On Commonsense Domains within the Winograd Schema Challenge

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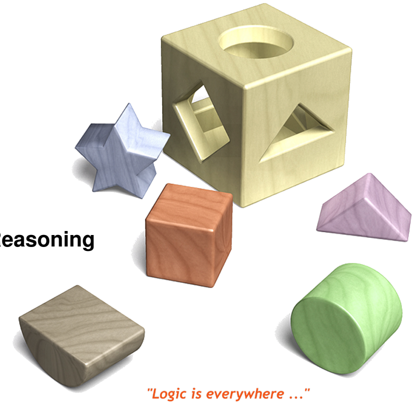
- Winograd Schema Challenge
- Previous Approaches
- Knowledge Types Identification and Reasoning
- Categorization of Winograd Schemas
- Conclusion



Motivation

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

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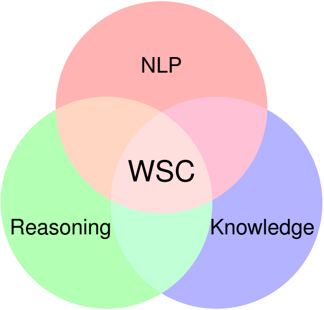

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One ambiguous pronoun	it
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- **Characteristics:**
  - Easy to answer for an adult English speaker
  - Always contains special word
  - Google proof

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

- Machine learning and deep learning techniques
- Knowledge-based system with reasoning procedures

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

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Semantic relations categories (2019)	-	100-34% - 100-100%	138-14% - 111-80%	-provided Reasoning Algorithm -identified 12 commonsense types which capture the entire WSC

A Simple Method for Commonsense Reasoning (Trinh and Le, 2018)

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- **Language models assign scores to both sentences**

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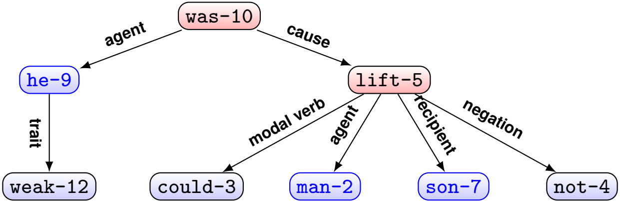
- Solver
  1. Semantic graph of the input sentence and question
  2. Semantic graph representation of background knowledge
  3. Graph merging
  4. Project question graph on the merged graph
  5. Answer - the node from the merged graph which is from the same domain as the unknown node from the question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

Semantic graph representation[1]

- **“The man couldn’t lift his son because he was so weak”.**



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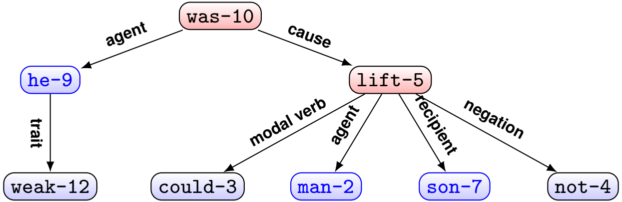

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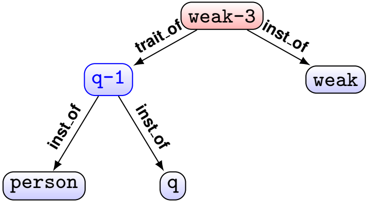

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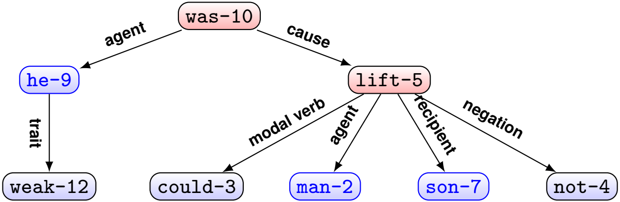

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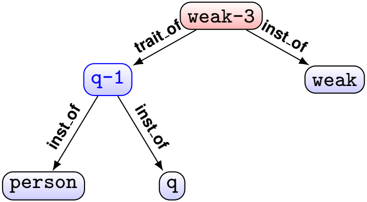
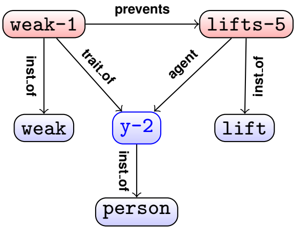


- “weak y prevents y lifts”



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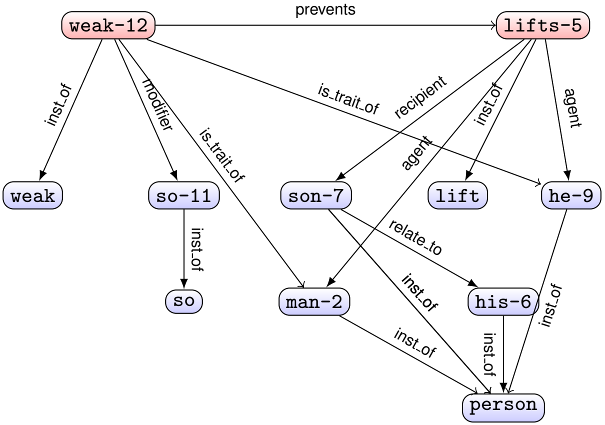

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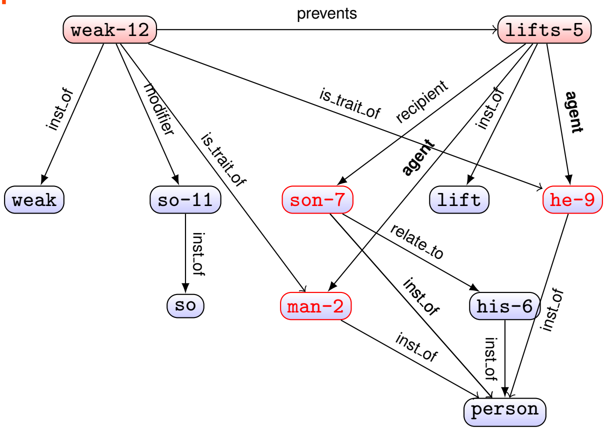


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ans(q-1,he-9), ans(q-1,man-2)

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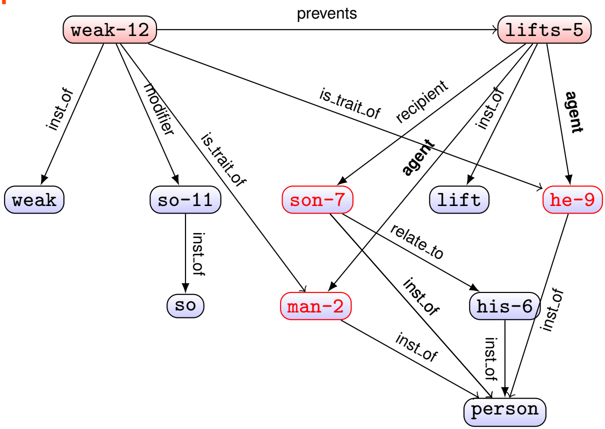


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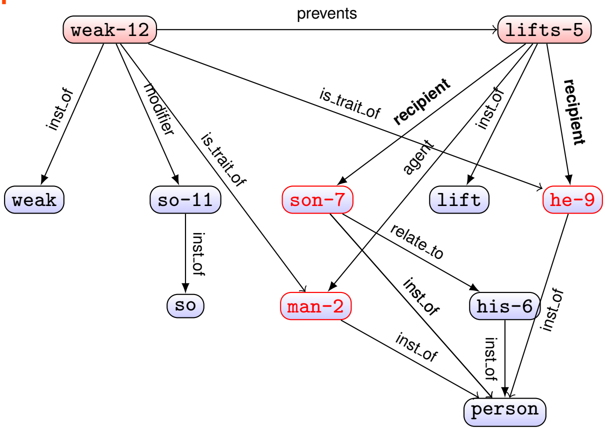


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Categorization of Winograd Schemas

- **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

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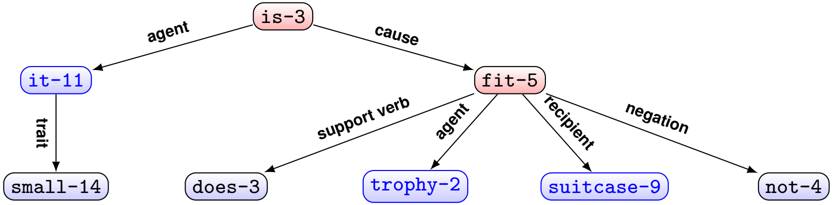

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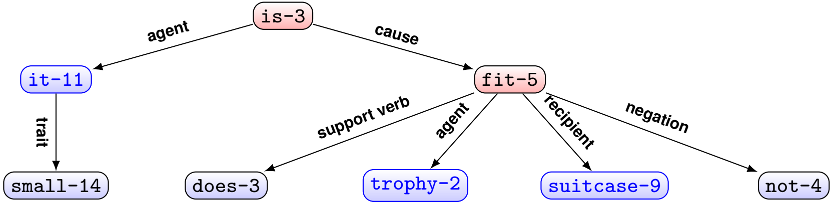

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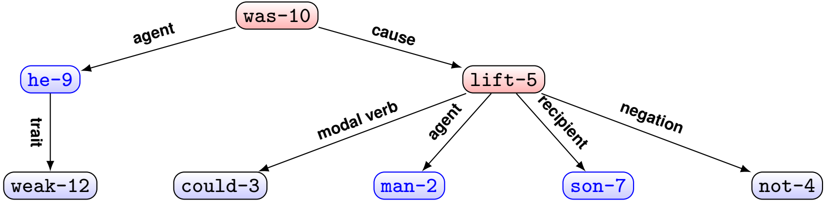

Reasoning

- **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**

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  - **Overview of different approaches towards WSC**
  - **None achieves close to 90% accuracy**
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- **Thank you!**

References

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