



# Laplace, Fiedler, & Markov: A Graph Reconstruction Problem

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- 1 Motivation
- 2 Laplacian and Fiedler
- 3 Partitioning Process
- 4 Computational Methods
- 5 Reconstructibility
- 6 Quarrels, Queries, and Quotes

# Dedication

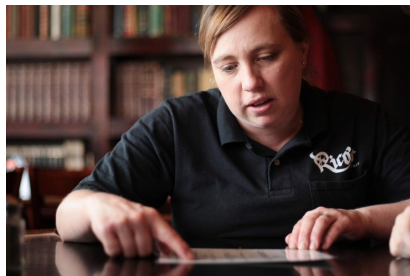


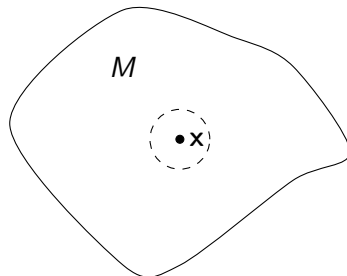
Figure 1: Tawny - Human Extraordinaire

## Question (Asked at Rico's)

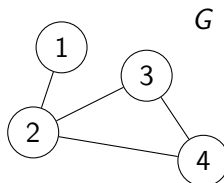
There are 3 bags with  $k$  objects in each. Each pair of bags share  $k - 1$  objects though no bag is the same. How many objects *must* all three share?

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- Let  $x$  be some element in a set  $M$ . Define some function  $u$  over points in  $M$  (i.e. temperature).
- At  $x$ , calculate the difference between the value of  $u$  over some neighborhood of  $x$  and its value at  $x$  (i.e.  
$$\Delta u_x = \frac{d^2 u}{dx_1^2} + \frac{d^2 u}{dx_2^2} + \dots + \frac{d^2 u}{dx_n^2}$$
). Think second derivative test.
- The Laplacian  $\Delta u$  can tell us about the "propagation" of  $u$  over  $M$ .



- Let  $i$  be some node in a graph  $G$ . Define some function  $f$  over nodes in  $G$  (i.e. temperature).
- At  $i$ , calculate the difference between the value of  $f$  over the neighbors of  $i$  and its value at  $i$  (i.e.  
$$L(f(i)) = \sum_{j \sim i} f(i) - f(j).$$
- The Laplacian  $L$  can tell us about the "propagation" of  $f$  through  $G$ .



# Questions of Quantity

## Question

Given a function  $u$  over  $M$ , how can we measure how well  $u$  propagates?

## Question

Given a function  $f$  over  $G$ , how can we measure how well  $f$  propagates?

# Questions of Quantity

## Answer

In the discrete case, through the exploration of the *edge conductance*  $\phi(G)$  for  $S \subset V$ :

$$\phi(S) = \frac{|E(S, V \setminus S)|}{\text{vol}(S)} \text{ and } \phi(G) = \min_S \phi(S)$$

where  $\text{vol}(S) = \sum_{v \in S} \deg(v)$



# Questions of Location

## Question

Given a set  $M$ , how can we find where  $u$  does not propagate well?

## Question

Given a graph  $G$ , how can we find where  $f$  does not propagate well?

## Answer

This line of questioning leads to the *Sparsest Cut Problem*. The goal of which is to find the edges  $E(S, V \setminus S)$  such that  $\phi(S)$  is minimized. This problem is very much NP Hard, but approximation algorithms exist. Some rely on what we call the Fiedler vector!

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# Preliminaries

## Definition

Let  $G = (V, E)$  be an undirected graph on  $n$  nodes. The *Laplacian* of  $G$  is the matrix  $L = L(G) \in M_n$  defined as follows:

$$L_{ij} = \begin{cases} \text{degree of node } i & \text{if } i = j \\ -1 & \text{if } i \neq j \text{ and node } i \sim \text{node } j \\ 0 & \text{if } i \neq j \text{ and node } i \not\sim \text{node } j \end{cases}$$

with eigenvalues  $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$ .

Properties:

- $L$  is symmetric, positive-semidefinite  $\implies L$  has nonnegative eigenvalues
- 0 is an eigenvalue of  $L$  corresponding to the all ones vector  $\mathbb{1}$

# Fiedler Miracles

## Definition

We call the second smallest eigenvalue of  $L$ ,  $\lambda_2$ , and its corresponding eigenvector the *Fiedler value* and *Fiedler vector* respectively.

## Theorem

*For undirected  $G$ , we obtain Cheeger's Inequality:*

$$\frac{\lambda_2}{2} \leq \phi(G) \leq \sqrt{2\lambda_2}$$

*Informally, the amount of "bottlenecking" in a graph is bounded by the Fiedler value.*

# Fiedler Miracles

## Theorem

*For undirected  $G$ , we obtain Cheeger's Inequality:*

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*Informally, the amount of "bottlenecking" in a graph is bounded by the Fiedler value.*

## Theorem

*Let  $G = (V, E)$  be a connected graph and let  $x$  be its corresponding Fiedler vector. Then the subgraphs induced by the vertex sets  $V_1 = \{i : x_i > 0\}$  and  $V_2 = V \setminus V_1$  are connected. Informally, we can partition  $G$  in to two connected components using the entries of the Fiedler vector.*

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# To Do

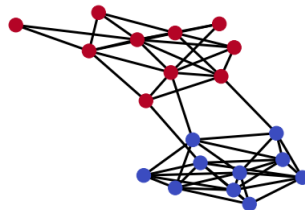
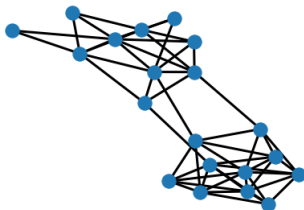
- ① partitioning process and examples with their fiedler vector and value:
  - ① graph with phi fiedler entries
  - ② real nasty horrible unintuitive graph
  - ③ another fun graph

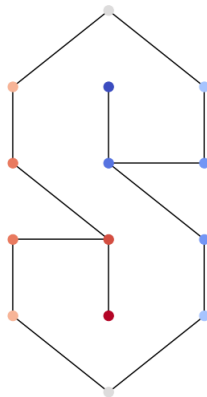
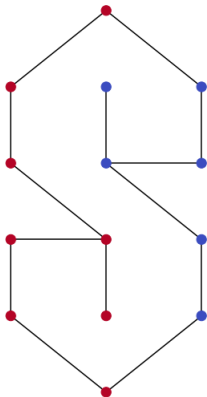
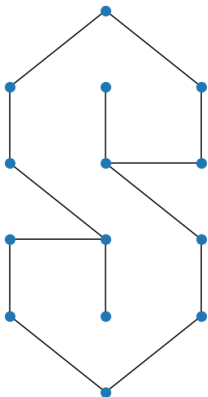
Intuition:

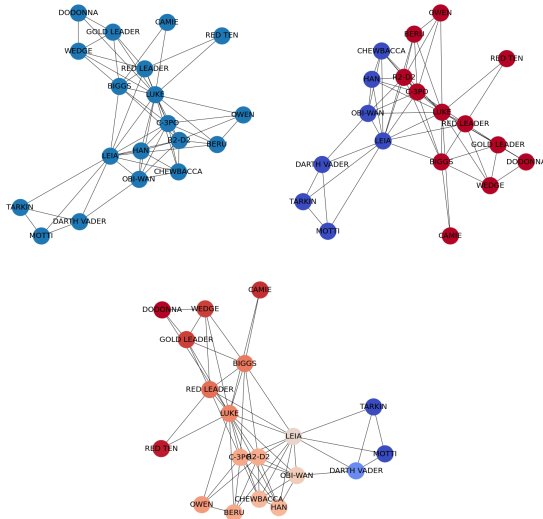
- There is a bottleneck in the graph  $G$ .
- The bottleneck is approximated by the Fiedler value.
- Using the Fiedler vector, cutting edges that connect oppositely signed nodes will result in a relatively efficient bi-partition cut.

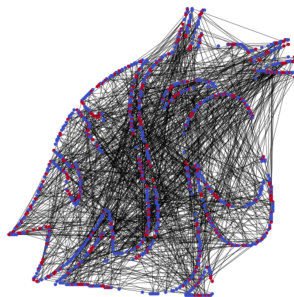
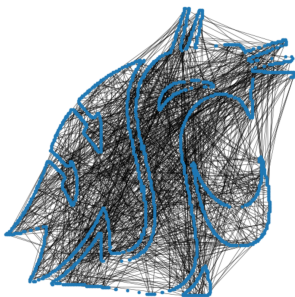


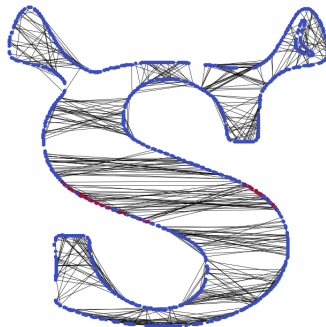
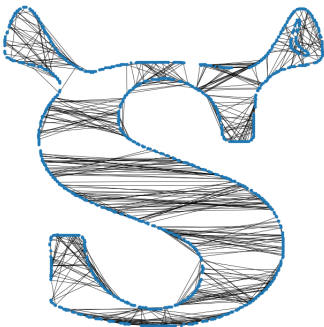




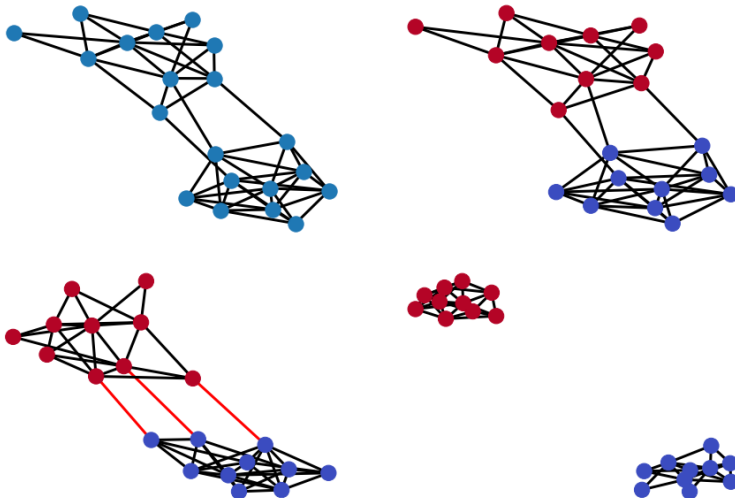








# The Process



## Question

Given a Fiedler-partitioned graph  $G$ , is the Fiedler cut unique for every  $x$  or every  $\lambda$ ? Is it unique for every pair  $(x, \lambda)$ ?

## Question

Given a  $x$ ,  $\lambda$ , or the pair  $(x, \lambda)$ , is there a way to generate graphs with  $(x, \lambda)$  as their Fiedler vector and Fiedler value?



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# MCMC!

# Brief Overview of Metropolis-Hastings

## General Idea:

- We want to sample from distribution  $P$  over space  $X$ , but we cannot compute probabilities directly.
- So, we apply some score function  $f$  over  $X$  and pick a proposal distribution  $Q$  over  $X$  (ideally one that we know/that is easy to compute/has specific properties/etc).
- We start at some state  $x_n$  and generate a proposal state  $y$  using  $Q$ .
- Comparing our scores, we compute an acceptance probability

$$\alpha = \min \left( 1, \frac{f(y)}{f(x_n)} \frac{Q_{y, x_n}}{Q_{x_n, y}} \right)$$

- Pick a number  $\beta$  uniformly at random from  $[0, 1]$ .
- If  $\beta < \alpha$ ,  $x_{n+1} = y$ . If not,  $x_{n+1} = x_n$ .

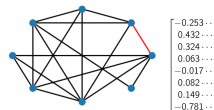
# First Steps

- Initialize: Start at some step  $x_n$  in our Markov chain.
- Proposal: Generate a proposed next step  $y$ .
- Transition: Calculate acceptance probability  $\alpha$ . Compare to uniformly random  $\beta \in [0, 1]$ . Accept if  $\beta < \alpha$ . Stay otherwise.
- Convergence: Wait!

- Initialize:

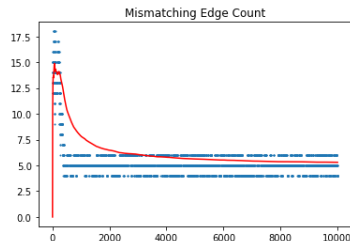
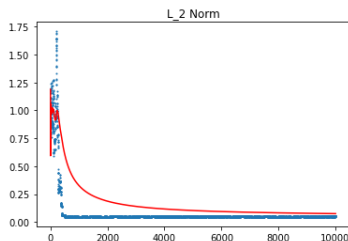


- Proposal:



- Transition: Calculate  $\alpha$  where  $f(x) \propto \|fied_x - fied_{desired}\|_2$ . Compare. Accept/Reject.
- Convergence: Wait!

# Results



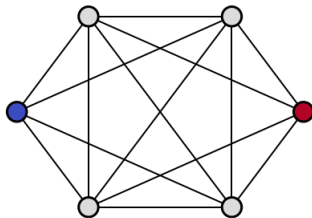
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# MCMC Implications on Uniqueness

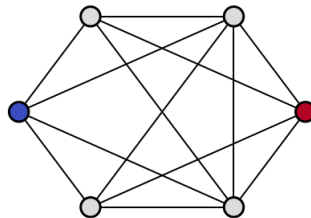
- 1 An immediate observation can be made from working with MCMC in this way:

Depending on the desired graph, some proposal states will continue to be accepted even after convergence to within an arbitrary distance of the desired distribution.

- 2 In other words, some graphs do not have a unique adjacency structure corresponding to their Fiedler vector!



$$\sigma(L(G)) = \{0, 4, 6, 6, 6, 6\}$$



$$\sigma(L(G)) = \{0, 4, 4, 6, 6, 6\}$$



# Combinatorial Intuition

- "Good Reconstructible":
  - ① Given a Fiedler vector  $x$  and collection of neighborhoods  $S_i$  of node  $i \in V(G)$
  - ② What we want is the size of  $S_i$  to be as small as possible for every node in  $G$
  - ③  $|S_i| = 1$  for all  $i$  in  $G$  implies uniquely reconstructible!
- "Bad Reconstructible":
  - ① Given a Fiedler vector  $x$  and collection of neighborhoods  $S_i$  of node  $i \in V(G)$
  - ② What we want is the size of  $S_i$  to be as large as possible for every node in  $G$

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# Hmm...

- 1 Can we guarantee existence or non-existence of any edge in  $G$  given  $(x, \lambda)$ ?
- 2 Can we find a graph with a uniquely determined Fiedler cut? If so, count all the graphs like this.
- 3 We can reconstruct a graph entirely if we know all of its eigenvalues and eigenvectors. What properties of  $G$  allow us to reconstruct the graph if we know  $k < n$  of them?
- 4 What methods allow us to most quickly estimate the edges in  $G$ ?