Activity-Based Community Detection

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Graph Exploitation Symposium
August 9th 2011

This work is sponsored by the Office of Naval Research under Air Force Contract FA8721-05-C-0002. Opinions, interpretations, conclusions and recommendations are those of the author and are not necessarily endorsed by the United States Government.
Adding structural information to spatial-temporal data enables higher-level, cross-domain understanding.
Motivating Example:
Wide Area Motion Imagery (WAMI)

How can we detect threatening people/places/things and then use that information to prioritize human effort

**Imagery + Tracks + Multi-INT Detections**

**Focus Points**

**Algorithmic Assistance**

Where in space and time should I devote resources?

\[ P_{\text{Site}} (\text{Threat} \mid \text{Data}) \]

Which vehicle should I be following?

\[ P_{\text{Track}} (\text{Threat} \mid \text{Site}) \]

Does the vehicle track make a good association?

\[ P(\text{Break} \mid \text{Track}) \]

= Multi-INT Detections
Motivating Example:
Wide Area Motion Imagery (WAMI)

How can we detect threatening people/places/things and then use that information to prioritize human effort

Imagery + Tracks + Multi-INT Detections

Graph Abstraction

\[ P_{\text{Site}} (\text{Threat} | \text{Data}) \]

\[ P_{\text{Track}} (\text{Threat} | \text{Site}) \]
Cued Community Detection on Graphs

**Goal:** Detection of hidden communities embedded in a large background populations

**Approach:** Cued community detection algorithms on dynamic graphs

Graph representation of a social network:

- **Network Topology:**
  - Set of all possible associations
  - Provides the substrate upon which interactions occur

- **Network Dynamics:**
  - Local interactions throughout an observation period
Outline

• Network Community Detection
  – Background
  – Activity-Based Dynamics

• Data and Results
  – Simulated Data
  – MOVINT Data
  – Email Data

• Network Exploration
  – Methodology
  – Initial Results

• Summary and Future Work
Community Detection Background:
Global Methods

- Homophily assumption: Detection of densely connected groups of nodes, with only sparse connections between groups

- Edge counting techniques:

  Hamiltonian minimization (Reichardt and Bornholdt)

  \[
  \arg \min_C H(C) = \sum_{\{i,j\} \in V} -a A_{ij} \delta(c_i, c_j) + b (1 - A_{ij}) \delta(c_i, c_j) \\
  + c A_{ij} (1 - \delta(c_i, c_j)) - d (1 - A_{ij})(1 - \delta(c_i, c_j))
  \]

  within group edges within group non-edges
  between group edges between group non-edges

  Modularity maximization (Newman)

  \[
  \arg \max_C Q = -H(C) = \sum_{\{i,j\} \in V} \left( A_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i, c_j)
  \]
Community Detection Background: Local Methods

- These algorithms iteratively update each node’s attributes based on the attributes of its neighbors.

\[
P_i = f(\{P_j\})
\]

- Examples include:
  - Local modularity (Clauset)
  - Label propagation (Raghavan et al., Gregory)
  - HITS* (Kleinberg)

Still based on homophily: members of the same community are more likely to interact.

*Hyperlink-Induced Topic Search
Membership Propagation

Inferring community membership using local learning

Estimate a node’s membership based on neighboring nodes

- Inspired by HITS* (Kleinberg)
- Diffusion-like iterative updates

\[ P_i = f\left\{ P_j \right\} \quad \text{where} \quad j \in N(i) \]

\[ P_i = \alpha \left( \frac{\lambda}{|N(i)|} \sum_{j \in N(i)} P_j + (1 - \lambda) \max_{j \in N(i)} P_j \right) \]

- Average neighbor membership
- Maximum neighbor membership

0.95 0.50

0.05 0.15

\[ P_i = 0.65 \]

*SMP 08/09/2011

*Hyperlink-Induced Topic Search
Membership Propagation

Inferring community membership using local learning

Estimate a node’s membership based neighboring nodes

- Inspired by HITS* (Kleinberg)
- Diffusion-like iterative updates

*Hyperlink-Induced Topic Search
Real world social networks:
- Communities are diffuse (i.e. not tightly connected)
- People act on behalf of different communities at different times

**Affiliation-Based Community Detection**
Densely connected groups of nodes, with sparser connections between groups

**Activity-Based Community Detection**
Subset of nodes engaging in an coordinated sequence of finite-duration activities

Static Graph

Space-Time Graph
Dynamic Membership Potential

• A node's potential to act as a member of a specific community can vary over time
  – e.g. Between 9-5 I have my Lincoln hat on
  – This is similar to the role vector in Mixed Membership Blockmodel

• Membership probability now propagates depending on a node's role at the time of the interaction
  – The challenge is to estimate role in between interactions
Dynamic Membership Propagation

Detection of nodes acting in a coordinated manner over time

Estimate time-varying membership based on edge times
- Define a kernel function matched to expected community behavior (e.g. co-occurrence of interactions)

\[ K(t) = \quad P_i(t) = \]
Dynamic Membership Propagation

Detection of nodes acting in a coordinated manner over time

Estimate time-varying membership based on edge times

- Define a kernel function matched to expected community behavior (e.g. co-occurrence of interactions)

\[
P_{s_i}(t) = \alpha_s \left( \frac{\lambda}{E(s_i)} \sum_{v \in E(s_i)} P_{s_v}(t_{e_{iv}})K(t-t_{e_{iv}}) + (1-\lambda) \max_{v \in E(s_i)} P_{s_v}(t_{e_{iv}})K(t-t_{e_{iv}}) \right)
\]

where...

\[
E(s_i) = \text{Set of edges connected to } s_i
\]

\[
e_{iv} = \text{An edge between } s_i \text{ and } s_v
\]
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Simulated Graph Data

Concept: Generate the topology independently of the dynamics
- Generate topology using static generators
- Generate a dynamic process on top of the topology
  Foreground – Coordinated Message Passing
  Background – Random Connection Timing

Foreground Graph

Background Graph
Simulated insurgent network hierarchy embedding in a large civilian traffic in Baghdad

NGA Threat Scenario: IED Attack

IDA* Background Model: Civilian Traffic in Baghdad

4000 Actors
6000 Locations
100,000 Movement Tracks

*Institute for Defense Analysis
Email Graph Data

Enron email dataset from Patrick Perry
- Nodes represent email accounts for higher management
- Edges represent emails sent between people
- Coloring is by department
Community Detection Results

- **Simulated Data**
- **Baghdad Data (MOVINT)**
- **Enron Data (Email)**

Graphs showing the probability of detection versus the probability of false alarm for different methods:
- Spectral
- Local Modularity
- Static TP
- Dynamic TP

<table>
<thead>
<tr>
<th>Method</th>
<th>Baghdad Data</th>
<th>Simulated Data</th>
<th>Enron Data</th>
</tr>
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<tbody>
<tr>
<td>Spectral</td>
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<td>Local Modularity</td>
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<td>Static TP</td>
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Network Discovery

Workload Prioritization

• The amount of data for an analyst to look at grows exponentially
  – Following only a few vehicles from one sensor can lead to hundreds of possible new sites and vehicles to investigate
  – This problem affects all aspects of data forensics

• Network Exploration Workflow
  – Given a set of information, what evidence do I collect next?

Methodology

1. Propagate membership across network
2. Identify nodes with maximal membership
3. Identify edges with maximal membership
4. Grow graph
5. Repeat
Network Discovery
Workload Prioritization

Prioritization Strategies:

- **Random Search**
  
  Explore tracks randomly starting from a tip node

- **Breath First Search**
  
  Explores nodes closest to the tip node with lowest degree first

- **Membership Prop**
  
  Explores nodes with highest threat first

- **Dynamic Membership Prop**
  
  Explores tracks with highest threat first

Prioritization discovers 87% of the insurgent network using only 0.5% of the total potential edges.
Summary

• Static structure alone is often insufficient to accurately characterize social groups.

• Activity-based communities are defined by a set of nodes engaging in a coordinated sequence activities
  – Disease and rumor spreading
  – Collaboration between colleagues
  – Coordinated activities between insurgent cells