Statistical Learning II

Lecture 10 - BSS

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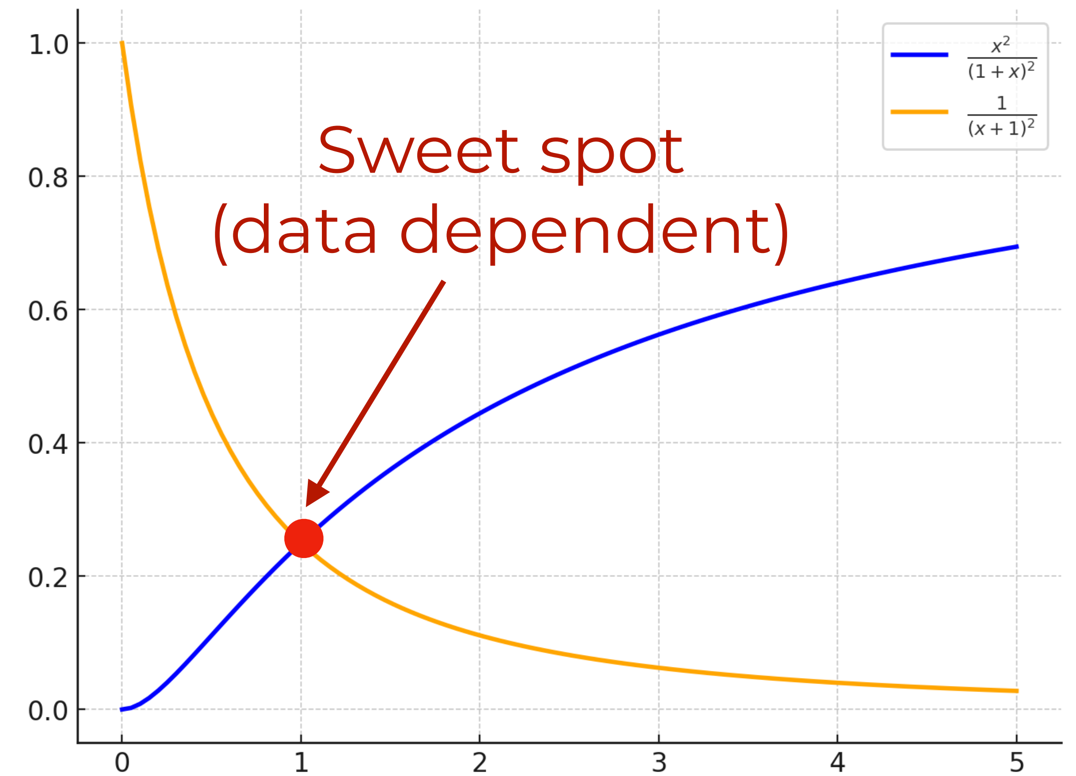
Risk of ridge

Considering the SVD of $\boldsymbol{X} = \sum_{k=1}^{\text{rank}(X)} \sigma_k \boldsymbol{u}_k \boldsymbol{v}_k^\top$, we can also write:

$$\mathscr{B} = \frac{1}{n} \sum_{k=1}^{\text{rank}(X)} \frac{(n\lambda)^2 \sigma_k^2 \langle \boldsymbol{v}_k, \boldsymbol{\theta}_\star \rangle^2}{(\sigma_k^2 + n\lambda)^2} \qquad \mathscr{V} = \sigma^2 \sum_{k=1}^{\text{rank}(X)} \frac{\sigma_k^4}{(\sigma_k^2 + n\lambda)^2}$$

Remarks:

- For $\lambda \to 0^+$, we get the OLS excess risk
- $\mathscr{B}(\lambda)$ is an increasing function of λ
- $\mathscr{V}(\lambda)$ is a decreasing function of λ



Interpretation of variance

Let $\boldsymbol{A} \in \mathbb{R}^{d\times d}$ be a positive definite matrix with decreasing eigenvalues $\mathrm{spec}(\boldsymbol{A}) = \{\lambda_k : k = 1,\cdots,d\}$. Define the cumulative:

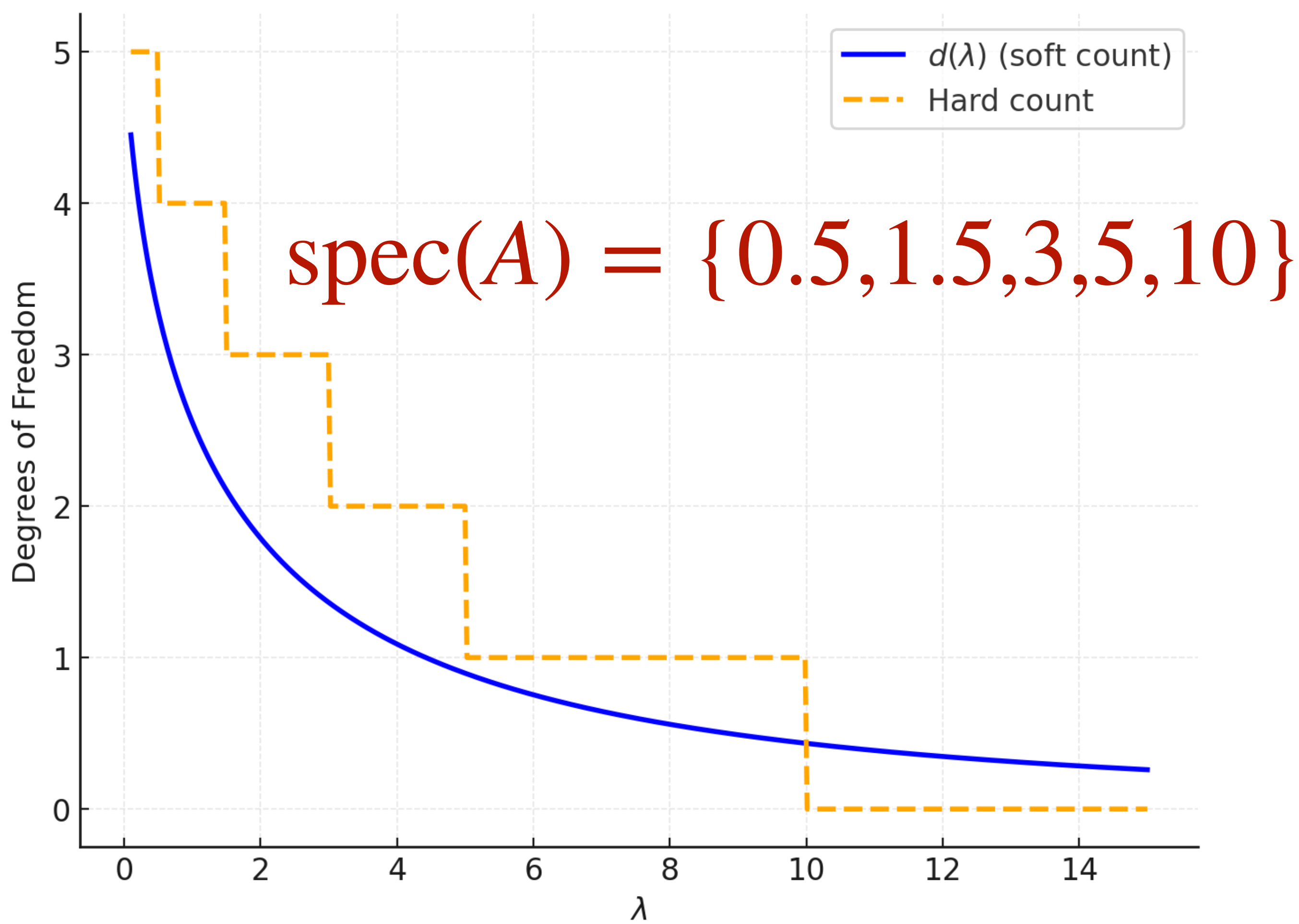
$$\phi(\lambda) = \#\{k : \lambda_k > \lambda\}$$

"Count eigenvalues bigger than λ"

The variance of the ridge risk can be seen as a soft version:

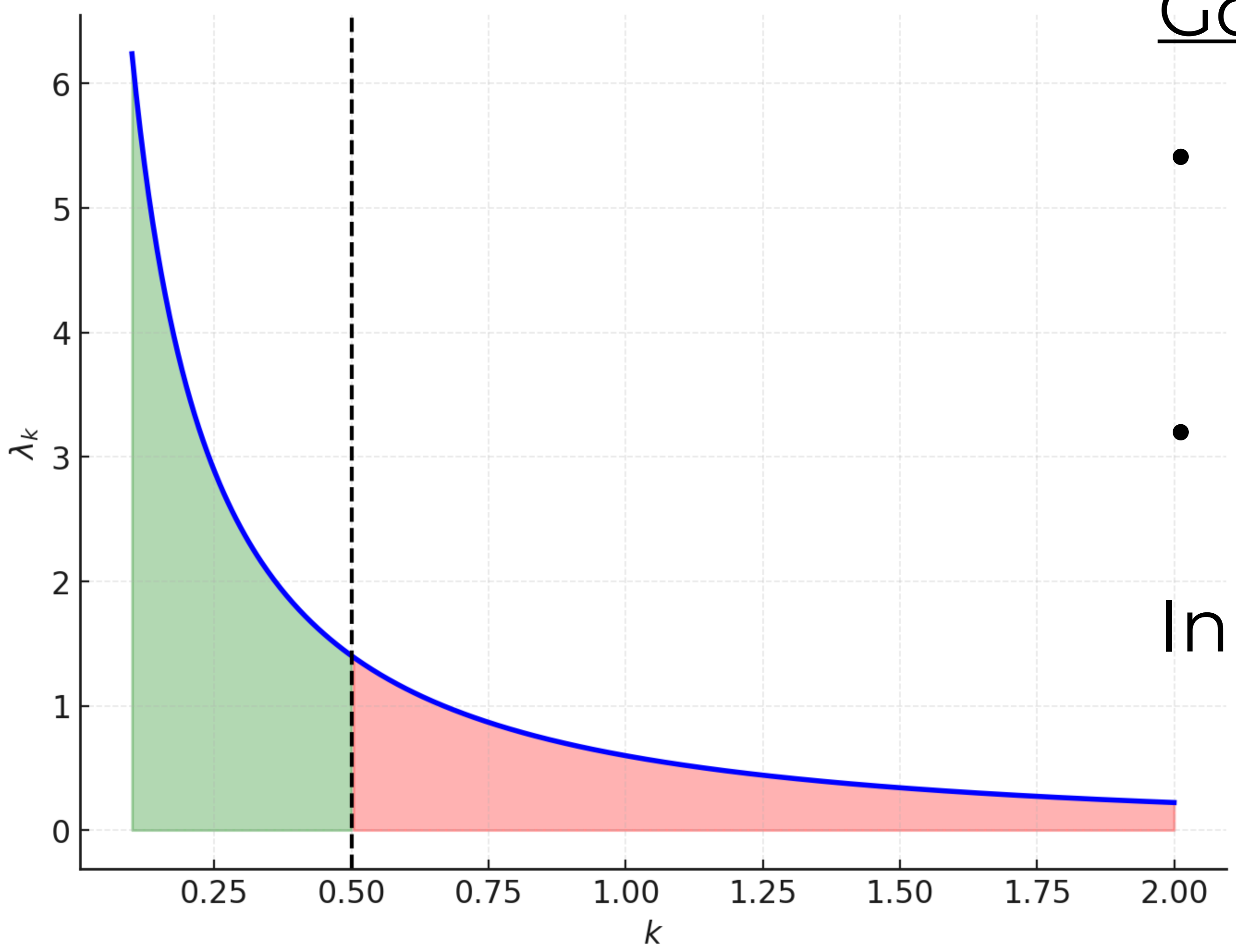
$$\mathrm{d}f_2(\lambda) = \sum_{k=1}^{d} \frac{\lambda_k^2}{(\lambda_k + \lambda)^2}$$

- Fast decay: small λ
- Slow decay: large λ



Choosing regularisation

$\mathrm{d}f_2(\lambda)$



Low-frequency High-frequency

Goal: pick λ such that:

- directions in $\boldsymbol{X}$ that better correlate with $\boldsymbol{\theta}_\star$ are retained
- Shrink remaining directions

In practice, cross-validation...

Best subset selection & the LASSO

Pitfalls of ridge

The ridge estimation performs uniform shrinkage.

$$\hat{\boldsymbol{\theta}}_\lambda(\boldsymbol{X}, \boldsymbol{y}) = \frac{1}{n}\left(\frac{1}{n}\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I}_d\right)^{-1} \boldsymbol{X}^\top \boldsymbol{y}$$

In other words: ℓ_2 regularisation will control the overall norm $||\hat{\boldsymbol{\theta}}_\lambda||_2^2$ by reducing each entry equally

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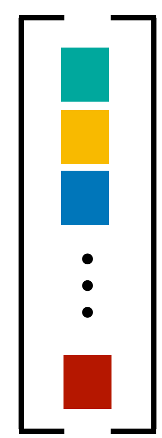
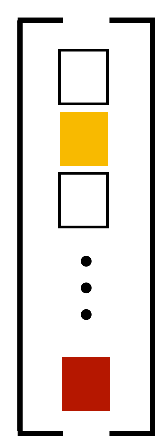
- Good if $\boldsymbol{\theta}_\star$ is a dense vector

$$\boldsymbol{\theta}_{\star,j} \neq 0 \qquad i = 1, \cdots, d$$

$\boldsymbol{\theta}_\star =$ 

- Bad if $\boldsymbol{\theta}_\star$ is a sparse vector

$$\boldsymbol{\theta}_{\star,j} = \begin{cases} 0 & j \in S \subset \{1,\ldots,d\} \\ \neq 0 & j \in \{1,\ldots,d\} \backslash S \end{cases}$$

$\boldsymbol{\theta}_\star =$ 

Sparsity is everywhere

Many signals of interest admit a sparse representation in a particular basis.

$$f(\boldsymbol{x}) = \sum_{k \geq 0} f_k \psi_k(\boldsymbol{x})$$

basis

coefficients

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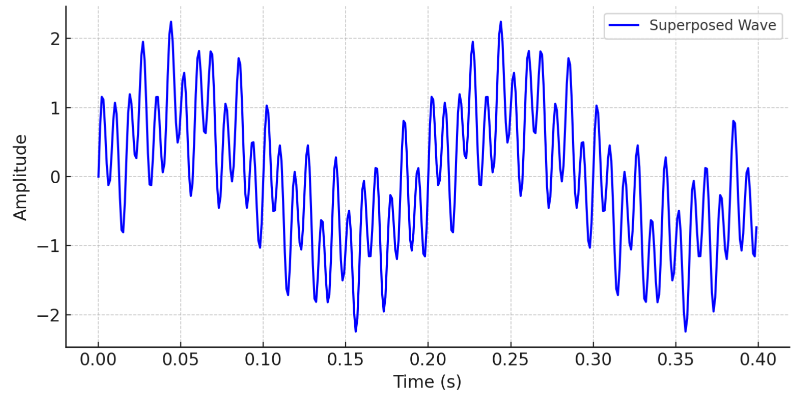
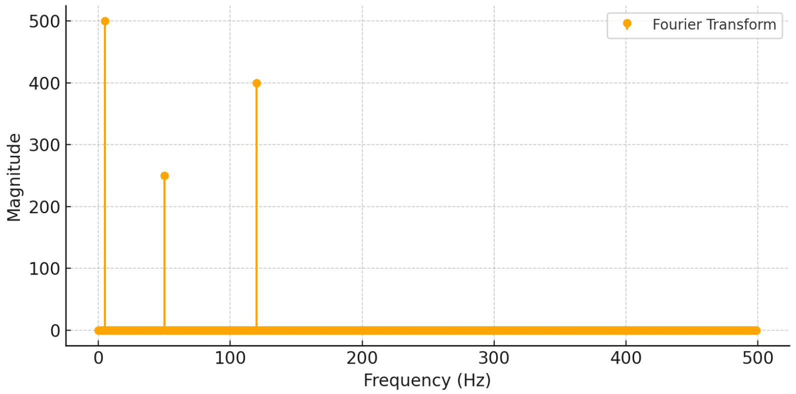
Example: superposition of sine waves



$$f(t) = \sin(10\pi t) + 0.5\sin(100\pi t) + 0.8\sin(240\pi t)$$

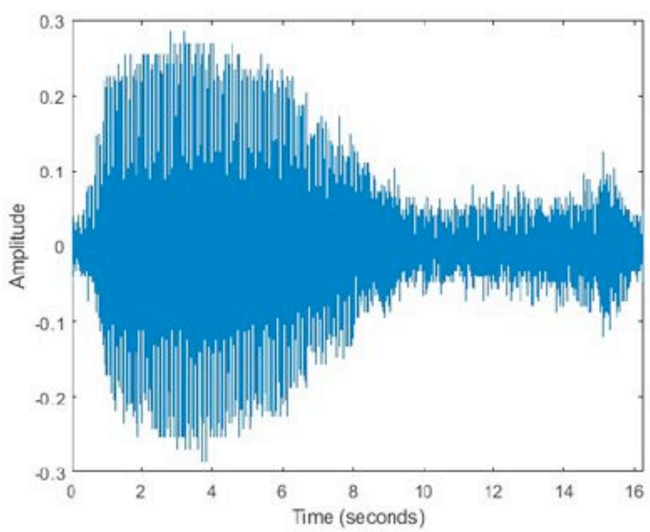


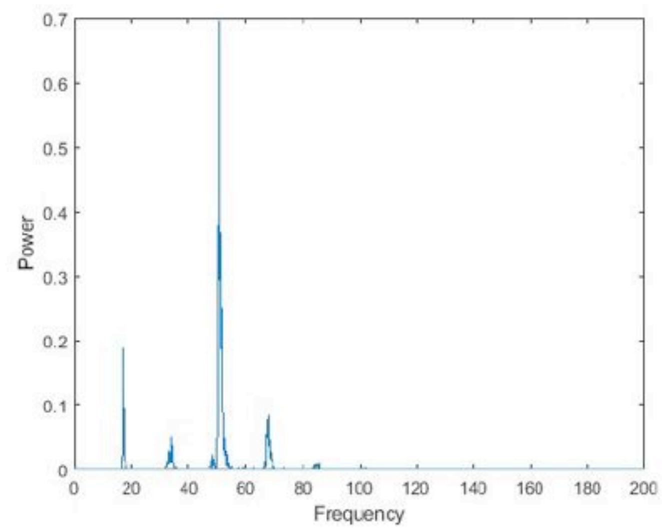
$$\hat{f}(\omega) = \delta_5 + 0.5\ \delta_{50} + 0.8\ \delta_{120}$$

Sparsity is everywhere

Examples:

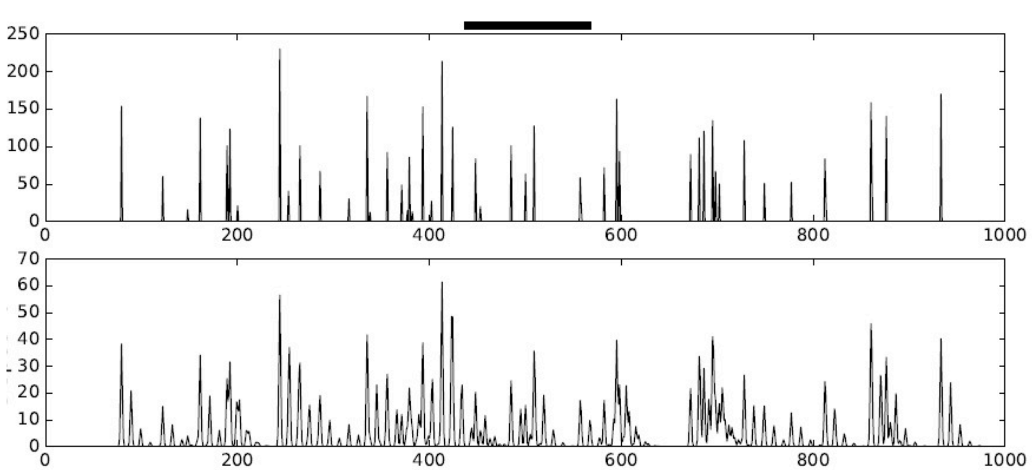
Sound





Images

Scientific signals (mass spectrography)



And many more…

- Portfolio selection (finance)
- Networks (power grids)
- electroencephalogram
- Etc…

Best subset selection

Idea: encourage solutions which are sparse.

$$\min_{\boldsymbol{\theta} \in \mathbb{R}^d} \frac{1}{2n} \sum_{i=1}^{n} \left(y_i - \langle \boldsymbol{\theta}, \boldsymbol{x}_i \rangle\right)^2 + \lambda ||\boldsymbol{\theta}||_0$$

where $||\cdot||_0 : \mathbb{R}^d \to \{0,1,\ldots,d\}$ is the ℓ_0-“norm”: ⚠ Strictly not a norm

$$||\boldsymbol{\theta}||_0 = \sum_{j=1}^{d} \mathbb{I}(\theta_j \neq 0) = \text{\# non-zero entries}$$

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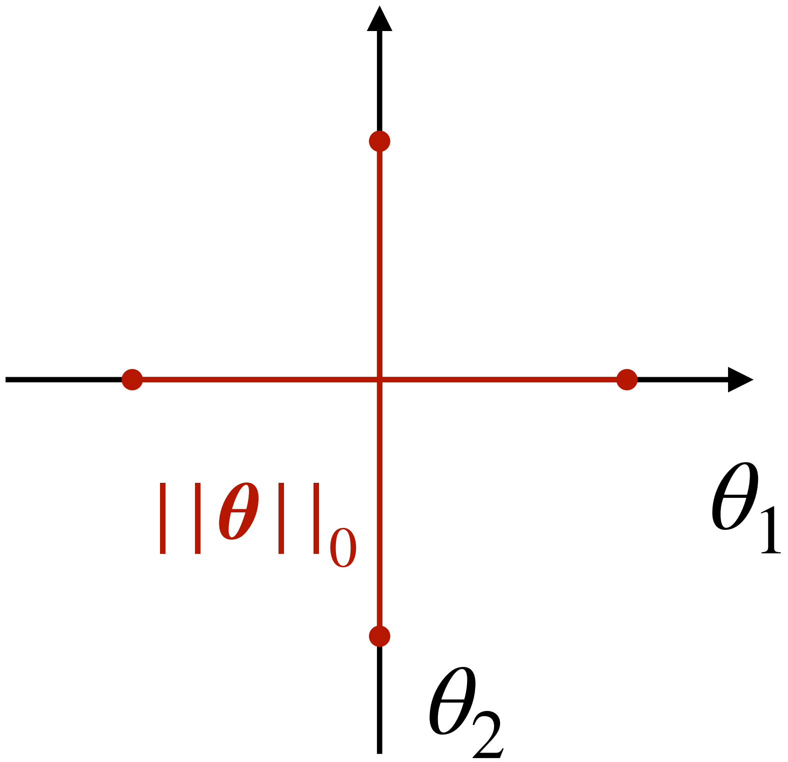
Hence, $\lambda \geq 0$ controls the desired sparsity level

- Large $\lambda \gg 1$: encourage more sparsity
- Small $\lambda \ll 1$: encourage less sparsity

BSS: visualisation



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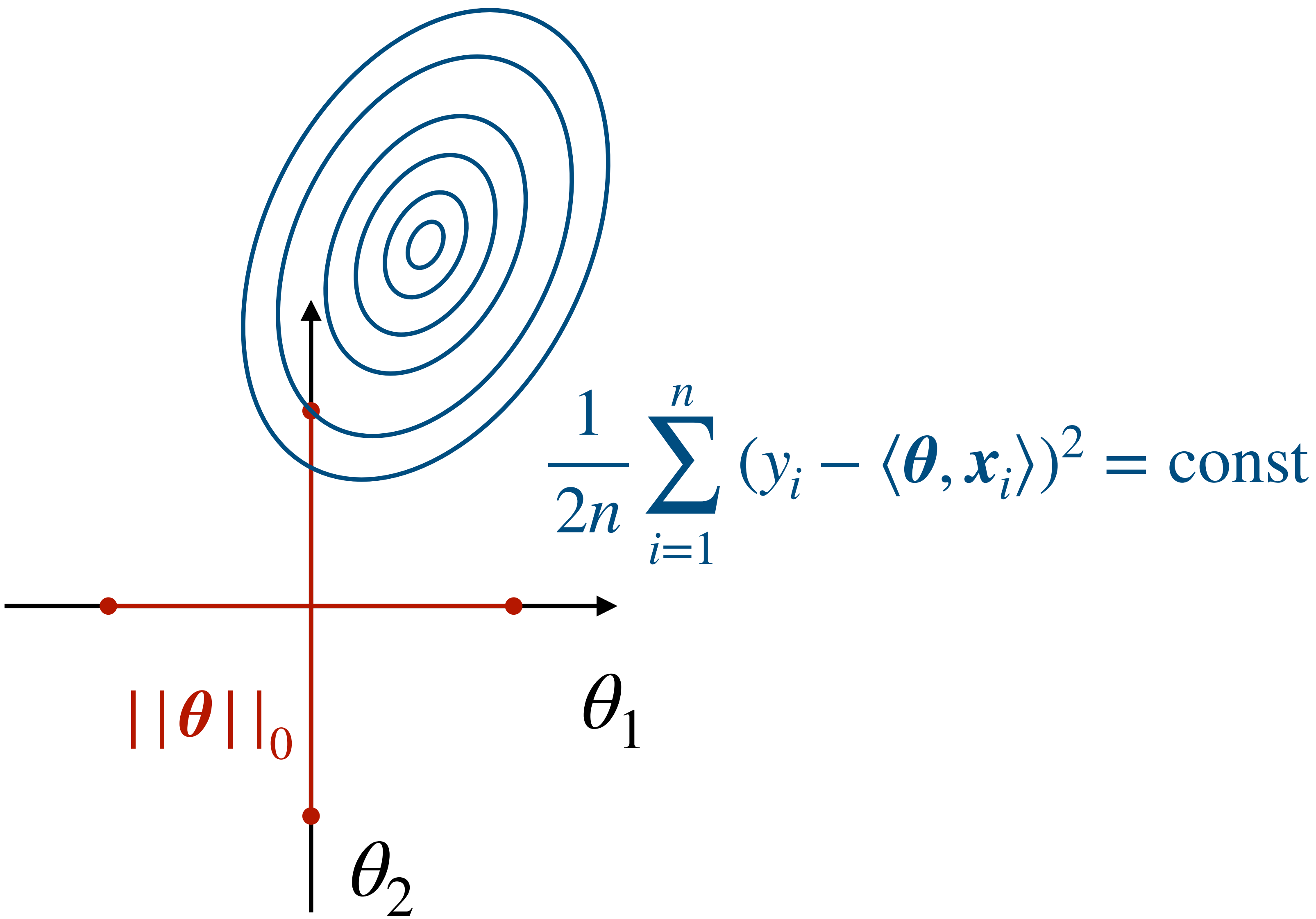

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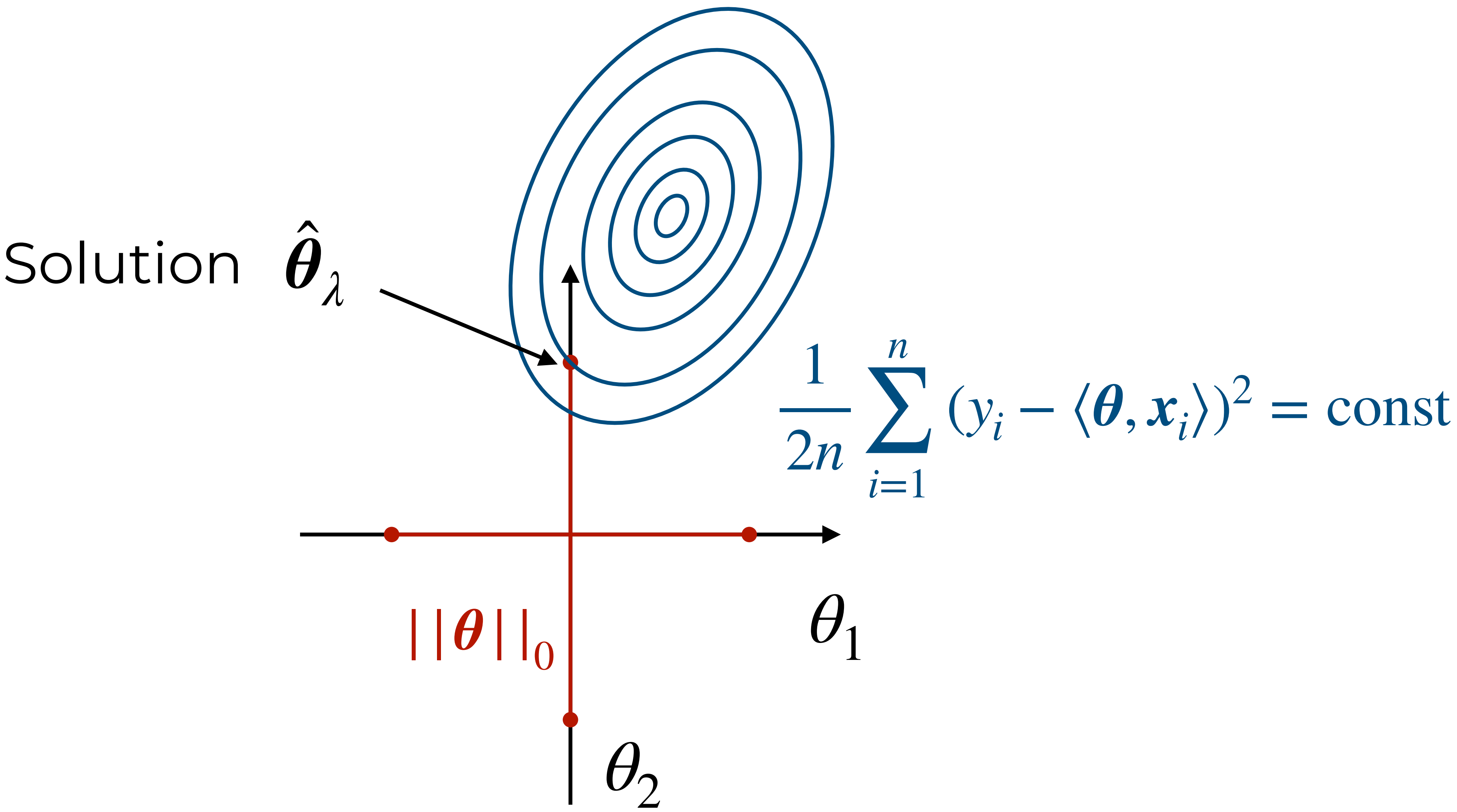

BSS: orthogonal covariates

To get some intuition about this problem, let's consider a simplified setting: assume the covariates are orthogonal

$$\boldsymbol{X}^\top \boldsymbol{X} = \boldsymbol{I}_d \qquad (n \geq d)$$

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Then, we can rewrite:

$$||\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\theta}||_2^2 = ||\boldsymbol{y}||_2^2 + \boldsymbol{\theta}^\top \boldsymbol{X}^\top \boldsymbol{X} \boldsymbol{\theta} - 2\boldsymbol{\theta}^\top \boldsymbol{X}^\top \boldsymbol{y}$$

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$$= ||\boldsymbol{y}||_2^2 + ||\boldsymbol{\theta}||_2^2 - 2\boldsymbol{\theta}^\top \boldsymbol{z} \qquad (\boldsymbol{z} = \boldsymbol{X}^\top \boldsymbol{y} \in \mathbb{R}^d)$$

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$$\boldsymbol{X}^\top \boldsymbol{X} = \boldsymbol{I}_d \qquad (n \geq d)$$

Therefore, under the above:

$$\min_{\boldsymbol{\theta} \in \mathbb{R}^d} \frac{1}{2n} \sum_{i=1}^{n} \left(y_i - \langle \boldsymbol{\theta}, \boldsymbol{x}_i \rangle\right)^2 + \lambda ||\boldsymbol{\theta}||_0$$

Is equivalent to:

$$\min_{\boldsymbol{\theta} \in \mathbb{R}^d} \frac{1}{2n} ||\boldsymbol{z} - \boldsymbol{\theta}||_2^2 + \lambda ||\boldsymbol{\theta}||_0$$

Which is a simpler problem since it factorises coordinate-wise.

BSS: orthogonal covariates

Coordinate-wise, we need to solve

$$\min_{\theta_j \in \mathbb{R}} L(\theta_j) := \left\{ \frac{1}{2n}(z_j - \theta_j)^2 + \lambda \mathbb{I}(\theta_j \neq 0) \right\}$$

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- In case (a), solution is $\hat{\theta}^{(1)}_{\lambda,j} = 0$
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Hence, the solution is given by:

$$\hat{\theta}_{\lambda,j} = \begin{cases} 0 & \text{if } z_j^2 < 2n\lambda \\ z_j & \text{if } z_j^2 \geq 2n\lambda \end{cases}$$

"Hard threshold" function

BSS: orthogonal covariates

Putting together, the solution of the BSS problem:

$$\min_{\boldsymbol{\theta}\in\mathbb{R}^d} \frac{1}{2n}\sum_{i=1}^{n}\left(y_i - \langle \boldsymbol{\theta}, \boldsymbol{x}_i\rangle\right)^2 + \lambda||\boldsymbol{\theta}||_0$$

Under the assumption of $\boldsymbol{X}^\top\boldsymbol{X} = \boldsymbol{I}_d$ is given by:

$$\hat{\boldsymbol{\theta}}_\lambda = H_{\sqrt{2n\lambda}}(\boldsymbol{X}^\top\boldsymbol{y})$$

Where:

$$H_\lambda(z) = \begin{cases} 0 & \text{if } |z| < \lambda \\ z & \text{otherwise} \end{cases}$$