

Embedding Methodology and Statistics for Inference

Sancar Adali

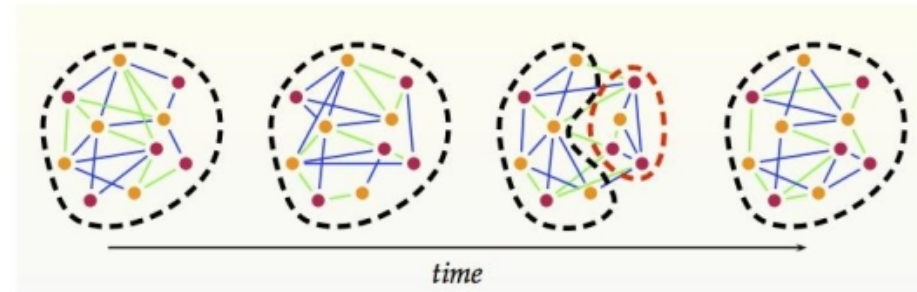


July 29, 2013



FROM DATA TO STATISTICS

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CAPABILITIES AND IMPLEMENTATIONS

- Compute statistics from time series of graphs (TSG)
- Out-of-sample extension for adjacency spectral embedding
- Faster Embedding by the use of OOS-embedding
- Dissimilarity computation for multivariate time series
- Tensor Decomposition for time series data (adj. matrices, multivariate data)
- Fast computation of local statistics in very large graphs



CAPABILITIES AND IMPLEMENTATIONS

Software

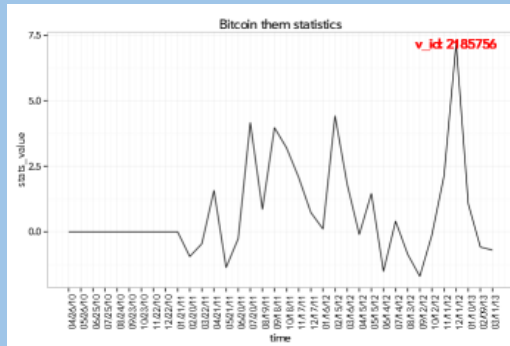
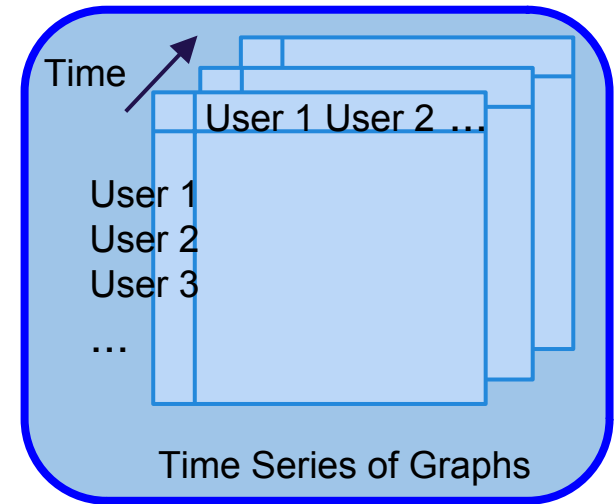
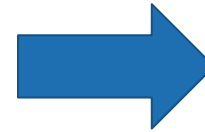
- R packages: ScanStats, AdjMatEmbed, DissTimeSeries
- Python: Large-graph invariants , MySQL-igraph for TSG
- igraph C/C++ library (devel branch)



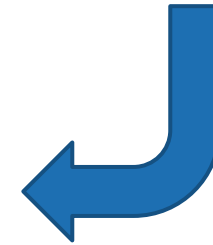
BITCOIN DATA ANALYSIS

BITCOIN

Sender	Receiver	Transaction amount	TimeStamp



Time Series of Scan Statistics



BITCOIN



- Various anomaly detections using the normalized statistics.
- The vertices which are the sources of anomalous activity should be investigated further.



Kiva

- Joint embedding of all entities (lender, loan, partner, borrower)
- Relationship between entities of different kinds
-> Adjacency matrix of graph (entities -> vertices)
- Lender-lender graph: edges



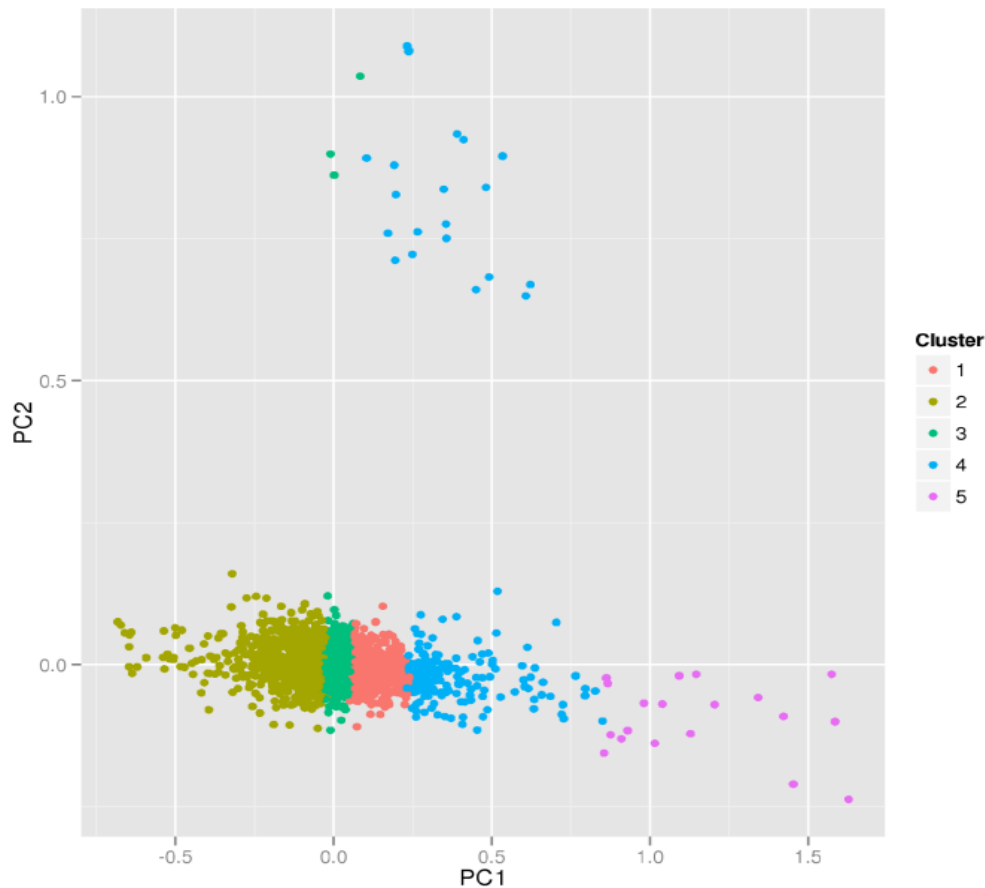
EMBEDDING APPROACH

Fast Embedding via out-of-sample extension

- Embed the most active lenders in-sample
- Repeat until all entities have been embedded:
 - Embed a batch from the remaining entities via out-of-sample extension
- Cluster the embedded entities



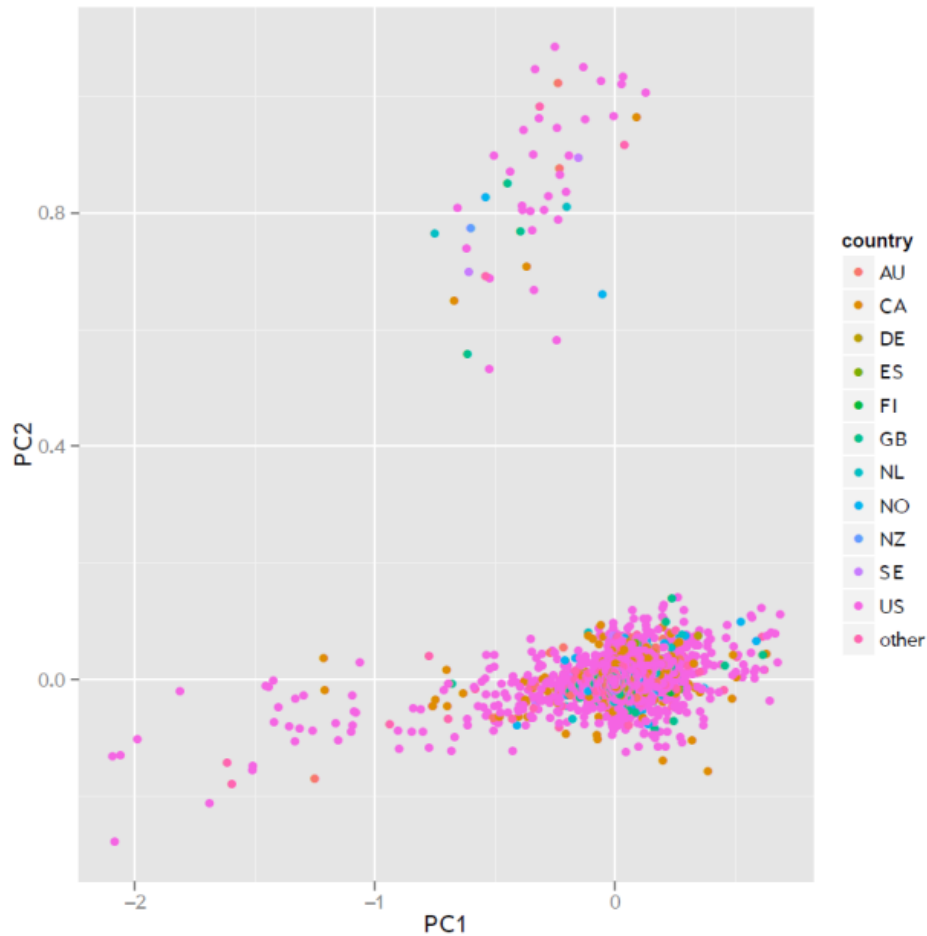
Kiva Entity Embedding



- Embedding of 720K Kiva lenders
- Other entity types will be OOS embedded



Kiva Entity Embedding



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- Other entity types will be OOS embedded



Scan Statistics for Anomaly Detection

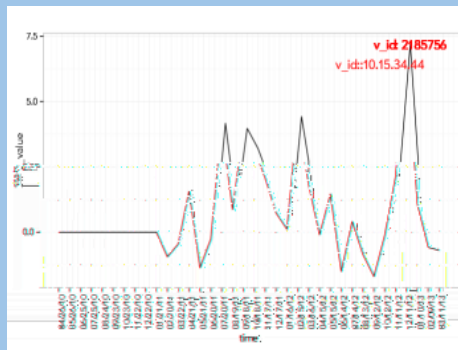
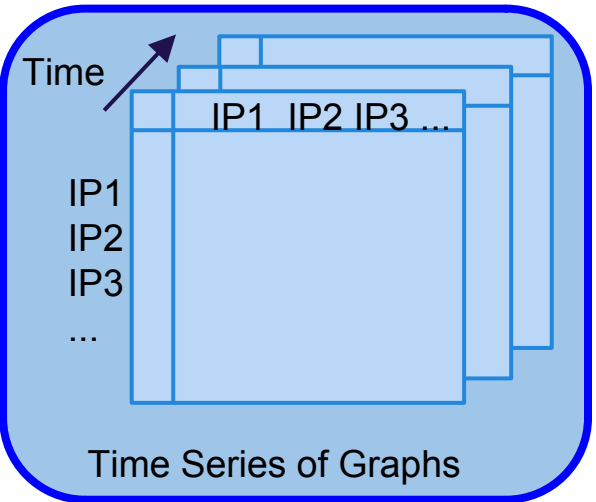
Count # Trace Region Number Dest IP
Type UnixTimestamp

FULL TRACE 0 1352674806 10015 200.7.37.90

Delimited list of Hop #:IP Address: Differential latency

```
1:61.213.146.1:5.722|2:61.213.169.213:1.041|3:61.213.169.149:0.426|4:129.250.2.20:0.611|5:
129.250.4.189:90.071|6:129.250.5.43:97.507|7:80.239.128.213:98.217|8:213.155.134.210:117.
217|9:80.91.247.170:128.856|10:213.248.80.14:155.167|11:80.91.252.62:187.517|12:213.248.
89.162:184.885|13:63.245.5.61:222.085|14:63.245.5.75:224.174|15:63.245.22.22:231.622|16:
200.7.33.19:241.330|17:200.7.33.10:245.638|18:200.7.33.90:245.028|19:200.7.37.90:240.727
```

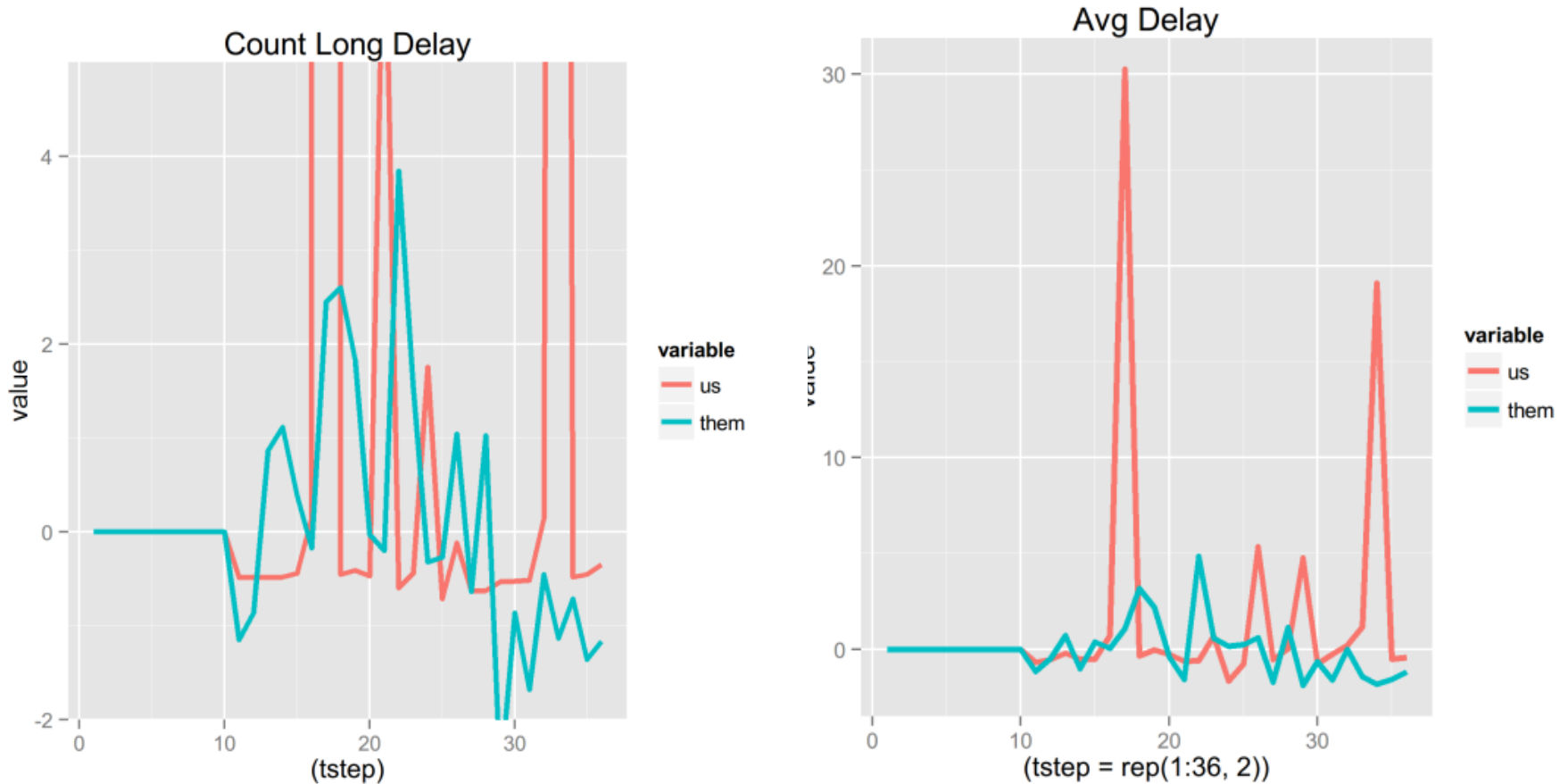
Traceroutes



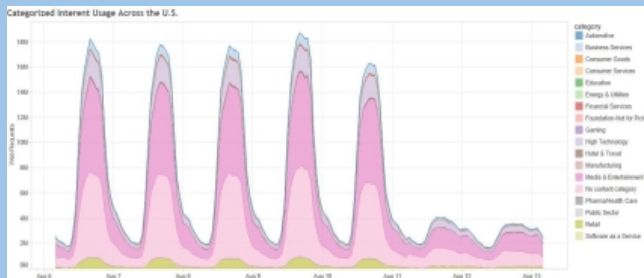
Time Series of Scan Statistics



Scan Statistics for Anomaly Detection

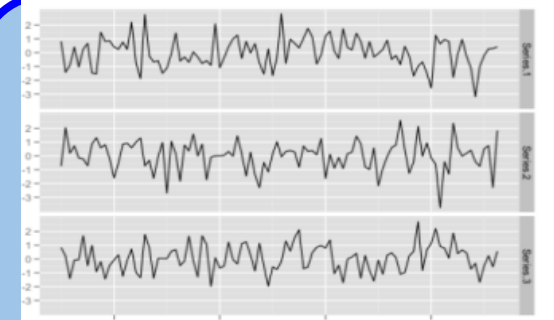


Embedding dissimilarities between CIDR Traffic

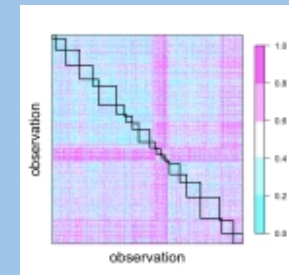


CIDR Hourly Traffic for each category

Aggregate by
summing the traffic for
each week



Multivariate Time Series

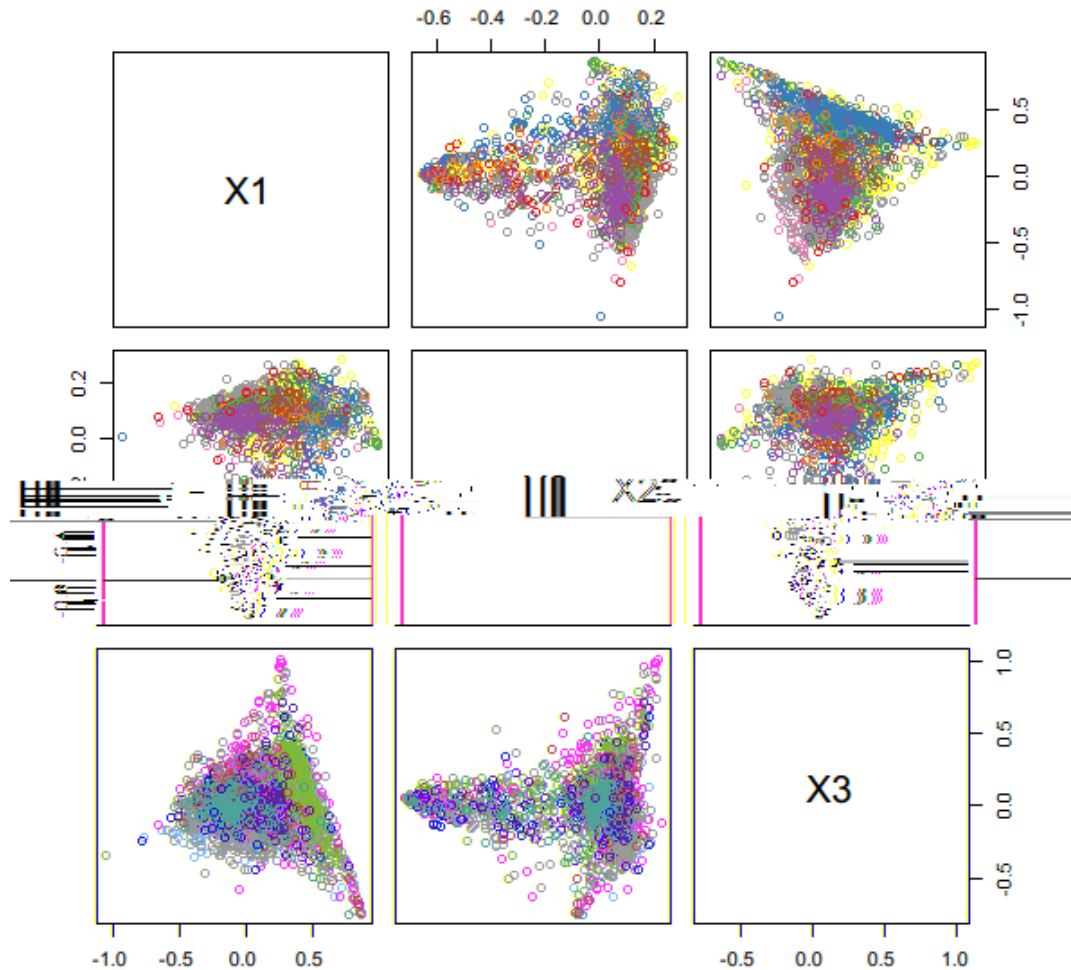


Dissimilarity Representation



Embedding via MDS





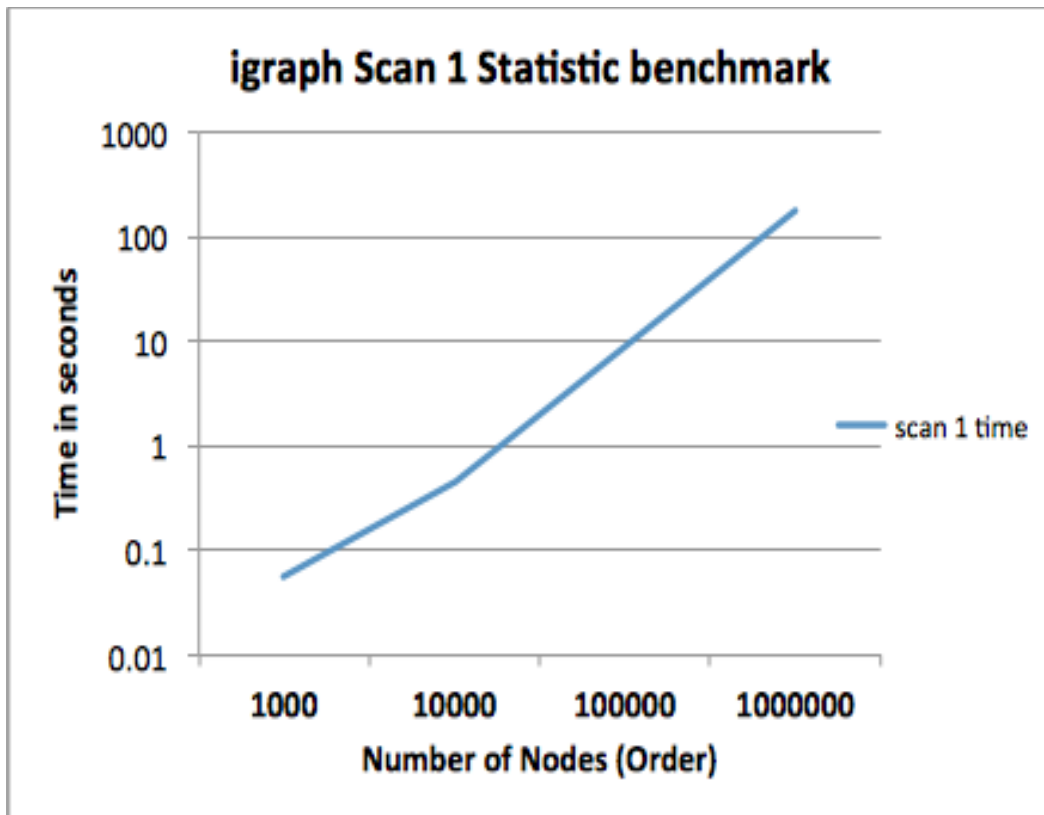
- CIDRs based on China (blue) show a clustering pattern



3D Plot of CIDR Embedding



Scan 1 Statistic & Spectral Embedding



igraph 0.7 introduces:

- Fast implementation of Scan 1 Statistic exact and approximate invariant
- Fast spectral embedding of adjacency matrices using ARPACK



PNNL/Stanford/Purdue : Ryan Hafen (Akamai-Traceroute, Akamai-CIDR)

BBN/Raytheon: Walter Andrews (Kiva)

Oculus: Peter Schrettlen (Bitcoin)

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Thank you.

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