

EXAM : Linear models

The duration of the exam is 3 hours.

General questions

- 1) Show that the hat matrix $H = X(X^T X)^{-1} X^T$ is an orthogonal projector onto the column space of X .
- 2) What is the orthogonal projection of $\mathbf{y} = (Y_1, \dots, Y_n) \in \mathbb{R}^n$ on $\text{Vect}(\mathbf{1}_n)$, with $\mathbf{1}_n = (1, \dots, 1)^T \in \mathbb{R}^n$?
- 3) Express the pseudo inverse of X thanks to its SVD : $X = \sum_{i=1}^r s_i \mathbf{u}_i \mathbf{v}_i^T$.
- 4) Show that the variance of the OLS estimator θ is $\text{Var}(\theta) = \sigma^2 \sum_{i=1}^r s_i^{-2} \mathbf{v}_i \mathbf{v}_i^T$.
- 5) Describe the "PCA before OLS" technique.
- 6) Let $X \in \mathbb{R}^n$ be normally distributed $X \sim \mathcal{N}(\mu_X, \Sigma_X)$ and Y an affine transformation of X , $Y = LX + u$ with $L \in \mathbb{R}^{m \times n}$, $u \in \mathbb{R}^m$ deterministic. Then Y is also normally distributed with mean μ_Y and covariance Σ_Y , $Y \sim \mathcal{N}(\mu_Y, \Sigma_Y)$. Show that $\mu_Y = u + L\mu_X$ and $\Sigma_Y = L\Sigma_X L^T$.

Ordinary Least Squares (OLS)

- 7) Let $Y = (Y_1, \dots, Y_n)^T \in \mathbb{R}^n$ and $X = (\mathbf{1}_n, \tilde{X}) \in \mathbb{R}^{n \times (p+1)}$, $\mathbf{1}_n = (1, \dots, 1)^T \in \mathbb{R}^n$. The identity matrix of dimension n is denoted as I_n . Denote the residuals as $\hat{\epsilon} = Y - \hat{Y}$. Let $\hat{\theta} \in \arg \min_{\theta \in \mathbb{R}^{p+1}} \|Y - X\theta\|_2^2$ and $\hat{Y} = (\hat{Y}_1, \dots, \hat{Y}_n)^T = X\hat{\theta}$.
 - (a) Show that $\min_{\theta \in \mathbb{R}^{p+1}} \|Y - X\theta\|_2^2 \leq \min_{\theta_0 \in \mathbb{R}} \|Y - \mathbf{1}_n \theta_0\|_2^2$
 - (b) Show that $\arg \min_{\theta_0 \in \mathbb{R}} \|Y - \mathbf{1}_n \theta_0\|_2^2 = \bar{Y} = n^{-1} \sum_{i=1}^n Y_i$
 - (c) Deduce the following inequality $\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \leq 1$
 - (d) State the normal equations for the OLS and use it to show that

$$\begin{aligned} \langle \hat{\epsilon}, X \rangle &= 0 \\ \langle \hat{\epsilon}, \hat{Y} \rangle &= 0 \\ \langle \hat{\epsilon}, \bar{Y} \mathbf{1}_n \rangle &= 0. \end{aligned} \tag{1}$$

- (e) Show that we can write the R^2 as

$$R^2 = 1 - \frac{\|Y - \hat{Y}\|^2}{\|Y - \bar{Y} \mathbf{1}_n\|^2} = \frac{\|\hat{Y} - \bar{Y} \mathbf{1}_n\|^2}{\|Y - \bar{Y} \mathbf{1}_n\|^2}.$$

- (f) Elaborate on when $R = 0$ and $R = 1$.
- 8) Give the coordinate descent algorithm for the OLS specifying the gradients.
- 9) Show that if X is full column rank the OLS estimator is unique.

Ridge

10) We consider the Ridge problem in the following points,

$$\hat{\theta}_{\lambda}^{\text{rdg}} = \arg \min_{\theta \in \mathbb{R}^p} (\|y - X\theta\|_2^2 + \lambda \|\theta\|_2^2)$$

Give a closed-for expression for $\hat{\theta}_{\lambda}^{\text{rdg}}$. When is it unique?

11) Give an expression for the prediction for a new point x_0 and the residuals ϵ_{δ} . Show that $\mathbb{E}[\epsilon_{\delta}] = [I_n - X(X^T X + \lambda I_n)^{-1} X^T] X \hat{\theta}_{\lambda}^{\text{rdg}}$.

12) Show that the ridge regression estimator for dataset (X, Y) can be obtained by ordinary least squares regression on an augmented data set (\tilde{X}, \tilde{Y}) . Both X and Y are augmented by adding p rows. Specify the values of those rows.

LASSO. Here again $X \in \mathbb{R}^{n \times p}$.

13) Let $\Omega = \text{diag}(w_1, \dots, w_n)$ with $w_i > 0$ for all i . Express (justifying) the coordinate descent algorithm for the following problem

$$\hat{\theta}_n = \arg \min_{\theta \in \mathbb{R}^p} (Y - X\theta)^T \Omega (Y - X\theta) + 2\lambda \|\theta\|_1$$

(hint (indication) : when solving the previous problem over one single direction it can be expressed into a simpler problem where the function $\eta_{\lambda}(z) = \arg \min_{x \in \mathbb{R}} (z - x)^2 + 2\lambda|x|$ is useful)

14) (a) Show that 0 is a solution of the Lasso $\min_{\theta} \|Y - X\theta\|_2^2 + 2\lambda \|\theta\|_1$ if and only if

$$Y^T X \theta \leq \theta^T X^T X \theta / 2 + \lambda \|\theta\|_1, \quad \forall \theta \in \mathbb{R}^p$$

(b) Show that for all $u = (u_1, \dots, u_K)^T$, $v = (v_1, \dots, v_K)^T$, it holds that $|u^T v| \leq \|u\|_1 \max_{1 \leq k \leq K} |v_k|$

(c) Show that $Y^T X \theta \leq \lambda_{\max} \|\theta\|_1$ with $\lambda_{\max} = \max_{k=1, \dots, p} |X_k^T Y|$ and $X = (X_1, \dots, X_p)$.

(d) Deduce that if $\lambda \geq \lambda_{\max}$ then 0 is one solution of the Lasso.

(e) Deduce that if $\lambda \geq \lambda_{\max}$, then 0 is the unique solution of the Lasso. One can start by considering $\theta \neq 0$ such that

$$Y^T X \theta = \theta^T X^T X \theta / 2 + \lambda \|\theta\|_1,$$

and then the 2 cases : $\theta \in \ker(X)$ and its contrary.

Tests and CI

15) Chi-square test for the variance : In the framework of the linear model of Question 7, we suppose in addition that the vector of noises ϵ is Gaussian of covariance matrix $\sigma^2 \mathbb{I}_n$.

(a) We are interested in the variance of the noises σ^2 . Recall the expression for the unbiased estimator $\hat{\sigma}^2$ seen in class for this quantity. What is the distribution of $(n - p - 1) \hat{\sigma}^2 / \sigma^2$?

(b) Deduce a confidence interval for σ^2 constructed from $\hat{\sigma}^2$ and the quantiles 0.025 and 0.975 of the probability distribution. What is the confidence level of this interval?

(c) Denote q_a, q_b the quantiles 0.025 and 0.975 respectively. Is $q_a = -q_b$?

16) We want to design a test to see if the coefficient θ_j is equal to 1.

- (a) Detail the test, including : the null and alternative hypotheses, the statistic, the probability distribution of the statistic, the p-value, the rejection region for a α -level test, and the first order risk.
 - (b) For a given database and a given coefficient j , we obtain in this test a p-value p_1 . What is the decision of the test of acceptance or rejection according to α ?
 - (c) What is the type-I error?
- 17) Let X_1, \dots, X_n be Gaussian variables of known variance σ^2 and unknown mean μ . Detail a hypothesis test for $\mu > 1$.

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