

An introduction to Entity Search

Uma Sawant

IIT Bombay, LinkedIn

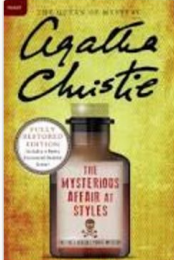
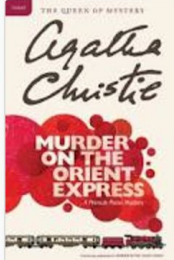
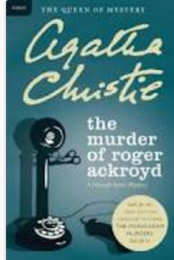

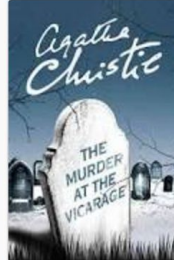
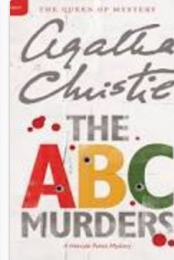

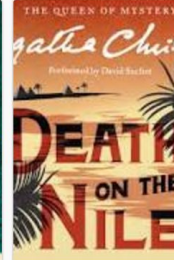
February 2017

Query : agatha christie books

agatha christie books

All Books Images News Videos More Settings Tools

Agatha Christie > Books Most popular first

 <p>The Mysterious Affair at Styles 1920</p>	 <p>Murder on the Orient Express 1924</p>	 <p>The Murder of Roger Ackroyd 1926</p>	 <p>The Secret Adversary 1922</p>	 <p>The Murder at the Vicarage 1930</p>	 <p>The A.B.C. Murders 1936</p>	 <p>The Murder on the Links 2014</p>	 <p>Death on the Nile 1937</p>
---	--	---	--	---	--	---	---

Agatha Christie bibliography - Wikipedia

https://en.wikipedia.org/wiki/Agatha_Christie_bibliography

Agatha Christie (1890–1976) was an English crime novelist, short story writer and playwright. ... Additionally she wrote two volumes of poetry, two autobiographical books and six romantic works under the pseudonym Mary Westmacott. One of ...

[Novels](#) · [Short story collections](#) · [Miscellany](#) · [Broadcast works](#)

Shop for agatha chris... on Google Sponsored





The World's Favourite: And Then There Were None, Murder on the Orient
₹ 374 - Amazon India

Query : deep learning researchers

What I want



What I get

deep learning researchers  

[All](#) [News](#) [Images](#) [Videos](#) [Maps](#) [More](#) [Settings](#) [Tools](#)

About 1,42,00,000 results (0.69 seconds)

Scholarly articles for deep learning researchers
[Deep learning](#) - LeCun - Cited by 1805
[Recent advances in deep learning for speech research](#) ... - Deng - Cited by 213
[Learning deep architectures for AI](#) - Bengio - Cited by 3434

Deep Learning Research Groups « Deep Learning
[deeplearning.net/deep-learning-research-groups-and-labs/](#) ▾
Oct 20, 2016 - Some labs and research groups that are actively working on deep learning: University of Toronto - Machine Learning Group (Geoffrey Hinton, ...

This Is The Cutting Edge Of Deep Learning Research - Forbes
[www.forbes.com/sites/quora/.../this-is-the-cutting-edge-of-deep-learning-research/](#) ▾
Aug 5, 2016 - Contain inflammatory attacks of a personal, racial or religious nature or expressions of bigotry or discrimination. Contain gross exaggeration or unsubstantiated claims; violates the privacy rights of any third party or are unreasonably harmful or offensive to an individual or community.

How To Launch Your Career In Deep Learning Research - Forbes
[www.forbes.com/sites/quora/.../how-to-launch-your-career-in-deep-learning-research/](#) ▾
Aug 12, 2016 - What's your advice for undergrads who want to do research in deep learning or a

Query : universities known for neuroscience

What I want



Stanford



John Hopkins



Yale



U. Chicago

What I get

universities known for neuroscience

All News Maps Images Videos More Search tools

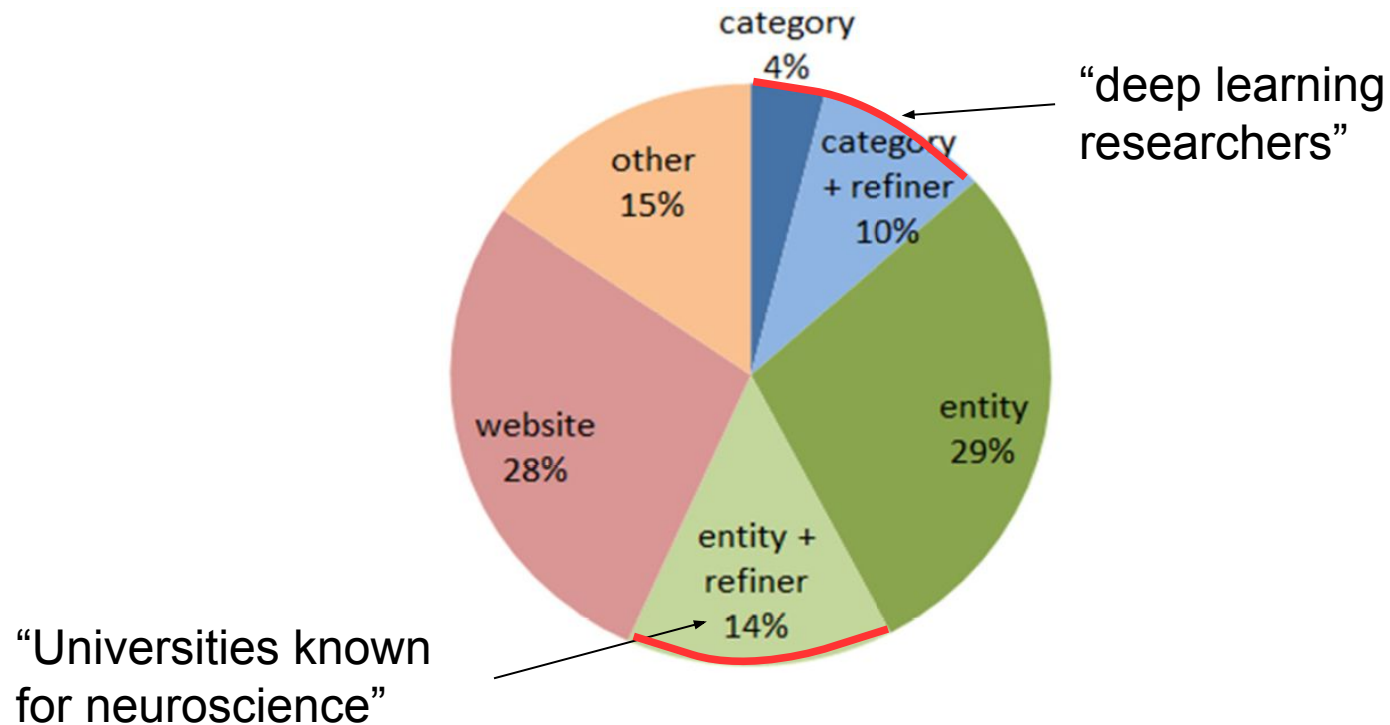
About 92,60,000 results (0.47 seconds)

Top Neuroscience and Behavior Universities in the World ...
www.usnews.com/education/best...universities/neuroscience-behavior
See the US News rankings for the world's top universities in Neuroscience and Behavior. Compare the academic programs at the world's best universities.
University College London · University of California--San ...

2015 Best Colleges Offering Neuroscience Degrees
colleges.startclass.com/d/o/Neuroscience
Looking for the best colleges offering Neuroscience Degrees? ... Compare Neuroscience Degrees 2120. The Columbia University in the City of New Yo ...

Neuroscience / Neurobiology - US News & World Report
grad-schools.usnews.rankingsandreviews.com > ... > Biological Sciences
See the top ranked neuroscience and neurobiology programs at US News. Use the best neuroscience and neurobiology program rankings to find the right ... High Schools · Online Programs · Community Colleges · Global Universities.

~28% of Web search queries



The big picture

Medical, satellite, VoIP,
personal assistants, games,
scanners, email, instant
messaging, IOT,
peer-to-peer, security
systems ...

Information explosion

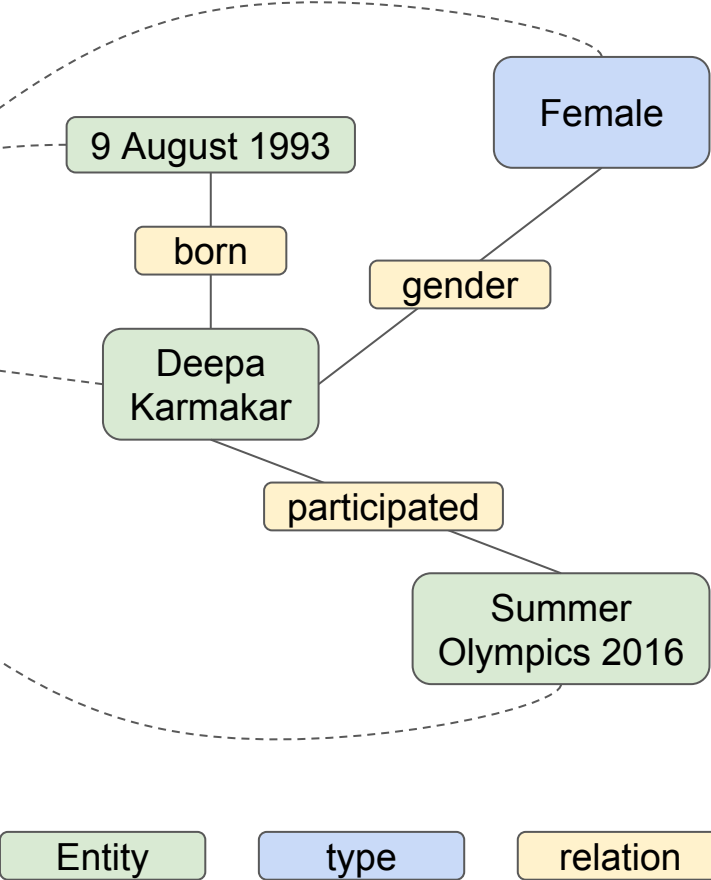
How to organize
and search this big
data?



Users want direct
answers

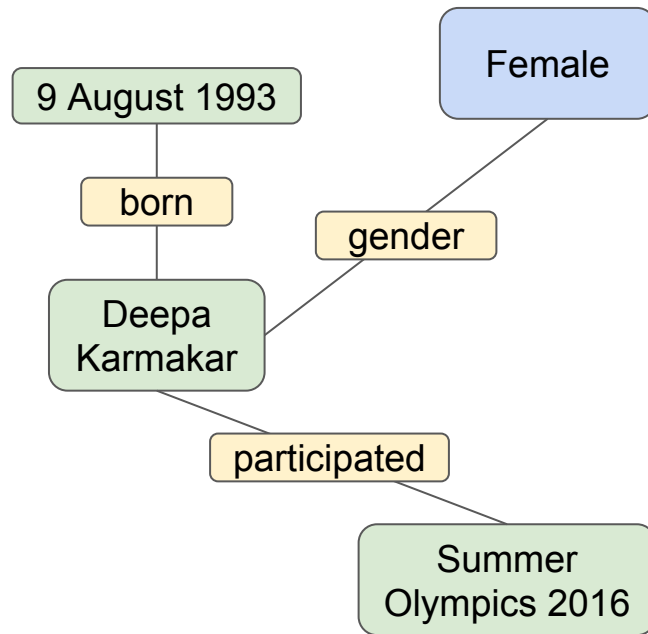
Documents vs. entities (dual view)

Dipa Karmakar
Dipa Karmakar (born 9 August 1993) is an artistic gymnast who represented India at the 2016 Summer Olympics. She is the first Indian female gymnast ...



Knowledge graph

1. High precision (subject, relation, object) fact triplets
2. Not all information from Web is present in KG
3. Extracted using natural language resources and tools e.g. pos tagger, dictionaries, rule based systems ...
4. Example : Wikipedia (infobox), Freebase, dbpedia



Knowledge graph (KG) of entities, types, relations

Problem statement : KG-driven entity search

Given structured information in a knowledge graph, how to answer any query?

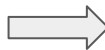
Problem statement : KG-driven entity search

entity-seeking

Given structured information in a knowledge graph, how to answer any query?

Entity - seeking queries	Other queries
Who is the lead singer of Euphoria band?	How did world war 2 unfold?
olympics most award winning country	If $a = 2$, $b = 5$, what is $a * b$?
Name the deepest lake in the world.	How to make vanilla icing?

spanish poet died civil war
Which spanish poet died in the civil war?



Federico_Garcia_Lorca

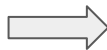
Talk outline

- Overview of entity search
- Challenges in building an entity search system
- Query interpretation and ranking for entity search
 - Discriminative and Generative models for joint QI and ranking
 - Deep learning
- Experiments and results

How does an entity search engine work?

Query to answer

spanish poet died civil war
Which spanish poet died in the civil war?



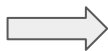
Federico_Garcia_Lorca

Recipe

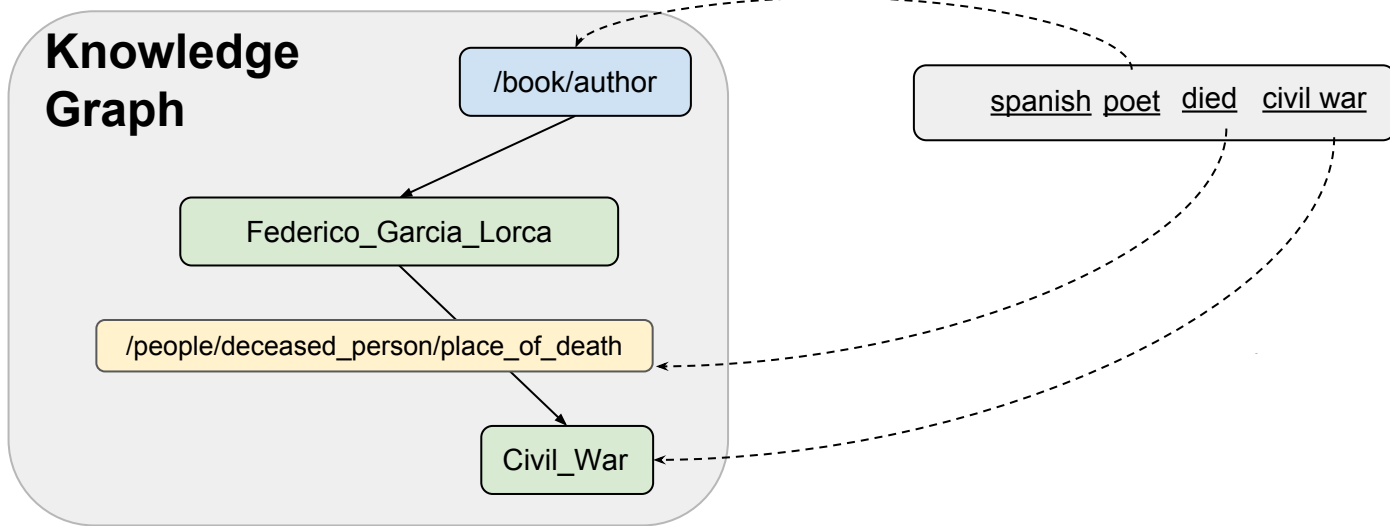
1. Find a structured interpretation of the query by recognizing 'semantic hints'
 - a. Entities
 - b. Types
 - c. Relations
2. Execute the structured query on the knowledge graph.

Query to answer

spanish poet died civil war
Which spanish poet died in the civil war?



```
?x /people/deceased_person/place_of_death Civil_War .  
?x /type/object/type /book/author
```

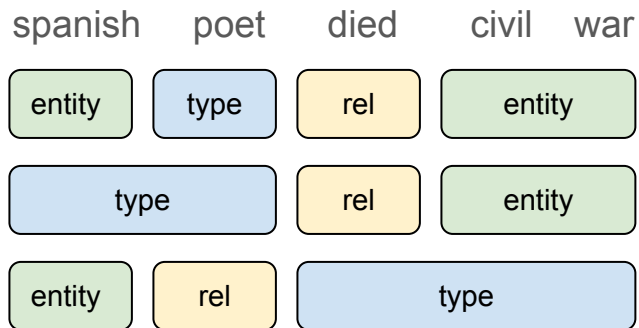


What is the difficulty?

But ... there is a wall between query and answer!

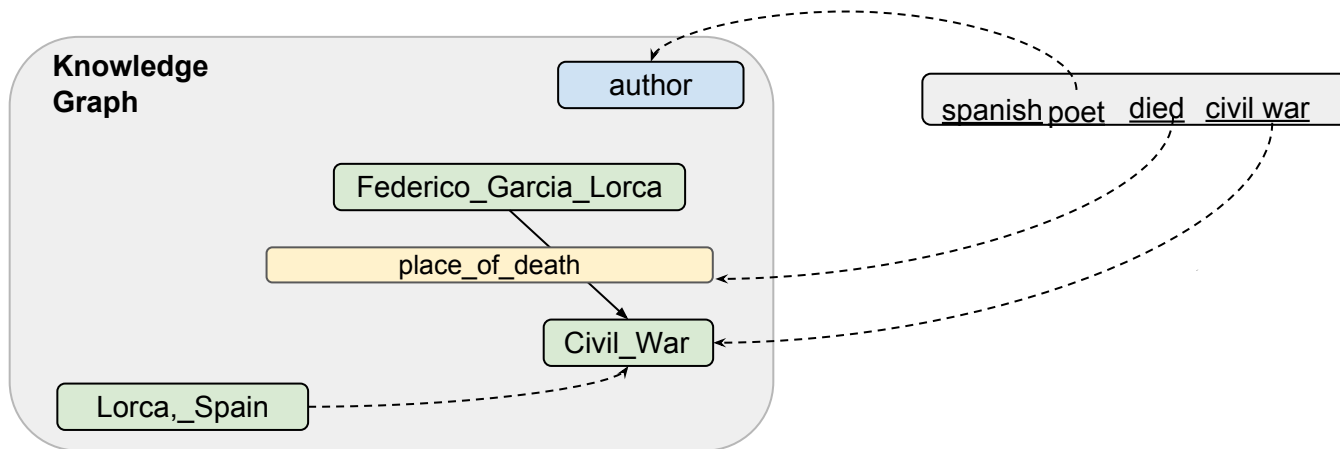
- Query understanding is difficult
 - a. Many correct / incorrect interpretations
 - b. Query syntax cannot always be depended on (keyword queries have no syntax)

Example :



But ... there is a wall between query and answer!

- Incomplete / noisy information sources
 - a. Missing KG links
 - b. Incorrect KG links
 - c. Information needed to answer a query may be scattered in multiple places



But ... there is a wall between query and answer!

- Other challenges such as Web-scale data, index design, distributed processing, parallelization ... (not in focus for this talk)

How do I solve this problem?

Our method

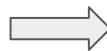
1. Entity ranking problem (instead of graph query identification problem)
 - a. For each input query q , generate output ranking over entities using any number of information sources

Our method

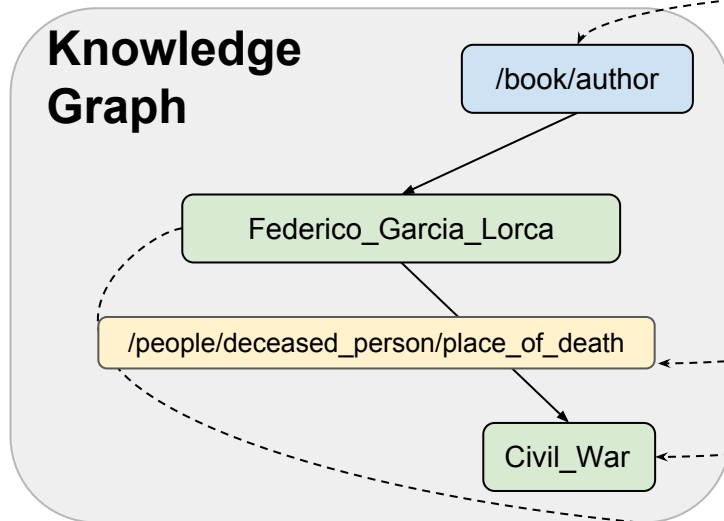
1. Entity ranking problem
 - a. For each input query q , generate output ranking over entities
2. Incomplete / noisy information sources
 - a. Use both annotated corpus and KG as information sources

Query to answer

spanish poet died civil war
Which spanish poet died in the civil war?



Federico_Garcia_Lorca



spanish poet died civil war

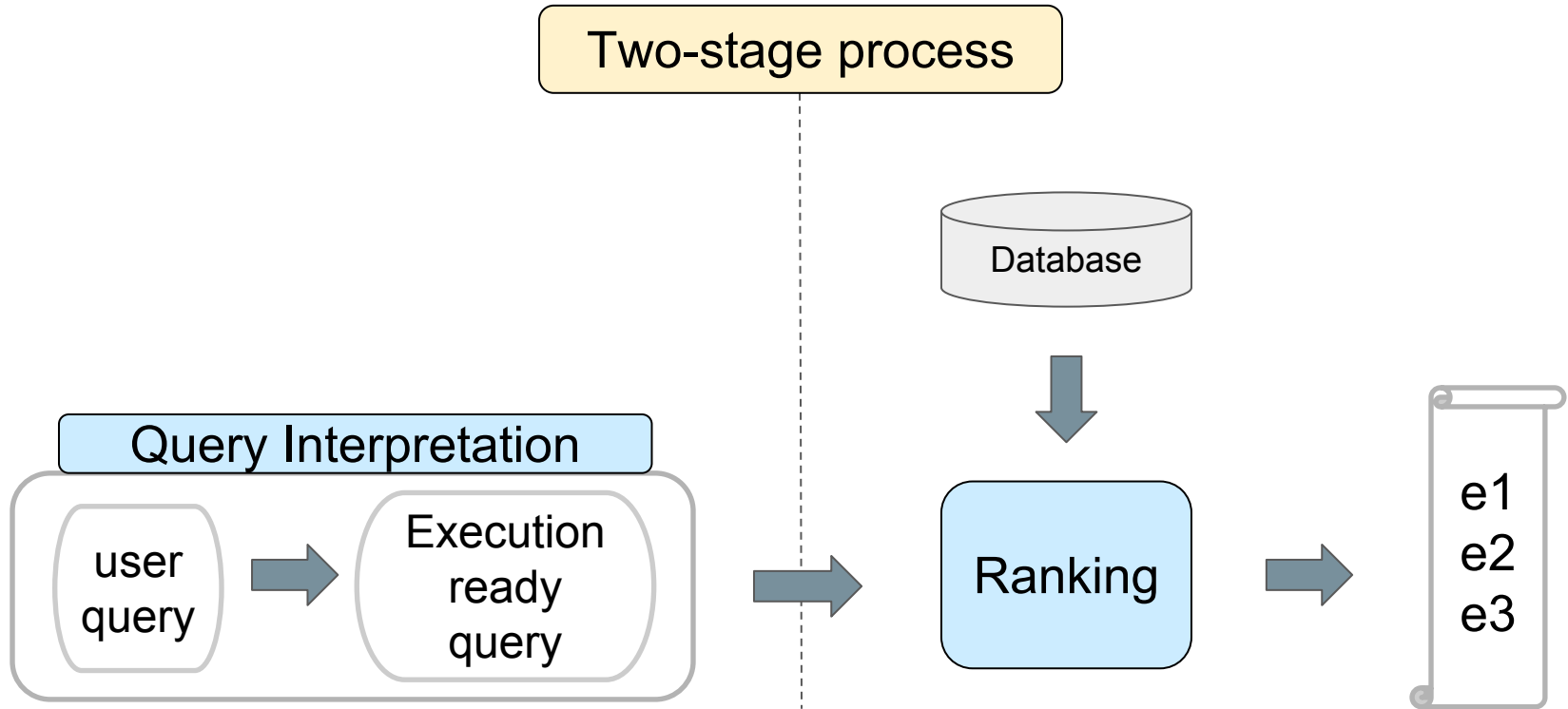
**Entity-annotated
Web corpus**

Lorca , the spanish playwright
was executed during the civil
unrest in ...

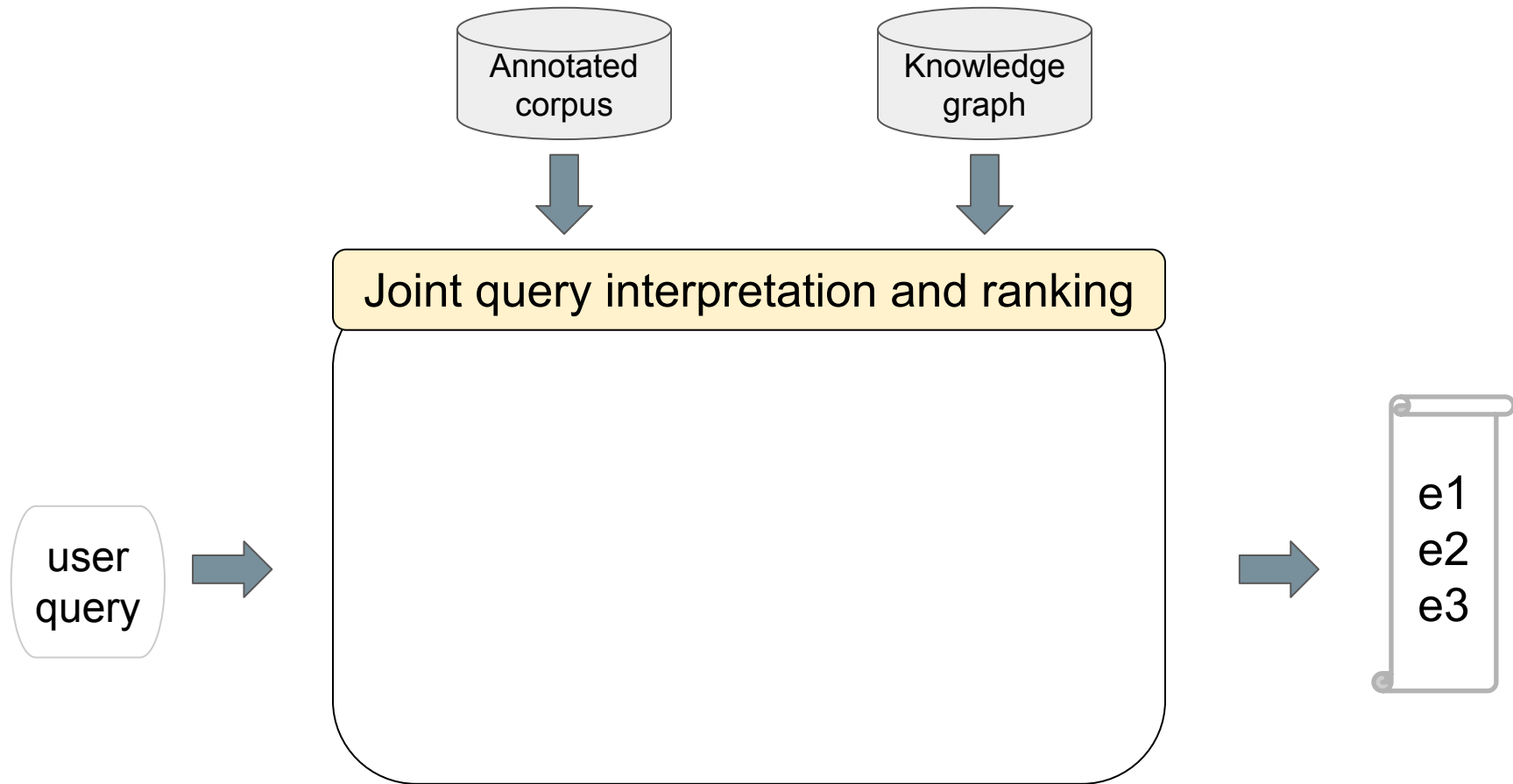
Our method

1. Entity ranking problem
 - a. For each input query q , generate output ranking over entities
2. Incomplete / noisy information sources
 - a. Use both annotated corpus and KG as information sources
3. Query interpretation is difficult
 - a. Ideal query interpretation as a latent variable
 - b. Consider many possible interpretations and jointly solve the interpretation and ranking problem

Simplified view of related work



Our approach



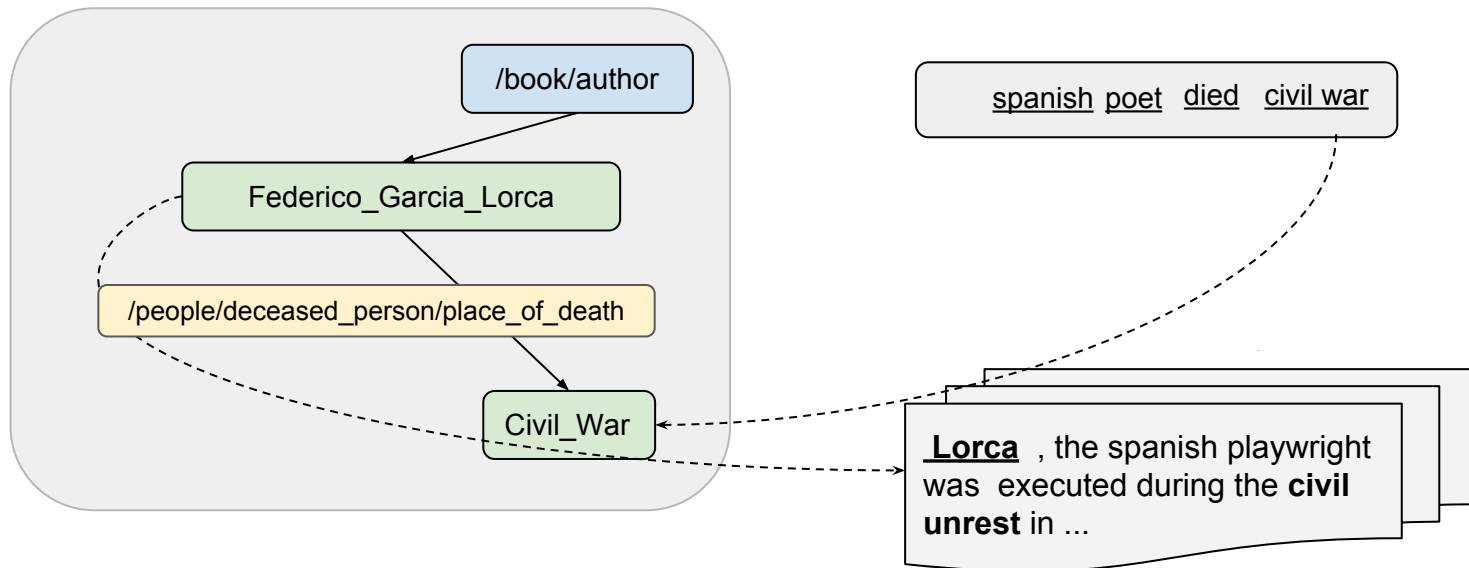
Our approach (recipe)

1. Generate candidate interpretations and hence candidate answer entities
2. Gather supporting evidence / features from KG and corpus
3. Run discriminative / generative models to perform joint interpretation and ranking

Candidate generation

Input : Query q

1. Identify in-query entities E_1
2. Gather text snippets containing query words and an entity
3. Identify answer entity set E_2
 - a. Neighbours of E_1 in KG
 - b. Entities that occur in corpus snippets
4. All the KG paths between E_1 and E_2 , and corpus snippets are candidate query interpretations I



Feature generation

Goal : Generate a feature vector to describe the match between query q , candidate interpretation \mathbb{I} and candidate answer entity e

Features :

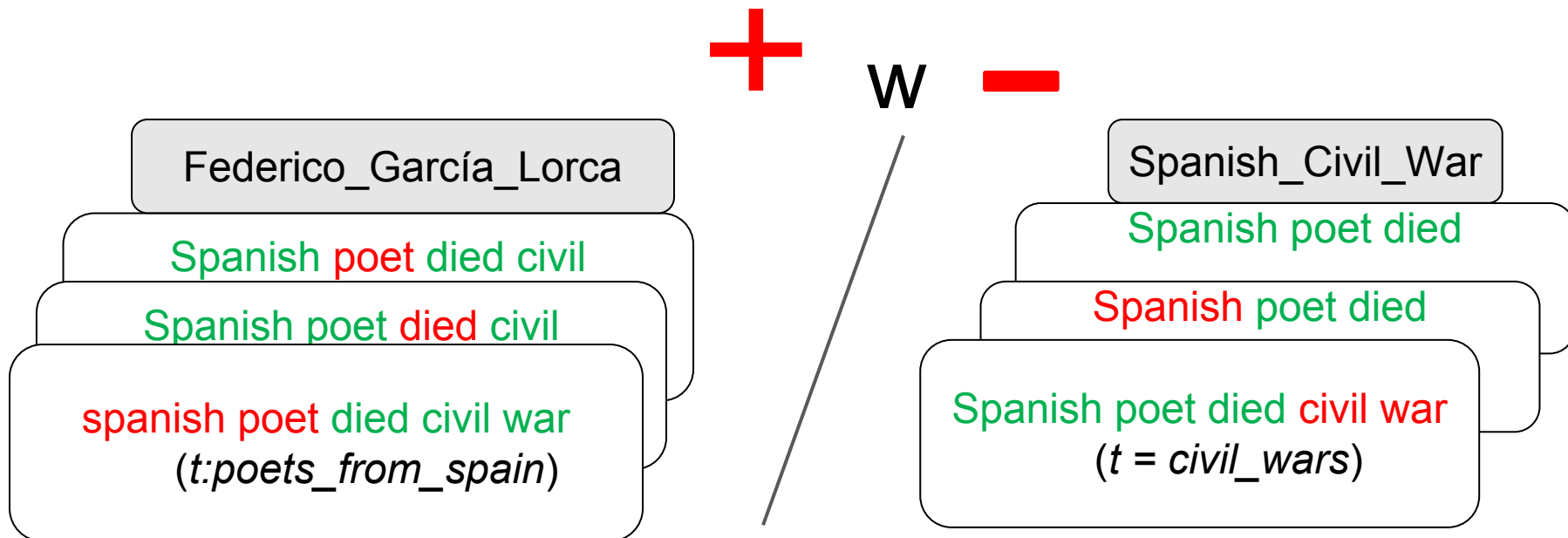
1. Entity tagger score for query entity
2. Match score for (q, t)
3. Match score for (q, r)
4. Corpus snippet score for q
5. Deep neural networks ! (a.k.a. The magic wand)
6. ...

Models for joint QI and Ranking

1. Goal : Correct entity should score higher than incorrect entity
2. Constraint : Ideal interpretation unknown
3. Models :
 - a. Latent Variable Discriminative Model (LVDT)
 - b. Graphical model

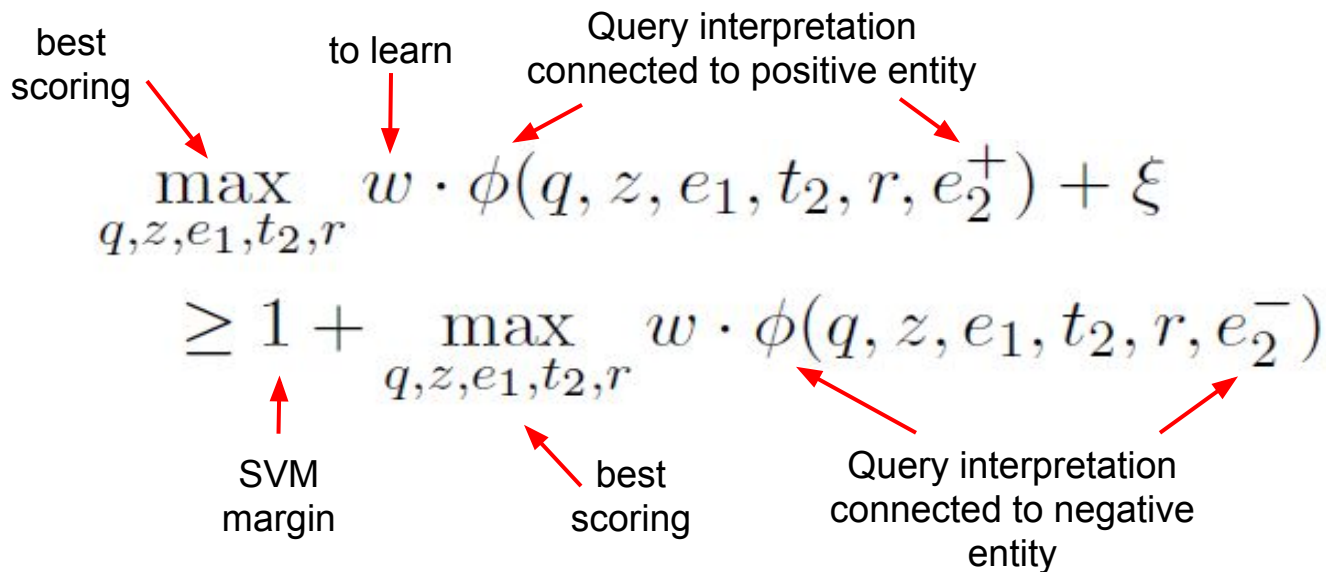
Model 1 : Latent Variable Discriminative Model

q : spanish poet died civil war



LVDT formulation

- Constraints based on best scoring interpretation
 - Find weight vector s.t. Best scoring positive entity interpretation scores higher than best scoring negative entity interpretation
- Non convex formulation, solved via alternative optimization



The diagram shows the LVDT formulation with several annotations and arrows:

- best scoring**: Points to the $\max_{q,z,e_1,t_2,r}$ term in the first equation.
- to learn**: Points to the weight vector w .
- Query interpretation connected to positive entity**: Points to the e_2^+ term in the first equation.
- SVM margin**: Points to the constant 1 in the inequality.
- best scoring**: Points to the $\max_{q,z,e_1,t_2,r}$ term in the second equation.
- Query interpretation connected to negative entity**: Points to the e_2^- term in the second equation.

$$\max_{q,z,e_1,t_2,r} w \cdot \phi(q, z, e_1, t_2, r, e_2^+) + \xi$$
$$\geq 1 + \max_{q,z,e_1,t_2,r} w \cdot \phi(q, z, e_1, t_2, r, e_2^-)$$

LVDT complete formulation

$$\min_{w, \xi, u} \frac{1}{2} \|w\|^2 + \frac{C}{|\mathcal{Q}|} \sum_{q \in \mathcal{Q}} \frac{1}{|\mathcal{E}_q^+| |\mathcal{E}_q^-|} \sum_{e_2^+ \in \mathcal{E}_q^+, e_2^- \in \mathcal{E}_q^-} \xi_{q, e_2^+, e_2^-}$$

$$\forall q, e_2^+, e_2^-, e_1', t_2', r' :$$

$$\sum_{z, e_1, t_2, r} u(q, z, e_1, t_2, r, e_2^+) w \cdot \phi(q, z, e_1, t_2, r, e_2^+)$$

$$\geq 1 - \xi_{q, e_2^+, e_2^-} + w \cdot \phi(q, z, e_1', t_2', r', e_2^-)$$

$$u(q, z, e_1, t_2, r, e_2^+) \in \{0, 1\}$$

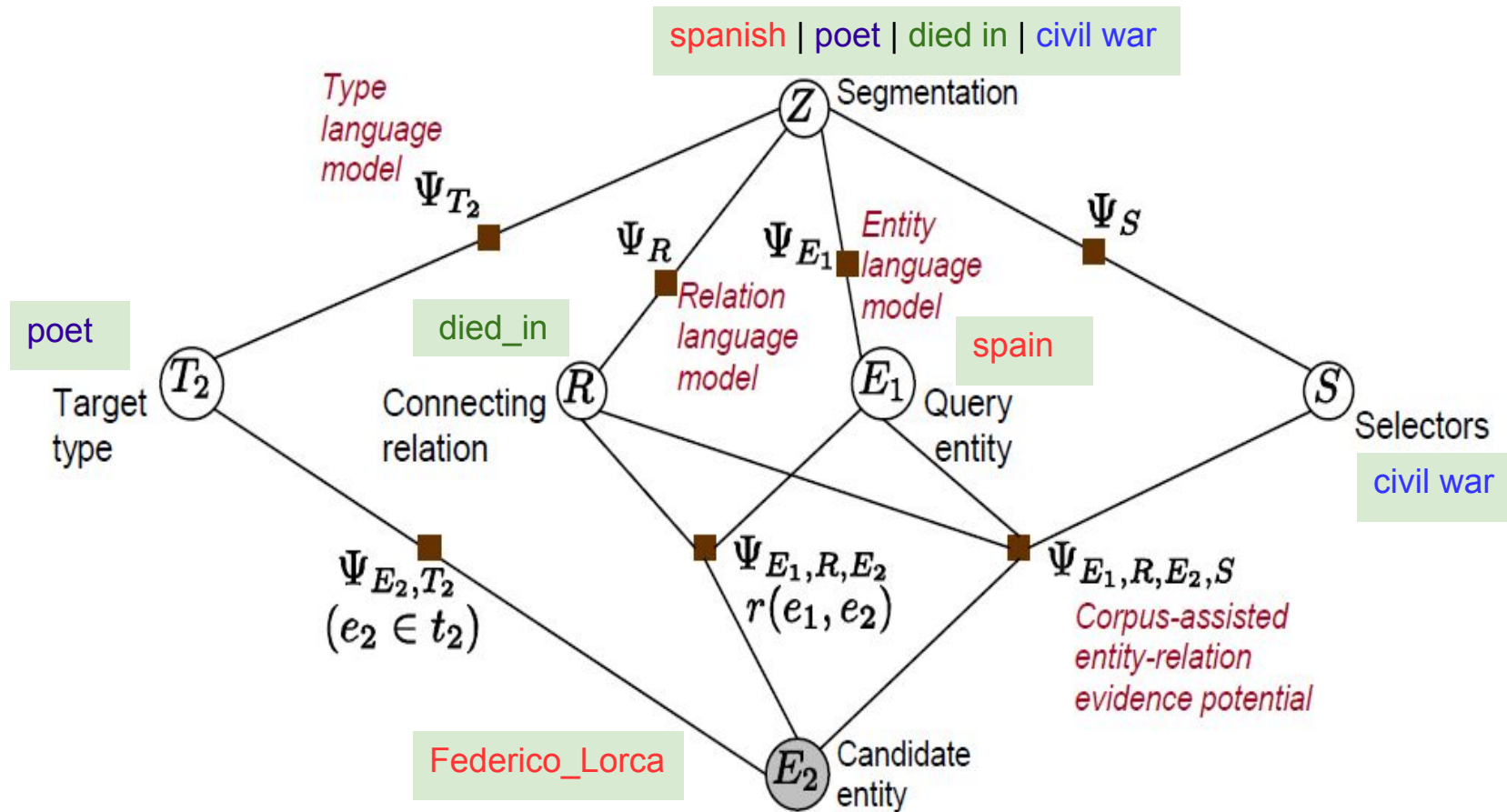
$$\forall q, e_2^+ : \sum_{z, e_1, t_2, r} u(q, z, e_1, t_2, r, e_2^+) = 1$$

$$\forall q, e_2^+, e_2^- : \xi_{q, e_2^+, e_2^-} \geq 0$$

Model 2 : Graphical model

- Generative model represented as a graph
- Nodes = variables (observed evidence or hidden parameters)
- Edges = dependencies between variables
- Potentials = Unnormalized weights on the edges, indicate connection strength
- Inference = Assign best values to nodes

Model 2 : Graphical model



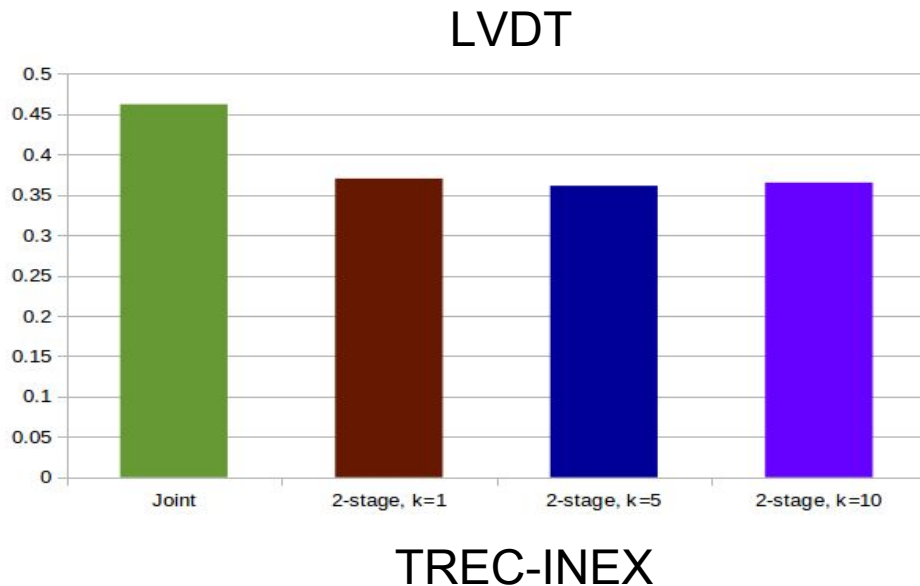
Experiment setup

- Freebase knowledge graph
 - ~29 million entities, 14K types, ~4.6K relation types
- FACC1/ClueWeb09B entity-annotated corpus :
 - 50 million pages, ~13 annotations per page
- Querysets

Source	Queryset	#queries	Type
TREC-INEX	TI-KW	704	Keyword
	TI-NLQ	704	Well-formed
WebQuestions	WQ-KW	803	Keyword
	WQ-NLQ	5810	Well-formed

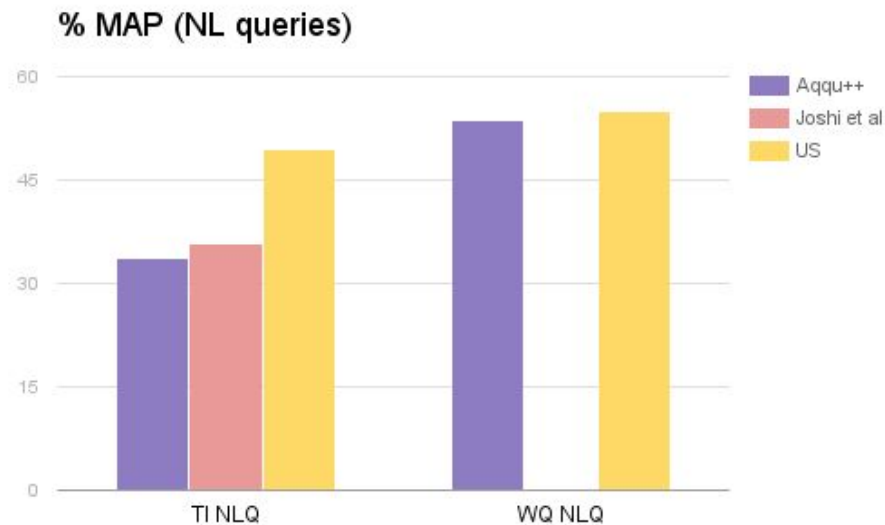
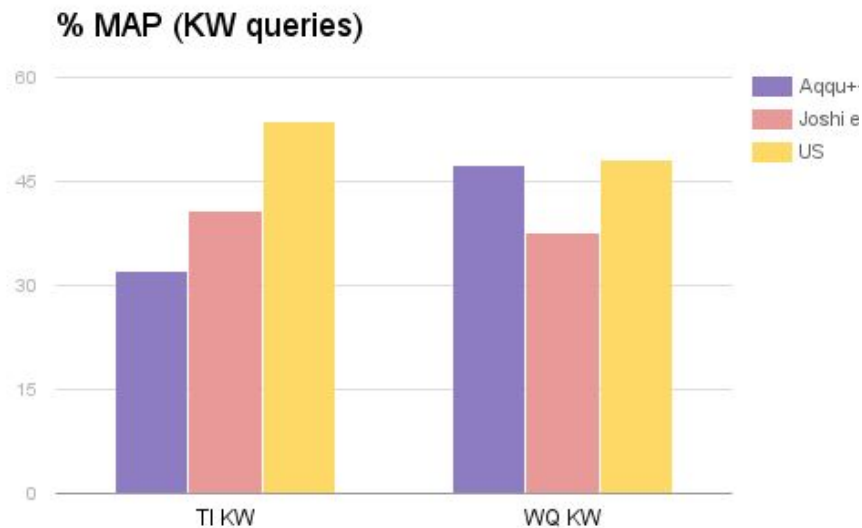
Does joint query interpretation and ranking work better than two-stage?

- Setting : Compare two-stage type-predictor + ranking with our models
- State-of-the-art target type predictor (Balog et. al.)
- Union of k types to improve recall
- Launch type-restricted query on corpus + graph



Conclusion : Upto 10% absolute gain through joint prediction and ranking

End-to-end comparison with related work



- 1 to 15% absolute MAP gain over Joshi 2014 and Aqqu++

Failure analysis

- Good
 - Queries including qualifiers such as ‘first’, ‘oldest’ (Who was the first U.S. president ever to resign?)
 - Incomplete knowledge graph (president sworn on airplane)
 - No clear query entity e_1 (Which Kennedy died first?)
- Bad
 - When to trust which information source?
 - Corpus popularity promotes incorrect entities : Jon_Stewart ranked above Madeleine_Smithberg for “creator of the daily show”
 - Failure of type/relation CNNs

Take-away

1. Entity search is a critical component of Web search, but non-trivial.
2. Knowledge graph and corpus offer complementary benefits.
3. Joint query and interpretation performs better than two-stage approach.

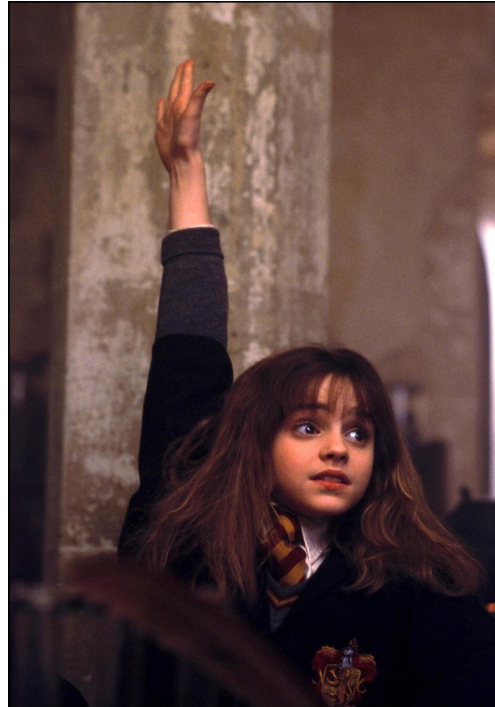
End-to-end entity search systems

1. Aqqu : http://ad-publications.informatik.uni-freiburg.de/CIKM_freebase_qa_BH_2015_materials/
2. Sempre : <http://www-nlp.stanford.edu/software/sempré/>
3. CSAW : <https://www.cse.iitb.ac.in/~soumen/doc/CSAW/>
4. Ours (work in progress)

References

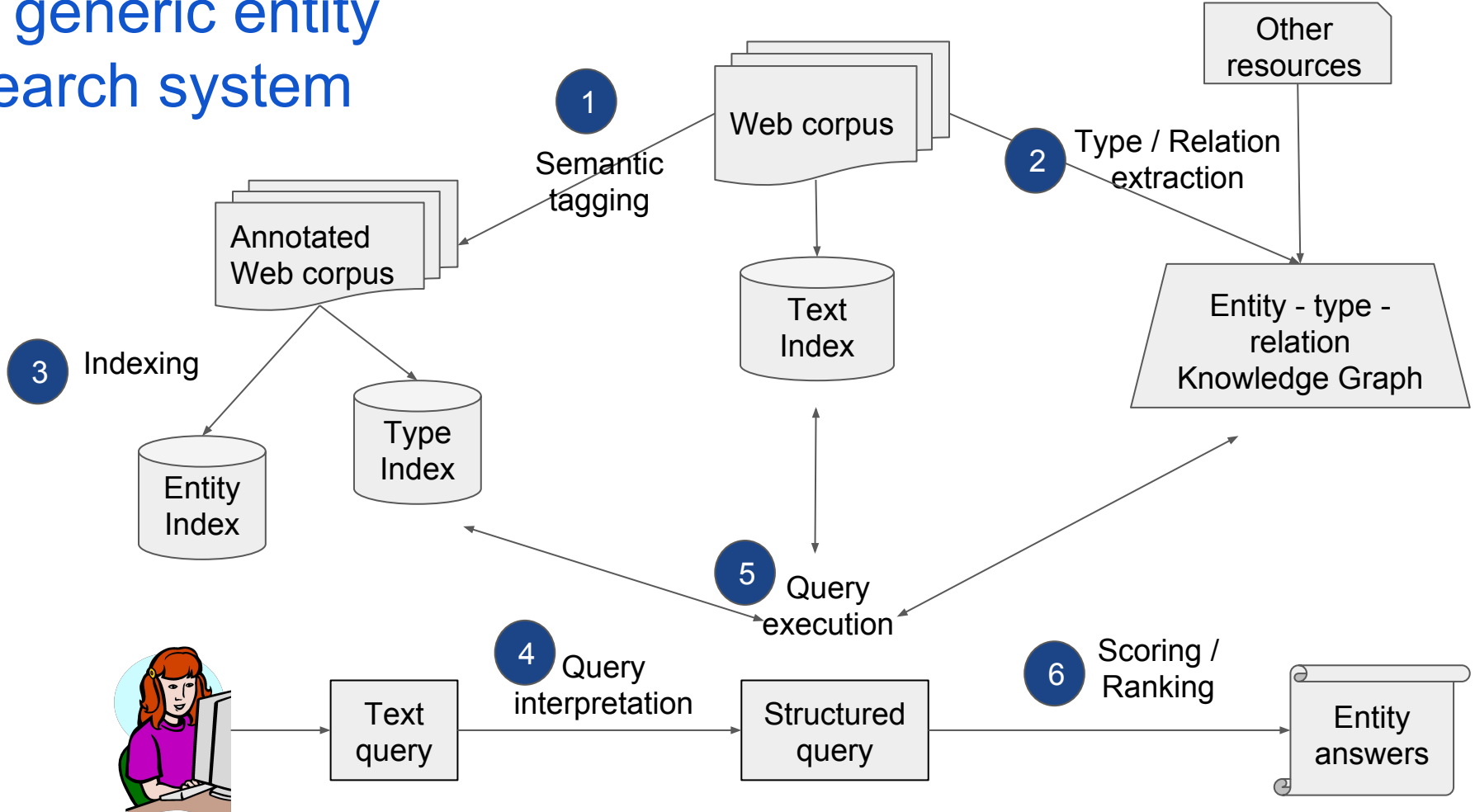
1. Features and aggregators for ranking interpreted entity search queries (Technical report)
2. Joint query (type) interpretation and ranking for entity-seeking queries (WWW 2013)
3. Corpus and knowledge graph driven query segmentation and ranking (EMNLP 2014)
4. Hannah Bast and Elmar Haussmann. More accurate question answering on freebase. (CIKM 2015).
5. Aliaksei Severyn and Alessandro Moschitti. 2015. 829 Learning to rank short text pairs with convolutional 830 deep neural networks. (SIGIR '15)
6. Antoine Bordes, Sumit Chopra, and Jason Weston. (2014). Question answering with subgraph embeddings

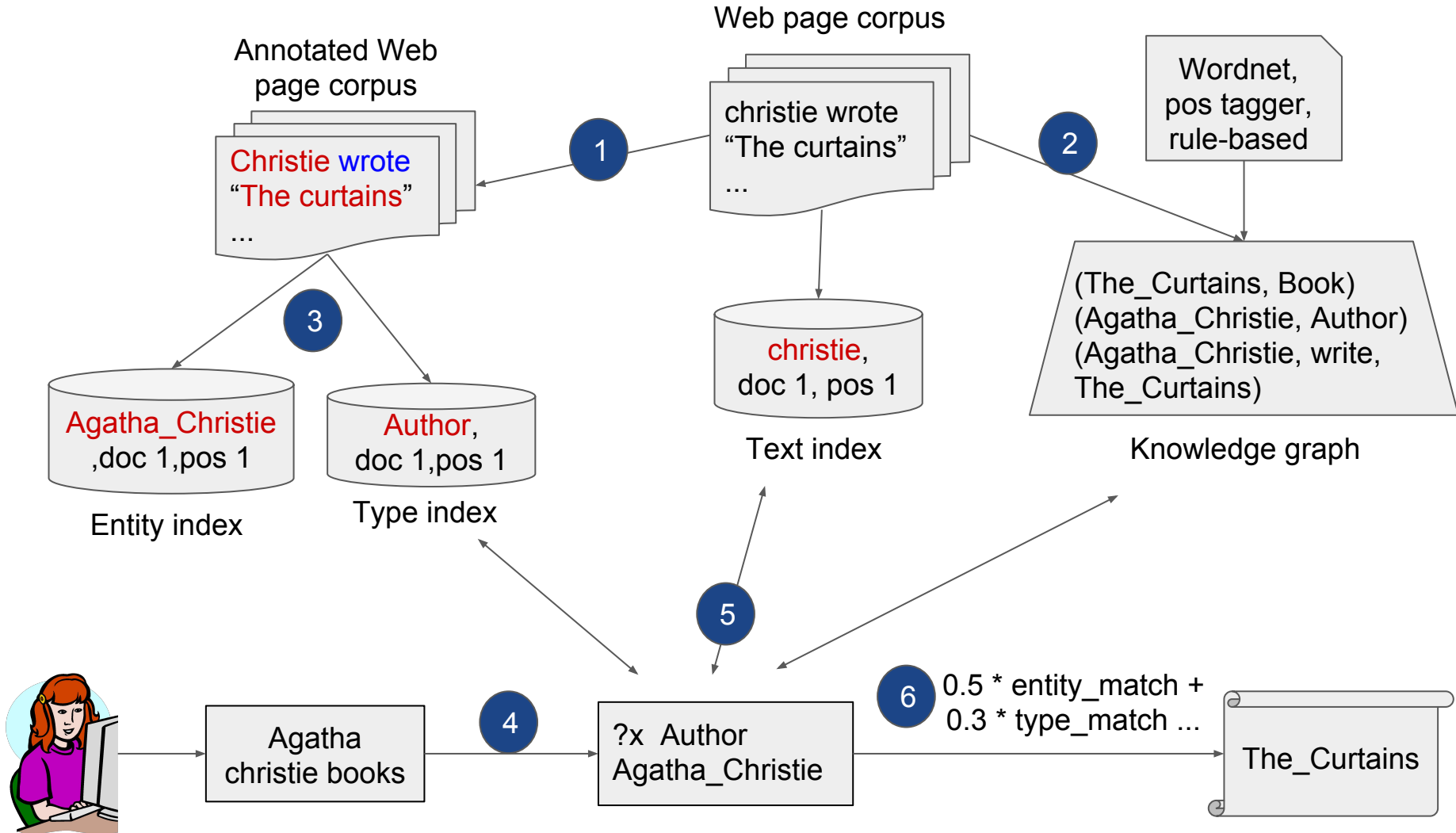
Thank you! Questions? Comments?



Extra slides

A generic entity search system





Related work (bridge query to answer gap)

1. Query understanding

- a. Feature engineering using hand-created features ([Bast2015](#)) vs. Deep neural networks ([Dong2015](#), [Stagg2015](#), Sawant2017),
- b. Take advantage of natural language syntax e.g. semantic parsers ([Berant2013](#), [Berant2014](#), [Berant2016](#)) vs. segmentation based models for keyword queries ([Sawant2013](#), [Joshi2014](#))
- c. Two-staged approach of query interpretation followed by ranking ([Berant2013](#)) vs Joint query interpretation and ranking ([Sawant2013](#), [Joshi2014](#))

Related work (bridge query to answer gap)

1. Query understanding
2. Incomplete / noisy information sources
 - a. Enrich KG facts with text descriptions ([Robust QA](#))
 - b. Add more facts to KG ([Renoun](#), [Reverb](#))
 - c. Discover new types and add to KG ([Universal schema](#))
 - d. Discover missing entity annotations in the Web corpus ([TMI](#))
 - e. Combine information from KG and corpus ([Sawant2013](#), [Joshi2014](#))
 - f. Add type annotations to Web corpus ([FIGER](#))

Related work (bridge query to answer gap)

1. Query understanding
2. Incomplete / noisy information sources
3. Getting to the perfect answer
 - a. Pose it as a “KG query prediction problem” : Returns an answer set after KG query execution.
Know when you don't know the answer
 - i. [Berant2013](#), [Berant2014](#), [Dong2015](#), [Stagg2015](#), [Berant2016](#), ...
 - ii. Problem : no order between answer set, need ideal interpretation as labeled data
 - b. Pose the problem as a “entity ranking problem” : allow ordering between answer entities.
 - i. [Sawant2013](#), [Joshi2014](#),
 - ii. Problem : will always have an answer, even for invalid questions.

Tools for annotating and indexing corpus and graph

1. Indexing : Lucene (<http://lucene.apache.org/core/>), mg4j (<http://mg4j.di.unimi.it/>)
2. Tagging text with wikipedia entities : tagme (<https://tagme.d4science.org/tagme/>), wikipedia miner (<https://sourceforge.net/projects/wikipedia-miner/>)
3. Querying an existing graph : http://ad-publications.informatik.uni-freiburg.de/CIKM_freebase_qa_BH_2015.materials/ This software queries a graph index loaded in virtuoso and performs question answering .

Graphical model toolkit

Keving Murphy has a comprehensive list --

<https://www.cs.ubc.ca/~murphyk/Software/bnsoft.html>

Datasets / querysets

1. ClueWeb12 and ClueWeb09 Web corpus --
 - a. <http://lemurproject.org/clueweb12/>
 - b. <http://lemurproject.org/clueweb09/>
2. Freebase entity annotations for the above --
 - a. <http://lemurproject.org/clueweb12/FACC1/>,
 - b. <http://lemurproject.org/clueweb09/FACC1/>
3. Question-answer querysets --
 - a. <https://worksheets.codalab.org/worksheets/0xba659fe363cb46e7a505c5b6a774dc8a/>
 - b. <http://bit.ly/1OCKbVW>
4. Linked Open Data : Haven't used this myself, but recommended by others --
<http://linkeddata.org/home>