PART I - THEORY Q.

MLE

$$f(X_i) = \frac{1}{\sqrt{2\pi^7 6}} e^{-\frac{(X_i - \mu)^7}{26^2}}, \text{ for each } i$$

Ozizn.

We can rewrite it as

F(
$$x_{\bar{1}}, x_{\bar{1}+1}, \dots x_n$$
) $6, \mu$) = $\left(\frac{1}{2\pi^7 6}\right)^n e^{-\sum_{i=1}^n \frac{(x_{\bar{1}} - \mu)^n}{26^2}}$
Since all point are independent.

In order to find MLE, it is enough to take the partial derivative of the function above. However, we can simplify the process by the considering the log likelihood of the function which is:

Constant in terms of 2f

which is:
$$\operatorname{constant in terms of } \frac{\partial f}{\partial \mu}$$

$$\operatorname{ln}\left(f(x_{1,1}-x_{1})-n\operatorname{ln}(6)\right) = -n\operatorname{ln}(\sqrt{2\pi})-n\operatorname{ln}(6)$$

$$-\sum_{1=1}^{\infty}\frac{(x_{1}-\mu)^{2}}{26^{2}}\operatorname{the part that needs to be considered in the }$$

To find the MLE for "": portial derivative

$$\frac{\partial f(x_1, x_2 - x_n \mid 6, \mu)}{\partial \mu} = \sum_{i=1}^n \frac{(x_i - \mu)}{6^2} = 0$$

$$\sum_{i=1}^{n} (x_i - \mu) = 0 \Rightarrow \sum_{i=1}^{n} x_i = \sum_{i=1}^{n} \mu = n.\mu$$

$$\Rightarrow \hat{\mu} = \sum_{i=1}^{n} x_i' = \overline{x}$$

3- As in the first example, we need to multiply the probabilities of each sample to find the likelihood, which is in this case:

$$L(\theta) = \left[P(x=0)\right]^{2}, \left[P(x=1)\right]^{3}, \left[P(x=2)\right]^{3}, \left[P(x=3)\right]^{2}$$

$$= \left(\frac{2\theta}{3}\right)^{2} \left(\frac{\theta}{3}\right)^{3}, \left(\frac{2(1-\theta)}{3}\right)^{3} \left(\frac{1-\theta}{3}\right)^{2}$$

To compute the partial oberivative easily, we can use log likelihood as in the first example:

$$\Rightarrow 2\log^{\frac{1}{3}} + 2\log\theta + 3\log^{\frac{1}{3}} + 3\log\theta + 3\log^{\frac{2}{3}} + 3\log(1-\theta) + 2\log^{\frac{1}{3}} + 2\log(1-\theta)$$

Since we take the derivative with respect to θ , we can ignore constant values.

$$\Rightarrow 5 \log(\theta) + 5 \log(1-\theta)$$

$$\frac{dl(\theta)}{d\theta} = 5 \cdot \frac{1}{\theta} + 5 \cdot \frac{1}{\theta} = 0$$

$$\Rightarrow |\hat{\theta}| = 0.5$$

NAIVE BAYES

1 - Even though there is no example of Red, Domostic, SUV in our dataset, we still can find the probability of that car's being stolen thanks to Näive Bayes.

P(To Stolen | Red, Domestic, SUU) =>
(first case, it is stolen)

P (Red | yes) P (Domostic | yes) P (SUV | yes) P (Stolen=yes)
P (Red). P (Domestic) P (SUV)

$$\Rightarrow \left(\frac{3}{5}, \frac{3}{5}, \frac{2}{5}, \frac{5}{10}\right) / \left(\frac{1}{2}, \frac{4}{6}, \frac{1}{2}\right) = 0,43$$

For, stolen = no

P(Red Ino) P(Domestic Ino) P(BUV|no) P(stelen=no)
P(Red Ino) P(stelen=no)
P(Red Ino) P(stelen=no)

$$= \left(\frac{2}{5}, \frac{2}{5}, \frac{2}{5}, \frac{5}{10}\right) / \frac{5}{10} \cdot \frac{4}{6}, \frac{5}{10} = 0.19$$

Since 0,43 > 0,19, the car is STOLEN.

NAÏVE BAYES

$$=\frac{\frac{1}{4},\frac{2}{4},\frac{3}{4},\frac{4}{9}}{\frac{5}{9},\frac{3}{9},\frac{4}{9}}=0,52$$

Now, calculate the probability

$$= \frac{\frac{4}{5}, \frac{1}{5}, \frac{1}{5}, \frac{5}{9}}{\frac{5}{9}, \frac{3}{9}, \frac{4}{9}} = 0,22$$

So, the probability
$$\Rightarrow \frac{0.52}{0.52 + 0.22} = \frac{\%70}{}$$

NAIVE BAYES

$$= \frac{\frac{1}{4}, \frac{2}{4}, \frac{4}{9}}{\frac{5}{9}, \frac{3}{9}} = \frac{10,3}{10,3}$$