

Review Assignment 1

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1 Probability theory review

Solve each of the following problems and show all the steps of your working.

1. Show that the covariance matrix is always symmetric and positive semidefinite.

The $(i; j)^{th}$ element of the covariance matrix Σ is given by

$$\Sigma_{ij} = E[(X_i - \mu_i)(X_j - \mu_j)] = E[(X_j - \mu_j)(X_i - \mu_i)] = \Sigma_{ji}$$

so that the covariance matrix is symmetric.

For an arbitrary vector u ,

$$\begin{aligned} u^T \Sigma u &= u^T E[(X - \mu)(X - \mu)^T] u = E[(u^T (X - \mu)(X - \mu)^T) u] \\ &= E[((X - \mu)^T u)^T (X - \mu)^T u] = E[((X - \mu)^T u)^2] \geq 0 \end{aligned}$$

so that the covariance matrix is positive semi-definite.

2. $X \in \mathbb{R}^n$ and $Y \in \mathbb{R}^m$ are independent random variables. Their expectations and covariances are $E[X] = 0$, $\text{cov}[X] = I$, $E[Y] = \mu$ and $\text{cov}[Y] = \sigma I$, where I is the identity matrix of the appropriate size and σ is a scalar. What is the expectation and covariance of the random variable $z = AX + Y$, where $A \in \mathbb{R}^{m \times n}$?

The expectation of Z can be obtained from the definition by applying the linearity of expectation,

$$E[Z] = E[AX + Y] = AE[x] + E[Y] = 0 + \mu = \mu$$

The covariance of Z is $\text{Cov}[Z] = E[ZZ^T] - E[Z]E[Z]^T = E[ZZ^T] - \mu\mu^T$. Substituting the definition of Z , we get the expression below.

$$\begin{aligned}
E[ZZ^\top] &= E[(AX + Y)(AX + Y)^\top] = \\
&= E[AXX^\top A^\top + YX^\top A^\top + AXY^\top + YY^\top] = \\
&= AE[XX^\top]A^\top + E[YX^\top]A^\top + AE[XY^\top] + E[YY^\top]
\end{aligned}$$

Here we can substitute $E[XX^\top] = I$ and $E[YY^\top] = \sigma I + \mu\mu^\top$. Because X and Y are independent, $E[XY^\top] = E[X]E[Y^\top] = 0$, similarly $E[YX^\top] = 0$. We get $E[ZZ^\top] = AA^\top + \sigma I + \mu\mu^\top$, therefore $\text{Cov}[Z] = AA^\top + \sigma I$.

3. Thomas and Viktor are friends. It is Friday night and Thomas does not have a phone. Viktor knows that there is a $2/3$ probability that Thomas goes to the party to downtown. There are 5 pubs in downtown and there is an equal probability of Thomas going to any of them if he goes to the party. Viktor already looked for Thomas in 4 of the bars. What is the probability of Viktor ending Thomas in the last bar?

The sample space is

$$S = f\{\text{home, pub 1, pub 2, pub 3, pub 4, pub 5}\}$$

and the probability of the events are $P(\text{home}) = 1/3$ and $P(\text{pub } i) = \frac{2}{15}$. We need to compute $P(\text{pub 5} | \text{not in pub 1} \dots 4)$. Using the Bayes rule,

$$\begin{aligned}
P(\text{pub 5} | \text{not in pub 1} \dots 4) &= \\
\frac{P(\text{pub 5} \cap \text{not in pub 1} \dots 4)}{P(\text{not in pub 1} \dots 4)} &= \frac{\frac{2}{15}}{\frac{7}{15}} = \frac{2}{7}
\end{aligned}$$

4. Derive the mean for the Beta Distribution, which is defined as

$$\text{Beta}(x|a, b) = \frac{1}{B(a, b)} a^{-1} (1-x)b^{-1} \quad (1)$$

where $B(a, b)$, $\Gamma(a)$ are Beta and Gamma functions respectively:

$$B(a, b) \triangleq \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)} \quad (2)$$

and

$$\Gamma(x) \triangleq \int_0^\infty u^{x-1} e^{-u} du \quad (3)$$

Hint: Use integration by parts.

$$\begin{aligned}
E(x) &= \frac{1}{\text{Beta}(a, b)} \int_0^1 x^a (1-x)^{b-1} dx \\
&= \frac{\text{Beta}(a+1, b)}{\text{Beta}(a, b)} \\
&= \frac{\Gamma(a+1)\Gamma(b)}{\Gamma(a+b+1)} \cdot \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \\
&= \frac{a}{a+b} \cdot \frac{\Gamma(a)\Gamma(b)\Gamma(a+b)}{\Gamma(a)\Gamma(b)\Gamma(a+b)} \\
&= \frac{a}{a+b}
\end{aligned}$$

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5. Let $A \in \mathbb{R}^{n \times n}$ be a positive definite square matrix, $b \in \mathbb{R}^n$, and c be a scalar. Prove that

$$\int_{x \in \mathbb{R}^n} e^{-\frac{1}{2}x^T A x - x^T b - c} dx = \frac{(2\pi)^{n/2} |A|^{-1/2}}{e^{c - \frac{1}{2}b^T A^{-1}b}}$$

Hint: Use the fact that the integral of the Gaussian probability density function of a random variable with mean μ and covariance Σ is 1.

$$\begin{aligned}
\frac{(2\pi)^{n/2} |A|^{-1/2}}{e^{c - \frac{1}{2}b^T A^{-1}b}} &= \int_{x \in \mathbb{R}^n} e^{-\frac{1}{2}x^T A x - x^T b - c} dx \\
&= \int_{x \in \mathbb{R}^n} e^{-\frac{1}{2}(x+A^{-1}b)^T A (x+A^{-1}b) + \frac{1}{2}b^T A^{-1}b - c} dx \\
&= \sqrt{(2\pi)^n |\Sigma|} \cdot e^{\frac{1}{2}b^T A^{-1}b - c} \int_{x \in \mathbb{R}^n} \frac{1}{\sqrt{(2\pi)^n |\Sigma|}} e^{-\frac{1}{2}(x+A^{-1}b)^T A (x+A^{-1}b)} dx \\
&= \sqrt{(2\pi)^n |\Sigma|} \cdot e^{\frac{1}{2}b^T A^{-1}b - c} \cdot 1 \\
&= \frac{\sqrt{(2\pi)^n |\Sigma|}}{e^{\frac{1}{2}b^T A^{-1}b - c}}
\end{aligned}$$

6. From the definition of conditional probability of multiple random variables, show that

$$f(x_1, x_2, \dots, x_n) = f(x_1) \prod_{i=2}^n f(x_i | x_1, \dots, x_{i-1})$$

where x_1, \dots, x_n are random variables and f is a probability density function of its arguments.

$$P(x_1 \cap x_2 \cap \cdots \cap x_n) = P(x_1) \prod_{i=2}^n P(x_i | x_1, \dots, x_{i-1})$$

When $n = 2$

$$\begin{aligned} P(x_1 \cap x_2) &= P(x_1) \prod_{i=2}^n P(x_i | x_1) \\ &= P(x_1) P(x_2 | x_1) \end{aligned}$$

$$P(x_1 \cap x_2 \cap \cdots \cap x_{n-1} \cap x_n) = P(x_n | x_1 \cap x_2 \cap \cdots \cap x_{n-1} \cap x_n) P(x_1 \cap x_2 \cap \cdots \cap x_{n-1} \cap x_n)$$