

Bayesian Statistics I

Lecture 2 - Poisson data. Prior elicitation. Invariant priors.

Mattias Villani

Department of Statistics
Stockholm University

Department of Computer and Information Science
Linköping University



 mattiasvillani.com

 [@matvil](https://twitter.com/matvil)



 [mattiasvillani](https://github.com/mattiasvillani)

Lecture overview

- The Poisson model
- Conjugate priors
- Prior elicitation
- Jeffreys' prior

Poisson model

■ Model

$$y_1, \dots, y_n | \theta \stackrel{iid}{\sim} \text{Pois}(\theta)$$

■ Poisson distribution

$$p(y) = \frac{\theta^y e^{-\theta}}{y!}$$

■ Likelihood from iid Poisson sample $y = (y_1, \dots, y_n)$

$$p(y|\theta) = \left[\prod_{i=1}^n p(y_i|\theta) \right] \propto \theta^{(\sum_{i=1}^n y_i)} \exp(-\theta n),$$

■ Prior

$$p(\theta) \propto \theta^{\alpha-1} \exp(-\theta\beta) \propto \text{Gamma}(\alpha, \beta)$$

which contains the info: $\alpha - 1$ counts in β observations.

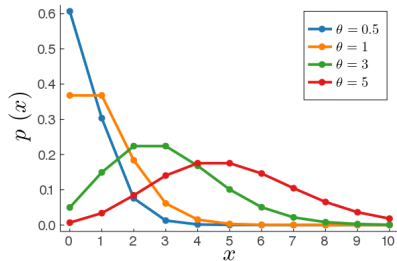
Poisson distribution

$X \sim \text{Pois}(\theta)$ for $X \in 0, 1, 2, \dots$

$$p(x) = \frac{\theta^x e^{-\theta}}{x!}$$

$$\mathbb{E}(X) = \theta$$

$$\mathbb{V}(X) = \theta$$



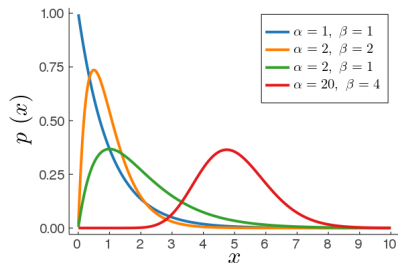
Gamma distribution

$X \sim \text{Gamma}(\alpha, \beta)$ for $X > 0$.

$$p(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$$

$$\mathbb{E}(X) = \frac{\alpha}{\beta}$$

$$\mathbb{V}(X) = \frac{\alpha}{\beta^2}$$



Poisson posterior

■ Posterior

$$\begin{aligned} p(\theta|y_1, \dots, y_n) &\propto \left[\prod_{i=1}^n p(y_i|\theta) \right] p(\theta) \\ &\propto \theta^{\sum_{i=1}^n y_i} \exp(-\theta n) \theta^{\alpha-1} \exp(-\theta \beta) \\ &= \theta^{\alpha + \sum_{i=1}^n y_i - 1} \exp[-\theta(\beta + n)], \end{aligned}$$

which is proportional to $\text{Gamma}(\alpha + \sum_{i=1}^n y_i, \beta + n)$.

■ Prior-to-Posterior mapping

Model: $y_1, \dots, y_n | \theta \stackrel{iid}{\sim} \text{Pois}(\theta)$

Prior: $\theta \sim \text{Gamma}(\alpha, \beta)$

Posterior: $\theta | y_1, \dots, y_n \sim \text{Gamma}(\alpha + \sum_{i=1}^n y_i, \beta + n)$.

Example - Number of bids in eBay auctions

■ Data:

- ▶ Number of placed bids in $n = 1000$ eBay coin auctions.
- ▶ Sum of counts: $\sum_{i=1}^n y_i = 3635$.
- ▶ Average number bids per auction: $\bar{y} = 3635/1000 = 3.635$.

■ Prior: $\alpha = 2$, $\beta = 1/2$.

$$E(\theta) = \frac{\alpha}{\beta} = 4$$

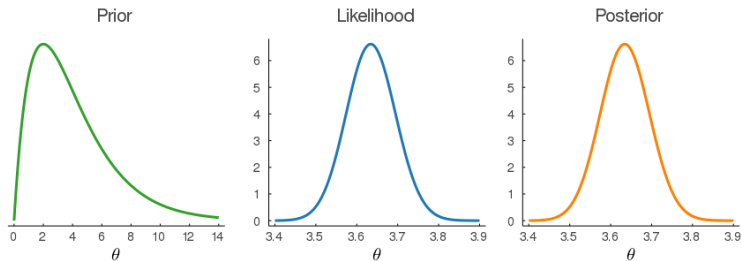
$$SD(\theta) = \frac{\alpha}{\beta^2} = 2.823$$

■ Posterior

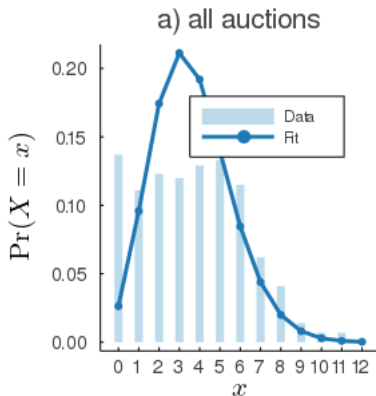
$$E(\theta|y) = \frac{\alpha + \sum_{i=1}^n y_i}{\beta + n} = \frac{2 + 3635}{1/2 + 1000} \approx 3.635.$$

$$SD(\theta|y) = \left(\frac{\alpha + \sum_{i=1}^n y_i}{(\beta + n)^2} \right)^{1/2} \approx 0.060.$$

eBay data - Posterior of θ



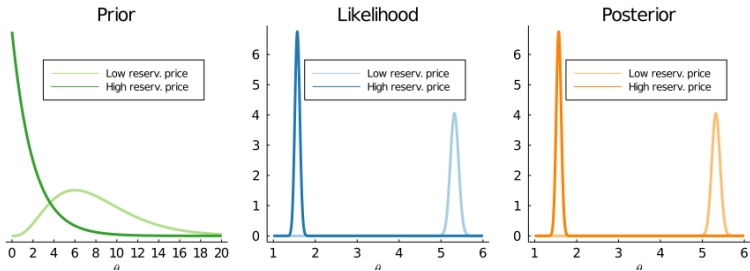
eBay data - model fit at $\theta = \mathbb{E}(\theta|x)$



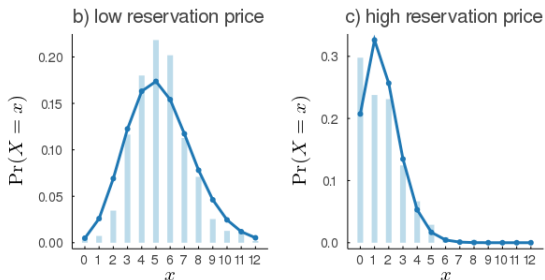
eBay - low/high seller's reservation price

- The data is very heterogenous. Some auctions start with very high reservations prices (lowest price accepted by the seller).
- Split the data into auctions with low/high reservation prices.
- **Low reservation price auctions:**
 - ▶ $n = 550$ eBay coin auctions.
 - ▶ Posterior mean: 5.321 bids.
- **High reservation price auctions:**
 - ▶ $n = 450$ eBay coin auctions.
 - ▶ Posterior mean: 1.576 bids.

eBay data split on reservation price



eBay data - model fit at $\mathbb{E}(\theta|x)$



- Better fits, but still not good enough.
- Lab 3: Fit **Poisson regression** with reservation price as continuous covariate.

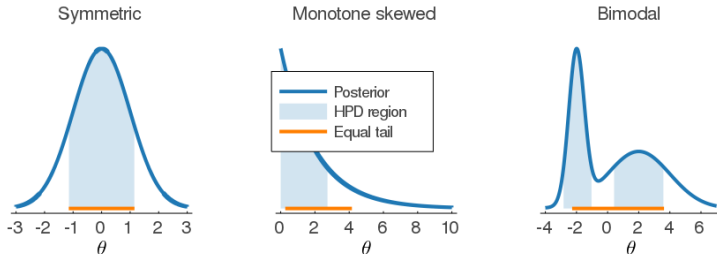
Posterior intervals

- **Bayesian 95% credible interval**: the probability that the unknown parameter θ lies in the interval is 0.95.
- 95% **equal-tail interval**: from 2.5% to 97.5% percentile.
- Approximate 95% **credible interval**

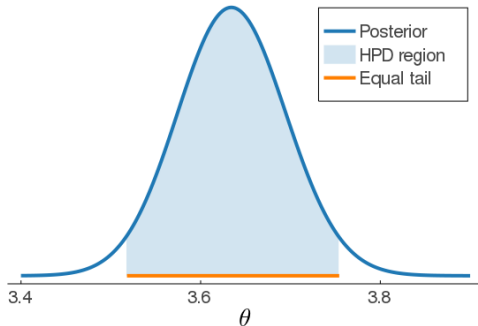
$$E(\theta|y) \pm 1.96 \cdot SD(\theta|y)$$

- **Highest Posterior Density (HPD)** interval contains the θ values with highest pdf.

Illustration of different interval types



Credible intervals - eBay auction data



Conjugate priors

- Normal likelihood: Normal prior \rightarrow Normal posterior.
- Bernoulli likelihood: Beta prior \rightarrow Beta posterior.
- Poisson likelihood: Gamma prior \rightarrow Gamma posterior.
- **Conjugate priors**: A prior is conjugate to a model if the prior and posterior belong to the **same distributional family**.

a family of prior distributions \mathcal{P} is **conjugate** for
a family of likelihoods $\mathcal{L} = \{p(x|\theta), \theta \in \Theta\}$ if

$$p(\theta) \in \mathcal{P} \Rightarrow p(\theta|x) \in \mathcal{P} \quad \text{for all } p(x|\theta) \in \mathcal{L}$$

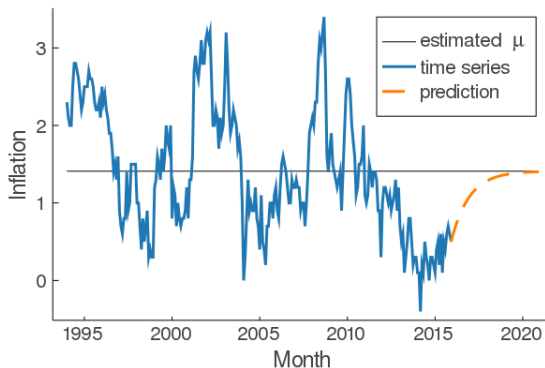
Autoregressive time series model

- **Autoregressive process** of order p - $AR(p)$

$$y_t = \mu + \phi_1(y_{t-1} - \mu) + \dots + \phi_p(y_{t-p} - \mu) + \varepsilon_t, \quad \varepsilon_t \stackrel{iid}{\sim} N(0, \sigma^2)$$

- Unconditional mean: $\mathbb{E}(y_t) = \mu$. Long run forecast attraction.

$$\mathbb{E}(y_{T+h} | y_{1:T}) \rightarrow \mu \text{ as } h \rightarrow \infty.$$



Prior elicitation - AR(p)

■ Autoregressive process

$$y_t = \mu + \phi_1(y_{t-1} - \mu) + \dots + \phi_p(y_{t-p} - \mu) + \varepsilon_t$$

■ Expert prior on the unconditional mean: $\mu \sim N(\mu_0, \tau_0^2)$.

■ Regularization prior on ϕ_1, \dots, ϕ_p

$$\phi_k \sim N\left(\mu_k, \frac{\tau^2}{k^2}\right) \text{ independently apriori}$$

▶ Prior mean on persistent AR(1): $\mu_1 = 0.8, \mu_2 = \dots = \mu_p = 0$

▶ $\mathbb{V}(\phi_k) = \frac{\tau^2}{k^2}$. Coeff on “longer” lags more likely to be small.

■ Hierarchical prior

▶ Hard to specify τ^2 ? Put a prior on it!

▶ $\phi_k | \tau^2 \sim N\left(\mu_k, \frac{\tau^2}{k^2}\right)$ and $\tau^2 \sim \chi_v^2$.

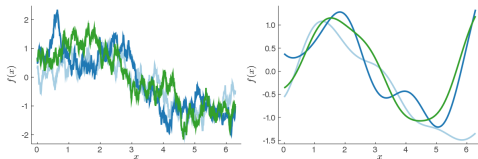
▶ Gives a posterior on global shrinkage τ^2 .

Prior elicitation

Smoothness priors

- ▶ a version of regularization priors
- ▶ nonlinear regression function $f(\cdot)$ is believed to be smooth

$$y = f(x) + \varepsilon$$



Noninformative priors

- ▶ **Uniform:** $\theta \sim \text{Beta}(1, 1)$.
Issue 1: same as prior sample with one success and one failure.
Issue 2: not uniform for $\phi = \log \frac{\theta}{1-\theta}$.
- ▶ **Zero prior sample size:** $\theta \sim \text{Beta}(\epsilon, \epsilon)$ with $\epsilon \downarrow 0$.
Posterior $\rightarrow \text{Beta}(s, f)$.
Issue: posterior is improper if $s = 0$ or $f = 0$.

Invariant prior

■ Observed information

$$J_{\theta, x} = - \frac{\partial^2 \ln p(x|\theta)}{\partial \theta^2} \Big|_{\theta = \hat{\theta}}$$

■ Fisher information

$$I(\theta) = E_{x|\theta} (J_{\theta, x})$$

■ Jeffreys' rule to construct prior

$$p(\theta) = I(\theta)^{1/2}.$$

■ Invariance under 1:1 parameter transformation $\phi = g(\theta)$.

Example: $\phi = \log \frac{\theta}{1-\theta}$.

▶ Specify $p_{\theta}(\theta)$ directly

▶ Specify $p_{\phi}(\phi)$ and then obtain $p_{\theta}(\theta) = p_{\phi}(g^{-1}(\theta)) \left| \frac{dg^{-1}(\theta)}{d\theta} \right|$.

Jeffreys' prior for Bernoulli sampling

$$x_1, \dots, x_n | \theta \stackrel{iid}{\sim} \text{Bern}(\theta).$$

$$\ln p(x|\theta) = s \ln \theta + f \ln(1 - \theta)$$

$$\frac{d \ln p(x|\theta)}{d\theta} = \frac{s}{\theta} - \frac{f}{(1 - \theta)}$$

$$\frac{d^2 \ln p(x|\theta)}{d\theta^2} = -\frac{s}{\theta^2} - \frac{f}{(1 - \theta)^2}$$

$$I(\theta) = \frac{E_{x|\theta}(s)}{\theta^2} + \frac{E_{x|\theta}(f)}{(1 - \theta)^2} = \frac{n\theta}{\theta^2} + \frac{n(1 - \theta)}{(1 - \theta)^2} = \frac{n}{\theta(1 - \theta)}$$

Thus, the Jeffreys' prior is

$$p(\theta) = |I(\theta)|^{1/2} \propto \theta^{-1/2} (1 - \theta)^{-1/2} \propto \text{Beta}(1/2, 1/2).$$

Jeffreys' prior for negative binomial sampling

- Jeffreys' prior:

$$n|\theta \stackrel{iid}{\sim} \text{NegBin}(s, \theta).$$

$$\ln p(x|\theta) = \ln \binom{n-1}{s-1} + s \ln \theta + f \ln(1-\theta)$$

$$\frac{d^2 \ln p(x|\theta)}{d\theta^2} = -\frac{s}{\theta^2} - \frac{f}{(1-\theta)^2}$$

$$I(\theta) = \frac{s}{\theta^2} + \frac{E_{n|\theta}(n-s)}{(1-\theta)^2} = \frac{s}{\theta^2} + \frac{s/\theta - s}{(1-\theta)^2} = \frac{s}{\theta^2(1-\theta)}$$

- Thus, the Jeffreys' prior is

$$p(\theta) = |I(\theta)|^{1/2} \propto \theta^{-1}(1-\theta)^{-1/2} \propto \text{Beta}(\theta|0, 1/2).$$

- Jeffreys' prior is **improper**, but the posterior is proper:
 $\theta|n \sim \text{Beta}(s, f + 1/2)$ which is proper since $s \geq 1$.
- Jeffreys' prior **violates the likelihood principle** because $I(\theta)$ is sampling-based.