

Gaussian weighted stochastic block model

Exact recovery: statistical and algorithmic thresholds

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Background: The binary Stochastic block model

- (Unobserved) Community labels $\sigma^* : [n] \rightarrow \{\pm 1\}$ such $\langle \sigma^*, 1 \rangle = 0$.
- (Observed) A random graph $G = ([n], E)$ with Adjacency matrix A such that

$$A(i, j) = A(j, i) \sim \begin{cases} \text{Ber}(p) & \text{if } \sigma^*(i) = \sigma^*(j) \\ \text{Ber}(q) & \text{if } \sigma^*(i) \neq \sigma^*(j) \end{cases}$$

- (Task) Recover σ^* exactly up to a global sign flip.
- (Output) $\hat{\sigma} : [n] \rightarrow \{\pm 1\}$ such that $\#\{i \in [n] : \hat{\sigma}(i) = \sigma^*(i)\} = n$.
- (Regime of interest) $p = \frac{a \log n}{n}$, $q = \frac{b \log n}{n}$ with $a > b > 0$ constants.
- (Parameter of interest) SNR $(a, b) = \frac{|\sqrt{a} - \sqrt{b}|}{\sqrt{2}}$.

The Gaussian weighted stochastic block model (our model)

- (Unobserved) Community labelling $\sigma^* : [n] \rightarrow \{\pm 1\}$ such $\langle \sigma^*, \mathbf{1} \rangle = 0$.
- (Observed) A weighted random graph $G = ([n], (w_e)_{e \in \binom{[n]}{2}})$ such that

$$A(i, j) = A(j, i) \sim \begin{cases} \mathcal{N}(\mu_1, \tau^2) & \text{if } \sigma^*(i) = \sigma^*(j) \\ \mathcal{N}(\mu_2, \tau^2) & \text{if } \sigma^*(i) \neq \sigma^*(j) \end{cases}$$

- (Task) Recover σ^* exactly up to a global sign flip.
- (Output) $\hat{\sigma} : [n] \rightarrow \{\pm 1\}$ such that $\#\{i \in [n] : \hat{\sigma}(i) = \sigma^*(i)\} = n$.
- (Regime of interest) $\mu_1 = \alpha \sqrt{\frac{\log n}{n}}$, $\mu_2 = \beta \sqrt{\frac{\log n}{n}}$ with $\alpha > \beta$ and $\tau > 0$ constants.
- (Parameter of interest) SNR $(\alpha, \beta) = \frac{|\alpha - \beta|}{\tau \sqrt{2}}$.

The objects of interest

- $\hat{\sigma}_{MLE} = \operatorname{argmax} \sum_{i,j} A_{ij} \sigma_i \sigma_j = \operatorname{Tr}(A \sigma \sigma^T)$ subject to $\sigma \in \{\pm 1\}^n$, $\langle \sigma, \mathbf{1} \rangle = 0$.
- $\hat{Y}_{SDP} = \operatorname{argmax} \operatorname{Tr}(AY)$ subject to $Y \succeq 0$, $Y_{ii} = 1 \forall i \in [n]$, $\operatorname{Tr}(JY) = 0$.
- $\hat{\sigma}_{Spec} = \operatorname{sign}(\operatorname{argmax} \sum_{i,j} A_{ij} v_i v_j = \operatorname{Tr}(A v v^T))$ subject to $v \in \mathbb{S}^{n-1}$, $\langle v, \mathbf{1} \rangle = 0$.

Results: Binary and the Gaussian model

(previous results for the binary model)

- If $\text{SNR}(a, b) = \frac{|\sqrt{a}-\sqrt{b}|}{\sqrt{2}} < 1$

$$\mathbb{P}(\hat{\sigma}_{MLE} = \sigma^*) \not\rightarrow 1 [ABH, 2014]$$

- If $\text{SNR}(a, b) = \frac{|\sqrt{a}-\sqrt{b}|}{\sqrt{2}} > 1$

$$\mathbb{P}(\hat{\sigma}_{MLE} = \sigma^*) \rightarrow 1 [ABH, 14]$$

$$\mathbb{P}(\hat{Y}_{SDP} = \sigma^* \sigma^{*T}) \rightarrow 1 [HWX, 16]$$

$$\mathbb{P}(\hat{\sigma}_{Spec} = \sigma^*) \rightarrow 1 [AFYZ, 19]$$

(our results for the Gaussian model)

- If $\text{SNR}(\alpha, \beta) = \frac{|\alpha-\beta|}{\tau\sqrt{2}} < 1$

$$\mathbb{P}(\hat{\sigma}_{MLE} = \sigma^*) \not\rightarrow 1$$

- If $\text{SNR}(\alpha, \beta) = \frac{|\alpha-\beta|}{\tau\sqrt{2}} > 1$

$$\mathbb{P}(\hat{\sigma}_{MLE} = \sigma^*) \rightarrow 1$$

$$\mathbb{P}(\hat{Y}_{SDP} = \sigma^* \sigma^{*T}) \rightarrow 1$$

$$\mathbb{P}(\hat{\sigma}_{Spec} = \sigma^*) \rightarrow 1$$

- Statistical possibility and impossibility of the MLE is established through First and Second Moment methods.
- Proof for the Semidefinite Programming (SDP) estimator involves a clever dual certificate argument.
- Spectral estimator's proof requires entrywise analysis of eigenvectors.

- It resolves the exact recovery problem for the planted spin glass (spiked Wigner).
- It is also shown that exactly recovering two equal-sized community is an easier problem than exactly recovering a densely weighted community of size $n/2$.
- More precisely we need $\text{SNR}(\alpha, \beta) > 2$ to be able to exactly recover (through the SDP procedure) a densely weighted community of size $n/2$.

The Gaussian weighted planted dense subgraph model

- (Unobserved) Community labelling $\sigma^* : [n] \rightarrow \{\pm 1\}$ such $\langle \sigma^*, \mathbf{1} \rangle = 0$.
- (Observed) A weighted random graph $G = ([n], (w_e)_{e \in \binom{[n]}{2}})$ such that

$$A(i, j) = A(j, i) \sim \begin{cases} \mathcal{N}(\mu_1, \tau^2) & \text{if } \sigma^*(i) = \sigma^*(j) = 1 \\ \mathcal{N}(\mu_2, \tau^2) & \text{otherwise} \end{cases}$$

- (Task) Recover σ^* exactly up to a global sign flip.
- (Output) $\hat{\sigma} : [n] \rightarrow \{\pm 1\}$ such that $\#\{i \in [n] : \hat{\sigma}(i) = \sigma^*(i)\} = n$.
- (Regime of interest) $\mu_1 = \alpha \sqrt{\frac{\log n}{n}}$, $\mu_2 = \beta \sqrt{\frac{\log n}{n}}$ with $\alpha > \beta$ and $\tau > 0$ constants.
- (Parameter of interest) SNR $(\alpha, \beta) = \frac{|\alpha - \beta|}{\tau \sqrt{2}}$.

- [ABH] Emmanuel Abbe, Afonso S. Bandeira, Georgina Hall: Exact Recovery in the Stochastic Block Model ABH.
- [AFWZ] Emmanuel Abbe, Jianqing Fan, Kaizheng Wang, Yiqiao Zhong: Entrywise Eigenvector Analysis of Random Matrices with Low Expected Rank AFWZ
- [HWX] Bruce Hajek, Yihong Wu, Jiaming Xu : Achieving Exact Cluster Recovery Threshold via Semidefinite Programming HWX
- [PK] Aaradhya Pandey, Sanjeev Kulkarni (forthcoming draft): Gaussian weighted Stochastic block model: Statistical and algorithmic thresholds

Thank You!