

Solutions Manual to Pattern Recognition and Machine Learning

Hiromichi Inawashiro

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1 Introduction

1.1

Let

$$E(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^N (y(x_n, \mathbf{w}) - t_n)^2. \quad (1.1)$$

Setting the derivative to zero gives

$$\mathbf{0} = \sum_{n=1}^N \frac{\partial y(x_n, \mathbf{w})}{\partial \mathbf{w}} (y(x_n, \mathbf{w}) - t_n). \quad (1.2)$$

Substituting

$$y(x_n, \mathbf{w}) = \sum_{j=0}^M w_j x_n^j \quad (1.3)$$

gives

$$0 = \sum_{n=1}^N x_n^i \left(\sum_{j=0}^M w_j x_n^j - t_n \right). \quad (1.4)$$

Therefore,

$$\operatorname{argmin}_{w_j} E(\mathbf{w}) = \left\{ w_j \mid \sum_{j=0}^M A_{ij} w_j = T_i \right\}, \quad (1.5)$$

where

$$\begin{aligned} A_{ij} &= \sum_{n=1}^N x_n^{i+j}, \\ T_i &= \sum_{n=1}^N x_n^i t_n. \end{aligned} \quad (1.6)$$

1.2

Let

$$\tilde{E}(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^N (y(x_n, \mathbf{w}) - t_n)^2 + \frac{\lambda}{2} \|\mathbf{w}\|^2. \quad (1.7)$$

Setting the derivative to zero gives

$$\mathbf{0} = \sum_{n=1}^N \frac{\partial y(x_n, \mathbf{w})}{\partial \mathbf{w}} (y(x_n, \mathbf{w}) - t_n) + \lambda \mathbf{w}. \quad (1.8)$$

Substituting

$$y(x_n, \mathbf{w}) = \sum_{j=0}^M w_j x_n^j \quad (1.9)$$

gives

$$0 = \sum_{n=1}^N x_n^i \left(\sum_{j=0}^M w_j x_n^j - t_n \right) + \lambda w_i. \quad (1.10)$$

Therefore,

$$\operatorname{argmin}_{w_j} E(\mathbf{w}) = \left\{ w_j \mid \sum_{j=0}^M \tilde{A}_{ij} w_j = T_i \right\}, \quad (1.11)$$

where

$$\begin{aligned} \tilde{A}_{ij} &= \sum_{n=1}^N x_n^{i+j} + \lambda \delta_{ij}, \\ T_i &= \sum_{n=1}^N x_n^i t_n. \end{aligned} \quad (1.12)$$

1.3

Let a , o and l be the events where an apple, orange and lime are selected respectively. The probability that an apple is selected is given by

$$p(a) = p(a|r)p(r) + p(a|b)p(b) + p(a|g)p(g). \quad (1.13)$$

Substituting $p(a|r) = \frac{3}{10}$, $p(r) = \frac{1}{5}$, $p(a|g) = \frac{1}{2}$, $p(r) = \frac{1}{5}$, $p(a|g) = \frac{3}{10}$ and $p(g) = \frac{3}{5}$ gives

$$p(a) = \frac{17}{50}. \quad (1.14)$$

If an orange is selected, the probability that it came from the geen box is given by

$$p(g|o) = \frac{p(g, o)}{p(o)}. \quad (1.15)$$

Here,

$$\begin{aligned} p(g, o) &= p(o|g)p(g), \\ p(o) &= p(o|r)p(r) + p(o|b)p(b) + p(o|g)p(g). \end{aligned} \quad (1.16)$$

Substituting $p(o|r) = \frac{2}{5}$, $p(r) = \frac{1}{5}$, $p(o|b) = \frac{1}{2}$, $p(b) = \frac{1}{5}$, $p(o|g) = \frac{3}{10}$ and $p(g) = \frac{3}{5}$ gives $p(g, o) = \frac{9}{50}$ and $p(o) = \frac{9}{25}$. Therefore,

$$p(g|o) = \frac{1}{2}. \quad (1.17)$$

1.4

Let

$$x = g(y) \quad (1.18)$$

and \hat{x} and \hat{y} be the locations of the maximum of $p_x(x)$ and $p_y(y)$ respectively. Let us assume that there exists $\epsilon > 0$ such that $g'(y) \neq 0$ for $|y - \hat{y}| < \epsilon$. Then, Taking the derivative of the transformation

$$p_y(y) = p_x(g(y)) |g'(y)| \quad (1.19)$$

and substituting $y = \hat{y}$ gives

$$0 = g'(\hat{y})p'_x(g(\hat{y})) + p_x(g(\hat{y}))g''(\hat{y}). \quad (1.20)$$

Therefore, in general,

$$\hat{x} \neq g(\hat{y}). \quad (1.21)$$

Here, let us assume that

$$g(y) = ay + b. \quad (1.22)$$

Then, Taking the derivative of the transformation and substituting $y = \hat{y}$ gives

$$0 = p'_x(g(\hat{y})). \quad (1.23)$$

Therefore,

$$\hat{x} = g(\hat{y}). \quad (1.24)$$

1.5

By the definition,

$$\text{var } f(x) = E(f(x) - E f(x))^2. \quad (1.25)$$

The right hand side can be written as

$$E((f(x))^2 - 2f(x) E f(x) + (E f(x))^2) = E(f(x))^2 - (E f(x))^2. \quad (1.26)$$

Therefore,

$$\text{var } f(x) = E(f(x))^2 - (E f(x))^2. \quad (1.27)$$

1.6

By the definition,

$$\text{cov}(x, y) = E((x - E x)(y - E y)). \quad (1.28)$$

The right hand side can be written as

$$E xy - E(x E y) - E(y E x) + E(E x E y) = E xy - E x E y. \quad (1.29)$$

The right hand side can be written as

$$\int xyp(x, y)dxdy - \int xp(x)dx \int yp(y)dy. \quad (1.30)$$

If x and y are independent, by the definition,

$$f(x, y) = f(x)f(y). \quad (1.31)$$

Then,

$$\int xyp(x, y)dxdy = \int p(x)dx \int p(y)dy. \quad (1.32)$$

Therefore,

$$\text{cov}(x, y) = 0. \quad (1.33)$$

1.7

Let

$$I = \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}x^2\right) dx. \quad (1.34)$$

Then

$$I^2 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x^2 + y^2)\right) dx dy. \quad (1.35)$$

By the transformation from Cartesian coordinates (x, y) to polar coordinates (r, θ) , the right hand side can be written as

$$\int_0^{\infty} \int_0^{2\pi} \exp\left(-\frac{1}{2\sigma^2}r^2\right) \begin{vmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{vmatrix} dr d\theta = 2\pi \int_0^{\infty} \exp\left(-\frac{1}{2\sigma^2}r^2\right) r dr. \quad (1.36)$$

By the transformation $s = \frac{r}{\sigma}$, the right hand side can be written as

$$2\pi\sigma^2 \int_0^{\infty} \exp\left(-\frac{1}{2}s^2\right) s ds = 2\pi\sigma^2 \left[-\exp\left(-\frac{1}{2}s^2\right)\right]_0^{\infty}. \quad (1.37)$$

Therefore,

$$I = (2\pi\sigma^2)^{\frac{1}{2}}. \quad (1.38)$$

By the definition,

$$\mathcal{N}(x|\mu, \sigma^2) = (2\pi\sigma^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right). \quad (1.39)$$

Then

$$\int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) dx = (2\pi\sigma^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) dx. \quad (1.40)$$

By the transformation $t = x - \mu$, the right hand side can be written as

$$(2\pi\sigma^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}t^2\right) dt = (2\pi\sigma^2)^{-\frac{1}{2}} I. \quad (1.41)$$

Therefore,

$$\int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) dx = 1. \quad (1.42)$$

1.8

Let x be a variable such that

$$p(x) = \mathcal{N}(x|\mu, \sigma^2). \quad (1.43)$$

Then

$$\mathbb{E} x = \int_{-\infty}^{\infty} x \mathcal{N}(x|\mu, \sigma^2) dx. \quad (1.44)$$

By the definition, the right hand side can be written as

$$(2\pi\sigma^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} x \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) dx. \quad (1.45)$$

By the transformation $y = x - \mu$, it can be written as

$$(2\pi\sigma^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} (y + \mu) \exp\left(-\frac{1}{2\sigma^2}y^2\right) dy. \quad (1.46)$$

Since

$$(2\pi\sigma^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} y \exp\left(-\frac{1}{2\sigma^2}y^2\right) dy = 0, \quad (1.47)$$

and

$$(2\pi\sigma^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} \mu \exp\left(-\frac{1}{2\sigma^2}y^2\right) dy = \mu \int_{-\infty}^{\infty} \mathcal{N}(y|\mu, \sigma^2) dy, \quad (1.48)$$

we have

$$\mathbb{E} x = \mu. \quad (1.49)$$

By the definition,

$$\int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) dx = 1 \quad (1.50)$$

can be written as

$$(2\pi\sigma^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) dx = 1. \quad (1.51)$$

Taking the derivative with respect to σ^2 gives

$$\begin{aligned} & (2\pi)^{-\frac{1}{2}} \left(-\frac{1}{2}\right) (\sigma^2)^{-\frac{3}{2}} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) dx \\ & + (2\pi\sigma^2)^{-\frac{1}{2}} \int_{-\infty}^{\infty} \frac{1}{2} (\sigma^2)^{-2} (x-\mu)^2 \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) dx = 0. \end{aligned} \quad (1.52)$$

The left hand side can be written as

$$\begin{aligned} -\frac{1}{2}(\sigma^2)^{-1} \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) dx + \frac{1}{2}(\sigma^2)^{-2} \int_{-\infty}^{\infty} (x - \mu)^2 \mathcal{N}(x|\mu, \sigma^2) dx \\ = -\frac{1}{2}(\sigma^2)^{-1} + \frac{1}{2}(\sigma^2)^{-2} \text{var } x. \end{aligned} \quad (1.53)$$

Therefore,

$$\text{var } x = \sigma^2. \quad (1.54)$$

1.9

Let

$$\mathcal{N}(x|\mu, \sigma^2) = (2\pi\sigma^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right). \quad (1.55)$$

Setting its derivative with respect to x to zero gives

$$0 = (2\pi\sigma^2)^{-\frac{1}{2}} \left(-\frac{1}{\sigma^2}(x - \mu)\right) \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right). \quad (1.56)$$

Therefore, the mode is given by μ .

Similarly, let

$$\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) = (2\pi)^{-\frac{D}{2}} (\det \boldsymbol{\Sigma})^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right). \quad (1.57)$$

Setting its derivative with respect to \mathbf{x} to zero gives

$$\mathbf{0} = -(2\pi)^{-\frac{D}{2}} (\det \boldsymbol{\Sigma})^{-\frac{1}{2}} (\boldsymbol{\Sigma}^{-1} + (\boldsymbol{\Sigma}^{-1})^\top) (\mathbf{x} - \boldsymbol{\mu}) \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right). \quad (1.58)$$

Therefore, the mode is given by $\boldsymbol{\mu}$.

1.10

By the definition,

$$\mathbb{E}(x + y) = \int \int (x + y) p(x, y) dx dy. \quad (1.59)$$

The right hand side can be written as

$$\int x \left(\int p(x, y) dy \right) dx + \int y \left(\int p(x, y) dx \right) dy = \int xp(x) dx + \int yp(y) dy. \quad (1.60)$$

By the definition, the right hand side can be written as

$$E x + E y. \quad (1.61)$$

Therefore,

$$E(x + y) = E x + E y. \quad (1.62)$$

Similarly, by the definition,

$$\text{var}(x + y) = E (x + y - E(x + y))^2 \quad (1.63)$$

By the result above and the definition, the right hand side can be written as

$$\begin{aligned} E (x - E x)^2 + 2 E ((x - E x) (y - E y)) + E (y - E y)^2 \\ = \text{var } x + 2 \text{cov}(x, y) + \text{var } y. \end{aligned} \quad (1.64)$$

If x and y are independent, then

$$\text{cov}(x, y) = 0, \quad (1.65)$$

by 1.6. Therefore,

$$\text{var}(x + y) = \text{var } x + \text{var } y. \quad (1.66)$$

1.11

Let \mathbf{x} be a set of N variables such that

$$\ln p(\mathbf{x}|\mu, \sigma^2) = -\frac{N}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu)^2. \quad (1.67)$$

To maximise it with respect to μ and σ^2 , setting the partial derivatives to zero gives

$$\begin{aligned} 0 &= \frac{1}{\sigma^2} \sum_{n=1}^N (x_n - \mu), \\ 0 &= -\frac{N}{2\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum_{n=1}^N (x_n - \mu)^2. \end{aligned} \quad (1.68)$$

Therefore,

$$\begin{aligned}\mu_{\text{ML}} &= \frac{1}{N} \sum_{n=1}^N x_n, \\ \sigma_{\text{ML}}^2 &= \frac{1}{N} \sum_{n=1}^N (x_n - \mu_{\text{ML}})^2.\end{aligned}\tag{1.69}$$

1.12

Let x_m and x_n be independent variables. Then

$$\mathbb{E} x_m x_n = \mathbb{E} x_m \mathbb{E} x_n.\tag{1.70}$$

If they are samples from the Gaussian distribution with mean μ and variance σ^2 , the right hand side is given by μ^2 . On the other hand, by the definition,

$$\mathbb{E} x_n^2 = \text{var } x_n + (\mathbb{E} x_n)^2.\tag{1.71}$$

If x_n is a sample from the Gaussian distribution with mean μ and variance σ^2 , the right hand side is given by $\sigma^2 + \mu^2$. Therefore,

$$\mathbb{E} x_m x_n = \mu^2 + \delta_{mn} \sigma^2.\tag{1.72}$$

Here, since

$$\mu_{\text{ML}} = \frac{1}{N} \sum_{n=1}^N x_n,\tag{1.73}$$

we have

$$\mathbb{E} \mu_{\text{ML}} = \frac{1}{N} \sum_{n=1}^N \mathbb{E} x_n.\tag{1.74}$$

Therefore,

$$\mathbb{E} \mu_{\text{ML}} = \mu.\tag{1.75}$$

Similarly, since

$$\sigma_{\text{ML}}^2 = \frac{1}{N} \sum_{n=1}^N (x_n - \mu_{\text{ML}})^2,\tag{1.76}$$

we have

$$\mathbb{E} \sigma_{\text{ML}}^2 = \frac{1}{N} \sum_{n=1}^N \mathbb{E} (x_n - \mu_{\text{ML}})^2.\tag{1.77}$$

The right hand side can be written as

$$\frac{1}{N} \sum_{n=1}^N \mathbb{E} (x_n^2 - 2\mu_{\text{ML}} x_n + \mu_{\text{ML}}^2) = \frac{1}{N} \sum_{n=1}^N \mathbb{E} x_n^2 - \frac{2}{N} \mathbb{E} \left(\mu_{\text{ML}} \left(\sum_{n=1}^N x_n \right) \right) + \mathbb{E} \mu_{\text{ML}}^2. \quad (1.78)$$

The first term of the right hand side can be written as

$$\frac{1}{N} \sum_{n=1}^N (\mu^2 + \sigma^2) = \mu^2 + \sigma^2, \quad (1.79)$$

while the second and third terms can be written as

$$-2 \mathbb{E} \mu_{\text{ML}}^2 + \mathbb{E} \mu_{\text{ML}}^2 = -\mathbb{E} \mu_{\text{ML}}^2. \quad (1.80)$$

Here,

$$\mathbb{E} \mu_{\text{ML}}^2 = \mathbb{E} \left(\frac{1}{N} \sum_{n=1}^N x_n \right)^2. \quad (1.81)$$

The right hand side can be written as

$$\frac{1}{N^2} \sum_{n=1}^N \mathbb{E} x_n^2 + \frac{2}{N^2} \sum_{1 \leq m < n \leq N} \mathbb{E} x_m x_n = \frac{1}{N} (\mu^2 + \sigma^2) + \frac{N-1}{N} \mu^2. \quad (1.82)$$

Therefore,

$$\mathbb{E} \mu_{\text{ML}}^2 = \mu^2 + \frac{1}{N} \sigma^2. \quad (1.83)$$

Thus,

$$\mathbb{E} \sigma_{\text{ML}}^2 = \frac{N-1}{N} \sigma^2. \quad (1.84)$$

1.13

Let $\{x_n\}$ be a set of variables whose mean is μ and variance is σ^2 . Then

$$\mathbb{E} \left(\frac{1}{N} \sum_{n=1}^N (x_n - \mu)^2 \right) = \frac{1}{N} \sum_{n=1}^N \mathbb{E} (x_n - \mu)^2. \quad (1.85)$$

The right hand side can be written as

$$\frac{1}{N} \sum_{n=1}^N \mathbb{E} (x_n^2 - 2\mu x_n + \mu^2) = \frac{1}{N} \sum_{n=1}^N \mathbb{E} x_n^2 - \frac{2\mu}{N} \sum_{n=1}^N \mathbb{E} x_n + \mu^2. \quad (1.86)$$

The first term of the right hand side can be written as

$$\frac{1}{N} \sum_{n=1}^N (\mu^2 + \sigma^2) = \mu^2 + \sigma^2, \quad (1.87)$$

while the second term can be written as

$$-\frac{2\mu}{N} \sum_{n=1}^N \mu = -2\mu^2. \quad (1.88)$$

Therefore,

$$\mathbb{E} \left(\frac{1}{N} \sum_{n=1}^N (x_n - \mu)^2 \right) = \sigma^2. \quad (1.89)$$

1.14

Let

$$\begin{aligned} w_{ij}^S &= \frac{1}{2}(w_{ij} + w_{ji}), \\ w_{ij}^A &= \frac{1}{2}(w_{ij} - w_{ji}). \end{aligned} \quad (1.90)$$

Then

$$\begin{aligned} w_{ij} &= w_{ij}^S + w_{ij}^A, \\ w_{ij}^S &= w_{ji}^S, \\ w_{ij}^A &= -w_{ji}^A. \end{aligned} \quad (1.91)$$

Here,

$$\sum_{i=1}^D \sum_{j=1}^D w_{ij}^A x_i x_j = \frac{1}{2} \sum_{i=1}^D \sum_{j=1}^D (w_{ij} - w_{ji}) x_i x_j. \quad (1.92)$$

The right hand side can be written as

$$\frac{1}{2} \left(\sum_{i=1}^D \sum_{j=1}^D w_{ij} x_i x_j - \sum_{i=1}^D \sum_{j=1}^D w_{ji} x_i x_j \right) = 0. \quad (1.93)$$

Therefore,

$$\sum_{i=1}^D \sum_{j=1}^D w_{ij}^A x_i x_j = 0. \quad (1.94)$$

Additionally,

$$\sum_{i=1}^D \sum_{j=1}^D w_{ij} x_i x_j = \sum_{i=1}^D \sum_{j=1}^D (w_{ij}^S + w_{ij}^A) x_i x_j. \quad (1.95)$$

The right hand side can be written as

$$\sum_{i=1}^D \sum_{j=1}^D w_{ij}^S x_i x_j + \sum_{i=1}^D \sum_{j=1}^D w_{ij}^A x_i x_j = \sum_{i=1}^D \sum_{j=1}^D w_{ij}^S x_i x_j, \quad (1.96)$$

where the result above is used. Therefore,

$$\sum_{i=1}^D \sum_{j=1}^D w_{ij} x_i x_j = \sum_{i=1}^D \sum_{j=1}^D w_{ij}^S x_i x_j. \quad (1.97)$$

Finally, since the matrix w_{ij}^S is a $D \times D$ symmetric matrix, its number of independent parameters is $\frac{D(D+1)}{2}$.

1.15

Let $n(D, M)$ be the number of independent parameters of a polynomial in D dimensions and M orders. Then

$$n(1, M) = n(1, M - 1) = 1. \quad (1.98)$$

Let us assume that

$$n(D, M) = \sum_{i=1}^D n(i, M - 1). \quad (1.99)$$

The independent terms of a polynomial in $D + 1$ dimensions and M orders can be split into 1. the ones of a polynomial in D dimensions and M orders and 2. the ones generated by multiplying the ones in $D + 1$ dimensions and M orders by the $D + 1$ th variable. Therefore,

$$n(D + 1, M) = n(D, M) + n(D + 1, M - 1). \quad (1.100)$$

Thus,

$$n(D + 1, M) = \sum_{i=1}^{D+1} n(i, M - 1). \quad (1.101)$$

Hence, the assumption is proved by induction on D .

Additionally,

$$\sum_{i=1}^1 \frac{(i+M-2)!}{(i-1)!(M-1)!} = 1. \quad (1.102)$$

Let us assume that

$$\sum_{i=1}^D \frac{(i+M-2)!}{(i-1)!(M-1)!} = \frac{(D+M-1)!}{(D-1)!M!}. \quad (1.103)$$

Then

$$\sum_{i=1}^{D+1} \frac{(i+M-2)!}{(i-1)!(M-1)!} = \frac{(D+M-1)!}{(D-1)!M!} + \frac{(D+M-1)!}{D!(M-1)!}. \quad (1.104)$$

The right hand side can be written as

$$\frac{D(D+M-1)! + M(D+M-1)!}{D!M!} = \frac{(D+M)!}{D!M!}. \quad (1.105)$$

Therefore, the assumption is proved by induction on D .

Finally, by 1.14,

$$n(D, 2) = \frac{D(D+1)}{2}. \quad (1.106)$$

Let us assume that

$$n(D, M) = \frac{(D+M-1)!}{(D-1)!M!}. \quad (1.107)$$

Then, by the result above,

$$n(D, M+1) = \sum_{i=1}^D n(i, M). \quad (1.108)$$

By the assumption and result above, the right hand side can be written as

$$\sum_{i=1}^D \frac{(i+M-1)!}{(i-1)!M!} = \frac{(D+M)!}{(D-1)!(M+1)!}. \quad (1.109)$$

Therefore, the assumption is proved by induction on M .

1.16

Let $N(D, M)$ be the number of independent parameters in all of the terms up to and including the ones of D dimensions and M orders. Then, by 1.15,

$$N(D, M) = \sum_{m=0}^M n(D, m), \quad (1.110)$$

where

$$n(D, m) = \frac{(D + m - 1)!}{(D - 1)!m!}. \quad (1.111)$$

Additionally,

$$N(D, 0) = 1. \quad (1.112)$$

Let us assume that

$$\sum_{m=0}^M n(D, m) = \frac{(D + M)!}{D!M!}. \quad (1.113)$$

Then

$$\sum_{m=0}^{M+1} n(D, m) = \frac{(D + M)!}{D!M!} + \frac{(D + M)!}{(D - 1)!(M + 1)!}. \quad (1.114)$$

The right hand side can be written as

$$\frac{(M + 1)(D + M)! + D(D + M)!}{D!(M + 1)!} = \frac{(D + M + 1)!}{D!(M + 1)!}. \quad (1.115)$$

Therefore, the assumption is proved by induction on M . Thus,

$$N(D, M) = \frac{(D + M)!}{D!M!}. \quad (1.116)$$

Additionally, by the approximation

$$n! \simeq n^n \exp(-n), \quad (1.117)$$

the right hand side can be approximated as

$$\frac{(D + M)^{D+M} \exp(-(D + M))}{D^D \exp(-D) M^M \exp(-M)} = \frac{(D + M)^{D+M}}{D^D M^M}. \quad (1.118)$$

The right hand side can be written as

$$D^M \left(1 + \frac{M}{D}\right)^D \left(\frac{1}{M} + \frac{1}{D}\right)^M = M^D \left(1 + \frac{D}{M}\right)^M \left(\frac{1}{D} + \frac{1}{M}\right)^D. \quad (1.119)$$

Therefore, $N(D, M)$ can be approximated as D^M for $D \gg M$ and as M^D for $M \gg D$.

Finally, by the result above,

$$\begin{aligned} N(10, 3) &= 286, \\ N(100, 3) &= 176851, \\ N(1000, 3) &= 167668501. \end{aligned} \quad (1.120)$$

1.17

Let

$$\Gamma(x) = \int_0^\infty u^{x-1} \exp(-u) du. \quad (1.121)$$

Then

$$\Gamma(x+1) = \int_0^\infty u^x \exp(-u) du. \quad (1.122)$$

The right hand side can be written as

$$[-u^x \exp(-u)]_{u=0}^{u=\infty} + \int_0^\infty x u^{x-1} \exp(-u) du = x \Gamma(x). \quad (1.123)$$

Therefore,

$$\Gamma(x+1) = x \Gamma(x). \quad (1.124)$$

Since

$$\Gamma(1) = \int_0^1 \exp(-u) du, \quad (1.125)$$

and the right hand side can be written as 1,

$$\Gamma(1) = 0!. \quad (1.126)$$

For a positive integer x , let us assume that

$$\Gamma(x) = (x-1)!. \quad (1.127)$$

Then,

$$\Gamma(x+1) = x\Gamma(x), \quad (1.128)$$

where the right hand side can be written as $x!$. Therefore,

$$\Gamma(x+1) = x!. \quad (1.129)$$

Thus, the assumption is proved by induction on x .

1.18

Let us consider the transformation from Cartesian to polar coordinates

$$\prod_{i=1}^D \int_{-\infty}^{\infty} \exp(-x_i^2) dx_i = S_D \int_0^{\infty} \exp(-r^2) r^{D-1} dr, \quad (1.130)$$

where S_D is the surface area of a sphere of unit radius in D dimensions. By 1.7, the left hand side can be written as $\pi^{\frac{D}{2}}$. By the transformation $s = r^2$, the right hand side can be written as

$$\frac{S_D}{2} \int_0^{\infty} \exp(-s) s^{\frac{D-1}{2}} s^{-\frac{1}{2}} ds = \frac{S_D}{2} \Gamma\left(\frac{D}{2}\right). \quad (1.131)$$

Therefore,

$$S_D = \frac{2\pi^{\frac{D}{2}}}{\Gamma\left(\frac{D}{2}\right)}. \quad (1.132)$$

Additionally, the volume of the sphere can be written as

$$V_D = S_D \int_0^1 r^{D-1} dr. \quad (1.133)$$

The right hand side can be written as

$$S_D \left[\frac{r^D}{D} \right]_{r=0}^{r=1} = \frac{S_D}{D}. \quad (1.134)$$

Therefore,

$$V_D = \frac{S_D}{D}. \quad (1.135)$$

Finally, the results above reduce to

$$\begin{aligned} S_2 &= \frac{2\pi}{\Gamma(1)}, \\ V_2 &= \frac{S_2}{2}. \end{aligned} \tag{1.136}$$

Therefore,

$$\begin{aligned} S_2 &= 2\pi, \\ V_2 &= \pi. \end{aligned} \tag{1.137}$$

Similarly,

$$\begin{aligned} S_3 &= \frac{2\pi^{\frac{3}{2}}}{\Gamma(\frac{3}{2})}, \\ V_3 &= \frac{S_3}{3}. \end{aligned} \tag{1.138}$$

Therefore,

$$\begin{aligned} S_3 &= 4\pi, \\ V_3 &= \frac{4}{3}\pi. \end{aligned} \tag{1.139}$$

1.19

The volume of a cube of side 2 in D dimensions is 2^D . Therefore, the ratio of the volume of the cocentric sphere of radius 1 divided by the volume of the cube is given by

$$\frac{V_D}{2^D} = \frac{\pi^{\frac{D}{2}}}{D2^{D-1}\Gamma(\frac{D}{2})}, \tag{1.140}$$

by 1.18.

Additionally, by Stering's formula

$$\Gamma(x+1) \simeq (2\pi)^{\frac{1}{2}} \exp(-x) x^{\frac{x+1}{2}}, \tag{1.141}$$

the ratio can be approximated as

$$\frac{V_D}{2^D} \simeq \frac{\pi^{\frac{D}{2}}}{D2^{D-1}(2\pi)^{\frac{1}{2}} \exp\left(1 - \frac{D}{2}\right) \left(\frac{D}{2} - 1\right)^{\frac{D}{4}}}. \tag{1.142}$$

The right hand side can be written as

$$\frac{1}{2e(2\pi)^{\frac{1}{2}}} \frac{1}{D} \left(\frac{e^2 \pi^2}{8D - 16} \right)^{\frac{D}{4}}. \quad (1.143)$$

Therefore, the ratio goes to zero as $D \rightarrow \infty$.

Finally, the ratio of the distance from the center of the cube to one of the corners divided by the perpendicular distance to one of the sides is given by

$$\frac{\sqrt{\sum_{i=1}^D 1^2}}{1} = \sqrt{D}. \quad (1.144)$$

Therefore, the ration goes to ∞ as $D \rightarrow \infty$.

1.20

For a vector \mathbf{x} in D dimensions, let

$$p(\mathbf{x}) = (2\pi\sigma^2)^{-\frac{D}{2}} \exp\left(-\frac{\|\mathbf{x}\|^2}{2\sigma^2}\right). \quad (1.145)$$

Then

$$\int_{r \leq \|\mathbf{x}\| \leq r+\epsilon} p(\mathbf{x}) d\mathbf{x} = \int_r^{r+\epsilon} \int (2\pi\sigma^2)^{-\frac{D}{2}} \exp\left(-\frac{r'^2}{2\sigma^2}\right) J dr' d\phi, \quad (1.146)$$

where ϕ is the vector of the angular components of the polar corrdinate and J is the Jacobian of the transformation from the Cartesian to polar coordinate. For a sufficiently small ϵ , the right hand side can be approximated as

$$\begin{aligned} & (2\pi\sigma^2)^{-\frac{D}{2}} \exp\left(-\frac{r^2}{2\sigma^2}\right) \int_r^{r+\epsilon} \int J dr' d\phi \\ &= (2\pi\sigma^2)^{-\frac{D}{2}} \exp\left(-\frac{r^2}{2\sigma^2}\right) \int_{r \leq \|\mathbf{x}\| \leq r+\epsilon} d\mathbf{x}. \end{aligned} \quad (1.147)$$

Therefore,

$$\int_{r \leq \|\mathbf{x}\| \leq r+\epsilon} p(\mathbf{x}) d\mathbf{x} \simeq p(r)\epsilon, \quad (1.148)$$

where

$$p(r) = (2\pi\sigma^2)^{-\frac{D}{2}} S_D r^{D-1} \exp\left(-\frac{r^2}{2\sigma^2}\right), \quad (1.149)$$

and S_D is the surface area of a unit sphere in D dimensions.

Additionally, setting the derivative of $p(r)$ to zero gives

$$0 = (2\pi\sigma^2)^{-\frac{D}{2}} S_D \left((D-1)r^{D-2} - \frac{r^D}{\sigma^2} \right) \exp\left(-\frac{r^2}{2\sigma^2}\right). \quad (1.150)$$

Therefore, $p(r)$ is maximised at a single stationary point

$$\hat{r} = \sqrt{D-1}\sigma. \quad (1.151)$$

Additionally, by the expression of $p(r)$ above,

$$\frac{p(\hat{r} + \epsilon)}{p(\hat{r})} = \left(\frac{\hat{r} + \epsilon}{\hat{r}} \right)^{D-1} \exp\left(-\frac{2\hat{r}\epsilon + \epsilon^2}{2\sigma^2}\right). \quad (1.152)$$

Using the expression of \hat{r} above, the right hand side can be written as

$$\begin{aligned} & \exp\left((D-1)\ln\left(1 + \frac{\epsilon}{\hat{r}}\right) - \frac{2\hat{r}\epsilon + \epsilon^2}{2\sigma^2}\right) \\ &= \exp\left(\frac{\hat{r}^2}{\sigma^2}\ln\left(1 + \frac{\epsilon}{\hat{r}}\right) - \frac{2\hat{r}\epsilon + \epsilon^2}{2\sigma^2}\right). \end{aligned} \quad (1.153)$$

By the Taylor series

$$\ln(1+x) = x - \frac{1}{2}x^2 + o(x^3), \quad (1.154)$$

the right hand side can be approximated as

$$\exp\left(\frac{\hat{r}^2}{\sigma^2}\left(\frac{\epsilon}{\hat{r}} - \frac{\epsilon^2}{2\hat{r}^2}\right) - \frac{2\hat{r}\epsilon + \epsilon^2}{2\sigma^2}\right) = \exp\left(-\frac{\epsilon^2}{\sigma^2}\right). \quad (1.155)$$

Therefore,

$$p(\hat{r} + \epsilon) \simeq p(\hat{r}) \exp\left(-\frac{\epsilon^2}{\sigma^2}\right). \quad (1.156)$$

Finally, let a vector of length \hat{r} be $\hat{\mathbf{r}}$. Then, by the definition of $p(\mathbf{x})$,

$$\frac{p(\mathbf{0})}{p(\hat{\mathbf{r}})} = \exp\left(\frac{\hat{r}^2}{2\sigma^2}\right). \quad (1.157)$$

Substituting the expression of \hat{r} above, the right hand side can be written as $\exp\left(\frac{D-1}{2}\right)$. Therefore,

$$\frac{p(\mathbf{0})}{p(\hat{\mathbf{r}})} = \exp\left(\frac{D-1}{2}\right). \quad (1.158)$$

1.21

If $0 \leq a \leq b$, then

$$0 \leq a(b - a). \quad (1.159)$$

Therefore,

$$a \leq (ab)^{\frac{1}{2}}. \quad (1.160)$$

For a two-class classification problem of \mathbf{x} , let the classes be \mathcal{C}_1 and \mathcal{C}_2 and let the decision regions be \mathcal{R}_1 and \mathcal{R}_2 . Let us choose the decision regions to minimise the probability of misclassification. Then,

$$p(\mathbf{x}, \mathcal{C}_1) > p(\mathbf{x}, \mathcal{C}_2) \Rightarrow \mathbf{x} \in \mathcal{C}_1, \quad (1.161)$$

and

$$p(\mathbf{x}, \mathcal{C}_2) > p(\mathbf{x}, \mathcal{C}_1) \Rightarrow \mathbf{x} \in \mathcal{C}_2. \quad (1.162)$$

Then, using the inequality above,

$$\int_{\mathcal{R}_1} p(\mathbf{x}, \mathcal{C}_2) d\mathbf{x} \leq \int_{\mathcal{R}_1} (p(\mathbf{x}, \mathcal{C}_1)p(\mathbf{x}, \mathcal{C}_2))^{\frac{1}{2}} d\mathbf{x}, \quad (1.163)$$

and

$$\int_{\mathcal{R}_2} p(\mathbf{x}, \mathcal{C}_1) d\mathbf{x} \leq \int_{\mathcal{R}_2} (p(\mathbf{x}, \mathcal{C}_1)p(\mathbf{x}, \mathcal{C}_2))^{\frac{1}{2}} d\mathbf{x}. \quad (1.164)$$

Therefore,

$$\int_{\mathcal{R}_1} p(\mathbf{x}, \mathcal{C}_2) d\mathbf{x} + \int_{\mathcal{R}_2} p(\mathbf{x}, \mathcal{C}_1) d\mathbf{x} \leq \int (p(\mathbf{x}, \mathcal{C}_1)p(\mathbf{x}, \mathcal{C}_2))^{\frac{1}{2}} d\mathbf{x}. \quad (1.165)$$

1.22

Let

$$E L = \sum_k \sum_j \int_{\mathcal{R}_j} L_{kj} p(\mathbf{x}, \mathcal{C}_k) d\mathbf{x}. \quad (1.166)$$

If

$$L_{kj} = 1 - \delta_{kj}, \quad (1.167)$$

then the right hand side can be written as

$$\sum_k \sum_j \int_{\mathcal{R}_j} (p(\mathbf{x}, \mathcal{C}_k) - p(\mathbf{x}, \mathcal{C}_j)) d\mathbf{x} = \sum_j \int_{\mathcal{R}_j} \left(\sum_k p(\mathbf{x}, \mathcal{C}_k) - p(\mathbf{x}, \mathcal{C}_j) \right) d\mathbf{x}. \quad (1.168)$$

The right hand side can be written as

$$\sum_j \int_{\mathcal{R}_j} (p(\mathbf{x}) - p(\mathbf{x}, \mathcal{C}_j)) d\mathbf{x} = 1 - \sum_j \int_{\mathcal{R}_j} p(\mathbf{x}, \mathcal{C}_j) d\mathbf{x}. \quad (1.169)$$

Therefore,

$$\mathbb{E} L = 1 - \sum_j \int_{\mathcal{R}_j} p(\mathcal{C}_j | \mathbf{x}) p(\mathbf{x}) d\mathbf{x}. \quad (1.170)$$

Thus, minimising $\mathbb{E} L$ reduces to choosing the criterion to maximise the posterior probability $p(\mathcal{C}_j | \mathbf{x})$.

1.23

Let

$$\mathbb{E} L = \sum_k \sum_j \int_{\mathcal{R}_j} L_{kj} p(\mathbf{x}, \mathcal{C}_k) d\mathbf{x}. \quad (1.171)$$

The right hand side can be written as

$$\sum_j \int_{\mathcal{R}_j} \sum_k L_{kj} p(\mathbf{x}, \mathcal{C}_k) d\mathbf{x} = \sum_j \int_{\mathcal{R}_j} \left(\sum_k L_{kj} p(\mathcal{C}_k | \mathbf{x}) \right) p(\mathbf{x}) d\mathbf{x}. \quad (1.172)$$

Therefore,

$$\mathbb{E} L = \sum_j \int_{\mathcal{R}_j} \left(\sum_k L_{kj} p(\mathcal{C}_k | \mathbf{x}) \right) p(\mathbf{x}) d\mathbf{x}. \quad (1.173)$$

Thus, minimising $\mathbb{E} L$ reduces to choosing to minimise $\sum_k L_{kj} p(\mathcal{C}_k | \mathbf{x})$.

1.24 (Incomplete)

1.25

Let

$$\mathbb{E} L(\mathbf{t}, \mathbf{y}(\mathbf{x})) = \int \int \|\mathbf{y}(\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t}. \quad (1.174)$$

Then

$$\frac{\delta \mathbb{E} L(\mathbf{t}, \mathbf{y}(\mathbf{x}))}{\delta \mathbf{y}(\mathbf{x})} = 2 \int (\mathbf{y}(\mathbf{x}) - \mathbf{t}) p(\mathbf{x}, \mathbf{t}) d\mathbf{t}. \quad (1.175)$$

To minimise $E L(\mathbf{t}, \mathbf{y}(\mathbf{x}))$, setting the left hand side to zero gives

$$\mathbf{0} = \int (\mathbf{y}(\mathbf{x}) - \mathbf{t}) p(\mathbf{t}|\mathbf{x}) d\mathbf{t}. \quad (1.176)$$

The right hand side can be written as

$$\mathbf{y}(\mathbf{x}) \int p(\mathbf{t}|\mathbf{x}) d\mathbf{t} - \int \mathbf{t} p(\mathbf{t}|\mathbf{x}) d\mathbf{t} = \mathbf{y}(\mathbf{x}) - E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}). \quad (1.177)$$

Thus,

$$\mathbf{y}(\mathbf{x}) = E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}). \quad (1.178)$$

Finally, for a single target variable t , it reduces to

$$\mathbf{y}(\mathbf{x}) = E_t(t|\mathbf{x}). \quad (1.179)$$

1.26

Let

$$E L(\mathbf{t}, \mathbf{y}(\mathbf{x})) = \int \int \|\mathbf{y}(\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t}. \quad (1.180)$$

The right hand side can be written as

$$\begin{aligned} & \int \int \|\mathbf{y}(\mathbf{x}) - E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) + E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t} \\ &= \int \int \|\mathbf{y}(\mathbf{x}) - E_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t} \\ &+ 2 \int \int (\mathbf{y}(\mathbf{x}) - E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}))^\top (E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}) p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t} \\ &+ \int \int \|E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t}. \end{aligned} \quad (1.181)$$

Let us look at each term of the right hand side. The first term can be written as

$$\int \|\mathbf{y}(\mathbf{x}) - E_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\|^2 \left(\int p(\mathbf{x}, \mathbf{t}) d\mathbf{t} \right) d\mathbf{x} = \int \|\mathbf{y}(\mathbf{x}) - E_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\|^2 p(\mathbf{x}) d\mathbf{x}. \quad (1.182)$$

The second term can be written as

$$2 \int (\mathbf{y}(\mathbf{x}) - E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}))^\top \left(\int (E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}) p(\mathbf{t}|\mathbf{x}) d\mathbf{t} \right) p(\mathbf{x}) d\mathbf{x}. \quad (1.183)$$

Since

$$\begin{aligned}\int E_{\mathbf{t}}(\mathbf{t}|\mathbf{x})p(\mathbf{t}|\mathbf{x})d\mathbf{t} &= E_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\frac{\int p(\mathbf{x}, \mathbf{t})d\mathbf{t}}{p(\mathbf{x})}, \\ \int \mathbf{t}p(\mathbf{t}|\mathbf{x})d\mathbf{t} &= E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}),\end{aligned}\tag{1.184}$$

the second term is zero. The third term can be written as

$$\int \left(\int \|E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{t}|\mathbf{x})d\mathbf{t} \right) p(\mathbf{x})d\mathbf{x} = \int \text{var}_{\mathbf{t}}(\mathbf{t}|\mathbf{x})p(\mathbf{x})d\mathbf{x}.\tag{1.185}$$

Therefore,

$$E L(\mathbf{t}, \mathbf{y}(\mathbf{x})) = \int \|\mathbf{y}(\mathbf{x}) - E_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\|^2 p(\mathbf{x})d\mathbf{x} + \int \text{var}_{\mathbf{t}}(\mathbf{t}|\mathbf{x})p(\mathbf{x})d\mathbf{x}.\tag{1.186}$$

Thus, $E L(\mathbf{t}, \mathbf{y}(\mathbf{x}))$ is minimised if

$$\mathbf{y}(\mathbf{x}) = E_{\mathbf{t}}(\mathbf{t}|\mathbf{x}).\tag{1.187}$$

1.27

Let

$$E L_q = \int \int |y(\mathbf{x}) - t|^q p(\mathbf{x}, t) d\mathbf{x} dt.\tag{1.188}$$

Then

$$\frac{\delta E L_q}{\delta y(\mathbf{x})} = \int q|y(\mathbf{x}) - t|^{q-1} \text{sign}(y(\mathbf{x}) - t) p(\mathbf{x}, t) dt.\tag{1.189}$$

To minimise $E L_q$, setting the left hand side to zero gives

$$0 = \int |y(\mathbf{x}) - t|^{q-1} \text{sign}(y(\mathbf{x}) - t) p(t|\mathbf{x}) dt.\tag{1.190}$$

This is the condition that $y(\mathbf{x})$ must satisfy in order to minimise $E L_q$.

If $q = 1$, the condition can be written as

$$0 = \int_{y(\mathbf{x})}^{\infty} p(t|\mathbf{x}) dt - \int_{-\infty}^{y(\mathbf{x})} p(t|\mathbf{x}) dt.\tag{1.191}$$

Therefore, $y(\mathbf{x})$ is given by the conditional median.

1.28

Let us assume that

$$p(x, y) = p(x)p(y) \Rightarrow h(x, y) = h(x) + h(y). \quad (1.192)$$

Let $h(p)$ be a function to relate h and p . Then

$$h(p^2) = h(p) + h(p). \quad (1.193)$$

Therefore,

$$h(p^2) = 2h(p). \quad (1.194)$$

Let us assume that, for a positive integer n ,

$$h(p^n) = nh(p). \quad (1.195)$$

Then, by the first assumption,

$$h(p^{n+1}) = h(p^n) + h(p). \quad (1.196)$$

Therefore,

$$h(p^{n+1}) = (n+1)h(p). \quad (1.197)$$

Thus, the second assumption is proved by induction on n .

Additionally, for positive integers m and n ,

$$h(p^n) = h(p^{\frac{n}{m}m}). \quad (1.198)$$

By the second assumption, the left hand side can be written as $nh(p)$. By the first assumption, the right hand side can be written as $mh(p^{\frac{n}{m}})$. Therefore,

$$h(p^{\frac{n}{m}}) = \frac{n}{m}h(p). \quad (1.199)$$

Finally, by the continuity, for a positive real number a ,

$$h(p^a) = ah(p). \quad (1.200)$$

Taking the derivative with respect to a and substituting $a = 1$ gives

$$(p \ln p)h'(p) = h(p). \quad (1.201)$$

Therefore,

$$\int \frac{h'(p)}{h(p)} dp = \int \frac{1}{p \ln p} dp + C, \quad (1.202)$$

where C is a constant. Ignoring the constants, the left hand side can be written as $\ln h(p)$ and the right hand side can be written as $\ln(\ln p)$. Thus,

$$h(p) \propto \ln p. \quad (1.203)$$

1.29

Let x be an M -state discrete random variable. Then, by the definition,

$$H(x) = - \sum_{i=1}^M p(x_i) \ln p(x_i), \quad (1.204)$$

where

$$\sum_{i=1}^M p(x_i) = 1. \quad (1.205)$$

By Jensen's inequality,

$$\sum_{i=1}^M p(x_i) \ln \frac{1}{p(x_i)} \leq \ln \left(\sum_{i=1}^M 1 \right). \quad (1.206)$$

Therefore,

$$H(x) \leq \ln M. \quad (1.207)$$

1.30

Let

$$\begin{aligned} p(x) &= \mathcal{N}(x|\mu, \sigma^2), \\ q(x) &= \mathcal{N}(x|m, s^2). \end{aligned} \quad (1.208)$$

Then, by the definition,

$$\text{KL}(p||q) = - \int p(x) \ln \frac{q(x)}{p(x)} dx. \quad (1.209)$$

The right hand side can be written as

$$\begin{aligned} & - \int_{-\infty}^{\infty} p(x) \ln \frac{(2\pi s^2)^{-\frac{1}{2}} \exp\left(-\frac{(x-m)^2}{2s^2}\right)}{(2\pi \sigma^2)^{-\frac{1}{2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)} dx \\ & = - \int_{-\infty}^{\infty} p(x) \left(-\frac{1}{2} \ln \frac{s^2}{\sigma^2} - \frac{(x-m)^2}{2s^2} + \frac{(x-\mu)^2}{2\sigma^2} \right) dx. \end{aligned} \quad (1.210)$$

The right hand side can be written as

$$\ln \frac{s}{\sigma} \int_{-\infty}^{\infty} p(x) dx + \frac{1}{2s^2} \int_{-\infty}^{\infty} (x-m)^2 p(x) dx - \frac{1}{2\sigma^2} \int_{-\infty}^{\infty} (x-\mu)^2 p(x) dx. \quad (1.211)$$

The first term can be written as $\ln \frac{s}{\sigma}$. The second term can be written as

$$\frac{1}{2s^2} \int_{-\infty}^{\infty} (x - \mu + \mu - m)^2 p(x) dx = \frac{\sigma^2 + (\mu - m)^2}{2s^2}. \quad (1.212)$$

The third term can be written as $-\frac{1}{2}$. Therefore,

$$\text{KL}(p||q) = \ln \frac{s}{\sigma} + \frac{\sigma^2 + (\mu - m)^2}{2s^2} - \frac{1}{2}. \quad (1.213)$$

1.31

Let \mathbf{x} and \mathbf{y} be two variables. Then, by the definition,

$$\begin{aligned} H(\mathbf{x}) &= - \int p(\mathbf{x}) \ln p(\mathbf{x}) d\mathbf{x}, \\ H(\mathbf{y}) &= - \int p(\mathbf{y}) \ln p(\mathbf{y}) d\mathbf{y}, \\ H(\mathbf{x}, \mathbf{y}) &= - \int \int p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{x}, \mathbf{y}) d\mathbf{x} d\mathbf{y}. \end{aligned} \quad (1.214)$$

Note that

$$\begin{aligned} H(\mathbf{x}) &= - \int \left(\int p(\mathbf{x}, \mathbf{y}) d\mathbf{y} \right) \ln p(\mathbf{x}) d\mathbf{x}, \\ H(\mathbf{y}) &= - \int \left(\int p(\mathbf{x}, \mathbf{y}) d\mathbf{x} \right) \ln p(\mathbf{y}) d\mathbf{y}. \end{aligned} \quad (1.215)$$

Therefore,

$$H(\mathbf{x}) + H(\mathbf{y}) - H(\mathbf{x}, \mathbf{y}) = - \int \int p(\mathbf{x}, \mathbf{y}) \ln \frac{p(\mathbf{x})p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} d\mathbf{x} d\mathbf{y}. \quad (1.216)$$

Since

$$\int \int p(\mathbf{x}, \mathbf{y}) d\mathbf{x} d\mathbf{y} = 1, \quad (1.217)$$

Jensen's inequality can be used to write that

$$- \int \int p(\mathbf{x}, \mathbf{y}) \ln \frac{p(\mathbf{x})p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} d\mathbf{x} d\mathbf{y} \geq - \ln \left(\int \int p(\mathbf{x})p(\mathbf{y}) d\mathbf{x} d\mathbf{y} \right). \quad (1.218)$$

The right hand side can be written as

$$- \ln \left(\int p(\mathbf{x}) d\mathbf{x} \int p(\mathbf{y}) d\mathbf{y} \right) = 0. \quad (1.219)$$

Thus,

$$H(\mathbf{x}, \mathbf{y}) \leq H(\mathbf{x}) + H(\mathbf{y}). \quad (1.220)$$

1.32

Let \mathbf{x} be a vector of continuous variables and

$$\mathbf{y} = \mathbf{A}\mathbf{x}, \quad (1.221)$$

where \mathbf{A} is a nonsingular matrix. By the definition,

$$H(\mathbf{y}) = - \int p_y(\mathbf{y}) \ln p_y(\mathbf{y}) d\mathbf{y}. \quad (1.222)$$

By the transformation

$$p_y(\mathbf{y}) = p_x(\mathbf{A}\mathbf{x}) |\det \mathbf{A}^{-1}|, \quad (1.223)$$

the right hand side can be written as

$$- \int p_x(\mathbf{A}\mathbf{x}) \ln p_x(\mathbf{A}\mathbf{x}) |\det \mathbf{A}| d\mathbf{x} - \ln |\det \mathbf{A}^{-1}| \int p_y(\mathbf{y}) d\mathbf{y}. \quad (1.224)$$

By the transformation

$$\mathbf{x}' = \mathbf{A}\mathbf{x}, \quad (1.225)$$

the first term can be written as

$$- \int p_x(\mathbf{x}') \ln p_x(\mathbf{x}') d\mathbf{x}' = H(\mathbf{x}), \quad (1.226)$$

and the second term can be written as

$$- \ln |\det \mathbf{A}^{-1}| = \ln |\det \mathbf{A}|. \quad (1.227)$$

Therefore,

$$H(\mathbf{y}) = H(\mathbf{x}) + \ln |\det \mathbf{A}|. \quad (1.228)$$

1.33

Let x and y be two discrete random variables. By the definition,

$$H(y|x) = - \sum_i \sum_j p(x_i, y_j) \ln p(y_j|x_i). \quad (1.229)$$

If $H(y|x)$ is zero, then

$$0 = - \sum_i p(x_i) \sum_j p(y_j|x_i) \ln p(y_j|x_i). \quad (1.230)$$

Since

$$\begin{aligned} p(x_i) &\geq 0, \\ p(y_j|x_i) \ln p(y_j|x_i) &\leq 0. \end{aligned} \quad (1.231)$$

for all i and j , the equation reduces to

$$p(y_j|x_i) \ln p(y_j|x_i) = 0. \quad (1.232)$$

Therefore, $p(y_j|x_i)$ is zero or one. Thus, since

$$\sum_j p(y_j|x_i) = 1, \quad (1.233)$$

it can be written that

$$p(y_j|x_i) = \delta_{jj'(i)}, \quad (1.234)$$

where $j'(i)$ is unique for each i .

1.34

Let

$$\begin{aligned} L(p(x)) = & - \int_{-\infty}^{\infty} p(x) \ln p(x) dx + \lambda_1 \left(\int_{-\infty}^{\infty} p(x) dx - 1 \right) \\ & + \lambda_2 \left(\int_{-\infty}^{\infty} xp(x) dx - \mu \right) + \lambda_3 \left(\int_{-\infty}^{\infty} (x - \mu)^2 p(x) dx - \sigma^2 \right). \end{aligned} \quad (1.235)$$

Then

$$\frac{\delta L(p(x))}{\delta p(x)} = -\ln p(x) - 1 + \lambda_1 + \lambda_2 x + \lambda_3 (x - \mu)^2. \quad (1.236)$$

Setting the left hand side to zero gives

$$p(x) = \exp \left(-1 + \lambda_1 + \lambda_2 x + \lambda_3 (x - \mu)^2 \right). \quad (1.237)$$

Therefore,

$$p(x) = \exp \left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3} + \lambda_3 \left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3} \right) \right)^2 \right). \quad (1.238)$$

Substituting it to

$$\begin{aligned} \int_{-\infty}^{\infty} p(x) dx &= 1, \\ \int_{-\infty}^{\infty} xp(x) dx &= \mu, \\ \int_{-\infty}^{\infty} (x - \mu)^2 p(x) dx &= \sigma^2, \end{aligned} \quad (1.239)$$

gives

$$\begin{aligned} \exp \left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3} \right) \int_{-\infty}^{\infty} \exp \left(\lambda_3 \left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3} \right) \right)^2 \right) dx &= 1, \\ \exp \left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3} \right) \int_{-\infty}^{\infty} x \exp \left(\lambda_3 \left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3} \right) \right)^2 \right) dx &= \mu, \\ \exp \left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3} \right) \int_{-\infty}^{\infty} (x - \mu)^2 \exp \left(\lambda_3 \left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3} \right) \right)^2 \right) dx &= \sigma^2. \end{aligned} \quad (1.240)$$

By the transformation

$$y = \sqrt{-\lambda_3} \left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3} \right) \right), \quad (1.241)$$

they can be written as

$$\begin{aligned} \exp \left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3} \right) \int_{-\infty}^{\infty} \exp(-y^2) (-\lambda_3)^{-\frac{1}{2}} dy &= 1, \\ \exp \left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3} \right) \int_{-\infty}^{\infty} \left((-\lambda_3)^{-\frac{1}{2}} y + \mu - \frac{\lambda_2}{2\lambda_3} \right) \exp(-y^2) (-\lambda_3)^{-\frac{1}{2}} dy &= \mu, \\ \exp \left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3} \right) \int_{-\infty}^{\infty} \left((-\lambda_3)^{-\frac{1}{2}} y - \frac{\lambda_2}{2\lambda_3} \right)^2 \exp(-y^2) (-\lambda_3)^{-\frac{1}{2}} dy &= \sigma^2. \end{aligned} \quad (1.242)$$

Since

$$\begin{aligned}\int_{-\infty}^{\infty} \exp(-y^2) dy &= \Gamma\left(\frac{1}{2}\right), \\ \int_{-\infty}^{\infty} y \exp(-y^2) dy &= 0, \\ \int_{-\infty}^{\infty} y^2 \exp(-y^2) dy &= \Gamma\left(\frac{3}{2}\right),\end{aligned}\tag{1.243}$$

they can be written as

$$\begin{aligned}\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right) (-\lambda_3)^{-\frac{1}{2}} \Gamma\left(\frac{1}{2}\right) &= 1, \\ \exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right) \left(\mu - \frac{\lambda_2}{2\lambda_3}\right) (-\lambda_3)^{-\frac{1}{2}} \Gamma\left(\frac{1}{2}\right) &= \mu, \\ \exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right) \left((- \lambda_3)^{-\frac{3}{2}} \Gamma\left(\frac{3}{2}\right) + (-\lambda_3)^{-\frac{1}{2}} \frac{\lambda_2^2}{4\lambda_3^2} \Gamma\left(\frac{1}{2}\right)\right) &= \sigma^2.\end{aligned}\tag{1.244}$$

Therefore,

$$\begin{aligned}\lambda_1 &= 1 - \frac{1}{2} \ln(2\pi\sigma^2), \\ \lambda_2 &= 0, \\ \lambda_3 &= -\frac{1}{2\sigma^2}.\end{aligned}\tag{1.245}$$

Thus,

$$p(x) = (2\pi\sigma^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right).\tag{1.246}$$

1.35

Let x be a variable such that

$$p(x) = \mathcal{N}(x|\mu, \sigma^2).\tag{1.247}$$

Then, by the definition,

$$H(x) = - \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) \ln \mathcal{N}(x|\mu, \sigma^2) dx.\tag{1.248}$$

The right hand side can be written as

$$\begin{aligned}
& - \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) \left(-\frac{1}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}(x - \mu)^2 \right) dx \\
& = \frac{1}{2} \ln(2\pi\sigma^2) \int_{-\infty}^{\infty} \mathcal{N}(x|\mu, \sigma^2) dx + \frac{1}{2\sigma^2} \int_{-\infty}^{\infty} (x - \mu)^2 \mathcal{N}(x|\mu, \sigma^2) dx.
\end{aligned} \tag{1.249}$$

Therefore,

$$H(x) = \frac{1}{2} (1 + \ln(2\pi\sigma^2)). \tag{1.250}$$

1.36 (Incomplete)

Let f be a strictly convex function. Then, by the definition,

$$f(\lambda a + (1 - \lambda)b) \leq \lambda f(a) + (1 - \lambda)f(b), \tag{1.251}$$

where $a \leq b$ and $0 \leq \lambda \leq 1$. Let

$$x = \lambda a + (1 - \lambda)b. \tag{1.252}$$

Then, the inequality can be written as

$$f(x) \leq \frac{b - x}{b - a} f(a) + \frac{x - a}{b - a} f(b). \tag{1.253}$$

Let

$$g(x) = \frac{b - x}{b - a} f(a) + \frac{x - a}{b - a} f(b) - f(x). \tag{1.254}$$

Then,

$$g(x) \geq 0. \tag{1.255}$$

Additionally, for $x > a$,

$$g(x) = (x - a) \left(\frac{f(b) - f(a)}{b - a} - \frac{f(x) - f(a)}{x - a} \right). \tag{1.256}$$

By the mean value theorem, there exists c and y such that $a \leq c \leq b$, $a \leq y \leq x$ and

$$\begin{aligned}
f'(c) &= \frac{f(b) - f(a)}{b - a}, \\
f'(y) &= \frac{f(x) - f(a)}{x - a}.
\end{aligned} \tag{1.257}$$

Then, for $x > a$, the inequality reduces to

$$f'(y) \leq f'(c). \tag{1.258}$$

1.37

Let \mathbf{x} and \mathbf{y} be two variables. Then, by the definition,

$$H(\mathbf{x}, \mathbf{y}) = - \int \int p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{x}, \mathbf{y}) d\mathbf{x} d\mathbf{y}. \quad (1.259)$$

The right hand side can be written as

$$\begin{aligned} & - \int \int p(\mathbf{x}, \mathbf{y}) (\ln p(\mathbf{y}|\mathbf{x}) + \ln p(\mathbf{x})) d\mathbf{x} d\mathbf{y} \\ & = - \int \int p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{y}|\mathbf{x}) d\mathbf{x} d\mathbf{y} - \int \left(\int p(\mathbf{x}, \mathbf{y}) d\mathbf{y} \right) \ln p(\mathbf{x}) d\mathbf{x}. \end{aligned} \quad (1.260)$$

By the definition, the first term of the right hand side can be written as $H(\mathbf{y}|\mathbf{x})$ and the second term can be written as $H(\mathbf{x})$. Therefore,

$$H(\mathbf{x}, \mathbf{y}) = H(\mathbf{y}|\mathbf{x}) + H(\mathbf{x}). \quad (1.261)$$

1.38

Let f be a strictly convex function. Then, by the definition,

$$f(\lambda x_1 + (1 - \lambda)x_2) \leq \lambda f(x_1) + (1 - \lambda)f(x_2), \quad (1.262)$$

where $0 \leq \lambda \leq 1$. Let us assume that

$$f\left(\sum_{i=1}^M \lambda_i x_i\right) \leq \sum_{i=1}^M \lambda_i f(x_i), \quad (1.263)$$

where $\lambda_i \geq 0$ and

$$\sum_{i=1}^M \lambda_i = 1. \quad (1.264)$$

Here, let $\lambda_i \geq 0$ and

$$\sum_{i=1}^{M+1} \lambda_i = 1. \quad (1.265)$$

Then, by the definition,

$$f\left(\sum_{i=1}^{M+1} \lambda_i x_i\right) \leq \lambda_{M+1} f(x_{M+1}) + (1 - \lambda_{M+1}) f\left(\sum_{i=1}^M \frac{\lambda_i}{1 - \lambda_{M+1}} x_i\right). \quad (1.266)$$

By the assumption,

$$f\left(\sum_{i=1}^M \frac{\lambda_i}{1-\lambda_{M+1}} x_i\right) \leq \sum_{i=1}^M \frac{\lambda_i}{1-\lambda_{M+1}} f(x_i). \quad (1.267)$$

Therefore,

$$f\left(\sum_{i=1}^{M+1} \lambda_i x_i\right) \leq \lambda_{M+1} f(x_{M+1}) + (1-\lambda_{M+1}) \sum_{i=1}^M \frac{\lambda_i}{1-\lambda_{M+1}} f(x_i). \quad (1.268)$$

Thus,

$$f\left(\sum_{i=1}^{M+1} \lambda_i x_i\right) \leq \sum_{i=1}^{M+1} \lambda_i f(x_i). \quad (1.269)$$

Hence, the assumption is proved by induction on M .

1.39

Let x and y be two binary variables where

$$\begin{aligned} p(x=0, y=0) &= \frac{1}{3}, \\ p(x=0, y=1) &= \frac{1}{3}, \\ p(x=1, y=0) &= 0, \\ p(x=1, y=1) &= \frac{1}{3}. \end{aligned} \quad (1.270)$$

(a)

By the definition,

$$H(x) = - \sum p(x) \ln p(x). \quad (1.271)$$

By the distribution,

$$\begin{aligned} p(x=0) &= \frac{2}{3}, \\ p(x=1) &= \frac{1}{3}. \end{aligned} \quad (1.272)$$

Therefore,

$$H(x) = \ln 3 - \frac{2}{3} \ln 2. \quad (1.273)$$

(b)

By the definition,

$$H(y) = - \sum p(y) \ln p(y). \quad (1.274)$$

By the distribution,

$$\begin{aligned} p(y = 0) &= \frac{1}{3}, \\ p(y = 1) &= \frac{2}{3}. \end{aligned} \quad (1.275)$$

Therefore,

$$H(y) = \ln 3 - \frac{2}{3} \ln 2. \quad (1.276)$$

(c)

By the definition,

$$H(y|x) = - \sum p(x, y) \ln p(y|x). \quad (1.277)$$

By the definition,

$$\begin{aligned} p(y = 0|x = 0) &= \frac{p(x = 0, y = 0)}{p(x = 0)}, \\ p(y = 0|x = 1) &= \frac{p(x = 1, y = 0)}{p(x = 1)}, \\ p(y = 1|x = 0) &= \frac{p(x = 0, y = 1)}{p(x = 0)}, \\ p(y = 1|x = 1) &= \frac{p(x = 1, y = 1)}{p(x = 1)}. \end{aligned} \quad (1.278)$$

Then, by the distribution,

$$\begin{aligned} p(y = 0|x = 0) &= \frac{1}{2}, \\ p(y = 0|x = 1) &= 0, \\ p(y = 1|x = 0) &= \frac{1}{2}, \\ p(y = 1|x = 1) &= 1. \end{aligned} \quad (1.279)$$

Therefore,

$$H(y|x) = \frac{2}{3} \ln 2. \quad (1.280)$$

(d)

By the definition,

$$H(x|y) = - \sum p(x, y) \ln p(x|y). \quad (1.281)$$

By the definition,

$$\begin{aligned} p(x = 0|y = 0) &= \frac{p(x = 0, y = 0)}{p(y = 0)}, \\ p(x = 0|y = 1) &= \frac{p(x = 0, y = 1)}{p(y = 1)}, \\ p(x = 1|y = 0) &= \frac{p(x = 1, y = 0)}{p(y = 0)}, \\ p(x = 1|y = 1) &= \frac{p(x = 1, y = 1)}{p(y = 1)}. \end{aligned} \quad (1.282)$$

Then, by the distribution,

$$\begin{aligned} p(x = 0|y = 0) &= 1, \\ p(x = 0|y = 1) &= \frac{1}{2}, \\ p(x = 1|y = 0) &= 0, \\ p(x = 1|y = 1) &= \frac{1}{2}. \end{aligned} \quad (1.283)$$

Therefore,

$$H(x|y) = \frac{2}{3} \ln 2. \quad (1.284)$$

(e)

By the definition,

$$H(x, y) = - \sum p(x, y) \ln p(x, y). \quad (1.285)$$

Therefore,

$$H(x, y) = \ln 3. \quad (1.286)$$

(f)

By the definition,

$$I(x, y) = - \sum p(x, y) \ln \frac{p(x)p(y)}{p(x, y)}. \quad (1.287)$$

By the distribution, the right hand side can be written as

$$H(x) + H(y) - H(x, y). \quad (1.288)$$

Therefore,

$$I(x, y) = \ln 3 - \frac{4}{3} \ln 2. \quad (1.289)$$

1.40

Let $\{x_i\}$ be a set of points where $x_i > 0$, and let $\{\lambda_i\}$ be a set of coefficients where $\lambda_i \geq 0$ and

$$\sum_{i=1}^M \lambda_i = 1. \quad (1.290)$$

By Jensen's inequality,

$$\sum_{i=1}^M \lambda_i \ln x_i \leq \ln \left(\sum_{i=1}^M \lambda_i x_i \right). \quad (1.291)$$

Therefore,

$$\prod_{i=1}^M x_i^{\lambda_i} \leq \sum_{i=1}^M \lambda_i x_i. \quad (1.292)$$

Substituting

$$\lambda_i = \frac{1}{M} \quad (1.293)$$

gives

$$\left(\prod_{i=1}^M x_i \right)^{\frac{1}{M}} \leq \frac{1}{M} \sum_{i=1}^M x_i. \quad (1.294)$$

1.41

Let \mathbf{x} and \mathbf{y} be continuous variables. Then, by the definition,

$$I(\mathbf{x}, \mathbf{y}) = - \int \int p(\mathbf{x}, \mathbf{y}) \ln \frac{p(\mathbf{x})p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} d\mathbf{x}d\mathbf{y}. \quad (1.295)$$

The right hand side can be written as

$$\begin{aligned} & - \int \int p(\mathbf{x}, \mathbf{y}) \left(\ln p(\mathbf{x}) + \ln \frac{p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} \right) d\mathbf{x}d\mathbf{y} \\ & = - \int \left(\int p(\mathbf{x}, \mathbf{y}) d\mathbf{y} \right) \ln p(\mathbf{x}) d\mathbf{x} + \int \int p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{x}|\mathbf{y}) d\mathbf{x}d\mathbf{y}. \end{aligned} \quad (1.296)$$

By the definition, the first term of the right hand side can be written as $H(\mathbf{x})$ and the second term can be written as $-H(\mathbf{x}|\mathbf{y})$. Therefore,

$$I(\mathbf{x}, \mathbf{y}) = H(\mathbf{x}) - H(\mathbf{x}|\mathbf{y}). \quad (1.297)$$

By the definition,

$$I(\mathbf{x}, \mathbf{y}) = I(\mathbf{y}, \mathbf{x}). \quad (1.298)$$

Thus,

$$I(\mathbf{x}, \mathbf{y}) = H(\mathbf{y}) - H(\mathbf{y}|\mathbf{x}). \quad (1.299)$$

2 Probability Distributions

2.1

Let x be a variable such that

$$p(x|\mu) = \mu^x(1 - \mu)^{1-x}, \quad (2.1)$$

where $x \in \{0, 1\}$. Then,

$$\sum_x p(x|\mu) = 1. \quad (2.2)$$

By the definition,

$$\begin{aligned} \mathbb{E} x &= \mu, \\ \mathbb{E} x^2 &= \mu, \end{aligned} \quad (2.3)$$

Since

$$\text{var } x = \mathbb{E} x^2 - (\mathbb{E} x)^2, \quad (2.4)$$

we have

$$\text{var } x = \mu(1 - \mu). \quad (2.5)$$

By the definition,

$$\mathbb{H}(x) = - \sum_x p(x|\mu) \ln p(x|\mu). \quad (2.6)$$

Therefore,

$$\mathbb{H}(x) = -\mu \ln \mu - (1 - \mu) \ln(1 - \mu). \quad (2.7)$$

2.2

Let x be a variable such that

$$p(x|\mu) = \left(\frac{1 - \mu}{2} \right)^{\frac{1-x}{2}} \left(\frac{1 + \mu}{2} \right)^{\frac{1+x}{2}}, \quad (2.8)$$

where $x \in \{-1, 1\}$. Then,

$$\sum_x p(x|\mu) = 1. \quad (2.9)$$

By the definition,

$$\begin{aligned} \mathbb{E} x &= \mu, \\ \mathbb{E} x^2 &= 1, \end{aligned} \quad (2.10)$$

Since

$$\text{var } x = \mathbb{E} x^2 - (\mathbb{E} x)^2, \quad (2.11)$$

we have

$$\text{var } x = 1 - \mu^2. \quad (2.12)$$

By the definition,

$$H(x) = - \sum_x p(x|\mu) \ln p(x|\mu). \quad (2.13)$$

Therefore,

$$H(x) = -\frac{1-\mu}{2} \ln \frac{1-\mu}{2} - \frac{1+\mu}{2} \ln \frac{1+\mu}{2}. \quad (2.14)$$

2.3

By the definition,

$$\begin{aligned} \binom{N}{m} &= \frac{N!}{m!(N-m)!}, \\ \binom{N}{m-1} &= \frac{N!}{(m-1)!(N-m+1)!} \end{aligned} \quad (2.15)$$

Therefore,

$$\binom{N}{m} + \binom{N}{m-1} = \frac{(N-m+1)N! + mN!}{m!(N-m+1)!}. \quad (2.16)$$

By the definition, the right hand side can be written as

$$\frac{(N+1)!}{m!(N+1-m)!} = \binom{N+1}{m}. \quad (2.17)$$

Thus,

$$\binom{N}{m} + \binom{N}{m-1} = \binom{N+1}{m}. \quad (2.18)$$

Note that

$$1+x = \sum_{m=0}^1 \binom{1}{m} x^m. \quad (2.19)$$

Let us assume that

$$(1+x)^N = \sum_{m=0}^N \binom{N}{m} x^m. \quad (2.20)$$

Then,

$$(1+x)^{N+1} = \sum_{m=0}^N \binom{N}{m} x^m + \sum_{m=0}^N \binom{N}{m} x^{m+1}. \quad (2.21)$$

By the result above, the right hand side can be written as

$$\sum_{m=0}^N \binom{N}{m} x^m + \sum_{m=1}^{N+1} \binom{N}{m-1} x^m = 1 + x^{N+1} + \sum_{m=1}^N \binom{N+1}{m} x^m. \quad (2.22)$$

Therefore,

$$(1+x)^{N+1} = \sum_{m=0}^{N+1} \binom{N+1}{m} x^m. \quad (2.23)$$

Thus, the assumption is proved by induction on N .

Finally, let m be a variable such that

$$p(m|\mu) = \binom{N}{m} \mu^m (1-\mu)^{N-m}. \quad (2.24)$$

Then

$$\sum_{m=0}^N p(m|\mu) = \sum_{m=0}^N \binom{N}{m} \mu^m (1-\mu)^{N-m}. \quad (2.25)$$

By the result above, the right hand side can be written as

$$(1-\mu)^N \sum_{m=0}^N \binom{N}{m} \left(\frac{\mu}{1-\mu} \right)^m = (1-\mu)^N \left(1 + \frac{\mu}{1-\mu} \right)^N. \quad (2.26)$$

Therefore,

$$\sum_{m=0}^N p(m|\mu) = 1. \quad (2.27)$$

2.4

Let m be a variable such that

$$p(m|\mu) = \binom{N}{m} \mu^m (1-\mu)^{N-m}. \quad (2.28)$$

Then

$$E m = \sum_{m=0}^N m \binom{N}{m} \mu^m (1-\mu)^{N-m}. \quad (2.29)$$

Taking the derivative of

$$\sum_{m=0}^N \binom{N}{m} \mu^m (1-\mu)^{N-m} = 1 \quad (2.30)$$

with respect to μ gives

$$\sum_{m=0}^N m \binom{N}{m} \mu^{m-1} (1-\mu)^{N-m} - \sum_{m=0}^N (N-m) \binom{N}{m} \mu^m (1-\mu)^{N-m-1} = 0. \quad (2.31)$$

The first term of the left hand side can be written as $\frac{1}{\mu} E m$. Since

$$(N-m) \binom{N}{m} = N \binom{N-1}{m}, \quad (2.32)$$

the second term of the left hand side can be written as

$$-N \sum_{m=0}^{N-1} \binom{N-1}{m} \mu^m (1-\mu)^{N-m-1} = -N. \quad (2.33)$$

Therefore,

$$E m = N\mu. \quad (2.34)$$

Taking the second derivative of

$$\sum_{m=0}^N \binom{N}{m} \mu^m (1-\mu)^{N-m} = 1 \quad (2.35)$$

with respect to μ gives

$$\begin{aligned} & \sum_{m=0}^N m(m-1) \binom{N}{m} \mu^{m-2} (1-\mu)^{N-m} \\ & - 2 \sum_{m=0}^N m(N-m) \binom{N}{m} \mu^{m-1} (1-\mu)^{N-m-1} \\ & + \sum_{m=0}^N (N-m)(N-m-1) \binom{N}{m} \mu^m (1-\mu)^{N-m-2} = 0. \end{aligned} \quad (2.36)$$

The first term of the left hand side can be written as $\frac{1}{\mu^2} E m(m-1)$. Since

$$\begin{aligned} m(N-m) \binom{N}{m} &= N(N-1) \binom{N-2}{m-1}, \\ (N-m)(N-m-1) \binom{N}{m} &= N(N-1) \binom{N-2}{m}, \end{aligned} \quad (2.37)$$

the second and third term of the left hand side can be written as

$$\begin{aligned} -2N(N-1) \sum_{m=1}^{N-1} \binom{N-2}{m-1} \mu^{m-1} (1-\mu)^{N-m-1} &= -2N(N-1), \\ N(N-1) \sum_{m=0}^N \binom{N-2}{m} \mu^m (1-\mu)^{N-m-2} &= N(N-1). \end{aligned} \quad (2.38)$$

Therefore,

$$E m(m-1) = N(N-1)\mu^2. \quad (2.39)$$

Thus, since

$$\text{var } m = E m(m-1) + E m - (E m)^2, \quad (2.40)$$

we have

$$\text{var } m = N\mu(1-\mu). \quad (2.41)$$

2.5

By the definition,

$$\Gamma(a)\Gamma(b) = \int_0^\infty x^{a-1} \exp(-x) dx \int_0^\infty y^{b-1} \exp(-y) dy. \quad (2.42)$$

By the transformation $t = x + y$, the right hand side can be written as

$$\begin{aligned} &\int_0^\infty x^{a-1} \left(\int_x^\infty (t-x)^{b-1} \exp(-t) dt \right) dx \\ &= \int_0^\infty \left(\int_0^t x^{a-1} (t-x)^{b-1} dx \right) \exp(-t) dt. \end{aligned} \quad (2.43)$$

By the transformation $x = t\mu$, the right hand side can be written as

$$\begin{aligned} &\int_0^\infty \left(\int_0^1 (t\mu)^{a-1} t^{b-1} (1-\mu)^{b-1} t d\mu \right) \exp(-t) dt \\ &= \int_0^1 \mu^{a-1} (1-\mu)^{b-1} d\mu \int_0^\infty t^{a+b-1} \exp(-t) dt. \end{aligned} \quad (2.44)$$

By the definition, the second integral of the right hand side can be written as $\Gamma(a + b)$. Therefore,

$$\int_0^1 \mu^{a-1}(1 - \mu)^{b-1} d\mu = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a + b)}. \quad (2.45)$$

2.6

Let μ be a variable such that

$$p(\mu|a, b) = \frac{\Gamma(a + b)}{\Gamma(a)\Gamma(b)} \mu^{a-1}(1 - \mu)^{b-1}. \quad (2.46)$$

Then

$$\begin{aligned} E \mu &= \frac{\Gamma(a + b)}{\Gamma(a)\Gamma(b)} \int_0^1 \mu^a(1 - \mu)^{b-1} d\mu, \\ E \mu^2 &= \frac{\Gamma(a + b)}{\Gamma(a)\Gamma(b)} \int_0^1 \mu^{a+1}(1 - \mu)^{b-1} d\mu. \end{aligned} \quad (2.47)$$

Since

$$\begin{aligned} \int_0^1 \mu^a(1 - \mu)^{b-1} d\mu &= \frac{\Gamma(a + 1)\Gamma(b)}{\Gamma(a + b + 1)}, \\ \int_0^1 \mu^{a+1}(1 - \mu)^{b-1} d\mu &= \frac{\Gamma(a + 2)\Gamma(b)}{\Gamma(a + b + 2)}, \end{aligned} \quad (2.48)$$

we have

$$\begin{aligned} E \mu &= \frac{a}{a + b}, \\ E \mu^2 &= \frac{a(a + 1)}{(a + b)(a + b + 1)}. \end{aligned} \quad (2.49)$$

Since

$$\text{var } \mu = E \mu^2 - (E \mu)^2, \quad (2.50)$$

we have

$$\text{var } \mu = \frac{ab}{(a + b)^2(a + b + 1)}. \quad (2.51)$$

Since

$$\frac{\partial}{\partial \mu} p(\mu|a, b) = \frac{\Gamma(a + b)}{\Gamma(a)\Gamma(b)} \mu^{a-1}(1 - \mu)^{b-1} \left(\frac{a - 1}{\mu} - \frac{b - 1}{1 - \mu} \right), \quad (2.52)$$

we have

$$\text{mode } \mu = \frac{a - 1}{a + b - 2}. \quad (2.53)$$

2.7

Let m and l be a variable such that

$$p(m, l|\mu) = \binom{m+l}{m} \mu^m (1-\mu)^l, \quad (2.54)$$

where

$$p(\mu|a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \mu^{a-1} (1-\mu)^{b-1}. \quad (2.55)$$

By 2.6,

$$E(\mu|a, b) = \frac{a}{a+b}. \quad (2.56)$$

Note that

$$\mu_{\text{ML}} = \frac{m}{m+l}. \quad (2.57)$$

Since

$$p(\mu|m, l, a, b) \propto p(m, l|\mu)p(\mu|a, b), \quad (2.58)$$

we have

$$p(\mu|m, l, a, b) = \frac{\Gamma(m+l+a+b)}{\Gamma(m+a)\Gamma(l+b)} \mu^{m+a-1} (1-\mu)^{l+b-1}. \quad (2.59)$$

Therefore, by 2.6,

$$E(\mu|m, l, a, b) = \frac{m+a}{m+l+a+b}. \quad (2.60)$$

Thus,

$$E(\mu|m, l, a, b) = \lambda \mu_{\text{ML}} + (1-\lambda) E(\mu|a, b), \quad (2.61)$$

where

$$\lambda = \frac{m+l}{m+l+a+b}. \quad (2.62)$$

2.8 (Incomplete)

Let x and y be variables. Then, by the definition,

$$E x = \int x p(x) dx. \quad (2.63)$$

The right hand side can be written as

$$\int x \left(\int p(x, y) dy \right) dx = \int \left(\int x p(x|y) dx \right) p(y) dy. \quad (2.64)$$

Therefore,

$$E x = E_y (E_x(x|y)) . \quad (2.65)$$

By the definition,

$$\text{var } x = E (x - E x)^2 . \quad (2.66)$$

By the result above, the right hand side can be written as

$$\begin{aligned} & E_y (E_x ((x - E_x(x|y) + E_x(x|y) - E x)^2 | y)) \\ &= E_y (E_x ((x - E_x(x|y))^2 | y)) \\ &+ 2 E_y (E_x ((x - E_x(x|y)) (E_x(x|y) - E x) | y)) \\ &+ E_y (E_x ((E_x(x|y) - E x)^2 | y)) \end{aligned} \quad (2.67)$$

Let us look at each term of the right hand side. By the definition, the first term can be written as $E_y (\text{var}_x(x|y))$. The second term can be written as

$$2 E_y ((E_x(x|y) - E x) E_x ((x - E_x(x|y)) | y)) \quad (2.68)$$

By the result above, the third term can be written as

$$E_y (E_x(x|y) - E_y (E_x(x|y)))^2 = \text{var}_y (E_x(x|y)) . \quad (2.69)$$

Therefore,

$$\text{var } x = E_y (\text{var}_x(x|y)) + \text{var}_y (E_x(x|y)) . \quad (2.70)$$

2.9 (Incomplete)

For a vector $\boldsymbol{\mu}$ in 2 dimensions, 2.5 gives

$$\int_{\substack{\mu_1 + \mu_2 = 1 \\ \mu_1 \geq 0, \mu_2 \geq 0}} \mu_1^{\alpha_1 - 1} \mu_2^{\alpha_2 - 1} d\boldsymbol{\mu} = \frac{\Gamma(\alpha_1) \Gamma(\alpha_2)}{\Gamma(\alpha_1 + \alpha_2)} .$$

For a vector $\boldsymbol{\mu}$ in M dimensions, let us assume that

$$\int_{\substack{\sum_{k=1}^M \mu_k = 1 \\ \mu_k \geq 0}} \prod_{k=1}^M \mu_k^{\alpha_k - 1} d\boldsymbol{\mu} = \frac{\prod_{k=1}^M \Gamma(\alpha_k)}{\Gamma(\sum_{k=1}^M \alpha_k)} .$$

Then, for a vector $\boldsymbol{\mu}$ in $M + 1$ dimensions,

$$\int_{\substack{\sum_{k=1}^{M+1} \mu_k = 1 \\ \mu_k \geq 0}} \prod_{k=1}^{M+1} \mu_k^{\alpha_k - 1} d\boldsymbol{\mu} = \int_0^1 \mu_{M+1}^{\alpha_{M+1} - 1} \left(\int_{\substack{\sum_{k=1}^M \mu'_k = 1 - \mu_{M+1} \\ \mu'_k \geq 0}} \prod_{k=1}^M \mu'_k{}^{\alpha_k - 1} d\boldsymbol{\mu}' \right) d\mu_{M+1} .$$

where $\boldsymbol{\mu}'$ is the vector of the first M elements of $\boldsymbol{\mu}$. By the transformation

$$\boldsymbol{\mu}'' = \frac{1}{1 - \mu_{M+1}} \boldsymbol{\mu}', \quad (2.71)$$

the right hand side can be written as

$$\int_0^1 \mu_{M+1}^{\alpha_{M+1}-1} \left(\int_{\substack{\sum_{k=1}^M \mu_k''=1 \\ \mu_k'' \geq 0}} \left(\prod_{k=1}^M ((1 - \mu_{M+1}) \mu_k'')^{\alpha_k-1} \right) (1 - \mu_{M+1})^M d\boldsymbol{\mu}'' \right) d\mu_{M+1},$$

so that

$$\int_0^1 \mu_{M+1}^{\alpha_{M+1}-1} (1 - \mu_{M+1})^{\sum_{k=1}^M \alpha_k} \left(\int_{\substack{\sum_{k=1}^M \mu_k''=1 \\ \mu_k'' \geq 0}} \prod_{k=1}^M \mu_k''^{\alpha_k-1} d\boldsymbol{\mu}'' \right) d\mu_{M+1}.$$

By the assumption, it can be written as

$$\frac{\prod_{k=1}^M \Gamma(\alpha_k)}{\Gamma\left(\sum_{k=1}^M \alpha_k\right)} \frac{\Gamma(\alpha_{M+1}) \Gamma\left(\sum_{k=1}^M \alpha_k + 1\right)}{\Gamma\left(\sum_{k=1}^{M+1} \alpha_k + 1\right)} = \frac{\sum_{k=1}^M \alpha_k}{\sum_{k=1}^{M+1} \alpha_k} \frac{\prod_{k=1}^{M+1} \Gamma(\alpha_k)}{\Gamma\left(\sum_{k=1}^{M+1} \alpha_k\right)}. \quad (2.72)$$

Therefore,

$$\int \prod_{k=1}^{M+1} \mu_k^{\alpha_k-1} d\boldsymbol{\mu} = \frac{\prod_{k=1}^{M+1} \Gamma(\alpha_k)}{\Gamma\left(\sum_{k=1}^{M+1} \alpha_k\right)}? \quad (2.73)$$

Thus, the assumption is proved by induction on M .

2.10

Let $\boldsymbol{\mu}$ be a variable such that

$$p(\boldsymbol{\mu}|\boldsymbol{\alpha}) = \frac{\Gamma\left(\sum_{k=1}^K \alpha_k\right)}{\prod_{k=1}^K \Gamma(\alpha_k)} \prod_{k=1}^K \mu_k^{\alpha_k-1}. \quad (2.74)$$

Then

$$\begin{aligned} \mathbb{E} \mu_j &= \int \mu_j p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu}, \\ \mathbb{E} \mu_j^2 &= \int \mu_j^2 p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu}, \\ \mathbb{E} \mu_j \mu_l &= \int \mu_j \mu_l p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu}. \end{aligned} \quad (2.75)$$

If $j \neq l$, then the right hand sides can be written as

$$\begin{aligned} \frac{\Gamma\left(\sum_{k=1}^K \alpha_k\right) \frac{\Gamma(\alpha_j+1)}{\Gamma(\alpha_j)} \prod_{k=1}^K \Gamma(\alpha_k)}{\prod_{k=1}^K \Gamma(\alpha_k) \Gamma\left(\sum_{k=1}^K \alpha_k + 1\right)} &= \frac{\alpha_j}{\sum_{k=1}^K \alpha_k}, \\ \frac{\Gamma\left(\sum_{k=1}^K \alpha_k\right) \frac{\Gamma(\alpha_j+2)}{\Gamma(\alpha_j)} \prod_{k=1}^K \Gamma(\alpha_k)}{\prod_{k=1}^K \Gamma(\alpha_k) \Gamma\left(\sum_{k=1}^K \alpha_k + 2\right)} &= \frac{\alpha_j(\alpha_j + 1)}{\sum_{k=1}^K \alpha_k \left(\sum_{k=1}^K \alpha_k + 1\right)}, \\ \frac{\Gamma\left(\sum_{k=1}^K \alpha_k\right) \frac{\Gamma(\alpha_j+1)\Gamma(\alpha_l+1)}{\Gamma(\alpha_j)\Gamma(\alpha_l)} \prod_{k=1}^K \Gamma(\alpha_k)}{\prod_{k=1}^K \Gamma(\alpha_k) \Gamma\left(\sum_{k=1}^K \alpha_k + 2\right)} &= \frac{\alpha_j \alpha_l}{\sum_{k=1}^K \alpha_k \left(\sum_{k=1}^K \alpha_k + 1\right)}. \end{aligned} \quad (2.76)$$

Therefore,

$$\begin{aligned} \mathbb{E} \mu_j &= \frac{\alpha_j}{\sum_{k=1}^K \alpha_k}, \\ \mathbb{E} \mu_j^2 &= \frac{\alpha_j(\alpha_j + 1)}{\sum_{k=1}^K \alpha_k \left(\sum_{k=1}^K \alpha_k + 1\right)}, \\ \mathbb{E} \mu_j \mu_l &= \frac{\alpha_j \alpha_l}{\sum_{k=1}^K \alpha_k \left(\sum_{k=1}^K \alpha_k + 1\right)}. \end{aligned} \quad (2.77)$$

Since

$$\begin{aligned} \text{var } \mu_j &= \mathbb{E} \mu_j^2 - (\mathbb{E} \mu_j)^2, \\ \text{cov}(\mu_j, \mu_l) &= \mathbb{E} \mu_j \mu_l - \mathbb{E} \mu_j \mathbb{E} \mu_l, \end{aligned} \quad (2.78)$$

we have

$$\begin{aligned} \text{var } \mu_j &= \frac{\alpha_j \left(\sum_{k=1}^K \alpha_k - \alpha_j\right)}{\left(\sum_{k=1}^K \alpha_k\right)^2 \left(\sum_{k=1}^K \alpha_k + 1\right)}, \\ \text{cov}(\mu_j, \mu_l) &= -\frac{\alpha_j \alpha_l}{\left(\sum_{k=1}^K \alpha_k\right)^2 \left(\sum_{k=1}^K \alpha_k + 1\right)}. \end{aligned} \quad (2.79)$$

2.11

Let $\boldsymbol{\mu}$ be a variable such that

$$p(\boldsymbol{\mu}|\boldsymbol{\alpha}) = \frac{\Gamma\left(\sum_{k=1}^K \alpha_k\right)}{\prod_{k=1}^K \Gamma(\alpha_k)} \prod_{k=1}^K \mu_k^{\alpha_k-1}. \quad (2.80)$$

Then

$$\mathbb{E} \ln \mu_j = \int (\ln \mu_j) p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu}. \quad (2.81)$$

Since

$$\frac{\partial}{\partial \alpha_j} p(\boldsymbol{\mu}|\boldsymbol{\alpha}) = \left(\frac{\Gamma' \left(\sum_{k=1}^K \alpha_k \right)}{\Gamma \left(\sum_{k=1}^K \alpha_k \right)} - \frac{\Gamma'(\alpha_j)}{\Gamma(\alpha_j)} + \ln \mu_j \right) p(\boldsymbol{\mu}|\boldsymbol{\alpha}), \quad (2.82)$$

we have

$$\mathbb{E} \ln \mu_j = \frac{\partial}{\partial \alpha_j} \int p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu} + \left(\psi(\alpha_j) - \psi \left(\sum_{k=1}^K \alpha_k \right) \right) \int p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu}, \quad (2.83)$$

where

$$\psi(a) = \frac{d}{da} \ln \Gamma(a). \quad (2.84)$$

Therefore,

$$\mathbb{E} \ln \mu_j = \psi(\alpha_j) - \psi \left(\sum_{k=1}^K \alpha_k \right). \quad (2.85)$$

2.12

Let x be a variable such that

$$p(x|a, b) = \frac{1}{b-a}, \quad (2.86)$$

where $a < b$. Then

$$\int_a^b p(x|a, b) dx = 1. \quad (2.87)$$

Note that

$$\begin{aligned} \mathbb{E} x &= \int_a^b x p(x|a, b) dx, \\ \mathbb{E} x^2 &= \int_a^b x^2 p(x|a, b) dx. \end{aligned} \quad (2.88)$$

The right hand sides can be written as

$$\begin{aligned} \frac{1}{b-a} \int_a^b x dx &= \frac{1}{2}(a+b), \\ \frac{1}{b-a} \int_a^b x^2 dx &= \frac{1}{3}(a^2 + ab + b^2). \end{aligned} \quad (2.89)$$

Therefore,

$$\begin{aligned} \mathbb{E} x &= \frac{1}{2}(a + b), \\ \mathbb{E} x^2 &= \frac{1}{3} (a^2 + ab + b^2). \end{aligned} \quad (2.90)$$

Since

$$\text{var } x = \mathbb{E} x^2 - (\mathbb{E} x)^2, \quad (2.91)$$

we have

$$\text{var } x = \frac{1}{12}(b - a)^2. \quad (2.92)$$

2.13

Let \mathbf{x} be a variable in D dimensions and

$$\begin{aligned} p(\mathbf{x}) &= \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}), \\ q(\mathbf{x}) &= \mathcal{N}(\mathbf{x}|\mathbf{m}, \mathbf{L}). \end{aligned} \quad (2.93)$$

Then, by the definition,

$$\text{KL}(p||q) = - \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) \ln \frac{\mathcal{N}(\mathbf{x}|\mathbf{m}, \mathbf{L})}{\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma})} d\mathbf{x}. \quad (2.94)$$

Since

$$\ln \frac{\mathcal{N}(\mathbf{x}|\mathbf{m}, \mathbf{L})}{\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma})} = \ln \frac{(2\pi)^{-\frac{D}{2}} (|\det \mathbf{L}|)^{-\frac{1}{2}} \exp \left(-\frac{1}{2}(\mathbf{x} - \mathbf{m})^\top \mathbf{L}^{-1}(\mathbf{x} - \mathbf{m}) \right)}{(2\pi)^{-\frac{D}{2}} (|\det \boldsymbol{\Sigma}|)^{-\frac{1}{2}} \exp \left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu}) \right)}, \quad (2.95)$$

The right hand side can be written as

$$\begin{aligned} & \frac{1}{2} \ln \left| \frac{\det \mathbf{L}}{\det \boldsymbol{\Sigma}} \right| \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} \\ & + \frac{1}{2} \int (\mathbf{x} - \mathbf{m})^\top \mathbf{L}^{-1}(\mathbf{x} - \mathbf{m}) \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} \\ & - \frac{1}{2} \int (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu}) \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x}. \end{aligned} \quad (2.96)$$

Let us look at each term. Since

$$\int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} = 1, \quad (2.97)$$

the first term can be written as $\frac{1}{2} \ln \left| \frac{\det \mathbf{L}}{\det \mathbf{\Sigma}} \right|$. Since

$$(\mathbf{x} - \mathbf{m})^\top \mathbf{L}^{-1} (\mathbf{x} - \mathbf{m}) = (\mathbf{x} - \boldsymbol{\mu} + \boldsymbol{\mu} - \mathbf{m})^\top \mathbf{L}^{-1} (\mathbf{x} - \boldsymbol{\mu} + \boldsymbol{\mu} - \mathbf{m}), \quad (2.98)$$

the second term can be written as

$$\begin{aligned} & \frac{1}{2} \int (\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{L}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \mathbf{\Sigma}) d\mathbf{x} \\ & + (\boldsymbol{\mu} - \mathbf{m})^\top \mathbf{L}^{-1} \int (\mathbf{x} - \boldsymbol{\mu}) \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \mathbf{\Sigma}) d\mathbf{x} \\ & + \frac{1}{2} (\boldsymbol{\mu} - \mathbf{m})^\top \mathbf{L}^{-1} (\boldsymbol{\mu} - \mathbf{m}) \int \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \mathbf{\Sigma}) d\mathbf{x}. \end{aligned} \quad (2.99)$$

Since

$$\begin{aligned} & \int \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \mathbf{\Sigma}) d\mathbf{x} = 1, \\ & \int \mathbf{x} \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \mathbf{\Sigma}) d\mathbf{x} = \boldsymbol{\mu}, \\ & \int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \mathbf{\Sigma}) d\mathbf{x} = \mathbf{\Sigma}, \end{aligned} \quad (2.100)$$

it can be written as

$$\frac{1}{2} \text{tr} (\mathbf{L}^{-1} \mathbf{\Sigma}) + \frac{1}{2} (\boldsymbol{\mu} - \mathbf{m})^\top \mathbf{L}^{-1} (\boldsymbol{\mu} - \mathbf{m}). \quad (2.101)$$

Since

$$\int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \mathbf{\Sigma}) d\mathbf{x} = \mathbf{\Sigma}, \quad (2.102)$$

the third term can be written as

$$-\frac{1}{2} \text{tr} (\mathbf{\Sigma}^{-1} \mathbf{\Sigma}) = -\frac{D}{2} \quad (2.103)$$

Therefore,

$$\text{KL}(p||q) = \frac{1}{2} \left(\ln \left| \frac{\det \mathbf{L}}{\det \mathbf{\Sigma}} \right| + \text{tr} (\mathbf{L}^{-1} \mathbf{\Sigma}) + (\boldsymbol{\mu} - \mathbf{m})^\top \mathbf{L}^{-1} (\boldsymbol{\mu} - \mathbf{m}) - D \right). \quad (2.104)$$

2.14

Let \mathbf{x} be a variable in D dimensions and

$$\begin{aligned} L(p(\mathbf{x})) = & - \int p(\mathbf{x}) \ln p(\mathbf{x}) d\mathbf{x} + \lambda \left(\int p(\mathbf{x}) d\mathbf{x} - 1 \right) \\ & + \mathbf{l}^\top \left(\int \mathbf{x} p(\mathbf{x}) d\mathbf{x} - \boldsymbol{\mu} \right) + \mathbf{m}^\top \left(\int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top p(\mathbf{x}) d\mathbf{x} - \boldsymbol{\Sigma} \right) \mathbf{m}. \end{aligned} \quad (2.105)$$

Then

$$\frac{\delta L(p(\mathbf{x}))}{\delta p(\mathbf{x})} = -\ln p(\mathbf{x}) - 1 + \lambda + \mathbf{l}^\top \mathbf{x} + \mathbf{m}^\top (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{m}. \quad (2.106)$$

Setting the left hand side to zero gives

$$p(\mathbf{x}) = \exp(-1 + \lambda + \mathbf{l}^\top \mathbf{x} + \mathbf{m}^\top (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{m}), \quad (2.107)$$

so that

$$p(\mathbf{x}) = \exp(-1 + \lambda - \mathbf{l}^\top \mathbf{M} \mathbf{l} + (\mathbf{x} - \boldsymbol{\mu} - \mathbf{M} \mathbf{l})^\top \mathbf{M}^{-1} (\mathbf{x} - \boldsymbol{\mu} - \mathbf{M} \mathbf{l})), \quad (2.108)$$

where

$$\mathbf{M} = (\mathbf{m} \mathbf{m}^\top)^{-1}. \quad (2.109)$$

Substituting it to

$$\begin{aligned} \int p(\mathbf{x}) d\mathbf{x} &= 1, \\ \int \mathbf{x} p(\mathbf{x}) d\mathbf{x} &= \boldsymbol{\mu}, \\ \int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top p(\mathbf{x}) d\mathbf{x} &= \boldsymbol{\Sigma}, \end{aligned} \quad (2.110)$$

and the transformation

$$\mathbf{y} = \mathbf{x} - \boldsymbol{\mu} - \mathbf{M} \mathbf{l} \quad (2.111)$$

gives

$$\begin{aligned} \exp(-1 + \lambda - \mathbf{l}^\top \mathbf{M} \mathbf{l}) \int \exp(-\mathbf{y}^\top \mathbf{M}^{-1} \mathbf{y}) d\mathbf{y} &= 1, \\ \exp(-1 + \lambda - \mathbf{l}^\top \mathbf{M} \mathbf{l}) \int (\mathbf{y} + \boldsymbol{\mu} + \mathbf{M} \mathbf{l}) \exp(-\mathbf{y}^\top \mathbf{M}^{-1} \mathbf{y}) d\mathbf{y} &= \boldsymbol{\mu}, \\ \exp(-1 + \lambda - \mathbf{l}^\top \mathbf{M} \mathbf{l}) \int (\mathbf{y} + \mathbf{M} \mathbf{l}) (\mathbf{y} + \mathbf{M} \mathbf{l})^\top \exp(-\mathbf{y}^\top \mathbf{M}^{-1} \mathbf{y}) d\mathbf{y} &= \boldsymbol{\Sigma}. \end{aligned} \quad (2.112)$$

Since

$$\begin{aligned}\int \exp(-\mathbf{y}^\top \mathbf{y}) d\mathbf{y} &= \left(\Gamma\left(\frac{1}{2}\right) \right)^D, \\ \int \mathbf{y} \exp(-\mathbf{y}^\top \mathbf{y}) d\mathbf{y} &= \mathbf{0}, \\ \int \mathbf{y} \mathbf{y}^\top \exp(-\mathbf{y}^\top \mathbf{y}) d\mathbf{y} &= \Gamma\left(\frac{3}{2}\right) \left(\Gamma\left(\frac{1}{2}\right) \right)^{D-1} \mathbf{I},\end{aligned}\tag{2.113}$$

they can be written as

$$\begin{aligned}\exp(-1 + \lambda - \mathbf{I}^\top \mathbf{M} \mathbf{I}) \left(\Gamma\left(\frac{1}{2}\right) \right)^D (\det \mathbf{M})^{\frac{1}{2}} &= 1, \\ \exp(-1 + \lambda - \mathbf{I}^\top \mathbf{M} \mathbf{I}) (\boldsymbol{\mu} + \mathbf{M} \mathbf{I}) \left(\Gamma\left(\frac{1}{2}\right) \right)^D (\det \mathbf{M})^{\frac{1}{2}} &= \boldsymbol{\mu}, \\ \exp(-1 + \lambda - \mathbf{I}^\top \mathbf{M} \mathbf{I}) \left(\Gamma\left(\frac{3}{2}\right) \left(\Gamma\left(\frac{1}{2}\right) \right)^{D-1} \mathbf{M} + \mathbf{M} \mathbf{I} (\mathbf{M} \mathbf{I})^\top \left(\Gamma\left(\frac{1}{2}\right) \right)^D \right) (\det \mathbf{M})^{\frac{1}{2}} &= \boldsymbol{\Sigma}.\end{aligned}\tag{2.114}$$

Therefore,

$$\begin{aligned}\lambda &= 1 - \frac{D}{2} \ln \pi - \frac{1}{2} \ln(\det \mathbf{M}), \\ \mathbf{I} &= \mathbf{0}, \\ \mathbf{M} &= 2\boldsymbol{\Sigma}.\end{aligned}\tag{2.115}$$

Thus,

$$p(\mathbf{x}) = (2\pi)^{-\frac{D}{2}} (\det \boldsymbol{\Sigma})^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right).\tag{2.116}$$

2.15

Let \mathbf{x} be a variable in D dimensions such that

$$p(\mathbf{x}) = \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma}).\tag{2.117}$$

Then, by the definition,

$$\mathbf{H}(\mathbf{x}) = - \int \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma}) \ln \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x}.\tag{2.118}$$

The right hand side can be written as

$$\begin{aligned}
& - \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) \left(-\frac{D}{2} \ln(2\pi) - \frac{1}{2} \ln |\det \boldsymbol{\Sigma}| - \frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right) d\mathbf{x} \\
& = \left(\frac{D}{2} \ln(2\pi) + \frac{1}{2} \ln |\det \boldsymbol{\Sigma}| \right) \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} \\
& \quad + \frac{1}{2} \int (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x}.
\end{aligned} \tag{2.119}$$

Since

$$\begin{aligned}
& \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} = 1, \\
& \int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} = \boldsymbol{\Sigma},
\end{aligned} \tag{2.120}$$

the first and second term of the right hand side can be written as

$$\frac{D}{2} \ln(2\pi) + \frac{1}{2} \ln |\det \boldsymbol{\Sigma}| \tag{2.121}$$

and

$$\frac{1}{2} \text{tr}(\boldsymbol{\Sigma}^{-1} \boldsymbol{\Sigma}) = \frac{D}{2}. \tag{2.122}$$

Therefore,

$$H(\mathbf{x}) = \frac{D}{2} (1 + \ln(2\pi)) + \frac{1}{2} \ln |\det \boldsymbol{\Sigma}|. \tag{2.123}$$

2.16

Let x be a variable such that

$$x = x_1 + x_2, \tag{2.124}$$

where

$$\begin{aligned}
p(x_1) &= \mathcal{N}(x_1|\mu_1, \tau_1^{-1}), \\
p(x_2) &= \mathcal{N}(x_2|\mu_2, \tau_2^{-1}).
\end{aligned} \tag{2.125}$$

Then

$$p(x) = \int_{-\infty}^{\infty} p(x|x_2)p(x_2)dx_2. \tag{2.126}$$

The right hand side can be written as

$$\begin{aligned}
& \int_{-\infty}^{\infty} \mathcal{N}(x|\mu_1 + x_2, \tau_1^{-1}) \mathcal{N}(x_2|\mu_2, \tau_2^{-1}) dx_2 \\
&= \int_{-\infty}^{\infty} \left(\frac{\tau_1}{2\pi}\right)^{\frac{1}{2}} \exp\left(-\frac{\tau_1}{2}(x - \mu_1 - x_2)^2\right) \left(\frac{\tau_2}{2\pi}\right)^{\frac{1}{2}} \exp\left(-\frac{\tau_2}{2}(x_2 - \mu_2)^2\right) dx_2.
\end{aligned} \tag{2.127}$$

The logarithm of the integrand except the terms independent of x and z is given by

$$\begin{aligned}
& -\frac{\tau_1 + \tau_2}{2} \left(x_2 - \frac{\tau_1(x - \mu_1) + \tau_2\mu_2}{\tau_1 + \tau_2}\right)^2 - \frac{\tau_1}{2}(x - \mu_1)^2 - \frac{\tau_2}{2}\mu_2^2 + \frac{\tau_1 + \tau_2}{2} \left(\frac{\tau_1(x - \mu_1) + \tau_2\mu_2}{\tau_1 + \tau_2}\right)^2 \\
&= -\frac{\tau_1 + \tau_2}{2} \left(x_2 - \frac{\tau_1(x - \mu_1) + \tau_2\mu_2}{\tau_1 + \tau_2}\right)^2 - \frac{\tau_1\tau_2}{2(\tau_1 + \tau_2)}(x - \mu_1 - \mu_2)^2.
\end{aligned} \tag{2.128}$$

Therefore,

$$p(x) = \mathcal{N}(x | \mu_1 + \mu_2, \tau_1^{-1} + \tau_2^{-1}). \tag{2.129}$$

Thus, by 1.35,

$$H(x) = \frac{1}{2} (1 + \ln(2\pi) + \ln(\tau_1^{-1} + \tau_2^{-1})). \tag{2.130}$$

2.17

Let Σ be a matrix and

$$\begin{aligned}
\mathbf{S} &= \frac{1}{2} (\Sigma^{-1} + (\Sigma^{-1})^\top), \\
\mathbf{A} &= \frac{1}{2} (\Sigma^{-1} - (\Sigma^{-1})^\top).
\end{aligned} \tag{2.131}$$

Then

$$\Sigma^{-1} = \mathbf{S} + \mathbf{A}. \tag{2.132}$$

Therefore,

$$(\mathbf{x} - \boldsymbol{\mu})^\top \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) = (\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{S} (\mathbf{x} - \boldsymbol{\mu}) + (\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{A} (\mathbf{x} - \boldsymbol{\mu}). \tag{2.133}$$

The second term of the right hand side can be written as

$$\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^\top \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) - \frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^\top (\Sigma^{-1})^\top (\mathbf{x} - \boldsymbol{\mu}). \tag{2.134}$$

The second term of the right hand side can be written as

$$-\frac{1}{2} (\boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu}))^\top (\mathbf{x} - \boldsymbol{\mu}) = -\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}). \quad (2.135)$$

Thus,

$$(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{A} (\mathbf{x} - \boldsymbol{\mu}) = 0. \quad (2.136)$$

Hence

$$(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) = (\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{S} (\mathbf{x} - \boldsymbol{\mu}). \quad (2.137)$$

2.18

Let $\boldsymbol{\Sigma}$ be a $D \times D$ real symmetric matrix such that

$$\boldsymbol{\Sigma} \mathbf{u}_i = \lambda_i \mathbf{u}_i, \quad (2.138)$$

where $i = 1, \dots, D$ and \mathbf{u}_i are unit vectors. Taking the inner product with $\overline{\mathbf{u}}_i$ on both sides gives

$$\overline{\mathbf{u}}_i^\top \boldsymbol{\Sigma} \mathbf{u}_i = \lambda_i. \quad (2.139)$$

Since $\boldsymbol{\Sigma}$ is real and symmetric, the left hand side can be written as

$$\overline{\mathbf{u}}_i^\top \boldsymbol{\Sigma}^\top \mathbf{u}_i = (\overline{\boldsymbol{\Sigma} \mathbf{u}_i})^\top \mathbf{u}_i. \quad (2.140)$$

The right hand side can be written as

$$\overline{\lambda}_i \overline{\mathbf{u}}_i^\top \mathbf{u}_i = \overline{\lambda}_i. \quad (2.141)$$

Therefore,

$$\lambda_i = \overline{\lambda}_i. \quad (2.142)$$

Additionally, for $i \neq j$, taking the inner product with \mathbf{u}_j on both sides of the original equation gives

$$\mathbf{u}_j^\top \boldsymbol{\Sigma} \mathbf{u}_i = \lambda_i \mathbf{u}_j^\top \mathbf{u}_i. \quad (2.143)$$

Since $\boldsymbol{\Sigma}$ is symmetric, the left hand side can be written as

$$\mathbf{u}_j^\top \boldsymbol{\Sigma}^\top \mathbf{u}_i = (\boldsymbol{\Sigma} \mathbf{u}_j)^\top \mathbf{u}_i. \quad (2.144)$$

The right hand side can be written as $\lambda_j \mathbf{u}_j^\top \mathbf{u}_i$. Therefore,

$$\lambda_i \mathbf{u}_j^\top \mathbf{u}_i = \lambda_j \mathbf{u}_j^\top \mathbf{u}_i. \quad (2.145)$$

Thus, if $\lambda_i \neq \lambda_j$, then

$$\mathbf{u}_j^\top \mathbf{u}_i = 0. \quad (2.146)$$

2.19

Let Σ be a $D \times D$ real symmetric matrix such that

$$\Sigma \mathbf{u}_i = \lambda_i \mathbf{u}_i, \quad (2.147)$$

where $i = 1, \dots, D$ and \mathbf{u}_i are unit vectors. Let

$$\begin{aligned} \Lambda &= \text{diag}(\lambda_1, \dots, \lambda_D), \\ \mathbf{U} &= [\mathbf{u}_1 \cdots \mathbf{u}_D]. \end{aligned} \quad (2.148)$$

Then

$$\Sigma \mathbf{U} = \mathbf{U} \Lambda. \quad (2.149)$$

By 2.18,

$$\mathbf{U}^\top \mathbf{U} = \mathbf{I}. \quad (2.150)$$

Therefore,

$$\begin{aligned} \Sigma &= \mathbf{U} \Lambda \mathbf{U}^\top, \\ \Sigma^{-1} &= \mathbf{U} \Lambda^{-1} \mathbf{U}^\top, \end{aligned} \quad (2.151)$$

Thus,

$$\begin{aligned} \Sigma &= \sum_{i=1}^D \lambda_i \mathbf{u}_i \mathbf{u}_i^\top, \\ \Sigma^{-1} &= \sum_{i=1}^D \frac{1}{\lambda_i} \mathbf{u}_i \mathbf{u}_i^\top. \end{aligned} \quad (2.152)$$

2.20

Let Σ be a $D \times D$ real symmetric matrix such that

$$\Sigma \mathbf{u}_i = \lambda_i \mathbf{u}_i, \quad (2.153)$$

where $i = 1, \dots, D$ and \mathbf{u}_i are unit vectors. Let

$$\begin{aligned} \Lambda &= \text{diag}(\lambda_1, \dots, \lambda_D), \\ \mathbf{U} &= [\mathbf{u}_1 \cdots \mathbf{u}_D]. \end{aligned} \quad (2.154)$$

By 2.19,

$$\mathbf{a}^\top \Sigma \mathbf{a} = \mathbf{b}^\top \Lambda \mathbf{b}, \quad (2.155)$$

where

$$\mathbf{b} = \mathbf{U}^\top \mathbf{a}. \quad (2.156)$$

The right hand side can be written as $\sum_{i=1}^D \lambda_i b_i^2$. Therefore, the necessary and sufficient condition for

$$\mathbf{a}^\top \mathbf{\Sigma} \mathbf{a} > 0 \quad (2.157)$$

for any real vector \mathbf{a} is

$$\lambda_i > 0. \quad (2.158)$$

2.21

Let $\mathbf{\Sigma}$ be a $D \times D$ real symmetric matrix. Then the number of independent parameters is $\frac{D(D+1)}{2}$.

2.22

Let $\mathbf{\Sigma}$ be a $D \times D$ symmetric matrix and

$$\mathbf{\Sigma} \mathbf{\Lambda} = \mathbf{I}. \quad (2.159)$$

Taking the transpose of the both sides gives

$$\mathbf{\Lambda}^\top \mathbf{\Sigma} = \mathbf{I}. \quad (2.160)$$

Therefore,

$$\mathbf{\Lambda}^\top = \mathbf{\Lambda}. \quad (2.161)$$

2.23

Let $\mathbf{\Sigma}$ be a $D \times D$ real symmetric matrix such that

$$\mathbf{\Sigma} \mathbf{u}_i = \lambda_i \mathbf{u}_i, \quad (2.162)$$

where $i = 1, \dots, D$ and \mathbf{u}_i are unit vectors. Let

$$\begin{aligned} \mathbf{\Lambda}' &= \text{diag} \left(\lambda_1^{-\frac{1}{2}}, \dots, \lambda_D^{-\frac{1}{2}} \right), \\ \mathbf{U} &= [\mathbf{u}_1 \cdots \mathbf{u}_D]. \end{aligned} \quad (2.163)$$

By 2.19,

$$\int_{(\mathbf{x}-\boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})=\Delta} d\mathbf{x} = \int_{(\mathbf{x}-\boldsymbol{\mu})^\top \mathbf{U}\boldsymbol{\Lambda}'\boldsymbol{\Lambda}'^\top \mathbf{U}^\top (\mathbf{x}-\boldsymbol{\mu})=\Delta} d\mathbf{x}. \quad (2.164)$$

By the transformation

$$\mathbf{y} = \boldsymbol{\Lambda}'^\top \mathbf{U}^\top (\mathbf{x} - \boldsymbol{\mu}) \quad (2.165)$$

and the property

$$\mathbf{U}^\top \mathbf{U} = \mathbf{I}, \quad (2.166)$$

the right hand side can be written as

$$\int_{\|\mathbf{y}\|^2=\Delta} \left| \det \left(\mathbf{U}\boldsymbol{\Lambda}'^{-1} \right) \right| d\mathbf{y} = |\det \boldsymbol{\Sigma}|^{\frac{1}{2}} \int_{\|\mathbf{y}\|^2=\Delta} d\mathbf{y}. \quad (2.167)$$

Therefore,

$$\int_{(\mathbf{x}-\boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})=\Delta} d\mathbf{x} = |\det \boldsymbol{\Sigma}|^{\frac{1}{2}} \Delta^D V_D, \quad (2.168)$$

where

$$V_D = \int_{\|\mathbf{x}\|=1} d\mathbf{x}. \quad (2.169)$$

2.24

Let

$$\begin{bmatrix} \mathbf{X} & \mathbf{Y} \\ \mathbf{Z} & \mathbf{W} \end{bmatrix} = \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{C} & \mathbf{D} \end{bmatrix}^{-1}.$$

Then

$$\begin{aligned} \mathbf{XA} + \mathbf{YC} &= \mathbf{I}, \\ \mathbf{XB} + \mathbf{YD} &= \mathbf{O}, \\ \mathbf{ZA} + \mathbf{WC} &= \mathbf{O}, \\ \mathbf{ZB} + \mathbf{WD} &= \mathbf{I}. \end{aligned} \quad (2.170)$$

By the second and third equations,

$$\begin{aligned} \mathbf{Y} &= -\mathbf{XBD}^{-1}, \\ \mathbf{W} &= -\mathbf{ZAC}^{-1}. \end{aligned} \quad (2.171)$$

Substituting them to the first and fourth equation gives

$$\begin{aligned} \mathbf{X}(\mathbf{A} - \mathbf{BD}^{-1}\mathbf{C}) &= \mathbf{I}, \\ \mathbf{Z}(\mathbf{B} - \mathbf{AC}^{-1}\mathbf{D}) &= \mathbf{I}. \end{aligned} \quad (2.172)$$

Therefore,

$$\begin{bmatrix} \mathbf{X} & \mathbf{Y} \\ \mathbf{Z} & \mathbf{W} \end{bmatrix} = \begin{bmatrix} (\mathbf{A} - \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1} & -(\mathbf{A} - \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1}\mathbf{B}\mathbf{D}^{-1} \\ (\mathbf{B} - \mathbf{A}\mathbf{C}^{-1}\mathbf{D})^{-1} & -(\mathbf{B} - \mathbf{A}\mathbf{C}^{-1}\mathbf{D})^{-1}\mathbf{A}\mathbf{C}^{-1} \end{bmatrix}.$$

2.25

Let \mathbf{x} be a variable in D dimensions such that

$$p(\mathbf{x}) = \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}), \quad (2.173)$$

where

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_a \\ \mathbf{x}_b \\ \mathbf{x}_c \end{bmatrix}, \boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}_a \\ \boldsymbol{\mu}_b \\ \boldsymbol{\mu}_c \end{bmatrix}, \boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{aa} & \boldsymbol{\Sigma}_{ab} & \boldsymbol{\Sigma}_{ac} \\ \boldsymbol{\Sigma}_{ba} & \boldsymbol{\Sigma}_{bb} & \boldsymbol{\Sigma}_{bc} \\ \boldsymbol{\Sigma}_{ca} & \boldsymbol{\Sigma}_{cb} & \boldsymbol{\Sigma}_{cc} \end{bmatrix}.$$

Let

$$\boldsymbol{\Lambda} = \boldsymbol{\Sigma}^{-1}, \quad (2.174)$$

where

$$\boldsymbol{\Lambda} = \begin{bmatrix} \boldsymbol{\Lambda}_{aa} & \boldsymbol{\Lambda}_{ab} & \boldsymbol{\Lambda}_{ac} \\ \boldsymbol{\Lambda}_{ba} & \boldsymbol{\Lambda}_{bb} & \boldsymbol{\Lambda}_{bc} \\ \boldsymbol{\Lambda}_{ca} & \boldsymbol{\Lambda}_{cb} & \boldsymbol{\Lambda}_{cc} \end{bmatrix}.$$

Then

$$\begin{aligned} & -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu}) \\ = & -\frac{1}{2}(\mathbf{x}_a - \boldsymbol{\mu}_a)^\top \boldsymbol{\Lambda}_{aa}(\mathbf{x}_a - \boldsymbol{\mu}_a) - \frac{1}{2}(\mathbf{x}_a - \boldsymbol{\mu}_a)^\top \boldsymbol{\Lambda}_{ab}(\mathbf{x}_b - \boldsymbol{\mu}_b) - \frac{1}{2}(\mathbf{x}_a - \boldsymbol{\mu}_a)^\top \boldsymbol{\Lambda}_{ac}(\mathbf{x}_c - \boldsymbol{\mu}_c) \\ & - \frac{1}{2}(\mathbf{x}_b - \boldsymbol{\mu}_b)^\top \boldsymbol{\Lambda}_{ba}(\mathbf{x}_a - \boldsymbol{\mu}_a) - \frac{1}{2}(\mathbf{x}_b - \boldsymbol{\mu}_b)^\top \boldsymbol{\Lambda}_{bb}(\mathbf{x}_b - \boldsymbol{\mu}_b) - \frac{1}{2}(\mathbf{x}_b - \boldsymbol{\mu}_b)^\top \boldsymbol{\Lambda}_{bc}(\mathbf{x}_c - \boldsymbol{\mu}_c) \\ & - \frac{1}{2}(\mathbf{x}_c - \boldsymbol{\mu}_c)^\top \boldsymbol{\Lambda}_{ca}(\mathbf{x}_a - \boldsymbol{\mu}_a) - \frac{1}{2}(\mathbf{x}_c - \boldsymbol{\mu}_c)^\top \boldsymbol{\Lambda}_{cb}(\mathbf{x}_b - \boldsymbol{\mu}_b) - \frac{1}{2}(\mathbf{x}_c - \boldsymbol{\mu}_c)^\top \boldsymbol{\Lambda}_{cc}(\mathbf{x}_c - \boldsymbol{\mu}_c). \end{aligned} \quad (2.175)$$

Excluding the terms independent of \mathbf{x}_a , the right hand side can be written as

$$-\frac{1}{2}(\mathbf{x}_a - \boldsymbol{\mu}_{a|b,c})^\top \boldsymbol{\Sigma}_{a|b,c}^{-1}(\mathbf{x}_a - \boldsymbol{\mu}_{a|b,c}), \quad (2.176)$$

where

$$\begin{aligned} \boldsymbol{\mu}_{a|b,c} &= \boldsymbol{\mu}_a - \boldsymbol{\Lambda}_{aa}^{-1}\boldsymbol{\Lambda}_{ab}(\mathbf{x}_b - \boldsymbol{\mu}_b) - \boldsymbol{\Lambda}_{aa}^{-1}\boldsymbol{\Lambda}_{ac}(\mathbf{x}_c - \boldsymbol{\mu}_c), \\ \boldsymbol{\Sigma}_{a|b,c} &= \boldsymbol{\Lambda}_{aa}^{-1}. \end{aligned} \quad (2.177)$$

Therefore,

$$p(\mathbf{x}_a|\mathbf{x}_b, \mathbf{x}_c) = \mathcal{N}(\mathbf{x}_a|\boldsymbol{\mu}_{a|b,c}, \boldsymbol{\Sigma}_{a|b,c}). \quad (2.178)$$

Multiplying both sides by $p(\mathbf{x}_c)$ and integrating both sides with respect to \mathbf{x}_c gives

$$p(\mathbf{x}_a|\mathbf{x}_b) = \int \mathcal{N}(\mathbf{x}_a|\boldsymbol{\mu}_{a|b,c}, \boldsymbol{\Sigma}_{a|b,c})p(\mathbf{x}_c)d\mathbf{x}_c. \quad (2.179)$$

Thus,

$$p(\mathbf{x}_a|\mathbf{x}_b) = \mathcal{N}(\mathbf{x}_a|\boldsymbol{\mu}_{a|b}, \boldsymbol{\Sigma}_{a|b}), \quad (2.180)$$

where

$$\begin{aligned} \boldsymbol{\mu}_{a|b} &= \boldsymbol{\mu}_a - \boldsymbol{\Lambda}_{aa}^{-1}\boldsymbol{\Lambda}_{ab}(\mathbf{x}_b - \boldsymbol{\mu}_b) + \boldsymbol{\Lambda}_{aa}^{-1}\boldsymbol{\Lambda}_{ac}\boldsymbol{\mu}_c, \\ \boldsymbol{\Sigma}_{a|b} &= \boldsymbol{\Lambda}_{aa}^{-1}. \end{aligned} \quad (2.181)$$

2.26 (Incomplete)

Since

$$\mathbf{I} = (\mathbf{A} + \mathbf{BCD})(\mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{BCDA}^{-1}) + (\mathbf{BCDA}^{-1})^2, \quad (2.182)$$

we have

$$(\mathbf{A} + \mathbf{BCD})^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{B}(\mathbf{C}^{-1} + \mathbf{DA}^{-1}\mathbf{B})\mathbf{DA}^{-1}. \quad (2.183)$$

2.27

Let \mathbf{x} and \mathbf{z} be two variables. Then

$$\mathbf{E}(\mathbf{x} + \mathbf{z}) = \int \int (\mathbf{x} + \mathbf{z})p(\mathbf{x}, \mathbf{z})d\mathbf{x}d\mathbf{z}. \quad (2.184)$$

The right hand side can be written as

$$\int \mathbf{x} \left(\int p(\mathbf{x}, \mathbf{z})d\mathbf{z} \right) d\mathbf{x} + \int \mathbf{z} \left(\int p(\mathbf{x}, \mathbf{z})d\mathbf{x} \right) d\mathbf{z} = \int \mathbf{x}p(\mathbf{x})d\mathbf{x} + \int \mathbf{z}p(\mathbf{z})d\mathbf{z}. \quad (2.185)$$

The right hand side can be written as $\mathbf{E} \mathbf{x} + \mathbf{E} \mathbf{z}$. Therefore,

$$\mathbf{E}(\mathbf{x} + \mathbf{z}) = \mathbf{E} \mathbf{x} + \mathbf{E} \mathbf{z}. \quad (2.186)$$

Additionally,

$$\text{cov}(\mathbf{x} + \mathbf{z}) = \int \int (\mathbf{x} + \mathbf{z} - \mathbf{E}(\mathbf{x} + \mathbf{z})) (\mathbf{x} + \mathbf{z} - \mathbf{E}(\mathbf{x} + \mathbf{z}))^\top p(\mathbf{x}, \mathbf{z}) d\mathbf{x} d\mathbf{z}. \quad (2.187)$$

The right hand side can be written as

$$\begin{aligned} & \int \int (\mathbf{x} - \mathbf{E} \mathbf{x}) (\mathbf{x} - \mathbf{E} \mathbf{x})^\top p(\mathbf{x}, \mathbf{z}) d\mathbf{x} d\mathbf{z} + \int \int (\mathbf{x} - \mathbf{E} \mathbf{x}) (\mathbf{z} - \mathbf{E} \mathbf{z})^\top p(\mathbf{x}, \mathbf{z}) d\mathbf{x} d\mathbf{z} \\ & + \int \int (\mathbf{z} - \mathbf{E} \mathbf{z}) (\mathbf{x} - \mathbf{E} \mathbf{x})^\top p(\mathbf{x}, \mathbf{z}) d\mathbf{x} d\mathbf{z} + \int \int (\mathbf{z} - \mathbf{E} \mathbf{z}) (\mathbf{z} - \mathbf{E} \mathbf{z})^\top p(\mathbf{x}, \mathbf{z}) d\mathbf{x} d\mathbf{z}. \end{aligned} \quad (2.188)$$

The first and fourth terms can be written as $\text{cov } \mathbf{x}$ and $\text{cov } \mathbf{z}$. If \mathbf{x} and \mathbf{z} are independent, the second and third terms can be written as

$$\begin{aligned} & \int (\mathbf{x} - \mathbf{E} \mathbf{x}) p(\mathbf{x}) d\mathbf{x} \int (\mathbf{z} - \mathbf{E} \mathbf{z})^\top p(\mathbf{z}) d\mathbf{z} = \mathbf{O}, \\ & \int (\mathbf{z} - \mathbf{E} \mathbf{z}) p(\mathbf{z}) d\mathbf{z} \int (\mathbf{x} - \mathbf{E} \mathbf{x})^\top p(\mathbf{x}) d\mathbf{x} = \mathbf{O}. \end{aligned} \quad (2.189)$$

Therefore,

$$\text{cov}(\mathbf{x} + \mathbf{z}) = \text{cov } \mathbf{x} + \text{cov } \mathbf{z}. \quad (2.190)$$

2.28 (Incomplete)

Let

$$\mathbf{z} = \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix},$$

where

$$\mathbf{E} \mathbf{z} = \begin{bmatrix} \boldsymbol{\mu} \\ \mathbf{A}\boldsymbol{\mu} + \mathbf{b} \end{bmatrix}$$

and

$$\text{cov } \mathbf{z} = \begin{bmatrix} \boldsymbol{\Lambda}^{-1} & \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top \\ \mathbf{A} \boldsymbol{\Lambda}^{-1} & \mathbf{L}^{-1} + \mathbf{A} \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top \end{bmatrix}.$$

Then

$$\begin{aligned}
\int (\mathbf{x} - \boldsymbol{\mu}) (\mathbf{x} - \boldsymbol{\mu})^\top p(\mathbf{x}) d\mathbf{x} &= \boldsymbol{\Lambda}^{-1}, \\
\int \int (\mathbf{x} - \boldsymbol{\mu}) (\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b})^\top p(\mathbf{x}, \mathbf{y}) d\mathbf{x} d\mathbf{y} &= \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top, \\
\int \int (\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b}) (\mathbf{x} - \boldsymbol{\mu})^\top p(\mathbf{x}, \mathbf{y}) d\mathbf{x} d\mathbf{y} &= \mathbf{A} \boldsymbol{\Lambda}^{-1}, \\
\int (\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b}) (\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b})^\top p(\mathbf{y}) d\mathbf{y} &= \mathbf{L}^{-1} + \mathbf{A} \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top.
\end{aligned} \tag{2.191}$$

2.29

Let

$$\mathbf{R} = \begin{bmatrix} \boldsymbol{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A} & -\mathbf{A}^\top \mathbf{L} \\ -\mathbf{L} \mathbf{A} & \mathbf{L} \end{bmatrix}.$$

Then, by 2.24,

$$\mathbf{R}^{-1} = \begin{bmatrix} \boldsymbol{\Lambda}^{-1} & \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top \\ \mathbf{A} \boldsymbol{\Lambda}^{-1} & \mathbf{L}^{-1} + \mathbf{A} \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top \end{bmatrix}.$$

2.30

Let

$$\mathbf{R}^{-1} = \begin{bmatrix} \boldsymbol{\Lambda}^{-1} & \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top \\ \mathbf{A} \boldsymbol{\Lambda}^{-1} & \mathbf{L}^{-1} + \mathbf{A} \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top \end{bmatrix}.$$

Then

$$\mathbf{R}^{-1} \begin{bmatrix} \boldsymbol{\Lambda} \boldsymbol{\mu} - \mathbf{A}^\top \mathbf{L} \mathbf{b} \\ \mathbf{L} \mathbf{b} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\mu} \\ \mathbf{A} \boldsymbol{\mu} + \mathbf{b} \end{bmatrix}.$$

2.31

Let \mathbf{y} be a variable such that

$$\mathbf{y} = \mathbf{x} + \mathbf{z}, \tag{2.192}$$

where

$$\begin{aligned}
p(\mathbf{x}) &= \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_{\mathbf{x}}, \boldsymbol{\Sigma}_{\mathbf{x}}), \\
p(\mathbf{z}) &= \mathcal{N}(\mathbf{z} | \boldsymbol{\mu}_{\mathbf{z}}, \boldsymbol{\Sigma}_{\mathbf{z}}).
\end{aligned} \tag{2.193}$$

By the definition,

$$p(\mathbf{y}) = \int p(\mathbf{y}|\mathbf{x})p(\mathbf{x})d\mathbf{x}. \quad (2.194)$$

The right hand side can be written as

$$\int \mathcal{N}(\mathbf{y}|\mathbf{x} + \boldsymbol{\mu}_z, \boldsymbol{\Sigma}_z) \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_x, \boldsymbol{\Sigma}_x) d\mathbf{x}. \quad (2.195)$$

The logarithm of the integrand except the terms independent of \mathbf{x} and \mathbf{y} is given by

$$-\frac{1}{2}(\mathbf{y} - \mathbf{x} - \boldsymbol{\mu}_z)^\top \boldsymbol{\Sigma}_z^{-1}(\mathbf{y} - \mathbf{x} - \boldsymbol{\mu}_z) - \frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_x)^\top \boldsymbol{\Sigma}_x^{-1}(\mathbf{x} - \boldsymbol{\mu}_x). \quad (2.196)$$

The first and second order terms can be written as

$$-\mathbf{x}^\top (\boldsymbol{\Sigma}_z^{-1} \boldsymbol{\mu}_z - \boldsymbol{\Sigma}_x^{-1} \boldsymbol{\mu}_x) + \mathbf{y}^\top \boldsymbol{\Sigma}_z^{-1} \boldsymbol{\mu}_z = \mathbf{u}^\top \mathbf{v} \quad (2.197)$$

and

$$-\frac{1}{2}\mathbf{x}^\top (\boldsymbol{\Sigma}_x^{-1} + \boldsymbol{\Sigma}_z^{-1}) \mathbf{x} + \frac{1}{2}\mathbf{x}^\top \boldsymbol{\Sigma}_z^{-1} \mathbf{y} + \frac{1}{2}\mathbf{y}^\top \boldsymbol{\Sigma}_z^{-1} \mathbf{x} - \frac{1}{2}\mathbf{y}^\top \boldsymbol{\Sigma}_z^{-1} \mathbf{y} = -\frac{1}{2}\mathbf{u}^\top \mathbf{R} \mathbf{u}, \quad (2.198)$$

respectively, where

$$\mathbf{u} = \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix}, \mathbf{v} = \begin{bmatrix} \boldsymbol{\Sigma}_x^{-1} \boldsymbol{\mu}_x - \boldsymbol{\Sigma}_z^{-1} \boldsymbol{\mu}_z \\ \boldsymbol{\Sigma}_z^{-1} \boldsymbol{\mu}_z \end{bmatrix}, \mathbf{R} = \begin{bmatrix} \boldsymbol{\Sigma}_x^{-1} & -\boldsymbol{\Sigma}_z^{-1} \\ -\boldsymbol{\Sigma}_z^{-1} & \boldsymbol{\Sigma}_z^{-1} \end{bmatrix}.$$

Therefore, the logarithm of the integrand except the terms independent of \mathbf{u} can be written as

$$-\frac{1}{2}(\mathbf{u} - \mathbf{R}^{-1}\mathbf{v})^\top \mathbf{R}(\mathbf{u} - \mathbf{R}^{-1}\mathbf{v}), \quad (2.199)$$

where

$$\mathbf{R}^{-1} = \begin{bmatrix} \boldsymbol{\Sigma}_x & \boldsymbol{\Sigma}_x \\ \boldsymbol{\Sigma}_x & \boldsymbol{\Sigma}_x + \boldsymbol{\Sigma}_z \end{bmatrix}, \mathbf{R}^{-1}\mathbf{v} = \begin{bmatrix} \boldsymbol{\mu}_x \\ \boldsymbol{\mu}_x + \boldsymbol{\mu}_z \end{bmatrix}.$$

by 2.29 and 2.30. Thus,

$$p(\mathbf{y}) = \mathcal{N}(\mathbf{y}|\boldsymbol{\mu}_x + \boldsymbol{\mu}_z, \boldsymbol{\Sigma}_x + \boldsymbol{\Sigma}_z). \quad (2.200)$$

2.32

Let \mathbf{x} and \mathbf{y} be variables such that

$$\begin{aligned} p(\mathbf{x}) &= \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}^{-1}), \\ p(\mathbf{y}|\mathbf{x}) &= \mathcal{N}(\mathbf{y}|\mathbf{Ax} + \mathbf{b}, \mathbf{L}^{-1}). \end{aligned} \quad (2.201)$$

By the definition,

$$p(\mathbf{y}|\mathbf{x})p(\mathbf{x}) = p(\mathbf{x}|\mathbf{y})p(\mathbf{y}). \quad (2.202)$$

The logarithm of the left hand side except the terms independent of \mathbf{x} and \mathbf{y} is given by

$$-\frac{1}{2}(\mathbf{y} - \mathbf{Ax} - \mathbf{b})^\top \mathbf{L}(\mathbf{y} - \mathbf{Ax} - \mathbf{b}) - \frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Lambda}(\mathbf{x} - \boldsymbol{\mu}). \quad (2.203)$$

Since the first term can be written as

$$\begin{aligned} & -\frac{1}{2}(\mathbf{y} - \mathbf{A}(\mathbf{x} - \boldsymbol{\mu}) - \mathbf{A}\boldsymbol{\mu} - \mathbf{b})^\top \mathbf{L}(\mathbf{y} - \mathbf{A}(\mathbf{x} - \boldsymbol{\mu}) - \mathbf{A}\boldsymbol{\mu} - \mathbf{b}) \\ &= -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{A}^\top \mathbf{L} \mathbf{A}(\mathbf{x} - \boldsymbol{\mu}) + (\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{A}^\top \mathbf{L}(\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b}) \\ & \quad -\frac{1}{2}(\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b})^\top \mathbf{L}(\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b}), \end{aligned} \quad (2.204)$$

the logarithm except the terms independent of \mathbf{x} and \mathbf{y} can be written as

$$\begin{aligned} & -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu} - \mathbf{z})^\top (\boldsymbol{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A})(\mathbf{x} - \boldsymbol{\mu} - \mathbf{z}) + \frac{1}{2}\mathbf{z}^\top (\mathbf{A}^\top \mathbf{L} \mathbf{A} + \boldsymbol{\Lambda}) \mathbf{z} \\ & -\frac{1}{2}(\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b})^\top \mathbf{L}(\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b}) \\ &= -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu} - \mathbf{z})^\top (\boldsymbol{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A})(\mathbf{x} - \boldsymbol{\mu} - \mathbf{z}) - \frac{1}{2}(\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b})^\top \mathbf{M}(\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b}), \end{aligned} \quad (2.205)$$

where

$$\begin{aligned} \mathbf{z} &= (\boldsymbol{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A})^{-1} \mathbf{A}^\top \mathbf{L}(\mathbf{y} - \mathbf{A}\boldsymbol{\mu} - \mathbf{b}), \\ \mathbf{M} &= \mathbf{L} - \mathbf{L} \mathbf{A} (\boldsymbol{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A})^{-1} \mathbf{A}^\top \mathbf{L}. \end{aligned} \quad (2.206)$$

we have

$$\boldsymbol{\mu} + \mathbf{z} = (\boldsymbol{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A})^{-1} (\mathbf{A}^\top \mathbf{L}(\mathbf{y} - \mathbf{b}) + \boldsymbol{\Lambda}\boldsymbol{\mu}). \quad (2.207)$$

By 2.26,

$$(\boldsymbol{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A})^{-1} = \boldsymbol{\Lambda}^{-1} - \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top (\mathbf{L}^{-1} + \mathbf{A} \boldsymbol{\Lambda}^{-1} \mathbf{A}^\top)^{-1} \mathbf{A} \boldsymbol{\Lambda}^{-1}. \quad (2.208)$$

Therefore,

$$\mathbf{M} = (\mathbf{L}^{-1} + \mathbf{A}\mathbf{\Lambda}^{-1}\mathbf{A}^\top)^{-1}. \quad (2.209)$$

Thus,

$$\begin{aligned} p(\mathbf{x}|\mathbf{y}) &= \mathcal{N}(\mathbf{x} | (\mathbf{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A})^{-1} (\mathbf{A}^\top \mathbf{L} (\mathbf{y} - \mathbf{b}) + \mathbf{\Lambda} \boldsymbol{\mu}), (\mathbf{\Lambda} + \mathbf{A}^\top \mathbf{L} \mathbf{A})^{-1}), \\ p(\mathbf{y}) &= \mathcal{N}(\mathbf{y} | \mathbf{A} \boldsymbol{\mu} + \mathbf{b}, \mathbf{L}^{-1} + \mathbf{A} \mathbf{\Lambda}^{-1} \mathbf{A}^\top). \end{aligned} \quad (2.210)$$

2.33

Refer to 2.32.

2.34

Let \mathbf{X} be a set of N variables such that

$$\ln p(\mathbf{X} | \boldsymbol{\mu}, \boldsymbol{\Sigma}) = -\frac{ND}{2} \ln(2\pi) - \frac{N}{2} \ln(\det \boldsymbol{\Sigma}) - \frac{1}{2} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_n - \boldsymbol{\mu}). \quad (2.211)$$

To maximise it with respect to $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$, setting the partial derivatives to zero gives

$$\begin{aligned} \mathbf{0} &= \sum_{n=1}^N (\boldsymbol{\Sigma}^{-1} + (\boldsymbol{\Sigma}^{-1})^\top) (\mathbf{x}_n - \boldsymbol{\mu}), \\ \mathbf{O} &= -\frac{N}{2} (\boldsymbol{\Sigma}^{-1})^\top + \frac{1}{2} (\boldsymbol{\Sigma}^{-1})^2 \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu})(\mathbf{x}_n - \boldsymbol{\mu})^\top. \end{aligned} \quad (2.212)$$

Therefore,

$$\begin{aligned} \boldsymbol{\mu}_{\text{ML}} &= \frac{1}{N} \sum_{n=1}^N \mathbf{x}_n, \\ \boldsymbol{\Sigma}_{\text{ML}} &= \frac{1}{N} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})(\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})^\top. \end{aligned} \quad (2.213)$$

2.35

Let \mathbf{x} be a variable such that

$$p(\mathbf{x}) = \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}). \quad (2.214)$$

Then

$$\mathbb{E} \mathbf{x} \mathbf{x}^\top = \int \mathbf{x} \mathbf{x}^\top \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x}. \quad (2.215)$$

The right hand side can be written as

$$\begin{aligned} & \int (\mathbf{x} - \boldsymbol{\mu} + \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu} + \boldsymbol{\mu})^\top \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} \\ &= \int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} + \boldsymbol{\mu} \int (\mathbf{x} - \boldsymbol{\mu})^\top \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} \\ &+ \left(\int (\mathbf{x} - \boldsymbol{\mu}) \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} \right) \boldsymbol{\mu}^\top + \boldsymbol{\mu} \boldsymbol{\mu}^\top \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x}. \end{aligned} \quad (2.216)$$

Since

$$\begin{aligned} \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} &= 1, \\ \int \mathbf{x} \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} &= \boldsymbol{\mu}, \\ \int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} &= \boldsymbol{\Sigma}, \end{aligned} \quad (2.217)$$

the right hand side can be written as $\boldsymbol{\Sigma} + \boldsymbol{\mu} \boldsymbol{\mu}^\top$. Therefore,

$$\mathbb{E} \mathbf{x} \mathbf{x}^\top = \boldsymbol{\Sigma} + \boldsymbol{\mu} \boldsymbol{\mu}^\top. \quad (2.218)$$

Additionally, let \mathbf{x}_n and \mathbf{x}_m be variables such that

$$\begin{aligned} p(\mathbf{x}_n) &= \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}, \boldsymbol{\Sigma}), \\ p(\mathbf{x}_m) &= \mathcal{N}(\mathbf{x}_m|\boldsymbol{\mu}, \boldsymbol{\Sigma}). \end{aligned} \quad (2.219)$$

If $n \neq m$, then

$$\mathbb{E} \mathbf{x}_n \mathbf{x}_m^\top = \mathbb{E} \mathbf{x}_n \mathbb{E} \mathbf{x}_m^\top. \quad (2.220)$$

The right hand side can be written as $\boldsymbol{\mu} \boldsymbol{\mu}^\top$. Therefore,

$$\mathbb{E} \mathbf{x}_n \mathbf{x}_m^\top = \delta_{nm} \boldsymbol{\Sigma} + \boldsymbol{\mu} \boldsymbol{\mu}^\top. \quad (2.221)$$

Finally, let $\mathbf{x}_1, \dots, \mathbf{x}_N$ be variables such that

$$p(\mathbf{x}_n) = \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}, \boldsymbol{\Sigma}). \quad (2.222)$$

By 2.34,

$$\begin{aligned} \boldsymbol{\mu}_{\text{ML}} &= \frac{1}{N} \sum_{n=1}^N \mathbf{x}_n, \\ \boldsymbol{\Sigma}_{\text{ML}} &= \frac{1}{N} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})(\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})^\top. \end{aligned} \quad (2.223)$$

Then

$$\mathbb{E} \boldsymbol{\Sigma}_{\text{ML}} = \frac{1}{N} \sum_{n=1}^N \mathbb{E}(\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})(\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})^\top. \quad (2.224)$$

The right hand side can be written as

$$\begin{aligned} & \frac{1}{N} \sum_{n=1}^N \mathbb{E} \mathbf{x}_n \mathbf{x}_n^\top - \frac{1}{N^2} \sum_{n=1}^N \mathbb{E} \left(\sum_{n=1}^N \mathbf{x}_n \right) \mathbf{x}_n^\top - \frac{1}{N^2} \sum_{n=1}^N \mathbb{E} \mathbf{x}_n \left(\sum_{n=1}^N \mathbf{x}_n \right)^\top \\ & + \frac{1}{N^3} \sum_{n=1}^N \mathbb{E} \left(\sum_{n=1}^N \mathbf{x}_n \right) \left(\sum_{n=1}^N \mathbf{x}_n \right)^\top. \end{aligned} \quad (2.225)$$

The first term can be written as $\boldsymbol{\Sigma} + \boldsymbol{\mu}\boldsymbol{\mu}^\top$. The second and third terms can be written as

$$-\frac{1}{N} ((\boldsymbol{\Sigma} + \boldsymbol{\mu}\boldsymbol{\mu}^\top) + (N-1)\boldsymbol{\mu}\boldsymbol{\mu}^\top) = -\frac{1}{N} \boldsymbol{\Sigma} - \boldsymbol{\mu}\boldsymbol{\mu}^\top. \quad (2.226)$$

The fourth term can be written as

$$\frac{1}{N^2} (N(\boldsymbol{\Sigma} + \boldsymbol{\mu}\boldsymbol{\mu}^\top) + N(N-1)\boldsymbol{\mu}\boldsymbol{\mu}^\top) = \frac{1}{N} \boldsymbol{\Sigma} + \boldsymbol{\mu}\boldsymbol{\mu}^\top. \quad (2.227)$$

Therefore,

$$\mathbb{E} \boldsymbol{\Sigma}_{\text{ML}} = \frac{N-1}{N} \boldsymbol{\Sigma}. \quad (2.228)$$

2.36

Let x_1, \dots, x_N be variables such that

$$p(x_n) = \mathcal{N}(x_n | \mu, \sigma^2). \quad (2.229)$$

Let us assume that μ is known. Then, by 2.34,

$$\sigma_{\text{ML}}^{2(N)} = \frac{1}{N} \sum_{n=1}^N (x_n - \mu)^2. \quad (2.230)$$

The right hand side can be written as

$$\frac{1}{N} (x_N - \mu)^2 + \frac{1}{N} \sum_{n=1}^{N-1} (x_n - \mu)^2 = \frac{1}{N} (x_N - \mu)^2 + \frac{N-1}{N} \sigma_{\text{ML}}^{2(N-1)}. \quad (2.231)$$

Therefore,

$$\sigma_{\text{ML}}^{2(N)} = \sigma_{\text{ML}}^{2(N-1)} + \frac{1}{N} \left((x_N - \mu)^2 - \sigma_{\text{ML}}^{2(N-1)} \right). \quad (2.232)$$

Since

$$\frac{\partial}{\partial \sigma^2} (-\ln p(x_n | \sigma^2)) = \frac{1}{2\sigma^2} - \frac{1}{2(\sigma^2)^2} (x_n - \mu)^2, \quad (2.233)$$

we have

$$\sigma_{\text{ML}}^{2(N)} = \sigma_{\text{ML}}^{2(N-1)} - \frac{\sigma_{\text{ML}}^{2(N-1)}}{N} \frac{\partial}{\partial \sigma_{\text{ML}}^{2(N-1)}} \left(-\ln p(x_N | \sigma_{\text{ML}}^{2(N-1)}) \right). \quad (2.234)$$

2.37

Let $\mathbf{x}_1, \dots, \mathbf{x}_N$ be variables such that

$$p(\mathbf{x}_n) = \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}, \boldsymbol{\Sigma}). \quad (2.235)$$

Let us assume that $\boldsymbol{\mu}$ is known. Then, by 2.34,

$$\boldsymbol{\Sigma}_{\text{ML}}^{(N)} = \frac{1}{N} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu})(\mathbf{x}_n - \boldsymbol{\mu})^\top. \quad (2.236)$$

The right hand side can be written as

$$\begin{aligned} & \frac{1}{N} (\mathbf{x}_N - \boldsymbol{\mu})(\mathbf{x}_N - \boldsymbol{\mu})^\top + \frac{1}{N} \sum_{n=1}^{N-1} (\mathbf{x}_n - \boldsymbol{\mu})(\mathbf{x}_n - \boldsymbol{\mu})^\top \\ &= \frac{1}{N} (\mathbf{x}_N - \boldsymbol{\mu})(\mathbf{x}_N - \boldsymbol{\mu})^\top + \frac{N-1}{N} \boldsymbol{\Sigma}_{\text{ML}}^{(N-1)}. \end{aligned} \quad (2.237)$$

Therefore,

$$\Sigma_{\text{ML}}^{(N)} = \Sigma_{\text{ML}}^{(N-1)} + \frac{1}{N} \left((\mathbf{x}_N - \boldsymbol{\mu})(\mathbf{x}_N - \boldsymbol{\mu})^\top - \Sigma_{\text{ML}}^{(N-1)} \right). \quad (2.238)$$

Since

$$\frac{\partial}{\partial \Sigma} (-\ln p(x_n | \Sigma)) = -\frac{1}{2} (\Sigma^{-1})^\top + \frac{1}{2} (\Sigma^{-1})^2 (\mathbf{x}_N - \boldsymbol{\mu})(\mathbf{x}_N - \boldsymbol{\mu})^\top, \quad (2.239)$$

we have

$$\Sigma_{\text{ML}}^{(N)} = \Sigma_{\text{ML}}^{(N-1)} - \frac{\Sigma_{\text{ML}}^{(N-1)}}{N} \frac{\partial}{\partial \Sigma_{\text{ML}}^{(N-1)}} \left(-\ln p(\mathbf{x}_N | \Sigma_{\text{ML}}^{(N-1)}) \right). \quad (2.240)$$

2.38

Let x_1, \dots, x_N be variables such that

$$\begin{aligned} p(x_n | \mu) &= \mathcal{N}(x_n | \mu, \sigma^2), \\ p(\mu) &= \mathcal{N}(\mu | \mu_0, \sigma_0^2). \end{aligned} \quad (2.241)$$

By the definition,

$$p(\mu | \mathbf{x}) p(\mathbf{x}) = p(\mathbf{x} | \mu) p(\mu). \quad (2.242)$$

The logarithm of the right hand side excpt the terms independent of \mathbf{x} and μ can be written as

$$-\frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu)^2 - \frac{1}{2\sigma_0^2} (\mu - \mu_0)^2. \quad (2.243)$$

The first term can be written as

$$-\frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu_{\text{ML}} + \mu_{\text{ML}} - \mu)^2 = -\frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu_{\text{ML}})^2 - \frac{N}{2\sigma^2} (\mu_{\text{ML}} - \mu)^2. \quad (2.244)$$

where

$$\mu_{\text{ML}} = \frac{1}{N} \sum_{n=1}^N x_n, \quad (2.245)$$

as derived in 2.34. Therefore, the logarithm except the terms independent of \mathbf{x} and μ can be written as

$$\begin{aligned} & -\frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu_{\text{ML}})^2 - \frac{N}{2\sigma^2} (\mu_{\text{ML}} - \mu)^2 - \frac{1}{2\sigma_0^2} (\mu - \mu_0)^2 \\ & = -\frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu_{\text{ML}})^2 - \frac{1}{2\sigma_N^2} (\mu - \mu_N)^2 + \frac{\mu_N^2}{2\sigma_N^2}, \end{aligned} \quad (2.246)$$

where

$$\begin{aligned} \mu_N &= \frac{N\sigma_0^2}{N\sigma_0^2 + \sigma^2} \mu_{\text{ML}} + \frac{\sigma^2}{N\sigma_0^2 + \sigma^2} \mu_0, \\ \sigma_N^2 &= \frac{\sigma^2 \sigma_0^2}{N\sigma_0^2 + \sigma^2}. \end{aligned} \quad (2.247)$$

Therefore,

$$p(\mu|\mathbf{x}) = \mathcal{N} \left(\mu \mid \frac{N\sigma_0^2}{N\sigma_0^2 + \sigma^2} \mu_{\text{ML}} + \frac{\sigma^2}{N\sigma_0^2 + \sigma^2} \mu_0, \frac{\sigma^2 \sigma_0^2}{N\sigma_0^2 + \sigma^2} \right). \quad (2.248)$$

2.39 (Incomplete)

Let x_1, \dots, x_N be variables such that

$$\begin{aligned} p(x_n|\mu) &= \mathcal{N}(x_n|\mu, \sigma^2), \\ p(\mu) &= \mathcal{N}(\mu|\mu_0, \sigma_0^2). \end{aligned} \quad (2.249)$$

Then, by 2.38,

$$p(\mu|\mathbf{x}) = \mathcal{N}(\mu|\mu_N, \sigma_N^2), \quad (2.250)$$

where

$$\begin{aligned} \mu_N &= \frac{\sigma_0^2}{N\sigma_0^2 + \sigma^2} \sum_{n=1}^N x_n + \frac{\sigma^2}{N\sigma_0^2 + \sigma^2} \mu_0, \\ \sigma_N^2 &= \frac{\sigma^2 \sigma_0^2}{N\sigma_0^2 + \sigma^2}. \end{aligned} \quad (2.251)$$

Then

$$\begin{aligned} \mu_N &= \frac{(N-1)\sigma_0^2 + \sigma^2}{N\sigma_0^2 + \sigma^2} \mu_{N-1} + \frac{\sigma_0^2}{N\sigma_0^2 + \sigma^2} x_N + \frac{\sigma^2 - \sigma_0^2}{N\sigma_0^2 + \sigma^2} \mu_0, \\ \sigma_N^2 &= \frac{(N-1)\sigma_0^2 + \sigma^2}{N\sigma_0^2 + \sigma^2} \sigma_{N-1}^2. \end{aligned} \quad (2.252)$$

2.40

Let $\mathbf{x}_1, \dots, \mathbf{x}_N$ be variables such that

$$\begin{aligned} p(\mathbf{x}_n|\boldsymbol{\mu}) &= \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}, \boldsymbol{\Sigma}), \\ p(\boldsymbol{\mu}) &= \mathcal{N}(\boldsymbol{\mu}|\boldsymbol{\mu}_0, \boldsymbol{\Sigma}). \end{aligned} \quad (2.253)$$

By the definition,

$$p(\boldsymbol{\mu}|\mathbf{X})p(\mathbf{X}) = p(\mathbf{X}|\boldsymbol{\mu})p(\boldsymbol{\mu}). \quad (2.254)$$

The logarithm of the right hand side except the terms independent of \mathbf{X} and $\boldsymbol{\mu}$ can be written as

$$-\frac{1}{2} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_n - \boldsymbol{\mu}) - \frac{1}{2} (\boldsymbol{\mu} - \boldsymbol{\mu}_0)^\top \boldsymbol{\Sigma}_0^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0). \quad (2.255)$$

The first term can be written as

$$\begin{aligned} & -\frac{1}{2} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}} + \boldsymbol{\mu}_{\text{ML}} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}} + \boldsymbol{\mu}_{\text{ML}} - \boldsymbol{\mu}) \\ &= -\frac{1}{2} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}}) - \frac{N}{2} (\boldsymbol{\mu}_{\text{ML}} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\boldsymbol{\mu}_{\text{ML}} - \boldsymbol{\mu}). \end{aligned} \quad (2.256)$$

where

$$\boldsymbol{\mu}_{\text{ML}} = \frac{1}{N} \sum_{n=1}^N \mathbf{x}_n, \quad (2.257)$$

as derived in 2.34. Therefore, the logarithm except the terms independent of \mathbf{X} and $\boldsymbol{\mu}$ can be written as

$$\begin{aligned} & -\frac{1}{2} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}}) - \frac{N}{2} (\boldsymbol{\mu}_{\text{ML}} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\boldsymbol{\mu}_{\text{ML}} - \boldsymbol{\mu}) \\ & - \frac{1}{2} (\boldsymbol{\mu} - \boldsymbol{\mu}_0)^\top \boldsymbol{\Sigma}_0^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0) \\ &= -\frac{1}{2} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_n - \boldsymbol{\mu}_{\text{ML}}) - \frac{1}{2} (\boldsymbol{\mu} - \boldsymbol{\mu}_N)^\top \boldsymbol{\Sigma}_N^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_N) \\ & + \frac{1}{2} \boldsymbol{\mu}_N^\top \boldsymbol{\Sigma}_N^{-1} \boldsymbol{\mu}_N, \end{aligned} \quad (2.258)$$

where

$$\begin{aligned}\boldsymbol{\mu}_N &= (N\boldsymbol{\Sigma}_0^{-1} + \boldsymbol{\Sigma}^{-1})^{-1} (N\boldsymbol{\Sigma}_0^{-1}\boldsymbol{\mu}_{\text{ML}} + \boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}_0), \\ \boldsymbol{\Sigma}_N &= (N\boldsymbol{\Sigma}_0^{-1} + \boldsymbol{\Sigma}^{-1})^{-1}.\end{aligned}\tag{2.259}$$

Therefore,

$$p(\boldsymbol{\mu}|\mathbf{X}) = \mathcal{N}\left(\boldsymbol{\mu} \mid (N\boldsymbol{\Sigma}_0^{-1} + \boldsymbol{\Sigma}^{-1})^{-1} (N\boldsymbol{\Sigma}_0^{-1}\boldsymbol{\mu}_{\text{ML}} + \boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}_0), (N\boldsymbol{\Sigma}_0^{-1} + \boldsymbol{\Sigma}^{-1})^{-1}\right).\tag{2.260}$$

2.41

By the definition,

$$\text{Gam}(\lambda|a, b) = \frac{b^a}{\Gamma(a)} \lambda^{a-1} \exp(-b\lambda).\tag{2.261}$$

Then

$$\int_0^\infty \text{Gam}(\lambda|a, b) d\lambda = \frac{b^a}{\Gamma(a)} \int_0^\infty \lambda^{a-1} \exp(-b\lambda) d\lambda.\tag{2.262}$$

By the transformation

$$\lambda' = b\lambda,\tag{2.263}$$

the right hand side can be written as

$$\frac{b^a}{\Gamma(a)} \int_0^\infty \left(\frac{\lambda'}{b}\right)^{a-1} \exp(-\lambda') \frac{1}{b} d\lambda' = \frac{1}{\Gamma(a)} \int_0^\infty \lambda'^{a-1} \exp(-\lambda') d\lambda'.\tag{2.264}$$

The right hand side can be written as

$$\frac{1}{\Gamma(a)} \Gamma(a) = 1.\tag{2.265}$$

Therefore,

$$\int_0^\infty \text{Gam}(\lambda|a, b) d\lambda = 1.\tag{2.266}$$

2.42

Let λ be a variable such that

$$p(\lambda) = \text{Gam}(\lambda|a, b).\tag{2.267}$$

By the definition,

$$\text{Gam}(\lambda|a, b) = \frac{b^a}{\Gamma(a)} \lambda^{a-1} \exp(-b\lambda). \quad (2.268)$$

Then

$$\text{E } \lambda = \frac{b^a}{\Gamma(a)} \int_0^\infty \lambda^a \exp\left(-\frac{\lambda}{b}\right) d\lambda. \quad (2.269)$$

By the transformation

$$\lambda' = b\lambda, \quad (2.270)$$

the right hand side can be written as

$$\frac{b^a}{\Gamma(a)} \int_0^\infty \left(\frac{\lambda'}{b}\right)^a \exp(-\lambda') \frac{1}{b} d\lambda' = \frac{1}{b\Gamma(a)} \int_0^\infty \lambda'^a \exp(-\lambda') d\lambda'. \quad (2.271)$$

The right hand side can be written as

$$\frac{1}{b\Gamma(a)} \Gamma(a+1) = \frac{a}{b}. \quad (2.272)$$

Therefore,

$$\text{E } \lambda = \frac{a}{b}. \quad (2.273)$$

Additionally,

$$\text{E } \lambda^2 = \frac{b^a}{\Gamma(a)} \int_0^\infty \lambda^{a+1} \exp\left(-\frac{\lambda}{b}\right) d\lambda. \quad (2.274)$$

By the transformation

$$\lambda' = b\lambda, \quad (2.275)$$

the right hand side can be written as

$$\frac{b^a}{\Gamma(a)} \int_0^\infty \left(\frac{\lambda'}{b}\right)^{a+1} \exp(-\lambda') \frac{1}{b} d\lambda' = \frac{1}{b^2\Gamma(a)} \int_0^\infty \lambda'^{a+1} \exp(-\lambda') d\lambda'. \quad (2.276)$$

The right hand side can be written as

$$\frac{1}{b^2\Gamma(a)} \Gamma(a+2) = \frac{a(a+1)}{b^2}. \quad (2.277)$$

Therefore,

$$E \lambda^2 = \frac{a(a+1)}{b^2}. \quad (2.278)$$

By the definition,

$$\text{var } \lambda = E \lambda^2 - (E \lambda)^2. \quad (2.279)$$

Therefore,

$$\text{var } \lambda = \frac{a}{b^2}. \quad (2.280)$$

Finally, setting the derivative of $\text{Gam}(\lambda|a, b)$ with respect to λ to zero gives

$$0 = \frac{b^a}{\Gamma(a)} \left(\frac{a-1}{\lambda} - b \right) \lambda^{a-1} \exp \left(-\frac{\lambda}{b} \right). \quad (2.281)$$

Therefore,

$$\text{mode } \lambda = \frac{a-1}{b}. \quad (2.282)$$

2.43

Let

$$p(x|\sigma^2, q) = \frac{q}{2\Gamma\left(\frac{1}{q}\right)} (2\sigma^2)^{-\frac{1}{q}} \exp\left(-\frac{|x|^q}{2\sigma^2}\right). \quad (2.283)$$

Then

$$\int_{-\infty}^{\infty} p(x|\sigma^2, q) dx = \frac{q}{\Gamma\left(\frac{1}{q}\right)} (2\sigma^2)^{-\frac{1}{q}} \int_0^{\infty} \exp\left(-\frac{x^q}{2\sigma^2}\right) dx. \quad (2.284)$$

By the transformation

$$x' = \frac{x^q}{2\sigma^2}, \quad (2.285)$$

the right hand side can be written as

$$\begin{aligned} & \frac{q}{\Gamma\left(\frac{1}{q}\right)} (2\sigma^2)^{-\frac{1}{q}} \int_0^{\infty} \exp(-x') (2\sigma^2)^{\frac{1}{q}} \frac{1}{q} x'^{\frac{1}{q}-1} dx' \\ &= \frac{1}{\Gamma\left(\frac{1}{q}\right)} \int_0^{\infty} x'^{\frac{1}{q}-1} \exp(-x') dx'. \end{aligned} \quad (2.286)$$

The right hand side can be written as

$$\frac{1}{\Gamma\left(\frac{1}{q}\right)} \Gamma\left(\frac{1}{q}\right) = 1. \quad (2.287)$$

Therefore,

$$\int_{-\infty}^{\infty} p(x|\sigma^2, q) dx = 1. \quad (2.288)$$

Additionally,

$$p(x|\sigma^2, 2) = \frac{1}{\Gamma\left(\frac{1}{2}\right)} (2\sigma^2)^{-\frac{1}{2}} \exp\left(-\frac{x^2}{2\sigma^2}\right). \quad (2.289)$$

Therefore,

$$p(x|\sigma^2, 2) = \mathcal{N}(x|0, \sigma^2). \quad (2.290)$$

Finally, let $\mathbf{t} = (t_1, \dots, t_N)^\top$ and $\mathbf{X} = \{x_1, \dots, x_N\}$ such that

$$t_n = y(\mathbf{x}_n, \mathbf{w}) + \epsilon_n, \quad (2.291)$$

where

$$p(\epsilon_n) = p(\epsilon_n|\sigma^2, q). \quad (2.292)$$

Therefore, the logarithm of $p(\epsilon_n)$ except the terms independent of \mathbf{w} and σ^2 can be written as

$$-\frac{|\epsilon_n|^q}{2\sigma^2} - \frac{1}{q} \ln(2\sigma^2). \quad (2.293)$$

Thus, the logarithm of $p(\mathbf{t}|\mathbf{X}, \mathbf{w}, \sigma^2)$ except the terms independent of \mathbf{w} and σ^2 can be written as

$$-\frac{1}{2\sigma^2} \sum_{n=1}^N |y(\mathbf{x}_n, \mathbf{w}) - t_n|^q - \frac{N}{q} \ln(2\sigma^2). \quad (2.294)$$

2.44

Let x_1, \dots, x_N be variables such that

$$\begin{aligned} p(x_n|\mu, \tau) &= \mathcal{N}(x_n|\mu, \tau^{-1}), \\ p(\mu, \tau) &= \mathcal{N}(\mu|\mu_0, (\beta\tau)^{-1}) \text{Gam}(\tau|a, b). \end{aligned} \quad (2.295)$$

By the definition,

$$p(\mu, \tau | \mathbf{x}) p(\mathbf{x}) = p(\mathbf{x} | \mu, \tau) p(\mu, \tau). \quad (2.296)$$

The right hand side except the terms independent of \mathbf{x} , μ and τ can be written as

$$\begin{aligned} & \tau^{\frac{N}{2}} \exp \left(-\frac{\tau}{2} \sum_{n=1}^N (x_n - \mu)^2 \right) \tau^{\frac{1}{2}} \exp \left(-\frac{\beta \tau}{2} (\mu - \mu_0)^2 \right) \tau^{a-1} \exp(-b\tau) \\ &= \tau^{a+\frac{N-1}{2}} \exp \left(-\frac{N\tau}{2} (\bar{x} - \mu)^2 - \frac{\beta \tau}{2} (\mu - \mu_0)^2 - b\tau - \frac{\tau}{2} \sum_{n=1}^N (x_n - \bar{x})^2 \right). \end{aligned} \quad (2.297)$$

where

$$\bar{x} = \frac{1}{N} \sum_{n=1}^N x_n. \quad (2.298)$$

Since

$$-\frac{N\tau}{2} (\bar{x} - \mu)^2 - \frac{\beta \tau}{2} (\mu - \mu_0)^2 = -\frac{(N + \beta)\tau}{2} \left(\mu - \frac{N\bar{x} + \beta\mu_0}{N + \beta} \right)^2 - \frac{N\beta\tau(\bar{x} - \mu_0)^2}{2(N + \beta)}, \quad (2.299)$$

the right hand side can be written as

$$\tau^{a+\frac{N-1}{2}} \exp \left(-\frac{(N + \beta)\tau}{2} \left(\mu - \frac{N\bar{x} + \beta\mu_0}{N + \beta} \right)^2 - \left(b + \frac{N\beta(\bar{x} - \mu_0)^2}{2(N + \beta)} + \frac{1}{2} \sum_{n=1}^N (x_n - \bar{x})^2 \right) \tau \right). \quad (2.300)$$

Therefore,

$$\begin{aligned} p(\mu, \tau | \mathbf{x}) &= \mathcal{N} \left(\mu \mid \frac{N\bar{x} + \beta\mu_0}{N + \beta}, ((N + \beta)\tau)^{-1} \right) \\ &\quad \text{Gam} \left(\tau \mid a + \frac{N + 1}{2}, b + \frac{N\beta(\bar{x} - \mu_0)^2}{2(N + \beta)} + \frac{1}{2} \sum_{n=1}^N (x_n - \bar{x})^2 \right). \end{aligned} \quad (2.301)$$

2.45 (Incomplete)

Let \mathbf{x} be a variable in D dimensions such that

$$p(\mathbf{x}) = \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Lambda}^{-1}). \quad (2.302)$$

Then

$$p(\mathbf{X}|\mathbf{\Lambda}) = \prod_{n=1}^N \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}, \mathbf{\Lambda}^{-1}). \quad (2.303)$$

The right hand side except the terms independent of $\mathbf{\Lambda}$ can be written as

$$\begin{aligned} & (\det \mathbf{\Lambda})^{\frac{N}{2}} \exp \left(-\frac{1}{2} \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu})^\top \mathbf{\Lambda} (\mathbf{x}_n - \boldsymbol{\mu}) \right) \\ &= (\det \mathbf{\Lambda})^{\frac{N}{2}} \exp \left(-\frac{1}{2} \text{tr} (\mathbf{W}^{-1} \mathbf{\Lambda}) \right), \end{aligned} \quad (2.304)$$

where

$$\mathbf{W}^{-1} = \sum_{n=1}^N (\mathbf{x}_n - \boldsymbol{\mu})(\mathbf{x}_n - \boldsymbol{\mu})^\top. \quad (2.305)$$

2.46

Let x be a variable such that

$$p(x|\mu, \tau, a, b) = \mathcal{N}(x|\mu, \tau^{-1}) \text{Gam}(\tau|a, b). \quad (2.306)$$

Then

$$p(x|\mu, a, b) = \int_0^\infty \mathcal{N}(x|\mu, \tau^{-1}) \text{Gam}(\tau|a, b) d\tau. \quad (2.307)$$

The right hand side can be written as

$$\begin{aligned} & \int_0^\infty \left(\frac{\tau}{2\pi} \right)^{\frac{1}{2}} \exp \left(-\frac{\tau}{2} (x - \mu)^2 \right) \frac{b^a}{\Gamma(a)} \tau^{a-1} \exp(-b\tau) d\tau \\ &= (2\pi)^{-\frac{1}{2}} \frac{b^a}{\Gamma(a)} \int_0^\infty \tau^{a-\frac{1}{2}} \exp \left(-\left(b + \frac{(x - \mu)^2}{2} \right) \tau \right) d\tau. \end{aligned} \quad (2.308)$$

By the transformation

$$\tau' = \left(b + \frac{(x - \mu)^2}{2} \right) \tau, \quad (2.309)$$

the integral of the right hand side can be written as

$$\int_0^\infty \left(\frac{\tau'}{b + \frac{(x - \mu)^2}{2}} \right)^{a-\frac{1}{2}} \exp(-\tau') \frac{d\tau'}{b + \frac{(x - \mu)^2}{2}} = \Gamma \left(a + \frac{1}{2} \right) \left(b + \frac{(x - \mu)^2}{2} \right)^{-a-\frac{1}{2}}. \quad (2.310)$$

Therefore,

$$p(x|\mu, \tau, a, b) = (2\pi)^{-\frac{1}{2}} \frac{\Gamma(a + \frac{1}{2})}{\Gamma(a)} b^a \left(b + \frac{(x - \mu)^2}{2} \right)^{-a - \frac{1}{2}}. \quad (2.311)$$

Let

$$\begin{aligned} \nu &= 2a, \\ \lambda &= \frac{a}{b}. \end{aligned} \quad (2.312)$$

Then

$$p(x|\mu, \lambda, \nu) = \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})} \left(\frac{\lambda}{\pi\nu} \right)^{\frac{1}{2}} \left(1 + \frac{\lambda(x - \mu)^2}{\nu} \right)^{-\frac{\nu+1}{2}}. \quad (2.313)$$

2.47

By the definition,

$$\text{St}(x|\mu, \lambda, \nu) = \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})} \left(\frac{\lambda}{\pi\nu} \right)^{\frac{1}{2}} \left(1 + \frac{\lambda(x - \mu)^2}{\nu} \right)^{-\frac{\nu+1}{2}}. \quad (2.314)$$

By the transformation

$$y = \frac{\lambda(x - \mu)^2}{\nu}, \quad (2.315)$$

the right hand side except the terms independent of x can be written as

$$(1 + y)^{-\frac{\lambda(x - \mu)^2}{2y} - \frac{1}{2}}. \quad (2.316)$$

In the limit $y \rightarrow \infty$, it becomes

$$\exp \left(-\frac{\lambda}{2}(x - \mu)^2 \right). \quad (2.317)$$

Therefore, in the limit $\nu \rightarrow \infty$, $\text{St}(x|\mu, \lambda, \nu)$ becomes $\mathcal{N}(x|\mu, \lambda^{-1})$.

2.48

Let \mathbf{x} be a variable in D dimensions such that

$$p(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}, \eta, \nu) = \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, (\eta\boldsymbol{\Lambda})^{-1}) \text{Gam} \left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2} \right). \quad (2.318)$$

Then

$$p(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}, \nu) = \int_0^\infty \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, (\eta\boldsymbol{\Lambda})^{-1}) \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta. \quad (2.319)$$

The right hand side can be written as

$$\begin{aligned} & \int_0^\infty (2\pi)^{-\frac{D}{2}} (\det(\eta\boldsymbol{\Lambda}))^{\frac{1}{2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \eta \boldsymbol{\Lambda} (\mathbf{x} - \boldsymbol{\mu})\right) \frac{(\frac{\nu}{2})^{\frac{\nu}{2}}}{\Gamma(\frac{\nu}{2})} \eta^{\frac{\nu}{2}-1} \exp\left(-\frac{\nu}{2}\eta\right) d\eta \\ &= (2\pi)^{-\frac{D}{2}} \frac{(\frac{\nu}{2})^{\frac{\nu}{2}}}{\Gamma(\frac{\nu}{2})} (\det \boldsymbol{\Lambda})^{\frac{1}{2}} \int_0^\infty \eta^{\frac{D+\nu}{2}-1} \exp\left(-\frac{1}{2}(\nu + (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Lambda} (\mathbf{x} - \boldsymbol{\mu}))\eta\right) d\eta. \end{aligned} \quad (2.320)$$

By the transformation

$$\eta' = \frac{1}{2}(\nu + (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Lambda} (\mathbf{x} - \boldsymbol{\mu}))\eta, \quad (2.321)$$

the integral of the right hand side can be written as

$$\begin{aligned} & \int_0^\infty \left(\frac{2\eta'}{\nu + (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Lambda} (\mathbf{x} - \boldsymbol{\mu})}\right)^{\frac{D+\nu}{2}-1} \exp(-\eta') \frac{2}{\nu + (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Lambda} (\mathbf{x} - \boldsymbol{\mu})} d\eta' \\ &= \left(\frac{2}{\nu + (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Lambda} (\mathbf{x} - \boldsymbol{\mu})}\right)^{\frac{D+\nu}{2}} \Gamma\left(\frac{D+\nu}{2}\right). \end{aligned} \quad (2.322)$$

Therefore,

$$p(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}, \nu) = \frac{\Gamma(\frac{D+\nu}{2})}{\Gamma(\frac{\nu}{2})} \frac{(\det \boldsymbol{\Lambda})^{\frac{1}{2}}}{(\pi\nu)^{\frac{D}{2}}} \left(1 + \frac{(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Lambda} (\mathbf{x} - \boldsymbol{\mu})}{\nu}\right)^{-\frac{D+\nu}{2}}. \quad (2.323)$$

2.49

Let \mathbf{x} be a variable such that

$$p(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}, \nu) = \text{St}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}, \nu). \quad (2.324)$$

By the definition,

$$\text{St}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}, \nu) = \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, (\eta\boldsymbol{\Lambda})^{-1}) \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta. \quad (2.325)$$

First,

$$\mathbf{E} \mathbf{x} = \int \mathbf{x} \text{St}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}, \nu) d\mathbf{x}. \quad (2.326)$$

The right hand side can be written as

$$\begin{aligned} & \int \mathbf{x} \left(\int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, (\eta\boldsymbol{\Lambda})^{-1}) \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta \right) d\mathbf{x} \\ &= \int \left(\int \mathbf{x} \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, (\eta\boldsymbol{\Lambda})^{-1}) d\mathbf{x} \right) \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta. \end{aligned} \quad (2.327)$$

The right hand side can be written as

$$\boldsymbol{\mu} \int \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta = \boldsymbol{\mu}. \quad (2.328)$$

Therefore,

$$\mathbf{E} \mathbf{x} = \boldsymbol{\mu}. \quad (2.329)$$

Additionally,

$$\text{cov} \mathbf{x} = \int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \text{St}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Lambda}, \nu) d\mathbf{x}. \quad (2.330)$$

The right hand side can be written as

$$\begin{aligned} & \int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \left(\int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, (\eta\boldsymbol{\Lambda})^{-1}) \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta \right) d\mathbf{x} \\ &= \int \left(\int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^\top \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, (\eta\boldsymbol{\Lambda})^{-1}) d\mathbf{x} \right) \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta. \end{aligned} \quad (2.331)$$

The right hand side can be written as

$$\int (\eta\boldsymbol{\Lambda})^{-1} \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta = \boldsymbol{\Lambda}^{-1} \frac{\left(\frac{\nu}{2}\right)^{\frac{\nu}{2}}}{\Gamma\left(\frac{\nu}{2}\right)} \int \eta^{\frac{\nu}{2}-2} \exp\left(-\frac{\nu}{2}\eta\right) d\eta. \quad (2.332)$$

By the transformation

$$\eta' = \frac{\nu}{2}\eta, \quad (2.333)$$

the integral of the right hand side can be written as

$$\int \left(\frac{2}{\nu}\eta'\right)^{-\frac{\nu}{2}-2} \exp(-\eta') \frac{2}{\nu} d\eta' = \left(\frac{2}{\nu}\right)^{\frac{\nu}{2}-1} \Gamma\left(\frac{\nu}{2} - 1\right). \quad (2.334)$$

Therefore, the right hand side can be written as

$$\mathbf{\Lambda}^{-1} \frac{\left(\frac{\nu}{2}\right)^{\frac{\nu}{2}}}{\Gamma\left(\frac{\nu}{2}\right)} \left(\frac{2}{\nu}\right)^{\frac{\nu}{2}-1} \Gamma\left(\frac{\nu}{2}-1\right) = \frac{\frac{\nu}{2}}{\frac{\nu}{2}-1} \mathbf{\Lambda}^{-1}. \quad (2.335)$$

Thus,

$$\text{cov } \mathbf{x} = \frac{\nu}{\nu-2} \mathbf{\Lambda}^{-1}. \quad (2.336)$$

Finally, setting the derivative of $\text{St}(\mathbf{x}|\boldsymbol{\mu}, \mathbf{\Lambda}, \nu)$ with respect to \mathbf{x} to zero gives

$$\mathbf{0} = -\frac{1}{2} (\mathbf{\Lambda} + \mathbf{\Lambda}^\top) (\mathbf{x} - \boldsymbol{\mu}) \int \eta \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, (\eta \mathbf{\Lambda})^{-1}) \text{Gam}\left(\eta \mid \frac{\nu}{2}, \frac{\nu}{2}\right) d\eta. \quad (2.337)$$

Therefore,

$$\text{mode } \mathbf{x} = \boldsymbol{\mu}. \quad (2.338)$$

2.50

By the definition,

$$\text{St}(\mathbf{x}|\boldsymbol{\mu}, \mathbf{\Lambda}, \nu) = \frac{\Gamma\left(\frac{D+\nu}{2}\right) (\det \mathbf{\Lambda})^{\frac{1}{2}}}{\Gamma\left(\frac{\nu}{2}\right) (\pi\nu)^{\frac{D}{2}}} \left(1 + \frac{(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{\Lambda} (\mathbf{x} - \boldsymbol{\mu})}{\nu}\right)^{-\frac{D+\nu}{2}}. \quad (2.339)$$

By the transformation

$$y = \frac{(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{\Lambda} (\mathbf{x} - \boldsymbol{\mu})}{\nu}, \quad (2.340)$$

the right hand side except the terms independent of \mathbf{x} can be written as

$$(1+y)^{-\frac{(\mathbf{x}-\boldsymbol{\mu})^\top \mathbf{\Lambda} (\mathbf{x}-\boldsymbol{\mu})}{2y} - \frac{D}{2}}. \quad (2.341)$$

In the limit $y \rightarrow \infty$, it becomes

$$\exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{\Lambda} (\mathbf{x} - \boldsymbol{\mu})\right). \quad (2.342)$$

Therefore, in the limit $\nu \rightarrow \infty$, $\text{St}(\mathbf{x}|\boldsymbol{\mu}, \mathbf{\Lambda}, \nu)$ becomes $\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \mathbf{\Lambda}^{-1})$.

2.51

We have

$$\exp(iA) \exp(-iA) = 1. \quad (2.343)$$

The left hand side can be written as

$$(\cos A + i \sin A)(\cos A - i \sin A) = \cos^2 A + \sin^2 A. \quad (2.344)$$

Therefore,

$$\cos^2 A + \sin^2 A = 1. \quad (2.345)$$

Additionally,

$$\cos(A - B) = \operatorname{Re}(\exp(i(A - B))). \quad (2.346)$$

The right hand side can be written as

$$\operatorname{Re}(\exp(iA) \exp(-iB)) = \operatorname{Re}((\cos A + i \sin A)(\cos B - i \sin B)). \quad (2.347)$$

The right hand side can be written as $\cos A \cos B + \sin A \sin B$. Therefore,

$$\cos(A - B) = \cos A \cos B + \sin A \sin B. \quad (2.348)$$

Finally,

$$\sin(A - B) = \operatorname{Im}(\exp(i(A - B))). \quad (2.349)$$

The right hand side can be written as

$$\operatorname{Im}(\exp(iA) \exp(-iB)) = \operatorname{Im}((\cos A + i \sin A)(\cos B - i \sin B)). \quad (2.350)$$

The right hand side can be written as $\sin A \cos B - \cos A \sin B$. Therefore,

$$\sin(A - B) = \sin A \cos B - \cos A \sin B. \quad (2.351)$$

2.52 (Incomplete)

Let θ be a variable such that

$$p(\theta|\theta_0, m) = \frac{1}{2\pi I_0(m)} \exp(m \cos(\theta - \theta_0)), \quad (2.352)$$

where

$$I_0(m) = \frac{1}{2\pi} \int_0^{2\pi} \exp(m \cos \theta) d\theta. \quad (2.353)$$

By the Taylor series

$$\cos \alpha = 1 - \frac{1}{2}\alpha^2 + O(\alpha^4) \quad (2.354)$$

and the transformation

$$\xi = m^{\frac{1}{2}}(\theta - \theta_0), \quad (2.355)$$

we have

$$\exp(m \cos(\theta - \theta_0)) = \exp\left(m \left(1 - \frac{1}{2}(\theta - \theta_0)^2 + O((\theta - \theta_0)^4)\right)\right). \quad (2.356)$$

2.53

Let θ_0 be a parameter such that

$$\sum_{n=1}^N \sin(\theta_n - \theta_0) = 0. \quad (2.357)$$

The left hand side can be written as

$$\sum_{n=1}^N (\sin \theta_n \cos \theta_0 - \cos \theta_n \sin \theta_0) = \cos \theta_0 \sum_{n=1}^N \sin \theta_n - \sin \theta_0 \sum_{n=1}^N \cos \theta_n. \quad (2.358)$$

Therefore,

$$\theta_0 = \arctan \left(\frac{\sum_{n=1}^N \sin \theta_n}{\sum_{n=1}^N \cos \theta_n} \right). \quad (2.359)$$

2.54

Let θ be a variable such that

$$p(\theta|\theta_0, m) = \frac{1}{2\pi I_0(m)} \exp(m \cos(\theta - \theta_0)), \quad (2.360)$$

where

$$I_0(m) = \frac{1}{2\pi} \int_0^{2\pi} \exp(m \cos \theta) d\theta. \quad (2.361)$$

Setting the first and second derivatives with respect to θ to zero gives

$$\begin{aligned} 0 &= -m \sin(\theta - \theta_0) p(\theta|\theta_0, m), \\ 0 &= (m^2 \sin^2(\theta - \theta_0) - m \cos(\theta - \theta_0)) p(\theta|\theta_0, m). \end{aligned} \quad (2.362)$$

Therefore,

$$\begin{aligned}\arg\max_{\theta} p(\theta|\theta_0, m) &= \theta_0, \\ \arg\min_{\theta} p(\theta|\theta_0, m) &= \theta_0 - \pi \operatorname{sgn}(\theta_0 - \pi).\end{aligned}\tag{2.363}$$

2.55

Let

$$\theta_0^{\text{ML}} = \arctan \left(\frac{\sum_{n=1}^N \sin \theta_n}{\sum_{n=1}^N \cos \theta_n} \right).\tag{2.364}$$

Let

$$\begin{aligned}\bar{r} \cos \bar{\theta} &= \frac{1}{N} \sum_{n=1}^N \cos \theta_n, \\ \bar{r} \sin \bar{\theta} &= \frac{1}{N} \sum_{n=1}^N \sin \theta_n.\end{aligned}\tag{2.365}$$

Then

$$\theta_0^{\text{ML}} = \bar{\theta}.\tag{2.366}$$

Here,

$$\frac{1}{N} \sum_{n=1}^N \cos (\theta_n - \theta_0^{\text{ML}}) = \left(\frac{1}{N} \sum_{n=1}^N \cos \theta_n \right) \cos \theta_0^{\text{ML}} + \left(\frac{1}{N} \sum_{n=1}^N \sin \theta_n \right) \sin \theta_0^{\text{ML}}.\tag{2.367}$$

By the result above, the right hand side can be written as

$$\bar{r} \cos^2 \bar{\theta} + \bar{r} \sin^2 \bar{\theta} = \bar{r}.\tag{2.368}$$

Therefore,

$$\frac{1}{N} \sum_{n=1}^N \cos (\theta_n - \theta_0^{\text{ML}}) = \bar{r}.\tag{2.369}$$

2.56

By the definition,

$$\text{Beta}(\mu|a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \mu^{a-1} (1-\mu)^{b-1}.\tag{2.370}$$

The right hand side can be written as

$$\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \exp((a-1)\ln\mu + (b-1)\ln(1-\mu)) \quad (2.371)$$

Therefore, the natural parameters are given by

$$\boldsymbol{\eta} = \begin{bmatrix} a-1 \\ b-1 \end{bmatrix}.$$

Additionally, by the definition,

$$\text{Gam}(\lambda|a, b) = \frac{b^a}{\Gamma(a)} \lambda^{a-1} \exp(-b\lambda). \quad (2.372)$$

The right hand side can be written as

$$\frac{b^a}{\Gamma(a)} \exp((a-1)\ln\lambda - b\lambda). \quad (2.373)$$

Therefore, the natural parameters are given by

$$\boldsymbol{\eta} = \begin{bmatrix} a-1 \\ -b \end{bmatrix}.$$

Finally, for

$$p(\theta|\theta_0, m) = \frac{1}{2\pi I_0(m)} \exp(m \cos(\theta - \theta_0)), \quad (2.374)$$

where

$$I_0(m) = \frac{1}{2\pi} \int_0^{2\pi} \exp(m \cos \theta) d\theta, \quad (2.375)$$

the right hand side can be written as

$$\frac{1}{2\pi I_0(m)} \exp(m \cos \theta_0 \cos \theta + m \sin \theta_0 \sin \theta). \quad (2.376)$$

Therefore, the natural parameters are given by

$$\boldsymbol{\eta} = \begin{bmatrix} m \cos \theta_0 \\ m \sin \theta_0 \end{bmatrix}.$$

2.57

By the definition,

$$\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) = (2\pi)^{-\frac{D}{2}} (\det \boldsymbol{\Sigma})^{-\frac{1}{2}} \exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right). \quad (2.377)$$

Therefore,

$$\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) = h(\mathbf{x})g(\boldsymbol{\eta}) \exp(\boldsymbol{\eta}^\top \mathbf{u}(\mathbf{x})), \quad (2.378)$$

where

$$\begin{aligned} h(\mathbf{x}) &= (2\pi)^{-\frac{D}{2}}, \\ g(\boldsymbol{\eta}) &= (\det(-2\boldsymbol{\eta}_2))^{-\frac{1}{2}} \exp \left(\frac{1}{4} \boldsymbol{\eta}_1^\top \boldsymbol{\eta}_2^{-1} \boldsymbol{\eta}_1 \right), \\ \boldsymbol{\eta} &= \begin{bmatrix} \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu} \\ -\frac{1}{2} \boldsymbol{\Sigma}^{-1} \end{bmatrix}, \\ \mathbf{u}(\mathbf{x}) &= \begin{bmatrix} \mathbf{x} \\ \mathbf{x} \mathbf{x}^\top \end{bmatrix}. \end{aligned}$$

2.58

Let \mathbf{x} be a variable such that

$$p(\mathbf{x}|\boldsymbol{\eta}) = h(\mathbf{x})g(\boldsymbol{\eta}) \exp(\boldsymbol{\eta}^\top \mathbf{u}(\mathbf{x})). \quad (2.379)$$

Then, taking the first derivative of

$$\int p(\mathbf{x}|\boldsymbol{\eta}) d\mathbf{x} = 1 \quad (2.380)$$

with respect to $\boldsymbol{\eta}$ gives

$$\nabla g(\boldsymbol{\eta}) \int h(\mathbf{x}) \exp(\boldsymbol{\eta}^\top \mathbf{u}(\mathbf{x})) d\mathbf{x} + g(\boldsymbol{\eta}) \int \mathbf{u}(\mathbf{x}) h(\mathbf{x}) \exp(\boldsymbol{\eta}^\top \mathbf{u}(\mathbf{x})) d\mathbf{x} = \mathbf{0}. \quad (2.381)$$

The left hand side can be written as

$$\frac{\nabla g(\boldsymbol{\eta})}{g(\boldsymbol{\eta})} \int p(\mathbf{x}|\boldsymbol{\eta}) d\mathbf{x} + \int \mathbf{u}(\mathbf{x}) p(\mathbf{x}|\boldsymbol{\eta}) d\mathbf{x} = \frac{\nabla g(\boldsymbol{\eta})}{g(\boldsymbol{\eta})} + \mathbb{E} \mathbf{u}(\mathbf{x}). \quad (2.382)$$

Therefore,

$$\mathbb{E} \mathbf{u}(\mathbf{x}) = -\frac{\nabla g(\boldsymbol{\eta})}{g(\boldsymbol{\eta})}. \quad (2.383)$$

Thus,

$$\mathbf{E} \mathbf{u}(\mathbf{x}) = -\nabla \ln g(\boldsymbol{\eta}). \quad (2.384)$$

Taking the second derivative with respect to $\boldsymbol{\eta}$ gives

$$\begin{aligned} \nabla \nabla g(\boldsymbol{\eta}) \int h(\mathbf{x}) \exp(\boldsymbol{\eta}^\top \mathbf{u}(\mathbf{x})) d\mathbf{x} + 2\nabla g(\boldsymbol{\eta}) \int \mathbf{u}(\mathbf{x})^\top h(\mathbf{x}) \exp(\boldsymbol{\eta}^\top \mathbf{u}(\mathbf{x})) d\mathbf{x} \\ + g(\boldsymbol{\eta}) \int \mathbf{u}(\mathbf{x}) \mathbf{u}(\mathbf{x})^\top h(\mathbf{x}) \exp(\boldsymbol{\eta}^\top \mathbf{u}(\mathbf{x})) d\mathbf{x} = \mathbf{O}. \end{aligned} \quad (2.385)$$

The left hand side can be written as

$$\begin{aligned} \frac{\nabla \nabla g(\boldsymbol{\eta})}{g(\boldsymbol{\eta})} \int p(\mathbf{x}|\boldsymbol{\eta}) d\mathbf{x} + \frac{2\nabla g(\boldsymbol{\eta})}{g(\boldsymbol{\eta})} \int \mathbf{u}(\mathbf{x})^\top p(\mathbf{x}|\boldsymbol{\eta}) d\mathbf{x} + \int \mathbf{u}(\mathbf{x}) \mathbf{u}(\mathbf{x})^\top p(\mathbf{x}|\boldsymbol{\eta}) d\mathbf{x} \\ = \frac{\nabla \nabla g(\boldsymbol{\eta})}{g(\boldsymbol{\eta})} - 2 \mathbf{E} \mathbf{u}(\mathbf{x}) \mathbf{E} \mathbf{u}(\mathbf{x})^\top + \mathbf{E} (\mathbf{u}(\mathbf{x}) \mathbf{u}(\mathbf{x})^\top). \end{aligned} \quad (2.386)$$

Therefore,

$$\mathbf{E} (\mathbf{u}(\mathbf{x}) \mathbf{u}(\mathbf{x})^\top) = -\frac{\nabla \nabla g(\boldsymbol{\eta})}{g(\boldsymbol{\eta})} + \frac{2\nabla g(\boldsymbol{\eta})(\nabla g(\boldsymbol{\eta}))^\top}{g^2(\boldsymbol{\eta})}. \quad (2.387)$$

By the definition,

$$\text{cov} \mathbf{u}(\mathbf{x}) = \mathbf{E} (\mathbf{u}(\mathbf{x}) \mathbf{u}(\mathbf{x})^\top) - \mathbf{E} \mathbf{u}(\mathbf{x}) \mathbf{E} \mathbf{u}(\mathbf{x})^\top. \quad (2.388)$$

Thus,

$$\text{cov} \mathbf{u}(\mathbf{x}) = -\frac{\nabla \nabla g(\boldsymbol{\eta})}{g(\boldsymbol{\eta})} + \frac{\nabla g(\boldsymbol{\eta})(\nabla g(\boldsymbol{\eta}))^\top}{g^2(\boldsymbol{\eta})}. \quad (2.389)$$

Hence,

$$\text{cov} \mathbf{u}(\mathbf{x}) = -\nabla \nabla \ln g(\boldsymbol{\eta}). \quad (2.390)$$

2.59

Let

$$p(x|\sigma) = \frac{1}{\sigma} f\left(\frac{x}{\sigma}\right). \quad (2.391)$$

Then

$$\int p(x|\sigma) dx = \frac{1}{\sigma} \int f\left(\frac{x}{\sigma}\right) dx. \quad (2.392)$$

By the transformation

$$x' = \frac{x}{\sigma}, \quad (2.393)$$

the right hand side can be written as

$$\frac{1}{\sigma} \int f(x') \sigma dx' = \int f(x') dx'. \quad (2.394)$$

Therefore, $p(x|\sigma)$ will be normalised if $f(x)$ is normalised.

2.60

Let \mathbf{x} be a variable such that

$$\mathbf{x} \in \mathcal{R}_i \Rightarrow p(\mathbf{x}) = h_i, \quad (2.395)$$

where

$$\int_{\mathcal{R}_i} d\mathbf{x} = \Delta_i. \quad (2.396)$$

Since

$$\int p(\mathbf{x}) d\mathbf{x} = 1, \quad (2.397)$$

we have

$$\sum_i h_i \Delta_i = 1. \quad (2.398)$$

Let N be the total number of observations and n_i be the number of observations which fall in \mathcal{R}_i . Then, the logarithm of the likelihood is given by

$$\ln \left(\prod_i h_i^{n_i} \right) = \sum_i n_i \ln h_i, \quad (2.399)$$

where

$$\sum_i n_i = N. \quad (2.400)$$

Setting the derivatives of

$$\sum_i n_i \ln h_i + \lambda \left(\sum_i h_i \Delta_i - 1 \right) \quad (2.401)$$

with respect to h_i and λ to zero gives

$$\begin{aligned}\frac{n_i}{h_i} + \lambda \Delta_i &= 0, \\ \sum_i h_i \Delta_i - 1 &= 0.\end{aligned}\tag{2.402}$$

Therefore,

$$\begin{aligned}\lambda &= -N, \\ h_i &= \frac{n_i}{N \Delta_i}.\end{aligned}\tag{2.403}$$

Thus, the maximum likelihood estimator for the $\{h_i\}$ is $\frac{n_i}{N \Delta_i}$.

2.61 (Incomplete)

Let \mathbf{x} be a variable and $\mathbf{x}_1, \dots, \mathbf{x}_N$ be observations. Let

$$p(\mathbf{x}) = \frac{K}{NV(\mathbf{x})},\tag{2.404}$$

where

$$V(\mathbf{x}) = \int_{\|\mathbf{x}' - \mathbf{x}\| \leq \|\mathbf{x}_{(K)} - \mathbf{x}\|} d\mathbf{x}',\tag{2.405}$$

K is a constant and $\mathbf{x}_{(K)}$ is the K th nearest observation from the point \mathbf{x} .

3 Linear Models for Regression

3.1

By the definition,

$$\tanh a = \frac{\exp(a) - \exp(-a)}{\exp(a) + \exp(-a)}. \quad (3.1)$$

The right hand side can be written as

$$\frac{1 - \exp(-2a)}{1 + \exp(-2a)} = \frac{2}{1 + \exp(-2a)} - 1. \quad (3.2)$$

By the definition

$$\sigma(a) = \frac{1}{1 + \exp(-a)}, \quad (3.3)$$

the right hand side can be written as

$$\tanh a = 2\sigma(2a) - 1. \quad (3.4)$$

Let

$$y(x_n, \mathbf{w}) = w_0 + \sum_{j=1}^M w_j \sigma\left(\frac{x - \mu_j}{s}\right). \quad (3.5)$$

By the result above, the right hand side can be written as

$$w_0 + \sum_{j=1}^M w_j \frac{\tanh\left(\frac{x - \mu_j}{2s}\right) + 1}{2} = w_0 + \frac{1}{2} \sum_{j=1}^M w_j + \frac{1}{2} \sum_{j=1}^M w_j \tanh\left(\frac{x - \mu_j}{2s}\right). \quad (3.6)$$

Therefore, $y(x_n, \mathbf{w})$ is equivalent to

$$y(x_n, \mathbf{u}) = u_0 + \sum_{j=1}^M u_j \tanh\left(\frac{x - \mu_j}{2s}\right), \quad (3.7)$$

where

$$\begin{aligned} u_0 &= w_0 + \frac{1}{2} \sum_{j=1}^M w_j, \\ u_j &= \frac{w_j}{2}, \quad j = 1, \dots, M. \end{aligned} \quad (3.8)$$

3.2 (Incomplete)

Let \mathbf{t} be a vector of N dimensions and Φ be an $N \times M$ matrix whose n th column is given by ϕ_n . Then

$$\mathbf{y} = \Phi (\Phi^\top \Phi)^{-1} \Phi^\top \mathbf{t} \quad (3.9)$$

an orthogonal projection of \mathbf{t} onto the space?

3.3

Let

$$E_D(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^N r_n (t_n - \mathbf{w}^\top \phi(\mathbf{x}_n))^2. \quad (3.10)$$

Setting the derivative to zero gives

$$\mathbf{0} = - \sum_{n=1}^N r_n \phi(\mathbf{x}_n) (t_n - \mathbf{w}^\top \phi(\mathbf{x}_n)). \quad (3.11)$$

The right hand side can be written as

$$- \sum_{n=1}^N r_n t_n \phi(\mathbf{x}_n) + \left(\sum_{n=1}^N r_n \phi(\mathbf{x}_n) \phi(\mathbf{x}_n)^\top \right) \mathbf{w}. \quad (3.12)$$

Therefore,

$$\underset{\mathbf{w}}{\operatorname{argmin}} E_D(\mathbf{w}) = (\Phi' \Phi'^\top)^{-1} \Phi'^\top \mathbf{t}', \quad (3.13)$$

where

$$\Phi' = \begin{bmatrix} \sqrt{r_1} \phi(\mathbf{x}_1)^\top \\ \vdots \\ \sqrt{r_N} \phi(\mathbf{x}_N)^\top \end{bmatrix}, \mathbf{t}' = \begin{bmatrix} \sqrt{r_1} t_1 \\ \vdots \\ \sqrt{r_N} t_N \end{bmatrix}.$$