

HW #3

1.

$\theta \sim \text{Beta}(a, b)$ s.t.

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

$$B(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$$

$$\Gamma(x+1) = x \Gamma(x)$$

Mean of θ :

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

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

$$= \left[\frac{\Gamma(a+1)\Gamma(b)}{\Gamma(a+b+1)} \right] \left[\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \right] = \left[\frac{a \Gamma(a)\Gamma(b)}{\Gamma(a+b)\Gamma(a+b)} \right] \left[\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \right]$$

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

We know $\text{Var}[\theta] = E[\theta^2] - E[\theta]^2$

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

$$= \frac{B(a+2, b)}{B(a, b)} = \left[\frac{\Gamma(a+2) \Gamma(b)}{\Gamma(a+b+2)} \right] \left[\frac{\Gamma(a+b)}{\Gamma(a) \Gamma(b)} \right]$$

∴

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

$$\text{Var}[\theta] = E[\theta^2] - E[\theta]^2$$

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

∴

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

for mode, we want to find when $\nabla_{\theta} P(\theta; a, b) = 0$ on $[0, 1]$.

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

$$\begin{aligned} \text{So, } (a-1)(1-\theta) &= (b-1)\theta \\ (a+b-2)\theta &= (a-1) \end{aligned}$$

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

2. Show $\text{Cat}(x|\mu) = \prod_{i=1}^k \mu_i^{x_i}$

Recall...

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

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

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

Since $\sum_{i=1}^k \mu_i = 1$ $\sum_{i=1}^k x_i = 1$ we need to

specify $k-1$ of these since x_k & μ_k will be determined at the end:

$$\mu_k = 1 - \sum_{i=1}^{k-1} \mu_i$$

$$x_k = 1 - \sum_{i=1}^{k-1} x_i$$

$$\therefore \text{Cat}(x|\mu) = \exp \left(\sum_{i=1}^k x_i \log(\mu_i) \right)$$

$$= \exp \left(\sum_{i=1}^{k-1} x_i \log(\mu_i) + x_k \log(\mu_k) \right)$$

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

$$= \exp \left[\sum_{i=1}^{k-1} \pi_i (\log(\mu_i) - \log(\mu_k)) + \log(\mu_k) \right]$$

$$= \exp \left[\sum_{i=1}^{k-1} \pi_i \log \left(\frac{\mu_i}{\mu_k} \right) + \log(\mu_k) \right]$$

\therefore let vector η be:

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

we can see that $\mu_i = \mu_k e^{\eta_i}$

$$\therefore \mu_k = 1 - \sum_{i=1}^{k-1} \mu_i = 1 - \sum_{i=1}^{k-1} \mu_k e^{\eta_i}$$

$$= 1 - \mu_k \sum_{i=1}^{k-1} e^{\eta_i}$$

$$= \frac{1}{1 + \sum_{i=1}^{k-1} e^{\eta_i}}$$

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

In form of exponential family, we get:

$$b(\eta) = 1 \quad T(x) = x$$

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

Therefore, $\text{cat}(x|\mu)$ is in the exponential family. $\mu = S(\eta)$ is softmax function which implies generalized linear model.