Machine Learning in Anomaly Detection

Complex Networks

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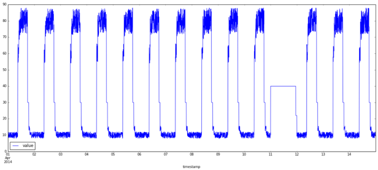
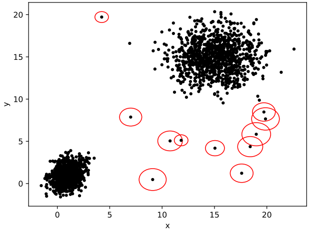
Anomalies? Outliers?

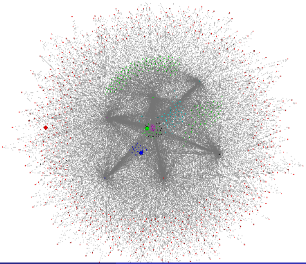
Anomaly



Clouds of points (multi-dimensional)



Complex Network



Outline

What is Anomaly?

Anomaly Definition [CBK09]

Anomaly is a pattern in the data that does not conform to the expected behavior.

- Anomalies are often related to significant real life entities
  - Cyber/Network intrusions, Image Processing / Video surveillance
  - Insurance/Credit card fraud
  - Industrial damage
  - Novel topic in text mining, Customer segmentation
- When an anomaly occurs, its consequences can be quite dramatic and quite often in a negative sense.

Why do we try to detect anomalies?

- Prevention (crime, device failure, production optimization, etc.)
- Novelty detection (technology trends, opinion)
- Knowledge extension (differences from known principles, laws)

Anomaly Basic Characteristics

Observations

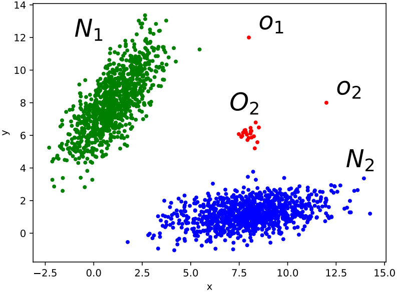
- Pattern . . . repeated
- Expected . . . "expected value" - extremal values, rare occurrences
- Expected behavior . . . subsets, temporally repeated
- Conform . . . simillarity, difference, distance, measurable

An anomaly as a data object (or a group of objects) that is [ATK15]

- **Rare** . . . e.g. a rare combination of categorical attribute values,
- **Isolated** . . . e.g. far-away point in n-dimensional space,
- **Surprising** . . . e.g. data instances do not fit well in a mental/statistical model.
- It requires too **many bits** to describe under the Minimum Description Length (MDL) principle [Ris78, Gru05].

Simple Example - Multidimensional Space [CBK09]

- N_1 and N_2 are regions of "normal" behavior
- Points o_1 and o_2 are anomalies
- Points in region O_3 are anomalies



Normal behavior

- **Normal distribution** . . . $N(\mu, \sigma)$.
  Further, it will be referred as Gaussian distribution
- **Normal behavior/pattern** . . . it is expected, not anomalous.

Key Challenges [CBK09]

- Defining a representative normal region is challenging
  - The *boundary* between normal and anomalous behavior is often not precise
  - The exact notion of an outlier is different for different *application domains*
- Availability of labeled data for training/validation
- Data might contain noise
  - Normal data - noise - anomaly
- Normal behavior keeps evolving, i.e. it is not static

Anomaly Types [CBK09]

- **Point/Global** Anomalies
  - An individual data instance is anomalous w.r.t. the data
- **Contextual** Anomalies
  - An individual data instance is anomalous within a context
  - Requires a notion of *context*
  - Also referred to as conditional anomalies [SWJR07]
- **Collective** Anomalies
  - A collection of related data instances is anomalous
  - The individual instances within a collective anomaly are not anomalous by themselves
  - Requires a relationship among data instances
    - Sequential Data
    - Spatial Data
    - Graph Data
- Online Anomaly Detection
- Distributed Anomaly Detection

Point Anomaly Types Taxonomy [CBK09]

- Classification based
  - Rule based
  - Bayesian Networks based
  - Neural Networks based
  - SVM based
- Nearest Neighbor Based
  - With respect to each instance local neighborhood
  - Density Based
    - Local Outlier Factor (LOF)
    - Connectivity-based Outlier Factor (COF)
  - Distance Based
- Clustering Based
  - With respect to the cluster each instance belongs to
- Statistical
  - Parametric
    - Gaussian model
    - Regression model
  - Non-parametric
    - Histogram based
    - Kernel function based
- Others
  - Information Theory
  - Spectral Decomposition
  - Visualization Based

Input Data [Agg17]

- Record data
  - Univariate
  - Multivariate
- Attributes
  - Binary/Boolean
  - Categorical
  - Continuous
  - Hybrid
- Relations
  - Sequential
    - Temporal
  - Spatial
  - Spatio-temporal
  - **Long range correlations**
  - **Graph**
- Data Quality
  - Data Fusion
  - Data Cleansing
  - Consistency maintenance
- Processing
  - Online/Offline processing
  - Distributed processing
  - **Analysis** × **Production**
    - Feature/Property searching/selection
    - Selected features detection
- Data Volume
  - Dense/**Sparse**
  - Low/High dimensions
  - Low/**Large volumes**
  - Big data
  - Internet of Things

Input Data - The Old Kingdom of Egypt [MD15]



- Continuous . . . tomb dimensions
- Categorical . . . titles
- Binary, boolean . . . titles
- Multivariate . . . people, titles, tombs
- Temporal . . . dynasties, king reigns
- Spatio-temporal . . . location of tombs in time

Output of Anomaly Detection [CBK09]

- **Score**
  - Each test instance is assigned an anomaly score
  - E.g. Euclidean, Mahalanobis, Frobenius norms
  - Allows the output to be ranked
  - Requires an additional threshold parameter
- **Label**
  - Each test instance is given a normal or anomaly label
  - This is especially true of classification-based approaches

Data Supervision [HA04]

Availability of class labels reflected by data processing

- **Supervised** Anomaly Detection
  - Labels available for both normal data and anomalies
    - $\Longrightarrow$ machine learning
    - $\Longrightarrow$ the classification problem is often **highly imbalanced**
- **Semi-supervised** Anomaly Detection
  1. Labels available only for **normal** data
     - $\Longrightarrow$ one-class learning, **thresholding**
  2. Labels available only for **anomalous** data
     - $\Longrightarrow$ one-class learning
     - $\Longrightarrow$ highly tuned commercial tools for network monitoring and analysis
- **Unsupervised** Anomaly Detection
  - No labels assumed
  - Often based on the assumption that anomalies are very **rare** compared to normal data
    - $\Longrightarrow$ clustering

What is an outlier? [KKZ10, Agg17]

Hawkins (1980) [Haw80]

An **outlier** is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism.

Barnett and Lewis (1994) [BL94]

An outlying observation, or **outlier**, is one that appears to deviate markedly from other members of the sample in which it occurs.

- Statistics-based intuition
- Normal data objects follow a "generating mechanism", e.g. some given statistical process
- Abnormal objects deviate from this generating mechanism

Grubbs's Test [Gru50, Gru69]

- To detect **a single outlier in a univariate data** set that follows an approximately **Normal (Gaussian) distribution**
- Also known as the maximum normed residual test
- The test considers the maximum absolute difference between observations $x_i$and the mean $\bar{x}$, normalised with respect to the sample standard deviation s:

$$G_{\max} = \max_i \left|\frac{x_i - \bar{x}}{s}\right|$$

- And considers the chance of such an extreme value occurring given the number of observations, given that the data are Normally distributed.
  - H_0: The observation is not different than the sample population.
  - H_a: The observation is different than the sample population.

Test statistics

- Significance level α
- Critical region: for the two-sided test, the hypothesis of no outliers is rejected if

$$G > \frac{(N-1)}{\sqrt{N}} \sqrt{\frac{(t_\alpha/(2N), N-2)^2}{N-2+(t_\alpha/(2N), N-2)^2}}$$

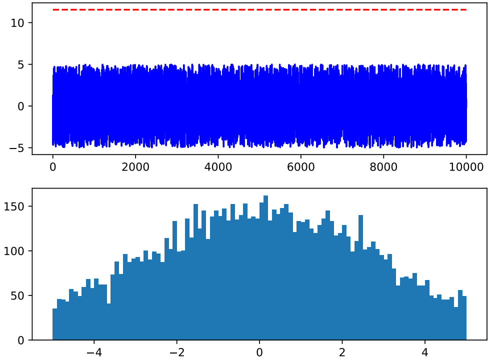
with $t_\alpha/(2N), N-2$ denoting the critical value of the t distribution with $(N-2)$ degrees of freedom and a significance level of $\alpha/(2N)$.

Grubbs's Test - Example [Gru50, Gru69, HA04]

Example 1

- $n = 93, \bar{x} = 52.2, s = 1.38, G_{\max} = (57.0 - 52.2)/1.38 = 3.49$
- From the G table at $n = 93$ and $\alpha = 0.05$ the critical value is 3.18.
- Since $3.49 > 3.18$, reject H_0.
- The observation is from a different population $(G_{3.49}, p < 0.025)$.

- The test gives false results for some especially **asymmetric** distributions.
- A significant **gap** between the data produced by the normal bounded generating process and the level at which observations are treated as outliers.
- $N(0, 3)$ truncated by $[-5, 5]$
- Significance level $\alpha = 0.05$
- An outlier detected above 11.55



Thresholds based Extreme Value Theory [Mar17b]

- Let $X_1, \ldots, X_N$ be a (discrete) sequence of independent random variables having a common distribution function F that is unknown.
- A given volume (**block**) of n observations to which we relate occurrences of extremal values
- The distribution of block maxima is created.
- We set a threshold τ as a robust estimate of the upper bound of signal values

$$\tau = p_{0.975,n} + \mathsf{iqr}_n$$

  - where n is a sufficiently large block size depending on the application problem and its setup,
  - percentile $p_{0.975,n}$,
  - iqr_n is the interquartile range used instead of the standard deviation.

$$\mathsf{iqr}_n = p_{0.75,n} - p_{0.25,n}$$

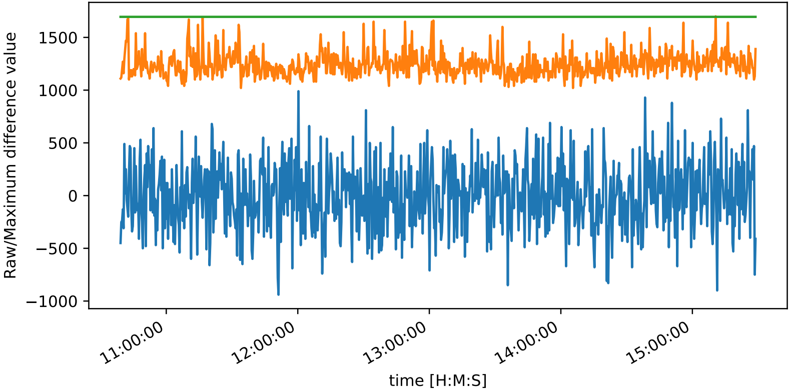
Extreme Value Theory (EVT) [Col01]

- $\{X_1, X_2, X_3, \ldots\}$ is a sequence of iid random variables
- The **block maxima** $Z_{n,i} = \max(X_1, \ldots X_n)$, $i = 1, \ldots, m$
- A random variable Z is said to have a **generalised extreme value distribution** (GEV) [Jen55] with scale parameter $\sigma > 0$, location parameter μ and shape parameter ξ, if its cumulative distribution function is

$$G(z) = \exp\{-[1 + \xi(\frac{z-\mu}{\sigma})]^{-1/\xi}\} \tag{1}$$

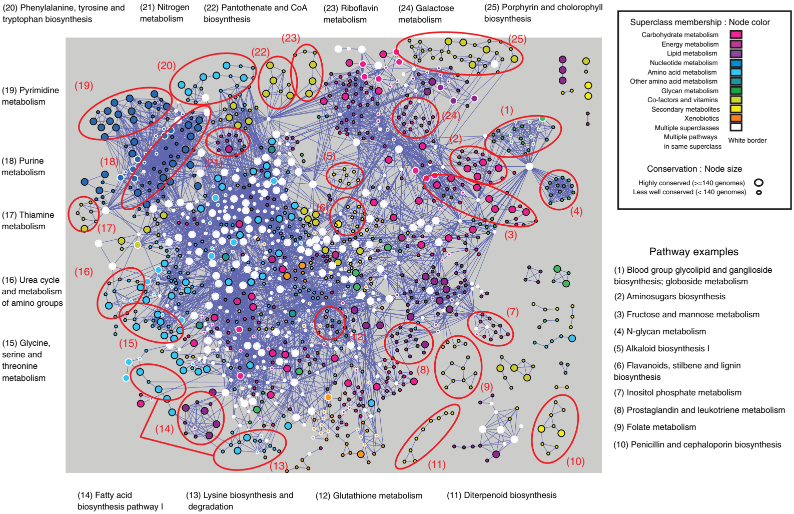
- defined on the set $\{z : 1 + \xi(z - \mu)/\sigma > 0\}$,
- where the parameters satisfy $-\infty < \mu < \infty$, $\sigma > 0$, $-\infty < \xi < \infty$
- The shape parameter ξ split the GEV family into three subfamilies
  - $\xi > 0$ . . . the **Frechet** family which density decays polynomially and $z_+ = \infty$.
  - The limit of $G(z)$ for $\xi \to 0$ leads the **Gumbel** family which density decays exponentially and $z_+ = \infty$.
  - $\xi < 0$ . . . the **Weibull** family, z_+ is finite, **the threshold**

Example - EVT based Threshold [Col01]

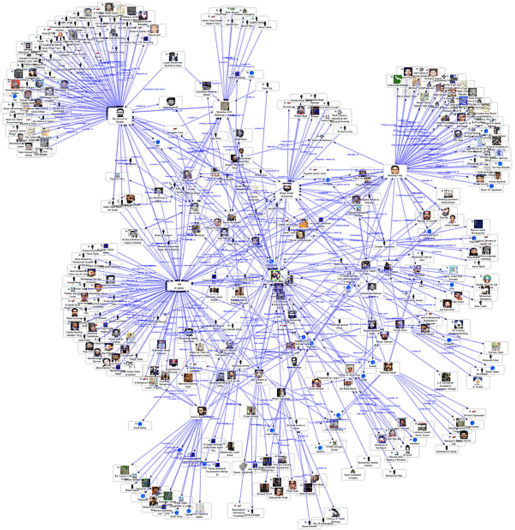


- Linear optical sensor stream data,
- **Blue** - the subsampled raw signal, **Orange** - block maxima,
- **Green** - the threshold

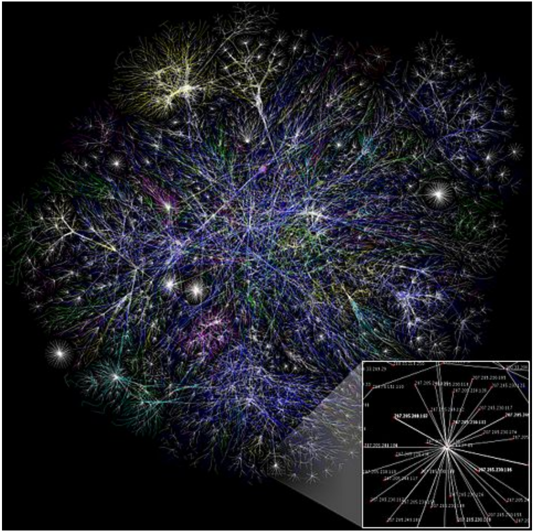
Conservation within the global metabolic network [PASP09]



Link Analysis of the Al Qaeda Terrorist Network [FMS]

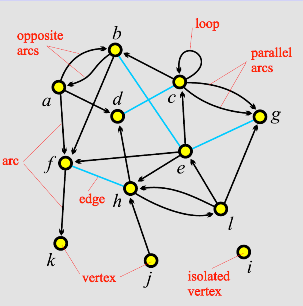


Internet map in 1995 [Bri95]



Graph [Weh13]

A graph is a set of vertices and a set of lines between pairs of vertices.



- **Actor** - vertex, node, point
- **Relation** - line, edge, arc, link, tie
  - Edge = undirected line, $\{c, d\}$
    c and d are end vertices
  - Arc = directed line, (a, d)
    a is the initial vertex, (source, start)
    d is the terminal vertex, (target, end)
  - Parallel (multiple) arcs/edges are only allowed in multigraphs with more than one relation (set of lines).
  - Loop (self-choice)

We focus on simple graphs!

A simple undirected graph has no loops and no parallel edges.
A simple directed graph has no parallel arcs.

Network [Weh13]

Network

A network consists of a graph and additional information on the vertices or the lines of the graph.

Formally, a network $\mathcal{N} = (\mathcal{V}, \mathcal{L}, \mathcal{P}, \mathcal{W})$ consists of:

- A graph $\mathcal{G} = (\mathcal{V}, \mathcal{L})$, where
  - $\mathcal{V}$ is the set of vertices,
  - $\mathcal{A}$ is the set of arcs,
  - $\mathcal{E}$ is the set of edges, and
  - $\mathcal{L} = \mathcal{E} \cup \mathcal{A}$ is the set of lines.
- $\mathcal{P}$ vertex value functions / properties: $p : \mathcal{V} \to A$
- $\mathcal{W}$ line value functions / weights: $w : \mathcal{L} \to B$

- **Long range dependencies** vs. multidimensional space
- **Specific topological properties**
- **Large/Huge volumes** of **sparse** data records

Networks Focused on Relations [Weh13]

RELATIONS MATTER!

Contrasted with both an *atomistic* perspective or a *whole-group* perspective

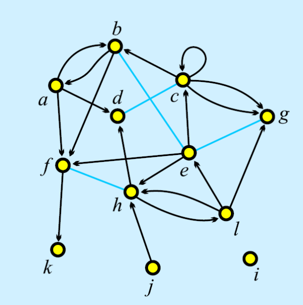
Social Network Analysis (SNA)

- Humanities and social science
- Activities and structures tied with people
  - Shopping basket analysis, targeted advertising
  - Enterprise processes analysis(people cooperation, good distribution)

Complex Network Analysis (CNA)

- Uses the same method as SNA
- Applied to all domains of human acting
- Biology, military, computer network, citations, telecommunication

Vertex Degree [Weh13]



- **Degree** of vertex i,
  $deg(i) = d_i = k_i = \sum_{j=1}^{n} A_{ij}$
  = the number of lines with i as end-vertex,
  (end-vertex is both initial and terminal)
- **Indegree** of vertex i, $indeg(i), deg^{+}(i)$
  $= k_i^{\text{in}} = \sum_{j=1}^{n} A_{ij}$ the number of lines with v as terminal vertex
- **Outdegree** of vertex j, $outdeg(j), deg^{-}(j)$
  $= k_j^{\text{out}} = \sum_{i=1}^{n} A_{ij}$ the number of lines with j as initial vertex.

Example 2

$n = 12,\ m = 23,\ deg^{+}(e) = 3,\ deg^{-}(e) = 5,\ deg(e) = 6$

$$\sum_{v \in \mathcal{V}} deg^{+}(v) = \sum_{v \in \mathcal{V}} deg^{-}(v) = |\mathcal{A}| + 2|\mathcal{E}|$$

Network Fundamental Matrices [New10, EK10]

- The **adjacency matrix** $\mathbf{A}$ of a simple graph is the matrix with element A_{ij} such that

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge between vertices } i \text{ and } j, \\ 0 & \text{otherwise} \end{cases}$$

- The adjacency matrix of a directed network has matrix elements

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge from } j \text{ to } i, \\ 0 & \text{otherwise} \end{cases}$$

- The **graph Laplacian** is the matrix

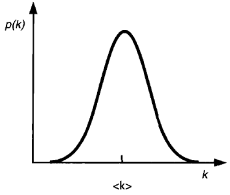
$$\mathbf{L} = \mathbf{D} - \mathbf{A}$$

where

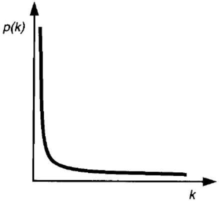
$$\mathbf{D} = \begin{pmatrix} k_1 & 0 & 0 & \cdots \\ 0 & k_2 & 0 & \cdots \\ 0 & 0 & k_3 & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

Degree Heterogeneity [Weh13]

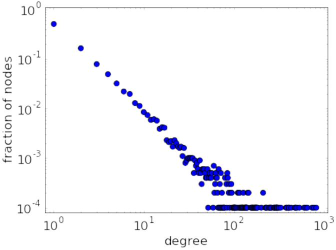
- Not all nodes show the same activity (degree) in networks.
- Some nodes show an astounding activity.
- Degree is most of all a question of tie formation cost.
  - Preferential attachment
  - Fitness model



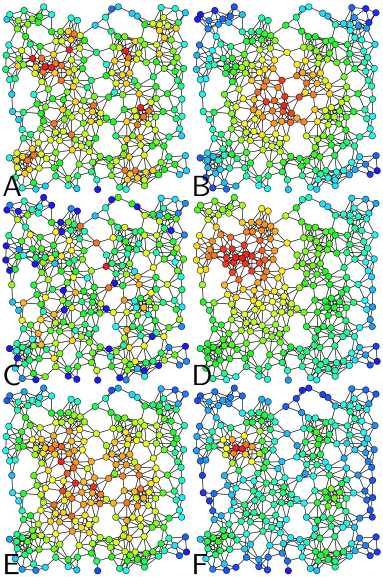
Gaussian



Skewed Distributions



Centrality Measures - Importance of Nodes [Roc12]

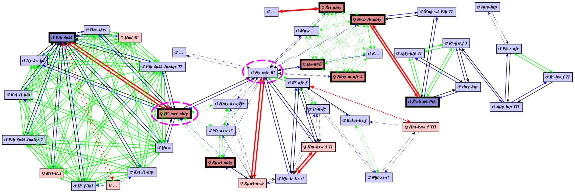


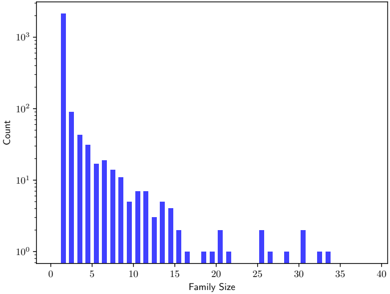
- Low → middle → high values
- **A** Degree centrality,
  - Node Activity
- **B** Closeness centrality,
  - Distance to other nodes
- **C** Betweenness centrality,
  - Intermediate Position
- **D** Eigenvector centrality,
  - Important nodes have important friends
- **E** Katz centrality,
  - The relative influence of a node within a network
- **F** Alpha centrality
  - Important nodes have important friends for asymmetric relations

Egypt Data - Family Formation [DM15]

Ny-wśr-Rꜥ	0.647
Ḫꜥ-mrr-nbty	0.424
Nwb-ỉb-nbty	0.351
Śꜥnḫ-wỉ-Ptḥ	0.290
Rꜥ-ḫw.f I	0.180
Rꜥ-nfr.f	0.139
ꜣḫty-ḥtp III	0.139
Ptḥ-špśś	0.082
Pḥ-r-nfr III	0.048
Šrt-nbty I	0.048

People with
the top 10 highest betweenness





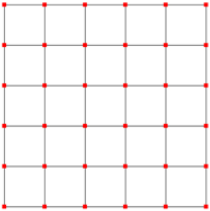
Extended family size distribution

Random Graphs

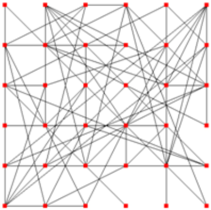
- Basic idea
  - Edges are added at random between a fixed number N of vertices
  - Each instance is a snapshot at a particular time of a stochastic process, starting with unconnected vertices and for every time unit adding a new edge
- Four basic models of complex networks
  - Regular lattices (meshes) and trees
  - Erdös-Renyi Random Graphs (ER)
    - A disconnected set of nodes that are paired with a uniform probability.
  - Watts-Strogatz Models [WS98] (SW)
    - **Small-world networks**
    - Connections between the nodes in a regular graph were rewired with a certain probability
  - Barabási-Albert Model [BAJ99] (SF)
    - **Scale-free networks** characterized by a highly heterogeneous degree distribution, which follows a "power-law"

$$P(k) \sim k^{-\gamma}$$

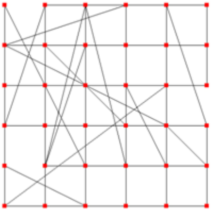
Complex Network Models [GDZ+15]



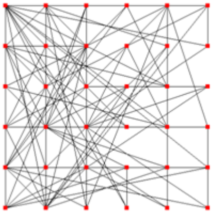
(a) Regular lattice ($p = 0$)



(b) Random network ($p = 1$)



(c) Small-world ($p = 0.01$)



(d) Scale-free ($n_0 = 3$, $m_0 = 3$)

Summary of Approaches [New06, Weh13, CRTV07, HK13]

- The **density** of graph is the proportion of present lines to the maximum possible number of lines.
- **Clustering coefficient** is a measure of the degree to which nodes in a graph tend to cluster together

Global clustering coefficient [HK13]

the ratio of the total number of triangles to the total number of connected triplets.

$$C_g = \frac{2\sum_{i=1}^{N} \ell_i}{\sum_{i=1}^{N} d_i(d_i - 1)}$$

- **Modularity** ... is - up to a normalization constant - the number of edges within communities c minus those for a **null model**
  - *"A good division of a network into communities is not merely one in which there are few edges between communities; it is one in which there are fewer than expected edges between communities".*

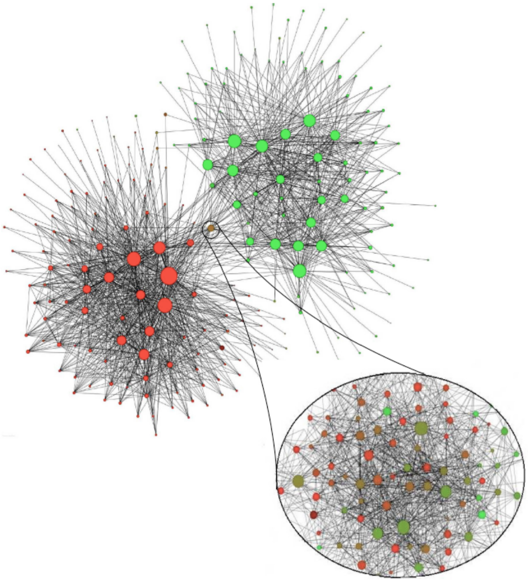
Modularity [New06, BGLL08, New10]

- The **modularity** is, up to a multiplicative constant, the number of edges falling within groups minus the expected number in an equivalent network with edges placed at random, but with the same node degree distribution.
- A weighted network
- c_i . . . a community of a given node i

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{d_i d_j}{2m} \right] \delta(c_i, c_j)$$

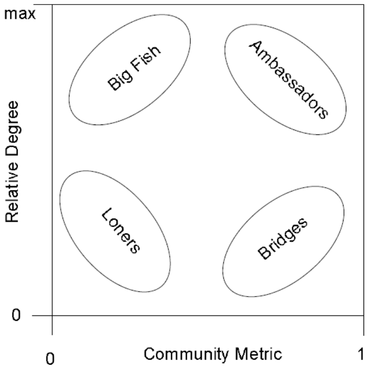
- where
  - A_{ij} . . . weight of the edge between i and j, adjacency matrix
  - $d_i = \sum_j A_{ij}$ . . . degree of i
  - $m = \frac{1}{2} \sum_{i,j} A_{ij}$ . . . total weight
  - $d_i d_j / 2m$ . . . the *expected* number of edges between vertices d_i and d_j
  - $\delta(u, v)$ is 1 if $u = v$ and 0 otherwise
  - $Q \in [-1, 1]$

Belgian Mobile Phone Network - Louvain Method [BGLL08]



- 2.6 millions customers
- Language: Dutch, English, French, German,
- 6.3 millions links
- Weights ... number of call + sms
- Red ... French,
- $> 93\%$ segregated,
- The center ... Brussels

Community-based Node Roles [STE07]



- An *authority* . . . how much knowledge, information, etc. held by a node on a topic.
- A *hub* . . . how well a node 'knows' where to find information on a given topic.
- An *ambassador* has links to many nodes from different communities
- A *big fish* has links only to other nodes in the same community
- A *bridge* . . . serves as bridges between a small number of communities
- A *Loner* . . . a low relative degree and low community score.

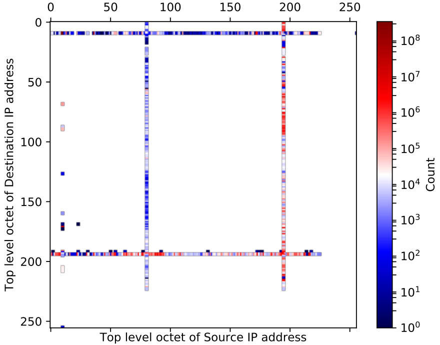
NETFLOW Primary Statistics

- **Netflow**
  - Condensed records on a packet flow
  - Several packets are merged into one netflow record
  - Only 14-20 aggregated metrics

An enterprise traffic as a netflow sample taken during 9 days:

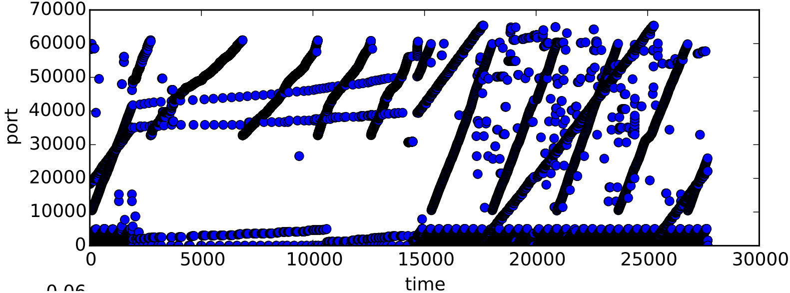
Statistics	Value
Total transported data volume	13,995,690,457,765 $[B]$
Packet count	20,131,367,095
Netflow count	617,326,053
IP address count	686,168
Source IP address count	614,150
Destination IP address count	392,881
Different P2P connections count	2,412,481

Top Level IP Network Projection - Data Sparsity



- Focused on the network of source and destination IP addresses
- Top level octets of IP addresses (160.30.29.17 $\Longrightarrow$ 160)
- A very sparse space
- A rather restricted source domain of IP addresses (as expected)

Port Scanning from xxx.xxx.18.120 - Logical Time Progress



- 617,326,053 netflows $\approx$ 60,000 samples $\times$ sample size 10.000
- $\Longrightarrow$ 60,000 samples might be still visualized with difficulties
- $\Longrightarrow$ 1.000 events can be easily missed with 10,000 sample size

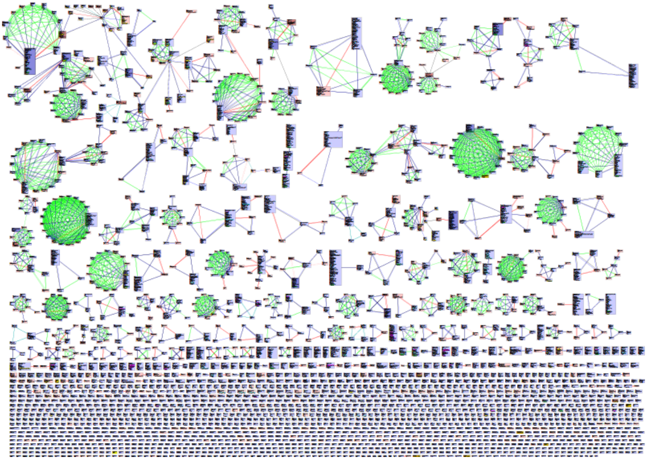
Masters of Social Network Analysis [RP13, Weh13]

- US National Security Agency
- Maintains large programs in social network analysis
- Believed to process 2×10^{10} node and tie updating events per day
- Result:
  "Better Person Centric Analysis"

Types

- **94 entity/node** types
  (*phone numbers*, *e-mail addresses*, *IP addresses*, etc.)
- **164 relationship** types to build "community of interest" profiles
  (*travelsWith*, *hasFather*, *sentForumMessage*, *employs*, etc.)

Egypt Data - Family Recognition

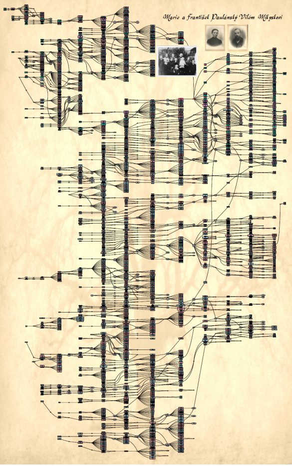


circular layout (yEd)

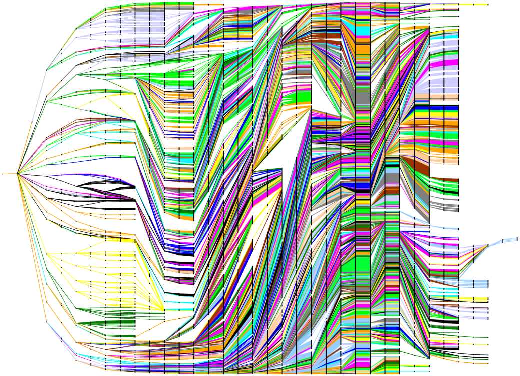
A family:

- Using family designation
  - husband, wife, son, etc.
- A connected graph component
- Sparse data assumed
- Transformed into family tree using marriage nodes

Family Trees[Mar17a]

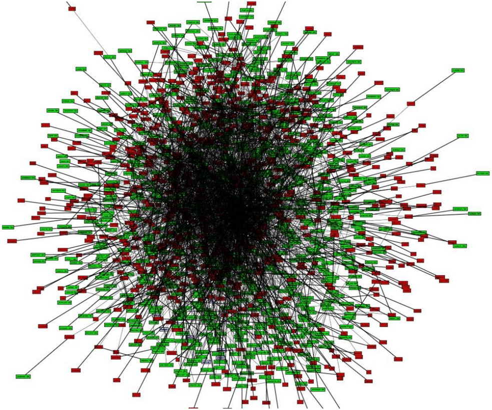


multitree-like tree driven layout, Graphviz



- Taxonomic information ITIS on plants, animals, fungi, and microbes,
- A phylogenetic tree with 945.352 nodes
- **multitree-like tree driven layout**

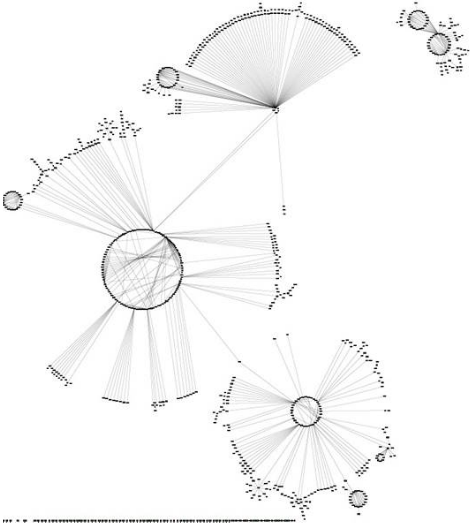
Dependancy of External Symbols in Mainframe Assembly Software



Fruchterman-Reingold force-driven layout

- A software product . . . over 10.000.000 lines of code
- Over 400 modules . . . red
- External symbols . . . green
- Thick line . . . the definition of a symbol
- Thin line . . . a reference to a symbol
-
- *Where should the developer start with a bug analysis?*

Assembly Software - Recovered Architecture



double-circular layout - yEd

Approach to Complex Networks

- One needs to distinguish between **analysis** and **production** phases
- Some phenomena appear only with sufficiently large data volumes (emergent events)
- Volume
  - A number of suitable tools ... HDF5, ElasticSearch, Clouds
  - Capable to operate with terabytes of data
- Visualization
  - Critical if anomaly features are not known
  - At present, there is no obvious choice of a tool and a network layout given a particular problem.
  - Tools do not often scale with data volumes (> 10.000 nodes, 10^5 edges)
  - GGobi, Pajek, NetworkX, SNAP, Tulip, Gephi, Cytospace, yEd, D3.js
  - Aspects: data volume, interactions with the user

Network Anomalies [ATK15]

Networks

- Structured graph data
- Features/properties attached to nodes and edges
- Long-range correlations (data objects exhibit inter-dependencies)
- Specific topological patterns

Various settings of a general framework

- Unsupervised vs. (semi-)supervised approaches,
- Statis vs. dynamic graphs,
- Attributed vs. plain graphs.
- Effectiveness, scalability, generality, and robustness aspects.
- Class imbalance and asymmetric error (rare abnormal $\times$ normal)
- Root cause analysis: Why is it anomalous?

Anomalies in Static Plain Graphs [ATK15]

- **Structure** based methods
  - **Feature** based approaches
    - *Extract features and used outlier detection graph-centric features*
    - Node-level features (centralities, local clustering coefficient)
    - Node-group-level features (compactness, density, modularity)
    - Global measures (number of connected components, principal eigenvalue)
    - Egonet (1-step neighborhood around a node) (OddBall)
  - **Proximity** based approaches
    - *Measure closeness/proximity of objects*
    - Importance of nodes (PageRank, Personalized PageRank, SimRank)
- **Community** based methods
  - *Search for "bridge" nodes/edges that do not directly belong to any community*
    1. How to find the community of a given node?
    2. How to quantify the level of the given node to be a bridge node?
  - Matrix Factorization
    - Boolean/Binary Matrix Factorization (BMF)
    - Non-negative Matrix Factorization (NMF)

Anomalies in Static Attributed graphs [ATK15]

- **Structure** based methods
  - *Identify substructures that are rare structurally*
  - Connectivity, attributes
- **Community** based methods
  - *Aim to identify community outliers (nodes)*
  - CODA …an **unsupervised learning algorithm**
  - GOutRank …searches for **a subset of relevant attributes**
- **Relational learning** based methods
  - *Exploit the relationships between the objects to assign them into classes*
  - **Naive Bayes models** for local attributes
  - **Probabilistic relational models** (PRMs)

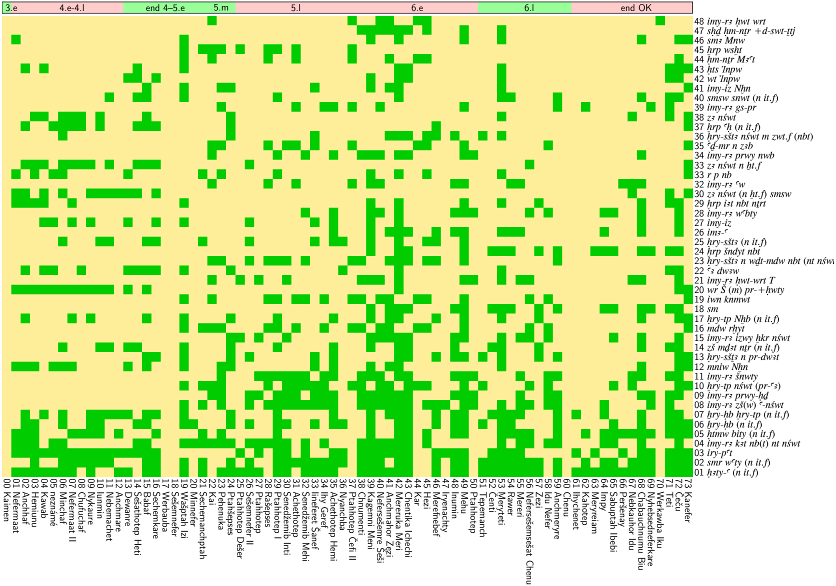
Anomaly Detection in Dynamics Graphs [ATK15]

- **Feature** based events
  - *"graph footprints" and metrics,*
  - Maximum Common Subgraph (MCS)
  - Graph Edit Distance (GED)
  - Hamming distance
- **Decomposition** based events
  - *matrix or tensor decomposition of the time-evolving graphs*
  - **Singular Value Decomposition (SVD)**
  - **Non-negative Matrix Factorization (NMF)**
  - Compact Matrix Decomposition (CMD)
  - Streaming Tensor Analysis (STA)
- **Community/cluster** based events
  - *graph communities over time*
  - **clustering, community detection, co-clustering**
  - **MDL-based, Bayesian anomaly detection method**
- **Window** based events
  - *"moving window analysis"*
  - k-step neighborhood

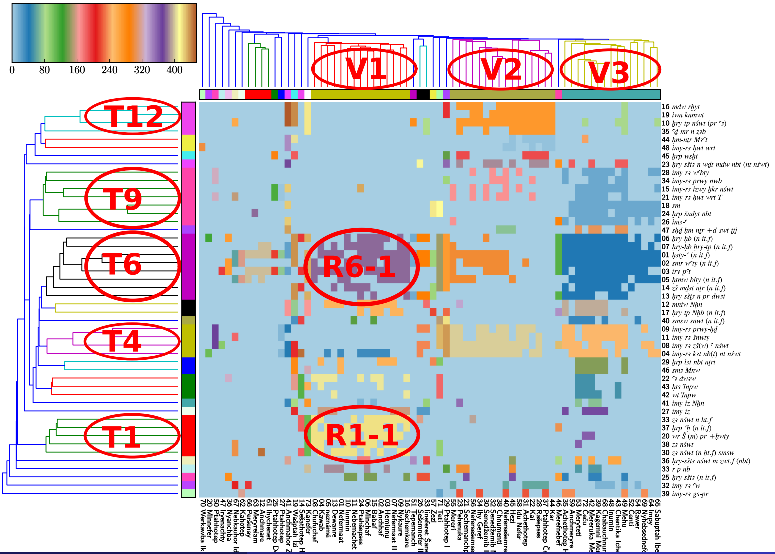
Rebellion [Eps02, Wil04, Wil99]

- This project models the rebellion of a subjugated population against a central authority.
- If the level of population wanders grievance against the central authority is high enough, and their perception of the risks involved is low enough, they openly rebel.
- The cops wander around randomly and arrest people who are actively rebelling.
- **Punctuated equilibrium** — periods of quiescence followed by periods of rebellion.

Titles of Viziers [DMBC17]

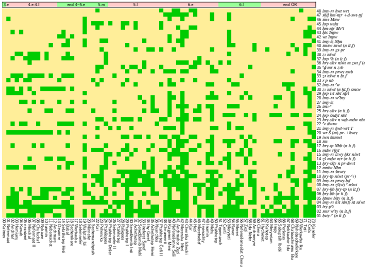


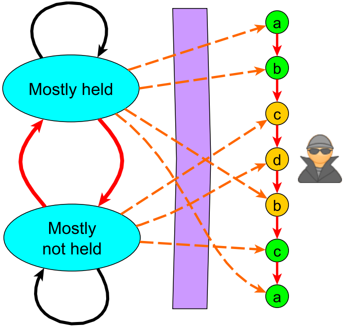
Titles of Viziers - Jaccard, Single Linkage Clustering [DMBC17, JD88]



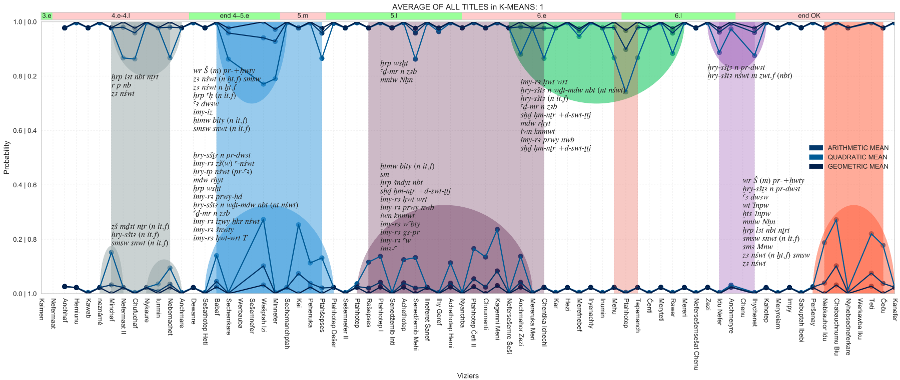
Hidden Markov Model on Titles [DMBC17]

- A sequence of viziers
- A sequence of appearances for each title
- A general model of title life (2 states)
- Focus on title occurrence change (red)
- A model of a title subset change
- Identification of periods when with a higher probability
  - A subset of titles started to appear
  - A subset of titles stopped to appear
- Identification of titles contributing to changes



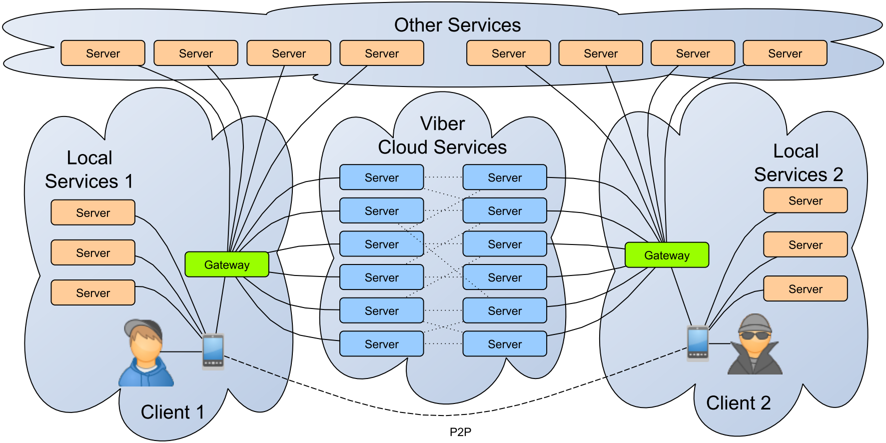


The Old Kingdom Administration Rise

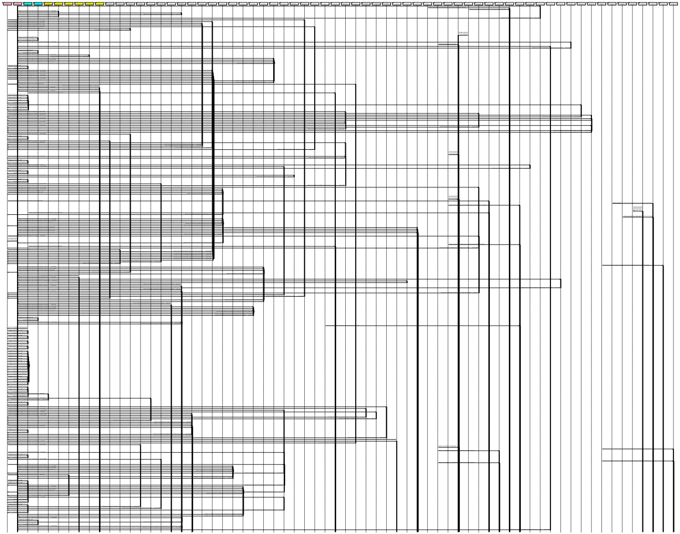


- Probability means of join changes in title occurrences
- Non-informative titles threshold (*feature selection*)
- Top – vanishing titles
- Bottom – rising titles
- Epochs match conclusions of Egyptologists

Exemplar (Viber) Environment [MBKK15]



Example Capture Characteristics - Message Sequences [MBKK15]

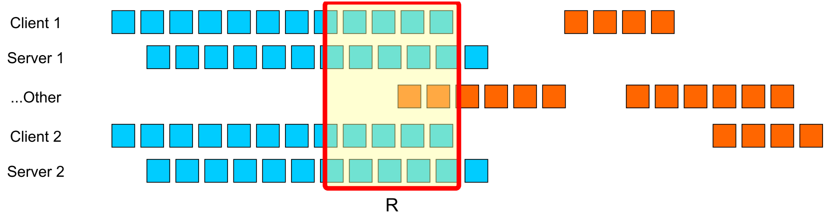


- 138882 PCAP blocks
- 1788 transport sessions
- 2 clients
- 22 viber.com servers
- 150 peers of 2 clients
- 5660 possible concurrent sessions
- How to analyze?

Concurrent Communication Detection [MBKK15]

Selection of IP nodes

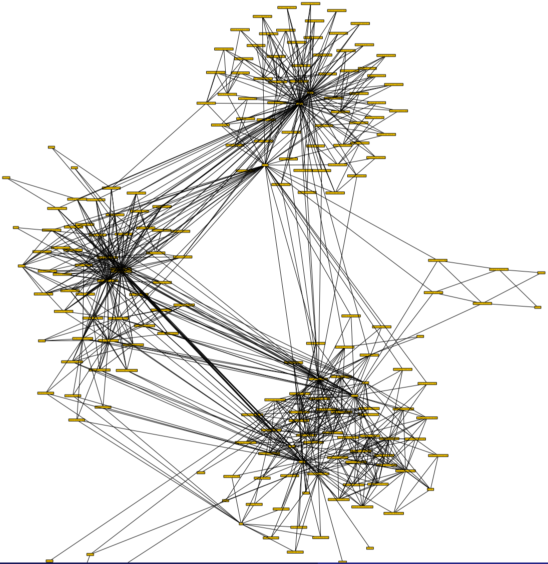
- *viber.com* servers $\rightarrow$ viber clients $\rightarrow$ other Viber servers
- Classified based on entropy based characteristics of TCP/IP distributions



$$s(a,b) = \frac{\sum_{\forall i,j: t_a[i]-t_b[j]<R} R/(t_a[i]-t_b[j])}{\sum_{\forall i,j: t_a[i]-t_b[j]<R} 1}$$

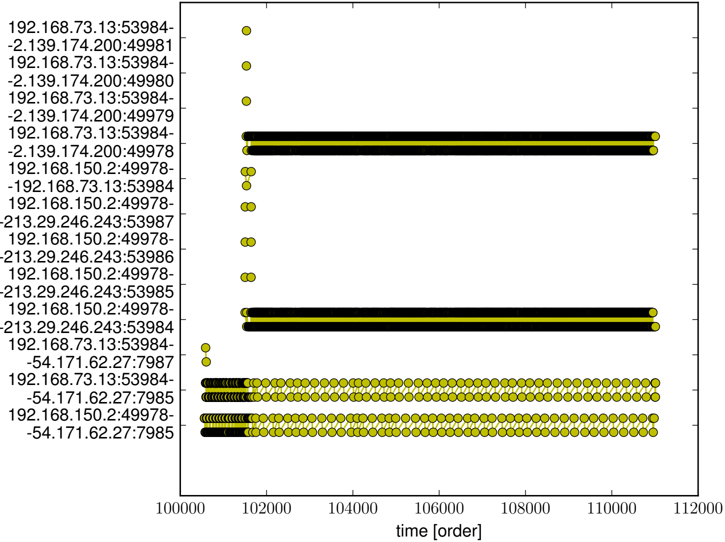
In our experiments: $R = 50ms, \quad s(a,b) > 0.001$

UDP Packet Sequence Concurrency as a Complex Network [MBKK15]



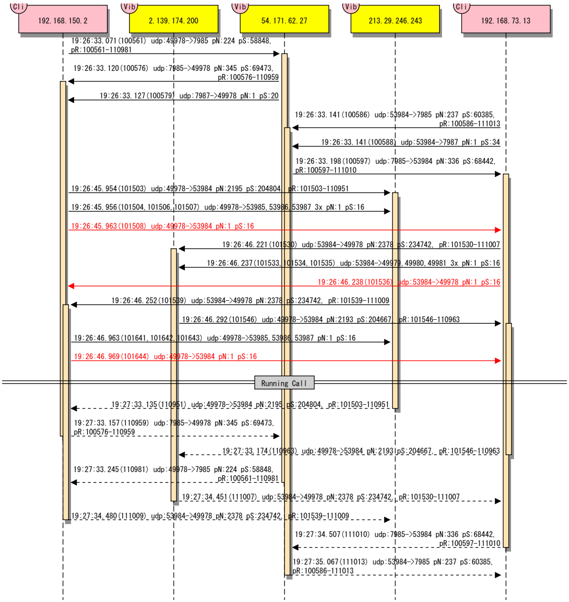
- Captures with two clients
- **Communities** of concurrent sessions
- Some clusters related to only one client
- Interesting clusters consist of nodes of **both** clients

UDP Packet Sequence Concurrency - Packet Timing [MBKK15]



- Signals
- Calls
- Keep-alive packets
- Direct client to client packets

Voice Call [MBKK15]



Conclusions

- A brief introduction to **anomaly and outlier detection**,
- **Complex networks** introduced as a representation of data with
  - Large-range dependencies,
  - Specific types of dependency topologies,
  - Large/huge volume of data.
- Anomalies might be detected using traditional **machine learning** methods with
  - Adjustments to huge data,
  - Special null models,
  - Special graph/network topological features
  - Community detection (topology/relation based $\times$ clustering)
- Applicable to many diverse domains

THANK YOU

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