

Homework 3

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Problem 1.

Solution:

1. Finding the mean of θ :

Since θ follows a continuous distribution, from the definition of $E[\theta]$:

$$\begin{aligned} E[\theta] &= \int_0^1 \theta (\mathbb{P}(\theta|a, b)) d\theta \\ \Leftrightarrow E[\theta] &= \int_0^1 \theta \left(\frac{1}{B(a, b)} \theta^{a-1} (1 - \theta)^{b-1} \right) d\theta \\ \Leftrightarrow E[\theta] &= \frac{1}{B(a, b)} \theta^{a-1} (1 - \theta)^{b-1} \int_0^1 \theta (1 - \theta)^{b-1} d\theta \\ \Leftrightarrow E[\theta] &= \frac{B(a+1, b)}{B(a, b)} \\ \Leftrightarrow E[\theta] &= \frac{a\Gamma(a)\Gamma(b)}{(a+b)\Gamma(a+b)} \cdot \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} = \boxed{\frac{a}{a+b}} \end{aligned}$$

2. Finding the mode of θ : The mode of θ is the value having the highest probability in its distribution, meaning the derivative of its probability distribution w.r.t $\theta = 0$. Hence, we have:

$$\begin{aligned} \frac{d(\mathbb{P}(\theta, a, b))}{d\theta} &= 0 \\ \Leftrightarrow (a-1)\theta^{a-2}(1-\theta)^{b-1} - (b-1)\theta^{a-1}(1-\theta)^{b-2} &= 0 \\ \Leftrightarrow (a-1)\theta^{a-2}(1-\theta)^{b-1} &= (b-1)\theta^{a-1}(1-\theta)^{b-2} \end{aligned}$$

Since Beta distribution is defined within the $(0, 1)$ interval, $\theta \neq 0$ and $1 - \theta \neq 0$, meaning we can divide both sides by $((\theta)(1 - \theta))^{a-2}$

$$\begin{aligned} \rightarrow (a-1)(1-\theta) &= (b-1)\theta \\ \Leftrightarrow (a+b-2)\theta &= a-1 \end{aligned}$$

$$\Leftrightarrow \theta = \boxed{\frac{a-1}{a+b-2}}$$

3. Finding the variance of θ : Since $Var(\theta) = E[\theta^2] - E[\theta]^2$, and we knew $E[\theta]$ from (1), we can find $E[\theta^2]$ in a similar manner:

$$\begin{aligned}
 E[\theta^2] &= \int_0^1 \theta^2 \mathbb{P}(\theta, a, b) d\theta \\
 \Leftrightarrow E[\theta^2] &= \frac{1}{B(a, b)} \int_0^1 \theta a + 1(1 - \theta)^{b-1} d\theta \\
 \Leftrightarrow E[\theta^2] &= \frac{B(a + 2, b)}{B(a, b)} \\
 \Leftrightarrow E[\theta^2] &= \frac{a(a + 1)\Gamma(a)\Gamma(b)}{(a + b)(a + b + 1)\Gamma(a + b)} \cdot \frac{\Gamma(a + b)}{\Gamma(a)\Gamma(b)} = \frac{a(a + 1)}{(a + b)(a + b + 1)}
 \end{aligned}$$

Having $E[\theta^2]$, $E[\theta]$, variance of θ is:

$$\begin{aligned}
 Var(\theta) &= \frac{a(a + 1)}{(a + b)(a + b + 1)} - \frac{a^2}{(a + b)^2} \\
 \Leftrightarrow Var(\theta) &= \frac{a^3 + a^2b + a^2 + ab - (a^3 + a^2b + a^2)}{(a + b + 1)(a + b)^2} = \boxed{\frac{ab}{(a + b + 1)(a + b)^2}}
 \end{aligned}$$

Problem 2.

Solution: The exponential family is in the form:

$$\mathbb{P}(\mathbf{y}, n) = a(\mathbf{y})e^{n^T T(\mathbf{y}) - a(n)}$$

To show that the multinomial distribution is in the exponential family, we can try to fit as much as we can:

$$\begin{aligned}
 Cat(\mathbf{x}|\mu) &= e^{\log(\prod_{i=1}^K \mu_i^{x_i})} \\
 \Leftrightarrow Cat(\mathbf{x}|\mu) &= e^{\sum_{i=1}^K \log(\mu_i^{x_i})} = e^{\sum_{i=1}^K x_i \log(\mu_i)} \\
 \Leftrightarrow Cat(\mathbf{x}|\mu) &= e^{\sum_{i=1}^{K-1} x_i \log(\frac{\mu_i}{\mu_K}) + \log(\mu_K)}
 \end{aligned}$$

Therefore, we can have the vector n be $[\log(\frac{\mu_1}{\mu_K}) \dots \log(\frac{\mu_{K-1}}{\mu_K})]^T$

Since $\mu_i = \mu_K \cdot e^n$, we have:

$$\mu_K = 1 - \sum_{i=1}^{K-1} \mu_i = 1 - \sum_{i=1}^{K-1} \mu_K e^n$$

Hence, we can assign $b(n) = 1$, $T(\mathbf{x}) = \mathbf{x}$, and $a(n) = -\log(\mu_K) = \log(1 + \sum_{i=1}^{K-1} e^n)$. Since every component of the exponential family matches with the distribution, we can conclude that $Cat(\mathbf{x}|\mu)$ belongs to the exponential family. If we assign μ to the Softmax function, we will have the Softmax regression, which implies the generalized linear model of this distribution is the same as Softmax regression. \square