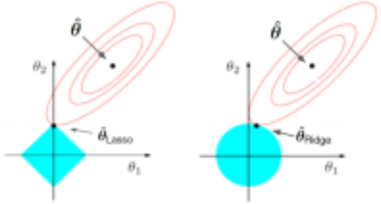
LASSO VS. RIDGE GEOMETRY

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^{n} \left(y^{(i)} - f\left(\mathbf{x}^{(i)} \mid \boldsymbol{\theta} \right) \right)^2 \qquad \text{s.t. } \|\boldsymbol{\theta}\|_p^p \leq t$$



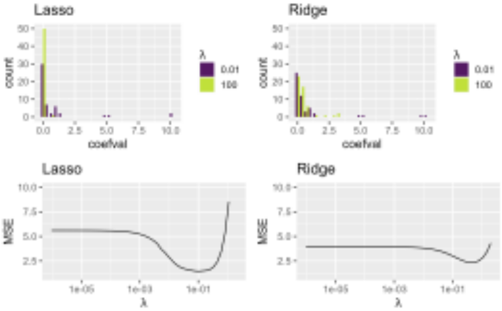
- In both cases (and for sufficiently large λ), the solution which minimizes $\mathcal{R}_{\text{reg}}(\boldsymbol{\theta})$ is always a point on the boundary of the feasible region.
- As expected, $\hat{\boldsymbol{\theta}}_{\text{lasso}}$ and $\hat{\boldsymbol{\theta}}_{\text{ridge}}$ have smaller parameter norms than $\hat{\boldsymbol{\theta}}$.
- For lasso, solution likely touches a vertex of constraint region. Induces sparsity and is a form of variable selection.
- For $p > n$: lasso selects at most n features ▸ Zou and Hastie 2005.

COEFFICIENT PATHS AND 0-SHRINKAGE / 2

Example 2: High-dim., corr. simulated data: $p = 50$; $n = 100$

$$y = 10 \cdot (x_1 + x_2) + 5 \cdot (x_3 + x_4) + 1 \cdot \sum_{j=5}^{14} x_j + \epsilon$$

36/50 vars are noise; $\epsilon \sim \mathcal{N}(0, 1)$; $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \Sigma)$; $\Sigma_{k,l} = 0.7^{|k-l|}$



REGULARIZATION AND FEATURE SCALING / 2

- Let the DGP be $y = \sum_{j=1}^{5} \theta_j x_j + \varepsilon$ for $\boldsymbol{\theta} = (1, 2, 3, 4, 5)^\top$, $\varepsilon \sim \mathcal{N}(0, 1)$
- Suppose x_5 was measured in m but we change the unit to cm ($\tilde{x}_5 = 100 \cdot x_5$):

Method	$\hat{\theta}_1$	$\hat{\theta}_2$	$\hat{\theta}_3$	$\hat{\theta}_4$	$\hat{\theta}_5$	MSE
OLS	0.984	2.147	3.006	3.918	**5.205**	0.812
OLS Rescaled	0.984	2.147	3.006	3.918	**0.052**	0.812

- Estimate $\hat{\theta}_5$ gets scaled by $1/100$ while other estimates and MSE are invariant
- Running ridge regression with $\lambda = 10$ on same data shows that rescaling of of x_5 does not result in inverse rescaling of $\hat{\theta}_5$ (everything changes!)
- This is because $\hat{\theta}_5$ now lives on small scale while $L2$ constraint stays the same. Hence remaining estimates can "afford" larger magnitudes.

Method	$\hat{\theta}_1$	$\hat{\theta}_2$	$\hat{\theta}_3$	$\hat{\theta}_4$	$\hat{\theta}_5$	MSE
Ridge	0.709	1.874	2.661	3.558	**4.636**	1.366
Ridge Rescaled	0.802	1.943	2.675	3.569	**0.051**	1.08

- For lasso, especially for very correlated features, we could arbitrarily force a feature out of the model through a unit change.

CORRELATED FEATURES: $L1$ VS $L2$ / 2

More detailed answer: The "random" decision is in fact a complex deterministic interaction of data geometry (e.g., corr. structures), the optimization method, and its hyperparamters (e.g., initialization). The theoretical reason for this behavior relates to the convexity of the penalties ▸ Zou and Hastie 2005.

Considering perfectly collinear features $x_4 = x_5$ in the last example, we can obtain some more formal intuition for this phenomenon:

- Because $L2$ penalty is *strictly* convex:
  $x_4 = x_5 \implies \hat{\theta}_{4,ridge} = \hat{\theta}_{5,ridge}$ (grouping prop.)
- $L1$ penalty is not *strictly* convex. Hence, no unique solution exists if $x_4 = x_5$, and sum of coefficients can be arbitrarily allocated to both features while remaining minimizers (no grouping property!):
  For any solution $\hat{\theta}_{4,lasso}, \hat{\theta}_{5,lasso}$, equivalent minimizers are given by
  $\tilde{\theta}_{4,lasso} = s \cdot (\hat{\theta}_{4,lasso} + \hat{\theta}_{5,lasso})$ and $\tilde{\theta}_{5,lasso} = (1-s) \cdot (\hat{\theta}_{4,lasso} + \hat{\theta}_{5,lasso})\ \forall s \in [0,1]$
  $\theta_{4,lasso} = s \cdot (\theta_{4,lasso} + \theta_{5,lasso})$ and $\theta_{5,lasso} = (1-s) \cdot (\theta_{4,lasso} + \theta_{5,lasso})\ \forall s \in [0,1]$