

Bayesian Methods

David S. Rosenberg

New York University

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Classical Statistics

Parametric Family of Densities

- A **parametric family of densities** is a set

$$\{p(y \mid \theta) : \theta \in \Theta\},$$

- where $p(y \mid \theta)$ is a density on a **sample space** \mathcal{Y} , and
 - θ is a **parameter** in a [finite dimensional] **parameter space** Θ .
- This is the common starting point for a treatment of classical or Bayesian statistics.

Density vs Mass Functions

- In this lecture, whenever we say “density”, we could replace it with “mass function.”
- Corresponding integrals would be replaced by summations.
- (In more advanced, measure-theoretic treatments, they are each considered densities w.r.t. different base measures.)

Frequentist or “Classical” Statistics

- Parametric family of densities

$$\{p(y | \theta) | \theta \in \Theta\}.$$

- Assume that $p(y | \theta)$ governs the world we are observing, for some $\theta \in \Theta$.
- If we knew the right $\theta \in \Theta$, there would be no need for statistics.
- Instead of θ , we have data \mathcal{D} : y_1, \dots, y_n sampled i.i.d. $p(y | \theta)$.
- Statistics is about how to get by with \mathcal{D} in place of θ .

- One type of statistical problem is **point estimation**.
- A **statistic** $s = s(\mathcal{D})$ is any function of the data.
- A statistic $\hat{\theta} = \hat{\theta}(\mathcal{D})$ taking values in Θ is a **point estimator** of θ .
- A good point estimator will have $\hat{\theta} \approx \theta$.

Desirable Properties of Point Estimators

- Desirable statistical properties of point estimators:
 - **Consistency:** As data size $n \rightarrow \infty$, we get $\hat{\theta}_n \rightarrow \theta$.
 - **Efficiency:** (Roughly speaking) $\hat{\theta}_n$ is as accurate as we can get from a sample of size n .
- **Maximum likelihood estimators** are consistent and efficient under reasonable conditions.

The Likelihood Function

- Consider parametric family $\{p(y \mid \theta) : \theta \in \Theta\}$ and i.i.d. sample $\mathcal{D} = (y_1, \dots, y_n)$.
- The density for sample \mathcal{D} for $\theta \in \Theta$ is

$$p(\mathcal{D} \mid \theta) = \prod_{i=1}^n p(y_i \mid \theta).$$

- $p(\mathcal{D} \mid \theta)$ is a function of \mathcal{D} and θ .
- For fixed θ , $p(\mathcal{D} \mid \theta)$ is a density function on \mathcal{Y}^n .
- For fixed \mathcal{D} , the function $\theta \mapsto p(\mathcal{D} \mid \theta)$ is called the **likelihood function**:

$$L_{\mathcal{D}}(\theta) := p(\mathcal{D} \mid \theta).$$

Maximum Likelihood Estimation

Definition

The **maximum likelihood estimator (MLE)** for θ in the model $\{p(y, \theta) \mid \theta \in \Theta\}$ is

$$\hat{\theta}_{\text{MLE}} = \underset{\theta \in \Theta}{\operatorname{argmax}} L_{\mathcal{D}}(\theta).$$

- Maximum likelihood is just one approach to getting a point estimator for θ .
- **Method of moments** is another general approach one learns about in statistics.
- Later we'll talk about **MAP** and **posterior mean** as approaches to point estimation.
 - These arise naturally in Bayesian settings.

Coin Flipping: Setup

- Parametric family of mass functions:

$$p(\text{Heads} \mid \theta) = \theta,$$

for $\theta \in \Theta = (0, 1)$.

- Note that every $\theta \in \Theta$ gives us a different probability model for a coin.

Coin Flipping: Likelihood function

- Data $\mathcal{D} = (H, H, T, T, T, T, T, H, \dots, T)$
 - n_h : number of heads
 - n_t : number of tails
- Assume these were i.i.d. flips.
- **Likelihood function** for data \mathcal{D} :

$$L_{\mathcal{D}}(\theta) = p(\mathcal{D} \mid \theta) = \theta^{n_h} (1 - \theta)^{n_t}$$

- This is the probability of getting the flips in the order they were received.

Coin Flipping: MLE

- As usual, easier to maximize the log-likelihood function:

$$\begin{aligned}\hat{\theta}_{\text{MLE}} &= \arg \max_{\theta \in \Theta} \log L_{\mathcal{D}}(\theta) \\ &= \arg \max_{\theta \in \Theta} [n_h \log \theta + n_t \log(1 - \theta)]\end{aligned}$$

- First order condition:

$$\begin{aligned}\frac{n_h}{\theta} - \frac{n_t}{1 - \theta} &= 0 \\ \iff \theta &= \frac{n_h}{n_h + n_t}.\end{aligned}$$

- So $\hat{\theta}_{\text{MLE}}$ is the empirical fraction of heads.

Bayesian Statistics: Introduction

- Introduces a new ingredient: the **prior distribution**.
- A **prior distribution** $p(\theta)$ is a distribution on parameter space Θ .
- A prior reflects our belief about θ , **before seeing any data**..

A Bayesian Model

- A [parametric] Bayesian model consists of two pieces:

- ① A parametric family of densities

$$\{p(\mathcal{D} \mid \theta) \mid \theta \in \Theta\}.$$

- ② A **prior distribution** $p(\theta)$ on parameter space Θ .

- Putting pieces together, we get a joint density on θ and \mathcal{D} :

$$p(\mathcal{D}, \theta) = p(\mathcal{D} \mid \theta)p(\theta).$$

The Posterior Distribution

- The **posterior distribution** for θ is $p(\theta \mid \mathcal{D})$.
- Prior represents belief about θ before observing data \mathcal{D} .
- Posterior represents the **rationally “updated” belief** about θ , after seeing \mathcal{D} .

Expressing the Posterior Distribution

- By Bayes rule, can write the posterior distribution as

$$p(\theta | \mathcal{D}) = \frac{p(\mathcal{D} | \theta)p(\theta)}{p(\mathcal{D})}.$$

- Let's consider both sides as functions of θ , for fixed \mathcal{D} .
- Then both sides are densities on Θ and we can write

$$\underbrace{p(\theta | \mathcal{D})}_{\text{posterior}} \propto \underbrace{p(\mathcal{D} | \theta)}_{\text{likelihood}} \underbrace{p(\theta)}_{\text{prior}}.$$

- Where \propto means we've dropped factors independent of θ .

Coin Flipping: Bayesian Model

- Parametric family of mass functions:

$$p(\text{Heads} \mid \theta) = \theta,$$

for $\theta \in \Theta = (0, 1)$.

- Need a prior distribution $p(\theta)$ on $\Theta = (0, 1)$.
- A distribution from the Beta family will do the trick...

Coin Flipping: Beta Prior

- Prior:

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

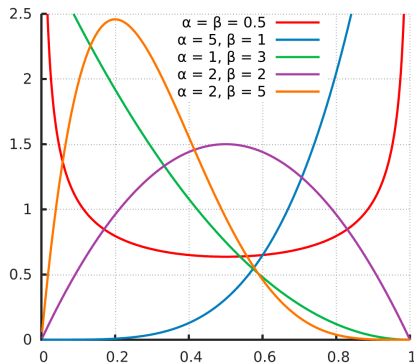


Figure by Horas based on the work of Krishnavedala (Own work) [Public domain], via Wikimedia Commons

http://commons.wikimedia.org/wiki/File:Beta_distribution_pdf.svg.

Coin Flipping: Beta Prior

- **Prior:**

$$\begin{aligned}\theta &\sim \text{Beta}(h, t) \\ p(\theta) &\propto \theta^{h-1} (1-\theta)^{t-1}\end{aligned}$$

- **Mean of Beta distribution:**

$$\mathbb{E}\theta = \frac{h}{h+t}$$

- **Mode of Beta distribution:**

$$\arg \max_{\theta} p(\theta) = \frac{h-1}{h+t-2}$$

for $h, t > 1$.

Coin Flipping: Posterior

- Prior:

$$\begin{aligned}\theta &\sim \text{Beta}(h, t) \\ p(\theta) &\propto \theta^{h-1} (1-\theta)^{t-1}\end{aligned}$$

- Likelihood function

$$L(\theta) = p(\mathcal{D} \mid \theta) = \theta^{n_h} (1-\theta)^{n_t}$$

- Posterior density:

$$\begin{aligned}p(\theta \mid \mathcal{D}) &\propto p(\theta)p(\mathcal{D} \mid \theta) \\ &\propto \theta^{h-1} (1-\theta)^{t-1} \times \theta^{n_h} (1-\theta)^{n_t} \\ &= \theta^{h-1+n_h} (1-\theta)^{t-1+n_t}\end{aligned}$$

Posterior is Beta

- Prior:

$$\begin{aligned}\theta &\sim \text{Beta}(h, t) \\ p(\theta) &\propto \theta^{h-1} (1-\theta)^{t-1}\end{aligned}$$

- Posterior density:

$$p(\theta \mid \mathcal{D}) \propto \theta^{h-1+n_h} (1-\theta)^{t-1+n_t}$$

- Posterior is in the beta family:

$$\theta \mid \mathcal{D} \sim \text{Beta}(h + n_h, t + n_t)$$

- Interpretation:

- Prior initializes our counts with h heads and t tails.
- Posterior increments counts by observed n_h and n_t .

Sidebar: Conjugate Priors

- Interesting that posterior is in same distribution family as prior.
- Let π be a family of prior distributions on Θ .
- Let P parametric family of distributions with parameter space Θ .

Definition

A family of distributions π is **conjugate to** parametric model P if for any prior in π , the posterior is always in π .

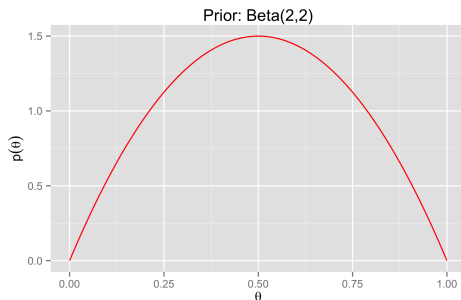
- The beta family is conjugate to the coin-flipping (i.e. Bernoulli) model.
- The family of all probability distributions is conjugate to any parametric model. [Trivially]

Example: Coin Flipping - Concrete Example

- Suppose we have a coin, possibly biased (**parametric probability model**):

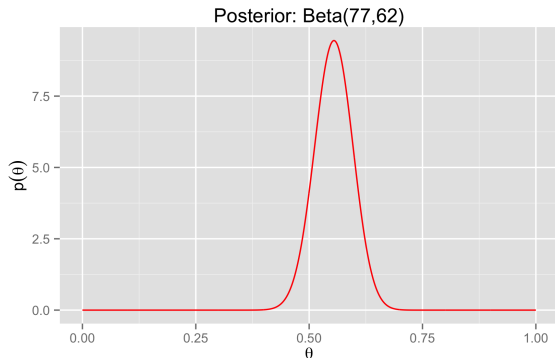
$$p(\text{Heads} \mid \theta) = \theta.$$

- Parameter space** $\theta \in \Theta = [0, 1]$.
- Prior distribution:** $\theta \sim \text{Beta}(2, 2)$.



Example: Coin Flipping

- Next, we gather some data $\mathcal{D} = \{H, H, T, T, T, T, T, H, \dots, T\}$:
- Heads: 75 Tails: 60
 - $\hat{\theta}_{\text{MLE}} = \frac{75}{75+60} \approx 0.556$
- **Posterior distribution:** $\theta \mid \mathcal{D} \sim \text{Beta}(77, 62)$:



Bayesian Point Estimates

- So we have posterior $\theta \mid \mathcal{D} \dots$
- But we want a point estimate $\hat{\theta}$ for θ .
- Common options:
 - **posterior mean** $\hat{\theta} = \mathbb{E}[\theta \mid \mathcal{D}]$
 - **maximum a posteriori (MAP) estimate** $\hat{\theta} = \arg \max_{\theta} p(\theta \mid \mathcal{D})$
 - Note: this is the **mode** of the posterior distribution

What else can we do with a posterior?

- Look at it.
- Extract “**credible set**” for θ (a Bayesian confidence interval).
 - e.g. Interval $[a, b]$ is a 95% **credible set** if

$$\mathbb{P}(\theta \in [a, b] \mid \mathcal{D}) \geq 0.95$$

- The most “Bayesian” approach is **Bayesian decision theory**:
 - Choose a loss function.
 - Find action **minimizing expected risk w.r.t. posterior**

Bayesian Decision Theory

Bayesian Decision Theory

- Ingredients:
 - **Parameter space** Θ .
 - **Prior**: Distribution $p(\theta)$ on Θ .
 - **Action space** \mathcal{A} .
 - **Loss function**: $\ell : \mathcal{A} \times \Theta \rightarrow \mathbf{R}$.
- The **posterior risk** of an action $a \in \mathcal{A}$ is

$$\begin{aligned} r(a) &:= \mathbb{E}[\ell(\theta, a) \mid \mathcal{D}] \\ &= \int \ell(\theta, a) p(\theta \mid \mathcal{D}) d\theta. \end{aligned}$$

- It's the **expected loss under the posterior**.
- A **Bayes action** a^* is an action that minimizes posterior risk:

$$r(a^*) = \min_{a \in \mathcal{A}} r(a)$$

Bayesian Point Estimation

- General Setup:
 - Data \mathcal{D} generated by $p(y \mid \theta)$, for unknown $\theta \in \Theta$.
 - Want to produce a **point estimate** for θ .
- Choose the following:
 - **Prior** $p(\theta)$ on $\Theta = \mathbf{R}$.
 - **Loss** $\ell(\hat{\theta}, \theta) = (\theta - \hat{\theta})^2$
- Find **action** $\hat{\theta} \in \Theta$ that minimizes **posterior risk**:

$$\begin{aligned} r(\hat{\theta}) &= \mathbb{E} \left[(\theta - \hat{\theta})^2 \mid \mathcal{D} \right] \\ &= \int (\theta - \hat{\theta})^2 p(\theta \mid \mathcal{D}) d\theta \end{aligned}$$

Bayesian Point Estimation: Square Loss

- Find **action** $\hat{\theta} \in \Theta$ that minimizes **posterior risk**

$$r(\hat{\theta}) = \int (\theta - \hat{\theta})^2 p(\theta | \mathcal{D}) d\theta.$$

- Differentiate:

$$\begin{aligned} \frac{dr(\hat{\theta})}{d\hat{\theta}} &= - \int 2(\theta - \hat{\theta}) p(\theta | \mathcal{D}) d\theta \\ &= -2 \int \theta p(\theta | \mathcal{D}) d\theta + 2\hat{\theta} \underbrace{\int p(\theta | \mathcal{D}) d\theta}_{=1} \\ &= -2 \int \theta p(\theta | \mathcal{D}) d\theta + 2\hat{\theta} \end{aligned}$$

Bayesian Point Estimation: Square Loss

- Derivative of posterior risk is

$$\frac{dr(\hat{\theta})}{d\hat{\theta}} = -2 \int \theta p(\theta | \mathcal{D}) d\theta + 2\hat{\theta}.$$

- First order condition $\frac{dr(\hat{\theta})}{d\hat{\theta}} = 0$ gives

$$\begin{aligned}\hat{\theta} &= \int \theta p(\theta | \mathcal{D}) d\theta \\ &= \mathbb{E}[\theta | \mathcal{D}]\end{aligned}$$

- Bayes action for square loss** is the posterior mean.

Bayesian Point Estimation: Absolute Loss

- **Loss:** $\ell(\theta, \hat{\theta}) = |\theta - \hat{\theta}|$
- **Bayes action for absolute loss is the posterior median.**
 - That is, the median of the distribution $p(\theta | \mathcal{D})$.
 - Show with approach similar to what was used in Homework #1.

Bayesian Point Estimation: Zero-One Loss

- Suppose Θ is discrete (e.g. $\Theta = \{\text{english}, \text{french}\}$)
- **Zero-one loss:** $\ell(\theta, \hat{\theta}) = 1(\theta \neq \hat{\theta})$
- **Posterior risk:**

$$\begin{aligned}r(\hat{\theta}) &= \mathbb{E} \left[1(\theta \neq \hat{\theta}) \mid \mathcal{D} \right] \\&= \mathbb{P}(\theta \neq \hat{\theta} \mid \mathcal{D}) \\&= 1 - \mathbb{P}(\theta = \hat{\theta} \mid \mathcal{D}) \\&= 1 - p(\hat{\theta} \mid \mathcal{D})\end{aligned}$$

- **Bayes action** is

$$\hat{\theta} = \arg \max_{\theta \in \Theta} p(\theta \mid \mathcal{D})$$

- This $\hat{\theta}$ is called the **maximum a posteriori (MAP)** estimate.
- The MAP estimate is the **mode** of the posterior distribution.

Summary

Recap and Interpretation

- Prior represents belief about θ before observing data \mathcal{D} .
- Posterior represents the **rationally “updated” beliefs** after seeing \mathcal{D} .
- All inferences and action-taking are based on the posterior distribution.
- In the Bayesian approach,
 - No issue of “choosing a procedure” or justifying an estimator.
 - Only choices are
 - **family of distributions**, indexed by Θ , and the
 - **prior distribution** on Θ
 - For decision making, need a **loss function**.
 - Everything after that is **computation**.

1 Define the model:

- Choose a parametric family of densities:

$$\{p(\mathcal{D} \mid \theta) \mid \theta \in \Theta\}.$$

- Choose a distribution $p(\theta)$ on Θ , called the **prior distribution**.

2 After observing \mathcal{D} , compute the **posterior distribution** $p(\theta \mid \mathcal{D})$.

3 Choose **action** based on $p(\theta \mid \mathcal{D})$.