

1. (a). Let  $\lambda$  be the largest eigenvalue of the sample covariance matrix  $S_n = \frac{1}{n} \sum_{i=1}^n x_i x_i^T$  and let  $v$  be the corresponding unit eigenvector.

Then,  $S_n v = \lambda v$ .

$$\text{Let } \Sigma = \sigma^2 I_{p \times p} + \lambda_0 u u^T, \quad Z_i = \Sigma^{-\frac{1}{2}} x_i.$$

then  $Z_i \sim N(0, I_p)$ ,

and  $P_n = \frac{1}{n} \sum_{i=1}^n Z_i Z_i^T = \frac{1}{n} Z Z^T$  is a Wishart random matrix whose eigenvalues follow the Marcenko-Pastur distribution.

$$S_n = \frac{1}{n} X X^T = \frac{1}{n} \Sigma^{\frac{1}{2}} Z Z^T \Sigma^{\frac{1}{2}} = \Sigma^{\frac{1}{2}} P_n \Sigma^{\frac{1}{2}}$$

$$\Rightarrow \Sigma^{\frac{1}{2}} P_n \Sigma^{\frac{1}{2}} v = \lambda v \Rightarrow P_n \Sigma (\Sigma^{-\frac{1}{2}} v) = \lambda (\Sigma^{-\frac{1}{2}} v)$$

So  $\lambda$  and  $\Sigma^{-\frac{1}{2}} v$  are the eigenvalue and eigenvector of  $P_n \Sigma$ .

Suppose  $c \Sigma^{-\frac{1}{2}} v = w$ , where  $c$  makes  $w$  a unit eigenvector,

$$\begin{aligned} \text{so } c^2 &= c^2 v^T v = w^T \Sigma w = w^T (\sigma^2 I_p + \lambda_0 u u^T) w \\ &= \lambda_0 (u^T w)^2 + \sigma^2 \end{aligned}$$

$$\text{and } P_n \Sigma w = \lambda w \Rightarrow P_n (\lambda_0 u u^T + \sigma^2 I_p) w = \lambda w$$

$$\Rightarrow (\lambda I_p - \sigma^2 P_n) w = \lambda_0 P_n u (u^T w)$$

If  $\lambda I_p - \sigma^2 P_n$  is invertible,

$$\text{then } w = \lambda_0 (\lambda I_p - \sigma^2 P_n)^{-1} P_n u (u^T w) \quad (1)$$

$$u^T w = \lambda_0 u^T (\lambda I_p - \sigma^2 P_n)^{-1} P_n u (u^T w),$$

$$\text{if } u^T w \neq 0, \quad 1 = \lambda_0 u^T (\lambda I_p - \sigma^2 P_n)^{-1} P_n u \quad (2)$$

the eigenvalue decomposition of  $P_n$  is:  $P_n = L \Lambda L^T$ ,  $\Lambda = \text{diag}(\lambda_i)$ ,  $\lambda_i$  in descending order,  $L^T L = L L^T = I_p$ ,  $w = [l_1, \dots, l_p] \in \mathbb{R}^{p \times p}$

$$\text{Let } \alpha_i = l_i^T u, \quad \alpha = [\alpha_1, \dots, \alpha_p]^T \in \mathbb{R}^{p \times 1},$$

$$\text{then } u = \sum_{i=1}^p \alpha_i l_i = L^T \alpha.$$

$$(2) \Rightarrow 1 = \lambda_0 u^T [L (\lambda I_p - \sigma^2 \Lambda)^{-1} L^T] (L \Lambda L^T) u$$

$$= \lambda_0 \alpha^T (\lambda I_p - \sigma^2 \Lambda)^{-1} \Lambda \alpha$$

$$= \lambda_0 \sum_{i=1}^p \frac{\lambda_i}{\lambda - \sigma^2 \lambda_i} \alpha_i^2, \quad \text{where } \sum_{i=1}^p \alpha_i^2 = 1 \quad (**)$$

Since  $L$  consists of a random orthonormal basis on a sphere,  $\alpha_i$  will concentrate on its mean  $\alpha_i = \frac{1}{\sqrt{p}}$ .

For large  $p$ ,  $\lambda_i \sim \mu^{MP}(\lambda_i)$  can be thought sampled from  $\mu^{MP}$ .

(\*) can be considered as MC integration w.r.t. MP distribution.

$$I = \lambda_0 \frac{1}{P} \sum_{i=1}^P \frac{\lambda_i}{\lambda - \sigma^2 \lambda_i} \sim \lambda_0 \int_a^b \frac{t}{\lambda - \sigma^2 t} d\mu^{MP}(t),$$

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

WLOG, assume  $\sigma^2 = 1$ .

$$I = \lambda_0 \int_a^b \frac{t}{\lambda - t} d\mu^{MP}(t) \xrightarrow[\text{transform}]{\text{Stieltjes}} \frac{\lambda_0}{4\gamma} [2\lambda - (a+b) - 2\sqrt{(\lambda-a)(\lambda-b)}]$$

If  $\text{SNR} = \lambda_0 > \sqrt{\gamma}$ ,

$$1) \text{ if } \lambda \geq b, \text{ then } I = \frac{\lambda_0}{4\gamma} [2\lambda - (a+b) - 2\sqrt{(\lambda-a)(\lambda-b)}]$$

$$\text{and } a = (1 - \sqrt{\gamma})^2, \quad b = (1 + \sqrt{\gamma})^2$$

$$\text{then } \lambda = \lambda_0 + 1 + \gamma + \frac{\gamma}{\lambda_0} = (1 + \lambda_0) (1 + \frac{\gamma}{\lambda_0})$$

2) if  $a \leq \lambda \leq b$ , then  $S_n$  has its primary eigenvalue

$\lambda$  within  $\text{supp}(\mu^{MP})$ , so it's undistinguishable from the noise  $P_n$ .

In case 1), for general  $\sigma^2 \neq 1$ ,  $\frac{\lambda}{\sigma^2} = (1 + \frac{\lambda_0}{\sigma^2}) (1 + \frac{\gamma}{\lambda_0 \sigma^2})$

$$\Rightarrow \lambda = (1+R) (1 + \frac{\gamma}{R}) \sigma^2, \\ \text{where } R = \lambda_0 / \sigma^2 \text{ is the SNR.}$$

(b) Generate  $n$  i.i.d samples from the distribution,

then find the largest eigenvalue  $\lambda$  of the sample covariance matrix,

$$\text{and then solve } \text{Eq: } \lambda = (1+R) (1 + \frac{\gamma}{R}),$$

$R$  is the estimation of SNR

$$(c). \quad \text{From (1), } I = W^T W = \lambda_0^2 (W^T U) U^T P_n (\lambda I_p - \sigma^2 P_n)^{-2} P_n U (U^T W) \\ = \lambda_0^2 |U^T W|^2 U^T P_n (\lambda I_p - \sigma^2 P_n)^{-2} P_n U$$

$$\Rightarrow |U^T W|^2 = \lambda_0^2 U^T P_n (\lambda I_p - \sigma^2 P_n)^{-2} P_n U$$

$$(MC\text{-integration}) \sim \lambda_0^2 \int_a^b \frac{t^2}{(\lambda - \sigma^2 t)^2} d\mu^{MP}(t) \quad (\text{WLOG, } \sigma^2 = 1)$$

$$\xrightarrow[\text{Stieltjes transform}]{\text{Stieltjes transform}} \frac{\lambda_0^2}{4\gamma} [-4\lambda + (a+b) + 2\sqrt{(\lambda-a)(\lambda-b)}] + \frac{\lambda(2\lambda - (a+b))}{\sqrt{(\lambda-a)(\lambda-b)}}$$

$$\text{Using } \lambda = (1+R) (1 + \frac{\gamma}{R}), \text{ then } |U^T W|^2 = \frac{1 - \frac{\gamma}{R^2}}{1 + \gamma + \frac{2\gamma}{R}}.$$

$$|U^T V|^2 = (\frac{1}{c} U^T \sum_{i=1}^c W)^2 = \frac{1}{c^2} ((R U U^T + I_p)^{\frac{1}{2}} U)^T W)^2$$

$$\begin{aligned}
 (\sum u = \sqrt{1+R}u) &= \frac{1}{c^2} ((\sqrt{1+R}u)^T w)^2 \\
 &= \frac{(1+R)(u^T w)^2}{R(u^T w)^2 + 1} = \frac{1 - \frac{Y}{R^2}}{1 + \frac{Y}{R}} = |\langle u, v \rangle|^2
 \end{aligned}$$