Social Network Clustering

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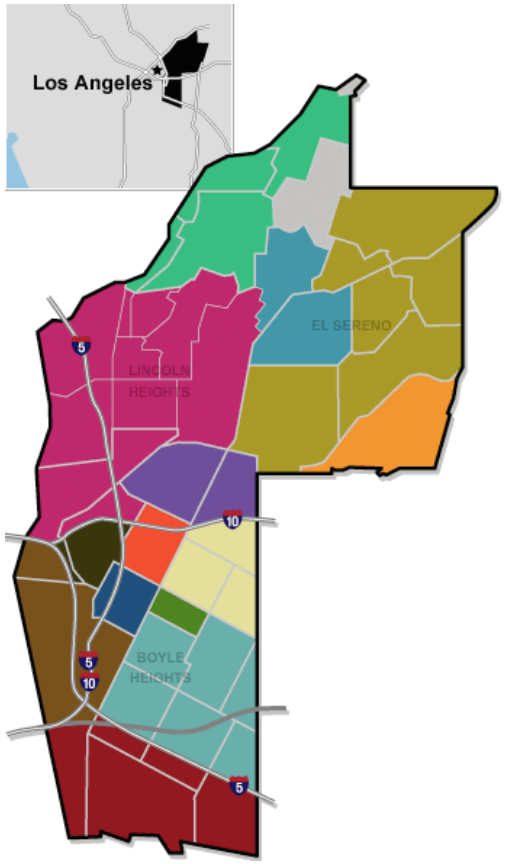
Outline

Hollenbeck Gang Activity

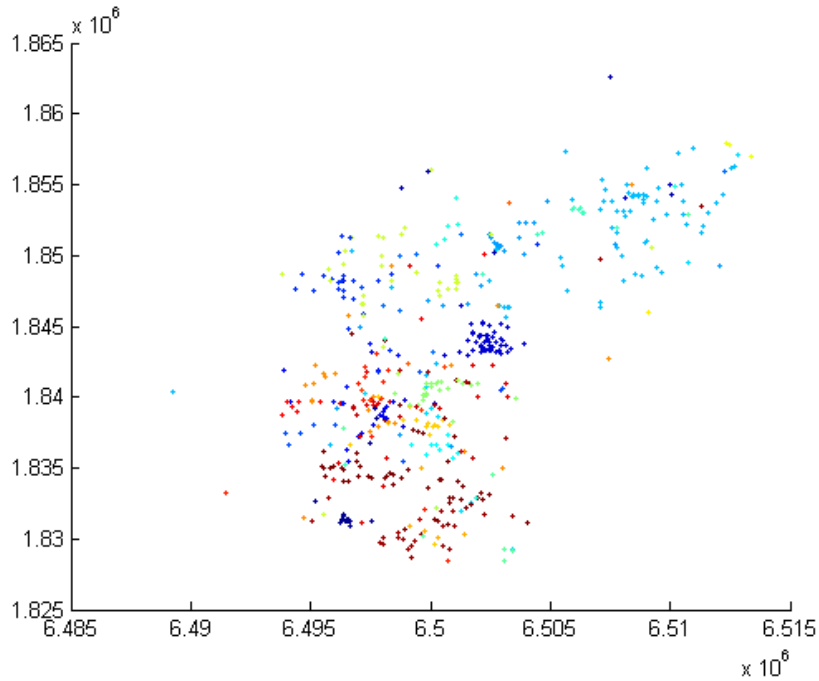
- Hollenbeck has an area of approximately 15.2 miles.
- In this area, 31 violent gangs reside.
- Hollenbeck is one of the top three most violent LA policing regions.
- Gang violence in this region has existed since before WWII.



Hollenbeck Gang Activity

The LAPD has provided an Excel database of non-criminal stops they have made in the Hollenbeck area. The data includes:

- time of stop
- location (gang territory and coordinates)
- gang affiliation
- sex
- age
- ethnicity

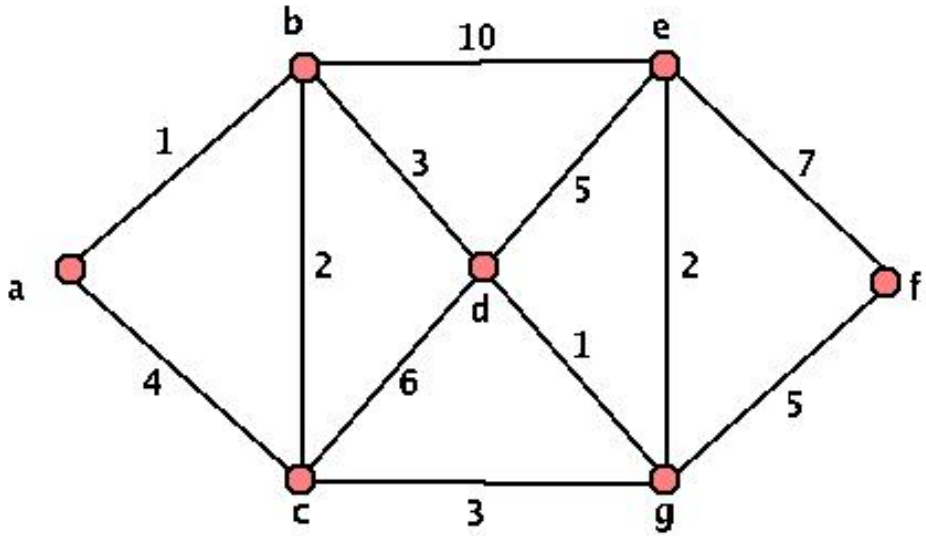


Goals

- Use clustering techniques to predict unknown gang affiliations.
- Detect other social structures that may not be captured by gang affiliation.

Graph Models

- Convert individuals into nodes.
- Edge weights indicate similarity.
- Unfortunately, data is sparse.

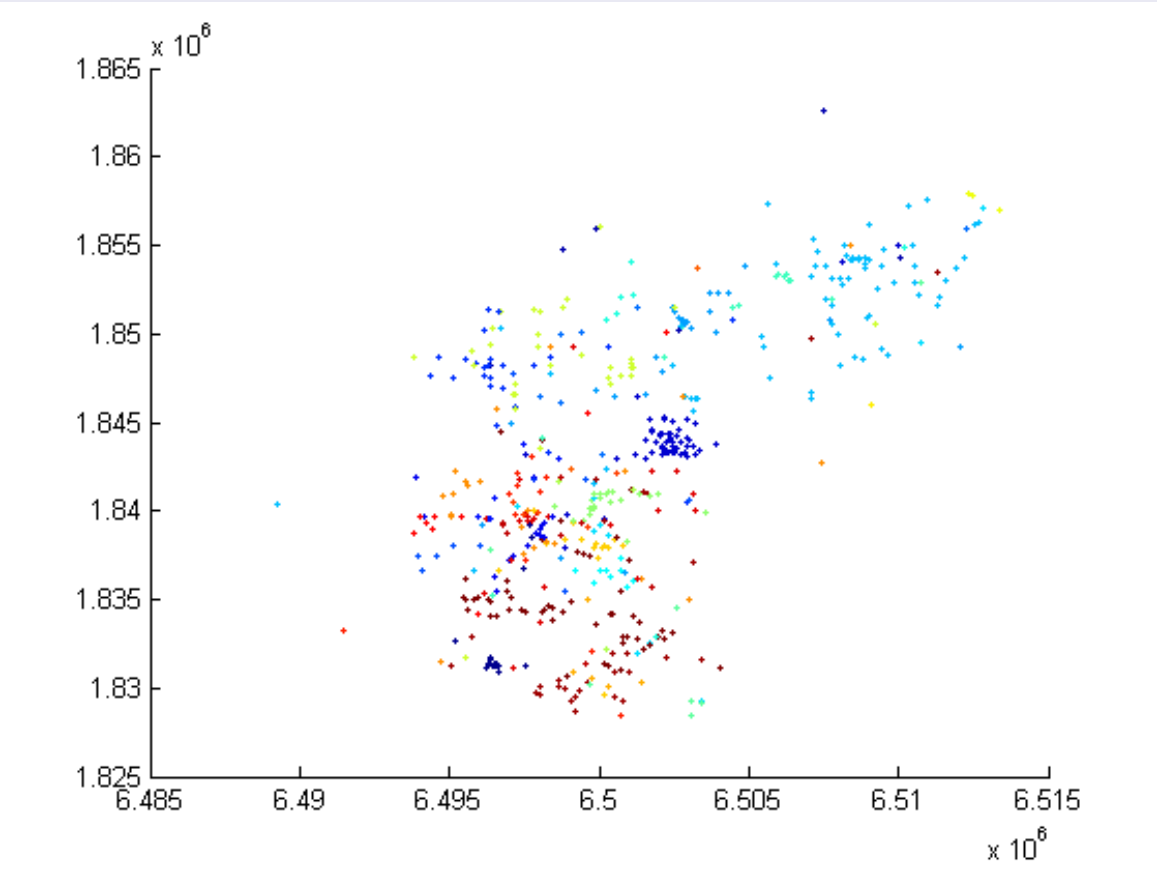


Choosing a Measure of Similarity

- A function of Euclidean distance
- Dot product of feature vector
  - Gang territory
  - Individuals and their gang associations
  - Individual to individual interactions

Results

Actual Gang Clusters



Outline

K-means algorithm

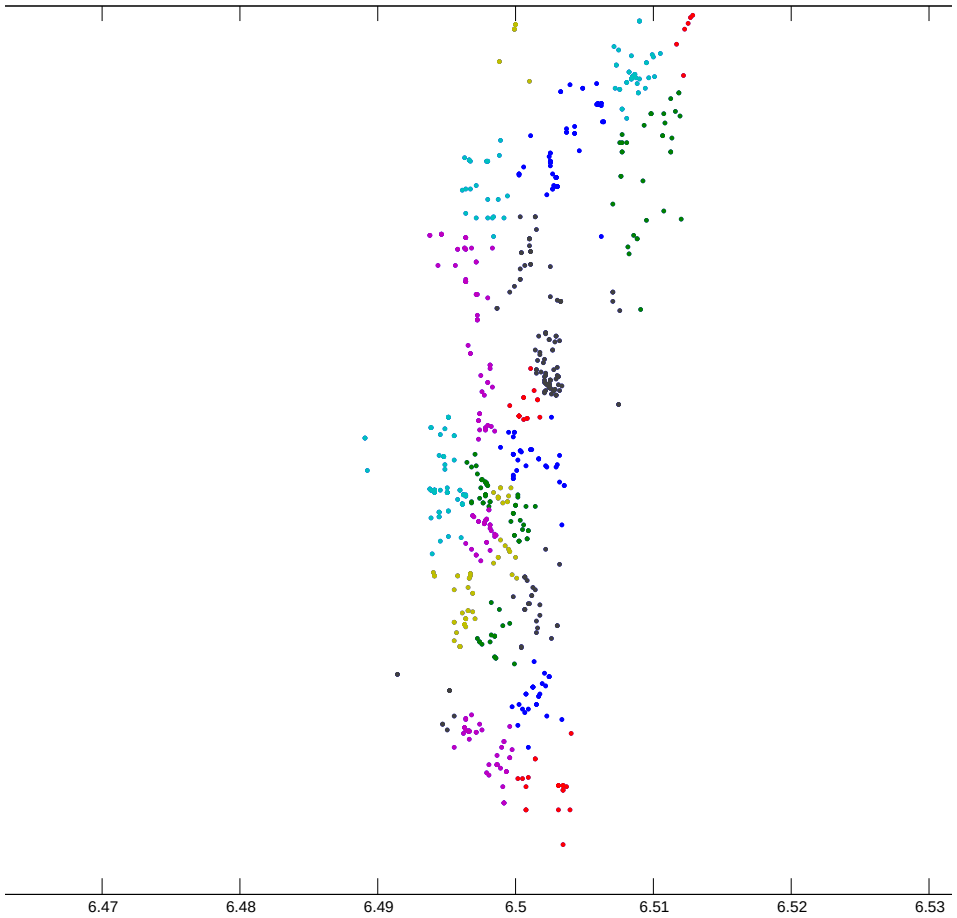
Algorithm

- Choose number of partitions.
- Compute centroids.
- Shift centers to the centroid of their affiliated points.
- Repeat until equilibrium is achieved.

Cons

The K-means algorithm only accounts for location. We hope to utilize more of the data.

Results: K-means Approach



A Metric for Cluster Evaluation

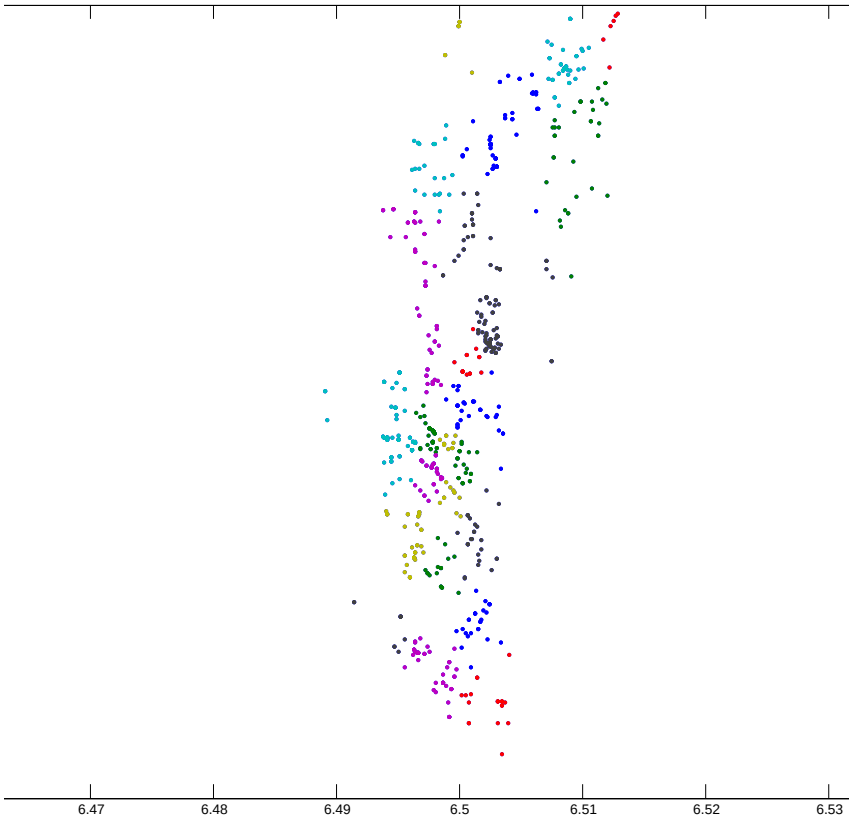
- We define **purity** to be

$$purity(\Omega, \mathbb{C}) = \frac{1}{N} \sum_{k} max_j |\omega_k \cap c_j|$$

  where $\Omega = \{\omega_1, \cdots, \omega_K\}$ are the clusters and $\mathbb{C} = \{c_1, \cdots, c_j\}$ are the actual classes.
- Another measure we used was **Adjusted Mutual Information** which may be more appropriate since our gangs vary significantly in size.

Results: K-means Approach

Purity ≈ 0.4 and *AMI* ≈ 0.4

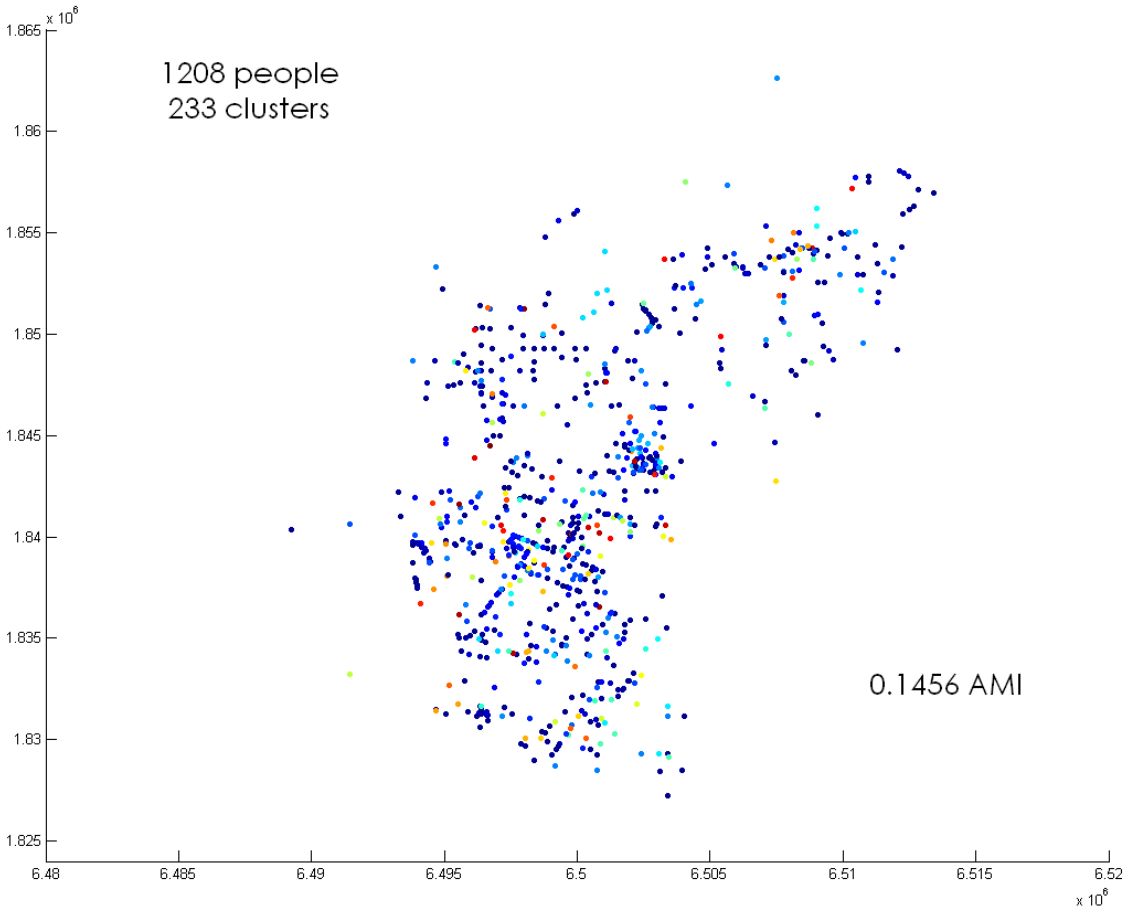


Modularity Maximization

- Modularity compares the number of edges within a cluster to the number expected
- Maximize modularity.
- We can calculate the change in modularity at each step and stop when the change is not positive

[M.J. Newman, 2006]

Results: Modularity Maximization



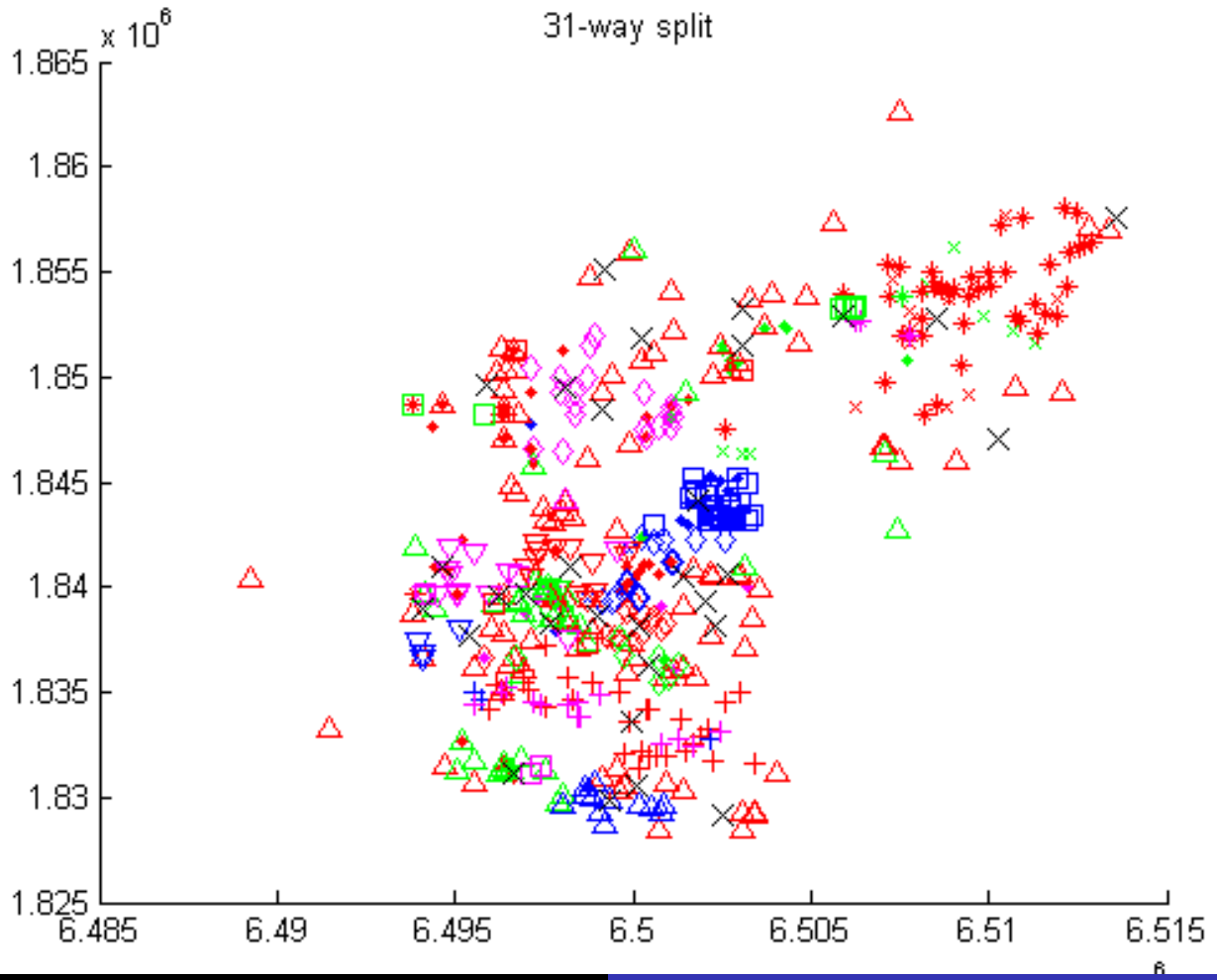
Convergence of Iterated Correlations (CONCOR)

- Compute correlations of entries to the mean of rows/columns
- Continue to calculate the correlations of the correlation matrix until we are left with $+1$ and -1.
- The method is repeated on each cluster to achieve a finer partition.

[Wasserman, 1994]

Results: CONCOR

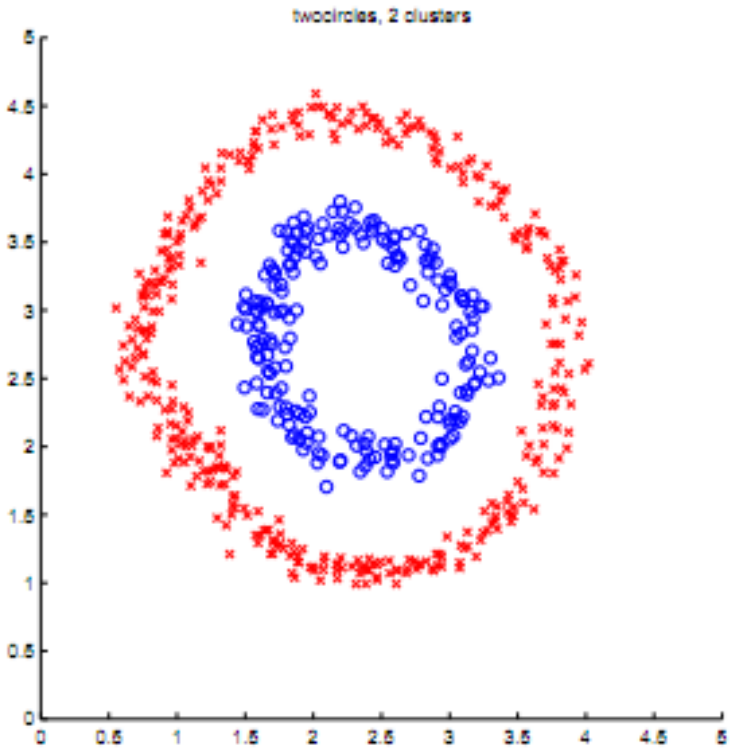
Purity ≈ 0.5 and *AMI* ≈ 0.46.

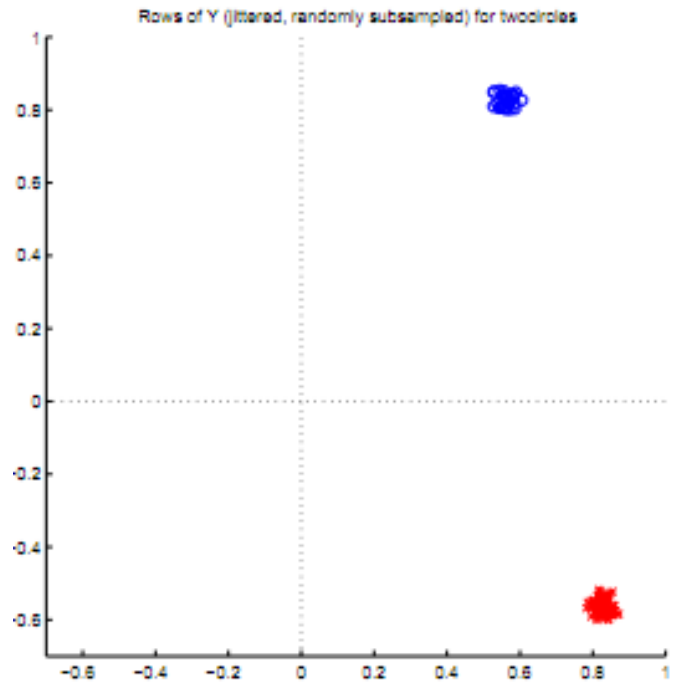


Outline

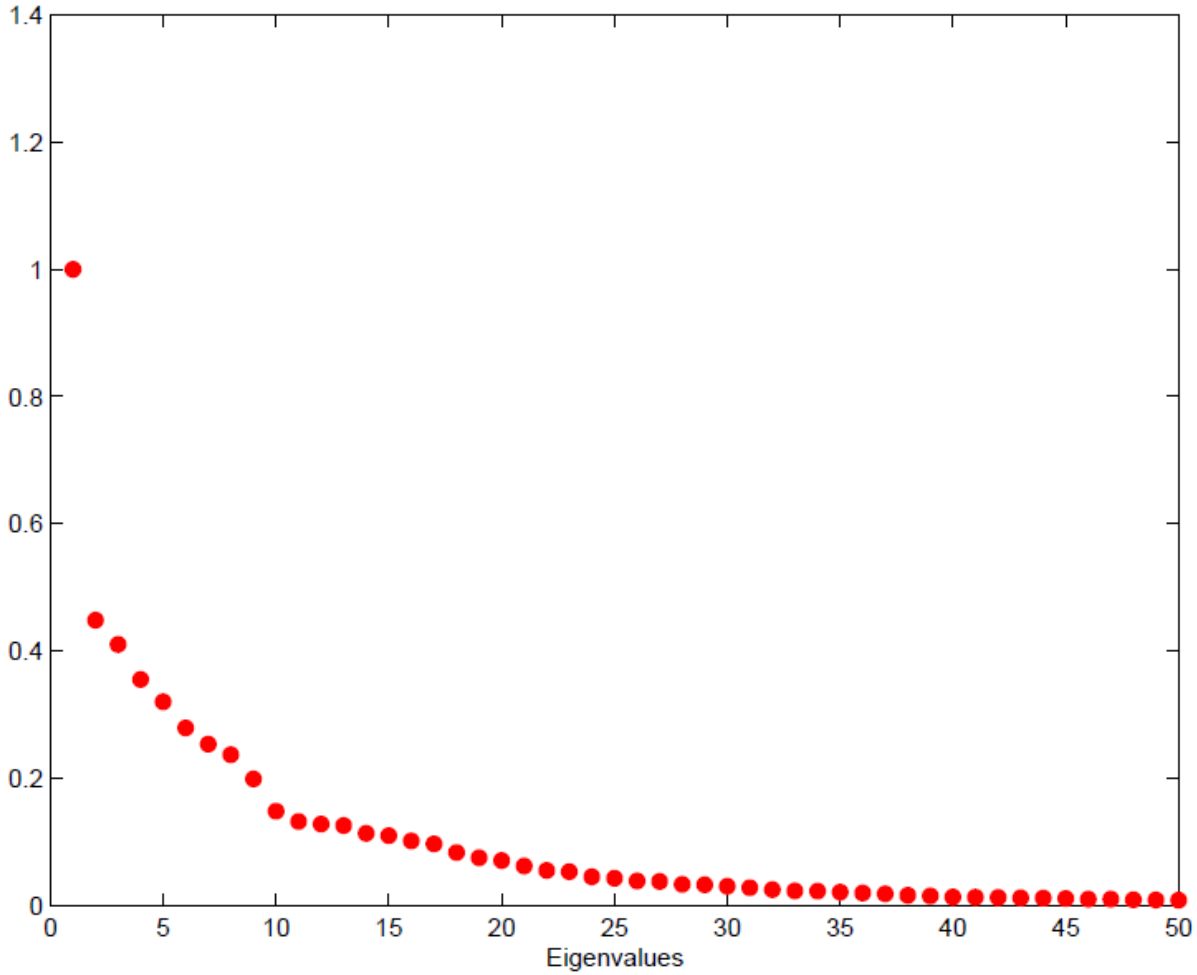
Spectral Clustering

- Create a matrix of eigenvectors of the Adjacency matrix.
- The eigenvectors capture the axes which contain the most variation in the data.
- Run k-means algorithm on new space.

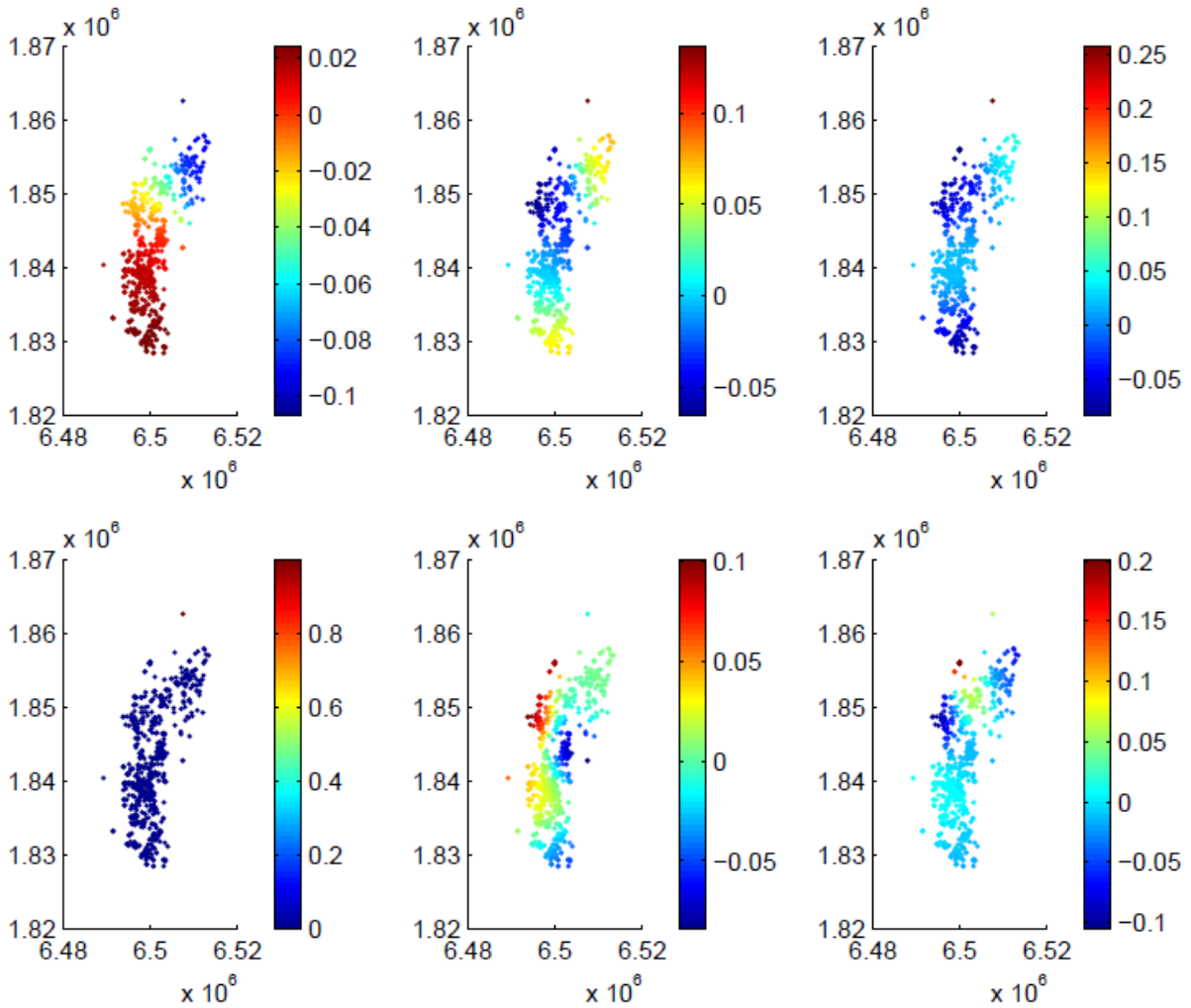




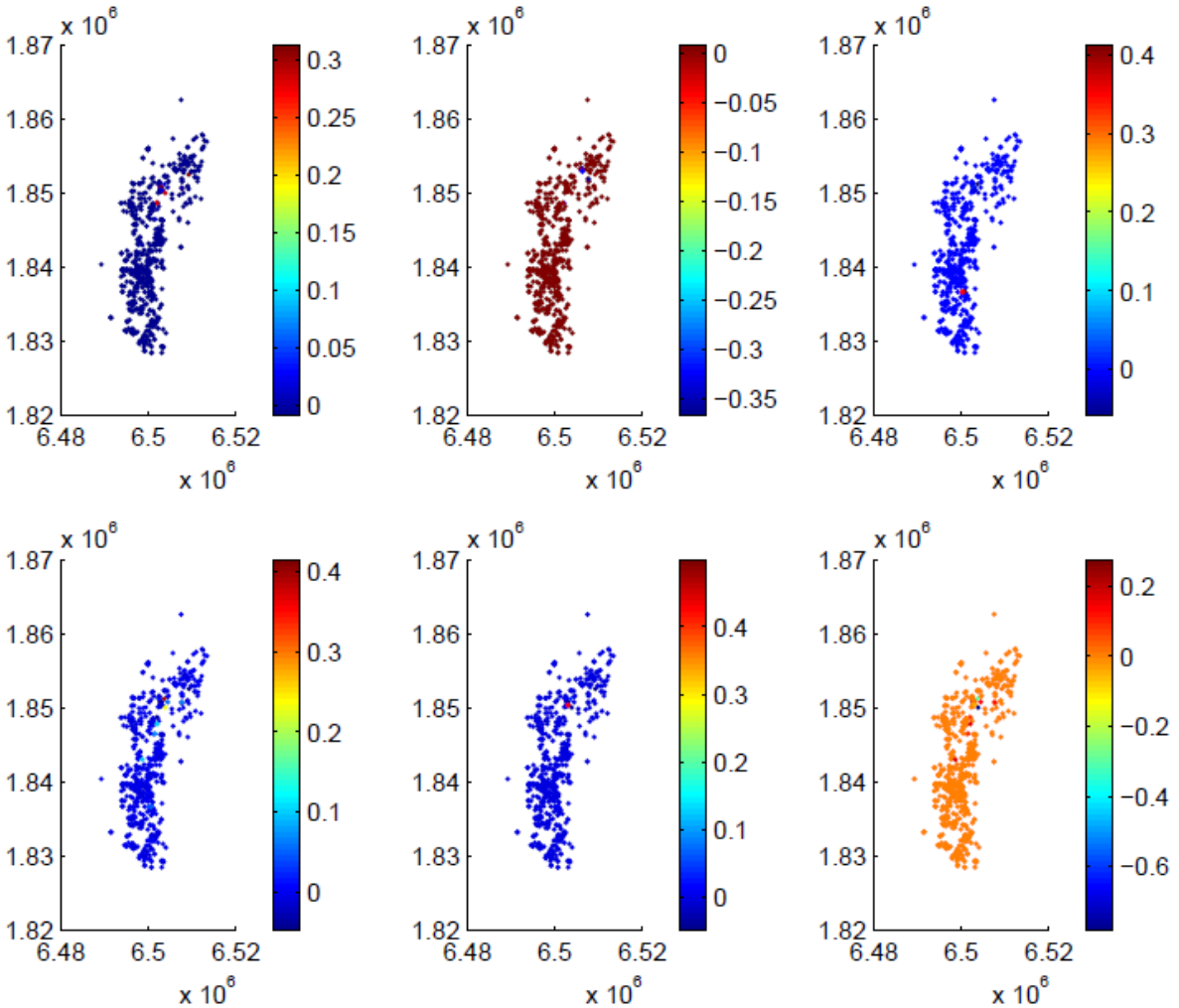
Eigenvalues



Eigenvector Plots: Distance Only



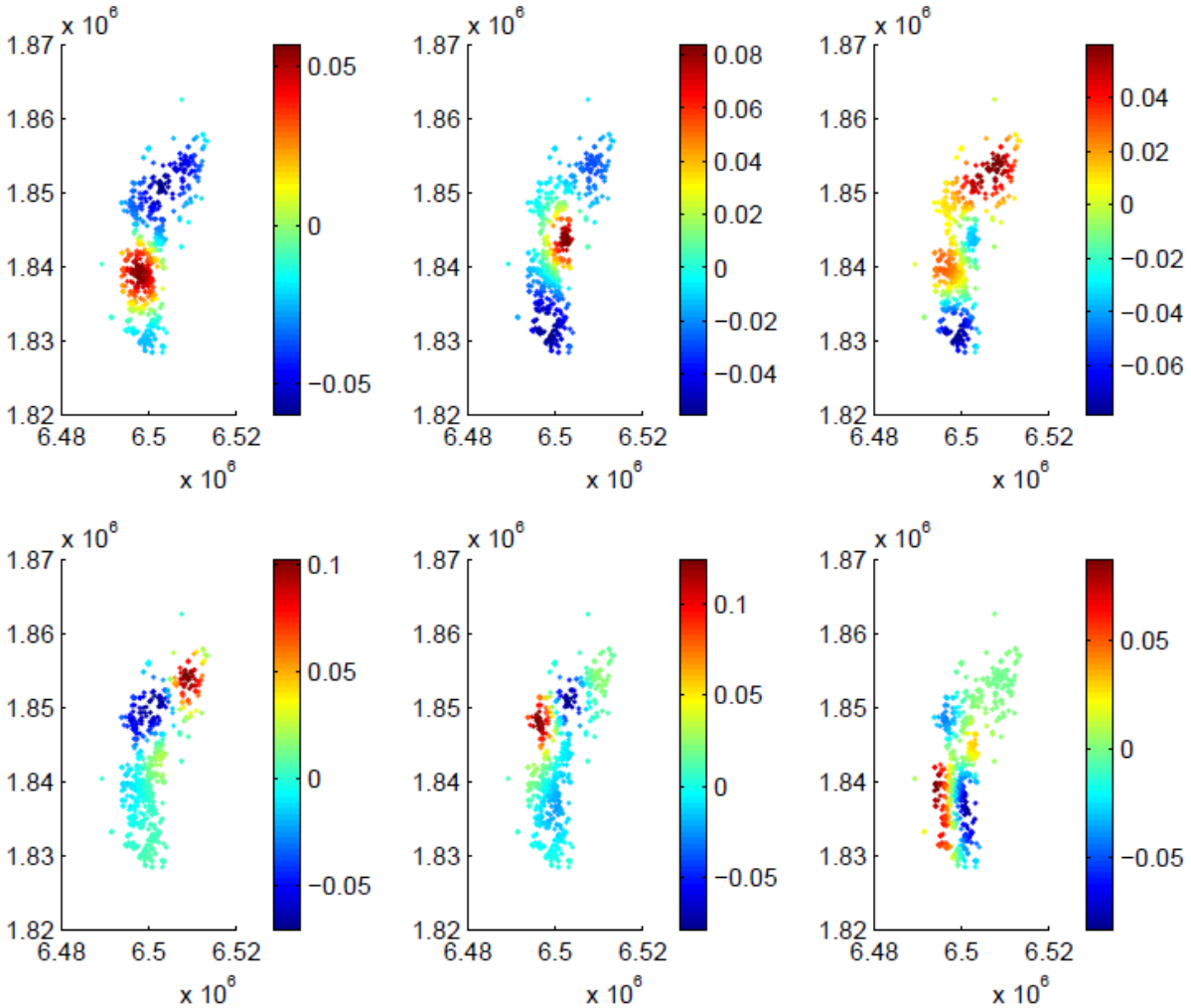
Eigenvector Plots: Social Information Only



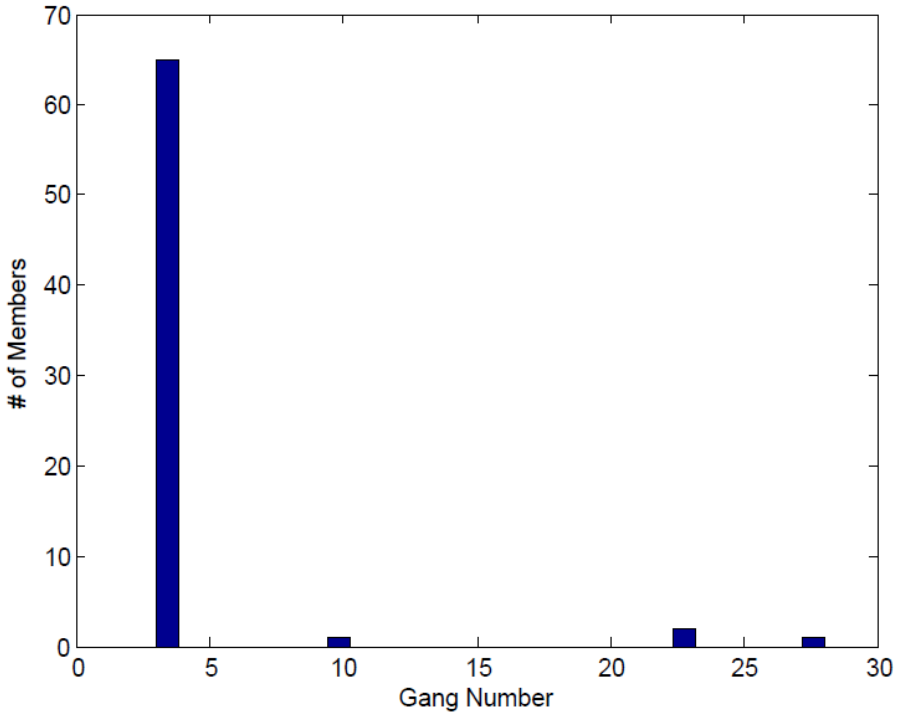
Where to go from here?

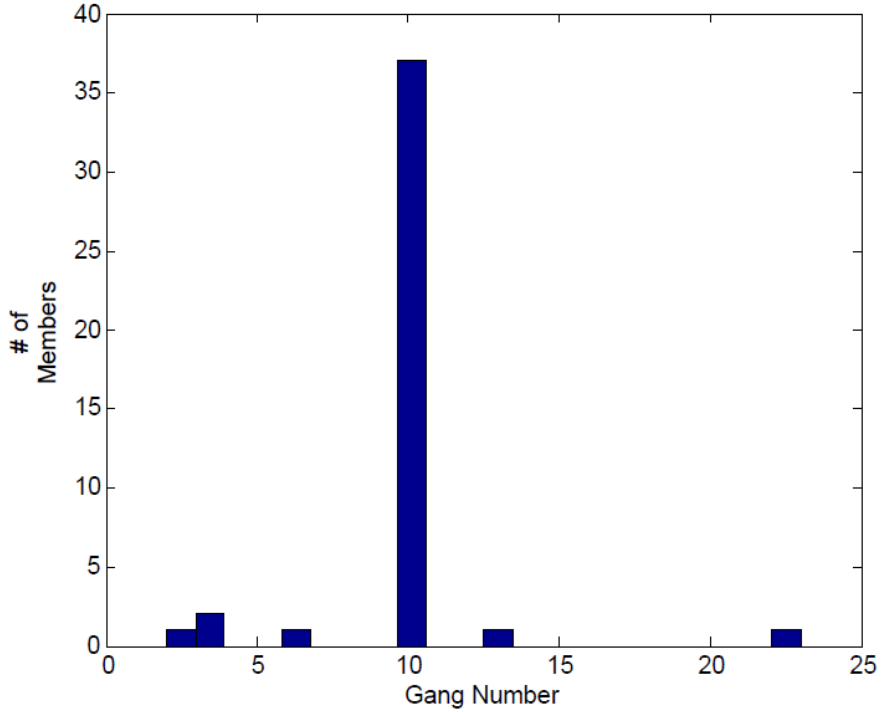
- The geographic data provides no insights.
- The social data is so sparse that its eigenvectors are completely useless alone.
- We decided to combine the two adjacency matrices, $\alpha A + (1 - \alpha)B$, where α is a weighting parameter.

Eigenvector Plots: Combined



Clustering Results





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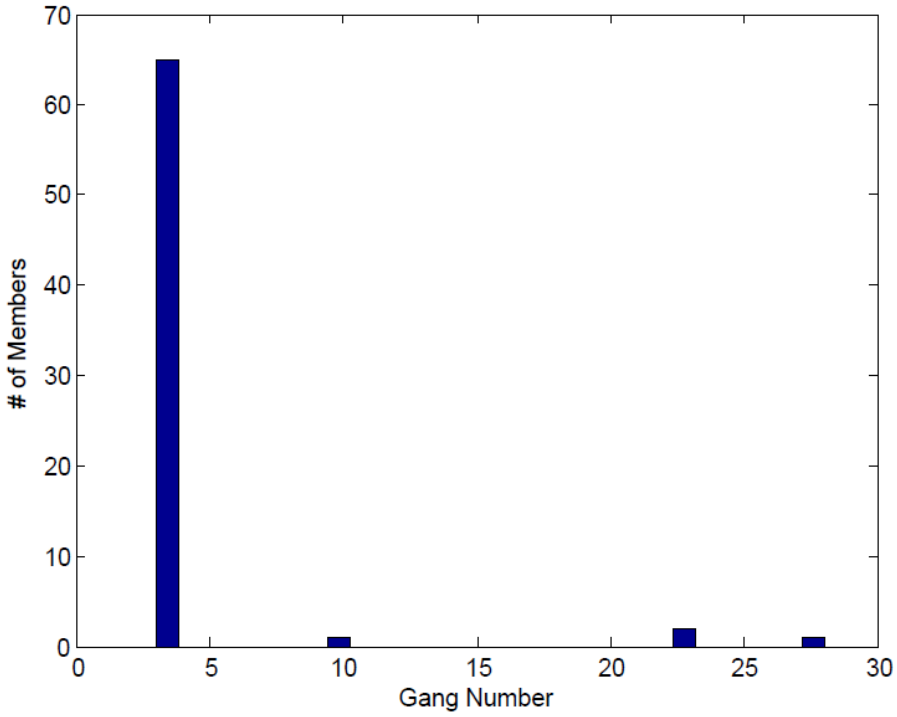

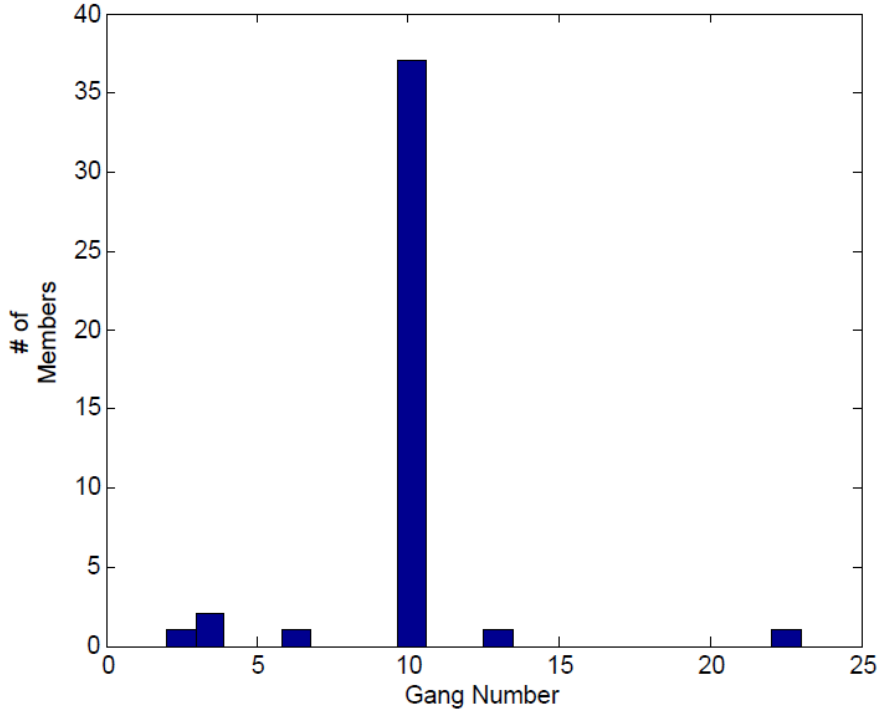

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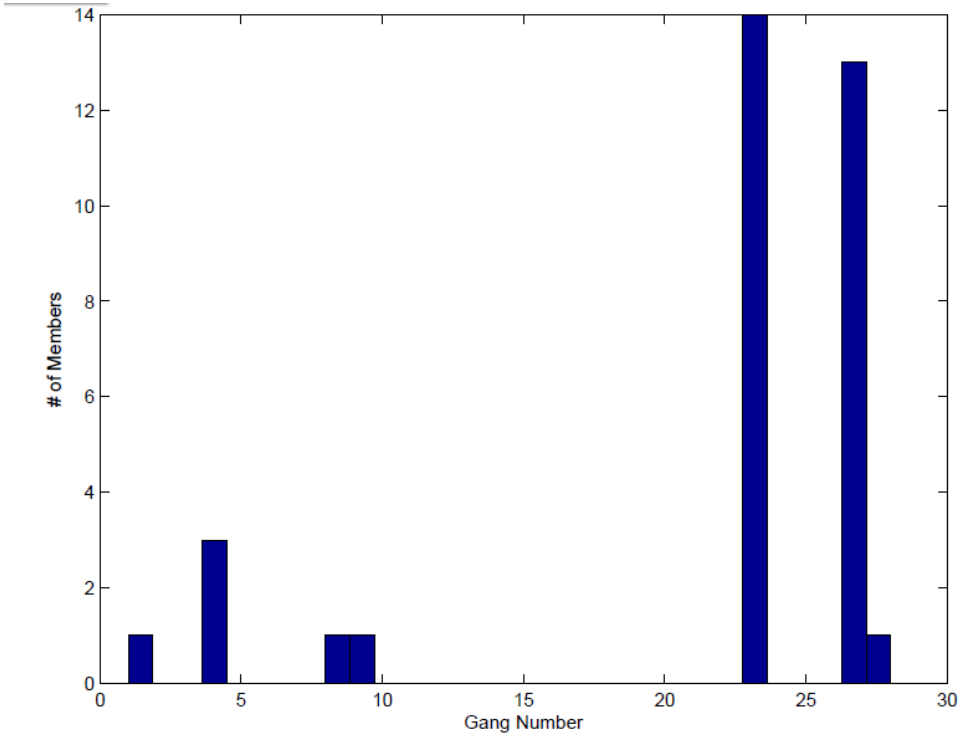
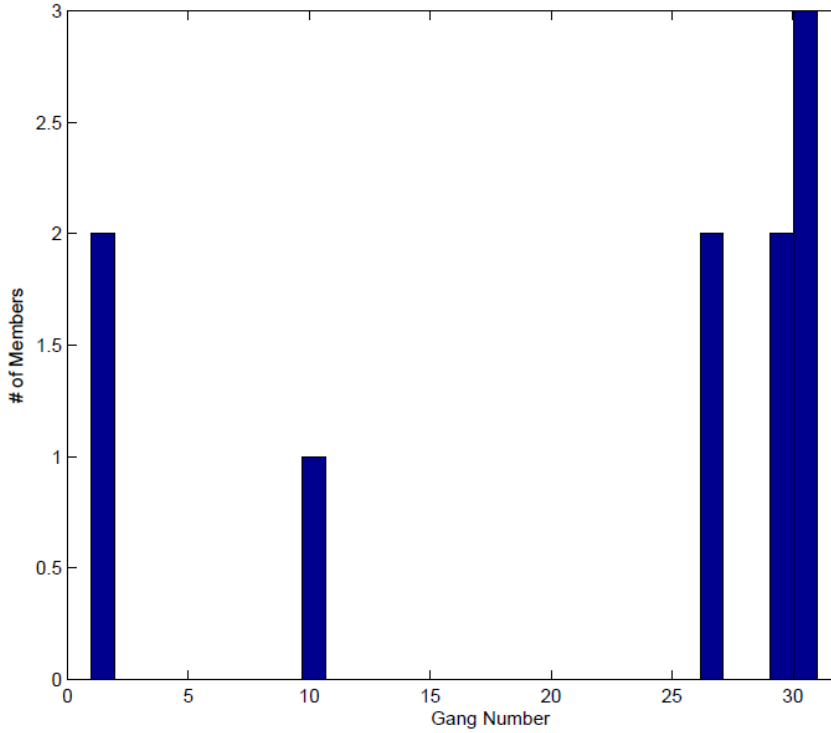
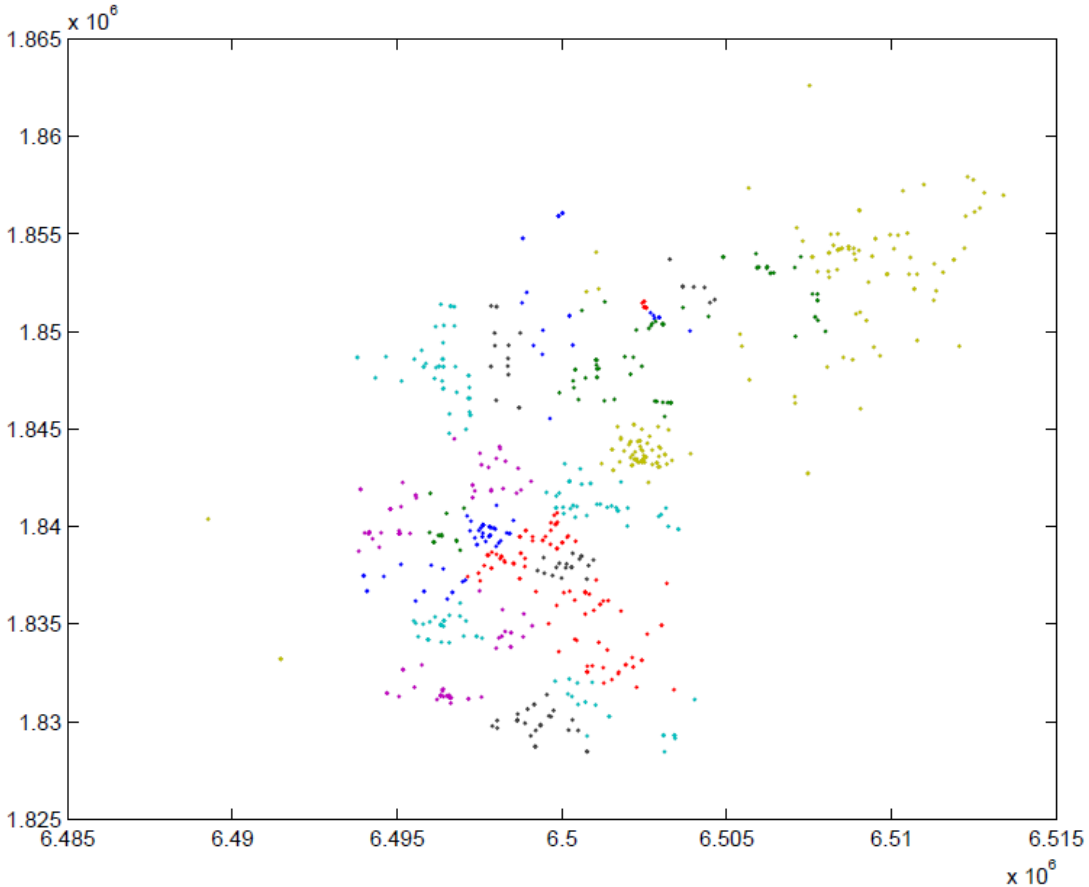




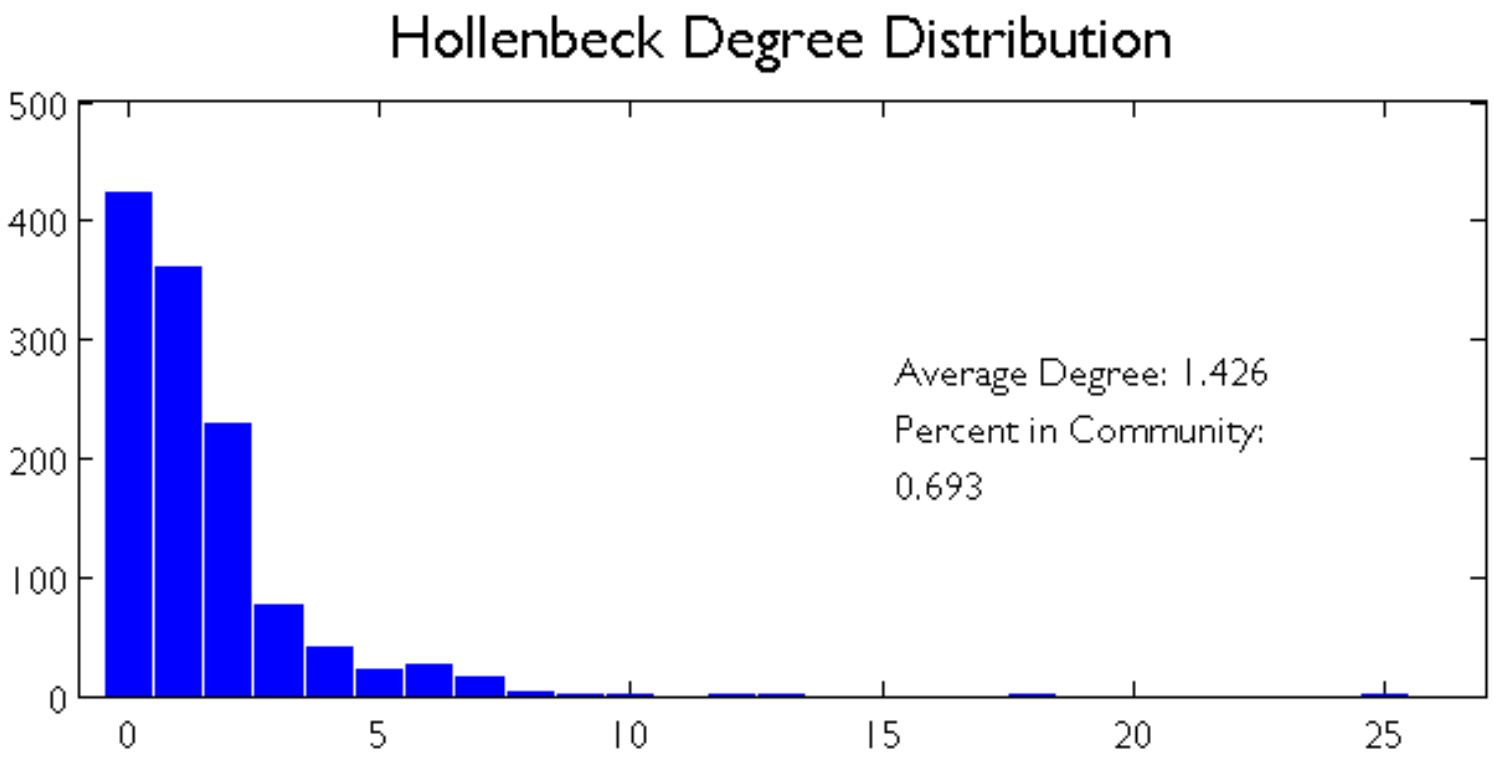
Results: Spectral Approach

Purity $\approx .7$ and *AMI* $\approx .65$



Outline

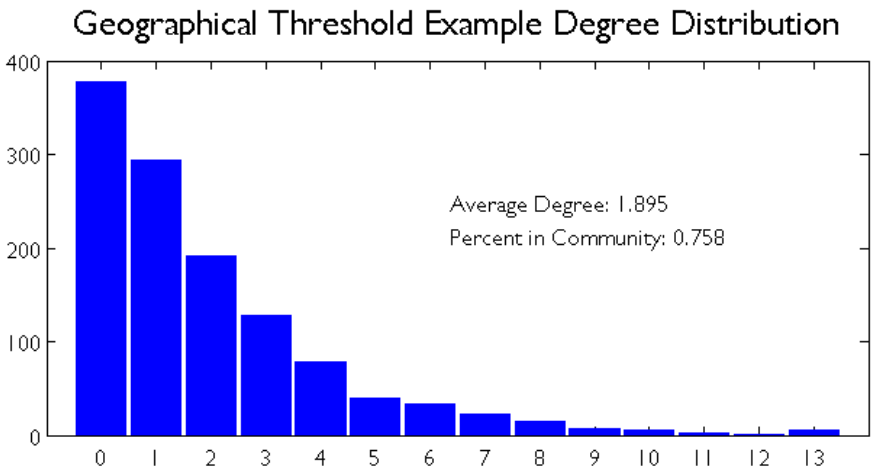
Artificial Data



Artificial Data

Inputs:

- Number of people
- Number of communities
- Gang multiplier
- Threshold
- $G(x, y) = \frac{(\eta_x + \eta_y)\sigma}{dist(x,y)} (1 + M\delta_{ij})$

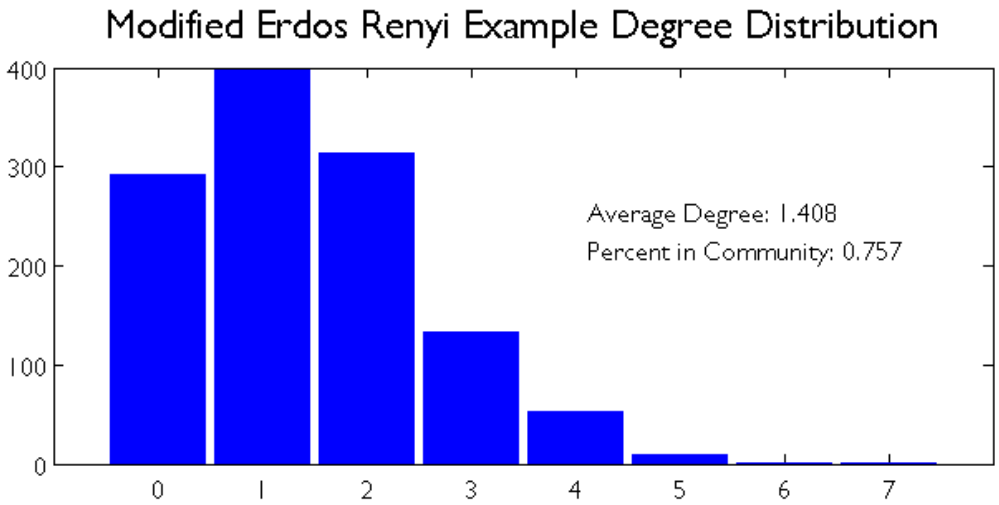


[N Masuda, 2005]

Artificial Data

Inputs:

- Number of people
- Number of gangs
- Probability within gangs
- Probability outside gangs

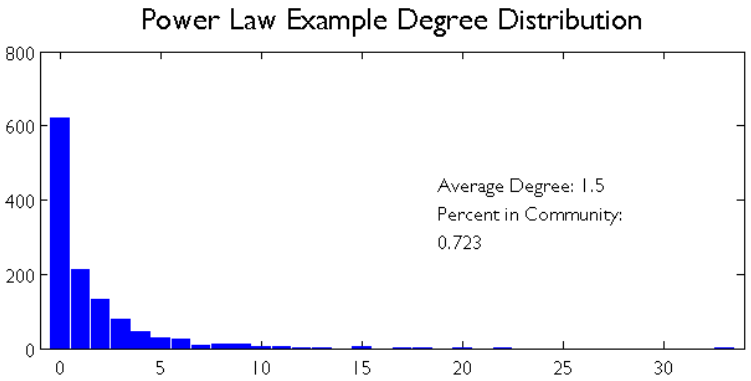


[A. Lancichinetti, 2008]

Artificial Data

Inputs:

- Number of people
- Number of gangs
- Average degree
- Mixing parameter



[E.N. Gilbert, 1959]

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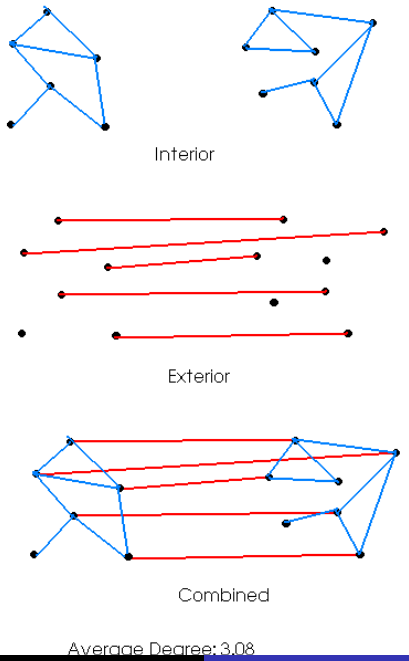

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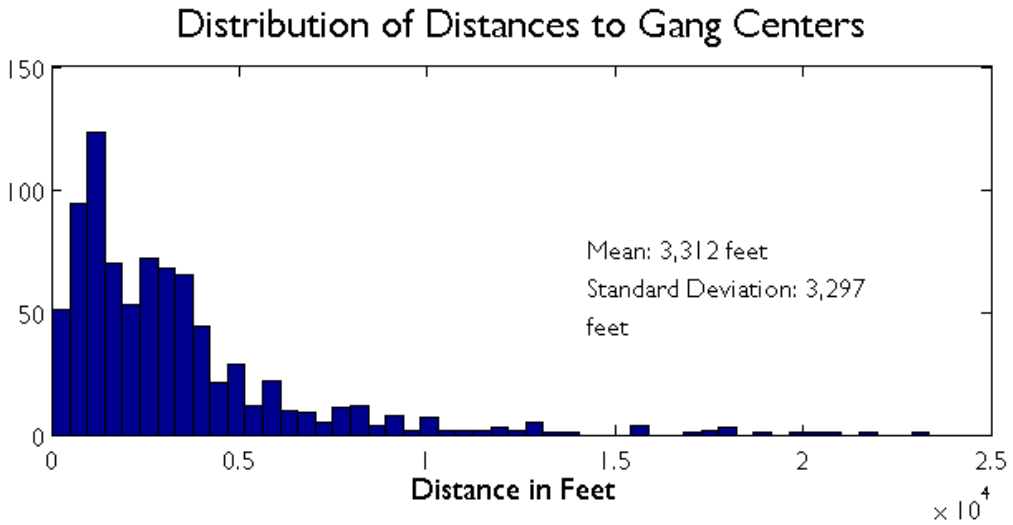

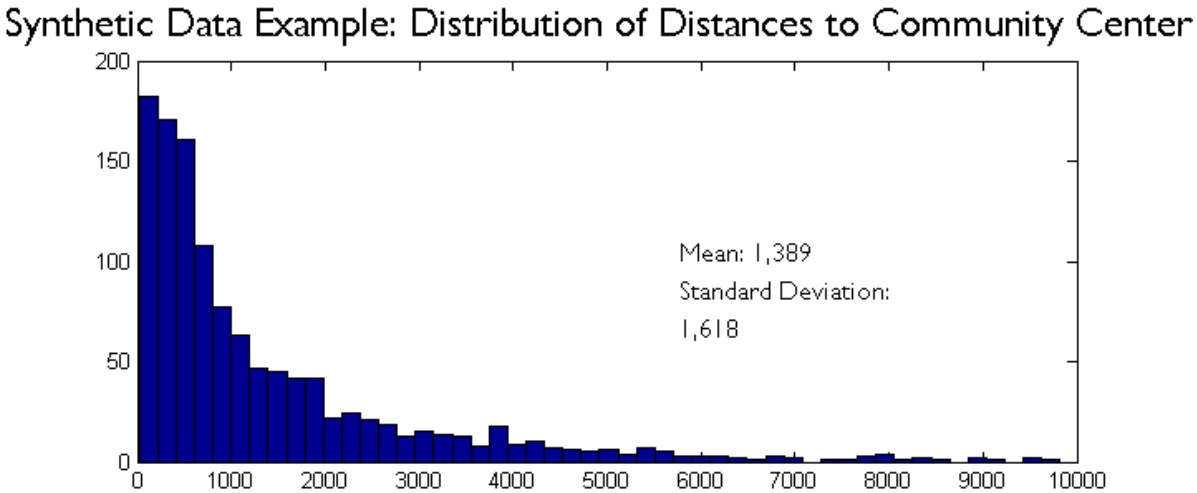

Outline

Future Work

- Matrix Completion and Link Prediction
- Robustness of Algorithms
- Artificial Testing Data

Acknowledgements

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