

Feel free to work with other students, but make sure you write up the homework and code on your own (no copying homework or code; no pair programming). Feel free to ask students or instructors for help debugging code or whatever else, though.

distribution of θ user to vary (a, b) ?

1 (Murphy 2.16) Suppose $\theta \sim \text{Beta}(a, b)$ such that

$$\mathbb{P}(\theta; a, b) = \frac{1}{B(a, b)} \theta^{a-1} (1-\theta)^{b-1} = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1-\theta)^{b-1}$$

where $B(a, b) = \Gamma(a)\Gamma(b)/\Gamma(a+b)$ is the Beta function and $\Gamma(x)$ is the Gamma function. Derive the mean, mode, and variance of θ .

θ is a random continuous variable

$\theta \in [0, 1]$ as a given constraint of Beta functions

$$E(\theta) = \int_0^1 \theta \mathbb{P}(\theta; a, b) d\theta$$

$$= \int_0^1 \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^a (1-\theta)^{b-1} d\theta$$

$$= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \cdot \frac{\Gamma(a+1)\Gamma(b)}{\Gamma(a+b+1)} \int_0^1 \frac{\Gamma(a+b+1)}{\Gamma(a+1)\Gamma(b)} \theta^a (1-\theta)^{b-1} d\theta$$

$$= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \cdot \frac{\Gamma(a+1)\cancel{\Gamma(b)}}{\Gamma(a+b+1)} = \frac{(a+b-1)! a!}{(a-1)!(a+b)!}$$

$$= \frac{a}{a+b}$$

$$\mathbb{P}(\theta; a+1, b) = \frac{\Gamma(a+b+1)}{\Gamma(a+1)\Gamma(b)} \theta^a (1-\theta)^{b-1}$$

$\int_0^1 \mathbb{P}(\theta; a+1, b) d\theta = 1$ because it's a probability density function of θ when $\theta \in [0, 1]$

$\Gamma(n) = (n-1)!$ for discrete parameter

mode of continuous random variable: pdf attains max value

$$\mathbb{P}(\theta; a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1-\theta)^{b-1}$$

normalizing constant \therefore ignore

$$\Rightarrow \text{maximize } f = \theta^{a-1} (1-\theta)^{b-1}$$

$$f' = (a-1)\theta^{a-2} (1-\theta)^{b-1} - (b-1)\theta^{a-1} (1-\theta)^{b-2}$$

$$= \theta^{a-2} (1-\theta)^{b-2} ((a-1)(1-\theta) - (b-1)\theta)$$

$$= \theta^{a-2} (1-\theta)^{b-2} (-a\theta + a + \theta - 1 - b\theta + b) = \theta^{a-2} (1-\theta)^{b-2} (\theta(2-a-b) + (a-1)) = 0$$

$$\theta = 0, 1, \frac{1-a}{2-a-b}$$

$$c) \quad \text{Var}(x) = E[x^2] - \mu^2 = \int x^2 f(x) dx - \mu^2 \quad \text{--- definition of variance}$$

$$\text{Var}(\theta) = E[\theta^2] - \frac{a^2}{(a+b)^2} = \int_0^1 \theta^2 \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1-\theta)^{b-1} d\theta - \frac{a^2}{(a+b)^2}$$

$$= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \cdot \frac{\Gamma(a+2)\Gamma(b)}{\Gamma(a+b+2)} \int \frac{\Gamma(a+b+2)}{\Gamma(a+2)\Gamma(b)} \theta^{a+1} (1-\theta)^{b-1} d\theta - \frac{a^2}{(a+b)^2}$$

$\underbrace{\hspace{10em}}_{=1}$

$$= \frac{(a+1)a}{(a+b+1)(a+b)} - \frac{a^2}{(a+b)^2} = \frac{(a+1)(a+b)a - a^2(a+b+1)}{(a+b+1)(a+b)^2} = \frac{ab}{(a+b+1)(a+b)^2}$$

2 (Murphy 9) Show that the multinomial distribution

$$\text{Cat}(\mathbf{x}|\boldsymbol{\mu}) = \prod_{i=1}^K \mu_i^{x_i}$$

is in the exponential family and show that the generalized linear model corresponding to this distribution is the same as multinomial logistic regression (softmax regression).

form of exponential probability functions:

$$P(\mathbf{x}; \boldsymbol{\mu}) = b(\mathbf{x}) \exp(\boldsymbol{\eta}^T T(\mathbf{x}) - a(\boldsymbol{\eta}))$$

First transform $\text{Cat}(\mathbf{x}|\boldsymbol{\mu})$ to exponential form as follows

$$\begin{aligned} \text{Cat}(\mathbf{x}|\boldsymbol{\mu}) &= \exp\left[\log\left(\prod_{i=1}^K \mu_i^{x_i}\right)\right] \\ &= \exp\left[\sum_{i=1}^K x_i \log \mu_i\right] = \exp\left[\sum_{i=1}^K x_i \log \mu_i\right] \end{aligned}$$

$$= \exp\left[\sum_{i=1}^{K-1} x_i \log \mu_i + x_K \log(\mu_K)\right] \quad \text{--- checked answer key here}$$

$$= \exp\left[\sum_{i=1}^{K-1} x_i \log\left(\frac{\mu_i}{\mu_K}\right) + \log(\mu_K)\right]$$

$$\text{let } \boldsymbol{\eta} = \begin{bmatrix} \log\left(\frac{\mu_1}{\mu_K}\right) \\ \log\left(\frac{\mu_{K-1}}{\mu_K}\right) \end{bmatrix} \quad \text{--- checked answer key}$$

$$\mu_K = 1 - \sum_{i=1}^{K-1} \mu_i = 1 - \sum_{i=1}^{K-1} \mu_K e^{\eta_i} = \frac{1}{1 + \sum_{i=1}^{K-1} e^{\eta_i}}$$

now $\boldsymbol{\mu}$ is softmax of $\boldsymbol{\eta}$ we defined earlier

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