Chapter IR:VI

VI. IR Applications

- Web Technology
- Web Graph
- Web Crawling
- Web Archiving
- Web Content Extraction
- Near-duplicate Detection
- Link Analysis

- The Treachery of Answers
- Argument Retrieval Problems
- Argument Ranking I
- Argument Ranking II
- Argumentation-Related Resources
- Argument Search Engines
- Argument Search Evaluation I
- Argument Search Evaluation II

Google

how long do cats live

Cat / Lifespan

15 years

Domesticated

Feedback

How Long Do Cats Live? | petMD

www.petmd.com/blogs/thedailyvet/.../**how_long_do_cats_live**-11496

Aug 8, 2011 - This question, typically rephrased as, "**How long** will my **cat** (or dog, horse, etc.) **live**," is something veterinarians hear on a daily basis.

Aging Cats: Changes, Health Problems, Food, and More

pets.webmd.com/**cats**/guide/aging-**cats**-qa

WebMD veterinarian experts answer common questions **cat** owners have ... What else can you expect as your **cat** ages? ... Q: **How long do cats** usually **live**?

What Is the Life Span of the Common Cat? - Cats - About.com

cats.about.com › About Home › Cats

How long is the common **cat** supposed to **live**? Questions and answers from the About Guide to **Cats**.

Ageing - How long do cats live | Adelaide Animal Hospital

adelaidevet.com.au/pet.../**how-long-do-cats-live**-ageing-and-your-feline

Life expectancy depends on many things, including one important factor - whether your cat is an indoor-only cat or an outdoor cat. Indoor cats generally live from **12-18 years** of age. Many may live to be in their early 20s. The oldest reported cat lived to be an

Cat

Animal

The domestic cat or the feral cat is a small, typically furry, carnivorous mammal. They are often called house cats when kept as indoor pets or simply cats when there is no need to distinguish them from other felids and felines. Wikipedia

Scientific name: Felis catus

Lifespan: 15 years (Domesticated)

Gestation period: 64 – 67 days

Higher classification: Felis

Daily sleep: 12 – 16 hours

Mass: 3.6 – 4.5 kg (Adult)

Feedback

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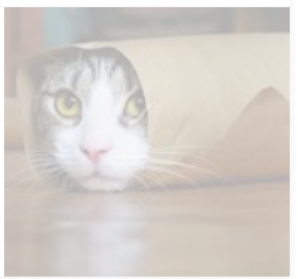

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Konrad Lischka

How does Google know when my cat will die?

23. September 2015 by Konrad Lischka, in Blog @en

How long do cats live? Exactly 15 years says Google.com. Not “10 to 15”, not “about 15 years”, but “15 years”. That sounds like a definitive answer. It’s Google’s answer to the search query “How long do cats live”.

The Treachery of Answers

Retrieving answers as a retrieval paradigm:

- Users ask questions that concern them.
- Search engines return direct answers from knowledge bases and the web.

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The dilemma of the direct answer: [Potthast/Hagen/Stein 2020]

> The dilemma of the direct answer is a user's choice between convenience and diligence when using an information retrieval system.

The impact on society of giving direct answers at scale is not well-understood.

The Treachery of Answers

Remarks:

- Copyright notice:
  - “La Trahison des réponses” (2020; “The Treachery of Answers”) by the Webis Group is licensed CC BY-NC 2.0.
  - “La Trahison des réponses” is a derivation from “La Trahison des images” (1929; “The Treachery of Images”) by René Magritte.
  - The canvas and handwriting have been derived from a 2019 public domain reproduction of Magritte’s painting by Thomas Hawk at publicdelivery.org.
  - The image of the cat has been taken from a public domain reproduction of the painting “Sitting Cat” (1815) by Jean Bernard Duvivier at rawpixel.com.
  - The cat’s image was kindly colorized manually by user BlueBudgieOne on Reddit’s /r/colorizationrequests.

Argument Retrieval Problems

Basic Argument Model

Conclusion	*Mankind will be able to travel to other galaxies.*

Premise 1	*Photon drives can take you up to relativistic velocities.*
Premise 2	*In August 2019 Lightsail2 demonstrated its functioning.*
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Argument:

- A conclusion (claim) supported by premises (reasons). [Walton et al. 2008]
  Conclusion and premises are considered as propositions.
- Conveys a stance on a controversial topic. [Freeley and Steinberg, 2009]
  Assignment of truth values to the propositions:
  $\mathcal{I}(\text{“}\textit{Mankind will be able to travel to other galaxies.}\text{”}) = 1,\ \mathcal{I}(\text{“}\textit{Photon} \ldots\text{”}) = 1,\ \ldots$
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Argument Retrieval Problems

Basic Argument Model

Thesis / Major claim t *Human beings will colonize other planets.*

A_{pro}

c_1 *Mankind will be able to travel to other galaxies.*

P_1

p_1 *Photon drives can take you up to relativistic velocities.*

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Note: $c_1 \succ t$

- "c_1 supports t" (entailment in a cogent, nonobligatory sense)
- "t is compatible with c_1" (but the real argumentation focus)

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A_{con}:

c_2 *Mankind will never explore other galaxies.*

P_2:

p_4 *Matter cannot pass through wormholes.*

p_5 *Hawking explained why time travel is impossible.*

Argument Retrieval Problems

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Note:

- The standard interpretation $\mathcal{I}$ of all propositions, $t,\ c_i,\ p_j$, is 1 (true).
- $c_1 \approx \neg\, c_2$ "$\neg\, c_2$ is a paraphrase of c_1"

$\Rightarrow$ c_2 can be expressed as c_1 with opposite truth assignment, $\mathcal{I}(c_1) = 0,\ \mathcal{I}(c_2) = 1$

Argument Retrieval Problems

(1) Argument Relevance Π_{rel}

Query *Will human beings colonize other planets?*

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Given in Π_{rel} :

- information need, expressed as query, $q \in Q$
- set of arguments, $\mathbf{A} = \{(c_1, P_1), (c_2, P_2), \ldots, (c_n, P_n)\}$

$*$ (possibly hidden) human selection of the relevant arguments, $\mathbf{A}_q^*$, $q \in Q$

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Sought in Π_{rel} :

- a relevance function $\rho : Q \times \mathbf{A} \to \{0, 1\}$, such that ...

  the macro-averaged F-measure (precision, recall) regarding $\mathbf{A}_q^*$, $q \in Q$, is maximum

Argument Retrieval Problems

(2) Argument Ranking Π_{rank}

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Sought in Π_{rank} :

- a ranking function $\sigma : Q \times \mathcal{P}(\mathbf{A}) \to \Pi$, such that ...

  the mean rank correlation $\overline{\tau}$ regarding $\pi^*_{\mathbf{A}_q}$, $q \in Q$, is maximum

Argument Retrieval Problems

(3) – (7) Further Problems

3. Π_{counter} Retrieve the “best” counterargument

   Given: query q, argument set $\mathbf{A}$, argument A

4. Π_{sameside} Retrieve (all) arguments with the same stance

   Given: argument set $\mathbf{A}$, argument A

5. Π_{argdoc} Is the document argumentative?

   Given: document d

6. Π_{argquery} Is the query argumentative?

   Given: query q

7. Π_{argsum} Summarize an argument.

   Given: argument A

Argument Retrieval Problems

(3) – (7) Further Problems

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Notes:

- Π_{counter} can be cast as Π_{rank} if the query is negated.
- Π_{argdoc} and Π_{argquery} are decision problems.
- Π_{counter} and Π_{sameside} can be cast as decision problems as well.
- Challenge: development of domain-independent or "topic-agnostic" approaches.

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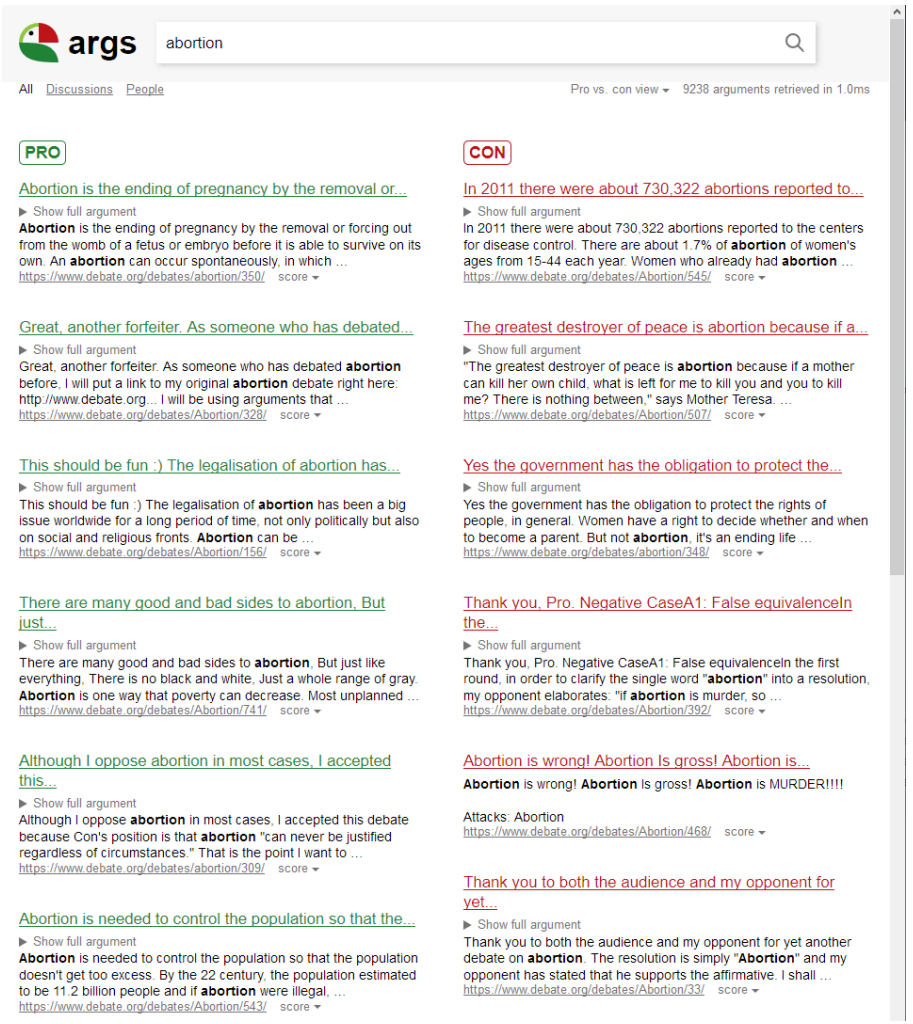
Argument Ranking I



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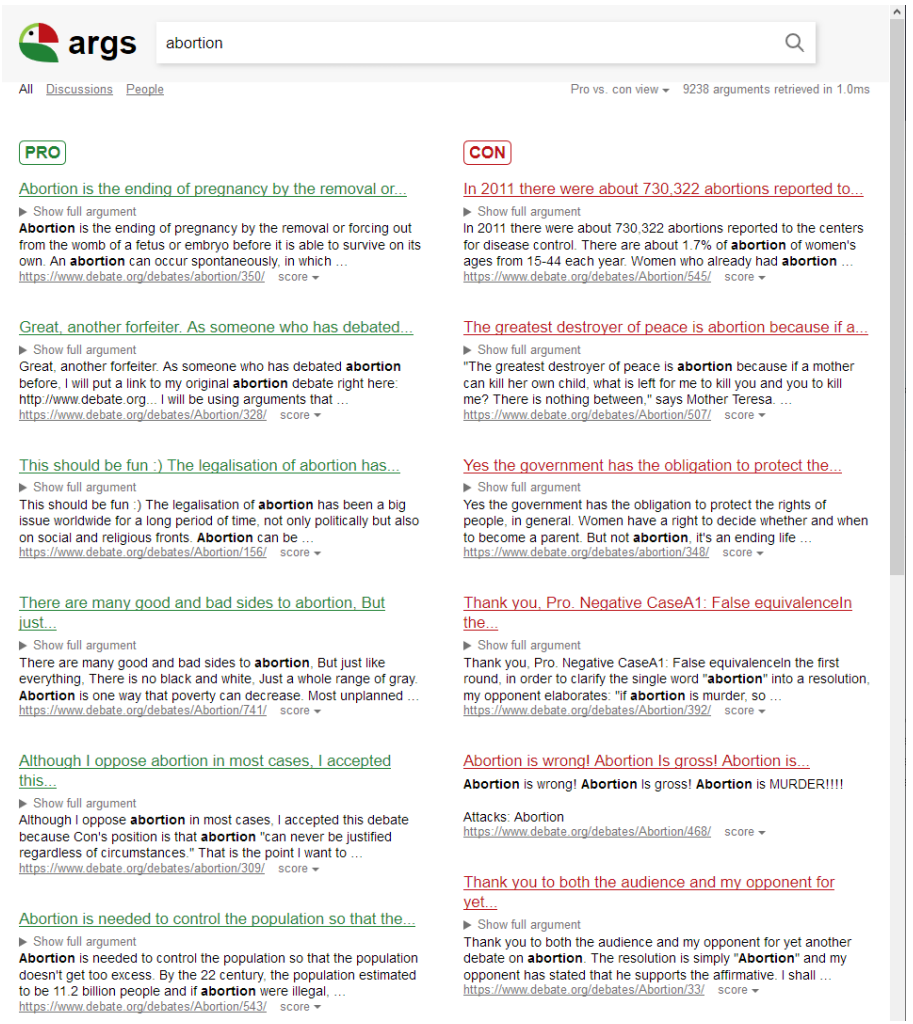

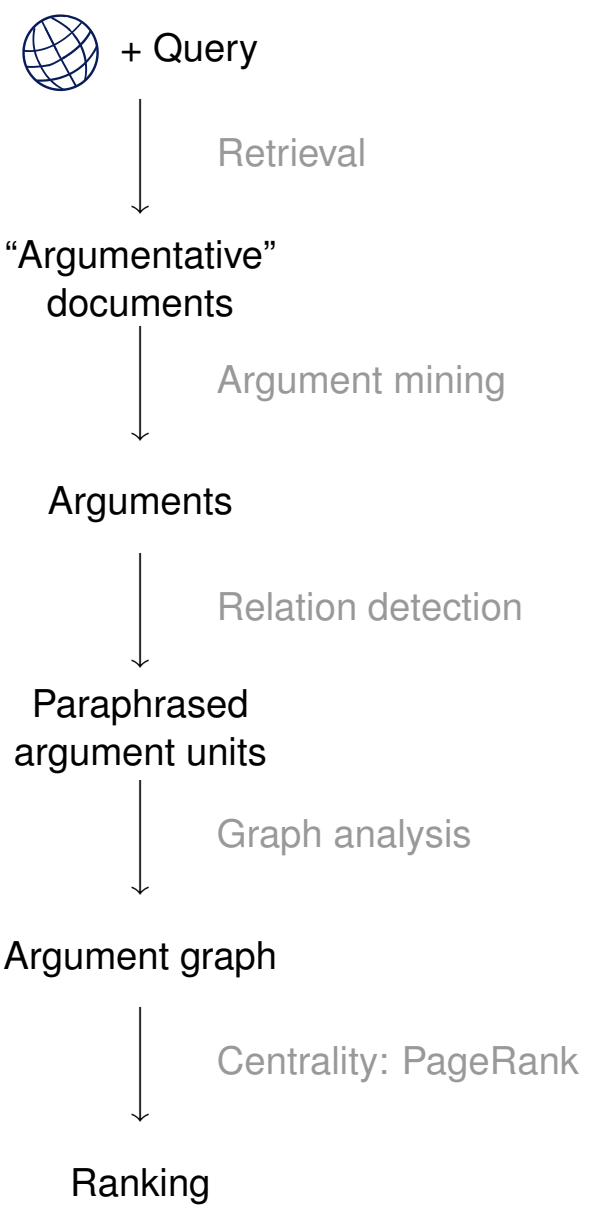

Argument Ranking I

Query *Reintroduce death penalty?*

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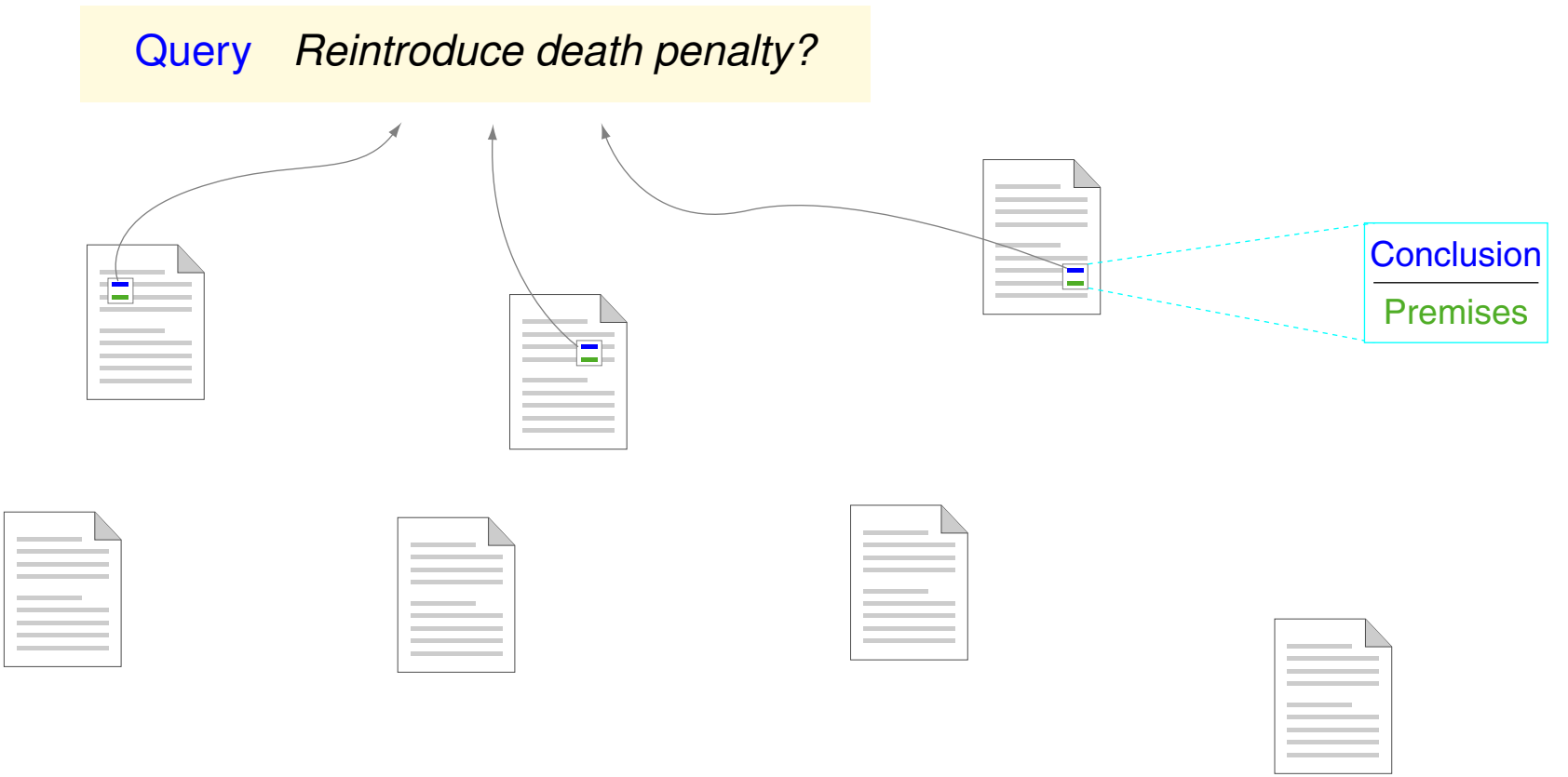

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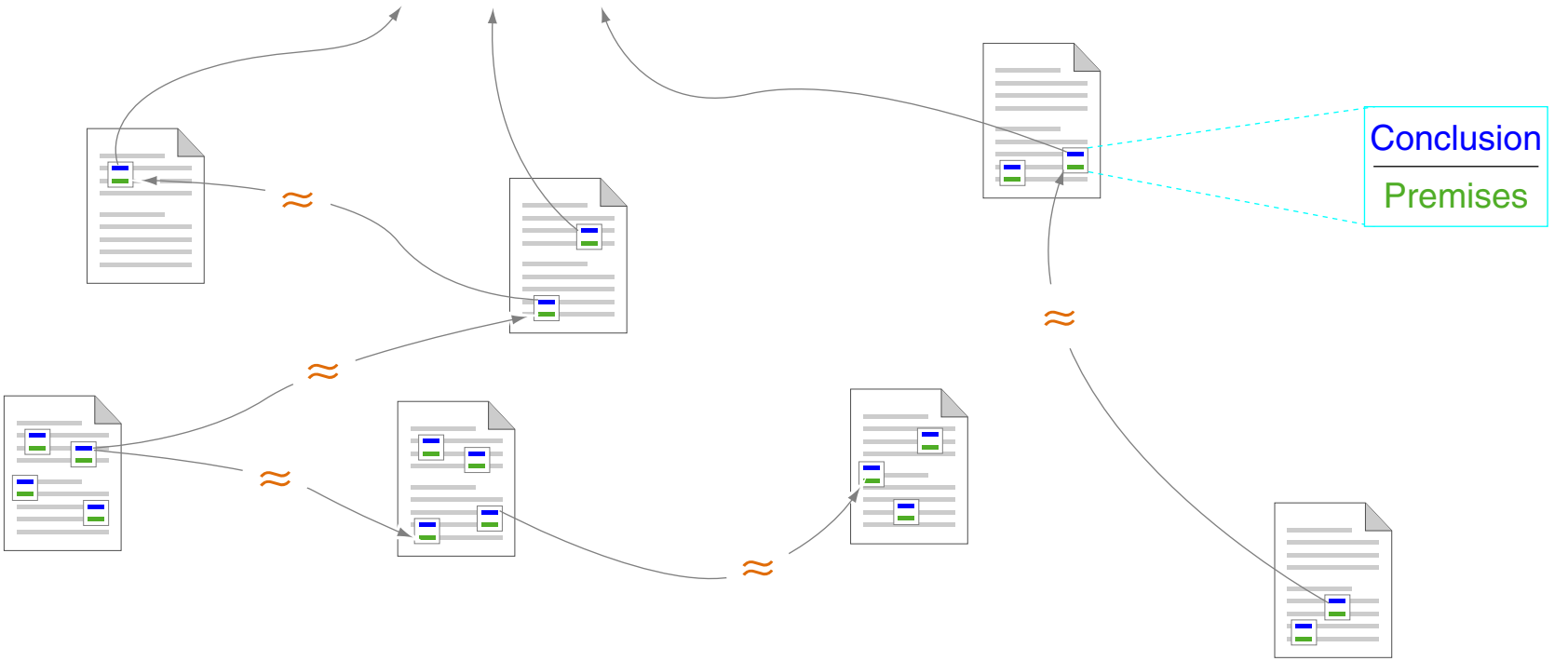

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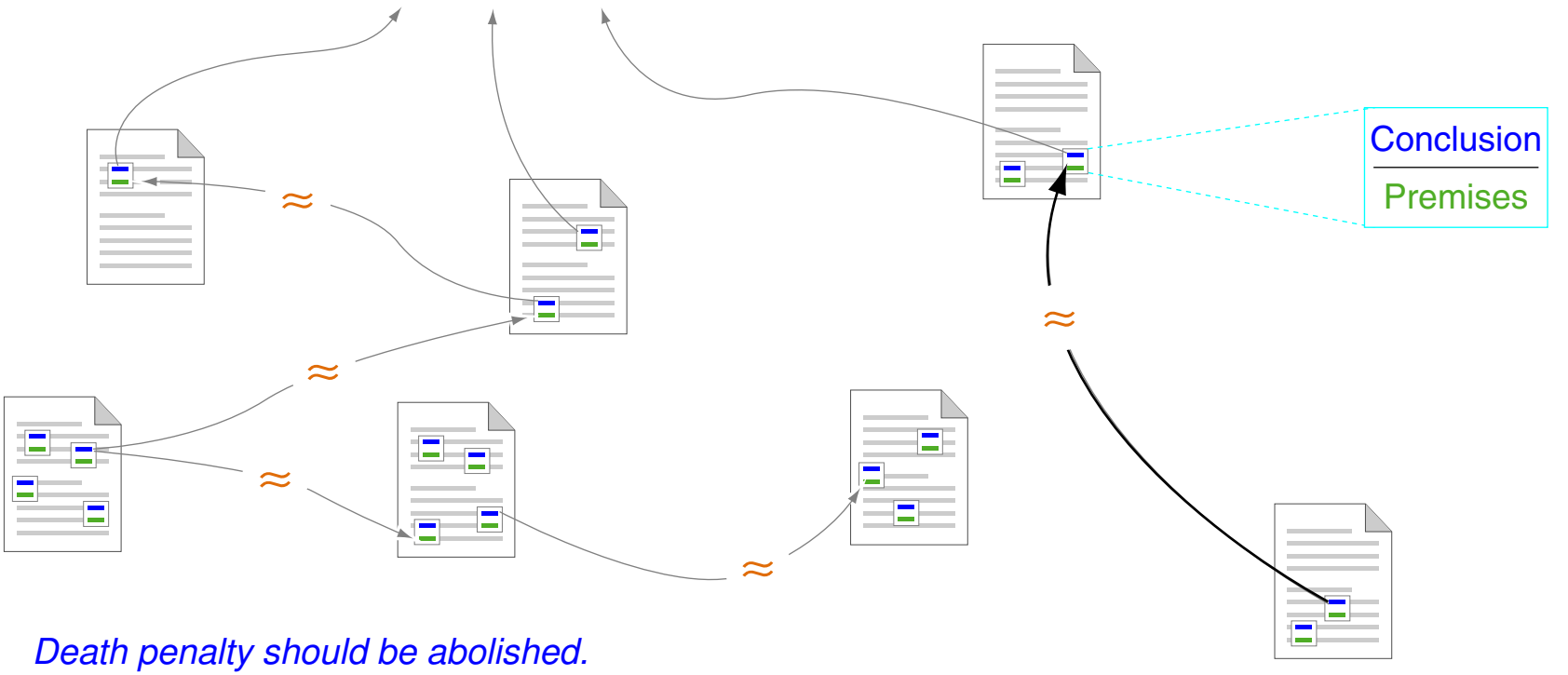

Death penalty should be abolished.

It does not prevent people from committing crimes.

≈

The death penalty doesn't deter people from committing serious violent crimes.

A survey of the UN on the relation between the death penalty and homicide rates gave no support to the deterrent hypothesis.

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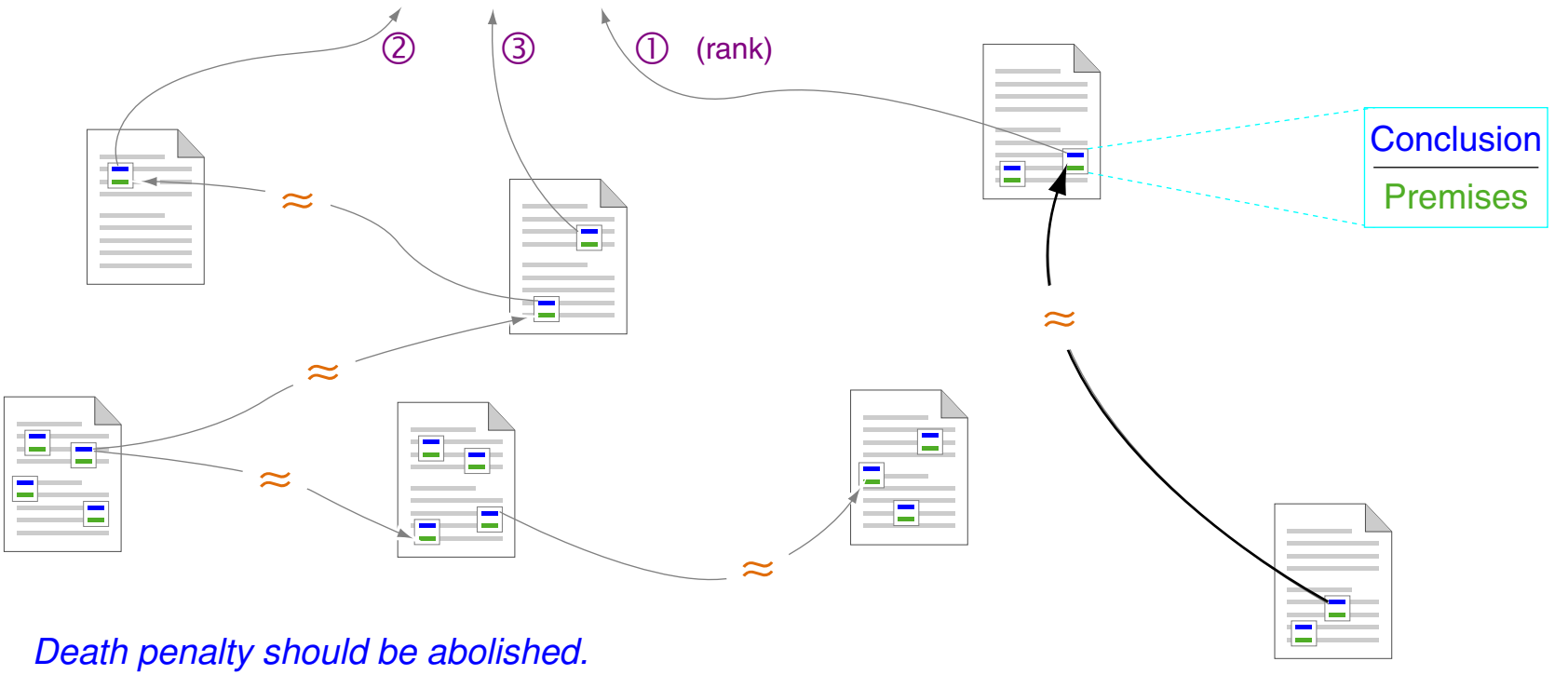

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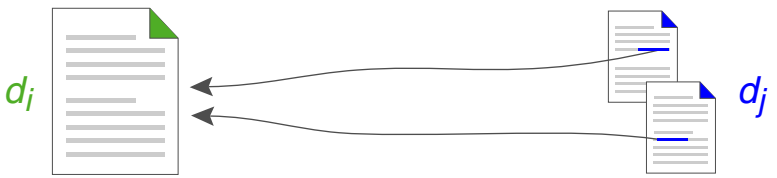
Original PageRank [Page et al. 1999]



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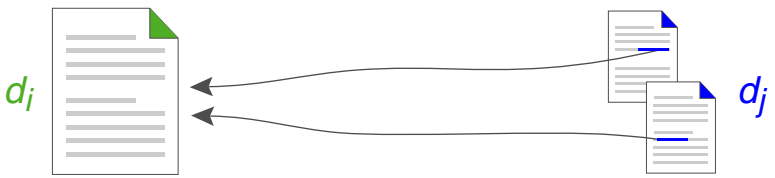

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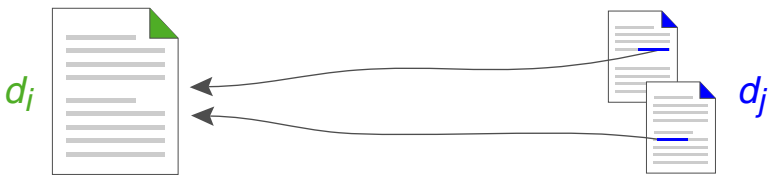

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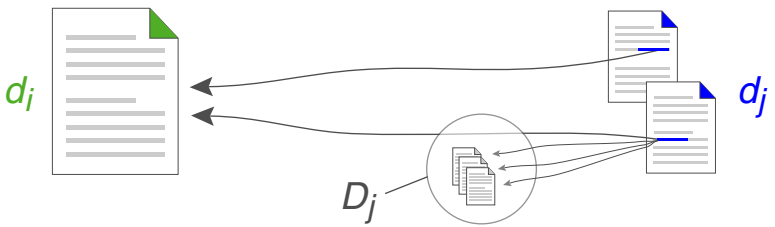

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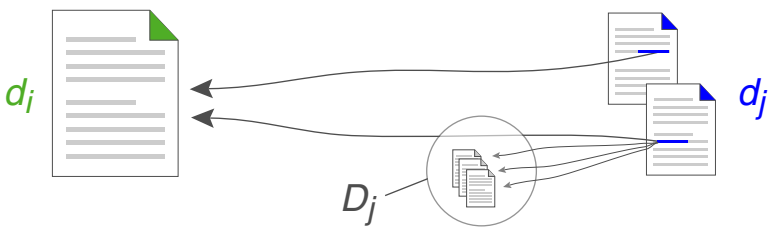

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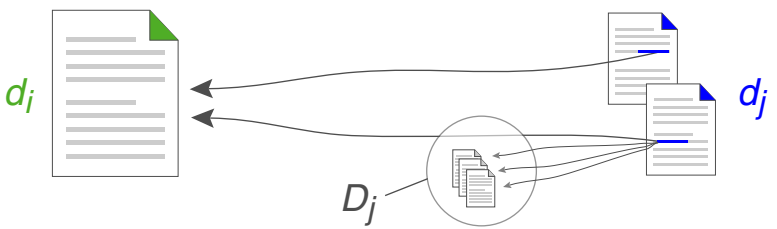

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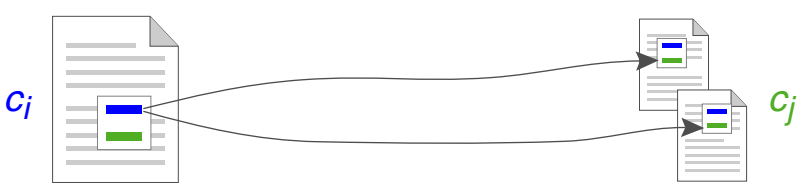

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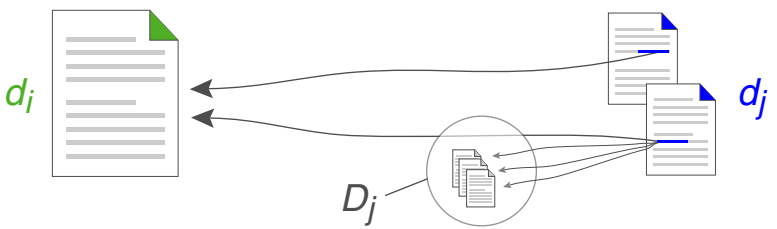

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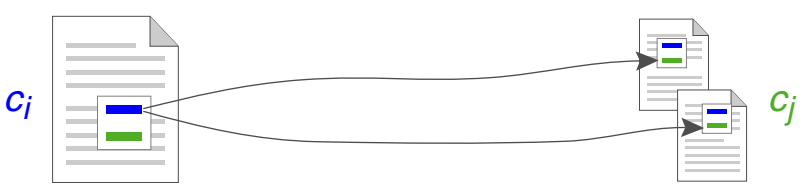

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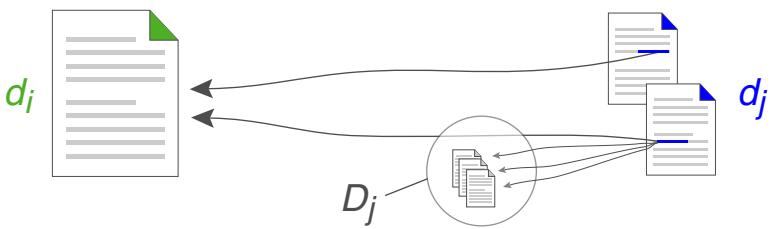
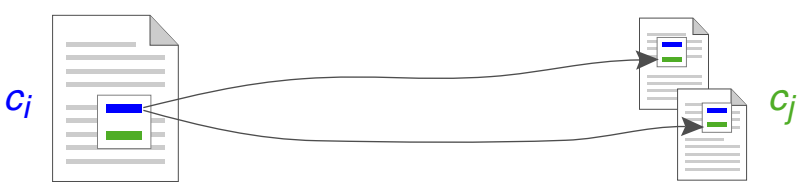


Original PageRank [Page et al. 1999]

1. ground relevance + recursive relevance
2. d_j links to $d_i \rightsquigarrow$ increase PageRank(d_i)
3. reward exclusive links
4. uniform ground relevances (sum to 1)

$$\hat{p}(c_i) = (1-\alpha) \cdot \frac{p(d_i) \cdot |D|}{|A|} + \alpha \cdot \sum_j \frac{\hat{p}(c_j)}{|P_j|}$$



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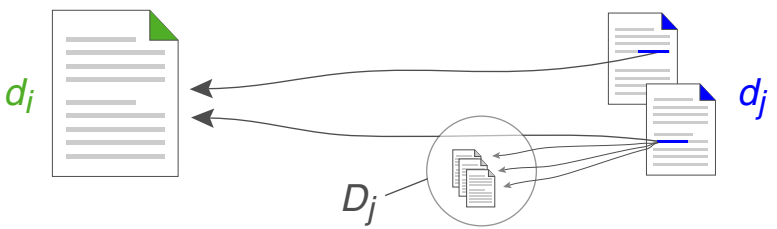

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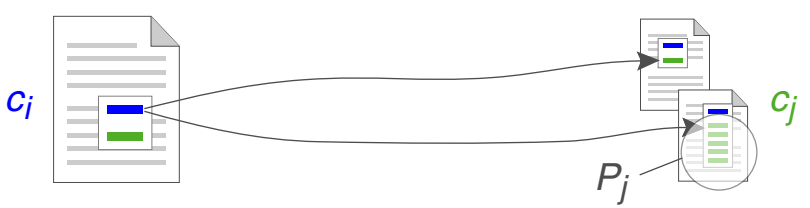

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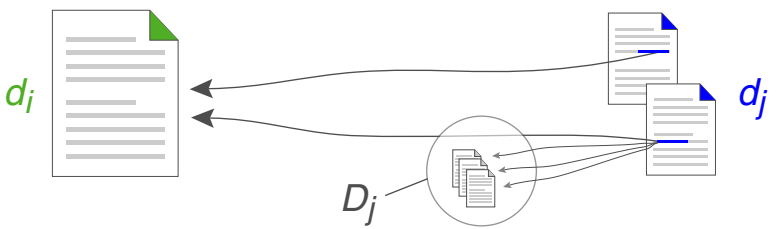

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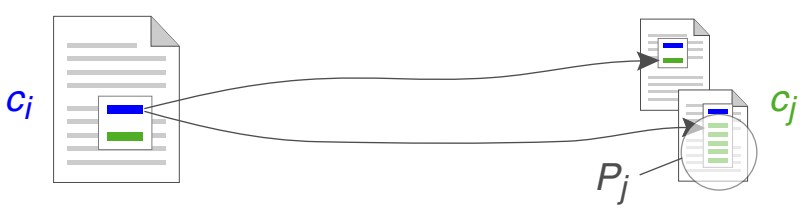

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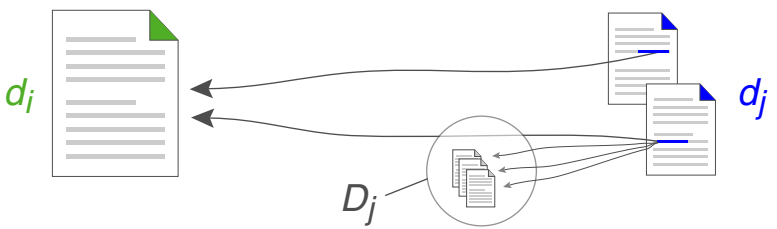

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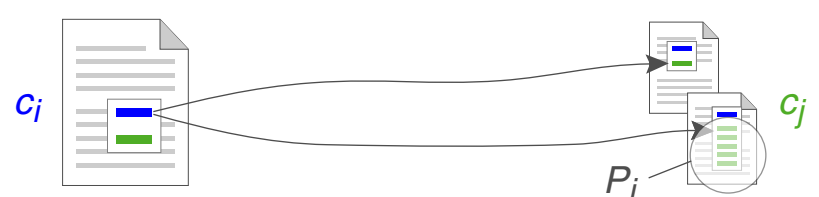

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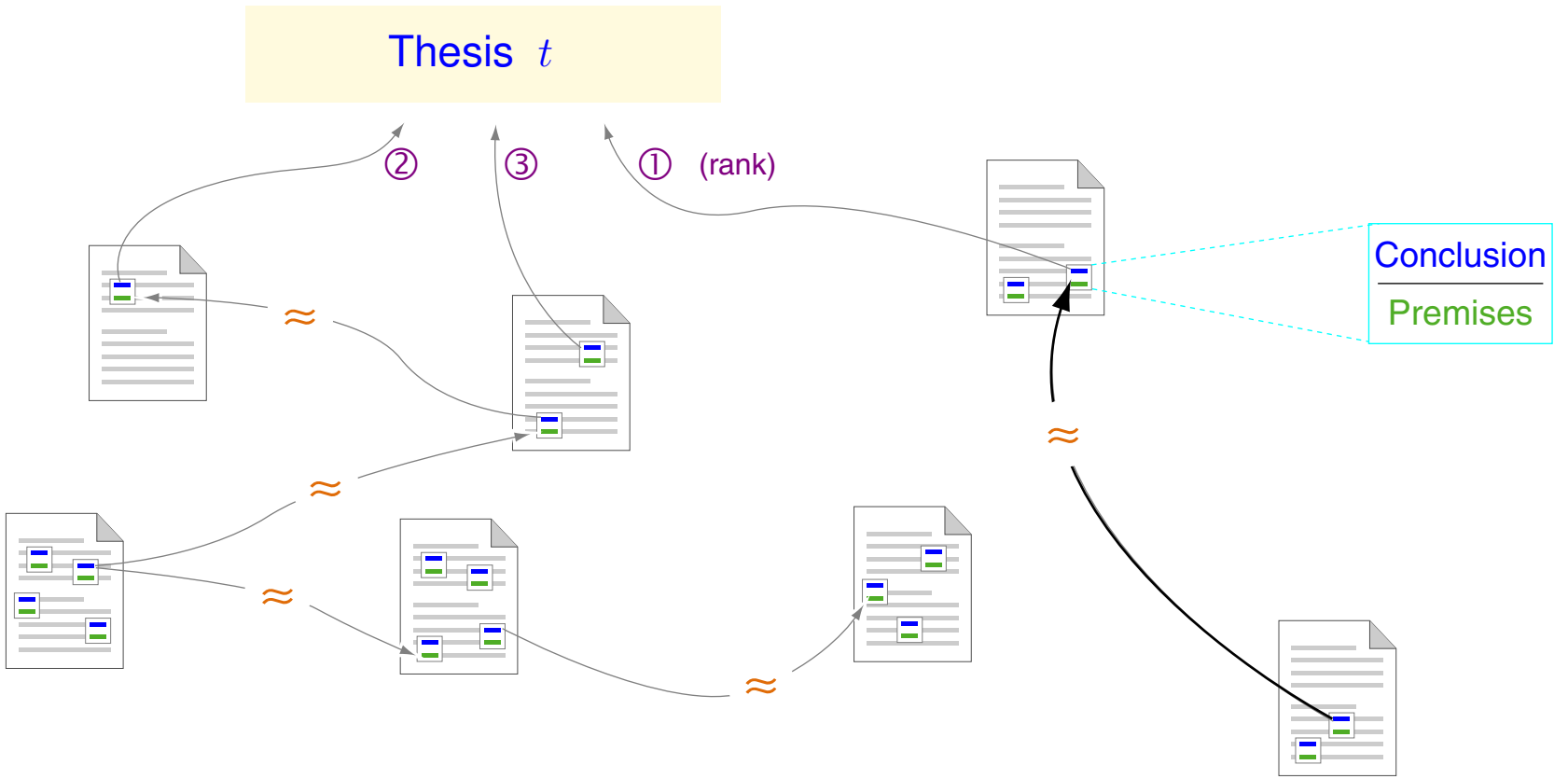
3. reward exclusive premises
4. ground strength $\sim$ PageRank

"Reversal of Evidence"

PageRank: Author cannot enforce links to their web page.
ArgRank: Author cannot enforce use of their argument.

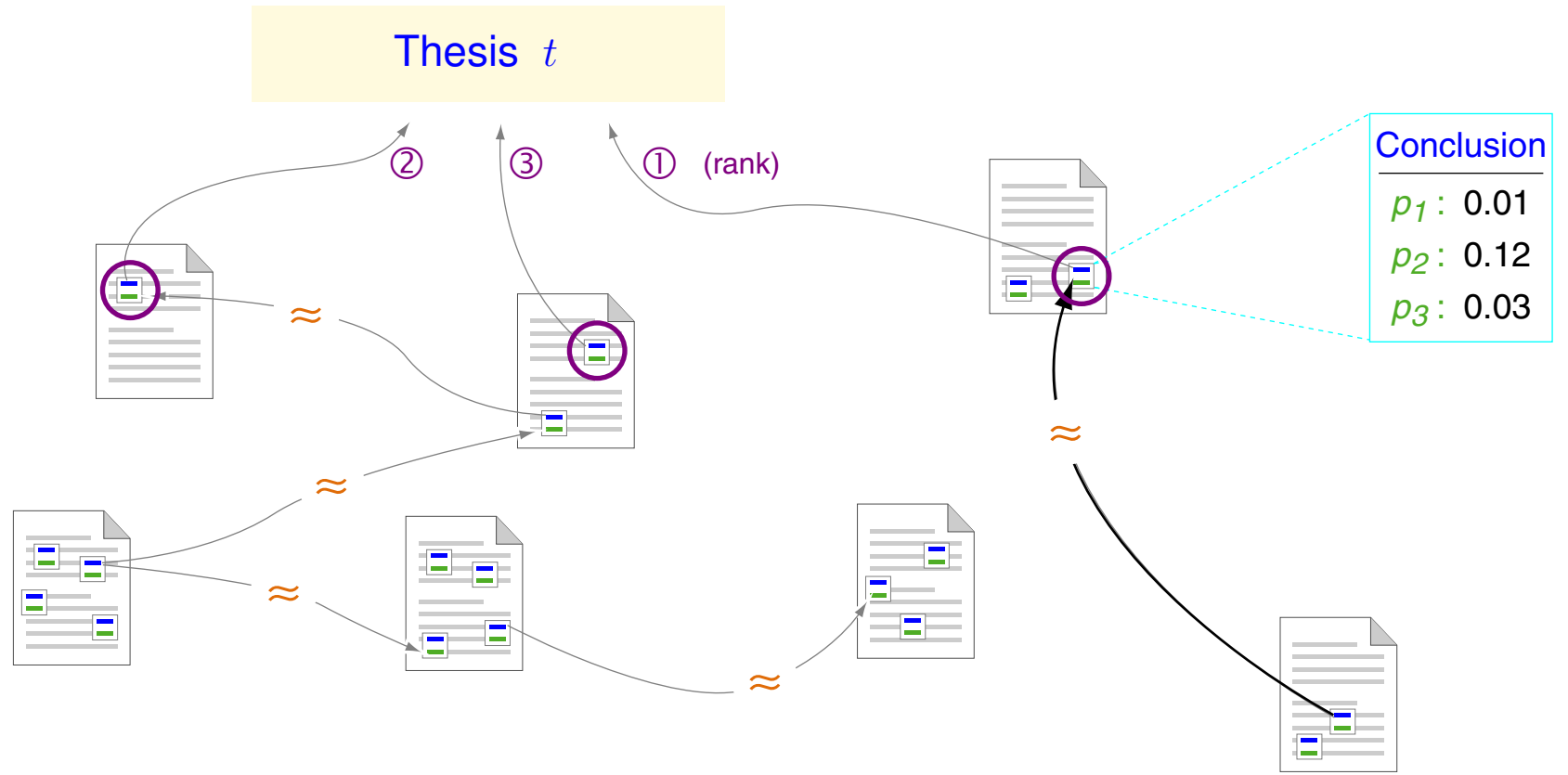
Argument Ranking I

From Premise Scores to Argument Ranks



Argument Ranking I

From Premise Scores to Argument Ranks



How to weigh the premise scores of the matching arguments?

(maximum, average, etc.)

Argument Ranking I

Case Study: Graph Construction

Construction of a raw graph using 57 corpora from the Argument Web :

28 875 Argument units, used in . . .

17 877 Arguments

Processing steps towards an argument graph:

3 113 Conclusions with $\geq$ 1 argument, where . . .

498 have multiple premises, from which . . .

70 have a relevant claim, from which . . .

32 are used in 110 intelligible arguments.

Argument Ranking I

Case Study: Graph Construction

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Processing steps towards an argument graph:

3 113 Conclusions with $\geq$ 1 argument, where . . .

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70 have a relevant claim, from which . . .

32 are used in 110 intelligible arguments.

Acquisition of a ranking ground truth:

- 7 experts from NLP and IR ranked all arguments (110) for each conclusion (32)
- $\tau = 0.59$ as highest agreement between two experts (mean: $\tau = 0.36$)

Argument Ranking I

Case Study: Results

Ranking approach	Premise score computation				Best
	Minimum	Average	Maximum	Sum	
	τ	τ	τ	τ	τ
1. ArgRank	**0.01**	0.02	0.11	**0.28**	**0.28**
2. Frequency	–0.10	–0.03	–0.01	0.10	0.10
3. Similarity	–0.13	–0.05	0.01	0.02	0.02
4. Sentiment	**0.01**	**0.11**	**0.12**	0.12	0.12
5. Most premises	-	-	-	-	0.19
6. Random	-	-	-	-	0.00

Approach 1: An argument's relevance corresponds to the ArgRank of its premises.

Argument Ranking I

Case Study: Results

Ranking approach	Premise score computation				Best
	Minimum	Average	Maximum	Sum	
	τ	τ	τ	τ	τ
1. ArgRank	**0.01**	0.02	0.11	**0.28**	**0.28**
2. Frequency	–0.10	–0.03	–0.01	0.10	0.10
3. Similarity	–0.13	–0.05	0.01	0.02	0.02
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5. Most premises	-	-	-	-	0.19
6. Random	-	-	-	-	0.00

Approach 2: An argument's relevance corresponds to the frequency of its premises in the graph.

Argument Ranking I

Case Study: Results

Ranking approach	Premise score computation				Best
	Minimum	Average	Maximum	Sum	
	τ	τ	τ	τ	τ
1. ArgRank	**0.01**	0.02	0.11	**0.28**	**0.28**
2. Frequency	–0.10	–0.03	–0.01	0.10	0.10
3. Similarity	–0.13	–0.05	0.01	0.02	0.02
4. Sentiment	**0.01**	**0.11**	**0.12**	0.12	0.12
5. Most premises	-	-	-	-	0.19
6. Random	-	-	-	-	0.00

Approach 3: An argument's relevance corresponds to the Jaccard similarity of its premises to its conclusion.

Argument Ranking I

Case Study: Results

Ranking approach	Premise score computation				Best
	Minimum	Average	Maximum	Sum	
	τ	τ	τ	τ	τ
1. ArgRank	**0.01**	0.02	0.11	**0.28**	**0.28**
2. Frequency	–0.10	–0.03	–0.01	0.10	0.10
3. Similarity	–0.13	–0.05	0.01	0.02	0.02
4. Sentiment	**0.01**	**0.11**	**0.12**	0.12	0.12
5. Most premises	-	-	-	-	0.19
6. Random	-	-	-	-	0.00

Approach 4: An argument's relevance corresponds to the positivity of its words in the premises according to SentiWordNet.

Argument Ranking I

Case Study: Results

Ranking approach	Premise score computation				Best
	Minimum	Average	Maximum	Sum	
	τ	τ	τ	τ	τ
1. ArgRank	**0.01**	0.02	0.11	**0.28**	**0.28**
2. Frequency	–0.10	–0.03	–0.01	0.10	0.10
3. Similarity	–0.13	–0.05	0.01	0.02	0.02
4. Sentiment	**0.01**	**0.11**	**0.12**	0.12	0.12
5. Most premises	-	-	-	-	0.19
6. Random	-	-	-	-	0.00

Approach 5: An argument's relevance corresponds to its number of premises.

Argument Ranking I

Case Study: Results

Ranking approach	Premise score computation				Best
	Minimum	Average	Maximum	Sum	
	τ	τ	τ	τ	τ
1. ArgRank	**0.01**	0.02	0.11	**0.28**	**0.28**
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5. Most premises	-	-	-	-	0.19
6. Random	-	-	-	-	0.00

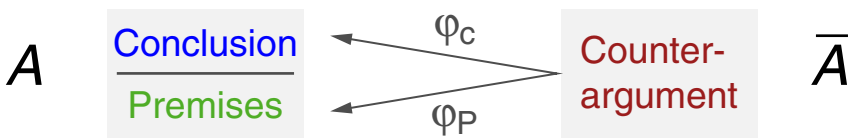
Approach 6: The relevance is decided randomly.

Argument Ranking II [idebate]

Argument Ranking II [idebate]

Idea: Given an argument A, the best counterargument $\overline{A}^*$ employs premises that are similar wrt. topic, but takes the opposite stance.

➜ Consider both similarities to the premises and conclusion [Walton 2009]:



Argument Ranking II

Idea: Given an argument A, the best counterargument $\overline{A}^*$ employs premises that are similar wrt. topic, but takes the opposite stance.

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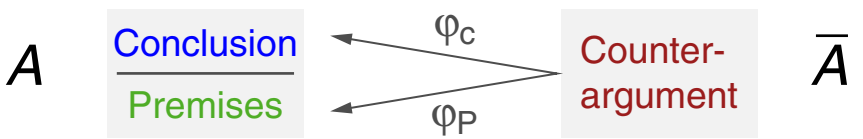

How to compute these similarities?

How to combine these similarities?

(= What is a sensible hypothesis space of promising model functions?)

Argument Ranking II

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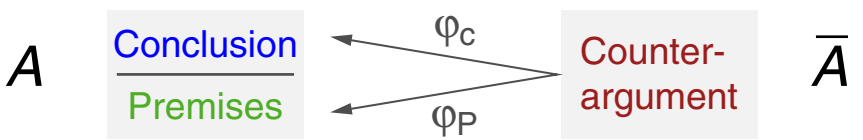

Proposed model function to rank counterarguments [Wachsmuth et al., 2018]:

$$R(A, \overline{A}) = \alpha \cdot \underbrace{\left(\varphi_{\text{conclusion}} \circ \varphi_{\text{Premises}}\right)}_{\text{topic similarity} \rightarrow \max} - (1-\alpha) \cdot \underbrace{\left(\varphi_{\text{conclusion}} \circ \varphi_{\text{Premises}}\right)}_{\text{stance similarity} \rightarrow \min}$$

where

- φ combines both word and embedding similarities
- $\circ \in \{\min, \max, +, *\}$
- $\alpha \in [0; 1]$

Argument Ranking II

Corpus and Analysis

Theme	Debates	Points	Counters
Culture	46	278	278
Digital freedoms	48	341	341
Economy	95	590	588
⋮			
Sport	23	130	130
$\sum$	**1069**	**6779**	**6753**

Corpus:

- based on the iDebate.org portal
- Download: ArguAna Counterargs

Argument Ranking II

Corpus and Analysis

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Corpus:

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- Download: ArguAna Counterargs

Retrieval experiments (selected results) :

Find the best counterargument within . . .	True-to-false ratio	Accuracy*
all counters of the same debate	1 : 3	0.75
all counters of the same theme	1 : 136	0.54
all arguments of the entire portal	1 : 2 800	0.32

* The parameters for $R(A, \overline{A})$ were determined by a systematic ranking analysis.

Chapter IR:VI

VI. IR Applications

- Web Technology
- Web Graph
- Web Crawling
- Web Archiving
- Web Content Extraction
- Near-duplicate Detection
- Link Analysis

- The Treachery of Answers
- Argument Retrieval Problems
- Argument Ranking I
- Argument Ranking II
- Argumentation-Related Resources
- Argument Search Engines
- Argument Search Evaluation I
- Argument Search Evaluation II

Argumentation-Related Resources

Argumentation-Related Resources

Leverage effort*	Resource type	Examples
very low	Technology	
low	Corpora	
medium	Debate portals	
high	Discussion pages	
very high	Articles	

* Estimated effort / expertise to exploit a resource of the respective type within own research.

Argumentation-Related Resources

Leverage effort*	Resource type		Examples
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medium	Debate portals	English German	Kialo idebate Debatepedia Argumentia
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very high	Articles	Editorials, Essays Legal Scientific publications	New York Times ACL anthology

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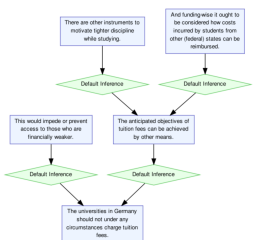
Argumentation-Related Resources

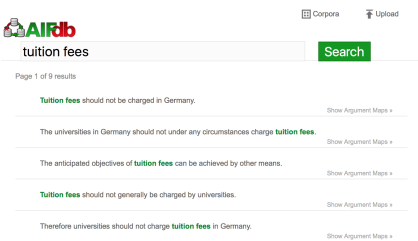
The Argument Web [Library]

AIFdb Corpora



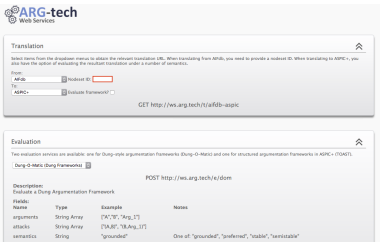
Structured argument data in uniform format

AIFdb Search



Search interface for argument resources

ARG-tech API

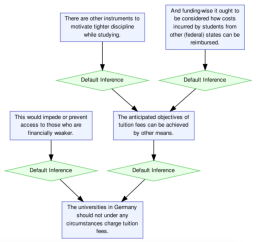


Several argument web services

Argumentation-Related Resources

The Argument Web [Library]

AIFdb Corpora



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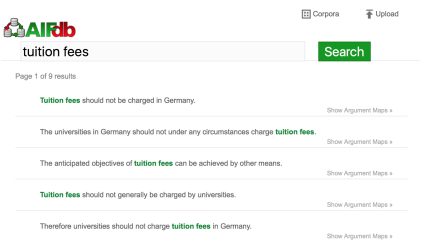

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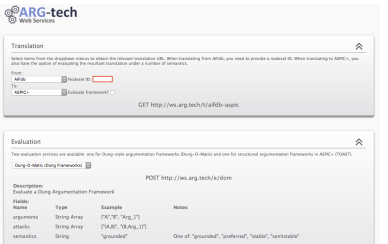
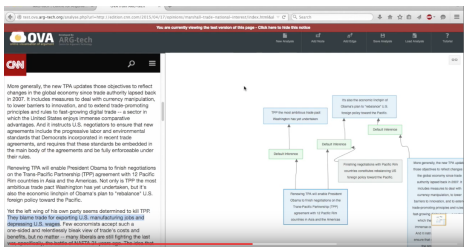


Several argument web services

Argublogging

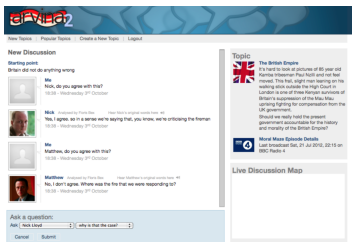
Widget for argument annotation in blogs

OVA



Online visualization and analysis of arguments

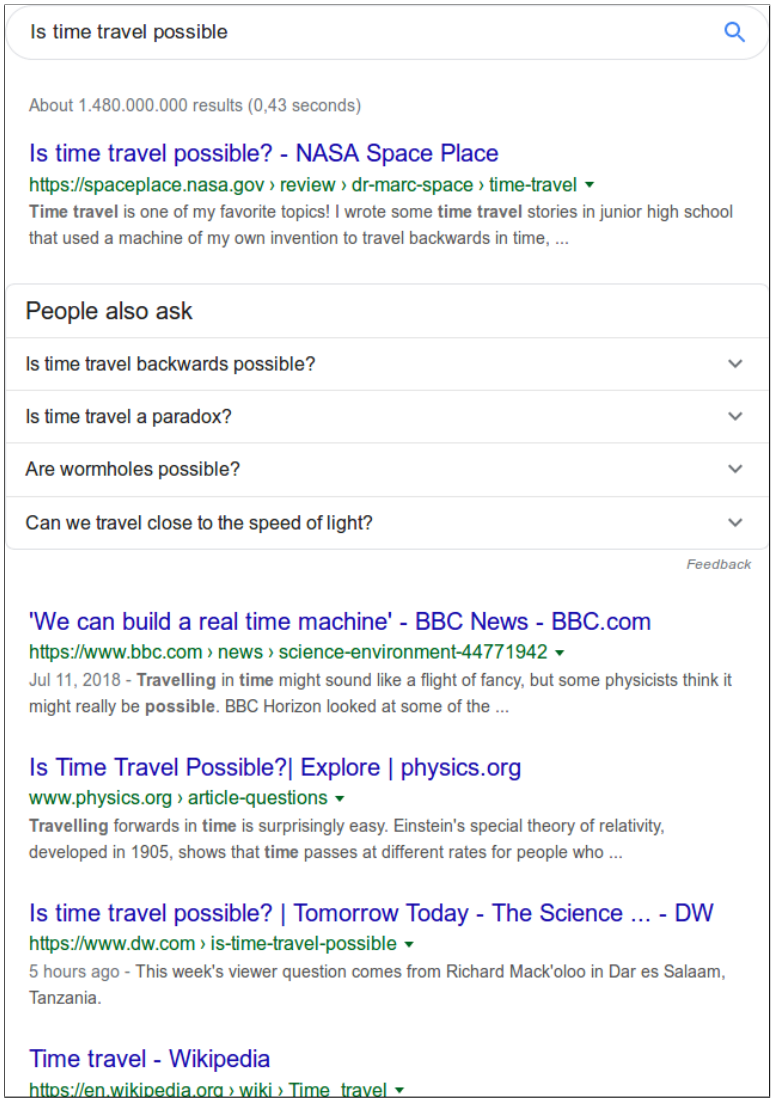
Arvina



Dialogue platform based on AIFdb

Argument Search Engines

Vision of Argument Search



Argument Search Engines*

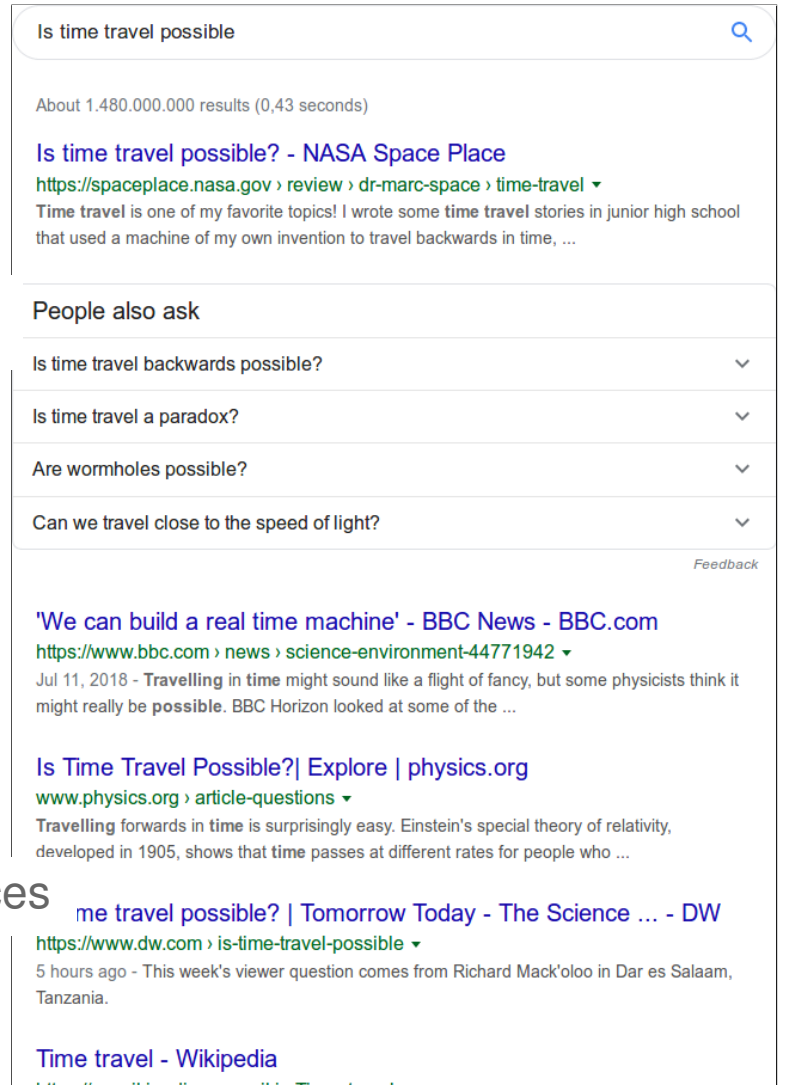
Vision of Argument Search

Arguments in future web search:

- support forming opinions
- make it easy to find relevant arguments
- deliberation: learn about other views
- education: learn to debate

Search results should . . .

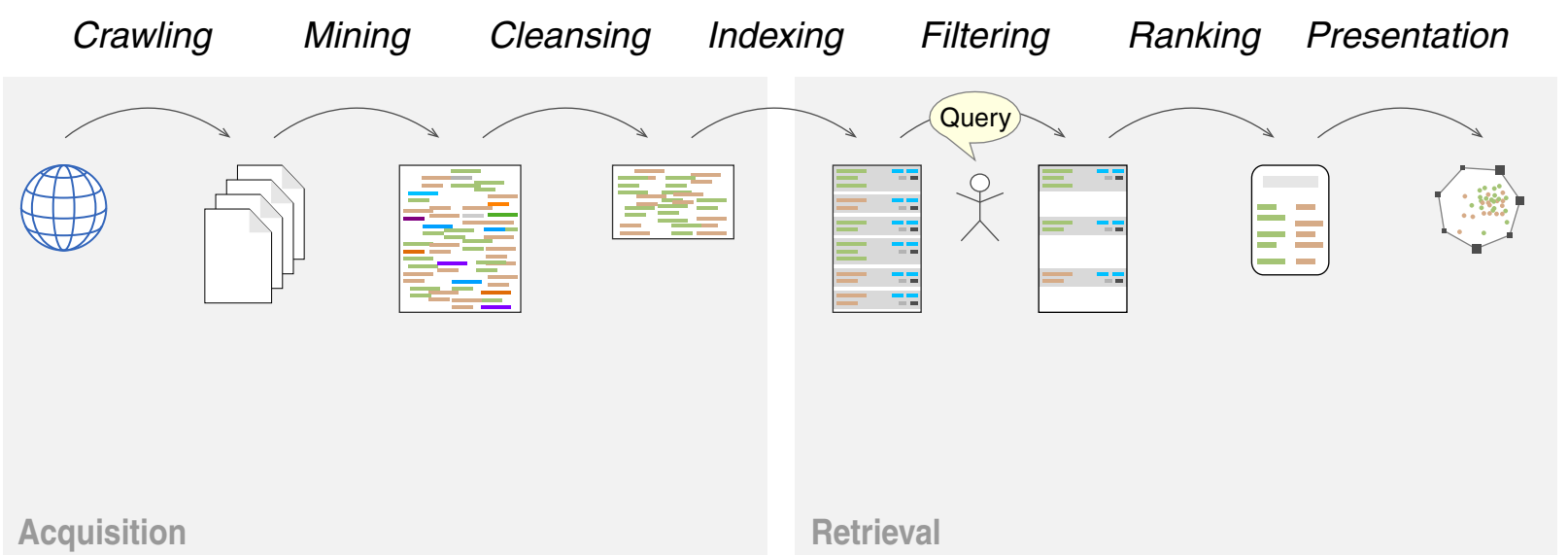
- rank the best arguments highest
- cover diverse aspects
- cover reliable and heterogeneous sources
- be up-to-the-minute
- be traceable and evaluable



* Wachsmuth: Argumentation Retrieval and Analysis. IR Autumn School ASIRF (2018).

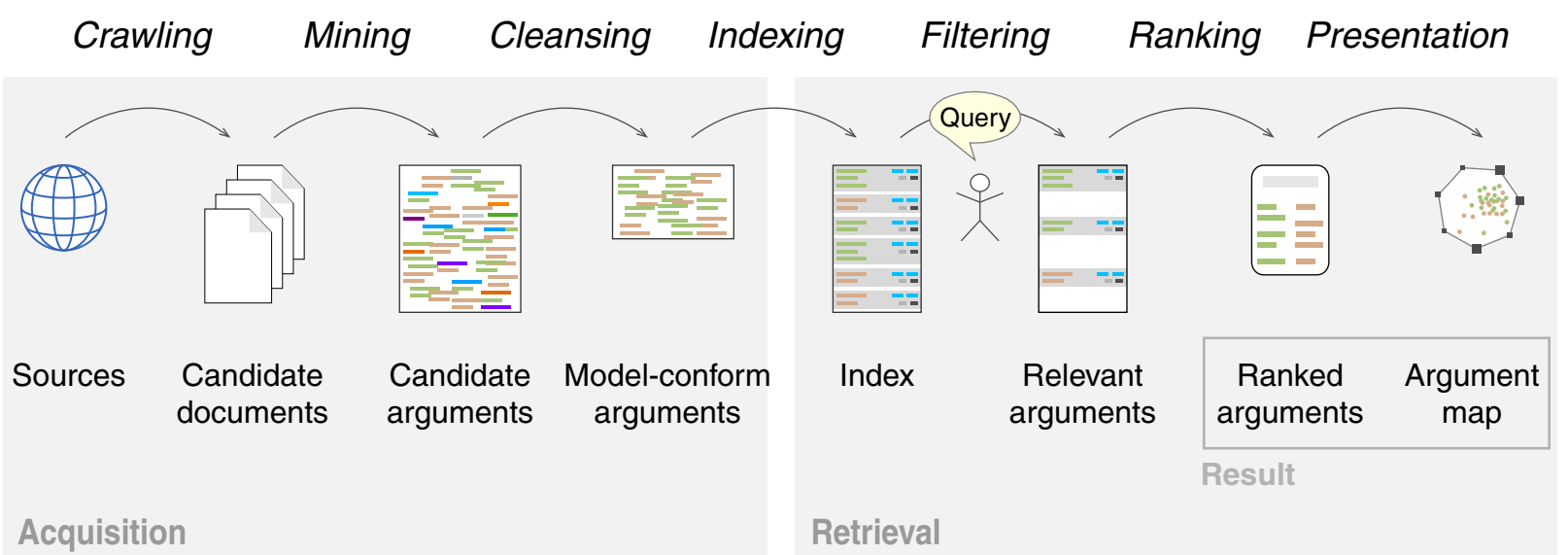
Argument Search Engines

Basic Elements and Process



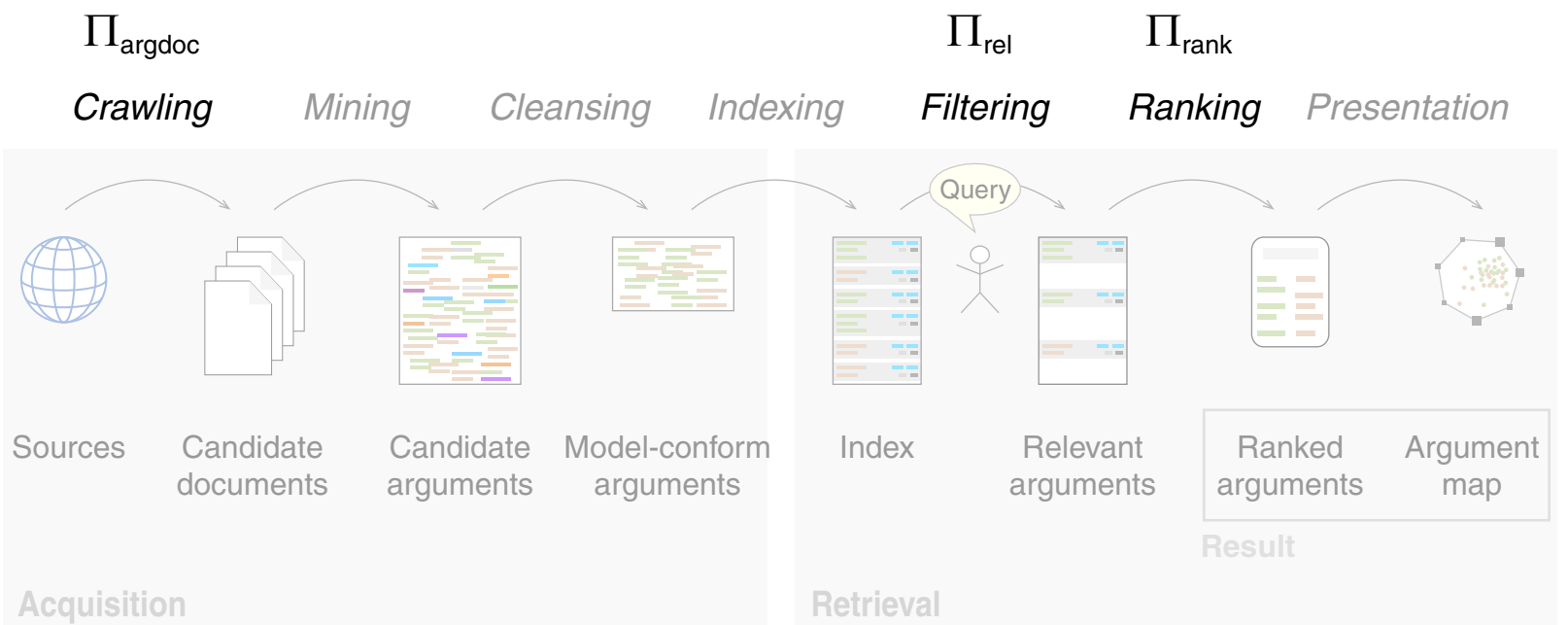
Argument Search Engines

Basic Elements and Process



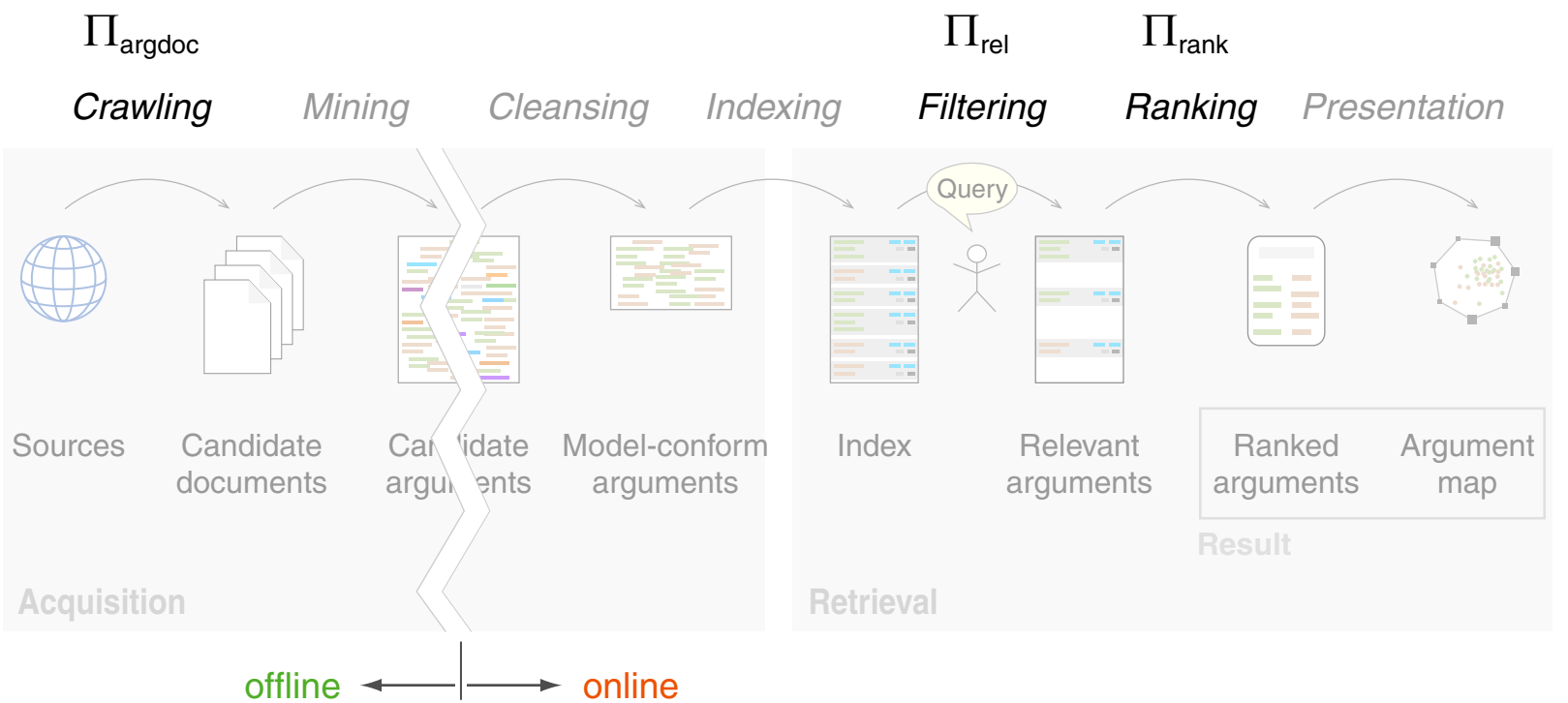
Argument Search Engines

Basic Elements and Process



Argument Search Engines

Basic Elements and Process

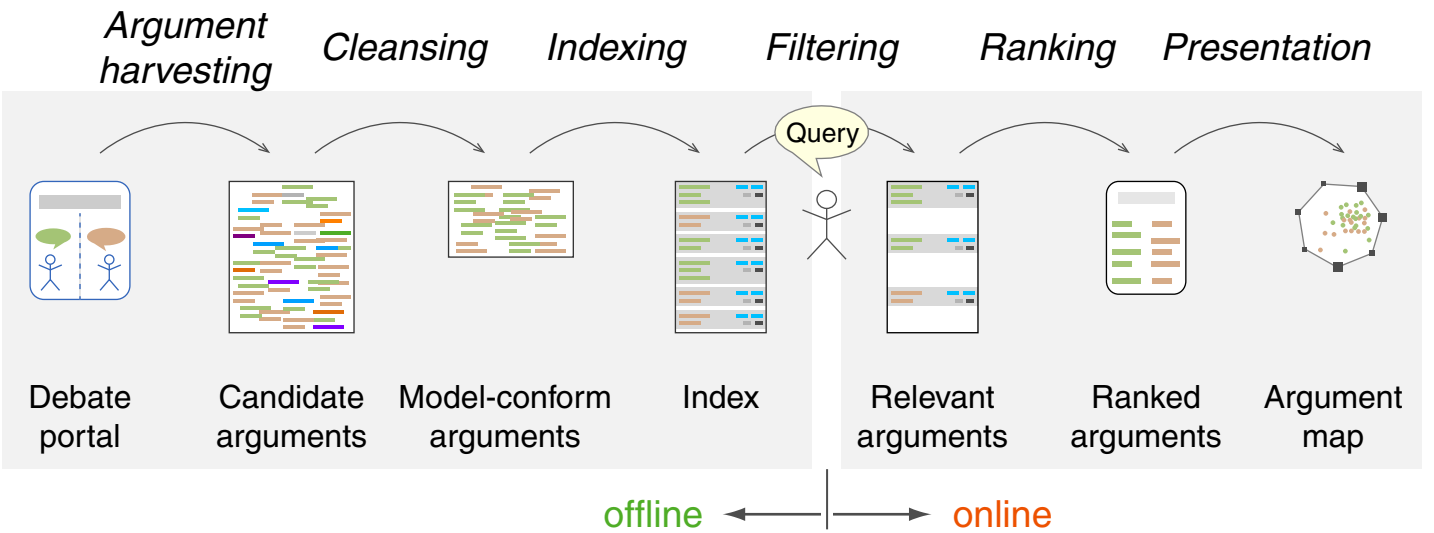


Acquisition paradigm [Ajjour et al. 2019] :

- distribution of processing steps regarding offline time and online time
- tradeoff between precision, recall, and topicality

Argument Search Engines

Acquisition Paradigms: (a) args.me [Demo]



- Research focus: argument ranking
- Supervision level: medium (distantly supervised)

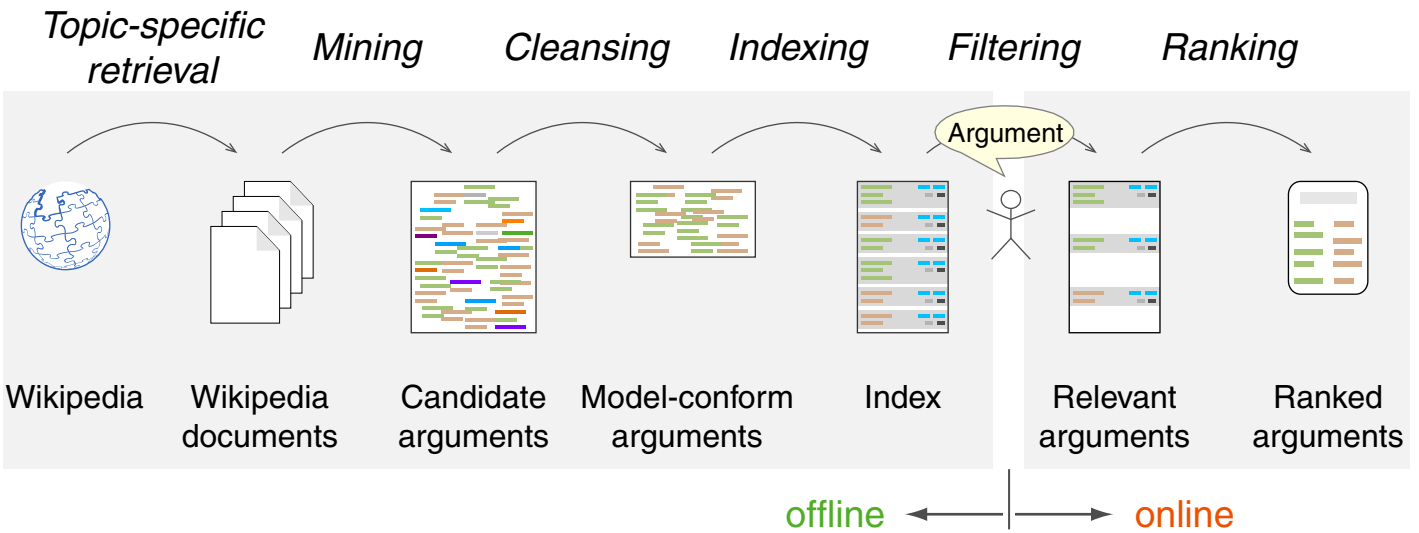
→ Effectiveness profile: high precision, low recall

→ Stance balance: guaranteed

→ Efficiency: high

Argument Search Engines

Acquisition Paradigms: (b) IBM Debater [Project]



- Research focus: debating technology
- Supervision level: medium (recognized source)

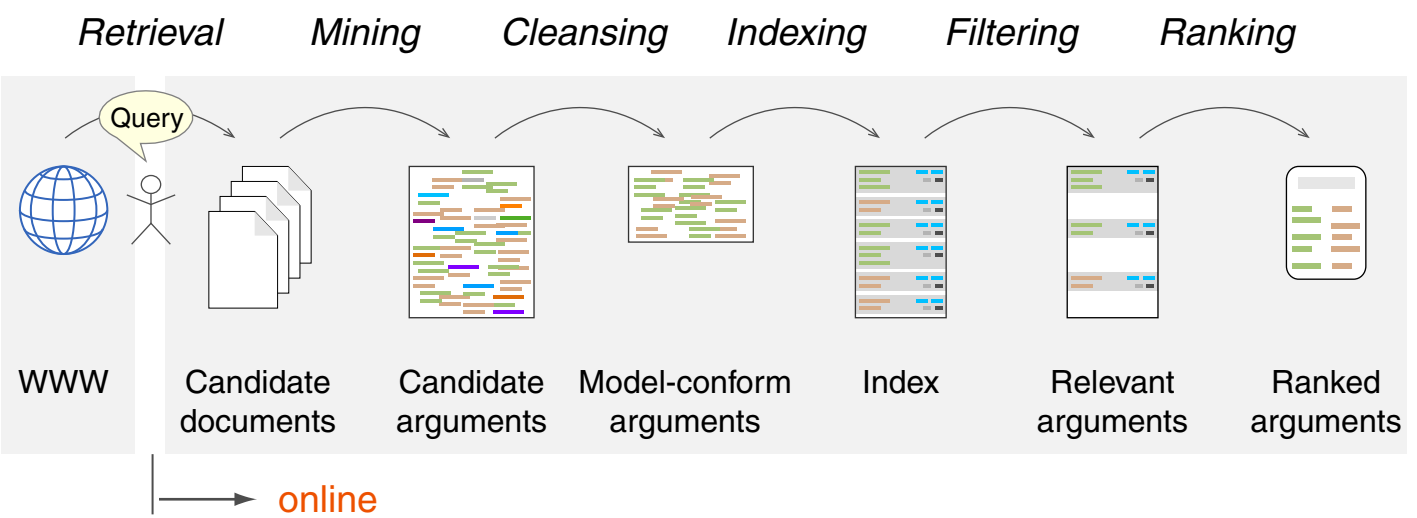
➜ Effectiveness profile: high precision, high recall on topic

➜ Stance balance: guaranteed

➜ Efficiency: high

Argument Search Engines

Acquisition Paradigms: (c) ArgumenText [Demo]



- Research focus: argument mining
- Supervision level: low

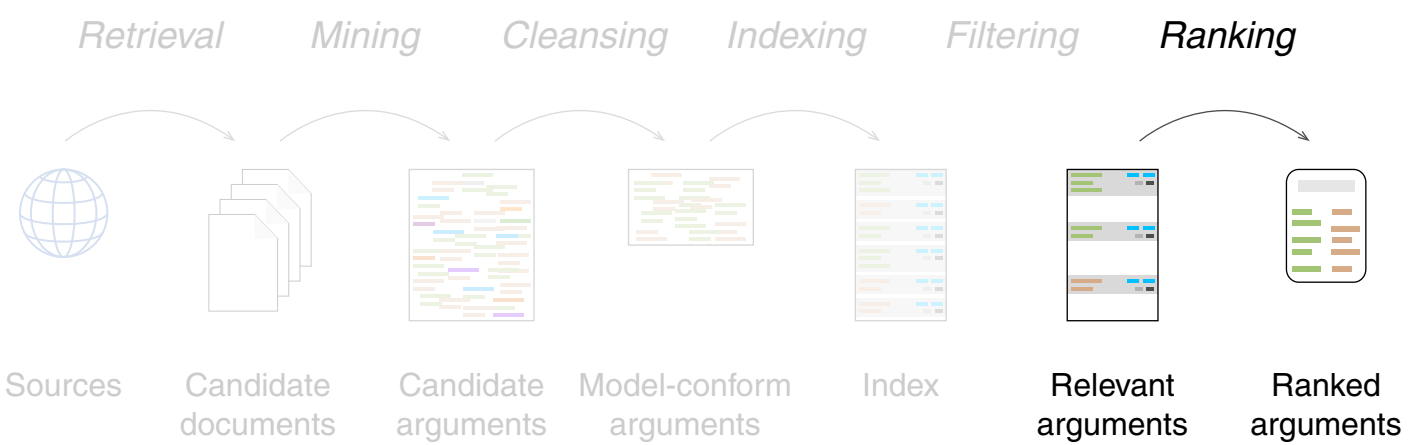
→ Effectiveness profile: low precision, high recall

→ Stance balance: cannot be guaranteed

→ Efficiency: low

Argument Search Engines

Ranking Paradigms in IR



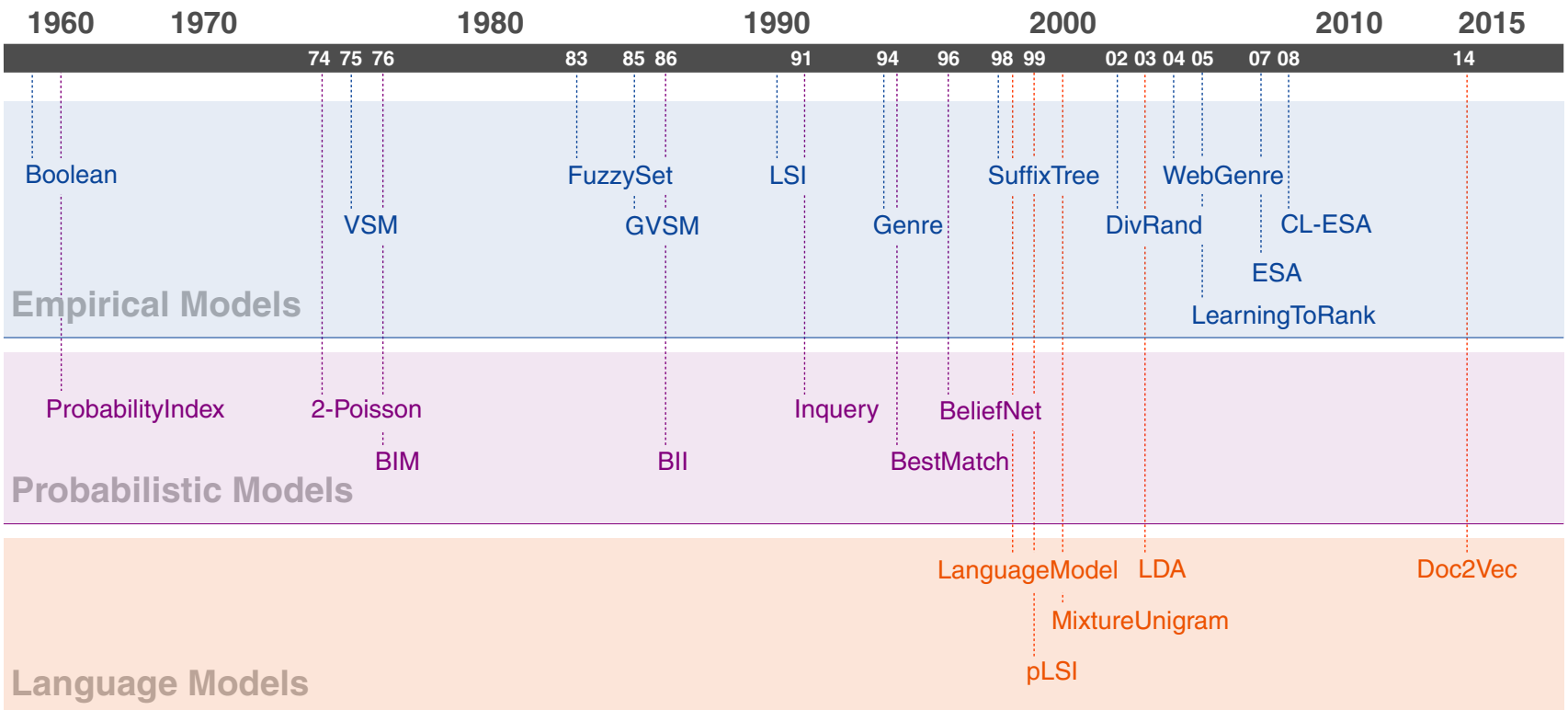
Designing a ranking algorithm:

- Analyze conclusions, premises, or both?
- Use fulltext or elite terms only?
- Exploit metadata and sentiment?
- Analyze relations between arguments?

...

Argument Search Engines

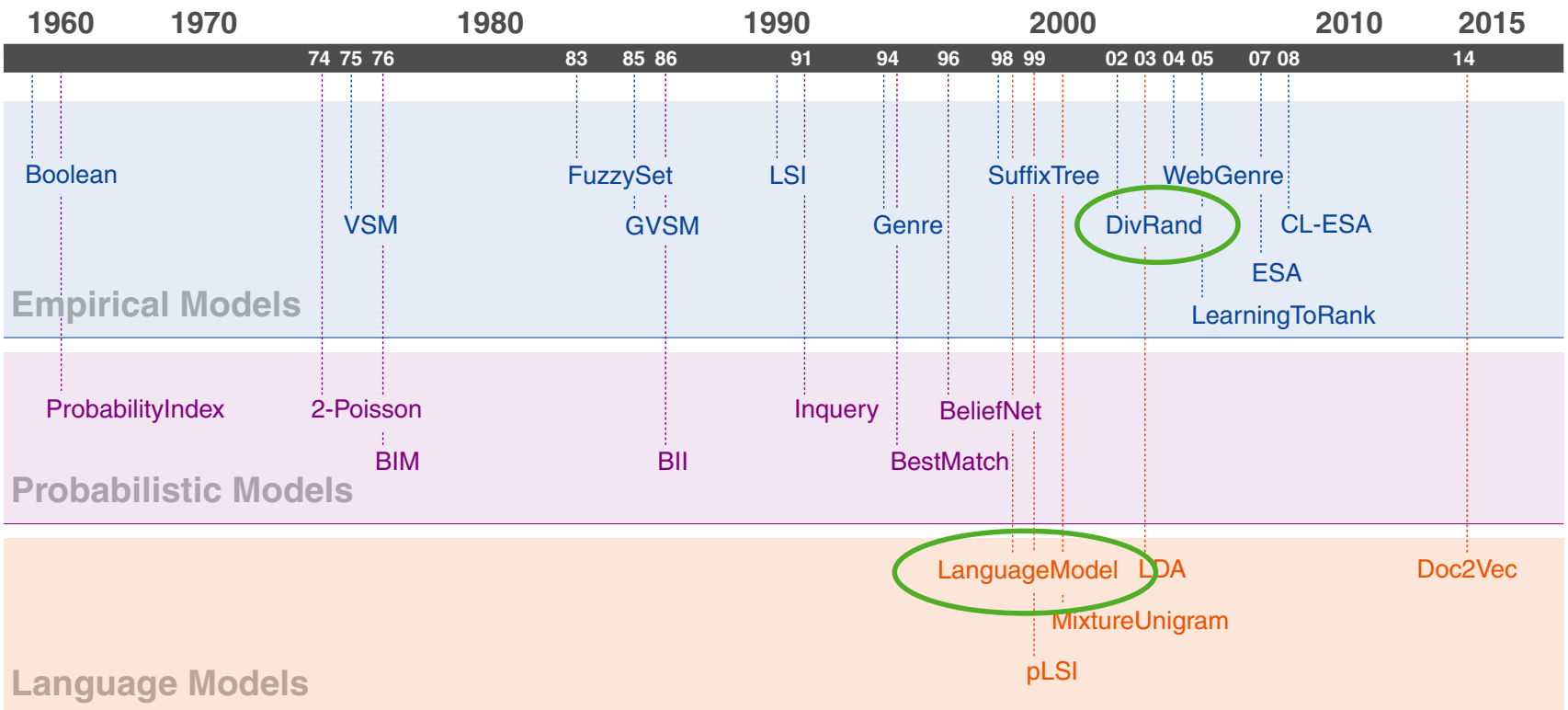
Ranking Paradigms in IR



[Stein et al. 2017]

Argument Search Engines

Ranking Paradigms in IR



- New research indicates that *Divergence from Randomness* and *Language Models* are the currently most effective retrieval models to address Π_{rank}.

  [Pottast et al. 2019]

Argument Search Engines

More on Args [args.me]

Argument sources:

#	Debate Portal	Argument Units	Arguments	Debates
1	idebate.org	16 084	15 384	698
2	debatepedia.org	34 536	33 684	751
3	debatewise.org	39 576	33 950	2 252
4	debate.org	210 340	182 198	28 045
5	forandagainst.com	29 255	26 224	3 038
$\sum$		329 791	291 440	34 784

Design decisions:

- Argument model: conclusion + 1 premise with stance information
- Query: free text phrase, interpreted as AND query
- Retrieval: exact matching against conclusion
- Ranking: BM25F based on conclusion (1.0), premise (0.5), and debate (0.2)

Argument Search Engines

More on Args [args.me]

Top queries (Sep.'17 – Apr.'19):

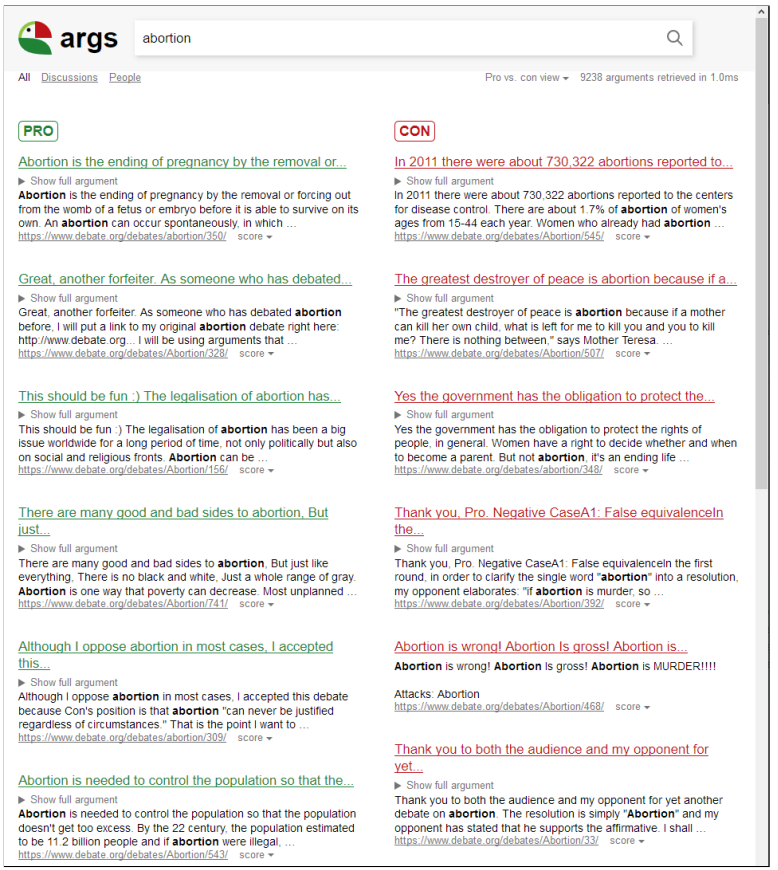
	Query	Absolute	Relative
1	`climate change`	251	3.5%
2	`feminism`	193	2.7%
3	`abortion`	158	2.2%
4	`trump`	146	2.0%
5	`brexit`	128	1.8%
6	`death penalty`	73	1.0%
7	`google`	58	0.8%
8	`vegan`	57	0.8%
9	`nuclear energy`	56	0.8%
10	`donald trump`	47	0.7%

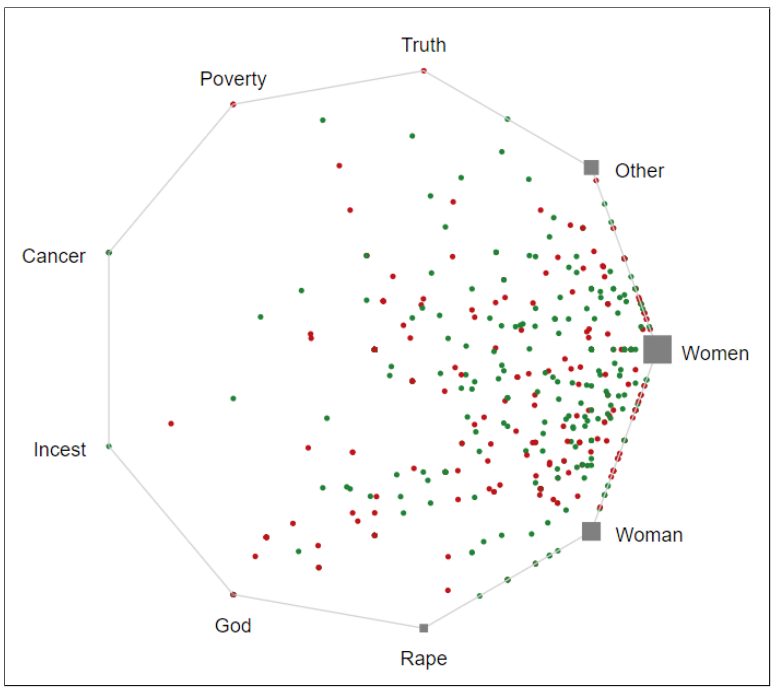
Coverage of 1082 Wikipedia controversial issues:

- 78% match with ≥ 1 argument
- 42% match with ≥ 1 conclusion

Argument Search Engines

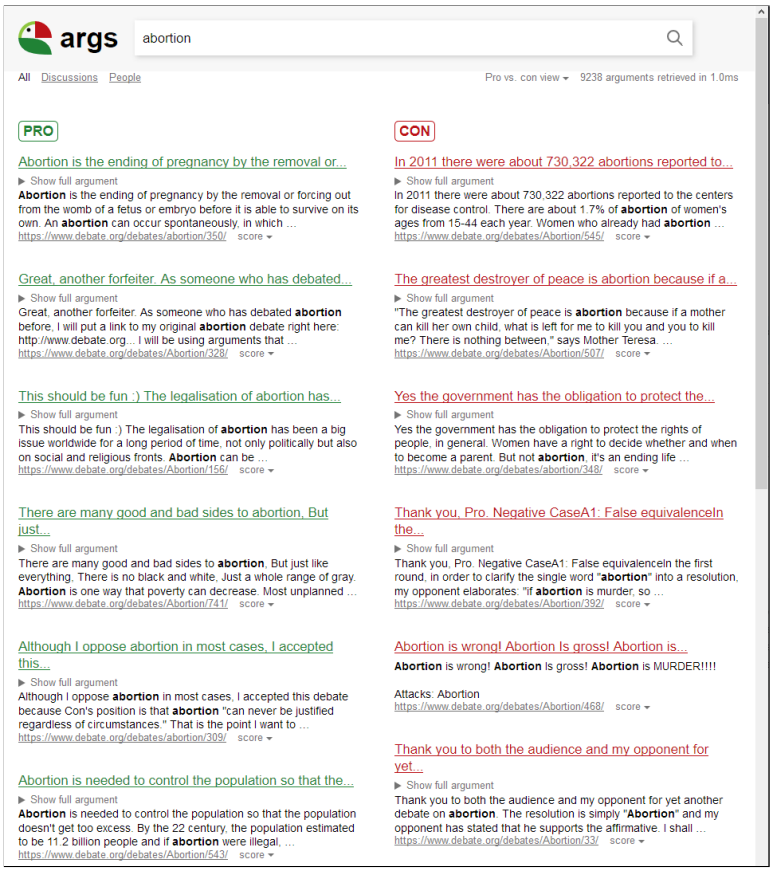
Presentation and Analytics

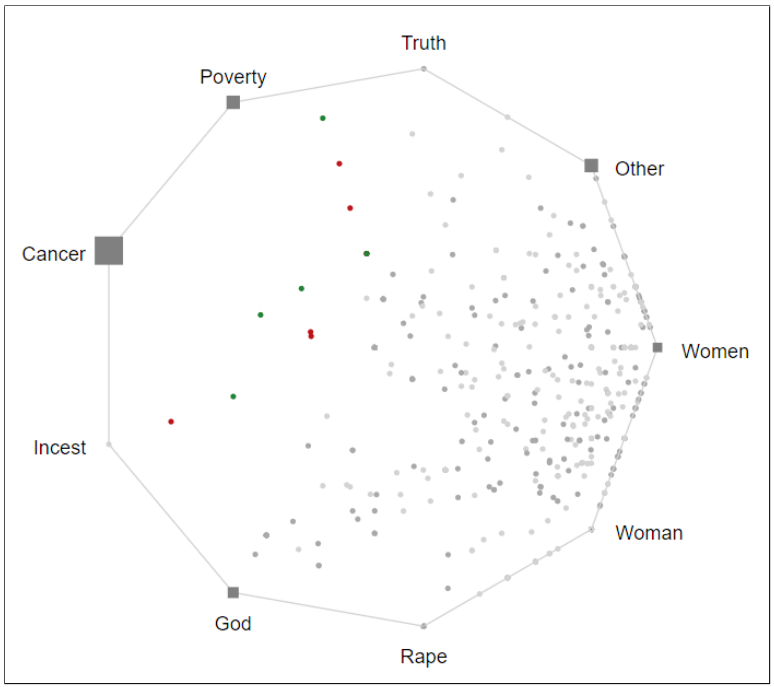




Argument Search Engines

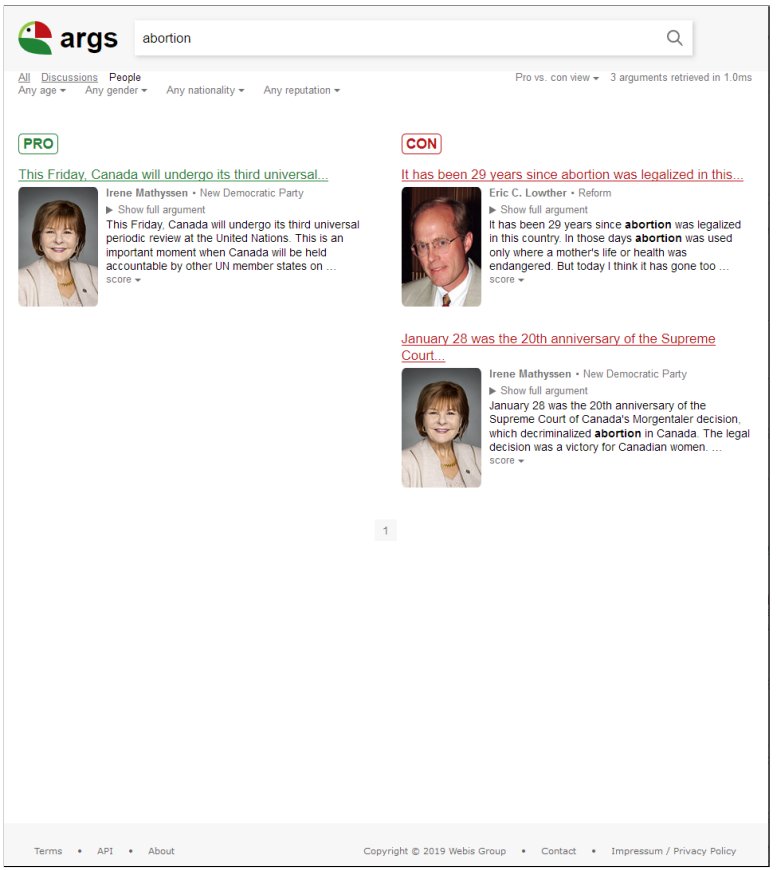
Presentation and Analytics

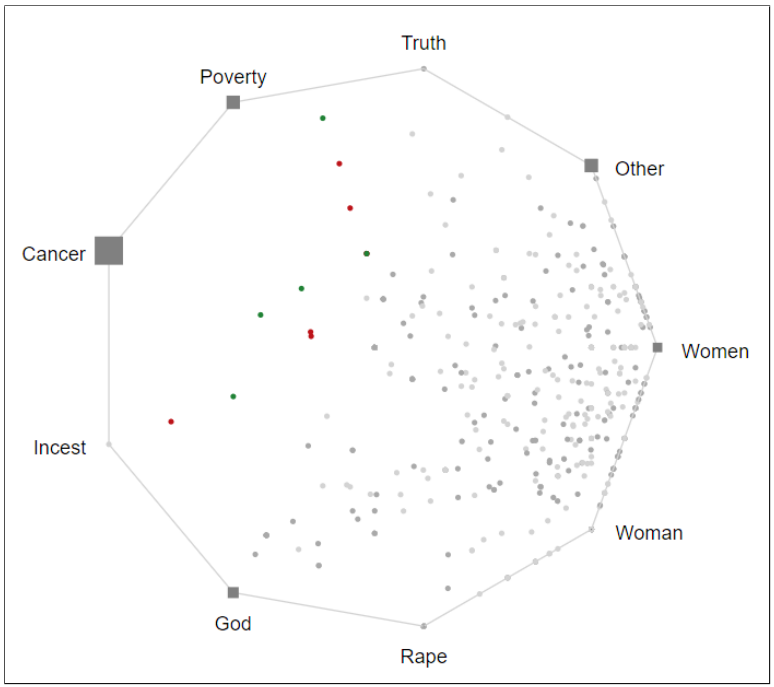




Argument Search Engines

Presentation and Analytics





Chapter IR:VI

VI. IR Applications

- Web Technology
- Web Graph
- Web Crawling
- Web Archiving
- Web Content Extraction
- Near-duplicate Detection
- Link Analysis

- The Treachery of Answers
- Argument Retrieval Problems
- Argument Ranking I
- Argument Ranking II
- Argumentation-Related Resources
- Argument Search Engines
- Argument Search Evaluation I
- Argument Search Evaluation II

SameSide @ ArgMining 2019

1st Shared Task on Same Side Stance Classification

Roxanne El Baff
Yamen Ajjour
Khalid Al-Khatib
Henning Wachsmuth
Philipp Cimiano
Basil Ell
Benno Stein

[sameside.webis.de]

Argument Search Evaluation I

Same Side Stance Classification [sameside.webis.de]

Task: Given two arguments regarding a certain topic,
decide whether or not the two arguments have the same stance.

Topic: “Gay marriage should be legalized.”

Argument 1
Marriage is a commitment to love and care for your spouse till death. This is what is heard in all wedding vows. Gays can clearly qualify for marriage according to these vows, and any definition of marriage deduced from these vows.

Argument 2
Marriage is the institution that forms and upholds for society, its values and symbols are related to procreation. To change the definition of marriage to include same-sex couples would destroy its function.

Argument Search Evaluation I

Same Side Stance Classification [sameside.webis.de]

Task: Given two arguments regarding a certain topic, decide whether or not the two arguments have the same stance.

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Argument 2
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Argument 1
Marriage is a commitment to love and care for your spouse till death. This is what is heard in all wedding vows. Gays can clearly qualify for marriage according to these vows, and any definition of marriage deduced from these vows.

Argument 2
Gay marriage should be legalized since denying some people the option to marry is dscrimenatory and creates a second class of citizens.

Argument Search Evaluation I

Same Side Stance Classification [sameside.webis.de]

Task: Given two arguments regarding a certain topic, decide whether or not the two arguments have the same stance.

Topic: “Gay marriage should be legalized.”

Argument 1
Marriage is a commitment to love and care for your spouse till death. This is what is heard in all wedding vows. Gays can clearly qualify for marriage according to these vows, and any definition of marriage deduced from these vows.

Argument 2
Marriage is the institution that forms and upholds for society, its values and symbols are related to procreation. To change the definition of marriage to include same-sex couples would destroy its function.

○≠○
different side

Argument 1
Marriage is a commitment to love and care for your spouse till death. This is what is heard in all wedding vows. Gays can clearly qualify for marriage according to these vows, and any definition of marriage deduced from these vows.

Argument 2
Gay marriage should be legalized since denying some people the option to marry is dscrimenatory and creates a second class of citizens.

○=○
same side

Argument Search Evaluation I

Same Side Stance Classification: Task Rationale

Same side classification needs not to distinguish topic-specific pro- / con-vocabulary.

→ ”Only” argument similarity within a stance needs to be assessed.

→ Same side classification may be solved in a topic-agnostic fashion.

Applications:

- measure the bias strength within argumentation
- structure a discussion
- find out who or what is challenging me in a discussion
- filter wrongly labeled stances in a large argument corpus
- . . .

Argument Search Evaluation I

Same Side Stance Classification: Tasks Details

Two topics (domains):

1. Should gay marriage be legalized?
2. Should abortion be legalized?

Within domain setting:

Training.	Instances from both domains.
Test.	Instances from both domains.

Cross domain setting:

Training.	Instances from abortion.
Test.	Instances from gay marriage.

Argument Search Evaluation I

Same Side Stance Classification: Tasks Details

Two topics (domains):

1. Should gay marriage be legalized?
2. Should abortion be legalized?

Within domain setting:

Training. Instances from both domains.
Test. Instances from both domains.

Cross domain setting:

Training. Instances from abortion.
Test. Instances from gay marriage.

Form of an instance:

1. Name of the topic (domain) d.
2. Argument 1 from $\mathbf{A}_d$.
3. Argument 2 from $\mathbf{A}_d$.
4. One of $\{ \bigcirc{=}\bigcirc, \bigcirc{\neq}\bigcirc \}$.

Timeline:

8.6. 2019: Training data online.
14.6. 2019: Submission open.
21.7. 2019: Submission closed.
1.8. 2019: 6th ArgMining workshop.

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

	Gay marriage			Abortion			All		
Team	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc
Trier University	0.90	0.73	0.83	0.79	0.59	0.71	**0.85**	0.66	0.77
Leipzig University	0.80	0.78	0.79	0.78	0.68	0.75	0.79	0.73	0.77
IBM Research	0.73	0.63	0.70	0.64	0.54	0.62	0.69	0.59	0.66
TU Darmstadt	0.74	0.56	0.68	0.63	0.48	0.60	0.68	0.52	0.64
Düsseldorf University	0.76	0.35	0.62	0.65	0.32	0.57	0.70	0.33	0.60
LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

	Gay marriage			Abortion			All		
Team	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc
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IBM Research	0.73	0.63	0.70	0.64	0.54	0.62	0.69	0.59	0.66
TU Darmstadt	0.74	0.56	0.68	0.63	0.48	0.60	0.68	0.52	0.64
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...									

Argument Search Evaluation I

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TU Darmstadt	0.74	0.56	0.68	0.63	0.48	0.60	0.68	0.52	0.64
Düsseldorf University	0.76	0.35	0.62	0.65	0.32	0.57	0.70	0.33	0.60
LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

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Trier University	0.90	0.73	0.83	0.79	0.59	0.71	**0.85**	0.66	0.77
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IBM Research	0.73	0.63	0.70	0.64	0.54	0.62	0.69	0.59	0.66
TU Darmstadt	0.74	0.56	0.68	0.63	0.48	0.60	0.68	0.52	0.64
Düsseldorf University	0.76	0.35	0.62	0.65	0.32	0.57	0.70	0.33	0.60
LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

	Gay marriage			Abortion			All		
Team	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc
Trier University	0.90	0.73	0.83	0.79	0.59	0.71	**0.85**	0.66	0.77
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Düsseldorf University	0.76	0.35	0.62	0.65	0.32	0.57	0.70	0.33	0.60
LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

Trier University. BERT (large, uncased, sequence length 512), tuning for 3 epochs.

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

	Gay marriage			Abortion			All		
Team	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc
Trier University	0.90	0.73	0.83	0.79	0.59	0.71	**0.85**	0.66	0.77
Leipzig University	0.80	0.78	0.79	0.78	0.68	0.75	0.79	0.73	0.77
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Düsseldorf University	0.76	0.35	0.62	0.65	0.32	0.57	0.70	0.33	0.60
LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

Leipzig University. BERT (uncased, sequence length 512, tuning for 5 epochs), loss function: sigmoid_binary_crossentrophy.

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

	Gay marriage			Abortion			All		
Team	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc
Trier University	0.90	0.73	0.83	0.79	0.59	0.71	**0.85**	0.66	0.77
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LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

IBM Research. Two BERT models fine-tuned in cascade starting from the vanilla BERT model.

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

	Gay marriage			Abortion			All		
Team	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc
Trier University	0.90	0.73	0.83	0.79	0.59	0.71	**0.85**	0.66	0.77
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LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

TU Darmstadt. Microsoft's Multi-Task Deep Neural Network mt-dnn. Basis for the mt-dnn is BERT (large). No hyper-parameter tuning, 4 epochs.

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

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LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

Düsseldorf University. Manhattan LSTM – a siamese network – which measures the similarity of both arguments. Document embeddings via BERT (base, uncased, not fine-tuned, sequence length 512 tokens).

Argument Search Evaluation I

Same Side Stance Classification: Results "Within Domain"

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Team	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc
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LMU	0.53	1.00	0.55	0.53	1.00	0.55	0.53	1.00	0.55
...									

LMU. Bert (base). Arguments organized as graph: edges are weighted with the confidence that arguments agree and confidence that they disagree. If known from training set that the arguments agree or disagree the confidence is 0 and 1 or 1 and 0 accordingly.

Argument Search Evaluation I

Same Side Stance Classification: Results "Cross Domain"

	Gay marriage (large)			Gay marriage (small)		
Team	Pre	Rec	Acc	Pre	Rec	Acc
LMU	0.67	0.53	0.63	0.78	0.61	0.72
TU Darmstadt	0.64	0.59	0.63	0.71	0.63	0.68
IBM Research	0.62	0.49	0.60	0.74	0.43	0.64
Paderborn University	0.60	0.38	0.56	0.79	0.33	0.62
Trier University	0.69	0.16	0.54	**1.00**	0.20	0.60
Düsseldorf University	0.72	0.53	0.66	0.68	0.37	0.60
...						

Argument Search Evaluation I

Same Side Stance Classification: Results "Cross Domain"

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...						

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...						

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Düsseldorf University	0.72	0.53	0.66	0.68	0.37	0.60
...						

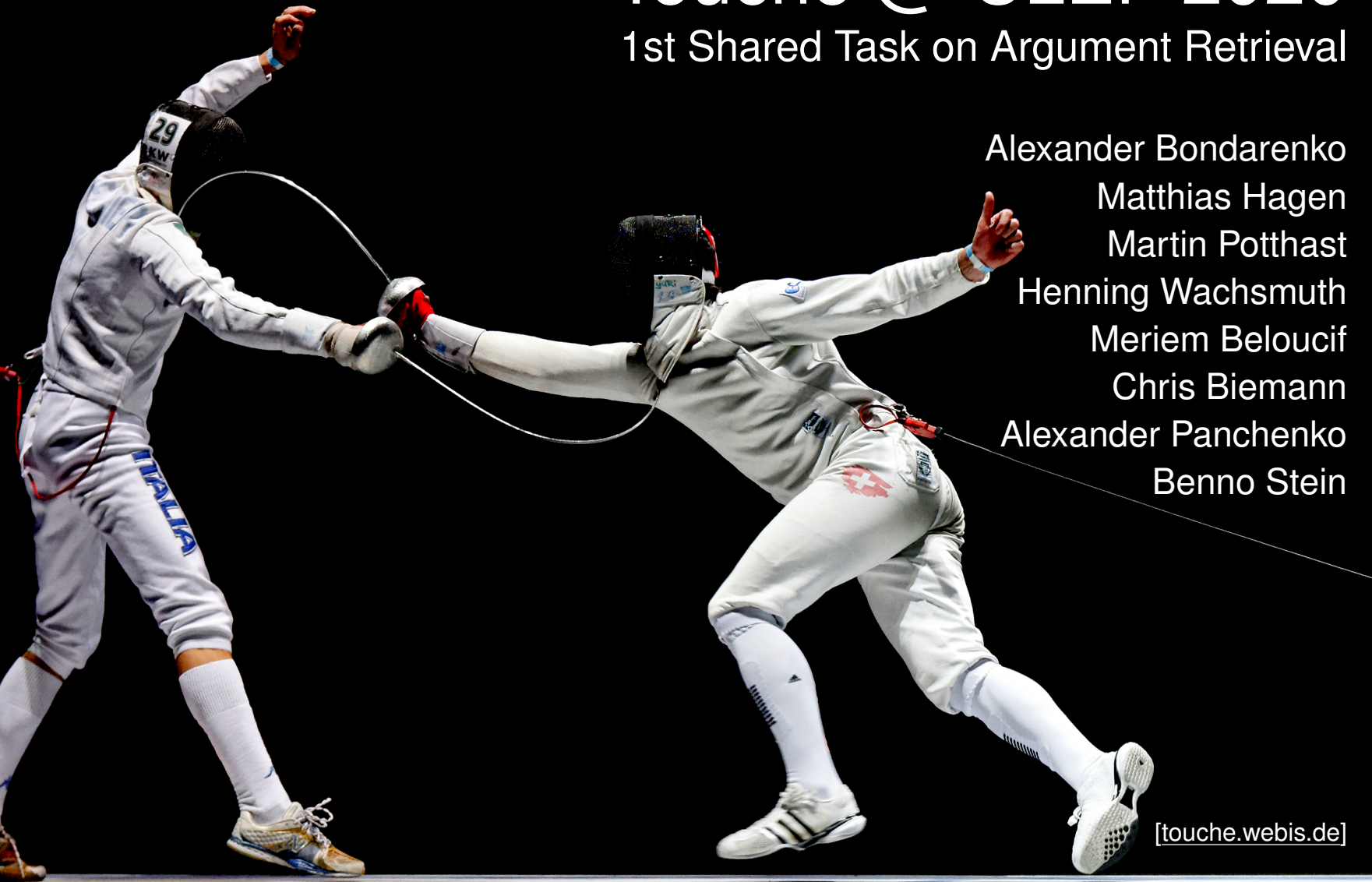
Most of the submitted classifiers are robust regarding:

- imbalances between domain proportions in training and test
- imbalances between domain proportions within test
- imbalances between same side / different side proportions

Touché @ CLEF 2020

1st Shared Task on Argument Retrieval

Alexander Bondarenko
Matthias Hagen
Martin Potthast
Henning Wachsmuth
Meriem Beloucif
Chris Biemann
Alexander Panchenko
Benno Stein



[touche.webis.de]

Argument Search Evaluation II

Argument Retrieval Task @ CLEF 2020 [touche.webis.de]

Task 1: Supporting argumentative conversations

- Scenario: Users search for arguments on controversial topics
- Task: Retrieve “strong” pro/con arguments on the topic
- Data: 300,000 “arguments” (short text passages)

Argument Search Evaluation II

Argument Retrieval Task @ CLEF 2020 [touche.webis.de]

Task 1: Supporting argumentative conversations

- Scenario: Users search for arguments on controversial topics
- Task: Retrieve “strong” pro/con arguments on the topic
- Data: 300,000 “arguments” (short text passages)

Task 2: Answering comparative questions with arguments

- Scenario: Users face personal decisions from everyday life
- Task: Retrieve arguments for “Is X better than Y for Z?”
- Data: ClueWeb12 or ChatNoir [chatnoir.eu]

- Run submissions similar to “classical” TREC tracks
- Software submissions via TIRA [tira.io]

Argument Search Evaluation II

Supporting Argumentative Conversations: Results

Team	Run	nDCG@5
Dread Pirate Roberts	1	0.808
Swordsman (Baseline)	-	0.756
Dread Pirate Roberts	2	0.755
Aragorn	1	0.684
Dread Pirate Roberts	3	0.598
Zorro	-	0.573
...		

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Dread Pirate Roberts. Retrieval: DirichletLM/Similarity-based. Augmentation: Language modeling.

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Swordsman (Baseline). Retrieval: DirichletLM.

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Aragorn: Retrieval. BM25. (Re)ranking Feature: Premise prediction.

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Zorro: Retrieval. BM25. (Re)ranking Feature: Quality + NER.

Argument Search Evaluation II

Answering Comparative Questions with Arguments: Results

Team	Run	nDCG@5
Bilbo Baggins	-	0.580
Puss in Boots (ChatNoir)	-	0.568
Inigo Montoya	-	0.567
Katana	1	0.564
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Bilbo Baggins. Representation: Bag of words. Query processing: Named entities, comp. aspects. (Re-)Ranking features: Credibility, support.

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Puss in Boots (ChatNoir). Representation: Bag of words. (Re-)Ranking features: BM25F, SpamRank.

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Inigo Montoya. Representation: Bag of words. Query processing: Tokens & logic. OR. (Re-)Ranking features: Argum. units (TARGER).

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Katana. Representation: Diff. language models. Query processing: Diff. language models. (Re-)Ranking features: Comparativeness score.

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