

Q1. Maximum Likelihood Estimation of λ

$$1. \log P(D|\lambda) = \log \frac{\lambda^{\sum x_i} e^{-n\lambda}}{\prod_{i=1}^n x_i!} = \sum_{i=1}^n x_i \log \lambda - n\lambda - \log \prod_{i=1}^n x_i!$$

$$2. \frac{d}{d\lambda} [\log P(D|\lambda)] = \frac{\sum x_i}{\lambda} - n - 0 = \sum_{i=1}^n x_i \frac{1}{\lambda} - N$$

$$3. \frac{\sum x_i}{\lambda} - n = 0$$

$$\frac{\sum x_i}{\lambda} = \bar{x}$$

$$\hat{\lambda} = \frac{\sum x_i}{n} = \hat{x}$$

Thus, we know λ is the average number of occurrences.

Q2. Maximum A Posteriori Estimate of λ with a Gamma Prior

$$1. \text{ Let } f(x_i|\lambda) = e^{\lambda} \frac{\lambda^{x_i}}{x_i!}; x_i = 0, 1, 2, 3, \dots \quad f(x_i) = \frac{\beta^\alpha \lambda^{x_i} e^{-\lambda \beta}}{\Gamma(\alpha)}$$

where λ is greater than zero.

$$\Rightarrow f(x_i, \lambda) = \prod_{i=1}^N f(x_i|\lambda) f(\lambda) = \frac{e^{-N\lambda} \lambda^{\sum_{i=1}^N x_i}}{\prod_{i=1}^N x_i!} \times \frac{e^{-\lambda \beta} \lambda^{\alpha-1} \beta^\alpha}{\Gamma(\alpha)}$$

$$f(x) = \int_x^\infty f(x_i, \lambda) d\lambda = \int_0^\infty \frac{\beta^\alpha}{\prod_{i=1}^N x_i! \Gamma(\alpha)} e^{-N\lambda} e^{-\lambda \beta} \lambda^{\sum_{i=1}^N x_i} \lambda^{\alpha-1} d\lambda$$

$$= \frac{\beta^\alpha}{\prod_{i=1}^N x_i! \Gamma(\alpha)} \int_0^\infty e^{-\lambda(N+\beta)} \lambda^{\sum_{i=1}^N x_i + \alpha - 1} d\lambda$$

$$= \frac{\beta^\alpha}{\prod_{i=1}^N x_i! \Gamma(\alpha)} \times \frac{\Gamma(\sum_{i=1}^N x_i + \alpha)}{(N+\beta) \sum_{i=1}^N x_i + \alpha}$$

$$= \frac{1}{\Gamma(\sum_{i=1}^N x_i + \alpha)} e^{-\lambda(N+\beta)} \lambda^{\sum_{i=1}^N x_i + \alpha - 1} (N+\beta)^{\sum_{i=1}^N x_i + \alpha}$$

$$\ln P(\lambda|D) = -\ln \left[\Gamma(\sum_{i=1}^N x_i + \alpha) \right] - \lambda(N+\beta) + (\alpha \lambda) \left(\sum_{i=1}^N x_i + \alpha - 1 \right)$$

$$+ \ln(N+\beta) \left(\sum_{i=1}^N x_i + \alpha \right) = (-\lambda(N+\beta)) + (\alpha \lambda) \left(\sum_{i=1}^N x_i + \alpha - 1 \right)$$

$$2. \frac{\partial}{\partial \lambda} P(\lambda | D) = -(N+B) + \frac{\sum_{i=1}^N x_i + \lambda - 1}{\lambda}$$

$$3. -(N+B) + \frac{\sum_{i=1}^N x_i + \lambda - 1}{\lambda} = 0$$

$$\sum_{i=1}^N x_i + \lambda - 1 = \lambda(N+B)$$

$$\lambda = \frac{\sum_{i=1}^N x_i + \lambda - 1}{N+B} = \hat{\lambda} \Rightarrow \text{be the Mapestimator of } \lambda$$

Q3 Deriving the Posterior of a Poisson-Gamma Model

$$\log P(\lambda | D) \propto \log(D|\lambda) + \log(\lambda)$$

$$P(\lambda | D) = P(D|\lambda) \cdot P(\lambda)$$

$$= \prod_{i=1}^n \frac{\beta^\alpha \lambda^{\alpha-1} e^{-\beta\lambda}}{F(\lambda)} \cdot \frac{\beta^\alpha \lambda^{\alpha-1} e^{-\beta\lambda}}{F(\lambda)}$$

$$\propto e^{-N\lambda} \cdot \lambda^{\sum_{i=1}^n x_i} \cdot \lambda^{\alpha-1} e^{-\beta\lambda}$$

$$\propto e^{-\lambda(N+B)} \cdot \lambda^{\left(\sum_{i=1}^n x_i + \lambda - 1\right)}$$

There, $P(\lambda | D) \propto \text{Gamma}\left(\sum_{i=1}^n x_i + \lambda - 1, \beta + n\right)$