AGI-23
INLP Workshop

# Interfacing Linguistics and Logic: Unleashing LLMs through AAMR and Predicate Logic

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# Introduction

**Motivation**

- Lots of knowledge is encoded in natural text.
- Large Language Models (LLMs) exhibit impressive language capabilities, often appearing to solve intricate logic problems.
- However, there are simple logic problems where they falter, illustrating an essential truth: LLMs are not reasoning engines, but sophisticated stochastic parrots.

## Example:

AS

Given these premises:

The bald eagle chases the bear.

The bear needs the bald eagle.

If someone chases the bald eagle then they do not chase the bear.

If someone needs the bald eagle then the bald eagle eats the bear.

If someone needs the bear then the bear is red.

If someone eats the bear then they are cold.

If someone is cold then they are not kind.

If someone eats the bear and they are not cold then the bear is not round.

Is this true?

The bear is red

*from ProofWriter dataset

**Example:**

Let's analyze each premise:

1. The bald eagle chases the bear.
2. The bear needs the bald eagle.
3. If someone chases the bald eagle then they do not chase the bear.
4. If someone needs the bald eagle then the bald eagle eats the bear.
5. If someone needs the bear then the bear is red.
6. If someone eats the bear then they are cold.
7. If someone is cold then they are not kind.
8. If someone eats the bear and they are not cold then the bear is not round.

From these premises, we can conclude the following:

1. Since the bear needs the bald eagle, according to statement 4, the bald eagle eats the bear.
2. Also, since the bear needs the bald eagle, according to statement 5, the bear is red.

So yes, the bear is red.

# Introduction

**Proposal**

- We aim to combine the strengths of LLMs in language understanding with the rigorous logical reasoning capabilities of dedicated logic systems.

- We propose to use LLMs to convert natural language into representations that can be effectively interpreted and processed by logic engines.

# Introduction

**Two Approaches**

Natural Language ➜ Abstract Meaning Representation ➜ Augmented AMR

Natural Language ➜ Predicate Logic ➜ Logic Engine

They can complement each other!

# NL ➜ AMR

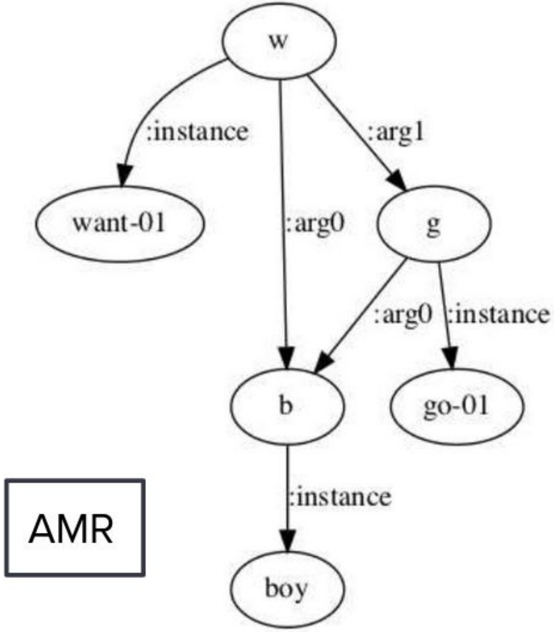
Shin et al (2021, 2022) proposed ways to use LLMs for semantic parsing in specific domains.

They generated a direct mapping between NL and meaning representations from LLM’s pretrained on code.

# NL → AMR

We are building a pipeline to test different LLMs and techniques to produce AMR parses:

- Commercial and open-source models
- Constrained parsing: partial parse checker
- Beam search
- Prompt engineering: construction of prompts for few-shot learning
- Fine-tuning models: full and LoRA's




*The boy wants to go*

## Preliminary Results

| Corpus | amr_tutorial | fd2f_sentences | some_sentences |
|---|---|---|---|
| gpt-4[^1] | 0.85 | 0.47 | 0.85 |
| gpt-3.5-turbo[^1] | 0.74 | 0.38 | 0.82 |
| text-davinci-003 (constrained) | 0.80 | 0.42 | 0.78 |
| codex[^3] | 0.83 | NA | NA |
| -------------------------------- | ------------- | --------------- | ---------------- |
| codegen-350M-multi (constrained) | 0.55 | 0.21 | 0.54 |
| codegen-350M-multi | 0.48 | 0.14 | 0.54 |
| codegen-2B-multi | 0.69 | 0.19 | 0.66 |
| tuned-codegen-2B-multi[^2] | 0.55 | 0.58 | 0.74 |
| codegen-6B-multi[^3] | NA | NA | 0.54 |
| codegen-16B-multi[^3] | NA | NA | 0.41 |
| -------------------------------- | ------------- | --------------- | ---------------- |
| llama 7B | 0 | 0 | 0 |
| tuned-llama 7B[^2] | 0.87 | 0.77 | 0.99 |
| llama 30B | 0.55 | 0.17 | 0.25 |
| llama 65B | 0.74 | 0.3 | 0.41 |
| alpaca-lora 65B | 0.73 | 0.10 | 0.54 |

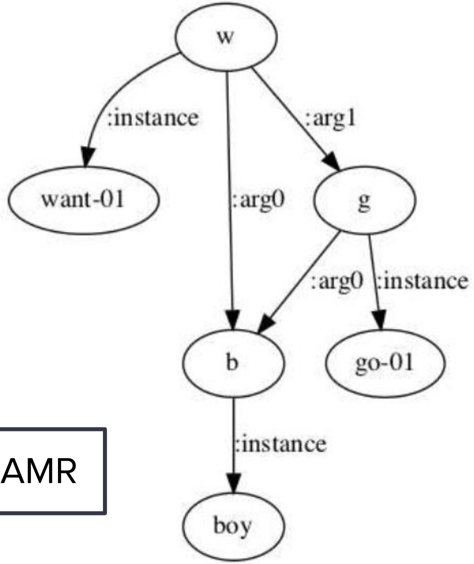
- [^1] Unconstrained version due to the unavailability/limitation of the current OpenAI APIs.
- [^2] Fine-tuned model on the publicly available AMR datasets
- [^3] Results from an older version of the checker or prompt. May be updated in the future.

# AMR ➔ AAMR

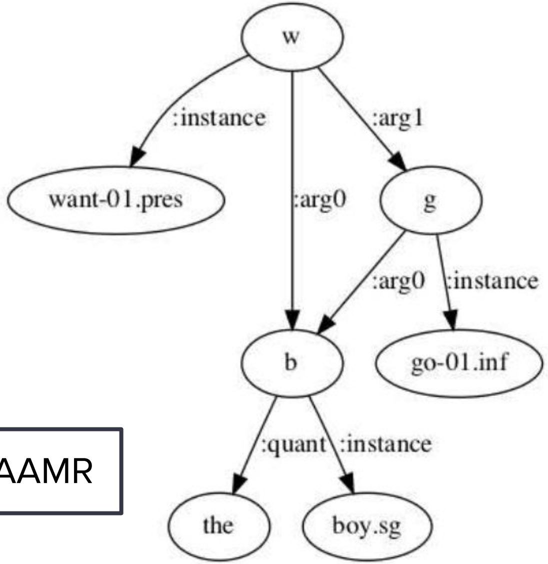
Stabler suggested a subtle augmentation of AMR formalism, to keep useful information from a sentence in a graph representation

*The boy wants to go*

AMR




AAMR



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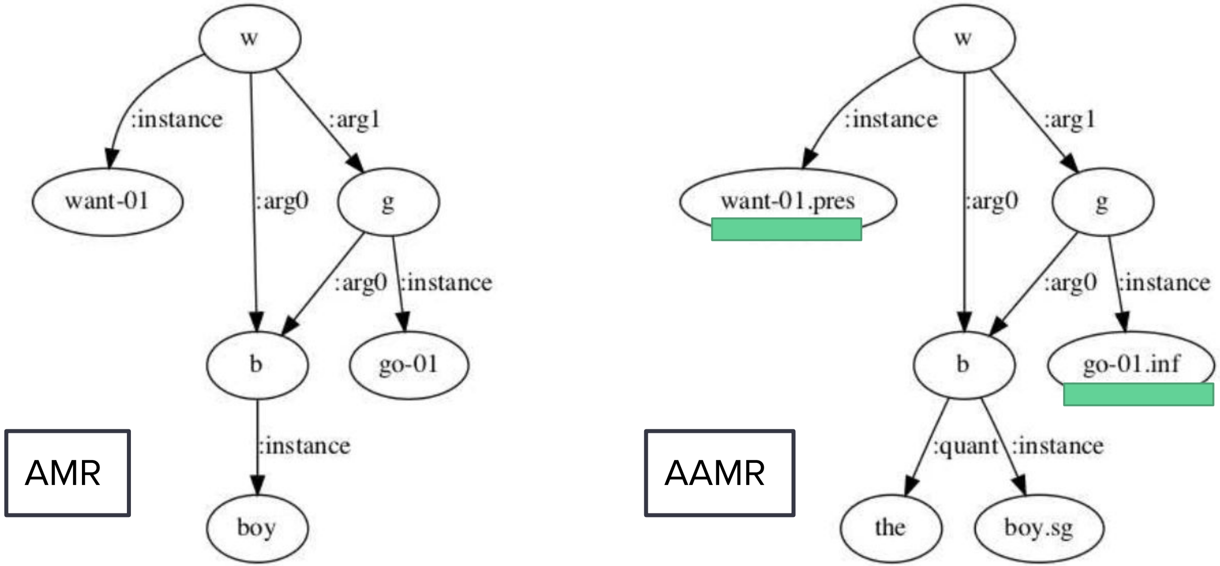

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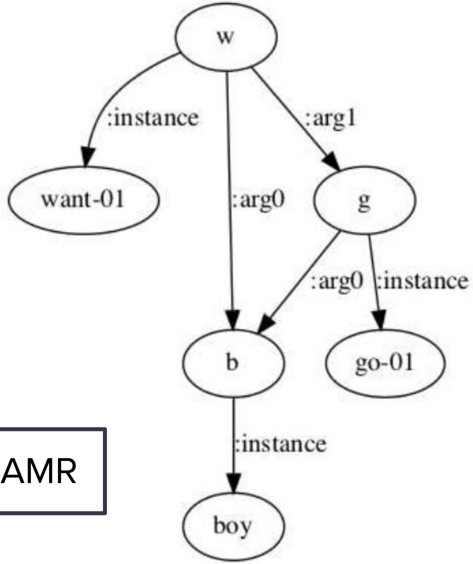
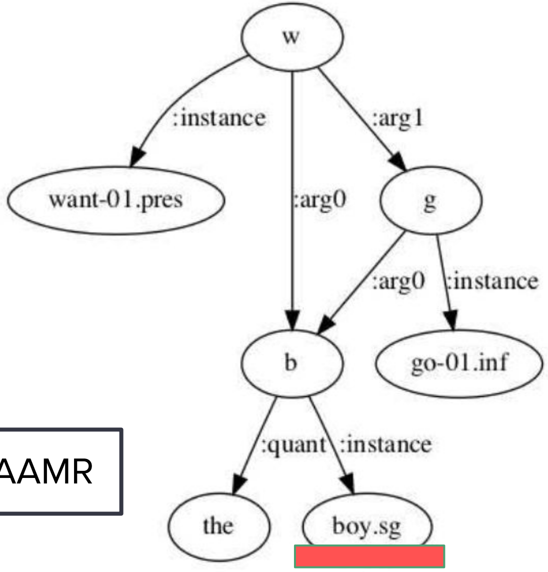



AMR




AAMR

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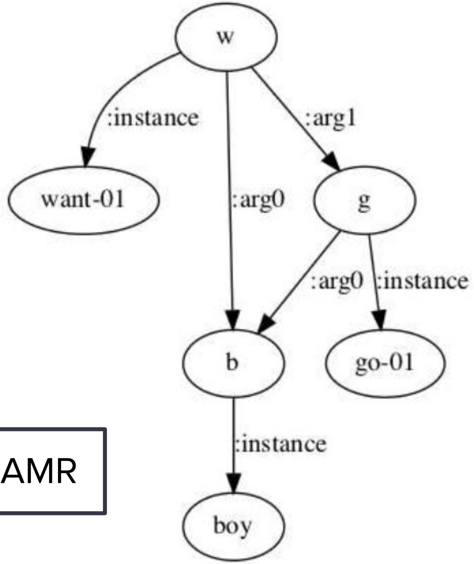
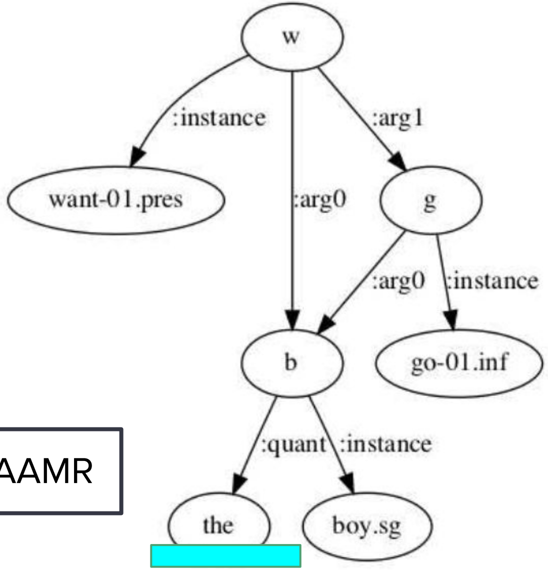



AMR




AAMR

# AMR ➔ AAMR

We briefly explored LLM's capabilities to generate AAMR from AMR and the original sentence.

sentence: The marble is white.
AMR: (w / white-03 :ARG1 (m / marble))
AAMR: (w / white-03.pres :ARG1 (m / marble.sg :QUANT the))

sentence: The marble was white.
AMR: (w / white-03 :ARG1 (m / marble))
AAMR: (w / white-03.past :ARG1 (m / marble.sg :QUANT the))

# AMR ➔ AAMR

We briefly explored LLM's capabilities to generate AAMR from AMR and the original sentence.

Sentence: For every boy, there's a girl who calls that boy's dog by some special name

AMR

```
(g / girl
 :ARG0-of (c / call-01
  :ARG1 (d / dog
   :poss (b / boy
    :mod (e / every)))
  :ARG2 (n / name
   :mod (p / pet)
   :ARG1-of (s / special-02)
   :mod (s2 / some))))
```

AAMR

```
(g / girl.sg
 :ARG0-of (c / call-01.pres
  :ARG1 (d / dog.sg
   :poss (b / boy.sg
    :QUANT every))
  :ARG2 (n / name.sg
   :mod (p / pet)
   :ARG1-of (s / special-02.pres)
   :mod (s2 / some)))
```

# NL → Predicate Logic

Although LLMs can’t solve some logic problems, they are great at converting them to predicate logic.

AS

Translate the following sentences to predicate logic

(1) The only animals in this house are cats;
(2) Every animal is suitable for a pet, that loves to gaze at the moon;
(3) When I detest an animal, I avoid it;
(4) No animals are carnivorous, unless they prowl at night;
(5) No cat fails to kill mice;
(6) No animals ever take to me, except what are in this house;
(7) Kangaroos are not suitable for pets;
(8) None but carnivora kill mice;
(9) I detest animals that do not take to me;
(10) Animals, that prowl at night, always love to gaze at the moon.

# NL ➔ Predicate Logic

(1) The only animals in this house are cats;

(1) $\forall x\ (\text{Animal}(x) \land \text{InHouse}(x) \rightarrow \text{Cat}(x))$

Explanation: For all x, if x is an animal and x is in the house, then x is a cat.

(2) Every animal is suitable for a pet, that loves to gaze at the moon;

(2) $\forall x\ ((\text{Animal}(x) \land \text{LovesMoonGazing}(x)) \rightarrow \text{SuitableForPet}(x))$

Explanation: For all x, if x is an animal and x loves to gaze at the moon

then x is suitable for a pet.

# Predicate Logic ➔ Logic engine

We can then feed predicates to a **logic engine** to solve the problem.

Working with two logic engines:

- PLN in OpenCog: WIP
- Pyprover: DEMO

# Next Steps

- **Integrate with OpenCog Hyperon**
- **Create a larger (NL → Logic) mapping corpus**
  - Wikipedia, SUMO Ontology
- **Evaluate performance**
  - Generalize to more elaborate logic problems
- **If necessary, improve mappings from the LLMs**
  - Preserve linguistic information in final representation, e.g. tense, plurality
  - Test and fine-tune open source models

# References

Richard Shin et al. 2021. ***Constrained language models yield few-shot semantic parsers***. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP'21). Association for Computational Linguistics, https://doi.org/10.18653/v1/2021.emnlp-main.608

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