

Time Series of Dot Product Graphs

David J. Marchette

dmarchette@gmail.com

Collaborators: Carey Priebe, Ed Scheinerman and others

Naval Surface Warfare Center
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Outline

Introduction

Modeling Random Graphs

Dot Product Graphs

Model Fitting

Model Selection

Interstate Alliances



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Introduction

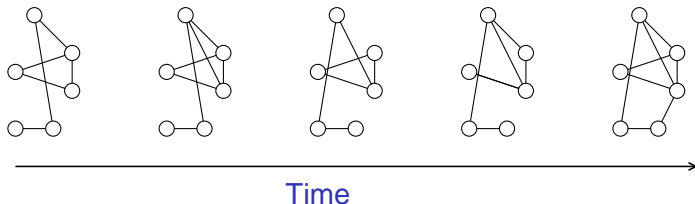
- ▶ Pattern recognition applications today involve very complex, high dimensional, and huge data sets.
- ▶ Traditional methods in \mathbb{R}^d are no longer sufficient.
- ▶ What's needed are methods to operate on complex, changing data types.
- ▶ This talk will focus on one specific type of problem: recognition of changes (anomalies) in a time series of graphs.



What is a Time Series of Graphs?

A time series of graphs is:

- ▶ A graph valued random variable indexed by time.
- ▶ An ordered sequence of random graphs.



Why?

Time series of graphs are becoming more and more common:

- ▶ Communication graphs
- ▶ Social networks
- ▶ Biological networks

We need methods to:

- ▶ Model the time series
- ▶ Detect changes in the underlying model
- ▶ Interpret the model within the framework of the application



Analysis of Time Series of Graphs

The traditional way of analyzing time series of graphs is to convert to a time series of real numbers (or vectors) and use standard time series methods.

- ▶ Compute an invariant of each graph:
 - ▶ Number/density of edges
 - ▶ Maximal clique size
 - ▶ Scan statistic
- ▶ So $G_1, G_2, \dots, G_t, \dots \Rightarrow \mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_t, \dots$



Another Approach

Model the time series as a random variable indexed by time:

- ▶ Define a random graph model.
- ▶ Parameterize the model in some way.
- ▶ Let the parameter vary in time.



Erdős-Rényi Random Graphs

The simplest and most common type of random graph is the Erdős-Rényi random graph:

- ▶ Given a probability p
- ▶ Place an edge $v_i v_j$ between vertices v_i and v_j with probability p .
- ▶ This results in a “time series” of independent random graphs.
- ▶ We can change this to a more interesting time series by making p depend on time: p_t .
- ▶ How can we extend this to a more interesting/relevant model?



Social Network Motivation

- ▶ A social network is a set of vertices corresponding to “actors” (individual entities) and edges representing relationships.
- ▶ Our intuition is that actors with similar interests should be related: In some sense, the probability of an edge should be proportional to the amount of overlap of interests.



Intersection Graph

- ▶ Each vertex v_i has associated with it a (random) set S_i .
- ▶ Place an edge $v_i v_j$ between vertices v_i and v_j if $S_i \cap S_j \neq \emptyset$ (or $|S_i \cap S_j| > \tau$).
- ▶ The randomness of the graph results from the random sets.
- ▶ Alternatively, one could place the edge with probability
$$p_{ij} = \frac{|S_i \cap S_j|}{|S_i \cup S_j|}.$$
- ▶ In this case, the sets need not be random, but the graph still is, and the edges are no longer independent.



Random Dot Product Graphs (Scheinerman)

- ▶ Each vertex v_i has associated with it a vector x_i .
- ▶ Place an edge $v_i v_j$ between vertices v_i and v_j with probability proportional to $x_i x_j$, the dot product of x_i and x_j .
- ▶ Thus $p_{ij} = f(x_i x_j)$. I will use the identity function in this talk.
- ▶ The edges in the random graph are no longer independent.
- ▶ Further, this can be interpreted in the manner of our social network motivation.
- ▶ Random dot product graphs are generalizations of intersection graphs, and a special case of the latent position model.
- ▶ We can now make a time series model by placing a time series model on the vectors x .



Social Networks Revisited

The attributes of an actor define the vector associated with the actor.

$$\left\{ \begin{array}{l} \textit{Religion} \\ \textit{Education} \\ \textit{Sports} \\ \textit{Food} \\ \textit{TV} \end{array} \right\} \Rightarrow \left\{ \begin{array}{l} \textit{categorical} \\ \textit{ordinal} \\ \textit{categorical} \\ \textit{high - dimensional} \\ \textit{categorical} \end{array} \right\} \not\Rightarrow \left\{ \begin{array}{l} 0.2 \\ 0.4 \\ 0.01 \\ 0.5 \end{array} \right\}$$

Note that the vector does not necessarily correspond to any simple (known or even knowable) mapping of the attributes.

“It’s only a model.” M. Python.



Groups

- ▶ We will assume that there are a small number (K) of distinct vectors.
 - ▶ For regularization.
 - ▶ To detect underlying groupings of the data.
- ▶ These groups correspond to sets of vertices with the same within-group probability and inter-group probabilities.



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Fitting the Model

Given a graph (or a collection of graphs) how do we determine the vectors?

- ▶ Important issues:
 - ▶ How many distinct x vectors are there? (What is K ?)
 - ▶ What is the dimensionality d of x ?
- ▶ Several methods have been suggested, given that we know d , the dimensionality of the vectors x . We will assume an arbitrary value for d ($d = 2$).



Maximum Likelihood Approach

The edges are not independent, but they are conditionally independent (given the vectors x). Thus the likelihood is:

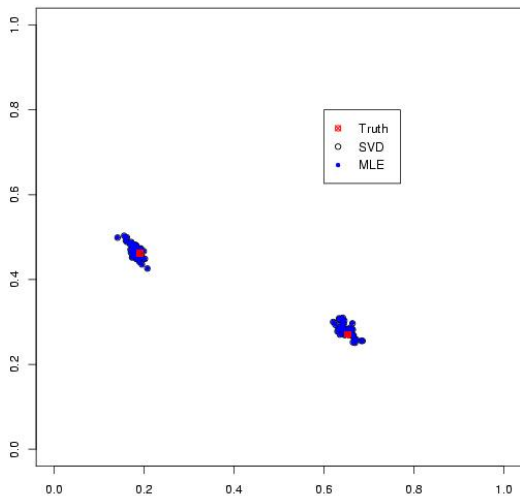
$$\begin{aligned}L(G) &= \left(\prod_{ij \in E} (x_i x_j) \right) \left(\prod_{ij \notin E} (1 - x_i x_j) \right) \\ &= \prod_{ij} (x_i x_j)^{a_{ij}} (1 - x_i x_j)^{1 - a_{ij}} \\ I(G) &= \sum_{ij} a_{ij} \log(x_i x_j) + (1 - a_{ij}) \log(1 - x_i x_j)\end{aligned}$$

Select X to maximize $I(G)$. Note that the extension to multiple graphs is easy, assuming independence.



Example

100 Graphs



Comments

These aren't really what one gets when one runs these algorithms.

- ▶ Any rotation of a solution is a solution.
- ▶ Thus the solutions needed to be rotated into the first quadrant.
- ▶ I rotated them so that the center fell on the 45° line.
- ▶ This is critical when considering time series, and detecting change points.
- ▶ I used procrustes to match the vectors.



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Model Selection: d

How does one choose the dimension d ?

- ▶ Relying on a questionnaire or one's intuition is a **bad** idea.
- ▶ Try $d = 1$. If the fit is good, stop. If not try $d = 2 \dots$
- ▶ Pick d arbitrarily and proceed blindly.



Model Selection: K

Suppose there are only K distinct values (associated with K distinct populations) for the x vector; how to find K ?

- ▶ Proposal 1:
 1. Derive a penalty for K .
 2. Use maximum penalized likelihood.
- ▶ Proposal 2:
 1. Fit x unconstrained (using whatever method works).
 2. Treat the n values of x as d -dimensional observations in \mathbb{R}^d (or appropriate sub-manifold). Use a model selection algorithm in this space to select K .
 3. Re-fit x constrained by the selected model.
- ▶ Proposal 3:
 1. Cluster the vertices of the graph.
 2. Use this clustering to select K .
- ▶ I'll use proposal 2.

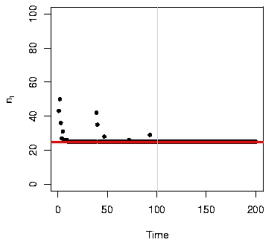
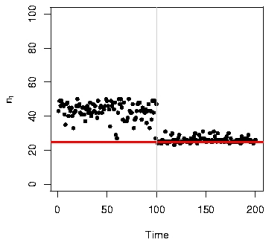
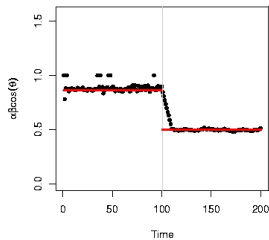
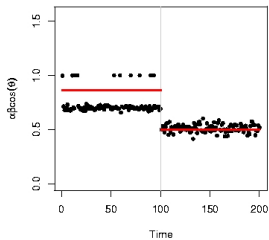


Time Series

- ▶ Rather than treat each graph independently, we'll average within a window W .
- ▶ The adjacency matrix now becomes the average of the adjacency matrices, an estimate of the edge probabilities.
- ▶ This assumes (approximate) independence in the window.
- ▶ Want W small to detect changes.
- ▶ Want W large to improve fit.



An Example: Changepoint in Vectors

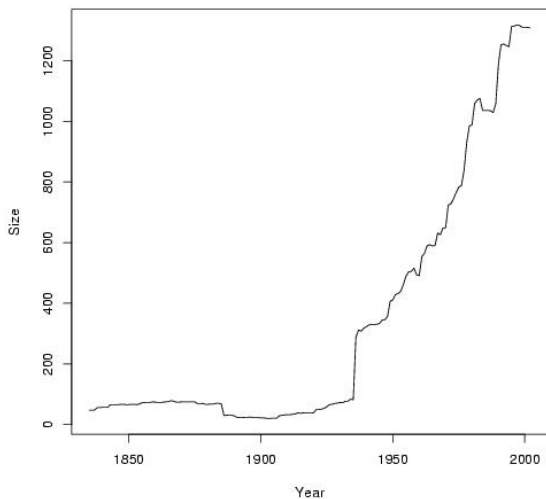


Interstate Alliances

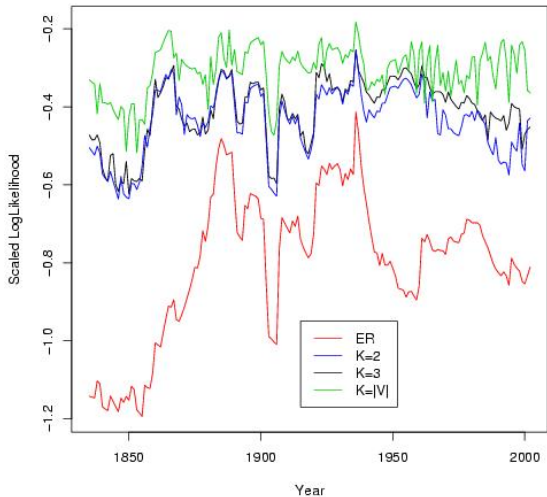
- ▶ Data from 1816-2000.
- ▶ One graph per year:
 - ▶ Each country (nation state) is a vertex.
 - ▶ Each edge indicates an alliance between countries:
 - ▶ 0 or NA – no alliance.
 - ▶ 1 – defense pact.
 - ▶ 2 – neutrality pact.
 - ▶ 3 – nonaggression pact.
 - ▶ We'll binarize to alliance vs. no alliance.
- ▶ $W = 20$.



Sizes of the Graphs



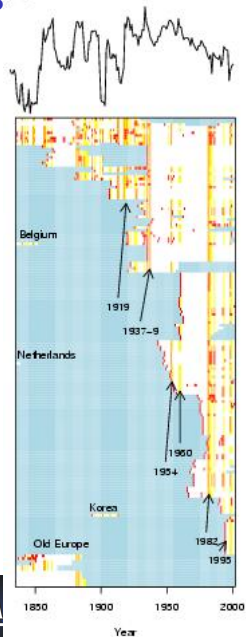
Scaled Log Likelihoods



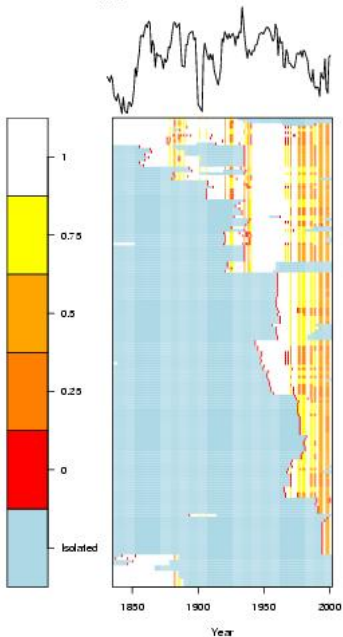
Scaled by $\frac{|V|(|V|-1)}{2}$.



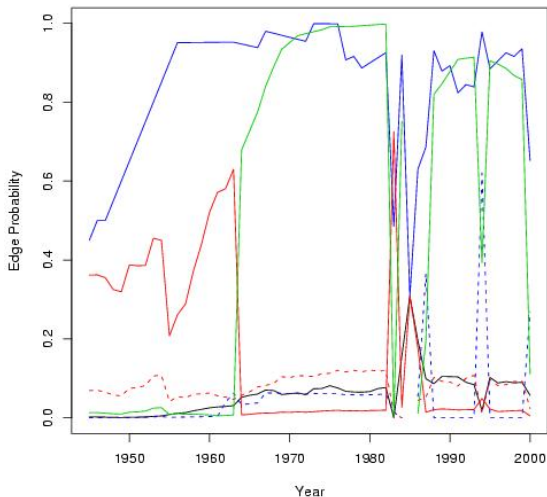
Groups^{K=3}



$K=2$

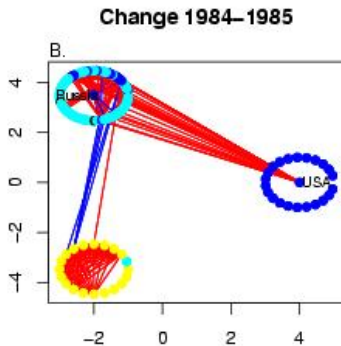
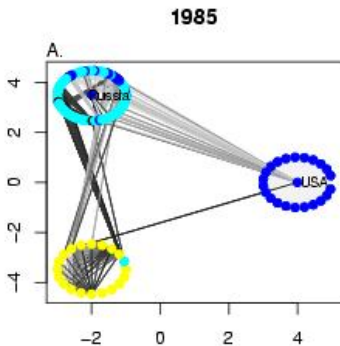


Group Probabilities

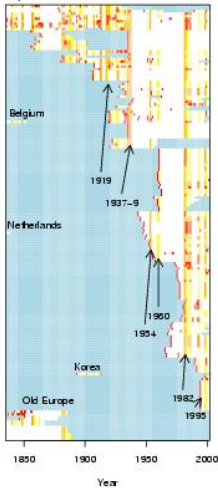
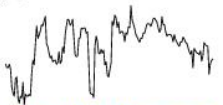


Russia=Red, USA=Blue, Others=Green

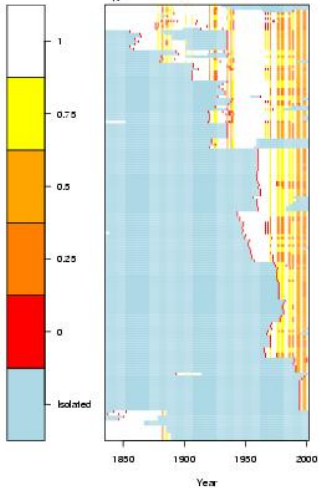
What Happened in 1985?



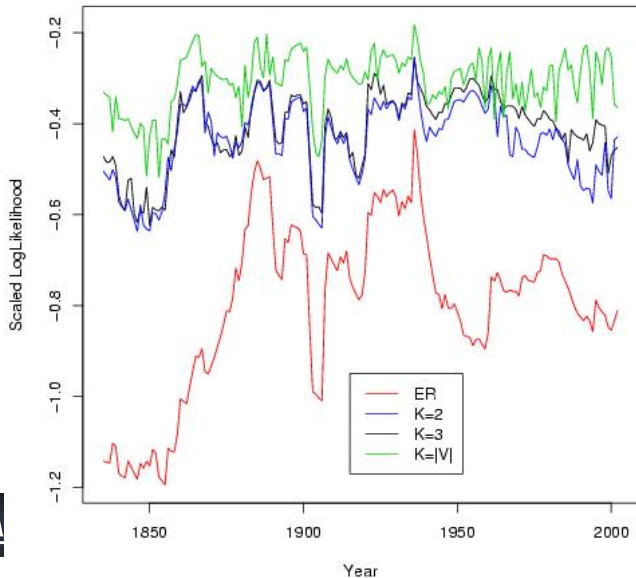
K=3



K=2



What is the right model?



Discussion

- ▶ These models provide rich classes from which to do inference on time series of graphs.
- ▶ Time series of graphs appear naturally in several areas of science.
- ▶ Much work remains to be done, both theoretically and in applications.
- ▶ Collaborators are welcome.

