On Commonsense Domains within the Winograd Schema Challenge

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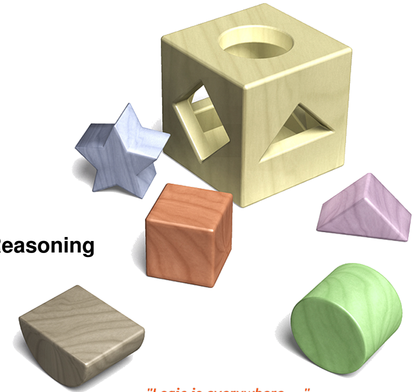
- Winograd Schema Challenge
- Previous Approaches
- Knowledge Types Identification and Reasoning
- Categorization of Winograd Schemas
- Conclusion



"Logic is everywhere ..."

Motivation

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

S: **The trophy does not fit into the brown suitcase because it is too [small/large].**
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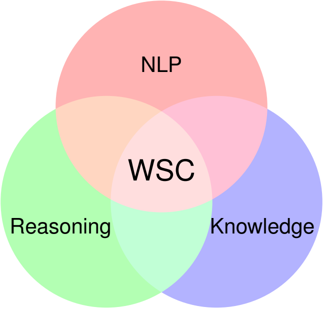

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  - **Sentence containing two nouns, one ambiguous pronoun and a special word**
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- **Winograd Schema:**
  - **Sentence containing two nouns, one ambiguous pronoun and a special word**
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- **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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Technique	**PDPs** Size Correct	**WSC** Size Correct	**WSC*** Size Correct	**Remarks**
Supervised ranking SVM model [?]	NA	NA	282 - 30% 205 - 73%	-provided additional dataset set -no evaluation on WSC dataset
Classification task with NN [?]	NA	282 - 100% 157 - 56%	282 - 30% 177 - 63%	-first to use substitution of the pronoun with the antecedents
Knowledge Enhanced Embeddings (KEE) [?]	60-100% 40 - 66.7%	NA	NA	-best results in the 2016 WSC competition
Google's language models [?]	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 [?]	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 [?]	NA	4 - 2.6% 4 - 100%	NA	-manual construction of graphs -first representation of WS as dependency graph
2 identified categories [?]	NA	71 -25% 49 - 69%	NA	-first attempt of identifying commonsense knowledge types -developed the KParser
Semantic relations categories [?]	NA	100 - 34% 100 - 100%	138 - 14% 111 - 80%	-provided Reasoning Algorithm -identified 12 commonsense types which capture the entire WSC
Knowledge hunting framework [?]	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**

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- 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[1] 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

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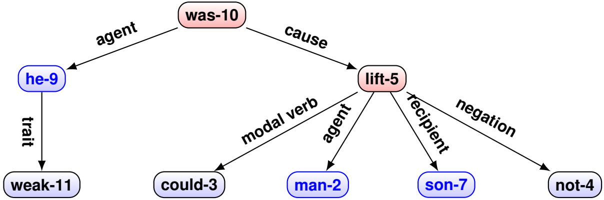
Semantic graph representation

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



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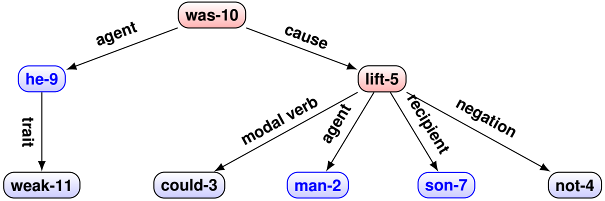

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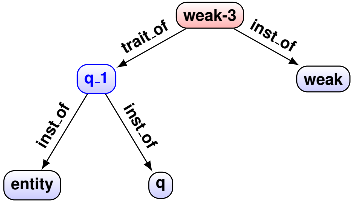

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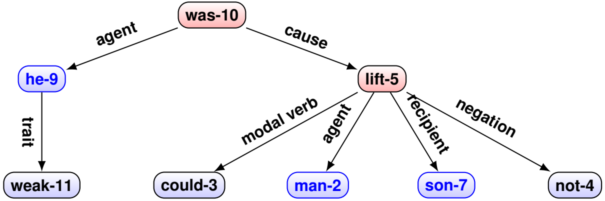

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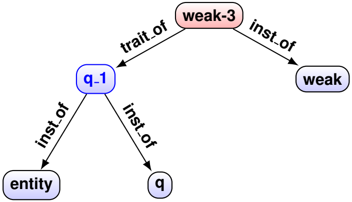
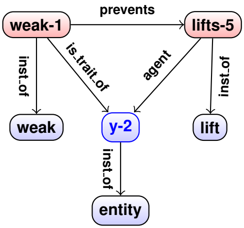


- “weak y prevents y lifts”



Categorization of Winograd Schemas

- **Motivation**
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- **Motivation**
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  - **Idea**
    1. **Analyze the input Winograd Schema and identify the domain**
    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]?

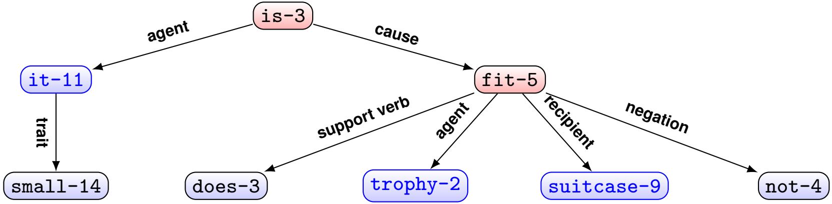
Annotation of Winograd Schemas

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

Category	**Annotator 1** # - %	**Annotator 2** # - %
Physical	36 - 24%	39 - 26%
Emotions	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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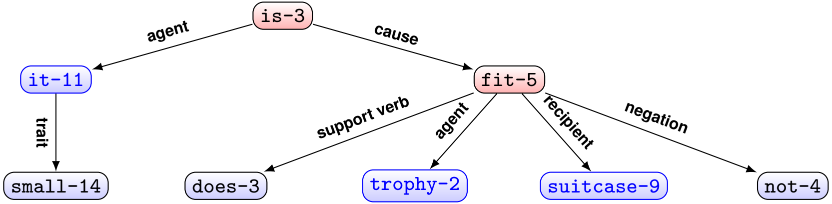

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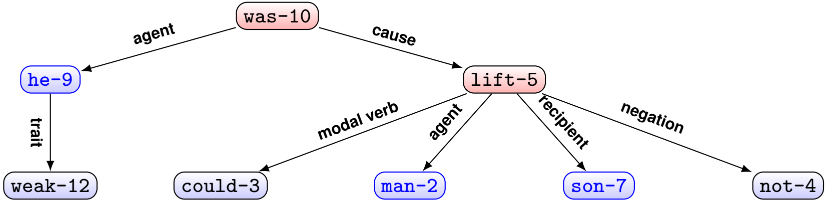

Reasoning

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

1. **has_k(small,is_trait_of,y) :- has_k(fits,recipient,y),**
   not has_k(fits,modifier,could).
2. **has_k(weak, is_trait_of,y) :- has_k(lift,agent,y),**
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     not has_k(lift,modifier,could).
- Reasoning Algorithm
- Change of background knowledge
  - has_k(weak,prevents,lift).

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!