# HEART: Statistics and Data Science With Networks

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#### Outline

Mutiple Graph Models

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Observe L graphs (L = number of layers)

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- Easy example: friendships evolving each year

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- How to perform spectral clustering?

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which is just Erdos-Renyi! So  $\bar{A}$  loses information. Ways around this: Paper 1, Paper 2, among others.

## Multilayer Random Graphs beyond Stochastic Blockmodels

- COSIE Model
- Multilayer RDPG
- Mixture Multilayer SBM
- Dimple
- Multilayer Networks with Vertex Community Flips
- More General Models

## Computing Graph Embeddings from Multiple Graphs

- Omnibus Embedding (*L* is not too big)
  - Paper 1
  - Paper 2
  - Paper 3

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- Omnibus Embedding (L is not too big)
  - Paper 1
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- What if L is big?
  - Tensor Methods
  - Bias-Adjusted Spectral Embedding
  - MASE (parallelizable)

#### **Practical Considerations**

- Typically want to obtain a single vertex representation for all graphs
- If L and n are both big, may not want to do complicated techniques for computing reasons
- Sometimes L is small, so omnibus embedding is not too bad
- Sometimes graphs are sparse, so need to design algorithms that allow for very sparse graphs