Abstract Meaning Representation

Formalism, Parsing & Generation and Application

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Formalism

What is AMR?

- Abstract Meaning Representation (AMR) is a semantic representation language.
- AMR graphs are **rooted, labeled, directed, acyclic** graphs (DAGs), comprising whole sentences.
- Graphs are intended to abstract away from representations, in the sense that sentences which are simialr in meaning should be assigned the same AMR, even if they are not identically worded.
    - The man described the mission as a disaster.
    - The man's description of the mission: disaster.
    - As the man described it, the mission was a disaster.

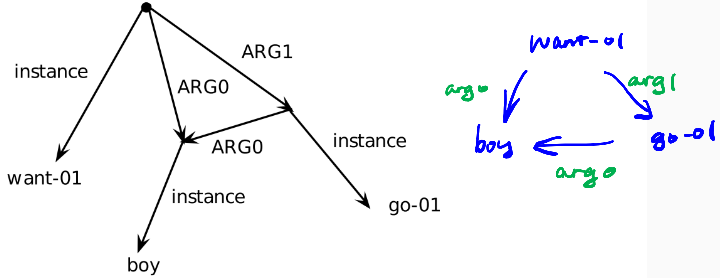


Figure 1: Equivalent formats for representating the meaning of “The boy wants to go”.

Motivation

Semantic Annotation and Meaning Representation

- Seperate annotations for named entities, co-reference, semantic relations, discourse connectives, temporal entities, etc.
- Each annotation has its own associated evaluation.
- Training data is split across many resources.
- Lacking a simple readable sembank of sentences paired with their whole-sentence, logical meanings.

AMR Content - Graph Nodes

- **Graph node:** entities, events, properties and states.
  - **words:** "boy"
  - **PropBank frameset:** "want-01"
  - **special keywords:**
    - **special entity types:** "date-entity", "word-region", etc.
    - **quantities:** "monetary-quantity", "distance-quantity", etc.
    - **logical conjunctions:** "and", etc.

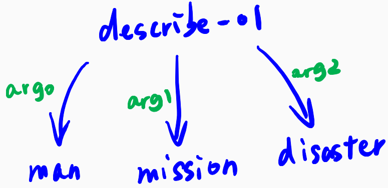
AMR Content - Graph Edges

- **Edges:** relations link entities (approximately 100 relations).
  - **Frame arguments (following PropBank conventions):** :arg0 - :arg5.
  - **General semantic relations:** :accompanier, :beneficiary, :cause, :degree, etc.
  - **Relations for quantities:** :quant, :unit, :scale.
  - **Relations for data-entities:** :day, :month, :year, :quarter, etc.
  - **Relations for list:** :op1 - :op10.

An Example for Paraphrase

- The man described the mission as a disaster.
- The man's description of the mission: disaster.
- As the man described it, the mission was a disaster.

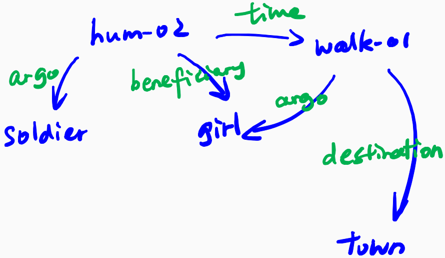
```
(d / describe-01
  :arg0 (m / man)
  :arg1 (m2 / mission)
  :arg2 (d / diaster)
```



General Semantic Relations & Co-reference

The sodier hummed to the girl as she walked to town

```
(s / hum-02
   :arg0 (s2 / soldier)
   :beneficiary (g / girl)
   :time (w / walk-01
      :arg0 g
      :destination (t / town)))
```



Inverse Relations

The top-level root of an AMR represents the focus of the sentence or phrase.

- The boy from the college sang.
- the college boy who sang ...

```
(s / sing-01
  :arg0 (b / boy
    :sourse (c / college)))
```

```
(b / boy
  :arg0-of (s / sing-01)
  :source (c / college))
```

sing-01 $\xrightarrow{\text{argo}}$ boy $\xrightarrow{\text{source}}$ college

boy $\xrightarrow{\text{argo-of}}$ sing-01

boy $\xrightarrow{\text{source}}$ college

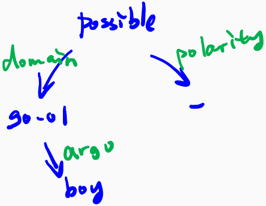
Models and negation

The boy did not go.

```
(g / go-01
  :arg0 (b / boy)
  :polarity -)
```

It's not possible for the boy to go

```
(p / possible
  :domain (g / go-01
    :arg0 (b / boy))
  :polarity -)
```



Current AMR Bank[1]

- 1,546 sentences from the novel “The Little Prince”
- 1,328 sentences of web data
- 1,110 sentences of web data (*)
- 926 sentences from Xinhua news (*)
- 214 sentences from CCTV broadcast conversation (*)

[1] Collections marked with a star (*) are also in the OntoNote corpus

Parsing & Generation

Neural AMR - Seq2seq Models

Convension

- parser: sequence to graph
- generation: graph to sequence

Why not seq2seq?

Problem

- **Data-sparsity:** reletively limited amount of labled data
- **Non-sequence:** non-sequential netural AMR graphs

Self-traning - to address the sparsity

1. Traning a parser on the dataset D of pairs of sentences and AMR graphs.
2. Self-traning, for each iteration:
   (1) parsing samples from a large, unlabeled corpus S_e.
   (2) creating a new set of parameters by training on S_e
   (3) fine-tuning those parameters on the original paired data.
   (4) increasing the size of the sample from S_e by an order of magnitude.
3. Using the parser to label AMRs for S_e and pre-training the generator.
4. Fine-tuning the generator on the original dataset D.

Graph Simplification - to address the non-sequence

US officials held an expert group meeting in January 2002 in New York.

```
(h / hold-04
  :arg0 (p2 / person)
    :arg0-of (h2 / have-org-role-91
      :arg1 (c2 / country
        :name (n3 / name
          :op1 ‘‘United’’ :op2 ‘‘States’’))
  :arg1 (m / meet-03
    :arg0 (p / person
      :arg1-of (e / expert-01)
        :arg2-of (g / group-01)))
  :time (d2 / date-entity :year 2002 :month 1)
  :location (c / city
    :name (n / name :op1 ‘‘New’’ :op2 ‘‘York’’)))
```

```
hold
  :arg0 person :arg0-of have-org-role :arg1 country :name name :op1 United :op2
States :arg2 official
  :arg1 meet :arg0 person :arg1-of expert :arg2-of group
  :time date-entity :year 2002 :month 1
  :location city :name name :op1 New :op2 York
```

Anonymization of Named Entities - to address the sparsity (1)

Open-class types (NEs, dates and numbers): 9.6% of sentences, 31.2% of vocabulary.

1. excluding `date` entities.
2. replacing these sub-graphs with a token indicating fine-grained type and an index i.
3. name entity anonymization
4. insertion of scope markers

Anonymization of Named Entities - to address the sparsity (2)

```
hold
  :arg0 person :arg0-of have-org-role :arg1 country :name name :op1 United :op2
States :arg2 official
  :arg1 meet :arg0 person :arg1-of expert :arg2-of group
  :time date-entity :year 2002 :month 1
  :location city :name name :op1 New :op2 York
```

****country_0 officials held an expert group meeting in month_0 year_0 in city_1.****

```
hold
  :arg0 person :arg0-of have-org-role :arg1 country_0 :arg2 official
  :arg1 meet :arg0 person :arg1-of expert :arg2-of group
  :time date-entity year_0 month_0
  :location city_1
```

****loc_0 officials held an expert group meeting in month_0 year_0 in loc_1.****

```
hold
  :arg0 person :arg0-of have-org-role :arg1 loc_0 :arg2 official
  :arg1 meet :arg0 person :arg1-of expert :arg2-of group
  :time date-entity year_0 month_0
  :location loc_1
```

Anonymization of Named Entities - to address the sparsity (3)

Insertion of scope markers

****loc_0 officials held an expert group meeting in month_0 year_0 in loc_1.****

```
hold
  :arg0 ( person :arg0-of ( have-org-role :arg1 loc_0
:arg2 official ) )
  :arg1 ( meet :arg0 ( person :arg1-of ( expert :arg2-of
group ) ) )
  :time ( date-entity year_0 month_0 )
  :location loc_1
```

Linearization

```
hold
  :arg0 person :arg0-of have-org-role :arg1 loc_0 :arg2 official
  :arg1 meet :arg0 person :arg1-of expert :arg2-of group
  :time date-entity year_0 month_0
  :location loc_1
```

- **Linearization Order:** depth first search, including backward traversing steps.
  `meet, :arg0, person, :arg1-of, expert, :arg2-of, group, :arg2-of, :arg1-of, :arg0`
- **Rendering Function:**

```
hold
  :arg0 ( person :arg0-of ( have-org-role :arg1 loc_0 :arg2 official ) )
  :arg1 ( meet :arg0 ( person :arg1-of ( expert :arg2-of group ) ) )
  :time ( date-entity year_0 month_0 )
  :location loc_1
```

Results

	Dev			Test		
Model	Prec	Rec	F1	Prec	Rec	F1
GIGA-20M	62.2	66.0	64.4	59.7	64.7	62.1
GIGA-2M	61.9	64.8	63.3	60.2	63.6	61.9
GIGA-200k	59.7	62.9	61.3	57.8	60.9	59.3
AMR-ONLY	54.9	60.0	57.4	53.1	58.1	55.5

Table 1: SMATCH score for AMR Parsing.

Model	Dev	Test
GIGA-20M	33.1	33.8
GIGA-2M	31.8	32.3
GIGA-200k	27.2	27.4
AMR-ONLY	21.7	22.0

Table 2: BLEU results for AMR Generation.

Application - taking Question Aswering (QA) for an example

20 Question Answering Tasks

- Developing intelligent agents is one of the long term goals of AI.
- Several chanllenges have been recently proposed that employs a Question-Answering (QA) based strategy to test an agent's understanding.
- Successfully answering their quesitons require competence on many sub-tasks:
  deduction, use of common-sense, abduction, co-reference, etc.
  推论？

Addressing a Question Answering Challenge

- **Statistical inference layer:** Abstract Meaning Representation Parser (AMR) (Banarescu et al. 2013; Flanigan et al. 2014).
- **Formal reasoning layer:** Answer Set Programming (ASP) (Gelfond and Lifschitz, 1988) language as the knowledge representation and reasoning language.
- **Translation layer:** Encoding the natural language sentences to the syntax of Event calculus with the help of the AMR parser (naive deterministic algorithm).

Step 1 - obtaining AMR representation

Mary grabbed the football.
Mary traveled to the office.
Mary took the apple there.
What is Mary carrying? A:football, apple
Mary left the football.
Daniel went back to the bedroom.
What is Mary carrying? A:apple

‘

‘Mary grabbed the football.”

```
(g / grab
  :arg0 (p / person
    :name (m / name :op1 Mary))
  :arg1 (f / football))
```

‘

‘What is Marry carrying?”

```
(c / carry
  :arg0 (p / person
  :name (m / name :op1 Mary))
  :arg1 (a / amr-unknown))
```

Event Calculus (1)

Predicate	Meaning
happensAt(F, T)	Event E occurs at time T
initiatedAt(F, T)	At time T a period of time for which fluent F holds is initiated
terminatedAt(F, T)	At time T a period of time for which fluent F holds is terminated
holdsAt(F, T)	Fluent F holds at time T
Axioms	
$holdsAt(F, T+1) \leftarrow initiatedAt(F, T).$	$holdsAt(F, T+1) \leftarrow holdsAt(F, T), not\ terminatedAt(F, T).$

Table 1: The basic predicates and axioms of Simple Discrete Event Calculus (SDEC)

Translation

Given a question-answering text, the translation module first converts the natural language sentences to the syntax of Event calculus.

- obtaining the AMR representation
- applying rule-based procedure to convert AMR graph to the syntax of Event calculus.

Event Calculus (2)

Mary grabbed the football.
Mary traveled to the office.
Mary took the apple there.
What is Mary carrying? A:football, apple
Mary left the football.
Daniel went back to the bedroom.
What is Mary carrying? A:apple

Narrative
happensAt(grab(mary,football),1).
happensAt(travel(mary,office),2).
happensAt(take(mary,apple),3).
happensAt(leave(mary,footbal;),5).
happensAt(go_back(daniel,bedroom),6).
Annotation
holdsAt(carry(mary,football),4).
holdsAt(carry(mary,apple),4).
holdsAt(carry(mary,apple),7).
not holdsAt(carry(mary,football),7).

Table 2: Representation of the Example 1 in Event Calculus

Answer Set Programming

$$initiatedAt(carry(A,O),T) \leftarrow \\ happensAt(take(A,O),T).$$

$$terminatedAt(carry(A,O),T) \leftarrow \\ happensAt(drop(A,O),T).$$

Learning Answer Set Program for QA

step 1

$$\triangle = \left\{ \begin{array}{l} initiatedAt(carry(mary, football), 1) \\ initiatedAt(carry(mary, apple), 3) \\ terminatedAt(carry(mary, football), 5) \end{array} \right\}$$

step 2

$$K = \left\{ \begin{array}{l} initiatedAt(carry(mary, football), 1) \\ \quad \leftarrow happensAt(grab(mary, football), 1). \\ initiatedAt(carry(mary, apple), 3) \\ \quad \leftarrow happensAt(take(mary, apple), 3). \\ terminatedAt(carry(mary, football), 6) \\ \quad \leftarrow happensAt(leave(mary, apple), 6). \end{array} \right\}$$

$$K_v = \left\{ \begin{array}{l} initiatedAt(carry(X, Y), T) \\ \quad \leftarrow happensAt(grab(X, Y), T). \\ initiatedAt(carry(X, Y), T) \\ \quad \leftarrow happensAt(take(X, Y), T). \\ terminatedAt(carry(X, Y), T) \\ \quad \leftarrow happensAt(leave(X, Y), T). \end{array} \right\}$$

the Results

TASK	MemNN	DMN	Our Method
1: Single Supporting Fact	100	100	100
2: Two Supporting Facts	100	98.2	100
3: Three Supporting facts	100	95.2	100
4: Two Argument Relations	100	100	100
5: Three Argument Relations	98	99.3	100
6: Yes/No Questions	100	100	100
7: Counting	85	96.9	100
8: Lists/Sets	91	96.5	100
9: Simple Negation	100	100	100
10: Indefinite Knowledge	98	97.5	100
11: Basic Coreference	100	99.9	100
12: Conjunction	100	100	100
13: Compound Coreference	100	99.8	100
14: Time Reasoning	99	100	100
15: Basic Deduction	100	100	100
16: Basic Induction	100	99.4	93.6
17: Positional Reasoning*	65	59.6	100
18: Size Reasoning	95	95.3	100
19: Path Finding	36	34.5	100
20: Agent's Motivations*	100	100	100
Mean Accuracy(%)	93.3	93.6	99.68

Other Applications

It is possible that AMR will significantly advance the state of art in one or more NLP tasks.

- Summerization (Liu et al., 2015)
- Event Detection (Li et al., 2015; Huang, 2016; Rao, 2017)
- Machine Translation (future work is expected)
    - data sparsity
    - limited performance on parsing and generation
    - the quality of AMR

References

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