

STAT J535: Chapter 5: Classes of Bayesian Priors

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- ▶ A prior distribution **must** be specified in a Bayesian analysis.
- ▶ The choice of prior can substantially affect posterior conclusions, especially when the sample size is not large.
- ▶ We now examine several broad methods of determining prior distributions.

- ▶ We know that **conjugacy** is a property of a prior **along with a likelihood** that implies the posterior distribution will have the same *distributional form* as the prior (just with different parameter(s)).
- ▶ We have seen some examples of conjugate priors:

Data/Likelihood	Prior
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1. Bernoulli \rightarrow Beta for p
2. Poisson \rightarrow Gamma for λ
3. Normal \rightarrow Normal for μ
4. Normal \rightarrow Inverse gamma for σ^2

Other examples:

1. Multinomial \rightarrow Dirichlet for p_1, p_2, \dots, p_k
2. Negative Binomial \rightarrow Beta for p
3. Uniform(0, θ) \rightarrow Pareto for upper limit
4. Exponential \rightarrow Gamma for β
5. Gamma (β unknown) \rightarrow Gamma for β
6. Pareto (α unknown) \rightarrow Gamma for α
7. Pareto (β unknown) \rightarrow Pareto for β

Conjugate Priors: Exponential Family

- ▶ Consider the family of distributions known as the **one-parameter exponential family**.
- ▶ This family consists of any distribution whose p.d.f. (or p.m.f.) can be written as:

$$f(x|\theta) = e^{[t(x)u(\theta)]} r(x)s(\theta)$$

where $t(x)$ and $r(x)$ do not depend on the parameter θ and $u(\theta)$ and $s(\theta)$ do not depend on x .

- ▶ Note that any such density can be written as

$$f(x|\theta) = e^{\{t(x)u(\theta) + \ln[r(x)] + \ln[s(\theta)]\}}$$

Conjugate Priors: Exponential Family

- ▶ If we observe an iid sample X_1, \dots, X_n , the joint density of the data is thus

$$f(\mathbf{x}|\theta) = e^{\{u(\theta) \sum_{i=1}^n t(x_i) + \sum_{i=1}^n \ln[r(x_i)] + n \ln[s(\theta)]\}}$$

- ▶ Consider a prior for θ (with the prior parameters k and γ) having the form:

$$p(\theta) = c(k, \gamma) e^{\{ku(\theta)\gamma + k \ln[s(\theta)]\}}$$

Conjugate Priors: Exponential Family

Then the posterior is

$$\begin{aligned}\pi(\theta|\mathbf{x}) &\propto f(\mathbf{x}|\theta)p(\theta) \\ &\propto \exp\left\{u(\theta) \sum t(x_i) + n \ln[s(\theta)] + ku(\theta)\gamma + k \ln[s(\theta)]\right\} \\ &= \exp\left\{u(\theta) \left[\sum t(x_i) + k\gamma\right] + (n+k) \ln[s(\theta)]\right\} \\ &= \exp\left\{(n+k)u(\theta) \left[\frac{\sum t(x_i) + k\gamma}{n+k}\right] + (n+k) \ln[s(\theta)]\right\}\end{aligned}$$

which is of the same form as the prior, except with “ k ” = $n + k$ and “ γ ” = $\frac{\sum t(x_i) + k\gamma}{n+k}$.

\Rightarrow If our data are iid from a one-parameter exponential family, then a conjugate prior will exist.

- ▶ Conjugate priors are mathematically convenient.
- ▶ Sometimes they are quite flexible, depending on the specific hyperparameters we use.
- ▶ But they reflect very specific prior knowledge, so we should be wary of using them unless we truly possess that prior knowledge.

- ▶ These priors intentionally provide very little specific information about the parameter(s).
- ▶ A classic uninformative prior is the *uniform* prior.
- ▶ A *proper* uniform prior integrates to a finite quantity.
- ▶ **Example 1:** For Bernoulli(θ) data, a uniform prior on θ is

$$p(\theta) = 1, \quad 0 \leq \theta \leq 1.$$

- ▶ This makes sense when θ has **bounded support**.

- ▶ **Example 2:** Consider $N(0, \sigma^2)$ data. If it is “reasonable” to assume, that, say $\sigma^2 < 100$, we could use the uniform prior

$$p(\sigma^2) = \frac{1}{100}, \quad 0 \leq \sigma^2 \leq 100$$

(even though σ^2 is not intrinsically bounded).

- ▶ An **improper** uniform prior integrates to ∞ :
- ▶ **Example 3:** $N(\mu, 1)$ data with

$$p(\mu) = 1, \quad -\infty < \mu < \infty.$$

- ▶ This is fine as long as the resulting **posterior** is proper.
- ▶ But be careful: Sometimes an improper prior will yield an improper posterior.