

$$Y_i \sim \mathcal{N}(0, \Sigma) \quad i=1, \dots, n$$

$$\Sigma = \sigma_x^2 u u^T + \sigma_\varepsilon^2 I_p, \quad \sigma_\varepsilon^2 = 1$$

$$\text{SNR } R = \frac{\sigma_x^2}{\sigma_\varepsilon^2} = \sigma_x^2$$

$$\hat{\Sigma}_n = \frac{1}{n} Y Y^T \quad Y = [Y_1, \dots, Y_n] \quad p \times n$$

Phase Transition

$$1) \quad \hat{\lambda}_{\max}(\hat{\Sigma}_n) \rightarrow \begin{cases} b & R \leq \sqrt{r} \\ f(\sigma_x^2, r) & R \geq \sqrt{r} \end{cases}$$

$$= (1 + \sigma_x^2) \left(1 + \frac{r}{\sigma_x^2}\right) = (1 + R^2) \left(1 + \frac{r}{R^2}\right) \sigma_\varepsilon^2$$

$$2) \quad |\langle \hat{v}_{\max}, u \rangle| \rightarrow \begin{cases} 0 & R \leq \sqrt{r} \\ \left(\frac{1 - \frac{r}{R^2}}{1 + r + \frac{2r}{R}} \right)^{\frac{1}{2}} < 1, & R \geq \sqrt{r} \end{cases}$$

$$\begin{aligned} \text{eig}(\hat{\Sigma}_n) &= \frac{1}{n} Y Y^T \\ &= \frac{1}{n} \underbrace{\Sigma^{-\frac{1}{2}} \Sigma \Sigma^{-\frac{1}{2}}}_{S_n} = \underbrace{\Sigma^{-\frac{1}{2}} S_n \Sigma^{-\frac{1}{2}}}_{\sim \Sigma^{-\frac{1}{2}} (\Sigma^{-\frac{1}{2}} S_n \Sigma^{-\frac{1}{2}}) \Sigma^{-\frac{1}{2}} = (S_n \Sigma)}_{\text{eigval}} \end{aligned}$$

$Y_i = \Sigma^{\frac{1}{2}} Z_i \quad Z_i \sim \mathcal{N}(0, I_p)$

$S_n = \frac{1}{n} Z Z^T \sim \text{MP dist. Wishart}$

(λ, v) $S_n \Sigma$ eigen pair

$$(*) \quad S_n \Sigma v = \lambda v \quad \|v\|_2 = 1$$

$$\hat{v} = c(\Sigma^{\frac{1}{2}} v) \quad \|\hat{v}\|_2 = 1 \quad \hat{\Sigma}_n = \Sigma^{\frac{1}{2}} S_n \Sigma^{\frac{1}{2}}$$

$$\hat{\Sigma}_n \hat{v} = \lambda \hat{v}$$

$$\begin{aligned} 1 &= \hat{v}^T \hat{v} = c^2 (\Sigma^{\frac{1}{2}} v)^T (\Sigma^{\frac{1}{2}} v) = c^2 v^T \Sigma v = c^2 v^T (\sigma_x^2 u u^T + I_p) v \\ &= c^2 \sigma_x^2 (u^T v)^2 + c^2 \Rightarrow c^2 = \frac{1}{\sigma_x^2 (u^T v)^2 + 1} \ll \sigma_\varepsilon^2 \end{aligned}$$

$$\Sigma = \sigma_x^2 u u^T + I_p$$

$$S_n (\sigma_x^2 u u^T + I_p) v = \lambda v$$

$$(\lambda I_p - \sigma_\varepsilon^2 I_p) v = \sigma_x^2 S_n u (u^T v)$$

$$(**) \quad \underline{v} = (\lambda I_p - \sigma_\varepsilon^2 S_n)^{-1} \sigma_x^2 S_n u \quad (\underline{u^T v})$$

$$\underline{u^T v} = u^T (\underline{Z})^{-1} \cdot \sigma_x^2 S_n u \quad (\underline{u^T v})$$

Assume $u^T v \neq 0$

$$1 = \sigma_x^2 u^T (\lambda I_p - \sigma_\varepsilon^2 S_n)^{-1} S_n u = \text{Wishart}$$

$$S_n = W^T \Lambda W^T \quad \Lambda = \text{diag}(\lambda_i)_{i=1, \dots, p} \sim \text{MP Law}$$

$$\alpha_i = W_i^T u \quad W^T W = W \cdot W^T = I_p.$$

$$1 = \sigma_x^2 \sum_{i=1}^p \frac{\lambda_i}{\lambda - \sigma_\varepsilon^2 \lambda_i} \alpha_i^2 \quad \lambda_i \sim \text{MP}$$

Assume rank-1 u. uniformly on S^{p-1} ; $\mathbb{E}(\alpha_i^2) \sim \frac{1}{p}$
 $\sum_{i=1}^p \alpha_i^2 = 1$

Monte Carlo Sum.

$$\sim \sigma_x^2 \frac{1}{p} \sum_{i=1}^p \frac{\lambda_i}{\lambda - \sigma_\varepsilon^2 \lambda_i} \sim \sigma_x^2 \int \frac{t}{\lambda - \sigma_\varepsilon^2 t} d\mu^{\text{MP}}(t)$$

$$\sigma_\varepsilon^2 = 1$$

Stieltjes Transform (Terry Tao 2011, RMT 网络)

$$S(z) = \int_{-\infty}^{+\infty} \frac{1}{t-z} d\mu^{\text{MP}}(t), \quad z \in \mathbb{C}$$

Hilbert transform

Lemma

(A)

$$\int \frac{t}{\lambda - t} d\mu^{MP}(t) = -\lambda s(\lambda) - 1$$

 $\lambda \in \mathbb{R}^+$

(B)

$$\int \frac{t^2}{(\lambda - t)^2} d\mu^{MP}(t) = \lambda^2 s'(\lambda) + 2\lambda s(\lambda) + 1$$

Proof: (A) $T(\lambda) = \int \frac{t}{\lambda - t} d\mu^{MP}(t)$

$$1 + T(\lambda) = \int \frac{\lambda - t + t}{\lambda - t} d\mu^{MP}(t) = \lambda \int \frac{1}{\lambda - t} d\mu^{MP}(t) = \lambda s(\lambda)$$

$$T(\lambda) = -\lambda s(\lambda) - 1 \quad \square$$

$$(B) \quad \int \frac{t^2}{(\lambda - t)^2} d\mu^{MP}(t) = -T(\lambda) - \lambda T'(\lambda) \quad \square$$

S-transform

$$S(z) = \frac{(1-\gamma) - z + \sqrt{(z-1+\gamma)^2 - 4\gamma z}}{2\gamma z}, \quad z \in \mathbb{D} \setminus \{0\}$$

Note:

$$\frac{1}{S(z) + z} = \frac{1}{1 + \gamma S(z)} \Rightarrow \text{poly}(S, z) = 0 \quad \uparrow \quad \text{largest root}$$

Lemma (A)

 $\lambda \geq b$

$$(**) \Rightarrow 1 = \frac{\sigma_x^2}{4\gamma} \left[2\lambda - (a+b) - 2 \sqrt{(\lambda-a)(\lambda-b)} \right]$$

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$$I = \frac{\sigma_x^2}{4\gamma} \left[2\lambda - (a+b) - 2\sqrt{(\lambda-a)(\lambda-b)} \right]$$

$\lambda \geq b$ holds.

$\lambda = b$ noise spectrum upper bound.

$$I = \frac{\sigma_x^2}{4\gamma} [b-a] = \frac{\sigma_x^2}{1\gamma}$$

$$a = (-\sqrt{\gamma})^2$$

$$b = (1+\sqrt{\gamma})^2$$

$$b-a = 4\gamma$$

$$\sigma_x^2 = \sqrt{\gamma} \quad (\text{SNR} = R = \sqrt{\gamma})$$

Phase-Transition boundary

$$\sigma_x^2 \geq \sqrt{\gamma} \quad \lambda = (1 + \sigma_x^2) \left(1 + \frac{\gamma}{\sigma_x^2} \right) = f(\sigma_x^2, \gamma)$$

$$= (1 + R) \left(1 + \frac{1}{R} \right) \sigma_x^2$$

biased of signal strength

(**) 左/右 同时 $V^T \cdot (**)$

$$I = V^T V = \left\| (u^T V) \sigma_x^2 (\lambda I_p - \sigma_\varepsilon^2 S_n)^T S_n u \right\|_2^2$$

$$= (u^T V)^2 \sigma_x^4 u^T S_n (\lambda I_p - \sigma_\varepsilon^2 S_n)^{-2} S_n u.$$

$$(u^T V)^{-2} = \sigma_x^4 \underbrace{u^T S_n (\lambda I_p - \sigma_\varepsilon^2 S_n)^{-2} S_n u}$$

$$S_n = W \Lambda W^T \quad \alpha_i = W_i^T u$$

$$= \sigma_x^4 \sum_{i=1}^p \frac{\lambda_i^2}{(\lambda - \sigma_\varepsilon^2 \lambda_i)^2} \alpha_i^2 \leftarrow \frac{1}{p}$$

$$\sim \sigma_x^4 \int \frac{t^2}{(\lambda - \sigma_\varepsilon^2 t)^2} d\mu^{\text{MP}}(t)$$

Lemma (B)

$$\sigma_\varepsilon^2 = 1 \Rightarrow = \frac{\sigma_x^4}{8r} \left[-4\lambda + (a+b) + 2 \sqrt{(\lambda-a)(\lambda-b)} + \frac{\lambda(2\lambda-(a+b))}{(\lambda-a)(\lambda-b)} \right]$$

$$u^T V^2 = \frac{1 - \frac{\gamma}{R^2}}{1 + \gamma + \frac{2\gamma}{R}}$$

$$\Rightarrow u^T \hat{V}^2 = u^T (C \hat{\Sigma}^{\frac{1}{2}} V) = \frac{1+R}{1+R(u^T V)^2} (u^T V)^2$$

$$= g(R, \gamma) < 1$$

$$\frac{1 - \frac{\gamma}{R^2}}{1 + \frac{\gamma}{\sigma_x^2}}$$

$$R > \sqrt{\gamma}$$

RMT MP law for Wishart

$$\Sigma = \sigma_x^2 uu^T + \sigma_z^2 I_p$$

$$\hat{\lambda}_{\max}(\hat{\Sigma}_n) \neq \sigma_x^2$$

$$= f(\sigma_x^2), \quad R \neq \sqrt{p} \quad \checkmark$$

$$\neq b, \quad R \leq \sqrt{p}$$

PC, \hat{V}_{\max} in conic neighborhood of u
 $g(R, \delta)$

Open. $\sigma_z^2 I_p$ homogeneous.
 $\text{diag}(\sigma_{\Sigma_i}^2)$ heterogeneous. ? Owen Wang

Rank-Sparsity: Robust PCA

$$\text{SDP} \quad uu^T + \text{sparse}$$

条件? Compressed Sensing

Candes, Ma, Wright, Recht, Joel Tropp