Using Knowledge Graphs for Text Retrieval

github.com/laura-dietz/tutorial-utilizing-kg

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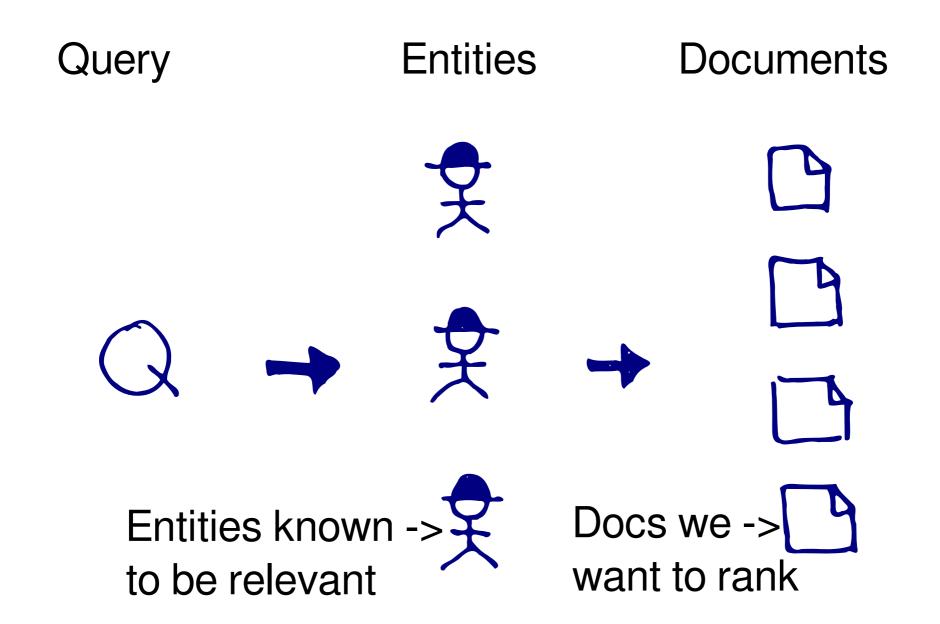
Wayne State University

Edgar Meij

Bloomberg L.P.

Please take the survey!

Document Retrieval with Entities



Outline

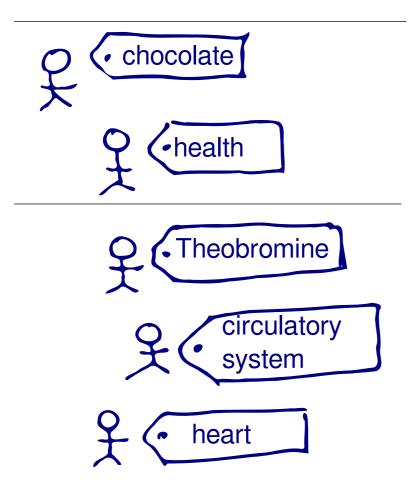
- 1. Matching entities in documents
- 2. Find relevant entities
- 3. Graph expansion
- 4. Entity types
- 5. Combination of multiple sources
- 6. Machine learning
- 7. Entity aspects

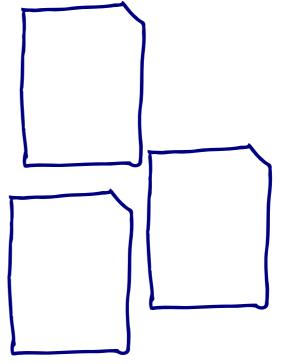
Different Queries - Different Entities

Query	EU UK relations	dark chocolate health benefits
Query	S EU S UK	chocolate health
Latent entities	• Brexit • Theresa May	Theobromine circulatory system heart
[Hasibi ICTIR16]	Named Entities	Concepts

Matching Entities in Documents

dark chocolate health benefits

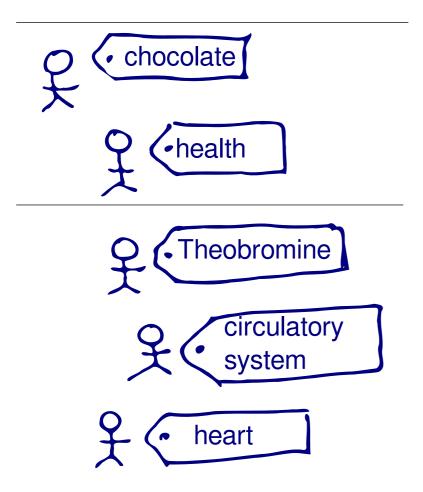




Which doc should be promoted in the ranking?

Matching Entities in Documents by Name

dark chocolate health benefits

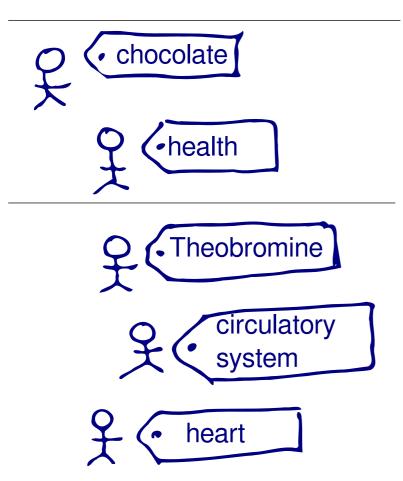


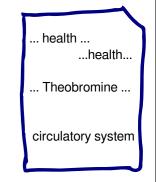
... health ...
...health...
... Theobromine ...
... dark chocolate ...
circulatory system

Should this doc be promoted in the ranking?

Matching Entities in Documents by Name

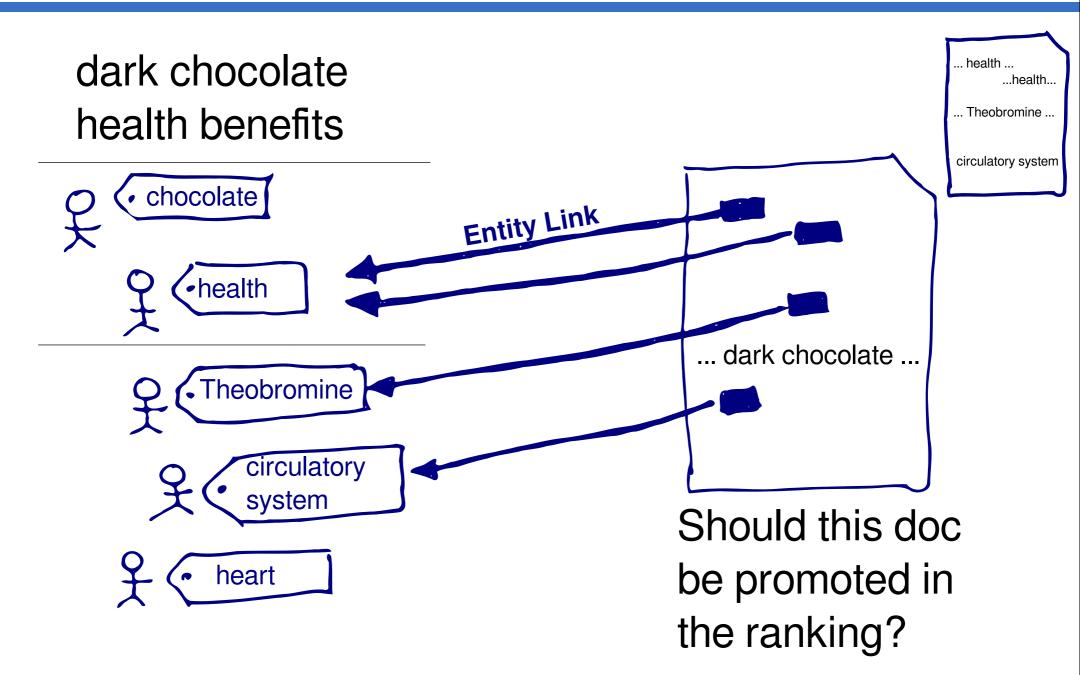
dark chocolate health benefits





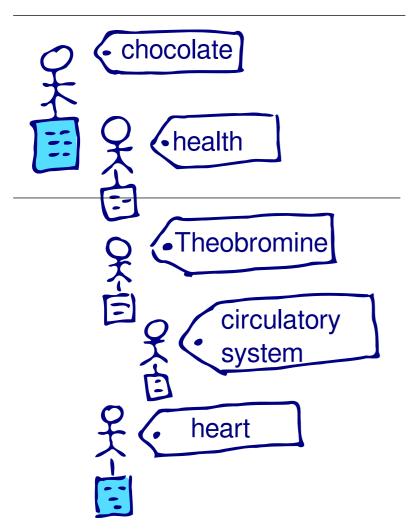
Should this doc be promoted in the ranking?

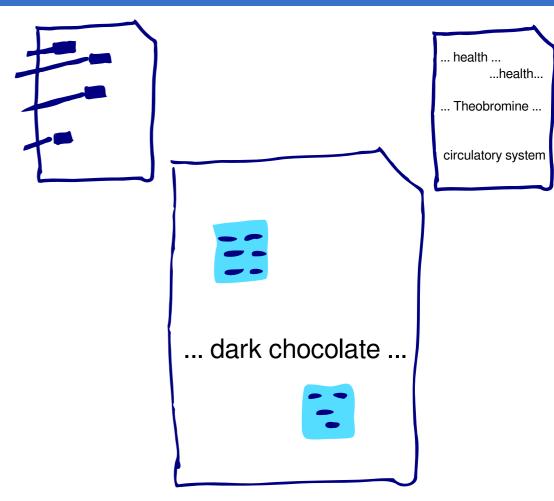
Matching Entities in Documents by Entity Links



Matching Entities in Documents by Article Terms

dark chocolate health benefits

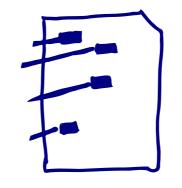


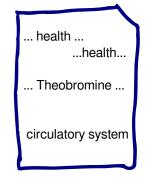


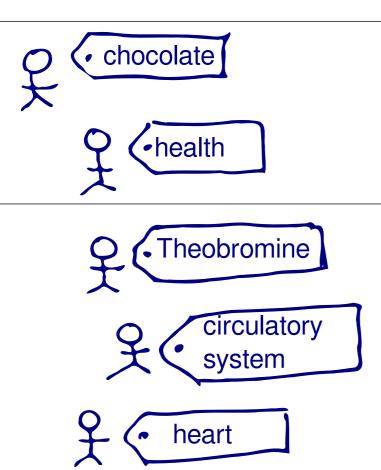
Should this doc be promoted in the ranking?

Matching Entities in Documents by Entity Links

dark chocolate health benefits

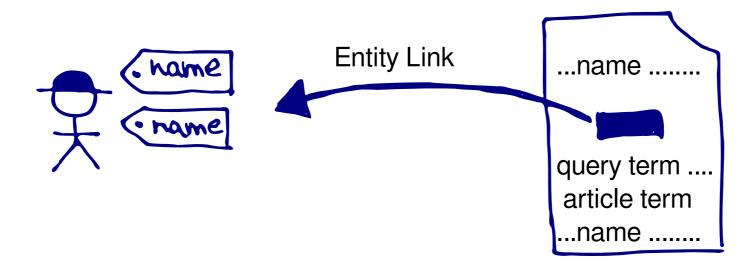






Should this doc be promoted in the ranking?

Using Entities as a Vocabulary of Concepts



$$score(\square) = \lambda_1 query terms +$$

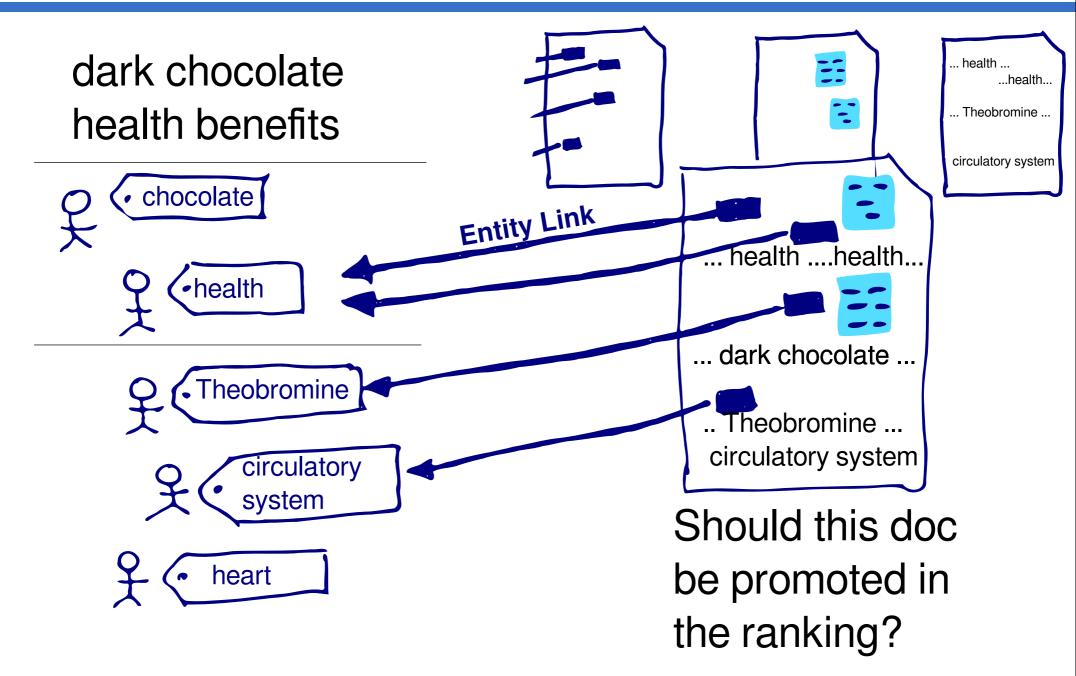
 λ_2 names +

use your favorite retrieval model here!

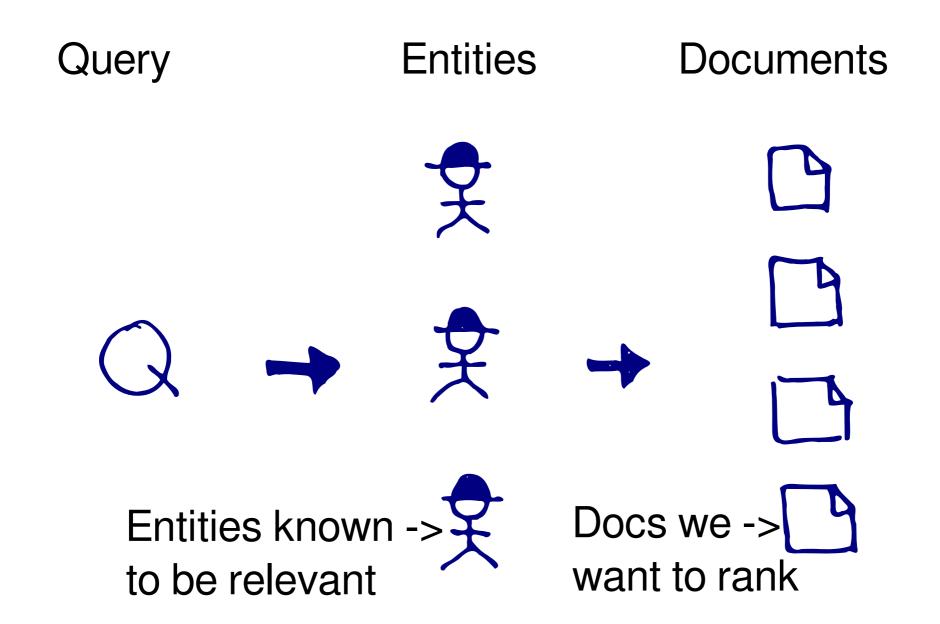
$$\lambda_3$$
entity links +

$$\lambda_4$$
article terms + ...

Combine All Names, Links, Terms



Document Retrieval with Entities



How to Find Relevant Entities?

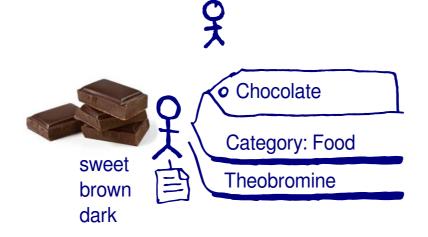
Query	EU UK relations	dark chocolate health benefits
Query entities	g EU g UK	chocolate health
Latent entities	Brexit Theresa May	Theobromine circulatory system heart
	Named Entities	Concepts

Find Relevant Entities

- 1. Matching entities in documents
- 2. Find relevant entities
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- 5. Combination of multiple sources
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Query Entities through Entity Linking

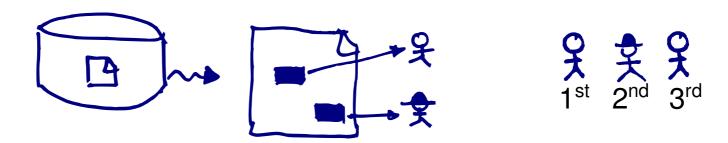
Query: dark chocolate health benefits



Latent Entities through Pseudo-Relev. Feedback

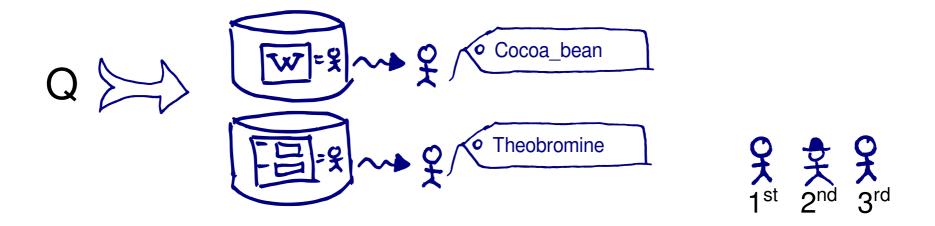
- 1. Retrieve preliminary documents
- 2. Entity link documents
- 3. Derive distribution over \$\foat{3}\$ (bag of entities) (see Relevance Model / RM3)

[Dalton SIGIR14, Liu IRJ15]



Latent Entities through Retrieval (e.g., Part 3)

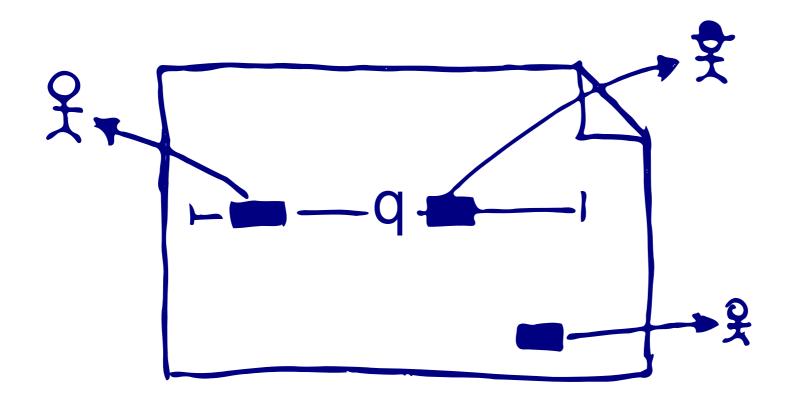
Retrieve entities from knowledge base to obtain ranking of entities E (with score)



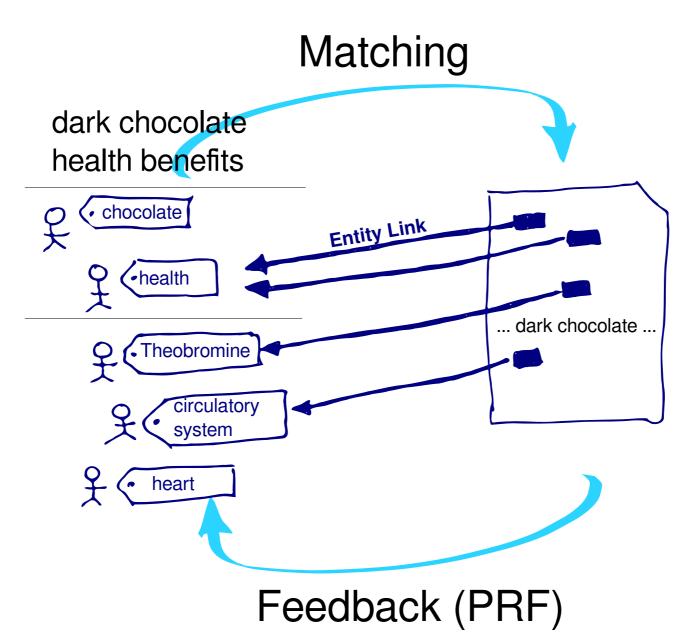
Latent Entities through Proximity to Query Words

Using distance between entity mentions and query words **q** as a measure for relevance.

[Petkova & Croft, 07]



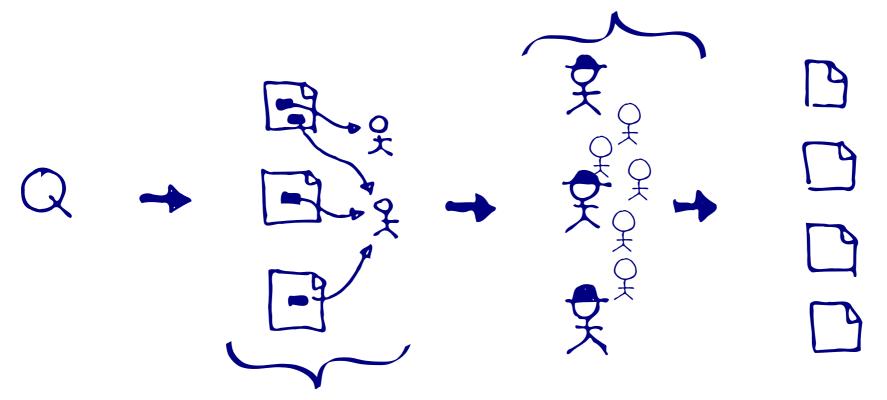
PRF is Inverse of Matching Entity Links



WSDM 2017 Tutorial on Utilizing KGs in Text-centric IR - github.com/laura-dietz/tutorial-utilizing-kg

Entity Expansion for Document Retrieval

Query entities + Object retrieval (Part 3)

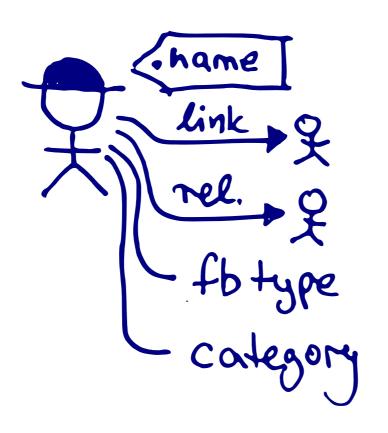


Pseudo-relevance feedback (RM3)

Document = bag of entity links (instead of terms)

Using More from the Knowledge Graph

So far we used names and entity links. But KGs have so much more information!



Names

Links and relations

Different taxonomic type systems

How can we make use of it?

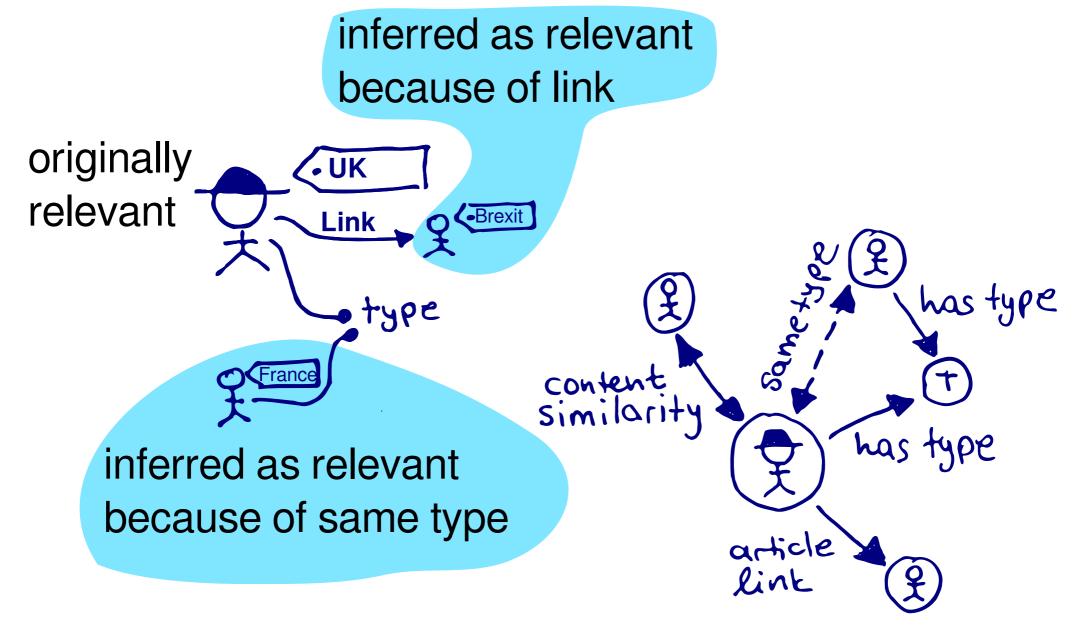
Graph Expansion

- 1. Matching entities in documents
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- 7. Entity aspects

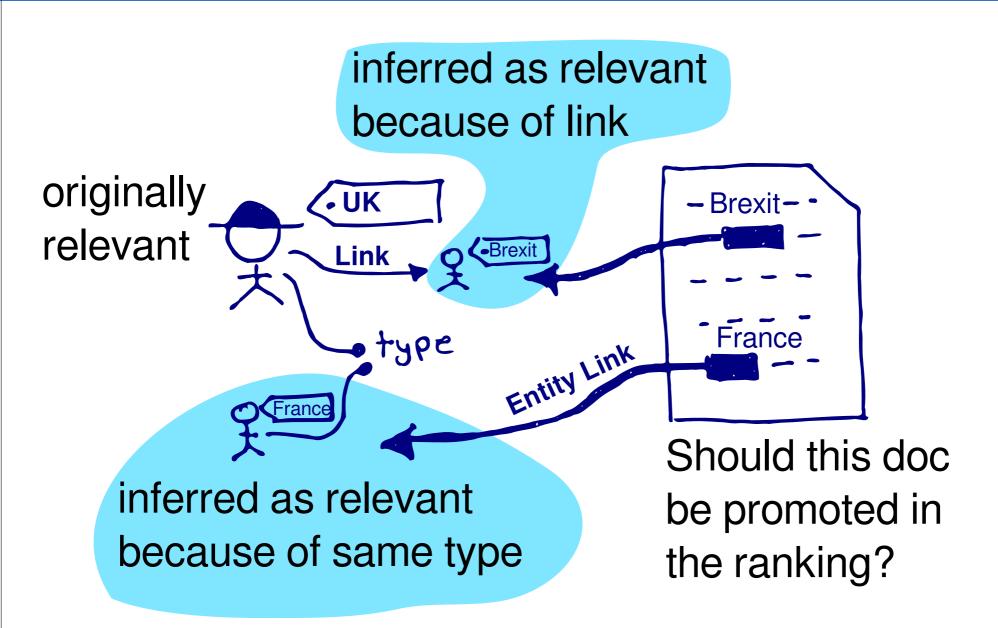
Using Relations and Types with Entity Links

inferred as relevant because of link originally • UK relevant has type content Similarity article

Using Relations and Types with Entity Links



Using Relations and Types with Entity Links

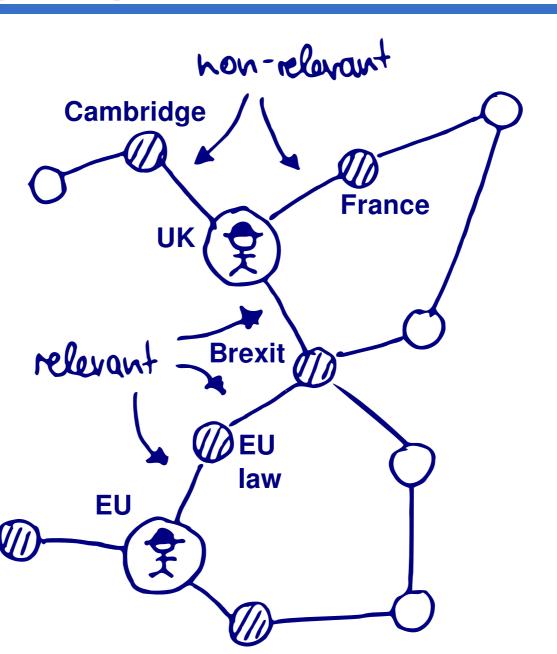


General Approach: Graph Expansion

So many connections in a knowledge graph

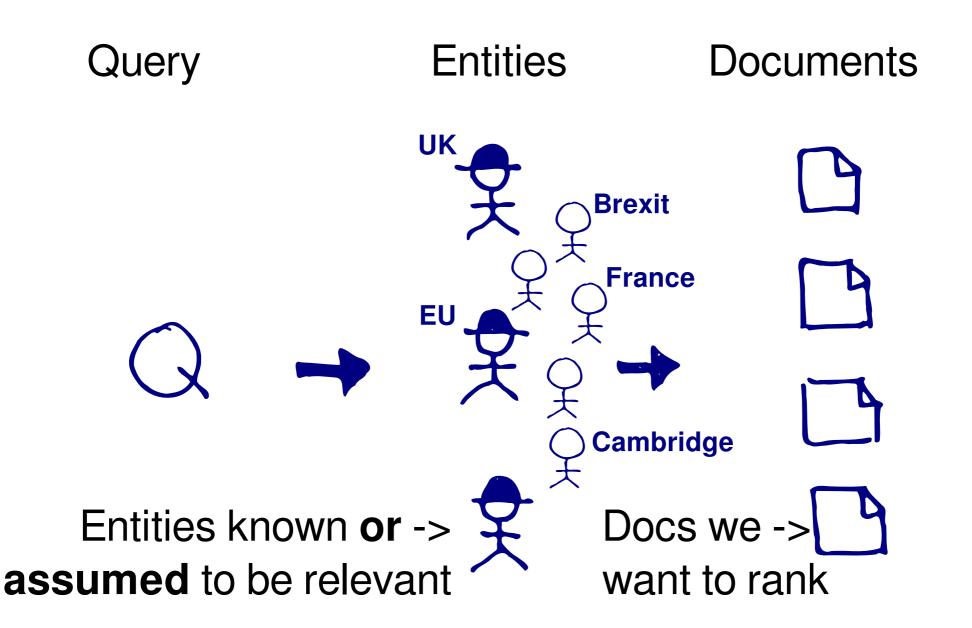
- Some are relevant!
- But many are only relevant in a certain (other?) context.

Expanding with non-relevant entities leads to low precision rankings.



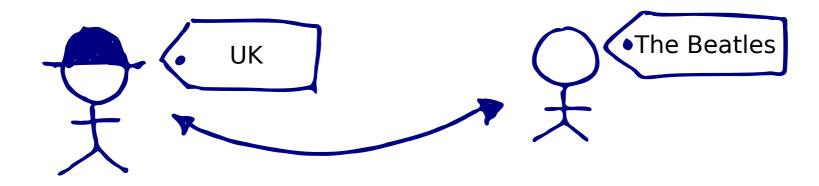
Theresa May

Document Retrieval with (More) Entities



KG expansion: A Potential Issue

Example query: EU UK relations Consider:



Correct connection, but:

The connection is not relevant in the context of "UK" as in "EU relations".

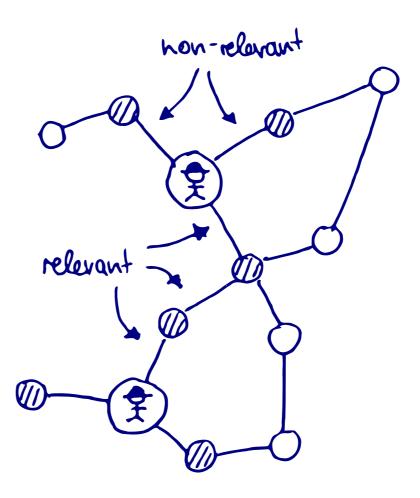
If we promote docs because they talk about The Beatles, we ruin an okay ranking.

Big Question

How to infer which other connected entities / nodes are relevant for the information need Q?

...and therefore safe for expansion?

Maybe entities in between query entities?

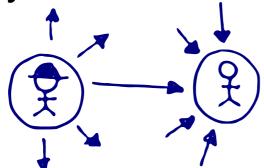


Weight Edges in the Knowledge Graph

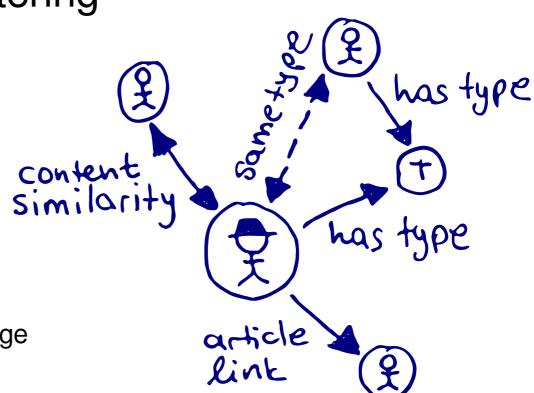
Using seed entity nodes and...

- Graph walks: PageRank / HITS, Shortest Paths
- Different edge types
- Edge weighting + Clustering

Exclusivity-based Entity Relatedness



fewer in/out links => more important edge [Hulpus WSDM13, Weiland ICTIR16]



Boston et al 2013: Wikimantic: Toward effective ...

Weight entities by:

M: How well Es article content matches the query

MR: How often **E** is linked by others (PageRank)

Method	F1 on TREC QA
M	76.92
M+d*MR	79.47

d=0.0001

Entity Aspects and the Graph Structure

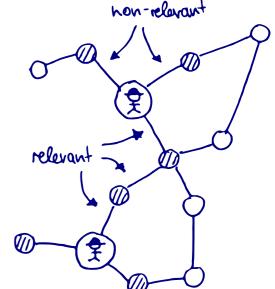
Edge weights and random walks help identify

popular connections. BUT...



An **open issue** remains:

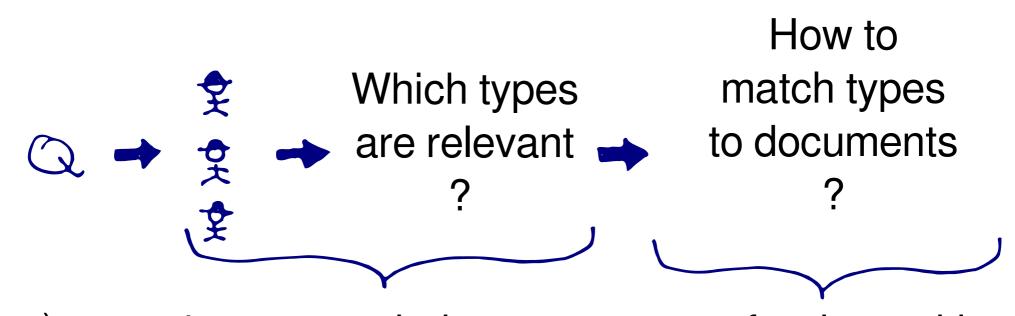
- Entities have multiple aspects
- Graph structure = overlay of all aspects
- How to identify:
 - 1. Which aspects of E are relevant for Q?
 - 2. How to select edges that are relevant?



Using Types and Categories

- 1. Matching entities in documents
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Entity Types Inferred through Entity Links



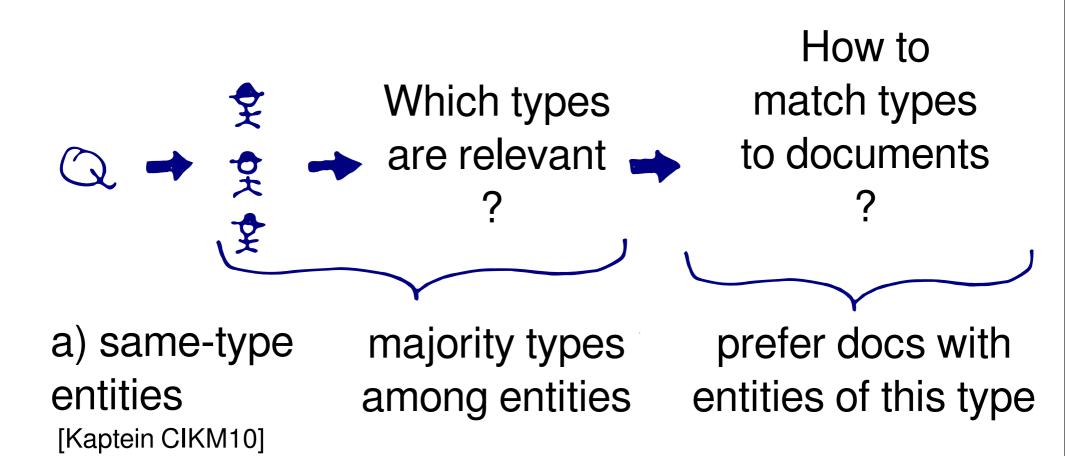
a) same-type entities
[Kaptein CIKM10]

majority types among entities

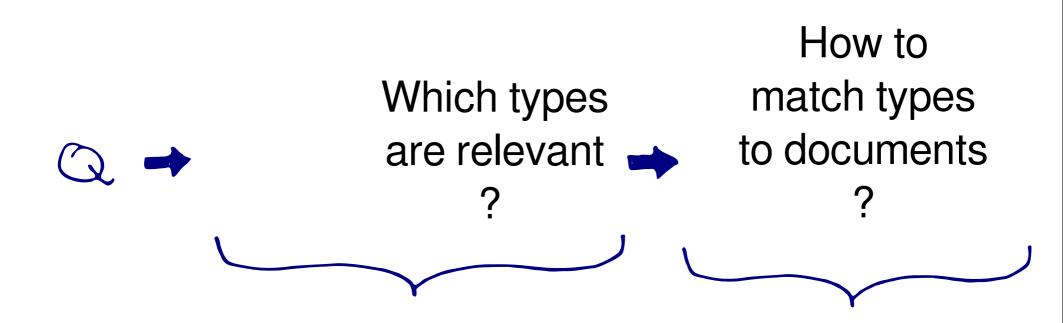
prefer docs with entities of this type

Method	MAP on INEX
Full Text	0.03
Link	0.09
Type+Link	0.13

Entity Types (inferred through entities)



Entity Types through Text Classification



b) term classifier [Xiong CIKM15] classify query terms with naive Bayes

classify documents with naive Bayes

Combination of Multiple Sources

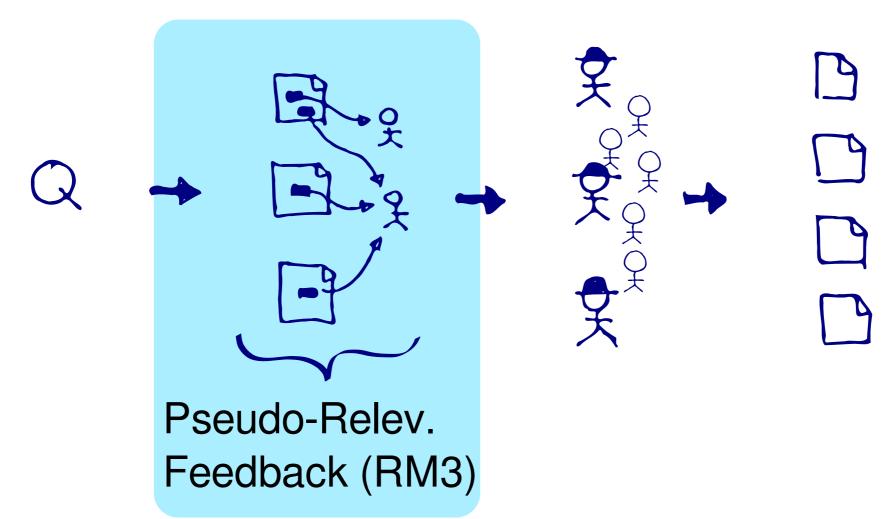
- 1. Matching entities in documents
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Complementary Sources

Typical approaches:

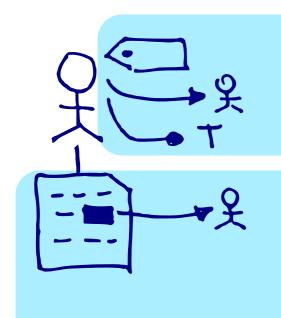
- 1) Use **complementary sources**: graph, article text, relevance feedback, type info
- 2) Use machine learning: Train weights for sources on test collection
- 3) Model relevant entity aspects

Source: Relevance Feedback with Entity Links



Document = bag of Entity Links
Proximity of query and Entity Links
[Petkova 2007, Dalton SIGIR14, Liu IRJ15]

Source: Object AND Article Content Retrieval



Entities as attribute-structured objects: Object retrieval (see Part 3 & [Hasibi ICTIR16])

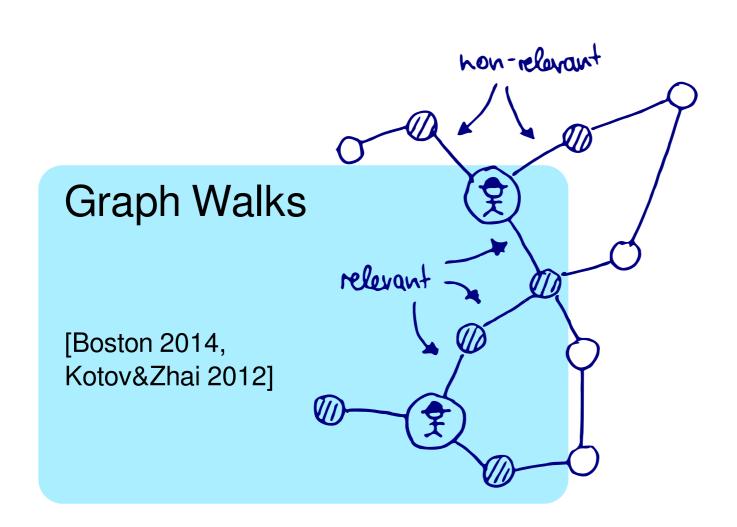
Entities as text:

Each article represents an Entity
Retrieve articles with keyword query Q

=> ranking / score of Entity

[Xiong ICTIR15, Dalton SIGIR14]

Source: Graph Structure and Walks



Machine Learning

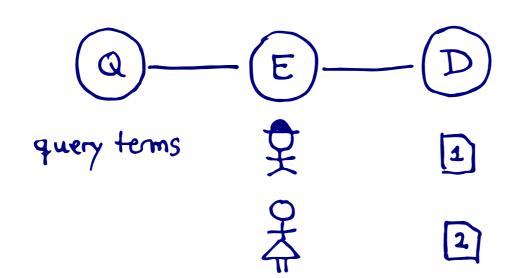
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Machine Learning / Probabilistic Models

Three approaches based on similar ideas:

- Dalton: Entity Query Feature Expansion
- Xiong: EsdRank
- Liu: Latent Entity Space

Probabilistic model with random variables Q,E,D.

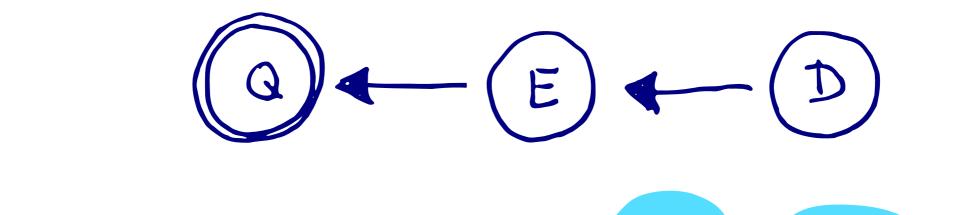


An edge represents a measure of compatability or similarity.

One possible value for E -> po

<- One possible value for D ground truth available (TREC)</p>

Latent Entity Space [Liu IRJ15]

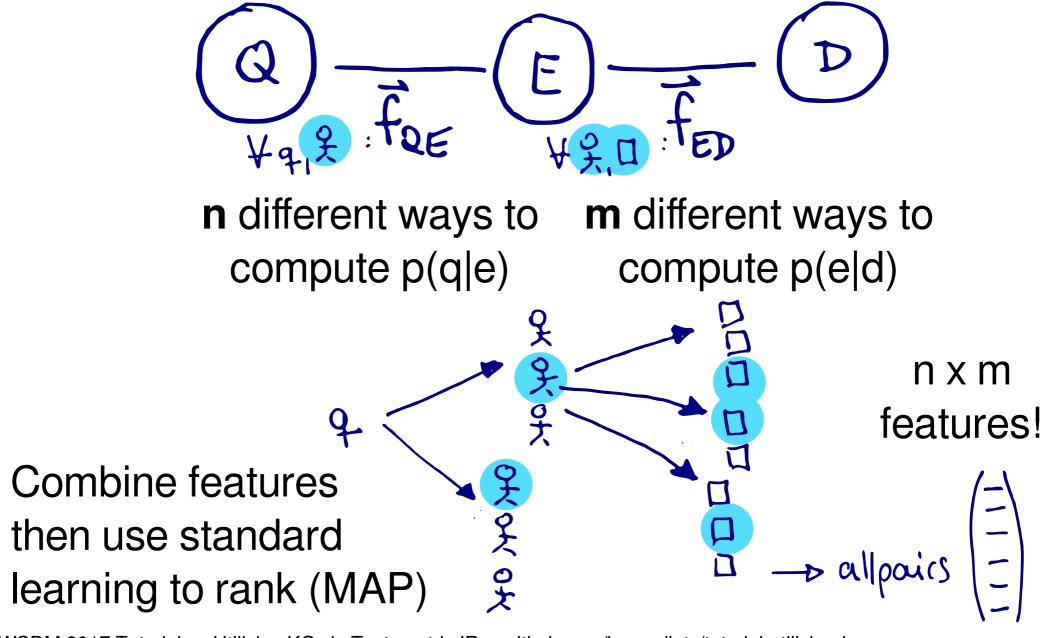


$$p(q|D=d,R=1) = \sum_{e \in \mathcal{E}} p(q|e) \cdot p(e|d)$$

similarity of similarity of LM(q) and LM(e) LM(e) and LM(d)

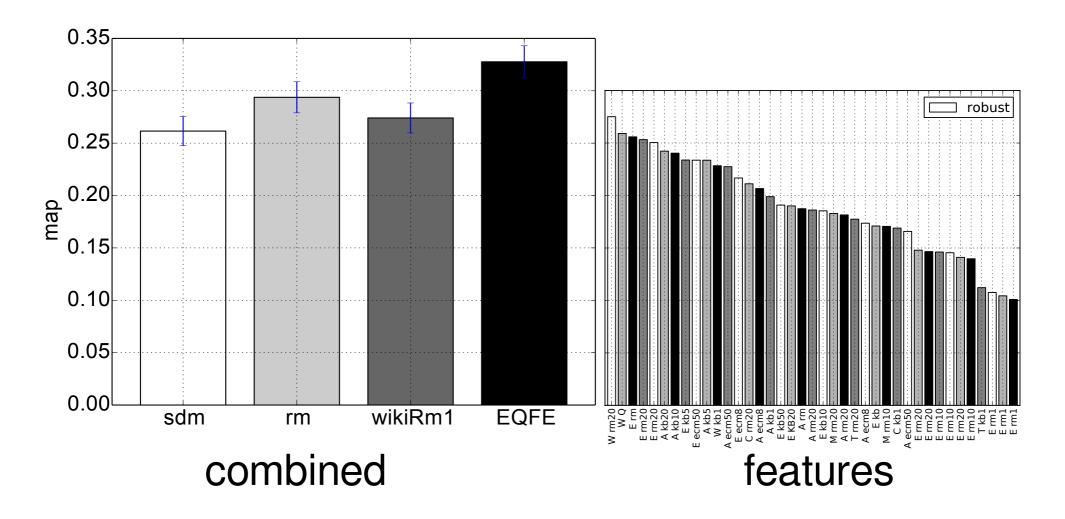
Wide range of experiments on which similarity measure / data source combination works best.

Entity Query Feature Expansion [Dalton SIGIR14]



Entity Query Feature Expansion [Dalton SIGIR14]

Results on Robust04 ad hoc document retrieval.

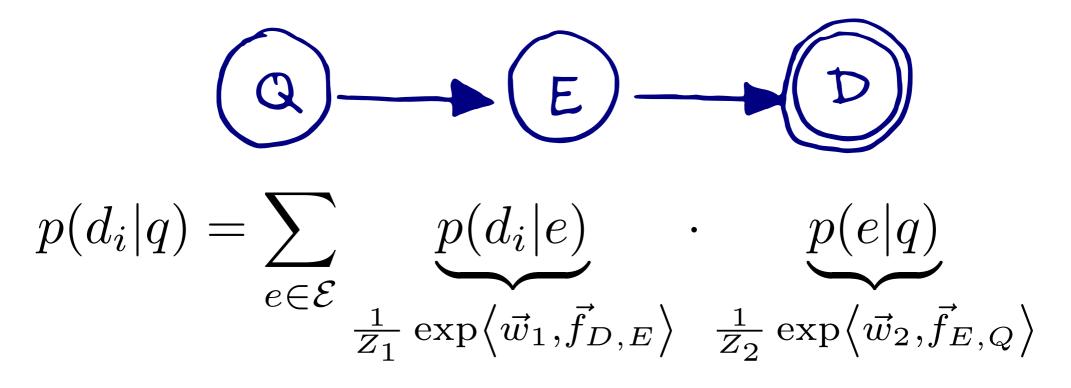


Relation to Query / Latent Concept Expansion

Various vocabularies, but all represented by sets

$$score(\square) = \lambda_1 ext{query terms} +$$
 $\lambda_2 ext{name} +$
 $\lambda_3 ext{entity link} +$
 $\lambda_4 ext{article terms} + \dots$

EsdRank [Xiong CIKM15]



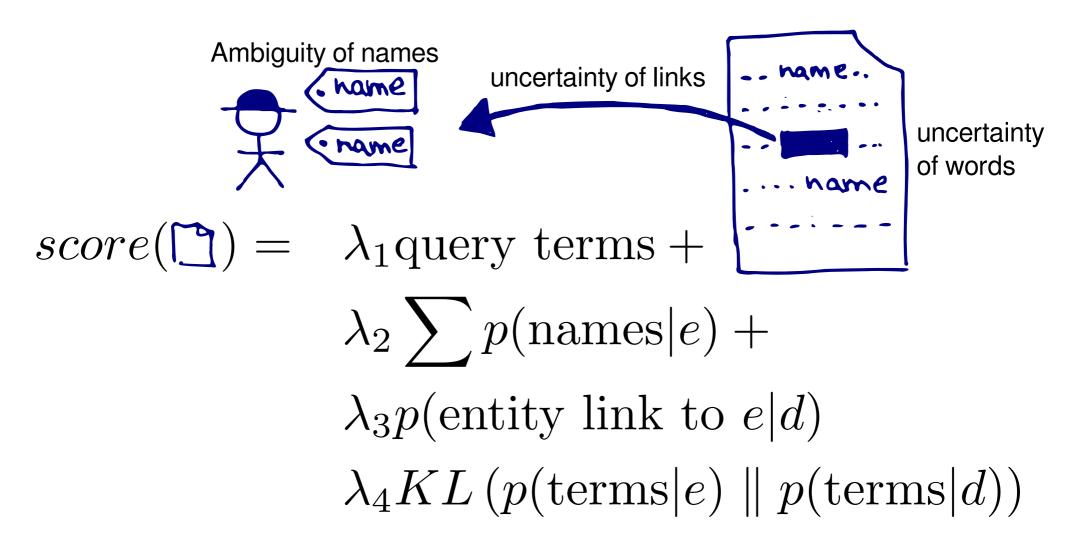
Discriminative probabilistic model based on Generalized linear models + EM Algorithm for learning weights w1, w2.

Only n+m features! But needs custom learning code.

Query Expansion with Uncertainties

Taking uncertainty and confidences into account.

[Raviv SIGIR16, Liu IRJ15]



Entity Aspects

- 1. Matching entities in documents
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Entity Aspects

Danger: An entity is relevant, but: only because of one aspect => many non-relevant aspects of relevant entities.

Example aspects about UK:

- still a member of the European Union
- is a constitutional monarchy
- the Raspberry Pi was invented in the UK
- there are many great UK bands

Depending on query, some are relevant, some not.

How to Represent Entity Aspects?

As terms? UK bands

brexit

As types?

As is-a?

Related entities?

Relations?

UK member of "European Union"

UK as a European country

UK Theresa_May

Theresa_May

prime_minister_of UK

Language Model

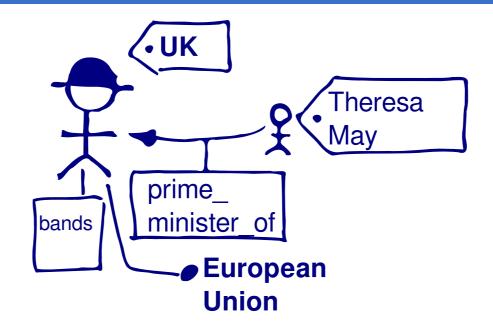
p(brexit)=0.4

p(leave)=0.25

p(immigration)=0.10

[Reinanda SIGIR15, Liu IRJ15, Prasojo CIKM15]

Entity Aspects: Using KG...

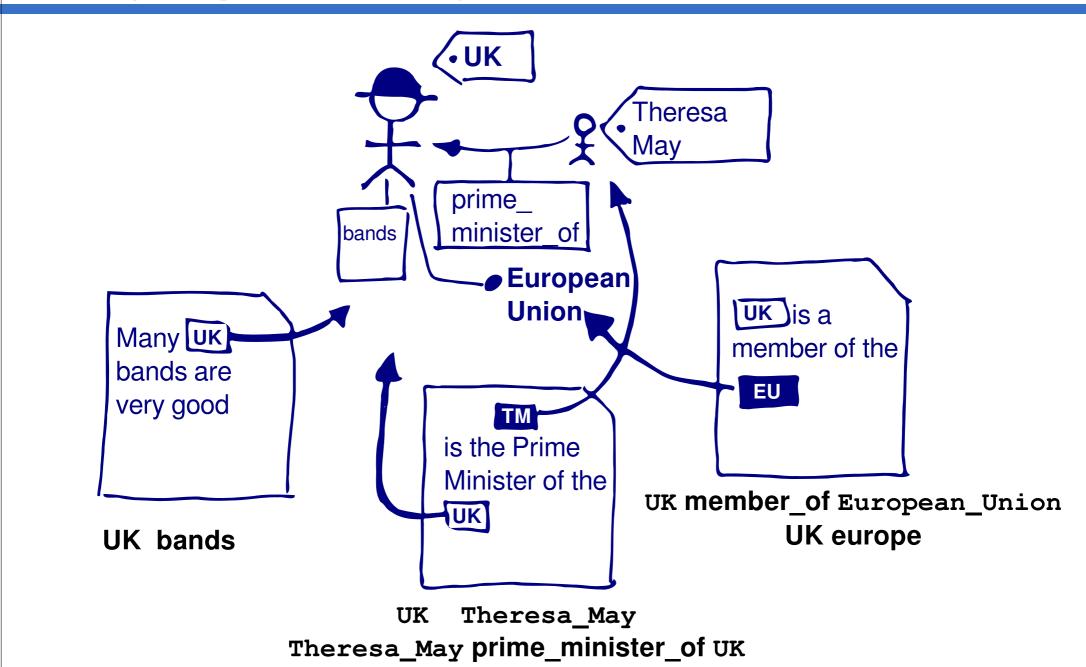


UK bands

UK member_of European Union UK europe

UK Theresa_May
Theresa_May prime_minister_of UK

Entity Aspects: Using KG and Text

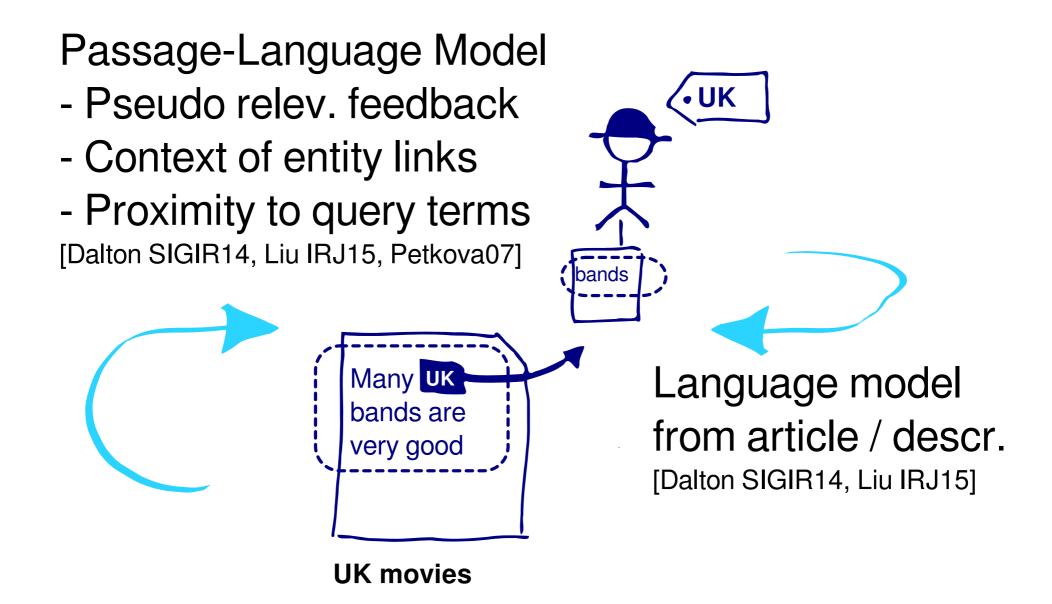


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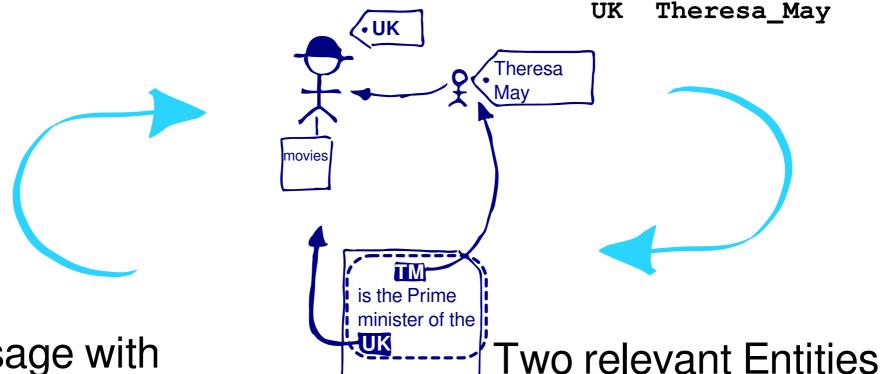
Entity Aspects: Infer Relevance, Match, Extract

1) Relevance: Which aspects are relevant? • UK Theresa 2) Match: prime minister of bands How to match in text? European UK is a Union Many UK member of the bands are EU pseudo very good is the Prime relevance inverse tasks Minister of the feedback UK member of European Union **UK** bands **UK** europe Theresa May 3) Extract: Theresa May prime minister of UK How to extract new aspects? (KB population)

Entity Aspects as Terms



Entity Aspects through Co-mentioned Entities



Passage with

- link to entity

- matching query terms

⇒ other entities relevant?

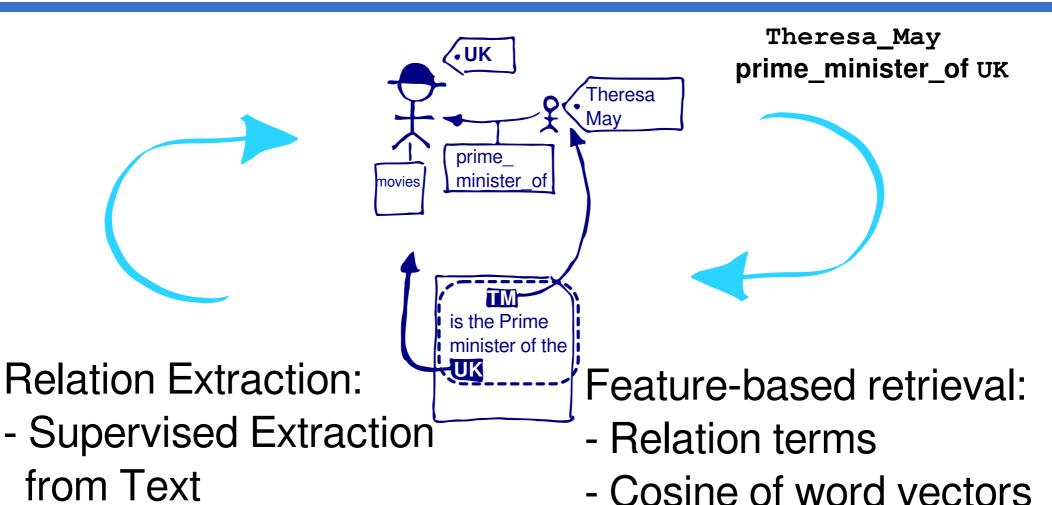
⇒ Promote documents that mention both

which are linked in KG

Infer & Extract Aspects

Match Aspects

Entity Aspects through Relations (Triples)



Infer & Extract Aspects

[Schuhmacher ECIR16]

Match Aspects

[Voskarides ACL15]

Extract/Infer relevant Entity Aspects?

- From collocations in pseudo-relevant documents
- From passages surrounding entity links
- Through graph analysis
- Frequency/proximity of entities in context
- Extracting a language model

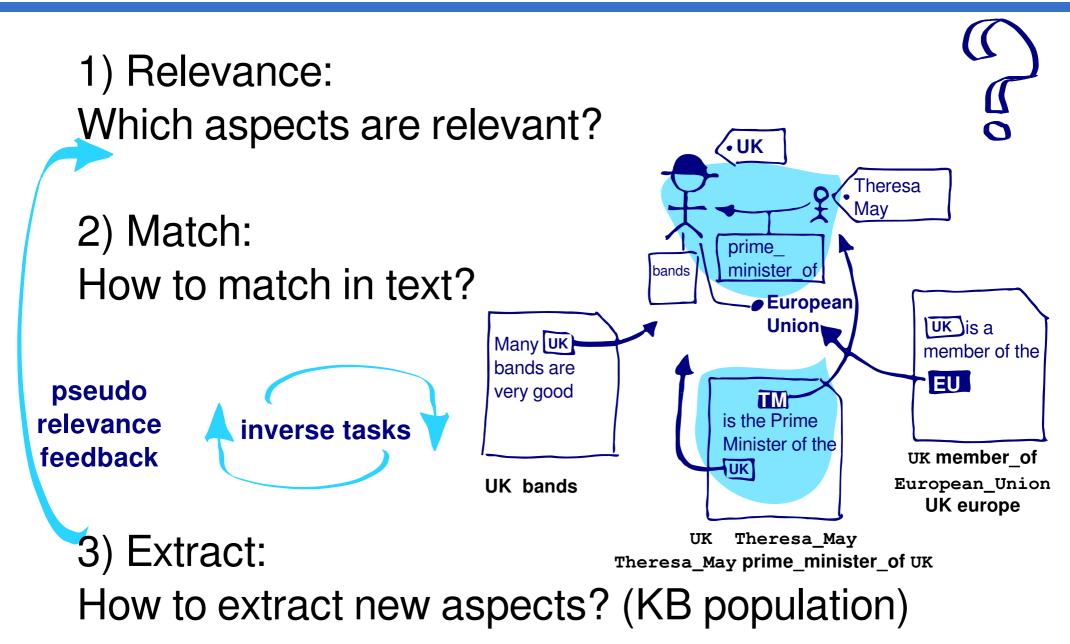
For your reference

Retrieving/Matching relevant Entity Aspects?

- Terms and entity links in documents
- Co-occurrence (AND versus OR)
- Proximity
- Frequency
- Probability under a language model
- Classification (e.g., Naive Bayes for types)
- Information extraction and matching

For your reference

Open Issue: Entity Aspects for Document Ranking



Summary (Part 4)

- 1. Matching entities in documents
- 2. Find relevant entities
- 3. Graph expansion
- 4. Entity types
- 5. Combination of multiple sources
- 6. Machine learning
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