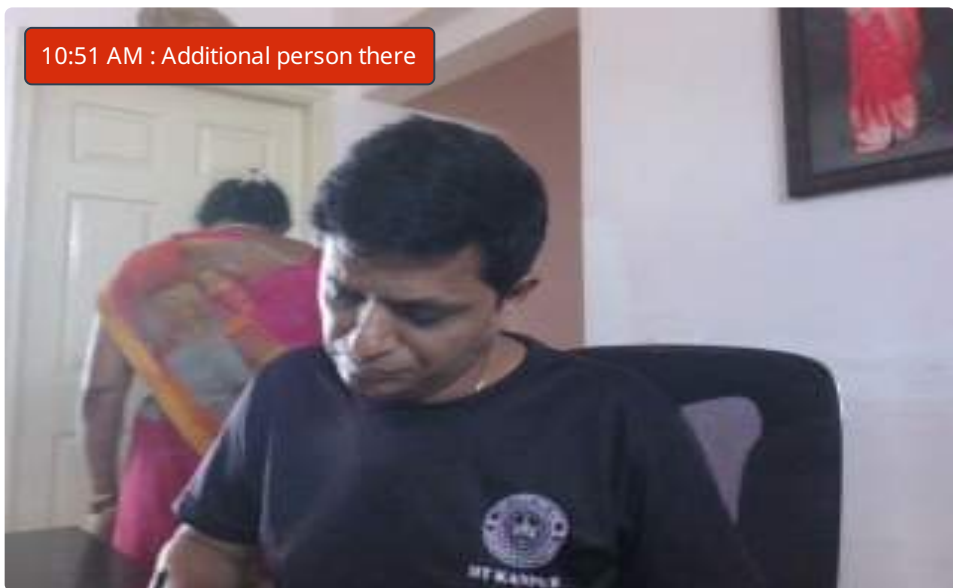
10:32 AM : Candidate Looking Away from Screen

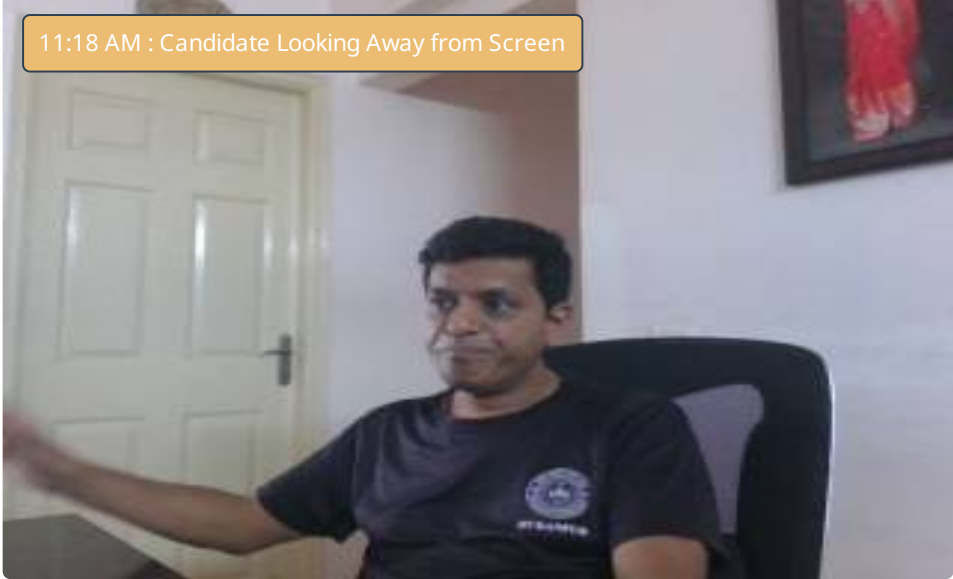
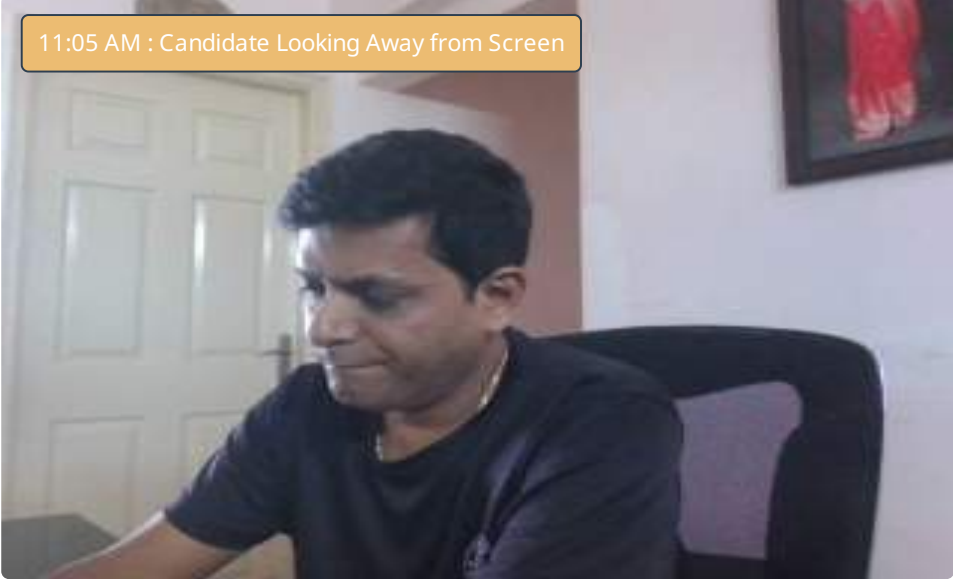


10:47 AM : Candidate Looking Away from Screen



10:51 AM : Additional person there





## About the Report

This Report is generated electronically on the basis of the inputs received from the assessment takers. This Report including the AI flags that are generated in case of availing of proctoring services, should not be solely used/relied on for making any business, selection, entrance, or employment-related decisions. Mettl accepts no liability from the use of or any action taken or refrained from or for any and all business decisions taken as a result of or reliance upon anything, including, without limitation, information, advice, or AI flags contained in this Report or sources of information used or referred to in this Report.

