Lecture 2. Random Matrix Theory and Phase Transitions of PCA

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Outline

How many components of PCA?

- Data matrix: $X = [x_1|x_2|\cdots|x_n] \in \mathbb{R}^{p\times n}$
- Centering data matrix: $Y = XH$ where

$$H = I - \frac{1}{n}\mathbf{1}\cdot\mathbf{1}^T$$

- PCA is given by top *left* singular vectors of $Y = USV^T$ (called loading vectors) by projections to $\mathbb{R}^p$, $z_j = u_j Y$
- MDS is given by top *right* singular vectors of $Y = USV^T$ as Euclidean embedding coordinates of n sample points
- But how many components shall we keep?

Recall: Horn's Parallel Analysis

- Data matrix: $X = [x_1|x_2|\cdots|x_n] \in \mathbb{R}^{p \times n}$

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,n} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{p,1} & X_{p,2} & \cdots & X_{p,n} \end{bmatrix}.$$

- Compute its principal eigenvalues $\{\hat{\lambda}_i\}_{i=1,\ldots,p}$

Recall: Horn's Parallel Analysis

- Randomly take p permutations of n numbers $\pi_1, \ldots, \pi_p \in S_n$ (usually π_1 is set as identity), noting that sample means are permutation invariant,

$$X^1 = \begin{bmatrix} X_{1,\pi_1(1)} & X_{1,\pi_1(2)} & \cdots & X_{1,\pi_1(n)} \\ X_{2,\pi_2(1)} & X_{2,\pi_2(2)} & \cdots & X_{2,\pi_2(n)} \\ \vdots & \vdots & \ddots & \vdots \\ X_{p,\pi_p(1)} & X_{p,\pi_p(2)} & \cdots & X_{p,\pi_p(n)} \end{bmatrix}.$$

- Compute its principal eigenvalues $\{\hat{\lambda}_i^1\}_{i=1,\ldots,p}$.
- Repeat such procedure for r times, we can get r sets of principal eigenvalues. $\{\hat{\lambda}_i^k\}_{i=1,\ldots,p}$ for $k = 1, \ldots, r$

Recall: Horn's Parallel Analysis (continued)

- For each $i = 1$, define the i-th p-value as the percentage of random eigenvalues $\{\hat{\lambda}_i^k\}_{k=1,\ldots,r}$ that exceed the i-th principal eigenvalue $\hat{\lambda}_i$ of the original data X,

$$\mathrm{pval}_i = \frac{1}{r}\#\{\hat{\lambda}_i^k > \hat{\lambda}_i : k = 1, \ldots, r\}.$$

- Setup a threshold q, e.g. $q = 0.05$, and only keep those principal eigenvalues $\hat{\lambda}_i$ such that $\mathrm{pval}_i < q$

Example

- Let's look at an example of Parallel Analysis
  - R: `https://github.com/yuany-pku/2017_CSIC5011/blob/master/slides/paran.R`
  - Matlab: `papca.m`
  - Python:

How does it work?

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- We are going to introduce an analysis based on Random Matrix Theory for *rank-one spike model*
- There is a **phase transition** in principal component analysis
  - If the signal is strong, principal eigenvalues are beyond the random spectrum and principal components are correlated with signal
  - If the signal is weak, all eigenvalues in PCA are due to random noise

Outline

Marčenko-Pastur Distribution of Noise Eigenvalues

- Let $x_i \sim \mathcal{N}(0, I_p)$ $(i = 1, \ldots, n)$ and $X = [x_1, x_2, \ldots, x_n] \in \mathbb{R}^{p \times n}$.

- The sample covariance matrix

$$\widehat{\Sigma}_n = \frac{1}{n} X X^T.$$

  is called Wishart (random) matrix.

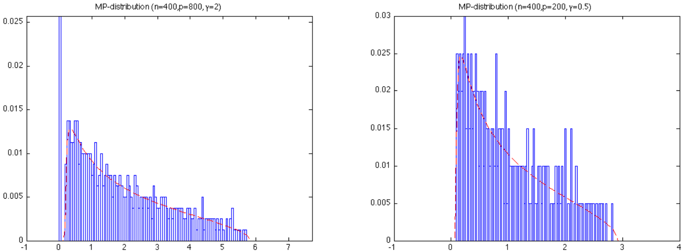
- When both n and p grow at $\frac{p}{n} \to \gamma \neq 0$, the distribution of the eigenvalues of $\widehat{\Sigma}_n$ follows the **Marčcenko-Pastur (MP) Law**

$$\mu^{MP}(t) = \left(1 - \frac{1}{\gamma}\right) \delta(t) I(\gamma > 1) + \begin{cases} 0 & t \notin [a, b], \\ \frac{\sqrt{(b-t)(t-a)}}{2\pi\gamma t} dt & t \in [a, b], \end{cases}$$

  where $a = (1 - \sqrt{\gamma})^2, b = (1 + \sqrt{\gamma})^2$.

Illustration of MP Law

- If $\gamma \leq 1$, MP distribution has a support on $[a, b]$;
- if $\gamma > 1$, it has an additional point mass $1 - 1/\gamma$ at the origin.



(a) (b)

Figure: Show by matlab: (a) Marčenko-Pastur distribution with $\gamma = 2$. (b) Marčenko-Pastur distribution with $\gamma = 0.5$.

Outline

Rank-one Spike Model

Consider the following rank-1 signal-noise model

$$Y = X + \varepsilon,$$

where

- the signal lies in an one-dimensional subspace $X = \alpha u$ with $\alpha \sim \mathcal{N}(0, \sigma_X^2)$;
- the noise $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2 \mathrm{I_p})$ is i.i.d. Gaussian.

Therefore $Y \sim \mathcal{N}(0, \Sigma)$ where the limiting covariance matrix Σ is rank-one added by a sparse matrix:

$$\Sigma = \sigma_X^2 u u^T + \sigma_\varepsilon^2 I_p.$$

When does PCA work?

- Can we recover signal direction u from principal component analysis on noisy measurements Y?

- It depends on the signal noise ratio, defined as

$$SNR = R := \frac{\sigma_X^2}{\sigma_\varepsilon^2}.$$

For simplicity we assume that $\sigma_\varepsilon^2 = 1$ without loss of generality.

Phase Transition of PCA

- Consider the scenario
$$\gamma = \lim_{p,n\to\infty} \frac{p}{n}. \tag{1}$$
as in applications, one never has infinite amount of samples and dimensionality

- A fundamental result by I. Johnstone in 2006 shows a phase transition of PCA:

Phase Transitions

- The primary (largest) eigenvalue of sample covariance matrix satisfies

$$\lambda_{\max}(\widehat{\Sigma}_n) \to \begin{cases} (1+\sqrt{\gamma})^2 = b, & \sigma_X^2 \le \sqrt{\gamma} \\ (1+\sigma_X^2)(1+\frac{\gamma}{\sigma_X^2}), & \sigma_X^2 > \sqrt{\gamma} \end{cases} \tag{2}$$

- The primary eigenvector (principal component) associated with the largest eigenvalue converges to

$$|\langle u, v_{\max}\rangle|^2 \to \begin{cases} 0 & \sigma_X^2 \le \sqrt{\gamma} \\ \frac{1-\frac{\gamma}{\sigma_X^4}}{1+\frac{\gamma}{\sigma_X^2}}, & \sigma_X^2 > \sqrt{\gamma} \end{cases} \tag{3}$$

Phase Transitions (continued)

In other words,

- If the signal is strong $SNR = \sigma_X^2 > \sqrt{\gamma}$, the primary eigenvalue goes beyond the random spectrum (upper bound of MP distribution), and the primary eigenvector is correlated with signal (in a cone around the signal direction whose deviation angle goes to 0 as $\sigma_X^2/\gamma \to \infty$);
- If the signal is weak $SNR = \sigma_X^2 \leq \sqrt{\gamma}$, the primary eigenvalue is buried in the random spectrum, and the primary eigenvector is random of no correlation with the signal.

Proof in Sketch

- Following the rank-1 model, consider random vectors $y_i \sim \mathcal{N}(0, \Sigma)$ $(i = 1, \ldots, n)$, where $\Sigma = \sigma_x^2 uu^T + \sigma_\varepsilon^2 I_p$ and u is an arbitrarily chosen unit vector ($\|u\|^2 = 1$) showing the signal direction.

- The sample covariance matrix is $\hat{\Sigma}_n = \frac{1}{n} \sum_{i=1}^n y_i y_i^T = \frac{1}{n} Y Y^T$ where $Y = [y_1, \ldots, y_n] \in \mathbb{R}^{p \times n}$. Suppose one of its eigenvalue is $\hat{\lambda}$ and the corresponding unit eigenvector is $\hat{v}$, so $\hat{\Sigma}_n \hat{v} = \lambda \hat{v}$.

- First of all, we relate the $\hat{\lambda}$ to the MP distribution by the trick:

$$z_i = \Sigma^{-\frac{1}{2}} y_i \to Z_i \sim \mathcal{N}(0, I_p). \tag{4}$$

  Then $S_n = \frac{1}{n} \sum_{i=1}^n z_i z_i^T = \frac{1}{n} Z Z^T$ ($Z = [z_1, \ldots, z_n]$) is a *Wishart* random matrix whose eigenvalues follow the *Marčenko-Pastur* distribution.

Proof in Sketch

- Notice that

$$\hat{\Sigma}_n = \frac{1}{n} Y Y^T = \Sigma^{1/2} (\frac{1}{n} Z Z^T) \Sigma^{1/2} = \Sigma^{\frac{1}{2}} S_n \Sigma^{\frac{1}{2}}$$

  and $(\hat{\lambda}, \hat{v})$ is eigenvalue-eigenvector pair of matrix $\hat{\Sigma}_n$. Therefore

$$\Sigma^{\frac{1}{2}} S_n \Sigma^{\frac{1}{2}} \hat{v} = \hat{\lambda} \hat{v} \;\Rightarrow\; S_n \Sigma (\Sigma^{-\frac{1}{2}} \hat{v}) = \hat{\lambda} (\Sigma^{-\frac{1}{2}} \hat{v}) \tag{5}$$

  In other words, $\hat{\lambda}$ and $\Sigma^{-\frac{1}{2}} \hat{v}$ are the eigenvalue and eigenvector of matrix $S_n \Sigma$.

- Define $v = c \Sigma^{-\frac{1}{2}} \hat{v}$ where the constant c makes v a unit eigenvector,

$$\begin{aligned} c^2 &= c^2 \hat{v}^T \hat{v} = v^T \Sigma v = v^T (\sigma_x^2 u u^T + \sigma_\varepsilon^2) v = \sigma_x^2 (u^T v)^2 + \sigma_\varepsilon^2) \\ &= R (u^T v)^2 + 1. \end{aligned} \tag{6}$$

Proof in Sketch

Now we have,

$$S_n \Sigma v = \hat{\lambda} v. \tag{7}$$

Plugging in the expression of Σ, it gives

$$S_n(\sigma_X^2 uu^T + \sigma_\varepsilon^2 I_p)v = \hat{\lambda} v$$

Rearrange the term with u to one side, we got

$$(\hat{\lambda} I_p - \sigma_\varepsilon^2 S_n)v = \sigma_X^2 S_n u(u^T v)$$

Assuming that $\hat{\lambda} I_p - \sigma_\varepsilon^2 S_n$ is invertible, then multiple its reversion at both sides of the equality, we get,

$$v = \sigma_X^2 \cdot (\hat{\lambda} I_p - \sigma_\varepsilon^2 S_n)^{-1} \cdot S_n u(u^T v). \tag{8}$$

Primary Eigenvalue $\hat{\lambda}$

- Multiply (8) by u^T at both side,

$$u^T v = \sigma_X^2 \cdot u^T(\hat{\lambda} I_p - \sigma_\varepsilon^2 S_n)^{-1} S_n u \cdot (u^T v)$$

that is, if $u^T v \neq 0$,

$$1 = \sigma_X^2 \cdot u^T(\hat{\lambda} I_p - \sigma_\varepsilon^2 S_n)^{-1} S_n u \tag{9}$$

Primary Eigenvalue $\hat{\lambda}$

- Assume that S_n has the eigenvalue decomposition $S_n = W\hat{\Lambda}W^T$, where $\Lambda = \mathbf{diag}(\lambda_i : i = 1, \dots, p)$ and $WW^T = W^T W = I_p$ $(W = [w_1, \dots, w_p] \in \mathbb{R}^{p \times p})$. Define $\alpha_i = w_i^T u$ and $\alpha = (\alpha_i) \in \mathbb{R}^p$. Hence $u = \sum_{i=1}^p \alpha_i w_i = W^T \alpha$. Now (9) leads to

  $$1 = \sigma_X^2 \cdot u^T [W(\hat{\lambda} I_p - \sigma_\varepsilon^2 \Lambda)^{-1} W^T][W \Lambda W^T] u = \sigma_X^2 \cdot \alpha^T (\hat{\lambda} I_p - \sigma_\varepsilon^2 \Lambda)^{-1} \Lambda \alpha$$

  which is

  $$1 = \sigma_X^2 \cdot \sum_{i=1}^p \frac{\lambda_i}{\hat{\lambda} - \sigma_\varepsilon^2 \lambda_i} \alpha_i^2 \tag{10}$$

  where $\sum_{i=1}^p \alpha_i^2 = 1$, α_i uniformly distributed around mean $1/\sqrt{p}$.

- For large p, $\lambda_i \sim \mu^{MP}(\lambda_i)$ and the sum (10) can be approximated by

  $$1 = \sigma_X^2 \cdot \frac{1}{p} \sum_{i=1}^p \frac{\lambda_i}{\hat{\lambda} - \sigma_\varepsilon^2 \lambda_i} \sim \sigma_X^2 \cdot \int_a^b \frac{t}{\hat{\lambda} - \sigma_\varepsilon^2 t} d\mu^{MP}(t) \tag{11}$$

  where $\sigma_\varepsilon^2 = 1$ by assumption.

Primary Eigenvalue $\hat{\lambda}$

- Using the Stieltjes transform,

$$\begin{aligned} 1 &= \sigma_X^2 \cdot \int_a^b \frac{t}{\hat{\lambda} - t} \frac{\sqrt{(b-t)(t-a)}}{2\pi\gamma t} dt \\ &= \frac{\sigma_X^2}{4\gamma} [2\hat{\lambda} - (a+b) - 2\sqrt{|(\hat{\lambda} - a)(b - \hat{\lambda})|}]. \end{aligned} \tag{12}$$

- For $\hat{\lambda} \geq b$ and $R = \sigma_X^2 \geq \sqrt{\gamma}$, we have

$$1 = \frac{\sigma_X^2}{4\gamma} [2\hat{\lambda} - (a+b) - 2\sqrt{(\hat{\lambda} - a)(\hat{\lambda} - b)}],$$

$$\Rightarrow \quad \hat{\lambda} = \sigma_X^2 + \frac{\gamma}{\sigma_X^2} + 1 + \gamma = (1 + \sigma_X^2)(1 + \frac{\gamma}{\sigma_X^2}).$$

Primary Eigenvalue $\hat{\lambda}$

Here we observe the following phase transitions for primary eigenvalue:

- If $\hat{\lambda} \in [a, b]$, then $\widehat{\Sigma}_n$ has its primary eigenvalue $\hat{\lambda}$ within $\mathrm{supp}(\mu^{MP})$, so it is undistinguishable from the noise.
- So $\hat{\lambda} = b$ is the phase transition where PCA works to pop up signal rather than noise. Then plugging in $\hat{\lambda} = b$ in (12), we get,

$$1 = \sigma_X^2 \cdot \frac{1}{4\gamma}[2b - (a+b)] = \frac{\sigma_X^2}{\sqrt{\gamma}} \Leftrightarrow \sigma_X^2 = \sqrt{\gamma} = \sqrt{\frac{p}{n}} \tag{13}$$

  Hence, in order to make PCA works, we need to let the signal-noise-ratio $R \geq \sqrt{\frac{p}{n}}$.

Primary Eigenvector $\hat{v}$

- As $\|v\|_2 = 1$, plugging v in Equation (8),

$$\begin{aligned} 1 &= v^T v = \sigma_X^4 \cdot v^T u u^T S_n (\lambda I_p - \sigma_\varepsilon^2 S_n)^{-2} S_n u u^T v \\ &= \sigma_X^4 \cdot (|v^T u|)[u^T S_n (\lambda I_p - \sigma_\varepsilon^2 S_n)^{-2} S_n u](|u^T v|) \end{aligned}$$

which implies that

$$|u^T v|^{-2} = \sigma_X^4 [u^T S_n (\lambda I_p - \sigma_\varepsilon^2 S_n)^{-2} S_n u]. \qquad (14)$$

- Using the same trick as the equation (9), we reach the following Monte-Carlo integration

$$\begin{aligned} |u^T v|^{-2} &= \sigma_X^4 [u^T S_n (\lambda I_p - \sigma_\varepsilon^2 S_n)^{-2} S_n u] \\ &\sim \sigma_X^4 \int_a^b \frac{t^2}{(\lambda - \sigma_\varepsilon^2 t)^2} d\mu^{MP}(t) \qquad (15) \end{aligned}$$

Primary Eigenvector $\hat{v}$

- For $\lambda \geq b$, from Stieltjes transform introduced later one can compute the integral as

$$
\begin{aligned}
|u^T v|^{-2} &= \sigma_X^4 \cdot \int_a^b \frac{t^2}{(\lambda - \sigma_\varepsilon^2 t)^2} d\mu^{MP}(t) \\
&= \frac{\sigma_X^4}{4\gamma} \left(-4\lambda + (a+b) + 2\sqrt{(\lambda - a)(\lambda - b)} + \dots \right. \\
&\qquad \left. + \frac{\lambda(2\lambda - (a+b))}{\sqrt{(\lambda - a)(\lambda - b)}} \right)
\end{aligned}
$$

from which it can be computed that (using $\hat{\lambda} = (1+\sigma_X^2)(1+\frac{\gamma}{\sigma_X^2})$ obtained above with $R = \sigma_X^2$)

$$
|u^T v|^2 = \frac{1 - \frac{\gamma}{\sigma_X^4}}{1 + \gamma + \frac{2\gamma}{\sigma_X^2}}.
$$

Primary Eigenvector $\hat{v}$

- Now we can compute the inner product of u and $\hat{v}$ that we are really interested in:

$$\begin{aligned}
|u^T \hat{v}|^2 &= (\frac{1}{c} u^T \Sigma^{\frac{1}{2}} v)^2 = \frac{1}{c^2}((\Sigma^{\frac{1}{2}} u)^T v)^2 \\
&= \frac{1}{c^2}((((\sigma_X^2 u u^T + I_p)^{\frac{1}{2}} u)^T v)^2 \\
&\stackrel{*}{=} \frac{1}{c^2}((\sqrt{(1+\sigma_X^2)} u)^T v)^2 \\
&\stackrel{**}{=} \frac{(1+\sigma_X^2)(u^T v)^2}{R(u^T v)^2 + 1}, \quad R = \sigma_X^2, \\
&= \frac{1 + R - \frac{\gamma}{R} - \frac{\gamma}{R^2}}{1 + R + \gamma + \frac{\gamma}{R}} = \frac{1 - \frac{\gamma}{R^2}}{1 + \frac{\gamma}{R}}
\end{aligned}$$

where the equality $(*)$ uses $\Sigma^{1/2} u = \sqrt{1+\sigma_X^2} u$, and the equality $(**)$ is due to the formula for c^2 (Equation (6) above). Note that this identity holds under the condition that $R \geq \sqrt{\gamma}$ to ensure the numerator above non-negative.

Stieltjes Transform

Define the Stieltjes Transformation of MP-density μ^{MP} to be

$$s(z) := \int_R \frac{1}{t-z} d\mu^{MP}(t), \;\; z \in C \tag{16}$$

Lemma (Bai-Silverstein'2011, Lemma 3.11)

$$s(z) = \frac{(1-\gamma) - z + \sqrt{(z-1-\gamma)^2 - 4\gamma z}}{2\gamma z}. \tag{17}$$

Stieltjes Transform (continued)

Lemma (2)

1.

$$\int_a^b \frac{t}{\lambda - t}\mu^{MP}(t)dt = -\lambda s(\lambda) - 1;$$

2.

$$\int_a^b \frac{t^2}{(\lambda - t)^2}\mu^{MP}(t)dt = \lambda^2 s'(\lambda) + 2\lambda s(\lambda) + 1$$

Proof of Lemma 2

Proof.

1. For convenience, define

$$T(\lambda) := \int_a^b \frac{t}{\lambda - t}\mu^{MP}(t)dt. \tag{18}$$

The first result follows from that

$$1+T(\lambda) = 1+\int_a^b \frac{t}{\lambda - t}\mu^{MP}(t)dt = \int_a^b \frac{\lambda - t + t}{\lambda - t}\mu^{MP}(t)dt = -\lambda s(\lambda).$$

2. From the definition of $T(\lambda)$, we have

$$\int_a^b \frac{t^2}{(\lambda - t)^2}\mu^{MP}(t)dt = -T(\lambda) - \lambda T^{'}(\lambda).$$

Combined with the first result, we reach the second one.

□

Open Problems

- If one can estimate the noise models, such as the rank-1 model here, then we can use random matrix theory (universality) or by simulations to find the number of principal components.
- Such a random matrix theory can not fully explain why Horn's Parallel Analysis, whose proof is open.
- In applications, noise models might not be homogeneous $\sigma_\varepsilon^2 I_p$. How to deal with heterogeneous noise models is open (Wang-Owen'2015 attacked this problem).
- Distributive PCA can exploit random matrix theory to decide the number of samples in local clients (Fan-Wang et al. 2019).