Gaussian vectors

1. Let Σ be a symmetric positive definite matrix of $\mathbb{R}^{n\times n}$. Provide a solution to sample a Gaussian vector with covariance matrix Σ based on i.i.d. standard Gaussian variables.

   It is enough to remark that $X = \mu + \Sigma^{1/2}\varepsilon \sim \mathcal{N}(\mu, \Sigma)$ where $\mu \in \mathbb{R}^d$ and $\varepsilon \sim \mathcal{N}(0, I_d)$.

2. Let ε be a random variable in $\{-1, 1\}$ such that $\mathbb{P}(\varepsilon = 1) = 1/2$. If $(X, Y)^\top \sim \mathcal{N}(0, I_2)$ explain why the following vectors are or are not Gaussian vectors.

   (a) $(X, \varepsilon X)$.
   Not Gaussian since the probability that $X + \varepsilon X = 0$ is $1/2$.

   (b) $(X, \varepsilon Y)$.
   Gaussian since coordinates are independent Gaussian random variables.

   (c) $(X, \varepsilon X + Y)$.
   Not Gaussian since the characteristic function of $(1 + \varepsilon)X + Y$ is not the Gaussian characteristic function.

   (d) $(X, X + \varepsilon Y)$.
   Gaussian as a linear transform of (b). Indeed,

   $$\begin{pmatrix} X \\ X + \varepsilon Y \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} X \\ \varepsilon Y \end{pmatrix}.$$

3. Let X be a Gaussian vector in $\mathbb{R}^n$ with mean $\mu \in \mathbb{R}^n$ and covariance matrix $\sigma^2 I_n$. Prove that the random variables $\bar{X}_n$ and $\widehat{\sigma}_n^2$ defined as

   $$\bar{X}_n = \frac{1}{n}\sum_{i=1}^n X_i \quad \text{and} \quad \widehat{\sigma}_n^2 = \frac{1}{n-1}\sum_{i=1}^n (X_i - \bar{X}_n)^2$$

   are independent.

   Let $\mathbb{1}_n$ the vector of $\mathbb{R}^n$ with all entries equal to 1. Then, $\bar{X}_n = n^{-1}\mathbb{1}_n^\top X$ and $(n-1)\sigma_n^2 = \|X - \bar{X}_n \mathbb{1}_n\|_2^2 = \|X - n^{-1}\mathbb{1}_n\mathbb{1}_n^\top X\|_2^2 = \|(I_n - (n^{-1/2}\mathbb{1}_n)(n^{-1/2}\mathbb{1}_n)^\top)X\|_2^2$. Note that $(n^{-1/2}\mathbb{1}_n)(n^{-1/2}\mathbb{1}_n)^\top$ is the orthogonal projection onto $\mathrm{span}(\mathbb{1}_n)$ and $I_n - (n^{-1/2}\mathbb{1}_n)(n^{-1/2}\mathbb{1}_n)^\top$ onto its orthogonal. The proof is completed by using Cochran's theorem.

Regression: prediction of a new observation

Consider the regression model given by

$$Y = X\beta_\star + \xi\,,$$

where $X \in \mathbb{R}^{n\times d}$ the $(\xi_i)_{1\leqslant i\leqslant n}$ are i.i.d. centered Gaussian random variables with variance $\sigma_\star^2$. Assume that $X^\top X$ has full rank and that $\beta_\star$ and $\sigma_\star^2$ are estimated by

$$\widehat{\beta}_n = (X^\top X)^{-1}X^\top Y \quad \text{and} \quad \widehat{\sigma}_n^2 = \frac{\|Y - X\widehat{\beta}_n\|^2}{n-d}\,.$$

Let $x_\star \in \mathbb{R}^d$ and assume that its associated observation $Y_\star = x_\star^\top\beta_\star + \varepsilon_\star$ is predicted by $\widehat{Y}_\star = x_\star^\top\widehat{\beta}_n$.

1. Provide the expression of $\mathbb{E}[(\widehat{Y}_\star - x_\star^\top \beta_\star)^2]$.

   By definition of $\widehat{\beta}_n$*,*

   $$\widehat{Y}_\star - x_\star^\top \beta_\star = x_\star^T(\widehat{\beta}_n - \beta_\star)\,,$$

   so that $\mathbb{E}[\widehat{Y}_\star] = x_\star^\top \beta_\star$ *and*

   $$\mathbb{E}[(\widehat{Y}_\star - x_\star^T \beta_\star)^2] = \mathbb{V}[\widehat{Y}_\star] = x_\star^\top \mathbb{V}[\widehat{\beta}_n] x_\star\,.$$

   On the other hand,

   $$\mathbb{V}[\widehat{\beta}_n] = (X^\top X)^{-1} X^\top \mathbb{V}[Y] X (X^T X)^{-1} = \sigma^2 (X^\top X)^{-1}\,.$$

   Therefore,

   $$\mathbb{E}[(\widehat{Y}_\star - x_\star^\top \beta_\star)^2] = \sigma^2 x_\star^\top (X^\top X)^{-1} x_\star\,.$$

2. Provide a confidence interval for $x_\star^\top \beta_\star$ with statistical significiance $1-\alpha$ for $\alpha \in (0,1)$.

   By the first question, $\widehat{Y}_\star$ *is a Gaussian random variable with mean* $x_\star^\top \beta_\star$ *and variance* $\sigma_\star^2 x_\star^\top (X^\top X)^{-1} x_\star$*. If* $z_{1-\alpha/2}$ *is the quantile of order* $1-\alpha/2$ *of the standard Gaussian variable,*

   $$\mathbb{P}\left(\frac{\left|\widehat{Y}_\star - x_\star^\top \beta_\star\right|}{\sigma_\star (x_\star^\top (X^\top X)^{-1} x_\star)^{1/2}} \leqslant z_{1-\alpha/2}\right) \geqslant 1-\alpha\,.$$

   Therefore, with probability larger than $1-\alpha$*,*

   $$x_\star^\top \beta_\star \in \left(\widehat{Y}_\star - \sigma_\star (x_\star^\top (X^\top X)^{-1} x_\star)^{1/2} z_{1-\alpha/2}\,;\, \widehat{Y}_\star + \sigma_\star (x_\star^\top (X^\top X)^{-1} x_\star)^{1/2} z_{1-\alpha/2}\right)\,.$$

Regression: linear estimators

Consider the regression model given, for all $1 \leqslant i \leqslant n$, by

$$Y_i = f^*(X_i) + \xi_i\,,$$

where for all $1 \leqslant i \leqslant n$, $X_i \in \mathsf{X}$, and the $(\xi_i)_{1\leqslant i\leqslant n}$ are i.i.d. centered Gaussian random variables with variance σ^2. In this exercise, f^* is estimated by a linear estimator of the form

$$\widehat{f}_n : x \mapsto \sum_{i=1}^n w_i(x) Y_i\,.$$

Prove that

$$\frac{1}{n}\mathbb{E}\left[\sum_{i=1}^n (\widehat{f}_n(X_i) - f^*(X_i))^2\right] = \frac{1}{n}\|W f^*(X) - f^*(X)\|_2^2 + \frac{\sigma^2}{n}\mathrm{Trace}(W^\top W)\,,$$

where $W = (w_i(X_j))_{1\leqslant i,j\leqslant n}$ and $f^*(X) = (f^*(X_1),\ldots,f^*(X_n))^\top$.

Note that

$$\frac{1}{n}\mathbb{E}\left[\sum_{i=1}^n (\widehat{f}_n(X_i) - f^*(X_i))^2\right] = \frac{1}{n}\mathbb{E}\left[\|WY - f^*(X)\|_2^2\right]\,,$$

where $Y = (Y_1,\ldots,Y_n)^\top$*. then, write*

$$\begin{aligned}\mathbb{E}\left[\|WY - f^*(X)\|_2^2\right] = \mathbb{E}\left[\|WY - Wf^*(X)\|_2^2\right] + \mathbb{E}\left[\|Wf^*(X) - f^*(X)\|_2^2\right] \\ + 2\mathbb{E}\left[\langle WY - Wf^*(X); Wf^*(X) - f^*(X)\rangle\right]\,.\end{aligned}$$

As $\mathbb{E}[Y] = f^*(X)$, *this yields*

$$\mathbb{E}\left[\|WY - f^*(X)\|_2^2\right] = \mathbb{E}\left[\|WY - Wf^*(X)\|_2^2\right] + \|Wf^*(X) - f^*(X)\|_2^2 .$$

The proof is completed by noting that

$$\mathbb{E}\left[\|WY - Wf^*(X)\|_2^2\right] = \mathbb{E}\left[(Y - f^*(X))^\top W^\top W(Y - f^*(X))\right] = \mathrm{Trace}\left(W^\top W \mathbb{V}[Y - f^*(X)]\right)$$

and $\mathbb{V}[Y - f^*(X)] = \sigma^2 I_n$.