Solutions Manual to
Pattern Recognition and Machine Learning

Hiromichi Inawashiro

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Contents

1 Introduction

1.1

Let

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

To minimise it, setting the derivative to zero gives

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

Substituting

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

gives

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

Therefore,

$$\sum_{j=0}^{M} A_{ij} w_j = T_i \tag{1.5}$$

where

$$A_{ij} = \sum_{n=1}^{N} x_n^{i+j},$$
$$T_i = \sum_{n=1}^{N} x_n^i t_n. \tag{1.6}$$

1.2

Let

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

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To minimise it, setting the derivative to zero gives

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

Substituting

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

gives

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

Therefore,

$$\sum_{j=0}^{M} \tilde{A}_{ij} w_j = T_i \tag{1.11}$$

where

$$\tilde{A}_{ij} = \sum_{n=1}^{N} x_n^{i+j} + \lambda \delta_{ij},$$

$$T_i = \sum_{n=1}^{N} x_n^i t_n. \tag{1.12}$$

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

$$p(a) = p(a|r)p(r) + p(a|b)p(b) + p(a|g)p(g). \tag{1.13}$$

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

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

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

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

Here,
$$p(g, o) = p(o|g)p(g),$$
$$p(o) = p(o|r)p(r) + p(o|b)p(b) + p(o|g)p(g). \tag{1.16}$$

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,

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

1.4

Let
$$x = g(y) \tag{1.18}$$

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

$$p_y(y) = p_x\left(g(y)\right)|g'(y)| \tag{1.19}$$

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

$$0 = g'(\hat{y})p_x'\left(g\left(\hat{y}\right)\right) + p_x\left(g\left(\hat{y}\right)\right)g''\left(\hat{y}\right). \tag{1.20}$$

Therefore, in general,
$$\hat{x} \neq g\left(\hat{y}\right). \tag{1.21}$$

Here, let us assume that

$$g(y) = ay + b. \tag{1.22}$$

Then, differentiating both sides of the transformation and substituting $y = \hat{y}$ gives
$$0 = p_x'\left(g\left(\hat{y}\right)\right). \tag{1.23}$$

Therefore,
$$\hat{x} = g\left(\hat{y}\right). \tag{1.24}$$

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1.5

By the definition,
$$\mathrm{var} f(x) = \mathrm{E}\left(f(x) - \mathrm{E}f(x)\right)^2. \tag{1.25}$$

The right hand side can be written as
$$\mathrm{E}\left((f(x))^2 - 2f(x)\mathrm{E}f(x) + (\mathrm{E}f(x))^2\right) = \mathrm{E}\left(f(x)\right)^2 - (\mathrm{E}f(x))^2. \tag{1.26}$$

Therefore,
$$\mathrm{var} f(x) = \mathrm{E}\left(f(x)\right)^2 - (\mathrm{E}f(x))^2. \tag{1.27}$$

1.6

By the definition,
$$\mathrm{cov}(x,y) = \mathrm{E}\left((x - \mathrm{E}x)(y - \mathrm{E}y)\right). \tag{1.28}$$

The right hand side can be written as
$$\mathrm{E}xy - \mathrm{E}(x\mathrm{E}y) - \mathrm{E}(y\mathrm{E}x) + \mathrm{E}(\mathrm{E}x\mathrm{E}y) = \mathrm{E}xy - \mathrm{E}x\mathrm{E}y. \tag{1.29}$$

The right hand side can be written as
$$\int xyp(x,y)dxdy - \int xp(x)dx \int yp(y)dy. \tag{1.30}$$

If x and y are independent, by the definition,
$$f(x,y) = f(x)f(y). \tag{1.31}$$

Then,
$$\int xyp(x,y)dxdy = \int p(x)dx \int p(y)dy. \tag{1.32}$$

Therefore,
$$\mathrm{cov}(x,y) = 0. \tag{1.33}$$

1.7

Let

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

Then

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

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

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

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

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

Therefore,

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

By the definition,

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

Then

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

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

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

Therefore,

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

1.8

Let x be a variable such that

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

Then

$$\mathrm{E}x = \int_{-\infty}^{\infty} x \mathcal{N}\left(x|\mu, \sigma^2\right) dx. \tag{1.44}$$

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

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

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

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

Since

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

and

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

we have

$$\mathrm{E}x = \mu. \tag{1.49}$$

By the definition,

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

can be written as

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

Differentiating both sides with respect to σ^2 gives

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

The left hand side can be written as

$$-\frac{1}{2}\left(\sigma^2\right)^{-1}\int_{-\infty}^{\infty}\mathcal{N}\left(x|\mu,\sigma^2\right)dx + \frac{1}{2}\left(\sigma^2\right)^{-2}\int_{-\infty}^{\infty}(x-\mu)^2\mathcal{N}\left(x|\mu,\sigma^2\right)dx$$

$$= -\frac{1}{2}\left(\sigma^2\right)^{-1} + \frac{1}{2}\left(\sigma^2\right)^{-2}\mathrm{var}x. \tag{1.53}$$

Therefore,

$$\mathrm{var}x = \sigma^2. \tag{1.54}$$

1.9

Let

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

Setting its derivative with respect to x to zero gives

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

Therefore, the mode is given by μ.

Similarly, let

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

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

$$\mathbf{0} = -\left(2\pi\right)^{-\frac{D}{2}}\left|\boldsymbol{\Sigma}\right|^{-\frac{1}{2}}\left(\boldsymbol{\Sigma}^{-1} + \left(\boldsymbol{\Sigma}^{-1}\right)^{\mathsf{T}}\right)(\mathbf{x}-\boldsymbol{\mu})\exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^{\mathsf{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right). \tag{1.58}$$

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

1.10

By the definition,

$$\mathrm{E}(x+y) = \int\int(x+y)p(x,y)dxdy. \tag{1.59}$$

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The right hand side can be written as

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

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

$$\mathrm{E}x + \mathrm{E}y.$$
(1.61)

Therefore,

$$\mathrm{E}(x+y) = \mathrm{E}x + \mathrm{E}y.$$
(1.62)

Similarly, by the definition,

$$\mathrm{var}(x+y) = \mathrm{E}\left(x + y - \mathrm{E}(x+y)\right)^2$$
(1.63)

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

$$\mathrm{E}\left(x - \mathrm{E}x\right)^2 + 2\mathrm{E}\left((x - \mathrm{E}x)(y - \mathrm{E}y)\right) + \mathrm{E}\left(y - \mathrm{E}y\right)^2$$
$$= \mathrm{var}x + 2\mathrm{cov}(x,y) + \mathrm{var}y.$$
(1.64)

If x and y are independent, then

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

by 1.6. Therefore,

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

1.11

Let

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

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

$$0 = \frac{1}{\sigma^2}\sum_{n=1}^{N}(x_n - \mu),$$

$$0 = -\frac{N}{2\sigma^2} + \frac{1}{2\left(\sigma^2\right)^2}\sum_{n=1}^{N}(x_n - \mu)^2.$$
(1.68)

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Therefore,

$$\mu_{\mathrm{ML}} = \frac{1}{N} \sum_{n=1}^{N} x_n,$$

$$\sigma_{\mathrm{ML}}^2 = \frac{1}{N} \sum_{n=1}^{N} (x_n - \mu_{\mathrm{ML}})^2. \tag{1.69}$$

1.12

Let x_m and x_n be independent variables. Then

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

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,

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

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,

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

Here, since

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

we have

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

Therefore,

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

Similarly, since

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

we have

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

The right hand side can be writen as

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

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

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

while the second and third terms can be writen as

$$-2\mathrm{E}\mu_{\mathrm{ML}}^2 + \mathrm{E}\mu_{\mathrm{ML}}^2 = -\mathrm{E}\mu_{\mathrm{ML}}^2. \tag{1.80}$$

Here,

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

The right hand side can be written as

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

Therefore,

$$\mathrm{E}\mu_{\mathrm{ML}}^2 = \mu^2 + \frac{1}{N}\sigma^2. \tag{1.83}$$

Thus,

$$\mathrm{E}\sigma_{\mathrm{ML}}^2 = \frac{N-1}{N}\sigma^2. \tag{1.84}$$

1.13

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

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

The right hand side can be writen as

$$\frac{1}{N}\sum_{n=1}^{N}\mathrm{E}\left(x_n^2 - 2\mu x_n + \mu^2\right) = \frac{1}{N}\sum_{n=1}^{N}\mathrm{E}x_n^2 - \frac{2\mu}{N}\sum_{n=1}^{N}\mathrm{E}x_n + \mu^2. \tag{1.86}$$

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

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

while the second term can be writen as

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

Therefore,

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

1.14

Let

$$w_{ij}^{\mathrm{S}} = \frac{1}{2}(w_{ij} + w_{ji}),$$
$$w_{ij}^{\mathrm{A}} = \frac{1}{2}(w_{ij} - w_{ji}).$$ (1.90)

Then

$$w_{ij} = w_{ij}^{\mathrm{S}} + w_{ij}^{\mathrm{A}},$$
$$w_{ij}^{\mathrm{S}} = w_{ji}^{\mathrm{S}},$$
$$w_{ij}^{\mathrm{A}} = -w_{ji}^{\mathrm{A}}.$$ (1.91)

Here,

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

The right hand side can be written as

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

Therefore,

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

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Additionally,

$$\sum_{i=1}^{D}\sum_{j=1}^{D}w_{ij}x_ix_j = \sum_{i=1}^{D}\sum_{j=1}^{D}\left(w_{ij}^{\mathrm{S}} + w_{ij}^{\mathrm{A}}\right)x_ix_j. \tag{1.95}$$

The right hand side can be written as

$$\sum_{i=1}^{D}\sum_{j=1}^{D}w_{ij}^{\mathrm{S}}x_ix_j + \sum_{i=1}^{D}\sum_{j=1}^{D}w_{ij}^{\mathrm{A}}x_ix_j = \sum_{i=1}^{D}\sum_{j=1}^{D}w_{ij}^{\mathrm{S}}x_ix_j, \tag{1.96}$$

where the result above is used. Therefore,

$$\sum_{i=1}^{D}\sum_{j=1}^{D}w_{ij}x_ix_j = \sum_{i=1}^{D}\sum_{j=1}^{D}w_{ij}^{\mathrm{S}}x_ix_j. \tag{1.97}$$

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   (Incomplete)

1.16   (Incomplete)

1.17

Let

$$\Gamma(x) = \int_0^{\infty} u^{x-1}\exp(-u)du. \tag{1.98}$$

Then

$$\Gamma(x+1) = \int_0^{\infty} u^{x}\exp(-u)du. \tag{1.99}$$

The right hand side can be written as

$$[-u^{x}\exp(-u)]_{u=0}^{u=\infty} + \int_0^{\infty} xu^{x-1}\exp(-u)du = x\Gamma(x). \tag{1.100}$$

Therefore,

$$\Gamma(x+1) = x\Gamma(x). \tag{1.101}$$

Since

$$\Gamma(1) = \int_0^1 \exp(-u)du, \tag{1.102}$$

and the right hand side can be written as 1,

$$\Gamma(1) = 0!. \tag{1.103}$$

For a positive integer x, let us assume that

$$\Gamma(x) = (x-1)!. \tag{1.104}$$

Then,

$$\Gamma(x+1) = x\Gamma(x), \tag{1.105}$$

where the right hand side can be written as

$$x(x-1)! = x!. \tag{1.106}$$

Therefore,

$$\Gamma(x+1) = x!. \tag{1.107}$$

Thus, the assumption is proved by induction on x.

1.18

Let us consider the transformation from Cartesian to polar coordinates

$$\prod_{i=1}^{D} \int_{-\infty}^{\infty} \exp\left(-x_i^2\right) dx_i = S_D \int_0^{\infty} \exp\left(-r^2\right) r^{D-1}dr, \tag{1.108}$$

where S_D is the surface area of a sphere of unit raidus 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

$$\frac{S_D}{2} \int_0^{\infty} \exp(-s)s^{\frac{D-1}{2}}s^{-\frac{1}{2}}ds = \frac{S_D}{2}\Gamma\left(\frac{D}{2}\right). \tag{1.109}$$

Therefore,

$$S_D = \frac{2\pi^{\frac{D}{2}}}{\Gamma\left(\frac{D}{2}\right)}. \tag{1.110}$$

Additionally, the volume of the sphere can can be written as

$$V_D = S_D \int_0^1 r^{D-1} dr. \tag{1.111}$$

The right hand side can be written as

$$S_D \left[\frac{r^D}{D} \right]_{r=0}^{r=1} = \frac{S_D}{D}. \tag{1.112}$$

Therefore,

$$V_D = \frac{S_D}{D}. \tag{1.113}$$

Finally, the results above reduce to

$$S_2 = \frac{2\pi}{\Gamma(1)},$$
$$V_2 = \frac{S_2}{2}. \tag{1.114}$$

Therefore,

$$S_2 = 2\pi,$$
$$V_2 = \pi. \tag{1.115}$$

Similarly,

$$S_3 = \frac{2\pi^{\frac{3}{2}}}{\Gamma\left(\frac{3}{2}\right)},$$
$$V_3 = \frac{S_3}{3}. \tag{1.116}$$

Therefore,

$$S_3 = 4\pi,$$
$$V_3 = \frac{4}{3}\pi. \tag{1.117}$$

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

$$\frac{V_D}{2^D} = \frac{\pi^{\frac{D}{2}}}{D2^{D-1}\Gamma\left(\frac{D}{2}\right)}, \tag{1.118}$$

by 1.18.

Additionally, by Stering's formula

$$\Gamma(x+1) \simeq (2\pi)^{\frac{1}{2}} \exp(-x) x^{\frac{x+1}{2}}, \tag{1.119}$$

the ratio can be approximated as

$$\frac{V_D}{2^D} \simeq \frac{\pi^{\frac{D}{2}}}{D2^{D-1}(2\pi)^{\frac{1}{2}} \exp\left(1 - \frac{D}{2}\right) \left(\frac{D}{2} - 1\right)^{\frac{D}{4}}}. \tag{1.120}$$

The right hand side can be written as

$$\frac{1}{2e(2\pi)^{\frac{1}{2}}} \frac{1}{D} \left(\frac{e^2\pi^2}{8D - 16}\right)^{\frac{D}{4}}. \tag{1.121}$$

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

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

$$\frac{\sqrt{\sum_{i=1}^{D} 1^2}}{1} = \sqrt{D}. \tag{1.122}$$

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

1.20

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

$$p(\mathbf{x}) = (2\pi\sigma^2)^{-\frac{D}{2}} \exp\left(-\frac{\|\mathbf{x}\|^2}{2\sigma^2}\right). \tag{1.123}$$

Integrating both sides from $\|\mathbf{x}\| = r$ to $\|\mathbf{x}\| = r + \epsilon$ gives

$$\int_{r \leq \|\mathbf{x}\| \leq r+\epsilon} p(\mathbf{x}) d\mathbf{x} = \int_r^{r+\epsilon} \int (2\pi\sigma^2)^{-\frac{D}{2}} \exp\left(-\frac{r'^2}{2\sigma^2}\right) J dr' d\boldsymbol{\phi}, \tag{1.124}$$

where $\boldsymbol{\phi}$ 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

$$(2\pi\sigma^2)^{-\frac{D}{2}} \exp\left(-\frac{r^2}{2\sigma^2}\right) \int_r^{r+\epsilon} \int J dr' d\boldsymbol{\phi}$$
$$= (2\pi\sigma^2)^{-\frac{D}{2}} \exp\left(-\frac{r^2}{2\sigma^2}\right) \int_{r \leq \|\mathbf{x}\| \leq r+\epsilon} d\mathbf{x}. \tag{1.125}$$

Therefore,

$$\int_{r \leq \|\mathbf{x}\| \leq r+\epsilon} p(\mathbf{x}) d\mathbf{x} \simeq p(r)\epsilon, \tag{1.126}$$

where

$$p(r) = (2\pi\sigma^2)^{-\frac{D}{2}} S_D r^{D-1} \exp\left(-\frac{r^2}{2\sigma^2}\right), \tag{1.127}$$

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

Secondly, to maximise $p(r)$, setting the derivative to zero gives

$$0 = (2\pi\sigma^2)^{-\frac{D}{2}} S_D \left((D-1)r^{D-2} - \frac{r^D}{\sigma^2}\right) \exp\left(-\frac{r^2}{2\sigma^2}\right). \tag{1.128}$$

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

$$\hat{r} = \sqrt{D-1}\sigma. \tag{1.129}$$

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

$$\frac{p(\hat{r}+\epsilon)}{p(\hat{r})} = \left(\frac{\hat{r}+\epsilon}{\hat{r}}\right)^{D-1} \exp\left(-\frac{2\hat{r}\epsilon + \epsilon^2}{2\sigma^2}\right). \tag{1.130}$$

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

$$\exp\left((D-1)\ln\left(1+\frac{\epsilon}{\hat{r}}\right) - \frac{2\hat{r}\epsilon + \epsilon^2}{2\sigma^2}\right)$$
$$= \exp\left(\frac{\hat{r}^2}{\sigma^2}\ln\left(1+\frac{\epsilon}{\hat{r}}\right) - \frac{2\hat{r}\epsilon + \epsilon^2}{2\sigma^2}\right). \tag{1.131}$$

By the Taylor series

$$\ln(1+x) = x - \frac{1}{2}x^2 + o\left(x^3\right), \tag{1.132}$$

16

the right hand side can be approximated as

$$\exp\left(\frac{\hat{r}^2}{\sigma^2}\left(\frac{\epsilon}{\hat{r}} - \frac{\epsilon^2}{2\hat{r}^2}\right) - \frac{2\hat{r}\epsilon + \epsilon^2}{2\sigma^2}\right) = \exp\left(-\frac{\epsilon^2}{\sigma^2}\right). \tag{1.133}$$

Therefore,

$$p\left(\hat{r} + \epsilon\right) \simeq p\left(\hat{r}\right)\exp\left(-\frac{\epsilon^2}{\sigma^2}\right). \tag{1.134}$$

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

$$\frac{p(\mathbf{0})}{p\left(\hat{\mathbf{r}}\right)} = \exp\left(\frac{\hat{r}^2}{2\sigma^2}\right). \tag{1.135}$$

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

$$\frac{p(\mathbf{0})}{p\left(\hat{\mathbf{r}}\right)} = \exp\left(\frac{D-1}{2}\right). \tag{1.136}$$

1.21

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

$$0 \le a(b-a). \tag{1.137}$$

Therefore,

$$a \le (ab)^{\frac{1}{2}}. \tag{1.138}$$

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,

$$p(\mathbf{x}, \mathcal{C}_1) > p(\mathbf{x}, \mathcal{C}_2) \Rightarrow \mathbf{x} \in \mathcal{C}_1, \tag{1.139}$$

and

$$p(\mathbf{x}, \mathcal{C}_2) > p(\mathbf{x}, \mathcal{C}_1) \Rightarrow \mathbf{x} \in \mathcal{C}_2. \tag{1.140}$$

Then, using the inequality above,

$$\int_{\mathcal{R}_1} p(\mathbf{x}, \mathcal{C}_2)d\mathbf{x} \le \int_{\mathcal{R}_1} (p(\mathbf{x}, \mathcal{C}_1)p(\mathbf{x}, \mathcal{C}_2))^{\frac{1}{2}} d\mathbf{x}, \tag{1.141}$$

and

$$\int_{\mathcal{R}_2} p(\mathbf{x}, \mathcal{C}_1)d\mathbf{x} \le \int_{\mathcal{R}_2} (p(\mathbf{x}, \mathcal{C}_1)p(\mathbf{x}, \mathcal{C}_2))^{\frac{1}{2}} d\mathbf{x}. \tag{1.142}$$

Therefore,

$$\int_{\mathcal{R}_1} p(\mathbf{x}, \mathcal{C}_2)d\mathbf{x} + \int_{\mathcal{R}_2} p(\mathbf{x}, \mathcal{C}_1)d\mathbf{x} \le \int (p(\mathbf{x}, \mathcal{C}_1)p(\mathbf{x}, \mathcal{C}_2))^{\frac{1}{2}} d\mathbf{x}. \tag{1.143}$$

1.22

Let

$$\mathrm{E}L = \sum_k \sum_j \int_{\mathcal{R}_j} L_{kj} p(\mathbf{x}, \mathcal{C}_k) d\mathbf{x}. \tag{1.144}$$

If

$$L_{kj} = 1 - \delta_{kj}, \tag{1.145}$$

then the right hand side can be written as

$$\sum_k \sum_j \int_{\mathcal{R}_j} \left(p(\mathbf{x}, \mathcal{C}_k) - p(\mathbf{x}, \mathcal{C}_j) \right) d\mathbf{x} = \sum_j \int_{\mathcal{R}_j} \left(\sum_k p(\mathbf{x}, \mathcal{C}_k) - p(\mathbf{x}, \mathcal{C}_j) \right) d\mathbf{x}. \tag{1.146}$$

The right hand side can be written as

$$\sum_j \int_{\mathcal{R}_j} \left(p(\mathbf{x}) - p(\mathbf{x}, \mathcal{C}_j) \right) d\mathbf{x} = 1 - \sum_j \int_{\mathcal{R}_j} p(\mathbf{x}, \mathcal{C}_j) d\mathbf{x}. \tag{1.147}$$

Therefore,

$$\mathrm{E}L = 1 - \sum_j \int_{\mathcal{R}_j} p(\mathcal{C}_j|\mathbf{x}) p(\mathbf{x}) d\mathbf{x}. \tag{1.148}$$

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

1.23

Let

$$\mathrm{E}L = \sum_k \sum_j \int_{\mathcal{R}_j} L_{kj} p(\mathbf{x}, \mathcal{C}_k) d\mathbf{x}. \tag{1.149}$$

The right hand side can be written as

$$\sum_j \int_{\mathcal{R}_j} \sum_k L_{kj} p(\mathbf{x}, \mathcal{C}_k) d\mathbf{x} = \sum_j \int_{\mathcal{R}_j} \left(\sum_k L_{kj} p(\mathcal{C}_k|\mathbf{x}) \right) p(\mathbf{x}) d\mathbf{x}. \tag{1.150}$$

Therefore,

$$\mathrm{E}L = \sum_j \int_{\mathcal{R}_j} \left(\sum_k L_{kj} p(\mathcal{C}_k|\mathbf{x}) \right) p(\mathbf{x}) d\mathbf{x}. \tag{1.151}$$

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

1.24 (Incomplete)

1.25

Let

$$\mathrm{E}L\left(\mathbf{t}, \mathbf{y}(\mathbf{x})\right) = \int \int \|\mathbf{y}(\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t}. \tag{1.152}$$

Then

$$\frac{\delta \mathrm{E}L\left(\mathbf{t}, \mathbf{y}(\mathbf{x})\right)}{\delta \mathbf{y}(\mathbf{x})} = 2 \int \left(\mathbf{y}(\mathbf{x}) - \mathbf{t}\right) p(\mathbf{x}, \mathbf{t}) d\mathbf{t}. \tag{1.153}$$

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

$$\mathbf{0} = \int \left(\mathbf{y}(\mathbf{x}) - \mathbf{t}\right) p(\mathbf{t}|\mathbf{x}) d\mathbf{t}. \tag{1.154}$$

The right hand side can be written as

$$\mathbf{y}(\mathbf{x}) \int p(\mathbf{t}|\mathbf{x}) d\mathbf{t} - \int \mathbf{t} p(\mathbf{t}|\mathbf{x}) d\mathbf{t} = \mathbf{y}(\mathbf{x}) - \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}). \tag{1.155}$$

Thus,

$$\mathbf{y}(\mathbf{x}) = \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}). \tag{1.156}$$

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

$$\mathbf{y}(\mathbf{x}) = \mathrm{E}_t(t|\mathbf{x}). \tag{1.157}$$

1.26

Let

$$\mathrm{E}L\left(\mathbf{t}, \mathbf{y}(\mathbf{x})\right) = \int \int \|\mathbf{y}(\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t}. \tag{1.158}$$

The right hand side can be written as

$$
\begin{aligned}
& \int \int \|\mathbf{y}(\mathbf{x}) - \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) + \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t} \\
&= \int \int \|\mathbf{y}(\mathbf{x}) - \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t} \\
&\quad + 2 \int \int \left(\mathbf{y}(\mathbf{x}) - \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\right)^{\mathsf{T}} \left(\mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}\right) p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t} \\
&\quad + \int \int \|\mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{x}, \mathbf{t}) d\mathbf{x} d\mathbf{t}.
\end{aligned}
\tag{1.159}
$$

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

$$\int \|\mathbf{y}(\mathbf{x}) - \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\|^2 \left(\int p(\mathbf{x}, \mathbf{t}) d\mathbf{t} \right) d\mathbf{x} = \int \|\mathbf{y}(\mathbf{x}) - \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\|^2 p(\mathbf{x}) d\mathbf{x}.$$

(1.160)

The second term can be written as

$$2 \int (\mathbf{y}(\mathbf{x}) - \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}))^{\mathsf{T}} \left(\int \left(\mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t} \right) p(\mathbf{t}|\mathbf{x}) d\mathbf{t} \right) p(\mathbf{x}) d\mathbf{x}.$$

(1.161)

Since

$$\int \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) p(\mathbf{t}|\mathbf{x}) d\mathbf{t} = \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) \frac{\int p(\mathbf{x}, \mathbf{t}) d\mathbf{t}}{p(\mathbf{x})},$$

$$\int \mathbf{t} p(\mathbf{t}|\mathbf{x}) d\mathbf{t} = \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}),$$

(1.162)

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

$$\int \left(\int \|\mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) - \mathbf{t}\|^2 p(\mathbf{t}|\mathbf{x}) d\mathbf{t} \right) p(\mathbf{x}) d\mathbf{x} = \int \mathrm{var}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) p(\mathbf{x}) d\mathbf{x}.$$

(1.163)

Therefore,

$$\mathrm{E}L\left(\mathbf{t}, \mathbf{y}(\mathbf{x}) \right) = \int \|\mathbf{y}(\mathbf{x}) - \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x})\|^2 p(\mathbf{x}) d\mathbf{x} + \int \mathrm{var}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}) p(\mathbf{x}) d\mathbf{x}.$$

(1.164)

Thus, $\mathrm{E}L\left(\mathbf{t}, \mathbf{y}(\mathbf{x}) \right)$ is mimimised if

$$\mathbf{y}(\mathbf{x}) = \mathrm{E}_{\mathbf{t}}(\mathbf{t}|\mathbf{x}).$$

(1.165)

1.27

Let

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

(1.166)

Then

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

(1.167)

To minimise $\mathrm{E}L_q$, setting the left hand side to zero gives

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

(1.168)

20

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

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

$$0 = \int_{y(\mathbf{x})}^{\infty} p(t|\mathbf{x})dt - \int_{-\infty}^{y(\mathbf{x})} p(t|\mathbf{x})dt. \qquad (1.169)$$

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

1.28

Let us assume that

$$p(x, y) = p(x)p(y) \Rightarrow h(x, y) = h(x) + h(y). \qquad (1.170)$$

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

$$h\left(p^2\right) = h(p) + h(p). \qquad (1.171)$$

Therefore,

$$h\left(p^2\right) = 2h(p). \qquad (1.172)$$

Let us assume that, for a positive integer n,

$$h\left(p^n\right) = nh(p). \qquad (1.173)$$

Then, by the first assumption,

$$h\left(p^{n+1}\right) = h\left(p^n\right) + h(p). \qquad (1.174)$$

Therefore,

$$h\left(p^{n+1}\right) = (n+1)h(p). \qquad (1.175)$$

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

Additionally, for positive integers m and n,

$$h\left(p^n\right) = h\left(p^{\frac{n}{m}m}\right). \qquad (1.176)$$

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 $mh\left(p^{\frac{n}{m}}\right)$. Therefore,

$$h\left(p^{\frac{n}{m}}\right) = \frac{n}{m}h(p). \qquad (1.177)$$

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

$$h\left(p^a\right) = ah(p). \tag{1.178}$$

Differentiating both sides with respect to a and substituting $a = 1$ gives

$$(p \ln p)h'(p) = h(p). \tag{1.179}$$

Therefore,

$$\int \frac{h'(p)}{h(p)} dp = \int \frac{1}{p \ln p} dp + C, \tag{1.180}$$

where C is a constant. Ignorting 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,

$$h(p) \propto \ln p. \tag{1.181}$$

1.29

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

$$\mathrm{H}(x) = -\sum_{i=1}^{M} p(x_i) \ln p(x_i), \tag{1.182}$$

where

$$\sum_{i=1}^{M} p(x_i) = 1. \tag{1.183}$$

By Jensen's inequality,

$$\sum_{i=1}^{M} p(x_i) \ln \frac{1}{p(x_i)} \leq \ln \left(\sum_{i=1}^{M} 1 \right). \tag{1.184}$$

Therefore,

$$\mathrm{H}(x) \leq \ln M. \tag{1.185}$$

1.30

Let

$$p(x) = \mathcal{N}\left(x|\mu, \sigma^2\right),$$
$$q(x) = \mathcal{N}\left(x|m, s^2\right). \tag{1.186}$$

Then, by the definition,

$$\mathrm{KL}\left(p||q\right) = -\int p(x)\ln\frac{q(x)}{p(x)}dx. \tag{1.187}$$

The right hand side can be written as

$$-\int_{-\infty}^{\infty} p(x)\ln\frac{(2\pi s^2)^{-\frac{1}{2}}\exp\left(-\frac{(x-m)^2}{2s^2}\right)}{(2\pi\sigma^2)^{-\frac{1}{2}}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}dx$$
$$= -\int_{-\infty}^{\infty} p(x)\left(-\frac{1}{2}\ln\frac{s^2}{\sigma^2} - \frac{(x-m)^2}{2s^2} + \frac{(x-\mu)^2}{2\sigma^2}\right)dx. \tag{1.188}$$

The right hand side can be written as

$$\ln\frac{s}{\sigma}\int_{-\infty}^{\infty} p(x)dx + \frac{1}{2s^2}\int_{-\infty}^{\infty}(x-m)^2 p(x)dx - \frac{1}{2\sigma^2}\int_{-\infty}^{\infty}(x-\mu)^2 p(x)dx. \tag{1.189}$$

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

$$\frac{1}{2s^2}\int_{-\infty}^{\infty}(x-\mu+\mu-m)^2 p(x)dx = \frac{\sigma^2 + (\mu-m)^2}{2s^2}. \tag{1.190}$$

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

$$\mathrm{KL}\left(p||q\right) = \ln\frac{s}{\sigma} + \frac{\sigma^2 + (\mu-m)^2}{2s^2} - \frac{1}{2}. \tag{1.191}$$

1.31

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

$$\mathrm{H}(\mathbf{x}) = -\int p(\mathbf{x})\ln p(\mathbf{x})d\mathbf{x},$$
$$\mathrm{H}(\mathbf{y}) = -\int p(\mathbf{y})\ln p(\mathbf{y})d\mathbf{y}, \tag{1.192}$$
$$\mathrm{H}(\mathbf{x}, \mathbf{y}) = -\int\int p(\mathbf{x}, \mathbf{y})\ln p(\mathbf{x}, \mathbf{y})d\mathbf{x}d\mathbf{y}.$$

23

Note that

$$H(\mathbf{x}) = -\int \left(\int p(\mathbf{x}, \mathbf{y}) d\mathbf{y} \right) \ln p(\mathbf{x}) d\mathbf{x},$$
$$H(\mathbf{y}) = -\int \left(\int p(\mathbf{x}, \mathbf{y}) d\mathbf{x} \right) \ln p(\mathbf{y}) d\mathbf{y}. \tag{1.193}$$

Therefore,

$$H(\mathbf{x}) + H(\mathbf{y}) - H(\mathbf{x}, \mathbf{y}) = -\int \int p(\mathbf{x}, \mathbf{y}) \ln \frac{p(\mathbf{x})p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} d\mathbf{x} d\mathbf{y}. \tag{1.194}$$

Since

$$\int \int p(\mathbf{x}, \mathbf{y}) d\mathbf{x} d\mathbf{y} = 1, \tag{1.195}$$

Jensen's inequality can be used to write that

$$-\int \int p(\mathbf{x}, \mathbf{y}) \ln \frac{p(\mathbf{x})p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} d\mathbf{x} d\mathbf{y} \geq -\ln \left(\int \int p(\mathbf{x})p(\mathbf{y}) d\mathbf{x} d\mathbf{y} \right). \tag{1.196}$$

The right hand side can be written as

$$-\ln \left(\int p(\mathbf{x}) d\mathbf{x} \int p(\mathbf{y}) d\mathbf{y} \right) = 0. \tag{1.197}$$

Thus,

$$H(\mathbf{x}, \mathbf{y}) \leq H(\mathbf{x}) + H(\mathbf{y}). \tag{1.198}$$

1.32

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

$$\mathbf{y} = \mathbf{A}\mathbf{x}, \tag{1.199}$$

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

$$H(\mathbf{y}) = -\int p_y(\mathbf{y}) \ln p_y(\mathbf{y}) d\mathbf{y}. \tag{1.200}$$

By the transformation

$$p_y(\mathbf{y}) = p_x(\mathbf{A}\mathbf{x}) \left| \det \mathbf{A}^{-1} \right|, \tag{1.201}$$

the right hand side can be written as

$$- \int p_x(\mathbf{Ax}) \ln p_x(\mathbf{Ax}) |\det \mathbf{A}| d\mathbf{x} - \ln \left|\det \mathbf{A}^{-1}\right| \int p_y(\mathbf{y}) d\mathbf{y}. \qquad (1.202)$$

By the transformation

$$\mathbf{x}' = \mathbf{Ax}, \qquad (1.203)$$

the first term can be written as

$$- \int p_x(\mathbf{x}') \ln p_x(\mathbf{x}') d\mathbf{x}' = \mathrm{H}(\mathbf{x}), \qquad (1.204)$$

and the second term can be written as

$$- \ln \left|\det \mathbf{A}^{-1}\right| = \ln |\det \mathbf{A}|. \qquad (1.205)$$

Therefore,

$$\mathrm{H}(\mathbf{y}) = \mathrm{H}(\mathbf{x}) + \ln |\det \mathbf{A}|. \qquad (1.206)$$

1.33

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

$$\mathrm{H}(y|x) = - \sum_i \sum_j p(x_i, y_j) \ln p(y_j|x_i). \qquad (1.207)$$

If $\mathrm{H}(y|x)$ is zero, then

$$0 = - \sum_i p(x_i) \sum_j p(y_j|x_i) \ln p(y_j|x_i). \qquad (1.208)$$

Since

$$p(x_i) \geq 0,$$
$$p(y_j|x_i) \ln p(y_j|x_i) \leq 0. \qquad (1.209)$$

for all i and j, the equation reduces to

$$p(y_j|x_i) \ln p(y_j|x_i) = 0. \qquad (1.210)$$

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

$$\sum_j p(y_j|x_i) = 1, \qquad (1.211)$$

it can be written that

$$p(y_j|x_i) = \delta_{jj'(i)}, \qquad (1.212)$$

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

1.34

Let

$$L(p(x)) = -\int_{-\infty}^{\infty} p(x)\ln p(x)dx + \lambda_1 \left(\int_{-\infty}^{\infty} p(x)dx - 1\right)$$
$$+ \lambda_2 \left(\int_{-\infty}^{\infty} xp(x)dx - \mu\right) + \lambda_3 \left(\int_{-\infty}^{\infty} (x-\mu)^2 p(x)dx - \sigma^2\right). \tag{1.213}$$

Then

$$\frac{\delta L(p(x))}{\delta p(x)} = -\ln p(x) - 1 + \lambda_1 + \lambda_2 x + \lambda_3(x-\mu)^2. \tag{1.214}$$

Setting the left hand side to zero gives

$$p(x) = \exp\left(-1 + \lambda_1 + \lambda_2 x + \lambda_3(x-\mu)^2\right). \tag{1.215}$$

Therefore,

$$p(x) = \exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3} + \lambda_3\left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3}\right)\right)^2\right). \tag{1.216}$$

Substituting it to

$$\int_{-\infty}^{\infty} p(x)dx = 1,$$
$$\int_{-\infty}^{\infty} xp(x)dx = \mu, \tag{1.217}$$
$$\int_{-\infty}^{\infty} (x-\mu)^2 p(x)dx = \sigma^2,$$

gives

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)\int_{-\infty}^{\infty} \exp\left(\lambda_3\left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3}\right)\right)^2\right) dx = 1,$$

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)\int_{-\infty}^{\infty} x\exp\left(\lambda_3\left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3}\right)\right)^2\right) dx = \mu,$$

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)\int_{-\infty}^{\infty} (x-\mu)^2\exp\left(\lambda_3\left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3}\right)\right)^2\right) dx = \sigma^2.$$

$$\tag{1.218}$$

By the transformation

$$y = \sqrt{-\lambda_3}\left(x - \left(\mu - \frac{\lambda_2}{2\lambda_3}\right)\right), \tag{1.219}$$

they can be written as

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)\int_{-\infty}^{\infty}\exp\left(-y^2\right)(-\lambda_3)^{-\frac{1}{2}}dy = 1,$$

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)\int_{-\infty}^{\infty}\left((-\lambda_3)^{-\frac{1}{2}}y + \mu - \frac{\lambda_2}{2\lambda_3}\right)\exp\left(-y^2\right)(-\lambda_3)^{-\frac{1}{2}}dy = \mu,$$

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)\int_{-\infty}^{\infty}\left((-\lambda_3)^{-\frac{1}{2}}y - \frac{\lambda_2}{2\lambda_3}\right)^2\exp\left(-y^2\right)(-\lambda_3)^{-\frac{1}{2}}dy = \sigma^2.$$

$$\tag{1.220}$$

Since

$$\int_{-\infty}^{\infty}\exp\left(-y^2\right)dy = \Gamma\left(\frac{1}{2}\right),$$

$$\int_{-\infty}^{\infty}y\exp\left(-y^2\right)dy = 0, \tag{1.221}$$

$$\int_{-\infty}^{\infty}y^2\exp\left(-y^2\right)dy = \Gamma\left(\frac{3}{2}\right),$$

they can be written as

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)(-\lambda_3)^{-\frac{1}{2}}\Gamma\left(\frac{1}{2}\right) = 1,$$

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)\left(\mu - \frac{\lambda_2}{2\lambda_3}\right)(-\lambda_3)^{-\frac{1}{2}}\Gamma\left(\frac{1}{2}\right) = \mu,$$

$$\exp\left(-1 + \lambda_1 - \frac{\lambda_2^2}{4\lambda_3}\right)\left((-\lambda_3)^{-\frac{3}{2}}\Gamma\left(\frac{3}{2}\right) + (-\lambda_3)^{-\frac{1}{2}}\frac{\lambda_2^2}{4\lambda_3^2}\Gamma\left(\frac{1}{2}\right)\right) = \sigma^2.$$

$$\tag{1.222}$$

Therefore,

$$\lambda_1 = 1 - \frac{1}{2}\ln\left(2\pi\sigma^2\right),$$

$$\lambda_2 = 0, \tag{1.223}$$

$$\lambda_3 = -\frac{1}{2\sigma^2}.$$

Thus,

$$p(x) = \left(2\pi\sigma^2\right)^{-\frac{1}{2}}\exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right). \tag{1.224}$$

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1.35

Let x be a variable such that

$$p(x) = \mathcal{N}(x|\mu, \sigma^2). \tag{1.225}$$

Then, by the definition,

$$H(x) = -\int_{-\infty}^{\infty} \mathcal{N}\left(x|\mu, \sigma^2\right) \ln \mathcal{N}\left(x|\mu, \sigma^2\right) dx. \tag{1.226}$$

The right hand side can be written as

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

$$= \frac{1}{2} \ln\left(2\pi\sigma^2\right) \int_{-\infty}^{\infty} \mathcal{N}\left(x|\mu, \sigma^2\right) dx + \frac{1}{2\sigma^2} \int_{-\infty}^{\infty} (x-\mu)^2 \mathcal{N}\left(x|\mu, \sigma^2\right) dx. \tag{1.227}$$

Therefore,

$$H(x) = \frac{1}{2}\left(1 + \ln\left(2\pi\sigma^2\right)\right). \tag{1.228}$$

1.36 (Incomplete)

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

$$f\left(\lambda a + (1-\lambda)b\right) \leq \lambda f(a) + (1-\lambda)f(b), \tag{1.229}$$

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

$$x = \lambda a + (1-\lambda)b. \tag{1.230}$$

Then, the inequality can be written as

$$f(x) \leq \frac{b-x}{b-a}f(a) + \frac{x-a}{b-a}f(b). \tag{1.231}$$

Let

$$g(x) = \frac{b-x}{b-a}f(a) + \frac{x-a}{b-a}f(b) - f(x). \tag{1.232}$$

Then,

$$g(x) \geq 0. \tag{1.233}$$

Additionally, for $x > a$,

$$g(x) = (x - a) \left(\frac{f(b) - f(a)}{b - a} - \frac{f(x) - f(a)}{x - a} \right). \tag{1.234}$$

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

$$f'(c) = \frac{f(b) - f(a)}{b - a},$$
$$f'(y) = \frac{f(x) - f(a)}{x - a}. \tag{1.235}$$

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

$$f'(y) \leq f'(c). \tag{1.236}$$

1.37

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

$$H(\mathbf{x}, \mathbf{y}) = - \int \int p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{x}, \mathbf{y}) d\mathbf{x} d\mathbf{y}. \tag{1.237}$$

The right hand side can be written as

$$- \int \int p(\mathbf{x}, \mathbf{y}) \left(\ln p(\mathbf{y}|\mathbf{x}) + \ln p(\mathbf{x}) \right) d\mathbf{x} d\mathbf{y}$$
$$= - \int \int p(\mathbf{x}, \mathbf{y}) \ln p(\mathbf{y}|\mathbf{x}) d\mathbf{x} d\mathbf{y} - \int \left(\int p(\mathbf{x}, \mathbf{y}) d\mathbf{y} \right) \ln p(\mathbf{x}) d\mathbf{x}. \tag{1.238}$$

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,

$$H(\mathbf{x}, \mathbf{y}) = H(\mathbf{y}|\mathbf{x}) + H(\mathbf{x}). \tag{1.239}$$

1.38

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

$$f \left(\lambda x_1 + (1 - \lambda) x_2 \right) \leq \lambda f(x_1) + (1 - \lambda) f(x_2), \tag{1.240}$$

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

$$f \left(\sum_{i=1}^{M} \lambda_i x_i \right) \leq \sum_{i=1}^{M} \lambda_i f(x_i),$$
(1.241)

where $\lambda_i \geq 0$ and

$$\sum_{i=1}^{M} \lambda_i = 1.$$
(1.242)

Here, let $\lambda_i \geq 0$ and

$$\sum_{i=1}^{M+1} \lambda_i = 1.$$
(1.243)

Then, by the definition,

$$f \left(\sum_{i=1}^{M+1} \lambda_i x_i \right) \leq \lambda_{M+1} f(x_{M+1}) + (1 - \lambda_{M+1}) f \left(\sum_{i=1}^{M} \frac{\lambda_i}{1 - \lambda_{M+1}} x_i \right).$$
(1.244)

By the assumption,

$$f \left(\sum_{i=1}^{M} \frac{\lambda_i}{1 - \lambda_{M+1}} x_i \right) \leq \sum_{i=1}^{M} \frac{\lambda_i}{1 - \lambda_{M+1}} f(x_i).$$
(1.245)

Therefore,

$$f \left(\sum_{i=1}^{M+1} \lambda_i x_i \right) \leq \lambda_{M+1} f(x_{M+1}) + (1 - \lambda_{M+1}) \sum_{i=1}^{M} \frac{\lambda_i}{1 - \lambda_{M+1}} f(x_i).$$
(1.246)

Thus,

$$f \left(\sum_{i=1}^{M+1} \lambda_i x_i \right) \leq \sum_{i=1}^{M+1} \lambda_i f(x_i).$$
(1.247)

Hence, the assumption is proved by induction on M.

1.39

Let x and y be two binary variables where

$$
\begin{aligned}
p(x = 0, y = 0) &= \frac{1}{3}, \\
p(x = 0, y = 1) &= \frac{1}{3}, \\
p(x = 1, y = 0) &= 0, \\
p(x = 1, y = 1) &= \frac{1}{3}.
\end{aligned}
\tag{1.248}
$$

(a)

By the definition,

$$
H(x) = -\sum p(x) \ln p(x).
\tag{1.249}
$$

By the distribution,

$$
\begin{aligned}
p(x = 0) &= \frac{2}{3}, \\
p(x = 1) &= \frac{1}{3}.
\end{aligned}
\tag{1.250}
$$

Therefore,

$$
H(x) = \ln 3 - \frac{2}{3} \ln 2.
\tag{1.251}
$$

(b)

By the definition,

$$
H(y) = -\sum p(y) \ln p(y).
\tag{1.252}
$$

By the distribution,

$$
\begin{aligned}
p(y = 0) &= \frac{1}{3}, \\
p(y = 1) &= \frac{2}{3}.
\end{aligned}
\tag{1.253}
$$

Therefore,

$$
H(y) = \ln 3 - \frac{2}{3} \ln 2.
\tag{1.254}
$$

(c)

By the definition,

$$H(y|x) = -\sum p(x,y) \ln p(y|x). \qquad (1.255)$$

By the definition,

$$
\begin{aligned}
p(y=0|x=0) &= \frac{p(x=0, y=0)}{p(x=0)}, \\
p(y=0|x=1) &= \frac{p(x=1, y=0)}{p(x=1)}, \\
p(y=1|x=0) &= \frac{p(x=0, y=1)}{p(x=0)}, \\
p(y=1|x=1) &= \frac{p(x=1, y=1)}{p(x=1)}.
\end{aligned}
\qquad (1.256)
$$

Then, by the distribution,

$$
\begin{aligned}
p(y=0|x=0) &= \frac{1}{2}, \\
p(y=0|x=1) &= 0, \\
p(y=1|x=0) &= \frac{1}{2}, \\
p(y=1|x=1) &= 1.
\end{aligned}
\qquad (1.257)
$$

Therefore,

$$H(y|x) = \frac{2}{3} \ln 2. \qquad (1.258)$$

(d)

By the definition,

$$H(x|y) = -\sum p(x,y) \ln p(x|y). \qquad (1.259)$$

By the definition,

$$p(x = 0|y = 0) = \frac{p(x = 0, y = 0)}{p(y = 0)},$$
$$p(x = 0|y = 1) = \frac{p(x = 0, y = 1)}{p(y = 1)},$$
$$p(x = 1|y = 0) = \frac{p(x = 1, y = 0)}{p(y = 0)}, \quad (1.260)$$
$$p(x = 1|y = 1) = \frac{p(x = 1, y = 1)}{p(y = 1)}.$$

Then, by the distribution,

$$p(x = 0|y = 0) = 1,$$
$$p(x = 0|y = 1) = \frac{1}{2},$$
$$p(x = 1|y = 0) = 0, \quad (1.261)$$
$$p(x = 1|y = 1) = \frac{1}{2}.$$

Therefore,

$$H(x|y) = \frac{2}{3}\ln 2. \quad (1.262)$$

(e)

By the definition,

$$H(x, y) = -\sum p(x, y)\ln p(x, y). \quad (1.263)$$

Therefore,

$$H(x, y) = \ln 3. \quad (1.264)$$

(f)

By the definition,

$$I(x, y) = -\sum p(x, y)\ln\frac{p(x)p(y)}{p(x, y)}. \quad (1.265)$$

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

$$H(x) + H(y) - H(x, y). \tag{1.266}$$

Therefore,

$$I(x, y) = \ln 3 - \frac{4}{3} \ln 2. \tag{1.267}$$

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

$$\sum_{i=1}^{M} \lambda_i = 1. \tag{1.268}$$

By Jensen's inequality,

$$\sum_{i=1}^{M} \lambda_i \ln x_i \leq \ln \left(\sum_{i=1}^{M} \lambda_i x_i \right). \tag{1.269}$$

Therefore,

$$\prod_{i=1}^{M} x_i^{\lambda_i} \leq \sum_{i=1}^{M} \lambda_i x_i. \tag{1.270}$$

Substituting

$$\lambda_i = \frac{1}{M} \tag{1.271}$$

gives

$$\left(\prod_{i=1}^{M} x_i \right)^{\frac{1}{M}} \leq \frac{1}{M} \sum_{i=1}^{M} x_i. \tag{1.272}$$

1.41

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

$$I(\mathbf{x}, \mathbf{y}) = - \int \int p(\mathbf{x}, \mathbf{y}) \ln \frac{p(\mathbf{x})p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} d\mathbf{x} d\mathbf{y}. \tag{1.273}$$

The right hand side can be written as

$$-\int\int p(\mathbf{x},\mathbf{y})\left(\ln p(\mathbf{x}) + \ln\frac{p(\mathbf{y})}{p(\mathbf{x},\mathbf{y})}\right)d\mathbf{x}d\mathbf{y}$$
$$= -\int\left(\int p(\mathbf{x},\mathbf{y})d\mathbf{y}\right)\ln p(\mathbf{x})d\mathbf{x} + \int\int p(\mathbf{x},\mathbf{y})\ln p(\mathbf{x}|\mathbf{y})d\mathbf{x}d\mathbf{y}. \quad (1.274)$$

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

$$\mathrm{I}(\mathbf{x},\mathbf{y}) = \mathrm{H}(\mathbf{x}) - \mathrm{H}(\mathbf{x}|\mathbf{y}). \quad (1.275)$$

By the definition,

$$\mathrm{I}(\mathbf{x},\mathbf{y}) = \mathrm{I}(\mathbf{y},\mathbf{x}). \quad (1.276)$$

Thus,

$$\mathrm{I}(\mathbf{x},\mathbf{y}) = \mathrm{H}(\mathbf{y}) - \mathrm{H}(\mathbf{y}|\mathbf{x}). \quad (1.277)$$

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2 Probability Distributions

2.1

Let x be a variable such that

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

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

$$\sum_x p(x|\mu) = 1. \tag{2.2}$$

By the definition,

$$\begin{aligned} \mathrm{E}x &= \mu, \\ \mathrm{E}x^2 &= \mu, \end{aligned} \tag{2.3}$$

Since

$$\mathrm{var}x = \mathrm{E}x^2 - (\mathrm{E}x)^2, \tag{2.4}$$

we have

$$\mathrm{var}x = \mu(1-\mu). \tag{2.5}$$

By the definition,

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

Therefore,

$$\mathrm{H}(x) = -\mu \ln \mu - (1-\mu) \ln(1-\mu). \tag{2.7}$$

2.2

Let x be a variable such that

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

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

$$\sum_x p(x|\mu) = 1. \tag{2.9}$$

By the definition,

$$\begin{aligned} \mathrm{E}x &= \mu, \\ \mathrm{E}x^2 &= 1, \end{aligned} \tag{2.10}$$

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

we have
$$\text{var}x = 1 - \mu^2. \tag{2.12}$$

By the definition,
$$\text{H}(x) = -\sum_x p(x|\mu) \ln p(x|\mu). \tag{2.13}$$

Therefore,
$$\text{H}(x) = -\frac{1-\mu}{2}\ln\frac{1-\mu}{2} - \frac{1+\mu}{2}\ln\frac{1+\mu}{2}. \tag{2.14}$$

2.3

By the definition,
$$\binom{N}{m} = \frac{N!}{m!(N-m)!},$$
$$\binom{N}{m-1} = \frac{N!}{(m-1)!(N-m+1)!} \tag{2.15}$$

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

By the definition, the right hand side can be written as
$$\frac{(N+1)!}{m!(N+1-m)!} = \binom{N+1}{m}. \tag{2.17}$$

Thus,
$$\binom{N}{m} + \binom{N}{m-1} = \binom{N+1}{m}. \tag{2.18}$$

Note that
$$1 + x = \sum_{m=0}^{1}\binom{1}{m}x^m. \tag{2.19}$$

Let us assume that
$$(1+x)^N = \sum_{m=0}^{N}\binom{N}{m}x^m. \tag{2.20}$$

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Then,

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

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

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

Therefore,

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

Thus, the assumption is proved by induction on N.

Finally, let m be a variable such that

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

Then

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

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

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

Therefore,

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

2.4

Let m be a variable such that

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

Then

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

Differentiating both sides of

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

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 $\frac{1}{\mu}\mathrm{E}m$. Since

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

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

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

Therefore,

$$\mathrm{E}m = N\mu. \qquad (2.34)$$

Differentiating both sides of

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

twice with respect to μ gives

$$\sum_{m=0}^{N} m(m-1)\binom{N}{m}\mu^{m-2}(1-\mu)^{N-m}$$
$$-2\sum_{m=0}^{N} m(N-m)\binom{N}{m}\mu^{m-1}(1-\mu)^{N-m-1} \qquad (2.36)$$
$$+\sum_{m=0}^{N}(N-m)(N-m-1)\binom{N}{m}\mu^m(1-\mu)^{N-m-2} = 0.$$

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

$$m(N-m)\binom{N}{m} = N(N-1)\binom{N-2}{m-1},$$

$$(N-m)(N-m-1)\binom{N}{m} = N(N-1)\binom{N-2}{m},$$

$$\tag{2.37}$$

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

$$-2N(N-1)\sum_{m=1}^{N-1}\binom{N-2}{m-1}\mu^{m-1}(1-\mu)^{N-m-1} = -2N(N-1),$$

$$N(N-1)\sum_{m=0}^{N}\binom{N-2}{m}\mu^m(1-\mu)^{N-m-2} = N(N-1).$$

$$\tag{2.38}$$

Therefore,

$$Em(m-1) = N(N-1)\mu^2. \tag{2.39}$$

Thus, since

$$\mathrm{var}m = Em(m-1) + Em - (Em)^2, \tag{2.40}$$

we have

$$\mathrm{var}m = N\mu(1-\mu). \tag{2.41}$$

2.5

By the definition,

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

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

$$\int_0^\infty x^{a-1}\left(\int_x^\infty (t-x)^{b-1}\exp(-t)dt\right)dx$$

$$= \int_0^\infty\left(\int_0^t x^{a-1}(t-x)^{b-1}dx\right)\exp(-t)dt.$$

$$\tag{2.43}$$

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

$$\int_0^\infty\left(\int_0^1 (t\mu)^{a-1}t^{b-1}(1-\mu)^{b-1}td\mu\right)\exp(-t)dt$$

$$= \int_0^1 \mu^{a-1}(1-\mu)^{b-1}d\mu\int_0^\infty t^{a+b-1}\exp(-t)dt.$$

$$\tag{2.44}$$

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

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

2.6

Let μ be a variable such that

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

Then

$$E\mu = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\int_0^1 \mu^a(1-\mu)^{b-1}d\mu,$$
$$E\mu^2 = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\int_0^1 \mu^{a+1}(1-\mu)^{b-1}d\mu. \tag{2.47}$$

Since

$$\int_0^1 \mu^a(1-\mu)^{b-1}d\mu = \frac{\Gamma(a+1)\Gamma(b)}{\Gamma(a+b+1)},$$
$$\int_0^1 \mu^{a+1}(1-\mu)^{b-1}d\mu = \frac{\Gamma(a+2)\Gamma(b)}{\Gamma(a+b+2)}, \tag{2.48}$$

we have

$$E\mu = \frac{a}{a+b},$$
$$E\mu^2 = \frac{a(a+1)}{(a+b)(a+b+1)}. \tag{2.49}$$

Since

$$\mathrm{var}\mu = E\mu^2 - (E\mu)^2, \tag{2.50}$$

we have

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

Since

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

we have

$$\mathrm{mode}\mu = \frac{a-1}{a+b-2}. \tag{2.53}$$

2.7

Let m and l be a variable such that

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

where

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

By 2.6,

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

Note that

$$\mu_{\text{ML}} = \frac{m}{m+l}. \tag{2.57}$$

Since

$$p(\mu|m, l, a, b) \propto p(m, l|\mu)p(\mu|a, b), \tag{2.58}$$

we have

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

Therefore, by 2.6,

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

Thus,

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

where

$$\lambda = \frac{m+l}{m+l+a+b}. \tag{2.62}$$

2.8 (Incomplete)

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

$$Ex = \int xp(x)dx. \tag{2.63}$$

The right hand side can be written as

$$\int x \left(\int p(x, y)dy \right) dx = \int \left(\int xp(x|y)dx \right) p(y)dy. \tag{2.64}$$

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Therefore,
$$\mathrm{E}x = \mathrm{E}_y \left(\mathrm{E}_x(x|y) \right). \tag{2.65}$$

By the definition,
$$\mathrm{var}x = \mathrm{E} \left(x - \mathrm{E}x \right)^2. \tag{2.66}$$

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

$$
\begin{aligned}
\mathrm{E}_y &\left(\mathrm{E}_x \left((x - \mathrm{E}_x(x|y) + \mathrm{E}_x(x|y) - \mathrm{E}x)^2 |y) \right) \right) \\
&= \mathrm{E}_y \left(\mathrm{E}_x \left((x - \mathrm{E}_x(x|y))^2 |y) \right) \right) \\
&+ 2\mathrm{E}_y \left(\mathrm{E}_x \left((x - \mathrm{E}_x(x|y)) (\mathrm{E}_x(x|y) - \mathrm{E}x) |y) \right) \right) \\
&+ \mathrm{E}_y \left(\mathrm{E}_x \left((\mathrm{E}_x(x|y) - \mathrm{E}x)^2 |y) \right) \right)
\end{aligned}
\tag{2.67}
$$

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

$$2\mathrm{E}_y \left((\mathrm{E}_x(x|y) - \mathrm{E}x) \mathrm{E}_x \left((x - \mathrm{E}_x(x|y)) |y) \right) \right) \tag{2.68}$$

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

$$\mathrm{E}_y \left(\mathrm{E}_x(x|y) - \mathrm{E}_y \left(\mathrm{E}_x(x|y) \right) \right)^2 = \mathrm{var}_y \left(\mathrm{E}_x(x|y) \right). \tag{2.69}$$

Therefore,
$$\mathrm{var}x = \mathrm{E}_y \left(\mathrm{var}_x(x|y) \right) + \mathrm{var}_y \left(\mathrm{E}_x(x|y) \right). \tag{2.70}$$

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

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

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

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

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

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

By the assumption, it can be written as

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

Therefore,

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

Thus, the assumption is proved by induction on M.

2.10

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

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

Then

$$\mathrm{E}\mu_j = \int \mu_j p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu},$$

$$\mathrm{E}\mu_j^2 = \int \mu_j^2 p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu}, \tag{2.75}$$

$$\mathrm{E}\mu_j\mu_l = \int \mu_j \mu_l p(\boldsymbol{\mu}|\boldsymbol{\alpha}) d\boldsymbol{\mu}.$$

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

$$\frac{\Gamma\left(\sum_{k=1}^{K}\alpha_k\right)}{\prod_{k=1}^{K}\Gamma(\alpha_k)} \frac{\frac{\Gamma(\alpha_j+1)}{\Gamma(\alpha_j)}\prod_{k=1}^{K}\Gamma(\alpha_k)}{\Gamma\left(\sum_{k=1}^{K}\alpha_k+1\right)} = \frac{\alpha_j}{\sum_{k=1}^{K}\alpha_k},$$

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

$$\frac{\Gamma\left(\sum_{k=1}^{K}\alpha_k\right)}{\prod_{k=1}^{K}\Gamma(\alpha_k)} \frac{\frac{\Gamma(\alpha_j+1)\Gamma(\alpha_l+1)}{\Gamma(\alpha_j)\Gamma(\alpha_l)}\prod_{k=1}^{K}\Gamma(\alpha_k)}{\Gamma\left(\sum_{k=1}^{K}\alpha_k+2\right)} = \frac{\alpha_j\alpha_l}{\sum_{k=1}^{K}\alpha_k\left(\sum_{k=1}^{K}\alpha_k+1\right)}.$$

Therefore,

$$\mathrm{E}\mu_j = \frac{\alpha_j}{\sum_{k=1}^{K}\alpha_k}.$$

$$\mathrm{E}\mu_j^2 = \frac{\alpha_j(\alpha_j+1)}{\sum_{k=1}^{K}\alpha_k\left(\sum_{k=1}^{K}\alpha_k+1\right)}, \quad (2.77)$$

$$\mathrm{E}\mu_j\mu_l = \frac{\alpha_j\alpha_l}{\sum_{k=1}^{K}\alpha_k\left(\sum_{k=1}^{K}\alpha_k+1\right)}.$$

Since

$$\mathrm{var}\mu_j = \mathrm{E}\mu_j^2 - (\mathrm{E}\mu_j)^2,$$
$$\mathrm{cov}\left(\mu_j,\mu_l\right) = \mathrm{E}\mu_j\mu_l - \mathrm{E}\mu_j\mathrm{E}\mu_l, \quad (2.78)$$

we have

$$\mathrm{var}\mu_j = \frac{\alpha_j\left(\sum_{k=1}^{K}\alpha_k - \alpha_j\right)}{\left(\sum_{k=1}^{K}\alpha_k\right)^2\left(\sum_{k=1}^{K}\alpha_k+1\right)},$$

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

2.11

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

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

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Then
$$\mathrm{E}\ln\mu_j = \int (\ln\mu_j)\, p(\boldsymbol{\mu}|\boldsymbol{\alpha})d\boldsymbol{\mu}. \qquad (2.81)$$

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

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

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

Therefore,
$$\mathrm{E}\ln\mu_j = \psi(\alpha_j) - \psi\left(\sum_{k=1}^{K}\alpha_k\right). \qquad (2.85)$$

2.12

Let x be a variable such that
$$p(x|a,b) = \frac{1}{b-a}, \qquad (2.86)$$

where $a < b$. Then
$$\int_a^b p(x|a,b)dx = 1. \qquad (2.87)$$

Note that
$$\mathrm{E}x = \int_a^b xp(x|a,b)dx,$$
$$\mathrm{E}x^2 = \int_a^b x^2 p(x|a,b)dx. \qquad (2.88)$$

The right hand sides can be written as
$$\frac{1}{b-a}\int_a^b xdx = \frac{1}{2}(a+b),$$
$$\frac{1}{b-a}\int_a^b x^2 dx = \frac{1}{3}\left(a^2 + ab + b^2\right). \qquad (2.89)$$

Therefore,

$$\mathrm{E}x = \frac{1}{2}(a+b),$$
$$\mathrm{E}x^2 = \frac{1}{3}\left(a^2 + ab + b^2\right). \tag{2.90}$$

Since

$$\mathrm{var}x = \mathrm{E}x^2 - \left(\mathrm{E}x\right)^2, \tag{2.91}$$

we have

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

2.13

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

$$p(\mathbf{x}) = \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}),$$
$$q(\mathbf{x}) = \mathcal{N}(\mathbf{x}|\mathbf{m}, \mathbf{L}). \tag{2.93}$$

Then, by the definition,

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

Since

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

The right hand side can be written as

$$\frac{1}{2}\ln\left|\frac{\det \mathbf{L}}{\det \boldsymbol{\Sigma}}\right| \int \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x}$$
$$+ \frac{1}{2}\int (\mathbf{x}-\mathbf{m})^\mathsf{T}\mathbf{L}^{-1}(\mathbf{x}-\mathbf{m})\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x} \tag{2.96}$$
$$- \frac{1}{2}\int (\mathbf{x}-\boldsymbol{\mu})^\mathsf{T}\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\mathbf{x}.$$

Let us look at each term. Since

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

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

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

the second term can be written as

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

Since

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

it can be written as

$$\frac{1}{2}\operatorname{tr}\left(\mathbf{L}^{-1}\boldsymbol{\Sigma}\right) + \frac{1}{2}(\boldsymbol{\mu} - \mathbf{m})^{\mathsf{T}}\mathbf{L}^{-1}(\boldsymbol{\mu} - \mathbf{m}). \quad (2.101)$$

Since

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

the third term can be written as

$$-\frac{1}{2}\operatorname{tr}\left(\boldsymbol{\Sigma}^{-1}\boldsymbol{\Sigma}\right) = -\frac{D}{2} \quad (2.103)$$

Therefore,

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

2.14

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

$$L(p(\mathbf{x})) = -\int p(\mathbf{x}) \ln p(\mathbf{x}) d\mathbf{x} + \lambda \left(\int p(\mathbf{x}) d\mathbf{x} - 1 \right)$$

$$+ \mathbf{l}^{\mathsf{T}} \left(\int \mathbf{x} p(\mathbf{x}) d\mathbf{x} - \boldsymbol{\mu} \right) + \mathbf{m}^{\mathsf{T}} \left(\int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}} p(\mathbf{x}) d\mathbf{x} - \boldsymbol{\Sigma} \right) \mathbf{m}.$$

$$(2.105)$$

Then

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

Setting the left hand side to zero gives

$$p(\mathbf{x}) = \exp\left(-1 + \lambda + \mathbf{l}^{\mathsf{T}} \mathbf{x} + \mathbf{m}^{\mathsf{T}}(\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}} \mathbf{m}\right), \qquad (2.107)$$

so that

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

where

$$\mathbf{M} = (\mathbf{m} \mathbf{m}^{\mathsf{T}})^{-1}. \qquad (2.109)$$

Substituting it to

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

$$\int \mathbf{x} p(\mathbf{x}) d\mathbf{x} = \boldsymbol{\mu}, \qquad (2.110)$$

$$\int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}} p(\mathbf{x}) d\mathbf{x} = \boldsymbol{\Sigma},$$

and the transformation

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

gives

$$\exp\left(-1 + \lambda - \mathbf{l}^{\mathsf{T}} \mathbf{M} \mathbf{l}\right) \int \exp\left(-\mathbf{y}^{\mathsf{T}} \mathbf{M}^{-1} \mathbf{y}\right) d\mathbf{y} = 1,$$

$$\exp\left(-1 + \lambda - \mathbf{l}^{\mathsf{T}} \mathbf{M} \mathbf{l}\right) \int (\mathbf{y} + \boldsymbol{\mu} + \mathbf{M} \mathbf{l}) \exp\left(-\mathbf{y}^{\mathsf{T}} \mathbf{M}^{-1} \mathbf{y}\right) d\mathbf{y} = \boldsymbol{\mu},$$

$$\exp\left(-1 + \lambda - \mathbf{l}^{\mathsf{T}} \mathbf{M} \mathbf{l}\right) \int (\mathbf{y} + \mathbf{M} \mathbf{l}) (\mathbf{y} + \mathbf{M} \mathbf{l})^{\mathsf{T}} \exp\left(-\mathbf{y}^{\mathsf{T}} \mathbf{M}^{-1} \mathbf{y}\right) d\mathbf{y} = \boldsymbol{\Sigma}.$$

$$(2.112)$$

Since

$$\int \exp\left(-\mathbf{y}^\mathsf{T}\mathbf{y}\right) d\mathbf{y} = \left(\Gamma\left(\frac{1}{2}\right)\right)^D,$$

$$\int \mathbf{y} \exp\left(-\mathbf{y}^\mathsf{T}\mathbf{y}\right) d\mathbf{y} = \mathbf{0}, \tag{2.113}$$

$$\int \mathbf{y}\mathbf{y}^\mathsf{T} \exp\left(-\mathbf{y}^\mathsf{T}\mathbf{y}\right) d\mathbf{y} = \Gamma\left(\frac{3}{2}\right)\left(\Gamma\left(\frac{1}{2}\right)\right)^{D-1}\mathbf{I},$$

they can be written as

$$\exp\left(-1 + \lambda - \mathbf{l}^\mathsf{T}\mathbf{M}\mathbf{l}\right)\left(\Gamma\left(\frac{1}{2}\right)\right)^D (\det \mathbf{M})^{\frac{1}{2}} = 1,$$

$$\exp\left(-1 + \lambda - \mathbf{l}^\mathsf{T}\mathbf{M}\mathbf{l}\right)(\boldsymbol{\mu} + \mathbf{M}\mathbf{l})\left(\Gamma\left(\frac{1}{2}\right)\right)^D (\det \mathbf{M})^{\frac{1}{2}} = \boldsymbol{\mu},$$

$$\exp\left(-1 + \lambda - \mathbf{l}^\mathsf{T}\mathbf{M}\mathbf{l}\right)\left(\Gamma\left(\frac{3}{2}\right)\left(\Gamma\left(\frac{1}{2}\right)\right)^{D-1}\mathbf{M} + \mathbf{M}\mathbf{l}(\mathbf{M}\mathbf{l})^\mathsf{T}\left(\Gamma\left(\frac{1}{2}\right)\right)^D\right)(\det \mathbf{M})^{\frac{1}{2}} = \boldsymbol{\Sigma}.$$
$$\tag{2.114}$$

Therefore,

$$\lambda = 1 - \frac{D}{2}\ln\pi - \frac{1}{2}\ln(\det \mathbf{M}),$$

$$\mathbf{l} = \mathbf{0}, \tag{2.115}$$

$$\mathbf{M} = 2\boldsymbol{\Sigma}.$$

Thus,

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

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,

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

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The right hand side can be written as

$$-\int \mathcal{N}\left(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}\right)\left(-\frac{D}{2}\ln(2\pi) - \frac{1}{2}\ln|\det \boldsymbol{\Sigma}| - \frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right)d\mathbf{x}$$
$$= \left(\frac{D}{2}\ln(2\pi) + \frac{1}{2}\ln|\det \boldsymbol{\Sigma}|\right)\int \mathcal{N}\left(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}\right)d\mathbf{x}$$
$$+ \frac{1}{2}\int (\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\mathcal{N}\left(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}\right)d\mathbf{x}.$$

$$(2.119)$$

Since

$$\int \mathcal{N}\left(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}\right)d\mathbf{x} = 1,$$
$$\int (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\mathcal{N}\left(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}\right)d\mathbf{x} = \boldsymbol{\Sigma},$$

$$(2.120)$$

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

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

and

$$\frac{1}{2}\operatorname{tr}\left(\boldsymbol{\Sigma}^{-1}\boldsymbol{\Sigma}\right) = \frac{D}{2}. \qquad (2.122)$$

Therefore,

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

2.16

Let

$$x = x_1 + x_2, \qquad (2.124)$$

where x_1 and x_2 are variables such that

$$p(x_1) = \mathcal{N}\left(x_1|\mu_1, \tau_1^{-1}\right),$$
$$p(x_2) = \mathcal{N}\left(x_2|\mu_2, \tau_2^{-1}\right). \qquad (2.125)$$

Then

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

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The right hand side can be written as

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

The right hand side can be written as

$$\int_{-\infty}^{\infty} \frac{(\tau_1\tau_2)^{\frac{1}{2}}}{2\pi} \exp\left(-\frac{\tau_1 + \tau_2}{2}\left(x_2 - \frac{\tau_1(x - \mu_1) + \tau_2\mu_2}{\tau_1 + \tau_2}\right)^2\right) dx_2$$
$$\exp\left(-\frac{\tau_1}{2}(x - \mu_1)^2 - \frac{\tau_2}{2}\mu_2^2 + \frac{\tau_1 + \tau_2}{2}\left(\frac{\tau_1(x - \mu_1) + \tau_2\mu_2}{\tau_1 + \tau_2}\right)^2\right)$$
$$\propto \exp\left(-\frac{\tau_1\tau_2}{2(\tau_1 + \tau_2)}(x - \mu_1 - \mu_2)^2\right).$$
(2.128)

Therefore,

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

Thus, by 1.35,

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

2.17

Let $\boldsymbol{\Sigma}$ be a matrix and

$$\mathbf{S} = \frac{1}{2}\left(\boldsymbol{\Sigma}^{-1} + \left(\boldsymbol{\Sigma}^{-1}\right)^{\mathsf{T}}\right),$$
$$\mathbf{A} = \frac{1}{2}\left(\boldsymbol{\Sigma}^{-1} - \left(\boldsymbol{\Sigma}^{-1}\right)^{\mathsf{T}}\right).$$
(2.131)

Then

$$\boldsymbol{\Sigma}^{-1} = \mathbf{S} + \mathbf{A}.$$
(2.132)

Therefore,

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

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

$$\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu}) - \frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\left(\boldsymbol{\Sigma}^{-1}\right)^{\mathsf{T}}(\mathbf{x} - \boldsymbol{\mu}). \tag{2.134}$$

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

$$-\frac{1}{2}\left(\boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right)^{\mathsf{T}}(\mathbf{x} - \boldsymbol{\mu}) = -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu}). \tag{2.135}$$

Thus,

$$(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\mathbf{A}(\mathbf{x} - \boldsymbol{\mu}) = 0. \tag{2.136}$$

Hence

$$(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu}) = (\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}}\mathbf{S}(\mathbf{x} - \boldsymbol{\mu}). \tag{2.137}$$

2.18

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

$$\boldsymbol{\Sigma}\mathbf{u}_i = \lambda_i\mathbf{u}_i, \tag{2.138}$$

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

$$\overline{\mathbf{u}_i}^{\mathsf{T}}\boldsymbol{\Sigma}\mathbf{u}_i = \lambda_i. \tag{2.139}$$

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

$$\overline{\mathbf{u}_i}^{\mathsf{T}}\overline{\boldsymbol{\Sigma}}^{\mathsf{T}}\mathbf{u}_i = \left(\overline{\boldsymbol{\Sigma}}\,\overline{\mathbf{u}_i}\right)^{\mathsf{T}}\mathbf{u}_i. \tag{2.140}$$

The right hand side can be writtet as

$$\overline{\lambda}_i\overline{\mathbf{u}}_i^{\mathsf{T}}\mathbf{u}_i = \overline{\lambda}_i. \tag{2.141}$$

Therefore,

$$\lambda_i = \overline{\lambda}_i. \tag{2.142}$$

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

$$\mathbf{u}_j^{\mathsf{T}}\boldsymbol{\Sigma}\mathbf{u}_i = \lambda_i\mathbf{u}_j^{\mathsf{T}}\mathbf{u}_i. \tag{2.143}$$

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

$$\mathbf{u}_j^{\mathsf{T}}\boldsymbol{\Sigma}^{\mathsf{T}}\mathbf{u}_i = (\boldsymbol{\Sigma}\mathbf{u}_j)^{\mathsf{T}}\mathbf{u}_i. \tag{2.144}$$

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

$$\lambda_i \mathbf{u}_j^\mathsf{T} \mathbf{u}_i = \lambda_j \mathbf{u}_j^\mathsf{T} \mathbf{u}_i. \tag{2.145}$$

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

$$\mathbf{u}_j^\mathsf{T} \mathbf{u}_i = 0. \tag{2.146}$$

2.19

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

$$\boldsymbol{\Sigma} \mathbf{u}_i = \lambda_i \mathbf{u}_i, \tag{2.147}$$

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

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

Then

$$\boldsymbol{\Sigma}\mathbf{U} = \mathbf{U}\boldsymbol{\Lambda}. \tag{2.149}$$

By 2.18,

$$\mathbf{U}^\mathsf{T}\mathbf{U} = \mathbf{I}. \tag{2.150}$$

Therefore,

$$\begin{aligned}
\boldsymbol{\Sigma} &= \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^\mathsf{T}, \\
\boldsymbol{\Sigma}^{-1} &= \mathbf{U}\boldsymbol{\Lambda}^{-1}\mathbf{U}^\mathsf{T},
\end{aligned} \tag{2.151}$$

Thus,

$$\begin{aligned}
\boldsymbol{\Sigma} &= \sum_{i=1}^{D} \lambda_i \mathbf{u}_i \mathbf{u}_i^\mathsf{T}, \\
\boldsymbol{\Sigma}^{-1} &= \sum_{i=1}^{D} \frac{1}{\lambda_i} \mathbf{u}_i \mathbf{u}_i^\mathsf{T}.
\end{aligned} \tag{2.152}$$

2.20

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

$$\boldsymbol{\Sigma} \mathbf{u}_i = \lambda_i \mathbf{u}_i, \tag{2.153}$$

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

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

By 2.19,

$$
\mathbf{a}^\mathsf{T} \boldsymbol{\Sigma} \mathbf{a} = \mathbf{b}^\mathsf{T} \boldsymbol{\Lambda} \mathbf{b},
\tag{2.155}
$$

where

$$
\mathbf{b} = \mathbf{U}^\mathsf{T} \mathbf{a}.
\tag{2.156}
$$

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

$$
\mathbf{a}^\mathsf{T} \boldsymbol{\Sigma} \mathbf{a} > 0
\tag{2.157}
$$

for any real vector $\mathbf{a}$ is

$$
\lambda_i > 0.
\tag{2.158}
$$

2.21

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

2.22

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

$$
\boldsymbol{\Sigma} \boldsymbol{\Lambda} = \mathbf{I}.
\tag{2.159}
$$

Taking the transpose of the both sides gives

$$
\boldsymbol{\Lambda}^\mathsf{T} \boldsymbol{\Sigma} = \mathbf{I}.
\tag{2.160}
$$

Therefore,

$$
\boldsymbol{\Lambda}^\mathsf{T} = \boldsymbol{\Lambda}.
\tag{2.161}
$$

2.23

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

$$\boldsymbol{\Sigma}\mathbf{u}_i = \lambda_i\mathbf{u}_i, \tag{2.162}$$

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

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

By 2.19,

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

By the transformation

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

and the property

$$\mathbf{U}^\intercal\mathbf{U} = \mathbf{I}, \tag{2.166}$$

the right hand side can be written as

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

Therefore,

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

where

$$V_D = \int_{\|\mathbf{x}\|=1} d\mathbf{x}. \tag{2.169}$$

2.24   (Incomplete)

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