

Week 5 Tutorial Tasks

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With a single predictor but a high-degree polynomial basis, the coding task illustrates

1. how a Gaussian prior prevents over-fit, and
2. how Bayesian credible bands differ from OLS confidence bands.

Theoretical Task: OLS vs Bayesian Linear Regression

We use a single predictor x but fit a degree- d polynomial basis

$$\phi(x) = [1, x, x^2, \dots, x^d]^\top.$$

Denote $X \in \mathbb{R}^{n \times (d+1)}$ with rows $\phi(x_i)^\top$, and observe noisy targets $y_i = f(x_i) + \varepsilon_i$, $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$. Assume that $d \leq n$ and x_i 's are distinct.

Task 1. Derive the ordinary least squares estimator $\hat{\beta}_{\text{OLS}}$ that minimizes the mean squared error $\|y - X\beta\|_2^2$.

Solution. Set gradient to zero:

$$\frac{\partial}{\partial \beta} \|y - X\beta\|_2^2 = 2X^\top(X\beta - y) \stackrel{!}{=} 0 \implies X^\top X \beta = X^\top y.$$

Since $X^\top X$ is invertible,

$$\boxed{\hat{\beta}_{\text{OLS}} = (X^\top X)^{-1} X^\top y.}$$

Task 2. Introduce a Gaussian prior $\beta \sim \mathcal{N}(0, \tau^2 I)$, where I denotes the identity matrix of appropriate dimension. Derive the posterior distribution $p(\beta | X, y)$.

Solution. The likelihood is $\mathcal{N}(X\beta, \sigma^2 I)$ and the prior on β is $\mathcal{N}(0, \tau^2 I)$. Then up to normalisation,

$$p(\beta | X, y) \propto \exp\left(-\frac{1}{2\sigma^2} \|y - X\beta\|^2 - \frac{1}{2\tau^2} \|\beta\|^2\right).$$

Collect the quadratic form in β :

$$-\frac{1}{2} \beta^\top \left(\frac{1}{\sigma^2} X^\top X + \frac{1}{\tau^2} I \right) \beta + \beta^\top \left(\frac{1}{\sigma^2} X^\top y \right) + \text{const.}$$

Completing the square yields a Gaussian posterior with

$$\Sigma_{\text{post}} = \left(\frac{1}{\sigma^2} X^\top X + \frac{1}{\tau^2} I \right)^{-1}, \quad \mu_{\text{post}} = \Sigma_{\text{post}} \frac{1}{\sigma^2} X^\top y,$$

so

$$\boxed{p(\beta | X, y) = \mathcal{N}(\mu_{\text{post}}, \Sigma_{\text{post}}).}$$

Task 3. Derive the pointwise 95% *confidence interval* under OLS and the 95% *credible interval* under the Bayesian posterior for the predicted value $\hat{f}(x_*) = \phi(x_*)^\top \beta$.

Solution.

- *OLS confidence interval.* The OLS estimate at x_* is $\hat{f}_{\text{OLS}}(x_*) = \phi(x_*)^\top \hat{\beta}_{\text{OLS}}$. Its sampling variance is

$$\text{Var}(\hat{f}_{\text{OLS}}(x_*)) = \sigma^2 \phi(x_*)^\top (X^\top X)^{-1} \phi(x_*).$$

A 95% confidence interval is

$$\hat{f}_{\text{OLS}}(x_*) \pm 1.96 \cdot \sigma \cdot \sqrt{\phi(x_*)^\top (X^\top X)^{-1} \phi(x_*)}.$$

- *Bayesian credible interval.* When you ask “What will I observe next?” you need to account for two sources of uncertainty:

1. Parameter uncertainty: the posterior spread in β ;
2. Observation noise: the fact that even if β were known exactly, each new ε still has variance σ^2 ;

Thus the prediction for a new input x_* is:

$$f(x_*) = \phi(x_*)^\top \beta + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2).$$

Using the law of total expectation:

$$\begin{aligned} \mathbb{E}[f(x_*) \mid X, y] &= \mathbb{E}[\phi(x_*)^\top \beta + \epsilon \mid X, y] \\ &= \phi(x_*)^\top \mathbb{E}[\beta \mid X, y] + \mathbb{E}[\epsilon] \\ &= \phi(x_*)^\top \mu_{\text{post}} + 0. \end{aligned}$$

Thus predictive mean is

$$\boxed{\mathbb{E}[f(x_*) \mid X, y] = \phi(x_*)^\top \mu_{\text{post}}}$$

By the law of total variance:

$$\begin{aligned} \mathbb{V}\text{ar}[f(x_*) \mid X, y] &= \mathbb{V}\text{ar}[\phi(x_*)^\top \beta + \epsilon \mid X, y] \\ &= \mathbb{V}\text{ar}[\phi(x_*)^\top \beta \mid X, y] + \mathbb{V}\text{ar}[\epsilon] \\ &= \phi(x_*)^\top \mathbb{V}\text{ar}(\beta \mid X, y) \phi(x_*) + \sigma^2 \\ &= \phi(x_*)^\top \Sigma_{\text{post}} \phi(x_*) + \sigma^2. \end{aligned}$$

Thus predictive variance is

$$\boxed{\mathbb{V}\text{ar}[f(x_*) \mid X, y] = \phi(x_*)^\top \Sigma_{\text{post}} \phi(x_*) + \sigma^2}$$

Since $f(x_*)$ given (X, y) is Gaussian, its $100(1 - \alpha)\%$ credible interval is:

$$\mu \pm z_{1-\alpha/2} \sqrt{\mathbb{V}\text{ar}},$$

where $z_{0.975} \approx 1.96$. By substituting the above values, the 95% credible interval to be

$$\boxed{\phi(x_*)^\top \mu_{\text{post}} \pm 1.96 \sqrt{\phi(x_*)^\top \Sigma_{\text{post}} \phi(x_*) + \sigma^2}}$$

Coding Task

Consider above polynomial regression when the underlying model is

$$y = \sin(2\pi x) + \varepsilon,$$

where $\varepsilon \sim \mathcal{N}(0, 0.3)$. Taking 30 linearly spaced x_i 's on $[0, 1]$, compute the above confidence intervals and credible intervals for $d = 20$.

Solution: Check the jupyter-notebook solution of this tutorial.