Entity-centric information access for high-end semantic applications

Simone Paolo Ponzetto

(joint work with Michael Schuhmacher,
Federico Nanni and Laura Dietz)

Hi!

Since 2016 professor of Information Systems at the University of Mannheim

Main research areas

- Knowledge Acquisition
- Natural Language Processing
- Computational Social Science

Fake News

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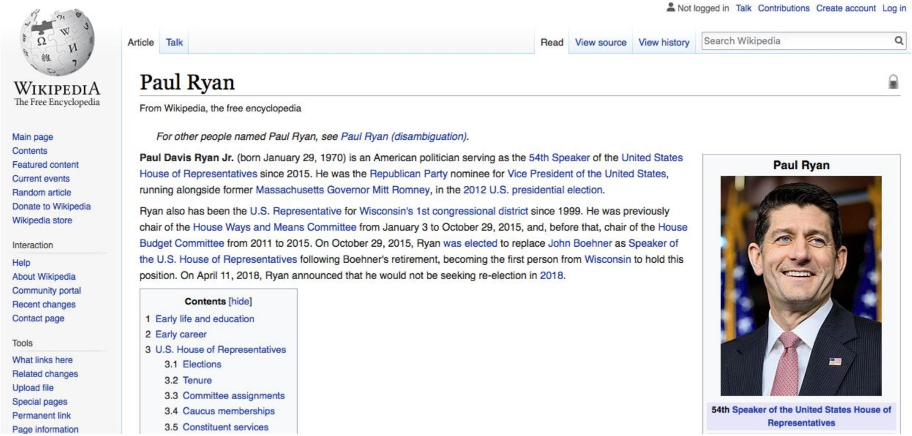

Source: Nicholas Thompson: LIE OR MISTAKE? PAUL RYAN'S MARATHONING PAST. The New Yorker, September 1, 2012

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Auf der Suche nach Bedeutung und Sinn...

We have the same problem for virtually any language...

Who is it?

“I like to drive. I can't drive any more.”

“Hey, I’m a nationalist and a globalist. I’m both.”

“I’ve actually been an activist Democrat and Republican”

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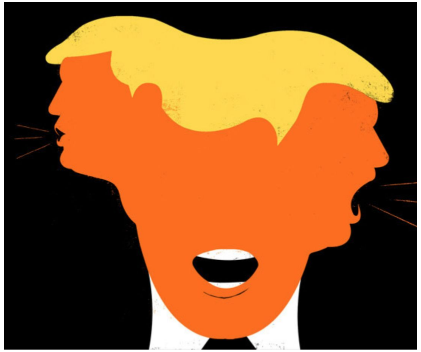

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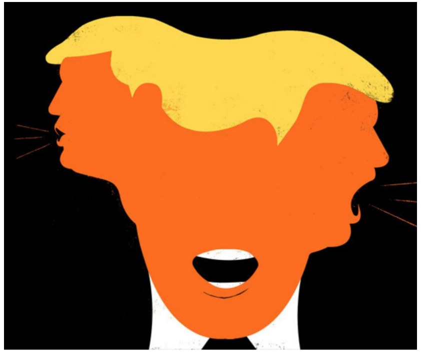

When I have to build a hotel, we're bombing the hell out of them. Lots of money. To those suffering, I say vote for Donald. #SyriaStrikes

[My next gag order will be on] journalism. They're the problem. I'll educate our country and get rid of politics. @RVAwonk #globalgagrule

Here's the thing, I horribly abuse women and LGBT citizens. You know that better than anybody. That's my plan to win.@UlrichJvV #ElectionDay

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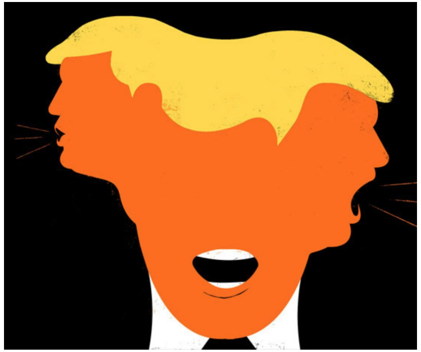

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- Knowledge-rich or entity-based NLP models might not yield the best performance on a wide range of complex tasks (as opposed to distributional methods)...

- ... BUT they are **quite useful when interacting with users (because of interpretability**)!

Reference Knowledge Bases

… and many others!

Entity Linking Tools

… and many others!

Three Tasks

1. Query-based entity ranking

2. Building entity-centric event collections

3. Entity-aspect linking

Web Search: What is Running?

Let's start with one of the most popular
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Query „*running technique*"

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2016 => **10 blue links**

Tips for Proper Running Form - Verywell Fit
https://www.verywellfit.com › Fitness › Running › Beginners
May 14, 2018 - Follow these 10 tips for proper **running form** to improve your performance. Learn the right posture, foot motion, and arm use to run your best.

Natural Running Form - USAF Marathon
https://www.usafmarathon.com/natural-running-form/
Running Form Principle 1: Run Tall Posture. Run tall – imagine your column being stacked under your head. Look **straight** ahead to the horizon. Ball of foot and heel are level on ground. To move forward lean in like giving a kiss.

Learn Pose Method of running technique to run faster! | Pose Method
https://posemethod.com/running/
Running technique in 3 easy steps. This method works for runners of all levels & is used by Physical Therapists to address running injuries.

The Five Most Common Running Form Mistakes – Competitor Running
https://running.competitor.com/.../the-five-most-common-running-form-mistakes_48...
Jun 12, 2013 - Good **running form** is essential for performance and injury prevention. We take a look at the five most common **running form** mistakes.

Proper Running Technique >> Best 3 Ways - Runtastic
https://www.runtastic.com/blog/en/proper-running-technique/
★★★★★ Rating: 4 - 1,256 reviews
Aug 8, 2017 - Looking to run faster, more efficient and injury-free? Try out these 3 ways to help with proper **running technique**.

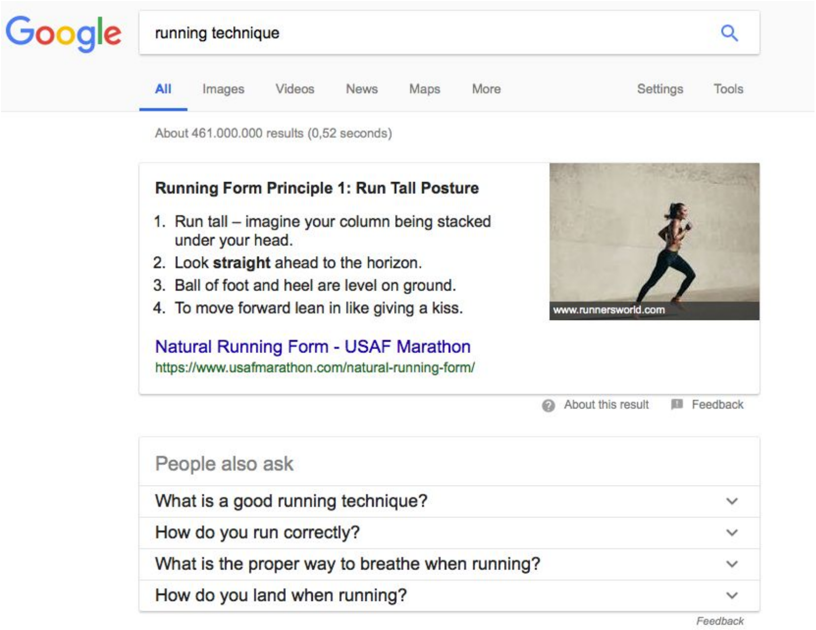
Good Running Form for Beginners | ACTIVE
https://www.active.com › Running › Articles
Learn proper **running form** as a beginner to avoid injuries and slow race times in the future. Use these visual cues from coach Brendan Cournane to identify in...

Web Search: What is Running?

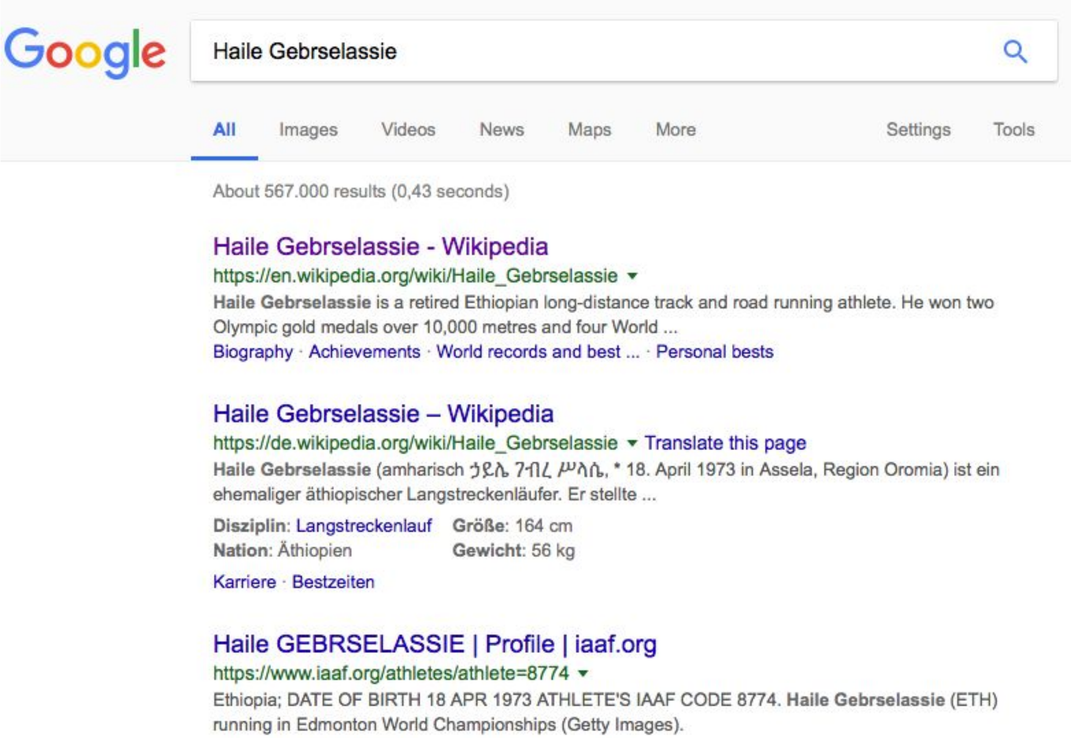
Let’s start with one of the most popular high-end tasks: Web search

Query „running technique“

2018 => **featured snippets**



Entity-centric Queries



Entity-centric Queries

Google

Haile Gebrselassie

All Images Videos News Maps More Settings Tools

About 567.000 results (0,43 seconds)

Haile Gebrselassie - Wikipedia
https://en.wikipedia.org/wiki/Haile_Gebrselassie
Haile Gebrselassie is a retired Ethiopian long-distance track and road running athlete. He won two Olympic gold medals over 10,000 metres and four World ...
Biography · Achievements · World records and best ... · Personal bests

Haile Gebrselassie – Wikipedia
https://de.wikipedia.org/wiki/Haile_Gebrselassie Translate this page
Haile Gebrselassie (amharisch ኃይሌ ገብረ ሥላሴ, * 18. April 1973 in Assela, Region Oromia) ist ein ehemaliger äthiopischer Langstreckenläufer. Er stellte ...
Disziplin: Langstreckenlauf **Größe**: 164 cm
Nation: Äthiopien **Gewicht**: 56 kg
Karriere · Bestzeiten

Haile GEBRSELASSIE | Profile | iaaf.org
https://www.iaaf.org/athletes/athlete=8774
Ethiopia; DATE OF BIRTH 18 APR 1973 ATHLETE'S IAAF CODE 8774. **Haile Gebrselassie** (ETH) running in Edmonton World Championships (Getty Images).

Haile Gebrselassie
Olympiasportler

Haile Gebrselassie ist ein ehemaliger äthiopischer Langstreckenläufer. Er stellte insgesamt 26 Weltrekorde auf, dominierte als mehrfacher Olympiasieger und Weltmeister ein Jahrzehnt lang die Distanzen von 3000 Meter bis 10.000 Meter und war von 2007 bis 2011 Inhaber des Weltrekordes im Marathon. Wikipedia

Geboren: 18. April 1973 (Alter 45 Jahre), Assela, Äthiopien

Größe: 1,64 m

Gewicht: 54 kg

Ehepartnerin: Alem Gebrselassie (verh. 1996)

Olympische Medaillen: Olympische Sommerspiele 2000/Leichtathletik – 10.000 m, MEHR

Filme: Der Einzelkämpfer von Atlanta

Query-based Entity Ranking

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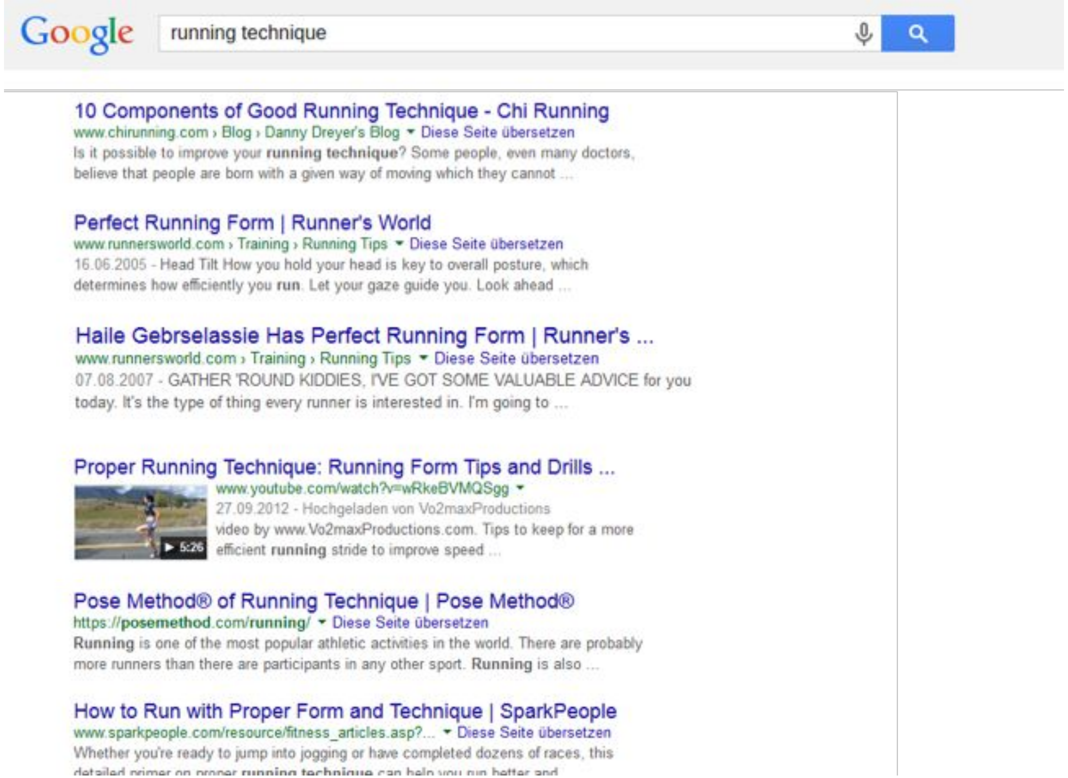

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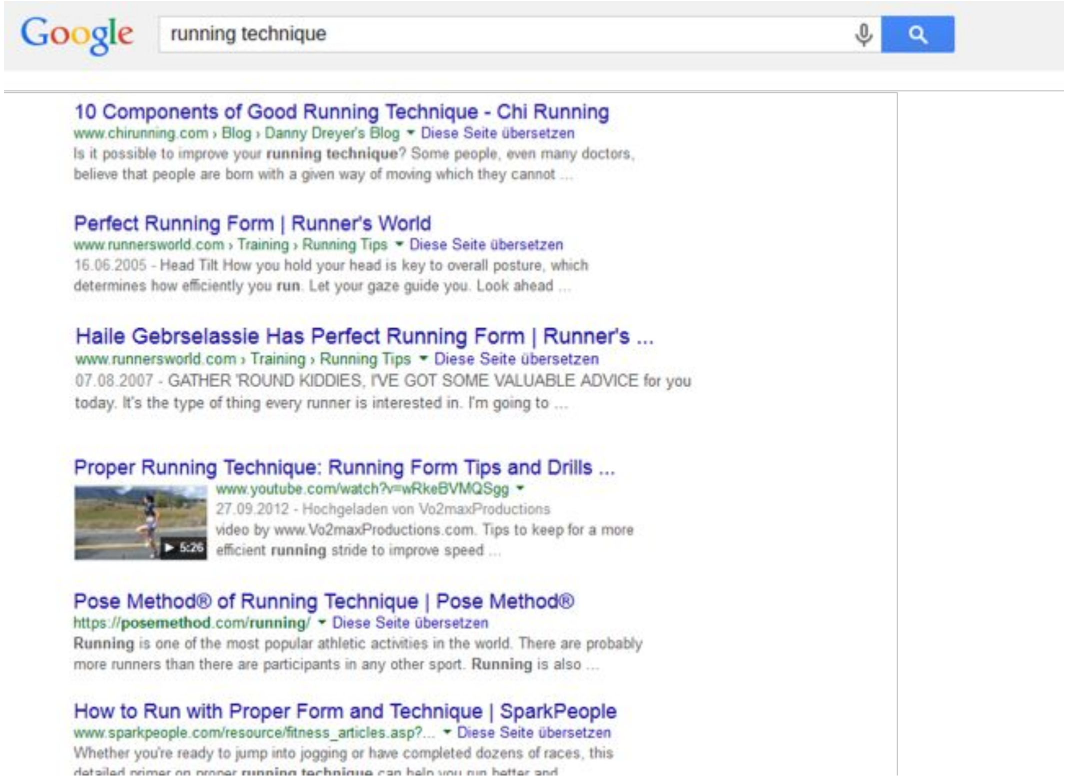

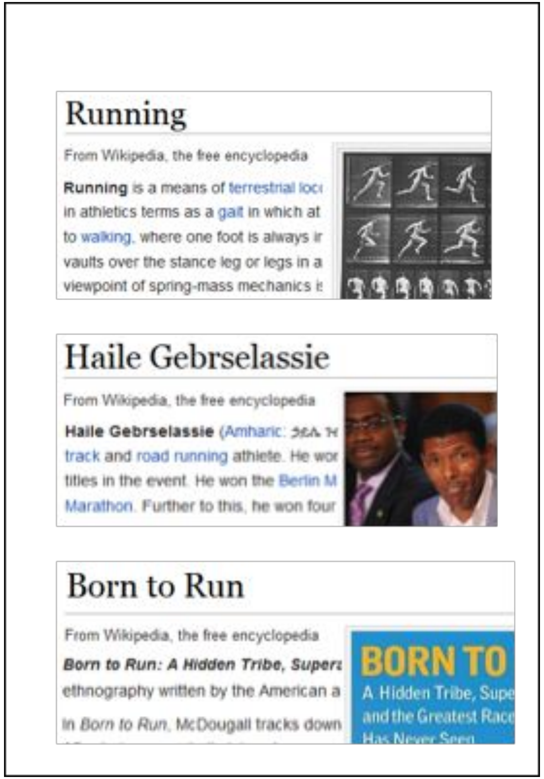

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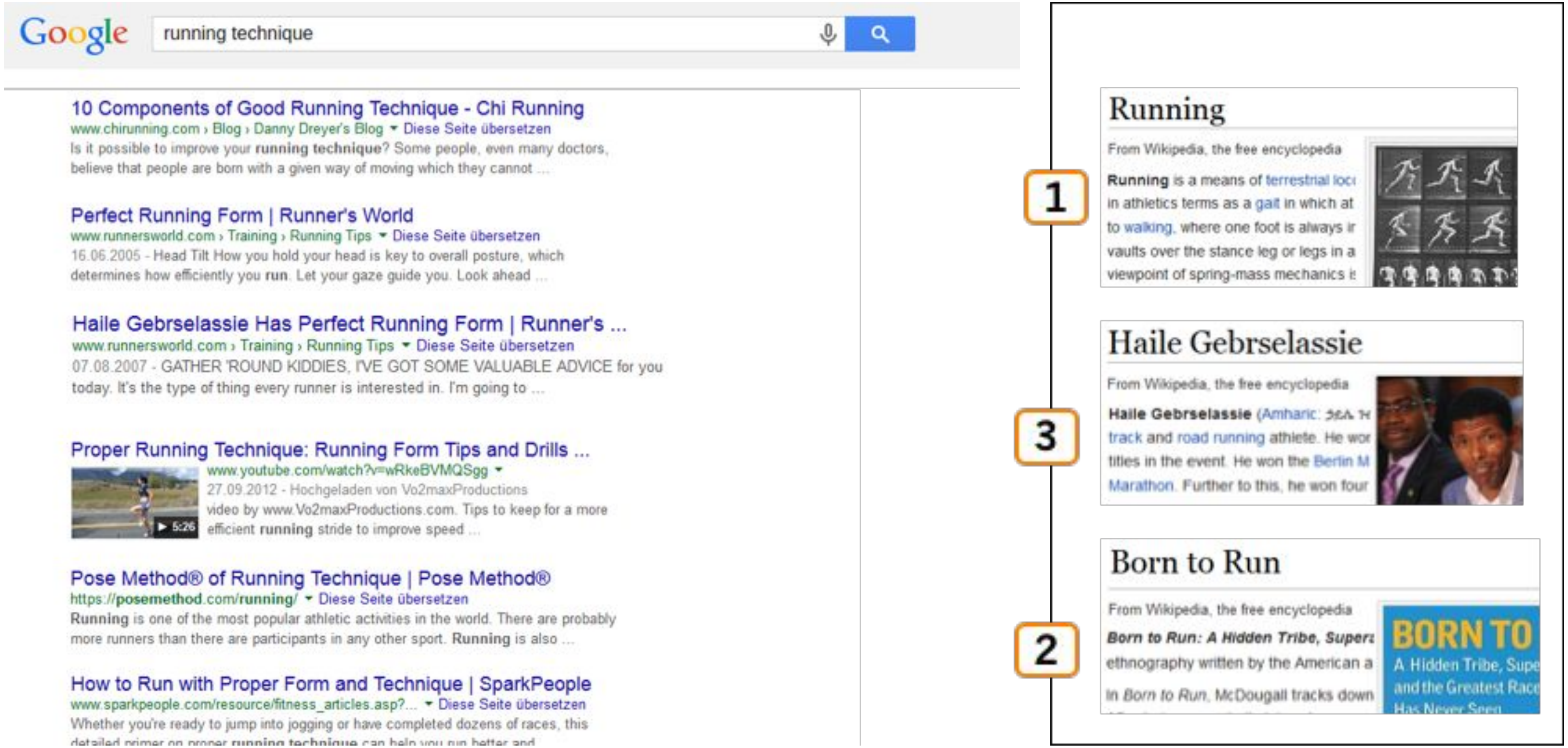

Entity Retrieval for General Web Queries

Michael Schuhmacher, Laura Dietz, Simone Paolo Ponzetto: **Ranking Entities for Web Queries Through Text and Knowledge**. *CIKM 2015*: 1461-1470

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- Answer entity type queries
  "*European countries where I can pay with Euros*" (INEX)

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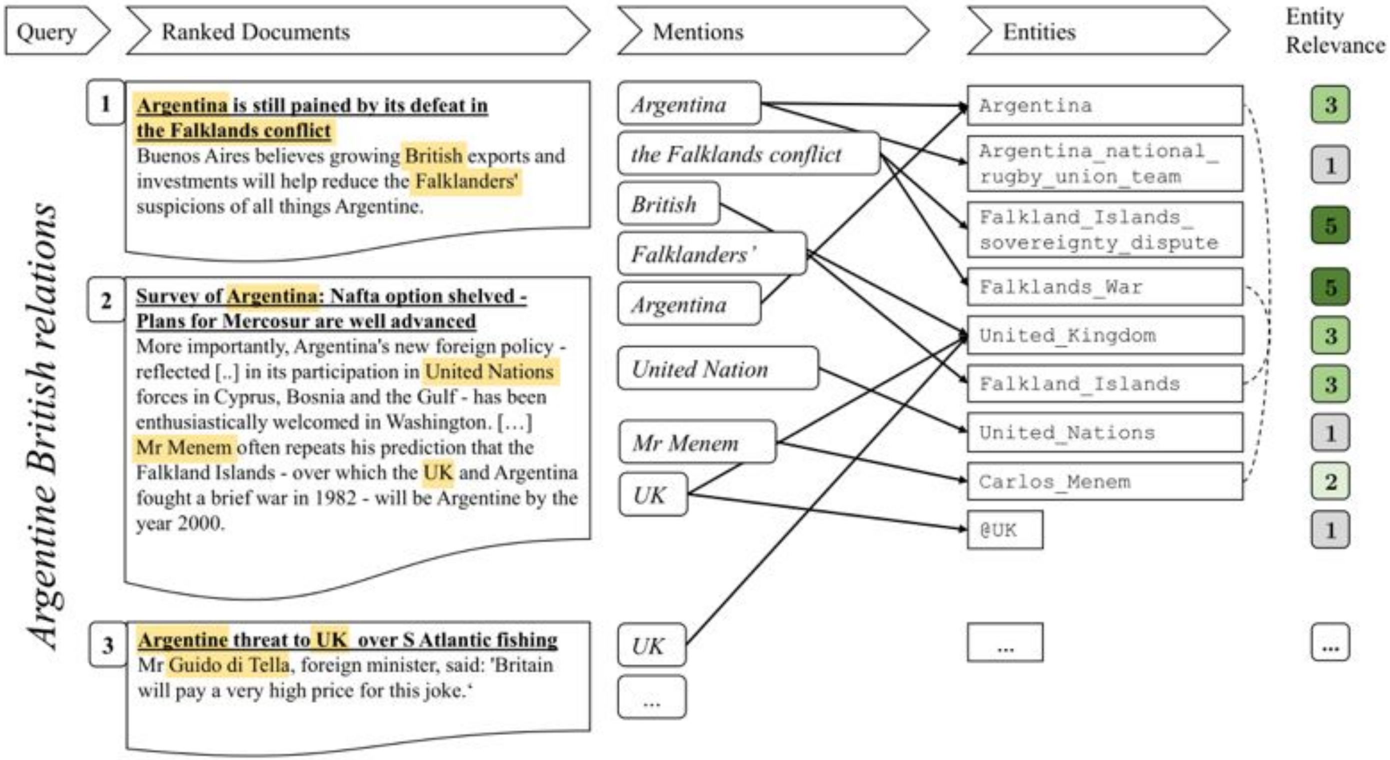
How we do it:

1. Retrieve Documents
2. Extract and Re-rank Entities

Running Example



Research Question and Experimental Framework

Given: The extracted entities

Question: Which features are helpful for ranking?

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Method Framework: Learning-to-Rank (LTR)

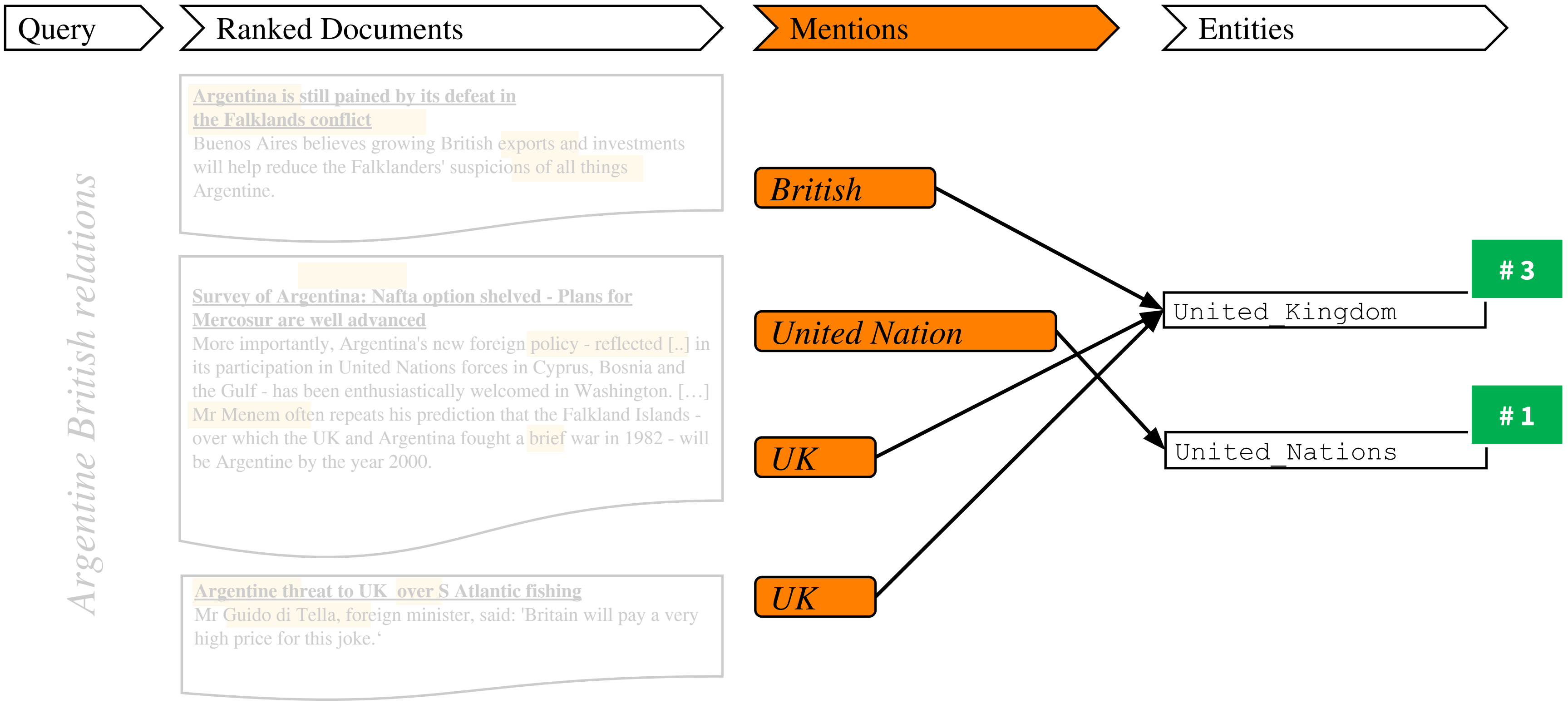
- Entity Relevance Features
- Labeled Data Set
- LTR Method

Entity Ranking Features in our LTR Setting

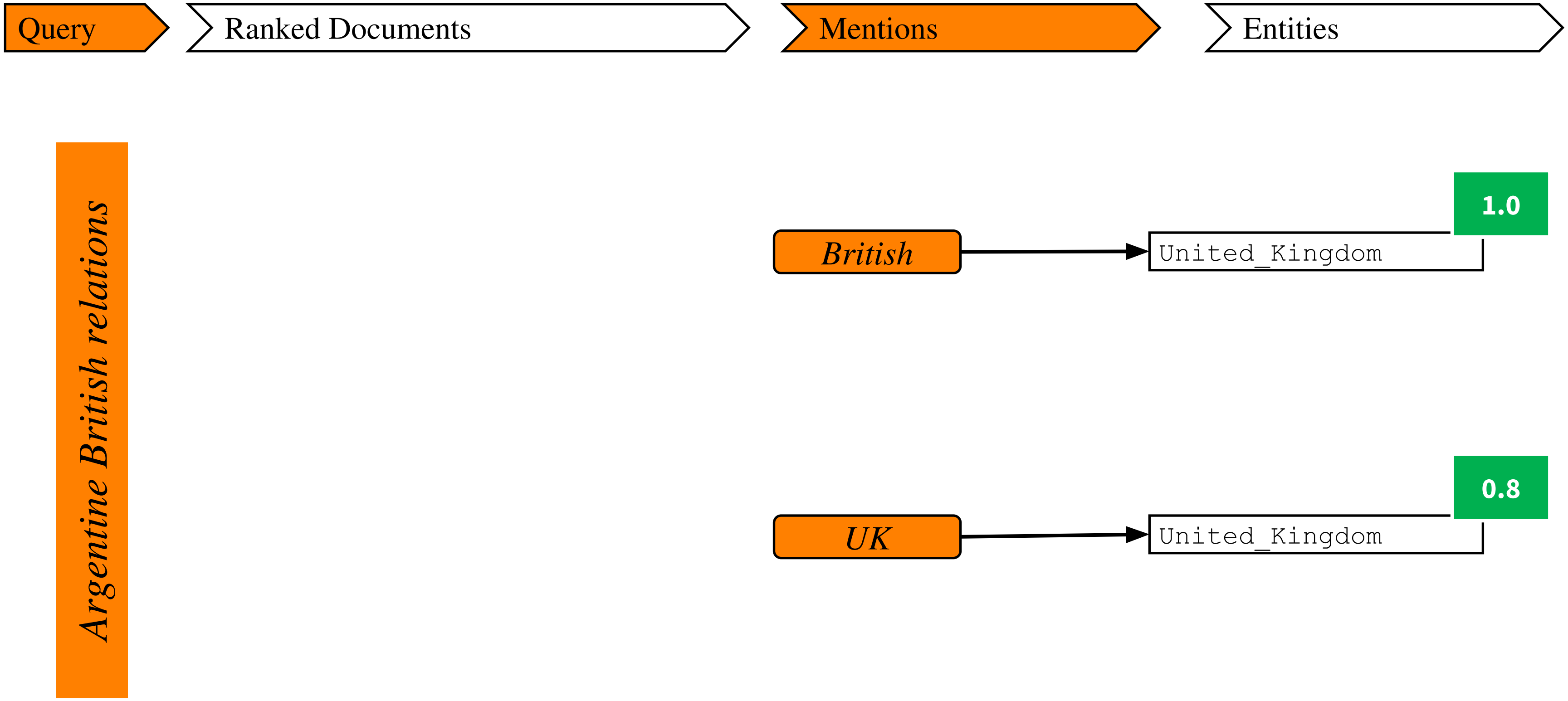
Learning-to-Rank (LTR)

- Entity Relevance Features
  1. Mention Features
  2. Query-Mention Features
  3. Query-Entity Features
  4. Entity-Entity Features
- Labeled Data Set
- LTR Method

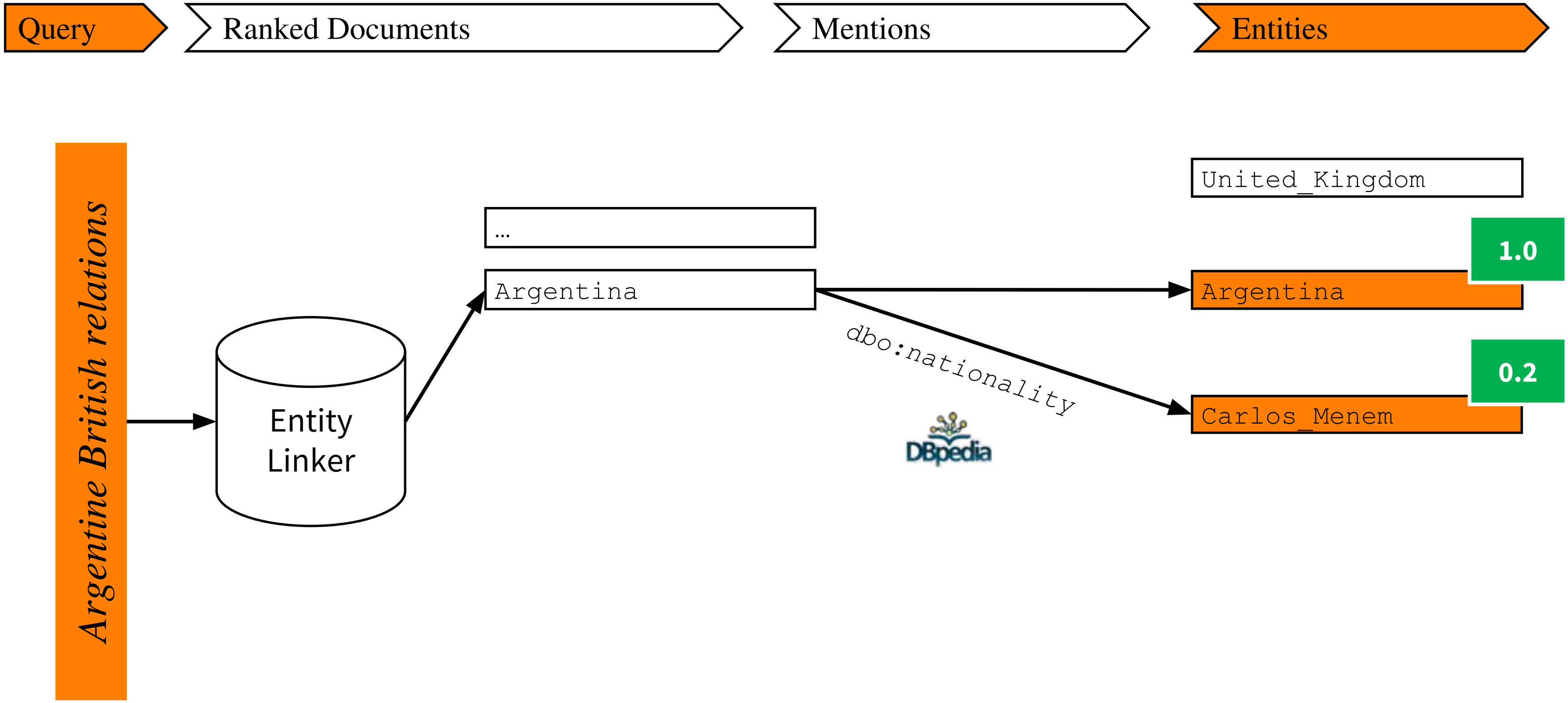
Mention Features



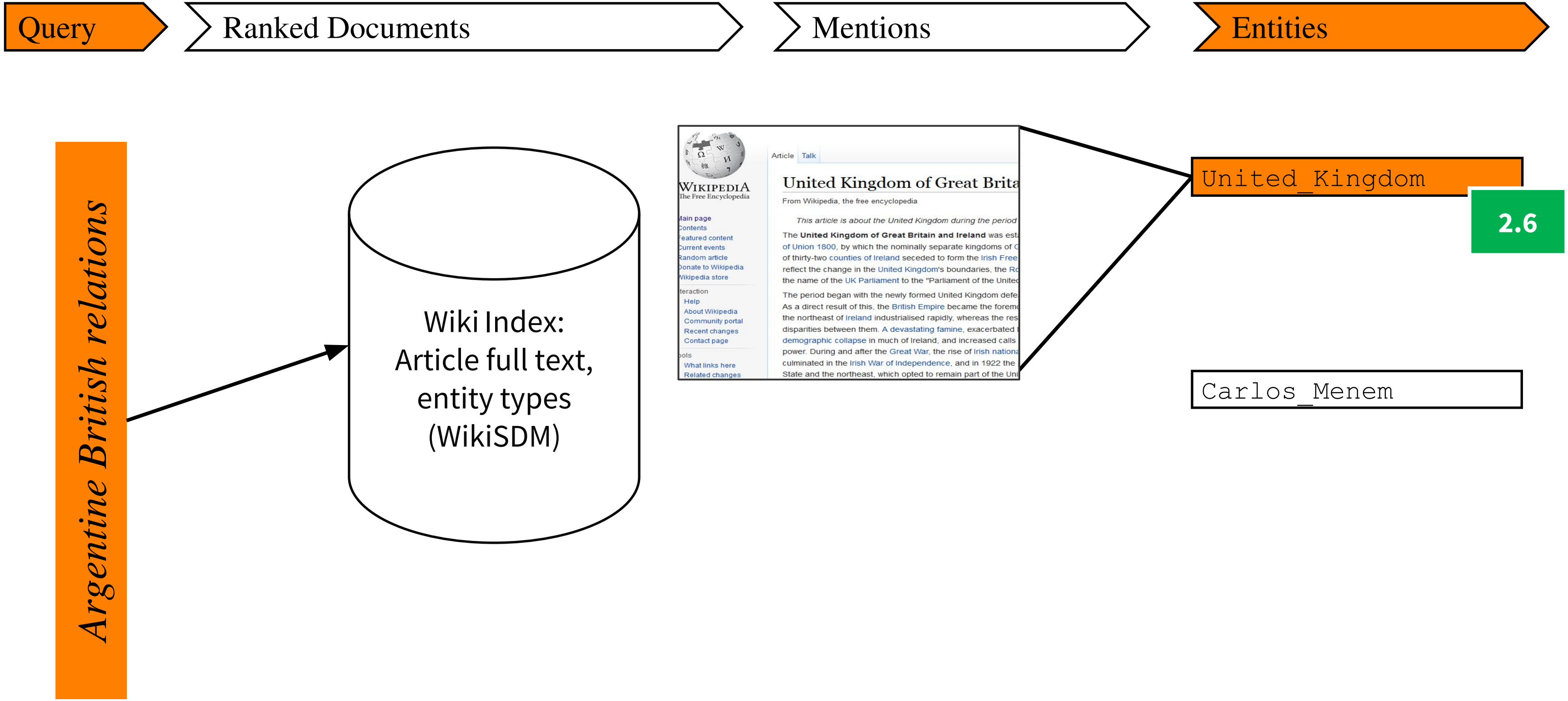
Query-Mention Features



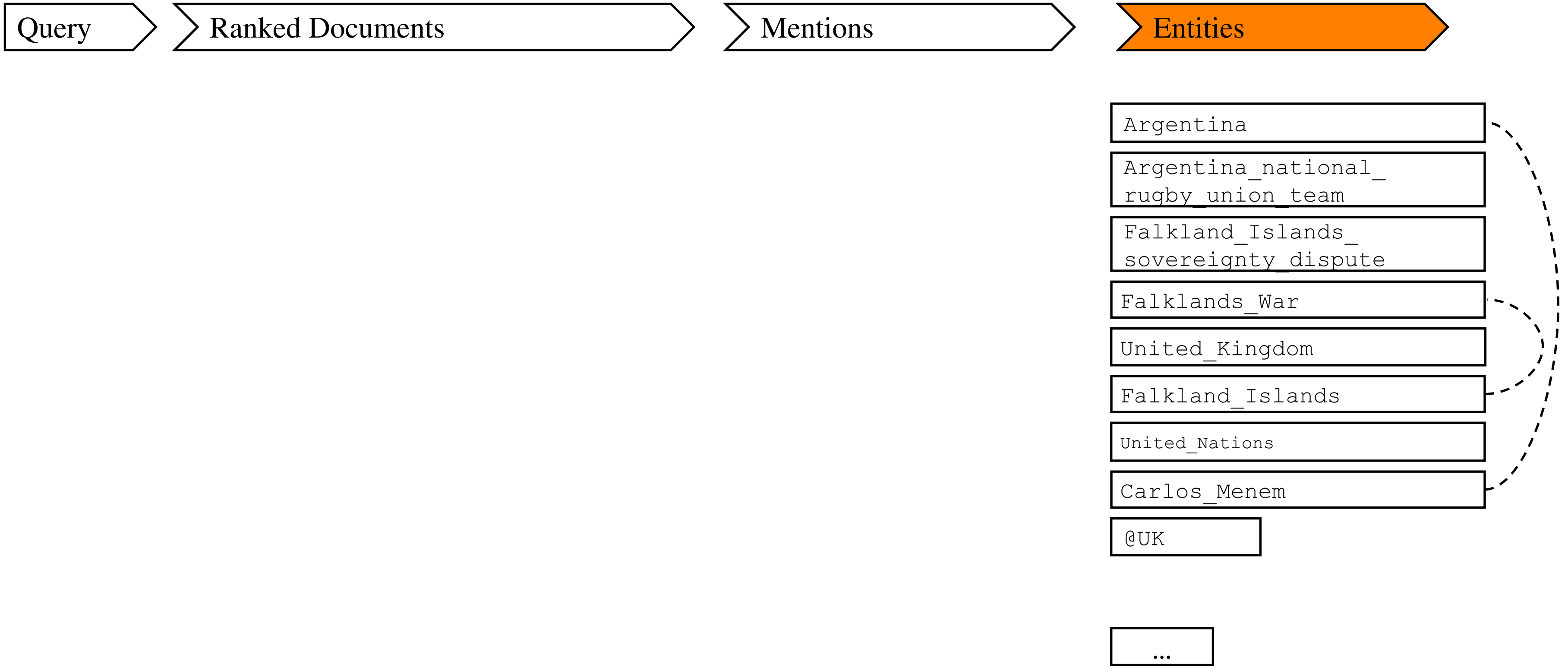
Query-Entity Features (Query -> Entity Linker -> Entities)



Query-Entity Features (Query -> Wikipedia Index)



Entity-Entity Features (using Dbpedia to compare entities)



Entity-Entity Features (using Dbpedia to compare entities)

Entities

Argentina

Carlos_Menem

Carlos Menem dbo:nationality Argentina

Falklands_War

Falkland_Islands

Falklands_War dbo:place Falkland_Islands

REWQ Datasets

Learning-to-Rank (LTR)

- Entity Relevance Features
- Labeled Data Set

	REWQ Robust04	REWQ Clueweb12
Doc collection	TREC Disk4+5	ClueWeb12
Queries	TREC Robust Track ‘04	TREC Web Track ‘13/14
# queries	25	22
Doc retrieval	EQFE (w/ entities)	SDM (text-only)
Top-k docs	19	20
Top-k entities	50	all
Entity linker	KB Bridge	FACC1
GS annotations	graded, 1-5	binary 0/1

- LTR Method

Learning Algorithms

Learning-to-Rank (LTR)

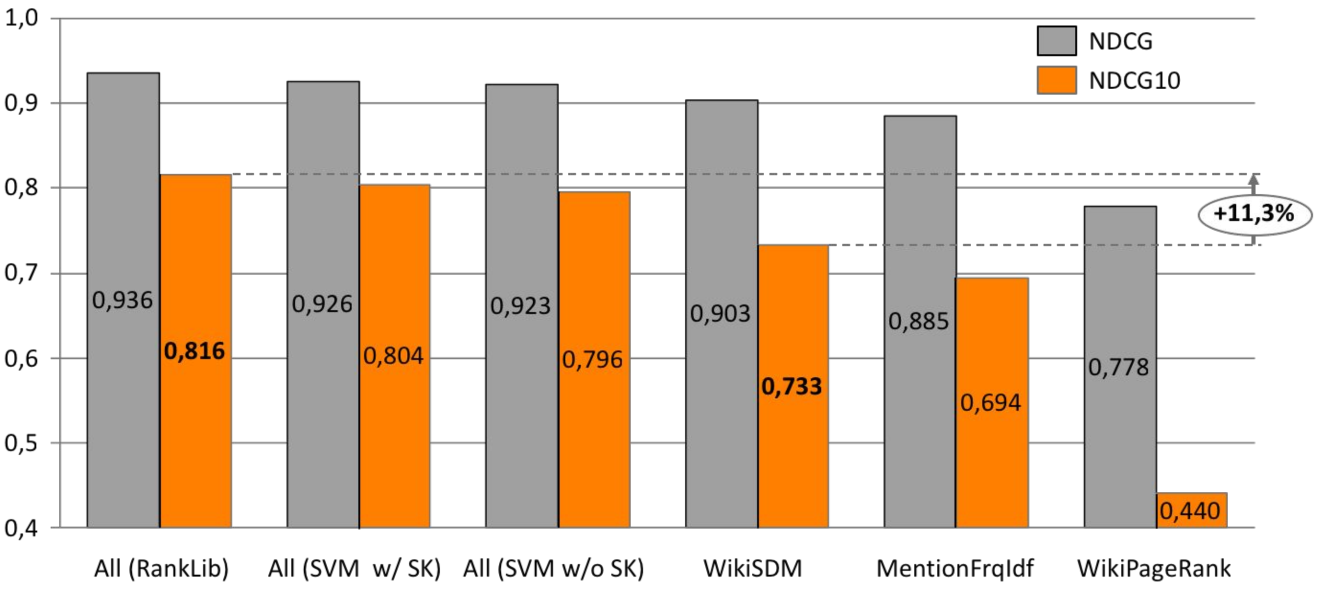
- Entity Relevance Features
- Labeled Data Set
- LTR Method

	Ranking SVM	**RankLib**
LTR type	Pairwise	Listwise
Method/Impl.	Joachims Ranking SVM	RankLib Coordinate Asc
Optimized metric	Disordered pairs	MAP

Retrieved Ranking for REWQ Rob04 (selected examples)

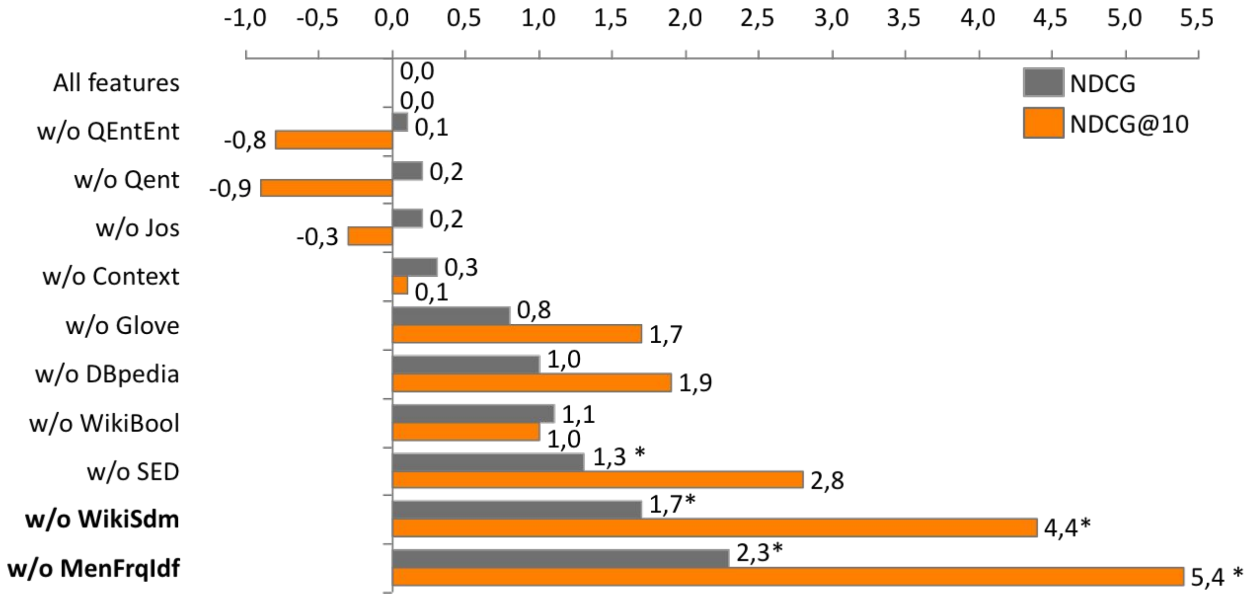
gt	ndcg	query	top-1 entity	top-2 entity	top-3 entity
5.0	.895	schengen agreement	Schengen_ Agreement	Schengen_Area	Schengen_ Information_ System
..	..	…	…	…	…
4.3	.879	poliomyelitis and post polio	Poliomyelitis	Polio_vaccine	Jonas_Salk
..	..	…	…	…	…
3.3	.748	argentine british relations	Foreign_relations_ of_Argentina	Argentina_national_rugb y_team	Falklands_War
..	..	…	…	…	…
1.9	.966	agoraphobia	Charles_M._Schulz	Snoopy	UGM-27_Polaris

Overall Results on REWQ Robust04



Feature combination sign. better than best single feature (+11.3% NDCG@10)

Feature Ablation Study (leave one-out) on REWQ Robust04



Doc Mention Frq and Wikipedia KB most important performance drivers

The Story so Far...

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- Combing document with entity retrieval gives overall high NDCG/MAP
- Two simple, but complementary feature are already helpful
  - **Document-based**: Mention frequency in query-specific documents (MenFrqIdf)
  - **Knowledge-based**: Full-text SDM on Wikipedia (WikiSDM)

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- We created two new gold standards for query-specific entity ranking

REWQ datasets available at http://rewq.dwslab.de

Building Entity-Centric Event Collections

Federico Nanni, Simone Paolo Ponzetto, Laura Dietz:
Building Entity-Centric Event Collections. *JCDL 2017*: 199-208

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- Laura Dietz (University of New Hampshire)
- Nikolay Marinov (University of Houston)

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Overall focus: using information from text and knowledge graphs to support research in **international relations**.

Political Scientists Study Events

Named Events

Identified by a common name: the **Orange Revolution**.

Named Events

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Different from Event Extraction!

In 2004, as part of the Orange Revolution, the constitution was changed.

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When / What / Event

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Different from Event Extraction!

When Named Event What Event

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Retrospective Analyses

Understanding how/whether **international events** have been discussed and perceived by **politicians**, **media**, **society**.

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The New York Times

INTERNET ARCHIVE

CONGRESS.GOV

Current Solution

Document filtering: collect all documents that contain **the event-name**.

Current Solution

Document filtering: collect all documents that contain **the event-name**.

Orange Revolution

(Ukraine - 2004)

Our Assumption

If you focus on the name of the event, you risk missing **its early stages**.

Orange Revolution

(Ukraine - 2004)

Our Assumption

If you focus on the name of the event, you risk missing **its early stages**.

Ukrainian presidential election, 2004

← 1999 | **October 31, November 21, December 26, 2004** | 2010 →

Nominee	**Viktor Yushchenko**	Viktor Yanukovych
Party	Independent	Party of Regions
Popular vote	**15,115,712**	12,848,528
Percentage	51.99%	44.20%

Orange Revolution

(Ukraine - 2004)

Our Approach

Using **related concepts** and **entities** to retrieve a comprehensive set of relevant documents.

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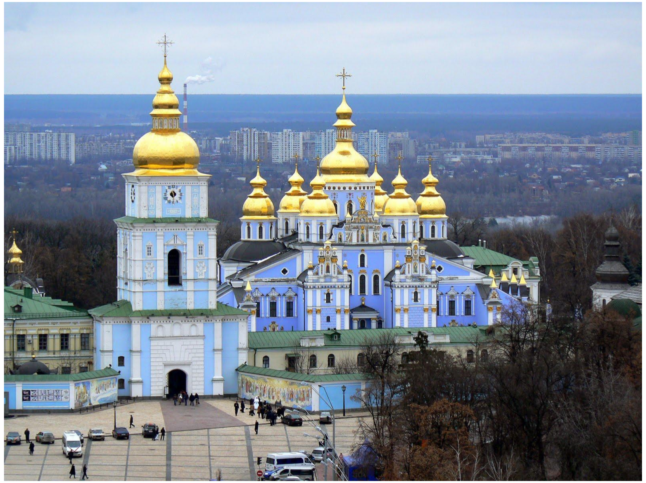
Using **related concepts** and **entities** to retrieve a comprehensive set of relevant documents.

Yulia Tymoshenko

Kiev



Russia

Our Approach

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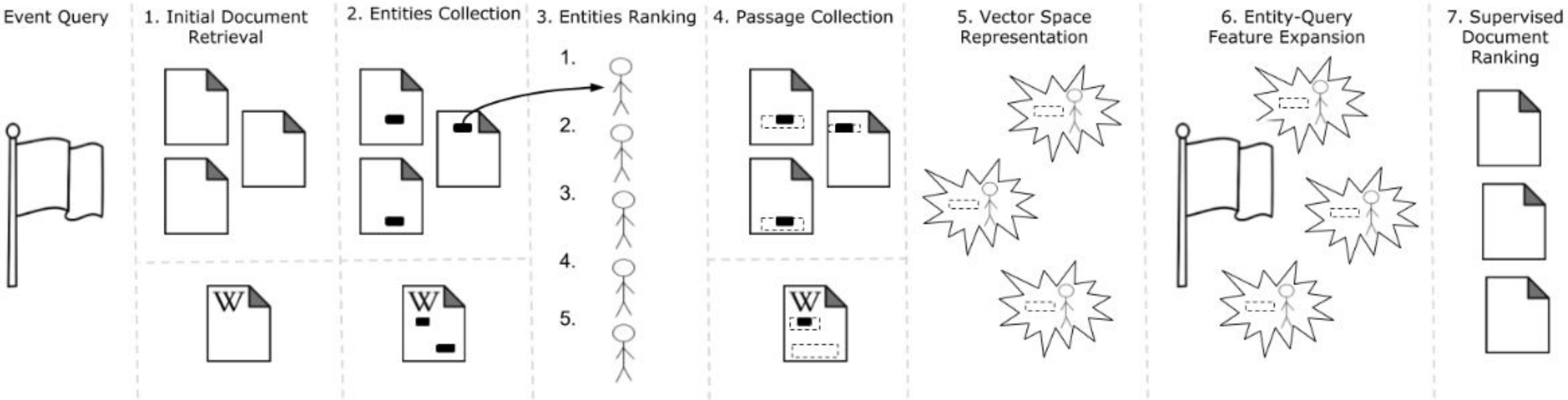


Case Studies

Types of event:

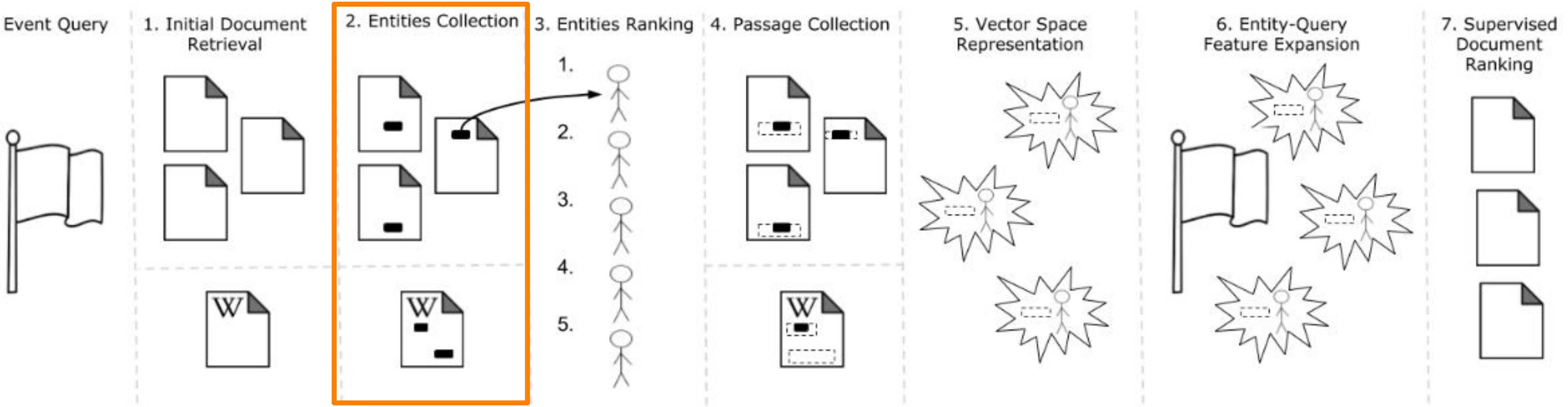
1) 15 unexpected elections
2) 15 political crises
3) 15 civil wars

Datasets:

1) New York Times Corpus
2) US Congressional Record
3) TREC KBA Stream Corpus

Our Approach

Using **related concepts** and **entities** to retrieve a comprehensive set of relevant documents.



Collecting Entities

Collect relevant entities from:

a) An initial pool of relevant documents (all entities mentioned in the **context** of the event-name).
b) Wikipedia page of the event, as **outlinks**.

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Method	Prec	Rec	F1
NELDA			
Info-Box			
Context			
Outlinks			
Cont+Out			

Collecting Entities

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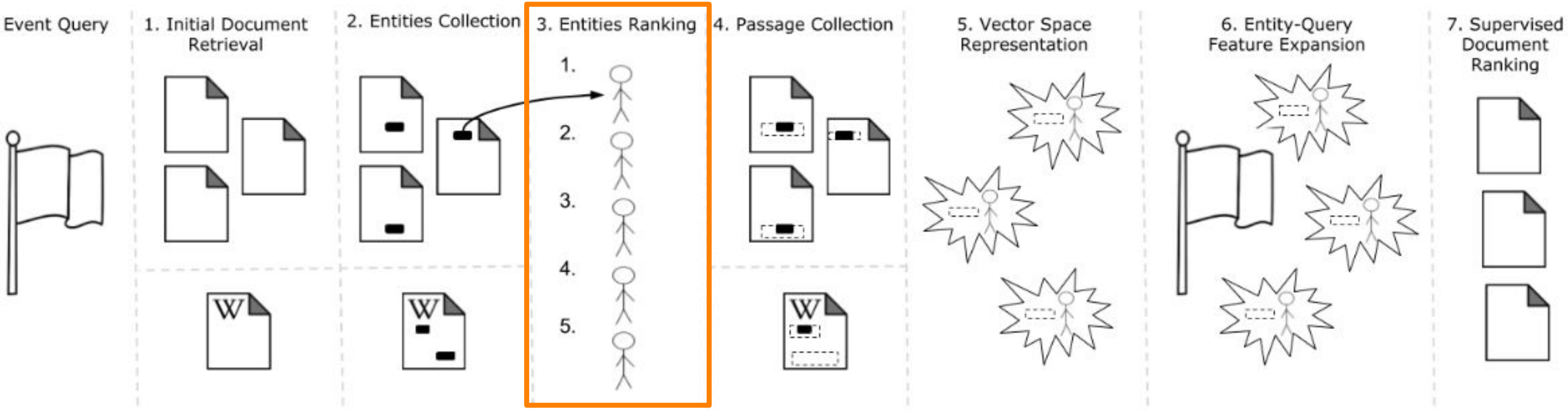
a) An initial pool of relevant documents (all entities mentioned in the **context** of the event-name).
b) Wikipedia page of the event, as **outlinks**.

Method	Prec	Rec	F1
NELDA	**1.00 ± 0.00**	0.13 ± 0.02	0.23 ± 0.02
Info-Box	0.88 ± 0.03	0.27 ± 0.05	0.41± 0.05
Context	0.52 ± 0.04	0.60 ± 0.05	0.55 ± 0.05
Outlinks	0.89 ± 0.03	0.53 ± 0.05	0.66 ± 0.05
Cont+Out	0.74 ± 0.04	**1.00 ± 0.00**	**0.85 ± 0.05**

Our Approach

Using **related concepts** and **entities** to retrieve a comprehensive set of relevant documents.



Ranking Entities

We use **RDF2Vec** (Ristoski et al., 2016) and rank by the cosine similarity of vector representation for each entity and the event.

Ranking Entities

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Method	MAP	P@5	P@10
ContFreq			
CheapEntRel			
RDF2Vec			

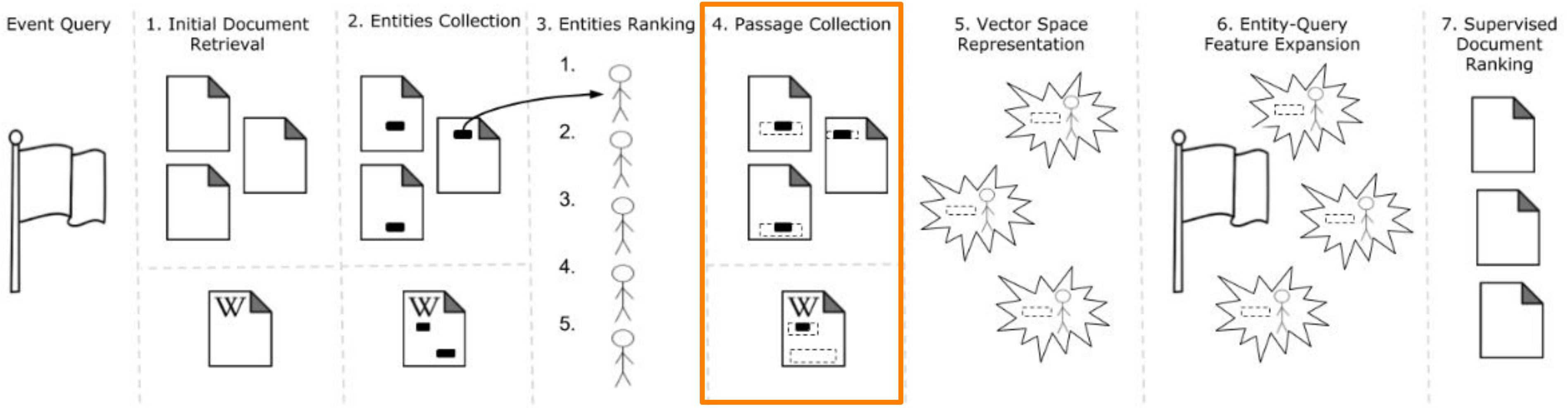
Ranking Entities

We use **RDF2Vec** (Ristoski et al., 2016) and rank by the cosine similarity of vector representation for each entity and the event.

Method	MAP	P@5	P@10
ContFreq	0.22 ± 0.03	0.55 ± 0.06	0.48 ± 0.05
CheapEntRel	0.51 ± 0.05	0.70 ± 0.05	0.62 ± 0.05
RDF2Vec	**0.65 ± 0.05**	**0.80 ± 0.06**	**0.74 ± 0.05**

Our Approach

Using **related concepts** and **entities** to retrieve a comprehensive set of relevant documents.



Getting Contextual Passages

For each relevant entity, we collect a **text snippet** from the **Wikipedia page of the event** by retrieving the first passage (i.e., three sentences) that contains a mention of the entity.

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Method	Prec	Rec	F1
Wiki-Intro			
NYT-Pass			
USC-Pass			
Wiki-Pass			

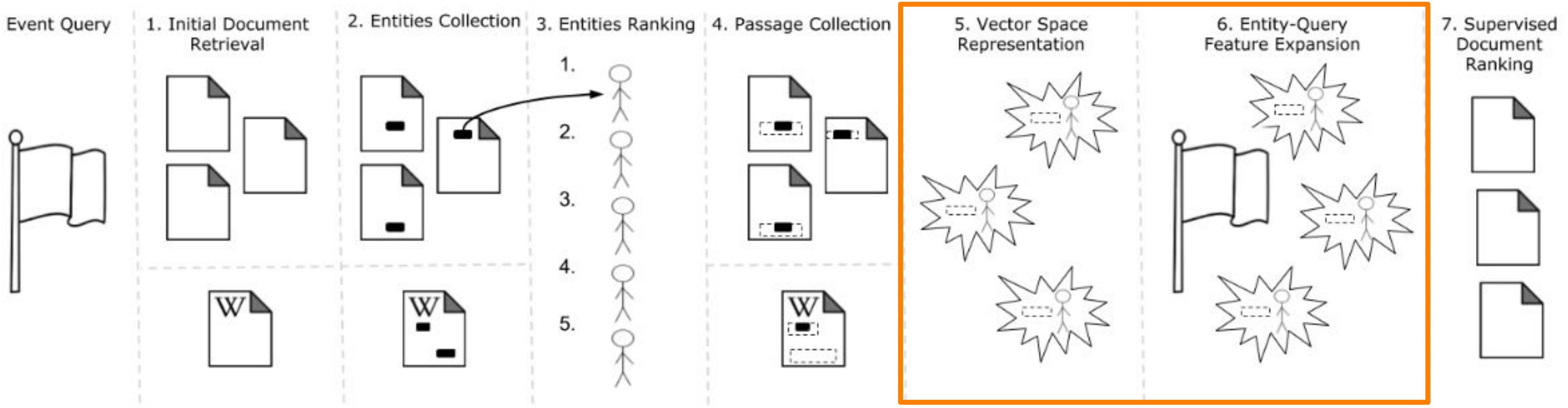
Getting Contextual Passages

For each relevant entity, we collect a **text snippet** from the **Wikipedia page of the event** by retrieving the first passage (i.e., three sentences) that contains a mention of the entity.

Method	**Prec**	**Rec**	**F1**
Wiki-Intro	0.45 ± 0.03	**1.00 ± 0.00**	0.62 ± 0.03
NYT-Pass	**0.99 ± 0.03**	0.36 ± 0.03	0.53 ± 0.03
USC-Pass	0.92 ± 0.03	0.19 ± 0.03	0.31 ± 0.03
Wiki-Pass	**0.99 ± 0.03**	0.83 ± 0.04	**0.89 ± 0.03**

Our Approach

Using **related concepts** and **entities** to retrieve a comprehensive set of relevant documents.



Query Expansion Approaches

Place

Entities

Passages (i.e., entities in context)

GloVe vector representation of Entities

GloVe vector representation of Passages **(our-light)**

Query Expansion Approaches

Place

Entities

Passages (i.e., entities in context)

GloVe vector representation of Entities

GloVe vector representation of Passages **(our-light)**

Cosine similarity between expanded query and document

Query Expansion Approaches

Place

Entities

Passages (i.e., entities in context)

GloVe vector representation of Entities

GloVe vector representation of Passages (our-light)

Cosine similarity between expanded query and document

All combined with Learning to Rank (our-full)

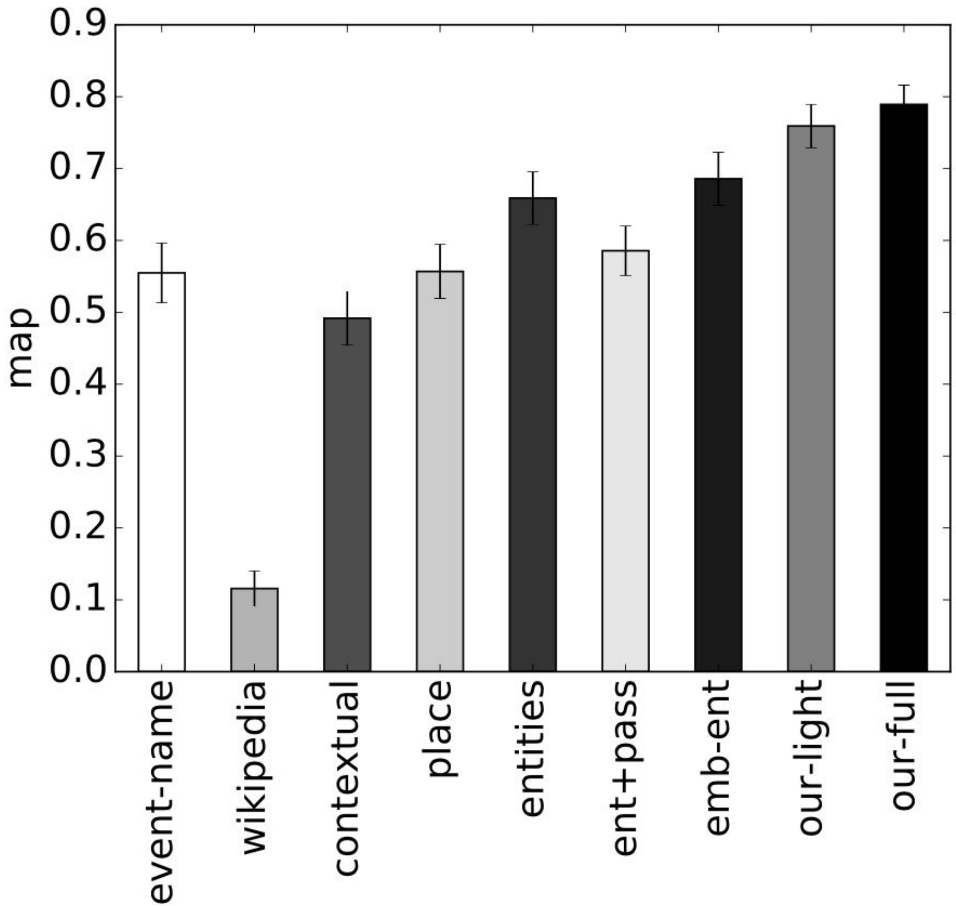
Baselines

Event-name

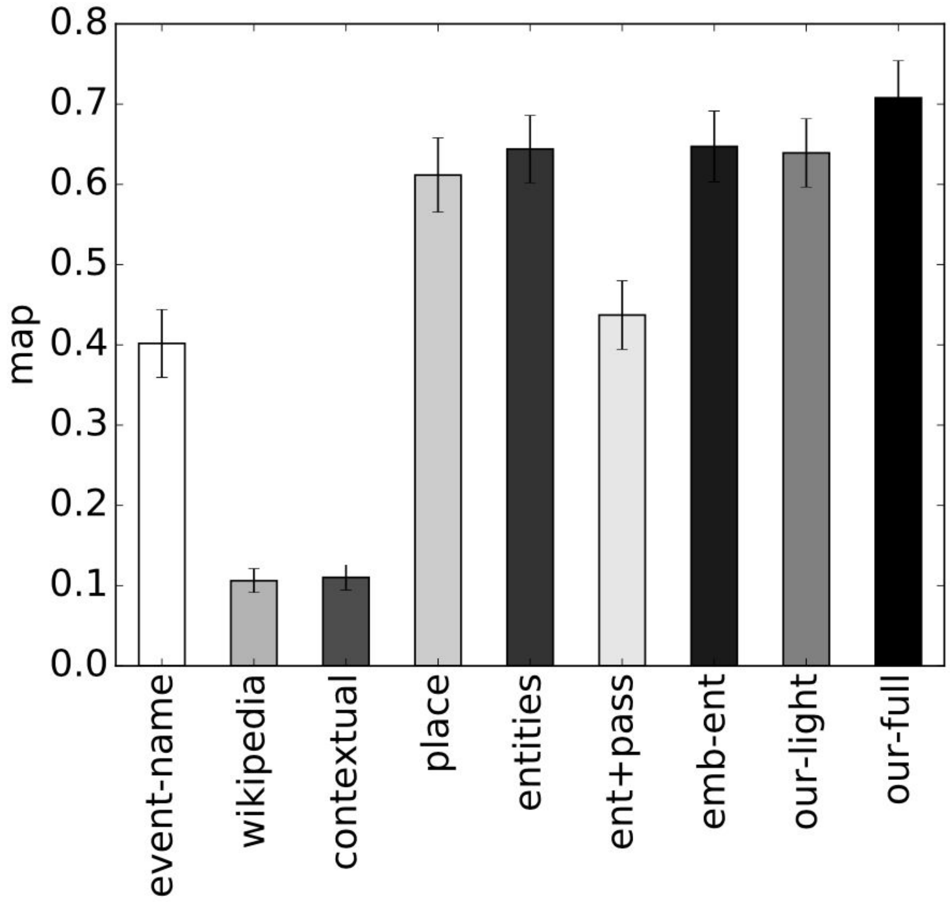
Wikipedia BoW

Contextual passages BoW

Evaluation on NY Times



Evaluation on US Congressional Record



MAP for Types of Events

Table 4: MAP for types of events on the NYT Corpus.

Method	Elections	Crises	Wars
event-name	0.64 ± 0.06	0.39 ± 0.06	0.61 ± 0.06
entities	0.63 ± 0.05	0.59 ± 0.06	0.76 ± 0.04
our-light	0.72 ± 0.05	0.73 ± 0.06	0.83 ± 0.04
our-full	**0.76 ± 0.04**	**0.74 ± 0.06**	**0.86 ± 0.04**

Table 5: MAP for types of events on the USC Corpus.

Method	Elections	Crises	Wars
event-name	0.32 ± 0.07	0.38 ± 0.06	0.52 ± 0.06
entities	0.65 ± 0.07	0.63 ± 0.06	0.65 ± 0.06
our-light	0.52 ± 0.06	**0.70 ± 0.05**	0.73 ± 0.06
our-full	**0.73 ± 0.05**	0.63 ± 0.09	**0.77 ± 0.08**

MAP for Types of Events

Table 4: MAP for types of events on the NYT Corpus.

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our-full	$\mathbf{0.73 \pm 0.05}$	0.63 ± 0.09	$\mathbf{0.77 \pm 0.08}$

% of Docs Missed Using the Event-Name

Type of Event	**Before**	**After**
Elections	16% ± 6	22% ± 7
Crises	63% ± 9	31% ± 6
Wars	14% ± 4	8% ± 2
All	30% ± 5	20% ± 4

Qualitative Study on TREC KBA

The story so far 2...

Federico Nanni, Simone Paolo Ponzetto, Laura Dietz:
Building Entity-Centric Event Collections. *JCDL 2017*: 199-208

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To build comprehensive event-collections it is **essential** to use a combination of relevant **entities** and **concepts**.

This is particularly true when studying the premises and early-stages of events such as **political crises**.

Data, resources, etc. @ **http://federiconanni.com/event-collections/**

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Data, resources, etc. @ **http://federiconanni.com/event-collections/**

Next Step: Identifying **entity-aspects** and **topics** for improving event-related document retrieval and collection building.

Entity Linking

Entity Linking

I’m watching the debate between Clinton and Sanders.

Entity Linking

I’m watching the debate between $\boxed{\text{Clinton}}$ and $\boxed{\text{Sanders.}}$

Entity Linking

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Entity Linking

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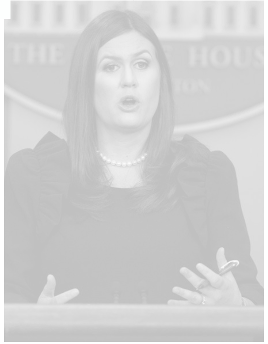

Limits of Entity Linking

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I’m watching the debate between Clinton and Sanders.

Hillary Rodham Clinton majored in political science.

Hillary Clinton is a former Senator for New York.

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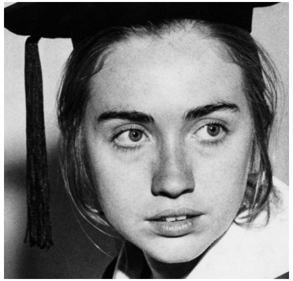

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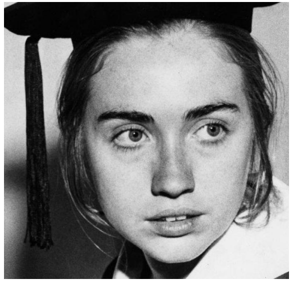

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Solution: Entity-Aspect Linking!

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Contents [hide]

Solution: Entity-Aspect Linking!

1

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Contents [hide]

Solution: Entity-Aspect Linking!

I'm watching the debate between Clinton[1] and Sanders.

Hillary Rodham Clinton[2] majored in political science.

Hillary Clinton is a former Senator for New York.

Contents [hide]

- 1 Early life and education 2
  - 1.1 Early life
  - 1.2 Wellesley College years
  - 1.3 Yale Law School and postgraduate studies
- 2 Marriage, family, law career and First Lady of Arkansas
  - 2.1 From the East Coast to Arkansas
  - 2.2 Early Arkansas years
  - 2.3 Later Arkansas years
  - 2.4 Bill Clinton presidential campaign of 1992
- 3 First Lady of the United States
  - 3.1 Health care and other policy initiatives
  - 3.2 Whitewater and other investigations
  - 3.3 Response to Lewinsky scandal
  - 3.4 Traditional duties
- 4 United States Senate
  - 4.1 2000 U.S. Senate election
  - 4.2 First term
  - 4.3 2006 re-election campaign
  - 4.4 Second term
- 5 2008 presidential campaign
- 6 U.S. Secretary of State
  - 6.1 Nomination and confirmation
  - 6.2 First half of tenure
  - 6.3 Second half of tenure
  - 6.4 Overall themes
  - 6.5 Benghazi attack and subsequent hearings
- 7 Email controversy
- 8 Clinton Foundation and speeches
- 9 2016 presidential campaign 1
- 10 Post-2016 election activities

Solution: Entity-Aspect Linking!

I'm watching the debate between Clinton [1] and Sanders.

Hillary Rodham Clinton [2] majored in political science.

Hillary Clinton [3] is a former Senator for New York.

Contents [hide]

Entity-Aspect Linking: A Few More Examples

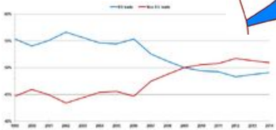
Hillary Clinton
2016 presidential campaign

Bernie Sanders
2016 presidential campaign

1. I'm watching the debate between **Clinton** and **Sanders**

Brexit
Impact on the United Kingdom

Issues in the United Kingdom European Union membership referendum, 2016
Economy



2. **#Brexit** will destroy the **UK welfare state**

European migrant crisis
Migrant routes, development and responses in individual countries

German Federal Election, 2017
Government formation

3. The **refugee crisis** had an impact on the **German election**

Entity-Aspect Linking

Federico Nanni, Simone Paolo Ponzetto, Laura Dietz: **Entity-Aspect Linking: Providing Fine-Grained Semantics of Entities in Context**. *JCDL 2018*: 49-58

Given: **an entity-mention in context** (e.g., tweet, sentence or paragraph)

Return: **a link to one from a set of predefined aspects** that captures the addressed topic

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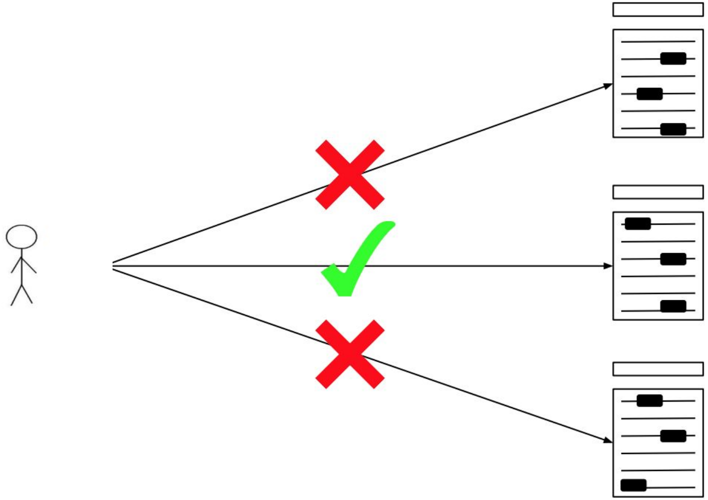
Given: **an entity-mention in context** (e.g., tweet, sentence or paragraph

Return: **a link to one from a set of predefined aspects** that captures the addressed topic

- Each entity aspect is *accompanied by a textual description and heading*
- We focus on Wikipedia as reference resource, i.e., each *top-level section of a Wikipedia page* defines one of the entity's specific aspects

Entity-Aspect Linking: How?

I'm watching the debate between **Clinton** and Sanders



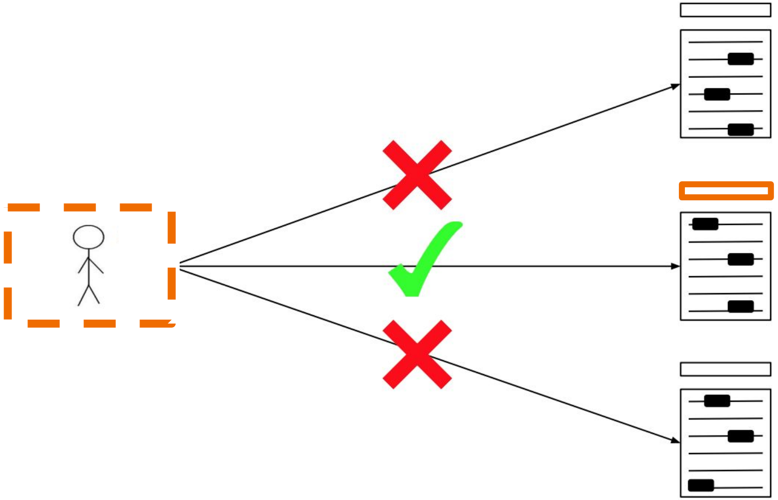
Early life and education

2016 Elections

US Senators

Aspect Representations as Headers

I'm watching the debate between **Clinton** and Sanders



Early life and education

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US Senators

Aspect Representations as Content

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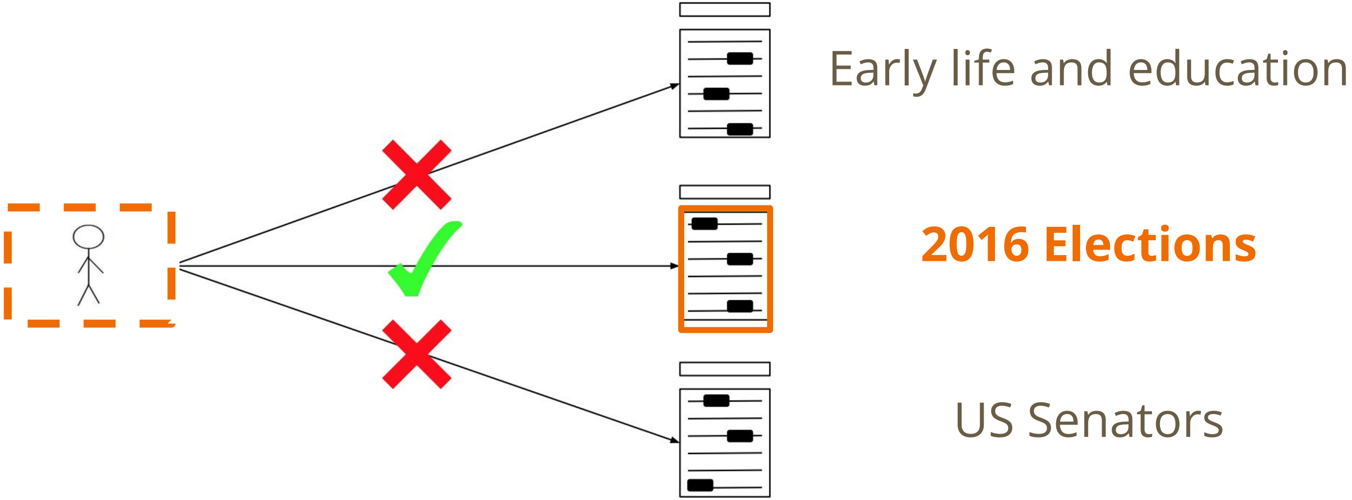
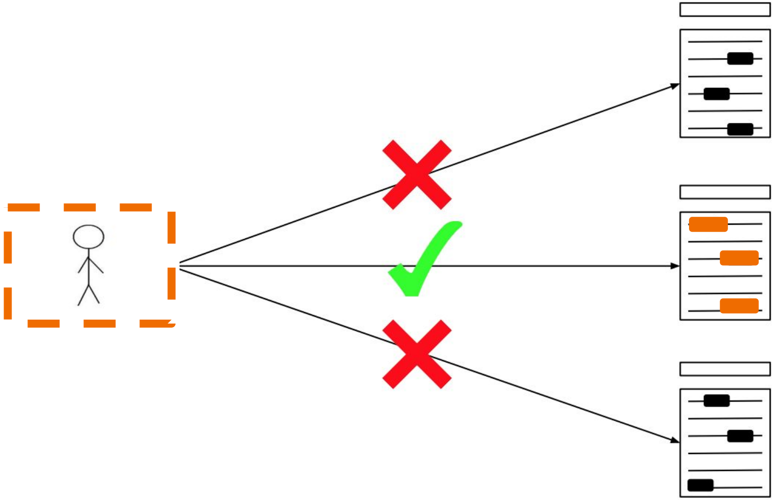


Aspect Representations as Entities

I'm watching the debate between **Clinton** and Sanders



Early life and education

2016 Elections

US Senators

Features

Sparse vector representations

- **tf-idf (cs)**: vanilla VSM (TF-IDF, cosine)
- **BM25**: Okapi BM25 score

Dense vector representations

- **w-emb (cs)**: cosine with pre-trained word embeddings (GloVe, 300d)
- **ent-emb (cs)**: cosine with pre-trained entity embeddings (RDF2Vec, 500d)

Bringing it All Together...

Representation	Features
Header	tf-idf (cs), BM25, w-emb (cs)
Content	tf-idf (cs), BM25, w-emb (cs)
Entity	tf-idf (cs), BM25, ent-emb (cs)

- Similarities and relevance scores are input to a list-wise learning-to-rank (L2R) algorithm

- We optimize for P@1 using coordinate ascent with linear normalization

Cool, But Are Entity-Aspects Useful?

Entity Ranking for Queries

Given: **a query**

Return: **a ranking of relevant entities**

Entity Ranking for Queries

Given: **a query**

Return: **a ranking of relevant entities**

“consequences brexit uk europe”

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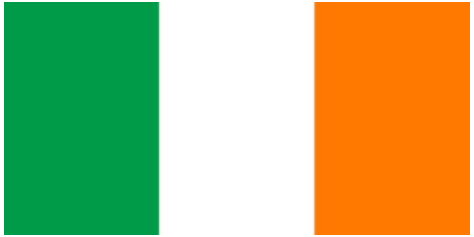

Entity Ranking for Queries

	Robust04		ClueWeb12	
Model	**MAP**	**P@5**	**MAP**	**P@5**
REWQ [40]				
Fusion [14]				
EAL				

Entity Ranking for Queries

	Robust04		ClueWeb12	
Model	**MAP**	**P@5**	**MAP**	**P@5**
REWQ [40]	-	0.79	-	**0.84**
Fusion [14]	0.57	0.85	0.39	0.82
EAL	**0.73**	**0.93**	**0.57**	0.74

Entity Ranking for Named Events

Given: **a named event**

Return: **a ranking of relevant entities**

Entity Ranking for Named Events

Given: **a named event**

Return: **a ranking of relevant entities**

dbr:Brexit

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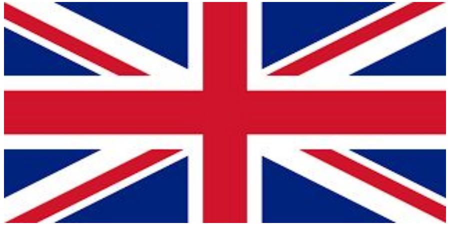
dbr:Brexit



Entity Ranking for Named Events

Model	**MAP**	**P@5**
RDF2Vec (cs)	0.65	0.80
EAL (EvAsp)		
EAL (EntAsp)		

EvAsp: rank on the basis of the similarity between the *entity name* and all sections on the *Wikipedia page of the event* (i.e., ***event aspects***)

EntAsp: rank on the basis of the similarity between the *event name* and all sections on the Wikipedia page of the entity (i.e., ***entity aspects***)

Entity Ranking for Named Events

Model	MAP	P@5
RDF2Vec (cs)	0.65	0.80
EAL (EvAsp)	0.74	0.73
EAL (EntAsp)	**0.82**	**0.90**

EvAsp: rank on the basis of the similarity between the *entity name* and all sections on the *Wikipedia page of the event* (i.e., ***event aspects***)

EntAsp: rank on the basis of the similarity between the *event name* and all sections on the Wikipedia page of the entity (i.e., ***entity aspects***)

Organizing Tweet Collections in Sub-Topics

Organizing Tweet Collections in Sub-Topics

Classify tweets into any of the 8 aspects from the Wikipedia page Issues in the United Kingdom European Union Membership Referendum, 2016

Organizing Tweet Collections in Sub-Topics

Topic	**# Tweets**
Economy	
Immigration	
Sovereignty and influence	
Security, law enforcement and defense	
Risk to the Unity of the United Kingdom	
Transatlantic Trade and Investment Partnership	
Enlargement of the European Union	
Proposed consequences of a vote to leave	
Total	
Excluded	
General	
Out-of-topic	

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Topic	# Tweets
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Transatlantic Trade and Investment Partnership	
Enlargement of the European Union	
Proposed consequences of a vote to leave	
Total	
Excluded	
General	270
Out-of-topic	108

Organizing Tweet Collections in Sub-Topics

Topic	# Tweets	
Economy		
Immigration		
Sovereignty and influence		
Security, law enforcement and defense		
Risk to the Unity of the United Kingdom		
Transatlantic Trade and Investment Partnership		
Enlargement of the European Union		
Proposed consequences of a vote to leave		
Total		
Excluded		
General	270	*The end is near **#brexit***
Out-of-topic	108	*Congrats!!! ICELAND 2-1 **Brexit** in Euro 2016*

Organizing Tweet Collections in Sub-Topics

Topic	# Tweets
Economy	
Immigration	
Sovereignty and influence	
Security, law enforcement and defense	
Risk to the Unity of the United Kingdom	
Transatlantic Trade and Investment Partnership	
Enlargement of the European Union	
Proposed consequences of a vote to leave	
Total	372
Excluded	
General	270
Out-of-topic	108

Organizing Tweet Collections in Sub-Topics

Topic	# Tweets
Economy	155
Immigration	52
Sovereignty and influence	50
Security, law enforcement and defense	3
Risk to the Unity of the United Kingdom	30
Transatlantic Trade and Investment Partnership	5
Enlargement of the European Union	12
Proposed consequences of a vote to leave	65
Total	372
Excluded	
General	270
Out-of-topic	108

Organizing Tweet Collections in Sub-Topics

Model	**P@1**
random baseline	
Ranking Approaches	
Content - BM25	
Content - w-emb (cs)	
EAL	
Classification Approaches	
Naive Bayes (tf-idf)	
SVM (tf-idf)	
Naive Bayes (w-emb)	
SVM (w-emb)	

Organizing Tweet Collections in Sub-Topics

Model	**P@1**
random baseline	0.12
Ranking Approaches	
Content - BM25	
Content - w-emb (cs)	
EAL	
Classification Approaches	
Naive Bayes (tf-idf)	0.27
SVM (tf-idf)	0.27
Naive Bayes (w-emb)	0.38
SVM (w-emb)	0.37

Organizing Tweet Collections in Sub-Topics

Model	**P@1**
random baseline	0.12
Ranking Approaches	
Content - BM25	0.37
Content - w-emb (cs)	0.36
EAL	**0.42**
Classification Approaches	
Naive Bayes (tf-idf)	0.27
SVM (tf-idf)	0.27
Naive Bayes (w-emb)	0.38
SVM (w-emb)	0.37

Entity-Aspect Linking

Federico Nanni, Simone Paolo Ponzetto, Laura Dietz: **Entity-Aspect Linking: Providing Fine-Grained Semantics of Entities in Context**. *JCDL 2018*: 49-58

1. A **New perspective** on entity linking.
2. Aimed at providing fine-grained **information** on entities in **context**.
3. Useful for **downstream tasks**.

Data, resources, etc. @ **http://federiconanni.com/entity-aspect-linking/**

That’s it Folks!

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- Keep on working on downstream applications (semantic indexing, search, summarization, etc.)

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