

Data-driven calibration of linear estimators with minimal penalties (Sylvain Arlot and Francis Bach)

Goals:

choosing the kernel in **multiple kernel Learning (MKL)**

choosing the regularization parameter in **kernel ridge regression**

⇔ **Select from multiple linear estimators** $\hat{Y} = A_\lambda Y$, $\lambda \in \Lambda$

Penalization approach: $\hat{\lambda} \in \arg \min_{\lambda \in \Lambda} \{ \|Y - A_\lambda Y\|^2 + \text{pen}(A_\lambda) \}$

Ideal penalty $\text{pen}(A_\lambda) = \sigma^2 \text{tr}(A_\lambda^2)$ leads to optimal selection, but depends on unknown noise variance σ^2

Minimal penalty $\text{pen}(A_\lambda) = C[2\text{tr}(A_\lambda) - \text{tr}(A_\lambda^2)]$ leads to a sharp jump in $\text{tr}A_{\hat{\lambda}(C)}$ around $C = \sigma^2$

Allows **data-driven** estimation of σ^2 and non-asymptotic **oracle inequalities**