

b.

Mean

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

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

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

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

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

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

Variance

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

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

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

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

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

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

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

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

mod

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

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

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

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

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

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

$$2. \quad \text{cat}(x|M) = \prod_{i=1}^k m_i^{x_i}$$

$$= \exp \left[\log \left(\prod_{i=1}^k m_i^{x_i} \right) \right]$$

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

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

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

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

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

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

$$\text{1st vector } \eta = \begin{bmatrix} \log \left(\frac{m_1}{m_k} \right) \\ \vdots \\ \log \left(\frac{m_{k-1}}{m_k} \right) \end{bmatrix}$$

$$m_i = m_k e^{\eta_i}$$

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

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

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

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

→

$$\text{cat}(x|M) = \exp(\eta^T x - a(\eta))$$

$$b(\eta) = 1$$

$$T(x) = x$$

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

∴ $\text{cat}(x|M)$ is in exponential family & $\eta = \text{SGN}$ which is softmax func distribution