

Maximum-likelihood and Bayesian parameter estimation

Andrea Passerini
passerini@disi.unitn.it

Machine Learning

Maximum likelihood/Maximum a-posteriori estimation

Maximum a-posteriori estimation

$$\theta_i^* = \operatorname{argmax}_{\theta_i} p(\theta_i | \mathcal{D}_i, y_i) = \operatorname{argmax}_{\theta_i} p(\mathcal{D}_i, y_i | \theta_i) p(\theta_i)$$

- Assumes a prior distribution for the parameters $p(\theta_i)$ is available

Maximum likelihood estimation (most common)

$$\theta_i^* = \operatorname{argmax}_{\theta_i} p(\mathcal{D}_i, y_i | \theta_i)$$

- maximizes the **likelihood** of the parameters with respect to the training samples
- no assumption about prior distributions for parameters

Note

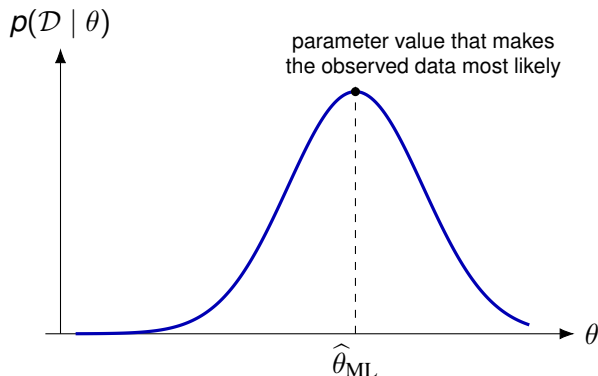
- Each class y_i is treated independently: replace $y_i, \mathcal{D}_i \rightarrow \mathcal{D}$ for simplicity

Likelihood as a function of the parameters

- The observed dataset $\mathcal{D}$ is fixed.
- The likelihood $p(\mathcal{D} | \theta)$ is viewed as a function of θ .
- Maximum likelihood selects the parameter value at the highest point of this function.

Important distinction

The likelihood is not a probability distribution over θ unless it is normalized and combined with a prior.

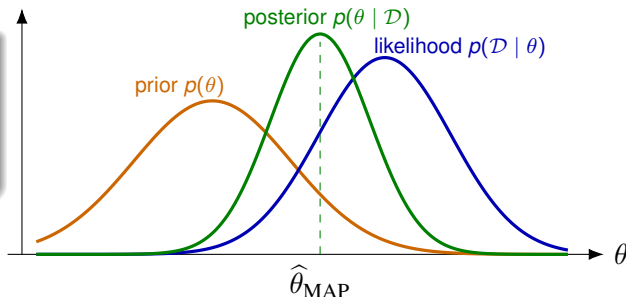


Maximum a-posteriori estimation

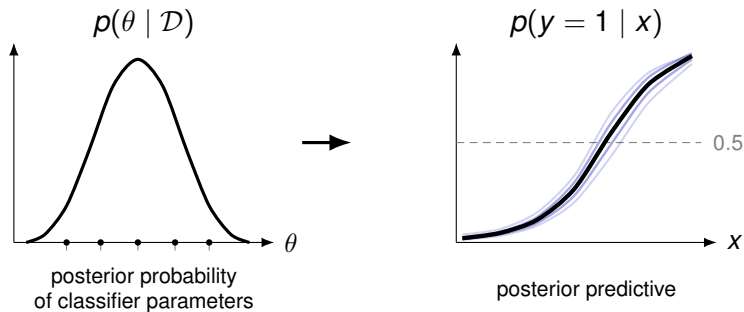
MAP principle

$$\begin{aligned}\hat{\theta}_{\text{MAP}} &= \operatorname{argmax}_{\theta} p(\theta \mid \mathcal{D}) \\ &= \operatorname{argmax}_{\theta} p(\mathcal{D} \mid \theta) p(\theta).\end{aligned}$$

- The likelihood favors parameters supported by the observations.
- The prior favors parameters considered plausible before seeing the data.
- The posterior combines both sources of information.



Bayesian Parameter Estimation for Classification



Bayesian prediction

Each parameter value defines a different probabilistic classifier $p(y = 1 | x, \theta)$. Instead of selecting a single parameter estimate, Bayesian estimation averages the predictions of all plausible classifiers according to their posterior probability:

$$p(y = 1 | x, \mathcal{D}) = \int p(y = 1 | x, \theta) p(\theta | \mathcal{D}) d\theta.$$

Sufficient statistics

Definition

- Any function on a set of samples $\mathcal{D}$ is a *statistic*
- A statistic $\mathbf{s} = \phi(\mathcal{D})$ is *sufficient* for some parameters θ if:

$$P(\mathcal{D}|\mathbf{s}, \theta) = P(\mathcal{D}|\mathbf{s})$$

- If θ is a random variable, a sufficient statistic contains all relevant information $\mathcal{D}$ has for estimating it:

$$p(\theta|\mathcal{D}, \mathbf{s}) = \frac{p(\mathcal{D}|\theta, \mathbf{s})p(\theta|\mathbf{s})}{p(\mathcal{D}|\mathbf{s})} = p(\theta|\mathbf{s})$$

Use

- A sufficient statistic allows to compress a sample $\mathcal{D}$ into (possibly few) values
- Sample mean and covariance are sufficient statistics for true mean and covariance of the Gaussian distribution

Conjugate priors

Definition

- Given a likelihood function $p(x|\theta)$
- Given a prior distribution $p(\theta)$
- $p(\theta)$ is a *conjugate prior* for $p(x|\theta)$ if the posterior distribution $p(\theta|x)$ is in the same family as the prior $p(\theta)$

Examples

Likelihood	Parameters	Conjugate prior
Binomial	p (probability)	Beta
Multinomial	$\mathbf{p}$ (probability vector)	Dirichlet
Normal	μ (mean)	Normal
Multivariate normal	μ_i (mean vector)	Normal

Probability distributions

Bernoulli distribution

- Two possible values (outcomes): 1 (success), 0 (failure).
- Parameters: p probability of success.
- Probability mass function:

$$P(x; p) = \begin{cases} p & \text{if } x = 1 \\ 1 - p & \text{if } x = 0 \end{cases}$$

- $E[x] = p$
- $\text{Var}[x] = p(1 - p)$

Example: tossing a coin

- Head (success) and tail (failure) possible outcomes
- p is probability of head

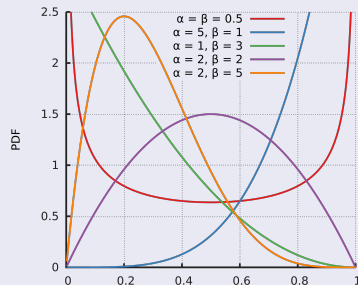
Probability distributions

Beta distribution

- Defined in the interval $[0, 1]$
- Parameters: α, β
- Probability density function:

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

- $E[x] = \frac{\alpha}{\alpha + \beta}$ $\Gamma(x + 1) = x\Gamma(x), \Gamma(1) = 1$
- $\text{Var}[x] = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)}$



Note

It models the posterior distribution of parameter p of a binomial distribution after observing $\alpha - 1$ independent events with probability p and $\beta - 1$ with probability $1 - p$.

Setting

- Boolean event: $x = 1$ for success, $x = 0$ for failure (e.g. tossing a coin)
- Parameters: θ = probability of success (e.g. head)
- Probability mass function

$$P(x|\theta) = \theta^x(1 - \theta)^{1-x}$$

- Beta conjugate prior:

$$P(\theta) = \frac{\Gamma(\alpha)}{\Gamma(\alpha_h)\Gamma(\alpha_t)}\theta^{\alpha_h-1}(1 - \theta)^{\alpha_t-1}$$

Bernoulli distribution

Maximum likelihood estimation: example

- Dataset $\mathcal{D} = \{H, H, T, T, T, H, H\}$ of N realizations (e.g. head/tail coin toss results)

- Likelihood function:

$$p(\mathcal{D}|\theta) = \theta \cdot \theta \cdot (1 - \theta) \cdot (1 - \theta) \cdot (1 - \theta) \cdot \theta \cdot \theta = \theta^h(1 - \theta)^t$$

- Maximum likelihood parameter:

$$\frac{\partial}{\partial \theta} \ln p(\mathcal{D}|\theta) = 0 \quad \Rightarrow \quad \frac{\partial}{\partial \theta} h \ln \theta + t \ln (1 - \theta) = 0$$

$$h \frac{1}{\theta} - t \frac{1}{1 - \theta} = 0$$

$$h(1 - \theta) = t\theta$$

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

- h, t are the sufficient statistics

Bayesian estimation: example

- Parameter posterior is proportional to:

$$P(\theta|\mathcal{D}) \propto P(\mathcal{D}|\theta)P(\theta) \propto \theta^h(1-\theta)^t\theta^{\alpha_h-1}(1-\theta)^{\alpha_t-1}$$

- i.e. the posterior has a beta distribution with parameters $h + \alpha_h, t + \alpha_t$:

$$P(\theta|\mathcal{D}) \propto \theta^{h+\alpha_h-1}(1-\theta)^{t+\alpha_t-1}$$

- The prediction for a new event is the expected value of the posterior beta:

$$\begin{aligned} P(x|\mathcal{D}) &= \int P(x|\theta)P(\theta|\mathcal{D})d\theta = \int \theta P(\theta|\mathcal{D})d\theta \\ &= \mathbb{E}_{P(\theta|\mathcal{D})}[\theta] = \frac{h + \alpha_h}{h + t + \alpha_h + \alpha_t} \end{aligned}$$

Interpreting priors

- Our prior knowledge is encoded as a number $\alpha = \alpha_h + \alpha_t$ of imaginary experiments
- we assume α_h times we observed heads
- α is called *equivalent sample size*
- $\alpha \rightarrow 0$ reduces estimation to the classical ML approach (frequentist)

Probability distributions

Multinomial distribution (one sample)

- Models the probability of a certain outcome for an event with m possible outcomes.
- Parameters: $p_1, \dots, p_m$ probability of each outcome
- Probability mass function:

$$P(x_1, \dots, x_m; p_1, \dots, p_m) = \prod_{i=1}^m p_i^{x_i}$$

- where $x_1, \dots, x_m$ is a vector with $x_i = 1$ for outcome i and $x_j = 0$ for all $j \neq i$.
- $E[x_i] = p_i$
- $\text{Var}[x_i] = p_i(1 - p_i)$
- $\text{Cov}[x_i, x_j] = -p_i p_j$

Probability distributions

Dirichlet distribution

- Defined: $\mathbf{x} \in [0, 1]^m$, $\sum_{i=1}^m x_i = 1$
- Parameters: $\alpha = \alpha_1, \dots, \alpha_m$
- Probability density function:

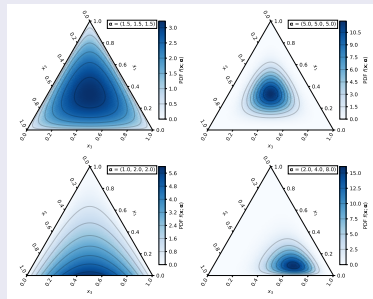
$$p(x_1, \dots, x_m; \alpha) = \frac{\Gamma(\alpha_0)}{\prod_{i=1}^m \Gamma(\alpha_i)} \prod_{i=1}^m x_i^{\alpha_i - 1}$$

- $E[x_i] = \frac{\alpha_i}{\alpha_0}$

where $\alpha_0 = \sum_{j=1}^m \alpha_j$

- $\text{Var}[x_i] = \frac{\alpha_i(\alpha_0 - \alpha_i)}{\alpha_0^2(\alpha_0 + 1)}$

$$\text{Cov}[x_i, x_j] = \frac{-\alpha_i \alpha_j}{\alpha_0^2(\alpha_0 + 1)}$$



Note

It models the posterior distribution of parameters $\mathbf{p}$ of a multinomial distribution after observing $\alpha_i - 1$ times each mutually exclusive event

Multinomial distribution

Setting

- Categorical event with r states $x \in \{x^1, \dots, x^r\}$ (e.g. tossing a six-faced dice)
- One-hot encoding $\mathbf{z}(x) = [z_1(x), \dots, z_r(x)]$ with $z_k(x) = 1$ if $x = x^k$, 0 otherwise.
- Parameters: $\theta = [\theta_1, \dots, \theta_r]$ probability of each state
- Probability mass function

$$P(x|\theta) = \prod_{k=1}^r \theta_k^{z_k(x)}$$

- Dirichlet conjugate prior:

$$P(\theta|\psi) = P(\theta|\alpha_1, \dots, \alpha_r) = \frac{\Gamma(\alpha)}{\prod_{k=1}^r \Gamma(\alpha_k)} \prod_{k=1}^r \theta_k^{\alpha_k - 1}$$

Maximum likelihood estimation: example

- Dataset $\mathcal{D}$ of N realizations (e.g. results of tossing a dice)
- Likelihood function:

$$p(\mathcal{D}|\theta) = \prod_{j=1}^N \prod_{k=1}^r \theta_k^{z_k(x_j)} = \prod_{k=1}^r \theta_k^{N_k}$$

- Maximum likelihood parameter:

$$\theta_k = \frac{N_k}{N}$$

- $N_1, \dots, N_r$ are the sufficient statistics

Multinomial distribution

Bayesian estimation: example

- Parameter posterior is proportional to:

$$P(\theta|\mathcal{D}) \propto P(\mathcal{D}|\theta)P(\theta) \propto \prod_{k=1}^r \theta_k^{N_k} \theta_k^{\alpha_k-1}$$

- i.e. the posterior has a Dirichlet distribution with parameters $N_k + \alpha_k, k = 1, \dots, r$:

$$P(\theta|\mathcal{D}) \propto \prod_{k=1}^r \theta_k^{N_k + \alpha_k - 1}$$

- The prediction for a new event is the expected value of the posterior Dirichlet:

$$P(x_k|\mathcal{D}) = \int \theta_k P(\theta|\mathcal{D}) d\theta = \mathbb{E}_{P(\theta|\mathcal{D})}[\theta_k] = \frac{N_k + \alpha_k}{N + \alpha}$$

Appendix

Additional reference material

Maximum-likelihood estimation

Multivariate Gaussian case: proof (mean)

- The gradient wrt to the mean is:

$$\nabla_{\boldsymbol{\mu}} \sum_{j=1}^n -\frac{1}{2}(\mathbf{x}_j - \boldsymbol{\mu})^t \boldsymbol{\Sigma}^{-1}(\mathbf{x}_j - \boldsymbol{\mu}) - \frac{1}{2} \ln (2\pi)^d |\boldsymbol{\Sigma}| =$$
$$\sum_{j=1}^n \boldsymbol{\Sigma}^{-1}(\mathbf{x}_j - \boldsymbol{\mu})$$

Note

$$\begin{aligned} \frac{\partial}{\partial \mathbf{x}} \mathbf{x}^T A \mathbf{x} &= A^T \mathbf{x} + A \mathbf{x} \\ &= 2A \mathbf{x} \quad \text{for symmetric } A \end{aligned}$$

Maximum-likelihood estimation

Multivariate Gaussian case: proof (mean)

- Setting the gradient to zero gives:

$$\sum_{j=1}^n \Sigma^{-1}(\mathbf{x}_j - \boldsymbol{\mu}) = \mathbf{0}$$

$$\sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu}) = \Sigma \mathbf{0} = \mathbf{0}$$

$$\sum_{j=1}^n \mathbf{x}_j = \sum_{j=1}^n \boldsymbol{\mu} = n \boldsymbol{\mu}$$

$$\boldsymbol{\mu} = \frac{1}{n} \sum_{j=1}^n \mathbf{x}_j$$

Multivariate Gaussian case: proof (covariance)

- The gradient wrt to the covariance is:

$$\begin{aligned} & \frac{\partial}{\partial \Sigma} \sum_{j=1}^n -\frac{1}{2}(\mathbf{x}_j - \boldsymbol{\mu})^t \Sigma^{-1}(\mathbf{x}_j - \boldsymbol{\mu}) - \frac{1}{2} \ln (2\pi)^d |\Sigma| = \\ & -\frac{1}{2} \left(\sum_{j=1}^n \frac{\partial}{\partial \Sigma} (\mathbf{x}_j - \boldsymbol{\mu})^t \Sigma^{-1}(\mathbf{x}_j - \boldsymbol{\mu}) + \sum_{j=1}^n \frac{\partial}{\partial \Sigma} \ln (2\pi)^d |\Sigma| \right) \end{aligned}$$

Maximum-likelihood estimation

Multivariate Gaussian case: proof (covariance)

$$\begin{aligned}\frac{\partial}{\partial \Sigma} (\mathbf{x}_j - \boldsymbol{\mu})^t \Sigma^{-1} (\mathbf{x}_j - \boldsymbol{\mu}) &= \\ (\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^t \frac{\partial}{\partial \Sigma} \Sigma^{-1} &= \\ -(\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^t \Sigma^{-2}\end{aligned}$$

Note

Use matrix derivative rule:

$$\frac{\partial}{\partial B} \text{tr}(ABC) = CA$$

Where $A = (\mathbf{x}_j - \boldsymbol{\mu})^t$, $B = \Sigma^{-1}$, $C = (\mathbf{x}_j - \boldsymbol{\mu})$ and $\text{tr}(ABC) = ABC$ as ABC is a scalar.

Maximum-likelihood estimation

Multivariate Gaussian case: proof (covariance)

$$\begin{aligned}\frac{\partial}{\partial \Sigma} \ln (2\pi)^d |\Sigma| &= \frac{1}{(2\pi)^d} |\Sigma|^{-1} \frac{\partial}{\partial \Sigma} (2\pi)^d |\Sigma| = \\ \frac{1}{(2\pi)^d} |\Sigma|^{-1} (2\pi)^d \frac{\partial}{\partial \Sigma} |\Sigma| &= |\Sigma|^{-1} |\Sigma| \Sigma^{-1} = \Sigma^{-1}\end{aligned}$$

Note

Use matrix derivative rule:

$$\frac{\partial}{\partial A} |A| = |A| A^{-1}$$

Multivariate Gaussian case: proof (covariance)

- Combining and putting equal to zero:

$$-\frac{1}{2} \left(\sum_{j=1}^n \overbrace{-(\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^t \Sigma^{-2}}^{\frac{\partial}{\partial \Sigma} (\mathbf{x}_j - \boldsymbol{\mu})^t \Sigma^{-1} (\mathbf{x}_j - \boldsymbol{\mu})} + \sum_{j=1}^n \underbrace{\Sigma^{-1}}_{\frac{\partial}{\partial \Sigma} \ln(2\pi)^d |\Sigma|} \right) = 0$$

Maximum-likelihood estimation

Multivariate Gaussian case: proof (covariance)

$$\sum_{j=1}^n \Sigma^{-1} = \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^t \Sigma^{-2}$$

$$\Sigma^2 \sum_{j=1}^n \Sigma^{-1} = \Sigma^2 \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^t \Sigma^{-2}$$

$$\sum_{j=1}^n \Sigma = \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^t$$

$$n\Sigma = \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^t$$

$$\Sigma = \frac{1}{n} \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^t$$

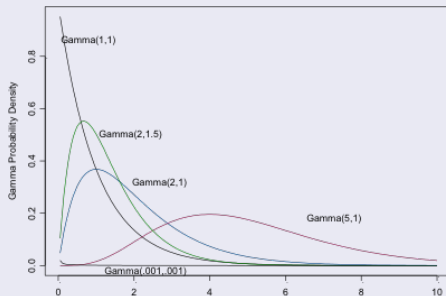
Bayesian estimation

Gamma distribution

- Defined in the interval $[0, \infty]$
- Parameters: $\alpha > 0$ (shape) $\beta > 0$ (rate)
- Probability density function:

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

- $E[x] = \frac{\alpha}{\beta}$
- $\text{Var}[x] = \frac{\alpha}{\beta^2}$



Note

Univariate normal case: unknown μ and $\lambda = 1/\sigma^2$

- Examples are drawn from:

$$p(x|\mu, \lambda) \sim N(\mu, 1/\lambda)$$

- The Prior of mean and precision is the NormalGamma distribution:

$$\begin{aligned} p(\mu, \lambda) &= p(\mu|\lambda)p(\lambda) = N(\mu|\mu_0, \frac{1}{\kappa_0\lambda})Ga(\lambda|\alpha_0, \beta_0) \\ &= NG(\mu, \lambda|\mu_0, \kappa_0, \alpha_0, \beta_0) \end{aligned}$$

Univariate normal case: unknown μ and $\lambda = 1/\sigma^2$

a posteriori parameter density

$$\begin{aligned} p(\mu, \lambda | \mathcal{D}) &= \frac{1}{\mathcal{D}} \prod_{j=1}^n \overbrace{\frac{\lambda^{1/2}}{\sqrt{2\pi}} \exp \left[-\frac{\lambda}{2} (x_j - \mu)^2 \right]}^{p(x_j | \mu, \lambda)} \overbrace{\frac{(\kappa_0 \lambda)^{1/2}}{\sqrt{2\pi}} \exp \left[-\frac{\kappa_0 \lambda}{2} (\mu - \mu_0)^2 \right]}^{p(\mu | \lambda)} \\ &\quad \underbrace{\frac{\beta_0^{\alpha_0}}{\Gamma(\alpha_0)} \lambda^{\alpha_0 - 1} \exp(-\beta_0 \lambda)}_{p(\lambda)} \\ &\propto \lambda^{\alpha_0 + n/2 - 1} \exp(-\beta_0 \lambda) \lambda^{1/2} \exp - \frac{\lambda}{2} \left[\sum_{j=1}^n (x_j - \mu)^2 - \kappa_0 (\mu - \mu_0)^2 \right] \end{aligned}$$

a posteriori parameter density is still NormalGamma

$$p(\mu, \lambda | \mathcal{D}) = NG(\mu, \lambda | \mu_n, \kappa_n, \alpha_n, \beta_n)$$

Univariate normal case: unknown μ and $\lambda = 1/\sigma^2$

a posteriori parameter density is still NormalGamma

$$p(\mu, \lambda | \mathcal{D}) = NG(\mu, \lambda | \mu_n, \kappa_n, \alpha_n, \beta_n)$$

where

$$\mu_n = \frac{\kappa_0 \mu_0 + n \hat{\mu}_n}{\kappa_0 + n}$$

$$\kappa_n = \kappa_0 + n$$

$$\alpha_n = \alpha_0 + n/2$$

$$\beta_n = \beta_0 + \frac{1}{2} \sum_{j=1}^n (x_j - \hat{\mu}_n)^2 + \frac{\kappa_0 n (\hat{\mu}_n - \mu_0)^2}{2(\kappa_0 + n)}$$

Univariate normal case: unknown μ and $\lambda = 1/\sigma^2$

Interpreting the posterior

- Posterior mean is weighted average of prior (μ_0) and sample (μ_n) means, weighted by κ_0 and n respectively

$$\mu_n = \frac{\kappa_0 \mu_0 + n \hat{\mu}_n}{k_0 + n}$$

- Posterior κ_n is increased by the number of samples n

$$\kappa_n = k_0 + n$$

- Posterior α_n is increased by half the number of samples n

$$\alpha_n = \alpha_0 + n/2$$

Univariate normal case: unknown μ and $\lambda = 1/\sigma^2$

Interpreting the posterior

- Posterior sum of squares (β_n) is sum of prior sum of squares (β_0) and sample sum of squares $\frac{1}{2} \sum_{j=1}^n (x_j - \hat{\mu}_n)^2$ and a term due to the discrepancy between the sample mean and the prior mean.

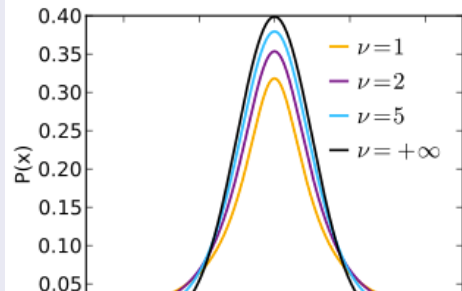
$$\beta_n = \beta_0 + \frac{1}{2} \sum_{j=1}^n (x_j - \hat{\mu}_n)^2 + \frac{\kappa_0 n (\hat{\mu}_n - \mu_0)^2}{2(\kappa_0 + n)}$$

Univariate normal case: unknown μ and $\lambda = 1/\sigma^2$

Computing the posterior predictive

$$\begin{aligned} p(x|\mathcal{D}) &= \int_{\mu} \int_{\lambda} p(x|\mu, \lambda) p(\mu, \lambda|\mathcal{D}) d\mu d\lambda \\ &= \frac{P(x, \mathcal{D})}{P(\mathcal{D})} = t_{2\alpha_n} \left(x | \mu_n, \frac{\beta_n(\kappa_n + 1)}{\alpha_n \kappa_n} \right) \end{aligned}$$

- It is a T-distribution with mean μ_n and precision $\frac{\beta_n(\kappa_n+1)}{\alpha_n \kappa_n}$ (proof omitted)



Bayesian estimation

Wishart distribution

- Defined over $d \times d$ positive semi-definite matrix
- Parameters: $\nu > d - 1$ (degree of freedom) $T > 0$ ($d \times d$ scale matrix)
- Probability density function:

$$p(X; \nu, T) = \frac{1}{2^{\nu d/2} |T|^{\nu/2} \Gamma_d(\nu/2)} |X|^{\frac{\nu-d-1}{2}} \exp -\frac{1}{2} \text{tr}(T^{-1} X)$$

- $E[X] = \nu T$
- $\text{Var}[X_{ij}] = \nu(T_i i^2 + T_{ii} T_{jj})$

Note

Used to model the prior distribution of the *precision* matrix (inverse covariance matrix, i.e. $\Lambda = \Sigma^{-1}$). T is the prior covariance

Multivariate normal case: unknown μ and Σ

- Examples are drawn from:

$$p(x|\mu, \Lambda) \sim N(\mu, \Lambda^{-1})$$

- The Prior of mean and precision is the NormalWishart distribution:

$$p(\mu, \Lambda) = p(\mu|\Lambda)p(\Lambda) = N(\mu|\mu_0, (\kappa_0\Lambda)^{-1})Wi(\Lambda|\nu, T)$$

Multivariate normal case: unknown μ and Σ

a posteriori parameter density

$$p(\mu, \Lambda | \mathcal{D}) = N(\mu | \mu_n (\kappa_n \Lambda)^{-1}) Wi(\Lambda | \nu_n, T_n)$$

where

$$\mu_n = \frac{\kappa_0 \mu_0 + n \hat{\mu}_n}{\kappa_0 + n}$$

$$T_n = T + \sum_{i=1}^n (x_i - \hat{\mu}_n)(x_i - \hat{\mu}_n)^T + \frac{\kappa n}{\kappa + n} (\mu_0 - \hat{\mu}_n)(\mu_0 - \hat{\mu}_n)^T$$

$$\nu_n = \nu + n \quad \kappa_n = \kappa + n$$

Computing the posterior predictive

$$p(x | \mathcal{D}) = t_{\nu_n - d + 1} \left(x | \mu_n, \frac{T_n(\kappa_n + 1)}{\kappa_n(\nu_n - d + 1)} \right)$$