Module V: Knowledge Graph Inference and Applications

2:20 pm - 3:30 pm

Knowledge Graph Inference

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

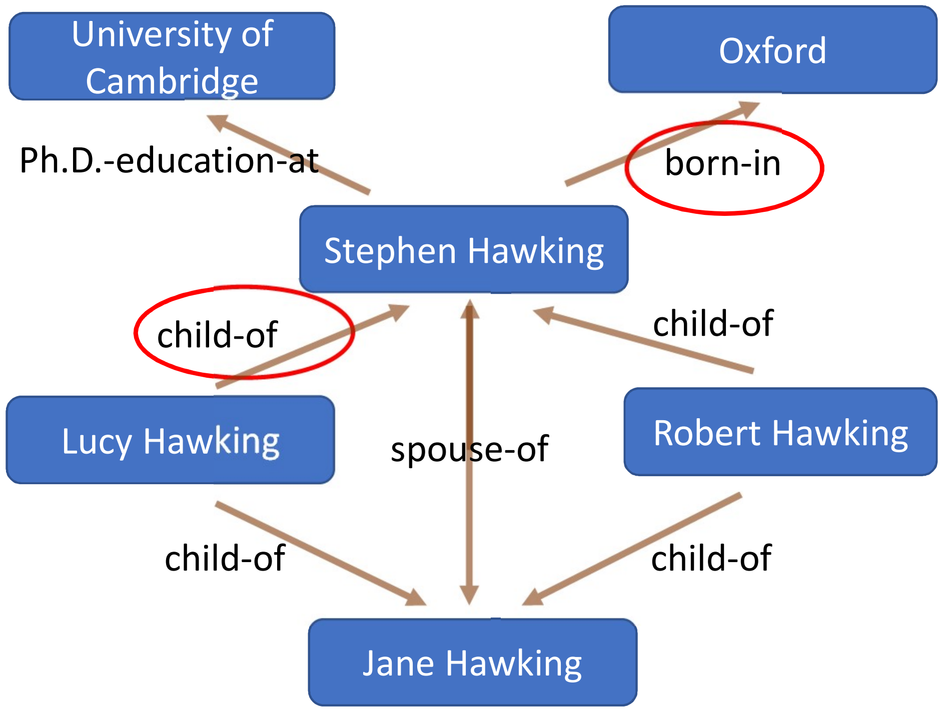
Knowledge Graph Applications

- Entity Recommendation

Lab 5 – Structural + Textual Similarity in ***MAG***

Module 5 Overview

KG Inference and Applications



KNOWLEDGE GRAPH INFERENCE -WHAT

KNOWLEDGE GRAPH INFERENCE - WHY

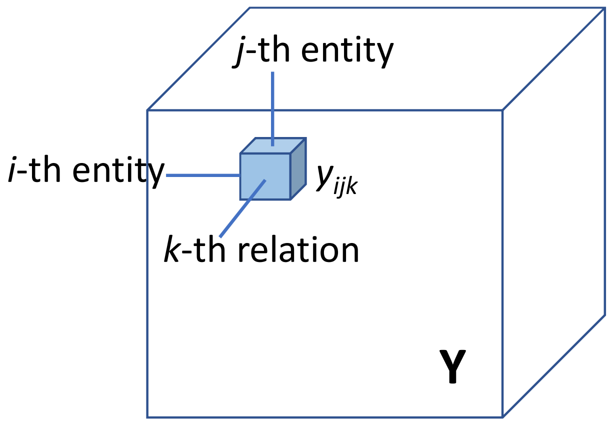
- Knowledge Base is largely incomplete
- Need systematic and scalable approaches to complete knowledge graph

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



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

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

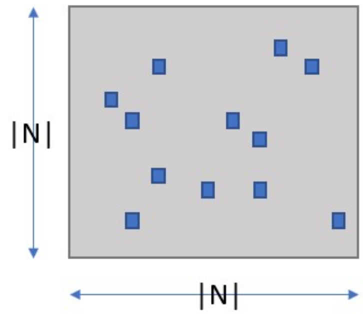
KNOWLEDGE GRAPH INFERENCE – HOW

PROBLEM FORMULATION

KNOWLEDGE GRAPH INFERENCE – HOW

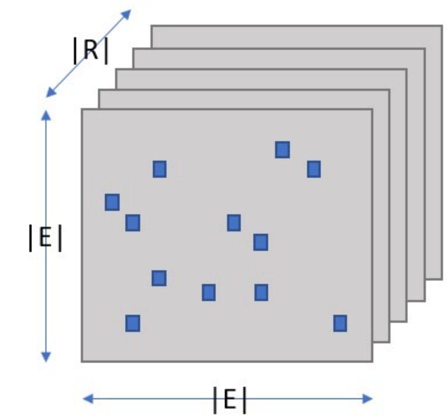
OVERVIEW

- 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



|N|: Number of Nodes in Graph

Graph



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

Knowledge Graph

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

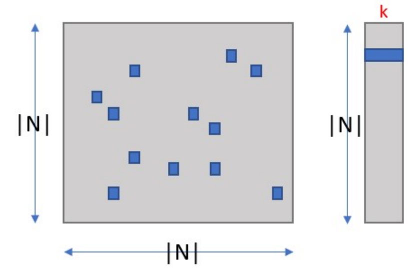
- ***Entity-Relation*** interaction
  - Linear : $A_k\, e_i$
  - Bilinear: $e_i^T W_k\, e_j$

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

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

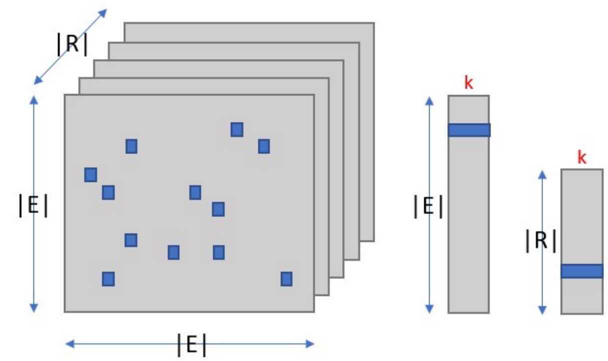
  - Negative sampling loss *Negative log-likelihood of the correct triples & sampled corrupted triples*

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



Graph

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



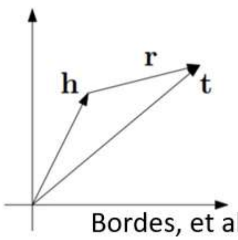
|E|: Number of Entities in Knowledge Graph
|R|: Number of Relations in Knowledge Graph
k: Dimensionality

Knowledge Graph

Time

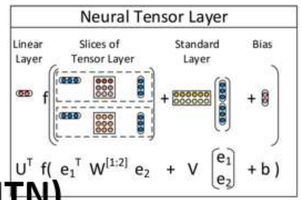
DistMult — 2015

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



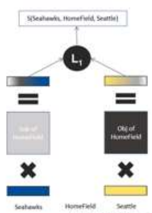
TransE — 2013

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



Neural Tensor Networks (NTN) — 2013

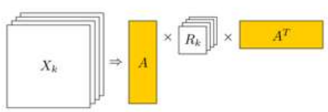
Socher, et al. ***NIPS***, Reasoning with neural tensor networks for knowledge base completion



Structured Embedding (SE) — 2011

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

Tensor Factorization



RESCAL — 2011

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

KNOWLEDGE GRAPH INFERENCE – HOW

LATENT FEATURE MODELS – MILESTONES

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	$O(n_e d + n_r d)$

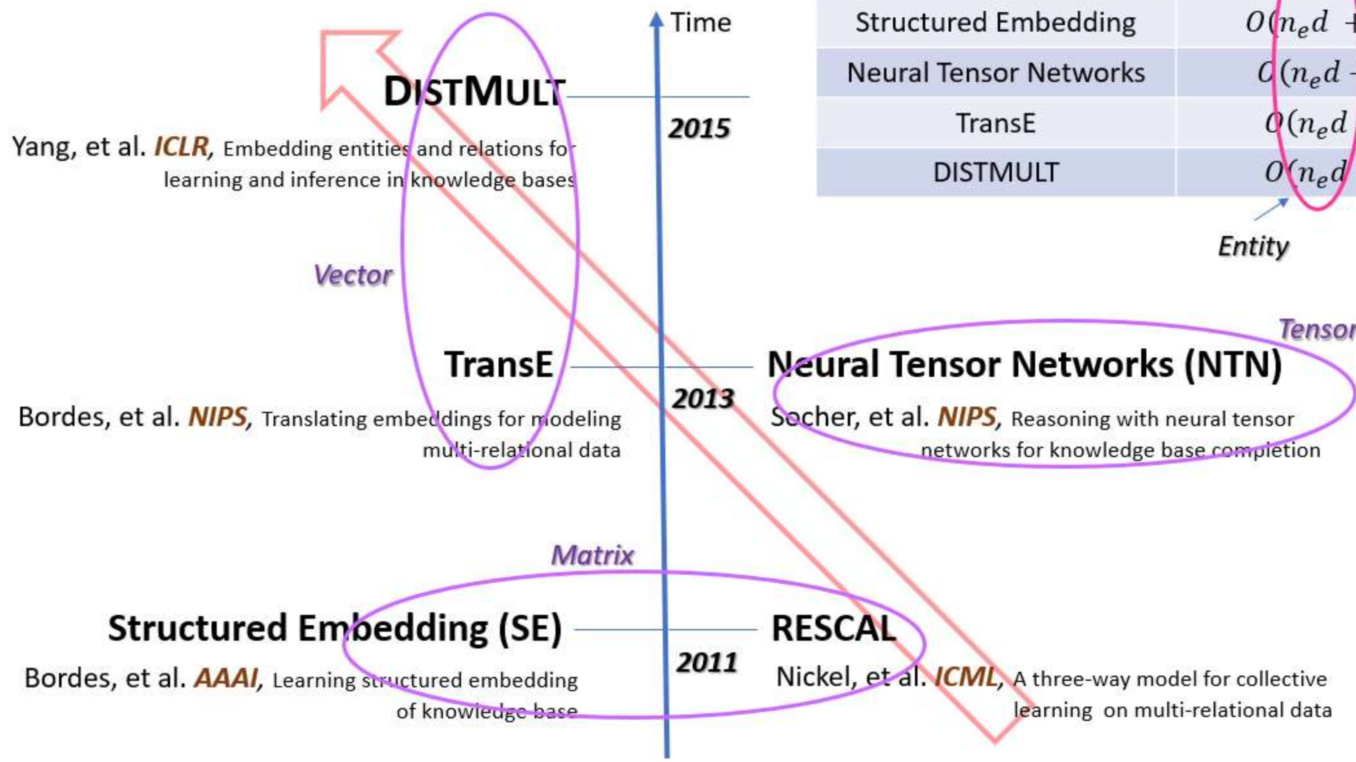
Matrix

Tensor

Vector

Entity

Relation

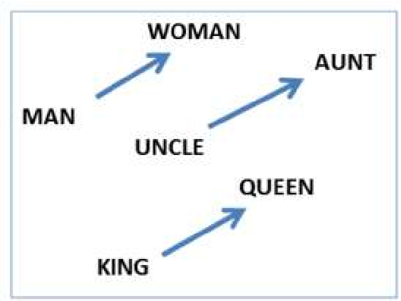


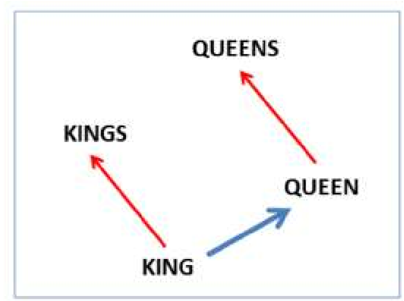
KNOWLEDGE GRAPH INFERENCE – HOW

LATENT FEATURE MODELS – SCALABILITY

- ***Co-occurrence*** based
  - Search user behavior
  - Wikipedia
  - Web documents

- ***Similarity*** based
  - Textual (tf-idf)
  - Embedding





KNOWLEDGE GRAPH APPLICATION

ENTITY RECOMMENDATION

Paper Recommendation

- ***Co-occurrence*** based
  - Co-citation
  - Co-author
  - Co-venue
  - Graph embedding

- ***Similarity*** based
  - Tf-idf
  - Word2Vec

KNOWLEDGE GRAPH APPLICATION

ENTITY RECOMMENDATION – CASE STUDY

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

Lab 5: Structural + Textual Similarity in MAG