

ML QUIZ ①

Kv2154

①

Problem 1

$$f(x_i; \theta_0, \theta_1, \theta_2, \dots, \theta_p) = \sum_{p=1}^p \theta_p x_i^p + \theta_0$$

Empirical risk $R(\theta)$

$$R(\theta) = \frac{1}{2N} \|y - X\theta\|^2 + \theta^T \theta + \lambda^T \theta$$

$$\frac{\partial R(\theta)}{\partial \theta} = \frac{\partial}{\partial \theta} \left[\frac{1}{2N} \|y - X\theta\|^2 + \theta^T \theta + \lambda^T \theta \right]$$

$$= \frac{\partial}{\partial \theta} \left[\frac{1}{2N} (y - X\theta)^T (y - X\theta) + \theta^T X^T X \theta + \lambda^T \theta \right]$$

$$= \frac{\partial}{\partial \theta} \left[\frac{1}{2N} (y^T y - 2y^T X \theta + \theta^T X^T X \theta) + \lambda^T \theta \right] + \frac{\partial}{\partial \theta} (\lambda^T \theta)$$

$$+ \frac{\partial}{\partial \theta} (\lambda^T \theta)$$

$$= \frac{1}{2N} (-2y^T X) + 2\theta^T X^T X + 2\lambda^T + \lambda^T$$

Finding Optimal Solution

$$\frac{1}{2N} (-2y^T X) + 2\theta^T X^T X + 2\lambda^T + \lambda^T = 0$$

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$$-\frac{1}{N} Y^T X + \frac{1}{N} Q^T X^T X + 2Q^T + \alpha^T = 0$$

~~$$\frac{1}{N} Q^T [X^T X + 2NI] = -\frac{1}{N} [Y^T X - NI]$$~~

$$Q^T = (Y^T X - NI) (X^T X + 2NI)^{-1}$$

$$Q^+ = ((Y^T X - NI)^T)^T ((Q^T X + 2NI)^{-1})^T$$

$$Q^+ = (X^T Y - NI) (X^T X + 2NI)^{-1}$$

Problem (2)

$$\omega = xy^2$$

$$x = r \cos \theta, y = r \sin \theta$$

$$r=2, \theta = \pi/4$$

~~2 $\frac{\partial \omega}{\partial x}$ + 2 $\frac{\partial \omega}{\partial y}$~~

$$\frac{\partial \omega}{\partial x} + \frac{\partial \omega}{\partial y}$$

~~$$= \frac{\partial}{\partial x} xy^2 \cdot \frac{\partial}{\partial r} r \cos \theta + \frac{\partial}{\partial y} xy^2 \cdot \frac{\partial}{\partial r} r \sin \theta$$~~

$$= y^2 \cdot \cos \theta + 2xy \cdot \sin \theta$$

$$= r^2 \sin^2 \theta \cos \theta + 2r^2 \sin^2 \theta \cos \theta$$

$$= 3r^2 \sin^2 \theta \cos \theta$$

$$= 3 \cdot 4 \cdot \sin^2 \left(\frac{\pi}{4} \right) \cdot \cos \left(\frac{\pi}{4} \right)$$

$$= 4.24264$$

Problem ③

$$f(x|\theta) = \frac{1}{\theta} x^{(1-\theta)/\theta}$$

(b) The maximum likelihood is given by

$$L(\theta) = \prod_{i=1}^n \frac{1}{\theta} x_i^{\frac{(1-\theta)}{\theta}}$$

The log likelihood is given by

$$\ell(\theta) = \log \left[\prod_{i=1}^n \frac{1}{\theta} x_i^{\frac{(1-\theta)}{\theta}} \right]$$

$$= \sum_{i=1}^n \log \left(\frac{1}{\theta} x_i^{\frac{(1-\theta)}{\theta}} \right)$$

$$= \sum_{i=1}^n \log \left(\frac{1}{\theta} \right) + \left(\frac{1-\theta}{\theta} \right) \sum_{i=1}^n \log x_i$$

$$\frac{d\ell(\theta)}{d\theta} = \sum_{i=1}^n \log \left(\frac{1}{\theta} \right) + \frac{1}{\theta} \sum_{i=1}^n \log x_i - \sum_{i=1}^n \log x_i$$

for MLE

$$\frac{d\ell(\theta)}{d\theta} = 0$$

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$$\frac{\partial}{\partial \theta} -n \log \theta + \frac{1}{\theta} \sum_{i=1}^n \log x_i - \sum_{i=1}^n \log x_i = 0$$

$$-\frac{n}{\theta} - \frac{1}{\theta} \sum_{i=1}^n \log x_i = 0$$

$$\frac{1}{\theta} \sum_{i=1}^n \log x_i = -\frac{n}{\theta}$$

$$\hat{\theta}_{MLE} = -\frac{1}{n} \sum_{i=1}^n \log x_i$$

$$x_1 = 0.10, x_2 = 0.22, x_3 = 0.55, x_4 = 0.36$$

$$= -\frac{1}{4} \left\{ \log(0.10) + \log(0.22) + \log(0.55) + \log(0.36) \right\}$$

$$= -\frac{1}{4} (-2.3026 - 1.5151 - 0.6162 - 1.0217)$$

$$= -\frac{1}{4} (-5.4546)$$

$$= 1.36365$$

Problem (4)

$$f(x, y) = xe^y, \text{ constraint } x^2 + y^2 = 2$$

$$\text{given, } f(x, y) = xe^y$$

$$g(x, y) = x^2 + y^2 - 2$$

$$\nabla f = \lambda \nabla g$$

$$\langle e^y, xe^y \rangle = \langle 2\lambda x, 2\lambda y \rangle, \text{ so we get eqn}$$

$$e^y = 2\lambda x \quad xe^y = 2\lambda y$$

$$\begin{aligned} \lambda &= \frac{e^y}{2x} \\ &\quad \lambda = \frac{xe^y}{2y} \end{aligned}$$

$$\frac{e^y}{2x} = \frac{xe^y}{2y}$$

$$y = x^2 \quad \text{--- (1)}$$

Sub, (1) in $g(x, y)$

$$y + y^2 = 2$$

$$y^2 + y - 2 = 0$$

$$y^2 + 2y - y - 2 = 0$$

$$y(y+2) - 1(y+2) = 0$$

$$(y+2)(y-1) = 0$$

$$y = 1, -2$$

$$x = 1, \sqrt{2}i \text{ (Not valid)}$$

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$$\therefore y = 1$$

$$x = 1, -1 \quad (\text{from } ①)$$

$$f(1, 1) = (1)e^{(1)} = e = 2.718$$

$$f(-1, 1) = (-1)e^1 = -e = -2.718$$

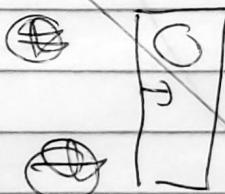
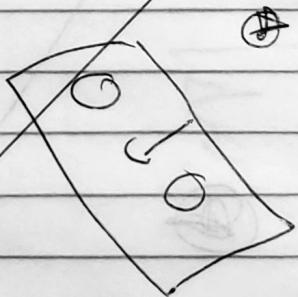
Extreme values are 2.718, -2.718

Problem ⑧

The VC Dimension of an axis-aligned rectangles in a 2D plane is 5.

→ Consider a space in which there are 3 data points

Now, for a given function $f(x, \theta)$, you can correctly classify the following distribution

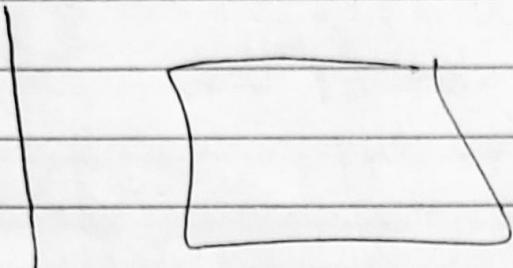


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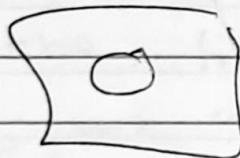
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Problem 5

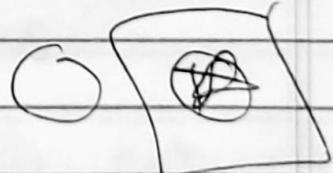
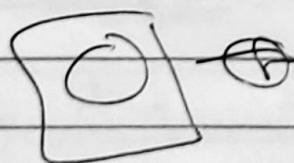
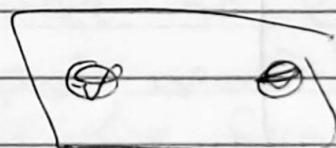
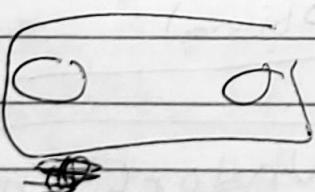
→ The axis aligned rectangle will be



Consider 2 data points O and \oplus
So for 1 point we get upto $2^1 = 2$ labelling.



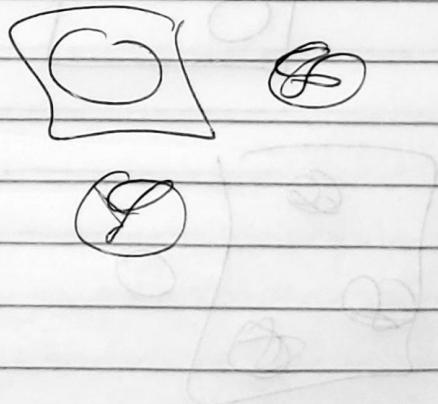
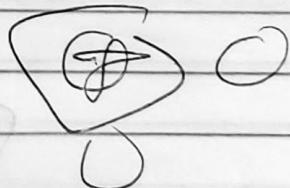
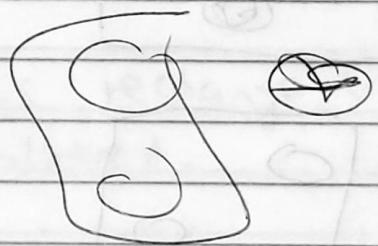
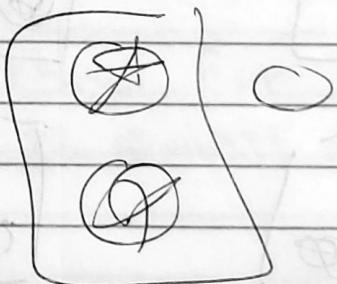
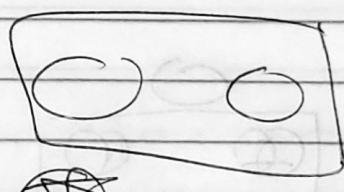
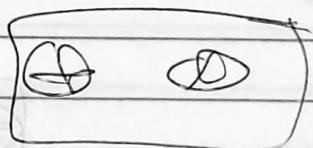
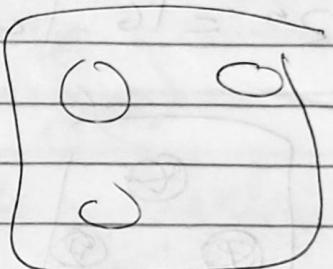
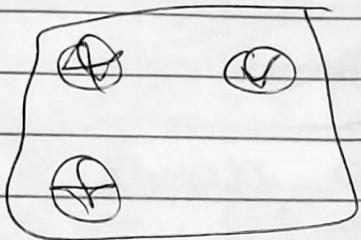
for 2 points there are upto $2^2 = 4$ labellings



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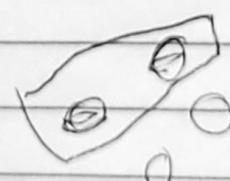
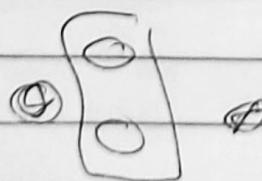
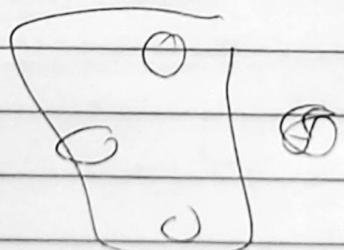
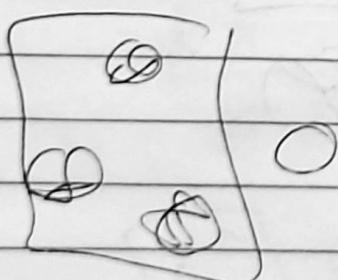
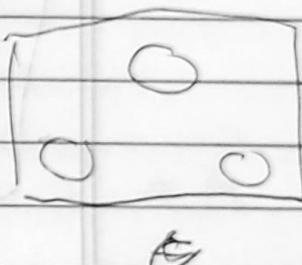
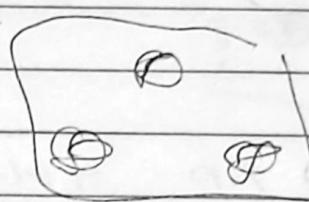
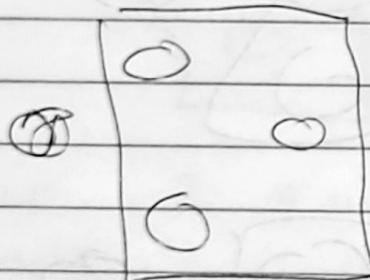
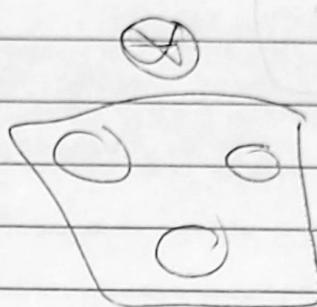
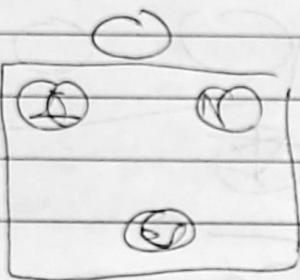
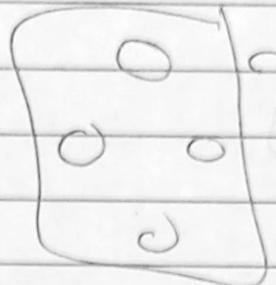
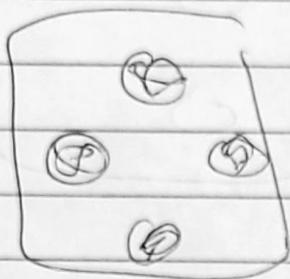
for 3 points upto $2^3 = 8$ labeling



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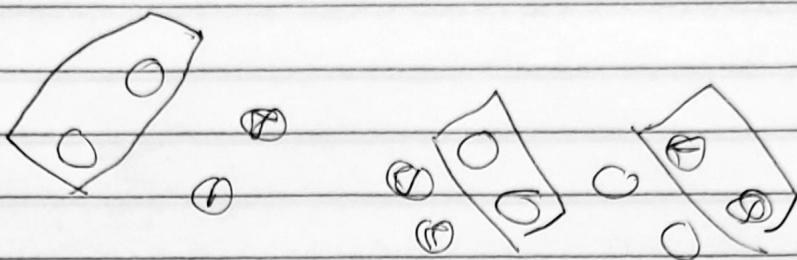
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For ~~3~~ points numbers of possibilities
 $2^4 = 16$ labeling-

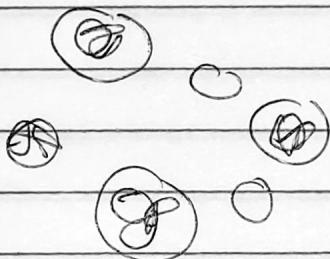


KVRISG

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5 points are total 32 labelings
Now, there are cases where it is
not possible to shatter all the points



Thus for a sliding axis rectangle VDio
4 points can be shattered.

(P) KV21S4

(D)

~~Thus, the VC dimensions of axis-aligned rectangles is at most 3 as not all sets of 4 points can be fully shattered.~~

Problem (6)

boxes = m probability of selecting $i = \frac{1}{m}$
ith box = n_i ; appres r_i oranges

Probability of selecting orange in i th box

~~Probability of selecting orange in i th box~~

$$P(A|B_i) = \frac{n_i}{n_i + r_i}$$

$$P(B_i | A) = P(A|B_i) \cdot P(B_i)$$

$$\sum_{i=1}^m P(B_i) \cdot P(A|B_i)$$

$$\frac{n_i}{n_i + r_i} \cdot \frac{1}{m}$$

$$\sum_{i=1}^m \frac{1}{m} \cdot \frac{n_i}{n_i + r_i}$$

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Probability that apple is from box i

$$P(B_j | A) = \frac{n_i}{n_j + r_j} \quad \text{imp}$$

$$\frac{n_i}{n_i + r_i} \quad \text{imp}$$

$$P(B_j | A) = \frac{n_i}{n_j + r_j}$$

Problem 7

$$M(f(x; w)) = \sum_{j=0}^m w_j x^j$$

$$\text{where } w = [w_0 \ w_1 \ \dots \ w_m]^T$$

Part 1,

from the figure, the most reasonable choice for m is $m = 3$, as it properly fits the distribution of data without any stray behavior of the function, which might add to the loss down the line.

From the figure we can conclude that at $m=9$, we are getting over fitting. As the said function transcends every point in the distribution and fits it with higher accuracy but this will cause an error as the dimension of the polynomial distribution becomes too specific for the given distribution and will add up to the loss of ~~other~~ distribution of data.

From the figure, (1) and (2) are under fitted for the distribution. The reason being that the curve of the graph (1) and (2)

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(12)

fit
Doesn't fit most of the data points thus generating higher loss of the distribution.

Part (b)

Squared loss

$$L(y_i; f(x_i; \omega)) = \frac{1}{2} (y_i - f(x_i; \omega))^2$$

