On Commonsense Domains within the Winograd Schema Challenge

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- Winograd Schema Challenge
- Previous Approaches
- Knowledge Types Identification and Reasoning
- Categorization of Winograd Schemas
- Conclusion





Motivation

- ▶ Winograd Schema Challenge (Levesque et al., 2012)
 - S: The trophy does not fit into the brown suitcase because it is too [small/large].
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| A special word | small/ large |
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- Characteristics:
 - Easy to answer for an adult English speaker
 - Always contains special word
 - Google proof

Competition

- Competition in 2016 at IJCAI-16
 - Two time-constraint rounds 210 min. each
 - Pronoun Disambiguation Problems (PDPs) 60
 - ▶ Parts of Winograd Schemas 150
 - Four competitors
 - Best result: 58% correctly resolved PDPs
 - There was no second round
- Current state-of-the-art (Radford et al., 2019) achieves 70.7% accuracy on the WSs dataset

Previous Approaches

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- ► Knowledge-based system with reasoning procedures

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| Technique | PDPs Size - Correct | WSC Size - Correct | WSC* Size - Correct | Remarks |
|--|------------------------|-----------------------|------------------------|---|
| Supervised ranking SVM model (2012) | - | - | 282-30% - 205-73% | -provided additional dataset set -no evaluation on WSC dataset |
| Classification task with NN (2018) | - | 282-100% - 157-56% | 282-30% - 177-63% | -first to use substitution of the pronoun with the antecedents |
| Knowledge Embeddings (2016) | 60-100% - 40-66.7% | - | - | -best results in the 2016 WSC competition |
| Google's language models (2018) | 60-100% - 42-70% | 273-100% - 173-63.7% | - | -no reasoning involved in the discovery of the correct answer -state-of-the-art for PDPs |
| OpenAl language models (2019) | - | 273-100% - 193-70.70% | - | -current state-of-the-art for WSC -requires a lot of data for training -results are not reproducible |
| Graphs with Relevance theory (2014) | - | 4-2.6% - 4-100% | - | -manual construction of graphs -first representation of WS as dependency graph |
| 2 identified categories (2015) | - | 71-25% - 49-69% | - | -first attempt of identifying commonsense knowledge types -developed the KParser |
| Semantic relations categories (2019) | - | 100-34% - 100-100% | 138-14% - 111-80% | which capture the entire WSC |
| Knowledge hunting framework (2018) | - | 273-100% - 119-43.5% | - | -refined query generation -developed an algorithm for scoring the retrieved sentences |

MICO*

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- Language models assign scores to both sentences

Score_{full} ("the trophy")= **P**(The trophy doesn't fit into the brown suitcase because **the trophy** is too small)

 $Score_{partial}$ ("the trophy")= P(is too big |The trophy doesn't fit into the brown suitcase because the trophy)

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- Evaluation and results
 - PDPs 70% accuracy
 - ▶ WSC 63.7% accuracy

Knowledge Types Identification and Reasoning (Sharma and Baral, 2018)

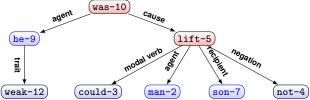
- ▶ Identified 12 knowledge types which cover the entire WSC dataset
- Categorization based on the structure of the Winograd sentence
- Developed a logical reasoning algorithm
- ► Evaluated on 100 problems from WSC and achieved 100% accuracy

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- Solver
 - 1. Semantic graph of the input sentence and question
 - 2. Semantic graph representation of background knowledge
 - 3. Graph merging
 - 4. Project question graph on the merged graph
 - Answer the node from the merged graph which is from the same domain as the unknown node from the question graph

Semantic graph representation¹

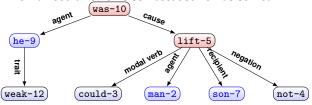
"The man couldn't lift his son because he was so weak".



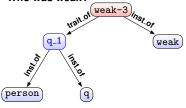
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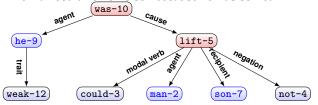
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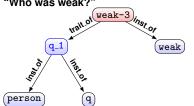
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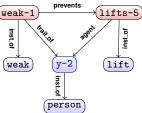
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▶ "Who was weak?"

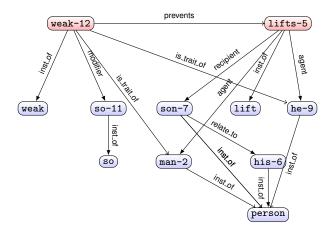


"weak y prevents y lifts"

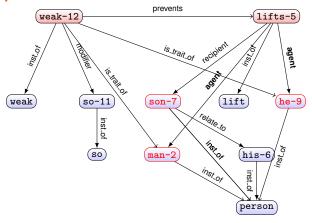


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Reasoning procedure

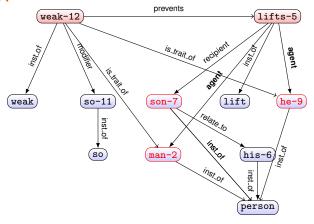


Reasoning procedure



```
has_k(weak,is_trait_of,y).
has_k(weak,prevents,lifts).
has_k(lifts,agent,y).
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Categorization of Winograd Schemas

- Motivation
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 - Current state-of-the-art has a poor performance
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 - ▶ Idea
 - Analyze the input Winograd Schema and identify the domain of the least necessary knowledge
 - 2. Search for knowledge specific to this domain
 - 3. Apply reasoning procedure
- Categorization based on the content of the Winograd sentence

Identified Categories

| Category | Example |
|--------------------------------------|--|
| Physical | S: John couldn't see the stage with Billy in front of him because he is so [short/tall]. |
| | Q: Who is so [short/tall]? |
| 2. Emotional | S: Frank felt [vindicated/crushed] when his longtime rival Bill |
| | revealed that he was the winner of the competition. |
| | Q: Who was the winner of the competition? |
| 3. Interactions | S: Joan made sure to thank Susan for all the help she had [given/received]. |
| | Q: Who had [given/received] help? |
| 4. Comparison | S: Joe's uncle can still beat him at tennis, even though he is 30 years [older/younger]. |
| | Q: Who is [older/younger]? |
| 5. Causal | S: Pete envies Martin [because/although] he is very successful. |
| | Q: Who is very successful? |
| Multiple knowledge | S: Sam and Amy are passionately in love, but Amy's parents are unhappy about it, |
| | because they are [snobs/fifteen]. |
| | Q: Who are [snobs/fifteen]? |
| | |

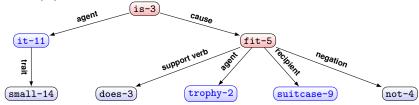
Annotation of Winograd Schemas

- Strong agreement between the annotators Cohen's kappa score 0.66
- Annotation Results

| Category | Annotator 1 | Annotator 2 |
|--------------------|-------------|-------------|
| Physical | 36-24% | 39-26% |
| Emotional | 7–4.6% | 9– 6% |
| Interactions | 44-29.3% | 24-16% |
| Comparison | 19–12.6% | 26-17.3% |
| Causal | 16-10.6% | 18–12% |
| Multiple knowledge | 28-18.6% | 34-22.6% |

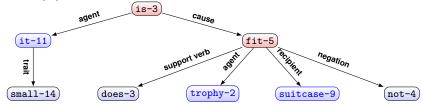
Graph Representation for Physical Category

1. The trophy doesn't fit into the brown suitcase because it's too small.

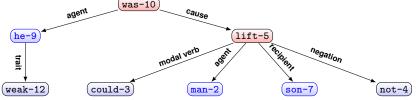


Graph Representation for Physical Category

1. The trophy doesn't fit into the brown suitcase because it's too small.



2. The man couldn't lift his son because he was so weak.



Reasoning

- Knowledge required for both examples is about physical features
- ▶ Similar reasoning rules for categorizing the traits

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- ► Knowledge required for both examples is about physical features
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- Reasoning Algorithm
- Change of background knowledge



▶ Contributions

- Overview of different approaches towards WSC
- ▶ None achieves close to 90% accuracy
- ▶ We analyzed the entire WSC corpus and identified 6 categories
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► Thank you!

References

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