# Module V: Knowledge Graph Inference and Applications

2:05 pm - 3:10 pm

# Module 5 Overview

## KG Inference and Applications

<u>Knowledge Graph Inference</u>

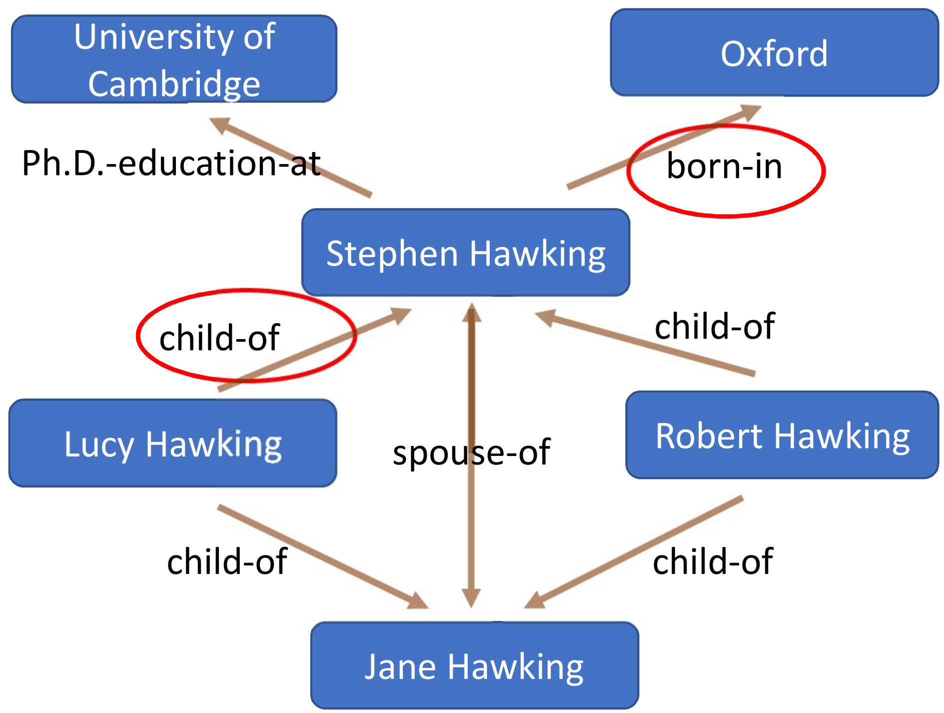
- What & Why
- How
  - Problem formulation & Overview
  - Knowledge Graph Embedding


<u>Knowledge Graph Applications</u>

- Entity Recommendation

<u>Lab 5 – Paper Recommendation in ***MAG***</u>

# Knowledge Graph Inference -- WHAT



# Knowledge Graph Inference -- WHY

- Knowledge Base is largely incomplete
- Need systematic and scalable approaches to complete knowledge graph

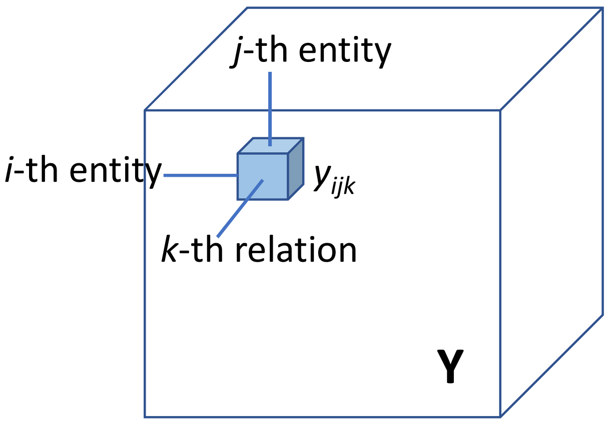
Freebase

| Relation | Percentage unknown | |
|---|---|---|
| | *All 3M* | *Top 100K* |
| PROFESSION | 68% | 24% |
| PLACE OF BIRTH | 71% | 13% |
| NATIONALITY | 75% | 21% |
| EDUCATION | 91% | 63% |
| SPOUSES | 92% | 68% |
| PARENTS | 94% | 77% |
| CHILDREN | 94% | 80% |
| SIBLINGS | 96% | 83% |
| ETHNICITY | 99% | 86% |

Incompleteness of Freebase for some relations that apply to entities of type PERSON. Left: all 3M Freebase PERSON entities. Right: only the 100K most frequent PERSON entities.

West, et al., WWW'14, Knowledge Base Completion via Search-Based Question Answering

# Knowledge Graph Inference -- HOW




$$Y_{ijk} = \begin{cases} 1, & \text{if the triple } (e_i, r_k, e_j) \text{ exists;} \\ 0, & \text{otherwise.} \end{cases}$$

Element-wise

$$Y \in \{0,1\}^{Ne \times Ne \times Nr}$$

adjacency tensor
(adjacency matrix)

$$P(Y)$$

Estimate the joint-distribution

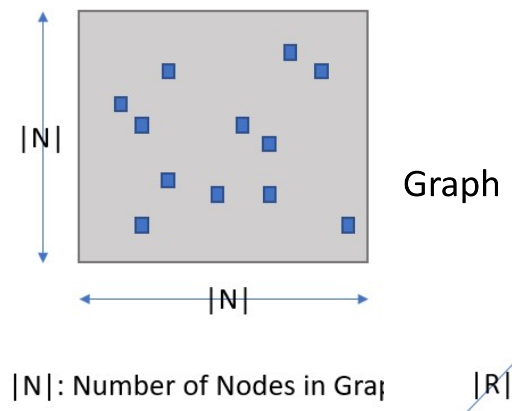
$$P(yijk)$$

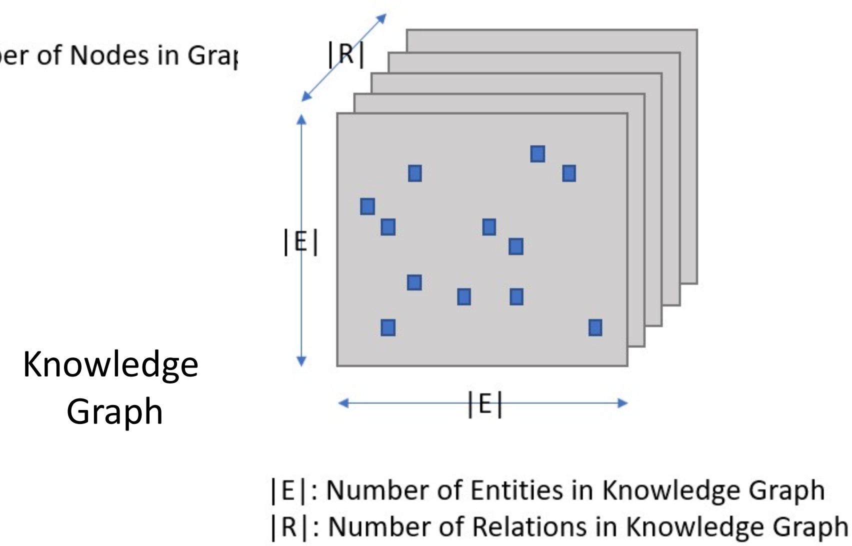
Predict *unobserved* triples

PROBLEM FORMULATION -- *STATISTICAL RELATIONAL LEARNING*

# Knowledge Graph Inference -- HOW

- Within existing KG
  - Graph feature model
    - "Similar" entities
      - Local – common neighbors
      - Global – random walk
      - Quasi-local – random walk with bounded length
  - Latent feature model
- Use external sources / information
  - QnA system



# Knowledge Graph Inference -- HOW

## LATENT FEATURE MODELS

- ***Entity*** Representation
  - Low dimensional vector: $e_i$
  - Initialization
    - Random
    - Average word vector with pre-trained vectors ( $V_{word}$ ), e.g.

$$e_{homo\ sapiens} = 0.5 \times (V_{homo} + V_{sapiens})$$

- ***Relation type*** representation
  - Each relation type as ***matrix***:
    - $W_k$ : bilinear weight matrix
    - $A_k$ : linear feature map
  - Each relation type as ***vector***: $r_k$

- ***Entity-Relation*** interaction
  - Linear : $A_k\, e_i$
  - Bilinear: $e_i^T W_k\, e_j$

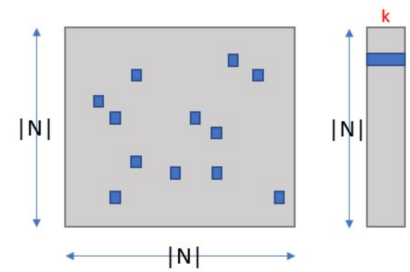
- ***Scoring function***
  - Margin-based ranking loss *Maximize the margin btw existing & non-existing triples*

$$\sum_{(s,r,o)\in T}\ \sum_{(s',r,o')\in T'(s,r,o)} max(0, 1 + f(s',r,o') - f(s,r,o))$$

  - Negative sampling loss *Negative log-likelihood of the correct triples & sampled corrupted triples*

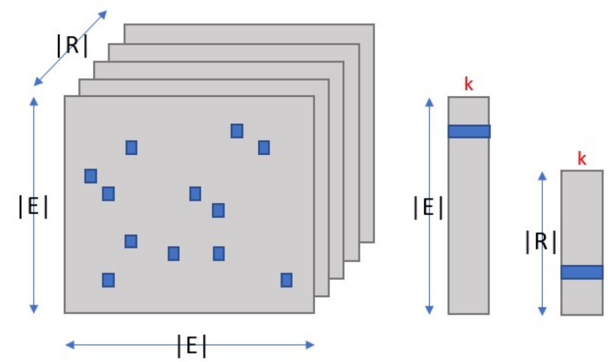
$$-\sum_{(s,r,o)\in T} \left( \log\sigma\big(f(s,r,o)\big) + \sum_{(s',r,o')\in T'(s,r,o)} \log\sigma\big(-f(s',r,o')\big) \right)$$

Graph




|N|: Number of Nodes in Graph
k: Dimensionality

Knowledge Graph




|E|: Number of Entities in Knowledge Graph
|R|: Number of Relations in Knowledge Graph
k: Dimensionality

# Knowledge Graph Inference -- HOW

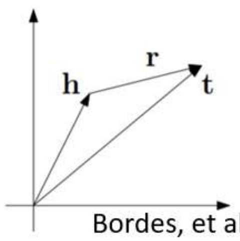
## LATENT FEATURE MODELS - MILESTONES

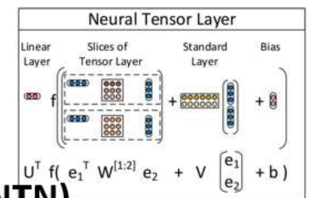
Time


**DistMult**

***2015***

Yang, et al. *ICLR*, Embedding entities and relations for learning and inference in knowledge bases



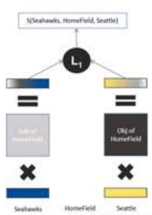

**TransE**

***2013***

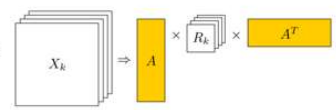
Bordes, et al. *NIPS*, Translating embeddings for modeling multi-relational data

**Neural Tensor Networks (NTN)**

Socher, et al. *NIPS*, Reasoning with neural tensor networks for knowledge base completion



Tensor Factorization




**Structured Embedding (SE)**

***2011***

Bordes, et al. *AAAI*, Learning structured embedding of knowledge base

**RESCAL**

Nickel, et al. *ICML*, A three-way model for collective learning on multi-relational data

# Knowledge Graph Inference -- HOW

## LATENT FEATURE MODELS - SCALABILITY

### Scalability [# of params]

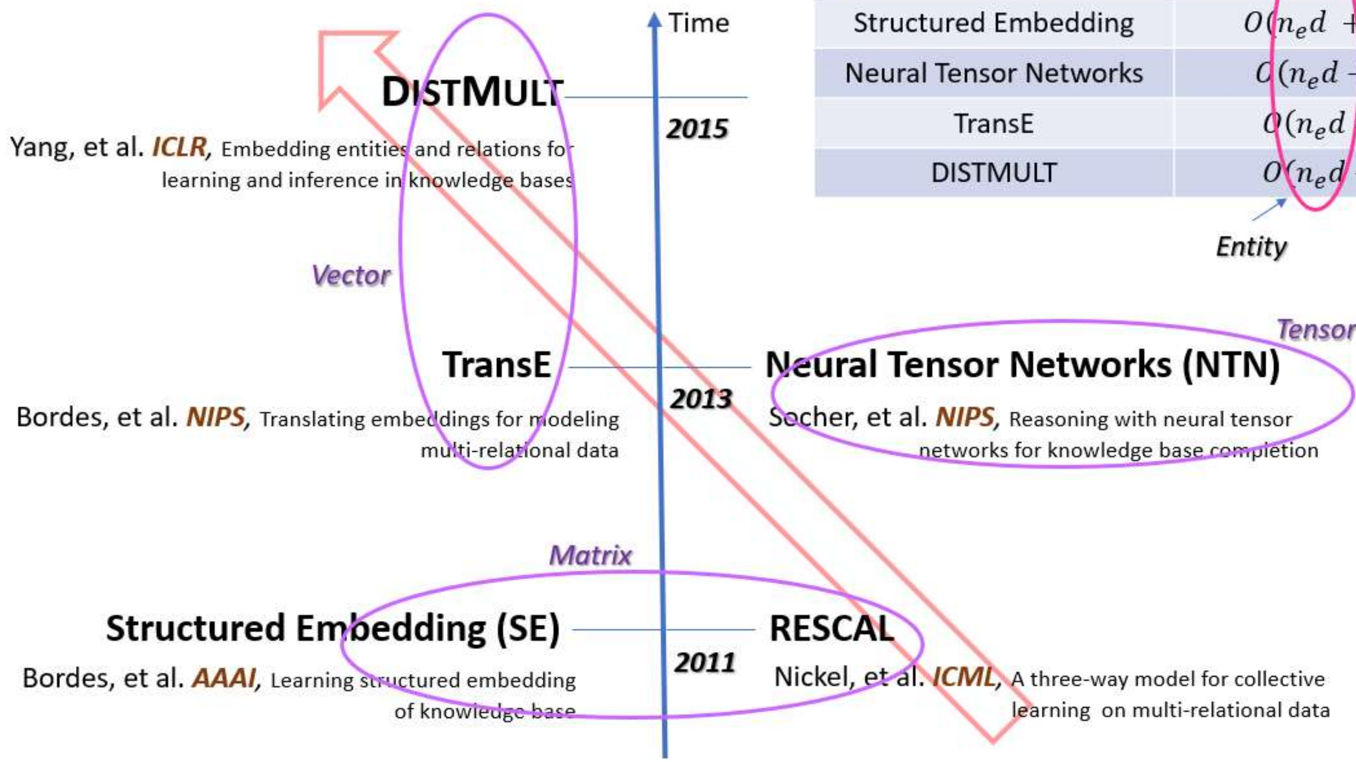
| Method | # of Parameters |
|---|---|
| RESCAL | $O(n_e d + n_r d^2)$ |
| Structured Embedding | $O(n_e d + 2n_r d^2)$ |
| Neural Tensor Networks | $O(n_e d + n_r d^3)$ |
| TransE | $O(n_e d + n_r d)$ |
| DISTMULT | $O(n_e d + n_r d)$ |

Matrix

Tensor

Vector

Entity Relation

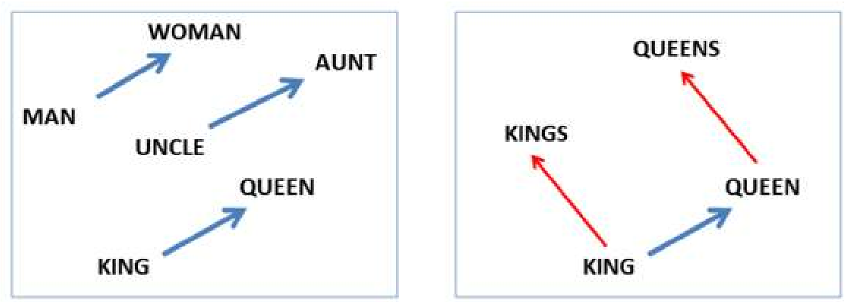


# Knowledge Graph Applications

## ENTITY RECOMMENDATION

- ***<u>Co-occurrence</u>*** based
  - Search user behavior
  - Wikipedia
  - Web documents

- ***<u>Similarity</u>*** based
  - Textual (tf-idf)
  - Embedding

# Knowledge Graph Applications

## ENTITY RECOMMENDATION – CASE STUDY

- ***Co-occurrence*** based
  - Co-citation
  - Co-author
  - Co-venue
  - Graph embedding
- ***Similarity*** based
  - Tf-idf
  - Word2Vec

Paper Recommendation

# Lab 5: Structural + Textual Similarity in MAG

- Task : Paper recommendation
  - Based on co-citation
  - Based on textual (tf-idf) similarity
  - Based on semantic (word embedding) similarity