

# Enriching Open-world Knowledge Graphs with Salient Negative Statements

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## Knowledge Graphs (KGs)

Die Hard cast members

#### **Traditional search**

#### Die Hard (1988) - IMDb

#### https://www.imdb.com/title/tt0095016 -

Web 20 Jul 1988 Die Hard: Directed by John McTiernan. With Bruce Willis, Bonnie Bedelia, Reginald VelJohnson, Paul Gleason, A New York City police officer tries to save his ...

#### Die Hard - Full Cast & Crew - TV Guide

#### https://www.tvguide.com/movies/die-hard/cast/2030360926 -

Web Alan Rickman Hans Gruber Reginald VelJohnson Sgt. Al Powell Bonnie Bedelia Holly McClane Alexander Godunov Karl Hart Bochner Harry Ellis Paul Gleason Dwayne ...

Director: John Mctiernan Content Rating: R

#### Die Hard Cast List: Actors and Actresses from Die Hard - Ranker

#### https://www.ranker.com/list/hard-cast-and-actors-in-this-movie/reference -

Web The cast members of Die Hard have been in many other movies, so use this list as a starting point to find actors or actresses that you may not be familiar with. Items on this ...

#### Die Hard (film series) - Wikipedia

#### https://en.wikipedia.org/wiki/Die Hard (film series) -

Web Die Hard is an American action film series that originated with Roderick Thorp's 1979 novel Nothing Lasts Forever. All five films revolve around the main character of John McClane , ....

#### The Die Hard Actors You May Not Know Passed Away - Looper

https://www.looper.com/732090/the-die-hard-actors-you-may-not-know... . Web 12 Jan 2022 . The Die Hard Actors You May Not Know Passed Away Paul Gleason, Apart

## With KGs

Die Hard



FSK 16 1988 - Action/Thriller - 2h 12m





B QI

Overview



Watch n

Cast

Bruce Willis John McClane

Alan Rickman Hans Gruber

Bonnie Bedelia

Reginald Holly Gennaro M. VelJohnson

William Atherton Richard Thornburg

About



IMDb

Die Hard | 30th Anniversary Trailer | 20th C ... 1:22 94 % 72 %  $(\hat{\mathbf{0}})$ Rotten Toma... Metacritic

89% liked this film () Google users

Hoping to spend Christmas with his estranged wife, detective John McClane arrives in LA. However, he learns about a hostage situation in an office building and his wife is one of the hostages.

Release date: July 22, 1988 (USA) Director: John McTiernan Sequel: Die Hard 2 Distributed by: 20th Century Studios Adapted from: Nothing Lasts Forever Budget: \$25-35 million

## **Types of KGs**

## (Subject, Predicate, Object) triples:

## Encyclopedic

Wikidata, DBpedia, YAGO

-- real-world entities

(Angela Merkel, birthPlace, Hamburg) (L3S, location, Lower Saxony)

#### • Commonsense

*ConceptNet, WebChild, COMET* -- everyday concepts



#### • Other

*KnowLife, Amazon Product Graph* -- Domain-specific or corporate projects

### **Knowledge Gap**

Web-scale KGs are incomplete.

-> They **DON'T** take a stance on **absent** information

KG (Bruce Willis, award, Emmy)

| Querying KG |        | Closed-world<br>Assumption<br>(CWA) |     | Open-world<br>Assumption<br>(OWA) |
|-------------|--------|-------------------------------------|-----|-----------------------------------|
| Willis,     | award, | Emmy)?                              | Yes | Yes                               |
| Willis,     | award, | Oscar)?                             | No  | Unknown                           |

**Knowledge Gap - Example** 

# Querying positive information

#### 🖣 Bruce Willis Emmy 🛛 🎍 🧕

#### Bruce Willis / Primetime Emmy Awards / Awards

Lead Actor - Drama Series 1987

Lead Actor - Drama Series 1986

### Querying absent (negative) information

#### Bruce Willis Oscar 🤳 💿

#### Bruce Willis - Awards - IMDb

https://www.imdb.com/name/nm0000246/awards -

| Übersicht | Biografie |
|-----------|-----------|
|-----------|-----------|

Filmografie (Auswahl)

Deutsche Synchrons >

Walter Bruce Willis (\* 19. Marz 1955 in Idar-Oberstein, Deutschland) ist ein ehemaliger US-amerikanischer Schauspieler. Seinen Durchbruch als Filmschauspieler hatte er 1988 mit dem Kinofilm Stirb langsam in der Rolle des John McClane, die er auch in mehreren Fortsetzungen verkörperte. Zuvor war er bereits durch die Fernsehserie Das Model und der Schnuffler bekannt...



Wikipedia - Text under CC-BY-SA licence

#### List of awards and nominations received by Bruce Willis

https://en.wikipedia.org/wiki/List\_of\_awards\_and\_nominations\_received... -

Web 16 rows · Bruce Willis awards' list Willis in 2018. The following is a List of awards and ...

| YEAR    | CATEGORY                                 | NOMINATED WORK              | RESULT    |
|---------|------------------------------------------|-----------------------------|-----------|
| 2022    | Worst Bruce Willis Performance in a 2021 | Survive the Game            | Rescinded |
| 2022    | Worst Bruce Willis Performance in a 2021 | Out of Death                | Rescinded |
| 2022    | Worst Bruce Willis Performance in a 2021 | Midnight in the Switchgrass | Rescinded |
| 2022    | Worst Bruce Willis Performance in a 2021 | Fortress                    | Rescinded |
| See all | 16 rows on en wikipedia.org              |                             |           |

# Solution: CWA Baseline ?

Awards of Bruce Willis in Wikidata: 7 awards -> negating 36K awards

**Overall: negating 150B statements** 

False negatives ~ 6%
NOT(Willis, award, Golden Globe)

True negatives ~ 87% (trivial)

NOT(Willis, award, honorary citizen of Bonn)

**True negatives ~ 7% (salient)** 

NOT(Willis, award, Oscar)

### Challenges

# 1) Identify candidate salient negatives about entities

thematic, interesting, unexpected

## 2) Scrutinize candidates

truly negative rather than missing positive



many NBA players become coaches after they retire



# This Talk

- Negation Inference from Encyclopedic KGs [AKBC20, JWS21]
- Negation Inference from Commonsense KGs [CIKM22]
- $\circ$  Use cases
  - Knowledge Exploration [VLDB21]
  - Demographic Analyses [ICWSM23]
- Can LLMs solve this problem?
- Take Away

## **Negation Inference from Encyclopedic KGs**

We propose the peer-based negation inference method

- -Given entity e in KG:
  - 1. Select highly related entities (peers)
  - 2. Postulate local CWA (within peer group)
  - 3. Infer <u>expectations</u> about <u>e</u> (*candidate* negatives)
  - 4. Score candidates by relative frequency
  - Output: salient negatives about e.

# **Highly Related Entities (Peers)**

Identify similar entities to e = Wilhelm Busch

# 1. Class-based similarity:

using KG's type system Professions of Busch? -> Illustrator, .. Other illustrators: *Bettina von Arnim, Karel Appel, ..* 

# 2. Graph-based similarity:

*counting shared predicate-object pairs* Busch AND Thomas Mann = 3% in common Both worked in Munich, speak German, ..

# 3. Embedding-based similarity:

using pre-trained embeddings SIM(vec(Busch), vec(Adolf Oberländer)) = 0.93

[A, Razniewski, Weikum AKBC20] Best Paper Award (conference attendees vote)<sup>10</sup>



#### **Postulate Local CWA**

Local CWA = assume *completeness* over selected parts of the KG, i.e., **peer-related** subgraph (*embedding-based*)



[A, Razniewski, Weikum AKBC20] Best Paper Award (conference attendees vote)<sup>11</sup>

### **Infer and Score Negatives**

- 1) Infer absent links as negative
- 2) Compute salience as relative frequency



## Main Evaluation Findings: Peer-based Inference

Assessments using crowdsourcing tasks (mturk.com)

- In biographic summaries about entities: best negatives-to-positives ratio 1:3
- Our method *outperforms* in **nDCG3** (rank by **salience**)
   CW baseline by **24%**; KGE methods by **17%**
- 3) Boost in correctness by 30% by enforcing the Partial Completeness Assumption (PCA) Infer NOT(s, p, o) for s iff (s, p, o') ∈ KG Downside: losing the ability to infer empty-object negatives, e.g., (child, none)

# **Limitation 1: Basic Peer Groups Construction**

- a) Multiple, unordered, labeled groups Class-based: Novelists: Saddam Hussein, ..
- b) Single, ordered, unlabeled group Embeddings-based similarity: Philip Pullman, ...



Goal - <u>Multiple</u> ordered labeled peer groups.

We propose the order-oriented version of the method.

[A, Razniewski, Weikum, Pan JWS21]

#### **Order-oriented Peer-based Negation Inference**

- New peering: (s, p, o, additional qualifier) member group member's order in the group label
- (J. K. Rowling, recipient, Locus for Best Novel, 2000)



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# **Order Reflected in Salience Computation**

#### Recipients of Locus for Best Novel Award



Score(
$$t$$
)  $\stackrel{\text{def}}{=} \operatorname{argmax}_{S[:m]} \left[ \alpha \quad \frac{\operatorname{FRQ}(t, S)}{\operatorname{VOL}(S)} + (1 - \alpha) \log \operatorname{FRQ}(t, S) \right]$ 

fraction of peers with <u>t</u> in S[:m] reward larger number of peers

 $\alpha = 0.5$ 

# Sample Results for J. K. Rowling on Full KG (Wikidata)



NOT male (but female), unlike 49 of the previous 68
 fellows of the Royal Society of Edinburgh



## **Main Evaluation Findings: Ordered Peers**

Assessments using crowdsourcing\* tasks (mturk.com)

Performance of *order-oriented* against original *peer-based inference*:

10% in Correctness\* and Salience\*

-46% in Entity Coverage (due to qualifier requirement!)

## **Limitation 2: Beyond Simple Negatives**

#### grounded negatives

universally negative



#### We propose a new type of negative statements: conditional negatives

## **Generating Conditional Negative Statements**

• By lifting grounded negatives, using <u>common</u> aspects, e.g., type, location, ..., of object nodes



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## Peer-based for Commonsense KGs (CSKGs)?

New challenges:

### 1. Loosely canonicalized

- Inference/ranking using exact match isn't sufficient
- 2. PCA for correctness
  - Isn't sufficient due to lack of expressive predicates

#### Loosely Canonicalized CSKGs



We propose <u>soft</u> instead of hard <u>match</u>: We compare sentence embeddings to capture similarity between phrases

 Phrase1=Phrase2 iff SIM (Phrase1, Phrase2) > α where α a tunable hyperparameter

[A, Razniewski, Weikum, Pan CIKM22] [Reimers, Gurevych EMNLP19]

#### **PCA as Correctness Signal?**

Recap: Partial Completeness Assumption (PCA) Infer NOT(s, p, o) for s iff (s, p, o')  $\in$  KG

Issue: CSKGs lack expressive predicates

- 10812 in Wikidata – encyclopedic

Child

- 19 in ConceptNet – commonsense

HasProperty

We propose using <u>an external source of knowledge</u> to scrutinize candidates: Probing pre-trained LM to find contradictions

#### **External Correctness Signal**

Find <u>contradiction</u> to candidates using external source of knowledge



Using **BERT**:

[MASK] have tusks.
-> elephants at rank k #6
-> drop candidate

[MASK] eat grass. -> elephants at rank #53 -> drop candidate

*k* should be <= *c*; a tunable hyperparameter

1. CW-baseline: absent links as negative NOT(elephant, MadeOf, wheat)

Main limitation

Salience

 Text-based: Mining query logs why can't elephants.. → run

Correctness

- 3. NegatER: Graph-based corruptions + rank using fine-tuned LM NOT(horse rider, IsA, pet) horse changed to horse rider
- Salience (Type-inconsistency)

 4. LM-based: Prompt GPT-3 (zero-shot setting)
 elephants don't have.. → tails

[Kassner, Schütze ACL20] [Safavi, Zhu, Koutra EMLP21] [Romero, Razniewski, Pal, Pan, Sakhadeo, Weikum CIKM19] Correctness

# Main Evaluation Findings: Negatives from CSKGs

Assessments using crowdsourcing\* tasks (mturk.com)

- CW last in Salience\*, NegatER second-to-last
- GPT-3 comparable to text-based:
   +/- 2% on all metrics

| <b>Our model</b> outperforms<br>GPT-3 in: | Model | Top negation<br>(elephant) |  |
|-------------------------------------------|-------|----------------------------|--|
| Salience*                                 | CW    | NOT(is a doctor)           |  |
| Recall                                    | GPT-3 | (not found in the wild)    |  |
| Groundtruth:<br>ConceptNet's negatives    | Ours  | NOT(is carnivorous)        |  |

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#### **Use Case: Knowledge Exploration**



Deploying peer-based negation inference: Salient negatives about 500K encyclopedic (Wikidata) entities from 11 classes.

d5demos.mpi-inf.mpg.de/negation



# Similarity function (e.g., entity embeddings), type of negation (e.g, conditional) Feedback feature

[A, Razniewski, Weikum, Pan VLDB21]

## **Use Case: Analyzing Communities of Interest**

| Asia          | 0.93 0 <mark>.0</mark> 7 |  |  |  |  |
|---------------|--------------------------|--|--|--|--|
| Oceania       | 0.90 0.10                |  |  |  |  |
| Africa        | 0.89 0.110               |  |  |  |  |
| Europe        | 0.88 0.120               |  |  |  |  |
| North America | 0.87 0.130               |  |  |  |  |
| South America | 0.84 0.160               |  |  |  |  |
| 0             | 0.2 0.4 0.6 0.8 1        |  |  |  |  |
| □ Male        |                          |  |  |  |  |

Study cultural differences in governing: Professions of political leaders Identifying underrepresented groups:

# Women as public office holders

| Area            | Top professions                            |
|-----------------|--------------------------------------------|
| Central Africa  | diplomat (0.27), economist (0.04), civil s |
| Eastern Africa  | diplomat (0.09), judge (0.03), lawyer (0.0 |
| Northern Africa | diplomat (0.12), ruler (0.12), lawyer (0.0 |
| Southern Africa | judge (0.28), lawyer (0.11), civil servant |
| Western Africa  | diplomat (0.17), lawyer (0.03), military j |
| Central America | lawyer (0.07), diplomat (0.07), writer (0. |
| North America   | lawyer (0.25), diplomat (0.06), judge (0.0 |
| South America   | lawyer (0.17), diplomat (0.05), military j |
| East Asia       | monarch (0.09), diplomat (0.07), lawyer    |
| South Asia      | diplomat (0.05), lawyer (0.03), economis   |
| Southeast Asia  | sovereign (0.09), judge (0.08), lawyer (0  |
| West Asia       | diplomat (0.12), sovereign (0.08), milita  |
| Eastern Europe  | diplomat (0.12), economist (0.04), lawye   |
| Northern Europe | judge (0.08), diplomat (0.04), monarch (   |
| Southern Europe | diplomat (0.07), lawyer (0.04), military j |
| Western Europe  | lawyer (0.13), judge (0.06), diplomat (0.0 |

Browser: wikiknowledge.onrender.com/demographics

[A, Razniewski, Pan ICWSM23]

Datasets: doi.org/10.5281/zenodo.7410436

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# LLMs for Generating Salient Negations? (anecdotal)

# Question: We ask Bing's Chatbot about Wilhelm Busch's children?

Correct answer: NO.





# LLMs for Generating Salient Negations? (anecdotal) - continued

#### Major challenge: prompt engineering.

1. Stephen Hawking was not a physicist.

\$

S

- 2. Stephen Hawking did not contribute to our understanding of black holes.
- 3. Stephen Hawking did not write "A Brief History of Time."
- 4. Stephen Hawking was not a member of the Royal Society.

#### Negated statements about Hawking -> wrong answers

### **Negative statements** about Hawking -> misunderstood prompt

\$ I apologize, but as an Al language model, it is not appropriate for me to provide negative statements about individuals, especially someone who was widely respected and accomplished like Stephen Hawking. It is important to maintain a respectful and ethical approach when discussing individuals and their achievements. I would be happy to provide information on Stephen Hawking's life and work, or answer any other questions you may have.

Certainly, here are some more negated statements about Stephen Hawking:

- 1. Stephen Hawking was not just a theoretical physicist, but also a cosmologist and author.
- Hawking did not receive his PhD in physics, but in cosmology from the University of Cambridge.
- 3. Contrary to popular belief, Hawking did not win a Nobel Prize in Physics, although he received numerous other awards and honors throughout his career.

**Guided prompt** -> relatively better answers (mixed with implicit positives)

# LLMs for Generating Salient Negations? (anecdotal)

Recap: Peer-based method outperformed GPT-3 in commonsense negatives.

# Question: Can ChatGPT do better than GPT-3 on commonsense concepts?

Salient negations about elephant.

| GPT-3                           | ChatGPT                                        |
|---------------------------------|------------------------------------------------|
| is not a type of animal         | do not have any natural predators in the wild. |
| does not have a tail.           | are not able to jump.                          |
| is not found in the dictionary. | do not have sweat glands.                      |

# LLMs for Generating Salient Negations? (anecdotal) - continued

# Question: Can ChatGPT do better than the peer-based inference method?

Peer-based ChatGPT Top-10 negations .. list of 10 correct and salient negated statements about J. K. Rowling.

| Entity  | Cor                   | rect       | Salient |                            | Sample                 |
|---------|-----------------------|------------|---------|----------------------------|------------------------|
| J. K.   | 0.8                   | 1 0        | 0.9     | 0                          | NOT(citizenship, U.S.) |
| Rowling | 0.0                   | <u> </u>   | 0.0     | Ŭ                          | is not above criticism |
| gorilla | 0.5                   | <u>0.9</u> | 0007    |                            | NOT(IsA, nocturnal)    |
|         |                       |            | 0.9     | <u>0.9</u> 0.7             | not solitary animals   |
| China   | China 0.9 0.2 0.8 0.7 | 0.0        | 0 0 0 7 | NOT(border with, Thailand) |                        |
| China   |                       | <u>U.0</u> | 0.7     | not without innovation     |                        |

# LLMs for Generating Salient Negations? (anecdotal) - continued

#### Ability to handle long tail entities.

Question: We ask ChatGPT to list negated statements about the former Lebanese Basketball player.



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# Take Away

- KGs lack meaningful negative knowledge
- Explicit negatives boost their usability
- Inference-based methods produce correct and salient negatives
   Thank you.

Open issues & opportunities:

- Subject coverage long tail entities
- Maintenance truly negative up until 2022: NOT(Zelensky, award, Time's Person of the Year)
- **o** LLMs for negation generation
  - Prompt engineering + scrutinize answers
  - Identify negatives with positive meaning Hawking wasn't only a theoretical physicist, but also..
- New interest: cultural commonsense KGs & text
   No-nos: *Tipping in Japan*, *Chewing gum in Singapore*

Resources: <u>mpi-inf.mpg.de/negation-in-kbs</u> W

Webpage: hibaarnaout.com

**Questions?**