Embedding-Based Techniques

MATRICES, TENSORS, AND NEURAL NETWORKS

Probabilistic Models: Downsides

Embeddings

Limitation to Logical Relations

需要人工定义规则

- Representation restricted by manual design
  - Clustering? Assymetric implications? 不對稱的含義
  - Information flows through these relations
- Difficult to generalize to unseen entities/relations

- Everything as dense vectors
- Can capture many relations
- Learned from data

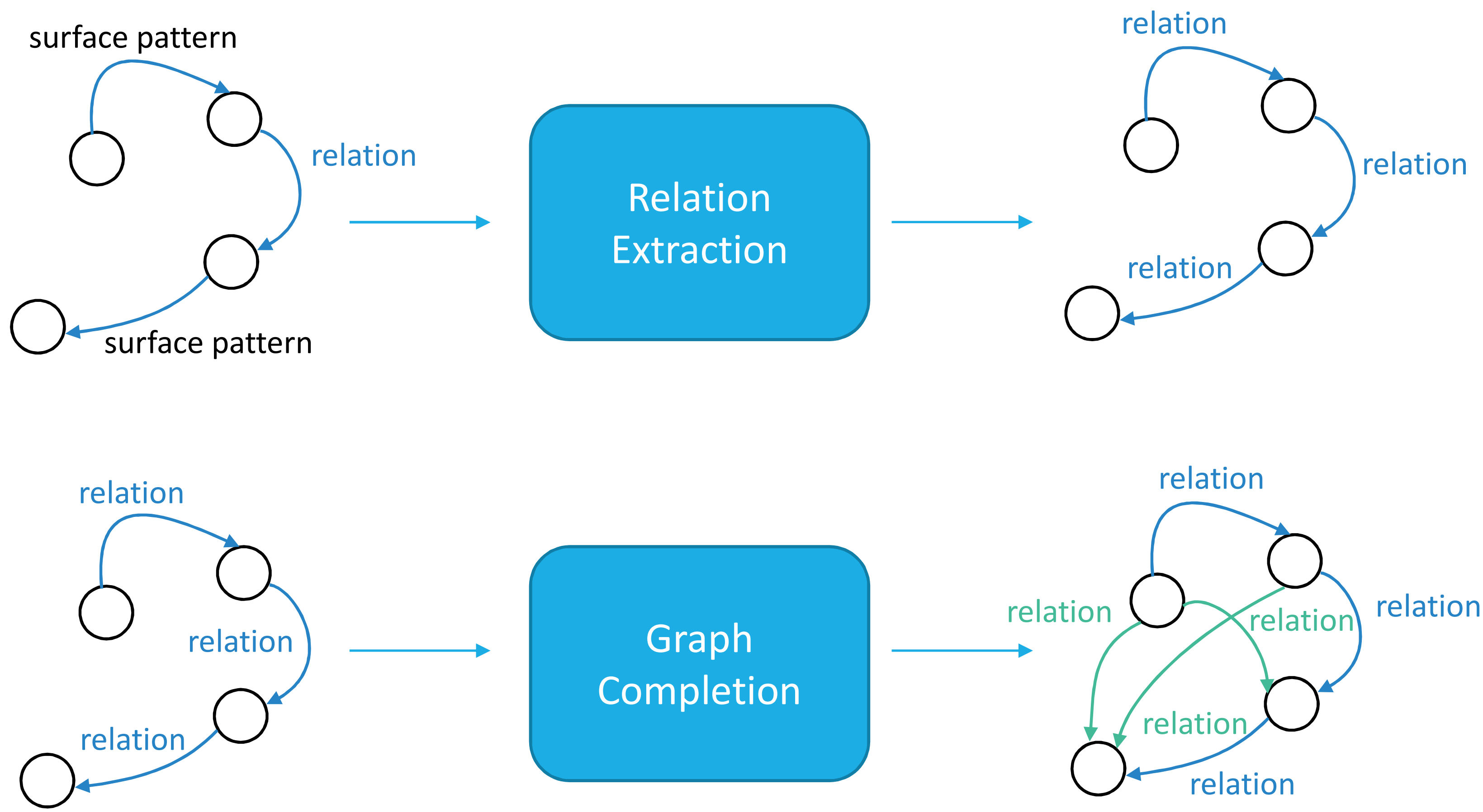
Computational Complexity of Algorithms

- Complexity depends on explicit dimensionality
  - Often NP-Hard, in size of data
  - More rules, more expensive inference
- Query-time inference is sometimes NP-Hard
- Not trivial to parallelize, or use GPUs

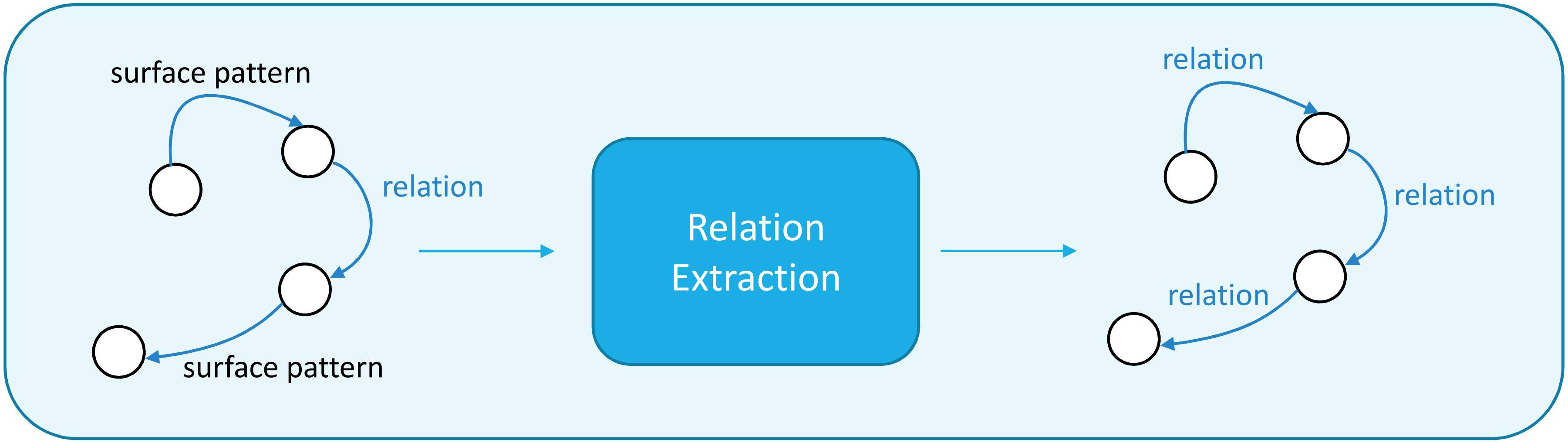
计算复杂度很高，难以利用 GPU 或并行计算

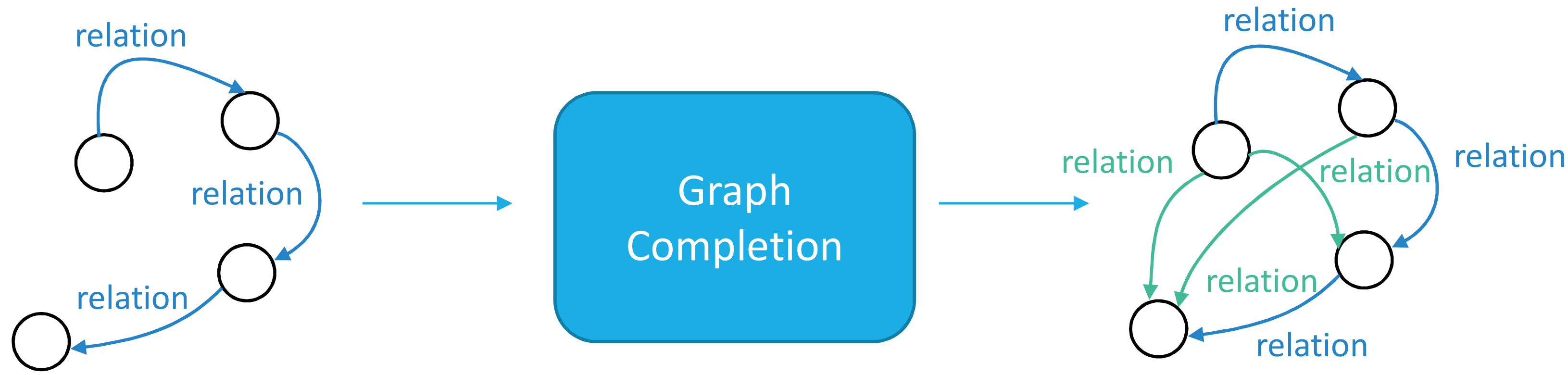
- Complexity depends on latent dimensions
- Learning using stochastic gradient, back-propagation
- Querying is often cheap
- GPU-parallelism friendly

Two Related Tasks



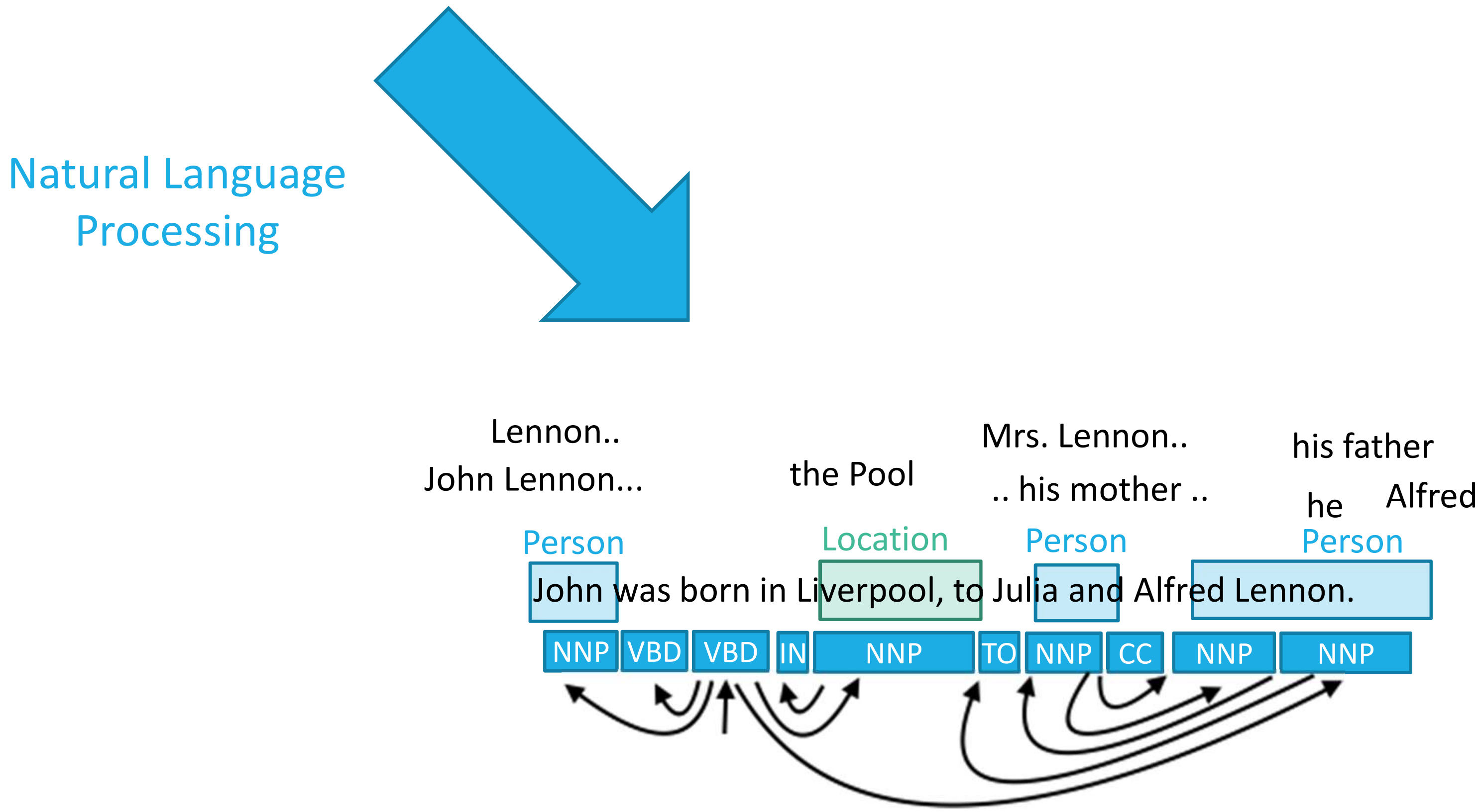
Two Related Tasks



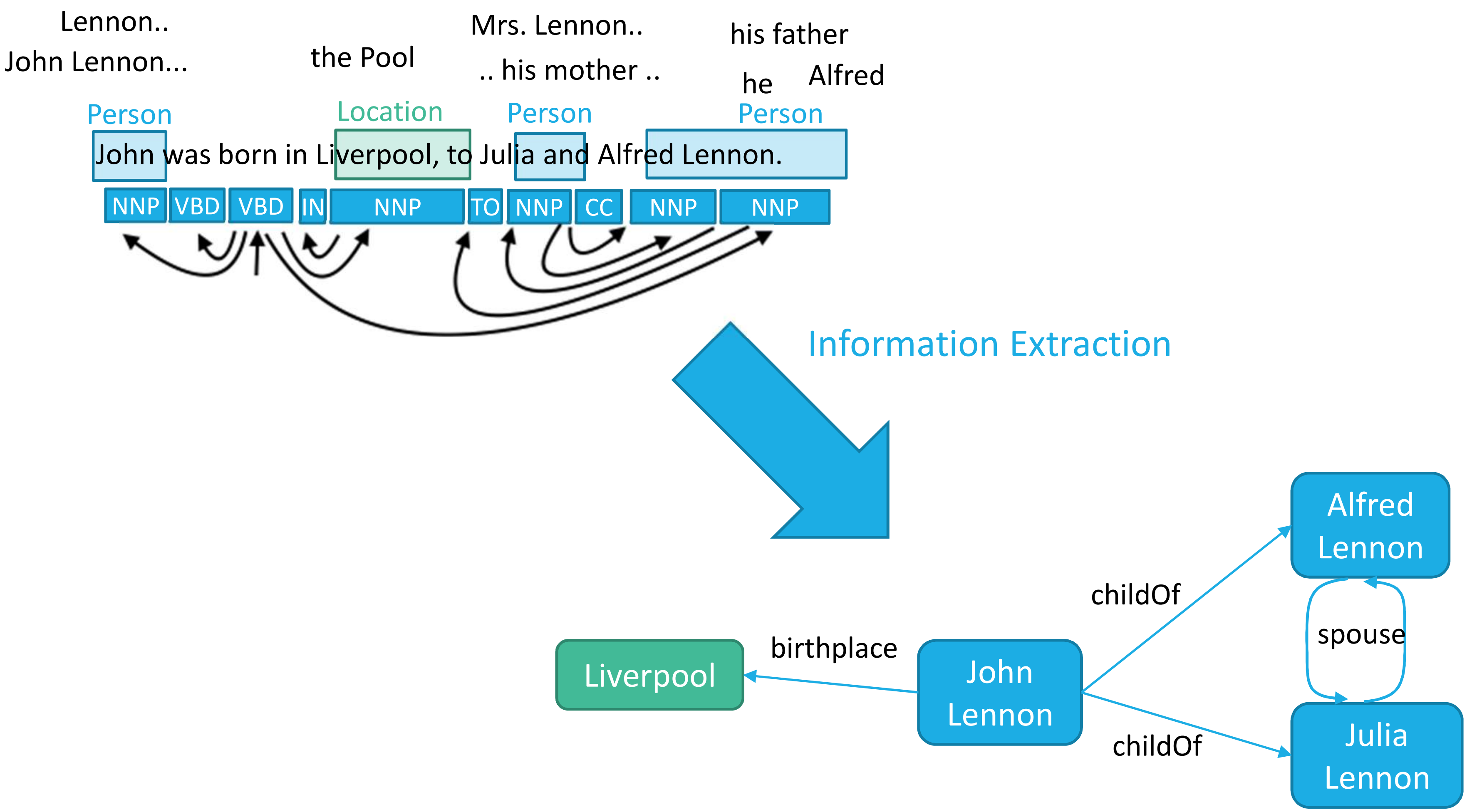


What is NLP?

John was born in Liverpool, to Julia and Alfred Lennon.

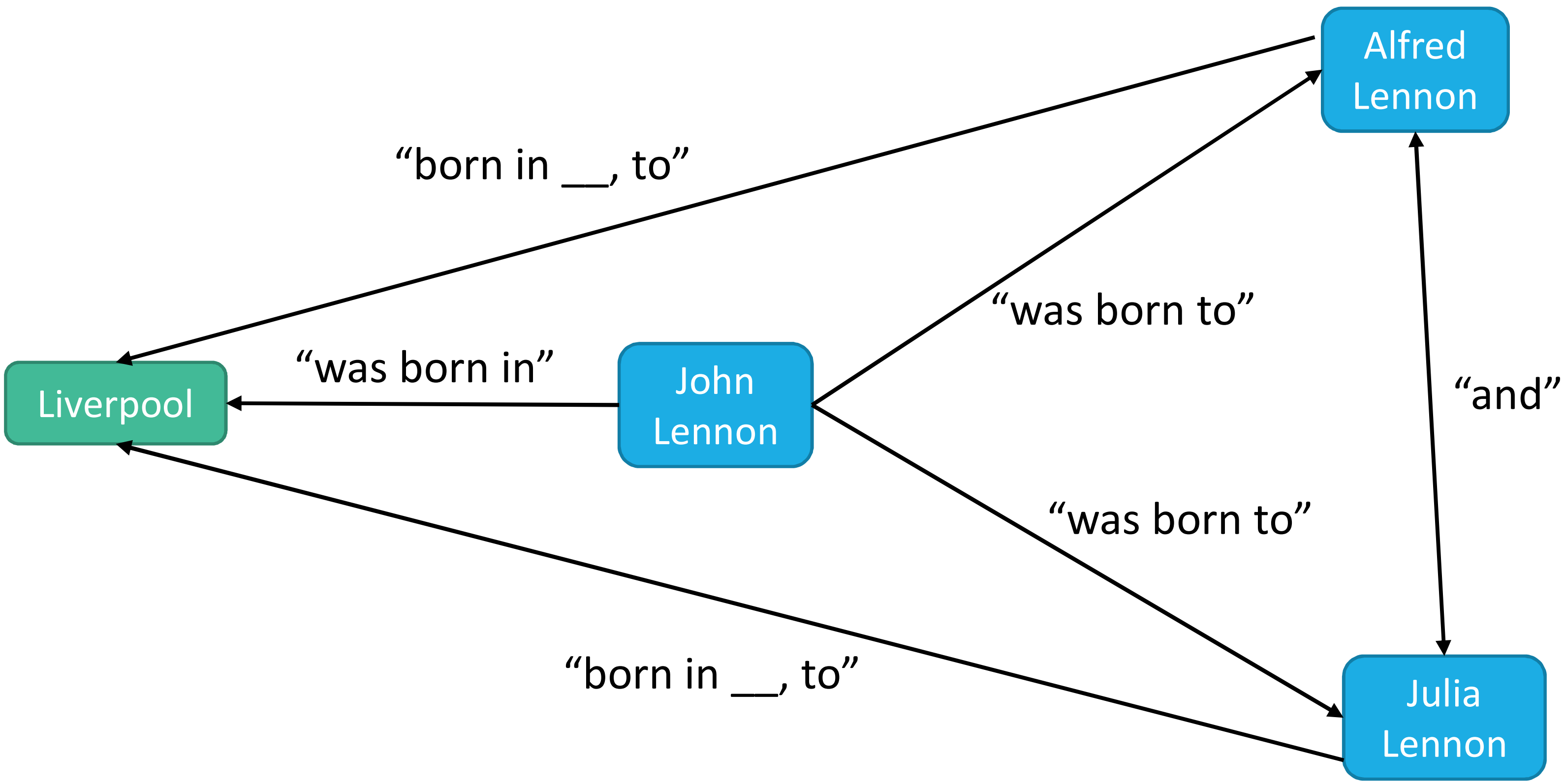


What is Information Extraction?



Relation Extraction From Text

John was born in Liverpool, to Julia and Alfred Lennon.



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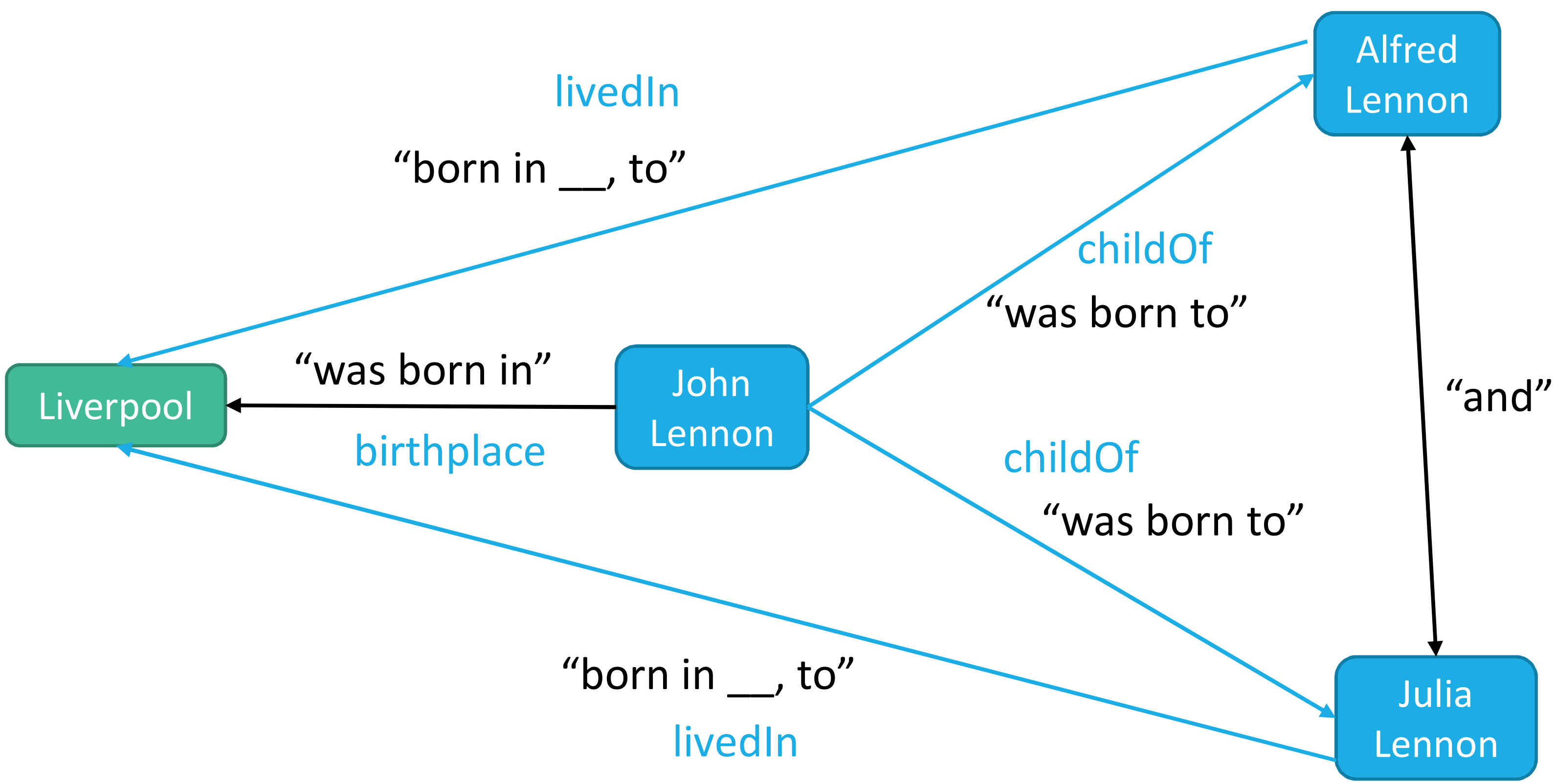
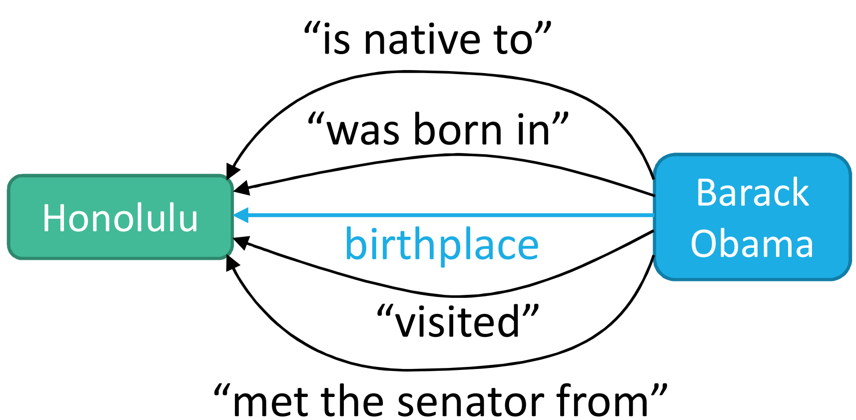


"Distant" Supervision

No direct supervision gives us this information.
Supervised: Too expensive to label sentences
Rule-based: Too much variety in language
Both only work for a small set of relations, i.e. 10s, not 100s



Relation Extraction as a Matrix

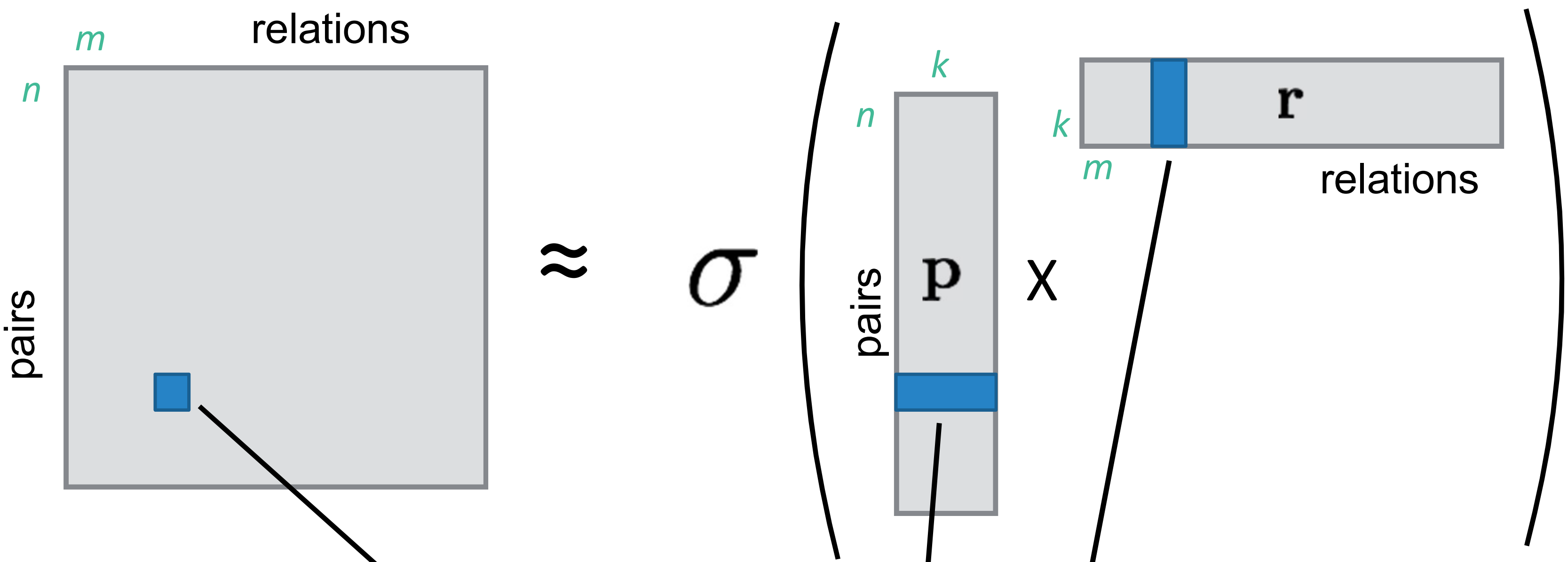
John was born in Liverpool, to Julia and Alfred Lennon.

Entity Pairs

	was born in <-nsubjpass-born<-nmod:in-	was born to	and	birthplace(X,Y)	spouse(X,Y)
John Lennon, Liverpool	1			?	
John Lennon, Julia Lennon		1			
John Lennon, Alfred Lennon		1			
Julia Lennon, Alfred Lennon			1		?
Barack Obama, Hawaii	1			1	
Barack Obama, Michelle Obama			1		1

我

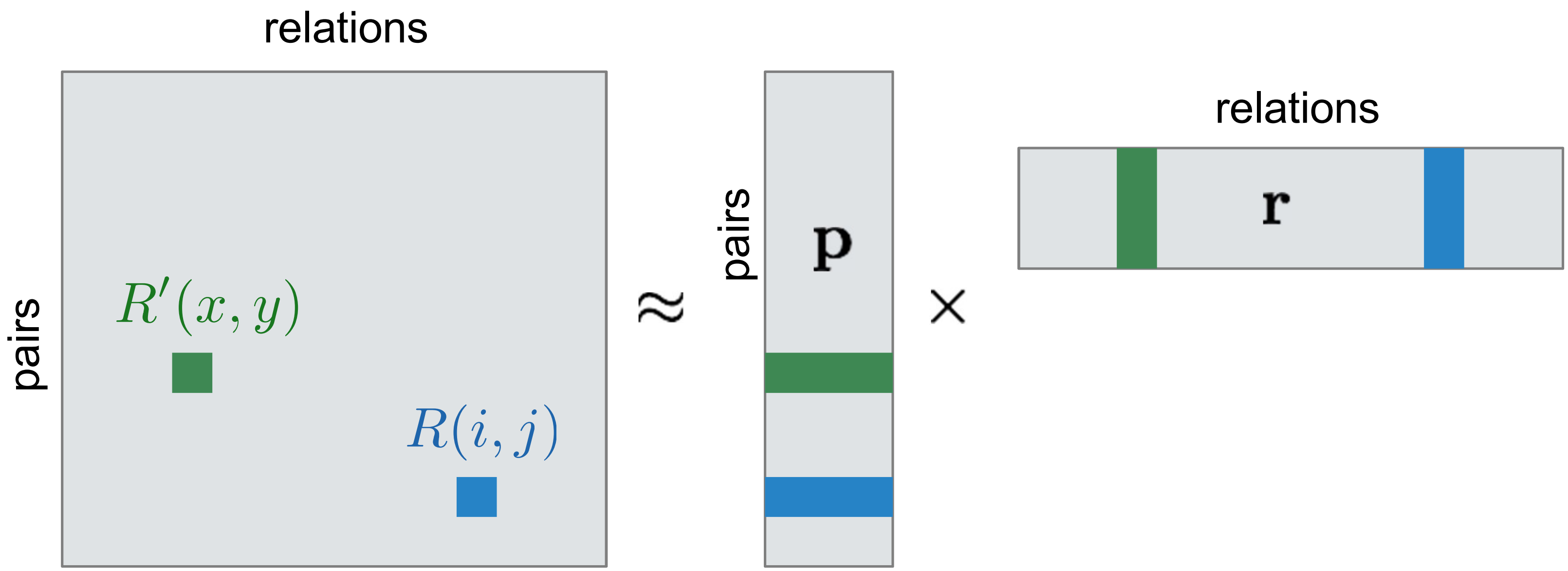
Matrix Factorization



bornIn(John,Liverpool)

$$P(R(i,j)) = \sigma(\mathbf{p}_{i,j} \cdot \mathbf{r}_R)$$

Training: Stochastic Updates



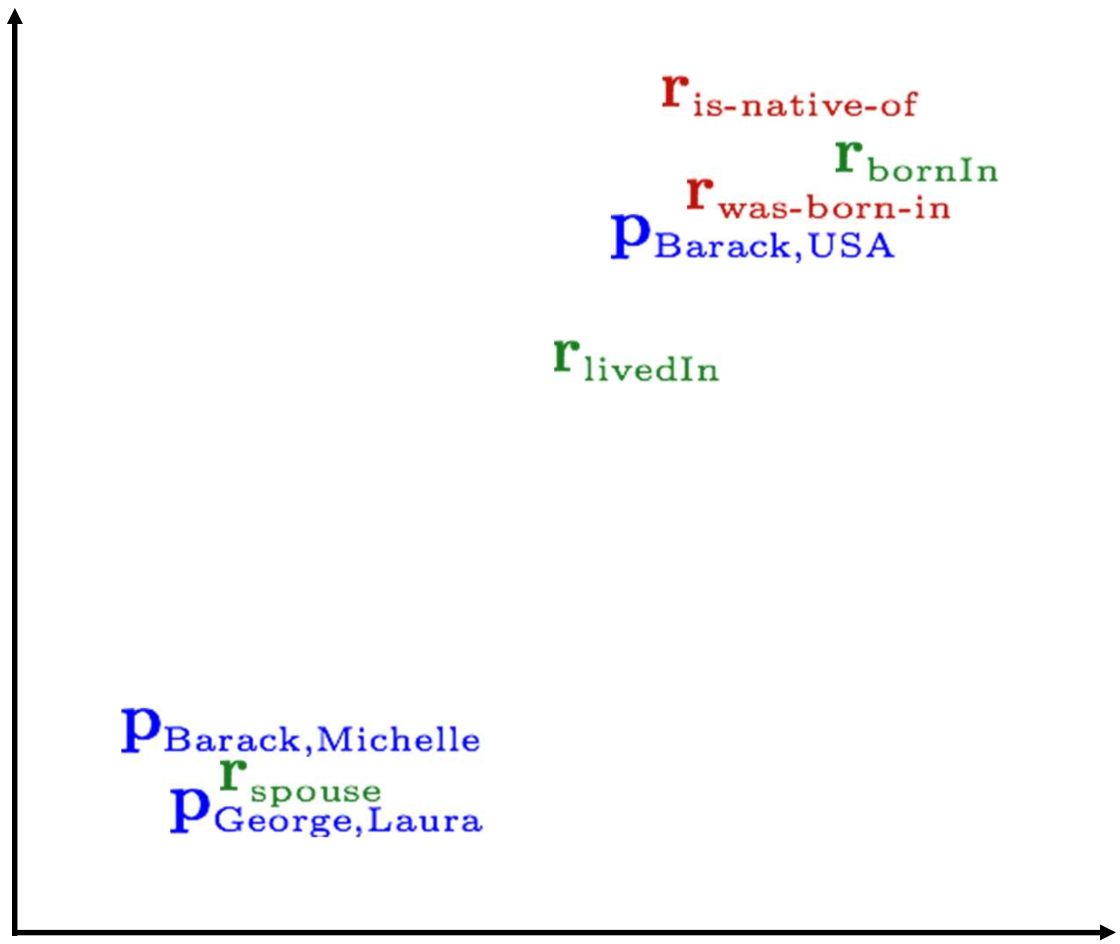
Pick an observed cell, $R(i,j)$:

- Update $\mathbf{p}_{ij}$ & $\mathbf{r}_R$ such that $R(i,j)$ is higher

Pick any random cell, assume it is negative:

- Update $\mathbf{p}_{xy}$ & $\mathbf{r}_{R'}$ such that $R'(x,y)$ is lower

Relation Embeddings



Embeddings ~ Logical Relations

Relation Embeddings, w

用embedding表示他們兩個關係的意義

- Similar embedding for 2 relations denote they are paraphrases
  - is married to, spouseOf(X,Y), /person/spouse
- One embedding can be contained by another
  - w(topEmployeeOf) $\subset$ w(employeeOf)
  - topEmployeeOf(X,Y) $\rightarrow$ employeeOf(X,Y)
- Can capture logical patterns, without needing to specify them!

抓到邏輯的概念，不需要特定去定義

Entity Pair Embeddings, v

Similar entity pairs denote similar relations between them

Entity pairs may describe multiple “relations”

independent foundedBy and employeeOf relations

Similar Embeddings

similar underlying embedding

similar embedding

	X **own percentage of** Y	X **buy stake in** Y
Time, Inc Amer. Tel. and Comm.	1	1
Volvo Scania A.B.		1
Campeau Federated Dept Stores		
Apple HP		

Successfully predicts "Volvo owns percentage of Scania A.B." from "Volvo bought a stake in Scania A.B."

Implications

X historian at Y → X professor at Y

(Freeman,Harvard)
→ (Boyle,OhioState)

	X **professor at** Y	X **historian at** Y
Kevin Boyle Ohio State		**1**
R. Freeman Harvard	**1**	

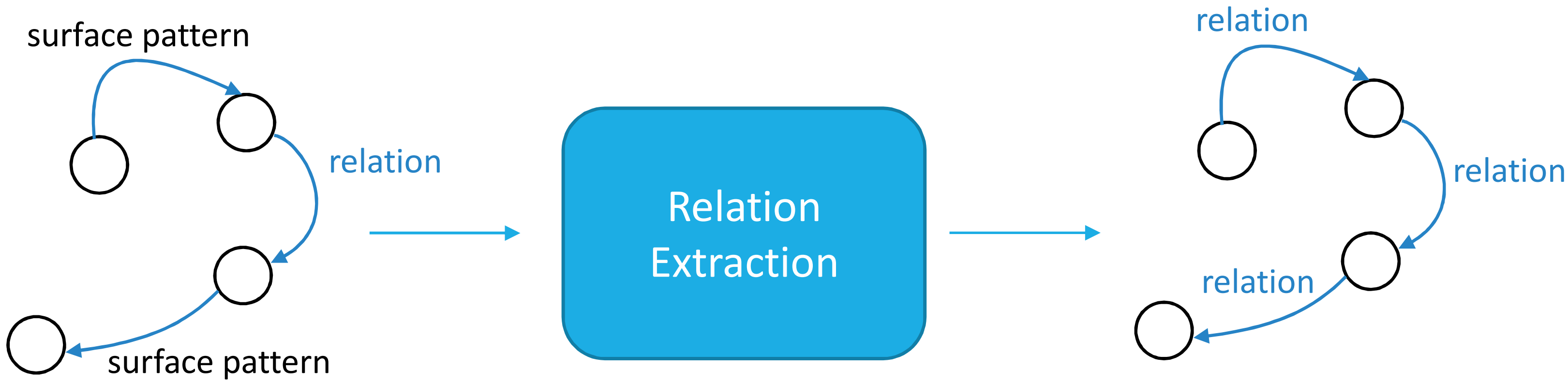
Learns asymmetric entailment:

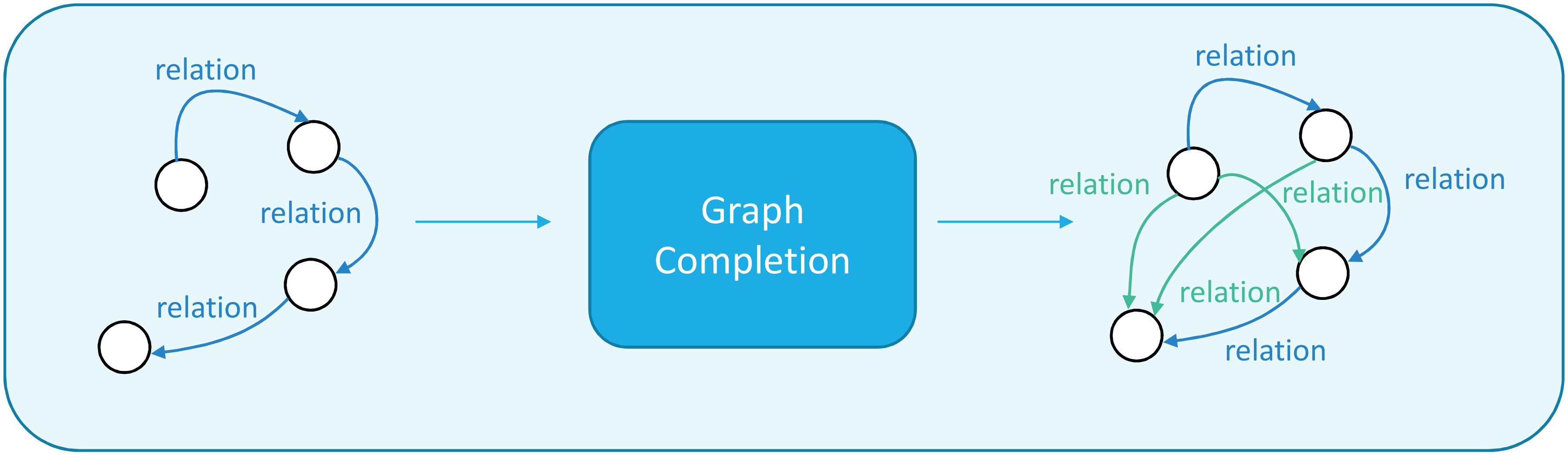
PER historian at UNIV $\rightarrow$ PER professor at UNIV

But,

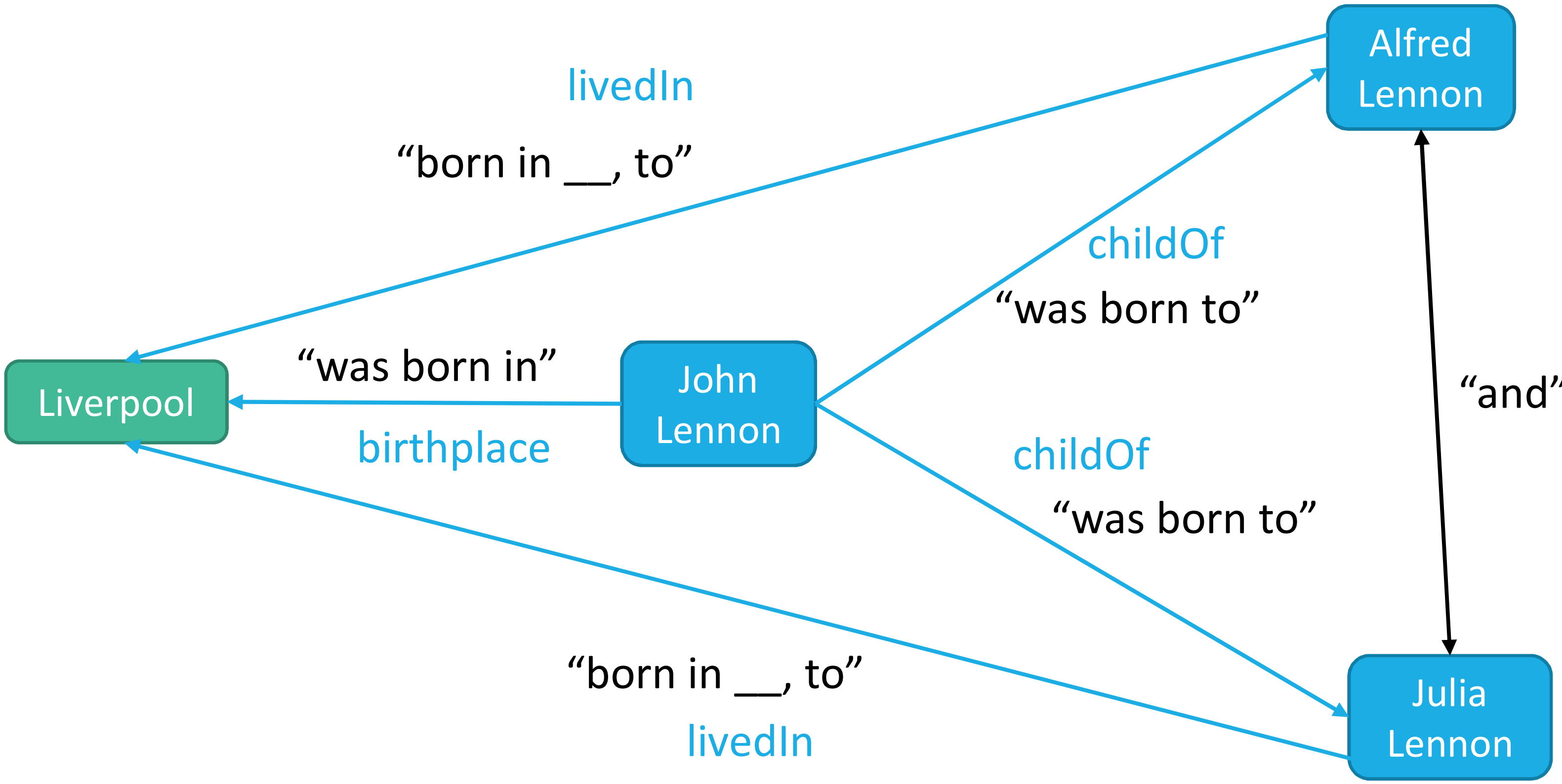
PER professor at UNIV $\not\rightarrow$ PER historian at UNIV

Two Related Tasks





Graph Completion



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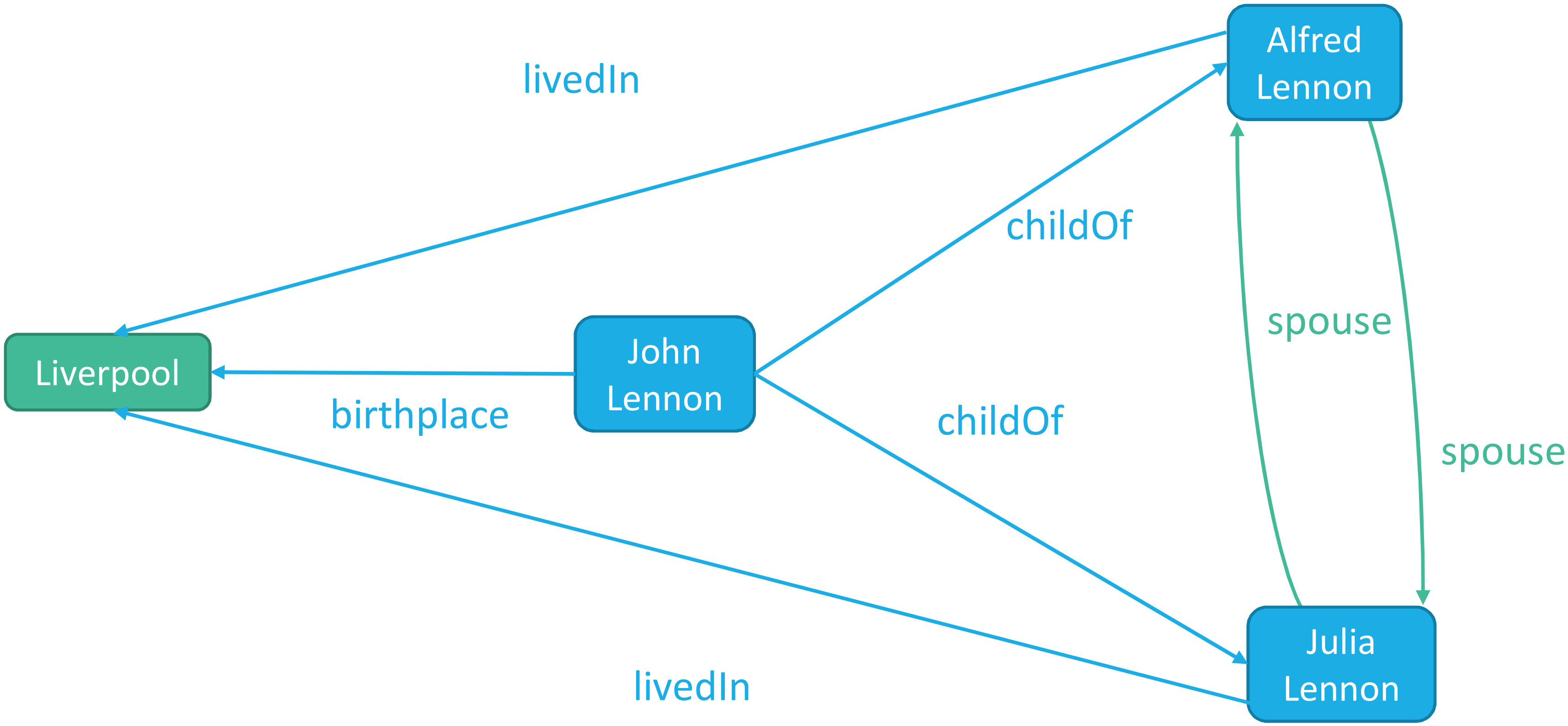
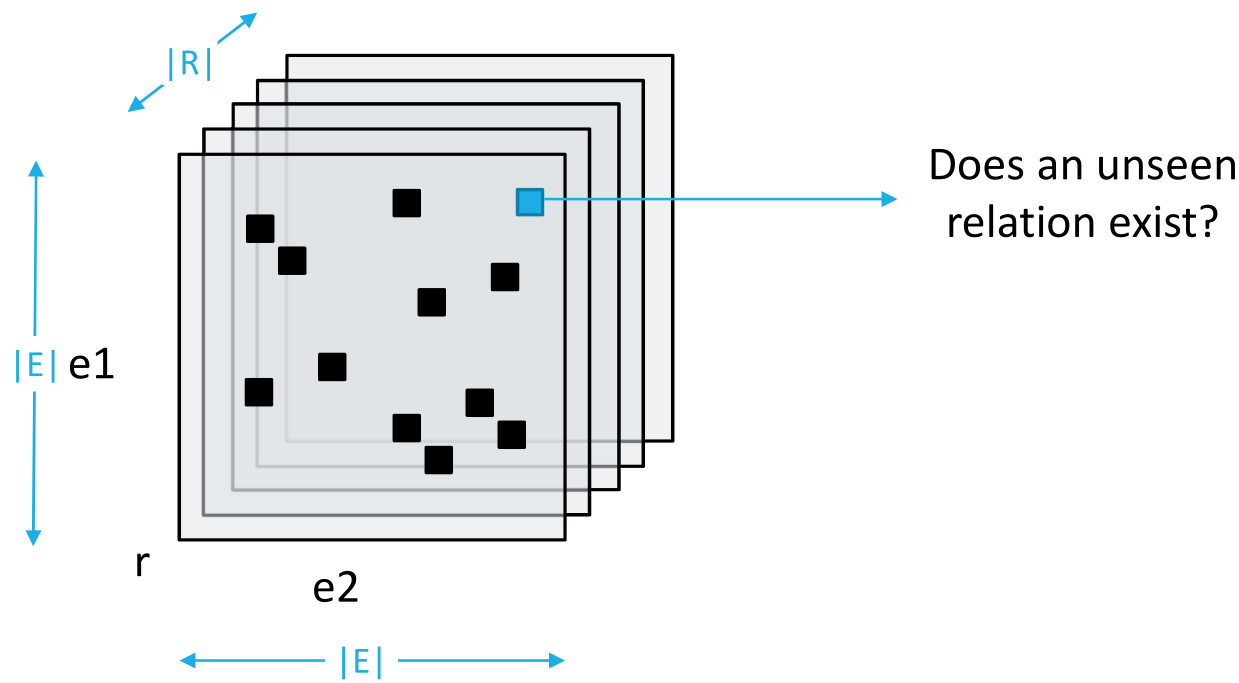
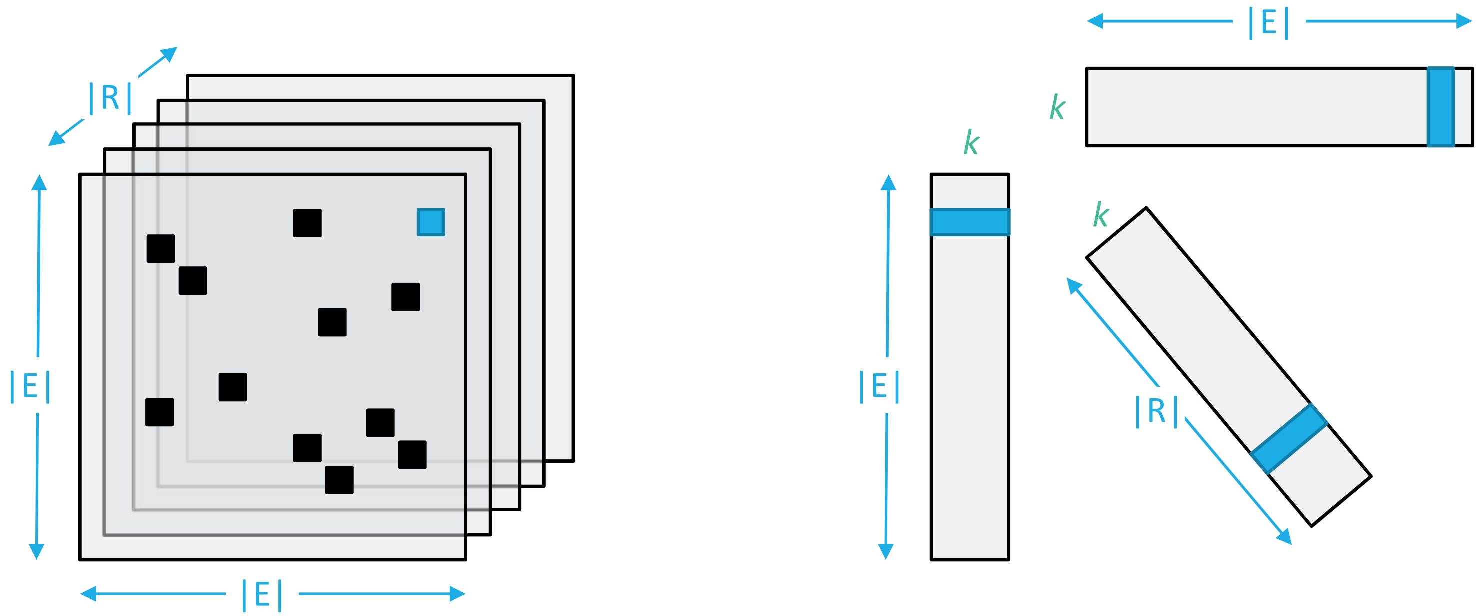


Tensor Formulation of KG



Factorize that Tensor



$$S(r(a,b)) = f(\mathbf{v}_r, \mathbf{v}_a, \mathbf{v}_b)$$

Many Different Factorizations

CANDECOMP/PARAFAC-Decomposition

$$S\left(r(a,b)\right) = \sum_k R_{r,k} \cdot e_{a,k} \cdot e_{b,k}$$

Tucker2 and RESCAL Decompositions

$$S\left(r(a,b)\right) = \left(\mathbf{R}_r \times \mathbf{e}_a\right) \times \mathbf{e}_b$$

Model E

$$S\left(r(a,b)\right) = \mathbf{R}_{r,1} \cdot \mathbf{e}_a + \mathbf{R}_{r,2} \cdot \mathbf{e}_b$$

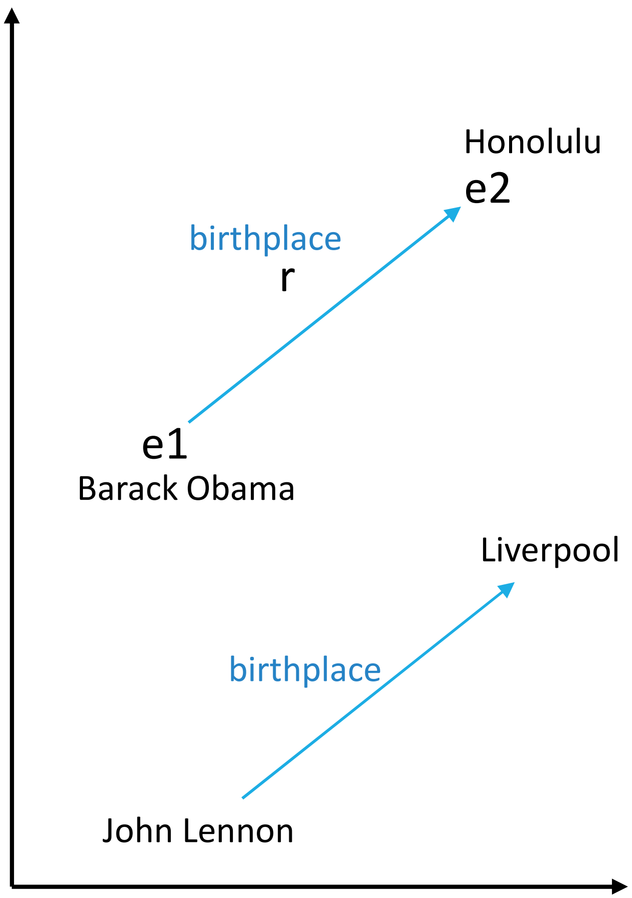
Holographic Embeddings

$$S(r(a,b)) = \mathbf{R}_r \times (\mathbf{e}_a \star \mathbf{e}_b)$$

Not tensor factorization (per se)

HOLE: Nickel et al, AAAI (2016), Model E: Riedel et al, NAACL (2013), RESCAL: Nickel et al, WWW (2012), CP: Harshman (1970), Tucker2: Tucker (1966)

Translation Embeddings



多元关系数据嵌入

TransE

$$S\left(r(a,b)\right) = -\|\mathbf{e}_a + \mathbf{R}_r - \mathbf{e}_b\|_2^2$$

TransE改进策略：

- 引入 Relation-Specific Entity Embeddings:

TransH 将知识嵌入到超平面

$$S\left(r(a,b)\right) = -\|\mathbf{e}_a^{\perp} + \mathbf{R}_r - \mathbf{e}_b^{\perp}\|_2^2$$

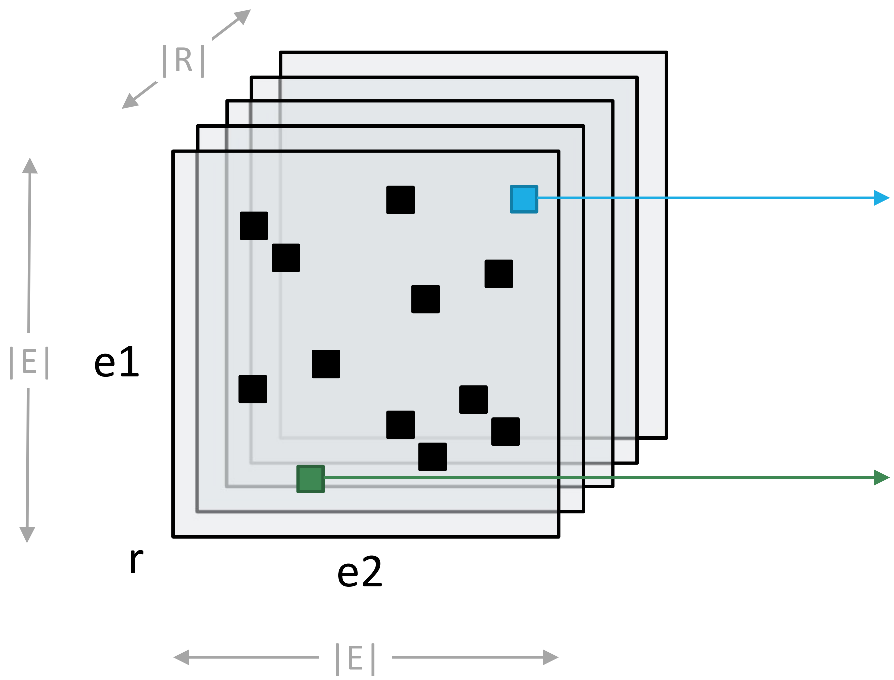
$$\mathbf{e}_a^{\perp} = \mathbf{e}_a - \mathbf{w}_r^T \mathbf{e}_a \mathbf{w}_r$$

TransR 实体和关系分开嵌入

$$S\left(r(a,b)\right) = -\|\mathbf{e}_a \mathbf{M}_r + \mathbf{R}_r - \mathbf{e}_b \mathbf{M}_r\|_2^2$$

TransE: Bordes et al. XXX (2011), TransH: Bordes et al. XXX (2011), TransR: Bordes et al. XXX (2011)

Parameter Estimation



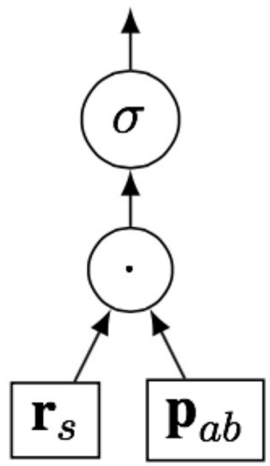
Observed cell: increase score

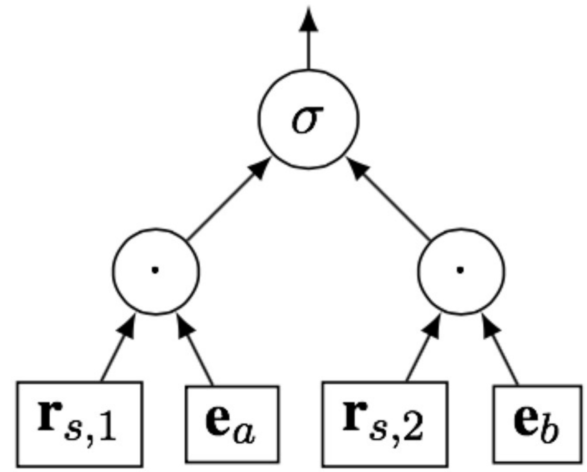
$$S\left(r(a,b)\right)$$

Unobserved cell: decrease score

$$S\left(r'(x,y)\right)$$

Matrix vs Tensor Factorization



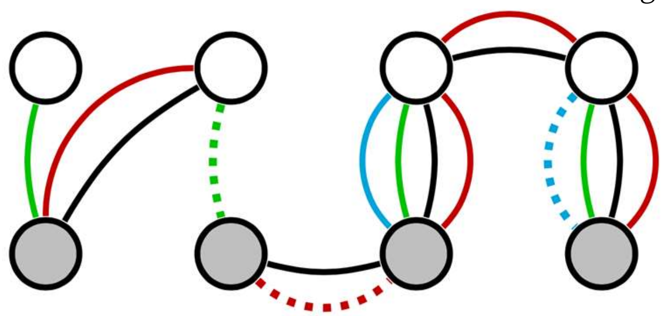


- Vectors for each entity pair
- Can only predict for entity pairs that appear in text together 一定要出現在同一個句子
- No sharing for same entity in different entity pairs

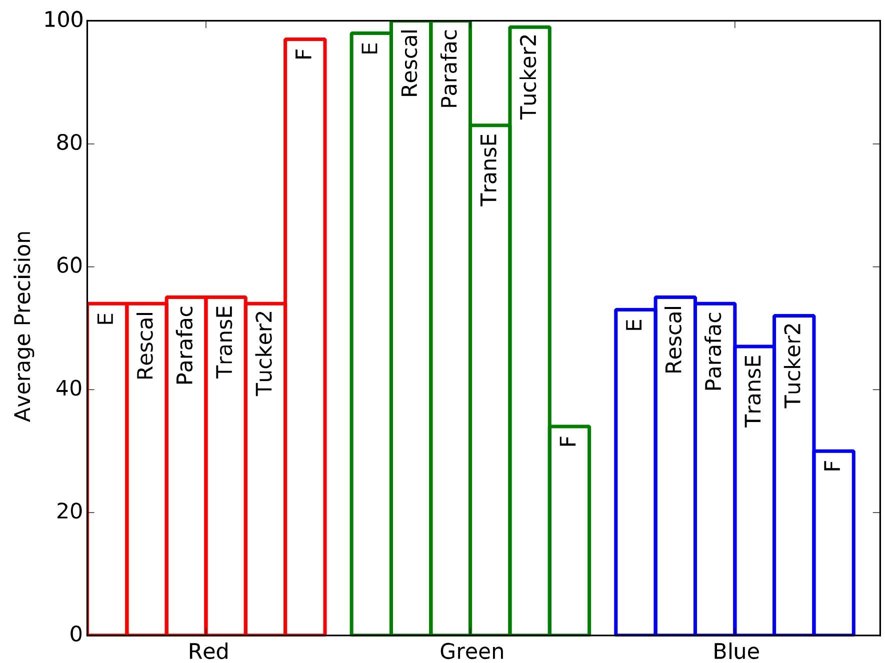
- Vectors for each entity
- Assume entity pairs are “low-rank”
  - But many relations are not!
  - Spouse: you can have only ~1
- Cannot learn pair specific information

What they can, and can't, do..

黑色線:觀察的data
RGB實線是training data
虛線是testing data

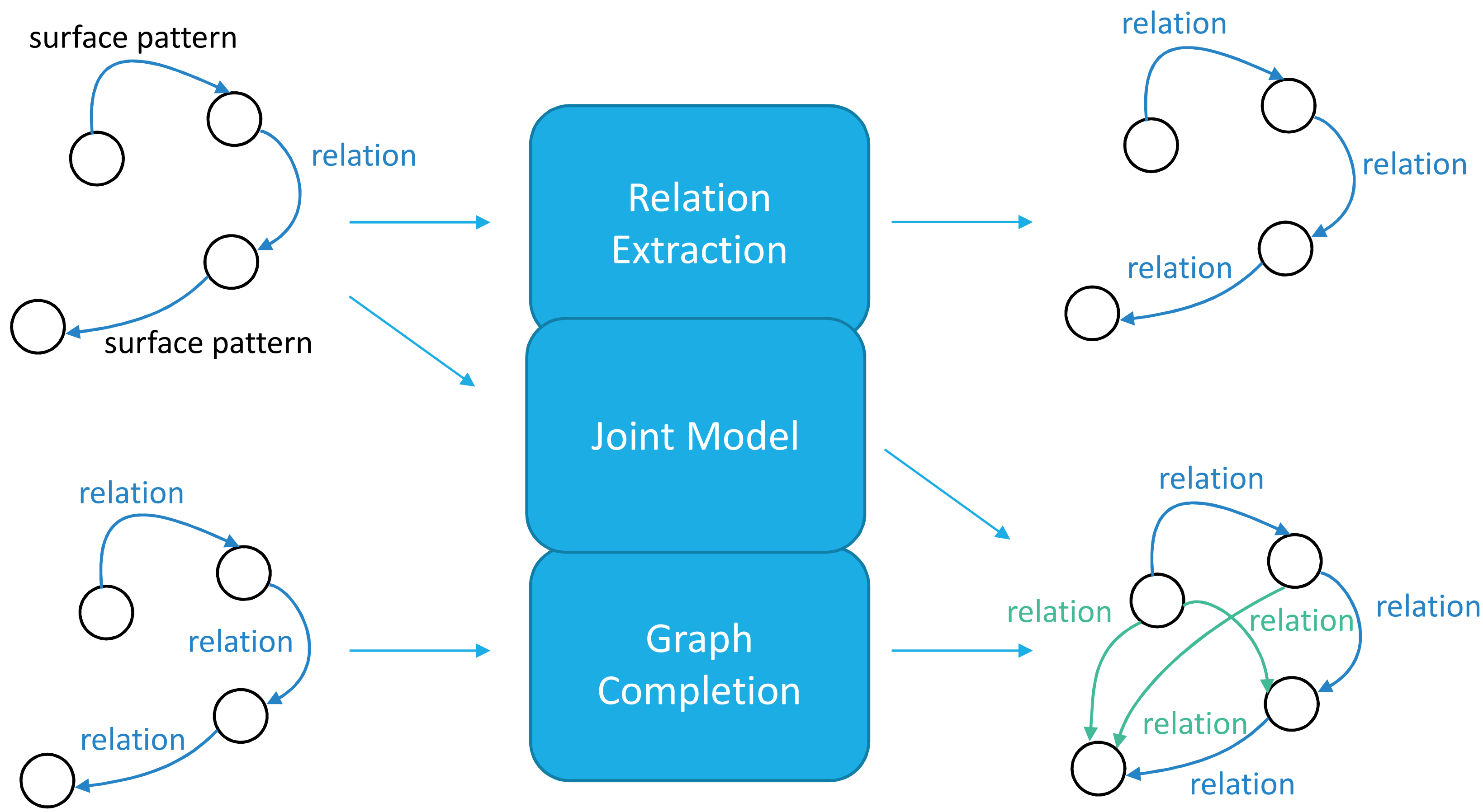


紅色是對已有聯結的預測性比較強
綠色的概化能力比較強(泛化)
藍色是綜合能力



- **Red**: deterministically implied by **Black**
  - needs *pair-specific* embedding
  - Only **F** is able to generalize
- **Green**: needs to estimate entity types
  - needs *entity-specific* embedding
  - Tensor factorization generalizes, **F** doesn't
- **Blue**: implied by **Red** and **Green**
  - Nothing works much better than random

Joint Extraction+Completion



Compositional Neural Models

So far, we're learning vectors for each entity/surface pattern/relation..

But learning vectors independently ignores "composition"

Composition in Surface Patterns

- Every surface pattern is not unique
- Synonymy: A is B's spouse.
  A is married to B.
- Inverse: X is Y's parent.
  Y is one of X's children.
- Can the representation learn this?

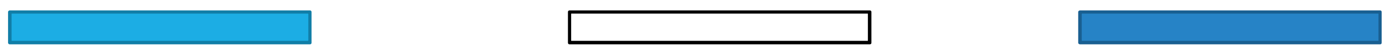
Composition in Relation Paths

- Every relation path is not unique
- Explicit: A parent B, B parent C
  A grandparent C
- Implicit: X bornInCity Y, Y cityInState Z
  X "bornInState" Z
- Can the representation capture this?

Composing Dependency Paths

這裡是沒看過，架設左邊是0右邊1 中間是0.5

... was born to ... ... ‘s parents are ... \parentsOf

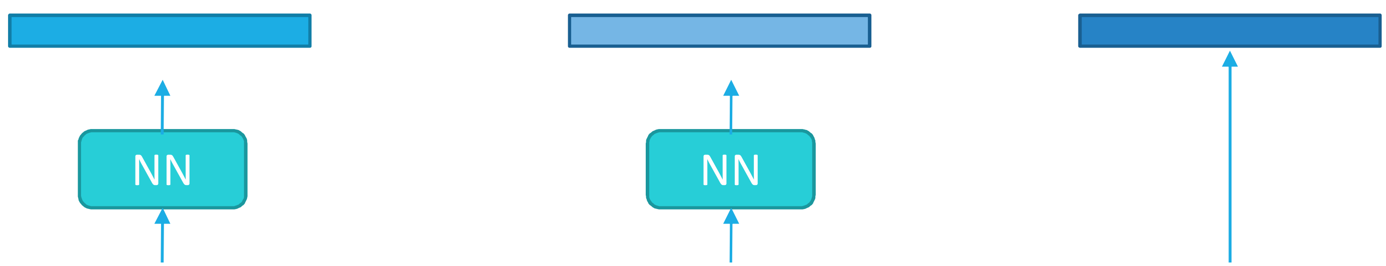


(never appears in training data)

看他能不能學到複合性的關係

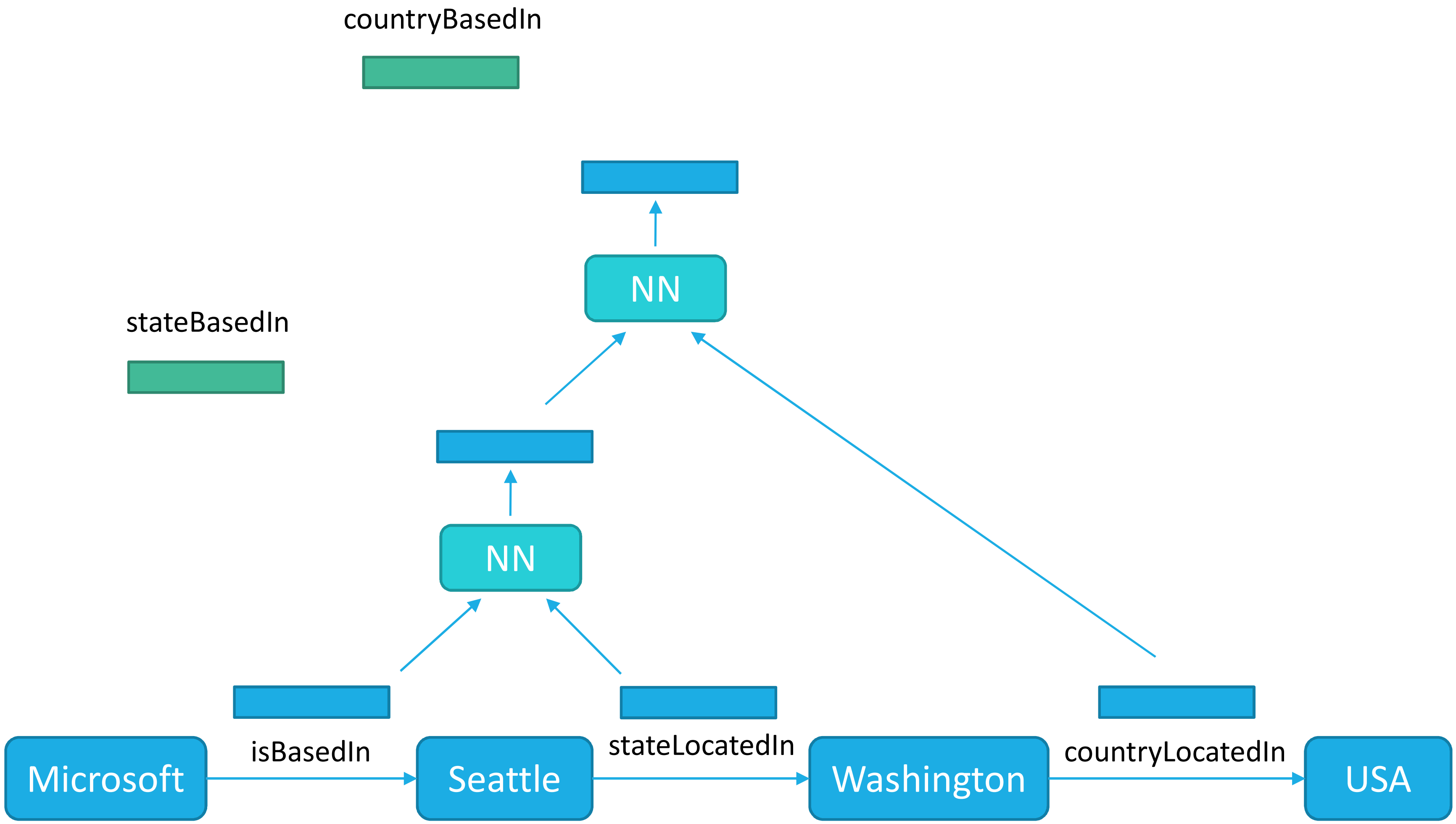
But we don’t need linked data to know they mean similar things…

Use neural networks to produce the embeddings from text!



... was born to ... ... ‘s parents are ... \parentsOf

Composing Relational Paths



Neelakantan et al (2015), http://www.aaai.org/ocs/index.php/SSS/SSS15/paper/viewFile/10254/10032
Lin et al, EMNLP (2015), https://arxiv.org/pdf/1506.00379.pdf

Review: Embedding Techniques

Two Related Tasks:

- Relation Extraction from Text
- Graph (or Link) Completion

Relation Extraction:

- Matrix Factorization Approaches

Graph Completion:

- Tensor Factorization Approaches

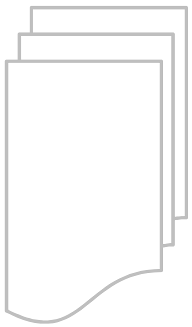
Compositional Neural Models

- Compose over dependency paths
- Compose over relation paths

Tutorial Overview

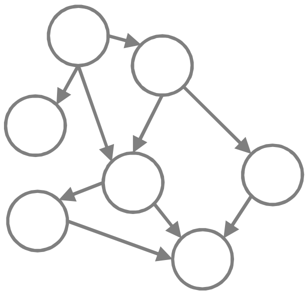
https://kgtutorial.github.io

Part 1: Knowledge Graphs



Part 2: Knowledge Extraction

Part 3: Graph Construction



Part 4: Critical Analysis