Entity Representation and Retrieval

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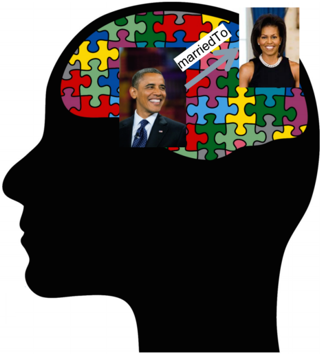
Knowledge Graphs

- A way to represent human knowledge in machine readable way
- *Subjects* correspond to entities designated by an identifier (URI `http://dbpedia.org/page/Barack_Obama` in case of DBpedia)
- Entities are connected with other entities, literals or scalars by relations or *predicates* (e.g. *hasGenre*, *knownFor*, *marriedTo*, *isPCmemberOf* etc.)
- Each triple represents a simple fact (e.g. <`http://dbpedia.org/page/Barack_Obama`, marriedTo, `http://dbpedia.org/page/Michelle_Obama`>)
- Many SPO triples → *knowledge graph*



Entity Retrieval from Knowledge Graph(s) (ERKG) (1)

- Users often search for specific material or abstract entities (objects), such as people, products or locations, instead of documents that merely mention them
- Answers are names of entities (or entity representations) rather than articles discussing them
- Users are willing to express their information need more elaborately than with a few keywords [Balog et al. 2008]
- Knowledge graphs are perfectly suited for addressing these information needs

Entity Retrieval from Knowledge Graph(s) (ERKG) (2)

- Assumes *keyword* queries (structured queries are studied more in the DB community)
- Different from entity linking, where the goal is to identify which entities a searcher refers to in her query (part 1)
- Different from ad hoc entity retrieval, which is focused on retrieving entities embedded in documents and using knowledge bases to improve document retrieval (part 3)
- Unique IR problem: there is *no notion of a document*
- Challenging IR problem: knowledge graphs are designed for graph-pattern queries and performing automated reasoning

Typical ERKG tasks

- **Entity Search**: simple queries aimed at finding a particular entity or an entity which is an attribute of another entity
    - *"Ben Franklin"*
    - *"Einstein Relativity theory"*
    - *"England football player highest paid"*
- **List Search**: descriptive queries with several relevant entities
    - *"US presidents since 1960"*
    - *"animals lay eggs mammals"*
    - *"Formula 1 drivers that won the Monaco Grand Prix"*
- **Question Answering**: queries are questions in natural language
    - *"Who founded Intel?"*
    - *"For which label did Elvis record his first album?"*

Research challenges in ERKG

ERKG requires accurate interpretation of unstructured textual queries and matching them with structured entity semantics:

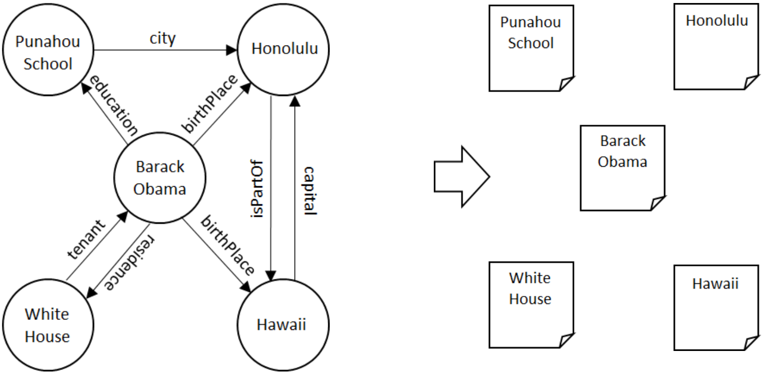
1. How to design entity representations that capture the semantics of entity properties/relations and are effective for entity retrieval?
2. How to develop accurate and efficient entity retrieval models?

Outline

- Entity representation
- Entity retrieval
- Entity ranking
- Entities and documents

From Entity Graph to Entity Documents

Build a textual representation (i.e. “document”) for each entity by considering all triples, where it stands as a subject (or object)

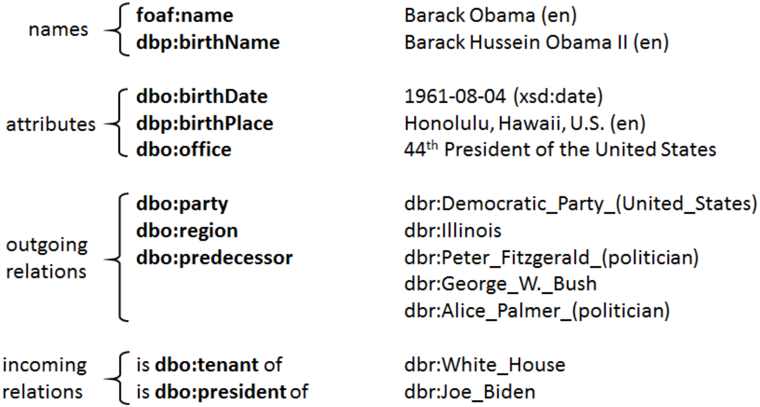


Structured Entity Documents (1)

- Entity descriptions are naturally structured, entities can be represented as fielded documents
- In the simplest case, each predicate corresponds to one document field
- However, there are infinitely many predicates → optimization of field importance weights is computationally intractable

Structured Entity Documents (2)

Predicate folding: group predicates together into a small set of predefined categories → entity documents with smaller number of fields



names	**foaf:name**	Barack Obama (en)
	dbp:birthName	Barack Hussein Obama II (en)
attributes	**dbo:birthDate**	1961-08-04 (xsd:date)
	dbp:birthPlace	Honolulu, Hawaii, U.S. (en)
	dbo:office	44th President of the United States
outgoing relations	**dbo:party**	dbr:Democratic_Party_(United_States)
	dbo:region	dbr:Illinois
	dbo:predecessor	dbr:Peter_Fitzgerald_(politician)
		dbr:George_W._Bush
		dbr:Alice_Palmer_(politician)
incoming relations	is **dbo:tenant** of	dbr:White_House
	is **dbo:president** of	dbr:Joe_Biden

Predicate Folding

- Grouping according to type (attributes, incoming/outgoing links)[Pérez-Agüera et al. 2010]
- Grouping according to importance (determined based on predicate popularity)[Blanco et al. 2010]

2-field Entity Document

[Neumayer, Balog et al., ECIR'12]

Each entity is represented as a two-field document:

title

object values belonging to predicates ending with "name", "label" or "title"

content

object values for 1000 most frequent predicates concatenated together into a flat text representation

3-field Entity Document

[Zhiltsov and Agichtein, CIKM'13]

Each entity is represented as a three-field document:

names
: literals of `foaf:name`, `rdfs:label` predicates along with tokens extracted from entity URIs

attributes
: literals of all other predicates

outgoing links
: names of entities in the object position

5-field Entity Document

[Zhiltsov, Kotov et al., SIGIR'15]

Each entity is represented as a five-field document:

names
: conventional names of entities, such as the name of a person or the name of an organization

attributes
: all entity properties, other than names

categories
: classes or groups, to which the entity has been assigned

similar entity names
: names of the entities that are very similar or identical to a given entity

related entity names
: names of entities in the object position

5-field Entity Document Example

Entity document for the DBpedia entity *Barack Obama*.

Field	**Content**
names	barack obama barack hussein obama ii
attributes	44th current president united states birth place honolulu hawaii
categories	democratic party united states senator nobel peace prize laureate christian
similar entity names	barack obama jr barak hussein obama barack h obama ii
related entity names	spouse michelle obama illinois state predecessor george walker bush

Hierarchical Entity Model

[Neumayer, Balog et al., ECIR'12]

Entity document fields are organized into a 2-level hierarchy:

- Predicate types are on the top level:

  name
  : subject is E, object is literal and predicate comes from a predefined list (e.g. `foaf:name` or `rdfs:label`) or ends with "name", "label" or "title"

  attributes
  : the subject is E, object is literal and the predicate is not of type name

  outgoing links
  : the subject is E and the object is a URI. URI is resolved by replacing it with entity name

  incoming links
  : E is an object, subject entity URI is resolved

- Individual predicates are at the bottom level

Dynamic Entity Representation

[Graus, Tsagkias et al., WSDM'16]

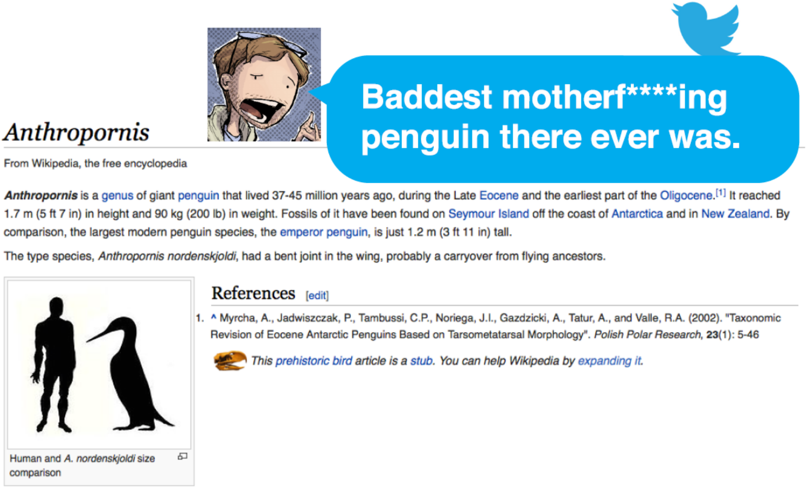
- **Problem:** vocabulary mismatch between entity's description in a knowledge base and the way people refer to the entity when searching for it
- Entity representations should account for:
  - **Context:** entities can appear in different contexts (e.g. `Germany` should be returned for queries related to World War II and 2014 Soccer World Cup)
  - **Time:** entities are not static in how they are perceived (e.g. `Ferguson, Missouri` before and after August 2014)

Approach (1)

Leverage collective intelligence provided by different entity description sources (KBs, web anchors, tweets, social tags, query log) to fill in the "vocabulary gap":

- Create and update entity representations based on different sources
- Combine different entity descriptions for retrieval at specific time intervals by dynamically assigning weights to different sources

Approach (2)



Anthropornis

From Wikipedia, the free encyclopedia

Anthropornis is a genus of giant penguin that lived 37-45 million years ago, during the Late Eocene and the earliest part of the Oligocene.[1] It reached 1.7 m (5 ft 7 in) in height and 90 kg (200 lb) in weight. Fossils of it have been found on Seymour Island off the coast of Antarctica and in New Zealand. By comparison, the largest modern penguin species, the emperor penguin, is just 1.2 m (3 ft 11 in) tall.

The type species, *Anthropornis nordenskjoldi*, had a bent joint in the wing, probably a carryover from flying ancestors.

Human and *A. nordenskjoldi* size comparison

References [edit]

1. ^ Myrcha, A., Jadwiszczak, P., Tambussi, C.P., Noriega, J.I., Gazdzicki, A., Tatur, A., and Valle, R.A. (2002). "Taxonomic Revision of Eocene Antarctic Penguins Based on Tarsometatarsal Morphology". *Polish Polar Research*, **23**(1): 5-46

This prehistoric bird article is a stub. You can help Wikipedia by expanding it.

Dynamic Entity Representation

Represent entities as fielded documents, in which each field corresponds to the content that comes from one description source:

- **Knowledge base:** anchor text of inter-knowledge base hyperlinks, redirects, category titles, names of entities that are linked from and to each entity in Wikipedia
- **Web anchors:** anchor text of links to Wikipedia pages from Google Wikilinks corpus
- **Twitter:** all English tweets that contain links to Wikipedia pages representing entities in the used snapshot
- **Delicious:** tags associated with Wikipedia pages in SocialBM0311 dataset
- **Queries:** queries that result in clicks on Wikipedia pages in the used snapshot

Entity Updates

The fields of entity document:

$$e = \{\bar{f}^e_{title}, \bar{f}^e_{text}, \bar{f}^e_{anchors}, \ldots, \bar{f}^e_{query}\}$$

are updated at each discretized time point $T = \{t_1, t_2, t_3, \ldots, t_n\}$

$$\bar{f}^e_{query}(t_i) = \bar{f}^e_{query}(t_{i-1}) + \begin{cases} \bar{q}, & \text{if } e_{clicked} \\ 0, & \text{otherwise} \end{cases}$$

$$\bar{f}^e_{tweets}(t_i) = \bar{f}^e_{tweets}(t_{i-1}) + \overline{tweet}_e$$

$$\bar{f}^e_{tags}(t_i) = \bar{f}^e_{tags}(t_{i-1}) + \overline{tag}_e$$

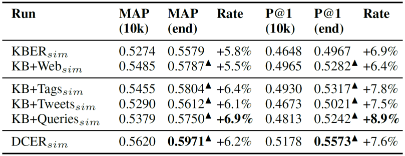
Each field's contribution towards the final entity score is determined based on features

Features

- **Field similarity**: TF-IDF cosine similarity of query and field f at time t_i
- **Field importance** (favor fields with more novel content): field's length in terms; field's length in characters; field's novelty at time t_i (favor fields with unseen, newly associated terms); number of updates to the field from t_0 through t_1
- **Entity importance** (favor recently updated entities): time since the last entity update

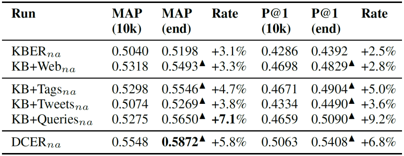
Classification-based ranker supervised by clicks learns the optimal feature weights

Results



Run	MAP (10k)	MAP (end)	Rate	P@1 (10k)	P@1 (end)	Rate
KBER$_{sim}$	0.5274	0.5579	+5.8%	0.4648	0.4967	+6.9%
KB+Web$_{sim}$	0.5485	0.5787▲	+5.5%	0.4965	0.5282▲	+6.4%
KB+Tags$_{sim}$	0.5455	0.5804▲	+6.4%	0.4930	0.5317▲	+7.8%
KB+Tweets$_{sim}$	0.5290	0.5612▲	+6.1%	0.4673	0.5021▲	+7.5%
KB+Queries$_{sim}$	0.5379	0.5750▲	**+6.9%**	0.4813	0.5242▲	**+8.9%**
DCER$_{sim}$	0.5620	**0.5971**▲	+6.2%	0.5178	**0.5573**▲	+7.6%

(a) adaptive runs



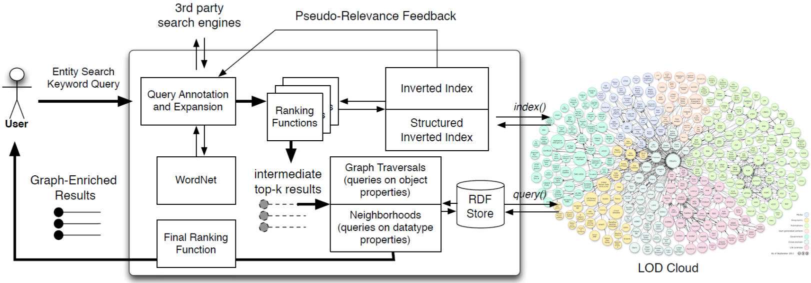
Run	MAP (10k)	MAP (end)	Rate	P@1 (10k)	P@1 (end)	Rate
KBER$_{na}$	0.5040	0.5198	+3.1%	0.4286	0.4392	+2.5%
KB+Web$_{na}$	0.5318	0.5493▲	+3.3%	0.4698	0.4829▲	+2.8%
KB+Tags$_{na}$	0.5298	0.5546▲	+4.7%	0.4671	0.4904▲	+5.0%
KB+Tweets$_{na}$	0.5074	0.5269▲	+3.8%	0.4334	0.4490▲	+3.6%
KB+Queries$_{na}$	0.5275	0.5650▲	**+7.1%**	0.4659	0.5090▲	+9.2%
DCER$_{na}$	0.5548	**0.5872**▲	+5.8%	0.5063	0.5408▲	+6.8%

(b) non-adaptive runs

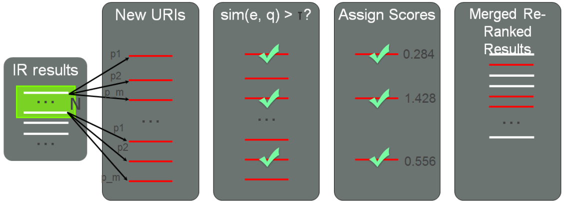
- Social tags are the best performing single entity description source
- KB+queries yields substantial relative improvement → added queries provide a strong signal for ranking the clicked entities
- Rankers that incorporate dynamic description sources (i.e KB+tags, KB+tweets and KB+queries) show the highest learning rate → entity content from these sources accounts for changes in entity representations over time

Architecture of ERKG Methods

[Tonon, Demartini et al., SIGIR'12]



Results Expansion Strategy



Take top-N docs.

Follow links/properties and get new URIs.

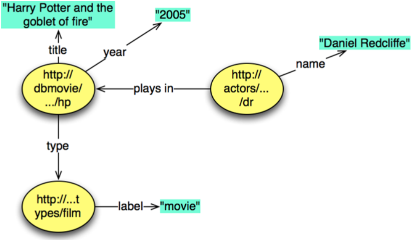
Filter new results by text similarity wrt the user query.

Scoring functions:
count sim > τ,
avg sim > τ,
Sum sim,
Avg sim,
Sum BM25 - ε

$\lambda \cdot \text{BM25}+$
$(1-\lambda)\cdot \text{score}$

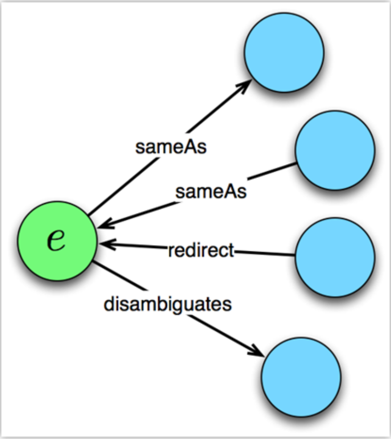
1. Retrieve an initial list of entities matching the query using standard retrieval function (BM25)
2. Expand the retrieved results by exploiting the structure of the knowledge graph (retrieved entities can be used as starting points for simple graph traversals, i.e. finding neighbors)
3. Filter out expanded results removing those with low similarity to the original query
4. Re-rank the results

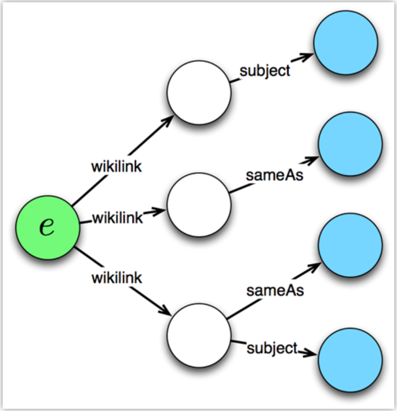
Result Expansion Strategies



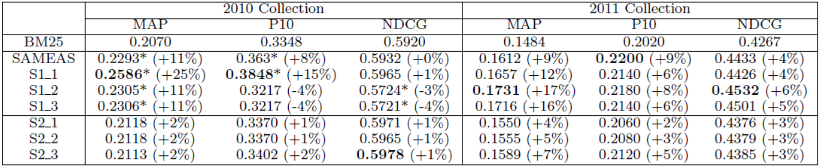
- Follow predicates leading to other entities
- Follow datatype properties leading to additional entity attributes
- Explore just the neighborhood of a node and the neighbors of neighbors

Predicates to Follow





Results



	2010 Collection			2011 Collection		
	MAP	P10	NDCG	MAP	P10	NDCG
BM25	0.2070	0.3348	0.5920	0.1484	0.2020	0.4267
SAMEAS	0.2293* (+11%)	0.363* (+8%)	0.5932 (+0%)	0.1612 (+9%)	**0.2200** (+9%)	0.4433 (+4%)
S1_1	**0.2586*** (+25%)	**0.3848*** (+15%)	0.5965 (+1%)	0.1657 (+12%)	0.2140 (+6%)	0.4426 (+4%)
S1_2	0.2305* (+11%)	0.3217 (-4%)	0.5724* (-3%)	**0.1731** (+17%)	0.2180 (+8%)	**0.4532** (+6%)
S1_3	0.2306* (+11%)	0.3217 (-4%)	0.5721* (-4%)	0.1716 (+16%)	0.2140 (+6%)	0.4501 (+5%)
S2_1	0.2118 (+2%)	0.3370 (+1%)	0.5971 (+1%)	0.1550 (+4%)	0.2060 (+2%)	0.4376 (+3%)
S2_2	0.2118 (+2%)	0.3370 (+1%)	0.5965 (+1%)	0.1555 (+5%)	0.2080 (+3%)	0.4379 (+3%)
S2_3	0.2113 (+2%)	0.3402 (+2%)	**0.5978** (+1%)	0.1589 (+7%)	0.2120 (+5%)	0.4385 (+3%)

- The simple `S1_1` approach which exploits <`owl:sameAs`> links plus Wikipedia redirect and disambiguation information performs best obtaining 25% improvement of MAP over the BM25 baseline on the 2010 datatset

Setting Field Weights

- Structured entity documents can be retrieved using structured document retrieval models (B25F, MLM)
- **Problem:** how to set the weights of document fields?
  - Heuristically: proportionate to the length of content in the field
  - Empirically: by optimizing the target retrieval metric using training queries

Fielded Sequential Dependence Model

[Zhiltsov, Kotov et al., SIGIR'15]

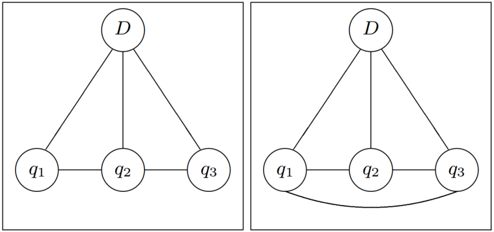
Previous research in ad-hoc IR has focused on two major directions:

- unigram bag-of-words retrieval models for multi-fielded documents
  - Ogilvie and Callan. Combining Document Representations for Known-item Search, SIGIR'03 (MLM)
  - Robertson et al. Simple BM25 Extension to Multiple Weighted Fields, CIKM'04 (BM25F)
- retrieval models incorporating term dependencies
  - Metzler and Croft. A Markov Random Field Model for Term Dependencies, SIGIR'05 (SDM)

Goal: to develop a retrieval model that captures both document structure and term dependencies

Sequential and Full Dependence Models

[Metzler and Croft, SIGIR'05]



Ranks w.r.t. $P_\Lambda(D|Q) = \sum_{i \in \{T,U,O\}} \lambda_i \; f_i(Q,D)$
Potential function for unigrams is QL:

$$f_T(q_i, D) = \log P(q_i|\theta_D) = \log \frac{tf_{q_i,D} + \mu \frac{cf_{q_i}}{|C|}}{|D| + \mu}$$

SDM only considers two-word sequences in queries, FDM considers all two-word combinations.

FSDM ranking function

FSDM incorporates document structure and term dependencies with the following ranking function:

$$
\begin{aligned}
P_\Lambda(D|Q) \overset{rank}{=} & \lambda_T \sum_{q \in Q} \tilde{f}_T(q_i, D) + \\
& \lambda_O \sum_{q \in Q} \tilde{f}_O(q_i, q_{i+1}, D) + \\
& \lambda_U \sum_{q \in Q} \tilde{f}_U(q_i, q_{i+1}, D)
\end{aligned}
$$

Separate MLMs for bigrams and unigrams give FSDM the flexibility to adjust the document scoring depending on the query type

MLM is a special case of FSDM, when $\lambda_T = 1, \lambda_O = 0, \lambda_U = 0$

FSDM ranking function

FSDM incorporates document structure and term dependencies with the following ranking function:

$$P_\Lambda(D|Q) \overset{rank}{=} \lambda_T \sum_{q \in Q} \tilde{f}_T(q_i, D) + \lambda_O \sum_{q \in Q} \tilde{f}_O(q_i, q_{i+1}, D) + \lambda_U \sum_{q \in Q} \tilde{f}_U(q_i, q_{i+1}, D)$$

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Separate MLMs for bigrams and unigrams give FSDM the flexibility to adjust the document scoring depending on the query type

MLM is a special case of FSDM, when $\lambda_T = 1, \lambda_O = 0, \lambda_U = 0$

FSDM ranking function

Potential function for unigrams in case of FSDM:

$$\tilde{f}_T(q_i, D) = \log \sum_j w_j^T P(q_i|\theta_D^j) = \log \sum_j w_j^T \frac{tf_{q_i,D^j} + \mu_j \frac{cf_{q_i}^j}{|C_j|}}{|D^j| + \mu_j}$$

Example

apollo astronauts who walked on the moon

FSDM ranking function

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Example

$\underbrace{\text{apollo astronauts}}_{\text{category}}$ who walked on the moon

FSDM ranking function

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Example

apollo astronauts who walked on the moon

category attribute

Experiments

- DBPedia 3.7 as a knowledge graph
- Queries from Balog and Neumayer. A Test Collection for Entity Search in DBpedia, SIGIR'13.

Query set	**Amount**	**Query types [Pound et al., 2010]**
SemSearch ES	130	Entity
ListSearch	115	Type
INEX-LD	100	Entity, Type, Attribute, Relation
QALD-2	140	Entity, Type, Attribute, Relation

Results

Query set	Method	MAP	P@10	P@20	b-pref
SemSearch ES	MLM-CA	0.320	0.250	0.179	0.674
	SDM-CA	0.254*	0.202*	0.149*	0.671
	FSDM	**0.386**$^{*}_{\dagger}$	**0.286**$^{*}_{\dagger}$	**0.204**$^{*}_{\dagger}$	**0.750**$^{*}_{\dagger}$
ListSearch	MLM-CA	0.190	0.252	0.192	0.428
	SDM-CA	0.197	0.252	0.202	**0.471***
	FSDM	**0.203**	**0.256**	**0.203**	0.466*
INEX-LD	MLM-CA	0.102	0.238	0.190	0.318
	SDM-CA	**0.117***	0.258	0.199	0.335
	FSDM	0.111*	**0.263***	**0.215**$^{*}_{\dagger}$	**0.341***
QALD-2	MLM-CA	0.152	0.103	0.084	0.373
	SDM-CA	0.184	0.106	0.090	0.465*
	FSDM	**0.195***	**0.136**$^{*}_{\dagger}$	**0.111***	**0.466***
All queries	MLM-CA	0.196	0.206	0.157	0.455
	SDM-CA	0.192	0.198	0.155	0.495*
	FSDM	**0.231**$^{*}_{\dagger}$	**0.231**$^{*}_{\dagger}$	**0.179**$^{*}_{\dagger}$	**0.517**$^{*}_{\dagger}$

FSDM limitation

In FSDM field weights are the same for all query concepts of the same type.

Example

capitals in Europe which were host cities of summer Olympic games

Parametric extension of FSDM

$$w^{T}_{q_i,j} = \sum_{k} \alpha^{U}_{j,k} \phi_k(q_i, j)$$

Parametric extension of FSDM

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- $\phi_k(q_i, j)$ is the the k-th feature value for unigram q_i in field j.

Parametric extension of FSDM

$$w^T_{q_i,j} = \sum_k \alpha^U_{j,k} \phi_k(q_i, j)$$

- $\phi_k(q_i, j)$ is the the k-th feature value for unigram q_i in field j.
- $\alpha^U_{j,k}$ are feature weights that we learn.

Parametric extension of FSDM

$$w^T_{q_i,j} = \sum_k \alpha^U_{j,k} \phi_k(q_i, j)$$

- $\phi_k(q_i, j)$ is the the k-th feature value for unigram q_i in field j.
- $\alpha^U_{j,k}$ are feature weights that we learn.

$$\sum_j w^T_{q_i,j} = 1, w^T_{q_i,j} \geq 0, \alpha^U_{j,k} \geq 0, 0 \leq \phi_k(q_i, j) \leq 1$$

Features

Source	Feature	Description	CT
Collection statistics	$FP(\kappa, j)$	Posterior probability $P(E_j \mid w)$.	UG BG
	$TS(\kappa, j)$	Top SDM score on j-th field when κ is used as a query.	BG

Features

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Collection statistics	$FP(\kappa, j)$	Posterior probability $P(E_j \| w)$.	UG BG
	$TS(\kappa, j)$	Top SDM score on j-th field when κ is used as a query.	BG
Stanford POS Tagger	$NNP(\kappa)$	Is concept κ a proper noun?	UG
	$NNS(\kappa)$	Is κ a plural non-proper noun?	UG BG
	$JJS(\kappa)$	Is κ a superlative adjective?	UG
Stanford Parser	$NPP(\kappa)$	Is κ part of a noun phrase?	BG
	$NNO(\kappa)$	Is κ the only singular non-proper noun in a noun phrase?	UG
	INT	Intercept feature $(= 1)$.	UG BG

Learning-to-Rank Entities

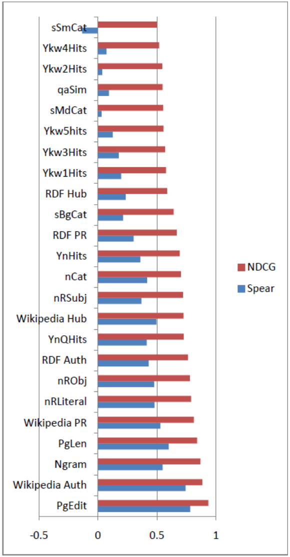
[Dali and Fortuna, WWW'11]

- Variety of features:
  - Popularity and importance of Wikipedia page: # of accesses from logs, # of edits, page length
  - RDF features: # of triples *E* is subject/object/subject and object is a literal, # of categories Wikipedia page for *E* belongs to, size of the biggest/smallest/median category
  - HITS scores and Pagerank of Wikipedia page and *E* in the RDF graph
  - # of hits from search engine API for the top 5 keywords from the abstract of Wikipedia page for *E*
  - Count of entity name in Google N-grams
- RankSVM learning-to-rank method

Evaluation

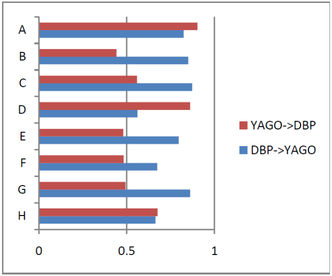
- Initial set of entities obtained using SPARQL queries
- 14 example queries for DBpedia and 27 example queries for Yago
- Example queries: "Which athlete was born in Philadelphia?", "List of Schalke 04 players", "Which countries have French as an official language?", "Which objects are heavier that the Iosif Stalin tank?"

Feature Importance



- Features approximating the importance, hub and authority scores, PageRank of Wikipedia page are effective
- PageRank and HITS scores on RDF graph are not effective (outperformed by simpler RDF features)
- Google N-grams is effective proxy for entity popularity, cheaper than search engine API
- Feature combinations improve both robustness and accuracy of ranking

Transfer Learning



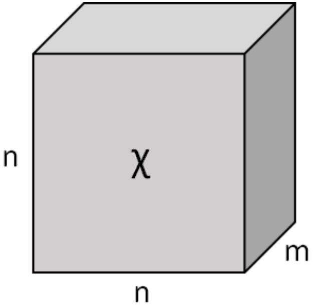
- Ranking model was trained on DBpedia questions and applied to Yago questions
- Only feature set A (all features) results in robust ranking model transfer
- In general, the ranking models for different knowledge graphs are non-transferable, unless they have been learned on large number of features
- The biggest inconsistencies occur on the models trained on graph based features → knowledge graphs preserve particularities reflecting their designer decisions

Latent Dimensional Representation

[Zhiltsov and Agichtein, CIKM'13]

- Compact representation of entities in low dimensional space by using a modified algorithm for tensor factorization
- Entities and entity-query pairs are represented with term-based and structural features

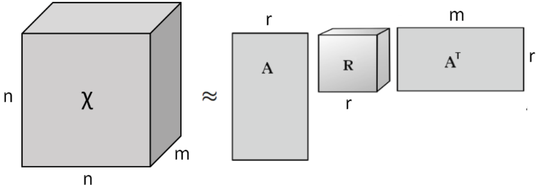
Knowledge Graph as Tensor



- For a knowledge graph with n distinct entities and m distinct predicates, we construct a tensor $\mathcal{X}$ of size $n \times n \times m$, where $\mathcal{X}_{ijk} = 1$, if there is k-th predicate between i-th entity and j-th entity, and $\mathcal{X}_{ijk} = 0$, otherwise
- Each k-th frontal tensor slice $\mathcal{X}_k$ is an adjacency matrix for the k-the predicate, which is sparse

RESCAL Tensor Factorization

[Nikel, Tresp, et al., WWW'12]



- Given r is the number of latent factors, we factorize each X_k into the matrix product:

$$X_k = A R_k A^T, k = \overline{1, m},$$

where A is a dense $n \times r$ matrix, a matrix of latent embeddings for entities, and R_k is an $r \times r$ matrix of latent factors

Retrieval Method

1. Retrieve initial set of entities using MLM
2. Re-rank the entities using Gradient Boosted Regression Tree (GBRT)

Features

#	Feature
Term-based features	
1	Query length
2	Query clarity
3	Uniformly weighted MLM score
4	Bigram relevance score for the "name" field
5	Bigram relevance score for the "attributes" field
6	Bigram relevance score for the "outgoing links" field
Structural features	
7	Top-3 entity cosine similarity, $cos(\mathbf{e}, \mathbf{e}_{top})$
8	Top-3 entity Euclidean distance, $\|\mathbf{e} - \mathbf{e}_{top}\|$
9	Top-3 entity heat kernel, $e^{-\frac{\|\mathbf{e}-\mathbf{e}_{top}\|^2}{\sigma}}$

Results

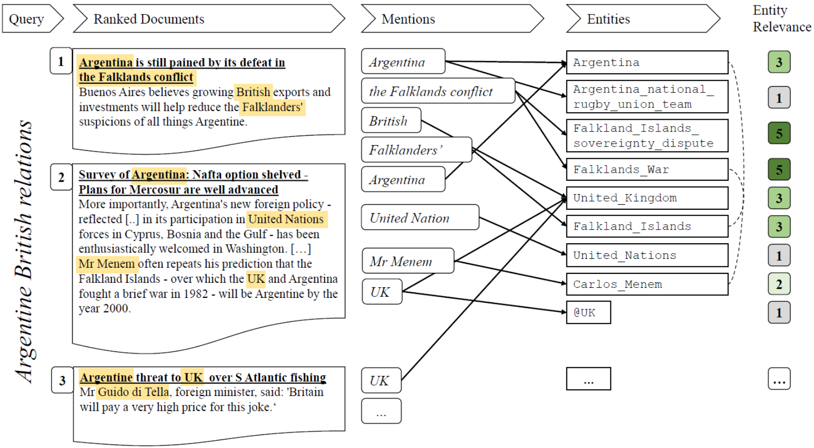
Features	Performance		
	NDCG	**MAP**	**P@10**
Term-based baseline	0.382	0.265	0.539
All features	**0.401** (+ 5.0%)*	**0.276** (+ 4.2%)	**0.561** (+ 4.1%)*

Ranking KG Entities using Top Documents

[Schuhmacher, Dietz et al., CIKM'15]

- **Motivation:** to address free-text web-style queries corresponding to complex information needs that cannot be satisfied by an entity or a list of homogeneous entities with the same type (e.g. "Argentine British relations")
- **Method:**
  1. Retrieve documents for a query using entity-aware (e.g. EQFE) or standard retrieval model (e.g. SDM)
  2. Link entity mentions in top-*k* documents to entities in a KB (e.g. using KBBridge) or use existing annotations of TREC collections (e.g. FACC1 for ClueWeb09/ClueWeb12)
  3. Rank linked entities using a learning-to-rank framework combining features based on document collection and structured KBs

Approach



Argentina is still pained by its defeat in the Falklands conflict
Buenos Aires believes growing British exports and investments will help reduce the Falklanders' suspicions of all things Argentine.

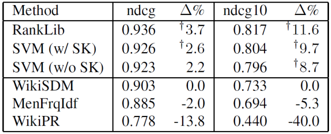
Survey of Argentina: Nafta option shelved - Plans for Mercosur are well advanced
More importantly, Argentina's new foreign policy - reflected [..] in its participation in United Nations forces in Cyprus, Bosnia and the Gulf - has been enthusiastically welcomed in Washington. […]
Mr Menem often repeats his prediction that the Falkland Islands - over which the UK and Argentina fought a brief war in 1982 - will be Argentine by the year 2000.

Argentine threat to UK over S Atlantic fishing
Mr Guido di Tella, foreign minister, said: 'Britain will pay a very high price for this joke.'

Features and rankers

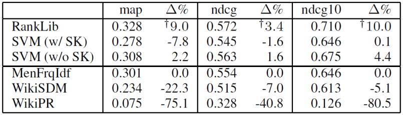
- Features:
  - **Mention:** # of entity occurrences in top retrieved documents weighted entity IDF (MenFrqIdf);
  - **Query-Mention:** normalized Levenshtein distance between the query and the mention (SED); similarity between aggregate representations of queries and mention context using GloVe (Glo) and JoBimText (Jo) distributional thesauri;
  - **Query-Entity:** (a) compare the set of linked query entities with top document entities – whether document entity is present in a query (QEnt); whether there is a path between between document and query entity (QEntEntSim) (b) retrieval with query keywords combined with text associated with document entities in KB – entities returned by Boolean model over Wikipedia articles (WikiBoolean); SDM retrieval score of top 1000 Wikipedia articles (WikiSDM)
  - **Entity-Entity:** whether there is a path between two entities in DBpedia KG
- Rankers: pairwise (SVM-rank with linear kernel and linear kernel combined with semantic smoothing kernel) and listwise (coordinate ascent using RankLib)

Results



Method	ndcg	Δ%	ndcg10	Δ%
RankLib	0.936	†3.7	0.817	†11.6
SVM (w/ SK)	0.926	†2.6	0.804	†9.7
SVM (w/o SK)	0.923	2.2	0.796	†8.7
WikiSDM	0.903	0.0	0.733	0.0
MenFrqIdf	0.885	-2.0	0.694	-5.3
WikiPR	0.778	-13.8	0.440	-40.0

(a) Robust04

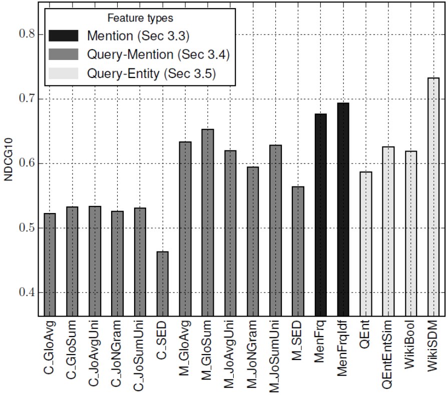


	map	Δ%	ndcg	Δ%	ndcg10	Δ%
RankLib	0.328	†9.0	0.572	†3.4	0.710	†10.0
SVM (w/ SK)	0.278	-7.8	0.545	-1.6	0.646	0.1
SVM (w/o SK)	0.308	2.2	0.563	1.6	0.675	4.4
MenFrqIdf	0.301	0.0	0.554	0.0	0.646	0.0
WikiSDM	0.234	-22.3	0.515	-7.0	0.613	-5.1
WikiPR	0.075	-75.1	0.328	-40.8	0.126	-80.5

(b) ClueWeb12

- Authoritativeness marginally correlates with relevance (entities ranked high by PageRank are very general)
- Best results are obtained when ranking using SDM (supported by INEX results) and normalized mention frequencies
- RankLib performs better than SVM-rank with or without semantic kernel

Feature importance



- Context query mention features (prefix C_) perform worse than their no-context counterparts (prefix M_)
- Context features based on edit distance and distributional similarity are not effective
- DBpedia-based features have positive but insignificant influence on the overall performance, while Wikipedia-based features show strong and significant influence

Takeaway messages

- Use dynamic entity representations built from different sources (not only KB)
- Use retrieval models that account for different query concept types (FSDM and PFSDM) rather than standard fielded document retrieval models (BM25F and MLM) to obtain candidate entities
- Expand candidate entities by following KG links and using top-retrieved documents
- Re-rank candidate entities by using a variety of features including latent dimensional entity representations

Thank you!

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