UNIVERSITÄT HEIDELBERG
ZUKUNFT SEIT 1386

Entity-centric Topic Extraction and Exploration: A Network-based Approach

Andreas Spitz and Michael Gertz

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Heidelberg University, Germany
Database Systems Research Group

A Topic From Recent News

term	score
skripal	0.83
nerve	0.77
agent	0.76
u.k.	0.61
russia	0.58
diplomat	0.45
intelligence	0.43
poison	0.33
daughter	0.19
yulia	0.17

Disadvantages of Traditional (LDA) Topics

Substantial runtime requirements that increase

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- with the number of topics

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Limited support for explorations of

- topic labels / topic descriptions
- relations between topics

Entity-centric Network Topics

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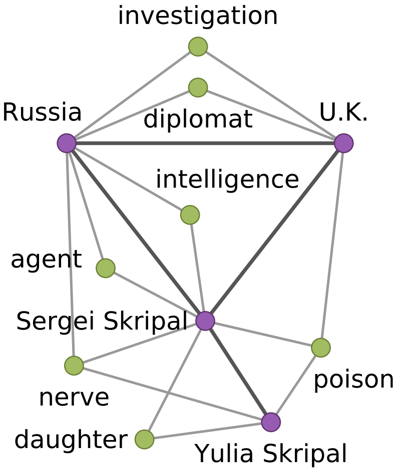
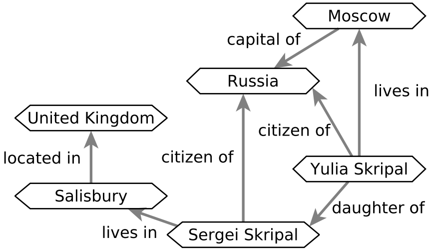


Implicit Entity Networks

What Are Implicit Entity Networks?



Knowledge Graph

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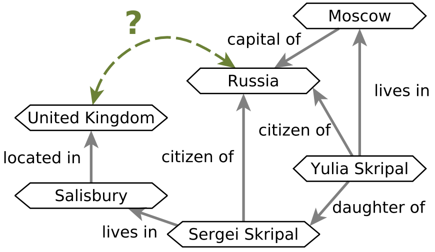

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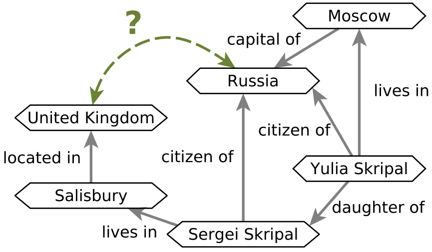

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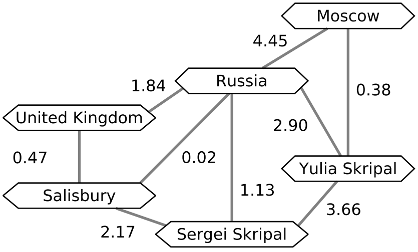

Implicit Network

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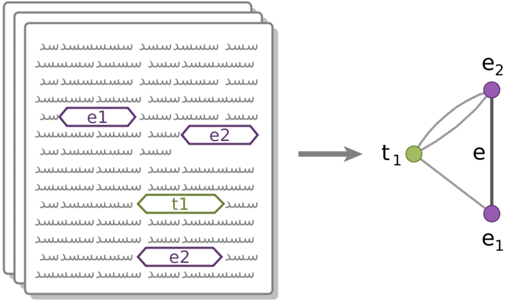
Extracting Implicit Networks From Text



annotated document collection

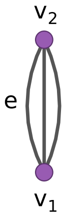
implicit network representation

D(e): documents in which edge e occurs
T(e): publication timestamps of documents D(e)
Δ(e): sentence distances between the nodes of e
c(e): total number of occurrences of edge e

Network Topic Construction

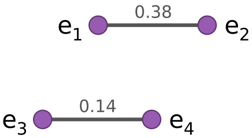
Parallel Edge Aggregation And Ranking

$$\omega(e) = 3 \cdot \Bigg[\underbrace{\frac{|D(v_1) \cup D(v_2)|}{|D(e)|}}_{\text{coverage}} + \underbrace{\frac{\max\{T(e)\} - \min\{T(e)\}}{|T(e)|}}_{\text{temporal coverage}} + \underbrace{\frac{c(e)}{\sum_{\delta \in \Delta(e)} \exp(-\delta)}}_{\text{distance}} \Bigg]^{-1}$$



D(e): documents in which edge e occurs
T(e): publication timestamps of documents D(e)
Δ(e): sentence distances between the nodes v1 and v2
c(e): total number of occurrences of edge e

Topic Extraction and Triangular Growth



Intuition:

- edges between entities correspond to seeds of topics

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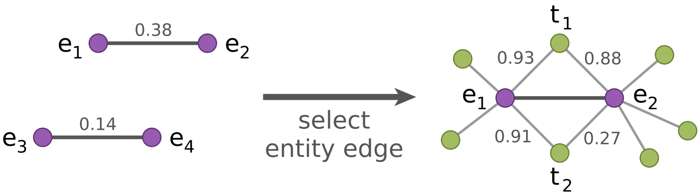

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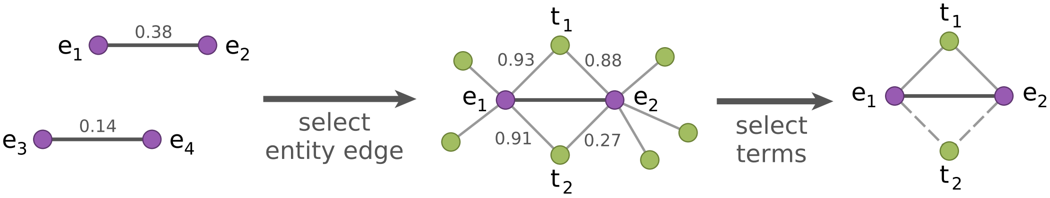

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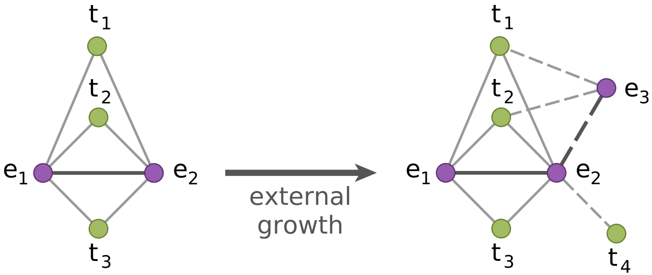
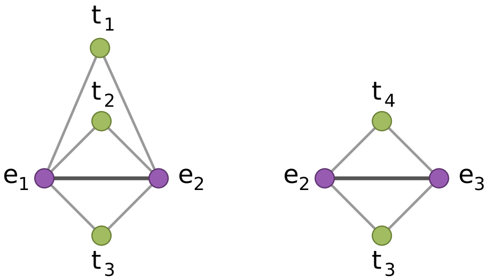
Topic Growth by External Nodes



For a demonstration of entity ranking in implicit networks see:

A. Spitz, S. Almasian, and M. Gertz. "EVELIN: Exploration of Event and Entity Links in Implicit Networks". In: *WWW Companion*. 2017. URL: `http://evelin.ifi.uni-heidelberg.de`

Topic Overlap and Merging Topics



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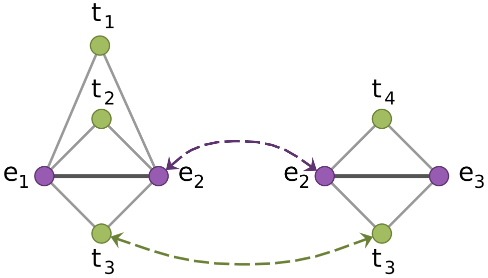

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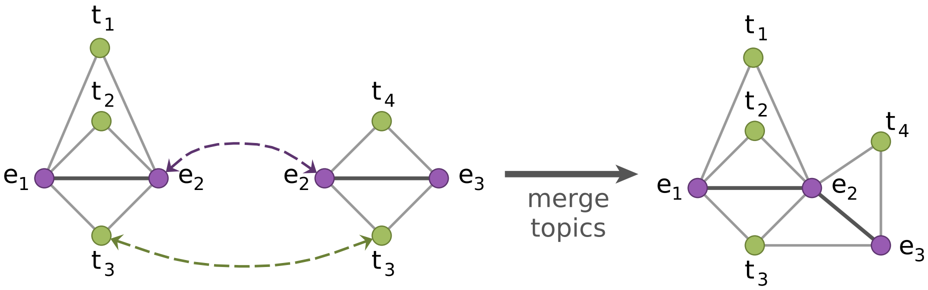

Topic Exploration

Overview: News Article Data

English news articles from RSS feeds:

- 14 news outlets (from US, UK, and AU)
- 6 months (Jun 1 - Nov 30, 2016)
- 127.5 thousand articles
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NLP processing pipeline:

- Part-of-speech and sentence tagging:
  Stanford POS tagger
- Entity classification:
  YAGO classes (LOC, ORG, PER)
- Named entity recognition and linking:

AMBIVERSE
Text to Knowledge

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- 6 months (Jun 1 - Nov 30, 2016)
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The resulting implicit network has

- 119.3 thousand entities
- 329.0 thousand terms
- 10.6 million edges

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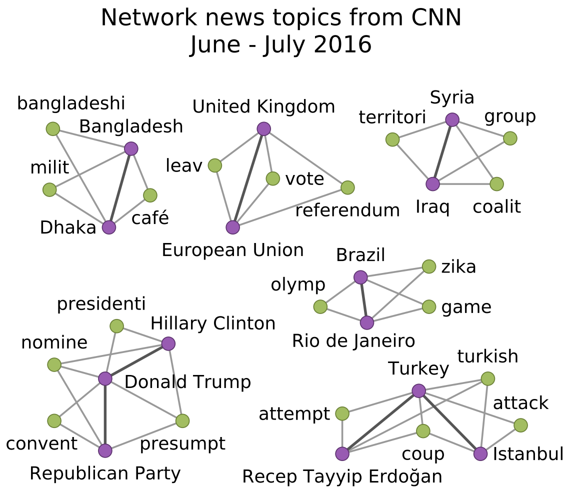
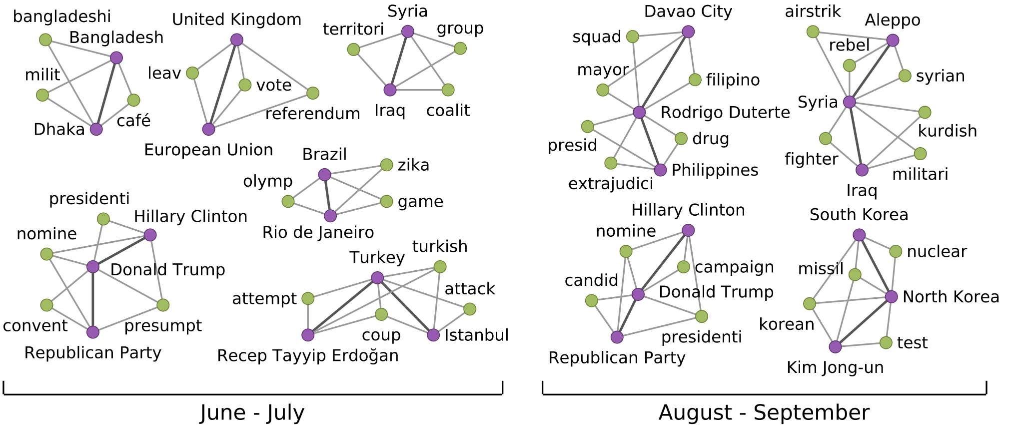
Network Topic Example



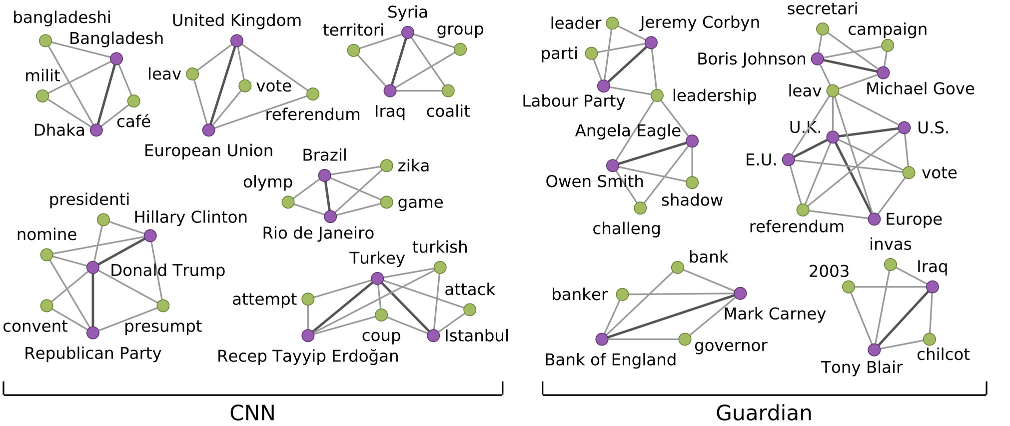
Network Topic Evolution

Network news topics from CNN (2016)



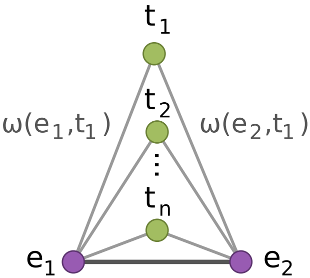
Topics Across Different News Outlets

Network news topics from June - July 2016



Comparison to Classic Topics

Term Ranking in Network Topics



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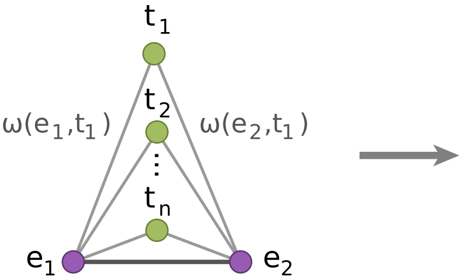


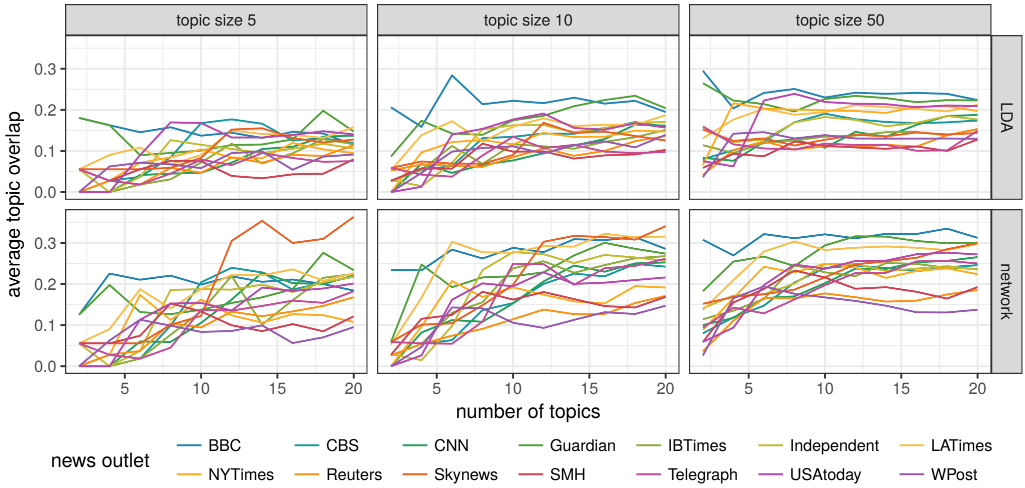
term	score
t_1	$\min\{\omega(e_1, t_1),\ \omega(e_2, t_1)\}$
t_2	$\min\{\omega(e_1, t_2),\ \omega(e_2, t_2)\}$
$\vdots$	$\vdots$
t_n	$\min\{\omega(e_1, t_n),\ \omega(e_2, t_n)\}$

Classic Topics From Network Topics

Beirut - Lebanon Q3820 - Q822		Russia - Moscow Q159 - Q649		Russia - Putin Q159 - Q7747		Trump - Obama Q22686 - Q76	
term	score	term	score	term	score	term	score
syrian	0.14	russian	0.28	russian	0.29	presid	0.40
rebel-held	0.12	soviet	0.06	presid	0.18	american	0.21
rebel	0.06	nato	0.06	annex	0.09	republican	0.19
cease-fir	0.05	diplomat	0.06	nato	0.08	democrat	0.19
bombard	0.05	syrian	0.06	hack	0.08	campaign	0.18
bomb	0.04	rebel	0.05	west	0.08	administr	0.17

Network news topics from the New York Times (Jun - Nov 2016)

Topic Overlap Comparison

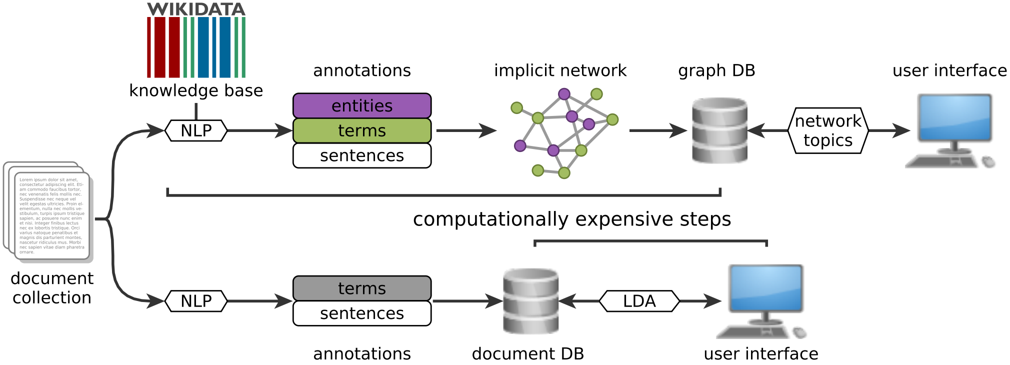


Discussion & Summary

Benefits of Entity-centric Network Topics

Benefits vs. traditional topics:

- faster extraction than LDA topics
- runtime contained in data preparation
- number of topics is flexible



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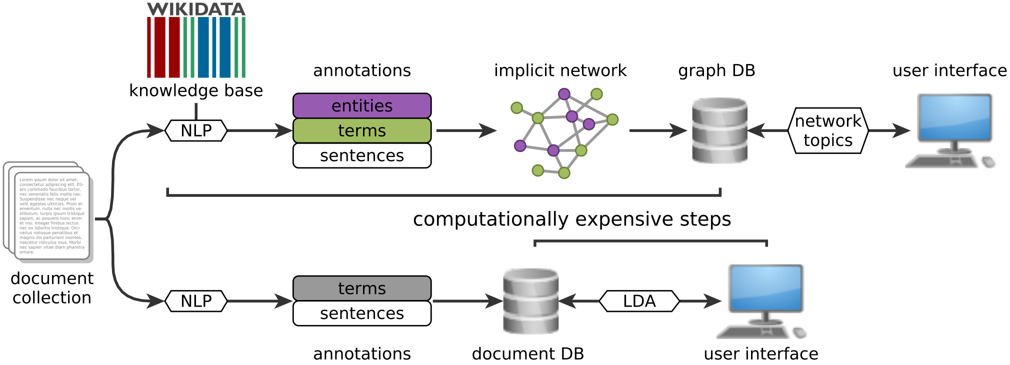
Stream compatibility:

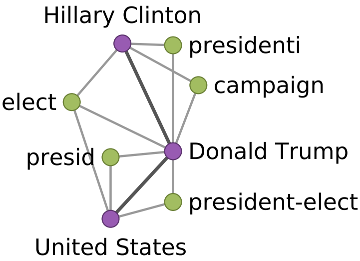
- document updates require only (sub-) graph updates



Flexibility of Entity-centric Network Topics

Intuitive exploration of topics:

- network visualizations instead of term lists
- entities act as labels for topics



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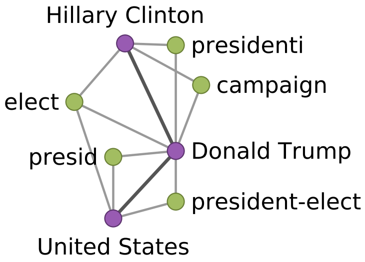
Efficient support of interactive explorations:

- Adding more topic seeds (edges):
  $\mathcal{O}(\log n)$ for edge lookup with index support
- Adding more descriptive terms:
  $\mathcal{O}(\langle k \rangle)$ for average node degree $\langle k \rangle$



Summary

Data and implementation are available online:

- [data] Implicit news network
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- [code] Topic exploration and extraction

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