

## Lecture 20: November 7

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## 20.1 Spiked Covariance Model

References: Johnson & Lu (2009); Paul (2007); Nadler (2008).

$$\Sigma_{p \times p} = \nu\theta\nu^T + \mathbf{I}_d,$$

in which  $\theta > 0, \nu \in \mathbb{S}^{p-1}$ ,  $\nu$  leading eigenvector,  $1 + \theta$  leading eigenvalue.

Let  $X_1, \dots, X_n$  iid,  $X_i \sim (0, \Sigma)$ .  $\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^n x_i x_i^T$ ,  $\hat{\nu}$  leading eigenvector of  $\hat{\Sigma}$ .  $\langle \nu, \hat{\nu} \rangle \not\rightarrow 0$  with high probability unless  $\frac{p}{n} \rightarrow 0$ .

$$\min_{\epsilon \in \{-1, 1\}} \|\epsilon \hat{\nu} - \nu\| \leq 2 \sin^2(\langle \hat{\nu}, \nu \rangle)$$

and by Davis-Kahan,

$$\min_{\epsilon \in \{-1, 1\}} \|\epsilon \hat{\nu} - \nu\| \leq \frac{8}{\theta^2} \|\hat{\Sigma} - \Sigma\|_{op}$$

Assuming  $X_i \in SG(\|\Sigma\|_{op})$ ,

$$\min_{\epsilon \in \{-1, 1\}} \|\epsilon \hat{\nu} - \nu\| \lesssim \frac{1 + \theta}{\theta} \min\left\{\sqrt{\frac{p + \log(1/\delta)}{n}}, \frac{p + \log(1/\delta)}{n}\right\}.$$

## 20.2 Sparse PCA

$$\Sigma_{p \times p} = \nu\theta\nu^T + \mathbf{I}_d,$$

in which  $\theta > 0, \nu \in \mathbb{S}^{p-1}$ ,  $\|\nu\|_0 \leq k \ll n, p$ ,  $\#\{i : \nu_i \neq 0\}$ .

Estimate  $\nu$  using  $\hat{\nu}$  where  $\hat{\nu}^T \hat{\Sigma} \hat{\nu} = \max_{u \in \mathbb{S}^{p-1}, \|u\|_0 \leq k'} u^T \hat{\Sigma} u$ ,  $k \leq k' \leq \frac{p}{2} \rightarrow$  not computationally feasible!!!

**Theorem 20.1** *Assume  $X_1, \dots, X_n \sim (0, \Sigma)$  such that  $X_i \in SG_p(\|\Sigma\|_{op})$ . Let  $\hat{\nu}$  be a solution to the sparse PCA. Then*

$$\min_{\epsilon \in \{-1, 1\}} \|\epsilon \hat{\nu} - \nu\| \leq \frac{1 + \theta}{\theta} \max\{\sqrt{B_n}, B_n\},$$

in which  $B_n = [(k + k') \log(ep/k + k') + \log(1/\delta)]/n$ , with probability  $\geq 1 - \delta$ .

*Proof:* Let  $s \subset \{1, \dots, p\}$ ,  $A(S) = (A_{ij})_{i,j \in s}$ ,  $x_s = (x_i)_{i \in s}$  and  $s = \text{supp}(\hat{\nu}) \cup \text{supp}(\nu)$ . We have that

$$\begin{aligned}
\theta \sin^2(\langle \hat{\nu}, \nu \rangle) &= \nu^T \Sigma \nu - \hat{\nu}^T \hat{\Sigma} \hat{\nu} \\
&= \nu^T \hat{\Sigma} \nu - \hat{\nu}^T \Sigma \hat{\nu} - \nu^T (\hat{\Sigma} - \Sigma) \nu \\
&\leq \hat{\nu}^T \hat{\Sigma} \nu - \hat{\nu}^T \Sigma \hat{\nu} - \nu^T (\hat{\Sigma} - \Sigma) \nu \\
&= \hat{\nu}^T (\hat{\Sigma} - \Sigma) \hat{\nu} - \nu^T (\hat{\Sigma} - \Sigma) \nu \\
&= \langle \hat{\Sigma} - \Sigma, \hat{\nu} \hat{\nu}^T - \nu \nu^T \rangle \\
&= \langle \hat{\Sigma}(s) - \Sigma(s), \hat{\nu}_s \hat{\nu}_s^T - \nu_s \nu_s^T \rangle \\
&\leq \|\hat{\Sigma}(s) - \Sigma(s)\|_{op} \|\hat{\nu}_s \hat{\nu}_s^T - \nu_s \nu_s^T\|_1 \\
&\leq \|\hat{\Sigma}(s) - \Sigma(s)\|_{op} \sqrt{2} \|\hat{\nu}_s \hat{\nu}_s^T - \nu_s \nu_s^T\|_2
\end{aligned}$$

Note that  $\text{rank}(\hat{\nu}_s \hat{\nu}_s^T - \nu_s \nu_s^T) \leq 2$ . Let's look separately at  $\hat{\nu}_s \hat{\nu}_s^T - \nu_s \nu_s^T$ .

$$\begin{aligned}
\|\hat{\nu}_s \hat{\nu}_s^T - \nu_s \nu_s^T\|_F &\leq \|\hat{\nu} \hat{\nu}^T - \nu \nu^T\|_F \\
&= \sqrt{2 \sin^2(\langle \hat{\nu}, \nu \rangle)}.
\end{aligned}$$

Then,  $\sin(\langle \hat{\nu}, \nu \rangle) \leq 2 \|\hat{\Sigma}(s) - \Sigma(s)\|_{op}$ , since  $\min_{\epsilon \in \{-1, 1\}} \|\epsilon \hat{\nu} - \nu\|^2 \leq \sin(\langle \hat{\nu}, \nu \rangle)$ .

We have shown that  $\min_{\epsilon \in \{-1, 1\}} \|\epsilon \hat{\nu} - \nu\|^2 \leq \frac{\sqrt{8}}{\theta} \sup_{s \in \{1, \dots, p\}, s \neq \emptyset, |s| \leq k+k'} \|\hat{\Sigma}(s) - \Sigma(s)\|_{op}$ .

$$\mathbb{P}\left(\sup_{s \in \{1, \dots, p\}, s \neq \emptyset, |s| \leq k+k'} \|\hat{\Sigma}(s) - \Sigma(s)\|_{op} \geq t \|\Sigma\|_{op}\right) \lesssim \binom{p}{k+k'} q^{k+k'} \exp\left(-\frac{n}{2} \{(t/32)^2 \wedge t/32\}\right)$$

Recall the inequality  $\binom{n}{k} \leq \left(\frac{en}{k}\right)^k$ .

Finish up the usual way.

## 20.3 Community detection in stochastic block model

Let  $A_{n \times n}$  symmetric be the adjacency matrix,  $A_{ij} = \mathbb{I}(i \text{ connected to } j)$ ,  $A_{ii} = 0$  all  $i$ .

### 20.3.1 Erdos - Renyi's Model

$$A_{ij} \sim \text{Bernoulli}(p), \text{ all } i < j.$$

More generally, one could assume  $A_{ij} \sim \text{Bernoulli}(p_{ij})$  independent (inhomogeneous Bernoulli model).

### 20.3.2 Stochastic Block Model

Next class!