

# Non-asymptotic and Asymptotic viewpoint of LASSO

DL Theory Talk #3

December 17, 2024

# Goals

- ▶ Resources of this slide: [https://www.stat.berkeley.edu/~songmei/Teaching/STAT260\\_Spring2021/Lecture\\_notes/scribe\\_lecture1.pdf](https://www.stat.berkeley.edu/~songmei/Teaching/STAT260_Spring2021/Lecture_notes/scribe_lecture1.pdf)
- ▶ Get a flavor of the difference between the non-asymptotic theory and the asymptotic theory using the example of LASSO.
- ▶ Introduce mean-field theory.

# LASSO: A Non-asymptotic View

Let  $\beta_0 \in \mathbb{R}^d$ ,  $X \in \mathbb{R}^{n \times d}$ ,  $\varepsilon \in \mathbb{R}^n$  and  $Y = X\beta_0 + \varepsilon \in \mathbb{R}^n$ . We consider the case  $d \gg n$  but hope that  $\beta_0$  is sparse in some sense (e.g.,  $\beta_0$  is  $k$ -sparse if  $\beta_0$  has  $k$  non-zero elements). To recover  $\beta_0$  given  $X$  and  $Y$ , we solve the following LASSO problem:

$$\hat{\beta} = \arg \min_{\beta} \frac{1}{2n} \|Y - X\beta\|_2^2 + \frac{\lambda}{n} \|\beta\|_1.$$

## Restricted Strong Convexity

### Definition: Restricted Strong Convexity(RSC)

We say a matrix  $A \in \mathbb{R}^{n \times d}$  satisfies the restricted strong convexity property, if there exists universal constants  $c_1$  and  $c_2$ , such that for any  $v \in \mathbb{R}^d$ , we have

$$\frac{\|Av\|_2^2}{n} \geq c_1 \|v\|_2^2 - c_2 \frac{\log d}{n} \|v\|_1^2. \quad (2)$$

Why this property is called restricted strong convexity? If we define  $f(x) = (1/2n)\|y - Ax\|_2^2$ , strong convexity property says that  $\nabla^2 f(x) \succeq c_1 I_d$ , so that for any direction  $v$ , we have

$$\frac{\|Av\|_2^2}{n} \geq c_1 \|v\|_2^2.$$

Restricted strong convexity simply says that  $f$  is strongly convex in the direction  $v$  when  $\|v\|_1$  is small.

# Non-asymptotic Result

## Theorem (Negahban et al. 2012)

For any  $X \in \mathbb{R}^{n \times d}$  satisfying the RSC property with constant  $c_1$  and  $c_2$ , there exists universal constant  $c < \infty$  (depending only on  $c_1, c_2$ ), such that as long as  $\lambda \geq 2\|X^\top w\|_\infty$ , for any  $\beta_0 \in \mathbb{R}^d$  and  $S \subseteq [d]$  with  $|S| \leq n/(c \log d)$ , the LASSO estimator  $\hat{\beta}$  satisfies

$$\|\hat{\beta} - \beta_0\|_2^2 \leq c \frac{\lambda^2 |S|}{n^2} + c \frac{\lambda}{n} \|\beta_{0,S^c}\|_1 + c \frac{\log d}{n} \|\beta_{0,S^c}\|_1^2.$$

# Asymptotic Result

## Theorem (Bayati and Montanari 2015)

We consider the asymptotic limit when  $n/d \rightarrow \delta \in (0, \infty)$  as  $d \rightarrow \infty$ . Let  $X \in \mathbb{R}^{n \times d}$  with  $X_{ij} \sim \mathcal{N}(0, 1/n)$ . Let  $\beta_0 \in \mathbb{R}^d$  with  $\beta_{0,i} \sim_{\text{iid}} \mathbb{P}_0$ . Let  $\epsilon \sim \mathcal{N}(0, \sigma^2 I_n)$ . Let  $\hat{\beta}$  be the LASSO estimator. Then we have

$$\lim_{d, n \rightarrow \infty} \frac{1}{d} \|\hat{\beta} - \beta_0\|_2^2 = \mathbb{E}_{(\mathbf{X}_0, Z) \sim \mathbb{P}_0 \times \mathcal{N}(0,1)} \left[ (\eta(\mathbf{X}_0 + \tau_* Z; \theta_*) - \mathbf{X}_0)^2 \right].$$

# Asymptotic Result

## Remark

The asymptotic error for high-dimensional LASSO estimator is equivalent to

$$\mathbb{E}_{\hat{X}, X_0} [(\hat{X} - X_0)^2],$$

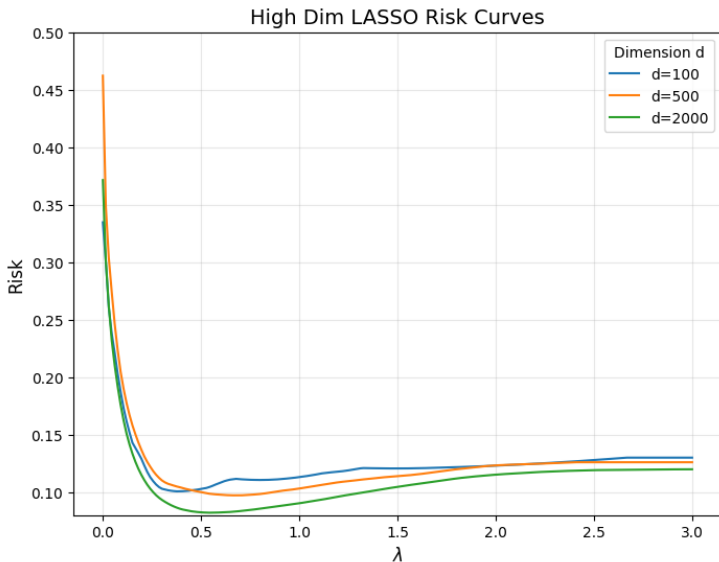
where  $(\hat{X}, X_0)$  following the distribution of

$$(X_0, Z) \sim \mathbb{P}_0 \times \mathcal{N}(0, 1), \quad Y = X_0 + \tau_* Z,$$

$$\hat{X} = \arg \min_v \{(Y - v)^2 + \tau_* \alpha_* |v|\} = \eta(Y, \tau_* \alpha_*).$$

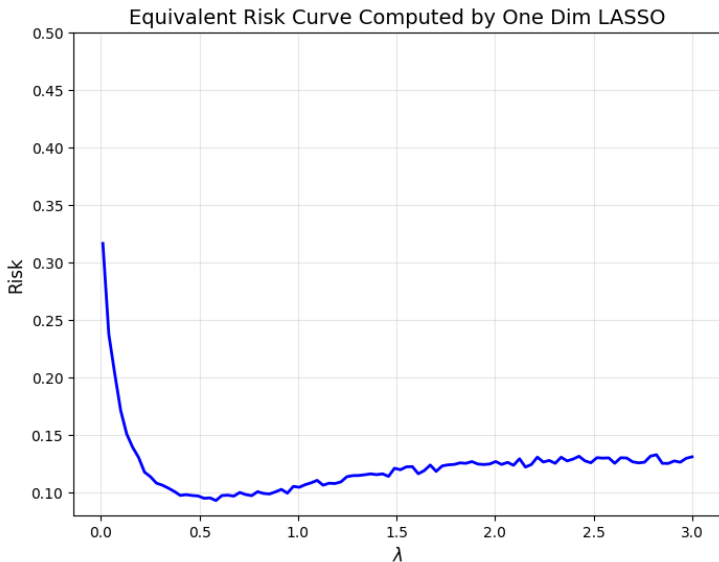
This can be interpreted as an one dimensional LASSO problem.

# Simulations





# Simulations

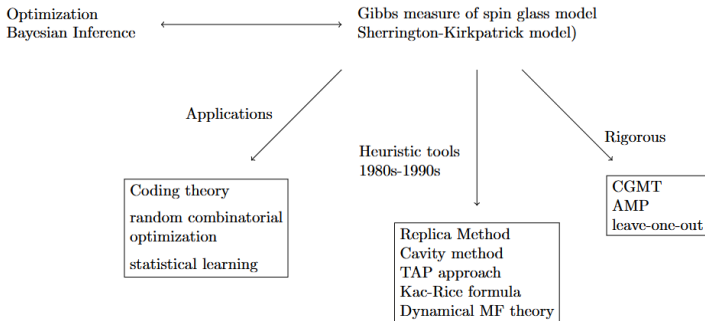


# Mean-field Theory Introduction



*In physics and probability theory, mean-field theory studies the behavior of high-dimensional random (stochastic) models by studying a simpler model that approximates the original by averaging over degrees of freedom.*

In our example, the LASSO problem is a high dimensional random model, while the one dimensional model in the previous remark is the simpler model that approximates the original one.

# Tools developed in statistical physics



# References I

-  Bayati, Mohsen and Andrea Montanari (2015). *The LASSO risk for gaussian matrices*. arXiv: 1008.2581 [math.ST]. URL: <https://arxiv.org/abs/1008.2581>.
-  Negahban, Sahand N. et al. (Nov. 2012). "A Unified Framework for High-Dimensional Analysis of  $M$ -Estimators with Decomposable Regularizers". In: *Statistical Science* 27.4. ISSN: 0883-4237. DOI: 10.1214/12-sts400. URL: <http://dx.doi.org/10.1214/12-STS400>.