Transcending Dependencies

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Symbolic representations?

- Do NN language models and end-end systems w/ lots of training data still need symbolic representations?
  - Lexical resources can improve LM performance *Majewska, et. al, ACL 2021, Gung & Palmer, IWCS 2021*
- We still need our NLP systems to
  - Adapt quickly to new domains, genres, languages w/out large amounts of training data (little or no data for low resource languages)
  - Be explainable, in spite of the opacity of NN's
  - Support reasoning for novel, complex tasks, i.e. robot navigation, "why" questions, decision making support in natural disasters
- Hybrid (Symbolic/NN) systems could be the answer

Outline – Compare and Contrast w/re recovering implicit information

Palmer, et. al, ACL-1986

- Briefly review
  - Universal dependencies
  - Proposition Bank – semantic role labels
- English Abstract Meaning Representations
  - Including implicit arguments and spatial relations
- Moving towards Uniform Meaning Representations
  - That are cross-linguistically general
  - Add temporal relations, logical form, tense, aspect and modality

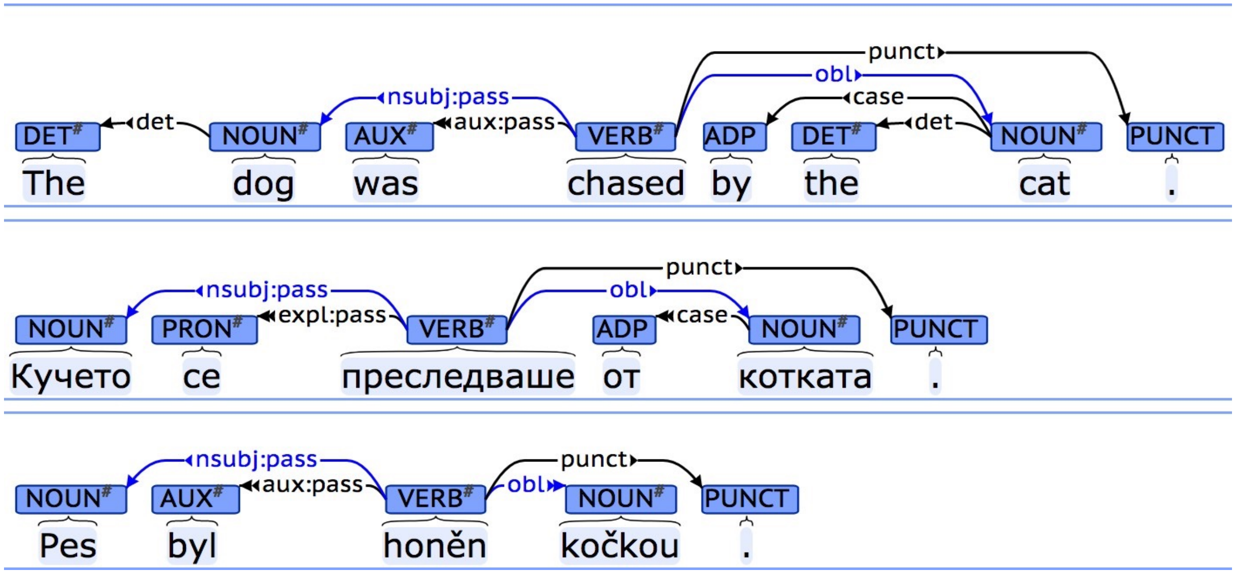
Universal Dependencies (UD)

UD is a cross-lingually consistent grammatical annotation scheme.

English

Bulgarian

Czech



(Version 2.7 treebanks are available at http://hdl.handle.net/11234/1-3424.
183 treebanks, 104 languages, released November 15, 2020.)

Abaza	1	<1K	Northwest Caucasian
Afrikaans	1	49K	IE, Germanic
Akkadian	2	23K	Afro-Asiatic, Semitic
Akuntsu	1	<1K	Tupian, Tupari
Albanian	1	<1K	IE, Albanian
Amharic	1	10K	Afro-Asiatic, Semitic
Ancient Greek	2	416K	IE, Greek
Apurina	1	<1K	Arawakan
Arabic	3	1,042K	Afro-Asiatic, Semitic
Armenian	1	52K	IE, Armenian
Assyrian	1	<1K	Afro-Asiatic, Semitic
Bambara	1	13K	Mande
Basque	1	121K	Basque
Belarusian	1	275K	IE, Slavic
Bhojpuri	2	6K	IE, Indic
Breton	1	10K	IE, Celtic
Bulgarian	1	156K	IE, Slavic
Buryat	1	10K	Mongolic
Cantonese	1	13K	Sino-Tibetan
Catalan	1	531K	IE, Romance
Chinese	5	285K	Sino-Tibetan

UD Parsing

The Stanford Natural Language Processing Group

2016

Penn TreeBank, English

Fast and accurate parsing in bulk

Data	Metric	Soochow U, China
Development (1700 sentences)	UAS 92.0	95.92
	LAS 89.7	94.16
Test (2416 sentences)	UAS 91.7	96.14
	LAS 89.5	94.49

Zhang, et. al, ACL 2020

SyntaxNet, 2017

Language	UAS	LAS
Bulgarian	91.33	86.77
Catalan	91.32	88.76
French	91.05	88.48
Hindi	93.73	90.10
Italian	90.73	87.71

Language	UAS	LAS
Japanese	95.33	93.99
Polish	91.32	86.83
Portuguese	90.60	88.12
Russian-SynTagRus	91.51	89.05
Spanish	90.32	87.16

(beat 95.74; 94.08)

Universal Dependencies have had a transformative effect. They

- Provide a clear, straightforward entrée to building dependency parsers; look a lot like ‘spans’!
- Open the door to NLP advances for dozens of languages
- Unify the community and gives equal time and space to many languages and their speakers
- The field owes a huge debt to this group! Thanks!

As wonderful as universal dependencies are, what don’t they do?

Do universal dependencies give us everything we want? Is there a better way to recover implicit information?

- *Gas could go to $ 10 a gallon.*
- *The president pardoned him for health reasons.*
- *My mother's birthday was yesterday and I forgot!*
- *He denied any wrongdoing.*
- *Not all yarn frogs easily.*

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Do universal dependencies give us everything we want?

- *Gas could go to $ 10 a gallon.*
- *The president pardoned him for health reasons.*
- *My mother's birthday was yesterday and I forgot!*

- How about Abstract Meaning Representations?
- Can we make AMRs as universal as grammatical dependencies?

Abstract Meaning Representation (AMR)

- NSF Funding (2009-2016)
  - STAGES - Statistical Translation And GEneration using Semantics
  - Colorado (PI), ISI, Rochester, Brandeis, Columbia
- DARPA DEFT funding (2012-2017)
  - USC-ISI, Colorado, LDC, CMU
  - First guidelines released April 24, 2012
  - LDC releases, recent one is 60K sentences with AMR's, funded by DARPA DEFT

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.

Abstract Meaning Representation (AMR)

- Basic “who-is-doing-what-to-whom”
- Cover entire 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/
- **PB** Same representations: *He described her as a genius/His description of her: a genius.*
- **AMR:** *ditto + As he described her, she is a genius.*

Proposition Bank

Kingsbury & Palmer, TLT 2003, Palmer, Palmer, Gildea, Kingsbury, CL 2005

Roleset id: hear.01 , *hear, physically hear*

, VerbNet: *See-30.1-1-1*, *Discover-84-1-1*,

FrameNet: Perception_experience Hear

: Arg0-PAG: *hearer* (Experiencer,Agent)

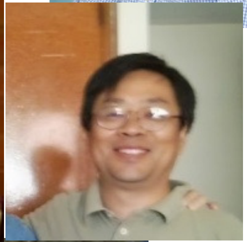
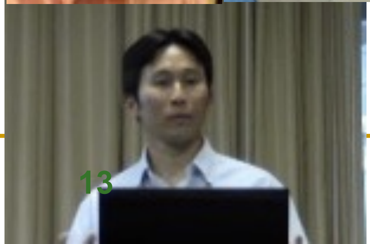
: Arg1-PPT: *utterance, sound* (Stimulus, Theme)

: Arg2-DIR: *speaker, source of sound* (Source)

- English 2M+, Chinese 1M+, Arabic .5M, Hindi/Urdu .6K, Korean
- NomBank for eventive and relational nouns, *Myers, et. al. LREC 04*

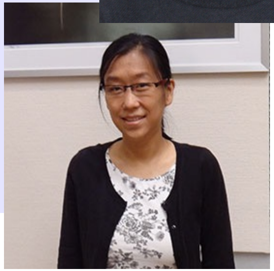
PropBank Language Experts

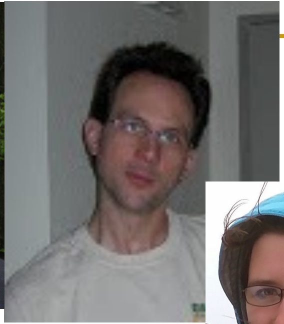


中文 (Chinese)

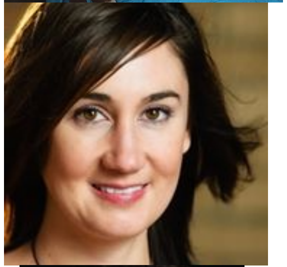
Wei-Te Chen, Nianwen Xue, Fei Xia, Shumin Wu, Zhibiao Wu



ENGLISH

Jena Hwang, Karin Kipper, Skatje Myers, Claire Bonial, Olga Babko-Malaya, Paul Kingsbury, Hoa Dang, Dan Gildea


PropBank Language Experts

(Arabic) عربى
Aous Mansouri,
Maha Foster

한국어 (Korean)
Jinho Choi,
Na-rae Han,
Chunghye

हिंदी (Hindi) and (Urdu) اردو
Bhuvana Narasimhan,
Ashwini Vaidya, Archna Bhatia, Riyaz Bhat,

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

AMR

```
(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))))))
```

(slide courtesy of Kevin Knight)

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

AMR/Propbank

```
(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))))))
```

"microbial virus"

ArgM-TMP

How is AMR really different from PropBank? Discourse relations

- Addition of discourse connectives:
  - *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

How is AMR 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.
  Merge of PB n,v, adj, → *O'Gorman, et. al., LREC 2018*
- Provides a (partial) representation for negation and modals; PropBank just marks them.

AMR combines multiple annotation layers

- PropBank
- Named Entity tagging
  - PERson, ORGanization, LOCation (LOTS more NE types)
- Time Expressions – TIMEX
- Coreference
  - ***Obama*** *won the election.* ***He****..*
- Discourse Relations
  - Contrast, concession, condition,…
- ….

Summarizing AMRs

- 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
  - partial interpretation of modality and negation
  - "some" implicit arguments/relations
  - AND equivalence relations for coreference – make it a graph (directed acyclic graph).

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%

Training data supporting…medical histories, tracking WMD's, patent searches, etc.

- Information Extraction
- Text editing
- Text summary / evaluation
- Question and answering
- Machine Translation evaluation

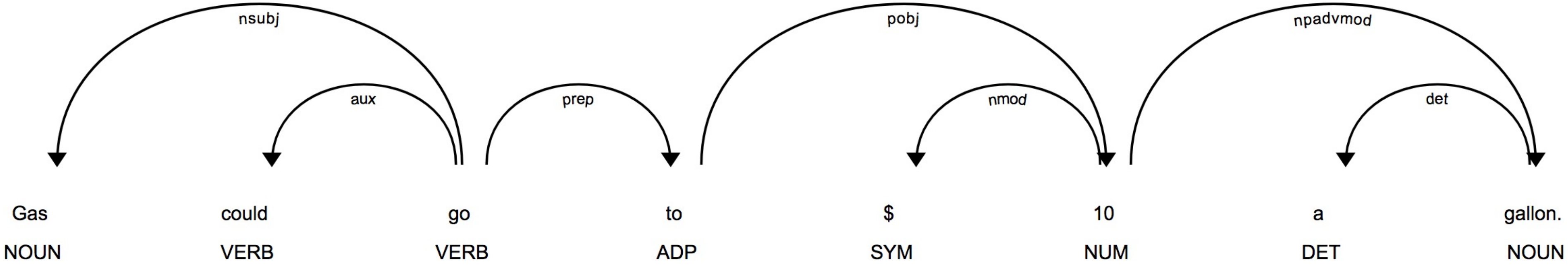
- AMR's improve over SRL by 2%-6% or more

How do we capture deep semantics? Recover implicit information, temporal and causal relations, etc.

- *Gas could go to $ 10 a gallon.*
- *The president pardoned him for health reasons.*
- *My mother's birthday was yesterday and I forgot!*

How do we capture Metonomy? UD

- *Gas could go to $ 10 a gallon.*



How do we capture Metonomy? AMR

- Introduction of understood, but not explicitly mentioned concepts:

  Gas could go to $ 10 a gallon

```
(p / possible
    :domain (g / go.01
        :ARG1 (t / thing
            :ARG2-of (p2 / price-01
                :ARG1 (g4 / gas
                    :quant (v2 / volume-quantity
                        :unit (g5 / gallon)
                        :quant 1))))
        :ARG4 (m2 / monetary-quantity
            :unit (d2 / dollar)
            :quant 10)))
```

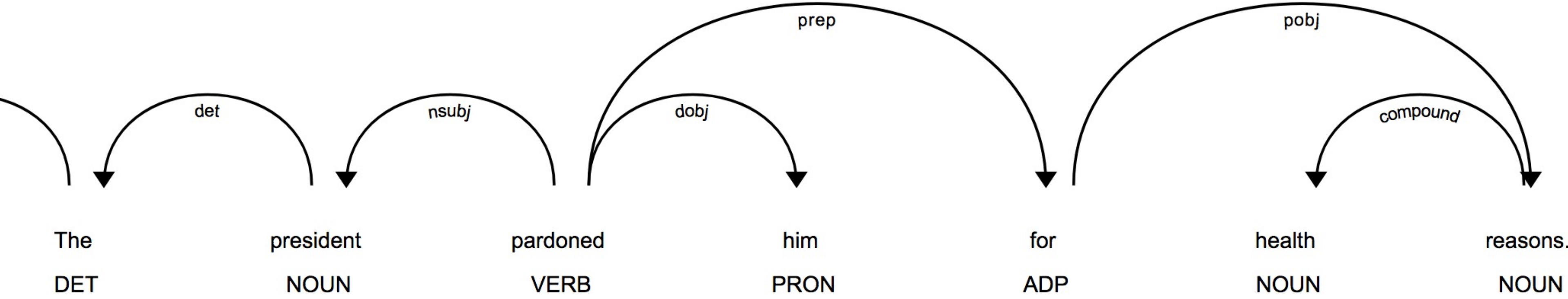
Examples of Metonymy*, Metonymy detection leads to more accurate, more informative information extraction

- *Ellie drank another glass (of wine).*
- *Boston ('s football team) won the SuperBowl.*
- *London ('s financial center management) is frightened of a no-deal Brexit.*
- *Supreme Court rejects Texas (AG's) suit.*
- ….

* *Thanks to James Pustejovsky for types*

How do we capture causation? UD

- *The president pardoned him for health reasons.*



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How do we capture causation? AMR

- *The president pardoned him for health reasons.*

```
(p3 / pardon-01
        :ARG0 (p / president)
        :ARG1 (h2 / he)
        :ARG1-of (c /cause-01
                :ARG0 (r / reason
                        :MOD (h /health))))
```

Causation examples* crucial for reasoning

- *Many have returned home, but some are still too fearful to go back.*
  fearful CAUSE go-NEG
- *[He] stated that heroin users are ill and need treatment.*

  are ill CAUSE need treatment.
- *An ambush triggered a day-long battle*

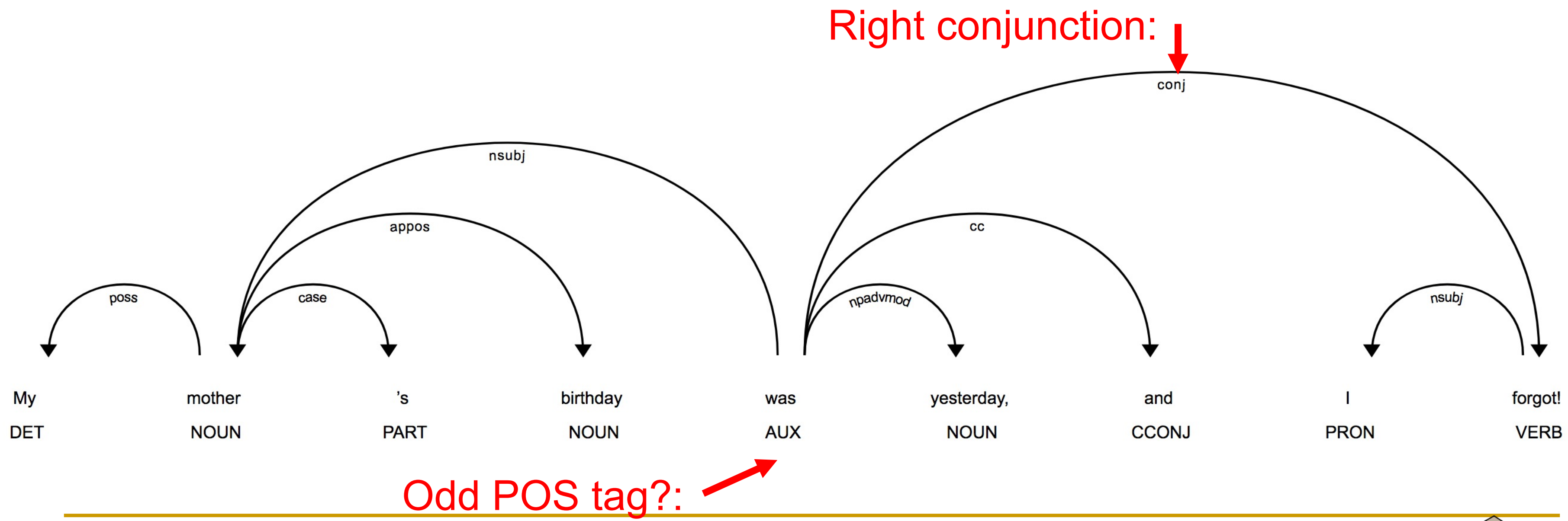
  ambush CAUSE battle
- *The wildfire began with a lightning strike.*

  lighting strike CAUSE wildfire

**Richer Event Description Annotation Guidelines*

How do we capture implicit arguments? UD

- *My mother's birthday was yesterday and I forgot!*



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How do we capture implicit arguments? AMR

- *My mother's birthday was yesterday and I forgot!**
- (a / and

```
(a / and
      :op1 (b / birthday
            :poss (p / person
                  :ARG0-of (h / have-rel-role-91
                        :ARG1 (i / i)
                        :ARG2 (m / mother)))
            :time (y / yesterday))
      :op2 (f / forget-01
            :ARG0 i
            :ARG1 b))
```


Example from my son, who did NOT forget!

Implicit argument examples* Anywhere from 10% to 30% of key event participants

Often refer to mentions from prior sentences

- *She found out [?].*
- *He signed [?].*
- *They won [?].*
- *My proposal is similar [to ?].*
- *She explained [?].*
- Dropped subjects in Chinese
- Clitics in Romance languages, …

**Thanks to Tim O'Gorman's dissertation and Chuck Fillmore*

Multi-sentence AMRs

- Add information about which words refer to the same thing, how events relate to each other on a timeline, chains of cause and effect between events, and other kinds of rich information needed for understanding.
- Focus here on referring expressions, inter-sentential coreference

Tim O'Gorman, et. al., AMR Beyond the Sentence: the Multi-sentence AMR corpus, COLING 2018

How do we capture temporal relations?

- *He denied any wrongdoing.*

Outline – Compare and Contrast

- Briefly review
  - Universal dependencies
  - Proposition Bank – semantic role labels
- English Abstract Meaning Representations
  - Including implicit arguments and spatial relations
- Moving towards Uniform Meaning Representations
  - That are cross-linguistically general
  - Add temporal relations, logical form, tense, aspect and modality

Uniform Meaning Representations

Designing Meaning Representation Workshops, ACL2019, COLING 2020

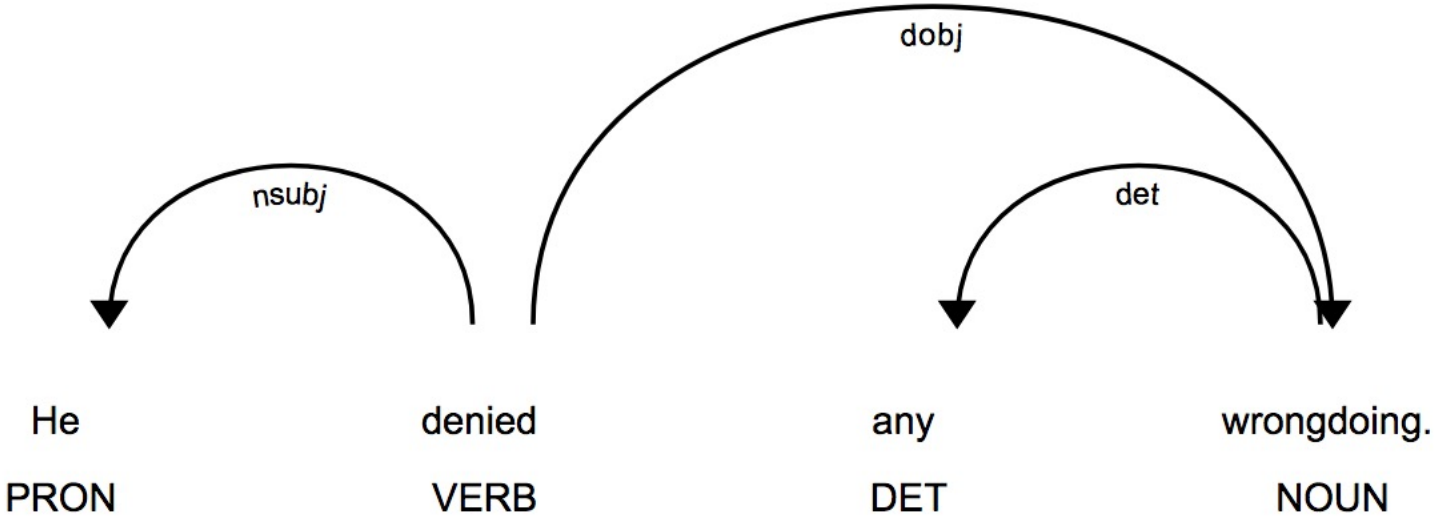
- Current NSF project
  - Brandeis (Nianwen Xue & James Pustejovsky) *DMR1, DMR2*
  - Colorado (Martha Palmer, Jim Martin, Andy Cowell) *DMR1, DMR2*
  - U of New Mexico (Bill Croft) *DMR1, DMR2*
- Ensure adequate coverage for multiple languages, especially low resource languages – requires *adapting* AMR
  - e.g., Arapaho, Kukama, English, Chinese, Hindi, Arabic, Spanish, Sanapaná
- ADD: **Tense, Aspect, Modality, Logical form** so that UMR can match formal semantic representations (MRS,DRT)

The whole team!

- Joint work with Jens Van Gysel, Meagan Vigus, Jayeol Chun, Kenneth Lai, Sara Moeller, Jiarui Yao, Jin Zhao, Tim O’Gorman, Andrew Cowell, William Croft, Chu-Ren Huang, Jan Hajiˇc, James Martin, Stephan Oepen, Martha Palmer, James Pustejovsky, Rosaa Vallejos

How do we capture temporal relations? UD

- *He denied any wrongdoing.*



How do we capture temporal relations? UMR

- s1: *Edmund Pope…. (s1p)*
- s3: *He denied any wrongdoing.*

```
(d / deny-01
    :ARG0 (h / he)
    :ARG1 (t / thing
        :ARG1-of (d2 / do-02
            :ARG0 h
            :ARG1-of (w / wrong-02))))
```

```
(s3 / sentence
    :temporal ((s3d :before DCT)
    :temporal (s3w :before s3d ) )
    :coref ((s3h :same-entity s1p)))
```

Crucial for medical histories (NIH), For identifying IED scenarios (DARPA), etc.

Adding Modality and Aspect to UMR

Van Gysel Jens, et. al., Designing a Uniform Meaning Representation for Natural Language Processing, KI-Kunstliche Intelligenz, 2021

- s1: *Edmund Pope…. (s1p)*
- s3: *He denied any wrongdoing.*

(d / deny-01
:Aspect Performance
:ARG0 (h / he)
:ARG1 (t / thing
:ARG1-of (d2 / do-02
:ARG0 h
:ARG1-of (w / wrong-02))))

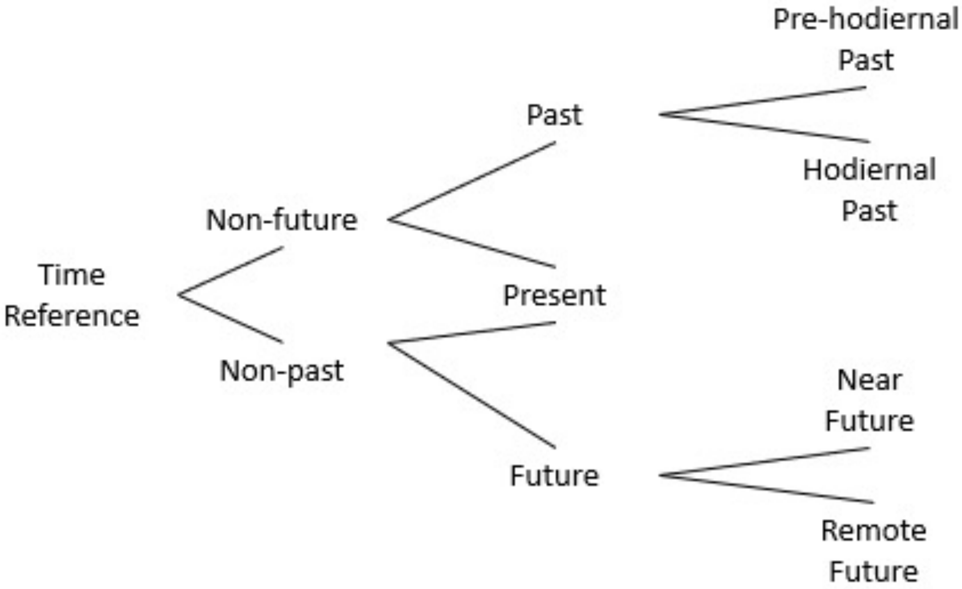
(s3 / sentence
:temporal ((s3d :before DCT)
:temporal (s3w :before s3d))
:modal ((s3d :AFF AUTH)
(s3d2 :NEG (s3h :AFF AUTH)))
:coref ((s3h :same-entity s1p)))

Cross-linguistically comparable treatment of new semantic domains (forthcoming)

- Person/Number: Lattices based on existing typological work (Corbett, CUP, 2000; Cysouw, OUP, 2003)
- Modality and negation in document-level structure (Boye, de Gruyter Mouton, 2012, see Vigus et al., DMR, 2019)
- Degree admodifiers: cross-linguistically applicable values based on common practice of field linguists
- Tense and Aspect, using lattices, (Van Gysel, et.al., DMR 2019)
- Etc.

Example: Temporal Reference

- Different languages divide semantic continua in different, motivated ways in their grammar



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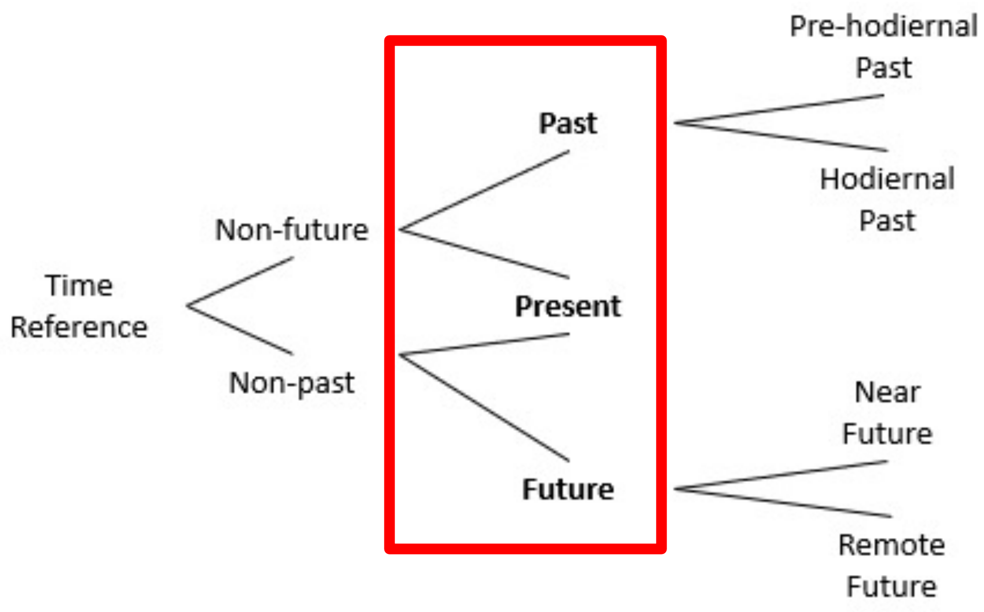
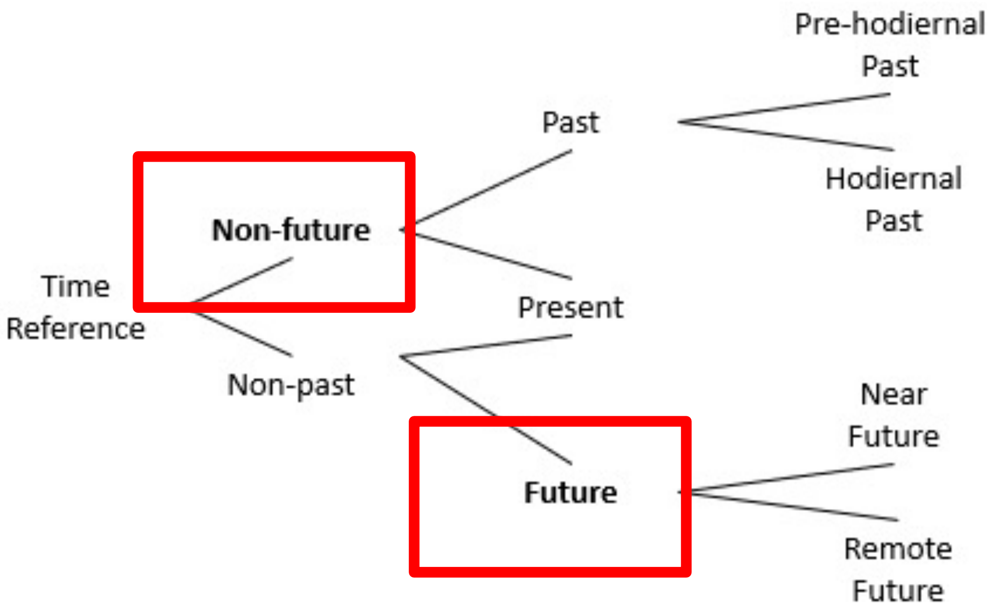
Example: Temporal Reference

- English: past – present – future



Example: Temporal Reference

- Hua (Haiman 1980): non-future - future



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Expansion of AMR/UMR to low-resource languages (Vigus et al. DMR 2020)

- Preliminary annotation of Sanapaná oral historical narratives (Van Gysel 2020)
  - Pilot annotation of 68 lines of text to test UMR annotation tool.

Endangered Languages Documentation Programme

Words	aplekeskamkehlta	akteyamoma
Morphemes	ap- le -kes -kam -ke =hlta	ak- teyam -om -a
Morpheme Gloss	2/3M.I sacar (p.ej. miel) APPL PST/HAB V1.NFUT =PHOD	2/3F.III pisar PST/HAB INF
Morpheme Cat	v:Any v v>v v:Any v:Any prt	v:Any v v:Any v:Any
Word Gloss	sacó	la escalera

UMR Penman Annotation:

```
(s6e / ellekeskama-00
  :actor (s6a / ap-)
  :theme (s6e2 / enteyamoma
        :other (s6a2 / ak-))
  :Aspect Performance
  :polarity +)
```


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Conclusion

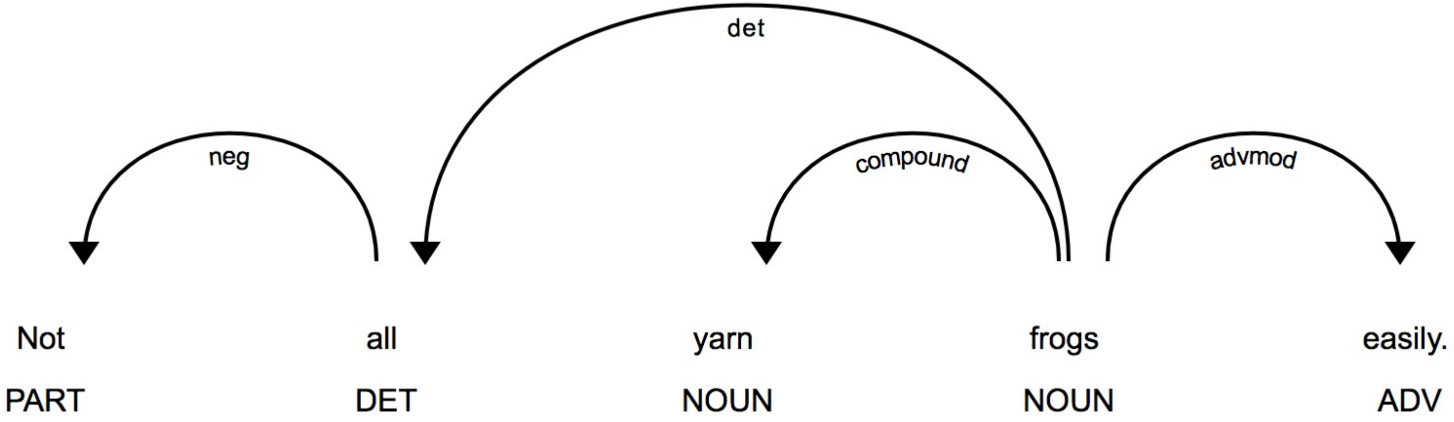
- Uniform Meaning Representations, provide a lightweight, flexible, *cross-linguistically general* format for capturing
  - Figurative language
  - Implicit arguments
  - Temporal and causal relations
  - Rich spatial configurations
  - Logical form
  - Tense, Aspect and Modality
- Both within and across sentences
- Are we done?

Bonn, et. al., LREC 2020

Lai, Donatelli, Pustejovsky, DMR 2020

Do universal dependencies give us what we need?

- *Not all yarn frogs easily.*



Do UMR's give us everything we want?

- *Not all yarn frogs easily.*

```
(f / frog-00
 :ARG1 (y / yarn
           :mod (a / all :polarity -))
    :ARG1-of (e / easy-05))
```

- *Word Embeddings? Maybe…..Verb + knitting?*
- Language use is endlessly creative, and new vocabulary, new usages and the long tail are always with us….

Acknowledgments

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- Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation, DARPA or NIH.