



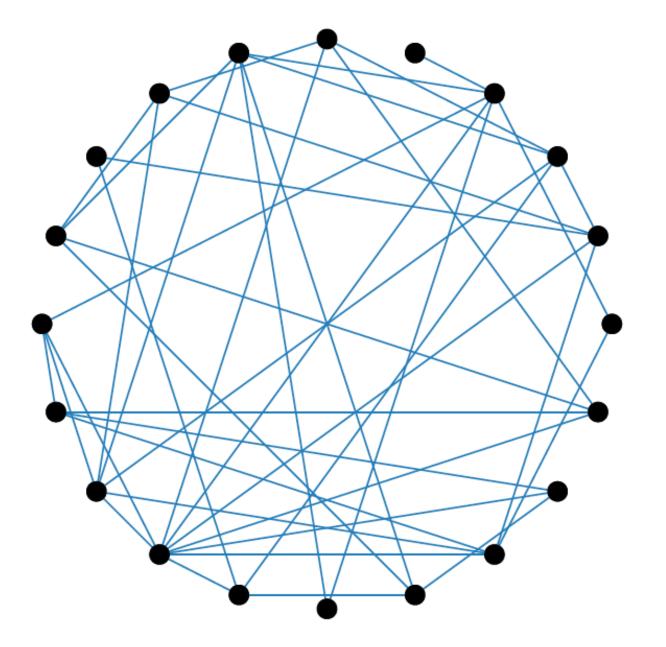
# Nonlinear Laplacians

Tunable principal component analysis under directional prior information

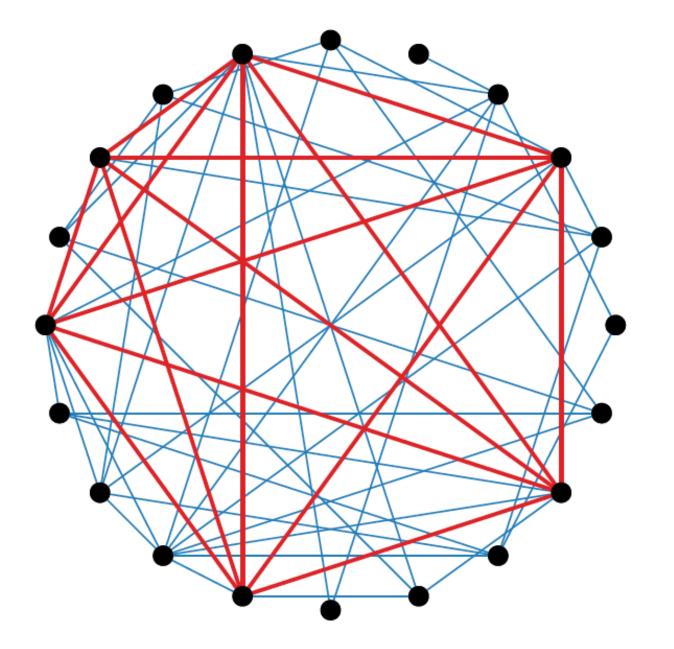
Yuxin Ma, Dmitriy (Tim) Kunisky

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• Draw G an Erdős–Rényi graph with n nodes. (Each edge independently with probability 1/2).



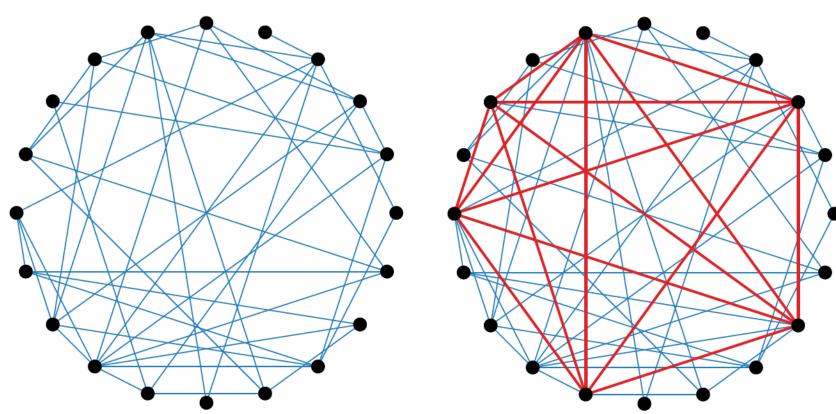
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#### Want to either

- **Detection:** decide whether  $S = \emptyset$ . (Whether a clique is planted).
- Estimation: produce  $\hat{S} \approx S$ . (Recover the clique).



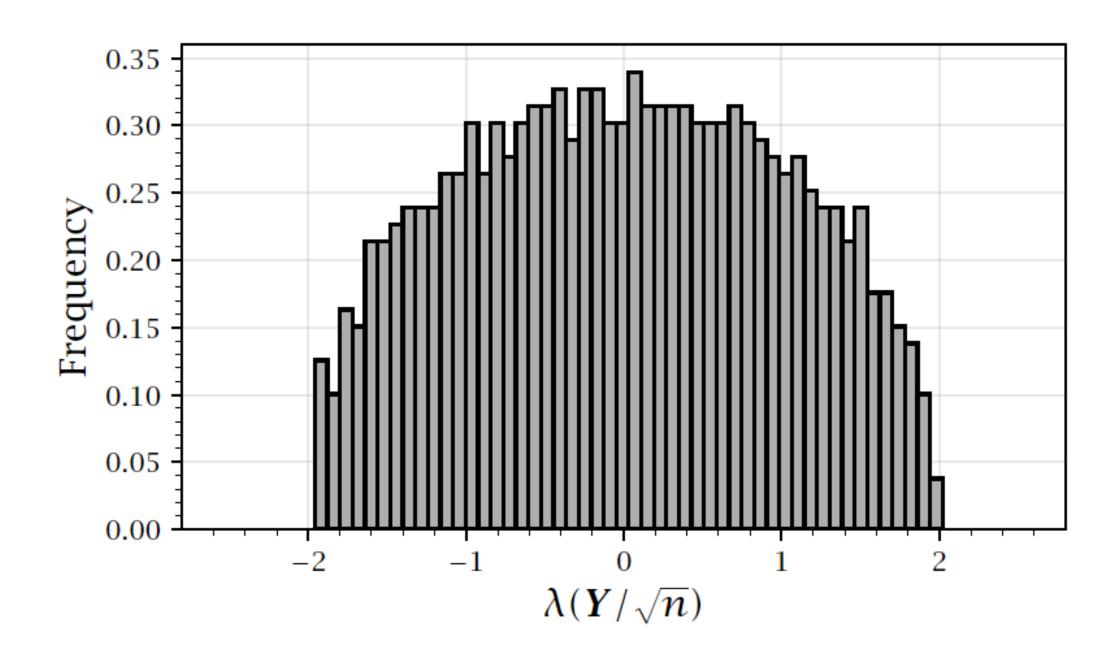
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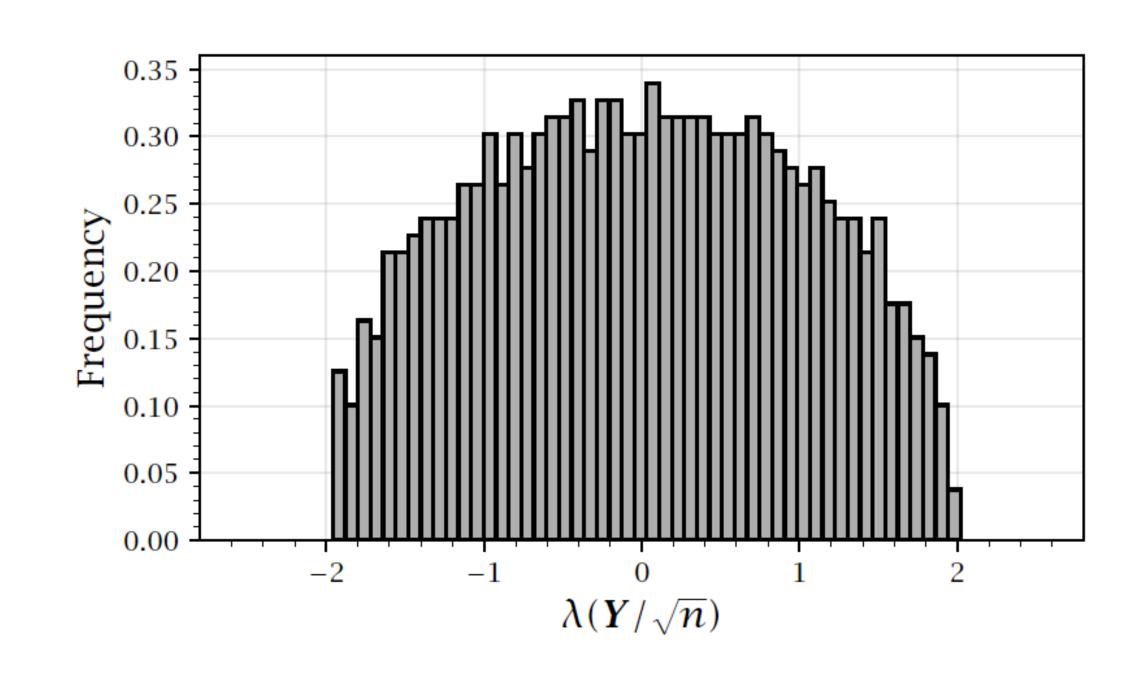
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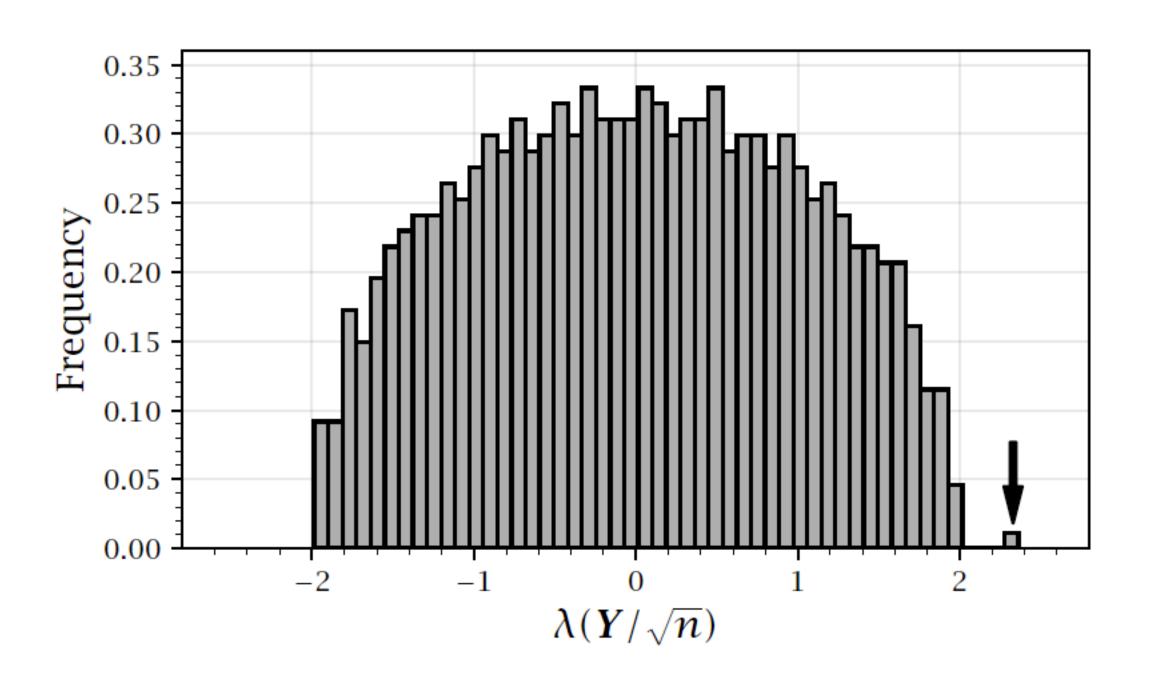
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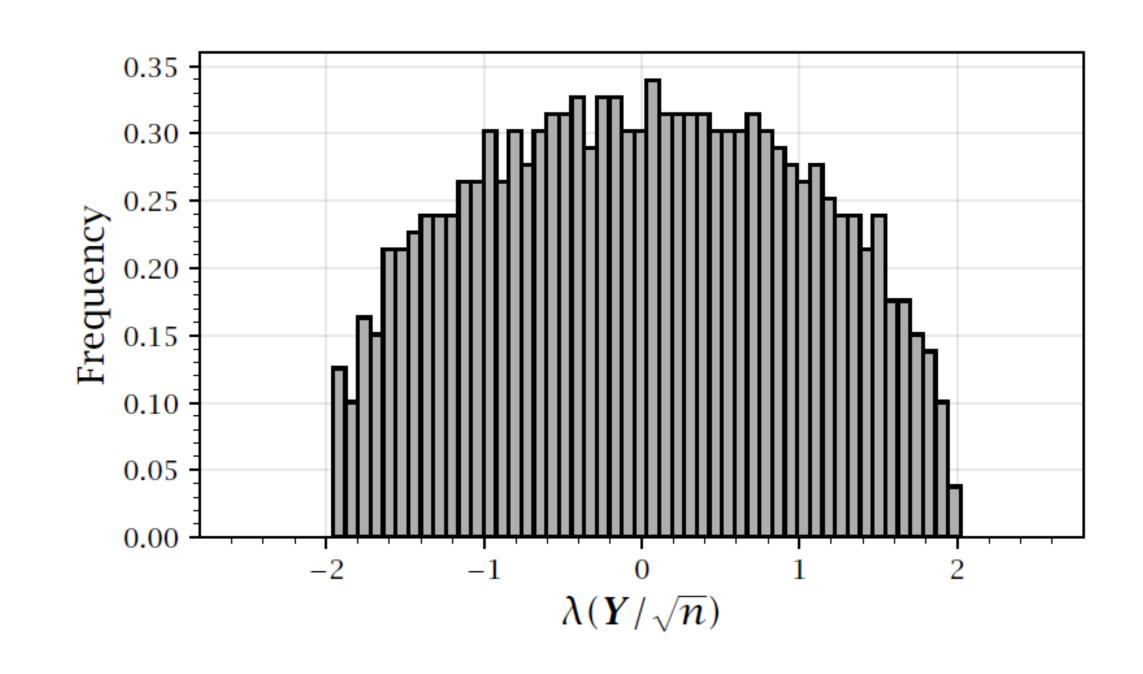
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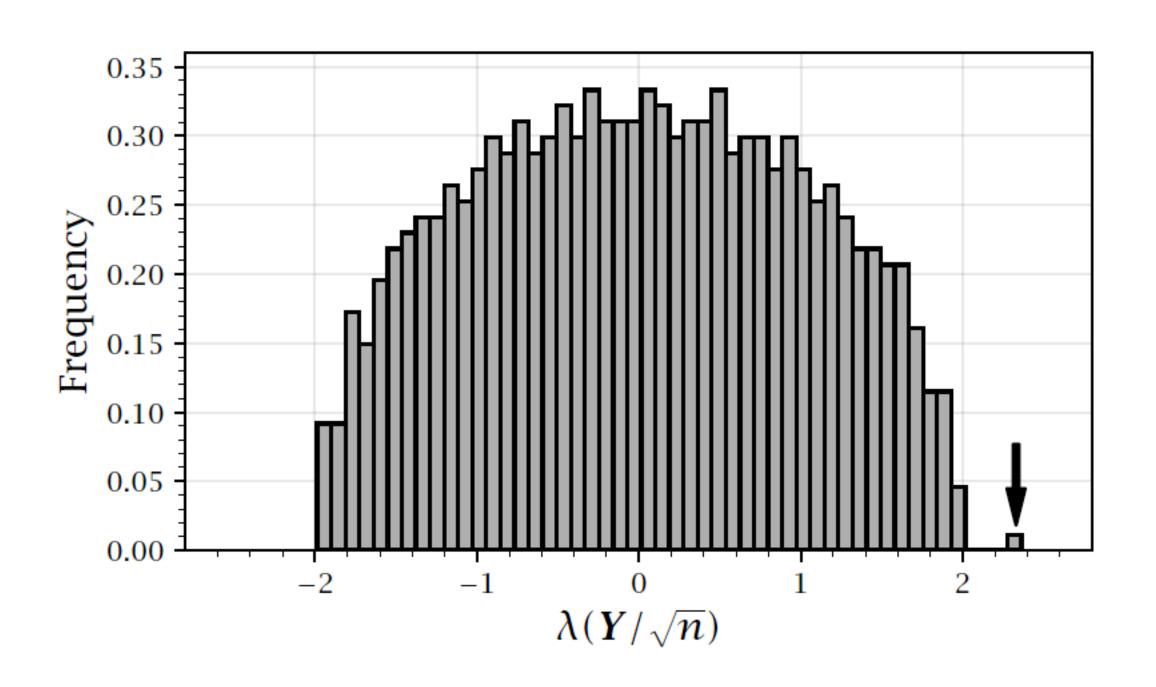




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- $\mathbf{Y} \approx \mathbf{1}_S \mathbf{1}_S^{\top} + \text{(i.i.d. noise matrix)}$
- Outlier eigenvalue  $\iff |S| > \sqrt{n}$





- Detection: decide there's a planted clique if  $\lambda_1\left(\frac{\mathbf{Y}}{\sqrt{n}}\right)>2+\varepsilon$  Estimation:  $v_1\left(\frac{\mathbf{Y}}{\sqrt{n}}\right)\approx\frac{\mathbf{1}_S}{\|\mathbf{1}_S\|}$

Non-trivial detection and estimation  $\iff |S| > \sqrt{n}$ 

The naive spectral algorithm discards crucial prior information: it works for any rank-one estimation  $\mathbf{Y} = xx^\top + (\text{i.i.d. noise matrix})$ 

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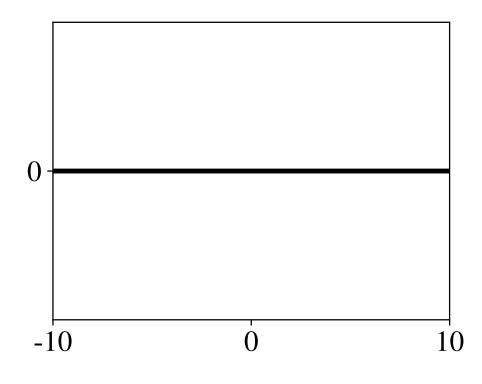
**Idea:** Use  $\lambda_1$ ,  $v_1$  of the Nonlinear Laplacian matrix

$$\mathbf{L}_{\sigma}(\mathbf{Y}) = \hat{\mathbf{Y}} + \operatorname{diag}(\sigma(\hat{\mathbf{Y}}\mathbf{1})), \quad \hat{\mathbf{Y}} = \frac{\mathbf{Y}}{\sqrt{n}}$$

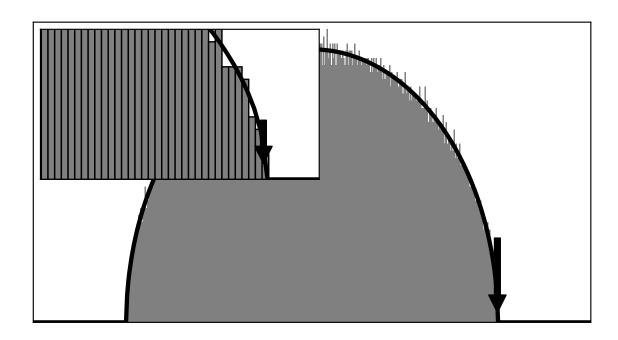
- ullet  $\hat{\mathbf{Y}}\mathbf{1}$  captures the degree information.
- $\sigma: \mathbb{R} \to \mathbb{R}$  bounded and monotone, applied entry-wise.

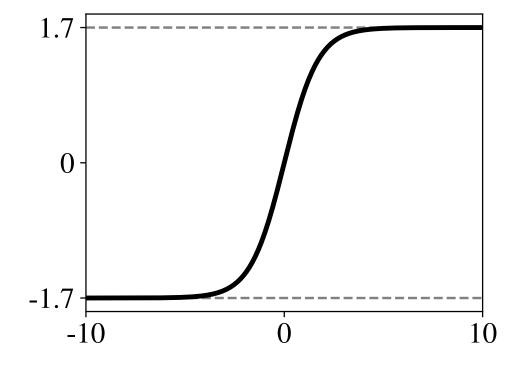
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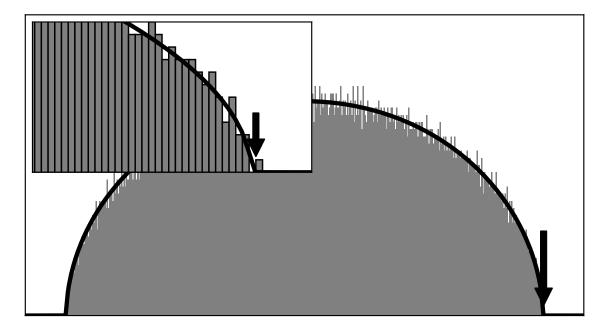
#### Nonlinearity $\sigma$



Eigenvalues: |S| = 0

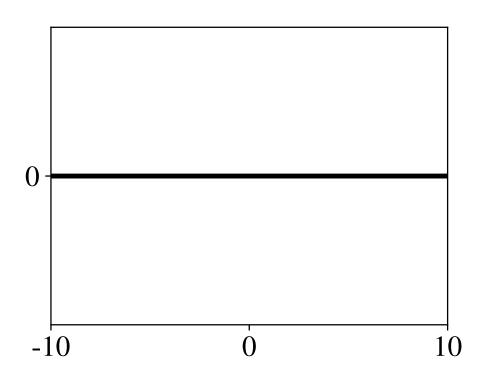




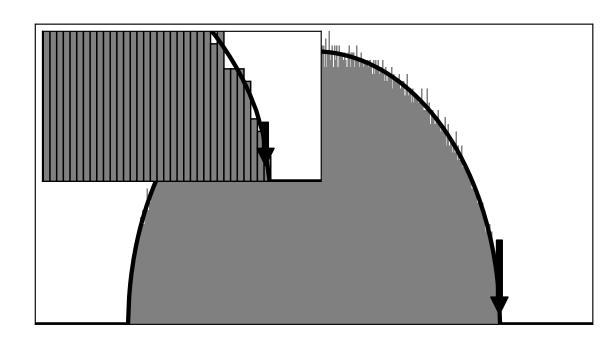


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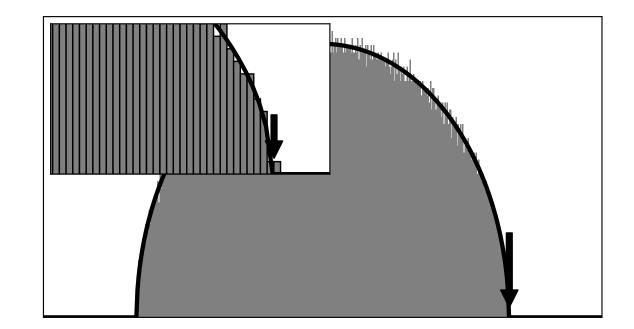
Nonlinearity  $\sigma$ 

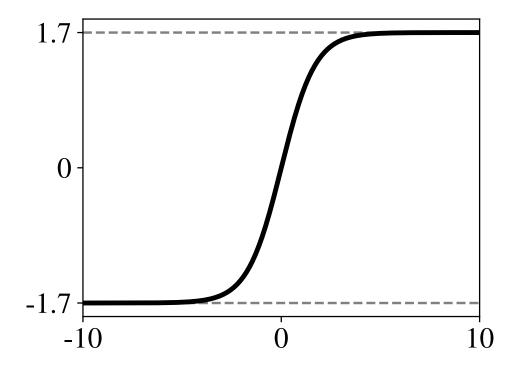


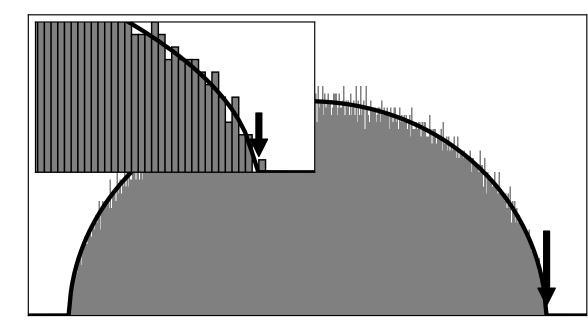
Eigenvalues: |S| = 0  $|S| = 0.9\sqrt{n}$ 

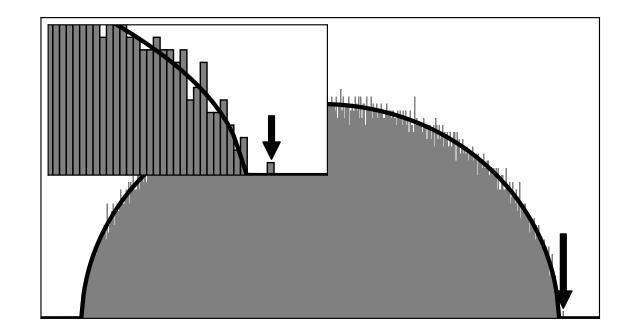


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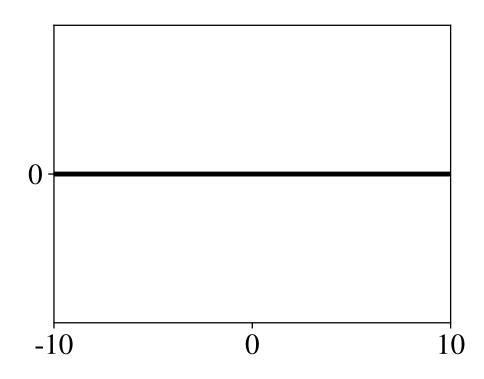




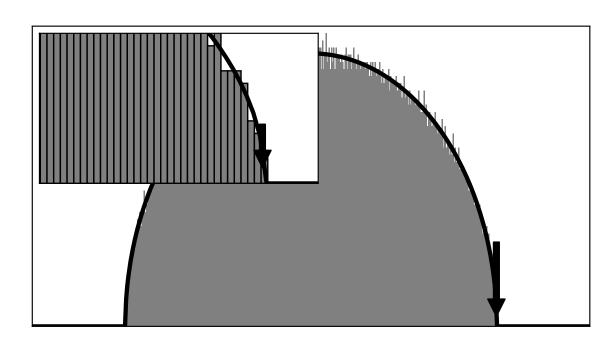


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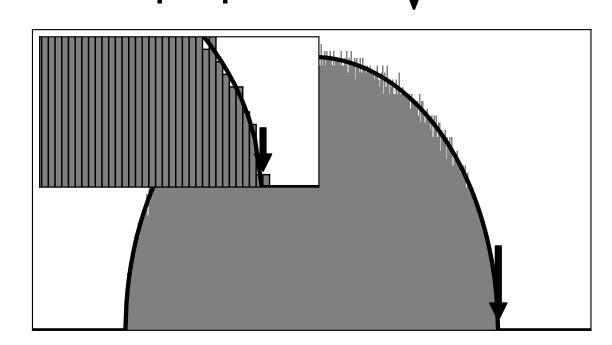
Nonlinearity  $\sigma$ 



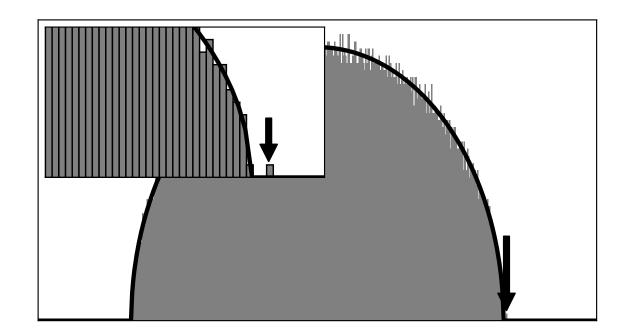
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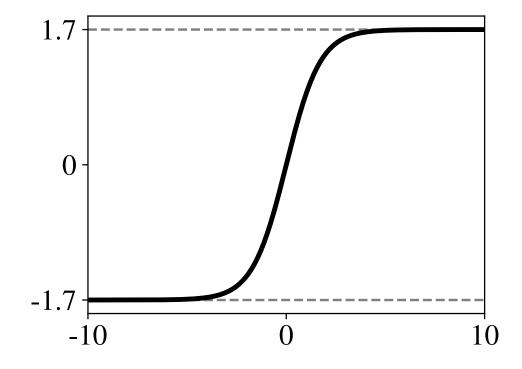


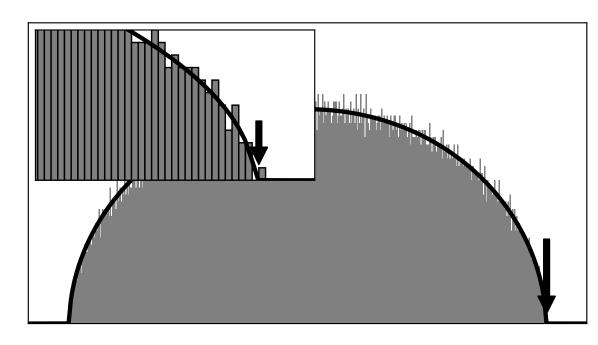
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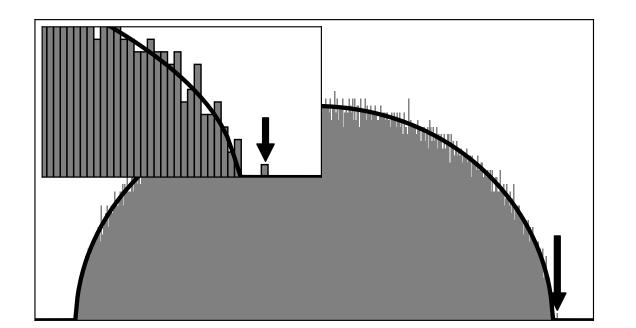


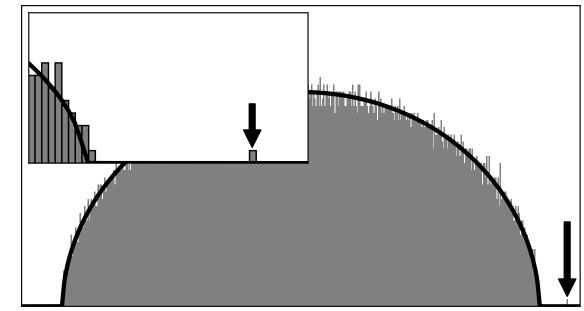
$$|S| = 1.2\sqrt{n}$$



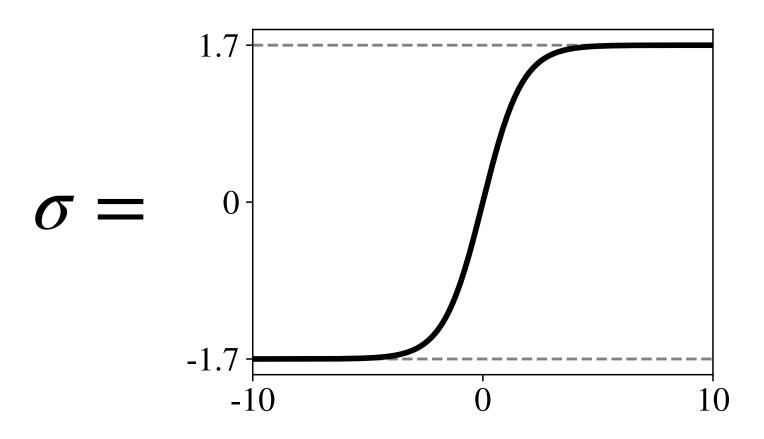








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- For any clique size  $<\sqrt{n}$ , neither the spectral information alone nor the degree information alone cannot detect.
- By combining them in this simple way, we achieve detection for any clique size  $> 0.76 \sqrt{n}$ .

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Poster on Thursday 4 Dec, 4:30 - 7:30 pm PST.