On the Distribution of the Adaptive LASSO Estimator – part II

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Outline

1. More on penalized LS (ML) estimators.
2. Penalized LS with orthogonal design.
3. Moving parameter asymptotics and model selection probabilities.
4. Computational issues.

Penalized LS (ML) estimators

Linear regression model

$$\mathbf{y} = \theta_1 \, \mathbf{x}_{.1} + \ldots \theta_k \, \mathbf{x}_{.k} + \boldsymbol{\varepsilon}$$

- response $\mathbf{y} \in \mathbb{R}^n$
- regressors $\mathbf{x}_{.i} \in \mathbb{R}^n$, $1 \leq i \leq k$
- errors $\boldsymbol{\varepsilon} \in \mathbb{R}^n$
- (unknown) parameter vector $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_k)' \in \mathbb{R}^k$

A penalized least-squares (LS) estimator $\hat{\theta}$ for $\boldsymbol{\theta}$ is given by

$$\hat{\theta} = \arg\min_{\boldsymbol{\theta} \in \mathbb{R}^k} \underbrace{\|\mathbf{y} - X\boldsymbol{\theta}\|^2}_{\text{likelihood or LS -part}} + \underbrace{p(\boldsymbol{\theta})}_{\text{penalty}}$$

The penalty function $p(\theta)$ involves a tuning parameter λ_n ($\lambda_n = 0$ corresponds to unpenalized/ordinary LS).
$X = [\mathbf{x}_{.1}, \ldots, \mathbf{x}_{.k}]$ the $n \times k$ regression matrix.

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Penalized LS (ML) Estimators (cont'd)

Clearly, different penalties give rise to different estimators.

- General class of Bridge-estimators (Frank & Friedman, 1993) using l_γ - type penalties

$$p(\boldsymbol{\theta}) = \lambda_n \sum_{i=1}^{k} |\theta_i|^\gamma$$

$\gamma = 2$: Ridge-estimator (Hoerl & Kennard, 1970)
$\gamma = 1$: LASSO (Tibshirani, 1996).

- Hard- and soft-thresholding estimators.
- Smoothly clipped absolute deviation (SCAD) estimator (Fan & Li, 2001).
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Relationship to classical PMS estimators

Brigde-estimators satisfy

$$\min \|y - X\boldsymbol{\theta}\|^2 + \lambda_n \sum_{i=1}^{k} |\theta_i|^\gamma \quad (0 < \gamma < \infty)$$

For $\gamma \to 0$, get

$$\min \|y - X\boldsymbol{\theta}\|^2 + \lambda_n \, \mathrm{card}\{i : \theta_i \neq 0\}$$

which yields a minimum C_p-type procedure such as AIC and BIC.
(l_γ-type penalty with "$\gamma = 0$")

Relationship to classical PMS-estimators (cont'd)

- For "$\gamma = 0$" procedures are computationally expensive.
- For $\gamma > 0$ (Bridge) estimators are more computationally tractable, especially for $\gamma \geq 1$ (convex objective function).
- For $\gamma \leq 1$, estimators perform model selection

$$P(\hat{\theta}_i = 0) > 0 \quad \text{if } \theta_i = 0$$

  Same for SCAD, hard- and soft-thresholding. Phenomenon is more pronounced for smaller γ.
- $\gamma = 1$ (LASSO and adaptive LASSO) as compromise between the wish to detect zeros and computational simplicity. (SCAD leads to a non-convex optimization problem.)

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Orthogonal design

Linear regression model

$$\mathbf{y} = \theta_1\,\mathbf{x}_{.1} + \ldots \theta_k\,\mathbf{x}_{.k} + \varepsilon$$

- X is non-stochastic, $n \times k$ and $rk(X) = k$.
- $\varepsilon \sim N_n(0, \sigma^2 \mathcal{I}_n)$
- σ^2 is known (wlog $\sigma^2 = 1$) and $X'X$ is diagonal, in particular $X'X = n\mathcal{I}_k$.

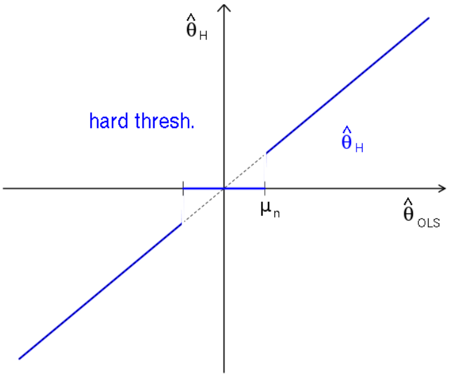
Again, wlog consider Gaussian location model $y_1, \ldots, y_n \overset{\text{iid}}{\sim} N(\theta, 1)$.

Then $\hat{\theta}_{\text{OLS}} = \hat{\theta}_{\text{MLE}} = \bar{y}$ and we want to choose between the restricted model $M_R = \{N(0,1)\}$ or the full model $M_U = \{N(\theta, 1) : \theta \in \mathbb{R}\}$.

Hard-thresholding $\hat{\theta}_{\text{H}}$

$$p(\theta) = n\left[\mu_n^2 - (|\theta| - \mu_n)^2 \mathbf{1}(|\theta| < \mu_n)\right]$$

$$\hat{\theta}_{\text{H}} = \bar{y}\,\mathbf{1}(|\bar{y}| > \mu_n)$$

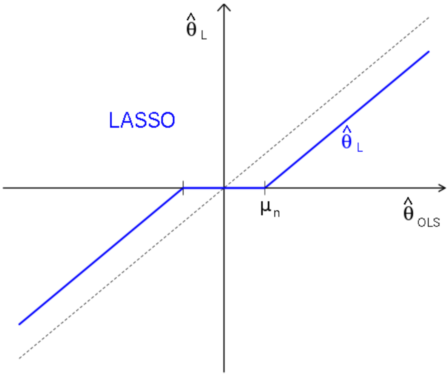


- Equivalent to a post-model estimator based on (eg) t-tests.
- Estimator is not continuous.
- Possesses an "oracle-property" if sparsely-tuned.

Soft-thresholding $\hat{\theta}_L$

$p(\theta) = 2n\mu_n|\theta|$

$\hat{\theta}_L = \text{sign}(\bar{y})\,(|\bar{y}| - \mu_n)_+$

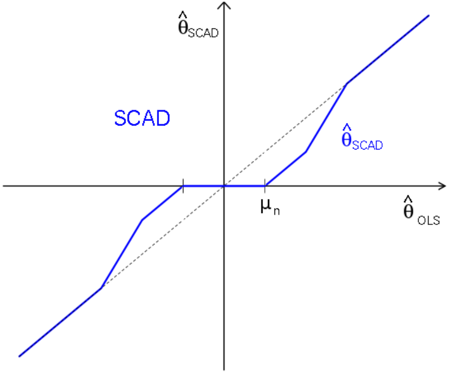


- Equivalent to LASSO.
- Bias problem! No "oracle-property".

Smoothly-clipped-absolute-deviation $\hat{\theta}_{\text{SCAD}}$

$p'(\theta) = \mu_n \left[\mathbf{1}(\theta \le \mu_n) + (a\mu_n - \theta)_+ / ((a-1)\mu_n) \, \mathbf{1}(\theta > \mu_n) \right]$,
where $a > 2$ is an additional tuning parameter.

$$\hat{\theta}_{\text{SCAD}} = \begin{cases} \text{sign}(\bar{y})(|\bar{y}| - \mu_n)_+ & \text{if } |\bar{y}| \le 2\mu_n \\ \left[(a-1)\bar{y} - \text{sign}(\bar{y}) a\mu_n\right] / (a-2) & \text{if } 2\mu_n < |\bar{y}| \le a\mu_n \\ \bar{y} & \text{if } |\bar{y}| > a\mu_n \end{cases}$$

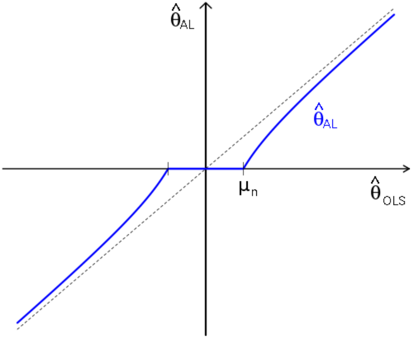


- Non-convex optimization problem.
- Possesses an "oracle-property" if sparsely-tuned.

Adaptive LASSO $\hat{\theta}_{\text{AL}}$

$$p(\theta) = 2n\mu_n^2|\theta|/|\bar{y}|$$

$$\hat{\theta}_{\text{AL}} = \begin{cases} 0 & \text{if } |\bar{y}| \le \mu_n \\ \bar{y} - \mu_n^2/\bar{y} & \text{if } |\bar{y}| > \mu_n \end{cases}$$



- Equivalent to non-negative Garotte (Breiman, 1995)
- Possesses an "oracle-property" if sparsely-tuned.

Why moving-parameter asymptotics?

Let's you see what's really going on in large samples if the convergence is not uniform with respect the underlying parameter.

- The unpenalized LS estimator is $\hat{\theta}_{\text{OLS}} = \bar{y}$ in our model with $\hat{\theta}_{\text{OLS}} \sim N(\theta, 1/n)$, so that

$$n^{1/2}(\hat{\theta}_{\text{OLS}} - \theta) \sim N(0, 1)$$

  for each sample size $n \in \mathbb{N}$, so the distribution is independent of θ.
- For $\hat{\theta}_{\text{AL}}$ (and other PLSEs), the distribution of $n^{1/2}(\hat{\theta}_{\text{AL}} - \theta)$ depends on θ in a complicated manner.

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$$\mathbf{1}(n^{1/2}\theta + x \geq 0)\, \Phi\left(-(n^{1/2}\theta - x)/2 + \sqrt{((n^{1/2}\theta + x)/2)^2 + n\mu_n^2}\right)$$
$$+ \mathbf{1}(n^{1/2}\theta + x < 0)\, \Phi\left(-(n^{1/2}\theta - x)/2 - \sqrt{((n^{1/2}\theta + x)/2)^2 + n\mu_n^2}\right)$$

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  for each sample size $n \in \mathbb{N}$, so the distribution is independent of θ.
- For $\hat{\theta}_{\text{AL}}$ (and other PLSEs), the distribution of $n^{1/2}(\hat{\theta}_{\text{AL}} - \theta)$ depends on θ in a complicated manner.
- Even for large n, the pointwise asymptotic distribution might be "far" from the finite-sample distribution of interest if the underlying convergence is not uniform, as we have seen yesterday.

Asymptotic model selection probabilities

Probability of choosing the restricted model M_R is given by

$$P_{n,\theta}(\hat{\theta} = 0) = \Phi(-n^{1/2}(\theta + \mu_n)) - \Phi(-n^{1/2}(\theta - \mu_n)),$$

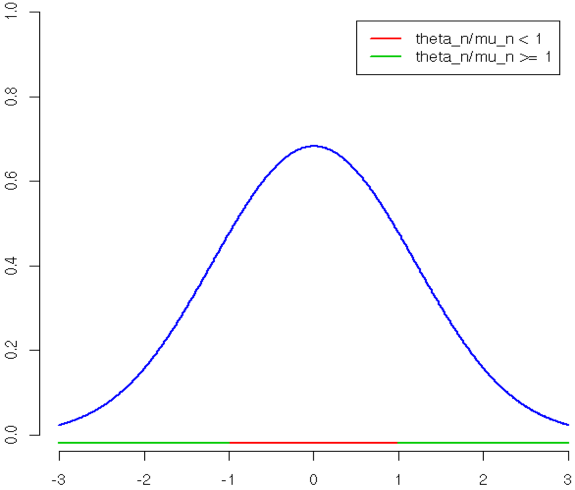
and clearly, the probability of choosing the unrestricted model M_U is

$$P_{n,\theta}(\hat{\theta} \neq 0) = 1 - P_{n,\theta}(\hat{\theta} = 0)$$

($\hat{\theta}$ any of the previous PLS estimators).

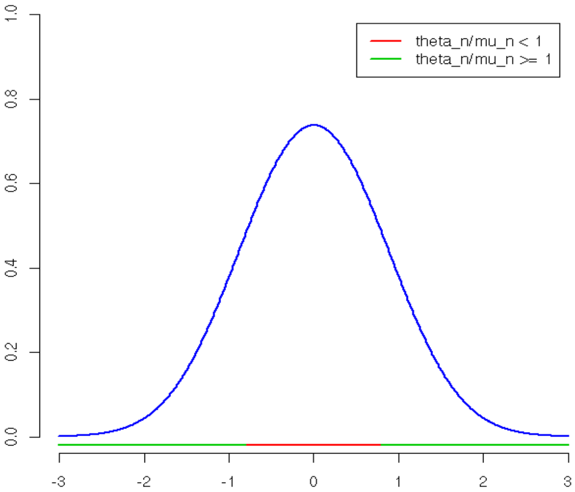
Asymptotic model selection probabilities

$n = 1, \qquad \mu_n = n^{-1/3}$ (consistent case)



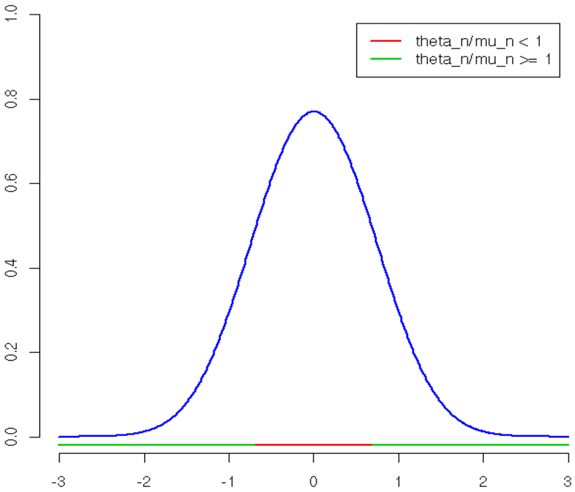
Asymptotic model selection probabilities

$n = 2, \qquad \mu_n = n^{-1/3}$ (consistent case)



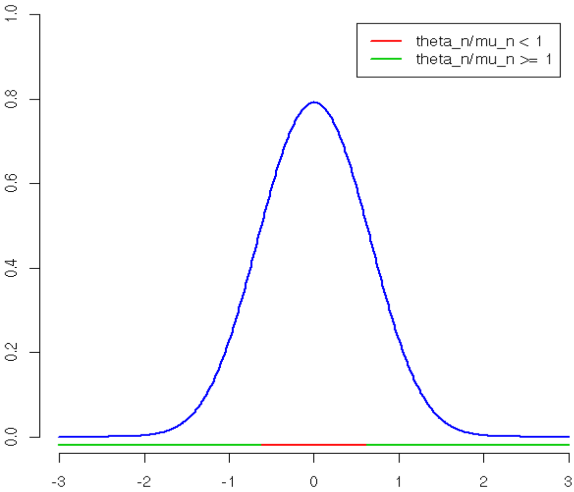
Asymptotic model selection probabilities

$n = 3, \qquad \mu_n = n^{-1/3}$ (consistent case)



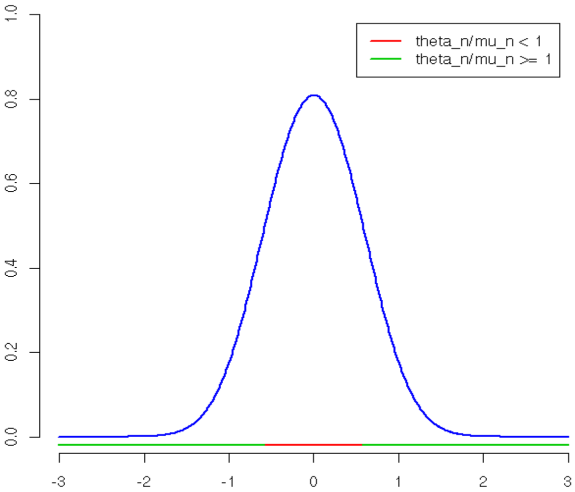
Asymptotic model selection probabilities

$n = 4, \qquad \mu_n = n^{-1/3}$ (consistent case)



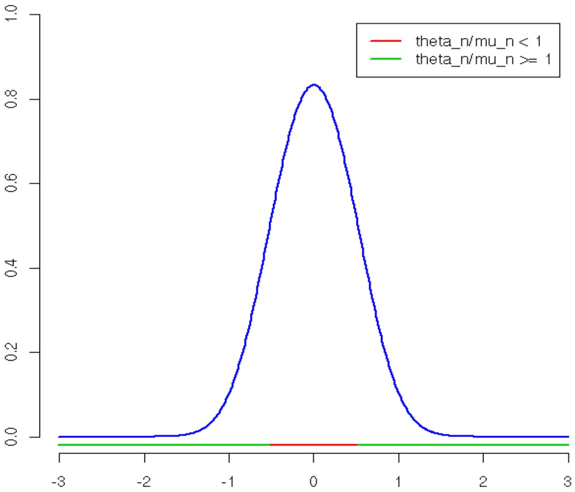
Asymptotic model selection probabilities

$n = 5, \qquad \mu_n = n^{-1/3}$ (consistent case)



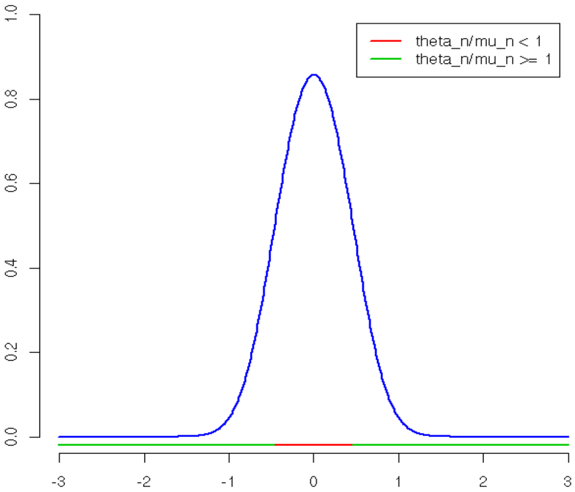
Asymptotic model selection probabilities

$$n = 7, \qquad \mu_n = n^{-1/3} \text{ (consistent case)}$$



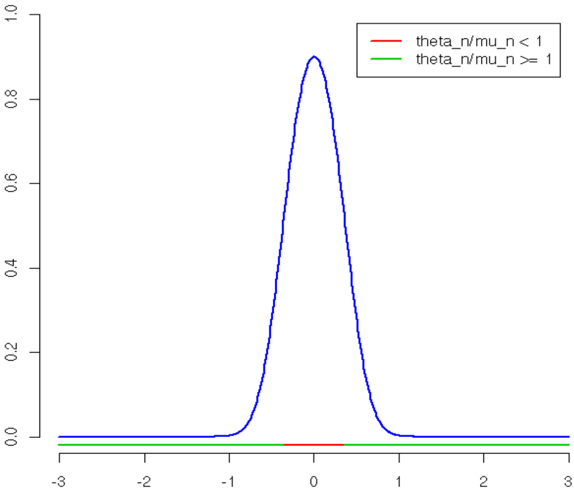
Asymptotic model selection probabilities

$n = 10, \qquad \mu_n = n^{-1/3}$ (consistent case)



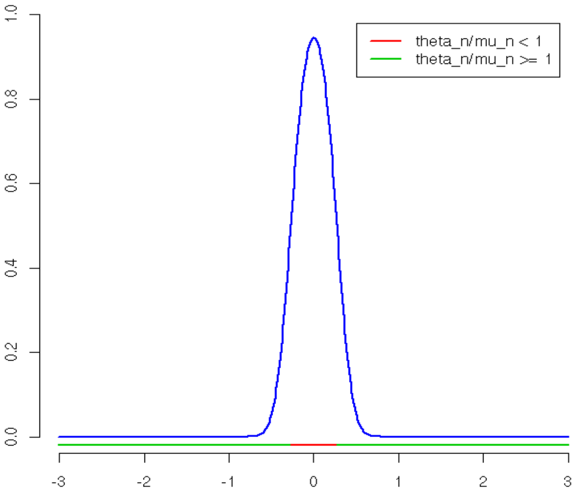
Asymptotic model selection probabilities

$n = 20, \qquad \mu_n = n^{-1/3}$ (consistent case)



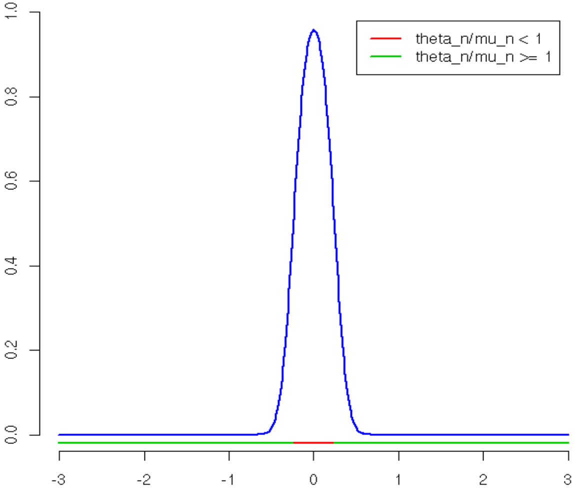
Asymptotic model selection probabilities

$$n = 50, \qquad \mu_n = n^{-1/3} \text{ (consistent case)}$$



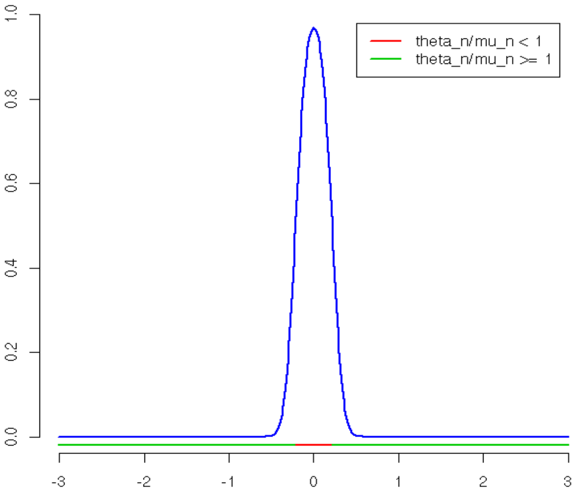
Asymptotic model selection probabilities

$n = 70, \qquad \mu_n = n^{-1/3}$ (consistent case)



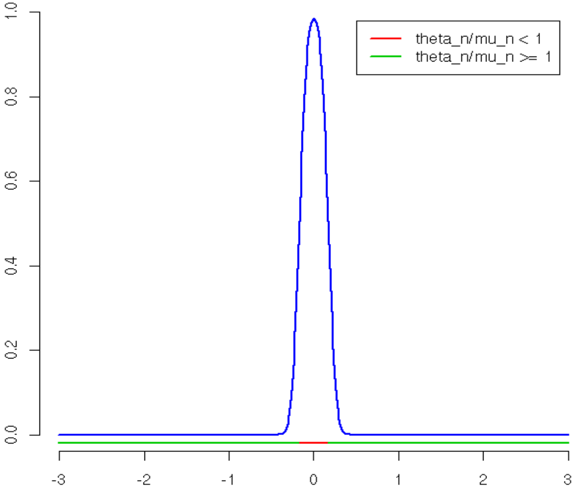
Asymptotic model selection probabilities

$n = 100, \quad \mu_n = n^{-1/3}$ (consistent case)



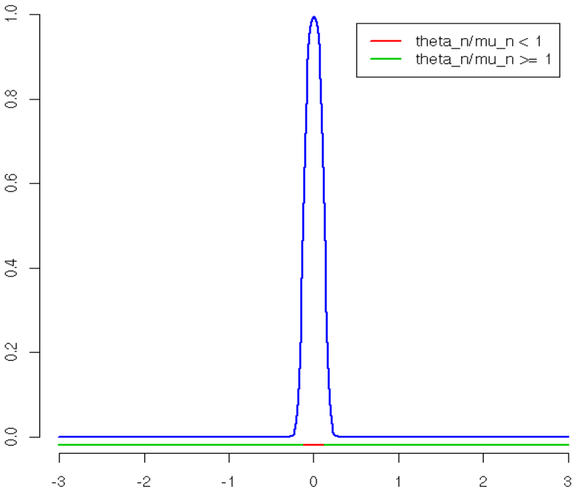
Asymptotic model selection probabilities

$n = 200, \quad \mu_n = n^{-1/3}$ (consistent case)



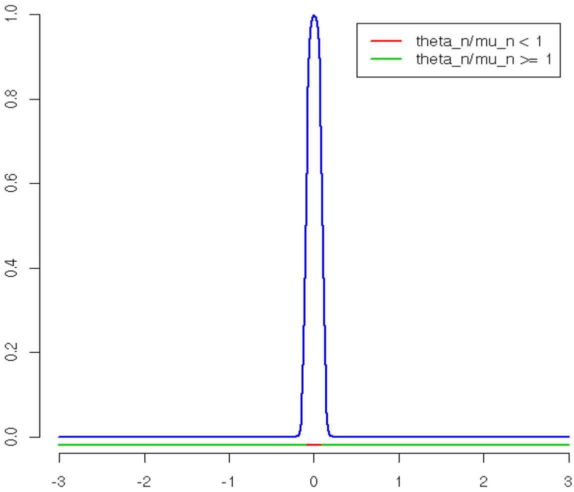
Asymptotic model selection probabilities

$$n = 500, \qquad \mu_n = n^{-1/3} \text{ (consistent case)}$$



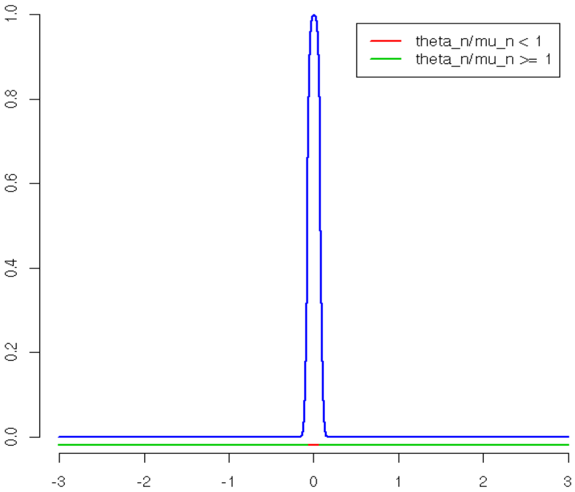
Asymptotic model selection probabilities

$n = 1000, \quad \mu_n = n^{-1/3}$ (consistent case)



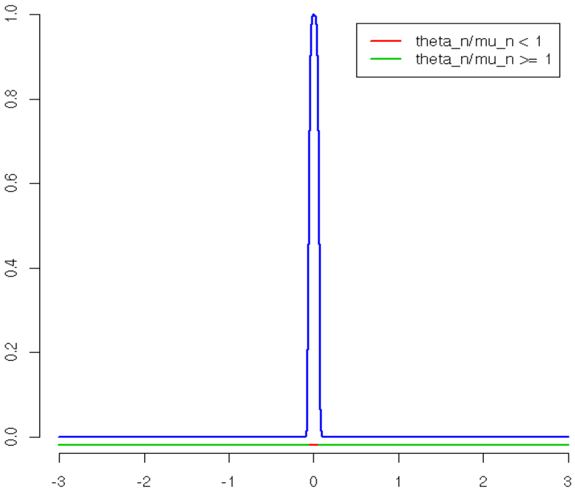
Asymptotic model selection probabilities

$n = 2000, \quad \mu_n = n^{-1/3}$ (consistent case)



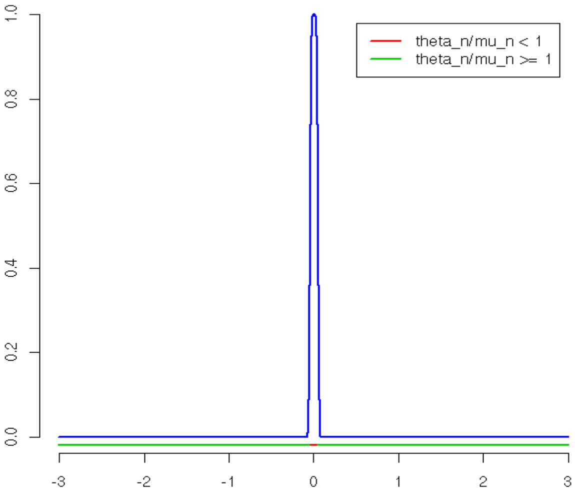
Asymptotic model selection probabilities

$n = 5000, \quad \mu_n = n^{-1/3}$ (consistent case)



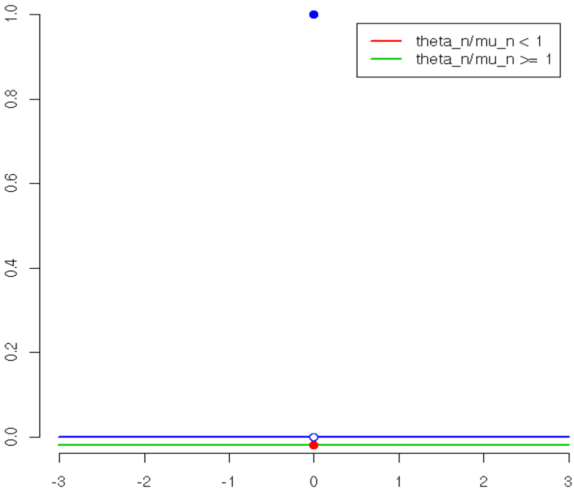
Asymptotic model selection probabilities

$n = 10000,\ \mu_n = n^{-1/3}$ (consistent case)



Asymptotic model selection probabilities

$n = \infty, \qquad \mu_n = n^{-1/3}$ (consistent case)



Model selection probabilities

1. Consistent case $\quad (\mu_n \to 0,\ n^{1/2}\mu_n \to \infty)$
   Assume $\theta_n/\mu_n \to \zeta \in \mathbb{R} \cup \{-\infty, \infty\}$. Then

$$\lim_{n\to\infty} P_{n,\theta_n}(\hat{\theta}_{\text{AL}} = 0) =$$

$$\begin{cases} 1 & \text{if } |\zeta| < 1 \\ \Phi(r) & \text{if } |\zeta| = 1,\ n^{1/2}(\mu_n - \zeta\theta_n) \to r \in \mathbb{R} \cup \{-\infty, \infty\} \\ 0 & \text{if } |\zeta| > 1 \end{cases}$$

Deviations of θ_n from 0 of order $n^{-1/2}$ are not detected at all!

2. Conservative case $\quad (\mu_n \to 0,\ n^{1/2}\mu_n \to m,\ 0 \le m < \infty)$
   Assume $\theta_n \in \mathbb{R}$ satisfies $n^{1/2}\theta_n \to \nu \in \mathbb{R} \cup \{-\infty, \infty\}$. Then

$$\lim_{n\to\infty} P_{n,\theta_n}(\hat{\theta}_{\text{AL}} = 0) = \Phi(-\nu + m) - \Phi(-\nu - m).$$

Deviations of θ_n from 0 of order $n^{-1/2}$ are detected with positive prob.

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Model selection probabilities - conclusions

- Consistent procedures cannot uncover deviations from zero of order $n^{-1/2}$. This matters e.g. since usually $n^{1/2}(\hat{\theta} - \theta)$ is considered.
- Conservative procedures do detect such deviations with positive probability.
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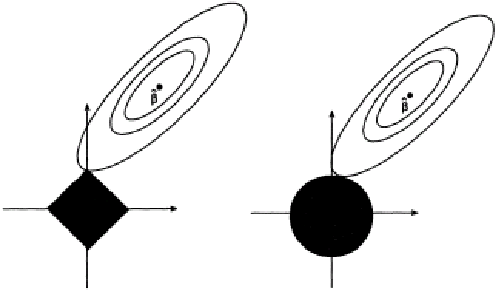

(Plot from Tibshirani (1996))

Computational issues for (adaptive) LASSO

- Clearly, the LASSO estimator $\hat{\theta}_L$ depends on the tuning parameter λ_n.
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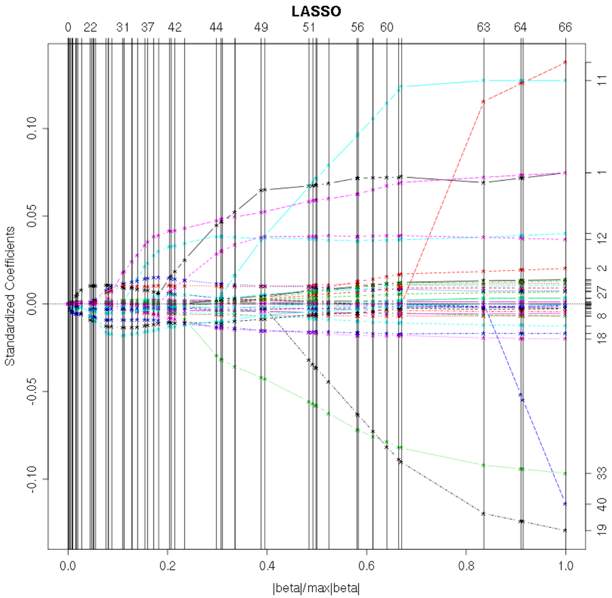
Solution paths



Choosing the tuning parameter

λ_n is usually chosen after computing the solutions paths $\hat{\theta}_L(\lambda_n)$, most often by

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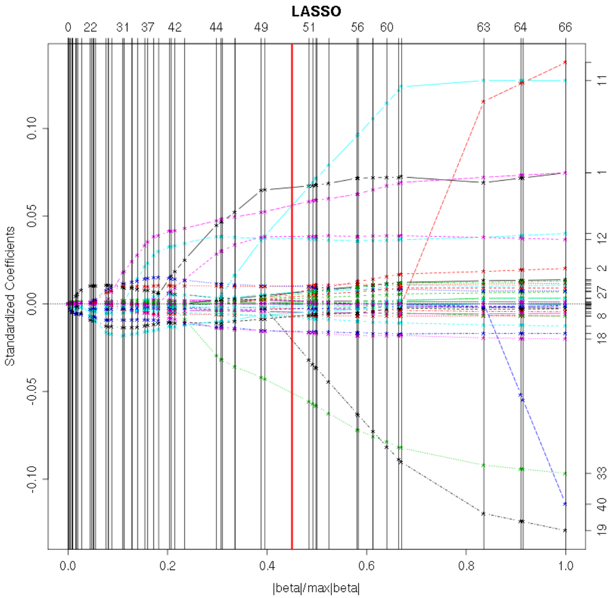

Summary

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