Bayesian Statistics I

Lecture 4 - Regression, Prediction and Decisions

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Lecture overview

- **Normal model** with conjugate prior
- The **linear regression** model
- **Prediction**
- **Decision making**

Linear regression

- The linear regression model in **matrix form**

$$\underset{(n\times 1)}{\mathbf{y}} = \underset{(n\times k)(k\times 1)}{\mathbf{X}\beta} + \underset{(n\times 1)}{\varepsilon}$$

$$\mathbf{y} = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}, \ \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_k \end{pmatrix}, \ \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

$$\mathbf{X} = \begin{pmatrix} \mathbf{x}_1' \\ \vdots \\ \mathbf{x}_n' \end{pmatrix} = \begin{pmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nk} \end{pmatrix}$$

- Usually $x_{i1} = 1$, for all i. β_1 is the intercept.
- **Likelihood**

$$\mathbf{y}|\beta, \sigma^2, \mathbf{X} \sim N(\mathbf{X}\beta, \sigma^2 I_n)$$

Linear regression - uniform prior

- Standard **non-informative prior**: uniform on $(\beta, \log \sigma^2)$

$$p(\beta, \sigma^2) \propto \sigma^{-2}$$

- **Joint posterior** of β and σ^2:

$$\begin{aligned} \beta|\sigma^2, \mathrm{y} &\sim N\left[\hat{\beta}, \sigma^2(\mathrm{X}'\mathrm{X})^{-1}\right] \\ \sigma^2|\mathrm{y} &\sim Inv\text{-}\chi^2(n-k, s^2) \end{aligned}$$

where $\hat{\beta} = (\mathrm{X}'\mathrm{X})^{-1}\mathrm{X}'\mathrm{y}$ and $s^2 = \frac{1}{n-k}(\mathrm{y} - \mathrm{X}\hat{\beta})'(\mathrm{y} - \mathrm{X}\hat{\beta})$.

- **Simulate** from the joint posterior by simulating from
  - $p(\sigma^2|\mathrm{y})$
  - $p(\beta|\sigma^2, \mathrm{y})$
- **Marginal posterior** of β :

$$\beta|\mathrm{y} \sim t_{n-k}\left[\hat{\beta}, s^2(X'X)^{-1}\right]$$

Linear regression - conjugate prior

- **Joint prior** for β and σ^2

$$\begin{aligned} \beta|\sigma^2 &\sim N\left(\mu_0, \sigma^2\Omega_0^{-1}\right) \\ \sigma^2 &\sim Inv - \chi^2\left(\nu_0, \sigma_0^2\right) \end{aligned}$$

- **Posterior**

$$\begin{aligned} \beta|\sigma^2, \mathrm{y} &\sim N\left[\mu_n, \sigma^2\Omega_n^{-1}\right] \\ \sigma^2|\mathrm{y} &\sim \mathrm{Inv}{-}\chi^2\left(\nu_n, \sigma_n^2\right) \end{aligned}$$

$$\begin{aligned} \mu_n &= \left(\mathrm{X}'\mathrm{X} + \Omega_0\right)^{-1}\left(\mathrm{X}'\mathrm{X}\hat{\beta} + \Omega_0\mu_0\right) \\ \Omega_n &= \mathrm{X}'\mathrm{X} + \Omega_0 \\ \nu_n &= \nu_0 + n \\ \nu_n\sigma_n^2 &= \nu_0\sigma_0^2 + \left(\mathrm{y}'\mathrm{y} + \mu_0'\Omega_0\mu_0 - \mu_n'\Omega_n\mu_n\right) \end{aligned}$$

Polynomial regression

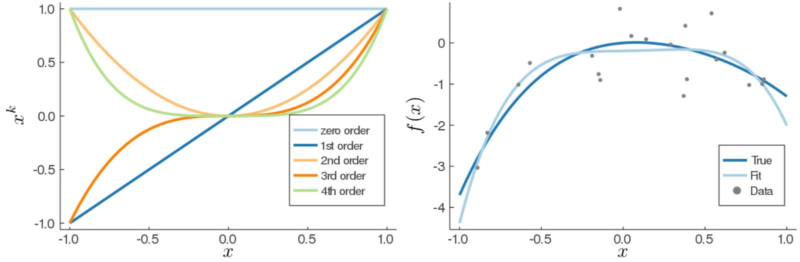
- **Polynomial regression**

$$f(x_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \ldots + \beta_k x_i^k.$$

$$\mathbf{y} = \mathbf{X}_P \beta + \varepsilon,$$

where

$$\mathbf{X}_P = (1, x, x^2, \ldots, x^k).$$



- Priors for **regularization** (ridge, lasso etc) in Lecture 6.

Prediction/Forecasting

- **Posterior predictive density** for future $\tilde{y}$ given observed y

$$p(\tilde{y}|\mathrm{y}) = \int_\theta p(\tilde{y}|\theta,\mathrm{y})p(\theta|\mathrm{y})d\theta$$

- IID data:

$$p(\tilde{y}|\mathrm{y}) = \int_\theta p(\tilde{y}|\theta)p(\theta|\mathrm{y})d\theta$$

- **Parameter uncertainty** in $p(\tilde{y}|\mathrm{y})$ by **averaging over** $p(\theta|\mathrm{y})$.

Prediction - Normal data, known variance

- Under the uniform prior $p(\theta) \propto c$, then

$$p(\tilde{y}|\mathrm{y}) = \int_\theta p(\tilde{y}|\theta)p(\theta|\mathrm{y})d\theta$$
$$\theta|\mathrm{y} \sim N(\bar{y}, \sigma^2/n)$$
$$\tilde{y}|\theta \sim N(\theta, \sigma^2)$$

Simulation algorithm:

1. Generate a **posterior draw** of θ ($\theta^{(1)}$) from $N(\bar{y}, \sigma^2/n)$
2. Generate a **predictive draw** of $\tilde{y}$ ($\tilde{y}^{(1)}$) from $N(\theta^{(1)}, \sigma^2)$
3. Repeat Steps 1 and 2 N times to output:
   - Sequence of posterior draws: $\theta^{(1)}, ..., \theta^{(N)}$
   - Sequence of predictive draws: $\tilde{y}^{(1)}, ..., \tilde{y}^{(N)}$.

Predictive distribution - Normal model

- $\theta^{(1)} = \bar{y} + \varepsilon^{(1)}$, where $\varepsilon^{(1)} \sim N(0, \sigma^2/n)$. (Step 1).
- $\tilde{y}^{(1)} = \theta^{(1)} + \upsilon^{(1)}$, where $\upsilon^{(1)} \sim N(0, \sigma^2)$. (Step 2).
- $\tilde{y}^{(1)} = \bar{y} + \varepsilon^{(1)} + \upsilon^{(1)}$.
- $\varepsilon^{(1)}$ and $\upsilon^{(1)}$ are independent.
- The sum of two normal random variables is normal so

$$
\begin{aligned}
E(\tilde{y}|\mathrm{y}) &= \bar{y} \\
V(\tilde{y}|\mathrm{y}) &= \frac{\sigma^2}{n} + \sigma^2 = \sigma^2\left(1 + \frac{1}{n}\right)
\end{aligned}
$$

$$
\tilde{y}|\mathrm{y} \sim N\left[\bar{y}, \sigma^2\left(1 + \frac{1}{n}\right)\right]
$$

Iteration laws

- Expectation with respect to what? Explicit:

$$\mathbb{E}_{\theta|\mathrm{y}}(\theta) \equiv \int \theta p(\theta|\mathrm{y}) d\theta$$

- **Law of iterated expectation** and **Law of total variance**.

Iteration laws

Law of iterated expectation:

$$\mathbb{E}_X(X) = \mathbb{E}_Y\left(\mathbb{E}_{X|Y}(X)\right)$$

Law of total variance:

$$\mathbb{V}_X(X) = \mathbb{E}_Y\left(\mathbb{V}_{X|Y}(X)\right) + \mathbb{V}_Y\left(\mathbb{E}_{X|Y}(X)\right)$$

Iteration laws for Bayes

Marginal posterior mean:

$$\mathbb{E}_{\theta_1|\mathbf{y}}(\theta_1) = \mathbb{E}_{\theta_2|\mathbf{y}}\left(\mathbb{E}_{\theta_1|\theta_2,\mathbf{y}}(\theta_1)\right)$$

Marginal posterior variance:

$$\mathbb{V}_{\theta_1}(\theta_1) = \mathbb{E}_{\theta_2|\mathbf{y}}\left(\mathbb{V}_{\theta_1|\theta_2,\mathbf{y}}(\theta_1)\right) + \mathbb{V}_{\theta_2|\mathbf{y}}\left(\mathbb{E}_{\theta_1|\theta_2,\mathbf{y}}(\theta_1)\right)$$

Predictive distribution - Normal model and prior

- Predictive distribution still normal (sum of normals is normal).
- Predictive mean conditional on θ is trivial:

$$E_{\tilde{y}|\theta}(\tilde{y}) = \theta$$

- "Remove the conditioning" on θ by averaging over posterior:

$$E(\tilde{y}|\mathrm{y}) = E_{\theta|\mathrm{y}}(\theta) = \mu_n \text{ (Posterior mean of } \theta\text{).}$$

- The predictive variance of $\tilde{y}$ by law of total variance

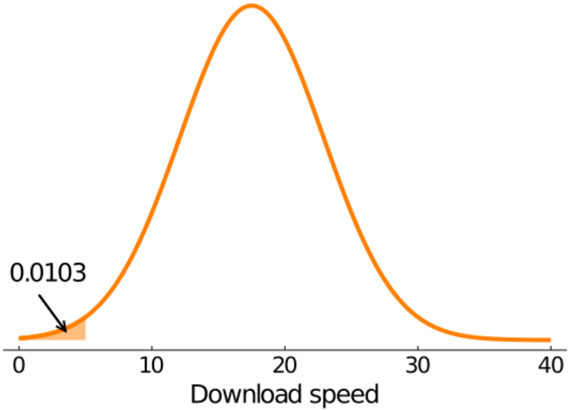
$$\begin{aligned} V(\tilde{y}|\mathrm{y}) &= E_{\theta|\mathrm{y}}[V_{\tilde{y}|\theta}(\tilde{y})] + V_{\theta|\mathrm{y}}[E_{\tilde{y}|\theta}(\tilde{y})] \\ &= E_{\theta|\mathrm{y}}(\sigma^2) + V_{\theta|\mathrm{y}}(\theta) \\ &= \sigma^2 + \tau_n^2 \end{aligned}$$

- So, predictive distribution is

$$\tilde{y}|\mathrm{y} \sim N(\mu_n, \sigma^2 + \tau_n^2).$$

Predictive distribution - Internet speed data

- My Netflix starts to buffer at speeds < 5Mbit. 🤬



Bayesian prediction for time series

Autoregressive process

$$y_t = \mu + \phi_1(y_{t-1} - \mu) + \ldots + \phi_p(y_{t-p} - \mu) + \varepsilon_t, \; \varepsilon_t \overset{iid}{\sim} N(0, \sigma^2)$$

Predictive distribution - AR process.

Input: time series $\mathbf{y}_{1:T} = (y_1, \ldots, y_T)$
number of predictive draws m.
forecast horizon h.

for i in $1{:}m$ **do**

$\mu, \phi_1, \ldots, \phi_p, \sigma \leftarrow \textsc{rPosteriorAR}(\mathbf{y}_{1:T}, \text{PriorSettings})$

$\varepsilon_{T+1} \leftarrow \textsc{rNorm}(0, \sigma)$

$\tilde{y}_{T+1} \leftarrow \mu + \phi_1(y_T - \mu) + \ldots + \phi_p(y_{T+1-p} - \mu) + \varepsilon_{T+1}$

$\varepsilon_{T+2} \leftarrow \textsc{rNorm}(0, \sigma)$

$\tilde{y}_{T+2} \leftarrow \mu + \phi_1(\tilde{y}_{T+1} - \mu) + \ldots + \phi_p(y_{T+2-p} - \mu) + \varepsilon_{T+2}$

$\vdots$

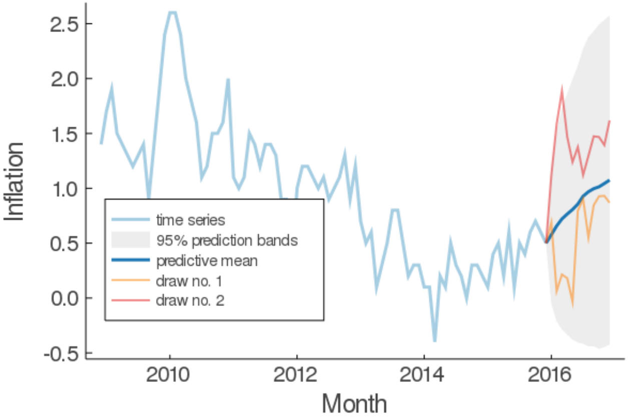
$\varepsilon_{T+h} \leftarrow \textsc{rNorm}(0, \sigma)$

$\tilde{y}_{T+h} \leftarrow \mu + \phi_1(\tilde{y}_{T+h-1} - \mu) + \ldots + \phi_p(\tilde{y}_{T+h-p} - \mu) + \varepsilon_{T+h}$

end

Output: m draws from the joint predictive density:
$p(\tilde{y}_{T+1}, \ldots, \tilde{y}_{T+h} | \mathbf{y}_{1:T})$.

Bayesian prediction of Swedish inflation



Predicting auction prices on eBay

- Problem: **Predicting the final price** in eBay coin auctions.
- **Data**: Bid from 1000 auctions on eBay.
  The highest bid is not observed (eBay proxy bidding).
- **Covariates** are auction-specific:
  - catalog value
  - seller's **reservation price**
  - quality
  - rating of seller etc
- Buyers are **strategic**.
  - Bid $\neq$ **valuation**.
  - **Bid function**, $b = \mathrm{BidFunction}(v)$, from **Game theory**.
  - Very complicated likelihood.

Simulating auction prices on eBay

Predictive distribution - auction price.

Input: training auction bids $\mathbf{Y}$
training auction covariates $\mathbf{X}$.
test auction covariates $\tilde{\mathbf{x}}$.
number of predictive draws m.

for i in $1{:}m$ **do**

$\mu, \sigma, \lambda \leftarrow \textsc{rPostAuction}(\mathbf{Y}, \mathbf{X}, \tilde{\mathbf{x}}, \text{Prior})$ # parameters

$\tilde{n} \leftarrow \textsc{rPois}(\lambda(\tilde{\mathbf{x}}))$ # number of bidders in test auction

$\tilde{\mathbf{v}}_{1:\tilde{n}} \leftarrow \textsc{rNorm}(\mu(\tilde{\mathbf{x}}), \sigma(\tilde{\mathbf{x}}))$ # valuations for all $\tilde{n}$ bidders

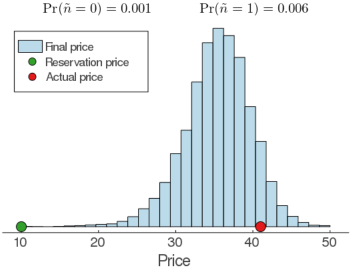
$b_{1:\tilde{n}} \leftarrow \textsc{BidFunction}(\tilde{\mathbf{v}}_{1:\tilde{n}}, \tilde{n}, \mu(\tilde{\mathbf{x}}), \sigma(\tilde{\mathbf{x}}))$ # bids

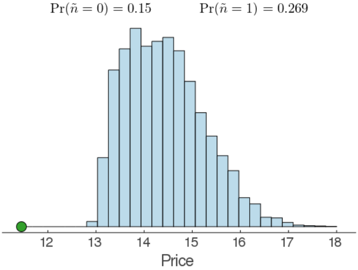
$\tilde{p} \leftarrow \textsc{SecondLargest}(b_{1:\tilde{n}})$ # final price

end

Output: m predictive draws of the final price $\tilde{p}$ for an auction with covariates $\tilde{\mathbf{x}}$.

Predicting auction prices on eBay





Decision Theory

- Let θ be an **unknown quantity**. **State of nature**. Examples: Future inflation, Global temperature, Disease.
- Let $a \in \mathcal{A}$ be an **action**. Ex: Interest rate, Energy tax, Surgery.
- Choosing action a when state of nature is θ gives **utility**

$$U(a, \theta)$$

- Alternatively **loss** $L(a, \theta) = -U(a, \theta)$.
- Loss table:

	θ_1	θ_2
a_1	$L(a_1, \theta_1)$	$L(a_1, \theta_2)$
a_2	$L(a_2, \theta_1)$	$L(a_2, \theta_2)$

- Example:

	Rainy	Sunny
Umbrella	20	10
No umbrella	50	0

Decision Theory

- Example **loss functions** when both a and θ are continuous:
  - **Linear**: $L(a,\theta) = |a-\theta|$
  - **Quadratic**: $L(a,\theta) = (a-\theta)^2$
  - **Lin-Lin**:

$$L(a,\theta) = \begin{cases} c_1 \cdot |a-\theta| & \text{if } a \leq \theta \\ c_2 \cdot |a-\theta| & \text{if } a > \theta \end{cases}$$

- Example:
  - θ is the number of items demanded of a product
  - a is the number of items in stock
  - Utility

$$U(a,\theta) = \begin{cases} p \cdot \theta - c_1(a-\theta) & \text{if } a > \theta \text{ [too much stock]} \\ p \cdot a - c_2(\theta - a)^2 & \text{if } a \leq \theta \text{ [too little stock]} \end{cases}$$

Optimal decision

- Ad hoc decision rules:
  - *Minimax*. Minimizes the maximum loss.
  - *Minimax-regret* ... bla bla bla ...
- **Bayesian theory**: maximize the **posterior expected utility**:

$$a_{bayes} = \text{argmax}_{a \in \mathcal{A}} \; E_{p(\theta|y)}[U(a, \theta)],$$

  where $E_{p(\theta|y)}$ denotes the posterior expectation.
- Using simulated draws $\theta^{(1)}, \theta^{(2)}, ..., \theta^{(N)}$ from $p(\theta|y)$:

$$E_{p(\theta|y)}[U(a, \theta)] \approx N^{-1} \sum_{i=1}^{N} U(a, \theta^{(i)})$$

- **Separation principle**:

1. First obtain $p(\theta|y)$
2. then form $U(a, \theta)$ and finally
3. choose a that maximes $E_{p(\theta|y)}[U(a, \theta)]$.

Choosing a point estimate is a decision

- Choosing a **point estimator** is a decision problem.
- Which to choose: posterior median, mean or mode?
- It depends on your loss function:
  - **Linear loss** $\rightarrow$ Posterior median
  - **Quadratic loss** $\rightarrow$ Posterior mean
  - **Zero-one loss** $\rightarrow$ Posterior mode
  - **Lin-Lin loss** $\rightarrow$ $c_2/(c_1 + c_2)$ quantile of the posterior