## STA 360: Assignment 3

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2. Since Z has distribution Binomial $(n, \theta)$ , the p.d.f. of z is:

$$p(z|\theta) = \binom{n}{z} \theta^z (1-\theta)^{n-z} \mathbb{1}(z \in S)$$

$$= \binom{n}{z} \exp\{\log[\theta^z (1-\theta)^{n-z}]\} \mathbb{1}(z \in S)$$

$$= \binom{n}{z} \exp\{\log \theta^z + \log(1-\theta)^{n-z}\} \mathbb{1}(z \in S)$$

$$= \binom{n}{z} \exp\{z \log \theta + (n-z) \log(1-\theta)\} \mathbb{1}(z \in S)$$

$$= \binom{n}{z} \exp\{z \log \theta + n \log(1-\theta) - z \log(1-\theta)\} \mathbb{1}(z \in S)$$

$$= \binom{n}{z} \exp\{z \log \frac{\theta}{1-\theta} + n \log(1-\theta)\} \mathbb{1}(z \in S)$$

$$= \binom{n}{z} \exp\{z \log \frac{\theta}{1-\theta} - n \log \frac{1}{1-\theta}\} \mathbb{1}(z \in S)$$

where  $S = \{0, 1, 2, ..., n\}$ . From here, we see that:

$$t(z) = z$$

$$\phi(\theta) = \log \frac{\theta}{1 - \theta}$$

$$\kappa(\theta) = n \log \frac{1}{1 - \theta}$$

$$h(z) = \binom{n}{z} \mathbb{1}(z \in S)$$

Thus, for a fixed n and given parameter  $\theta$ , Binomial $(n, \theta)$  distributions form a one-parameter exponential family.

3. Given that the generating distribution is p(x|a,b) = Gamma(x|a,b) where a is fixed, the form of this distribution is:

$$p(x_{1:n}|b) = \prod_{i=1}^{n} \frac{b^a}{\Gamma(a)} x_i^{a-1} e^{-bx_i}$$
$$\propto b^{an} e^{-b\sum x_i}$$

We will show that a conjugate prior for b is  $p(b) = \text{Gamma}(b|\alpha,\beta)$  by considering the corresponding

posterior distribution.

$$p(b|x_{1:n}) = p(b)p(x_{1:n}|b)$$

$$\propto \frac{\beta^{\alpha}}{\Gamma(\alpha)}b^{\alpha-1}e^{-\beta b}b^{an}e^{-b\sum x_i}$$

$$\propto b^{(\alpha+an)-1}e^{-b(\beta+\sum x_i)}$$

$$\propto \text{Gamma}(b|\alpha+an,\beta+\sum x_i)$$

Since the posterior, like the prior, is also a Gamma distribution, thus  $p(b) = \text{Gamma}(b|\alpha,\beta)$  is a conjugate prior for b.

5. Given conjugate prior  $p_{n_0,t_0}(\theta)$  and i.i.d. probability distributions  $p(x|\theta)$ , the posterior distribution  $p(\theta|x_{1:n})$  is the following:

$$p(\theta|x_{1:n}) = p_{n_0,t_0}(\theta) \prod_{i=1}^n p(x_i|\theta)$$

$$\propto \exp\{n_0 t_0 \phi(\theta) - n_0 \kappa(\theta)\} \prod_{i=1}^n \{\exp(\phi(\theta)t(x_i) - \kappa(\theta))h(x_i)\}$$

$$= \exp\{n_0 t_0 \phi(\theta) - n_0 \kappa(\theta)\} [\prod_{i=1}^n h(x_i)] \exp\{\sum_{i=1}^n (\phi(\theta)t(x_i) - \kappa(\theta))\}$$

$$\propto \exp\{n_0 t_0 \phi(\theta) - n_0 \kappa(\theta)\} \exp\{\sum_{i=1}^n (\phi(\theta)t(x_i) - \kappa(\theta))\}$$

$$= \exp\{n_0 t_0 \phi(\theta) - n_0 \kappa(\theta) + \phi(\theta) \sum_{i=1}^n t(x_i) - n\kappa(\theta)\}$$

$$= \exp\{(n_0 t_0 + \sum_{i=1}^n t(x_i))\phi(\theta) - (n_0 + n)\kappa(\theta)\}$$

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$$= \exp\{(n_0 t_0 + \sum_{i=1}^n t(x_i))\phi(\theta) - (n_0 t_0 + n)\kappa(\theta)\}$$

$$= \exp\{n't'\phi(\theta) - n'\kappa(\theta)\}$$

$$\propto p_{n',t'}(\theta)$$

where  $n' = n_0 + n$  and

$$t' = \frac{n_0 t_0 + \sum_{i=1}^{n} t(x_i)}{n_0 + n}$$

7. See image below:

To suppose {pa(0): of EH} is a conjugate family for some generator family, say a set G. By definition of conjugate family, the resulting presterior, where P(XIII (0) EG, is. Pilolxin) ox p(xin 10) Pa(0) of Px'(D) such that x'EH now, given the set A = { Z T; Px: (4): X1, -, X2 CH, TI EDE} AR = { TER = TI, TREZO, \$ TI = 1} Consider the following: Palolxin) & p(Kin 10) ET; Pa; (4) = 2 Ti; p(x1:n(0) px: (4) X ZT; Poli (by hypothesis) All X Pai'(0) since all Ti's are constant. Since Xi'EH, Pai(0) is also in A. Thus A is also a conjugate family of the same agrenata family G.

Additional exercise: Given prior distribution  $p(\theta)$  and generated distribution  $p(x|\theta)$ , the posterior distribution is as follows:

$$\begin{split} p(\theta|x_{1:n}) &= p(x_{1:n}|\theta)p(\theta) \\ &= \Big\{\prod_{i=1}^{n} \sqrt{\frac{\lambda}{2\pi}} \exp(-\frac{\lambda}{2}(x_{i} - \theta)^{2})\Big\} \sqrt{\frac{\lambda_{0}}{2\pi}} \exp(-\frac{\lambda_{0}}{2}(\theta - \mu_{0})^{2}) \\ &\propto \exp(-\frac{\lambda}{2} \sum_{i=1}^{n} (x_{i} - \theta)^{2}) \exp(\frac{\lambda_{0}}{2}(\theta - \mu_{0})^{2}) \\ &= \exp(-\frac{1}{2} [\lambda \sum_{i=1}^{n} (x_{i} - \theta)^{2} + \lambda_{0}(\theta - \mu_{0})^{2}]) \\ &= \exp(-\frac{1}{2} [\lambda \sum_{i=1}^{n} (x_{i}^{2} - 2x_{i}\theta + \theta^{2}) + \lambda_{0}(\theta^{2} - 2\theta\mu_{0} + \mu_{0}^{2})]) \\ &= \exp(-\frac{1}{2} [\lambda \sum_{i=1}^{n} x_{i}^{2} - 2\lambda\theta \sum_{i=1}^{n} x_{i} + n\lambda\theta^{2} + \lambda_{0}\theta^{2} - 2\lambda_{0}\theta\mu_{0} + \lambda_{0}\mu_{0}^{2}]) \\ &\propto \exp(-\frac{1}{2} [(n\lambda + \lambda_{0})\theta^{2} - 2(\lambda \sum_{i=1}^{n} x_{i} + 2\lambda_{0}\mu_{0})\theta]) \\ &= \exp(-\frac{n\lambda + \lambda_{0}}{2} [\theta^{2} - 2(\frac{\lambda \sum_{i=1}^{n} x_{i} + 2\lambda_{0}\mu_{0}}{n\lambda + \lambda_{0}})\theta]) \\ &\propto \exp(-\frac{n\lambda + \lambda_{0}}{2} (\theta - \frac{\lambda \sum_{i=1}^{n} x_{i} + 2\lambda_{0}\mu_{0}}{n\lambda + \lambda_{0}})^{2}) \\ &= \exp(-\frac{L}{2} (\theta - M)^{2}) \\ &\propto \operatorname{Normal}(\theta|M, L^{-1}) \end{split}$$

where  $L = n\lambda + \lambda_0$  and

$$M = \frac{\lambda \sum_{i=1}^{n} x_i + 2\lambda_0 \mu_0}{n\lambda + \lambda_0}$$