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CSE 512 Fall 2019 – Machine Learning – Homework 2

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Question 1

1.1.1

X follows Poisson distribution this means that function of x is

$$P(X=x_k|\lambda) = \frac{\lambda^k}{k!} e^{-\lambda}$$

Now, if we have to find the log likelihood, then

$$\log p = -\lambda - \sum_1^k \log(k!) + k \log(\lambda)$$

Here, $k = \sum_1^k (x_i)$ or

$$-\lambda - \sum_1^k \log(x_i) + \log(\lambda) \sum_1^k x_i$$

1.1.2

for MLE of this, we will differentiate w.r.t. λ and keep it to λ .

$$\max(x = k | \lambda)$$

$$\Rightarrow \frac{\partial}{\partial \lambda} \left(-\lambda - \sum_{i=1}^k \log(x_i) + \log(\lambda) \sum_{i=1}^k x_i \right)$$

$$= -1 + \frac{1}{\lambda} \sum_{i=1}^k x_i$$

keeping this to zero.

$$-1 + \frac{1}{\lambda} \sum_{i=1}^k x_i = 0.$$

$$\frac{1}{\lambda} \sum_{i=1}^k x_i = 1$$

$$\boxed{\sum_{i=1}^k x_i = \lambda}$$

1.1.3

1.1.2

for the given problem, the observed X , we will get MLE of λ as $\sum w_i$.

which means.

$$\begin{aligned}\sum_{i=1}^n w_i &= 4+12+3+5+6+9+10 \\ &= 49.\end{aligned}$$

Question 1.2

1.2.1

Here, we are given that the pdf for Gamma is

$$p(\lambda | \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda}$$

Now, for posterior let us combine the likelihood and prior which means.

$$p(\lambda | x) \propto \left(\frac{\beta^\alpha}{\Gamma(\alpha)} \right) \lambda^{\alpha-1} e^{-\beta\lambda}$$

$$\left(\frac{1}{\prod x_i} \right) \lambda^{\sum x_i} e^{-\lambda}$$

[\therefore from 1.1]

If we now ignore the proportionality constants i.e. $\frac{\beta^\alpha}{\Gamma(\alpha)}$ and

$\left(\frac{1}{\sum x_i} \right)$ we get

$$p(\lambda | x) \propto \lambda^{\sum x_i + \alpha - 1} e^{-(\beta + 1)\lambda}$$

This means that the posterior distribution is

$$P(\lambda | X) \propto \text{Gamma}(k + X - 1, \beta + 1)$$

1.2.2

Now, the MAP, we have to take the derivative of the log of the posterior

$$\log(p(\lambda|x)) \propto \log(\lambda^{\sum x_i + \alpha - 1} e^{-(\beta + 1)\lambda})$$

\downarrow
(L)

$$L = (\sum x_i + \alpha - 1) \log \lambda - (\beta + 1)\lambda$$

Diff. w.r.t. λ

$$\frac{\sum x_i + \alpha - 1}{\lambda} - (\beta + 1) = 0$$

$$\frac{\sum x_i + \alpha - 1}{\lambda} = \beta + 1$$

$$\boxed{\frac{\sum x_i + \alpha - 1}{\beta + 1} = \lambda}$$