Detecting a small community in a large network

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Social networks

Data: $n \times n$ adjacency matrix A (symmetric)

$$A(i,j) = \begin{cases} 1, & \text{an edge between nodes } i \text{ and } j \\ 0, & \text{otherwise} \end{cases}$$

with ${\it K}$ perceivable "communities" ${\cal C}_1, {\cal C}_2, \ldots, {\cal C}_{{\it K}}$

- Community: group of nodes that have more edges within than across
- ▶ The upper triangle of A are independent Bernoulli
- Let $W = A \mathbb{E}[A]$. For a rank-K matrix Ω ,

$$A = \underbrace{\Omega}_{\text{main signal}} - \underbrace{\operatorname{diag}(\Omega)}_{\text{secondary signal}} + \underbrace{W}_{\text{noise}}$$

Detecting a small community

$$H_0: K = 1$$
 vs. $H_1: K > 1$

- Focus: Some communities are very small
- E.g., Testing whether there is a small focused group in a large coauthorship network
- Includes clique detection as a special case (Alon et al, 1998; Arias-Castro-Verzelen, 2014)

Degree-Corrected Block Model (DCBM)

$$\Omega(i,j) = \frac{\theta_i \theta_j}{\theta_j} \cdot \pi'_i P \pi_j, \qquad \Longleftrightarrow \qquad \Omega = \Theta \Pi P \Pi' \Theta$$

- $\Pi = [\pi_1, \dots, \pi_n]' \in \mathbb{R}^{n, K}$, where $\pi_i \in \mathbb{R}^K$ models community label of node *i*: when $i \in C_k$, $\pi_i(\ell) = 1$ if $\ell = k$ and $\pi_i(\ell) = 0$ otherwise.
- P ∈ ℝ^{K,K} models community structure: P(k, ℓ) is the baseline connecting probability for communities k & ℓ.
- Θ = diag(θ₁,...,θ_n), where θ_i > 0 models degree heterogeneity of node i
- Reduces to stochastic block model if $\theta_i \equiv 1$.

Degree matching, why χ^2 may lose power

Jin, Ke, Luo (2021)

$$\chi^2$$
-test : $X = \sum_{i=1}^n (d_i - \bar{d})^2, \quad d_i ext{ is degree of node } i$

- χ² is powerful in degree-homogeneous models (SBM) (Arias-Castro-Verzelen, 2014)
- Why does it lose power in DCBM?
 - Degree matching: Can pair any alternative DCBM with a null model that has the same degree profile (in expectation)

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- Why does it lose power in DCBM?
 - Degree matching: Can pair any alternative DCBM with a null model that has the same degree profile (in expectation)
 - Proof: Sinkhorn's matrix scaling theorem

The sub-DCBM with K = 2

sub-DCBM: severely un-balanced DCBM

As K = 2, we only have two communities, C_0 and C_1 . For $m \ll n$, suppose

$$P(ext{node } i ext{ belongs to community } \mathcal{C}_k) = \left\{egin{array}{c} 1-m/n, & k=0, \ m/n, & k=1 \end{array}
ight.$$

$$\Omega(i,j) = \begin{cases} \theta_i \theta_j \cdot a, & \text{if } i, j \in \mathcal{C}_1, \\ \theta_i \theta_j \cdot c, & \text{if } i, j \in \mathcal{C}_0, \\ \theta_i \theta_j \cdot b, & \text{otherwise.} \end{cases} \text{ where } b = \frac{nc - (a+c)m}{n-2m}.$$

Lemma: This parameterizes all sub-DCBMs with K = 2.

The sub-DCBM with K = 2, II

- We can pair the sub-DCBM with a null model Ω(i, j) = α · θ_iθ_j so that for each node, the expected degrees under the null and alternative are matched
- ▶ Naive degree-based χ^2 -test is asymptotically powerless
- The SgnQ test (TBA) has much better power



Simulation setting: $(n, m, c) = (100, 10, 0.1), \ \theta_i \equiv 1$

Next

- ▶ The naive χ^2 -test may lose power
- Question: How to find a fast, broadly implementable, and powerful test?
- Answer. The SgnQ test (TBA)
- Proposed by Jin, Ke, Luo (2021) but never studied for severely unbalanced DCBM

Note. Most of our ideas work for general DCBM, but we focus on sub-DCBM for completeness.



$$\psi_n = \frac{Q_n - 2(\|\hat{\eta}\|^2 - 1)^2}{\sqrt{8(\|\hat{\eta}\|^2 - 1)^4}}$$

Parameter-free limiting null (SgnQ test)

Theorem. Suppose $\Omega = \alpha \theta \theta'$, where $\|\theta\|_1 = n$, $n\alpha \to \infty$, and $\alpha \theta^2_{\max} \log(n^2 \alpha) \to 0$. As $n \to \infty$, $\psi_n \to N(0, 1)$ in distribution.

Proof. Mild adaptation of Jin, Ke, Luo (2021).

- Nontriviality: DCBM has numerous unknown parameters. It took years' efforts to find a test with an explicit and parameter-free limiting null distribution
- Applications: We can obtain an approximate *p*-value and use it for (a) measuring co-authorship diversity and (b) setting termination rule in a recursive/hierarchical community detection scheme

Carroll's personalized coauthor network

Data: Paper attributes in 36 journals, 1975-2015 (*Ji-Jin-Ke-Li, 2022*). The coauthorship network restricted to Carroll and his co-authors.



Left: Carroll's network (only nodes with > 40 degrees are shown). The SgnQ p-value is 0.019. **Right:** An identified small community of 17 authors. Restricted to this sub-network, the SgnQ p-value is 0.682.

Power of the SgnQ test

▶ $\operatorname{Var}(Q_n) \approx (\|\widehat{\eta}\|^2 - 1)^4 \approx \lambda_1^4$, and by Weyl's theorem, we can't use a rank-1 matrix to well-approx. a rank-K one:

$$egin{aligned} & \mathcal{Q}_n = \sum_{i_1,i_2,i_3,i_4(\textit{distinct})} \widehat{\mathcal{A}}_{i_1i_2} \widehat{\mathcal{A}}_{i_2i_3} \widehat{\mathcal{A}}_{i_3i_4} \widehat{\mathcal{A}}_{i_4i_1} \ & pprox ext{trace}([\Omega - \widehat{\eta} \widehat{\eta}']^4) \geq C \sum_{k=2}^K \lambda_k^4. \end{aligned}$$

Therefore, the power of the SgnQ test hinges on

$$\frac{\sum_{k=2}^{K} \lambda_k^4}{\lambda_1^2} \asymp \left(\frac{\lambda_2}{\sqrt{\lambda_1}}\right)^4$$

Power of SgnQ under the sub-DCBM

In the sub-DCBM with K = 2, $|C_1| = m$ and $|C_0| = n - m$, and

$$\Omega(i,j) = \begin{cases} \theta_i \theta_j \cdot a, & \text{if } i, j \in \mathcal{C}_1, \\ \theta_i \theta_j \cdot c, & \text{if } i, j \in \mathcal{C}_0, \\ \theta_i \theta_j \cdot b, & \text{otherwise.} \end{cases} \quad \text{where } b = \frac{nc - (a+c)m}{n-2m}.$$

Theorem. Consider a sub-DCBM with K = 2 where $\theta_{\max} \leq C\theta_{\min}$ and $nc \to \infty$. Suppose as $n \to \infty$,

$$m(a-c)/\sqrt{cn} \to \infty$$

- For any fixed α , the power of level- α SgnQ test $\rightarrow 1$.
- Theorem also holds under severe degree-heterogeneity (with appropriate regularity conditions)



Phase transition

- Computationally easy: There is a polynomial-time test whose sum of type I and type II errors → 0.
- Statistically possible but computationally hard: For any poly-time test, sum of type I and type II errors → 1.
- Statistically impossible: For any test, the sum of type I and type II errors $\rightarrow 1$.



Phase transition (sub-DCBM, $m \gg \sqrt{n}$)

Theorem. In the sub-DCBM with K = 2, assume $\theta_{\max} \leq C\theta_{\min}$ and $nc \to \infty$. As $n \to \infty$,

Easy: if $m(a - c)/\sqrt{nc} \to \infty$, then SgnQ test satisfies Type I + Type II error $\to 0$

Hard: if $m(a - c)/\sqrt{nc} \rightarrow 0$, no poly-time test exists¹ with Type I + Type II error $\rightarrow 0$

Impossible: if $\sqrt{\frac{n}{m}} \cdot m(a-c)/\sqrt{nc} \to 0$, no test (even non-polytime) has Type I + Type II error $\to 0$

Therefore, there is a gap between **statistically possible** and **computationally possible**, but fortunately, the SgnQ test is optimal among all polynomial time tests.

¹conditionally on the *low-degree conjecture* (Hopkins, 2018)

Phase transition (sub-DCBM, $m \ll \sqrt{n}$)

The case of $m \ll \sqrt{n}$ is more complicated, and how to close the gap between **statistically possible** and **computationally possible** remains an open problem

Theorem. In the sub-DCBM model with K = 2, assume $\theta_{\max} \leq C\theta_{\min}$ and $nc \to \infty$. As $n \to \infty$,

Easy: if $m(a - c)/\sqrt{nc} \to \infty$, then SgnQ test satisfies Type I + Type II error $\to 0$

Hard: if $\frac{\sqrt{n}}{m} \cdot m(a-c)/\sqrt{nc} \to 0$, no poly-time test exists² with Type I + Type II error $\to 0$

Impossible: if $\sqrt{\frac{n}{m}} \cdot m(a-c)/\sqrt{nc} \rightarrow 0$, no test (even non-polytime) has Type I + Type II error $\rightarrow 0$

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Phase transition visualization

Recall that in the sub-DCBM with K = 2, $|C_1| = m$ and $|C_0| = n - m$, and

$$\Omega(i,j) = \begin{cases} \theta_i \theta_j \cdot a, & \text{if } i, j \in \mathcal{C}_1, \\ \theta_i \theta_j \cdot c, & \text{if } i, j \in \mathcal{C}_0, \\ \theta_i \theta_j \cdot b, & \text{otherwise.} \end{cases} \quad \text{where } b = \frac{nc - (a+c)m}{n-2m}.$$

For visualization, we fix parameters $\beta, \gamma \in (0, 1)$ and let

Small community size :
$$m = n^{1-\beta}$$

Nodewise SNR : $\frac{a-c}{\sqrt{c}} = n^{-\gamma}$.

Phase transition visualization, II



Take home message

- The SgnQ test is fast, has computable p-values, and is powerful against a broad class of alternatives.
- In broad network (or hypergraph) models, degree-based tests may lose power from *degree-matching*.
- If m ≪ √n, SgnQ test is the optimal polynomial time test. If m ≫ √n, it is an interesting open problem to close the statistical-computational gap.

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Thanks!