Lecture 2: Basic Bayesian calculus

Thibault Randrianarisoa

UTSC

January 14, 2026

Computer & Mathematical Sciences
UNIVERSITY OF TORONTO
SCARBOROUGH

Outline

- Frequentist vs. Bayesian

- Second part: Prior choice

Frequentist vs. Bayesian?

Frequentist approach: basic elements

Setup

- Data: $X_1, \ldots, X_n$ are viewed as random variables, generated i.i.d. from a distribution P_{θ_0}.
- Parameter: θ_0 is an *unknown but fixed* quantity (no probability distribution on θ_0).
- Randomness comes only from the sampling of the data.
- Probability is seen as the limit of the frequency of an event if I repeat an experiment indefinitely.

Main inferential tasks

- **Estimation:** construct an estimator $\hat{\theta}(X)$ with good long-run properties (bias, variance, risk, asymptotic normality).
- **Confidence sets:** build random sets $\mathcal{R}(X)$ such that $\mathbb{P}_\theta(\theta \in \mathcal{R}(X)) \approx 1 - \alpha$.
- **Hypothesis tests:** design tests $\varphi(X) \in \{0, 1\}$ with controlled type I error and good power.
- **Prediction:** predict a future observation X_{n+1} using $f(X_{n+1} \mid X_1, \ldots, X_n, \hat{\theta}_n)$.

Some drawbacks of the frequentist approach

1. Practical issues with small samples
   - Asymptotic theory may no longer be reliable for small n.
   - Comparison of estimators must use non-asymptotic criteria; many tools based on convergence in distribution (e.g. asymptotic confidence regions, test statistics) can become unusable.

2. Tension with the likelihood principle

   The likelihood principle says that all information about θ in an observation x is contained in the likelihood $L_\theta(X) = p_\theta(X)$.

   If two observations x_1, x_2 satisfy

$$L_\theta(x_1) = c\, L_\theta(x_2) \quad \forall\theta,$$

   they should lead to the same inference.

   Frequentist procedures can violate this, because they may depend on other aspects beyond the likelihood.

Some drawbacks of the frequentist approach

3. Maximum likelihood and prediction
   - The MLE, often viewed as "most efficient", may fail to exist or be non-unique in some models.
   - For prediction, the classical plug-in density

$$p_{\hat{\theta}_n}(X_{n+1} \mid X_1, \ldots, X_n) = \frac{p_{\hat{\theta}_n}(X_1, \ldots, X_n, X_{n+1})}{p_{\hat{\theta}_n}(X_1, \ldots, X_n)}$$

uses the data twice (to estimate θ and to condition), which can underestimate uncertainty (too narrow confidence intervals, overconfident forecasts).

Statistical experiment

- We observe a random object X taking values in a measurable space $(E, \mathcal{E})$ (like $\mathbb{R}^p$).
- The distribution of X is assumed to belong to a parametric model

$$\mathcal{P} = \{P_\theta : \theta \in \Theta\},$$

where the parameter space satisfies $\Theta \subset \mathbb{R}^d$ for some fixed $d \geqslant 1$.

Bayesian point of view

- First step: equip the parameter space Θ with a probability measure Π, called the prior distribution.
- The parameter becomes a random variable

$$\theta \sim \Pi \quad \text{on } \Theta.$$

Densities

We assume from now on that

- for every $\theta \in \Theta$, P_θ has a density $p_\theta(x)$ with respect to a sigma-finite measure μ on E:

$$dP_\theta(x) = p_\theta(x)\, d\mu(x);$$

- the prior Π has a density $\pi(\theta)$ with respect to a sigma-finite measure ν on Θ:

$$d\Pi(\theta) = \pi(\theta)\, d\nu(\theta).$$

Joint distribution of (X, θ)

We define the joint law $\mathcal{L}(\theta, X)$ by the density

$$(x, \theta) \mapsto \pi(\theta)\, p_\theta(x)$$

with respect to the product measure $\nu \otimes \mu$.

Posterior distribution and Bayes formula

Marginals and conditionals

From the joint density $\pi(\theta)p_\theta(x)$ we recover:

- the prior density of θ by integrating out x: $\forall\theta\in\Theta,\quad \int_E \pi(\theta)p_\theta(x)\,d\mu(x) = \pi(\theta)$
- the conditional law $X \mid \theta \sim P_\theta$ with density $p_\theta(x)$
- the marginal density of X with respect to μ: ⚠This is not $p_\theta(x)$

$$f(x) = \int_\Theta p_\theta(x)\,\pi(\theta)\,d\nu(\theta)$$

Posterior and Bayes formula

- The posterior distribution is the conditional law $\mathcal{L}(\theta \mid X)$, denoted $\Pi(\,\cdot \mid X)$.
- Under the density assumptions above, it admits a density w.r.t. ν (Bayes formula):

$$\forall\theta\in\Theta,\qquad \pi(\theta \mid X) = \frac{p_\theta(X)\,\pi(\theta)}{f(X)},$$

where $f(X) = \int_\Theta \pi(\theta')p_{\theta'}(X)\,d\nu(\theta')$ is the marginal likelihood.

Definition: Exchangeability

Random variables $X_1, \dots, X_n$ are exchangeable if for any permutation σ, the laws of $(X_1, \dots, X_n)$ and $\left(X_{\sigma(1)}, \dots, X_{\sigma(n)}\right)$ are identical.

De Finetti (1931): representation theorem

For any *exchangeable* sequence $(X_1, X_2, \dots)$ of $\{0,1\}$-valued random variables, there exists a unique probability density π on $[0,1]$ such that, for every n and every $x_1, \dots, x_n \in \{0,1\}$,

$$P(X_1 = x_1, \dots, X_n = x_n) = \int_0^1 \prod_{i=1}^n \theta^{x_i}(1-\theta)^{1-x_i} \pi(\theta)\, d\nu(\theta).$$

The joint law is a mixture of i.i.d. Bernoulli laws.

Why Bayesian? De Finetti's theorem

- Exchangeable binary data can always be represented as i.i.d. given a parameter θ with prior $\pi(\theta)$.

- The prior $\pi(\theta)$ is not an arbitrary trick: while we do not know what it is exactly, it always exists.

- De Finetti-type results extend to more general cases, giving a strong justification for Bayesian modeling.

Prior as information

A prior $\pi(\theta)$ is a probability measure/density that encodes uncertain information about the parameter θ before seeing the data.

The prior allows us to

- satisfy the likelihood principle: inferences depend on the likelihood $L_\theta(X)$ only
- represent all uncertainties about θ
- integrate external or expert knowledge a priori, instead of relying solely on the sample/observation X

Example: Gaussian model

Model.

$$X \mid \theta \sim \mathcal{N}(\theta, 1), \qquad \theta \sim \mathcal{N}(0, 1)$$

Densities (w.r.t. Lebesgue measure).

$$p_\theta(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x-\theta)^2}{2}\right), \qquad \pi(\theta) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\theta^2}{2}\right)$$

Posterior for one observation $X = x$.

$$\pi(\theta \mid X = x) \propto \pi(\theta)\, p_\theta(x) \propto \exp\left(-\frac{1}{2}\left[\theta^2 + (x-\theta)^2\right]\right)$$

Complete the square:

$$\theta^2 + (x-\theta)^2 = 2\left(\theta - \frac{x}{2}\right)^2 + \frac{x^2}{2}$$

Hence, up to a normalising constant,

$$\pi(\theta \mid X = x) \propto \exp\left(-\left(\theta - \frac{x}{2}\right)^2\right) \qquad \text{or, equivalently} \qquad \boxed{\theta \mid X = x \sim \mathcal{N}\left(\frac{x}{2}, \frac{1}{2}\right)}$$

Now take $X_1, \ldots, X_n$ i.i.d. given θ:

$$X_i \mid \theta \sim \mathcal{N}(\theta, 1), \qquad \theta \sim \mathcal{N}(0, 1)$$

Likelihood

$$\prod_{i=1}^{n} p_\theta(x_i) \propto \exp\left(-\frac{1}{2}\sum_{i=1}^{n}(x_i - \theta)^2\right)$$

Posterior

$$\pi(\theta \mid x_1, \ldots, x_n) \propto \pi(\theta)\prod_{i=1}^{n} p_\theta(x_i) \propto \exp\left(-\frac{1}{2}\left[\theta^2 + \sum_{i=1}^{n}(x_i - \theta)^2\right]\right)$$

Using $\bar{x}_n = \frac{1}{n}\sum_{i=1}^{n} x_i$ and completing the square,

$$\pi(\theta \mid x_1, \ldots, x_n) \propto \exp\left(-\frac{n+1}{2}\left(\theta - \frac{n\bar{x}_n}{n+1}\right)^2\right)$$ or, equivalently, $$\boxed{\theta \mid X_1, \ldots, X_n \sim \mathcal{N}\left(\frac{n\bar{X}_n}{n+1}, \frac{1}{n+1}\right)}$$

What do we look at in the posterior?

- Posterior mean

$$m_X \;=\; \mathbb{E}[\theta \mid X] \;=\; \int_\Theta \theta \, \mathrm{d}\pi(\theta \mid X).$$

- Posterior mode (MAP estimator)

$$\mathrm{mode}(\theta \mid X) \in \arg\max_{\theta \in \Theta} \pi(\theta \mid X) = \arg\max_{\theta \in \Theta} \pi(\theta) p_\theta(X),$$

  where $\pi(\theta \mid X)$ is the posterior density.

- Posterior dispersion
  - For $\Theta \subset \mathbb{R}$:

$$v_X \;=\; \mathrm{Var}(\theta \mid X) \;=\; \int_\Theta (\theta - m_X)^2 \, \mathrm{d}\pi(\theta \mid X).$$

  - For $\Theta \subset \mathbb{R}^d$:

$$\Sigma_X \;=\; \int_\Theta (\theta - m_X)(\theta - m_X)^\mathsf{T} \, \mathrm{d}\pi(\theta \mid X).$$

What do we look at in the posterior?

- Posterior quantiles
  Let $F_{\theta|X}$ be the cdf of $\pi(\cdot \mid X)$ and $F_{\theta|X}^{-1}$ its (generalised) inverse. For $p \in (0,1)$:

$$q_p(X) \;=\; F_{\theta|X}^{-1}(p)$$

  is the posterior p-quantile (for example $q_{1/2}(X)$ is the posterior median).

Linear regression model.
We observe (x_i, y_i), $i = 1, \ldots, n$, and assume

$$y_i = x_i^\top \theta + \varepsilon_i, \qquad \varepsilon_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2).$$

Penalized least squares. We choose $\hat{\theta}_n$ as a minimizer of

$$\sum_{i=1}^{n} (y_i - x_i^\top \theta)^2 + \text{pen}(\theta).$$

Typical choices:

- Ridge: $\text{pen}(\theta) = \lambda \|\theta\|_2^2$,
- Lasso: $\text{pen}(\theta) = \lambda \|\theta\|_1$.

Penalized linear regression: Bayesian view

Bayesian interpretation. Under the Gaussian noise model,

$$p_\theta(y_1, \dots, y_n) \propto \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^{n} (y_i - x_i^\top \theta)^2 \right)$$

is the likelihood. If we choose a prior

$$\pi(\theta) \propto \exp\big(-\operatorname{pen}(\theta) \big),$$

then we also have

$$\hat{\theta}_n = \arg\max_\theta \pi(\theta \mid y_1, \dots, y_n)$$

is a MAP estimator.

Penalty $\Longleftrightarrow$ prior

- Ridge: $\operatorname{pen}(\theta) = \lambda \|\theta\|_2^2 \Longrightarrow$ Gaussian prior $\pi(\theta) \propto \exp(-\lambda \|\theta\|_2^2)$.
- Lasso: $\operatorname{pen}(\theta) = \lambda \|\theta\|_1 \Longrightarrow$ Laplace prior $\pi(\theta) \propto \exp(-\lambda \|\theta\|_1)$.

Take-home message: penalized linear regression is Bayesian estimation with an explicit prior on θ (MAP).

Why even non-Bayesians may like Bayesian methods

Even a true non-Bayesian may like Bayesian methods, because

- they are elegant;
- they allow us to incorporate prior information in a principled way;
- they may be easier to implement in complex models.

A true non-Bayesian will still want to understand the performance of Bayesian procedures in a non-Bayesian framework: frequentist Bayesian theory (see Lecture 7)

Frequentist Bayesian theory. Assume the data X are generated under a fixed "true'" parameter θ_0 and consider the posterior $\Pi(\theta \in \cdot \mid X)$ as a random probability measure on the parameter space. We would like $\Pi(\theta \in \cdot \mid X)$ to put most of its mass near θ_0 for "most" samples X.

Asymptotic setting. For a growing sample $X^{(n)}$ where the information increases as $n \to \infty$, we want the posterior $\Pi(\theta \in \cdot \mid X^{(n)})$ to contract around θ_0 fast.

Prior choice

Why talk about priors?

- The prior Π encodes information we have about the parameter before seeing the data (expert opinion, physical constraints, etc.).
- Different priors can lead to very different posterior distributions $\pi(\cdot \mid X)$, especially with small samples.
- In many applications the available prior information is vague: several priors are compatible with it, so the choice is often partly arbitrary.

Criteria for choosing a prior

There are many possible criteria for selecting π.

- **Practical / computational:** choose priors that make posterior calculations simple, e.g. conjugate priors.
- **Invariance and objective rules:** priors such as Jeffreys prior are motivated by invariance or information arguments.
- **Empirical Bayes:** estimate hyperparameters of the prior from the data.
- **Hierarchical modelling:** use several levels of priors to represent different sources of variability or uncertainty.
- **Physical or qualitative information:** prior support reflects constraints on the parameter (positivity, being in a given interval, order restrictions, etc.).

These ideas will guide the different approaches to prior construction described in the following.

Subjectivist and objective viewpoints

Two Bayesian mindsets.

- Subjectivist: the prior represents genuine prior beliefs, informed by past experience and expert knowledge.
- Objective: the prior is not derived from personal beliefs, but constructed in order to "let the data speak" as much as possible (non informative priors, reference priors, empirical Bayes, ...).

Remarks:

- Prior information is rarely precise enough to determine a unique prior; several priors may be compatible with the same background information $\Rightarrow$ the choice is often partly arbitrary.
- There is no single universally correct prior, and the choice of prior has an impact on the inference.
- Ambiguity is not specific to Bayes: frequentists also choose among many estimators (MLE, penalized MLE, ...).

Objective ("non-informative") priors as regularization

- In many statistical learning methods, a prior can be viewed as a regularization term on the likelihood: it penalizes complex models and helps prevent overfitting.
- However, we often do not want to privilege any particular parametrization of θ.

Example

A variable X with Weibull law can be parametrized in different ways:

$$f(x \mid \eta, \beta) = \frac{\beta}{\eta^\beta} x^{\beta-1} \exp\big(-(x/\eta)^\beta\big) \mathbf{1}_{x \geqslant 0},$$

or, equivalently,

$$f(x \mid \mu, \beta) = \mu\beta x^{\beta-1} \exp\big(-\mu x^\beta\big) \mathbf{1}_{x \geqslant 0}.$$

The prior information we might have about X should not depend on whether we use (η, β) or (μ, β).

- Objective priors aim to encode only minimal information, in a way that is as invariant to reparametrization as possible.

Exercise

Let $\theta \in [1, 2]$ be the parameter of a model $X \sim p_\theta$. Assume we do not know anything else about X or about θ.

- We decide to use the prior $\theta \sim \mathcal{U}[1, 2]$.
- Now reparametrize the model in terms of

$$\phi = 1/\theta \in [1/2, 1],$$

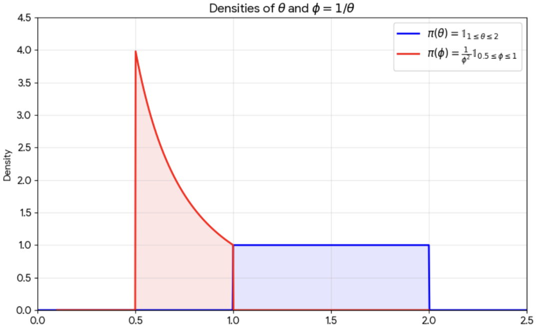
so that $X \sim q_\phi$, where $q_\phi = p_\theta$.

Question. Can we also choose a *uniform* prior

$$\phi \sim \mathcal{U}[1/2, 1] \; ?$$

Uniform priors?

We do not have the same prior if we put a uniform distribution on θ or ϕ



We used the change-of-variable formula $\pi_\phi(\phi) = \pi_\theta(h(\phi)) \left| \frac{dh}{d\phi} \right|$ for $h(\phi) = 1/\phi$.

Improper and weakly informative priors

- Objectively, we often only have very weak information such as *"the likelihood of a potential dataset should have this form"*.

- General construction rules can also lead to priors $\pi(\theta)$ that are not probability measures, in the sense that
$$\int_\Theta \pi(\theta)\,\mathrm{d}\theta = \infty.$$
These are called improper priors.

- In the literature they are sometimes called *non-informative* priors, but strictly speaking *no* prior is completely information-free. A better description is *weakly informative*.

Posterior with improper prior

⚠ Such priors are useful only if the resulting posterior is a proper probability distribution (integrable and normalizable).

Definition

Suppose we use an improper prior π on θ and assume that, for the observed data X,

$$\int_\Theta p_\theta(X)\,\mathrm{d}\pi(\theta) < \infty \quad \text{almost surely.}$$

Then the corresponding posterior distribution $\pi[\cdot \mid X]$ is a probability measure with density given by

$$\theta \longmapsto \pi(\theta \mid X) = \frac{p_\theta(X)\,\pi(\theta)}{\int_\Theta p_\theta(X)\,\pi(\theta)\,\mathrm{d}\nu(\theta)}.$$

Invariance principle

If we move from θ to $\eta = g(\theta)$ by a bijection g, the amount of prior information should not change:

$$\pi^*(\eta) = \left|\det \frac{\partial \eta}{\partial \theta}\right| \pi(g^{-1}(\eta))$$

should encode the same beliefs as $\pi(\theta)$.

To construct such a prior, Jeffreys proposes to use the Fisher information $I(\theta)$, which measures how informative the model P_θ is about θ.

Fisher information

Consider a regular parametric model $\{P_\theta,\ \theta \in \Theta\}$ on X with density $p_\theta(x)$ and log-likelihood

$$\ell_\theta(X) = \log p_\theta(X).$$

Score

$$\ell'_\theta(X) = \frac{\partial}{\partial\theta}\,\ell_\theta(X) = \frac{p'_\theta(X)}{p_\theta(X)}.$$

Fisher information at θ

$$I(\theta) = \mathbb{E}_\theta\big[\ell'_\theta(X)^2\big].$$

For an i.i.d. sample $X^{(n)} = (X_1, \ldots, X_n)$ from P_θ, the information adds up:

$$I_n(\theta) = n\, I(\theta).$$

Large $I(\theta)$ means the likelihood is very peaked around θ, so the data dominate the prior there.

Definition: Jeffreys prior, 1D

For $\Theta \subset \mathbb{R}$, if $I(\theta)$ exists, the Jeffreys prior is

$$\pi(\theta) = \sqrt{I(\theta)}.$$

- This construction uses only the model $p_\theta(x)$.
- Regions where the model is very informative ($I(\theta)$ large) receive more prior mass, so that the prior has less influence on the posterior.

Examples

- Bernoulli model $\mathcal{B}(\theta)$, $\theta \in (0, 1)$: $I(\theta) = \frac{1}{\theta(1-\theta)}$, hence

$$\pi(\theta) \propto \theta^{-1/2}(1-\theta)^{-1/2},$$

  i.e. a $\mathrm{Beta}(1/2, 1/2)$ prior.
- Normal model $X \mid \theta \sim \mathcal{N}(\theta, 1)$: $I(\theta) = 1$, so $\pi(\theta) \propto 1$ (improper flat prior).

Jeffreys prior in higher dimensions

For $\theta \in \Theta \subset \mathbb{R}^d$, the Fisher information matrix is

$$I_{ij}(\theta) = -\mathbb{E}_\theta\left[\frac{\partial^2}{\partial\theta_i\,\partial\theta_j} \log f(X \mid \theta)\right].$$

Definition: Jeffreys prior, d-dimensional

If $I(\theta)$ exists, define

$$\pi(\theta) \propto \sqrt{\det I(\theta)}.$$

Invariance property Let $\eta = g(\theta)$ be any smooth bijective reparametrization. If $\pi_\theta(\theta) \propto \sqrt{\det I(\theta)}$, then the induced density on η satisfies

$$\pi_\eta(\eta) \propto \sqrt{\det I(\eta)}.$$

Hence Jeffreys prior automatically respects the invariance principle.

Proof:

Exercise 1 (Exponential model). Let $X \mid \theta \sim \mathcal{E}(\theta)$ with rate $\theta > 0$.

- Compute the Fisher information $I(\theta)$.
- Deduce the Jeffreys prior $\pi(\theta) \propto \sqrt{I(\theta)}$.

Exercise 2 (Weibull model). Let X follow a Weibull law with two common parametrizations

$$p(x \mid \eta, \beta) = \frac{\beta}{\eta} c \left(\frac{x}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{x}{\eta}\right)^{\beta}\right] 1_{\{x \geqslant 0\}},$$

$$p(x \mid \mu, \beta) = \beta \mu x^{\beta-1} \exp(-\mu x^{\beta})\, 1_{\{x \geqslant 0\}}.$$

- Compute the Jeffreys prior in each parametrization.
- Check that the two expressions are coherent by using the change-of-variables formula.

Goal. Choose a prior family that is stable under Bayesian updating.

Definition (conjugate family)

Let $\mathcal{P} = \{P_\theta,\ \theta \in \Theta\}$ be a statistical model and $\mathcal{F}$ a family of prior distributions on Θ. We say that $\mathcal{F}$ is *conjugate* for $\mathcal{P}$ if, for every $\pi \in \mathcal{F}$, the posterior law $\pi[\cdot \mid X]$ also belongs to $\mathcal{F}$.

Why it is useful.

- Posterior has the same functional form as the prior; only hyperparameters change, not structural form.
- Closed forms for posterior mean, variance, credible sets, predictions, etc.
- Easy to simulate from the posterior if we know how to simulate from the prior.

Exponential family and natural conjugate priors

Consider a k-dimensional exponential family in natural form

$$p_\theta(x) = h(x)\exp\{\theta\cdot T(x) - \psi(\theta)\}, \qquad \theta\in\Theta\subset\mathbb{R}^k.$$

A standard **natural conjugate prior** for θ is

$$\pi(\theta\mid a,b) \propto \exp\{\theta\cdot a - b\,\psi(\theta)\}, \qquad a\in\mathbb{R}^k,\ \ b>0.$$

Given one observation x, Bayes rule gives the posterior

$$\pi(\theta\mid a,b,x) \propto \exp\{\theta\cdot(a+T(x)) - (b+1)\psi(\theta)\},$$

so the posterior is again in the same family, with updated hyperparameters

$$(a,b)\longrightarrow (a+T(x),\ b+1).$$

For a sample $x_1,\ldots,x_n$ the update is

$$(a,b)\longrightarrow \left(a+\textstyle\sum_{i=1}^n T(x_i),\ b+n\right).$$

Interpretation: prior as a virtual sample

For many natural exponential families one can reparameterize the conjugate prior as $\pi(\theta \mid x_0, m)$, where

$$\pi(\theta \mid x_0, m) \propto \exp\{\theta \cdot x_0 - m\,\psi(\theta)\}.$$

Then, you can show that:

- The prior predictive mean is

$$\mathbb{E}[X] = \int\int x \; p_\theta(x) \; \pi(\theta) dx d\theta = \frac{x_0}{m}.$$

- For a sample $\mathbf{x}_n = (x_1, \ldots, x_n)$ with empirical mean $\bar{x}$, the posterior predictive mean is

$$\mathbb{E}[X \mid \mathbf{x}_n] = \int\int x \; p_\theta(x) \; \pi(\theta \mid \mathbf{x}_n) dx d\theta \; = \; \frac{x_0 + n\bar{x}}{m + n}.$$

- x_0 is a prior guess for the mean.
- m behaves like the size of a *virtual sample* that carries the prior information: the posterior mean is a weighted average of x_0 and the empirical mean $\bar{x}$.

Natural conjugate priors for some common models

$f(x \mid \theta)$	$\pi(\theta)$	$\pi(\theta \mid x)$
$\mathcal{N}(\theta, \sigma^2)$	$\mathcal{N}(\mu, \tau^2)$	$\mathcal{N}\big(\varrho(\sigma^2\mu + \tau^2 x),\ \varrho\sigma^2\tau^2\big), \quad \varrho^{-1} = \sigma^2 + \tau^2$
$\text{Poisson}(\theta)$	$\text{Gamma}(\alpha, \beta)$	$\text{Gamma}(\alpha + x, \beta + 1)$
$\text{Gamma}(\nu, \theta)$	$\text{Gamma}(\alpha, \beta)$	$\text{Gamma}(\alpha + \nu, \beta + x)$
$\text{Binomial}(n, \theta)$	$\text{Beta}(\alpha, \beta)$	$\text{Beta}(\alpha + x, \beta + n - x)$
$\text{NegBin}(m, \theta)$	$\text{Beta}(\alpha, \beta)$	$\text{Beta}(\alpha + m, \beta + x)$
$\text{Multinomial}_k(\theta_1, \dots, \theta_k)$	$\text{Dirichlet}(\alpha_1, \dots, \alpha_k)$	$\text{Dirichlet}(\alpha_1 + x_1, \dots, \alpha_k + x_k)$
$\mathcal{N}(\mu, 1/\theta)$	$\text{Gamma}(\alpha, \beta)$	$\text{Gamma}\big(\alpha + \frac{1}{2},\ \beta + \frac{(\mu - x)^2}{2}\big)$
$X_1, \dots, X_n \mid \theta \sim \text{Unif}(0, \theta)$	$\text{Pareto}(\alpha, r)$	$\text{Pareto}(\alpha + n,\ r_X), \quad r_X = \max\{r, X_1, \dots, X_n\}$

Hierarchical Bayes: idea

Motivation.

- In many problems we need a prior on a parameter θ, but we are not sure how to choose it.
- We introduce a hyperparameter γ that controls a family of priors

$$\theta \mid \gamma \sim \pi(\theta \mid \gamma).$$

- Then we put a second–level prior on γ:

$$\gamma \sim \eta(\gamma).$$

Joint model.

$$\mathbb{P}(X, \theta, \gamma) = f(x \mid \theta)\, \pi(\theta \mid \gamma)\, \eta(\gamma).$$

Advantages.

- Provides a flexible framework for modeling families of priors.
- Allows us to encode partial prior information and share information across related parameters (random effects, panel data, etc.).
- Hyperparameters γ play the role of an *index* for a whole family $\{\pi(\cdot \mid \gamma)\}_{\gamma}$.

Hierarchical Bayes vs empirical Bayes

Hierarchical Bayes.

- We treat γ as an unknown random quantity:

$$\theta \mid \gamma \sim \pi(\theta \mid \gamma), \qquad \gamma \sim \eta(\gamma).$$

- Posterior inference is based on

$$\pi(\theta, \gamma \mid x) \propto f(x \mid \theta)\, \pi(\theta \mid \gamma)\, \eta(\gamma).$$

- Fully Bayesian: uncertainty on γ is propagated into the posterior of θ.

Empirical Bayes.

- We choose a parametric family of priors $\{\pi_\alpha(\theta)\}_{\alpha \in A}$ (e.g. Normal, Gamma, Beta).
- Use the data to estimate α (for example by marginal likelihood):

$$f_\alpha(x) = \int f(x \mid \theta)\, \pi_\alpha(\theta)\, d\theta, \quad \hat{\alpha} = \arg\max_\alpha f_\alpha(x).$$

- Then treat $\pi_{\hat{\alpha}}(\theta)$ as the prior and perform standard Bayes.

Gaussian model.

- Data: $X_1, \ldots, X_n \mid \theta \sim \mathcal{N}(\theta, 1)$ i.i.d.
- Prior family: $\theta \sim \mathcal{N}(\mu, 1)$, with hyperparameter μ.
- Marginal likelihood for one observation:

$$f_\mu(x) = \int \mathcal{N}(x \mid \theta, 1)\, \mathcal{N}(\theta \mid \mu, 1)\, d\theta = \mathcal{N}(x \mid \mu, 2).$$

- Maximizing $f_\mu(x)$ gives $\hat{\mu} = x$; for n observations, $\hat{\mu} = \bar{X}_n$.
- Empirical Bayes prior: $\theta \sim \mathcal{N}(\bar{X}_n, 1)$.

Poisson model.

- Data: $X_1, \ldots, X_n \mid \theta \sim \mathcal{P}(\theta)$ i.i.d.
- Prior family: $\theta \sim \mathrm{Exp}(\lambda)$.
- Empirical Bayes estimate: $\hat{\lambda} = 1/\bar{X}_n$, so the prior becomes $\theta \sim \mathrm{Exp}(1/\bar{X}_n)$.

Fusion of priors from multiple experts

Suppose we have M possible priors $\pi_1(\theta), \ldots, \pi_M(\theta)$ (e.g. from different experts), with weights $\omega_i \geqslant 0$, $\sum_{i=1}^M \omega_i = 1$.

Linear (arithmetic) pool.

$$\pi_{\text{lin}}(\theta) = \sum_{i=1}^{M} \omega_i \pi_i(\theta).$$

- Simple to define, but may be multi–modal and is not *externally Bayesian*: posterior of π_{lin} is not the same as the weighted sum of posteriors $\pi_i(\theta \mid x)$.

Logarithmic (geometric) pool.

$$\pi_{\log}(\theta) = \frac{\prod_{i=1}^{M} \pi_i(\theta)^{\omega_i}}{\int_\Theta \prod_{i=1}^{M} \pi_i(u)^{\omega_i}\, du}.$$

- Externally Bayesian: combining first, then updating, is coherent with updating each prior then combining.
- Can be characterized as the prior that minimizes a weighted sum of Kullback–Leibler divergences:

M

Different approaches

$$
\begin{aligned}
\alpha &\sim \pi(\alpha) \\
\beta \mid \alpha &\sim \pi(\beta \mid \alpha) \\
\theta \mid \alpha, \beta &\sim \pi(\theta \mid \alpha, \beta) \\
X \mid \theta &\sim p_\theta
\end{aligned}
$$

Different approaches

$$\alpha \sim \pi(\alpha)$$

$$\beta \mid \alpha \sim \pi(\beta \mid \alpha)$$

$$\theta \mid \alpha, \beta \sim \pi(\theta \mid \alpha, \beta)$$

$X \mid \theta \sim p_\theta$ Likelihood / Frequentist model

Different approaches

$$\alpha \sim \pi(\alpha)$$

$$\beta \mid \alpha \sim \pi(\beta \mid \alpha)$$

$$\theta \mid \alpha, \beta \sim \pi(\theta \mid \alpha, \beta)$$ Empirical Bayes / Bayesian model

$$X \mid \theta \sim p_\theta$$

Different approaches

$$\alpha \sim \pi(\alpha)$$

$$\beta \mid \alpha \sim \pi(\beta \mid \alpha) \qquad \text{Hierarchical Bayes}$$

$$\theta \mid \alpha, \beta \sim \pi(\theta \mid \alpha, \beta)$$

$$X \mid \theta \sim p_\theta$$

Different approaches

$$\alpha \sim \pi(\alpha)$$

Hierarchical Bayes

$$\beta \mid \alpha \sim \pi(\beta \mid \alpha)$$

$$\theta \mid \alpha, \beta \sim \pi(\theta \mid \alpha, \beta)$$

$$X \mid \theta \sim p_\theta$$