Tackling Domain-specific Winograd Schemas with Knowledge-based Reasoning and Machine Learning

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Introduction

- The **Winograd Schema Challenge (WSC)**[1] is to resolve the reference of pronouns occurring in natural language sentences.
- We tackle the WSC with knowledge-based reasoning(KR) and machine learning(ML). Here is an example from the WSC:

1. The trophy doesn't fit in the brown suitcase because **it** is too large.
   - The candidates : the trophy / the suitcase, Answer: **the trophy**
2. The trophy doesn't fit in the brown suitcase because **it** is too small.
   - The candidates : the trophy / the suitcase, Answer: **the suitcase**

Domains in WSC

- The thanking domain: the sentences that include "thank" and "grateful" were extracted from WinoGrande[2] (**171** out of 44K).
- Around **77%** of the sentences follow the five patterns.

High-level patterns in the thanking domain	
1	Candidate1 **owes** candidate2, and (so) pronoun is **doing good**
2	Candidate1 **owes** candidate2, and (so) pronoun is **receiving good**
3	Candidate1 **does good to** candidate2 because pronoun is **owing**
4	Candidate1 **gives thanks to** candidate2 because pronoun is **being owed**
5	Candidate1 **gives thanks to** candidate2 because pronoun is **owing**

Our Semantic-role Based KR Method

- Our KR method is built by modifying the method of Sharma[3].

1. Building a domain-specific knowledge base

- We define rules to derive semantic relations from K-Parser outputs

Semantic roles from K-Parser: X	Y	because relation	Semantic relationship
helper	being helped	No	Y owes X
helper	being helped	Yes	X does good to (repays) Y
giver	being given	No	Y owes X
giver	being given	Yes	X does good to (repays) Y
thanker	being thanked	Yes	X gives thanks to Y

2. Transforming a Winograd schema sentence into a high-level representation

- K-Parser and the domain-specific knowledge base are used.
- An example from WinoGrande: "**Kayla** cooked sticky white rice for **Jennifer**, and [**she**] was thanked for making such delicate rice."

Kayla	Jennifer	because relation	
giver	being given	No	Jennifer **owes** Kayla

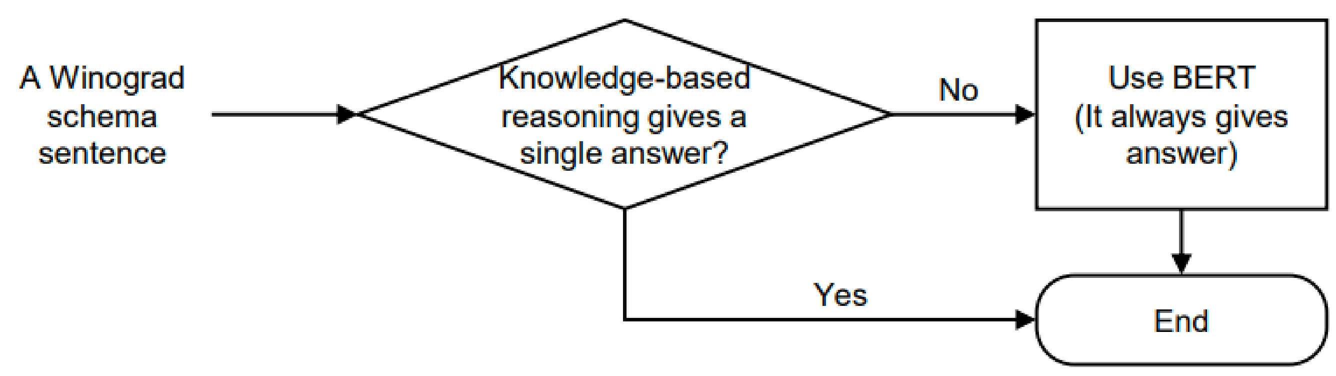
- **She** is **being thanked**, which is an instance of receiving good. Therefore, the sentence can be abstracted to **"Jennifer *owes* Kayla and she is *receiving good*."** This matches with the second high-level pattern.

3. Reasoning to derive the answer

- Answer Set Programming is used for reasoning.
- The answer can be derived by applying the background knowledge principles regarding the high-level patterns to **the abstracted sentence.**

Our Ensemble Method

- We propose a simple ensemble method by combining our semantic-role based KR method and ML (a fallback).



Robust Accuracy

- 'Robust Accuracy': A stricter form of accuracy measurement
- In addition to the switching[4], adding three more variants of each sentence by replacing the name of each candidate with the random name with the same gender
- **Predicting correctly on all the five sentences** is needed to be robustly accurate. Here is an example from WinoGrande (1: original, 2: switched, 3 ~ 5: replaced with random names):

The variants of the example sentence	
1	**Kayla** cooked sticky white rice for **Jennifer**, and [she] was thanked …
2	**Jennifer** cooked sticky white rice for **Kayla**, and [she] was thanked …
3	**Erin** cooked sticky white rice for **Tanya**, and [she] was thanked …
⋮	

Experiments

- The 80 paired Winograd schema sentences in the thanking domain were used for the experiments. In the first experiment, each pair was *split* into the train set and the test set, and in the second experiment, each pair was put together.

Results

- The accuracies and the robust accuracies of our ensemble model (KR + ML) are better than those of the other methods.
- The models that contain a language model were found to have lower robust accuracies than raw accuracies.

Model	First Experiment		Second experiment	
	Accuracy	Robust accuracy	Accuracy	Robust accuracy
GPT-2	50.0%	20.0%	57.5%	15.0%
BERT-large	57.5%	37.5%	57.5%	35.0%
Kocijan's BERT-large[5]	70.0%	62.5%	77.5%	70.0%
Kocijan's BERT-large further fine-tuned	47.5%	42.5%	75.0%	70.0%
Our KR method	72.5%	72.5%	37.5%	37.5%
Our ensemble method	**90.0%**	**85.0%**	**80.0%**	**72.5%**

Conclusion

- Our robust accuracy shows language models' predictions could be vulnerable to minor changes.
- We propose a high-level KR method based on semantic roles.
- Our keywords method is used to define the thanking domain, and it can be applied to specify other domains for future work.
- In our test set for the thanking domain, our ensemble method gives a better and more robust performance than the other approaches we tested.

References

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