

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.

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 .

By def $B(a, b) = \int_0^1 \theta^{a-1} (1-\theta)^{b-1} d\theta = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$ and $\Gamma(x+1) = x\Gamma(x)$. ← checked soln for this.

a) Find mean:

$$\mathbb{E}[\theta] = \int_0^1 \theta \mathbb{P}(\theta; a, b) d\theta = \int_0^1 \theta \left(\frac{1}{B(a, b)} \theta^{a-1} (1-\theta)^{b-1} \right) d\theta$$

$B(a, b)$ idpt
of $\theta^{\frac{1}{2}}$
combine $\theta^{\frac{1}{2}} \theta^{a-1}$

$$= \frac{1}{B(a, b)} \int_0^1 \theta^a (1-\theta)^{b-1} d\theta = \frac{B(a+1, b)}{B(a, b)} \quad \text{by def.}$$

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

$$= \left[\frac{a}{a+b} \right]$$

b) Find variance:

By def $\text{Var}[\theta] = \mathbb{E}[(\theta - \mathbb{E}[\theta])^2] = \mathbb{E}[\theta^2] - \mathbb{E}[\theta]^2$ (we have $\mathbb{E}[\theta]^2$ from above but not $\mathbb{E}[\theta^2]$)

$$\text{So, } \mathbb{E}[\theta^2] = \int_0^1 \theta^2 \left(\frac{1}{B(a, b)} \theta^{a-1} (1-\theta)^{b-1} \right) d\theta$$

(if $\Gamma(x+1) = x\Gamma(x)$
then $\Gamma(x+2) = (x+1)\Gamma(x+1)$
 $= x(x+1)\Gamma(x)$)

$$= \frac{1}{B(a, b)} \int_0^1 \theta^{a+1} (1-\theta)^{b-1} d\theta = \frac{B(a+2, b)}{B(a, b)} = \frac{\Gamma(a+2)\Gamma(b)}{\Gamma(a+b+2)} \cdot \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}$$

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

$$\mathbb{E}[\theta]^2 = \left(\frac{a}{a+b} \right)^2$$

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

$$\begin{aligned} \text{(cont'd)} \quad & \frac{-a^2(a+b+1) + a(a+1)(a+b)}{(a+b)^2(a+b+1)} = \frac{-(a^3 + a^2b + a^2) + (a^3 + a^2b + a^2 + ab)}{(a+b)^2(a+b+1)} \\ & = \left| \frac{ab}{(a+b)^2(a+b+1)} \right| \end{aligned}$$

c) Find mode: Calc when $\nabla_{\theta} P(\theta; a, b) = 0$ on $[0, 1]$.

\Rightarrow disregard constant $\frac{1}{B(a, b)}$ term:

$$\begin{aligned} \nabla_{\theta} P(\theta; a, b) &= \nabla_{\theta} [\theta^{a-1} (1-\theta)^{b-1}] = 0 \\ &= (a-1)\theta^{a-2}(1-\theta)^{b-1} + \theta^{a-1}(b-1)(1-\theta)^{b-2}(-1) \\ &= (a-1)\theta^{a-2}(1-\theta)^{b-1} - (b-1)\theta^{a-1}(1-\theta)^{b-2} = 0 \end{aligned}$$

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

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

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

$$(a-1)(1-\theta) = (b-1)\theta$$

$$a - a\theta - 1 + \theta = b\theta - \theta$$

$$a\theta + b\theta - 2\theta = a-1$$

$$\theta(a+b-2) = a-1$$

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

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).

Exponential family : $P(y; \eta) = b(y) \exp(\eta^T T(y) - a(\eta))$

① Rewrite distribution w/ exp & log!

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

b/c $\log(ab) = \log(a) + \log(b)$

$$= \exp \left(\sum_{i=1}^K x_i \log(\mu_i) \right)$$

(\star By def, $\sum_{i=1}^K \mu_i = 1$ & $\sum_{i=1}^K x_i = 1$. So, $\mu_K = 1 - \sum_{i=1}^{K-1} \mu_i$ & $x_K = 1 - \sum_{i=1}^{K-1} x_i$.)

Thus, from above :

$$\text{Cat}(\mathbf{x}|\boldsymbol{\mu}) = \exp \left(\sum_{i=1}^K x_i \log(\mu_i) \right) = \exp \left(\left(\sum_{i=1}^{K-1} x_i \log(\mu_i) \right) + x_K \log(\mu_K) \right)$$

honestly,
following similar-ish
ex in class

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

(checked sol'n
for these cuz
tbh, it's late)

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

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

$b(y)$ $T(y)$

So, according to the exp family form:

$$\boldsymbol{\eta} = \begin{bmatrix} \log \left(\frac{\mu_1}{\mu_K} \right) \\ \vdots \\ \log \left(\frac{\mu_{K-1}}{\mu_K} \right) \end{bmatrix}$$

Then $\mu_i = \mu_k e^{\eta_i}$ (b/c $\mu_k e^{\eta_i} = \mu_k e^{(\log \frac{\mu_i}{\mu_k})} = \mu_k (\frac{\mu_i}{\mu_k}) = \mu_i$)

Substitute $\rightarrow \mu_k = 1 - \sum_{i=1}^{k-1} \mu_i = 1 - \sum_{i=1}^{k-1} \mu_k e^{\eta_i} = 1 - \mu_k \sum_{i=1}^{k-1} e^{\eta_i} = \frac{1}{1 + \sum_{i=1}^{k-1} e^{\eta_i}}$

So $\mu_i = \mu_k e^{\eta_i} = \frac{1}{1 + \sum_{i=1}^{k-1} e^{\eta_i}} e^{\eta_i}$ Softmax form!

Thus

$$b(\eta) = 1$$

$$T(\vec{x}) = \vec{x}$$

$$a(\vec{\eta}) = -\log(\mu_k) = \log\left(1 + \sum_{i=1}^{k-1} e^{\eta_i}\right)$$

exponential
family
form