A Brief Overview of Abstract Meaning Representations

Martha Palmer, University of Colorado

(w/ thanks to Kevin Knight and Claire Bonial)

SYNSEM/MRI
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Goal of PropBank

- Supply consistent, simple, general purpose labeling of semantic roles
- Provide consistent argument labels across different syntactic realizations
- Support the training of automatic semantic role labelers
- Improved downstream IE, QA, RTE, MT evaluation, etc.

Goal of AMRs

- Supply consistent, simple, general purpose labeling of sentence semantics that seamlessly incorporates NE, SRL, DTB and fills in gaps.
- Provide consistent semantic representations across different syntactic realizations
- Support the training of automatic AMR parsers

Abstract Meaning Representation (AMR) - USC-ISI, Colorado, LDC, CMU

- How to consistently represent the meanings of sentences?
- Which concepts and relations?
- How to put them together?

- First guidelines released April 24, 2012
- *Laura Banarescu; Claire Bonial; Shu Cai; Madalina Georgescu; Kira Griffitt; Ulf Hermjakob; Kevin Knight; Philipp Koehn; Martha Palmer; Nathan Schneider, Abstract Meaning Representation for Sembanking, LAW-2013.*

- ISI Downloads:
  - 100 sentences from WSJ; 244 sentences from webtext, 80 with consensus agreement; The Little Prince, etc. – funded by NSF
- LDC – DARPA DEFT, 60K+ sentences

Abstract Meaning Representation (AMR)

- Basic "who-is-doing-what-to-whom"
- Cover all sentence content in single, rooted structure
- Builds upon PropBank
  - Uses PB rolesets: e.g. describe.01
    - Arg0: describer
    - Arg1: thing described
    - Arg2: secondary attribute, described-as
  - http://verbs.colorado.edu/propbank/framesets-english/

Abstract Meaning Representation (AMR)

- AMR composed of concepts and relations, not nouns and verbs
  - Currently ~100 relations, plus inverses
- AMR is not enslaved to syntax, or even mildly indentured:

He described her as a genius.	(d / describe-01
As he described her, she is a genius.	:ARG0 (h / he)
His description of her: a genius.	:ARG1 (s / she)
	:ARG2 (g / genius))

AMR vs. PB

He described her as a genius.	(d / describe-01
As he described her, she is a genius.	:ARG0 (h / he)
His description of her: a genius.	:ARG1 (s / she)
	:ARG2 (g / genius))

PropBank differences for 2nd sentence:
2 structures

Describe-01: same except for empty ARG2
Be-01: she-ARG1, genius-ARG2, as he described her-ADV

Copulas

She is a genius

- AMR

```
(g / genius
        :domain (s / she))
```

- PropBank

```
(b / be.01
        :arg0 (s / she)
        :arg1 (g / genius))
```

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AMR=PB: Single rooted structures, abstracts away from surface syntax

```
(s / see-01
        :ARG0 (b / boy)
        :ARG1 (g / girl
                :ARG0-of (w / want-01
                        :ARG1 b)))
```

- *The boy saw the girl who wanted him.*
- *The boy saw the girl who he was wanted by.*
- *The girl who wanted the boy was seen by him.*

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AMR=PB: Single rooted structures, abstracts away from surface syntax

```
(s / slice-01
        :ARG0 (w / woman)
        :ARG1 (o / onion))
```

- [T] *A woman is slicing an onion.*
- [H] *An onion is being sliced by a woman.*

AMR=PB: Single rooted structures, abstracts away from surface syntax

```
(w / woman : polarity -
      :ARG0-of (s / slice-01
            :ARG1 (o / onion)))
```

- [T] There is no woman slicing an onion.

```
(s / slice-01
      :ARG0 (w / woman)
      :ARG1 (o / onion))
```

- [H] *A woman is slicing an onion.*

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AMR=PB: Single rooted structures, abstracts away from surface syntax

```
(s / dice-01
        :ARG0 (w / woman)
        :ARG1 (c / carrot))
```

[T] The woman is dicing a carrot.

```
(s / slice-01
        :ARG0 (w / woman)
        :ARG1 (o / onion))
```

[H] *A woman is slicing an onion.*

AMR=PB: Single rooted structures, abstracts away from surface syntax

(s / dice-01
:ARG0 (w / woman)
:ARG1 (c / carrot))

[T] The woman is dicing a carrot.

(s / slice-01
:ARG0 (w / woman)
:ARG1 (o / onion))

[H] *A woman is slicing an onion.*

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Relational nouns

- [T] The guitar is being played by the man

```
(p / play-11
    :ARG0 (m / man)
    :ARG2 (g / guitar))
```

- [H] The man is a guitar player

```
(p / person
    :ARG0-of (p2 / play-11
        :ARG2 (g / guitar))
    :domain (m / man))
```

“John could not have heard about the professor’s creation of the microbial viruses that Mary sold to Russia yesterday.”

```
(p2 / possible
    :polarity -
    :domain (h / hear-01
          :ARG0 (p / person
              :name (n / name :op1 "John"))
          :ARG1 (c / create-01
                :ARG0 (p3 / professor)
                :ARG1 (v / virus
                      :mod (m / microbe)
                      :ARG1-of (s / sell-01
                            :ARG0 (p4 / person
                                :name (n2 / name :op1 "Mary"))
                            :ARG2 (c2 / country
                                :name (n3 / name :op1 "Russia"))
                             :time (y / yesterday))))))
```

Have-org-role-91 (also have-rel-role-91)

USC Associate Professor for Mathematics Jay Bartroff

```
(p / person :wiki - :name (n / name :op1 "Jay" :op2 "Bartroff")
   :ARG0-of (h / have-org-role-91
            :ARG1 (u / university :wiki
         "University_of_Southern_California"
                      :name (n2 / name :op1 "USC"))
            :ARG2 (p2 / professor
                  :mod (a / associate)
                  :topic (m / mathematics))))
```

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How is it really different from PropBank?

- Numbered Args, + ArgMs:
  - COM: Comitative
  - LOC: Locative
  - DIR: Directional
  - GOL: Goal
  - MNR: Manner
  - TMP: Temporal
  - EXT: Extent
  - REC: Reciprocals
  - PRD: Secondary Predication
  - PRP: Purpose
  - CAU: Cause
  - DIS: Discourse
  - ADV: Adverbials
  - ADJ: Adjectival
  - MOD: Modal
  - NEG: Negation
  - DSP: Direct Speech

How is it really different from PropBank? More semantic relations

- LOTS of additional relations/concepts in addition to numbered args, modifier tags of PB (types of ArgM's):

General semantic roles (incl. shortcuts): :accompanier ex :age ex :beneficiary ex :cause ex :concession ex :condition ex :consist-of ex :cost ex :degree ex :destination ex :direction ex :domain ex :duration ex :employed-by ex :example ex :extent ex :frequency ex :instrument ex :li ex :location ex :manner ex :meaning ex :medium ex :mod ex :mode ex :name ex :ord ex :part ex :path ex :polarity ex :polite ex :poss ex :purpose ex :role ex :source ex :subevent ex :subset ex :superset ex :time ex :topic ex :value ex

In quantities: :quant ex :unit ex :scale ex examples quantity types

In date entity: :day :month :year :weekday :time :timezone ex :quarter :dayperiod :season :year2 :decade :century :calendar ex :era ex :mod date-entity examples

Named Entity types - dozens

How is it really different from PropBank? Discourse relations

- Introduction of additional discourse elements:
  - *But* = contrast: “The House has voted to raise the ceiling to $ 3.1 trillion , **but** the Senate isn't expected to act until next week at the earliest*.”*
  - *Even though* = concession: “Workers described ‘clouds of blue dust’ that hung over parts of the factory, **even though** exhaust fans ventilated the area.”
- Penn Discourse Treebank – inter-sentential
- AMR – intra-sentential

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How is it really different from PropBank?

- Provides more structuring of noun phrases & prepositional phrases, intra-sentential coreference and discourse relations
- Collapses more ways of saying the same thing, making much more use of PropBank predicates.
- Provides a (partial) representation for negation and modals; PropBank just marks them.

Semantic similarity challenges

- Etymologically related terms are aliased, same representation
  - *destruction/destroy*
- What if they aren't etymologically related?
  - *fear.v/fear.n/afraid.adj*
  - *travel/take a trip?*
  - *desire/want???*
- Automatic clustering? Word embeddings?

Light Verb Constructions- differ

- Similarly to PropBank, AMR isn't confounded by syntactic idiosyncrasies, function words, and light verb constructions.
- PB ("*issue a warning*")
  - *issue* → issue.lv
  - *warning* → warn.01,
  - final REL= *issue_warning,*
    with warn.01 arguments
- AMR ("*issue a warning*" → warn-01)

PropBank Today – synched w/ AMR

- More flexible coverage
- http://propbank.github.io/
  - Noun annotation (re-merging NomBank frames)
    - Eventive nouns: *destruction, escape*
    - Stative nouns: *fault, love*
    - NOT relational nouns, *smoker* becomes

```
p4 / person
      :ARG0-of (s / smoke-02
```

  - Adjectives
    - *Comfortable, valuable*

Accuracy & Agreement

- AMR uses the *smatch* metric to calculate agreement rates against consensus AMR annotations
- 4 annotators provided AMRs for all 180 adjudicated sentences (100 wsj, 80 webtext)
- average *smatch* agreement rates with consensus AMRs were 0.83 (wsj) and 0.73 (webtext)
- PB IAA generally between 92-98%

AMR Approach to Constructions

Bonial, et. al., LREC 2018

Representing meanings associated with syntactic patterns required a novel approach:

Annotating constructions…

The more we include, the better the representation.

- Include.01, representation → represent.01, better → good.02
- Correlation → correlate.91

Adding Constructional Rolesets

Bonial, et. al., LREC 2018

- Degree-Related Constructions – Have-Degree-91:
  - Comparison
  - Superlative
  - Degree-consequence
- Quantity-Related Constructions – Have-Quant-91:
  - Comparison
  - Superlative
  - Quantity-consequence
- The X-er, The Y-er – Correlate-91
- Comparing Resemblance – Have-Degree-of-Resemblance-91

Degree-Related Constructions

Bonial, et. al., LREC 2018

Have-Degree-91
Arg1: domain, entity characterized by attribute
Arg2: attribute (e.g. tall)
Arg3: degree itself (e.g. more/most, less/least, equal)
Arg4: compared-to
Arg5: superlative: reference to superset
Arg6: consequence, result of degree

Comparison:

4. The girl is taller than the boy.

```
(h / have-degree-91
      :ARG1 (g / girl)
      :ARG2 (t / tall)
      :ARG3 (m / more)
      :ARG4 (b / boy))
```

i.e. *The girl is more tall compared to the boy.*

Superlative:

5. She is the tallest girl on the team.

```
(h / have-degree-91
      :ARG1 (s / she)
      :ARG2 (t / tall)
      :ARG3 (m / most)
      :ARG5 (g / girl
            :ARG0-of (h2 / have-org-role-91
                  :ARG1 (t2 / team))))
```

i.e. *She is the most tall of the girls on the team.*

Degree-Related Constructions

Bonial, et. al., LREC 2018

Have-Degree-91
Arg1: domain, entity characterized by attribute
Arg2: attribute (e.g. tall)
Arg3: degree itself (e.g. more/most, less/least, equal)
Arg4: compared-to
Arg5: superlative: reference to superset
Arg6: consequence, result of degree

Degree-Consequence:
The watch is too wide; therefore, it does not fit my wrist.
I was too tired to drive.

6. The watch is too wide for my wrist.

```
(h / have-degree-91
      :ARG1 (w / watch)
      :ARG2 (w2 / wide-02
            :ARG1 w)
      :ARG3 (t / too)
      :ARG6 (f / fit-06
            :ARG1 w
            :ARG2 (w3 / wrist
                  :part-of (i / i))))
```

Alexander knew Spencer too well to think him naive or thick-skulled.

```
(h / have-degree-91
    :ARG1 (w / know-01
        :ARG0 (p / person
            :name (n / name :op1 ”Alexander"))
        :ARG1 (p1 / person
            :name (n / name :op1 ”Spencer"))
    :ARG2 (w2 / well)
    :ARG3 (t / too)
    :ARG6 (t2 / think-01
        :ARG0 p
        :ARG2 p1
        :ARG3 (o / or
            :op1 naive
            :op2  thick-skulled)))
```

Alexander knew Spencer too well to think him naive or thick-skulled.

```
(h / have-degree-91
    :ARG1 (k / know-02
        :ARG0 (p / person :name (n / name :op1 "Alexander"))
        :ARG1 (p2 / person :name (n2 / name :op1 "Spencer")))
    :ARG2 (w / well)
    :ARG3 (t / too)
    :ARG6 (t2 / think-01
        :ARG0 p
        :ARG1 p2
        :ARG2 (o / or
            :op1 (n3 / naive)
            :op2 (s / skull
                :ARG1-of (t3 / thick-03)
                :part-of p2))))
```

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The X-er, The Y-er

Bonial, et. al., LREC 2018

Correlate-91
Arg1: X, degree/quant word modifying first item changing in relation to Arg2
Arg2: Y, degree/quant word modifying second item changing in relation to Arg1

10. The longer he is around, the more miserable I will be.

```
(c / correlate-91
      :ARG1 (m2 / more
            :ARG3-of (h2 / have-degree-91
                  :ARG1 (b / be-located-at-91
                        :ARG1 (h / he)
                        :ARG2 (a / around))
                  :ARG2 (l2 / long-03
                        :ARG1 b)))
      :ARG2 (m3 / more
            :ARG3-of (h3 / have-degree-91
                  :ARG1 (i / i)
                  :ARG2 (m / miserable))))
```

i.e. *An increase in how long he is around correlates with an increase in how miserable I am.*

Evaluation, Implementation

Bonial, et. al., LREC 2018

- New guidelines, rolesets piloted on 'Challenge Set'
  - 50 sentences from AMR 2.0
  - Selected using keyword searches, manual analysis
  - Represents variety of degree/quantity related constructions
  - Includes tricky cases with clear inconsistencies in past annotation
- Double annotated: 1 CU annotator, 1 SDL annotator
- Agreement: 88.6% ('smatch' score (Cai and Knight, 2013))
- Manual retrofitting of approximately 4700 annotations

Current Status

- AMR 3.0 released 2018
  - 59783 total AMRs
  - 6112 instances of degree/quantity-based constructions
- Coverage of constructional semantics: a layer of meaning critical for translation, natural language understanding
  - 4 construction entries added to the AMR lexicon
  - 5 distinct constructions

Bonial, et. al., LREC 2018

Use Case	Roleset/Relation	Count
Downtoners, intensifiers	Degree	4547
Comparison, superlative, degree-consequence	Have-Degree-91	4943
Comparison, superlative, quantity-consequence, quantity reification	Have-Quant-91	1122
Comparing resemblances	Have-Degree-of-Resemblance-91	9
The X-er, The Y-er	Correlate-91	38

Summarizing

- A more abstract labeled dependency tree
  - w/out function words
  - many nouns/adjectives have predicate-argument structures as well as verbs
  - wikified NE's
  - abstract discourse relations
  - interpretation of modality and negation
  - "some" implicit arguments/relations
  - AND equivalence relations for coreference – makes it a graph.

Challenges AMR doesn't address

- Sense distinctions and semantic similarity
- Metonymy, Metaphors, new usages
- Implicit arguments
- Tense and Aspect
- Logic
  - Scope
  - Singular/Plural, Definite/Indefinite
- Temporal and causal relations between events

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