On Commonsense Domains within the Winograd Schema Challenge

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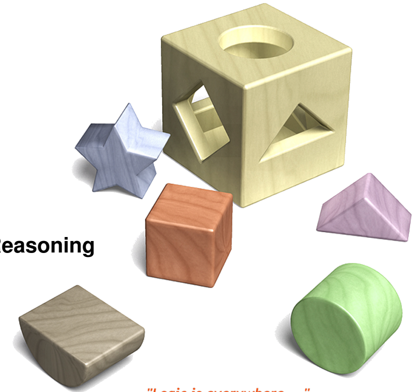
- Winograd Schema Challenge
- Previous Approaches
- Knowledge Types Identification and Reasoning
- Categorization of Winograd Schemas
- Conclusion



"Logic is everywhere ..."

Motivation

- **Winograd Schema Challenge (Levesque et al., 2012)**

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  Q: **What is too [small/large]?**

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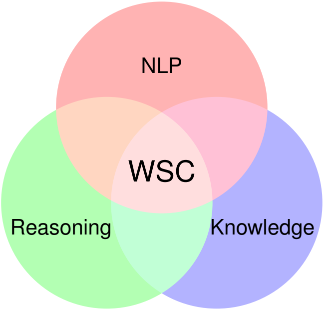

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Sentence containing two nouns	**trophy, suitcase**
One ambiguous pronoun	**it**
A special word	**small/ large**
Question about the referent of the pronoun	**What is too [small/large]**
Two possible answers	**The suitcase /the trophy**

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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

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Technique	PDPs Size - Correct	WSC Size - Correct	WSC* Size - Correct	Remarks
Supervised ranking SVM model [6]	NA	NA	282-30% - 205-73%	-provided additional dataset set -no evaluation on WSC dataset
Classification task with NN [3]	NA	282-100% - 157-56%	282-30% - 177-63%	-first to use substitution of the pronoun with the antecedents
Knowledge Embeddings [4]	60-100% - 40-66.7%	NA	NA	-best results in the 2016 WSC competition
Google's language models [9]	60-100% - 42-70%	273-100% - 173-63.7%	NA	-no reasoning involved in the discovery of the correct answer -state-of-the-art for PDPs
OpenAI language models [5]	NA	273-100% - 193-70.70%	NA	-current state-of-the-art for WSC -requires a lot of data for training -results are not reproducible
Graphs with Relevance theory [7]	NA	4-2.6% - 4-100%	NA	-manual construction of graphs -first representation of WS as dependency graph
2 identified categories [8]	NA	71-25% - 49-69%	NA	-first attempt of identifying commonsense knowledge types -developed the KParser
Semantic relations categories [1]	NA	100-34% - 100-100%	138-14% - 111-80%	-provided Reasoning Algorithm -identified 12 commonsense types which capture the entire WSC
Knowledge hunting framework [2]	NA	273-100% - 119-43.5%	NA	-refined query generation -developed an algorithm for scoring the retrieved sentences

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

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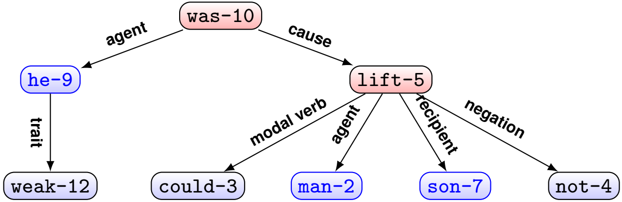
- Solver
  1. Semantic graph of the input sentence and question
  2. Semantic graph representation of background knowledge
  3. Graph merging
  4. Project question graph on the merged graph
  5. Answer - the node from the merged graph which is from the same domain as the unknown node from the question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

Semantic graph representation[1]

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



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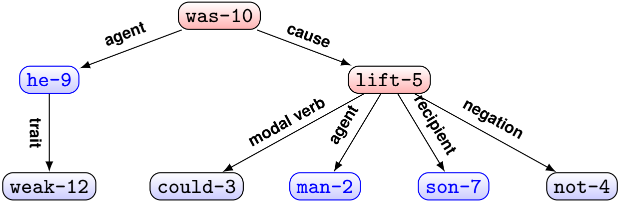
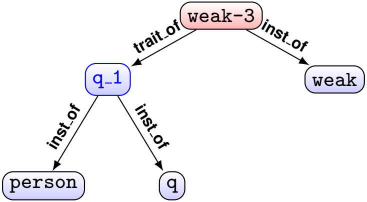


- "Who was weak?"



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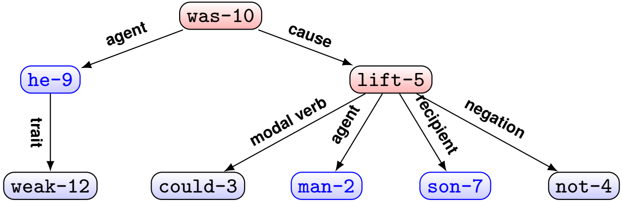

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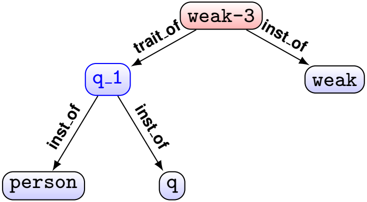
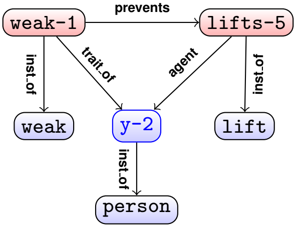


- “weak y prevents y lifts”



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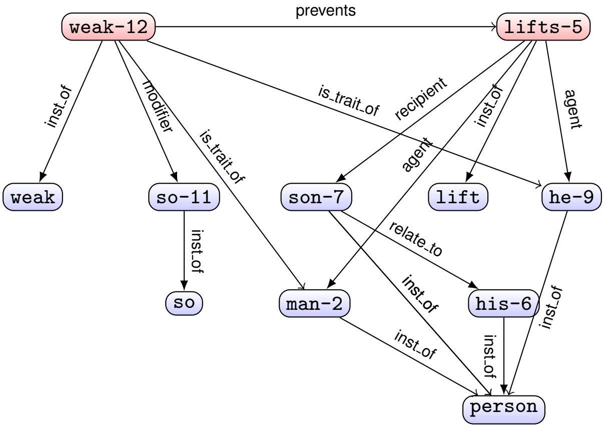
Reasoning procedure



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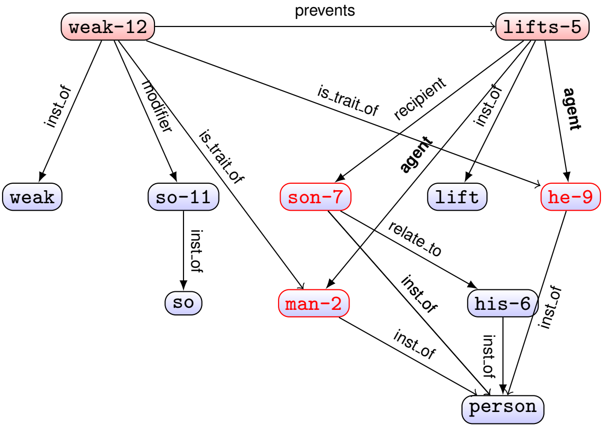


```
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has_k(weak,prevents,lifts).
has_k(lifts,agent,y).
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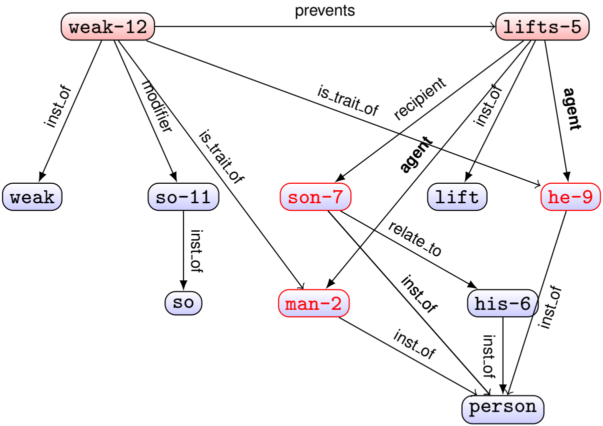
Reasoning procedure

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Categorization of Winograd Schemas

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- **Motivation**
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  - **Background knowledge is crucial for predicting the correct answer**
  - **Idea**
    1. **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
1. 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?
6. 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]?

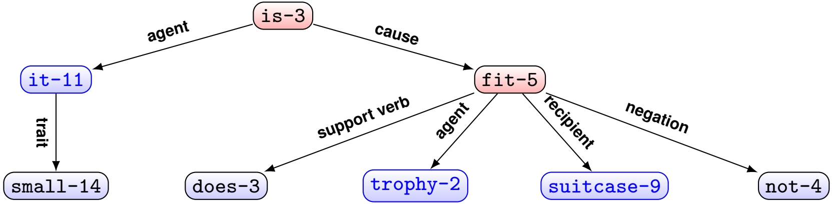
Annotation of Winograd Schemas

- **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.**



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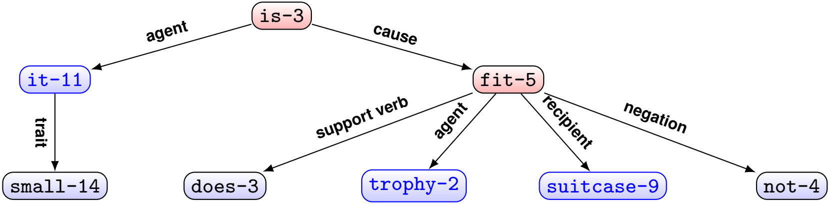

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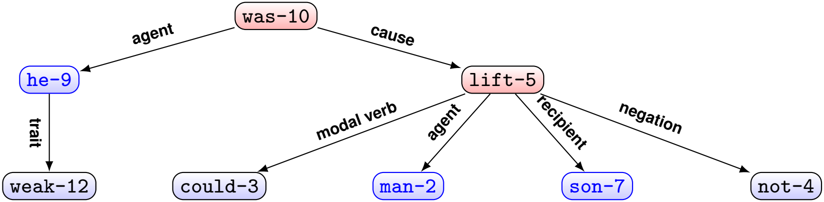

Reasoning

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

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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**
- **We identified a mistake in the Reasoning Algorithm and proposed a correction**

Future Work

- Formalization of the characteristics for each category
- Knowledge-enhanced neural networks

Thank you!

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