How do we get to general purpose NLU?

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Acknowledgments

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• Photo (kittens & puppy): Image by JacLou DL from Pixabay
This talk in a nutshell

• A whole pile of end-to-end systems does not general-purpose NLU make

• Systems, no matter how complex, trained only on form, won’t learn meaning
  • That’s not how babies do it either

• General-purpose NLU requires attention to linguistic structure and use

• Compositionality is key!
Outline

• Why this argument needs to be made

• Form v. meaning v. use v. world

• Linguistic knowledge (for developers and machines)

• Leveraging compositionality
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• Linguistic knowledge (for developers and machines)

• Leveraging compositionality
I've seen several different #NLProc folks suggesting today that it would be fun/interesting/worthwhile to use BERT or GPT-2 to fill in the redacted bits of the Mueller report. A short thread on why this is a terrible idea /1
“Unredacting”

I've seen several different #NLProc folks suggesting today BERT report

First: consider the importance of the ability to find news sources that you trust and how much interest there is in the document. If you put out a version of that document with invented text in place of the redactions, how long before someone reposts it as the real thing? /2
“Unredacting”

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I've seen several different #NLProc folks suggesting today BERT report.

8:31 PM

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First: consider the importance of the ability to find news source and the documentation with information before.

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How does that affect the discourse around what's actually contained in the (unredacted) version of the document, what it means, etc. both immediately and at some future point when the actual thing is available in full? How does it affect people's trust in reliable news? /3
I've seen several different #NLProc folks suggesting today BERT report.

First: consider the importance of the ability to find news sources in the document with information before.

How does that affect the discourse around what's actually contained in the document, what some future person full? How does

Second, examine why you think that BERT or GPT-2 generated answers would be interesting at all. Do you think that a big language model somehow can guess what the truth is and reveal it to you based on the rest of the document? /4
If so, you are wrong. Those are language models. They can only come up with sequences that are probable based on what's seen in the training data, given the prefix fed in. /5
“Unredacting”

If so, you are wrong. Those are language models. They can or can't be trained on fed in.

In other words, they can tell you about what's in the training data, not what's in the report. /6
“Unredacting”

If so, you are wrong. Those are language models. They can or can't be fed in.

In other words, they can tell you about what's in the training.

I haven't looked at the report, but I'm fairly confident the people doing the redacting would have been careful to do it in such a way that the redacted info furthermore is not predictable.

(And, ahem, that the black-out can't just be deleted...)
"Unredacting"

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If so, you are wrong. Those are language models. They can or cannot be fed in.

In other words, they can tell you about what's in the training.

I haven't looked at the report, but I'm fairly confident the people doing it in such a predictable way.

(And, ahem...)

So, please, just stop it with this idea. It's not funny nor helpful. If you're interested in applying #NLProc in ways relevant to the current political moment, how about working on e.g. rumor detection and tools that might help users think twice before retweeting/sharing? /fin
Word2vec and related methods are *shallow* approaches that trade expressivity for efficiency. Using word embeddings is like initializing a computer vision model with pretrained representations that only encode edges: they will be helpful for many tasks, but they fail to capture higher-level information that might be even more useful. A model initialized with word embeddings needs to learn from scratch not only to disambiguate words, but also to derive meaning from a sequence of words. This is the core aspect of language understanding, and it requires modeling complex language phenomena such as compositionality, polysemy, anaphora, long-term dependencies, agreement, negation, and many more. It should thus come as no surprise that NLP models initialized with these shallow representations still require a huge number of examples to achieve good performance.
“NLP’s ImageNet moment has arrived” (Sebastian Ruder: https://thegradient.pub/nlp-imagenet/)

Word2vec and related methods are *shallow* approaches that trade expressivity for efficiency. Using word embeddings is like initializing a computer vision model with pretrained representations that only encode edges: they will be helpful for many tasks, but they fail to capture higher-level information that might be even more useful. A model initialized with word embeddings needs to learn from scratch not only to disambiguate words, but also to derive meaning from a sequence of words. This is the core aspect of language understanding, and it requires modeling **long-term dependencies** and **world knowledge**.

In order to predict the most probable next word in a sentence, a model is required not only to be able to express syntax (the grammatical form of the predicted word must match its modifier or verb) but also model semantics. Even more, the most accurate models must incorporate what could be considered *world knowledge* or *common sense*. Consider the incomplete sentence "The service was poor, but the food was". In order to predict the succeeding word such as “yummy” or “delicious”, the model must not only memorize what attributes are used to describe food, but also be able to identify that the conjunction “but” introduces a contrast, so that the new attribute has the opposing sentiment of “poor”. 
Child language development requires more than just exposure to language (with or without vision)

• Learning from text only is not “just like babies do it”

• Early language acquisition is predicated on joint attention (Bruner 1985, Tomasello & Farrar 1986, inter alia)

• Even phonetic learning requires social engagement, exposure via TV or radio alone is insufficient (Kuhl 2007)
Outline

• Why this argument needs to be made

• **Form v. meaning v. use v. world**

• Linguistic knowledge (for developers and machines)

• Leveraging compositionality
Form v. meaning v. use v. world

• Form: text, speech, sign (+ paralinguistic information like gesture or tone)

• Conventional/standing meaning: logical form (or equivalent) that the linguistic system pairs with that form

• Communicative intent of the speaker: what they are publicly committed to by uttering that form (+ additional plausibly deniable inferences)

• Relationship between communicative intent & the world, e.g.:
  • True assertion, mistaken assertion, lie, accidentally true assertion, social act related to construction of social world, question about the interlocutor’s beliefs, …
Form v. meaning v. use v. world
Form v. meaning v. use v. world

- Form: ഒരു വാക്ക് ലോകത്തിലെ ഉപയോഗം
Form v. meaning v. use v. world

- **Form:** ഒരു ഭാഷ ഒരുക്കാവില

- **Conventional meaning:** “One language is never enough”
Form v. meaning v. use v. world

• Form: ഒന്ന് സവിശേഷതയും നമസ്കാരം

• Conventional meaning: “One language is never enough”

• Speaker intent: at a tourist market, after a long trip, while maintaining legacy code, …
Form v. meaning v. use v. world

• Form: ഒരു ഭാഷ ഒരിക്കൽ മതിയാവില്ല

• Conventional meaning: “One language is never enough”

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• Relationship to the world:
Form v. meaning v. use v. world

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• Relationship to the world: priceless!
Thought Experiment 1: Java
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• Model: Any model type at all
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• For current purposes: BERT (Devlin et al 2019), GPT-2 (Radford et al 2019), or similar
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- Test input: A single Java program, possibly even from the training data
- Expected output: Result of executing that program
Thought Experiment 2: English
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Thought Experiment 2: English

- Test input: A photograph plus a sentence like *How many dogs are jumping?* or *Kim said “What a cute puppy!” What is cute?*

- Expected output: *Three* or the region of the photo with the cute puppy.
That’s not fair!

• Of course not! What’s interesting about these thought experiments is what makes the tests unfair

• They’re unfair because the training data is insufficient for the task

• What’s missing: Meaning!
That’s not fair!

• Of course not! What’s interesting about these thought experiments is what makes the tests unfair

• They’re unfair because the training data is insufficient for the task

• What’s missing: Meaning!

You can’t learn meaning from form alone
So what do they learn?

• If the big transformers aren’t learning meaning, what makes them so effective?

• The ability to learn patterns:
  • Lexical similarity
  • Structural regularities
  • Artifacts in the data (Niven & Kao 2019)

• Useful, but not meaning and therefore not a path to general-purpose NLU
Adding Meaning to Training Data

- Stars on starred reviews (e.g. Yelp Inc, 2013)
- SQL queries paired with English queries (e.g. Zelle & Mooney, 1996)
- Paragraphs paired with hypotheses and entailment annotations (NLI datasets, e.g. Bowman et al, 2015)
- Photographs annotated with question/answer (VQA; Antol et al 2015)
- Word problems paired with algebraic equations (e.g. Kushman et al 2014)
- Voice assistant commands paired with expected actions

...
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How much of this is required before a system can learn what *insufficiently spicy* means?
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• **Linguistic knowledge (for developers and machines)**

• Leveraging compositionality
Complementary source of knowledge: Linguistics

- How language works
- Structures at varying levels
- How people learn language
- How people use language
- How language varies and changes over time
Linguistics in NLP

- Design of rule-based systems
- Design of annotation schemas to support machine learning
- Feature engineering in (older) machine learning
- Error analysis
#1 Morphosyntax is the difference between a sentence and a bag of words.

#20 Languages vary in how many morphemes they have per word (on average and maximally).

#46 Constraints ruling out some strings as ungrammatical usually also constrain the range of possible semantic interpretations of other strings.

#49 There is no one universal set of parts of speech, even among the major categories.

#88 Many (all?) languages have semantically empty words which serve as syntactic glue.
#4 Meaning derived from form is different from meaning in context of use.

#30 Words can have surprising nonce uses through meaning transfer.

#62 Evidentials encode the source a speaker credits the information to and/or the degree of certainty the speaker feels about it.

#76 Reference resolution depends on discourse structure.
#30 Words can have surprising nonce uses through meaning transfer

• Nunberg (2004) argues that it’s the predicates in (58a-e), not the arguments that bear transferred meanings

(58)  
  a. We are parked out back.
  b. I am parked out back and have been waiting for 15 minutes.
  c. *I am parked out back and may not start.
  d. Ringo squeezed himself into a narrow space.
  e. Yeats did not like to hear himself read in an English accent.
  f. The ham sandwich and salad at table 7 is getting impatient.

• (58f) involves a transferred predicate that is part of a noun phrase.
It’s challenging to represent the relationship between the meaning of an idiom and the meaning of its parts.

Nunberg et al (1994): Many idioms aren’t completely fixed phrases, but interact with internal modification (96a), information structure (96b), pronominal reference (96c), ellipsis (96d), and coordination (96e):

(96)   a. The team left no legal stone unturned.
      b. Those strings, he wouldn’t pull for you.
      c. We worried that Pat might spill the beans, but it was Chris who finally spilled them.
      d. My goose is cooked, but yours isn’t.
      e. Reinventing and Tilting At the Federal Windmill

Riehemann (2001): Distribute meaning of idiom across the words, but idiomatic words are only licensed by semantic constructions which also require the rest of the idiom to be present.
#79: Some linguistic expressions pass embedded presuppositions up, some don’t, and with others it depends

- Holes, plugs, and filters (Karttunen 1973)

- Holes:  
  (239)  
  a. Kim stopped smoking.
  b. Kim didn’t stop smoking.
  c. Kim hesitated to stop smoking.
  d. It surprised Sandy that Kim hesitated to stop smoking.
  e. Pat knew that it surprised Sandy that Kim hesitated to stop smoking.

- Plugs:  
  (240)  
  a. Kim promised the kids to introduce them to the present king of France.
  b. Kim accused the kids of hiding their candy.
  c. Kim asked Sandy to read the book again.
#79: Some linguistic expressions pass embedded presuppositions up, some don't, and with others it depends

- Holes, plugs, and filters (Karttunen 1973)

- Filters:

  (241)  a. Sandy believes that if the medicine cabinet door is open, then Kim’s cousin took an aspirin.
         b. Sandy believes that if Kim has a cousin, then Kim’s cousin took an aspirin.

  (242)  a. Sandy believes that Kim’s cousin had a headache and Kim’s cousin took an aspirin.
         b. Sandy believes that Kim has a cousin and Kim’s cousin took an aspirin.

  (243)  a. Sandy believes that either the medicine cabinet door is closed, or Kim’s cousin took an aspirin.
         b. Sandy believes that either Kim doesn’t have a cousin, or Kim’s cousin took an aspirin.
Why know these things?

- Better understanding of what is being fed into large machine learning models
- Better error analysis of what goes wrong
- Better understanding of the challenges between modern technology and full-scale, task-independent NLU
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A meaning representation system is compositional if (working definition; Bender et al 2015):

- it is grounded in a finite (possibly large) number of atomic symbol-meaning pairings
- it is possible to create larger symbol-meaning pairings by combining the atomic pairings through a finite set of rules;
- the meaning of any non-atomic symbol-meaning pairing is a function of its parts and the way they are combined;
- this function is possibly complex, containing special cases for special types of syntactic combination, but only draws on the immediate constituents and any semantic contribution of the rule combining them; and
- further processing will not need to destructively change a meaning representation created in this way to create another of the same type.
Semantic annotation survey:
Compositional layer

- Predicate-argument structure
- Partial constraints on:
  - Scope of negation and other operators
  - Restriction of quantifiers
  - Modality
  - Tense/aspect/mood
  - Information structure
- Discourse status of referents of NPs
- Politeness
- Possibly compositional, but not according to sentence grammar:
  - Coherence relations/rhetorical structure

- Under continuous development since 1993
- 1214 release: 225 syntactic rules, 70 lexical rules, 975 leaf lexical types
- Open-source and compatible with open-source DELPH-IN processing engines (www.delph-in.net)
- Broad-coverage: 85-95% on varied domains: newspaper text, Wikipedia, biomedical research literature (Flickinger et al 2010, 2012; Adolphs et al 2008)
  - Robust processing strategies enable 100% coverage
- Output: derivation trees paired with meaning representations in the Minimal Recursion Semantics framework---English Resource Semantics (ERS)
  - Emerging documentation at moin.delph-in.net/ErgSemantics
ERG: Examples

TOP: $h_0$
INDEX: $e_2$
RELS:
$h_4$: pron_rel(ARG0: $x_3$)
$h_5$: pronoun_q_rel(ARG0: $x_3$, RSTR: $h_6$, BODY: $h_7$)
$h_1$: "_forget_v_1_rel"(ARG0: $e_2$, ARG1: $x_3$, ARG2: $h_8$)
$h_9$: "_vote_v_1_rel"(ARG0: $e_{10}$, ARG1: $x_3$)

HCONS: $h_0 =_q h_1$, $h_6 =_q h_4$, $h_8 =_q h_9$

They forgot to vote.

[Diagram of ERG structure]
ERG: Examples

They forgot to vote.

[Diagram showing the parse tree and MRS for the sentence]
ERG: Examples
ERG: Examples

INDEX: e2
RELS:

h1: subord_rel(ARGO: e4, ARG1: h5, ARG2: h6)
h7: "_embarrassed/JJ_u_unknown_rel"(ARG0: e8, ARG1: i9)
h7: _over_p_rel(ARG0: e10, ARG1: e8, ARG2: x11)
h12: udef_q_rel(ARG0: x11, RSTR: h13, BODY: h14)
h15: nominalization_rel(ARG0: x11, ARG1: h16)
h16: "_let_v_l_rel"(ARG0: e17, ARG1: i18, ARG2: h19)
h20: pron_rel(ARG0: x21)
h22: pronoun_q_rel(ARG0: x21, RSTR: h23, BODY: h24)
h25: "_catch_v_l_rel"(ARG0: e26, ARG1: i27, ARG2: x21, ARG3: h28)
h25: _arg_d_rel(ARG0: e29, ARG1: e26, ARG2: x21)
h30: _on_p_rel(ARG0: e31, ARG1: x21, ARG2: x32)
h33: _the_q_rel(ARG0: x32, RSTR: h34, BODY: h35)
h36: "_verge_n_l_rel"(ARG0: x32)
h36: _of_p_rel(ARG0: e37, ARG1: x32, ARG2: x38)
h39: _such+a_q_rel(ARG0: x38, RSTR: h40, BODY: h41)
h42: "_naive/JJ_u_unknown_rel"(ARG0: e43, ARG1: x38)
h42: "_untruth_n_l_rel"(ARG0: x38)
h44: pron_rel(ARG0: x3)
h45: pronoun_q_rel(ARG0: x3, RSTR: h46, BODY: h47)
h48: "_cough_v_l_rel"(ARG0: e2, ARG1: x3)
h48: loc_nonspace_rel(ARG0: e49, ARG1: e2, ARG2: x50)
h51: udef_q_rel(ARG0: x50, RSTR: h52, BODY: h53)
h54: card_rel(CARG: "2", ARG0: e56, ARG1: x50)
h57: _or_c_rel(ARG0: e58, L-INDEX: e56, R-INDEX: e59, L-HNDL: h54, R-HNDL: h60)
h60: card_rel(CARG: "3", ARG0: e59, ARG1: x50)
h57: _times_n_l_rel"(ARG0: x50)
h62: "_in+order+to_x_rel"(ARG0: e63, ARG1: h64, ARG2: h65)
h66: _put_v_l_rel"(ARG0: e67, ARG1: x3, ARG2: x68, ARG3: h69)
h70: _the_q_rel(ARG0: x68, RSTR: h71, BODY: h72)
h73: "_little_a_l_rel"(ARG0: e74, ARG1: x68)
h73: _prince_n_of_rel"(ARG0: x68, ARG1: i75)
h76: _in_p_rel(ARG0: e77, ARG1: x68, ARG2: x78)
Redwoods: ERG-based treebanking (sembanking) (Oepen et al 2004)

• Minimal discriminants (Carter 1997): Properties of derivation trees partitioning parse forest per item

• Allows annotators to swiftly navigate even very large parse forests to select intended analysis or reject all analyses
  
  • 37,200 words of the Brown corpus annotated in 1400 minutes (1.7 sentences/min)

• All annotation decisions are recorded and can be rerun against updated parse forests produced by updated grammar versions

• Current Redwoods release (9th growth) includes 85,000 sentences of annotated text across genres including Wikipedia, tourism brochures, ...
Redwoods: ERG-based treebanking (sembanking) (Oepen et al 2004)

• Analyses can be viewed as full HPSG analyses, ERS only, or even simpler syntactic or semantic dependency representations

• Data source behind


  • ‘DM’ and ‘EDS’ representations in the CONLL 2019 shared task http://mrp.nlpl.eu/

• Unlimited ‘silver’ data can be generated at will using the grammar-based parser & treebank trained parse selection model

  • Beneficial in e.g. neural sentence realization (Hajdik et al 2019)
Why a grammar-based compositional approach?

• Importance of task-independent, sentence-meaning annotations

• Can created be done:

  • Non-compositionally, as in Abstract Meaning Representation (AMR; Langkilde & Knight 1998, Banarescu et al 2013)

  • Compositionally, by hand, as in PropBank (Kingsbury & Palmer 2002) and FrameNet (Baker et al 1998)

  • Compositionally, with a machine-readable grammar, as in Redwoods (Oepen et al 2004), TREPIL (Rosén et al 2005), or the Groningen Meaning Bank (Basile et al 2012)
Benefits of compositionality: Comprehensiveness

• Grammar-based compositional approach ⇒ Every word and syntactic structure must be accounted for, or specifically deemed semantically void

• Narrower paraphrase sets, compare AMR (1), (2) (Banarescu et al 2014) to ERS (3)

  (1)  a. No one ate.
  b. Every person failed to eat.

  (2)  a. The boy is responsible for the work.
  b. The boy is responsible for doing the work.
  c. The boy has the responsibility for the work.
Benefits of compositionality: Comprehensiveness

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• Narrower paraphrase sets, compare AMR (1), (2) (Banarescu et al 2014) to ERS (3)

(3) a. Kim thinks Sandy gave the book to Pat.
   b. Kim thinks that Sandy gave the book to Pat.
   c. Kim thinks Sandy gave Pat the book.
   d. Kim thinks the book was given to Pat by Sandy.
   e. The book, Kim thinks Sandy gave to Pat.
Benefits of compositionality: Comprehensiveness

- Task-independent semantic representations can’t abstract away from seemingly less relevant nuances of sentence meaning

- Compositional approach facilitates capturing more detail

\[
\begin{align*}
\langle h_1, & \\
& h_4 : \text{person}(0:6)(\text{ARG0 } x_5), \\
& h_6 : \text{no}_q(0:6)(\text{ARG0 } x_5, \text{RSTR } h_7, \text{BODY } h_8), \\
& h_2 : \text{eat}_v(7:11)(\text{ARG0 } e_3, \text{ARG1 } x_5, \text{ARG2 } i_9) \\
& \{ h_1 = q h_2, h_7 = q h_4 \} \\
\rangle
\end{align*}
\]

\[ (e / \text{eat-01} \\
\quad : \text{polarity} - \\
\quad : \text{ARG0} (p / \text{person} \\
\quad \quad : \text{mod} (e / \text{every})) \]

\[
\begin{align*}
\langle h_1, & \\
& h_4 : \text{every}_q(0:5)(\text{ARG0 } x_6, \text{RSTR } h_7, \text{BODY } h_5), \\
& h_8 : \text{person}_n(6:12)(\text{ARG0 } x_6), \\
& h_2 : \text{fail}_v(13:19)(\text{ARG0 } e_3, \text{ARG1 } h_9), \\
& h_{10} : \text{eat}_v(23:27)(\text{ARG0 } e_{11}, \text{ARG1 } x_6, \text{ARG2 } i_{12}) \\
& \{ h_1 = q h_2, h_7 = q h_8, h_9 = q h_{10} \} \\
\rangle
\end{align*}
\]
Benefits of Compositionality: Consistency

• Requiring meaning representations to be grounded in both the lexical items and syntactic structure of the strings being annotated significantly reduces the space of possible annotations

• Grammar based approach allows encoding of design decisions for machine application
  • Ex: arguments of *when*

• Human input still required, but choosing among representations is far simpler than authoring them
  • Development of grammar is still a big investment, but with big returns as the same grammar is applied over more and more text
Benefits of Compositionality: Scalability

• In amount of text annotated: Initial development of grammar pays off as it is applied to as much text as desired

• In genre diversity of the resource: One and the same grammar can be applied to texts from multiple different domains

  • Robustness techniques can compensate for lack of grammar coverage

• In the complexity of the annotations themselves: Grammar updates can be efficiently propagated across the treebank by reparsing corpus and rerunning annotation decisions (Oepen et al 2004)

  • Improve analyses of particular phenomena, or add layers of grammar-based annotation (e.g. partial constraints on information structure)
Inter-Annotator Agreement study

- Data source: Sentences sampled from Antoine de Saint Exupéry’s *The Little Prince*

- Three expert annotators

- Annotated 50-sentence trial set, then adjudicated, updating annotation guidelines as indicated

- Annotated 150-sentence sample set, then measured IAA, then produced adjudicated gold standard

- Repeat above steps with ‘bridging’ analyses in
Agreement Metrics

• NB: Chance-corrected IAA measures as yet unavailable for graph-structured annotations

• Exact match: Full ERS identical between annotators

• Elementary Dependency Match (Dridan & Oepen 2011)
  • Computed over sets of triples from reduction of ERS to Elementary Dependency Structures (EDS)
  • EDMa: Argument identification only
  • EDMna: Argument identification + predicate name identification
## IAA Results

<table>
<thead>
<tr>
<th>Metric</th>
<th>A vs. B</th>
<th>A vs. C</th>
<th>B vs. C</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exact Match</td>
<td>0.73</td>
<td>0.65</td>
<td>0.70</td>
<td>0.70</td>
</tr>
<tr>
<td>EDMₐ</td>
<td>0.93</td>
<td>0.92</td>
<td>0.94</td>
<td>0.93</td>
</tr>
<tr>
<td>EDMₙₐ</td>
<td>0.94</td>
<td>0.94</td>
<td>0.95</td>
<td>0.94</td>
</tr>
</tbody>
</table>

- Compare Banarescu et al (2013) triple-based IAA for AMR over web text of 0.71
This talk in a nutshell

• A whole pile of end-to-end systems does not general-purpose NLU make

• Systems, no matter how complex, trained only on form, won’t learn meaning
  • That’s not how babies do it either

• General-purpose NLU requires attention to linguistic structure and use

• Compositionality is key!
References


