Question Answering over Knowledge Graphs

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Introduction to Seminar on Selected Topics in Question Answering

Saarland University, Winter Semester 2020/21
About us

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Outline: QA over knowledge graphs

- **Background**: Setup, benchmarks, metrics
- **Simple QA**: Templates and embeddings
- **Complex QA**: Multiple entities and predicates
- **Heterogeneous sources**: Handling KGs and text
- **Conversational QA**: Implicit context in multi-turn setup
- **Take-home**: Summary and insights

**Prerequisites:**
- Basic IR, NLP, ML, DB
- Understanding of core neural techniques
- Interactivity 😊

- Representative methods from each task
- Families of algorithms to build up repertoire for approaching KG-QA
- Focus on methods (and not evaluation)
- Understand how to go from question to answer
Methodology

- Templates
- Graph embeddings
- Subgraph computations
- Belief propagation
- Graph traversal
- Sequence-to-sequence models
QA over knowledge graphs

- **Background**: Setup, benchmarks, metrics
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What is question answering over knowledge graphs all about?
Question Answering: Vital for Search

What are some films directed by Nolan?

Google Assistant

Hey Siri

amazon alexa
Question Answering: Vital for Search

What are some films directed by Nolan?

Christopher Nolan / Films directed

The Dark Knight
2008

Interstellar
2014

Google Assistant

Hey Siri

amazon alexa
Question Answering: Vital for Search

What are some films directed by Nolan?

- Direct answers to questions
- Enabled by knowledge graphs
- Saves time and effort
- Natural in voice UI

Christopher Nolan / Films directed

The Dark Knight 2008
Interstellar 2014
Simple questions involving one entity and relation

**QA over KGs**

- What is the capital of Germany?
  - Berlin

- Which club does Messi play for?
  - FC Barcelona

- What is the currency of India?
  - Indian rupee

- Where was Albert Einstein born?
  - Ulm

- What is the population of the USA?
  - 328.2 million (2019)
where was the father of messi born

1958
age 62 years

what was Nolan’s first film
with Christian Bale

Christian Bale first movie

Born in Haverfordwest, Wales, to English parents, Bale had his first starring role at age 13 in Steven Spielberg’s war film Empire of the Sun (1987).

Play with QA: Try out different formulations, entities, domains, complexities, assistants, sources, languages... to expose brittleness of SoTA and take community forward!
Significant progress has been made on knowledge base construction over the last fifteen years or so; but for question answering, which is one of the most valuable applications of KBs, we are still at the tip of iceberg!
What are the Oscar nominations of Nolan?
QA over knowledge graphs (KG-QA)

What are the Oscar nominations of Nolan?
What are the Oscar nominations of Nolan?

- YAGO [Suchanek et al. 2007]
- DBpedia [Auer et al. 2007]
- Freebase [Bollacker et al. 2008]
- Wikidata [Vrandečić and Krötzsch 2014]
What are the Oscar nominations of Nolan?

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Terminology varies across KGs

Here: Entities, predicates, types, literals

**QA over knowledge graphs (KG-QA)**
What are the Oscar nominations of Nolan?

- YAGO [Suchanek et al. 2007]
- DBpedia [Auer et al. 2007]
- Freebase [Bollacker et al. 2008]
- Wikidata [Vrandečić and Krötzsch 2014]

**Wikidata:** 12B facts, 84M entities, 7k predicates, 69k types
Which Oscar nominations did Nolan receive?

- <ChristopherNolan, gender, Male>
- <ChristopherNolan, type, Director>
- <ChristopherNolan, directed, Inception>
- <ChristopherNolan, nominatedFor, BestDirector>
- <BestDirector, type, AcademyAward>
- <ChristopherNolan, birthDate, 30 July 1970>
KG-QA Challenge 1: Bridge vocabulary gap

Which Oscar nominations did Nolan receive?

- <ChristopherNolan, gender, Male>
- <ChristopherNolan, type, Director>
- <ChristopherNolan, directed, Inception>
- <ChristopherNolan, nominatedFor, BestDirector>
- <BestDirector, type, AcademyAward>
- <ChristopherNolan, birthDate, 30 July 1970>
KG-QA Challenge 2: Query formulation

Which Oscar nominations did Nolan receive?

SELECT ?ANS
WHERE {
  ChristopherNolan nominatedFor ?ANS .
  ?ANS type AcademyAward
}

ChristopherNolan

nominatedFor

?ANS

type

AcademyAward

\(<ChristopherNolan, \text{gender, Male}>\\n<ChristopherNolan, \text{type, Director}>\\n<ChristopherNolan, \text{directed, Inception}>\\n<ChristopherNolan, \text{nominatedFor, BestDirector}>\\n<BestDirector, \text{type, AcademyAward}>\\n<ChristopherNolan, \text{birthDate, 30 July 1970}>
Which Oscar nominations did Nolan receive?

SELECT ?ANS
WHERE {
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}

Named Entity Recognition and Disambiguation (NERD) systems (aka Entity Detection and Linking): TagME, AIDA, Dandelion, Google NL API, MS Text Analytics, IBM NLU

Named Entity Recognition (NER): Stanford NER, spaCy
Answering with query

Which Oscar nominations did Nolan receive?

ChristopherNolan

SELECT ?ANS
WHERE {
  ChristopherNolan nominatedFor ?ANS .
  ?ANS type AcademyAward .
}

BestDirector

nominatedFor

ChristopherNolan

type

AcademyAward
Structured queries and logical forms

Which Oscar nominations did Nolan receive?

**Neo4j CYPHER Graph QL**

MATCH (sub: 'ChristopherNolan')-[nominatedFor]->(obj: AcademyAward) RETURN obj.name

**Lambda-calculus**

\( \lambda x. \text{nominatedFor}(\text{ChristopherNolan}, x) \land \text{Type}(x, \text{AcademyAward}) \)

**Lambda-DCS**

\( \text{nominatedFor. ChristopherNolan} \land \text{type.AcademyAward} \)

**SPARQL BGP**

SELECT ?ANS WHERE {
  ChristopherNolan nominatedFor ?ANS .
  ?ANS type AcademyAward  }

**BestDirector**

Question Answering over Knowledge Graphs
Reification: n-ary information in KGs

For which films was Nolan nominated for Oscars? When did Nolan get his Oscar nominations?

ChristopherNolan, gender, Male
ChristopherNolan, type, Director
ChristopherNolan, directed, Inception
ChristopherNolan, nominatedFor, BestDirector
BestDirector, type, AcademyAward
ChristopherNolan, birthDate, 30 July 1970
Reification: n-ary information in KGs

For which films was Nolan nominated for Oscars?
When did Nolan get his Oscar nominations?

- <ChristopherNolan, gender, Male>
- <ChristopherNolan, type, Director>
- <ChristopherNolan, directed, Inception>
- <ChristopherNolan, nominatedFor, BestDirector>
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- <ChristopherNolan, birthDate, 30 July 1970>
Reification: n-ary information in KGs

For which films was Nolan nominated for Oscars?
When did Nolan get his Oscar nominations?

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ChristopherNolan, type, Director
ChristopherNolan, directed, Inception
ChristopherNolan, nominatedFor, BestDirector
BestDirector, type, AcademyAward
ChristopherNolan, birthDate, 30 July 1970

ChristopherNolan, nominatedFor, 123
123, nominatedFor, BestDirector
123, forWork, Dunkirk
123, year, 2018
Qualifiers are a huge part of Wikidata

For which films was Nolan nominated for Oscars?
When did Nolan get his Oscar nominations?

Wikidata: Qualifiers, Statement-Ids. 6B triples part of reified facts!!
Questions that need reified triples

Who played Cobb in Inception?
Who did Leo play in Inception?
When did Neymar join PSG?
Who was Trump’s first wife?
US president in 2016?
...

Wikidata: Qualifiers, Statement-Ids
6B triples part of reified facts!!
# Explore Wikidata

**The Dark Knight**

(Q163872)

2008 British-American superhero film directed by Christopher Nolan

**TDK | Dark Knight**

- **Entity name / Subject:** The Dark Knight
- **Entity id:** Q163872
- **Entity desc:** 2008 British-American superhero film directed by Christopher Nolan
- **Entity aliases:** TDK | Dark Knight
- **Type:** instance of film
- **Type predicate:** genre
- **Predicate:** action film
- **Qualifier predicate:**
  - nominated for: Academy Award for Best Supporting Actor
    - statement is subject of: 81st Academy Awards
      - 81st Academy Awards nominee: Heath Ledger
      - point in time: 22 February 2009
- **Qualifier object:**
  - part of the series: The Dark Knight Trilogy
    - follows: Batman Begins
    - followed by: The Dark Knight Rises
      - series ordinal: 2
  - cast member:
    - Christian Bale: character role
      - 11 references
    - Michael Caine: character role
      - 4 references
    - Heath Ledger: character role
      - 9 references
    - Bruce Wayne: character role
      - Alfred Pennyworth: character role
      - Joker: character role
Explore Wikidata like a pro

- **Wikidata**: [https://www.wikidata.org/wiki/Wikidata:Main_Page](https://www.wikidata.org/wiki/Wikidata:Main_Page)
- **Wikidata data model**: [https://www.mediawiki.org/wiki/Wikibase/DataModel/Primer](https://www.mediawiki.org/wiki/Wikibase/DataModel/Primer)
- **Wikidata dumps**: [https://www.wikidata.org/wiki/Wikidata:Database_download](https://www.wikidata.org/wiki/Wikidata:Database_download)
- Download latest **n-triples** dump: [https://dumps.wikimedia.org/wikidatawiki/entities/](https://dumps.wikimedia.org/wikidatawiki/entities/)
- **Wikidata SPARQL Endpoint**: [https://query.wikidata.org/](https://query.wikidata.org/)
- **Wikidata statistics**: [https://stats.wikimedia.org/#!/wikidata.org](https://stats.wikimedia.org/#!/wikidata.org)
Play with QA (over Wikidata)

Diefenbach et al., QAnswer: A Question answering prototype bridging the gap between a considerable part of the LOD cloud and end-users, WWW 2019. Available at https://qanswer-frontend.univ-st-etienne.fr/
Benchmarks

- **Simple questions**
  - WebQuestions (Berant et al. 2013) over Freebase
  - SimpleQuestions (Bordes et al. 2015) over Freebase

- **Complex questions**
  - LC-QuAD 2.0 (Dubey et al 2018) over Wikidata + DBpedia
  - MetaQA (Zhang et al. 2018) over Freebase

- **Conversational questions**
  - ConvQuestions (Christmann et al. 2019) over Wikidata
  - CSQA (Saha et al. 2018) over Wikidata
Benchmarks

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Recent benchmarks over Wikidata

More realistic benchmarks are smaller but harder

Much higher numbers on semi-synthetic benchmarks

“Vulnerable” to neural methods

* Need reified triples for answering
Benchmarks

- **Simple questions**
  - [x] WebQuestions* (Berant et al. 2013) over Freebase
  - SimpleQuestions (Bordes et al. 2015) over Freebase

- **Complex questions**
  - [x] LC-QuAD 2.0* (Dubey et al. 2018) over Wikidata + DBpedia
    - MetaQA (Zhang et al. 2018) over Freebase

- **Conversational questions**
  - [x] ConvQuestions* (Christmann et al. 2019) over Wikidata
    - CSQA (Saha et al. 2018) over Wikidata

Many, many more:
- LC-QuAD (Trivedi et al. 2017)
- ComQA (Abujabal et al. 2019)
- GraphQuestions (Su et al. 2016)
- QALD (Usbeck et al. 2018)
- TempQuestions (Jia et al. 2018)
- ComplexWebQuestions (Talmor and Berant 2018)
- WikiMovies (Miller et al. 2016)
- ComplexQuestions (Bao et al. 2016)
Benchmarks: WebQuestions

- Real questions: Collected using the Google Suggest API
- Mostly simple questions using one fact or reified triple
- 3778 train, 2032 test questions
- Available at: https://nlp.stanford.edu/software/semper/

who was richard nixon married to?
what high school did harper lee go to?
what was the capital city of the east roman empire?
who plays ken barlow in coronation street?
where is the fukushima daiichi nuclear plant located?
Benchmarks: LC-QuAD 2.0

- Sampled SPARQL queries via templates, verbalized by crowdworkers
- Complex (and simple) questions involving multiple entities and relations
- 23954 train, 6046 test questions
- Available at: http://lc-quad.sda.tech/

What city is the twin city of Oslo and also the setting for “A Tree Grows in Brooklyn”?
What Empire used to have Istanbul as its capital?
How long was Shirley Temple the United States Ambassador to Ghana?
Were Dutch and Hungarian the official languages of the Holy Roman Empire?
Who replaced Albus Dumbledore as headmaster of Hogwarts?
**Benchmarks: ConvQuestions**

- Natural conversations by crowdworkers after choosing topic
- Both simple and complex
- Five domains
- 6720 train, 2240 dev, 2240 test conversations
- Available at: [https://convex.mpi-inf.mpg.de/](https://convex.mpi-inf.mpg.de/)

<table>
<thead>
<tr>
<th>Books</th>
<th>Movies</th>
<th>Soccer</th>
<th>Music</th>
<th>TV series</th>
</tr>
</thead>
<tbody>
<tr>
<td>When was the first book of the book series The Dwarves published?</td>
<td>Who played the joker in The Dark Knight?</td>
<td>Which European team did Diego Costa represent in the year 2018?</td>
<td>Led Zeppelin had how many band members?</td>
<td>Who is the actor of James Gordon in Gotham?</td>
</tr>
<tr>
<td>2003</td>
<td>Heath Ledger</td>
<td>Atlético Madrid</td>
<td>4</td>
<td>Ben McKenzie</td>
</tr>
<tr>
<td>What is the name of the second book?</td>
<td>When did he die?</td>
<td>Did they win the Super Cup the previous year?</td>
<td>Which was released first: Houses of the Holy or Physical Graffiti?</td>
<td>What about Bullock?</td>
</tr>
<tr>
<td>The War of the Dwarves</td>
<td>22 January 2008</td>
<td>No</td>
<td>Houses of the Holy</td>
<td>Donal Logue</td>
</tr>
<tr>
<td>Who is the author?</td>
<td>Batman actor?</td>
<td>Which club was the winner?</td>
<td>Is the rain song and immigrant song there?</td>
<td>Creator?</td>
</tr>
<tr>
<td>Markus Heitz</td>
<td>Christian Bale</td>
<td>Real Madrid C.F.</td>
<td>No</td>
<td>Bruno Heller</td>
</tr>
<tr>
<td>In which city was he born?</td>
<td>Director?</td>
<td>Which English club did Costa play for before returning to Atlético Madrid?</td>
<td>Who wrote those songs?</td>
<td>Married to in 2017?</td>
</tr>
<tr>
<td>Homburg</td>
<td>Christopher Nolan</td>
<td>Chelsea F.C.</td>
<td>Jimmy Page</td>
<td>Miranda Phillips Cowley</td>
</tr>
<tr>
<td>When was he born?</td>
<td>Sequel name?</td>
<td>Which stadium is this club's home ground?</td>
<td>Name of his previous band?</td>
<td>Wedding date first wife?</td>
</tr>
<tr>
<td>10 October 1971</td>
<td>The Dark Knight Rises</td>
<td>Stamford Bridge Stadium</td>
<td>The Yardbirds</td>
<td>19 June 1993</td>
</tr>
</tbody>
</table>
Metrics

- Answers as sets (for systems using explicit structured queries)
  - Precision, Recall, F1-Score

- Answers as ranked lists (systems w/o explicit queries: approx. graph search)
  - Precision@1, MRR, MAP
  - Hit@5

- Single answer
  - Accuracy

break duration 30 min.
30 measured in minutes.
Outline: QA over knowledge graphs

- **Background**: Setup, benchmarks, metrics
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- **Complex QA**: Multiple entities and predicates
- **Heterogeneous sources**: Handling KGs and text
- **Conversational QA**: Implicit context in multi-turn setup
- **Take-home**: Summary and insights
Getting started: Templates and embeddings
Foundational work in KG-QA

- Templates over RDF (Unger et al. 2012)
- DEANNA (Yahya et al. 2012, 2013)
- SEMPRE (Berant et al. 2013)
- PARALEX + OQA (Fader et al. 2013, 2014)
- Subgraph embeddings (Bordes et al. 2014)
- STAGG (Yih et al. 2015)
- AQQU (Bast and Haussman 2015)
Templates for KG-QA

- Interpretable

<table>
<thead>
<tr>
<th>Question</th>
<th>Question template</th>
</tr>
</thead>
<tbody>
<tr>
<td>Who is Inception’s director?</td>
<td>Who is &lt;NOUN1&gt;’s &lt;NOUN2&gt;?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Query</th>
<th>Query template</th>
</tr>
</thead>
<tbody>
<tr>
<td>?ANS director Inception</td>
<td>?ANS &lt;PRED1&gt; &lt;ENT1&gt;</td>
</tr>
</tbody>
</table>

1 SPARQL triple pattern
## Templates for KG-QA

- Generalizes to new domains

<table>
<thead>
<tr>
<th>Question</th>
<th>Question template</th>
</tr>
</thead>
<tbody>
<tr>
<td>Who is <strong>Inception</strong>’s <em>director</em>?</td>
<td>Who is <code>&lt;NOUN1&gt;</code>’s <code>&lt;NOUN2&gt;</code>?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Query</th>
<th>Query template</th>
</tr>
</thead>
<tbody>
<tr>
<td>?ANS <em>director</em> Inception</td>
<td>?ANS <code>&lt;PRED1&gt;</code> <code>&lt;ENT1&gt;</code></td>
</tr>
</tbody>
</table>

Who is Libya’s **president**?
Who is Messi’s **manager**?

1 SPARQL triple pattern
### Templates for KG-QA

<table>
<thead>
<tr>
<th>Question</th>
<th>Question template</th>
</tr>
</thead>
<tbody>
<tr>
<td>Who plays the role of Cobb in Inception?</td>
<td>Who &lt;VERB&gt; &lt;DT&gt; &lt;NOUN1&gt; &lt;PREP1&gt; &lt;NOUN2&gt; &lt;PREP2&gt; &lt;NOUN3&gt;?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Query</th>
<th>Query template</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inception castMember ?VAR</td>
<td>&lt;ENT1&gt; &lt;PRED1&gt; ?VAR</td>
</tr>
<tr>
<td>?VAR castMember ?ANS</td>
<td>?VAR &lt;PRED1&gt; ?ANS</td>
</tr>
<tr>
<td>?VAR characterRole Cobb</td>
<td>?VAR &lt;PRED2&gt; &lt;ENT2&gt;</td>
</tr>
</tbody>
</table>

Multiple SPARQL triple patterns
Limitations of templates

- Restricted coverage
- **Solution:** Learn templates
  - Question templates
  - Query templates
  - Slot alignments
- Proposed in the QUINT+NEQA framework (*Abujabal et al.* 2017, 2018)
Distant supervision from QA pairs

Question: Which Oscar award nomination did Nolan get for the film Dunkirk?
Answer: Best Director
Distant supervision from QA pairs

**Question:** Which Oscar award nomination did Nolan get for the film Dunkirk?
**Answer:** Best Director

- Retain shortest paths between question and answer entities
- Retain type information
Distant supervision from QA pairs

Question: Which Oscar award nomination did Nolan get for the film Dunkirk?
Answer: Best Director
Query: SELECT ?x WHERE { ChristopherNolan nominatedFor ?VAR . ?VAR nominatedFor ?ANS . ?VAR forWork Dunkirk . ?VAR type AcademyAward . }
Extract question phrases

which nomination

oscar nomination

get nomination

for film

oscar

get

which
did
did

oscar award

nomination

award

award nomination

Extract query items

which nomination  oscar nomination  get nomination  for film  oscar  get

which  did get  did  oscar award  nomination  award  award nomination

nominatedFor  forWork  AcademyAward
Create candidate alignments

- **Bipartite graph** with edge weights ([Yahya et al. 2012](#))
- **Weights** from lexicons $L_p$ and $L_T$ ([Abujabal et al. 2017](#), [Berant and Liang 2013](#))
Optimal mapping via Integer Linear Program (ILP)

- Best alignment of items with **Integer Linear Program (ILP)**
- **Constraint 1**: Each KG item obtained from at most one phrase
- **Constraint 2**: Token contributing to entity cannot contribute to any other phrase
- **Constraint 3**: One phrase can map to at most one type
Optimal mapping via Integer Linear Program (ILP)

- Best alignment of items with **Integer Linear Program (ILP)**
- **Constraint 1:** Each KG item obtained from at most one phrase
- **Constraint 2:** Token contributing to entity cannot contribute to any other phrase
- **Constraint 3:** One phrase can map to at most one type
Apply alignment to question-query

Which Oscar award nomination did Nolan get for the film Dunkirk?
Replace concrete items by roles
Drop unnecessary question words

Question template

Slot alignments

Query template
A continuous learning framework

Train system using (Q, A) pairs

Distant supervision to go from (Ques, Ans) to (Ques, query)

Align ques tokens to query tokens via lexicons and ILP

Generalize to create template

Train

Template-based answering

(Ques, Ans) history

Abujabal et al., Automated template generation for question answering over knowledge graphs, WWW 2017.
Abujabal et al., Never-ending learning for open-domain question answering over knowledge bases, WWW 2018.
Learn a template repository

Abujabal et al., Automated template generation for question answering over knowledge graphs, WWW 2017.
Abujabal et al., Never-ending learning for open-domain question answering over knowledge bases, WWW 2018.
Answering with templates

New question
What are the Academy Award nominations of Nolan?

Pairwise learning-to-rank model

Match

Template-based answering

Train

Template bank

(Ques, Ans) history

Abujabal et al., Automated template generation for question answering over knowledge graphs, WWW 2017.
Abujabal et al., Never-ending learning for open-domain question answering over knowledge bases, WWW 2018.
Close the loop with user feedback

New question: What are the Academy Award nominations of Nolan?

Match

Template bank

Template-based answering

Answer found

Use highest ranked Ques templates
Fetch and instantiate paired query templates to create query
Execute query over KG to get answer

QA pairs

User feedback on answers

Train

(Ques, Ans) history

Top-k (ques, ans) pairs

03 Nov 2020
Augment history on positive feedback

New question: What are the Academy Award nominations of Nolan?

Match

Template-based answering

Answer found

Train

Template bank

(Ques, Ans) history

Augment history

QA pairs

User feedback on answers

Add
Templates can fail

New question: Which Oscar nominations did Nolan receive?

Match

Template-based answering

Train

No answer found

Syntax mismatch!

Template bank

(Ques, Ans) history
Invoke similarity-based answering

New question: Which Oscar nominations did Nolan receive?

Match

Template-based answering

Train

No answer found

Match

Similarity-based answering

(Ques, Ans) history

Template bank

Query likelihood + Word2vec

What are the Academy Award nominations of Nolan?
Augment history

New question: Which Oscar nominations did Nolan receive?

- Match
- Template-based answering
  - No answer found
  - Similarity-based answering
  - QA pairs
  - User feedback on answers

- Train
- (Ques, Ans) history
  - Match
  - Add

03 Nov 2020
Learn new template

New question

Which Oscar nominations did Nolan receive?

Match

Template-based answering

Train

No answer found

Match

Similarity-based answering

(Ques, Ans) history

QA pairs

User feedback on answers

Template bank

Add

Generalize

03 Nov 2020
Never-ending learning with NEQA

New question

Which Oscar nominations did Nolan receive?
What are the Academy Award nominations of Nolan?

Match

Template-based answering

Template bank

No answer found

Syntactic equivalence

Similarity-based answering

QA pairs

Semantic equivalence

User feedback on answers

Add

(Ques, Ans) history

Train

Generalize
Templates: Wrap-up

- Key ideas: **Distant supervision** via shortest paths to go from (Question, Answer) to (Question, query) pair, **joint disambiguation via** Integer Linear Program

- **Template learning** also explored by Cui et al. (2017) and Hu et al. (2017)

- Works well for simple questions, but limited for **complex questions** (initial ideas in Abujabal et al. 2017, Cui et al. 2017, Hu et al. 2017)

- **Distant supervision** gets harder for complex cases

- **Similarity functions** and feedback extending scope of templates useful beyond QA?

- **Feedback in QA** subsequently investigated in QApedia (Kratzwald and Feuerriegel 2019) and IMPROVE-QA (Zhang et al. 2019)
QA with graph embeddings

- The **KEQA** model (Huang et al. 2019)
- Leverages knowledge graph embeddings (+ word embeddings)
- Uses the TransE Model (or TransE-like ...)
- Simple questions, no qualifiers
- Seminal work on neural QA in Bordes et al. (2014), Yih et al. (2015)
KEQA: Outline

Knowledge Graph

Huang et al., Knowledge graph embedding based question answering, WSDM 2019.

Question Answering over Knowledge Graphs
Rishiraj Saha Roy
Saarland University
03 Nov 2020
KEQA: Learn KG embeddings

Huang et al., Knowledge graph embedding based question answering, WSDM 2019.
KEQA: Using TransE

**TransE** (or TransE-like model) *(Bordes et al. 2013)*

- Head entity, predicate, tail entity
- Loss function using correct and corrupted triples

\[
\mathcal{L} = \sum_{(h, \ell, t) \in \mathcal{S}} \sum_{(h', \ell, t') \in \mathcal{S}'_{(h, \ell, t)}} \left[ \gamma + d(h + \ell, t) - d(h' + \ell, t') \right]_+
\]

\[
\mathcal{S}'_{(h, \ell, t)} = \{(h', \ell, t) | h' \in \mathcal{E}\} \cup \{(h, \ell, t') | t' \in \mathcal{E}\}
\]

- L2-norm of entity embeddings 1, predicates unconstrained

---

**Question Answering over Knowledge Graphs**

Rishiraj Saha Roy
Saarland University

03 Nov 2020
KEQA: Input question

Predicates:
\[ p_1, p_2, \ldots, p_m \]

Entities:
\[ e_1, e_2, e_3, e_4, e_5, \ldots, e_N \]

Question:
Which Olympics was in Australia?

Huang et al., Knowledge graph embedding based question answering, WSDM 2019.
KEQA: Learn to predict head and body

Knowledge Graph $G$

Predicates:
- $p_1$
- $p_2$
- ...
- $p_m$

Entities:
- $e_1$
- $e_2$
- $e_3$
- ...
- $e_N$

Question:
Which Olympics was in Australia?

Predicate Learning

Head Entity Learning

Bi-LSTM for word order
Attention for word importance
Learning representations generalization to unseen predicates at test time
KEQA: Use learnt models for prediction

TransE (or TransE-like model) (Bordes et al. 2013)
- Head entity, predicate, tail entity
- L2-norm of entity embeddings, predicates unconstrained

Huang et al., Knowledge graph embedding based question answering, WSDM 2019.
KEQA: Obtain tail from head and body

TransE (or TransE-like model) (Bordes et al. 2013)
- Head entity, predicate, tail entity
- L2-norm of entity embeddings 1, predicates unconstrained

Huang et al., Knowledge graph embedding based question answering, WSDM 2019.
KEQA: Put (head, body, tail) together

TransE (or TransE-like model) (Bordes et al. 2013)

- Head entity, predicate, tail entity
- L2-norm of entity embeddings 1, predicates unconstrained

Huang et al., Knowledge graph embedding based question answering, WSDM 2019.
KEQA: Search for closest fact in KG

Knowledge Graph $\mathcal{G}$

- **Predicate Embedding Space**
  - Predicates: $p_1, p_2, \ldots, p_m$
  - Predicate Learning

- **Entity Embedding Space**
  - Entities: $e_1, e_2, e_3, e_4, e_5, \ldots, e_N$
  - Head Entity Learning

**Question:** Which Olympics was in Australia?

**Predicted Fact:** $(\hat{e}_h, \hat{p}_l, \hat{e}_t)$

**Answer:** Find Closest Fact in $\mathcal{G}$

**Objective:**

$$\minimize_{(h, \ell, t) \in \mathcal{C}} \|p_\ell - \hat{p}_\ell\|^2 + \beta_1 \|e_h - \hat{e}_h\|^2 + \beta_2 \|f(e_h, p_\ell) - \hat{e}_t\|^2$$

**Get closest fact $F^*$ in KG using distance function**

**Object of $F^*$ is answer**

---

Huang et al., Knowledge graph embedding based question answering, WSDM 2019.
KEQA: Closest fact to answer

Knowledge Graph $G$

Question: Which Olympics was in Australia?

Predicate Embedding Space

Predicted Fact: $(\hat{e}_h, \hat{p}_l, \hat{e}_t)$

Head Entity Learning

Answer: Find Closest Fact in $G$

Get closest fact $F^*$ in KG using distance function

Object of $F^*$ is answer

Incorporate string similarity

Addl. neural model for head entity detection (HED)
Embeddings: Wrap-up

- Graph embeddings useful for simple questions, not clear for complex cases
- Embeddings and neural methods are ubiquitous now
- Much more than using pre-trained embeddings
- Leveraging sequence models (Bi-LSTMs, transformers) with attention
Outline: QA over knowledge graphs

- **Background:** Setup, benchmarks, metrics
- **Simple QA:** Templates and embeddings
- **Complex QA:** Multiple entities and predicates
- **Heterogeneous sources:** Handling KGs and text
- **Conversational QA:** Implicit context in multi-turn setup
- **Take-home:** Summary and insights
How can we answer more complex questions with multiple entities and predicates?
Complex questions

- Two basic types
  - Star joins
    - Who played for Barcelona and Real Madrid?
  - Chain joins
    - What is the profession of Messi’s father?

SELECT ?x WHERE
?x playedFor Barcelona .
?x playedFor RealMadrid .

SELECT ?y WHERE
?x fatherOf Messi .
?x profession ?y .
Complex questions

- **Much more**: Aggregations, comparatives, superlatives, reasoning, existential, temporal, ....

- Focus on **substructures** in questions and queries (Bhutani et al. 2019, Ding et al. 2019, Sun et al. 2020)

- Often rely on question **decomposition** (Bao et al. 2016, Talmor and Berant 2018, Sun et al. 2020)

- **Joint disambiguation** of question concepts (Yahya et al. 2012, Lu et al. 2019)

Which female **actor** played in *Casablanca* and is married to a writer who was born in Rome?

Where is the **founder** of Tesla born?

Who was the **second wife** of Tom Cruise?

Which **Portuguese speaking countries** import fish from Brazil?

Who wrote **more books**: Enid Blyton or Agatha Christie?

Which is the **third highest** mountain in Asia?

How many **movies** have the same director as *The Shawshank Redemption*?

**How many movies** were directed by the graduate of Burbank High School?

**Did any cosmonauts** die in the same place they were born in?
Complex questions

- Early efforts in Yahya et al. (2012)
- Further explorations in Bao et al. (2016), Abujabal et al. (2017) and Cui et al. (2017)
- Dedicated methods for complex questions in Ding et al. (2019), Hu et al. (2018), Luo et al. (2018), Bhutani et al. (2019), Lu et al. (2019), Vakulenko et al. (2019), ...
Complex QA: Structured query generation

- The **TextRay** system (Bhutani et al. CIKM 2019)
- Learning complex query patterns difficult for **data sparsity**
- **Decompose-execute-join** approach to complex questions
- Constructs complex query patterns using **simple queries**
- **Semantic matching** model learns simple queries using **distant supervision** from QA pairs
**TextRay: Computation plan**

- Predict computation plan upfront with supervised method
- Or with linguistic cues

---

**Single variable**

**Star join**

SELECT ?x WHERE
?x playedFor Barcelona.
?x playedFor RealMadrid.

---

**Two or more variables**

**Chain join**

SELECT ?y WHERE
?x fatherOf Messi.
?x profession ?y.

---

Bhutani et al., Learning to Answer Complex Questions over Knowledge Bases with Query Composition, CIKM 2019.
TextRay: Walkthrough

Which Portuguese speaking countries import fish from Brazil?

Staged query graph generation (Yih et al. ACL 2015)

\[ \phi \xrightarrow{A_c} S_c \xrightarrow{A_r} S_r \xrightarrow{A_e} S_c \xrightarrow{A_c} S_r \]

S1  S2  S3
Brazil  Portuguese  Brazilian Portuguese

a) Identify seed

Top-k entities

Bhutani et al., Learning to Answer Complex Questions over Knowledge Bases with Query Composition, CIKM 2019.
TextRay: Partial query graph

Which Portuguese speaking countries import fish from Brazil?

Staged query graph generation (Yih et al. ACL 2015)

a) Identify seed

- $s_1$: Brazil
- $s_2$: Portuguese
- $s_3$: Brazilian Portuguese

b) Identify main relation path

- $s_4$: Brazil
- currency
- $s_5$: Brazil
- import_from
- import_by
- $s_6$: Portuguese
- spoken_in

Top-k entities

Bhutani et al., Learning to Answer Complex Questions over Knowledge Bases with Query Composition, CIKM 2019.

Question Answering over Knowledge Graphs
Rishiraj Saha Roy
Saarland University
03 Nov 2020
TextRay: Partial query graph

Which Portuguese speaking countries import fish from Brazil?

Staged query graph generation (Yih et al. ACL 2015)

c) Identify constraints

Constraints: Qualifiers, dates, entities

Consult computation plan: Grow parallel branch of partial query

Bhutani et al., Learning to Answer Complex Questions over Knowledge Bases with Query Composition, CIKM 2019.
TextRay: Partial query graph

Which Portuguese speaking countries import fish from Brazil?

Staged query graph generation (Yih et al. ACL 2015)

Bhutani et al., Learning to Answer Complex Questions over Knowledge Bases with Query Composition, CIKM 2019.
TextRay: Partial query graph

Which Portuguese speaking countries import fish from Brazil?

Staged query graph generation (Yih et al. ACL 2015)

a) Identify seed

b) Identify main relation path

c) Identify constraints

Bhutani et al., Learning to Answer Complex Questions over Knowledge Bases with Query Composition, CIKM 2019.

Question Answering over Knowledge Graphs

Rishiraj Saha Roy

Saarland University

03 Nov 2020
TextRay: Partial query graph

Which Portuguese speaking countries import fish from Brazil?

Staged query graph generation (Yih et al. ACL 2015)

a) Identify seed
b) Identify main relation path
c) Identify constraints
d) Compose/Execute

Beam search to maintain top-k best derivations + Semantic similarity learned via LSTMs with attention

Bhutani et al., Learning to Answer Complex Questions over Knowledge Bases with Query Composition, CIKM 2019.
Complex QA: Computing compact subgraphs

- The **QUEST** system ([Lu et al. 2019](#))

- Works over open vocabulary quasi KGs ([Bhutani et al. 2019b](#), [Yin et al. 2015](#), [Fader et al. 2013, 2014](#))

- Augment quasi KGs with alignments and types

- Spot question cornerstones in quasi KG

- **Unsupervised compact subgraph computation:** Compute Group Steiner Tree (GST) with cornerstones as terminals for joint disambiguation of question concepts
Creating a quasi KG

<Nolan, directed, Inception>
<Inception, won, Best Sound>
<2011 Oscars, announced, Best Sound>
<Inception, nominated, Best Actor>
<The movie Inception, missed out, Golden Globe Awards>
<Chris Nolan, director of, The movie Inception>
<Inception’s script, edited by, Chris Nolan>
<Inception, lost to, The Social Network>
<Best Actor, declared at, 83rd Academy Awards>
<The Social Network, winner of, Best Screenplay>
<Golden Globes, announced, Best Screenplay>

Compile an open-vocabulary triple store

Triples can ideally come from text (via Open IE), KG, or both

Open IE extracts KG-style triples by running pattern extraction over raw text: Stanford Open IE, ClausIE, OpenIE 5.0, ...

Lu et al., Answering Complex Questions by Joining Multi-Document Evidence with Quasi Knowledge Graphs, SIGIR 2019.
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Inception

- won at 2011 Oscars
- directed by Nolan
- nominated for Best Actor
- nominated for Best Sound
- directed by Chris Nolan
- edited by Inception’s script
- lost to The Social Network at the 83rd Academy Awards
- announced at the 83rd Academy Awards
- announced as the winner of Best Screenplay at the Golden Globes
- missed out on a Golden Globe Award
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Inception
- won an Oscar
- directed by Chris Nolan
- nominated for Best Actor at the 83rd Academy Awards.
- announced at the 2011 Oscars
- edited by Inception’s script
- type: science thriller

The movie Inception
- lost to Best Screenplay
- type: film

The Social Network
- winner of Best Screenplay
- type: film

Golden Globe Awards
- announced

Golden Globes
- announced
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Entity types are useful for QA:
Add types from KG or running Hearst patterns over text
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Inception

2011 Oscars
83rd Academy Awards
declared at

Best Sound
Best Actor

won
announced

300
The Social Network

director of

Nolan
Chris Nolan

directed

science thriller
type

Golden Globe Awards

missed out

Best Screenplay

The movie Inception

lost to

Inception’s script

nominated

film
type

announced

Golden Globes

winner of
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Lightweight canonicalization helps:
Insert alignment edges using lexicons and similarity
Question: Which Nolan films won an Oscar but missed a Golden Globe?

1.0 Nolan
0.9 Chris Nolan
0.6 science thriller
0.9 Golden Globe Awards
1.0 missed out
1.0 The movie Inception
1.0 won
0.9 announced
0.6 Best Sound
0.9 directed
0.2 edited by
0.2 Inception’s script
0.3 director of
0.3 type
0.4 announced
0.4 nominated
0.4 lost to
0.4 83rd Academy Awards
0.4 declared at
0.4 film
0.3 Best Actor
0.1 The Social Network
0.1 type
0.1 winner of
0.1 Best Screenplay
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Towards compact subgraph:
Compute node weights using similarity with question words
Question: Which Nolan films won an Oscar but missed a Golden Globe?

- Inception
- 2011 Oscars
- 83rd Academy Awards
- won
- directed by
- nominated
- lost to
- announced
- best sound
- science thriller
- director of
- type
- announced
- Golden Globe Awards
- Golden Globes
- Best Screenplay
- winner of
- The Social Network
- The movie Inception
- Inception’s script
- declared at
- Best Actor
Question: Which Nolan films won an Oscar but missed a Golden Globe?
Question: Which Nolan films won an Oscar but missed a Golden Globe?

- **Inception** (2011 Oscars)
  - declared at 83rd Academy Awards
  - nominated
  - lost to The Social Network
  - directed by Nolan
  - edited by Chris Nolan
  - type: science thriller

- **Best Actor**

- **Best Sound**

- **Golden Globe Awards**
  - announced
  - missed out
  - winner of Best Screenplay
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Cornerstones appear in groups

- 83rd Academy Awards
- declared at
- Best Actor
- announced
- nominated
- The movie Inception
- lost to
- Best Screenplay
- winner of
- The Social Network
- type
- declared at
- Best Actor
- announced
- nominated
- The movie Inception
- lost to
- Best Screenplay
- winner of
- The Social Network
- type
- directed
- Nolan
- Chris Nolan
- won
- Golden Globe Awards
- type
- science thriller
Inception

2011 Oscars

83rd Academy Awards

declared at

Best Actor

film

nominated

won

announced

directed

director of

Chris Nolan

Nolan

science thriller

type

Golden Globe Awards

missed out

The movie Inception

Inception's script

lost to

The Social Network

Best Screenplay

winner of
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Answers lie on paths connecting cornerstones: Internal nodes on paths are answer candidates.

- Best Sound
- Nolan
- Chris Nolan
- science thriller
- won
- directed
- director of
- Golden Globe Awards
- announced
- declared at
- lost to
- won
- nominated
- type
- The movie Inception
- announced
- Best Screenplay
- The Social Network
- winner of
- film
- type
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Best Sound
- won
- announced

Nolan
- directed

Chris Nolan
- type

Inception
- edited by
- Inception’s script
- type

Golden Globe Awards
- director of
- missed out

Golden Globes
- announced

83rd Academy Awards
- declared at

Best Actor
- nominated
- film

The movie Inception
- lost to

The Social Network
- type

Best Screenplay
- winner of
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Shorter paths cleaner for finding answer candidates
Question: Which Nolan films won an Oscar but missed a Golden Globe?

- Inception
- 2011 Oscars
- 83rd Academy Awards
- Best Sound
- won
- announced
- directed
- Nolan
- directed of
- Chris Nolan
- Inception’s script
- edited by
- lost to
- nominated
- film
- type
- Best Screenplay
- winner of
- The Social Network
- type
- The movie Inception
- announced
- missed out
- Golden Globes
- Golden Globe Awards
- science thriller
- type
Question: Which Nolan films won an Oscar but missed a Golden Globe?
Question: Which Nolan films won an Oscar but missed a Golden Globe?
Question: Which Nolan films won an Oscar but missed a Golden Globe?
Question: Which Nolan films won an Oscar but missed a Golden Globe?
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Unsupervised computation of dense and compact subgraph:
Joint disambiguation of question concepts
Question: Which Nolan films won an Oscar but missed a Golden Globe?

2011 Oscars

Best Sound

won

announced

Nolan

directed

Inception

lost to

Golden Globes

announced

Best Screenplay

film type

The Social Network

winner of
Question: Which Nolan films won an Oscar but missed a Golden Globe?

Compute Group Steiner Tree (GST) on quasi-KG with cornerstones as terminals: Optimal connections between question concepts for faithful answering.

- Best Sound
- Nolan
- won
- announced
- directed
- lost to
- Best Screenplay
- The Social Network
- film
- type
- winner of
Question: Which Nolan films won an Oscar but missed a Golden Globe?

- Answers are nodes
- Cornerstones are not answers
- Only entities
- Must respect type constraints

2011 Oscars

Best Sound
Nolan
announced

directed

Inception

lost to

Golden Globes

announced

Best Screenplay

The Social Network

film
type

winner of
Question: Which Nolan films won an Oscar but missed a Golden Globe?

- Best Sound
  - won
  - announced
  - directed

- Inception

- Answers are nodes
- Cornerstones are not answers
- Only entities
- Must respect type constraints

- lost to
- type

- Best Screenplay
  - announced
  - The Social Network
  - winner of
Question: Which Nolan films won an Oscar but missed a Golden Globe?

- Best Sound
  - Inception

- Answers are nodes
- Cornerstones are not answers
- Only entities
- Must respect type constraints

- Best Screenplay
  - The Social Network
**Question:** Which Nolan films won an Oscar but missed a Golden Globe?

- Answers are nodes
- Cornerstones are not answers
- Only entities
- **Must respect type constraints**

- Inception
- The Social Network
Question: Which Nolan films won an Oscar but missed a Golden Globe?

- Answers ranked by aggregation
- Best answer chosen

<table>
<thead>
<tr>
<th>Inception</th>
<th>Number of GSTs</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of GSTs</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

The Social Network
Question: Which Nolan films won an Oscar but missed a Golden Globe?

- Answers ranked by multiple criteria
- Best answer chosen

Inception
Complex QA: Graph-based belief propagation

- The **Q Amp** system (Vakulenko et al. 2019)

- Interpretation
  - Parsing
  - Matching

- Reasoning
  - Message passing
  - Score aggregation

API access possible by appending the text of a question to https://kbqa-api.ai.wu.ac.at/ask?question=

For example, for “Name the municipality of Roberto Clemente Bridge?”, use:

https://kbqa-api.ai.wu.ac.at/ask?question=Name%20the%20municipality%20of%20Roberto%20Clemente%20Bridge%20?
Interpretation: Parsing by sequence labeling

Where is the **founder** of **Tesla** born?

P1 E1 P2

Use CRFs trained on labeled data

Predict question type: **SELECT**, COUNT, ASK
Interpretation: Matching

Where is the **founder** of **Tesla** born?

<table>
<thead>
<tr>
<th></th>
<th>P1</th>
<th>E1</th>
<th>P2</th>
</tr>
</thead>
<tbody>
<tr>
<td>founder</td>
<td>1</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>founded</td>
<td>0.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bornIn</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Use CRFs trained on labeled data

Predict question type: **SELECT, COUNT, ASK**
Reasoning: Message passing Hop 1

Where is the **founder** of **Tesla** born?

P1

Nicola Tesla 0.6

Tesla 1

Elon Musk 0

P2

Tesla coil 0.5

E1

P1

founder 1

Tesla 1

E1

founded 0.8

Nicola Tesla 0.6

Tesla coil 0.5

born In

Elon Musk

Pretoria

Lady Gaga

NYC

Steve Jobs

SF

Nicola Tesla

Croatia
Reasoning: Message passing Hop 1

Where is the **founder** of **Tesla** born?

- **Nicola Tesla**: 0.6 (born in Croatia)
- **Tesla**, founded 0.8
- **Tesla coil**, founded 0.5
- **Elon Musk**, founded 0.8

**P1**
- founder 1
- founded 0.8

**E1**
- Tesla 1
- Nicola Tesla 0.6
- Tesla coil 0.5

**P2**

**Elon Musk**
- Pretoria
- NYC
- SF
- Croatia
Reasoning: Message passing Hop 2
Reasoning: Message passing Hop 2

- Nicola Tesla bornIn Croatia 0.5
- Elon Musk bornIn Pretoria 0.8

- P2
  - bornIn 0.8
  - Elon Musk 0.8
  - Tesla coil 0.6
  - Nicola Tesla 0.5

- E2
  - founder
  - Nicola Tesla 1.0
  - Tesla coil 1.0

- founded
  - Elon Musk
  - Tesla
  - SpaceX

- bornIn
  - Elon Musk
  - Pretoria
  - Lady Gaga
  - NYC
  - Steve Jobs
  - SF
  - Nicola Tesla
  - Croatia
Reasoning: Message passing Hop 2

Where is the **founder** of **Tesla** born?

- **Nicola Tesla** born in **Croatia**
- **Elon Musk** born in **Pretoria**

Concepts:
- **P2**
  - bornIn: 0.8
  - P2: Elon Musk, 0.8; Tesla coil, 0.6; Nicola Tesla, 0.5

Constructs explanatory evidence
Efficient (2 seconds/question) for use of HDT + matrix operations
Complex questions: Wrap-up

- Complex KG-QA the sub-topic with the **highest attention**

- **Efficiency** generally an open issue: several partial queries executed in TextRay, a lot of similarity computations in QUEST, ...

- Bias in SoTA towards **certain classes**: QAmp (chains), QUEST (stars), ...

- How to reduce **large neighborhood sizes**? KGs are dense: considering full 2-hop neighborhoods often intractable due to popular entities or general entity types
Outline: QA over knowledge graphs

- **Background:** Setup, benchmarks, metrics
- **Simple QA:** Templates and embeddings
- **Complex QA:** Multiple entities and predicates
- **Heterogeneous sources:** Handling KGs and text
- **Conversational QA:** Implicit context in multi-turn setup
- **Take-home:** Summary and insights
How can we answer questions over heterogeneous sources?
QA over heterogeneous sources

- **Heterogeneous source**: System should tap into multiple KGs, or KG + Text
- **Why fuse?** Each source has its advantages and disadvantages
- **Early fusion**: GRAFT-Net ([Sun et al. 2018](https://example.com/sun2018)), PullNet ([Sun et al. 2019](https://example.com/sun2019))
- **Late fusion**: Ferrucci et al. (2010), Baudis (2015), Sun et al. (2015), Xu et al. (2016a, 2016b), Savenkov and Agichtein (2016)
Heterogeneous QA: Early fusion

- The **PullNet** system ([Sun et al. 2019](#))
- Fusion via KG **facts** and KG-entity **linked sentences**
- Built for **multi-hop** questions
- Uses **question-focused subgraph**
- **Judiciously expands context** subgraph
- Uses classifiers for **expansion points** and answers

---

PullNet: Handling heterogeneity

KG facts

<Christopher Nolan, birthplace, London>

<Memento, director, Nolan>

<Interstellar, castMember, Anne Hathaway>

Entity-linked sentences

Nolan is married to Emma Thomas.

Nolan directed Interstellar in 2010.

Guy Pearce was in Memento and Flynn.

PullNet: Graph model

**Interstellar**

**Nolan** directed **Interstellar** in 2010.

**London**

**Christopher Nolan**, birthplace, London

---

**Christopher Nolan**

- Edge exists if document mentions entity
- Node type: Entity

- Node type: KG Fact
- Edge exists if fact contains entity

---

**Memento, director, Nolan**

- No edges between facts and documents

**Nolan** is married to **Emma Thomas**.

---

**Memento**

- Node type: Document (sentence), KG-entity linked.

---

**Emma Watson**

Question: Who are the actors in movies directed by Nolan?
**Question:** Who are the actors in movies directed by Nolan?

**NERD system**

**ChristopherNolan**

---

**Question:** Who are the actors in movies directed by Nolan?

- **Nolan** directed *Interstellar* in 2010.
- *Memento*, director, Nolan.
- Nolan is married to Emma Thomas.

**Early fusion**

1. Pull sentences with linked entity from corpus (Lucene)
2. Pull facts of entity from the KG (using predicate similarity learned via LSTMs)
**Question:** Who are the actors in movies directed by Nolan?

1. **Nolan directed Interstellar in 2010.**
2. <ChristopherNolan, birthplace, London>
3. <Memento, director, Nolan>
4. **Nolan is married to Emma Thomas.**
Question: Who are the actors in movies directed by Nolan?

Nolan directed Interstellar in 2010.

Christopher Nolan

< Memento, director, Nolan >

Memento

Extract entities from new fact + doc nodes
Expand subgraph with these (not full neighborhood)
Question: Who are the actors in movies directed by Nolan?

Nolan directed Interstellar in 2010.

Christopher Nolan

<Interstellar, castMember, AnneHathaway>

Memento

Guy Pearce was in Memento and Flynn.

Supervised graph traversal

Get neighborhood of new entities
Predict most likely expansion points
**Question:** Who are the actors in movies directed by Nolan?

Nolan directed *Interstellar* in 2010.

Christopher Nolan

*Memento* is in the neighborhood of new entities.

Get neighborhood of new entities

Predict most likely expansion points

Guy Pearce was in *Memento* and *Flynn*.
Question: Who are the actors in movies directed by Nolan?

Nolan directed Interstellar in 2010.

Interstellar

Christopher Nolan

<Memento, director, Nolan>

Guy Pearce was in Memento and Flynn.

Memento

Guy Pearce

Anne Hathaway

Expand subgraph with new extractions
**Question:** Who are the actors in movies directed by Nolan?

- Nolan directed *Interstellar* in 2010.
- *Interstellar* was directed by Christopher Nolan.
- Anne Hathaway was a cast member in *Interstellar*.
- *Memento* was directed by Nolan.
- Guy Pearce was in *Memento* and *Flynn*.

**Iterative graph expansion**

Stop after 2 hops.
Question: Who are the actors in movies directed by Nolan?

Nolan directed Interstellar in 2010.

Christopher Nolan

Interstellar

<Interstellar, castMember, Anne Hathaway>

Anne Hathaway

<Memento, director, Nolan>

Memento

Guy Pearce was in Memento and Flynn.

Guy Pearce

Flynn

Predict answer over entity nodes in current subgraph
**Question:** Who are the actors in movies directed by Nolan?

- Nolan directed *Interstellar* in 2010.
- Anne Hathaway
- Christopher Nolan
- *Memento* (directed by Nolan)
- Guy Pearce
- Flynn

Guy Pearce was in *Memento* and *Flynn*.

Graph CNN-based classifier (GRAFT-Net) for both expansion point and answer prediction (Sun et al. 2018).
PullNet: Training

- Distant supervision with QA pairs
- Uses shortest paths between Q and A entities in KG
- Gold expansion points: Intermediate nodes on shortest paths
- Uses teacher forcing
- Gold answers: From benchmark

Closely related to multi-hop KGR

- Multi-hop knowledge graph reasoning (KGR) and knowledge graph completion (KGC) closely associated with multi-hop QA
- Bridge between neural and symbolic space
- MINERVA *(Das et al. 2018)* [Reinforcement learning]
- SRN *(Qiu et al. 2020)* [Reinforcement learning]
- DrKIT *(Dhingra et al. 2020)*
- Similar ideas explored for multi-hop MRC *(Asai et al. 2020)*
Heterogeneous QA: Unified resource

- **QAnswer** ([Diefenbach et al. 2019](#))
- Multiple KGs as unified triple store
- KG-agnostic approach for QA

---

Diefenbach et al., QAnswer: A Question answering prototype bridging the gap between a considerable part of the LOD cloud and end-users, WWW 2019.
Structured querying over multiple KGs

- QAnswer (Diefenbach et al. 2019)
- Multiple KGs as unified triple store
- KG-agnostic approach for QA

Diefenbach et al., QAnswer: A Question answering prototype bridging the gap between a considerable part of the LOD cloud and end-users, WWW 2019.
Expand question with candidate KG concepts

- QAnswer (Diefenbach et al. 2019)
  - Question: Give me actors born in Berlin.
  - Expansion: $R = \{\text{actor, TV actor, born in, Born, Berlin, Berlin Univ, West Berlin}\}$
- Multiple KGs as unified triple store
- KG-agnostic approach for QA

Diefenbach et al., QAnswer: A Question answering prototype bridging the gap between a considerable part of the LOD cloud and end-users, WWW 2019.
Generation of SPARQL queries with candidates

- QAnswer (Diefenbach et al. 2019)
- Multiple KGs as unified triple store
- KG-agnostic approach for QA

Efficient construction of SPARQL queries using a BFS of depth 2 on the KG (**exhaustive but valid**)

Enabled by **HDT** + additional indexing of KG (distances between object pairs)

**Question**

Give me actors born in Berlin.

**Expansion**

\[ R = \{\text{actor, TVActor, bornIn, Born, Berlin, BerlinUniv, WestBerlin}\} \]

**Query construction**

\[
\begin{align*}
\text{SELECT / ASK } & \text{?x} \\
\text{WHERE } & \{s1 \ s2 \ s3\} \\
\text{SELECT / ASK } & \text{?x} \\
\text{WHERE } & \{s1 \ s2 \ s3 \ . \ s4 \ s5 \ s6 \} \\
\text{SELECT } & \text{?x} \\
\text{WHERE } & \{\ ?x \ \text{bornIn} \ \text{Berlin} \ . \ ?x \ ?y \ \text{actor} \} \\
\text{SELECT } & \text{?x} \\
\text{WHERE } & \{\ ?x \ ?y \ \text{BerlinUniv} \ . \ ?x \ ?y \ \text{TVActor} \} \\
\end{align*}
\]
Structured querying over multiple KGs

- QAnswer (Diefenbach et al. 2019)
  - Give me actors born in Berlin.

- Multiple KGs as unified triple store
  - R = \{actor, TV actor, bornIn, Born, Berlin, Berlin Univ, West Berlin\}

- KG-agnostic approach for QA
  - SELECT / ASK ?x
  - WHERE \{s1 s2 s3 . s4 s5 s6 .\}
  - LTR (RankLib + coordinate ascent)
Structured querying over multiple KGs

- QAnswer (Diefenbach et al. 2019)
- Multiple KGs as unified triple store
- KG-agnostic approach for QA

Give me actors born in Berlin.

R = {actor, TV actor, bornIn, Born, Berlin, Berlin Univ, West Berlin}

SELECT / ASK ?x
WHERE {s1 s2 s3 . s4 s5 s6 .}

LTR (RankLib + coordinate ascent)

Top query score > threshold

Answer decision

Answer
Structured querying over multiple KGs

- QAnswer (Diefenbach et al. 2019)
  
- Multiple KGs as unified triple store

- KG-agnostic approach for QA

- Extremely efficient due to HDT and additional KG indexing 😊

- Syntax agnostic 😊

---

**Question**

Give me actors born in Berlin.

**Expansion**

R = {actor, TV actor, bornIn, Born, Berlin, Berlin Univ, West Berlin}

**Query construction**

SELECT / ASK ?x
WHERE {s1 s2 s3 . s4 s5 s6 .}

**Query ranking**

LTR (RankLib + coordinate ascent)

**Answer decision**

Top query score > threshold

**Answer**
Heterogeneous QA: Wrap-up

- Early fusion and unified representation truer to spirit of heterogeneous QA than late fusion
- PullNet uses early fusion 😊 and deals with complex questions 😊
- But in principle only for chain joins 😞
- Efficiency is an open issue (too many predictions), no. of hops assumed to be known 😞
- QAnswer is efficient 😊 and works over multiple KGs (largely unexplored) 😊
- But works mostly for relatively simple questions 😊
- Current systems still not truly unified: reliance on KG entities for linking and distant supervision, and a triplicated view of knowledge

break duration ?x . ?x measured in minutes .
Outline: QA over knowledge graphs

- **Background**: Setup, benchmarks, metrics
- **Simple QA**: Templates and embeddings
- **Complex QA**: Multiple entities and predicates
- **Heterogeneous sources**: Handling KG and text
- **Conversational QA**: Implicit context in multi-turn setup
- **Take-home**: Summary and insights
How can we deal with information needs spread over multi-turn conversations?
Conversational KG-QA

Which actor voiced the character Unicorn in The Last Unicorn?

Mia Farrow

Which role was voiced by Alan Arkin in the Last Unicorn?

Schmendrick

Who performed the songs in the movie The Last Unicorn?

America

What is the genre of the band that performed the songs in The Last Unicorn?

Folk rock

Who was the director of the movie The Last Unicorn?

Jules Bass
Conversational KG-QA

Which actor voiced the character Unicorn in The Last Unicorn?

Mia Farrow

And Alan Arkin was behind ...?

Schmendrick

The songs were by...?

America

Genre of this band?

Folk rock

By the way, who directed the movie?

Jules Bass
Conversational KG-QA

- Information needs **rarely one-off**
- Sequence of **follow-up questions** on a topic
- Analogous to **search sessions** and **interactive retrieval**
- Users want to simulate **natural experience** with assistant
- **Leave context unspecified** in follow-ups
Conversational KG-QA

- **Key challenges** in conversational (KG-)QA
  - Infer implicit context
  - Handle ad hoc formulations

- Initially explored over **small tables** as sequential QA ([Iyyer et al. 2017](#))

- Key direction for KG-QA now ([Saha et al. 2018](#), [Guo et al. 2018](#), [Christmann et al. 2019](#), [Shen et al. 2019](#))
Conversational QA: Graph traversal

- The **CONVEX** system *(Christmann et al. 2019)*

- Large topic jumps in conversations are rare: establish **localized KG context**

- Harness **KG-connectivity**: No need to complete/rewrite questions

- **Expand context judiciously** with relevant entities and predicates in neighborhood

- **Unsupervised** iterative graph traversal (c.f. supervised graph traversal in PullNet)

- CONVEX works on top of **any KG-QA system** to handle conversations
Initial context

Standalone KG-QA

NERD system

Which actor voiced the Unicorn in The Last Unicorn?

Mia Farrow

The Last Unicorn

voice actor

Mia Farrow

character role

The Unicorn
Initial context

Mia Farrow
Which actor voiced the Unicorn in The Last Unicorn?

And Alan Arkin was behind . . . ?

How to expand the context?
Judicious context expansion

Which actor voiced the Unicorn in The Last Unicorn?
And Alan Arkin was behind . . .?

Do not expand with the complete neighborhood!
Exploring context neighborhood

And Alan Arkin was behind . . . ?

political thriller

Folk

gender(7)

rock band
gender(4)

class

America
gender(1)

Pop rock
gender(1)

900 Miles

Your move (album)
song by

Folk rock

fantasy film

followed by

soundtrack album

The Last Unicorn Soundtrack

spouse

The Last Unicorn

Mia Farrow

character role(1)

voice actor(1)

Alan Arkin
gender(2)

occupational

Schmendrick

cast member

Frank Sinatra

gender(5)

character role(2)

The Unicorn

gender(6)

present in work

The Last Unicorn (novel)
present in work

The Unicorn

based on

present in work

The Last Unicorn Soundtrack
Exploring context neighborhood

And Alan Arkin was behind . . . ?

Alan Arkin

Schmendrick

cast member

generes

Argo

song by

900 Miles

political thriller

Folk

generes

rock band

class

Pop rock

generes

America

generes

Folk rock

Your move (album)

followed by

Mia Farrow

Frank Sinatra

occupation

singer

Vocal jazz

The Last Unicorn

voice actor

based on

present in work

character role

The Unicorn

The Last Unicorn

( novel )

 presente in work

genre

genre

genre

genre

genre

genre

genre

genre

genre

genre

genre

genre

genre
Find frontier nodes to define expansion border

And Alan Arkin was behind . . . ?

Alan Arkin

Schmendrick

character role(2)

voice actor(2)

The Last Unicorn

The Unicorn

The Last Unicorn (novel)

based on

present in work

character role(2)

Mia Farrow

voice actor(1)

The Last Unicorn Soundtrack

soundtrack album

genre(2)

fantasy film

song by

900 Miles

Argo

cast member

political thriller

genre(8)

rock band

class

Pop rock

genre(4)

America

genre(1)

Folk rock

Your move (album)

followed by

spouse

Frank Sinatra

occupation

Vocal jazz

singer

speculative fiction novel

genre(6)

present in work

based on

present in work
Context graph

Mia Farrow

Which actor voiced the Unicorn in The Last Unicorn?

And Alan Arkin was behind . . . ?

Graph expanded with relevant facts only
Context graph

Mia Farrow

Which actor voiced the Unicorn in The Last Unicorn?

And Alan Arkin was behind . . .?

So who performed the songs?

Graph expanded with relevant facts only
Context graph

Mia Farrow

Which actor voiced the Unicorn in The Last Unicorn?

And Alan Arkin was behind . . .?

So who performed the songs?

Genre of this band?

How to determine Frontier nodes?

Question Answering over Knowledge Graphs  
Rishiraj Saha Roy  
Saarland University  
03 Nov 2020
Frontier score

Matching similarity

$match\ (\text{candidate } c)$

Context relevance

$prox\ (\text{candidate } c)$

KG priors

$prior\ (\text{candidate } c)$

frontier\_score\ (\text{candidate } c) = h_1 \cdot match(c) + h_2 \cdot prox(c) + h_3 \cdot prior(c)$

With hyperparameters $h_1, h_2, h_3$
### Frontier nodes

#### Matching similarity

<table>
<thead>
<tr>
<th>Candidate</th>
<th>Match</th>
</tr>
</thead>
<tbody>
<tr>
<td>genre[1]</td>
<td>1.00</td>
</tr>
<tr>
<td>genre[2]</td>
<td>1.00</td>
</tr>
<tr>
<td>folk rock band</td>
<td>0.89</td>
</tr>
<tr>
<td>RSH-Gold for Cult Band</td>
<td>0.87</td>
</tr>
<tr>
<td>fantasy film</td>
<td>0.36</td>
</tr>
</tbody>
</table>

#### Context relevance

<table>
<thead>
<tr>
<th>Candidate</th>
<th>Prox</th>
</tr>
</thead>
<tbody>
<tr>
<td>genre[1]</td>
<td>0.91</td>
</tr>
<tr>
<td>folk rock band</td>
<td>0.86</td>
</tr>
<tr>
<td>RSH-Gold for Cult Band</td>
<td>0.86</td>
</tr>
<tr>
<td>genre[2]</td>
<td>0.34</td>
</tr>
<tr>
<td>fantasy film</td>
<td>0.36</td>
</tr>
</tbody>
</table>

#### KG priors

<table>
<thead>
<tr>
<th>Candidate</th>
<th>KG priors</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>genre[1]</td>
<td>0.56</td>
</tr>
<tr>
<td>genre[2]</td>
<td>0.56</td>
</tr>
<tr>
<td>folk rock band</td>
<td>0.34</td>
</tr>
<tr>
<td>RSH-Gold for Cult Band</td>
<td>0.01</td>
</tr>
</tbody>
</table>

---

**Fagin’s Threshold Algorithm (FTA) to retrieve top-k ranked nodes according to frontier score**
Frontier nodes

Genre of this band?

Frontier nodes
Answer to the question

- **Distance to Frontier nodes**
  - Weighted by the frontier score
  - `distance_F` => Explicit part

- **Distance to all nodes in context graph X**
  - Weighted by the turn they occurred in
  - `distance_X` => Implicit part

\[
\text{answer\_score}(\text{candidate } c) = h_4 \cdot \text{distance}_F + h_5 \cdot \text{distance}_X
\]
Answer detection

Genre of this band? 

Folk rock

Top-ranked node according to answer_score
Conversational QA: Sequence-to-sequence modeling

- The **MaSP** model (Shen et al. 2019)
- **Shared supervision** for tasks: Entity detection and answering
- **Grammar-based** semantic parsing model
- Designed to resolve **coreference** in conversations
- **Type-aware** entity detection
- Uses **transformers** for sequence encoding

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.
Sequence-to-sequence model

**Question:** Who released Pokemon?

Tree-structured KB-query

- **start**
- **filter(set, tp)**
- **find(set, p)**
- **tp: org**
- **set(e)**
- **p: Released by**
- **e: Pokemon**

Query as sequence

- **A1**
- **A15**
- **A4**
- **tp: org**
- **A17**
- **p: Released by**
- **e: Pokemon**

Transform by traversal

A1 A15 A4 A17 e:Pokemon p:ReleasedBy tp:org

---

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.

Question Answering over Knowledge Graphs | Rishiraj Saha Roy | Saarland University | 03 Nov 2020
Sequence-to-sequence model

NL question as sequence

Question: [CONTEXT] Who released that work?
Seq-to-seq: The MaSP model

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.
MaSP: Step-by-step

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.
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Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.
MaSP: Step-by-step

Entity Pointer

Entity Detection

Entity IOB and Entity Type Joint Classifier in $\{O, \{I,B\}\times \{\text{EntType}_k\}_{k=1}^N \}$

Contextual Encoder

Word Encoder

Which work features Pikachu

Prev Question

[SEP1] Pokémon

Prev Answer

[SEP2] Who released that work

Cur Question

[CTX]

P-CLF: Predicate Classifier

T-CLF: Type Classifier

A1 A15 T43229 A4 A17 EntPtr=6 P123

resulting Entity-pointed Logical Form

Publisher

P123

Pred

Ent

Decoder State

EntPtr=6

K

Organization

T43229

A15

A4

A1

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.
MaSP: Step-by-step

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.

Question Answering over Knowledge Graphs

Rishiraj Saha Roy

Saarland University

03 Nov 2020
MaSP: Step-by-step

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.
MaSP: Step-by-step

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.
MaSP: Step-by-step

P-CLF: Predicate Classifier
T-CLF: Type Classifier

A1 A15 T43229 A4 A17 EntPtr=6 P123

resulting Entity-pointed Logical Form

Entity Pointer
1-Which 4-Pikachu 6-Pokemon 8-Who

Entity Detection
NULL O T15619164 B T386724 B NULL O

Entity IOB and Entity Type Joint Classifier in \{O, \{I, B\} \times \{EntType_k\}_{k=1}^N\}

Pointer Network \text{Ptr-Net}(q, K) between States from Encoder and Decoder

Encoder States

Word Embed

Which work features Pikachu [SEP1] Pokemon [SEP2] Who released that work [CTX]

Prev Question Prev Answer Cur Question

Shen et al., Multi-Task Learning for Conversational Question Answering over a Large-Scale Knowledge Base, EMNLP 2019.
Execute query obtained via sequence decoding to get answer
Conversational QA: Wrap-up

- Unsupervised graph traversal is promising
- KG connections offer vital clues for initializing and expanding context
- But limited to relatively simple information needs in utterances
- Sequence-sequence models can capture context well
- But ConvQA is much more than coreference and ellipsis resolution
- Zero-coreference / zero-anaphora utterances common (“batman actor?”)
- Question completion may be intractable + overkill
Side glance: Table-QA

- Web tables also constitute a huge volume of the curated Web
- Represent canonical challenges of querying a large-scale KB
- Selected references below for the interested reader

  Zhang, CFGNN: Cross Flow Graph Neural Networks for Question Answering on Complex Tables, AAAI 2020.
  Wang et al., A Neural Question Answering Model Based on Semi-Structured Tables, COLING 2018.
  Jauhar et al., Tables as Semi-structured Knowledge for Question Answering, ACL 2016.
  Sun et al., Table Cell Search for Question Answering, WWW 2016.
  Pasupat and Liang, Compositional Semantic Parsing on Semi-Structured Tables, ACL 2015.
Outline: QA over knowledge graphs

- **Background:** Setup, benchmarks, metrics
- **Simple QA:** Templates and embeddings
- **Complex QA:** Multiple entities and predicates
- **Heterogeneous sources:** Handling KGs and text
- **Conversational QA:** Implicit context in multi-turn setup
- **Take-home:** Summary and insights
Summary and insights
Take-home messages

- Methodology
- Deployable system
- Open problems
Methodology

- Templates
- Graph embeddings
- Subgraph computations
- Belief propagation
- Graph traversal
- Sequence-to-sequence models
Methodology

- Templates: NEQA
- Graph embeddings: KEQA
- Subgraph computations: TextRay, QUEST, QAnswer
- Belief propagation: QAmp
- Graph traversal: PullNet, CONVEX
- Sequence-to-sequence models: MaSP
Methodology quad chart

<table>
<thead>
<tr>
<th>Degree of supervision</th>
<th>Query generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weakly/strongly supervised</td>
<td>MaSP, NEQA, TextRay</td>
</tr>
<tr>
<td>Unsupervised</td>
<td>QAnswer*</td>
</tr>
<tr>
<td>Explicit structured query</td>
<td>Without explicit query (approximate graph search)</td>
</tr>
</tbody>
</table>

* Ranker/labeler supervised

Question Answering over Knowledge Graphs
Rishiraj Saha Roy
Saarland University
03 Nov 2020
## Methodology quad chart

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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MaSP, TextRay, NEQA, D2A, Saha et al. 2018, SEMPRE, AQQU, STAGG, PARALEX, OQA, PARASEMPRE, Cai and Yates 2013</td>
<td>QAnswer*, DEANNA, Unger et al. 2012</td>
<td>Q Amp*, QUEST, CONVEX</td>
</tr>
</tbody>
</table>

* Ranker/labeler supervised
## Methodology quad chart

<table>
<thead>
<tr>
<th>Strongly supervised with (Q, q)</th>
<th>Cai and Yates 2013</th>
<th>-</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weakly supervised with (Q, A)</td>
<td>MaSP, NEQA, TextRay, D2A, Saha et al. 2018, SEMPRE, AQQU, STAGG</td>
<td>KEQA, PullNet, GRAFT-Net, GraphParser, Bordes et al. 2014</td>
<td>There is some interplay in current systems but largely open area</td>
</tr>
<tr>
<td>Weakly supervised with paraphrases</td>
<td>PARASEMPRE, PARALEX, OQA</td>
<td>-</td>
<td>Unsupervised subgraph computations with small degree of supervised neural learning..?</td>
</tr>
<tr>
<td>Unsupervised</td>
<td>QAnswer*, DEANNA, Unger et al. 2012</td>
<td>QAmp*, QUEST, CONVEX</td>
<td></td>
</tr>
</tbody>
</table>

| Explicit structured query | Without explicit query | Hybrid search methods? |
## Methodology: Pros and cons

<table>
<thead>
<tr>
<th>Aspect</th>
<th>With explicit structured query (SPARQL-like)</th>
<th>Without explicit structured query (approx. graph search)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple questions</td>
<td>☺</td>
<td>☺</td>
</tr>
<tr>
<td>Single answer</td>
<td>☺</td>
<td>☺</td>
</tr>
<tr>
<td>List answer</td>
<td>☺</td>
<td>☹?</td>
</tr>
<tr>
<td>Efficiency</td>
<td>☺</td>
<td>☹?</td>
</tr>
<tr>
<td>Complex questions</td>
<td>☹?</td>
<td>☺</td>
</tr>
<tr>
<td>Conversational questions</td>
<td>☹?</td>
<td>☺</td>
</tr>
<tr>
<td>Heterogenous sources</td>
<td>☹?</td>
<td>☺</td>
</tr>
<tr>
<td>Handling reified triples</td>
<td>☹?</td>
<td>☺</td>
</tr>
</tbody>
</table>

☺ Preferable
☺? Less preferable but scope for improvement
Methodology: Lessons learnt

- Templates good for simple questions, but hits hurdles for complex questions, and useless for conversational 😞
- Graph embeddings effective for simple questions 😊, not yet clear for complex scenarios...
- Sequence models (LSTM with attention) with pre-trained word embeddings very common
- Graph models generally more flexible (scope for node/edge types/weights)
Deploying a QA system

- Templates and unsupervised graph methods great way to get off the blocks with limited complexity
- Preferably with NER/NERD systems and pre-trained word embeddings
- Need seed data + domain knowledge
- Continuous learning with similarity function and feedback vital cogs
- Level of structure and heterogeneity in data and questions indicators of follow-up modeling
Open problems

- Unanswerability
- Interpretability
- Interactivity
- Efficiency
- Robustness
Open problems: Unanswerability

▪ Learn when to stay quiet and prevent embarrassment 😊
  ▪ Where was Messi’s father born?
  ▪ Who was the first man on Mars?

▪ Knowing when answer is:
  ▪ Not confident
  ▪ Not in KG
  ▪ Null

▪ Open and closed world assumptions

▪ Learn when to consult text
Open problems: Interpretability

- Are your system’s answers explainable? To the developer? What about the end user?
- Interpretability increases trust and guides user in case of mistakes
- Template- and graph-based methods construct interpretable evidence for answers - an unsolved concern for neural methods
- Sydorova et al. (2019) provide insights with input perturbation and evaluation of interpretability
- But very much an open problem!
Open problems: Interactivity

- Towards mixed initiative systems ([Radlinski and Craswell 2017](#))
- Can your system absorb feedback?
- Positive and negative feedback?
- What kinds of feedback?
- Can your system ask clarifications?
Open problems: Efficiency

- Critical component of QA systems
- Largely unexplored
- Identify bottlenecks
- Measure trade-offs
Open problems: Robustness

- Think out of the box benchmark
- What is open-domain question answering?
- What happens for entities not seen during training?
- What about unseen predicates and vocabulary?
Take-home messages

- Overview of state-of-the-art in KG-QA and their positioning
- Families of algorithms with a few specific instantiations
- Several open problems in the key areas of focus

Simple / complex / heterogeneous / conversational questions for me 😊 ?
QA@MPII-D5: Visit qa.mpi-inf.mpg.de

- **Course** on QA systems: [https://www.mpi-inf.mpg.de/question-answering-systems/](https://www.mpi-inf.mpg.de/question-answering-systems/)
- **CONVEX**: Conversational QA over KGs [CIKM 2019]: [https://convex.mpi-inf.mpg.de/](https://convex.mpi-inf.mpg.de/)
- **CROWN**: Conversational QA over passages [SIGIR 2020]: [https://crown.mpi-inf.mpg.de/](https://crown.mpi-inf.mpg.de/)
- **QUEST**: Complex question answering [SIGIR 2019]: [https://quest.mpi-inf.mpg.de/](https://quest.mpi-inf.mpg.de/)
- **TEQUILA**: Temporal question answering [CIKM 2018]: [https://tequila.mpi-inf.mpg.de/](https://tequila.mpi-inf.mpg.de/)
- **QUINT**: Template-based question answering [EMNLP 2017]: [https://quint.mpi-inf.mpg.de/](https://quint.mpi-inf.mpg.de/)
- Send an email to rishiraj@mpi.de in case of any issues!
Acknowledgements

- Gerhard Weikum for valuable feedback on slides
- Authors of several papers for sharing additional content
- Members of D5@MPII for inputs