

Cyber-Security: Learning from Relational Data

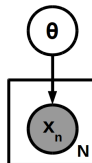
Piyush Rai

Dept. of CSE, IIT Kanpur

Nov 27, 2015

Probabilistic Machine Learning

- Machine Learning via probabilistic modeling of data



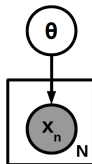
- Data assumed generated from a probability model

$$\mathbf{x}_1, \dots, \mathbf{x}_N \sim p(\mathbf{x}|\theta)$$

- Unified perspective**; subsume many paradigms in ML: regression, classification, clustering, dimensionality reduction, time-series analysis, etc.

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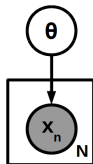
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- Handling **missing data, outliers, skewness, temporal evolution**, etc.
- Easily incorporate **prior beliefs**, quantify **uncertainty** (**Bayesian learning**)

Probabilistic Machine Learning

- Machine Learning via probabilistic modeling of data



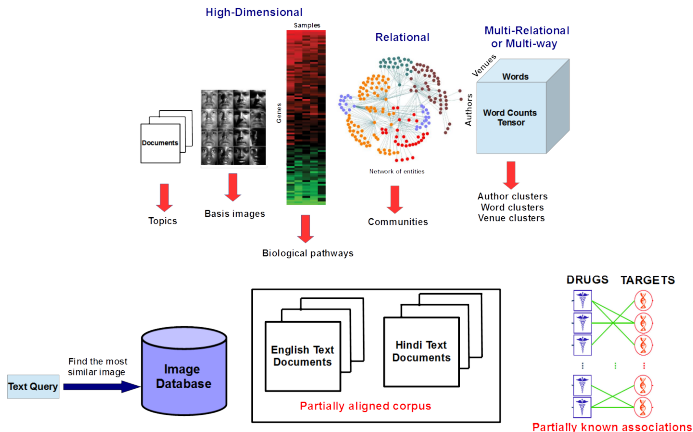
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- Handling **missing data, outliers, skewness, temporal evolution**, etc.
- Easily incorporate **prior beliefs**, quantify **uncertainty** (**Bayesian learning**)
- Enables principled combinations of simpler paradigms to solve complex tasks

My Research

- Learning from **complex, messy, heterogeneous** data
- Focus: **Feature representation** learning, **Cross-modal/Transfer Learning**, reducing **labeling costs**, **scalability** (online/distributed learning), **model-size adaptability** as data grows (nonparametric models)



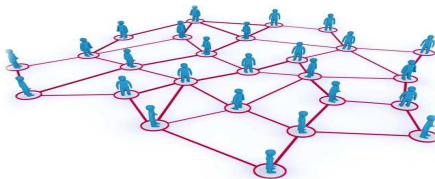
Relational Data in the “Networked” World



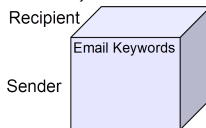
- A natural representation of various types of data in the cyber-space, e.g.,
 - Physical networks
 - Links between webpages
 - Links between users on social networks
 - Links across networks
- Almost all of this data is also **time-evolving** in nature

Relational Data as Graphs

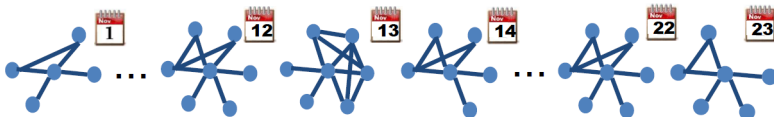
- Unipartite graphs and bipartite graphs



- Multi-dimensional graphs (“tensors”)

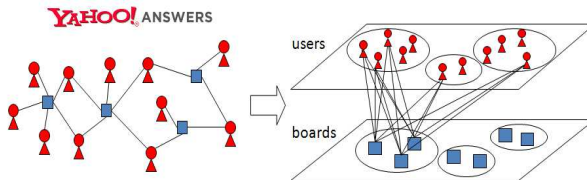


- Dynamic/time-evolving graphs

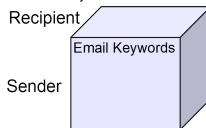


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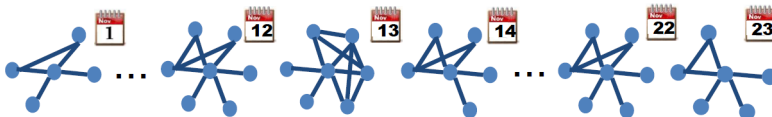
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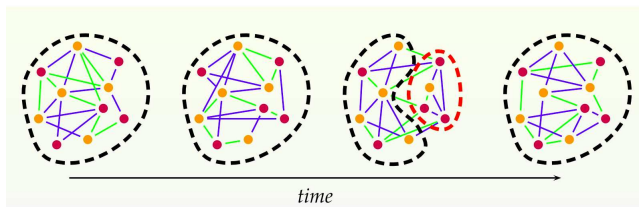


- Dynamic/time-evolving graphs



Cyber-Security Problems on Relational Data

- Anomaly detection
 - Anomalous nodes
 - Anomalous edges
 - Anomalous sub-communities
- Detecting/predicting change-points in evolving graphs

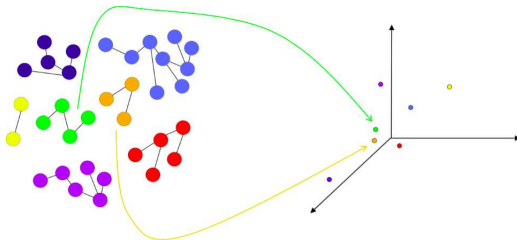


- Learning good representations of the data is key

Picture courtesy: <http://www.cis.jhu.edu/~parky/>

Embeddings to Represent Relational Data

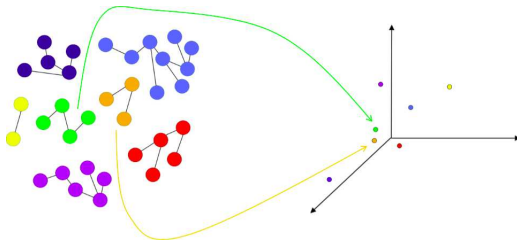
- Embedding relational data (graphs) to a vector space



- Allows performing various machine learning tasks such as clustering, classification, anomaly detection, etc., using the **learned embeddings**
- A challenging problem in general

Embeddings to Represent Relational Data

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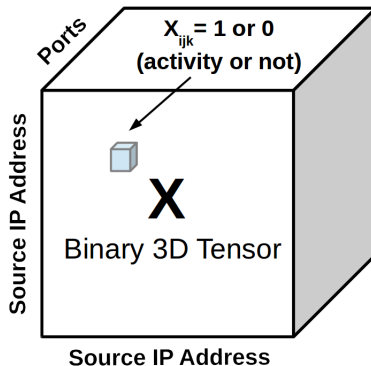


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- A challenging problem in general

[ICDM 2013, ICML 2014, ECML 2015, UAI 2015, NIPS 2015 + forthcoming]

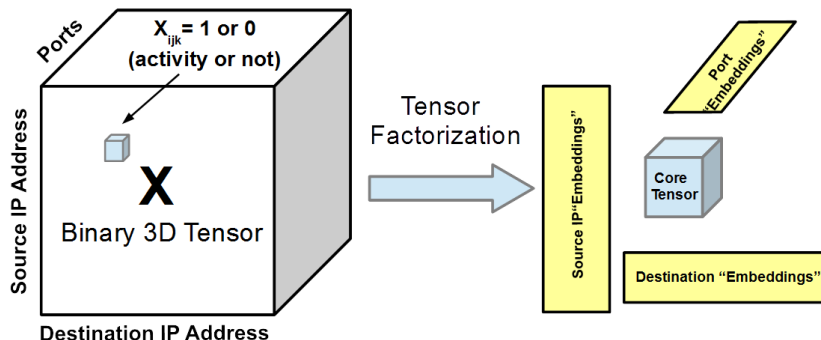
Tensors or “Multi-Relational” Data

Tensors are useful for encoding **multi-way relations**



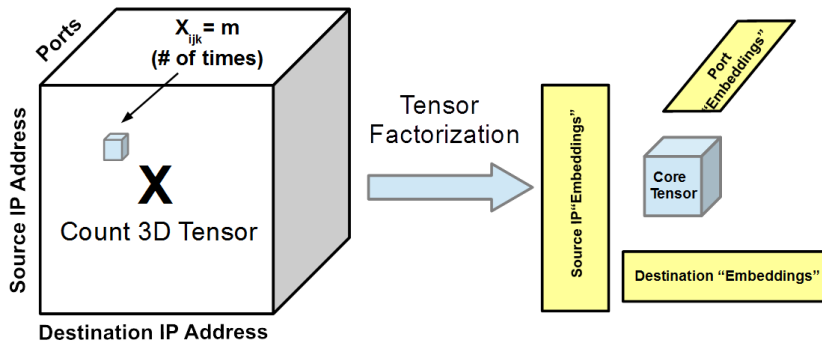
Tensor Factorization

Tensor factorization allows embeddings the entities of each “way” of the tensor



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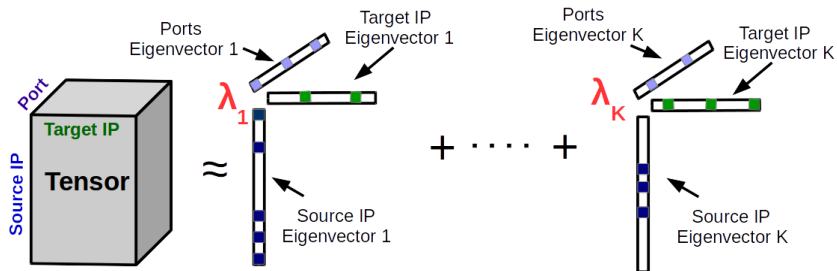
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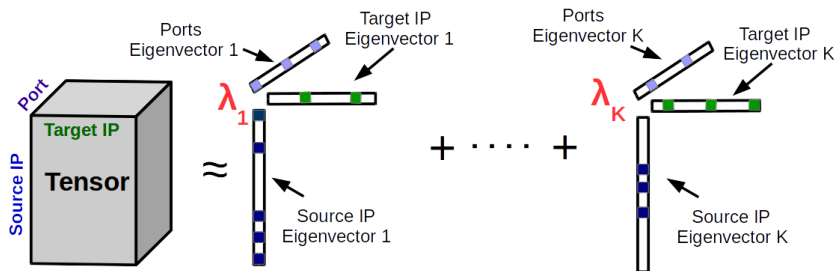
Embeddings can be used as a **feature representation**

Tensor Factorization

An SVD like approach: express a tensor as a weighted sum of K rank-one tensors

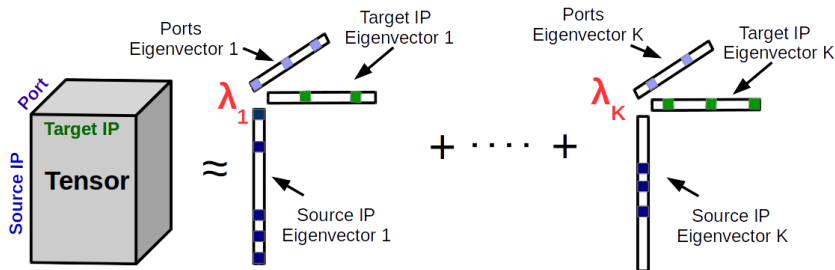


Tensor Factorization: Challenges



- Significant amounts of missing data
- Interpretability (desirable, e.g., sparse and non-negative eigenvectors)
- Modeling the time-dimension (useful for forecasting)
- Integrating sources of side-information
- Scalability for massive tensors

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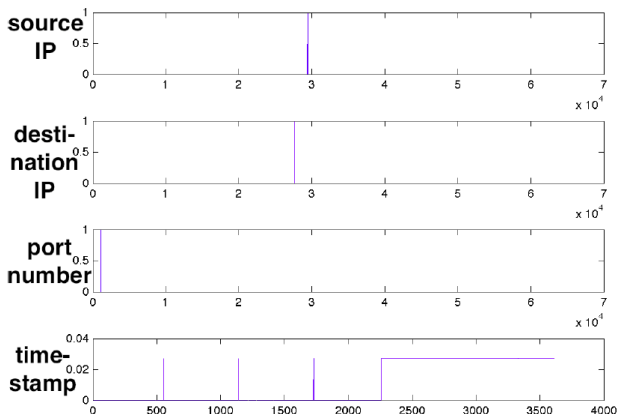
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[ICML 2014, AAAI 2015, ECML 2015, UAI 2015 + forthcoming]

Tensor Factorization for Anomaly Detection

Data: a four-way tensor $\text{Source IP} \times \text{Dest. IP} \times \text{Port} \times \text{Time}$

Eigenvectors of this tensor can identify normal vs anomalous behavior¹

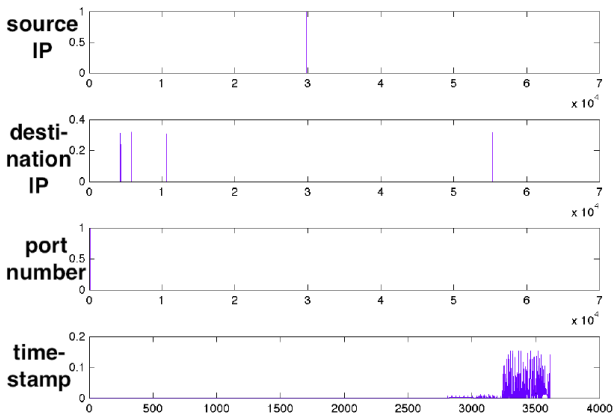


¹Koutra *et al.* (2012)

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Other Work Relevant to Cyber-Security

- Probabilistic modeling of rare-events
- Learning only from positive examples
- Time-series of count-data (via [Poisson Processes](#))
- Privacy preserving machine learning (private Bayesian inference)

Thanks! Questions?