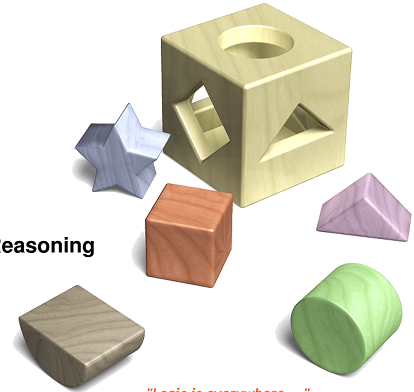
On Commonsense Domains within the Winograd Schema Challenge

Aneta Koleva
International Center for Computational Logic
Technische Universität Dresden
Germany

- 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].**

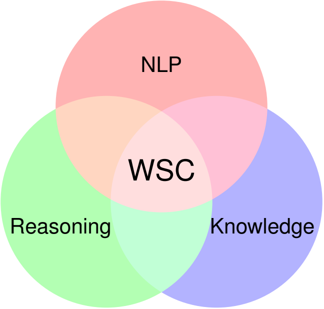
  Q: **What is too [small/large]?**

  A: **The suitcase/the trophy.**

Motivation

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

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



Winograd Schema Challenge

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

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

A: **The suitcase/the trophy.**

Winograd Schema Challenge

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

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

A: **The suitcase/the trophy.**

- **Winograd Schema:**

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**

Winograd Schema Challenge

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

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

A: **The suitcase/the trophy.**

- **Winograd Schema:**

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

- **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**

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 [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

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

- **Language models trained on unlabeled data**

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

- **Language models trained on unlabeled data**
  - **Recurrent Neural Networks**
  - **Trained on large datasets and on a dataset customized for WSC**

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

- **Language models trained on unlabeled data**
  - **Recurrent Neural Networks**
  - **Trained on large datasets and on a dataset customized for WSC**
- **Substitution of the ambiguous pronoun**
  - **The trophy doesn’t fit in the suitcase because the trophy is too big**
  - **The trophy doesn’t fit in the suitcase because the suitcase is too big**

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

- **Language models trained on unlabeled data**
  - **Recurrent Neural Networks**
  - **Trained on large datasets and on a dataset customized for WSC**
- **Substitution of the ambiguous pronoun**
  - **The trophy doesn't fit in the suitcase because the trophy is too big**
  - **The trophy doesn't fit in the suitcase because the suitcase is too big**
- **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**)

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

- **Language models trained on unlabeled data**
  - **Recurrent Neural Networks**
  - **Trained on large datasets and on a dataset customized for WSC**
- **Substitution of the ambiguous pronoun**
  - **The trophy doesn't fit in the suitcase because the trophy is too big**
  - **The trophy doesn't fit in the suitcase because the suitcase is too big**
- **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**)

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

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

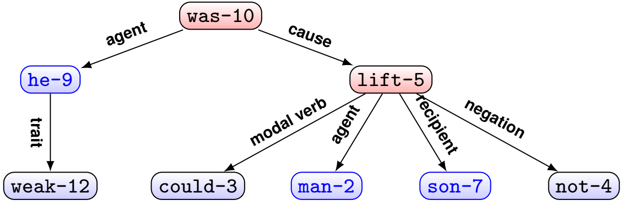
- Identified 12 knowledge types which cover the entire WSC dataset
- Categorization based on the structure of the Winograd sentence
- Developed a logical reasoning algorithm
- Evaluated on 100 problems from WSC and achieved 100% accuracy

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**
- **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]

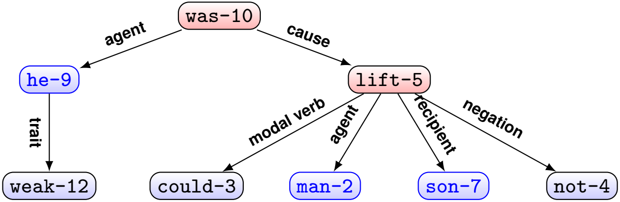
- "The man couldn't lift his son because he was so weak".



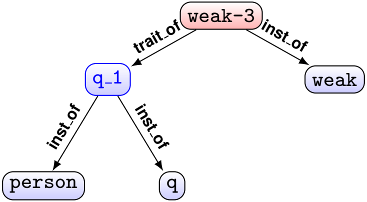
[1] kparser.org

Semantic graph representation[1]

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



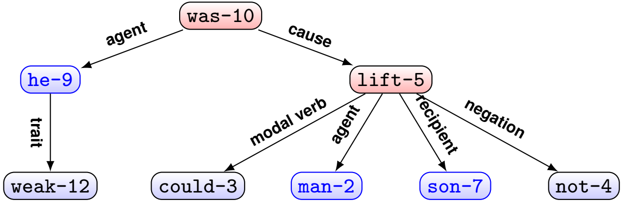
- "Who was weak?"



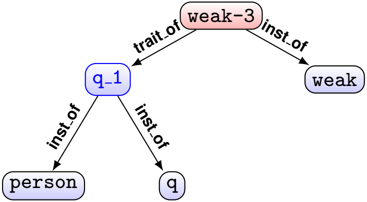
[1] kparser.org

Semantic graph representation[1]

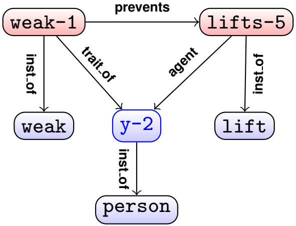
- "The man couldn't lift his son because he was so weak".



- "Who was weak?"

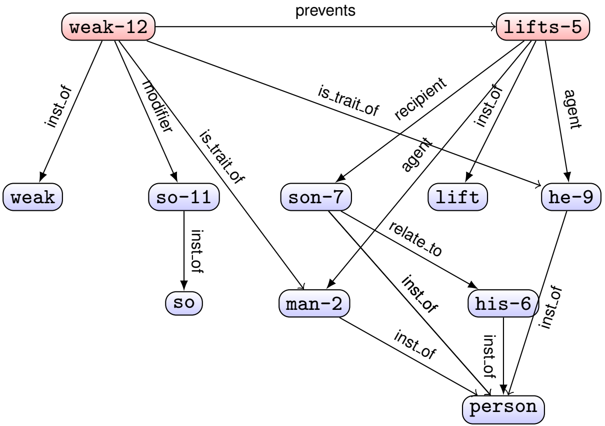


- "weak y prevents y lifts"

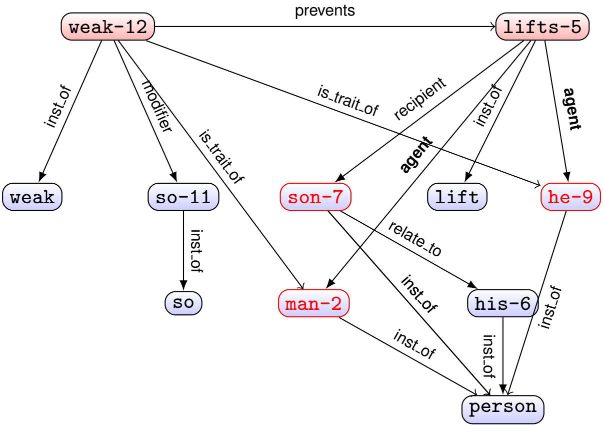


[1] kparser.org

Reasoning procedure

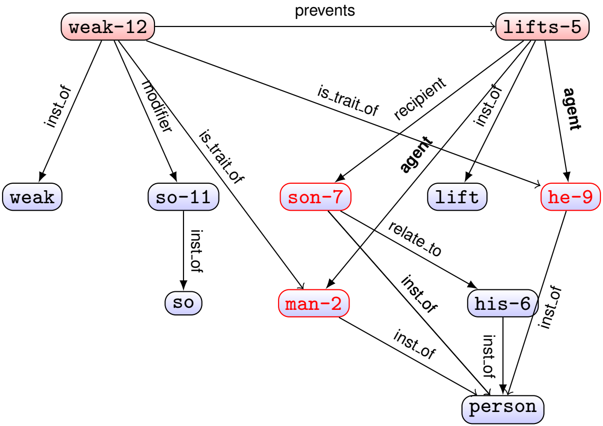


Reasoning procedure




```
has_k(weak,is_trait_of,y).          1
has_k(weak,prevents,lifts).         2
has_k(lifts,agent,y).               3
```

Reasoning procedure




```
has_k(weak,is_trait_of,y).
%has_k(weak,prevents,lifts).
has_k(lifts,agent,y).
```

Categorization of Winograd Schemas

- **Motivation**
  - **Current state-of-the-art has a poor performance**
  - **Background knowledge is crucial for predicting the correct answer**

Categorization of Winograd Schemas

- **Motivation**
  - **Current state-of-the-art has a poor performance**
  - **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]?

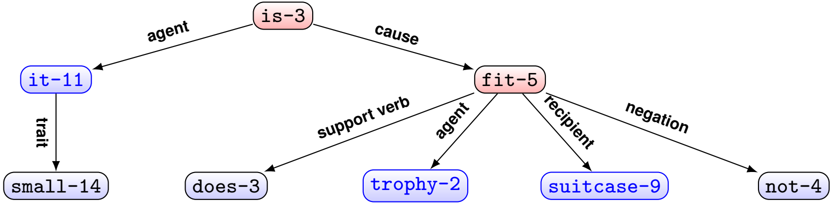
Annotation of Winograd Schemas

- **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%

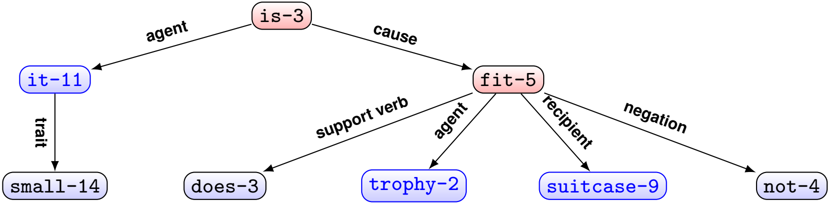
Graph Representation for Physical Category

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

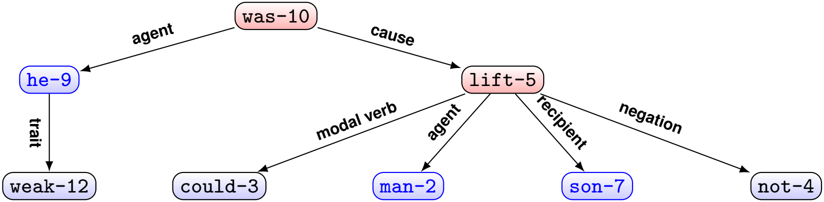


Graph Representation for Physical Category

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

```
has_k(small,is_trait_of,y) :- has_k(fit, recipient, y),
                              not has_k(fit,modifier,could).
has_k(weak,is_trait_of,y) :- has_k(lift, agent, y),
                             not has_k(lift,modifier,could).
```

Reasoning

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

```
has_k(small,is_trait_of,y) :- has_k(fit, recipient, y),
                              not has_k(fit,modifier,could).
has_k(weak,is_trait_of,y) :- has_k(lift, agent, y),
                             not has_k(lift,modifier,could).
```

- **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!

References

[1] C. Baral A. Sharma.
Commonsense knowledge types identification and reasoning for the winograd schema challenge, 2018.

[2] A. Emami, N. De La Cruz, A. Trischler, K. Suleman, and J. Chi Kit Cheung.
A knowledge hunting framework for common sense reasoning.
In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 1949–1958, 2018.

[3] Opitz J. and Frank A.
Addressing the winograd schema challenge as a sequence ranking task.
In Proceedings of the First International Workshop on Language Cognition and Computational Models, pages 41–52. Association for Computational Linguistics, 2018.

[4] Q. Liu, H. Jiang, Z. Ling, X. Zhu, S. Wei, and Y. Hu.
Combing context and commonsense knowledge through neural networks for solving winograd schema problems.
2016.

[5] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, and I. Sutskever.
Language models are unsupervised multitask learners, 2019.

[6] A. Rahman and V. Ng.
Resolving complex cases of definite pronouns: The winograd schema challenge.
In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, EMNLP-CoNLL 2012, July 12-14, 2012, Jeju Island, Korea, pages 777–789, 2012.

[7] P. Schüller.
Tackling winograd schemas by formalizing relevance theory in knowledge graphs.
In Principles of Knowledge Representation and Reasoning: Proceedings of the Fourteenth International Conference, KR 2014, Vienna, Austria, July 20-24, 2014, 2014.

[8] A. Sharma, Nguyen Ha Vo, Somak Aditya, and Chitta Baral.
Towards addressing the winograd schema challenge - building and using a semantic parser and a knowledge hunting module.
In Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, IJCAI 2015, Buenos Aires, Argentina, July 25-31, 2015, pages 1319–1325, 2015.

[9] Q. V. Le T. H. Trinh.
A simple method for commonsense reasoning.
2018.