

Bayesian Learning: Gaussian Models

ELG 5218 - Uncertainty Evaluation in Engineering Measurements and Machine Learning

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Roadmap (40 slides, 3 hours)

- ① **Gaussian models fundamentals:** Why Gaussians? Central Limit Theorem, conjugacy.
- ② **Known variance case:** Precision additivity, conjugate priors, weighted averaging.
- ③ **Online learning (sequential updates):** Recursive Bayesian filtering, streaming data.
- ④ **Unknown variance:** Normal-Gamma conjugate family, Student- t marginal, robustness.
- ⑤ **Monte Carlo methods:** Posterior sampling, functions of parameters, practical inference.
- ⑥ **Multivariate case:** Matrix algebra, sensor fusion, conditional independence.
- ⑦ **Discussion:** Advanced topics, extensions, exercises.

The Gaussian family: central to Bayesian inference

Four reasons Gaussians dominate:

- **Universality (CLT):** Sums of iid random variables \rightarrow Gaussian (approximately).
- **Analytical tractability:** Closed-form posterior, predictive, marginals, conditionals.
- **Conjugacy:** Normal prior \times Normal likelihood \Rightarrow Normal posterior.
- **Optimization:** Gaussian assumption \rightarrow convex inference, efficient algorithms.

Univariate density:

$$p(x | \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right).$$

Precision notation (cleaner for Bayesian updates):

$$\lambda = \frac{1}{\sigma^2} \quad \Rightarrow \quad p(x | \mu, \lambda) \propto \sqrt{\lambda} \exp\left(-\frac{\lambda(x - \mu)^2}{2}\right).$$

Multivariate Gaussian: covariance and precision

For $\mathbf{x} \in \mathbb{R}^d$:

Covariance form:

$$p(\mathbf{x} | \boldsymbol{\mu}, \Sigma) = (2\pi)^{-d/2} |\Sigma|^{-1/2} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu})\right).$$

Precision form (more convenient for updates):

$$\Lambda = \Sigma^{-1} \quad \Rightarrow \quad p(\mathbf{x} | \boldsymbol{\mu}, \Lambda) \propto |\Lambda|^{1/2} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \Lambda (\mathbf{x} - \boldsymbol{\mu})\right).$$

Key insight: Precision combines additively

In Bayesian updates, posterior precision = prior precision + data precision.
This additive structure is the **engine** driving conjugate family simplicity.

Covariance matrix properties (brief review)

Covariance between variables X_i and X_j :

$$\text{Cov}(X_i, X_j) = \mathbb{E}[(X_i - \mathbb{E}[X_i])(X_j - \mathbb{E}[X_j])].$$

Covariance matrix:

$$\Sigma = \mathbb{E}[(\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^T] = \begin{bmatrix} \sigma_1^2 & \text{Cov}(X_1, X_2) & \cdots \\ \text{Cov}(X_2, X_1) & \sigma_2^2 & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix}.$$

Correlation: $\rho_{ij} = \text{Cov}(X_i, X_j)/(\sigma_i \sigma_j) \in [-1, 1]$.

Why precision for Bayesian inference?

- Precisions in likelihood and prior **add directly**, not reciprocals.
- Posterior precision is always non-negative (automatic numerical stability).
- Computational benefits for high-dimensional problems.

Setup: Univariate Gaussian, known σ^2

Model: $x_1, \dots, x_n \mid \mu, \sigma^2 \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu, \sigma^2)$ with σ^2 known.

Likelihood (in precision form):

$$p(x_1, \dots, x_n \mid \mu) \propto \exp\left(-\frac{\lambda}{2} \sum_{i=1}^n (x_i - \mu)^2\right), \quad \lambda = \frac{1}{\sigma^2}.$$

Using the sum-of-squares identity:

$$\sum_{i=1}^n (x_i - \mu)^2 = \sum_{i=1}^n (x_i - \bar{x})^2 + n(\bar{x} - \mu)^2.$$

First term is data-independent, so:

$$p(x_1, \dots, x_n \mid \mu) \propto \exp\left(-\frac{n\lambda}{2}(\bar{x} - \mu)^2\right).$$

Interpretation: Likelihood is Gaussian in μ with precision $n\lambda = n/\sigma^2$.

Uniform (non-informative) prior

Prior: $p(\mu) \propto 1$ for $\mu \in \mathbb{R}$ (improper, but posterior is proper).

Posterior (via Bayes):

$$p(\mu | x_1, \dots, x_n) \propto p(x_1, \dots, x_n | \mu) \cdot p(\mu) \propto \exp\left(-\frac{n\lambda}{2}(\bar{x} - \mu)^2\right).$$

Recognizing this as Gaussian:

$$\mu | x_1, \dots, x_n \sim \mathcal{N}\left(\bar{x}, \frac{\sigma^2}{n}\right).$$

In precision form:

$$\lambda_n = \frac{n}{\sigma^2} = n\lambda, \quad \mu_n = \bar{x}.$$

Key observations

- Posterior mean = sample mean \bar{x} (frequentist MLE).
- Posterior variance shrinks as $1/n$.
- Posterior precision grows linearly with sample size.

Normal prior (conjugate case)

Prior: $\mu \sim \mathcal{N}(\mu_0, \sigma_0^2)$ with precision $\lambda_0 = 1/\sigma_0^2$.

Posterior: Also Gaussian with

$$\lambda_n = \lambda_0 + n\lambda, \quad \mu_n = \frac{\lambda_0\mu_0 + n\lambda\bar{x}}{\lambda_n}.$$

Rewritten (cleaner form):

$$\mu_n = \frac{\lambda_0\mu_0 + (n/\sigma^2)\bar{x}}{\lambda_0 + n/\sigma^2} = w\bar{x} + (1 - w)\mu_0,$$

where

$$w = \frac{\lambda_{\text{data}}}{\lambda_0 + \lambda_{\text{data}}} = \frac{n/\sigma^2}{\lambda_0 + n/\sigma^2}.$$

The golden rule: Precision Additivity

$$\lambda_{\text{posterior}} = \lambda_{\text{prior}} + \lambda_{\text{data}}$$

Posterior mean is precision-weighted average of prior and data.

Intuition: Precision-weighted averaging

- **High data precision** (n/σ^2 large): $w \approx 1$, posterior tracks data.
- **High prior precision** (λ_0 large): $w \approx 0$, posterior tracks prior.
- **Competing uncertainties:** Weight determined by relative precisions.
- **Posterior variance:** $\sigma_n^2 = 1/\lambda_n$, monotonically shrinks.

Example interpretation:

- Prior: expert opinion (uncertain, $\sigma_0 = 5$).
- Data: 10 precise measurements (noisy, $\sigma = 3$).
- Data precision $0.2/\sigma^2 > 0.04 =$ prior precision \Rightarrow data dominates.

Worked example: Internet speed measurement

Context: ISP claims average speed is 20 Mbps. You measure 5 times.

Data: $x = \{15.77, 20.5, 8.26, 14.37, 21.09\}$, $\bar{x} = 16.0$ Mbps.

Known measurement noise: $\sigma = 5$ Mbps $\Rightarrow \lambda = 0.04$.

Prior: $\mu_0 = 20$ Mbps, $\sigma_0 = 5$ Mbps $\Rightarrow \lambda_0 = 0.04$.

Posterior calculation:

$$\lambda_n = 0.04 + 5 \cdot 0.04 = 0.24 \quad \Rightarrow \quad \sigma_n^2 = 4.17.$$

$$\mu_n = \frac{0.04 \cdot 20 + 0.2 \cdot 16}{0.24} = \frac{0.8 + 3.2}{0.24} = 16.67 \text{ Mbps.}$$

$$w = \frac{0.2}{0.24} = 0.833 \quad \Rightarrow \quad \text{Data dominates (5× more precise).}$$

Conclusion: Posterior $\Pr(\mu > 20 \mid \text{data}) \approx 0.05$ (ISP claim is dubious).

Posterior for Internet speed measurement

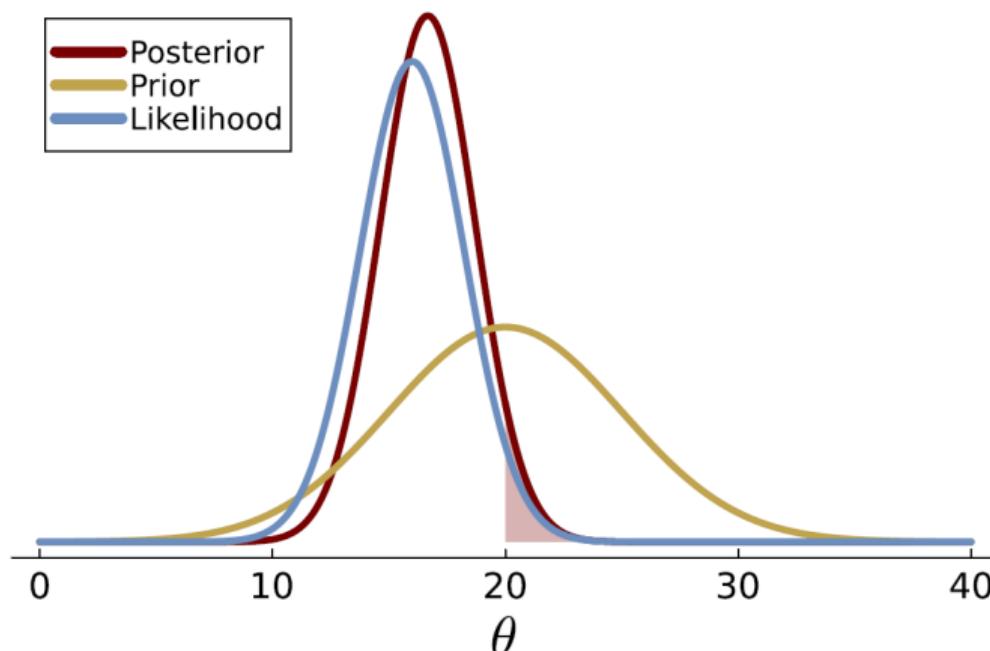


Figure: Prior-Likelihood-Posterior. The shaded region marks out $Pr(\theta > 20 | x_1, \dots, x_n)$.

Sensor fusion example: Temperature + Humidity

Scenario: Two correlated measurements (temperature, humidity).

True state: $\mu = \begin{bmatrix} 22^\circ C \\ 55\% \end{bmatrix}$, $\Sigma = \begin{bmatrix} 2 & 1.5 \\ 1.5 & 4 \end{bmatrix}$.

Data: $n = 15$ bivariate readings.

Prior (weak): $\mu_0 = \begin{bmatrix} 20 \\ 50 \end{bmatrix}$, independent prior on correlation.

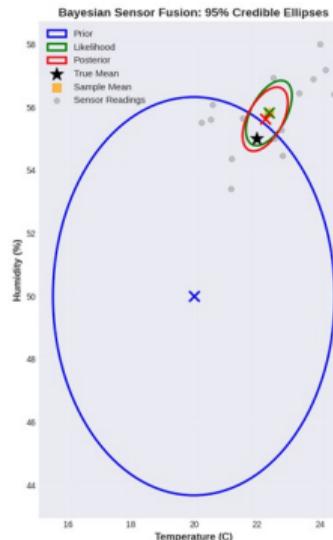
Matrix precision additivity:

$$\Lambda_n = \Lambda_0 + n\Sigma^{-1} = \text{prior precision} + \text{data precision}.$$

Posterior:

$$\Sigma_n = \Lambda_n^{-1}, \quad \mu_n = \Sigma_n(\Lambda_0\mu_0 + n\Sigma^{-1}\bar{x}).$$

Posterior for the fusion example



2D visualization:

- ① Prior: Ellipse centered at [20, 50] (weak, large).
- ② Likelihood: Ellipse centered at sample mean (from 15 readings).
- ③ Posterior: Ellipse centered at μ_n (tighter).
- ④ Correlation improvement (ellipse axes align with data).

Sequential vs. batch updating

Batch form:

$$p(\mu \mid x_1, \dots, x_n) = \frac{p(x_1, \dots, x_n \mid \mu)p(\mu)}{p(x_1, \dots, x_n)}.$$

Sequential form:

$$p(\mu \mid x_1, \dots, x_n) = \frac{p(x_n \mid \mu) \cdot p(\mu \mid x_1, \dots, x_{n-1})}{p(x_n \mid x_1, \dots, x_{n-1})}.$$

Key insight: Posterior at step $n - 1$ becomes the prior at step n .

Streaming advantage

- Never store all past data, only current posterior parameters.
- Each new observation x_n triggers one simple update.
- Perfect for sensor networks, real-time monitoring, online learning.
- Memory: $O(d)$ vs. $O(nd)$ for batch processing.

Recursive updating: precision and mean

Starting from $\mu \mid x_1, \dots, x_{n-1} \sim \mathcal{N}(\mu_{n-1}, \sigma_{n-1}^2)$, when x_n arrives:

Precision update:

$$\lambda_n = \lambda_{n-1} + \lambda = \lambda_{n-1} + \frac{1}{\sigma^2}.$$

Mean update (in learning rate form):

$$\mu_n = \mu_{n-1} + w_n(x_n - \mu_{n-1}),$$

where the learning rate is

$$w_n = \frac{\lambda}{\lambda_n} = \frac{1/\sigma^2}{\lambda_{n-1} + 1/\sigma^2}.$$

Interpretation

- w_n is the fractional move toward new observation (shrinks over time).
- As n increases, λ_n grows, so w_n shrinks (diminishing returns).
- Posterior variance $\sigma_n^2 = 1/\lambda_n$ monotonically decreases.

Example: Temperature sensor over time

Scenario: Noisy temperature sensor, true temperature $\mu = 22\text{C}$.

Setup:

- Measurement noise: $\sigma = 1.5\text{C} \Rightarrow \lambda = 0.444$.
- Prior: $\mu_0 = 20\text{C}$, $\sigma_0 = 3\text{C} \Rightarrow \lambda_0 = 0.111$.
- 20 sequential readings, typical values: $\{20.1, 22.3, 21.8, 23.1, \dots\}$.

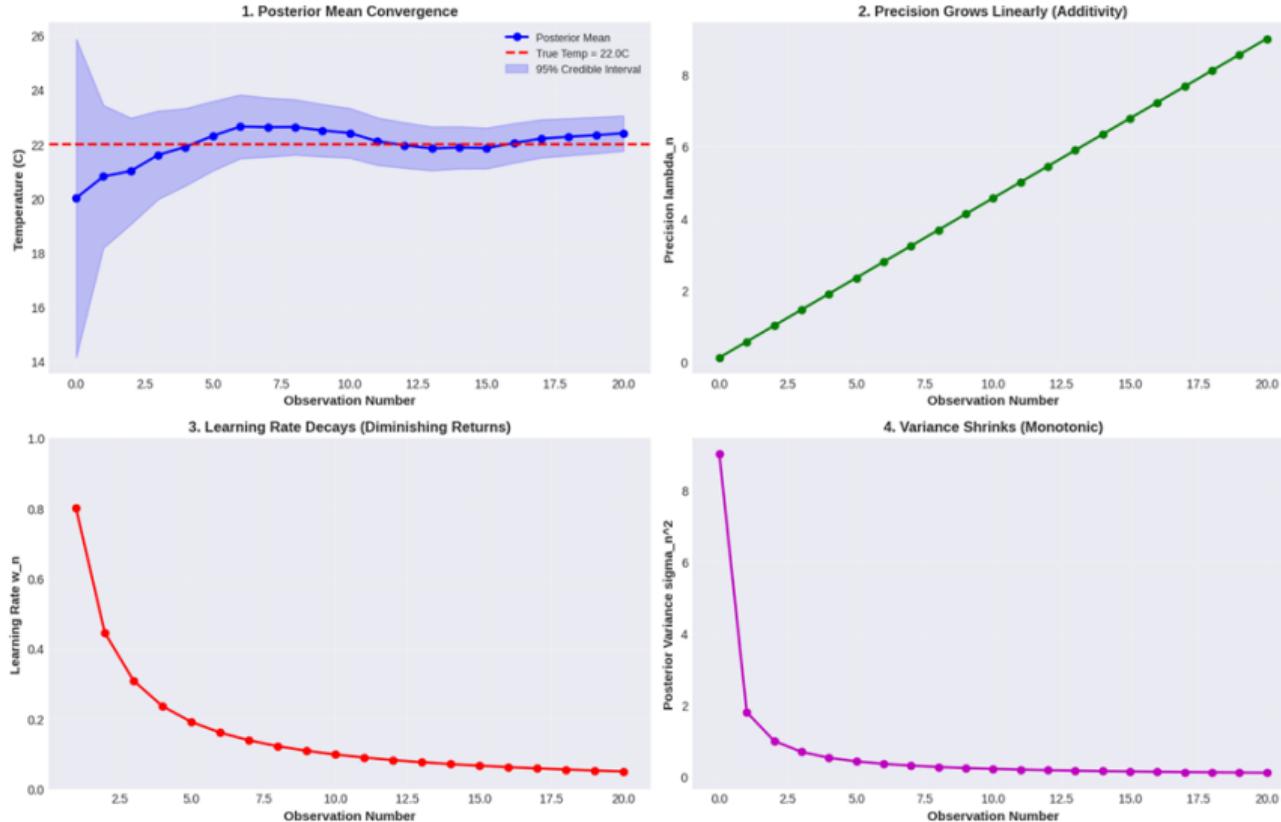
Dynamics:

n	λ_n	σ_n	w_n
1	0.556	1.342	0.800
5	2.333	0.655	0.190
10	4.556	0.468	0.097
20	8.889	0.335	0.050

Trend: Precision grows linearly, learning rate decays, variance shrinks monotonically.

Online learning dynamics

Online Learning Dynamics: Sequential Bayesian Updates



Why Bayesian online learning beats alternatives

Compare three approaches for 1M sensor readings:

	Storage	Updates	Recompute
Batch (store all)	$O(n)$	Once at end	Full posterior
Bayes online	$O(1)$	Each reading	Full posterior

Key advantage: Bayes online gives full posterior & uncertainty, not just point estimate.

Streaming Bayesian inference

Sequential updates are exact (not approximations). Posterior is proper at every step. No batch reprocessing needed. Natural uncertainty quantification.

Chi-square, Gamma, and why we care

Definition (sum of squares). If $Z_1, \dots, Z_k \stackrel{iid}{\sim} \mathcal{N}(0, 1)$, then

$$X = \sum_{i=1}^k Z_i^2 \sim \chi_k^2.$$

This makes χ^2 the natural distribution for *energy*, *squared error*, and *quadratic forms*.

Key relationship: Chi-square is a special case of the Gamma distribution.

$$X \sim \chi_k^2 \iff X \sim \text{Gamma}\left(\alpha = \frac{k}{2}, \theta = 2\right)$$

(using $\text{Gamma}(\text{shape } \alpha, \text{ scale } \theta)$). Equivalently, with rate $\beta = 1/\theta$:

$$X \sim \text{Gamma}\left(\alpha = \frac{k}{2}, \beta = \frac{1}{2}\right).$$

Why it matters (canonical results). If $x_1, \dots, x_n \stackrel{iid}{\sim} \mathcal{N}(\mu, \sigma^2)$, then

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2,$$

which drives: (i) confidence intervals for σ^2 , (ii) chi-square tests, (iii) Gaussian-conjugate updates (via Gamma on precision).

Visualization: probstats.org (interactive PDFs/CDFs for χ^2 and Gamma),

Inverse- χ^2 , scaled inverse- χ^2 , and Gamma priors on precision

Inverse- χ^2 (basic transform). If $X \sim \chi_\nu^2$, then

$$V = \frac{1}{X} \sim \text{Inv-}\chi_\nu^2.$$

Scaled inverse- χ^2 (Bayesian variance prior). A very common conjugate prior for a Normal variance σ^2 is:

$$\sigma^2 \sim \text{Scale-inv-}\chi^2(\nu, \tau^2), \quad \text{equivalently} \quad \sigma^2 \sim \text{Inv-Gamma}\left(\frac{\nu}{2}, \frac{\nu\tau^2}{2}\right),$$

(Inv-Gamma(shape, scale) parameterization).

Precision view (often cleaner). Let $\lambda = 1/\sigma^2$ (precision). Then:

$$\sigma^2 \sim \text{Inv-Gamma}\left(\frac{\nu}{2}, \frac{\nu\tau^2}{2}\right) \iff \lambda \sim \Gamma\left(\frac{\nu}{2}, \frac{\nu\tau^2}{2}\right)$$

(Gamma(shape, rate) parameterization for λ).

Visualizationn

Inverse- χ^2 / scaled inverse- χ^2 have heavy right tails (variance can be large). Interactive plots: probstats.org (Gamma, χ^2); Wolfram: InverseChiSquareDistribution.

Student- t distribution and its relationship to the Gaussian

Definition (location-scale Student- t). A random variable T has a Student- t distribution with ν degrees of freedom, location μ , and scale s if

$$T \sim t_\nu(\mu, s) \iff \frac{T - \mu}{s} \sim t_\nu.$$

Its density has heavier tails than a Gaussian (more mass far from the mean), especially for small ν . **Relationship to Gaussian.**

- As $\nu \rightarrow \infty$, $t_\nu(\mu, s) \Rightarrow \mathcal{N}(\mu, s^2)$ (tails become Gaussian).
- For $\nu > 1$, $\mathbb{E}[T] = \mu$; for $\nu > 2$, $\text{Var}(T) = \frac{\nu}{\nu - 2} s^2$ (larger than s^2).
- Small ν (e.g., $\nu \in [3, 10]$) yields strong robustness: outliers are less influential than under a Gaussian likelihood.

Where it appears in Bayesian inference. In the Normal model with unknown variance, integrating out σ^2 (with an Inv-Gamma / scaled-inv- χ^2 prior) yields a Student- t marginal for μ and a Student- t posterior predictive for new observations.

Quick visualization (interactive)

Overlay t_ν vs Gaussian for different ν : probstats.org. (Use as a screenshot figure or live demo.)

Challenge: Both μ and σ^2 unknown

Model: $x_1, \dots, x_n \mid \mu, \sigma^2 \stackrel{\text{iid}}{\sim} \mathcal{N}(\mu, \sigma^2)$ with both unknown.

Problem: Prior must specify joint $p(\mu, \sigma^2)$ with possible dependence.

Solution: Use conjugate factorization

$$p(\mu, \sigma^2) = p(\mu \mid \sigma^2) \cdot p(\sigma^2).$$

Conjugate choice:

- **Conditional:** $\mu \mid \sigma^2 \sim \mathcal{N}(\mu_0, \sigma^2/\kappa_0)$ (precision scales with σ^2).
- **Marginal:** $\sigma^2 \sim \text{Inv-}\chi^2(\nu_0, \sigma_0^2)$ (Inverse-Chi-squared prior).

Hyperparameters

μ_0 : prior mean for μ . κ_0 : prior “effective sample size” (scales prior variance). ν_0 : degrees of freedom for σ^2 prior. σ_0^2 : prior location guess for variance.

Gamma distribution for precision

Key shift: Instead of Inverse- χ^2 for variance, use Gamma for precision.

Gamma distribution (shape-rate parametrization):

$$\lambda \sim \text{Gamma}(\alpha, \beta) \quad \Rightarrow \quad p(\lambda) = \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda}.$$

Properties:

- Mean: $\mathbb{E}[\lambda] = \alpha/\beta$.
- Variance: $\text{Var}[\lambda] = \alpha/\beta^2$.
- Support: $\lambda > 0$ (necessary for precision).
- Conjugate: Gamma is conjugate to Normal likelihood.

Relationship to Inverse-Gamma:

$$\sigma^2 = 1/\lambda \sim \text{Inv-}\Gamma, \quad \text{if} \quad \lambda \sim \text{Gamma}.$$

Why Gamma for precision?

More numerically stable, directly expresses prior beliefs about precision (not variance). Simpler update equations.

Normal-Gamma conjugate prior

Joint prior (factorized):

$$p(\mu, \lambda) = p(\mu | \lambda) \cdot p(\lambda),$$

where

$$\begin{aligned}\mu | \lambda &\sim \mathcal{N}(\mu_0, (\kappa_0 \lambda)^{-1}), \\ \lambda &\sim \text{Gamma}(\alpha_0, \beta_0).\end{aligned}$$

Hyperparameters:

- μ_0, κ_0 : prior location and strength for μ .
- α_0, β_0 : shape and rate for precision.

Why this works: The likelihood factors as

$$p(x_1, \dots, x_n | \mu, \lambda) = (\text{term in } \mu) \times (\text{term in } \lambda),$$

so posterior is also Normal-Gamma with updated hyperparameters.

Posterior: Normal-Gamma family

Result (conjugate update):

$$p(\mu, \lambda \mid \text{data}) = \mathcal{N}(\mu \mid \mu_n, (\kappa_n \lambda)^{-1}) \cdot \text{Gamma}(\lambda \mid \alpha_n, \beta_n).$$

Update equations:

$$\kappa_n = \kappa_0 + n,$$

$$\mu_n = \frac{\kappa_0 \mu_0 + n \bar{x}}{\kappa_n},$$

$$\alpha_n = \alpha_0 + \frac{n}{2},$$

$$\beta_n = \beta_0 + \frac{1}{2} \left[\sum (x_i - \bar{x})^2 + \frac{\kappa_0 n}{\kappa_0 + n} (\bar{x} - \mu_0)^2 \right].$$

Interpretation:

- Posterior precision κ_n is prior + data (mixture weight).
- Posterior α_n, β_n encode both data variance and mean discrepancy.

Marginal posterior for μ : Student- t distribution

When we marginalize out the unknown λ :

$$p(\mu \mid \text{data}) = \int p(\mu \mid \lambda, \text{data}) p(\lambda \mid \text{data}) d\lambda \sim t_{\nu_n}(\mu_n, \sigma_n^2).$$

Degrees of freedom: $\nu_n = 2\alpha_n$.

Scale: $\sigma_n^2 = \frac{\beta_n}{\alpha_n \kappa_n}$.

Student- t density:

$$p(\mu \mid \text{data}) \propto \left(1 + \frac{\kappa_n(\mu - \mu_n)^2}{\nu_n \sigma_n^2}\right)^{-(\nu_n+1)/2}.$$

Why Student- t , not Gaussian?

Uncertainty in σ^2 creates heavier tails. Extreme values of μ are less surprising when variance is also unknown. Robustness to outliers.

Intuition: Heavy tails from variance uncertainty

Known σ^2 :

Posterior for μ is Gaussian with variance σ^2/n (tight).

Unknown σ^2 :

Posterior marginalizes over plausible σ^2 values:

$$p(\mu \mid \text{data}) = \int p(\mu \mid \sigma^2, \text{data})p(\sigma^2 \mid \text{data})d\sigma^2.$$

Some posterior draws have $\sigma^2 > \hat{\sigma}^2$ (true value underestimated) \Rightarrow wider credible intervals.
This averaging manifests as Student- t tails (heavier than Gaussian).

Robustness

Models estimating σ^2 are robust to outliers. Heavy tails allow occasional large deviations without dominating posterior.

Worked example: Internet speed (unknown variance)

Data: $n = 5$, $\bar{x} = 16.0$, $\sum(x_i - \bar{x})^2 = 67.6$ Mbps 2 .

Prior: $\mu_0 = 20$, $\kappa_0 = 1$, $\alpha_0 = 2.5$, $\beta_0 = 12.5$ (informative).

Posterior:

$$\kappa_n = 1 + 5 = 6,$$

$$\mu_n = \frac{1 \cdot 20 + 5 \cdot 16}{6} = 16.67,$$

$$\alpha_n = 2.5 + 2.5 = 5,$$

$$\beta_n = 12.5 + 33.8 + 3.33 = 49.6.$$

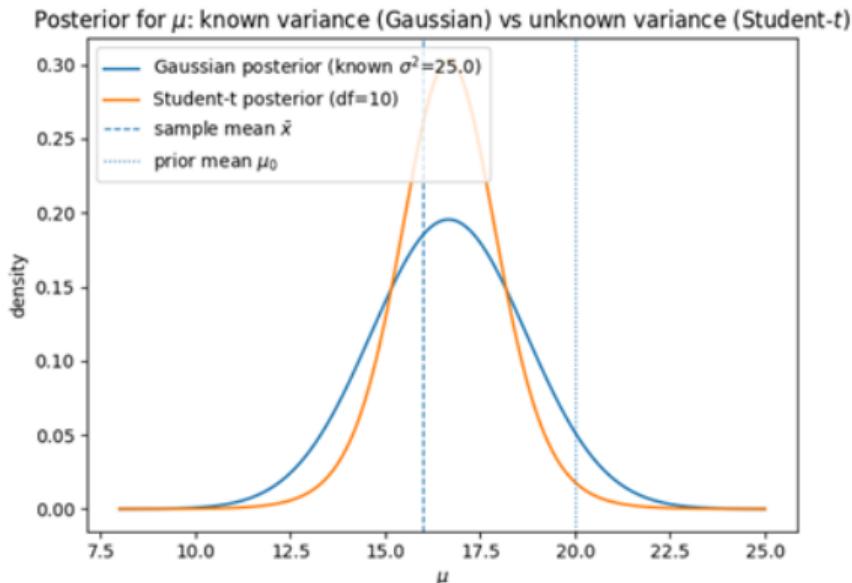
Marginal posterior for μ :

$$\mu \mid \text{data} \sim t_{10}(16.67, 1.65).$$

Posterior std: $\sqrt{1.65} \approx 1.28$ Mbps (wider than known- σ case).

Heavier tails: $\Pr(\mu > 20) \approx 0.09$ (vs. 0.05 in known case).

Student-*t* vs Gaussian



Summary: The Gaussian toolbox

- ① **Known variance:** Posterior is Gaussian. Precision additivity.
- ② **Online learning:** Sequential updates decay in influence. No batch reprocessing.
- ③ **Unknown variance:** Normal-Gamma posterior. Marginal μ is Student- t (heavier tails, robustness).
- ④ **Monte Carlo:** Simulate to compute expectations and functions of parameters.
- ⑤ **Multivariate:** Matrix precision additivity, conditioning, marginalization.
- ⑥ **Linear Gaussian:** Conditional, marginal, and predictive distributions all Gaussian.

Central principle

Precisions (inverse variances) combine additively. This algebraic property drives conjugacy, simplicity, and analytical tractability.

Exercise ideas for students

- ① Derive posterior for μ when prior is Exponential and likelihood is Gaussian (hint: not conjugate).
- ② Extend internet speed example to $n = 50$ measurements. Plot convergence of μ_n and learning rate w_n .
- ③ Prove: For Normal-Gamma posterior, $\mathbb{E}[\mu \mid \text{data}] = \mu_n$ and $\text{Var}[\mu \mid \text{data}] = \mathbb{E}_\lambda[\sigma_n^2] + \text{Var}_\lambda[\mu]$.
- ④ Implement online Bayesian filter for temperature sensor. Compare to exponential moving average (EMA).

References and further reading

- **Gelman et al. (2013):** “Bayesian Data Analysis” (3rd ed.). Chapters 2, 3.
- **Murphy (2012):** “Machine Learning: A Probabilistic Perspective”. Chapters 2, 3.
- **Bernardo & Smith (2009):** “Bayesian Theory”. Foundational reference.
- **Lecture notebooks:** “Gaussian_Models_Extended-1.ipynb” contains worked examples, interactive plots, and exercises.
- **Software:** PyMC3, Stan, NumPyro for Bayesian inference.

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