A Source Separation Approach to Temporal Graph Modelling for Computer Networks

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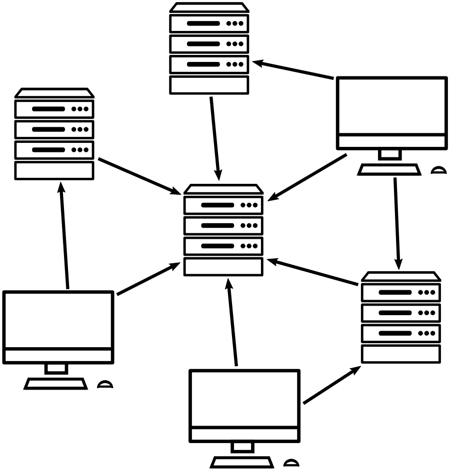
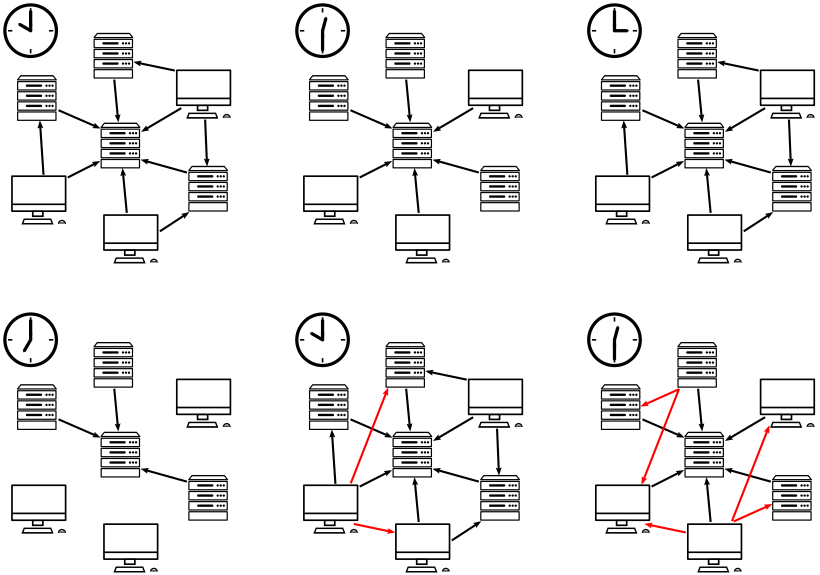
Context – Computer network monitoring



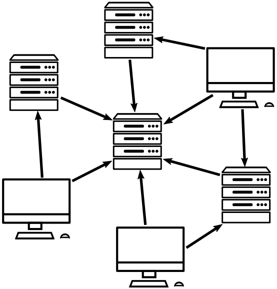
Network monitoring

- Traffic within an **enterprise network** analyzed to detect **malicious activity**
- Network traffic represented as a **directed graph**
- **Goal:** detect anomalous edges

Computer network monitoring – Temporal perspective



Definitions and problem statement



Definitions

- $(\mathcal{G}_t)_{t\geq 1}$ is a sequence of directed graphs with **shared node set** $\mathcal{V} = \{1, \ldots, N\}$
- $\mathbf{A}_t$ is the (binary, non-symmetric) adjacency matrix of $\mathcal{G}_t$

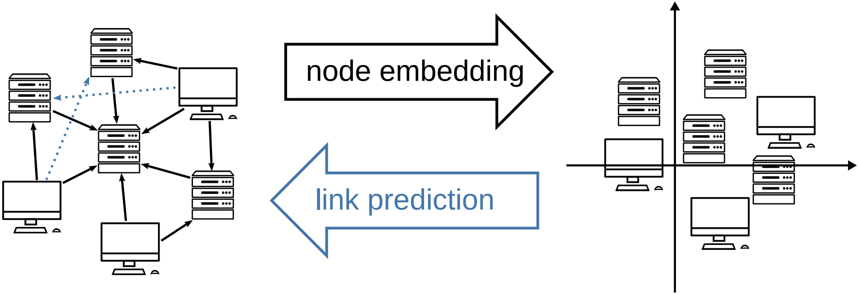
- **Problem:** given normal graphs $\mathcal{G}_1, \ldots, \mathcal{G}_T$, detect anomalous edges in new graphs $\mathcal{G}_t$ for $t > T$
- Equivalent to **temporal link prediction**: if we can predict normal edges, we can detect anomalous ones

Related work – Link prediction

Latent space models (aka MF, graph embedding, GNNs)

Workflow of most link prediction methods:

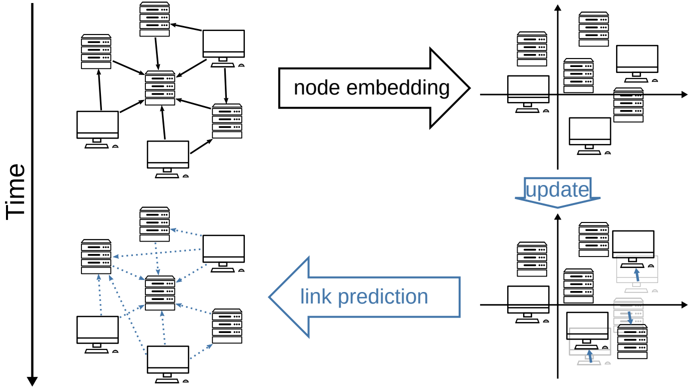
- Learn **node embeddings** $\{\mathbf{u}_i \in \mathbb{R}^K\}_{i \in \mathcal{V}}$ and **link predictor** $g : \mathbb{R}^K \times \mathbb{R}^K \to [0, 1]$ that maximize the probability of observed edges, $p(i, j) = g(\mathbf{u}_i, \mathbf{u}_j)$
- Predict new edges (i', j') using $g(\mathbf{u}_{i'}, \mathbf{u}_{j'})$



Related work – Dynamic latent space models

Generalizing latent space models to temporal graphs

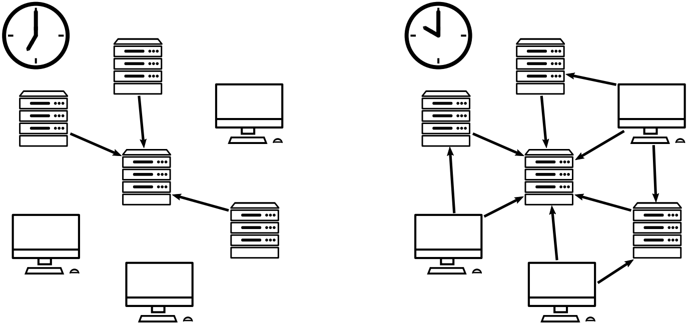
- Just replace $\mathbf{u}_i$ with a sequence $(\mathbf{u}_{i,t})_{t \geq 1}$
- Predict future embeddings using recursive Bayesian estimation [Lee et al., 2022] or RNNs [King and Huang, 2022]



The problem with dynamic latent space models

Dynamic LSM vs. network traffic dynamics

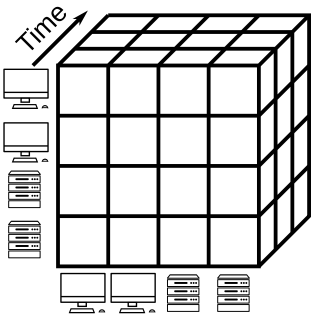
- In dynamic LSMs, temporal dynamics are **node-driven**: local, smooth evolution of the graph
- In enterprise networks, observed traffic undergoes **sharp, global variations**



Related work – Tensor factorization

Temporal graphs as tensors [Dunlavy et al., 2011]

The sequence $(\mathbf{A}_t)_{t=1,\dots,T}$ can be seen as a **3-mode tensor**, with modes standing for time step, origin and destination nodes.



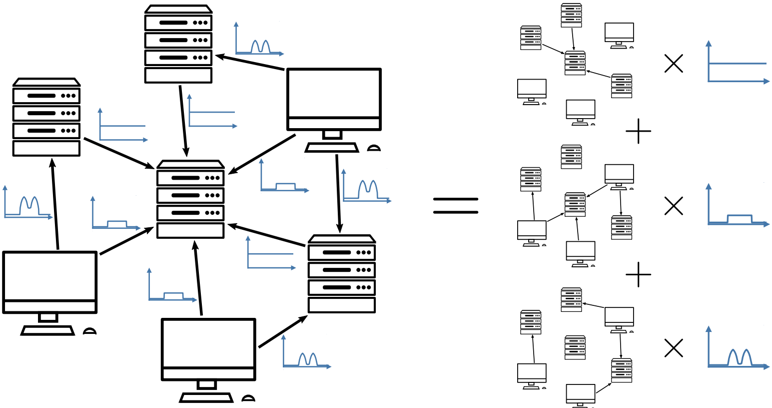
CANDECOMP/PARAFAC 3-mode tensor factorization:

$$\hat{\mathbf{A}}_t = \sum_{k=1}^{K} w_{tk} \mathbf{U}_k \mathbf{V}_k^\top,$$

with $\mathbf{U}_k, \mathbf{V}_k \in \mathbb{R}^{N \times 1}$ origin and destination embedding matrices.

Tensor factorization – Source separation interpretation

$$\hat{\mathbf{A}}_t = \sum_{k=1}^{K} w_{tk} \mathbf{U}_k \mathbf{V}_k^\top$$



An improved source separation approach

Tensor factorization models each source as a **rank-one matrix**.

- **Idea:** use richer models for the activity sources

Our approach: Superposed Nonnegative Matrix Factorization (SNMF)

- For each of L activity sources, define origin and destination embedding matrices $\mathbf{U}_\ell, \mathbf{V}_\ell \in \mathbb{R}_+^{N\times K}$
- For each time step t, define mixing coefficients $w_{t\ell}$ such that $\mathbf{A}_t = \sum_{\ell=1}^L w_{t\ell} \mathbf{U}_\ell \mathbf{V}_\ell^\top$

Model inference: Given adjacency matrices $(\mathbf{A}_1, \ldots, \mathbf{A}_T)$, find $\mathbb{U} = (\mathbf{U}_\ell)_{\ell=1}^L, \mathbb{V} = (\mathbf{V}_\ell)_{\ell=1}^L, \mathbf{W} = (w_{t\ell}) \in \mathbb{R}_+^{T\times L}$ minimizing

$$J(\mathbb{U}, \mathbb{V}, \mathbf{W}) = \frac{1}{2} \sum_{t=1}^T \left\| (\mathbf{1}_N - \mathbf{I}_N) \odot \left(\mathbf{A}_t - \sum_{\ell=1}^L w_{t\ell} \mathbf{U}_\ell \mathbf{V}_\ell^\top \right) \right\|_{\mathrm{F}}^2 + \lambda_1 \|\mathbf{W}\|_1 + \frac{\lambda_2}{2} \sum_{\ell=1}^L \left(\|\mathbf{U}_\ell\|_{\mathrm{F}}^2 + \|\mathbf{V}_\ell\|_{\mathrm{F}}^2 \right)$$

SNMF for temporal link prediction

After inference ($t > T$), given a new adjacency matrix $\mathbf{A}_t$:

- Predict mixing coefficients $\hat{\mathbf{w}}_t$ using a **seasonal model**:

  $$\hat{\mathbf{w}}_t = \textsc{Mean}(\mathbf{w}_{t'}; t' \in [t-1] : t \equiv t' \mod \tau),$$

  with period $\tau > 0$ (one week here)
- Predict adjacency matrix $\hat{\mathbf{A}}_t$ using $\hat{\mathbf{w}}_t$ and compute **anomaly score matrix** $\mathbf{A}_t - \hat{\mathbf{A}}_t$
- Compute **true mixing coefficients** $\mathbf{w}_t$ to update the seasonal model

Qualitative evaluation – Method

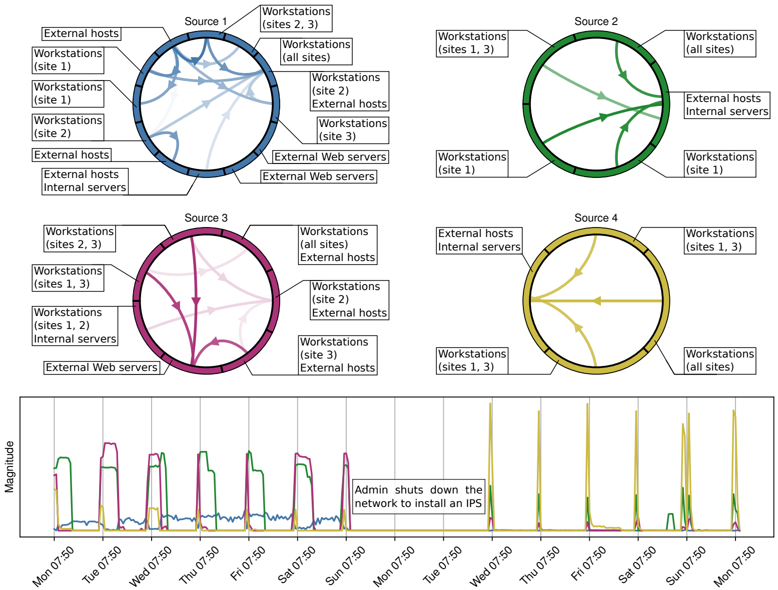
Dataset: VAST 2013 Mini-Challenge 3

- Simulated network traffic (enterprise network + external hosts)
- 1.4K hosts, 14 days
- Ground truth description of host roles and observed traffic

Goal: analyze the activity sources inferred by SNMF.

- For each source:
  - Cluster nodes based on their embeddings
  - Display predicted edges between clusters
- Plot mixing coefficients over time

Qualitative evaluation – Results



Quantitative evaluation – Method

Dataset: LANL CMSCSE

- Real-world enterprise network
- 12.7K hosts, 30 days
- Labelled malicious edges

Evaluation tasks

- Anomaly detection
- Temporal link prediction with sampled negative edges

Baseline methods

- Dynamic link predictors:
  - Tensor factorization (**PTF** [Eren et al., 2020])
  - Latent space model (**BME** [Lee et al., 2022])
- Static link predictors:
  - Matrix factorization (**HPF** [Sanna Passino et al., 2022])
  - Graph embedding (**GL-GV** [Bowman et al., 2020])
- Generic/naive baselines: EdgeBank [Poursafaei et al., 2022], SedanSpot [Eswaran and Faloutsos, 2018]

SNMF outperforms baselines in terms of AUC on anomaly detection and historical link prediction tasks.

Method	Anomaly	Random	Historical	Inductive
SNMF	**99.1**±**0.1**	98.4±0.0	**76.9**±**0.2**	98.2±0.1
PTF	97.6±0.9	98.6±0.0	68.5±0.2	96.7±0.3
BME	90.3±0.2	98.5±0.0	73.3±0.0	96.2±0.0
HPF	97.7±0.3	**99.1**±**0.0**	69.6±0.1	97.5±0.0
GL-GV	87.0±2.4	95.8±1.0	61.2±0.5	74.6±1.9
SedanSpot	63.6±7.3	51.2±2.2	54.7±1.4	53.2±2.7
EdgeBank$_\infty$	96.2±0.0	97.2±0.0	56.0±0.0	**98.3**±**0.0**
EdgeBank$_w$	96.0±0.0	97.0±0.0	58.0±0.0	98.1±0.0

Conclusion: The nature of temporal dynamics matters

Key takeaways

- Activity within enterprise networks has **specific temporal dynamics**
- Temporal graph models introduced in other domains are **not well-suited** to this context
- However, a **simple source separation approach** fits these dynamics rather well

Future research directions:

- Extension to **more complex data representations** than graphs
- **Better prediction** of the mixing coefficients
- Including **long-term dynamics** (concept drift, new nodes)

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