New edge prediction and anomaly-detection in dynamic networks

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Collaborators

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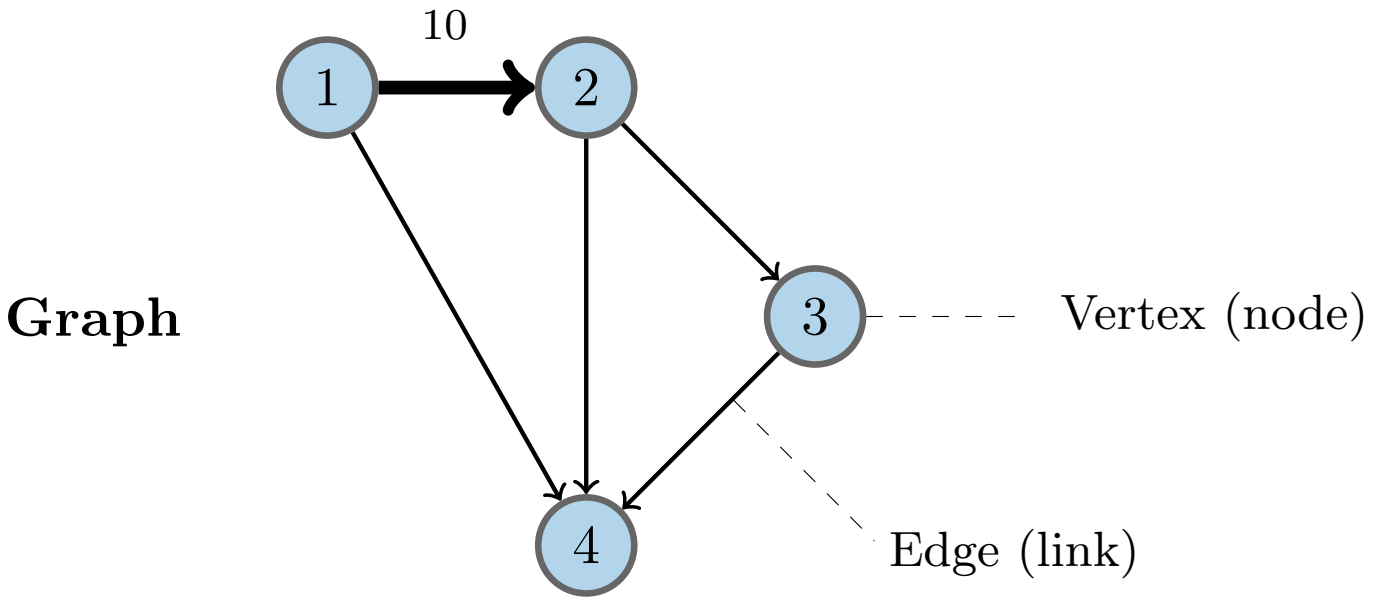
Overview of this talk

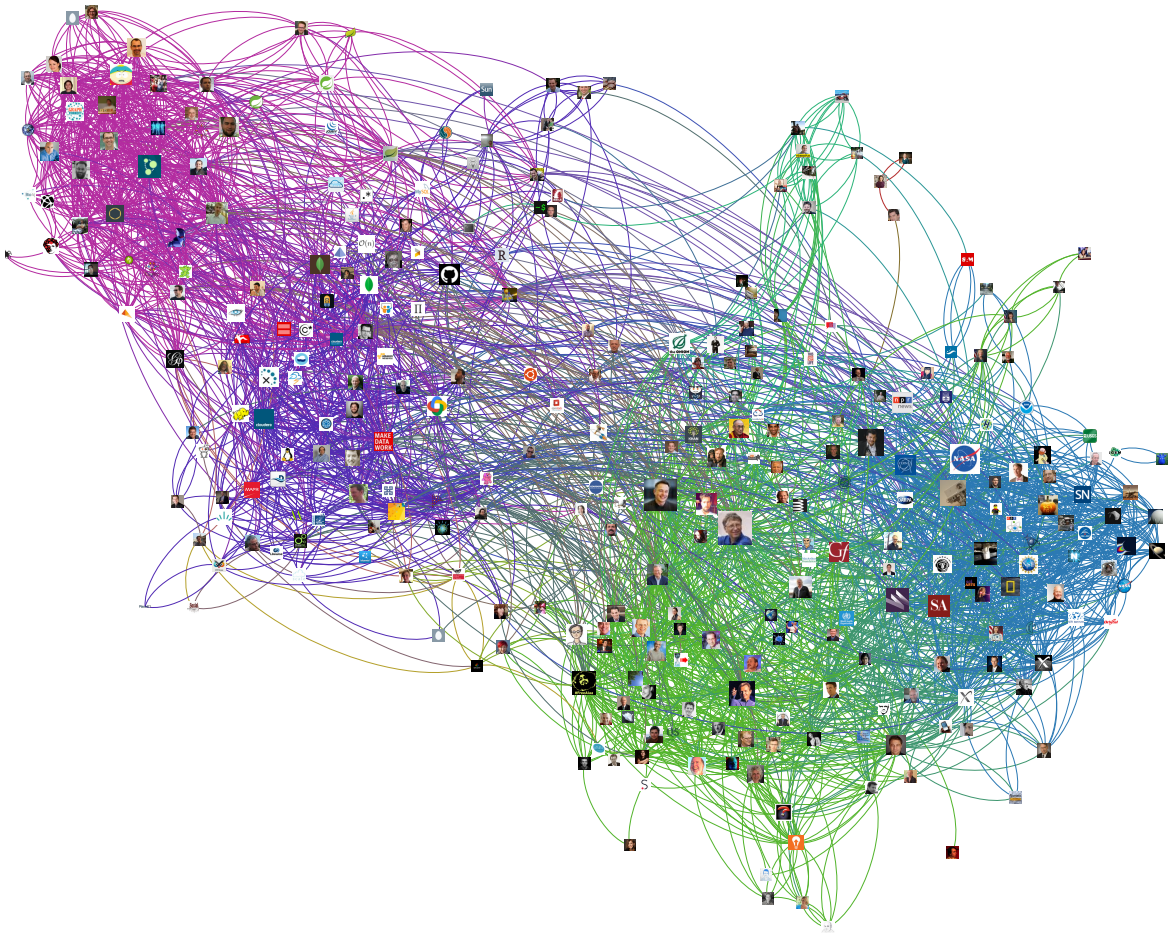
1. Introduction to network analysis
2. Longitudinal (dynamic) networks
3. The concept of new edges
4. Statistical anomaly-detection
5. Application to cyber-security
6. Some ideas for epidemiology applications

What is a network?

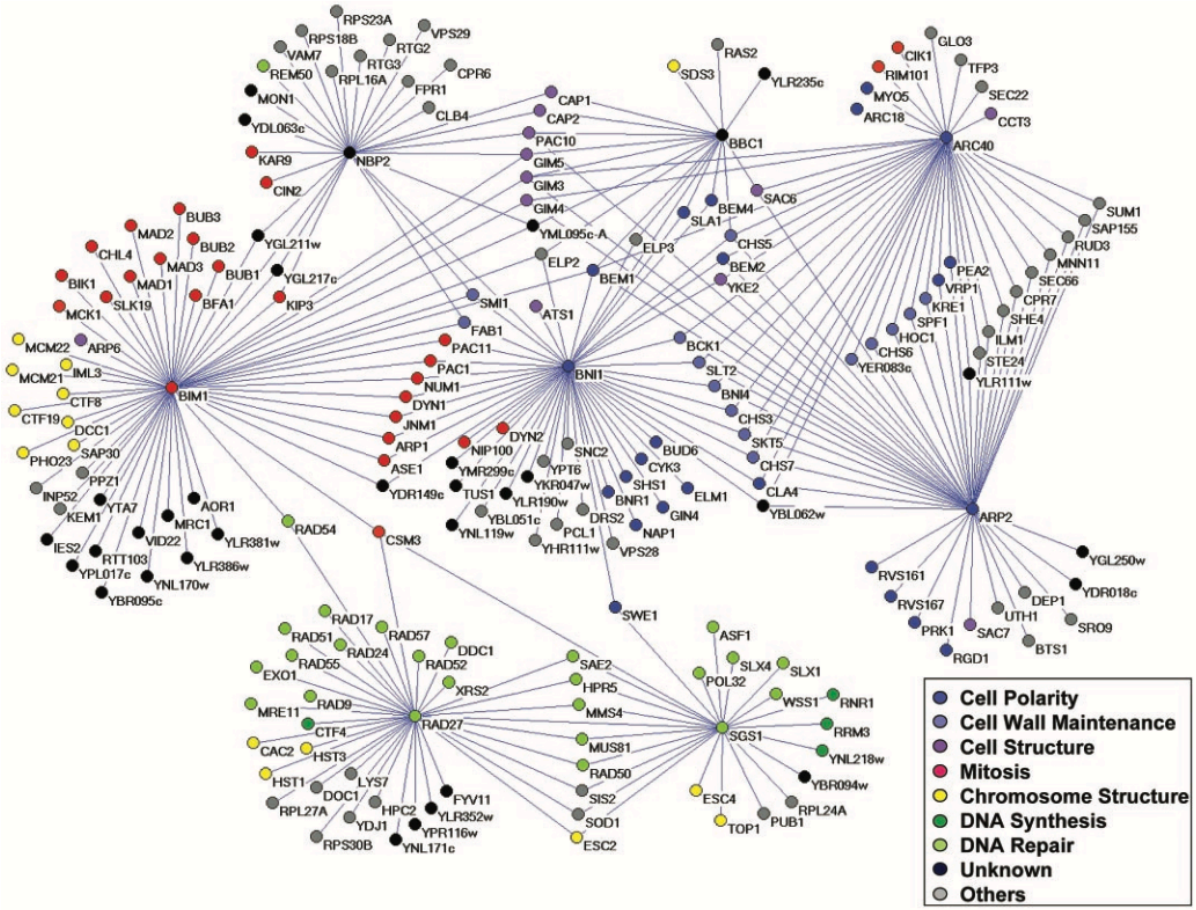


- ▷ a graph $G = (E, V)$: models the relationships between entities
- ▷ directed, undirected, weighted
- ▷ contributions from cell biology, engineering, epidemiology, neuro-science, sociology etc.

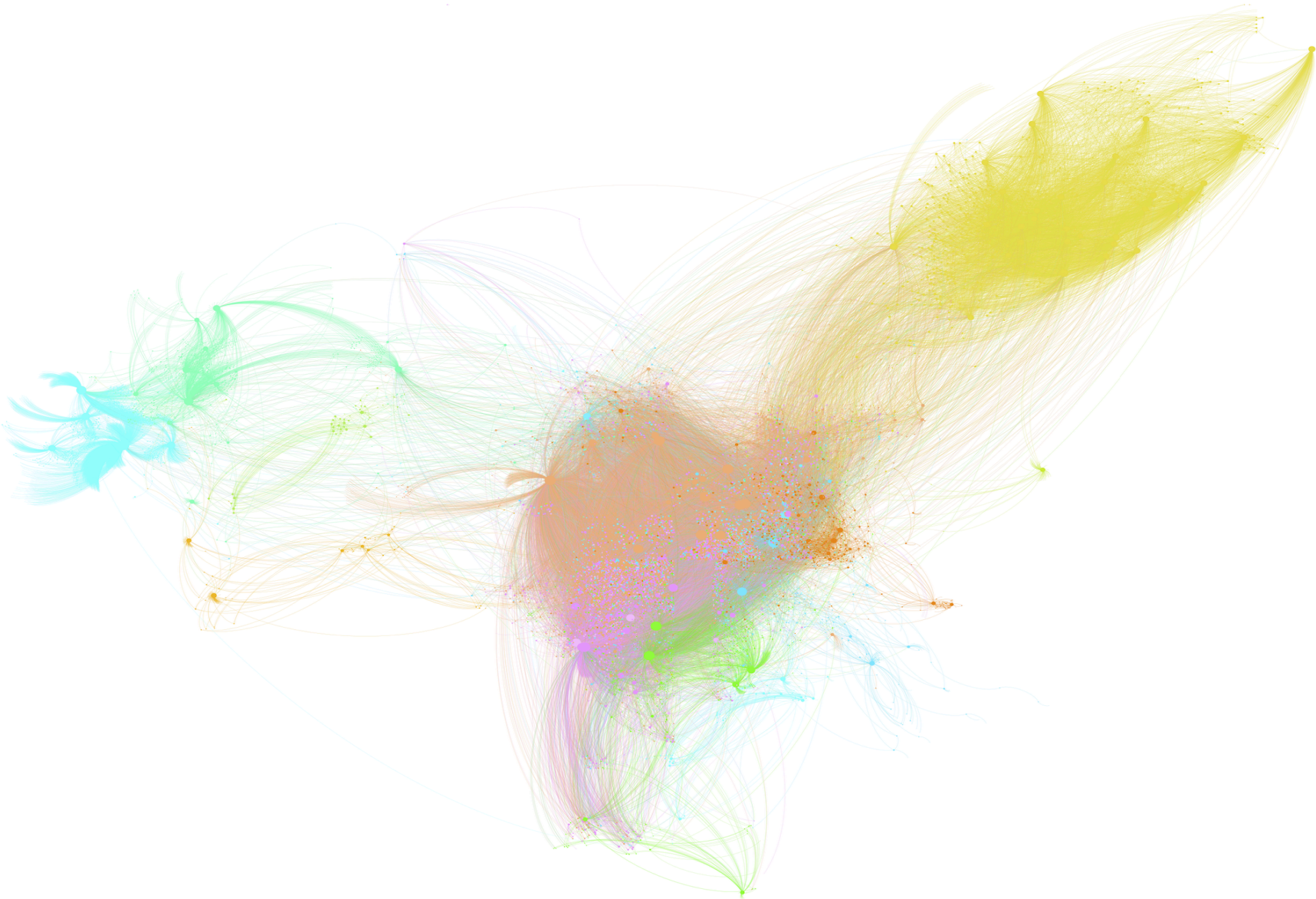
Examples: Social network (Twitter)



Examples: Genome network



Examples: Computer network (10min of traffic!)

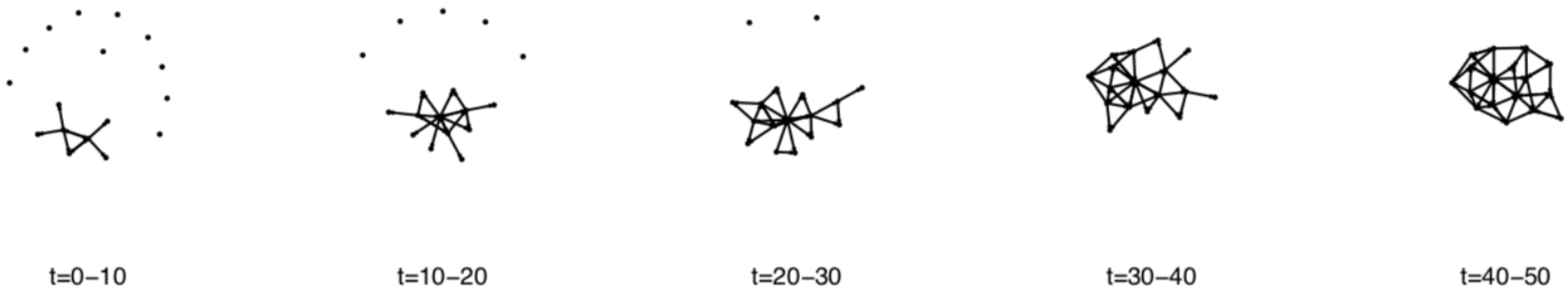


Static *vs.* dynamic

Static view: snapshot at a specific point in time ($\rightarrow$ cross-sectional data)

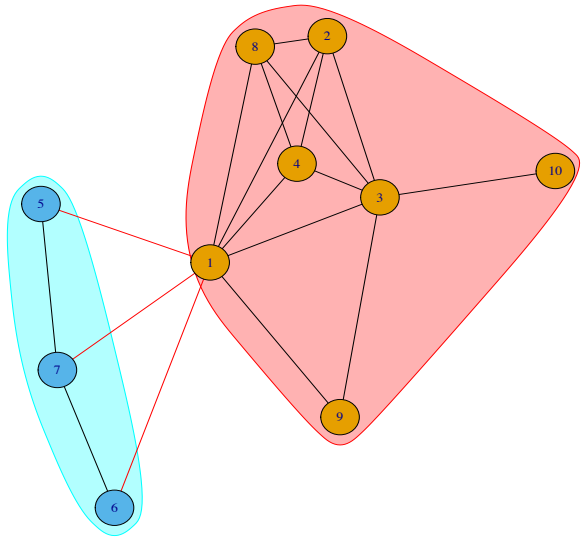
Dynamic view:

- follows the temporal evolution ($\rightarrow$ time-series data)
- fixed set of nodes
- evolving set of edges

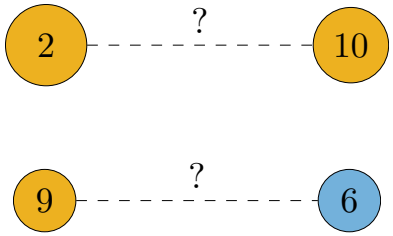


New edge prediction

New edges: edges not previously observed
Aim: predict new edges based on **existing structure** + **popularity**:
$\mathbb{P}\{\text{new edge at } t+1 | G_t\}$



How likely it is to observe the followings?

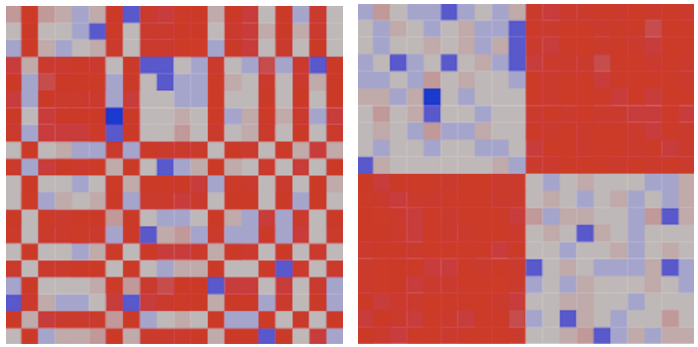


we propose a [Bayesian] PH model (Cox, 1972) for the conditional intensity, $\lambda_{ij}(t)$, of observing a new edge (i, j) after time t

Network structure (e.g. bi-clusters)

Adjacency matrix $A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots \\ \vdots & \vdots & \ddots & 0 \\ 1 & 0 & \dots & 1 \end{pmatrix}$

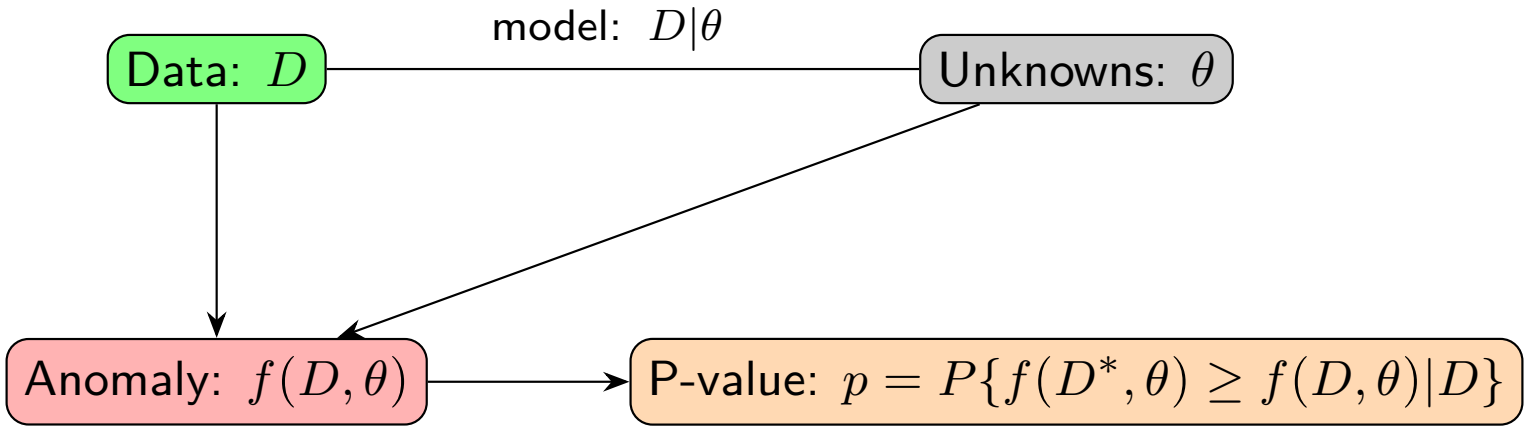
$$A(i,j) = \begin{cases} 1 & \text{if} \quad i \leftrightarrow j \\ 0 & \text{otherwise} \end{cases}$$



Original Reordered

- ▷ model-based hard-clustering (model-based similarity measures)
- ▷ heuristic dimensionality reduction (SVD, Spectral Clustering, K-means, PCA)
- ▷ flexible mixed-memberships/latent-features (LDA, Indian Buffet Process etc.)

Model-based anomaly-detection



$\mathbf{H}_0$: normal behaviour
$\mathbf{H}_1$: departure from model of normality learned

Anomaly: observation not compliant to learned network behaviour

Research can be performed from different perspectives:

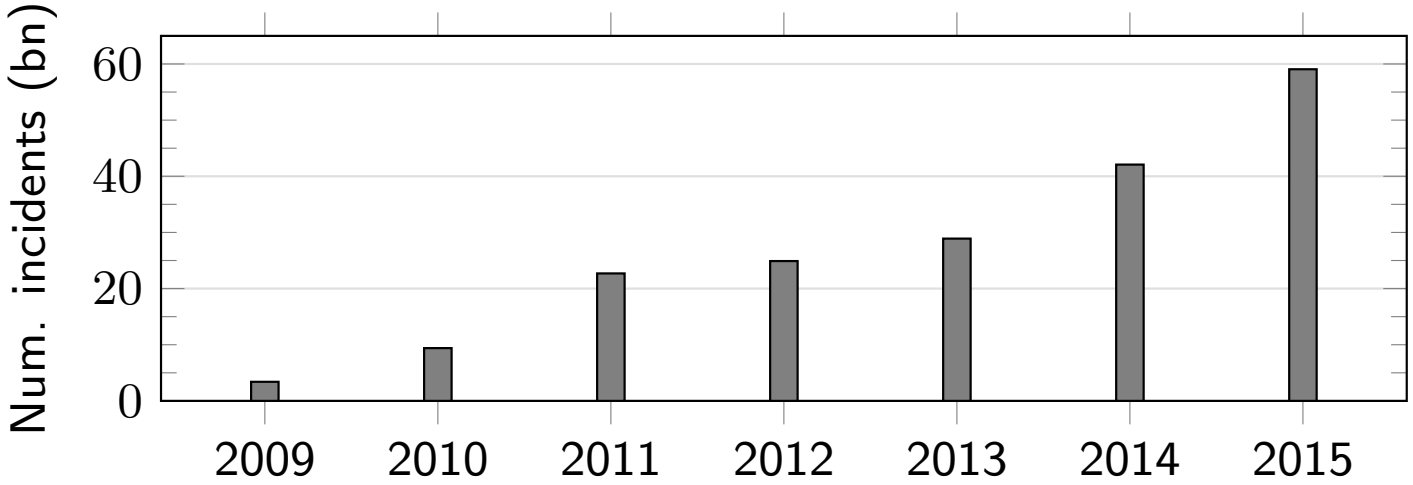
- whole graph (network structure)
- edges, nodes (temporal monitoring)

Cyber-security application

Context

Motivation: increasingly sophisticated, multi-stage cyber-attacks
e.g. *WannaCry 2017: 230,000 computers in 150 countries*

Global number of cyber incidents 2009-2015 (source: PwC)



(UK invested ∼1.9b in 2018)

Objective: monitor enterprise computer networks with really complex structure!

Challenges: computational speed and scalability (ideally, real-time detection)

Computer network data

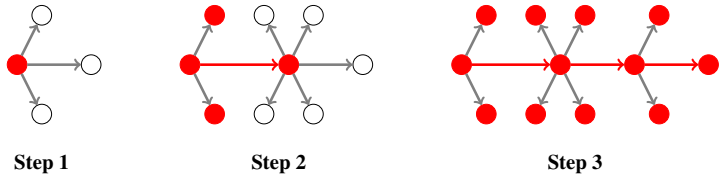
Variety:

- NetFlow data $\text{IP}_1 \rightarrow \text{IP}_2$ (time, duration, port, protocol, num. bytes...)
- Auth data (time, user, computer, success)
- Host-based data (run an agent on each host: time, process, parent process...)

Sources:

- Imperial College London (NetFlow)
- Los Alamos National Laboratory (90 days of traffic, 1 second resolution)

New edge intensity



New edges can be
- rarely, signal of anomaly
- regularly, formed by uninfected hosts

$$\lambda_{ij}(t) = \lambda(t)\exp\{\alpha \cdot (N_i^+(t), N_j^-(t), I_{i,1}(t), I_{i,2}(t)) + \beta_{ij} \cdot Z_{ij}(t)\} \times \mathbb{1}_{(I\times J)\setminus G_t\{(i,j)\}}$$

- $\lambda(t)$: 'seasonal' baseline (not parametrised)
- $N_i^+(t), N_j^-(t)$: time-varying in-degrees and out-degrees
- $I_{i,1}(t), I_{i,2}(t)$: time-varying indicators of new edge 'burstiness'
- $Z_{ij}(t)$: **matrix of attraction** $i \leftrightarrow j$ (similarity between nodes)

Cluster membership indicators

Dot-products of latent feature positions (IBP)

Application to Computer Network Data

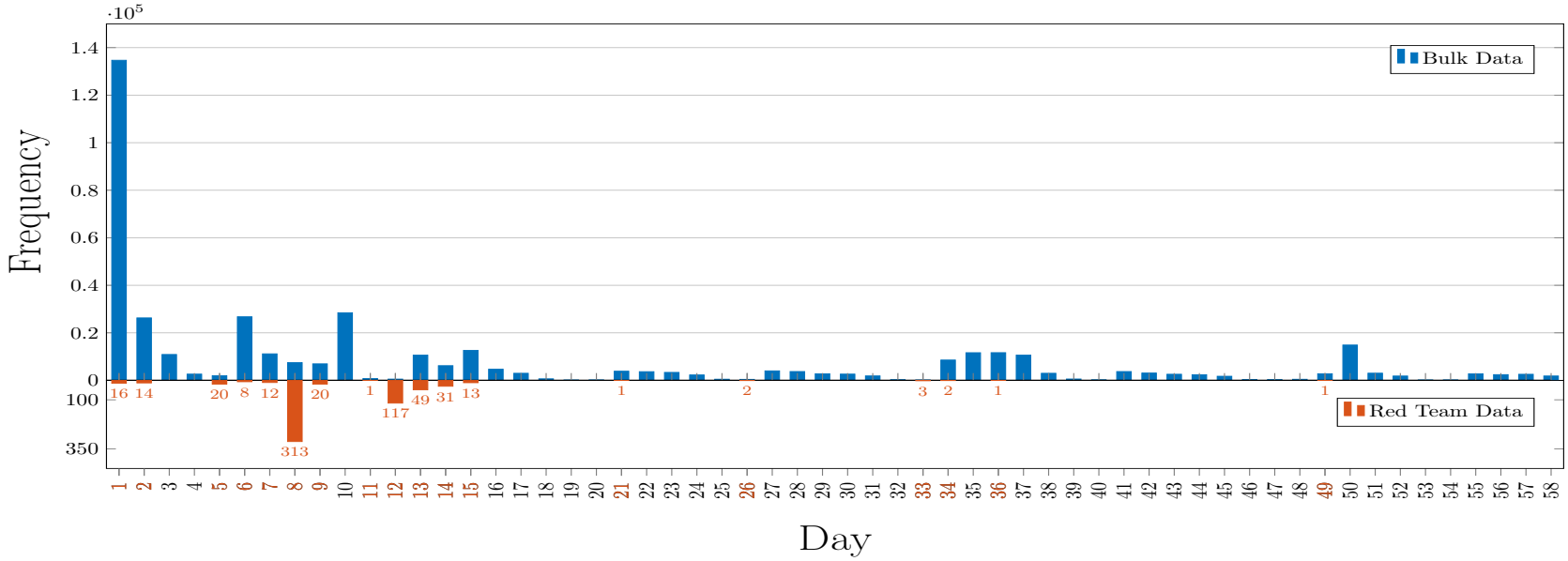
The LANL (Los Alamos National Laboratory) Data Set

Bulk:

- 1,648,275,307 events in total (58 days of traffic)
- 16,230 clients – 15,417 servers

Red Team:

- penetration testing: subset labelled as known compromised events
- 48,079 of the total records: 4 compromised clients



Model Prediction Performance

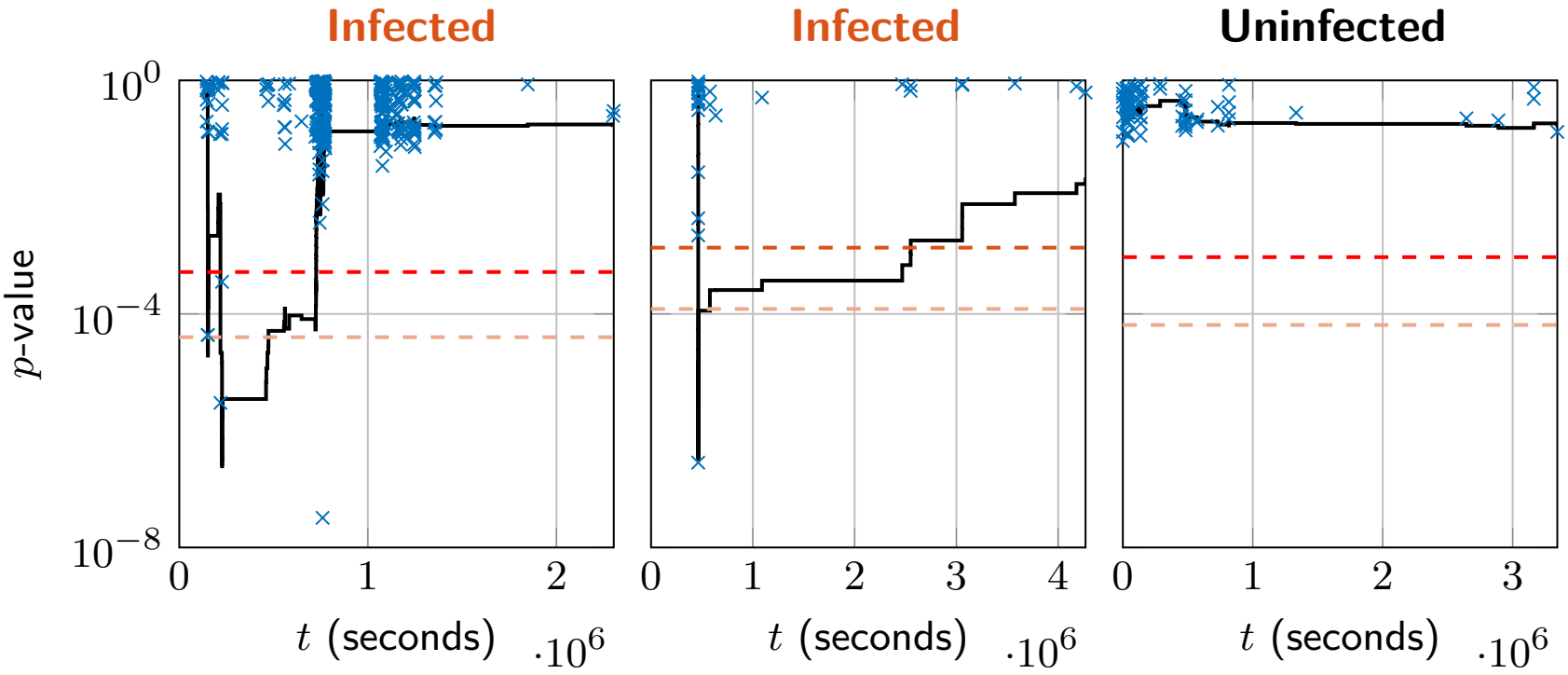
Method tested under both cluster and latent formulation:

- positive model coefficients: strong impact of degree and latent structure
- out-of-training log likelihood on the last 10,000 events

Model	**Log Likelihood**	**Iteration Time**
Cluster	-18804.34	81.4s
Latent-feature (IBP)	-18379.93	131.7s

We find that the latent feature model outperforms the cluster model

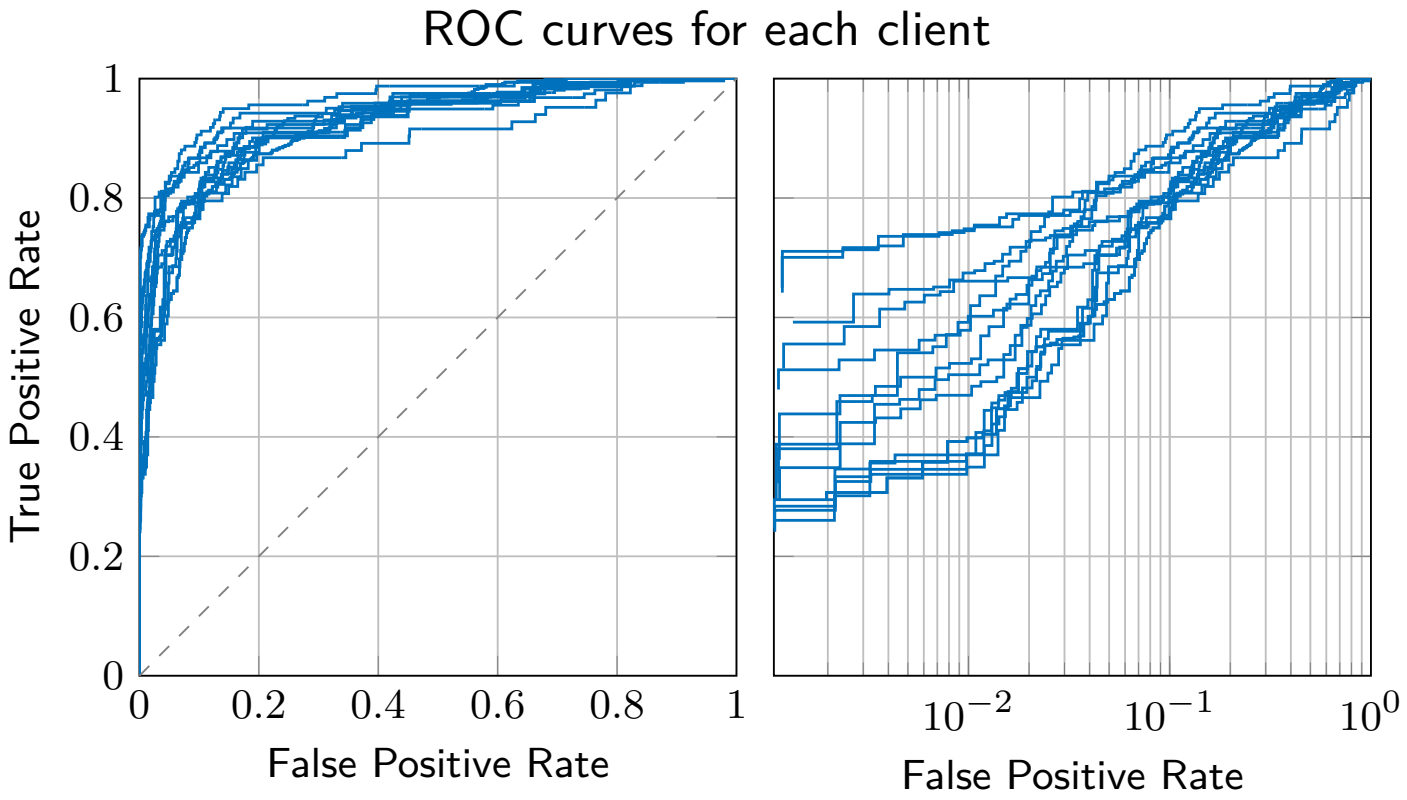
Anomaly-detection: control-charts



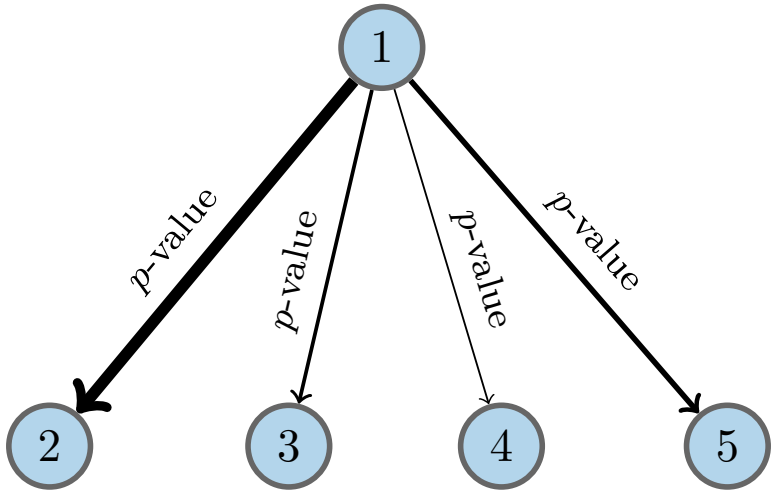
$$p_n = \frac{\sum_{(ij)\notin G_{t'_n}} \lambda_{ij}(t'_n)\mathbb{1}_{(0,\lambda_{i'_n j'_n}(t'_n)]}\{\lambda_{ij}(t'_n)\}}{\sum_{(i,j)\notin G_{t'_n}} \lambda_{ij}(t'_n)}$$

$$s_i(t) = \bar{\chi}^2_{2\{1+N_i^+(t)\}}\left(-2\sum_{n\geq 1}\mathbb{1}_{[0,t)}(t'^i_n)\log p^i_n\right) \text{ s.t. } \inf_{t\geq 0} s_i(t)$$

Anomaly-detection: ROC curves



Challenges

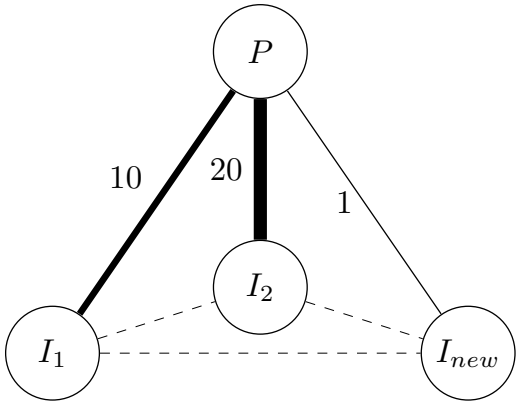


1. Robust model for predicting links/new links
2. How to robustly combine p-values (avoiding conservative tests)?
3. How to take into account different node degrees/edge weights?

How to exploit all of this in medical research?

Static prediction of clinical interventions

Suppose we have a network of interventions for a certain disease:



- compare interventions (cluster 'similar' interventions)
- Bayesian approach is attractive:
  - if meta-analysis is based only on few studies
  - if new study estimates different functions $\rightarrow$ combine multiple into single param. (hierarchical random-effects models)
  - only option when very complex models are used

How to exploit all of this in medical research?

Real-time prediction of clinical interventions

Monitor networks of interventions in ICUs (noisy, sparse, heterogeneous data)

- predict onset of multiple invasive treatments
- other similar survival analysis/ Cox models
    - static covariates: gender, age etc..
    - time-varying covariates: oxygen saturation, blood urea nitrogen etc..

Monitor networks of personalised healthcare

- high-frequency data (from mobile-devices etc..)
- descriptions of symptoms over time (text-mining)

Final Remarks

- Introduction to network analysis (static/dynamic)
- Prediction of new edges in a large network (based on network structure)
- Provide some insights on statistical anomaly-detection
- Results from cyber data $\rightarrow$ show good performance
- Some opportunities in the field of medical research
- Challenges still to be addressed:
  - effectively combine information from different edges (interventions)
  - Bayesian inference (MCMC): need fast methods

References

- Cox, D. R. (1972). "Regression models and life-tables (with discussion).". In: *Journal of the Royal Statistical Society, Series B* 34, pp. 187–220.
- Heard, N. and S. Metelli (2014). "Modelling new edge formation in a computer network through Bayesian variable selection". In: *Joint Intelligence and Security Informatics Conference (JISIC), 2014 European*. IEEE, pp. 272–275.
- Heard, N and P Rubin-Delanchy (2018). "Choosing between methods of combining p-values". In: *Biometrika* 105, pp. 239–246. DOI: biomet/asx076.
- Heard, N, P Rubin-Delanchy, and D Lawson (2014). "Filtering automated polling traffic in computer network flow data". In: IEEE, pp. 268–271. DOI: 10.1109/JISIC.2014.52.
- Metelli, S and NA Heard (2016). "Model-based clustering and new edge modelling in large computer networks". In: IEEE. DOI: 10.1109/ISI.2016.7745449.
- Metelli, S. and N.A. Heard (2018). "On Bayesian new edge modelling and anomaly detection in computer networks". Submitted to the Annals of Applied Statistics.

Thank you!