Module: COMP5450M – Knowledge Representation and Reasoning

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KRR Challenges and Potential

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# Introduction

# Examples

## Example 1

**Problem: From a collection of Winograd schemas, number 137 [1].**

*“I tried to paint a picture of an orchard, with lemons in the lemon trees, but they came out looking more like [light bulbs / telephone poles]. What looked like [light bulbs / telephone poles]?”[1]*

Here, the problem has two options: the objects “light bulbs” and “telephone poles”, which correspond to the two solutions – the subjects “lemons” and “lemon trees” – respectively. These solutions are instinctive to a human, who can intuit that light bulbs more closely resemble lemons and telephone poles more closely resemble lemon trees. For a machine, the syntax makes it difficult. The answer is not immediately available via search engine, one of the criteria for representing a Winograd schema [2].

To solve this problem using KRR methods, it first made sense to define a set of axioms which relate to common knowledge. From there, introducing inference rules contributes towards solving the problem in its entirety. Therefore, building a knowledge base using first-order logic seemed like a suitable strategy.

**Facts**

These facts are basic assumptions which relate to common knowledge; for example, the shape, general size, and colour of ubiquitous objects such as trees and lemons. This also includes semantic rules such as the fact that ‘lemons’ is the plural of ‘lemon’ etc.

Examples for the lemon object:

IsColour(Lemon, Yellow)

IsShape(Lemon, Oval)

IsLength(Lemon, Short)

IsDepth(Lemon, Thick)

IsWidth(Lemon, Wide)

IsPlural(Lemons, Lemon)

Similar facts are constructed for other basic objects such as trees, light bulbs and telephone poles.

**Inferences**

First we need to represent the objects having been painted (instantly deduced from the problem statement):

Paint(Orchard)

Paint(Orchard) -> ( Paint(Lemons) & Paint(Lemon\_trees) )

It holds true that if we paint an object, we can see what has been painted, and if we can see something, it always looks like at least one other thing (even if that thing is the object itself, or a splash of colour).

So we add:

all x ( Paint(x) -> See(x) )

all x ( See(x) -> exists y LooksLike(x,y) )

Now we need the fact that lemon trees are from the tree family, and that plants of the same type resemble each other (approximately).

IsPlantType(Lemon\_tree, Tree)

all x all y ( IsPlantType(x, y) -> LooksLike(x, y) )

Then we add transitivity and reflexivity for LooksLike:

all x all y all z ( ( LooksLike(x,y) & LooksLike(y,z) ) -> LooksLike(x,z) )

all x all y ( LooksLike(x,y) <-> LooksLike(y,x) )

Next we need to infer that two objects of the same length, depth, and width both have some (approximate) size which is equivalent:

all x all y ( ( exists l exists w exists d ( IsLength(x,l) & IsLength(y,l) & IsWidth(x,w) & IsWidth(y, w) & IsDepth(x,d) & IsDepth(x,d) ) ) -> exists v ( IsSize(x, v) & IsSize(y, v) ) )

Now we need to state that if an object resembles another, semantically, they do so in plural form as well:

all x all y all u all v ( ( LooksLike(x, u) & IsPlural(y, x) & IsPlural(v, u) ) -> LooksLike(y, v) ).

Furthermore, objects can only have one shape or size (although they can have multiple colours):

all x all w all y ( ( IsShape(x, w) & -(y=w) ) -> ( -IsShape(x,y) ) ).

all x all v all y ( ( IsSize(x, v) & -(y=v) ) -> ( -IsSize(x,y) ) ).

Finally, we deduce that if two objects x and y are the same shape, size and colour, then they look like each other, and vice versa.

all x all y ( ( exists z exists w exists v (IsShape(x,z) & IsShape(y,z) & IsColour(x,v) & IsColour(y, v) & IsSize(x, w) & IsSize(y, w) ) ) <-> LooksLike(x, y) ).

References

[1] Ernest Davis, Leora Morgenstern, Charles Ortiz. 2011. *The Winograd Schema Challenge: Collection of Winograd Schemas.* [Online]. Available from: <https://cs.nyu.edu/faculty/davise/papers/WinogradSchemas/WSCollection.html>

[2] Levesque H. J, Davis E., Morgenstern L. 2011. The Winograd Schema Challenge. *Proceedings of the Thirteenth International Conference on Principles of Knowledge Representation and Reasoning.* **13**, pp.552-561.

Word count: ~600 words.

## Example 2

**Sian’s Example**

During a game of tag, Ethan [chased/ran from] Luke because he was "it". Who was "it"?  
**Answer:**Ethan/Luke

In order to answer this the program will require additional knowledge and reasoning principles, primarily about the game of tag. We will first consider the knowledge that the program will need.

A large part of the knowledge are the rules of tag. First, tag is a game that multiple people play, and in tag you have exactly one person who is labelled as “it”. If the person who is labelled as “it” touches another person then that label transfers, so the original person no longer has the label “it” and the touched person does have the label “it”. Furthermore, if someone has the label “it” then they will try and give it away.

The other important part of knowledge that must be taught are the meanings of ‘chased’ and ‘ran from’. If one person chases another then the first person is trying to touch the second. If one person runs from another then the first person is trying to not be touched by the second.

There are also reasoning principles that must be taught. It can be assumed, that if all people involved are playing a game of tag, then one person chasing another means the first person is trying to touch the second and hence is “it”. If the first person is running away from the second then this conclusion switches around and the second person is “it”.

If the sentence has the option ‘chased’ in it, then the program should give the answer Ethan. This is because Ethan chased Luke, so Ethan is trying to touch Luke and therefore Ethan is trying to give his “it” away. Hence Ethan is currently “it”.

Alternatively, it the sentence has the option ‘ran from’ in it, then the program should give the answer Luke, as Ethan is trying to not get touched by Luke therefore Luke is “it”.

Logical Formula

In order to represent the two sentences in logical formula it is first required to define the constants, predicates and relations we need to build up the sentences. There are only two constants required for this, Ethan and Luke. There are also only two predicates required, we will take these as T(x) to represent ‘x is playing tag’ and IT(x) to represent ‘x is “it”’. Finally, we also require two relations. R(x,y) represents ‘x runs from y’ and C(x,y) represents ‘x chases y’. Using these we can then form the following two sentences.

(T(Ethan) & T(Luke) & C(Ethan,Luke)) -> IT(Ethan)

(T(Ethan) & T(Luke) & R(Ethan,Luke)) -> IT(Luke)

We will now represent some of the facts that are required to know the answer in logical formula. In order to do this we need to define one more relation, Tou(x,y) will represent ‘x is trying to touch y’. Now we can define the following sentences.

If two people play tag and one chases the other then the chaser is trying to touch the person being chased.

All x All y ((T(x) & T(y) & C(x,y)) -> Tou(x,y))

If two people play tag and one is running from the other the second person is trying to touch the first person.

All x All y ((T(x) & T(y) & R(x,y)) -> Tou(y,x))

If one person is trying to touch another the first person is “it”.

All x All y ((T(x) & T(y) & Tou(x,y)) -> IT(x))

## Example 3

**Sarah’s Section**

The Choices of Plausible Alternatives (COPA) dataset was developed by Andrew Gordon as an evaluation tool for “open-domain commonsense causal reasoning”. The dataset was heavily inspired from the Recognizing Textural Entailments (RTE) challenges. A RTE question consists of a text fragment and a hypothesis. The goal of this question is to determine if the truth of the hypothesis is entailed in the text fragment. For example:

*Text fragment: “Cavern Club sessions paid the Beatles £15 evenings and £5 lunchtime.*

*Hypothesis: The Beatles performed at Cavern Club at lunchtime.*

This is an example of positive entailment. Although RTE is a great evaluation tool for inferential capability it is not as useful for evaluating commonsense inference. Through the use of the RTE challenges the distinction between entailment and implication was made. Entailments are inferences that are necessarily true due to the meaning in the text. Whereas implications are inferences that are expected to be true due to likely causes, effects of the text or are default assumptions. The entailment between two text fragments is either strongly positive or negative whereas implications are judged by the degree of plausibility.

In order to test for commonsense casual implication, the COPA date set was developed (modified RTE). The dataset contains over 1000 questions with each question being composited of three parts: The premise and two plausible alternatives. The plausible alternatives demonstrate either the cause or the effect of the given premise. For example:

(Backward causal reasoning)

*Premise: The women met for coffee. What was the CAUSE of this?*

*Alternative 1: The cafe reopened in a new location.*

*Alternative 2: They wanted to catch up with each other.*

(Forward causal reasoning)

*Premise: The physician misdiagnosed the patient. What happened as a RESULT?*

*Alternative 1: The patient filed a malpractice lawsuit against the physician.*

*Alternative 2: The patient disclosed confidential information to the physician.*

In both examples either alternative is plausible, but the correct answer is the alternative that is the most plausible. Explain why this a good test e.g. how have they ensured that the system is reasoning not just guessing or using different methods (causality bridges)

*Premise: The man fell unconscious. What was the CAUSE of this?*

*Alternative 1: The assailant struck the man in the head.*

*Alternative 2: The assailant took the man's wallet.*

A causal bridge may be that injuries to the head cause unconsciousness.

# Conclusion

Sian’s Conclusion

This problem, under the conditions stated above, can be solved by knowledge, representation and reasoning methods. The condition required is that in a game of tag, you only run from the person who is “it” and you only chase people if you are “it”. Whilst this is true in the rules of the game it is not necessarily true in life and often in tag the players may not know who is “it” and run from any other players. Therefore, a possible answer to the original question is that neither Ethan or Luke are “it”. However, as we are given with the problem that either Ethan or Luke are “it”, it can be assumed by both humans and the computer program that the required condition holds.

To conclude, this exact problem can be solved by knowledge, representation and reasoning methods if it was given the conditions provided above. However, this solution would not be applicable to wider situations, due to nuances of the game, and therefore does not assist in the larger problem of a computer correctly solving all of the Winograd schema.

Emma section:

Using the first-order logic approach with the facts and inference rules as stated in example 1, running these rules through an automated system for solving theorems, such as Prover9, would successfully enable the computer to come to the conclusion that the solution ‘light bulbs’ refers to ‘lemons’ and ‘telephone poles’ refers to ‘lemon trees’, thus solving the pronoun disambiguation problem. One of the reasons this approach works well is that it allows the ability to successfully capture relations between objects and express information about a large domain in a compact way (Grosan C. et al 2011).

However, even though encoding this knowledge base could prove successful for this one example, this approach does not come without limitations. Firstly, the monotonic reasoning of this approach in general risks incomplete information and so may prove insufficient (Grosan C. et al 2011). Secondly, a computer may have to reason about potentially conflicting information within the same knowledge base. It is restricted to the domain it is given, and therefore wouldn’t perform well with uncertainty. Using non-monotonic KRR techniques – such as fuzzy logic or default rules - may prove more successful (Besnard P. 1989). For example, in 1 above, expressing the extent of resemblance may be more accurate. Lemons do not look exactly like light bulbs, and so a greater level of precision could be useful for capturing resemblance. Many similar problems could be found in the other Winograd schemas due to the complex, nuanced nature of language.

However, it should be noted that the KRR approach as a whole is limited. Logic rules rarely correspond to human thought processes, and so a computer may appear to be ‘thinking’ like a human, but really be following none of the same processes (the human brain processes information in myriad ways, often building on experience and context) (Dranovsky A. 2011). Additionally, this approach is not generalisable from one rule to the next: a whole new set of rules is required for each Winograd schema, rendering this approach tedious and inefficient.

It has been shown that Machine Learning techniques may be able to achieve a higher level of accuracy, by taking advantage of a large amount of online data for solving problems requiring commonsense knowledge; however, such techniques do not incorporate inference methodically like KRR techniques do and has a very computationally expensive training process [5]. Perhaps a combination of the two could be even more successful [5].

Word count: <400

# References