FTML practical session 9: 2023/05/26

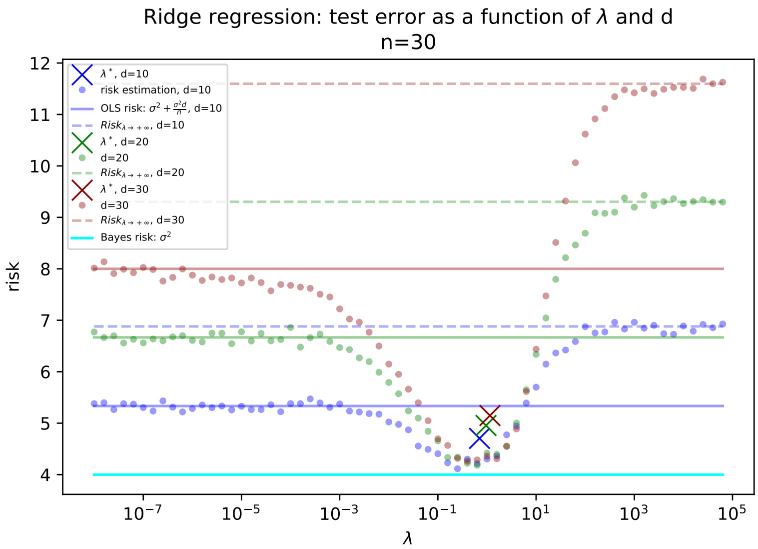

TABLE DES MATIÈRES

1 QUANTITATIVE EVALUTATION OF THE BENEFITS OF RIDGE REGRESSION

The goal of this exercise is to have a more concrete representations of situations where Ridge regression is useful. We will state some theoretical resutlts, and then find datasets for which these results apply.

1.1 Reminders of the theoretical results

We keep the same statistical setting as before (fixed design, linear model). We have seen in the previous classes that the excess risk is $\frac{\sigma^2 d}{n}$ for OLS (Ordinary least squares)

Definition 1. Ridge regression estimator

It is defined as

$$\hat{\theta}_\lambda = \arg\min_{\theta \in \mathbb{R}^d} \left(\frac{1}{n} ||y - X\theta||_2^2 + \lambda ||\theta||_2^2 \right) \tag{1}$$

Proposition. *The Ridge regression estimator is unique even if $X^T X$ is not inversible and is given by*

$$\hat{\theta}_\lambda = \frac{1}{n}(\hat{\Sigma} + \lambda I_d)^{-1} X^T y$$

Proposition. *We assume the linear model, with fixed design setting, with a Bayes estimator of θ^* and a noise with a variance of σ^2. Then, the ridge regression estimator has the following excess risk :*

$$E[R(\hat{\theta}_\lambda] - R^* = \lambda^2 \theta^{*T} (\hat{\Sigma} + \lambda I_d)^{-2} \hat{\Sigma} \theta^* + \frac{\sigma^2}{n} tr[\hat{\Sigma}^2 (\hat{\Sigma} + \lambda I_d)^{-2}] \tag{2}$$

Comments :

— We observe a bias / variance decomposition.

— We consider the bias term B :

$$B = \lambda^2 \theta^{*T} (\hat{\Sigma} + \lambda I_d)^{-2} \hat{\Sigma} \theta^* \tag{3}$$

  — The bias B increases when λ increases. It is an approximation error and does not depend on n.
  — When $\lambda = 0$ and $\hat{\Sigma}$ is invertible (which corresponds to OLS), $B = 0$.
  — When $\lambda \to +\infty$, $B \to \theta^{*T} \hat{\Sigma} \theta^*$.

— We consider the variance term V :

$$V = \frac{\sigma^2}{n} tr[\hat{\Sigma}^2 (\hat{\Sigma} + \lambda I_d)^{-2}] \tag{4}$$

  — The variance V decreases when λ increases. It is an estimation error and depends on n
  — When $\lambda = 0$ and $\hat{\Sigma}$ is invertible (which corresponds to OLS), $V = \frac{\sigma^2 d}{n}$.
  — When $\lambda \to +\infty$, $V \to 0$.
  — When $n \to +\infty$, $V \to 0$.

A natural question is whether it is possible to have a lower excess risk with Ridge regression than with OLS, which means an excess risk smaller than $\frac{\sigma^2 d}{n}$. We admit the following proposition.

Proposition. *With the choice*

$$\lambda^* = \frac{\sigma \sqrt{tr(\hat{\Sigma})}}{||\theta^*||_2 \sqrt{n}} \tag{5}$$

then

$$E[R(\hat{\theta}_\lambda] - R^* \leqslant \frac{\sigma \sqrt{tr(\hat{\Sigma})} ||\theta^*||_2}{\sqrt{n}} \tag{6}$$

with

$$\hat{\Sigma} = \frac{1}{n} X^T X \in \mathbb{R}^{d,d} \tag{7}$$

Hence, the convergence to 0 in OLS is in $\frac{1}{n}$, while it is in $\frac{1}{\sqrt{n}}$ for the ridge. However, for the ridge regression, the dependence in the noise if in σ, whereas it is σ^2 for OLS. Which one is preferrable will depend on the value of the constants, and will not necessary be the "fast" rate in $\mathcal{O}(\frac{1}{n})$.

1.2 Existence of a benefit

Find a setting (statistical values, dataset) for which the expected risk is strictly lower for Ridge regression than OLS.

Verify it with a simulation where you compare the test error of OLS and that of Ridge regression with a good choice of the regularization parameter λ.

1.3 Large bias

In some settings Ridge performs worse than OLS when λ is too large, as in figure 1. As we have seen, when $\lambda \to +\infty$:

— $V \to 0$ (variance)

— $B \to \theta^{*T}\hat{\Sigma}\theta^*$ (bias)

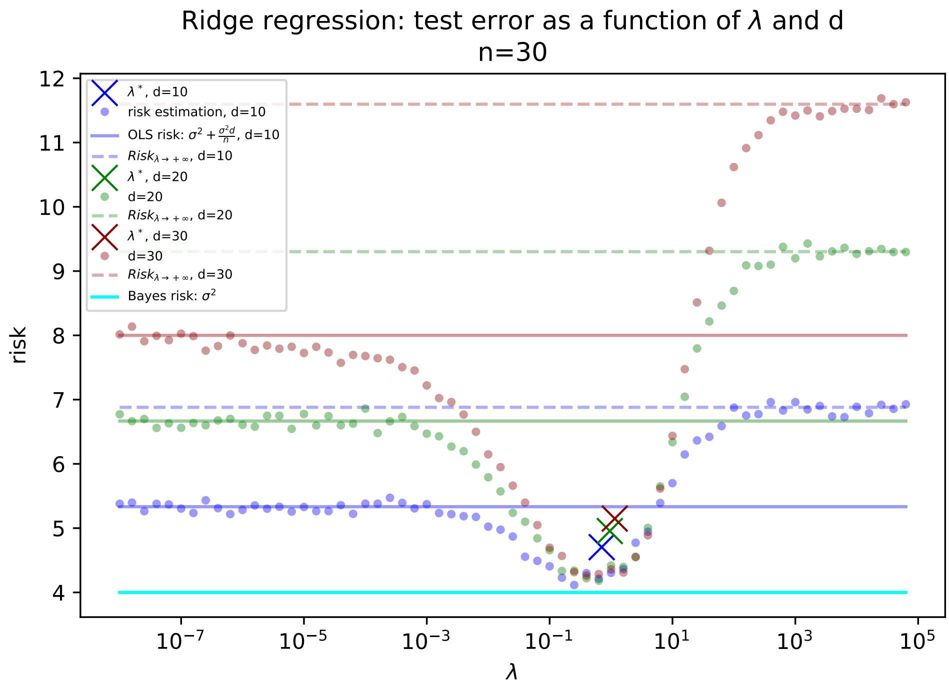

FIGURE 1 – Ridge and OLS, where Ridge performs bad for $\lambda \to +\infty$, because of the bias becomes large.

Given $\hat{\Sigma}$, how could we choose θ^* in order to have a high bias when $\lambda \to +\infty$? Implement a simulation in order to observe this large bias.

2 CROSS VALIDATION

In practical situations, we have also seen that the quantities involved in the computation of λ^* in 5 are typically unknown. Good values for λ are found by **cross-validation.**, with hyperparameter search methods (Gridsearch, Bayesian optimization, etc).

https://scikit-learn.org/stable/modules/cross_validation.html

Compare the best hyperparameters found by automated search methods with λ^*, and the test errors obtained with both, for various statistical settings / values of d, n, etc. In some contexts, there might exist some regularization parameter values that are **better** than λ^*, like in figure 3.

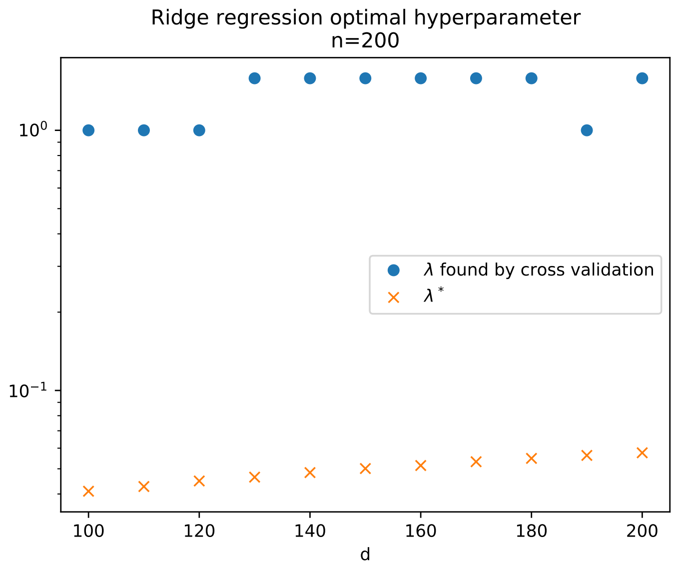

FIGURE 2 – Comparison of λ^* and of the values found by cross-validation, $n = 200$.

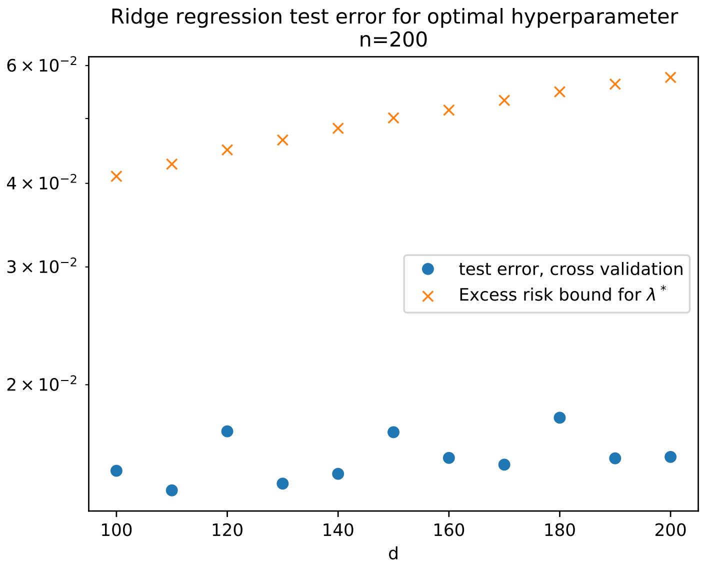

FIGURE 3 – Scores obtained for both parameters, $n = 200$

3 OVERPARAMETRIZED AND UNDERPARAMETRIZED REGIMES