Statistical Modeling 2
Exercise 1

January 30, 2017

1 Bayesian inference in simple conjugate families

A

$$
\begin{aligned}
p(w \mid x_1, \dots, x_N) &\propto p(x_1, \dots, x_N \mid w)p(w) && \text{(Bayes rule)} \\
&\propto \prod_{i=1}^{N} p(x_i|w) w^{a-1}(1-w)^{b-1} && \text{(indepence)} \\
&\propto w^s(1-w)^{N-s} w^{a-1}(1-w)^{b-1} && (\text{let } s = \textstyle\sum_{i=1}^N x_i) \\
&= w^{s+a-1}(1-w)^{N-s+b-1} \\
&\propto \text{Beta}(s+a, N-s+b)
\end{aligned}
$$

B

Let $f(x_1, x_2) = (y1, y2) = (x_1/(x_1 + x_2), x_1 + x_2)$, we have:

$$f^{-1}(y1, y2) = (x_1, x_2) = (y_1 y_2, y_2 - y_1 y_2)$$

We then calculate the Jacobian of f^{-1}:

$$
\begin{aligned}
\partial x_1/\partial y_1 &= y_2 \\
\partial x_1/\partial y_2 &= y_1 \\
\partial x_2/\partial y_1 &= -y_2 \\
\partial x_2/\partial y_2 &= 1 - y_1
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
|J(f^{-1})| &= \begin{vmatrix} y_2 & y_1 \\ -y_2 & 1 - y_1 \end{vmatrix} \\
&= y_2(1-y_1) + y_1 y_2 \\
&= y_2
\end{aligned}
$$

Let p_X be the joint density of (x_1, x_2). We have the joint density of y_1 and y_2:

$$\begin{aligned}
p(y_1, y_2) &= p_X(f^{-1}(y_1, y_2))|J(f^{-1}(y_1, y_2))| \\
&= \text{Ga}(y_1 y_2; a_1, 1)\text{Ga}(y2 - y_1 y_2; a_2, 1)y_2 \\
&= \frac{(y_1 y_2)^{a_1-1}\exp(-y_1 y_2)}{\Gamma(a_1)} \frac{((1-y_1)y_2)^{a_2-1}\exp(y_1 y_2 - y_2)}{\Gamma(a_2)} y_2 \\
&= \frac{y_1^{a_1-1} y_2^{a_1+a_2-1}(1-y_1)^{a_2-1}\exp(-y_2)}{\Gamma(a_1)\Gamma(a_2)}
\end{aligned}$$

The marginals are:

$$\begin{aligned}
p(y_1) &= \int_0^\infty p(y_1, y_2) dy_2 \\
&= \frac{y_1^{a_1-1}(1-y_1)^{a_2-1}}{\Gamma(a_1)\Gamma(a_2)} \int_0^\infty y_2^{a_1+a_2-1}\exp(-y_2) dy_2 \\
&= \frac{y_1^{a_1-1}(1-y_1)^{a_2-1}\Gamma(a_1+a_2)}{\Gamma(a_1)\Gamma(a_2)}
\end{aligned}$$

and

$$\begin{aligned}
p(y_2) &= \int_0^\infty p(y_1, y_2) dy_1 \\
&= \frac{y_2^{a_1+a_2-1}\exp(-y_2)}{\Gamma(a_1)\Gamma(a_2)} \int_0^\infty y_1^{a_1-1}(1-y_1)^{a_2-1} \\
&= \frac{y_2^{a_1+a_2-1}\exp(-y_2)}{\Gamma(a_1)\Gamma(a_2)} \text{Beta}(a_1, a_2)
\end{aligned}$$

We can simulate a Beta random variable by taking two Gamma random variable as x_1 and x_2 and evaluate y_1.

C

The posterior is:

$$
\begin{aligned}
p(\theta|x_1,\ldots,x_N) &\propto p(x_1,\ldots,x_N|\theta)p(\theta) \\
&= \prod_{i=1}^{N} \mathrm{N}(x_i;\theta,\sigma^2)\mathrm{N}(\theta;m,v) \\
&\propto \prod_{i=1}^{N} \exp\left(-\frac{(x_i-\theta)^2}{2\sigma^2}\right)\exp\left(-\frac{(\theta-m)^2}{2v}\right) \\
&= \prod_{i=1}^{N} \exp\left(-\frac{x_i^2-2x_i\theta+\theta^2}{2\sigma^2}\right)\exp\left(-\frac{\theta^2-2\theta m+m^2}{2v}\right) \\
&= \exp\left(\frac{-\sum_i x_i^2+2\sum_i x_i\theta-N\theta^2}{2\sigma^2}\right)\exp\left(\frac{-\theta^2+2\theta m-m^2}{2v}\right) \\
&= \exp\left(-\theta^2\left(\frac{N}{2\sigma^2}+\frac{1}{2v}\right)+\theta\left(\frac{\sum_i x_i}{\sigma^2}+\frac{m}{v}\right)-\frac{\sum_i x_i^2}{2\sigma^2}-\frac{m^2}{2v}\right)
\end{aligned}
$$

We then complete the square by setting the posterior to:

$$
\begin{aligned}
&= \exp\left[-a\left(\theta^2-2b\theta+b^2\right)\right] \\
&= \exp\left[-a\left(\theta-b\right)^2\right] \\
&= \exp\left[-\frac{(\theta-b)^2}{2(1/(2a))}\right]
\end{aligned}
$$

We calculate a, b by matching coefficients:

$$
\begin{aligned}
a &= \frac{N}{2\sigma^2}+\frac{1}{2v}=\frac{Nv+\sigma^2}{2\sigma^2 v} \\
2ab &= \frac{\sum_i x_i}{\sigma^2}+\frac{m}{v} \\
\implies b &= \frac{v\sum_i x_i+m\sigma^2}{v\sigma^2}\frac{\sigma^2 v}{Nv+\sigma^2} \\
&= \frac{v\sum_i x_i+m\sigma^2}{Nv+\sigma^2}
\end{aligned}
$$

The posterior is then:

$$
\begin{aligned}
&\mathrm{N}(b,1/(2a)) \\
=&\mathrm{N}\left(\frac{v\sum_i x_i+m\sigma^2}{Nv+\sigma^2},\frac{\sigma^2 v}{Nv+\sigma^2}\right)
\end{aligned}
$$

D

$$
\begin{aligned}
p(\omega \mid x_1, \ldots, x_N) &\propto \prod_{i=1}^{N} p(x_i \mid \theta, \omega) p(\omega) \\
&\propto \prod_{i=1}^{N} \omega^{1/2} \exp\left[-\frac{\omega}{2}(x_i - \theta)^2\right] \frac{b^a}{\Gamma(a)} \omega^{a-1} \exp(-b\omega) \\
&\propto \omega^{N/2+a-1} \exp\left[-\omega\left(b + \frac{\sum_i (x_i - \theta)^2}{2}\right)\right] \\
&\propto \mathrm{Ga}\left(a + \frac{N}{2}, b + \frac{\sum_i (x_i - \theta)^2}{2}\right)
\end{aligned}
$$

We have the posterior of the variance:

$$
p(\sigma^2 \mid x_1, \ldots, x_N) = \mathrm{IG}\left(a + \frac{N}{2}, b + \frac{\sum_i (x_i - \theta)^2}{2}\right)
$$

E

The posterior is:

$$
\begin{aligned}
p(\theta | x_1, \ldots, x_N) &\propto p(x_1, \ldots, x_N | \theta) p(\theta) \\
&= \prod_{i=1}^{N} \mathrm{N}(x_i; \theta, \sigma_i^2) \mathrm{N}(\theta; m, v) \\
&\propto \prod_{i=1}^{N} \exp\left(-\frac{(x_i - \theta)^2}{2\sigma_i^2}\right) \exp\left(-\frac{(\theta - m)^2}{2v}\right) \\
&= \exp\left(-\sum_{i=1}^{n} \frac{(x_i - \theta)^2}{2\sigma_i^2} - \frac{(\theta - m)^2}{2v}\right) \\
&= \exp\left[-\frac{1}{2}\left(\sum_{i=1}^{n} \frac{(x_i - \theta)^2}{\sigma_i^2} + \frac{(\theta - m)^2}{v}\right)\right] \\
&= \exp\left[-\frac{1}{2}\left(\sum_{i=1}^{n} \frac{x_i^2}{\sigma_i^2} + \sum_{i=1}^{n} \frac{-2x_i\theta}{\sigma_i^2} + \sum_{i=1}^{n} \frac{\theta^2}{\sigma_i^2} + \frac{\theta^2 - 2\theta m + m^2}{v}\right)\right] \\
&= \exp\left\{-\frac{1}{2}\left[\theta^2\left(\sum_{i=1}^{n} \frac{1}{\sigma_i^2} + \frac{1}{v}\right) - 2\theta\left(\sum_{i=1}^{N} \frac{x_i}{\sigma_i^2} + \frac{m}{v}\right) + \sum_{i=1}^{n} \frac{x_i^2}{\sigma_i^2} + \frac{m^2}{v}\right]\right\} \\
\text{set } &= \exp\left\{-\frac{1}{2}\left[a(\theta^2 - 2\theta b + b^2)\right]\right\} \\
&= \exp\left\{-\frac{1}{2}\left[\frac{(\theta - b)^2}{1/a}\right]\right\}
\end{aligned}
$$

Matching the coefficients, we have:

$$a = \sum_{i=1}^{n} \frac{1}{\sigma_i^2} + \frac{1}{v}$$
$$b = \left(\sum_{i=1}^{N} \frac{x_i}{\sigma_i^2} + \frac{m}{v}\right) / \left(\sum_{i=1}^{n} \frac{1}{\sigma_i^2} + \frac{1}{v}\right)$$

The posterior is:

$$\mathrm{N}(b, 1/a)$$

F

$$\begin{aligned}
p(x) &= \int_0^\infty p(x \mid \sigma^2) p(\sigma^2) d\sigma^2 \\
&= \int_0^\infty p(x \mid \omega) p(\omega) d\omega \\
&= \int_0^\infty \left(\frac{\omega}{2\pi}\right)^{1/2} \exp\left(-\frac{\omega}{2} x^2\right) \frac{b^a}{\Gamma(a)} \omega^{a-1} \exp(-b\omega) d\omega \\
&= \frac{b^a}{(2\pi)^{1/2}\Gamma(a)} \int_0^\infty \omega^{1/2+a-1} \exp\left(-\omega\left(\frac{x^2}{2} + b\right)\right) d\omega \\
&= \frac{b^a}{(2\pi)^{1/2}\Gamma(a)} \frac{\Gamma(a+1/2)}{(b + x^2/2)^{a+1/2}} && \text{(Gamma integral)} \\
&= \frac{\Gamma(a+1/2)}{(2\pi b)^{1/2}\Gamma(a)(1 + \frac{x^2}{2b})^{a+1/2}}
\end{aligned}$$

Let $\nu = 2a$ and $\lambda = a/b$, we have:

$$p(x) = \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\nu/2)} \left(\frac{\lambda}{\pi\nu}\right)^{1/2} \left(1 + \frac{\lambda x^2}{2}\right)^{-\frac{\nu+1}{2}}$$

This is the Student t distribution with ν degree of freedom and 'precision' λ.

2 The multivariate normal distribution

A

$$\begin{aligned}
\mathrm{cov}(x) &= E\{(x-\mu)(x-\mu)^T\} \\
&= E\{xx^T - x\mu^T - \mu x^T + \mu\mu^T\} \\
&= E(xx^T) - E(x)\mu^T - \mu E(x)^T + \mu\mu^T \\
&= E(xx^T) - \mu\mu^T
\end{aligned}$$

We have:

$$E(Ax+b) = AE(x) + b = A\mu + b$$

then

$$\begin{aligned}
\mathrm{cov}(Ax+b) &= E\{[(Ax+b)-(A\mu+b)][(Ax+b)-(A\mu+b)]^T\} \\
&= E\{(Ax-A\mu)(Ax-A\mu)^T\} \\
&= E\{A(x-\mu)(x-\mu)^T A^T\} \\
&= AE\{(x-\mu)(x-\mu)^T\}A^T \\
&= A\mathrm{cov}(x)A^T
\end{aligned}$$

B

$$\begin{aligned}
p(z) &= \prod_{i=1}^{p} p(z_i) \\
&= \frac{1}{(\sqrt{2\pi})^p} \exp\left(-\sum_{i=1}^{p} \frac{z_i^2}{2}\right) \\
&= \frac{1}{(\sqrt{2\pi})^p} \exp\left(-\frac{z^T z}{2}\right)
\end{aligned}$$

The MGF of z is:

$$\begin{aligned}
E(\exp(t^T z)) &= E\left[\exp\left(\sum_{i=1}^{p} t_i z_i\right)\right] \\
&= E\left[\prod_{i=1}^{p} \exp(t_i z_i)\right] \\
&= \prod_{i=1}^{p} E[\exp(t_i z_i)] \\
&= \prod_{i=1}^{p} \exp(t_i^2/2) \\
&= \exp\left[\sum_{i=1}^{p} t_i^2/2\right] \\
&= \exp(t^T t/2)
\end{aligned}$$

C

We need to prove that for all vector a not identically zero, the scalar quantity $z = a^T x$ is normally distributed if and only if

$$E[\exp(t^T x)] = \exp(t^T \mu + t^T \Sigma t/2)$$

(only if) We have that $z = a^T x$ is normally distributed:

$$\text{MGF}_z(s) = E[\exp(sa^T x)] = \exp(ms + vs^2/2)$$

Consider:

D

We have $z \sim \text{N}(0, \text{I})$ and $x = Lz + \mu$.
The MGF of x is:

$$E(\exp(t^T x)) = E[\exp(t^T Lz + t^T \mu)]$$

The expectation is with respect to z, $t^T \mu$ is a constant, we then look at:

$$\begin{aligned}
E[\exp(t^T Lz)] &= E\left[\exp\left(\sum_{i=1}^{p}\sum_{j=1}^{p} t_i L_{ij} z_j\right)\right] \\
&= E\left[\prod_{j=1}^{p} \exp\left(\sum_{i=1}^{p} t_i L_{ij} z_j\right)\right] \\
&= \prod_{j=1}^{p} E\left[\exp\left(\sum_{i=1}^{p} t_i L_{ij} z_j\right)\right] && \text{(indepence)} \\
&= \prod_{j=1}^{p} \text{MGF}_{z_j}\left(\sum_{i=1}^{p} t_i L_{ij}\right) \\
&= \prod_{j=1}^{p} \exp\left(\frac{1}{2}(t^T L_j)^2\right) \\
&= \prod_{j=1}^{p} \exp\left(\frac{1}{2} t^T L_j L_j^T t\right) \\
&= \exp\left(\frac{1}{2}\sum_{j=1}^{p} t^T L_j L_j^T t\right) \\
&= \exp\left(\frac{1}{2} t^T L L^T t\right)
\end{aligned}$$

Come back to the MGF of x:

$$E(\exp(t^T x)) = \exp\left(t^T \mu + \frac{1}{2} t^T L L^T t\right)$$

Therefore, $x \sim \text{N}(\mu, LL^T)$.

E

We have that x has a multivariate normal distribution: $x \sim \mathrm{N}(\mu, \Sigma)$. The covariance matrix Σ is symmetric positive definite and has a Cholesky decomposition:

$$\Sigma = LL^T$$

where L is a lower triangular matrix with positive diagonal entries and therefore invertible. Let

$$z = L^{-1}(x - \mu)$$

Consider the MGF of z:

$$\begin{aligned}
E[\exp(t^T z)] &= E[\exp(t^T L^{-1}(x - \mu))] \\
&= E[\exp(t^T L^{-1} x) \cdot \exp(-t^T L^{-1} \mu)] \\
&= \mathrm{MGF}_x(t^T L^{-1}) \cdot \exp(-t^T L^{-1} \mu) \\
&= \exp(t^T L^{-1} \mu + t^T L^{-1} \Sigma L^{-T} t/2) \cdot \exp(-t^T L^{-1} \mu) \\
&= \exp(t^T L^{-1} \Sigma L^{-T} t/2) \\
&= \exp(t^T L^{-1} (LL^T) L^{-T} t/2) \\
&= \exp(t^T t/2)
\end{aligned}$$

We conclude that z has standard multivariate normal distribution and that x can be written as an affine transformation of standard normal distribution.

F

Let z be standard multivariate Normal:

$$p_Z(z) \propto \exp\left(-\frac{z^t z}{2}\right)$$

By the previous result, we have that $x = Lz + \mu$ has multivariate Normal distribution. Since L is full rank, it is invertible, let $z = f(x) = L^{-1}(x - \mu)$

The pdf of x is:

$$\begin{aligned}
p_X(x) &= p_Z(f(x))|J_f(x)| \\
&\propto \exp\left(-\frac{(x-\mu)^T L^{-T} L^{-1} (x - \mu)}{2}\right) |L^{-1}| \\
&\propto \exp(-Q(x - \mu)/2)
\end{aligned}$$

G

By the previous results, x_1 and x_2 are affine transformation of independent standard Normal distribution. Let $z \sim \mathrm{N}(0, I)$

$$\begin{aligned} x_1 &= L_1 z + \mu_1 \\ x_2 &= L_2 z + \mu_2 \end{aligned}$$

We have:

$$\begin{aligned} y = Ax_1 + Bx_2 &= AL_1 z + A\mu_1 + BL_2 z + B\mu_2 \\ &= (AL_1 + BL_2)z + A\mu_1 + B\mu_2 \end{aligned}$$

We see that y is an affine transformation of independent standard Normal variables and therefore is multivariate Normal with mean $A\mu_1 + B\mu_2$ and variance

$$\begin{aligned} (AL_1 + BL_2)(AL_1 + BL_2)^T &= AL_1L_1^TA^T + AL_1L_2^TB^T + BL_2L_1^TA^T + BL_2L_2^TB^T \\ &= A\Sigma_1A^T + AL_1L_2^TB^T + BL_2L_1^TA^T + B\Sigma_2B^T \end{aligned}$$

3 Conditionals and marginals

A

Decompose the covariance matrix Σ and partition L into L_1 and L_2 where L_1 has k elements and corresponds to x_1.

$$\begin{aligned} \Sigma &= LL^T \\ &= \begin{pmatrix} L_1 \\ L_2 \end{pmatrix} \begin{pmatrix} L_1^T & L_2^T \end{pmatrix} \\ &= \begin{pmatrix} L_1L_1^T & L_1L_2^T \\ L_2L_1^T & L_2L_2^T \end{pmatrix} \end{aligned}$$

We have that $\Sigma_{11} = L_1L_1^T$. By the previous results, $x = Lz + \mu$ where z is a vector of independent standard Normal variables. Take the first k element, we have:

$$x_1 = L_1 z_1 + \mu_1$$

where z_1 is also a vector of independent standard Normal variables. Therefore, x_1 also has multivariate Normal distribution with mean mu_1 and variance $L_1L_1^T = \Sigma_{11}$.

B

$$\begin{aligned}
\begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}^{-1} &= \begin{pmatrix} (\Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})^{-1} & -\Sigma_{11}^{-1}\Sigma_{12}(\Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12})^{-1} \\ -\Sigma_{22}^{-1}\Sigma_{21}(\Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})^{-1} & (\Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12})^{-1} \end{pmatrix} \\
&= \begin{pmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{12}^T & \Omega 22 \end{pmatrix}
\end{aligned}$$

C

$$\begin{aligned}
\log p(x_1|x_2) &= \log p(x_1, x_2) - \log(x_2) \\
&= \text{const} - \frac{(x-\mu)^T \Sigma^{-1} (x-\mu)}{2} \\
&= \text{const} - \frac{1}{2} \left\{ \begin{pmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{pmatrix}^T \begin{pmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{12}^T & \Omega 22 \end{pmatrix} \begin{pmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{pmatrix} \right\} \\
&= \text{const} - \frac{1}{2} \left\{ (x_1 - \mu_1)^T \Omega_{11} (x_1 - \mu_1) + (x_2 - \mu_2)^T \Omega_{12}^T (x_1 - \mu_1) \right. \\
&\left. + (x_1 - \mu_1)^T \Omega_{12} (x_2 - \mu_2) + (x_2 - \mu_2)^T \Omega_{22}^T (x_2 - \mu_2) \right\} \\
&= \text{const} - \frac{1}{2} \left\{ (x_1 - \mu_1)^T \Omega_{11} (x_1 - \mu_1) + 2(x_1 - \mu_1)^T \Omega_{12} (x_2 - \mu_2) \right\} \\
&= \text{const} - \frac{1}{2} \left\{ x_1^T \Omega_{11} x_1 - x_1^T \Omega_{11} \mu_1 - \mu_1^T \Omega_{11} x_1 + 2 x_1^T \Omega_{12} x_2 - 2 x_1^T \Omega_{12} \mu_2 \right\} \\
&= \text{const} - \frac{1}{2} \left\{ x_1^T \Omega_{11} x_1 + x_1^T \left(-\Omega_{11}\mu_1 - \Omega_{11}^T \mu_1 + 2\Omega_{12} x_2 - 2\Omega_{12}\mu_2 \right) \right\} \\
&= \text{const} - \frac{1}{2} \left\{ x_1^T \Omega_{11} x_1 - 2 x_1^T \Omega_{11} \left(\mu_1 - \Omega_{11}^{-1}\Omega_{12} x_2 + \Omega_{11}^{-1}\Omega_{12}\mu_2 \right) \right\} \\
&= \text{const} - \frac{1}{2} \left\{ (x_1 - \mu_{1|2})^T \Omega_{11} (x_1 - \mu_{1|2}) \right\}
\end{aligned}$$

where:

$$\mu_{1|2} = \mu_1 - \Omega_{11}^{-1}\Omega_{12} x_2 + \Omega_{11}^{-1}\Omega_{12}\mu_2$$

We also have:

$$\begin{aligned}
\Omega_{11}^{-1}\Omega_{12} &= (\Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{12}^T)(-\Sigma_{11}^{-1})\Sigma_{12}(\Sigma_{22} - \Sigma_{12}^T\Sigma_{11}^{-1}\Sigma_{12})^{-1} \\
&= (-\Sigma_{12} + \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{12}^T\Sigma_{11}^{-1}\Sigma_{12})(\Sigma_{22} - \Sigma_{12}^T\Sigma_{11}^{-1}\Sigma_{12})^{-1} \\
&= (-\Sigma_{12}\Sigma_{22}^{-1}\Sigma_{22} + \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{12}^T\Sigma_{11}^{-1}\Sigma_{12})(\Sigma_{22} - \Sigma_{12}^T\Sigma_{11}^{-1}\Sigma_{12})^{-1} \\
&= -\Sigma_{12}\Sigma_{22}^{-1}(\Sigma_{22} - \Sigma_{12}^T\Sigma_{11}^{-1}\Sigma_{12})(\Sigma_{22} - \Sigma_{12}^T\Sigma_{11}^{-1}\Sigma_{12})^{-1} \\
&= -\Sigma_{12}\Sigma_{22}^{-1}
\end{aligned}$$

Therefore,

$$\mu_{1|2} = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(x_2 - \mu_2)$$

We conclude that $p(x_1|x_2)$ has Normal distribution with mean $\mu_{1|2}$ given above and variance $\Omega_{11}^{-1} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{12}^T$

4 Multiple regression: three classical principles for inference

4.1 A

In the least square estimate, we minimize:

$$\begin{aligned}
L(\beta) &= \sum_{i=1}^{n}(y_i - x_i^T\beta)^2 \\
&= (y - X\beta)^T(y - X\beta) \\
&= -y^Ty - y^TX\beta - \beta^TX^Ty + \beta^TX^TX\beta
\end{aligned}$$

where we define $y = (y_1, \ldots, y_n)^T$ as a $n \times 1$ vector and $X = (x_1^T; \ldots; x_n^T)$ as a $n \times p$ matrix. We take the derivative of L and set to 0:

$$\begin{aligned}
\frac{\partial L}{\partial \beta} &= -X^Ty - X^Ty + X^TX\beta + X^TX\beta \\
&= 2X^T(X\beta - y) \\
&\text{set } = 0 \\
\implies X^TX\beta &= X^Ty \\
\beta &= (X^TX)^{-1}X^Ty
\end{aligned}$$

In the maximum likelihood estimate, we maximize:

$$\begin{aligned}
L(\beta) &= \prod_{i=1}^{n} p(y_i \mid \beta, \sigma^2) \\
&= N(y \mid X\beta, \sigma^2 I) \\
&\propto \exp\left(-\frac{1}{2}(y - X\beta)^T\frac{1}{\sigma^2}I(y - X\beta)\right)
\end{aligned}$$

which is equivalent to minimize:

$$\begin{aligned}
&(y - X\beta)^T\frac{1}{\sigma^2}I(y - X\beta) \\
&\propto (y - X\beta)^T(y - X\beta)
\end{aligned}$$

which is the same as the least square objective function.

In the method of moment estimate, we set:

$$\text{cov}(y - X\beta, X_j) = 0$$

where X_j is the column j of X for $j = 1, \ldots, p$. We have:

$$\begin{aligned}
&\text{cov}(y - X\beta, X_j) = 0 \quad \forall j \\
\iff &(y - X\beta)^T X_j = 0 \quad \forall j \\
\iff &(y - X\beta)^T X = 0 \\
\iff &X^T(X\beta - y) = 0
\end{aligned}$$

This is the same as the equation that we solve in least square.

B

The weighted sum of squared error is:

$$L(\beta) = \sum_{i=1}^{n} w_i (y_i - x_i^T \beta)^2$$

We first take the derivative with respect to β:

$$\frac{\partial L}{\partial \beta} = \sum_{i=1}^{n} w_i (2)(y_i - x_i^T \beta)(-x_i)$$

Setting the derivative to 0, we have:

$$\begin{aligned}
\sum_{i=1}^{n} w_i x_i (y_i - x_i^T \beta) &= 0 \\
\iff \sum_{i=1}^{n} w_i x_i y_i - \sum_{i=1}^{n} w_i x_i x_i^T \beta &= 0 \\
\iff \sum_{i=1}^{n} w_i x_{ik} y_i - \sum_{i=1}^{n} w_i x_{ik} x_i^T \beta_k = 0 &\quad \forall k = 1, \ldots, p \\
\iff \beta_k = \frac{\sum_{i=1}^{n} w_i x_{ik} y_i}{\sum_{i=1}^{n} w_i x_{ik} x_i^T \beta_k} &\quad \forall k = 1, \ldots, p
\end{aligned}$$

The maximum likelihood under heteroskedastic Gaussian error is:

$$\begin{aligned}
L(\beta) &= \prod_{i=1}^{n} p(y_i \mid \beta, \sigma_i^2) \\
&= N(y \mid X\beta, C)
\end{aligned}$$

where the covariance matrix is C is a diagonal matrix such that $C_{ii} = \sigma_i^2$. We have that $C^{-1} = D$ is a diagonal matrix such that $D_{ii} = 1/\sigma_i^2$. The maximum likelihood is then:

$$L(\beta) = N(y \mid X\beta, C) \propto \exp\left(-\frac{1}{2}(y - X\beta)^T D(y - X\beta)\right)$$

Maximizing the that likelihood is the same as minimizing:

$$\begin{aligned}(y - X\beta)^T D(y - X\beta) &= \sum_{i=1}^{n}(y_i - x_i^T\beta)\frac{1}{\sigma^2}(y_i - x_i^T\beta) \\ &= \sum_{i=1}^{n} w_i(y_i - x_i^T\beta)^2\end{aligned}$$

where $w_i = \frac{1}{\sigma_i^2}$.

This is the same objective as the weighted least square.

5 Quantifying uncertainty: some basic frequentist ideas

In linear regression

A

The estimate is:

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

which is a linear combination of y. Since y has Normal distribution, $\hat{\beta}$ also has Normal distribution.

$$\begin{aligned}E(\hat{\beta}) &= (X^T X)^{-1} X^T E(y) \\ &= (X^T X)^{-1} X^T X\beta \\ &= \beta\end{aligned}$$

$$\begin{aligned}\text{cov}(\hat{\beta}) &= (X^T X)^{-1} X^T \text{cov}(x) X (X^T X)^{-T} \\ &= (X^T X)^{-1} X^T (\sigma^2 I) X (X^T X)^{-T} \\ &= \sigma^2 (X^T X)^{-1} X^T X (X^T X)^{-T} \\ &= \sigma^2 (X^T X)^{-T}\end{aligned}$$

B

We can estimate σ^2 by:

$$\hat{\sigma^2} = \frac{\sum_{i=1}^{n} \hat{\epsilon}_i^2}{n-2} = \frac{\sum_{i=1}^{n} (x_i\hat{\beta} - y_i)^2}{n-2} = \frac{(X\hat{\beta} - y)^T(X\hat{\beta} - y)}{n-2}$$

Propagating uncertainty

A

B

We first approximate f by a first order Taylor approximation:

$$\begin{aligned} f(\hat{\theta}) &\approx f(\theta) + f'(\theta)^T(\hat{\theta} - \theta) \\ &= f(\theta) + \sum_{i=1}^{p} f'(\theta_i)(\hat{\theta}_i - \theta_i) \end{aligned}$$

We then approximate the variance of f by the variance of the approximation:

$$\begin{aligned} \mathrm{var}[f(\hat{\theta})] &\approx \mathrm{var}[f(\theta) + \sum_{i=1}^{p} f'(\theta_i)(\hat{\theta}_i - \theta_i)] \\ &= \sum_{i=1}^{p} f'(\theta_i)^2 \mathrm{var}(\hat{\theta}_i) + \sum_{i \neq j} f'(\theta_i) f'(\theta_j) \mathrm{cov}(\hat{\theta}_i, \hat{\theta}_j) \\ &\approx \sum_{i=1}^{p} f'(\hat{\theta}_i)^2 \Sigma_{ii} + \sum_{i \neq j} f'(\hat{\theta}_i) f'(\hat{\theta}_j) \Sigma_{ij} \end{aligned}$$

For this to be a good approximation, f should be approximately linear around θ so that the Taylor approximation is close. We have also approximated $f'(\theta)$ by $f'(\hat{\theta})$, so we need $\hat{\theta}$ to be close to θ.

The bootstrap

A

```
> sqrt(diag(bcov))
 [1] 3.548986e+01 6.755316e-03 1.620715e-01 2.434152e-02 6.610008e-02 1.157898e-01 3.741294e
> sqrt(diag(betacovlm))
           x          xV5          xV6          xV7          xV8          xV9         xV10
3.832869e+01 7.251104e-03 1.741433e-01 2.376936e-02 6.929942e-02 1.247136e-01 3.943697e-04 1
```