Knowledge Graphs

and Conversational AI

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Outline

- Knowledge Graphs

- Knowledge Graph Embeddings (KGE) : ML + Logic

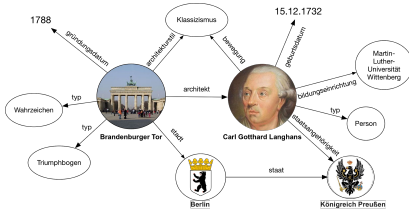- Question Answering over KGs (KGQA)

- Conversational AI

Background
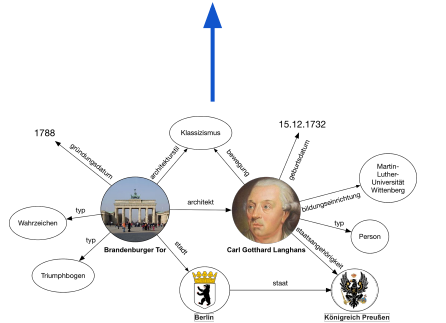
We build conversational AI platforms

Background

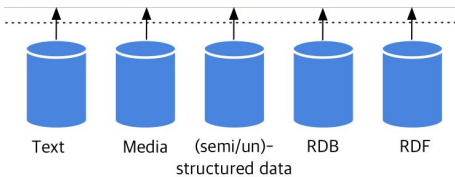We build conversational AI platforms

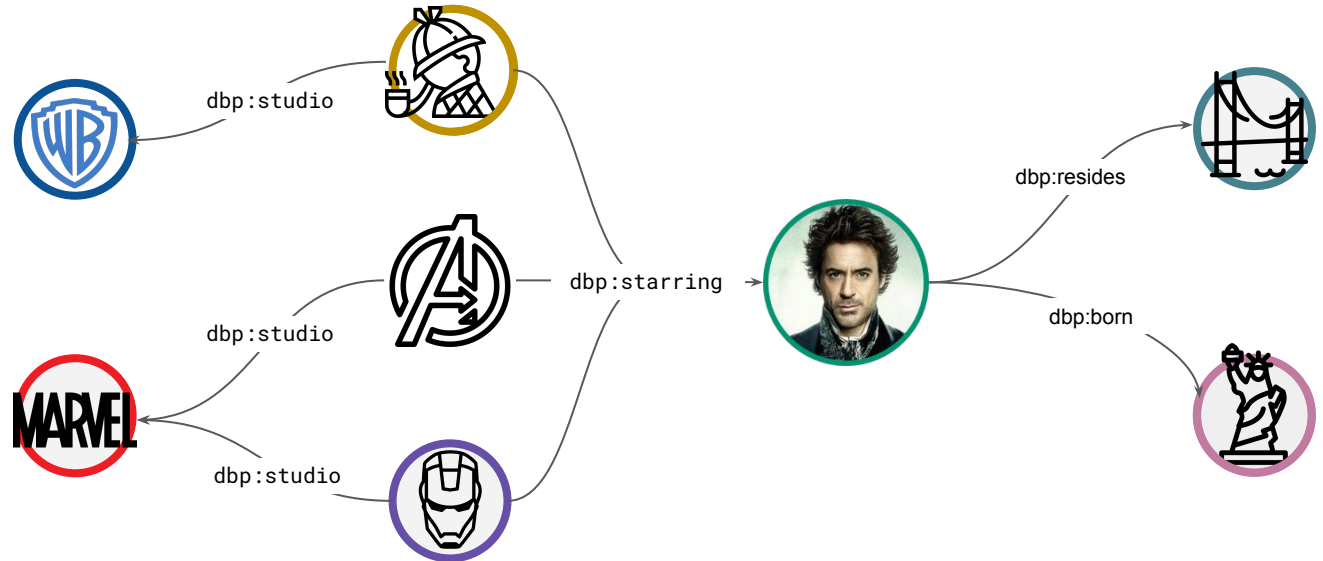Powered by knowledge graphs

Background

We build conversational AI platforms

Powered by knowledge graphs

Obtained by integrating heterogeneous data

Text Media (semi/un)– RDB RDF
structured data

Knowledge Graph

Knowledge Graph - Entities
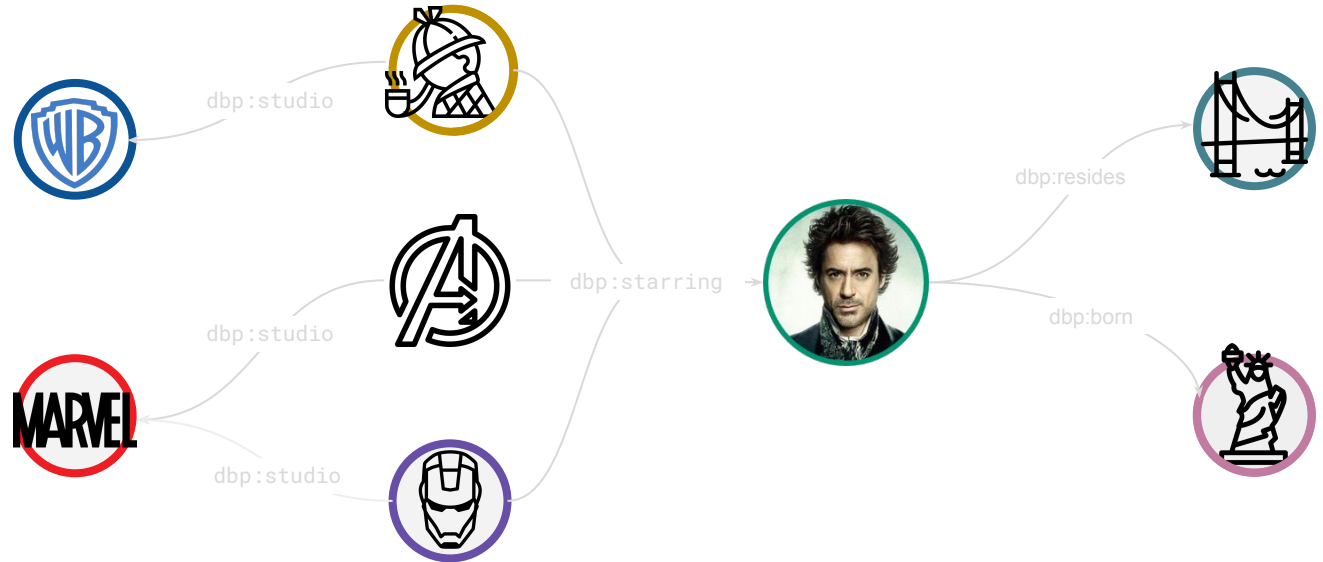
Knowledge Graph - Relations
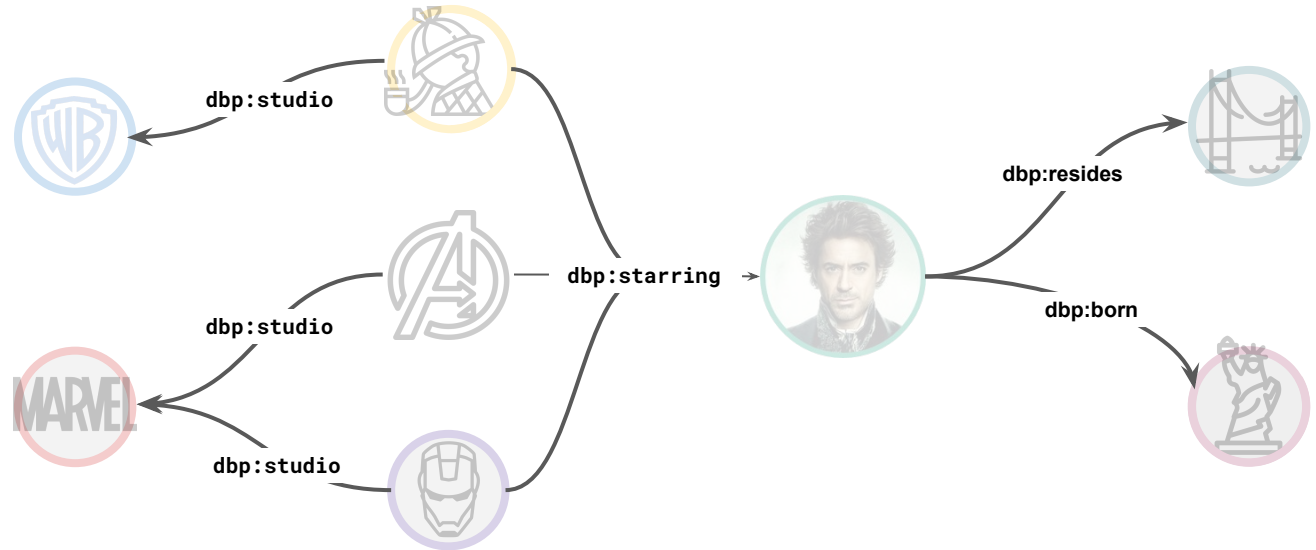
Knowledge Graph (real excerpt)
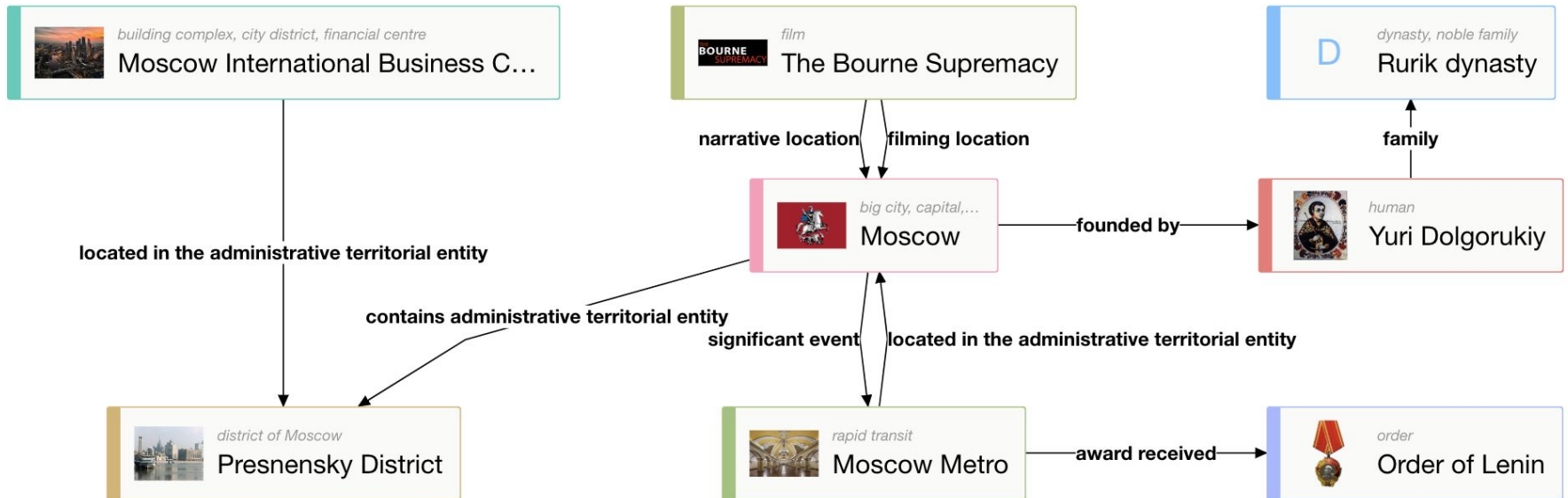
https://wikidata.metaphacts.com/

Available Knowledge Graphs

Knowledge Graphs

Open-domain: Wikidata, DBpedia

Biomed: Drugbank, SNOMED-CT, Bio2RDF

Ontologies

Industry 4.0: RAMI

Finance: FIBO, FRO, XBRL, FinReg

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Ontologies

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Custom

Enterprise Knowledge Graphs

Building Knowledge Graphs

Knowledge Graph

Semantic Data Integration

Structured Sources

XML, CSV, JSON

NoSQL

GraphDBs

APIs

RDF Storage

JSON

SQL

XML

CSV

Building Knowledge Graphs
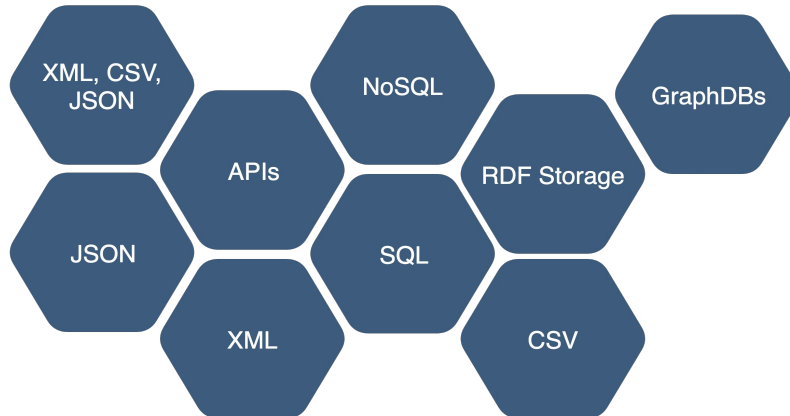
Knowledge Graph	Knowledge Graph
Semantic Data Integration	**Information Retrieval & NLP**
Structured Sources	**Unstructured Sources**

XML, CSV, JSON

NoSQL

GraphDBs

APIs

RDF Storage

JSON

SQL

XML

CSV
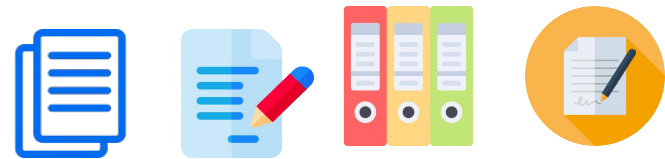
Tensor Factorization

Translation

Convolution

Graph Neural Nets

Knowledge Graph Embeddings

Goal: encode nodes so that **similarity in the embedding space (e.g., dot product)** approximates **similarity in the original network**

$\text{ENC}(u)$

$\text{ENC}(v)$

encode nodes

$\mathbf{z}_u$

$\mathbf{z}_v$

original network

embedding space

14
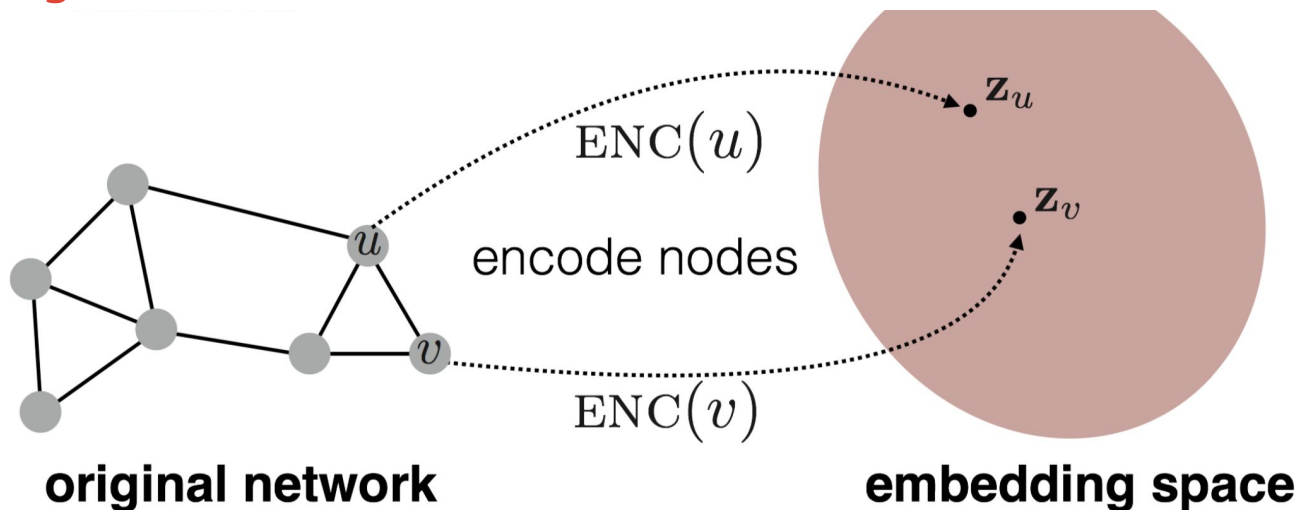
KGE - RESCAL

Goal - factorize a sparse 3D tensor to dense E and R

$$\mathbf{Y}_k \qquad \mathbf{EW}_k\mathbf{E}^\top$$

Nickel et al. A review of relational machine learning for knowledge graphs. IEEE. 2015

Tensor Factorization
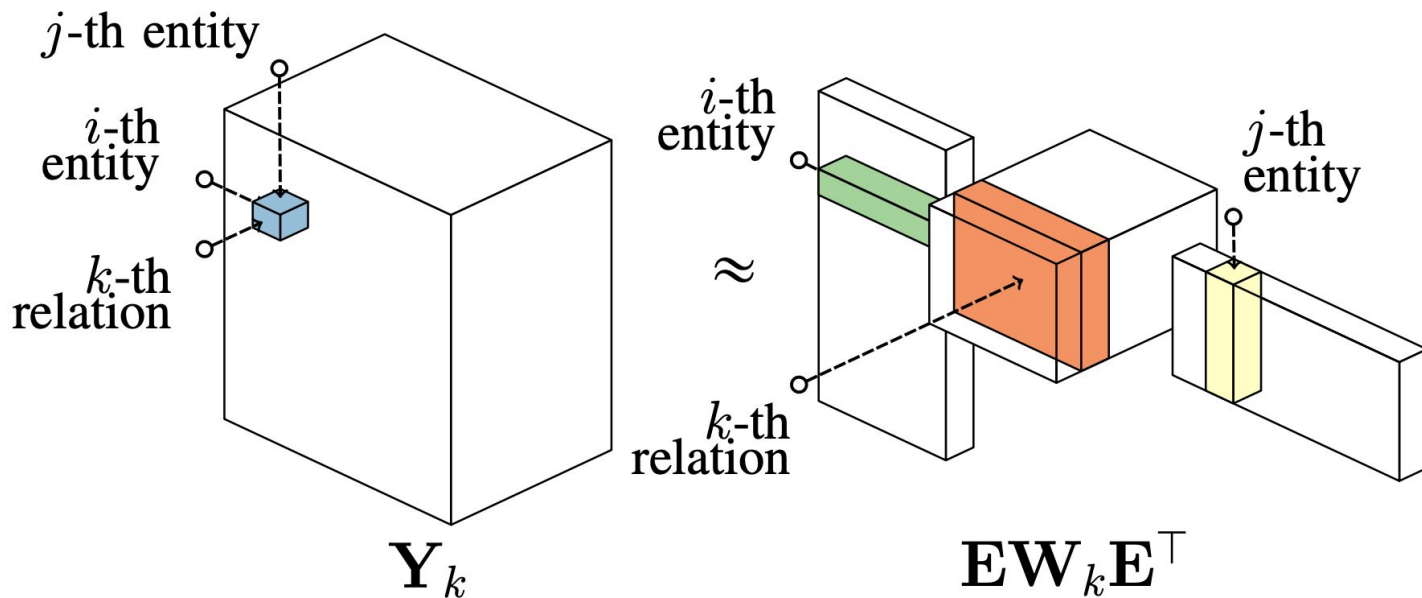
KGE - Expressivity & Rules

TF can be enriched with logical rules and can learn rules

Model	Score Function	Symmetry	Antisymmetry	Inversion	Composition
SE	$-\|W_{r,1}h - W_{r,2}t\|$	✗	✗	✗	✗
TransE	$-\|h + r - t\|$	✗	✓	✓	✓
TransX	$-\|g_{r,1}(h) + r - g_{r,2}(t)\|$	✓	✓	✗	✗
DistMult	$\langle h, r, t \rangle$	✓	✗	✗	✗
ComplEx	$\mathrm{Re}(\langle h, r, \bar{t} \rangle)$	✓	✓	✓	✗
RotatE	$-\|h \circ r - t\|$	✓	✓	✓	✓

Table 2: The pattern modeling and inference abilities of several models.

Sun et al. Rotate: Knowledge graph embedding by relational rotation in complex space. ICLR 2019
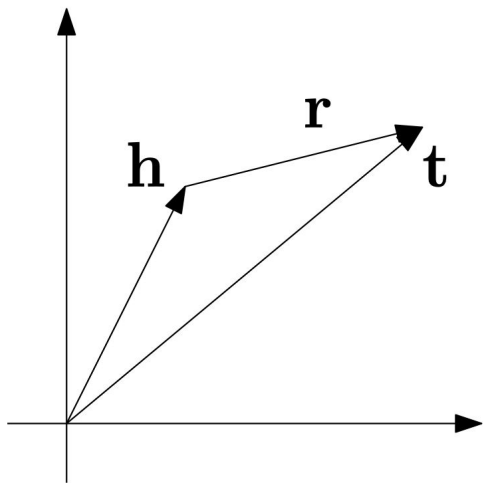
KGE - TransE

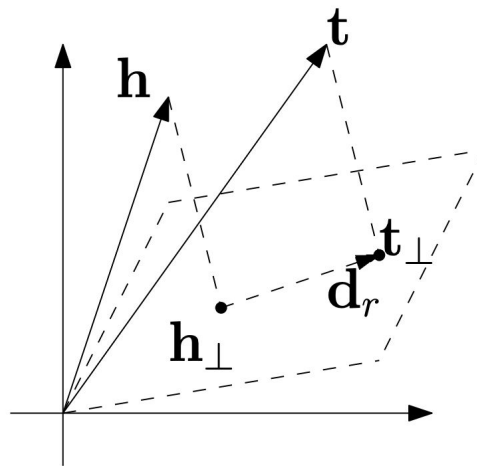Translate entities and relations into one embedding space

$$h + r \approx t \quad \text{Moscow} + \text{capitalOf} \approx \text{Russia}$$

(a) TransE   (b) TransH

Wang et al. Knowledge Graph Embedding by Translating on Hyperplanes. AAAI 2014

KGE - Hyperbolic

Goal: embed hierarchical structures into an n-dimensional Poincaré ball.
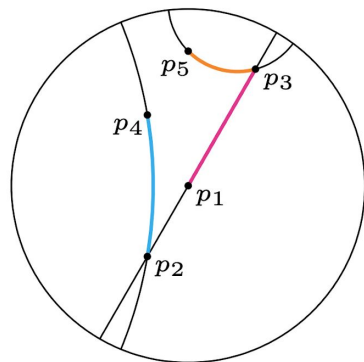
(a) Geodesics of the Poincaré disk   (b) Embedding of a tree in $\mathcal{B}^2$ (c) Growth of Poincaré distance
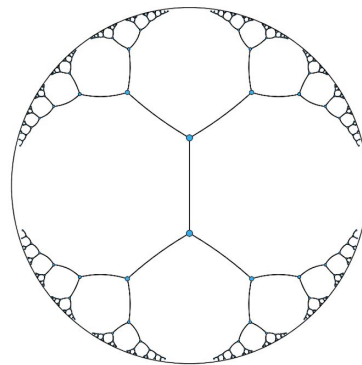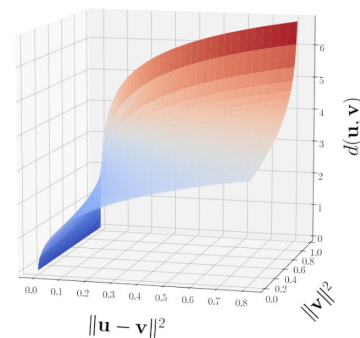
Figure 1: (a) Due to the negative curvature of $\mathcal{B}$, the distance of points increases exponentially (relative to their Euclidean distance) the closer they are to the boundary. (c) Growth of the Poincaré distance $d(\boldsymbol{u}, \boldsymbol{v})$ relative to the Euclidean distance and the norm of $\boldsymbol{v}$ (for fixed $\|\boldsymbol{u}\| = 0.9$). (b) Embedding of a regular tree in $\mathcal{B}^2$ such that all connected nodes are spaced equally far apart (i.e., all black line segments have identical hyperbolic length).

Nickel et al. Poincaré Embeddings for Learning Hierarchical Representations. NIPS 2017 AI Journey 2019

Tensor Factorization

Translation

Convolution

KGE - ConvE

Goal: CNNs for predicting a probability of the object

Minervini et al. Convolutional 2D Knowledge Graph Embeddings. AAAI 2018

Tensor Factorization

Translation
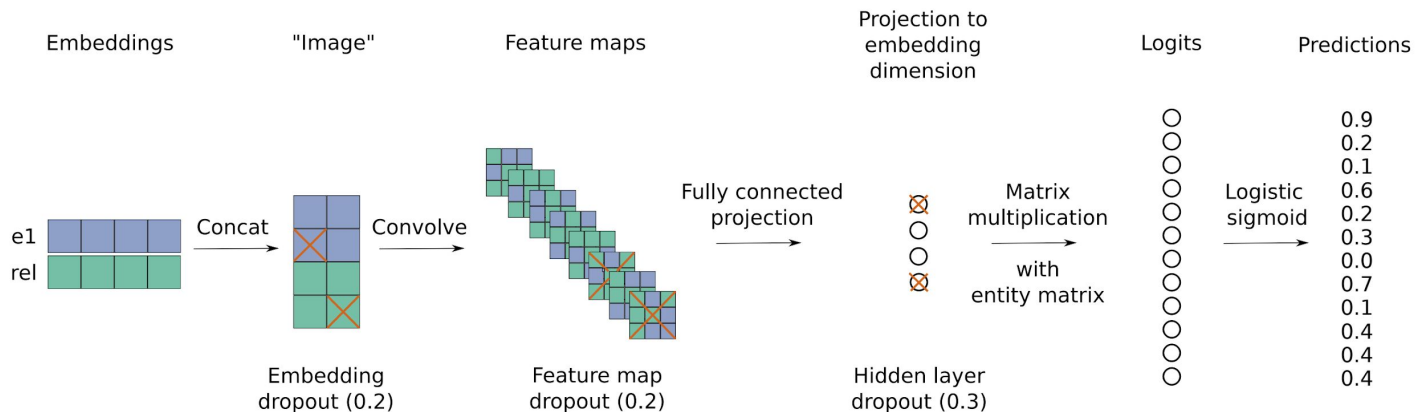
Convolution

Graph Neural Nets

KGE - Graph Networks

Goal: leverage topological graph characteristics

Veličković et al. Graph Attention Networks. ICLR 2018
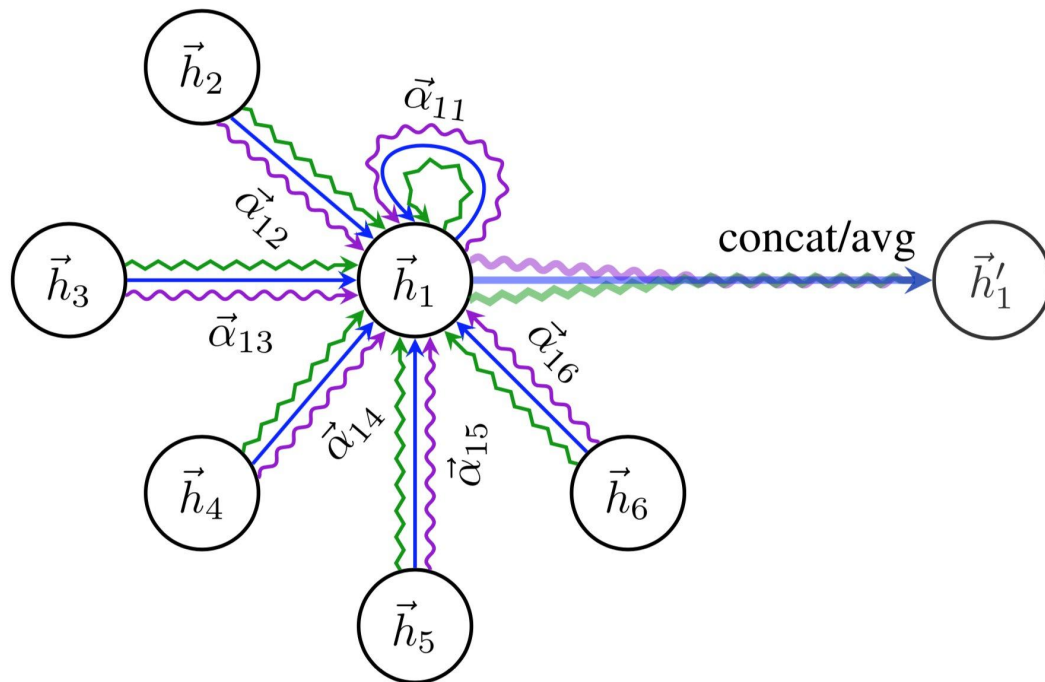
Question Answering over KGs

How many Marvel movies was Robert Downey Jr. casted in?

KGQA

How many **Marvel** **movies** was **Robert Downey Jr.** **casted** in?

```
SELECT COUNT(?uri) WHERE {
    ?uri dbp:studio dbr:Marvel_Studios.
    ?uri dbo:starring dbr:Robert_Downey_Jr
}
```

KGQA

All
marvel
movies

Every
thing
starring
RDJ

How many **Marvel** **movies** was **Robert Downey Jr.** **casted** in?

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KGQA

All marvel movies

Every thing starring RDJ

Find the intersection

How many **Marvel** **movies** was **Robert Downey Jr.** **casted** in?

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}
```

KGQA

All
marvel
movies

Every
thing
starring
RDJ

Find the
intersection

Count the
entities
left

How many Marvel movies was Robert Downey Jr. casted in?

```
SELECT COUNT(?uri) WHERE {
    ?uri dbp:studio dbr:Marvel_Studios.
    ?uri dbo:starring dbr:Robert_Downey_Jr
}
```

Entity Linking

Who is the CEO of **Apple**?

Apple belongs to which genus?

movie character
Downey played **Iron Man** in which year?

Who is the alter ego of **Iron man**?

comic character

Relation Linking

dbo:starring

Name all the movies in which **Robert Downey Jr** **Acted**?

Which movies have **RDJ**?

Flicks where I can see **Robert DJ**?

Find me all the films **casting** **Rober Downey Jr** ?

List all the movies **starring** **Robert Downey Junior**?

RDJ **has acted** in which movies?

Relation Linking - Implicit Predicates

Name all the movies in which **Robert Downey Jr** **Acted**?

Which movies have **RDJ**?

Flicks where I can see **Robert DJ**?

Find me all the films **casting** **Rober Downey Jr** ?

List all the movies **starring** **Robert Downey Junior**?

RDJ **has acted** in which movies?

Raw text-based dialogue systems

My name is John

Hello, John!

I left my keys in the kitchen. Can you find them?

In the kitchen
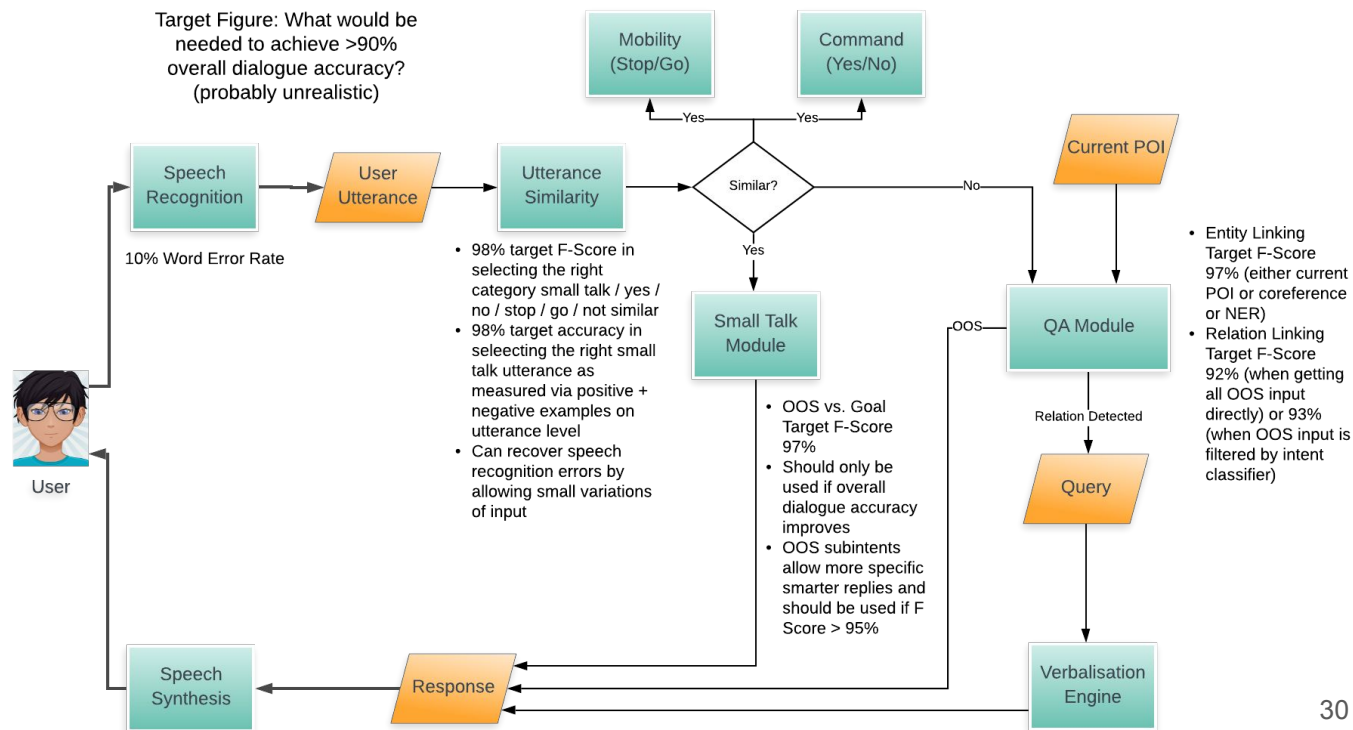
<Long input>

<excerpt from the long input>

- Mostly sequence to sequence over textual inputs

- Some basic causal NL inference (s1 follows s2)

- Effective on simple utterances over short paragraphs
  - No memory (with exceptions)
  - No format and justifiable knowledge

KGs & Conversational AI

Knowledge-driven in-car dialogue system (EN/DE)

Full DBpedia 2019 (wikidata branch)
- > 50M entities
- > 4B triples

Target Figure: What would be needed to achieve >90% overall dialogue accuracy? (probably unrealistic)

Speech Recognition

10% Word Error Rate

User Utterance

Utterance Similarity

- 98% target F-Score in selecting the right category small talk / yes / no / stop / go / not similar
- 98% target accuracy in seleecting the right small talk utterance as measured via positive + negative examples on utterance level
- Can recover speech recognition errors by allowing small variations of input

Similar?

Yes

No

Mobility (Stop/Go)

Command (Yes/No)

Yes

Yes

Current POI

Small Talk Module

- OOS vs. Goal Target F-Score 97%
- Should only be used if overall dialogue accuracy improves
- OOS subintents allow more specific smarter replies and should be used if F Score > 95%

OOS

QA Module

Relation Detected

- Entity Linking Target F-Score 97% (either current POI or coreference or NER)
- Relation Linking Target F-Score 92% (when getting all OOS input directly) or 93% (when OOS input is filtered by intent classifier)

Query

User

Speech Synthesis

Response

Verbalisation Engine
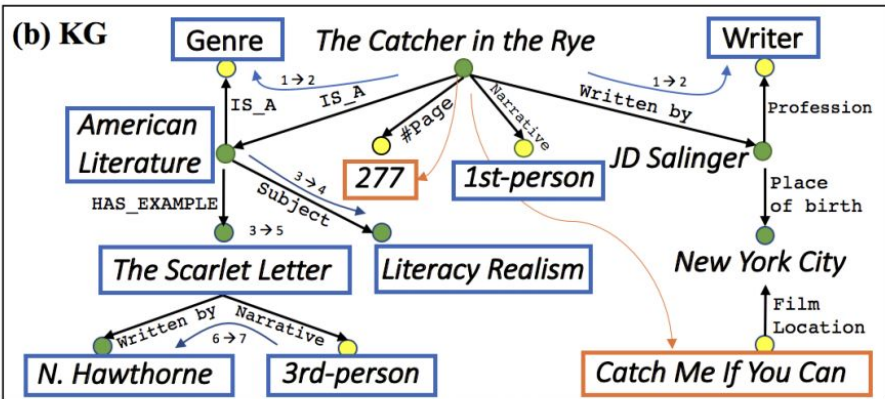
KGs & Conversational AI

Challenge: incorporate graph-based reasoning into dialogue systems over Knowledge Graphs

(a) Dialog

1. Can you recommend any classic books like *Catcher in the Rye*?
2. Do you prefer books by the same *author* or same *genre*?
3. I am interested in reading classic examples of *American literature*.
4. *Literary realism* is a common genre in classic *American literature*.
5. Do you prefer *First-person* or *Third-person narrative*?
6. I mostly prefer *third-person narrative*.
7. Consider reading the *Scarlet Letter*: a novel by *Nathaniel Hawthorne*.

(b) KG

Moon et al. OpenDialKG: Explainable Conversational Reasoning with Attention-based Walks over Knowledge Graphs. ACL 2019

AI Journey 2019

USER: What is the weapon used by HMS Regulus ?

SPEAKER: Torpedo 61

USER: Who is the manufacturer of that ranged weapon ?

SPEAKER: FFV

USER: Is that social group located in Seeley Union Elementary School District and Succivo ?

SPEAKER: NO

USER: Is Swedish Navy the facility operator of Torpedo 61 ?

SPEAKER: YES

USER: Which ranged weapons are used as weapons by atmost 140 ship types and aircraft power classes ?

SPEAKER: Mark 44, Mark 43, Torpedo 613

USER: Which ship types are the etymology of atmost 1 social group ?

SPEAKER: HMS Spica, HMS Invincible, HMS Queen Elizabeth

USER: How many military branches or organizations are the creator of the design for Mark 44 ?

SPEAKER: 2

USER: What are the port of registry of atleast 1 ship type ?

SPEAKER: Riga, Marseille, Bremerhaven

USER: Which ranged weapons are used as weapons by atleast 17 ship types or aircraft classes ?

SPEAKER: Torpedo 45, Mark 48 torpedo, Torpedo 61

So why you need graphs?

Implicit or explicit constraints on produced answers

How many children does Berlin Hbf have?

So why you need graphs?

How many children
does Berlin Hbf have?

Train stations
don't have kids

Implicit or explicit constraints on produced answers
- reduce candidates space
- help to fight the mushroom effect
- **ontologies help**

So why you need graphs?

Implicit or explicit constraints on produced answers
- reduce candidates space
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Complex QA via (sub)graphs aggregations

How many children does Berlin Hbf have?

Train stations don't have kids

What is the busiest train station in Germany?

So why you need graphs?

How many children does Berlin Hbf have?

Train stations don't have kids

What is the busiest train station in Germany?

Hamburg Hbf

Implicit or explicit constraints on produced answers
- reduce candidates space
- help to fight the mushroom effect
- **ontologies help**

Complex QA via (sub)graphs aggregations

```
select ?station ?visits where {
  ?station wdt:P31 wd:Q18543139 .     # central stations
  ?station wdt:P17 wd:Q183 .          # in Germany
  ?station wdt:P1373 ?visits .        # daily visits
} ORDER BY DESC(?visits) LIMIT 1      # sort
```

AI Journey 2019

So why you need graphs?

Takeaway 1

Graphs significantly improve reasoning compared to sole natural language inference

AI Journey 2019

So why you need graphs?

Takeaway 1

Graphs significantly improve reasoning compared to sole natural language inference
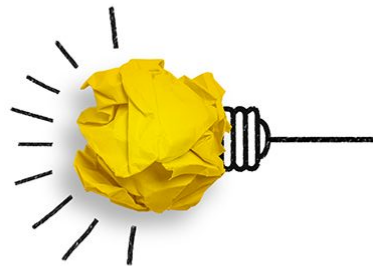
Takeaway 2

Reasoning outcomes are explainable and traceable

Enriched knowledge representations

KGs at scale and robust querying

Graph-based reasoning for complex QA

Possible directions

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NLG from graphs

Commonsense reasoning

Self-learning and knowledge extraction from dialogues