## On the Limits of Machine Knowledge: Completeness, Recall and Negation in Web-scale Knowledge Bases

Simon Razniewski, Hiba Arnaout, Shrestha Ghosh, Fabian Suchanek

- 1. Introduction & Foundations (Simon) 20 min
- 2. Predictive recall assessment (Fabian) 20 min
- 3. Counts from text and KB (Shrestha) 20 min
- 4. Negation (Hiba) 20 min
- 5. Wrap-up (Simon) 5 min







### **Open-world Assumption**

### 42 awards



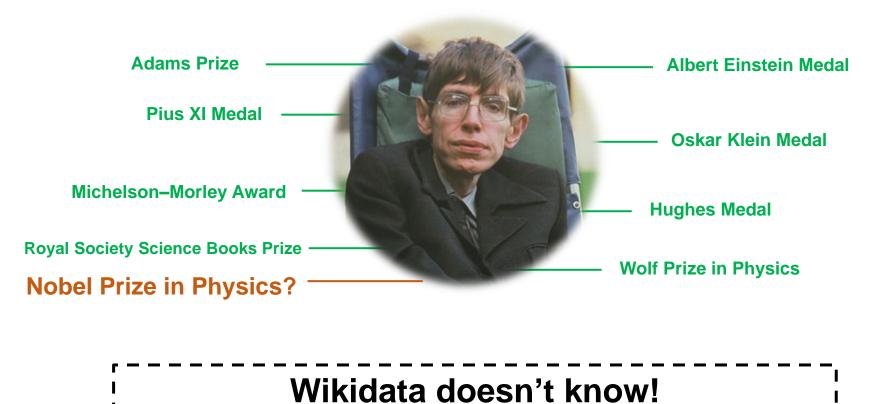
### **Open-world Assumption**

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### 42 awards



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

## 42 awards, 30000 awards



Existing positive-only KBs are <u>unaware</u> of negation. Set of negative statements is quasi-infinite!

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- Deleted statements
- 82% ontology modifications

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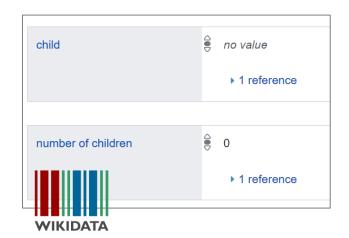


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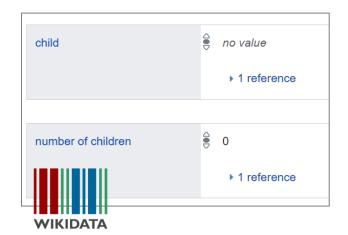
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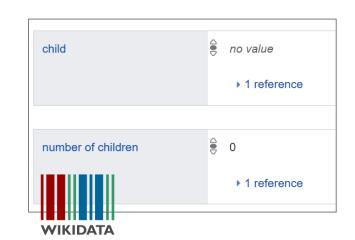
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**Advantages:** formalizes syntax for explicit negation addition, & some allows querying them (e.g., Wikidata SPARQL with o = no-value) **Limitations:** inherit same challenges from positive KBC, covers small domains, no active collection of useful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



### **Identify Interesting Negative Knowledge**

**Problem:** 

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Input:

Open-world KB.

Task:

Explicitly add salient negative statements to KB.

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¬ (award; Nobel Prize in Physics)





¬ (award; Academy Awards for Best Actress)

¬ (headquarters location; Silicon Valley)



**PART2: Text Extraction** 

**PART3: Pretrained Language Models** 

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

**PART2: Text Extraction** 

**PART3: Pretrained Language Models** 

### **Peer-based Negation Inference**

### **Input:**

Given entity e from KB.

#### Overview:

- 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.

What is a similar entity (peer)?

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#### Class-based

Stephen Hawking: Physicist

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#### **Jaccard-similarity**

predicate-object pairs shared by entities:
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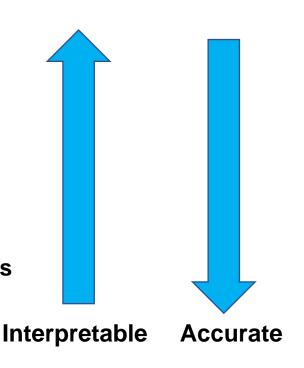
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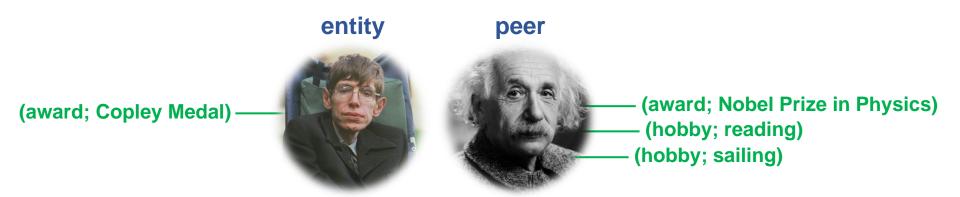
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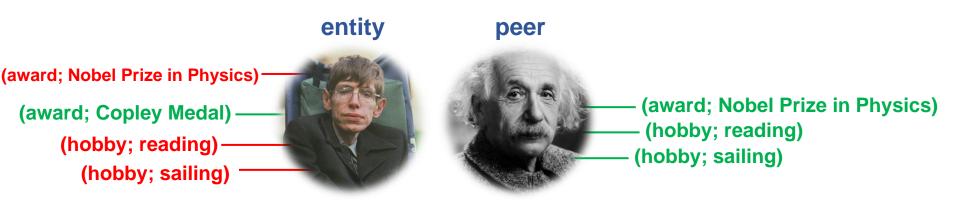




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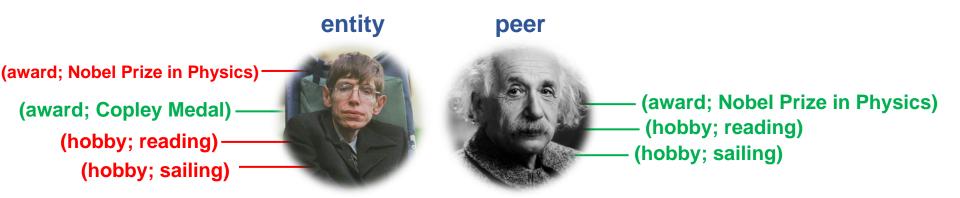


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Challenge: correctness of inferred negations.

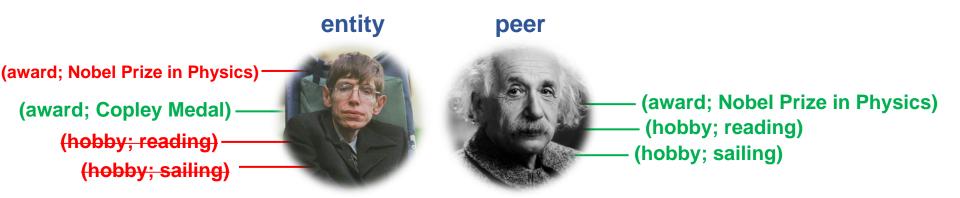
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Retain candidate only in presence of other values
(Hawking, award, {Copley Medal, ...}) ⊨ ¬ (award, Nobel Prize in Physics)
(Hawking, hobby, Ø) ⊭ ¬ (sailing, reading)
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Significantly boosts correctness of deductions: 57 to 84%.

### **Supervised Learning-to-rank Model**



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- B. Pointwise L2R: Obtain annotator judgments for statement interestingness [0..1] 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
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- 1. ¬ (award; Nobel Prize in Physics)
- 2. ¬ (citizen; U.S.)
- 3. ¬ (handedness; left)

### PART2: Text Extraction

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

Mining common factual mistakes from Wikipedia updates.

### **PART3: Pretrained Language Models**

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- Q why didn't stephen hawking
- why didn't stephen hawking get a nobel prize
- why didn't stephen hawking die
- why didn't stephen hawking get a knighthood

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  - ...
- Advantage: High precision
- Limitation: Very low recall



#### PART1: Statistical Inferences

#### **PART2: Text Extraction**

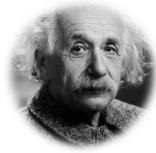
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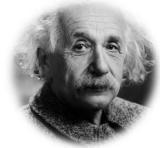


Revision 505

Einstein was born in Vienna. Revision 506

Einstein was born in Ulm.

- Anti-knowledge base (AKB)
   Create a knowledge base of common factual mistakes
   Complement the positive-only KB
- Main idea: Exploit entity/number swaps in Wikipedia update logs Web hits for correctness score
- Advantage: High correctness
- Limitation:
  Updates occur for a variety of reasons
  60% are not factual corrections
  controversial, synonyms, spelling mistake, etc.



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How to identify interesting negation?

#### **PART1: Statistical Inferences**

**PART2: Text Extraction** 

#### **PART3: Pretrained Language Models**

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

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```
(horse, IsA, expensive pet)
(cat, IsA, expensive pet)
(goldfish, IsA, expensive pet)
(horse, IsA, expensive car)
```

Wikinegata (online platform)



Browse interesting negations about Wikidata entities

Neguess (online quiz-game) Neguess?

Entity guessing game with negative clues

Anti-KB (dataset)



Ranked common factual mistakes from Wikipedia

ANION (dataset)



Google Hotel Search (online platform)



Hotel booking with negative features asserted



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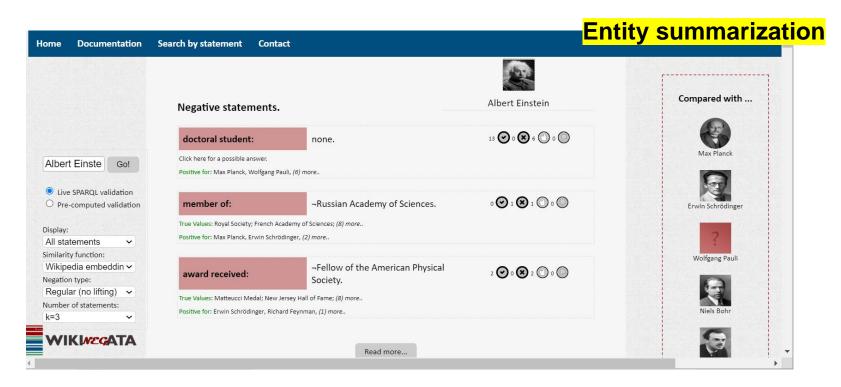
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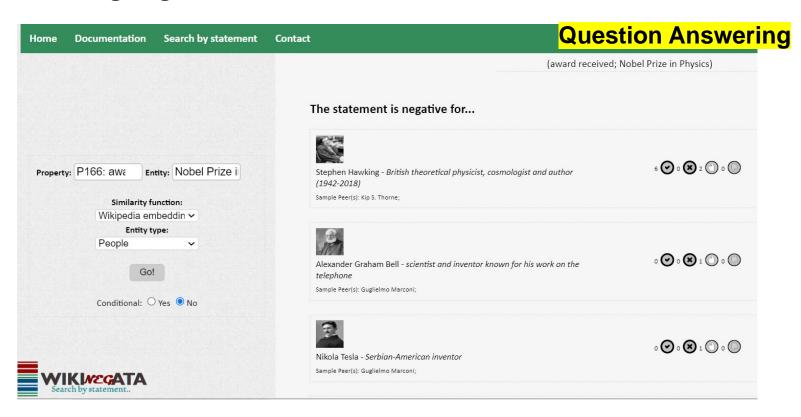


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   Come to the demo session [Blocks 1 & 3]!!
- Built upon the peer-based negation inference.
- Interesting negations about 0.5M Wikidata entities.



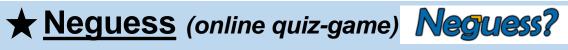


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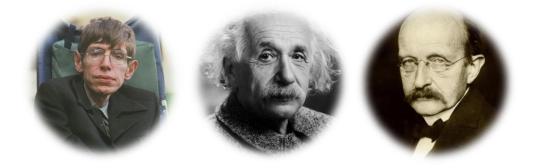
Commonsense KB focusing on negated events

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Entity-guessing game with interesting negations as clues.



Clue1: was *not* educated at Trinity College.

Clue2: did *not* <u>win Nobel Prize in Physics.</u>

Clue3: is *not* <u>German.</u>



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**Dataset of common factual mistakes:** mined from Wikipedia change log.



116k likely mistakes where people confuse entities or numbers

Penicillin was discovered in 1928 by Scottish scientist Alexander Baldwin.





Alexander Flemming.



Confidence score = 0.619

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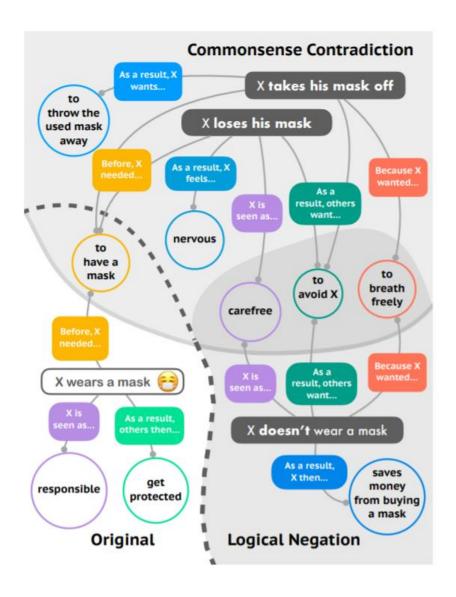
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ANION 61

 A new commonsense knowledge graph with 624K ifthen rules.

https://github.com/liweijiang/anion



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#### Data crawled from:

- Hotel websites
- Third-party services
- User reviews



#### Tood and drink ♠ Internet ✓ Wi-Fi free Restaurant Wi-Fi in public areas ✓ Bar Table service Policies & payments Room service Smoke-free property ✓ Breakfast extra charge Credit cards Breakfast buffet Debit cards Activities Cash ✓ Bicycle hire extra charge △ Services Boutique shopping ✓ Front desk 24-hour Pools ✓ Baggage storage ✓ Full-service laundry No pools No hot tub ✓ Lift Social hour Parking & transport ✓ Wake up calls ✓ Parking extra charge ✓ Gift shop ✓ Self parking extra charge ✓ Housekeeping daily Turndown service ✓ Wellness & Accessibility No spa Accessible Pets

No pets

Accessible lift

- 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 question answering systems (e.g., is Switzerland a member of the EU?)
- Methodologies include:
  - Statistical inference
  - Text extraction
  - Pretrained LMs.