Completeness, Recall, and Negation in Open-World Knowledge Bases

Simon Razniewski, Hiba Arnaout, Shrestha Ghosh, Fabian Suchanek

1. Introduction & Foundations (Simon)
2. Predictive recall assessment (Fabian)
3. Counts from text and KB (Shrestha)
4. **Negation (Hiba)**
5. Relative completeness & Wrap-up (Simon)

max planck institut informatik

TELECOM ParisTech

Open-world Assumption

42 awards

[Wikidata] - **Awards won by** Stephen Hawking

Open-world Assumption

42 awards

Adams Prize

Pius XI Medal

Michelson–Morley Award

Royal Society Science Books Prize

Nobel Prize in Physics?

Albert Einstein Medal

Oskar Klein Medal

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Wikidata doesn't know!

[Wikidata](#) - **Awards won by** Stephen Hawking

Problem

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Nobel Prize in Physics?

Existing positive-only KBs are _unaware_ of negation.

Wikidata - **Awards won by** Stephen Hawking

Problem

42 awards, 30000 awards

Existing positive-only KBs are _unaware_ of negation.
Set of negative statements is quasi-infinite!

Wikidata - **Awards won by** Stephen Hawking

State-of-the-art: KBs that include negative statements

- **Edit history**
  - Collaborative KBs, e.g., Wikidata
  - Deleted statements
  - 82% ontology modifications

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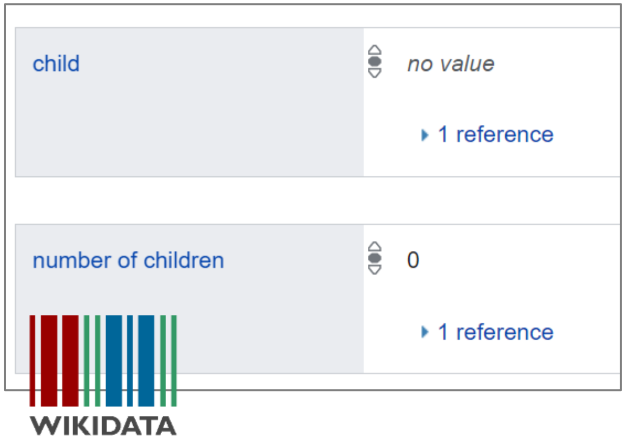

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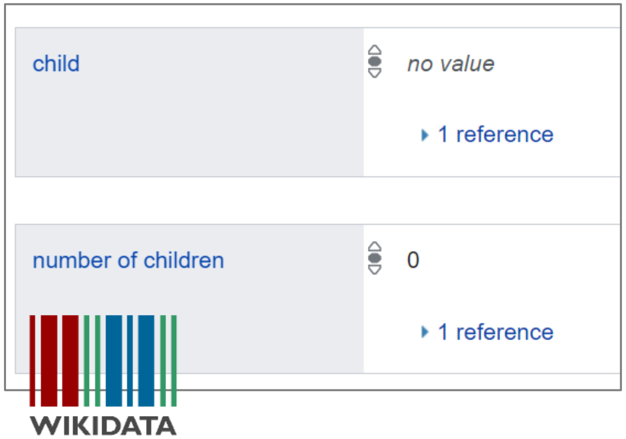

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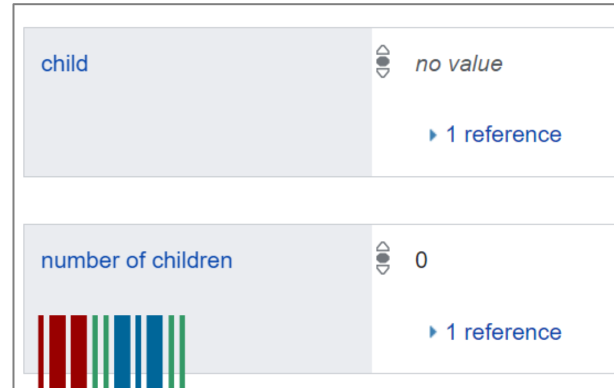

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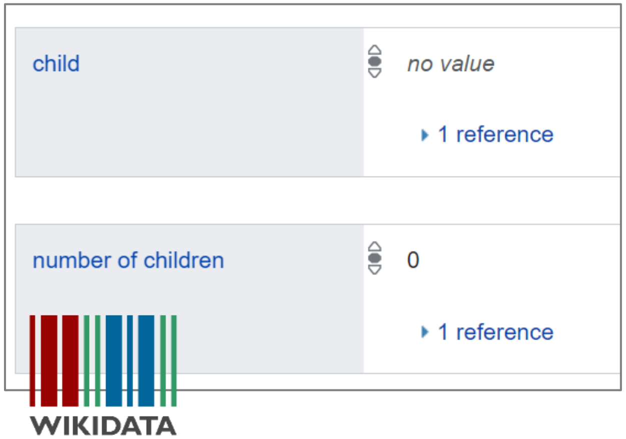


Advantages: formalizes syntax for explicit negation addition, & some allows querying them (e.g., Wikidata SPARQL with o = no-value)
Limitations: inherit same challenges from positive KBC, covers small domains, no active collection of useful negations

Identify Interesting Negative Knowledge

Problem:

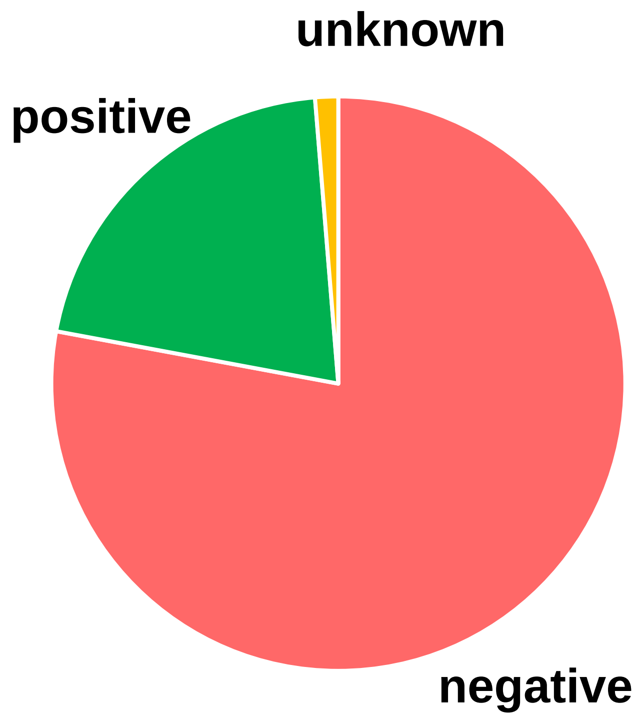
Existing positive-only KBs are <u>*unaware*</u> of negation.

Input:

Open-world KB.

Task:

Explicitly add *salient* negative statements to KB.



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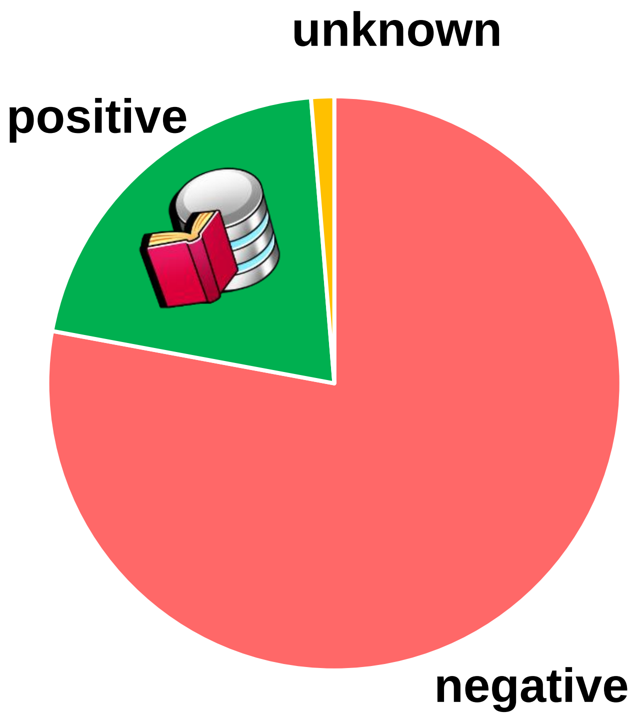

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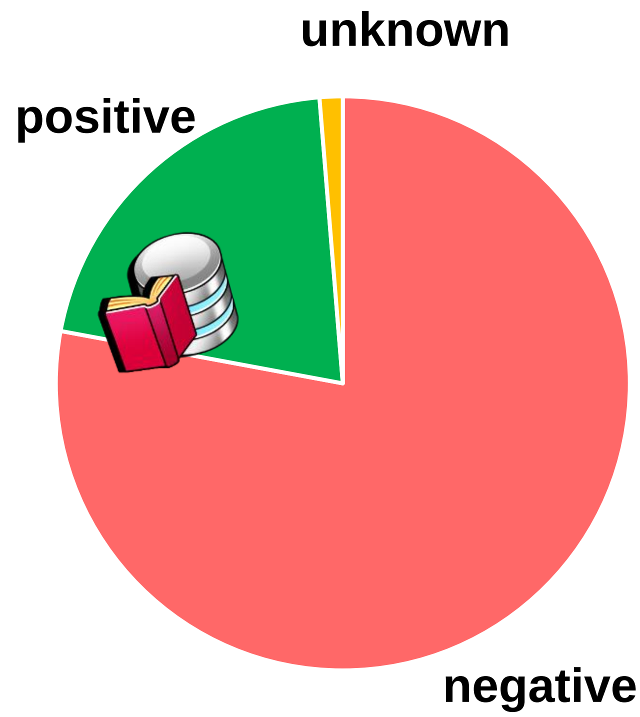

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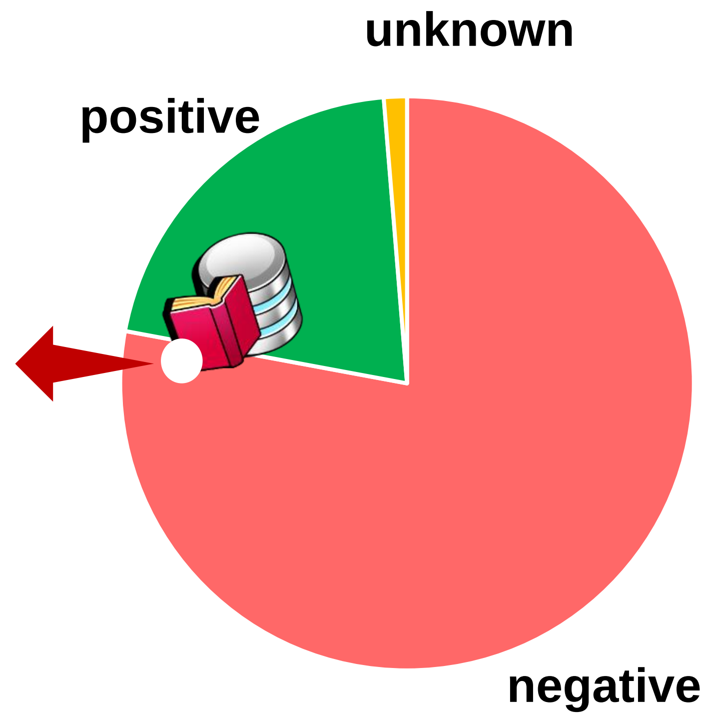
¬ (award; Nobel Prize in Physics)

¬ (award; Academy Awards for Best Actress)

¬ (headquarters location; Silicon Valley)



How to identify interesting negation?

PART1: Statistical Inferences

PART2: Text Extraction

PART3: Pretrained Language Models

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<u>PART1: Statistical Inferences</u>

★ **Infer from *existing* positive statements: Peer-based negation inference method.**

<u>PART2: Text Extraction</u>

<u>PART3: Pretrained Language Models</u>

PART1: Statistical Inferences
Peer-based Negation Inference

Input:
Given entity e from KB.

Steps:
1. **Peer-based candidate retrieval**
2. **Correctness filtering by local completeness assumption**
3. **Supervised ranking for higher saliency**

Output:
Top interesting negative statements about e.

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Collecting Highly Related Entities

What is a similar entity (peer) ?

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Class-based

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- **predicate-object pairs shared by entities:**
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- **Cosine of low-dimensional latent representations**
  Wikipedia embeddings

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Confounding factors:

- **Popularity**
- **Sequences**

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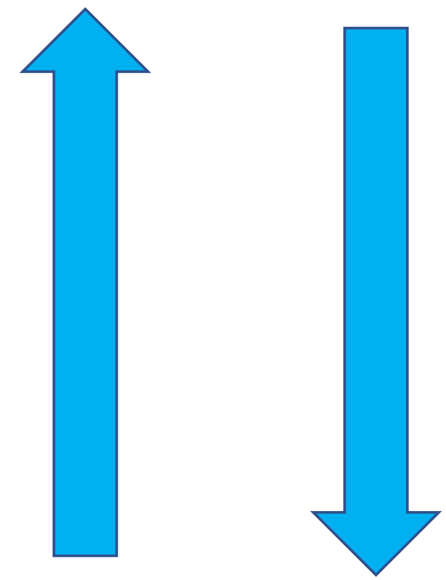

Interpretable **Accurate**

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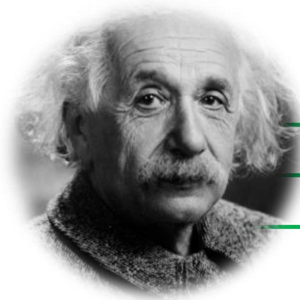
Retrieve Candidate Negations & Correctness Filter

entity

peer



(award; Copley Medal)

(award; Nobel Prize in Physics)

(hobby; reading)

(hobby; sailing)

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Every statement that applies to <u>at least</u> one peer is a *candidate negation*.

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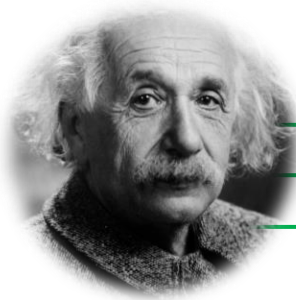

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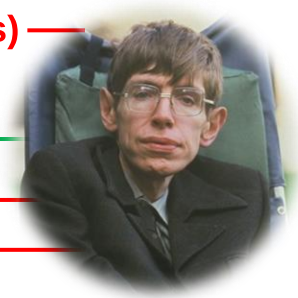

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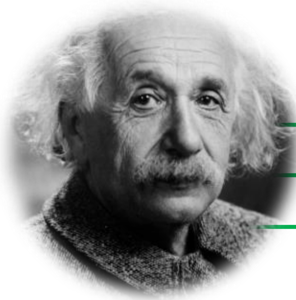

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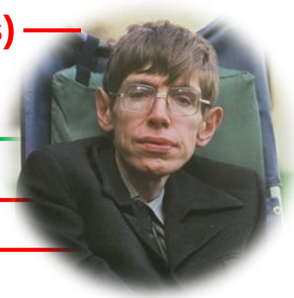

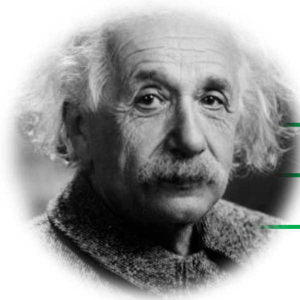

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Challenge: *correctness* of inferred negations.

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Retain candidate *only in presence of other values*

(Hawking, award, {Copley Medal, …}) $\vDash$ ¬ (award, Nobel Prize in Physics)

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Significantly boosts correctness of deductions: **57 to 84%.**

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Supervised Learning-to-rank Model

Candidates = [¬ (handedness; left); ¬ (citizen; U.S.); ¬ (award; Nobel Prize in Physics)]

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   peer frequency, object and predicate importance, and text signals.

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   Is it interesting that Stephen Hawking never received a Nobel in Physics?
   .. is not left-handed?

C. **Train supervised model to predict annotator scores**
   Linear Regression

D. **Rank assertions by predicted score**

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Advantages: recall, canonicalization
Limitations: correctness

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How to identify interesting negation?

PART1: Statistical Inferences

Infer from *existing* positive statements:
Peer-based negation inference method.
★ **Order-oriented peer-based inference.**

PART2: Text Extraction

PART3: Pretrained Language Models

PART1: Statistical Inferences
Negation Inference using Ordered Peers

- **Instead of binary peer relation, exploit order on peers:**
  - **Real-valued similarity functions (JS, Cosine distance, etc..)**
  - **Spatial/temporal data provided in KBs.**

Group= Best Picture Award winners

Arnaout, Razniewski, Weikum, and Pan "Negative Statements Considered Useful", JWS'21

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peers

e

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¬ (country; U.S.)
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Unlike previous 6 winners

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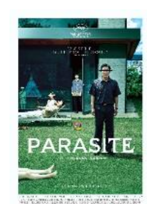

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Unlike 80% of the films in peer group

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Unordered v. Ordered peer-based negation inference

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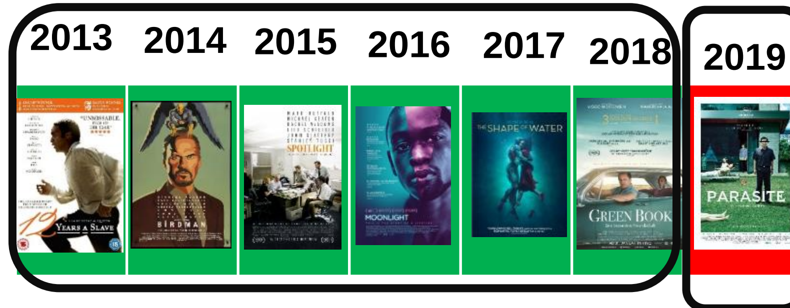
Group= films

peers



e

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Score(statement)=

$$\frac{\#\ peers\ with\ statement}{\#\ peers}$$

Score(statement, m)=

$$\frac{\#\ peers\ with\ statement(\text{within prefix length m})}{\#\ peers(\text{within prefix length m})}$$

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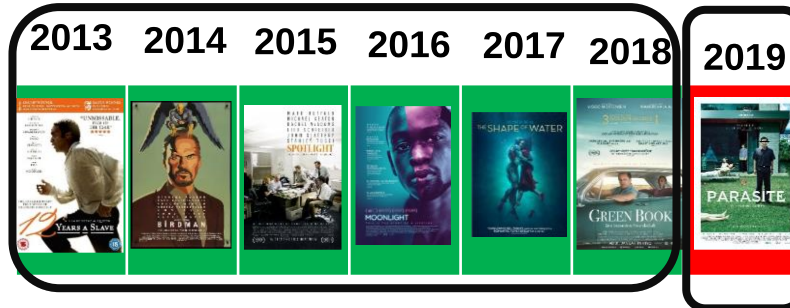

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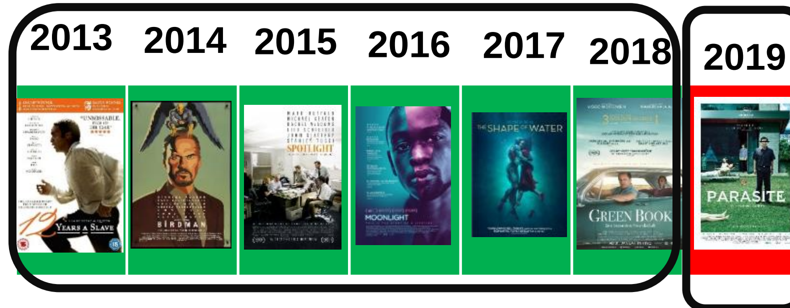

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1/1 = 1 (m=1)

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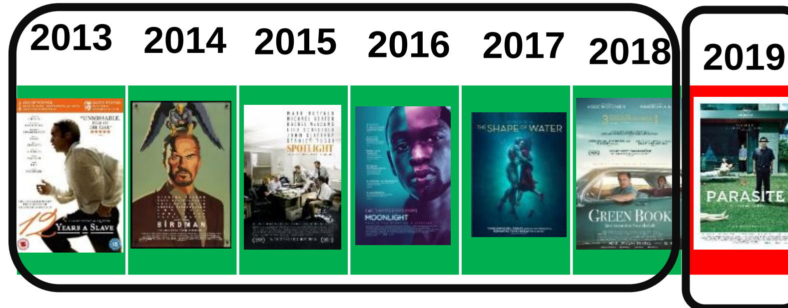

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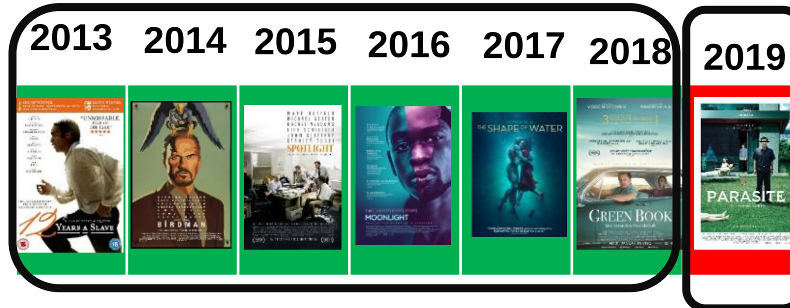

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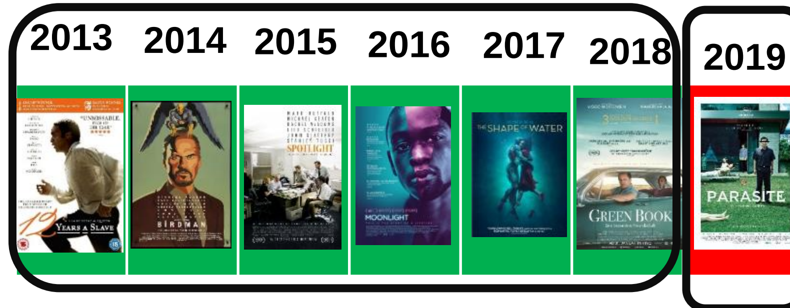

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$$\alpha \frac{\#\, peers\ with\ statement(\text{within prefix length m})}{\#\, peers(\text{within prefix length m})} + (1-\alpha)\log(\#peers)$$

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40 out of 100 similar films are

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Advantages: interpretability, canonicalization
Limitations: recall?

Arnaout, Razniewski, Weikum, and Pan "[Negative Statements Considered Useful]", JWS'21

How to identify interesting negation?

PART1: Statistical Inferences

PART2: Text Extraction

★ **Pattern-based query log extraction.**

Mining common factual mistakes from Wikipedia updates.

PART3: Pretrained Language Models

PART2: Text Extraction

Mine Negations from User Query Logs

Romero et al., "Commonsense Properties from Query Logs and Question Answering Forums", CIKM'19
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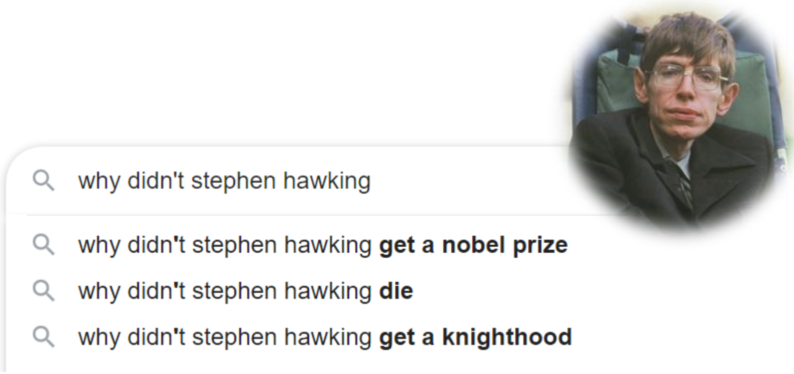

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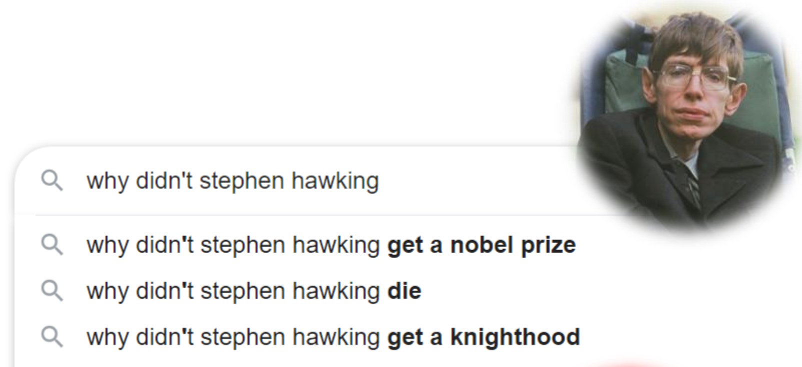

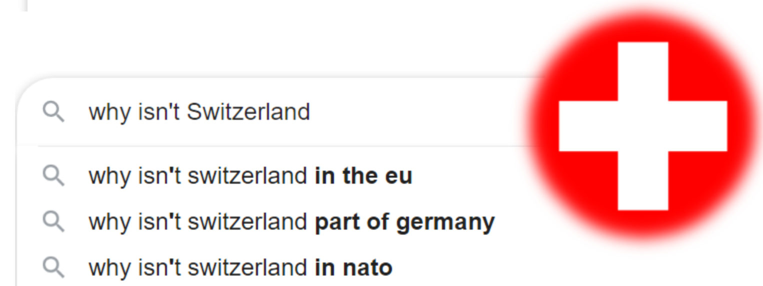

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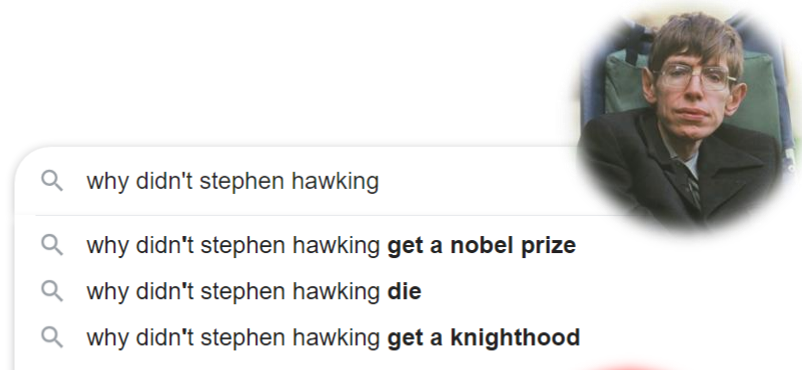

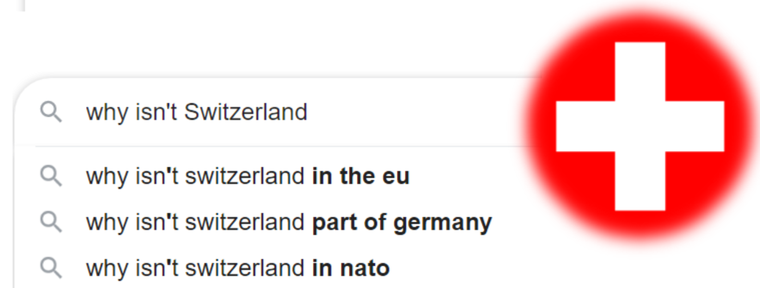

Advantages: relevance, correctness
Limitations: recall

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Mine Text Revisions

Karagiannis et al., "Mining an "Anti-Knowledge Base" from Wikipedia Updates with Applications to Fact Checking and Beyond", PVLDB'19

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- **Anti-knowledge base (AKB)**
  Create a knowledge base of *common factual mistakes*
  Complement the positive-only KB

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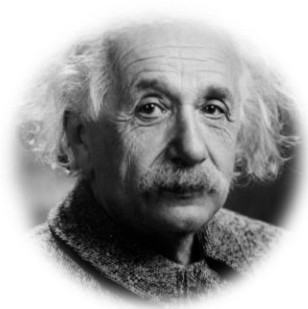

Revision 505

Einstein was born in Vienna.

Revision 506

Einstein was born in Ulm.

Karagiannis et al., "[Mining an "Anti-Knowledge Base" from Wikipedia Updates with Applications to Fact Checking and Beyond](#)", PVLDB'19

PART2: Text Extraction
Mine Text Revisions

Advantages: correctness
Limitations: relevance, updates occur for a variety of reasons (60% not factual corrections controversial, synonyms, spelling mistake, etc.)

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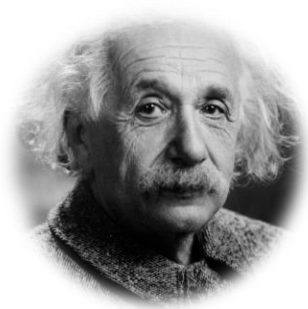

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PART3: Pretrained Language Models

★ **Generating meaningful commonsense negative knowledge: Generate corruptions & estimate contradictions.**

Generating Meaningful Negative Commonsense Knowledge

Safavi and Koutra, "Generating Negative Commonsense Knowledge", KR2ML at NeurIPS'20

Generating Meaningful Negative Commonsense Knowledge

- **Two-step framework:**

Generating Meaningful Negative Commonsense Knowledge

- **Two-step framework:**

1) **Generate corruptions**
   plausible candidate negatives by corrupting positives
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PART3: Pretrained Language Models

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(horse, IsA, expensive pet)
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Advantages: recall
Limitations: correctness (LM as source knowledge?)

Safavi and Koutra, "Generating Negative Commonsense Knowledge", KR2ML at NeurIPS'20

Summary

Venue	Method	Correctness	Relevance	Recall	Canonicalization
AKBC'20 Arnaout et al.	Peer-based				
JWS'21 Arnaout et al.	Peer-based (ordered)				
PVLDB'19 Karagiannis et al.	Anti-KB (mining revisions)				
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Projects

Wiki*nega*ta ***(online platform)***

Browse interesting negations about Wikidata entities

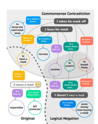
Neguess ***(online quiz-game)***

Entity guessing game with negative clues

Anti-KB ***(dataset)***

Ranked common factual mistakes from Wikipedia

ANION ***(dataset)***



Commonsense KB focusing on negated events

Google Hotel Search ***(online platform)***

Hotel booking with negative features asserted

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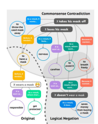
ANION ***(dataset)*** 

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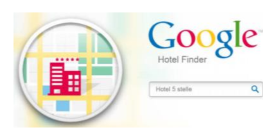
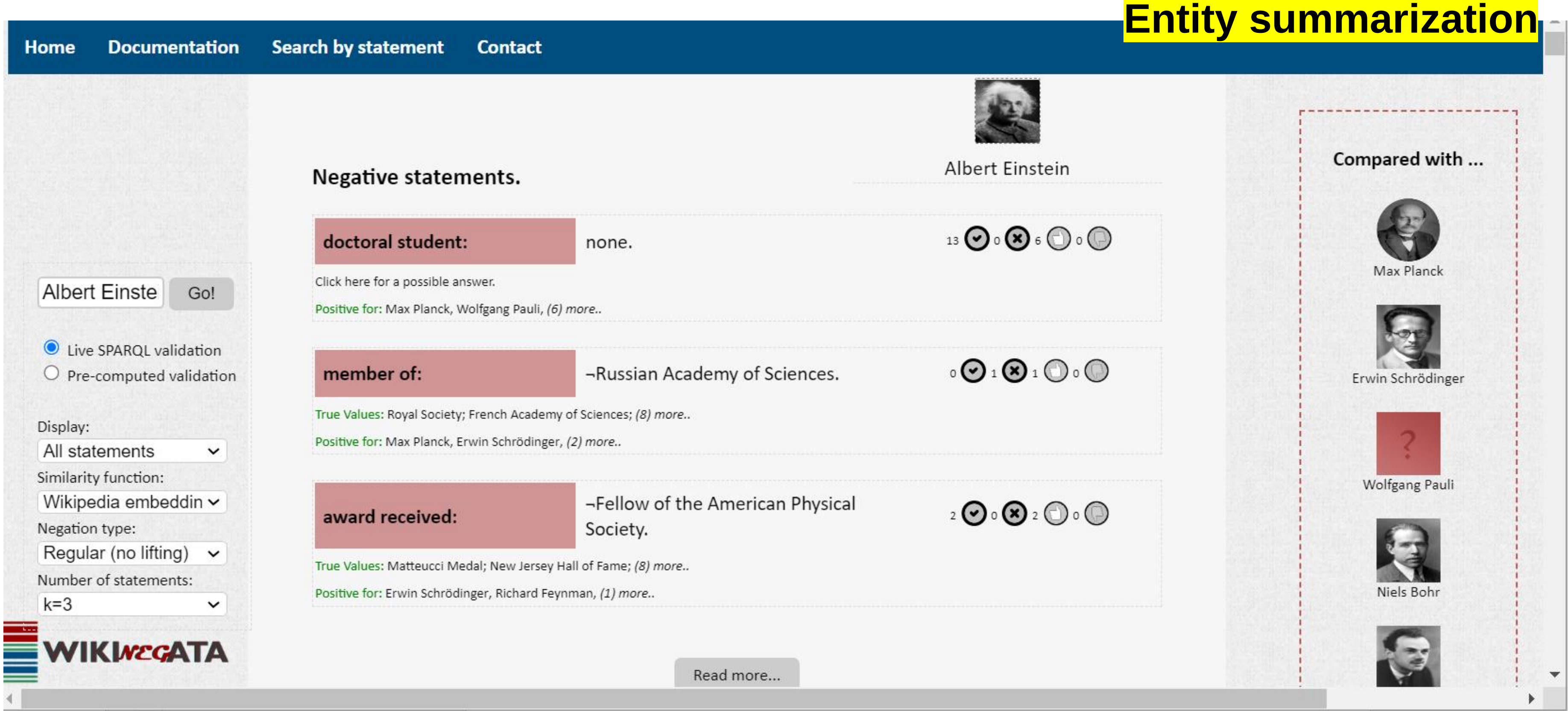
Google Hotel Search ***(online platform)*** 

Hotel booking with negative features asserted

- **Built upon the peer-based negation inference.**
- **Interesting negations about 0.5M Wikidata entities.**

Entity summarization



Arnaout et al., "Wikinegata: A Knowledge Base with Interesting Negative Statements", VLDB'21

d5demos.mpi-inf.mpg.de/negation/

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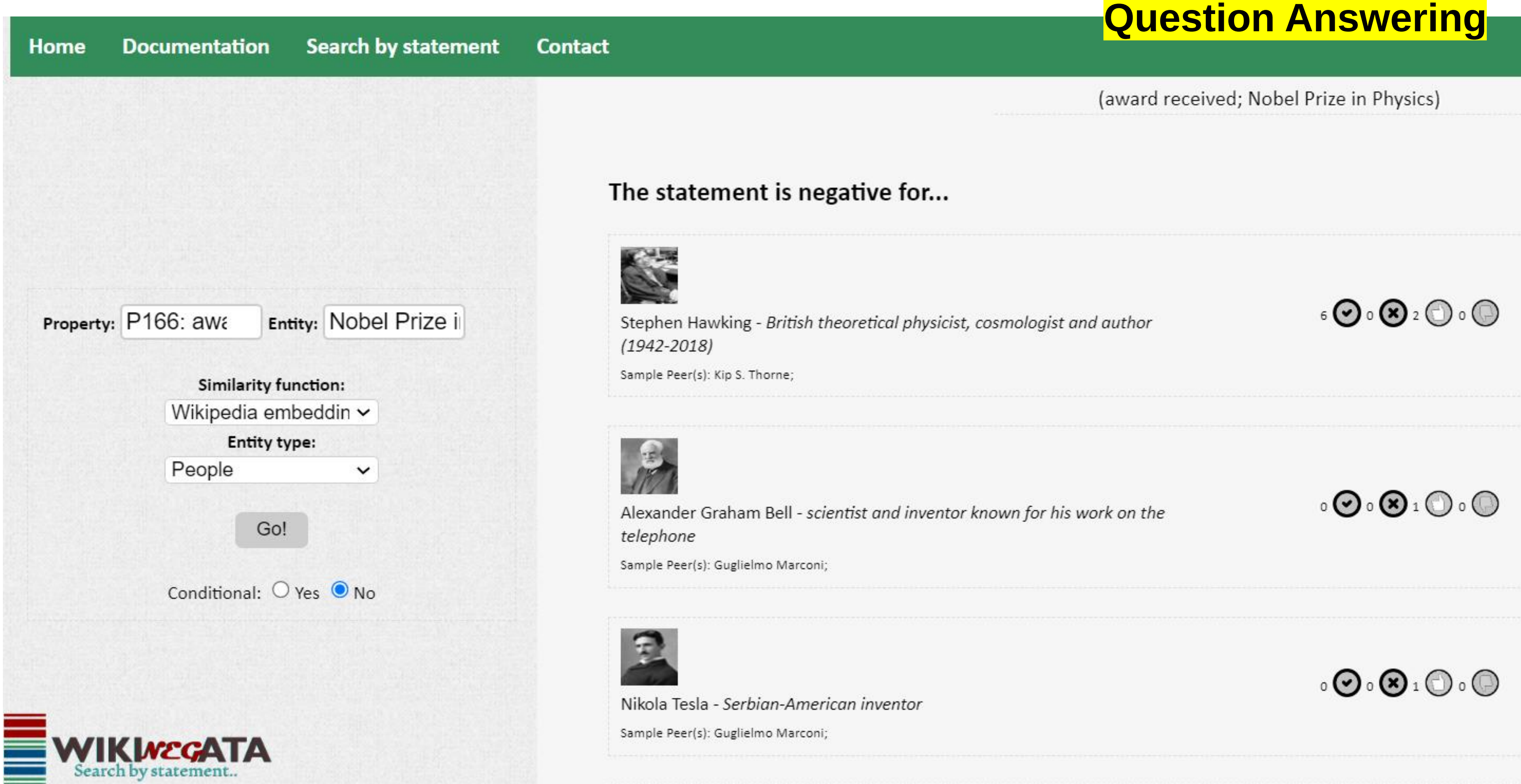
Question Answering



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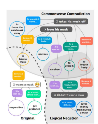
ANION ***(dataset)*** 

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Can you Neguess?

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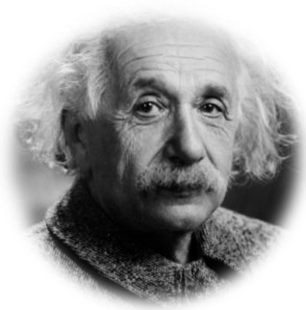


Clue1: was *not* educated at Trinity College.
Clue2: did *not* win Nobel Prize in Physics.
Clue3: is *not* German.

Biswas Bikram et al., "Neguess: Wikidata-entity guessing game withnegative clues", ISWC'21

Can you Neguess?

neguess.mpi-inf.mpg.de

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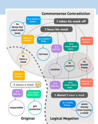

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Anti-knowledge base

Data available upon request

- **Dataset of common factual mistakes: mined from Wikipedia change log.**
- **<u>116k</u> likely mistakes where people confuse entities or numbers**

Penicillin was discovered in 1928 by Scottish scientist <u>Alexander Baldwin</u>.

<u>Alexander Flemming</u>.

Confidence (of actual mistake) score = 0.619

Karagiannis et al., "<u>Mining an "Anti-Knowledge Base" from Wikipedia Updates with Applications to Fact Checking and Beyond</u>", PVLDB'19

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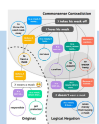
★ **<u>ANION</u>** ***(dataset)*** 

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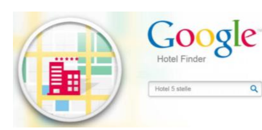
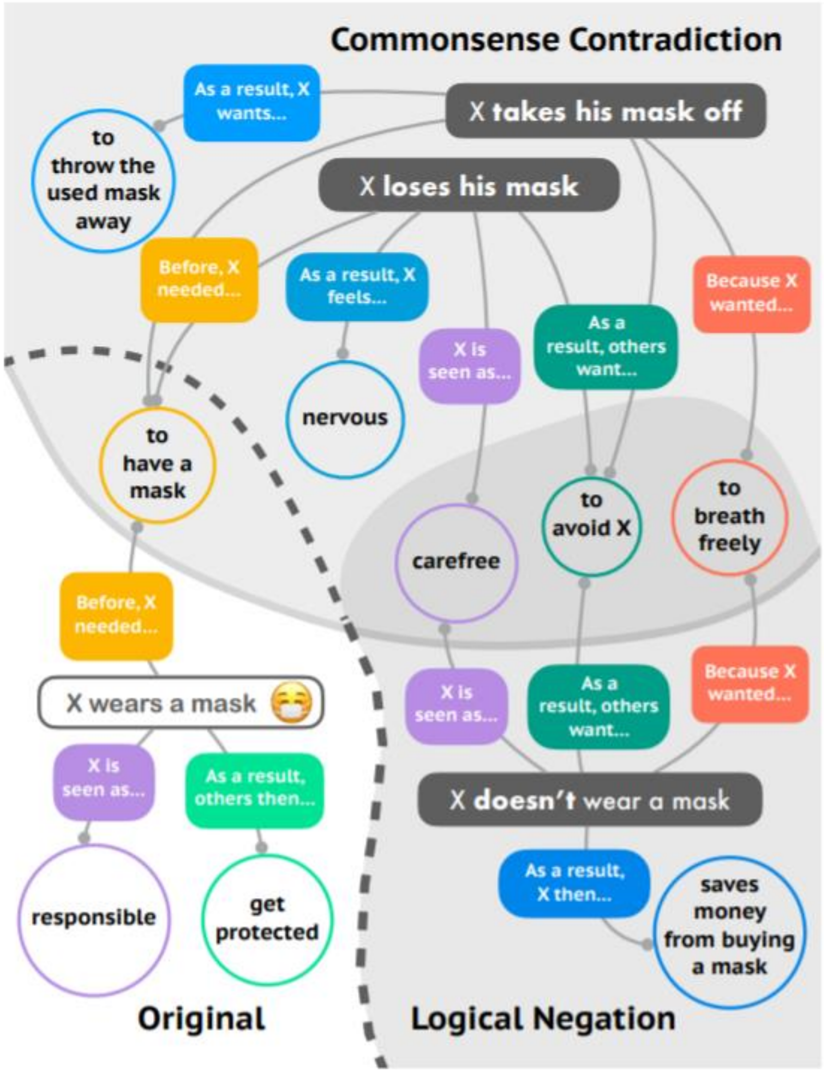
<u>Google Hotel Search</u> ***(online platform)*** 

Hotel booking with negative features asserted

ANION

- **A new commonsense knowledge graph with 624K if-then rules.**

https://github.com/liweijiang/anion



Jiang et al., "[I'm Not Mad: Commonsense Implications of Negation and Contradiction](#)", NAACL'21

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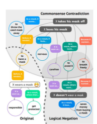

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Hotel booking with negative features asserted

Data crawled from:

- Hotel websites
- Third-party services
- User reviews

Internet

- ✓ Wi-Fi free
- ✓ Wi-Fi in public areas

Policies & payments

- ✓ Smoke-free property
- ✓ Credit cards
- ✓ Debit cards
- ✓ Cash

Services

- ✓ Front desk 24-hour
- ✓ Baggage storage
- ✓ Full-service laundry
- ✓ Lift
- ✓ Social hour
- ✓ Wake up calls
- ✓ Gift shop
- ✓ Housekeeping daily
- ✓ Turndown service

Accessibility

- ✓ Accessible
- ✓ Accessible lift

Food and drink

- ✓ Restaurant
- ✓ Bar
- ✓ Table service
- ✓ Room service
- ✓ Breakfast extra charge
- ✓ Breakfast buffet

Activities

- ✓ Bicycle hire extra charge
- ✓ Boutique shopping

Pools

- ⊘ No pools
- ⊘ No hot tub

Parking & transport

- ✓ Parking extra charge
- ✓ Self parking extra charge

Wellness

- ⊘ No spa

Pets

- ⊘ No pets

https://www.google.com/travel/hotels/

Takeaway: negation

- Current KBs lack negative knowledge
- Rising interest in the *explicit addition* of negation to OW KB.
- Negations highly relevant in many applications including:
  - Commercial decision making (e.g., hotel booking)
  - General-domain QA systems (e.g., is Switzerland a member of the EU?)
- Methodologies include:
  - Statistical inference
  - Text extraction
  - Pretrained LMs.