

The continued relevance of rule-based semantic parsing in the era of deep learning

An introduction to the Universal Natural Language Understanding project

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Background

- **Semantic parsing:**
text \rightarrow symbolic meaning representation
- **State of the art:** train a neural network
 - Gets good results!
 - F1 scores in the high 80s
- **However:**
 - task not as easy as assumed
 - problems with robustness/hallucination
 - 'black boxes' not theoretically satisfying
- **So:** we are building a rule-based system

Precision

$$\frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

e.g. prec. of 2/3 means 2 out of 3 +ves are true +ves

Recall/Sensitivity

$$\frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

e.g. recall of 2/3 means 2 out of 3 relevant items found

F1 score

$$2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

i.e. the harmonic mean of precision and recall

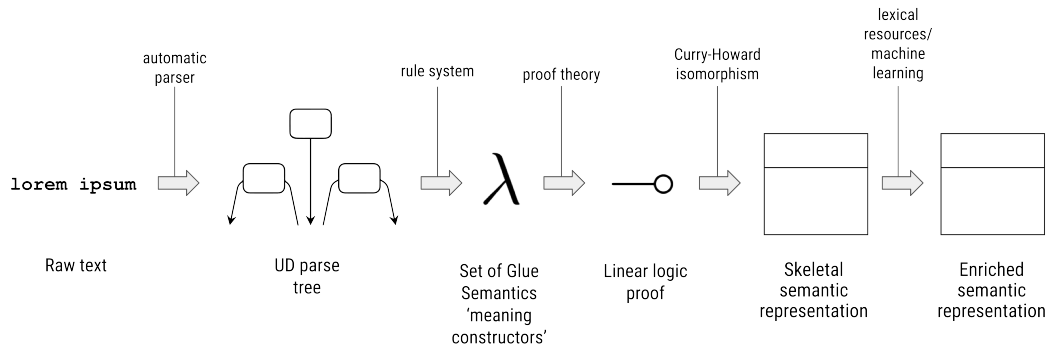
1. Background
2. The Universal Natural Language Understanding project
3. Universal Dependencies and semantic interpretation
4. Glue Semantics for UD
5. (Universal) rules for semantic interpretation
6. Comparison with the state of the art

The Universal Natural Language Understanding project

- *Universal Natural Language Understanding* is an RCN-funded project on computational semantics.
 - Dag Haug (PI)
 - Jamie Findlay (postdoc)
 - Ahmet Yildirim (senior engineer)
 - Saeedeh Salimifar (PhD fellow)
- It aims to build a system which can
 1. create rich, logic-based representations (specifically, DRSs); and
 2. do this for as many languages as possible.

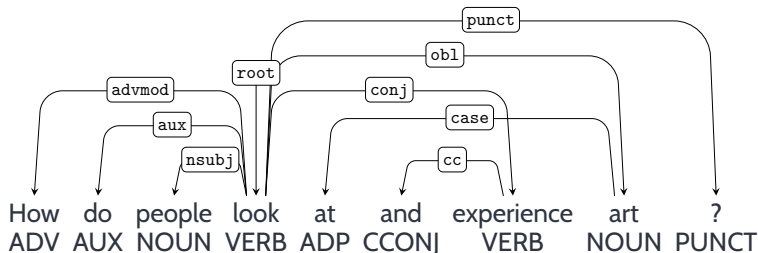
- The state of the art involves pure machine learning.
(van Noord et al. 2018; van Noord 2019; Evang 2019; Yıldırım & Haug 2023)
- Our approach combines machine learning with a rule-based core.
(Findlay et al. 2023)
 1. (shallow) syntactic parse (UD) (ML)
 2. symbolic meaning representation (DRS) (rule-based)
 3. further (e.g. lexical) enrichment (ML/rule-based)

Our pipeline



Universal Dependencies

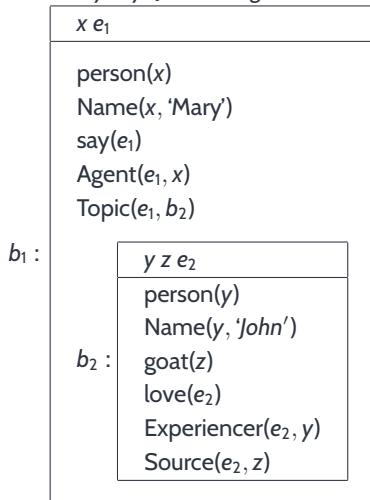
- We use a Universal Dependencies (UD) parse as our starting point. (Nivre et al. 2020)



- This is a shallow syntactic representation, which can therefore be hard to convert into a meaningful semantics.
 - Enhanced* Universal Dependencies add more semantically-relevant information, but have their limitations. (Findlay & Haug 2021)
- On the plus side, structures like this are available for 100+ languages.

Semantic representations

Mary says John likes goats.



Discourse Representation Structures (DRSs)

- discourse referents + conditions on discourse referents
- DRSs can be embedded inside other DRSs (also under negation, disjunction, modal operators, ...)
- Translatable to first-order logic for use with theorem provers.

(Kamp & Reyle 1993; Kamp et al. 2011)

The Parallel Meaning Bank

- One good reason for choosing DRS representations is the existence of the **Parallel Meaning Bank (PMB)**, which contains DRS representations for sentences in English, German, Dutch and Italian. (Abzianidze et al. 2017)

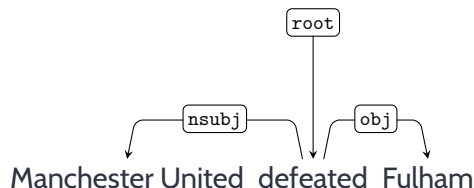
Manchester United defeated Fulham.

x1	x2	e1	t1
team(x1)			
Name(x1, manchester~united)			
time(t1)			
t1 < now			
defeat(e1)			
Time(e1, t1)			
Co-Agent(e1, x2)			
Agent(e1, x1)			
team(x2)			
Name(x2, fulham)			

b1 REF x1	% Manchester~United [0...17]
b1 Name x1 "manchester~united"	% Manchester~United [0...17]
b1 PRESUPPOSITION b3	% Manchester~United [0...17]
b1 team "n.01" x1	% Manchester~United [0...17]
b3 REF e1	% defeated [18...26]
b3 REF t1	% defeated [18...26]
b3 Agent e1 x1	% defeated [18...26]
b3 Co-Agent e1 x2	% defeated [18...26]
b3 TPR t1 "now"	% defeated [18...26]
b3 Time e1 t1	% defeated [18...26]
b3 defeat "v.01" e1	% defeated [18...26]
b3 time "n.08" t1	% defeated [18...26]
b2 REF x2	% Fulham [27...33]
b2 Name x2 "fulham"	% Fulham [27...33]
b2 PRESUPPOSITION b3	% Fulham [27...33]
b2 team "n.01" x2	% Fulham [27...33]
	% . [33...34]

Universal Dependencies and semantic interpretation

From UD tree to DRS



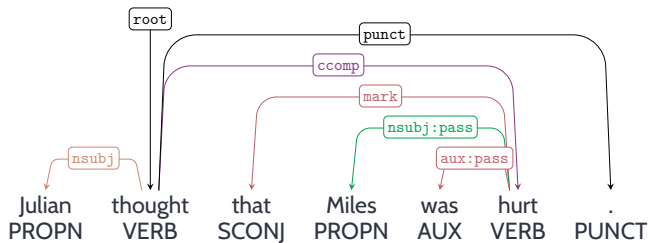
x1	x2	e1	t1
team(x1)			
Name(x1, manchester~united)			
time(t1)			
t1 < now			
defeat(e1)			
Time(e1, t1)			
Co-Agent(e1, x2)			
Agent(e1, x1)			
team(x2)			
Name(x2, fulham)			

- It looks like we only need to map tokens 1, 2, 3 to discourse referents x_1 , e_1/t_1 and x_2 , then do some labelling.
- There is some truth to this and it has inspired frameworks like UDepLambda.

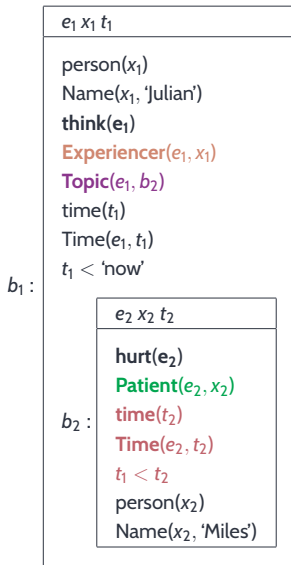
(Reddy et al. 2017)

- But the question is whether we can do more as the syntactic and semantic representations grow in complexity!

What UD offers



1. Consistent representations of most predicate-argument structures
2. Separation of function words and content words



What UD lacks

1. Predicate-argument relations, functional relations, and lemmas offer only coarse-grained information:
 - `nsubj` \mapsto *Agent* or *Experiencer* or something else?
 - `aux` – encodes tense, modality or something else?
 - sense disambiguation of lexical items?
2. The shallow UD structure leaves some meaningful relations unexpressed or under-expressed (e.g. control, coordination), and raises questions about compositionality.

- Montague-style compositionality poses two problems for a dependency grammar-style syntax:
 - the homomorphism problem
 - the lexical integrity problem
- (Haug & Findlay 2023)

Homomorphism Syntax and lexicon must jointly *determine* meaning (cf. QR), and syntax must be binary branching – not the case in a dependency grammar.

Lexical integrity Words are atoms, but sometimes we want them to contribute more than one meaning that can interact independently with other meanings.

- Even if we can translate UD syntactic nodes into lambda terms, it is not clear that the UD syntax is specific enough to guide the composition of those terms.
- So we take the lead from another framework with similar issues: **LFG + Glue Semantics**

Glue Semantics for UD

What is Glue?

- A theory of the syntax-semantics interface, originally developed for **Lexical Functional Grammar (LFG)**, and now the mainstream in LFG.

(Dalrymple et al. 1993; Dalrymple 1999; Asudeh 2022)

- Has been applied to other frameworks:
 - HPSG (Asudeh & Crouch 2002)
 - LTAG (Frank & van Genabith 2001)
 - Minimalism (Gotham 2018)
- Meanings are paired with a *composition logic* (a fragment of linear logic) to form a **meaning constructor**; semantic composition is deduction in the logic, mediated by the Curry-Howard isomorphism.

(Curry & Feys 1958; Howard 1980)

A crude characterisation would be that Glue Semantics is like categorial grammar and its semantics, but without the categorial grammar.

(Crouch & van Genabith 2000)

The idea behind Glue semantics

The syntax is not (and should not be!) specific enough to guide composition of lambda terms, so we introduce a specific combinatory logic for lambda terms.

$$\frac{\frac{\lambda x. \lambda y. \text{love}(x, y) : A \multimap B \multimap C \quad \text{naomi} : A}{\lambda y. \text{love}(\text{naomi}, y) : B \multimap C} \quad \text{jim} : B}{\text{love}(\text{naomi}, \text{jim}) : C}$$

- This looks a lot like categorial grammar!
- But decoupled from surface syntax, which is good for universality

The Curry-Howard isomorphism

Operations in the lambda calculus correspond to inference rules in the logic.

Function application : implication elimination

$$\frac{f : A \multimap B \quad a : A}{f(a) : B} \multimap_{\mathcal{E}}$$

Lambda abstraction : implication introduction

$$\frac{\begin{array}{c} [a : A]^1 \\ \vdots \\ f : B \end{array}}{\lambda x. f : A \multimap B} \multimap_{\mathcal{I},1}$$

Switching argument orders

Question: does making *love* type $A \multimap B \multimap C$ specify a particular composition order?

No, because...


$(A \multimap B \multimap C) \multimap (B \multimap A \multimap C)$ is a theorem of linear logic.

$$\frac{\frac{\lambda x. \lambda y. \text{love}(x, y) : A \multimap B \multimap C \quad [a : A]^1}{\lambda y. \text{love}(a, y) : B \multimap C} \quad [b : B]^2}{\text{love}(a, b) : C} \multimap_{\mathcal{I},1} \frac{\lambda x. \text{love}(x, b) : A \multimap C}{\lambda y. \lambda x. \text{love}(x, y) : B \multimap A \multimap C} \multimap_{\mathcal{I},2}$$

Other advantages

- There is also other stuff we get for free, like type raising operators:
 $A \multimap ((A \multimap B) \multimap B)$ is also a theorem.
- There is an efficient proof algorithm (based on CYK) and a good implementation (the Glue Semantics Workbench). (Hepple 1996; Lev 2007; Messmer & Zymla 2018)
- Glue's approach to scope solves the homomorphism problem.

Quantifier scope ambiguities

(1) *Someone loves everyone.*  $\exists > \forall$ – someone has a lot of love to give
 $\forall > \exists$ – everyone is loved

- Faced with the homomorphism problem, transformational theories treat this ambiguity as syntactic.
- Glue can treat it as genuinely semantic: different scopings correspond to different proofs from the same premises.

Quantifier scope ambiguity: surface scope

<div> <i>loves</i> $\lambda x. \lambda y. \text{love}(x, y) :$ $A \multimap B \multimap C$ </div>		<div> $[a : A]^1$ </div>	<div> <i>everyone</i> $\lambda P. \forall z. \text{person}(z) \rightarrow P(z) :$ $(B \multimap C) \multimap C$ </div>
<div> $\lambda y. \text{love}(a, y) :$ $B \multimap C$ </div>			
		<div> $\forall z. \text{person}(z) \rightarrow \text{love}(a, z) :$ C </div>	
		<div> $\lambda x. \forall z. \text{person}(z) \rightarrow \text{love}(x, z) :$ $A \multimap C$ </div>	<div> $\multimap_{\mathcal{I},1}$ </div>
		<div> $\exists x. \text{person}(x) \wedge (\forall z. \text{person}(z) \rightarrow \text{love}(z, x)) :$ C </div>	<div> <i>someone</i> $\lambda P. \exists x. \text{person}(x) \wedge P(x) :$ $(A \multimap C) \multimap C$ </div>

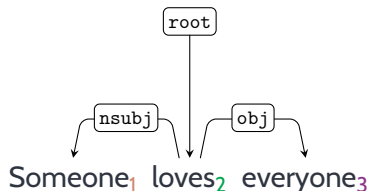
Quantifier scope ambiguity: inverse scope

$$\begin{array}{c}
 \boxed{\begin{array}{l} \text{loves} \\ \lambda x. \lambda y. \text{love}(x, y) : \\ A \multimap B \multimap C \end{array}} \quad [a : A]^1 \\
 \hline
 \lambda y. \text{love}(a, y) : \\
 \hline
 B \multimap C \quad [b : B]^2 \\
 \hline
 \text{love}(a, b) : \\
 \hline
 \frac{C}{\lambda x. \text{love}(x, b) :} \multimap_{\mathcal{I},1} \\
 A \multimap C \quad \boxed{\begin{array}{l} \text{someone} \\ \lambda P. \exists x. \text{person}(x) \wedge P(x) : \\ (A \multimap C) \multimap C \end{array}} \\
 \hline
 \exists x. \text{person}(x) \wedge \text{love}(x, b) : \\
 \hline
 \frac{C}{\lambda y. \exists x. \text{person}(x) \wedge \text{love}(x, y) :} \multimap_{\mathcal{I},2} \\
 B \multimap C \quad \boxed{\begin{array}{l} \text{everyone} \\ \lambda P. \forall z. \text{person}(z) \rightarrow P(z) : \\ (B \multimap C) \multimap C \end{array}} \\
 \hline
 \forall z. \text{person}(z) \rightarrow (\exists x. \text{person}(x) \wedge \text{love}(x, z)) : \\
 C
 \end{array}$$

Connecting up with the syntax

- The lexical entry of *loves* cannot really use atomic categories like *A*, *B* and *C*.
- Instead, we use a first-order system where predicates are **type constructors** that apply to nodes as terms to yield **types**.
- Writing $\hat{*}$ for the current node,
 - $E(\hat{*})$ is a type *e* meaning for that node
 - $T(\hat{*})$ is a type *t* meaning for that node
 - $E(\hat{*}) \multimap T(\hat{*})$ is a function type between the two (e.g. the type of a bare noun)
- Moreover, we can use **path descriptions** based on syntactic labels:
 - $E(\hat{*} \text{ nsubj})$ is a type *e* meaning for the current node's (nominal) subject
 - $E(\hat{*} \text{ obj})$ is a type *e* meaning for the current node's object
 - $E(\hat{*} \text{ nsubj}) \multimap E(\hat{*} \text{ obj}) \multimap T(\hat{*})$ is the type we need for *loves*

Another example



- Using \uparrow to refer to the current node's mother, we assign the following types:

someone $[E(\hat{*}) \multimap T(\uparrow)] \multimap T(\uparrow)$ i.e. $[E(1) \multimap T(2)] \multimap T(2)$

loves $E(\hat{*} \text{ nsubj}) \multimap E(\hat{*} \text{ obj}) \multimap T(\hat{*})$ i.e. $E(1) \multimap E(3) \multimap T(2)$

everyone $[E(\hat{*}) \multimap T(\uparrow)] \multimap T(\uparrow)$ i.e. $[E(3) \multimap T(2)] \multimap T(2)$

- This is isomorphic to the atomic types we used: $E(1) \mapsto A$, $E(3) \mapsto B$, $T(2) \mapsto C$, and so we get the same proofs

- Glue allows us to build logical representations from dependency trees without requiring arbitrary binarization or lexical decomposition.
- The syntax can underspecify the semantics – this also makes it easier to “offload” work to the interface.
 - E.g. restrictions on gaps in relative clauses.

(Haug & Findlay 2023: 28–30)

(Universal) rules for semantic interpretation

Rules for semantic interpretation

- Rules have two parts:
Condition(s) -> Meaning constructor
- UD tree inspected node by node, via custom Haskell script.
- Meanings expressed in format of Python NLTK package. (Garrette & Klein 2009)
- Sample ruleset available at <https://github.com/Universal-NLU/UNLU>.

Based on part of speech

```
coarsePos = PROPEN -> \X.(([], [Name(X, ':LEMMA:')])) : e(!) -o t(!)
```

$$\lambda X. \boxed{\text{Name}(X, \text{' :LEMMA:'})} : E(\hat{*}) \multimap T(\hat{*})$$

Based on UD relation

```
relation = nsubj; ^ {coarsePos = VERB} ->
\Q.\V.\F.(Q(\X.(V(\E.([ ], [nsubj(E,X)])) + F(E)))) :
((e(!) -o t(^)) -o t(^)) -o (x(^) -o x(^))
```

$$\lambda Q \lambda V \lambda F. Q(\lambda X. (V(\lambda E. \boxed{\text{nsubj}(E, X)} + F(E)))) : [[(E(\hat{*}) \multimap T(\uparrow)) \multimap T(\uparrow)] \multimap X(\uparrow) \multimap X(\uparrow)]$$

$(x \equiv \langle \langle v, t \rangle, t \rangle)$

Based on features

```
coarsePos = VERB; ~ aux.*; Tense = Pres ->  
\V.\F.(V(\E.([T], [time(T), EQ(T, 'now'), Time(E, T)]) + F(E)))) :  
x(!) -o x(!)
```

$$\lambda V \lambda F. V(\lambda E. \begin{array}{|l|} \hline T \\ \hline \text{time}(T) \\ T = \text{'now'} \\ \text{Time}(E, T) \\ \hline \end{array} + F(E)) : X(\hat{*}) \multimap X(\hat{*})$$

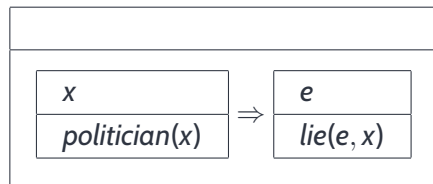
Dealing with structure-meaning interactions

Some meanings affect the structure of the DRS:

(2) *A politician lies.*

x e
$politician(x)$
$lie(e, x)$

(3) *Every politician lies.*



- We therefore allow some lemma-based rules for ‘logic words’ like quantifiers, negation, etc.
- Ideally these would be identifiable from features alone, but this is not the case.

Lemma-specific rules

```
relation = det; lemma = "every" ->
\P.\Q.([ ],[ ( ( [X],[ ]) + P(X) ) => (Q(X)) ) ] ) :
(e(^) -o t(^)) -o (e(^) -o t(^ ^)) -o t(^ ^)
```

$$\lambda P.\lambda Q. \left(\begin{array}{|c|} \hline X \\ \hline \end{array} + P(X) \right) \Rightarrow Q(X) : [E(\uparrow) \multimap T(\uparrow)] \multimap [E(\uparrow) \multimap T(\uparrow\uparrow)] \multimap T(\uparrow\uparrow)$$

Language parametrisation

```
1  "eng": {  
2    "stanza_lang_code": "en",  
3    "typological_features": {  
4      "negative_concord": "no",  
5      "sequence_of_tense": "yes",  
6      "grammatical_gender": "no"  
7    },  
8    "lexical_items": {  
9      "future_aux": "will",  
10     "definite_det": "(the|this|that)",  
11     "indefinite_det": "(a|some)",  
12     "universal_quantifier": "(every|each)",  
13     "infinitive_marker": "to",  
14     "conjunction": "and",  
15     "disjunction": "or"  
16   },  
17 }
```

- Mark-Matthias Zymla has developed a web interface for a rule-based semantic interpretation system based on LFG+Glue.
- Our system can also be accessed via this interface.

Comparison with the state of the art

At first sight, hopeless!

	PMB 2.2.0		PMB 3.0.0		PMB 4.0.0		
	dev	test	dev	test	dev	test	eval
van Noord et al. (2020)	86.1	88.3	88.4	89.3	–	–	–
Liu et al. (2021)	–	88.7	–	–	–	–	–
Yildirim & Haug (2023)	87.5	89.2	89.8	90.3	88.1	89.0	86.9

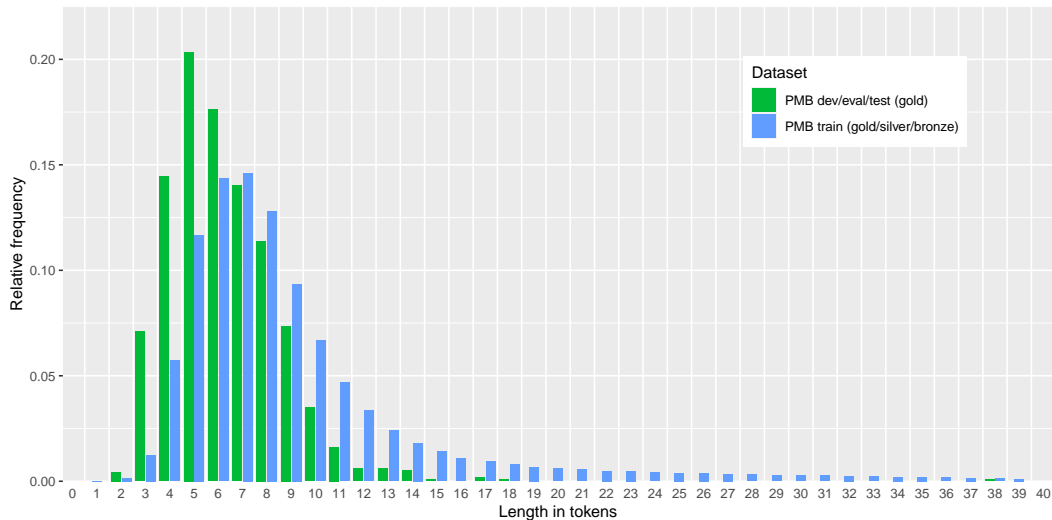
Table 1: Recently reported F1 scores for PMB 2.2.0, 3.0.0, and 4.0.0 datasets

Language	Raw	Structural
German (de)	30.8	59.6
English (en)	46.7	63.4
Italian (it)	30.7	58.9
Dutch (nl)	28.6	58.4
AVERAGE	34.2	60.1

Table 2: F1 scores from the rule-based system on PMB 4.0.0 test set

But DRS parsing isn't as easy as it seems ...

Sentence length in the PMB



The DRASTIC corpus

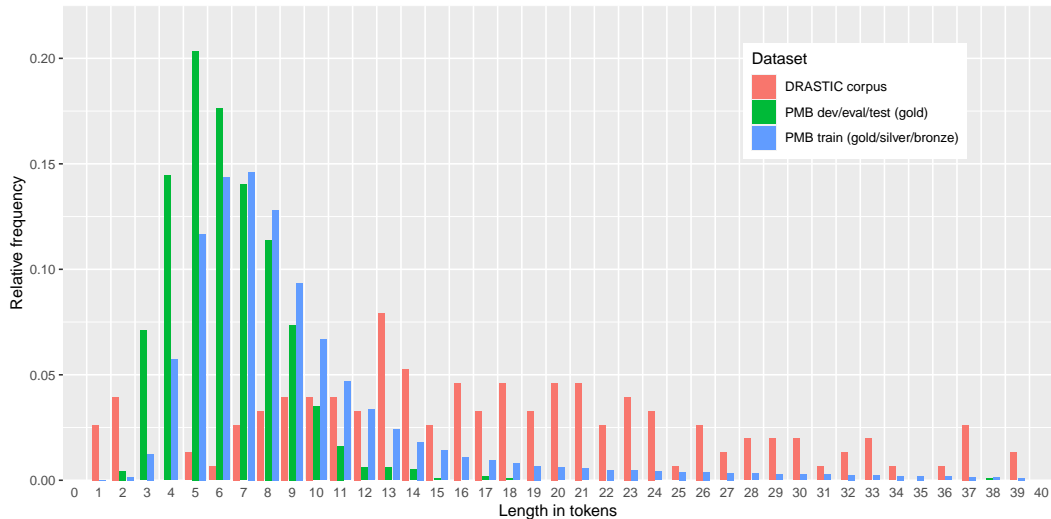
- To provide more representative test data, we annotated ~ 3000 words of naturally-occurring texts, taken from the GUM corpus.
(Zeldes 2017)
- We call this the DRASTIC corpus ('Discourse Representation Annotations with Sentence Texts of Increased Complexity').¹
(Haug et al. 2023)

(Sub-)corpus	Median	Mean	St.dev.
dvorak	23	23.9	9.68
marbles	17	19.6	12.4
nida	18	19.1	11.1
short-texts	13	12.8	4.29
DRASTIC (all)	17	18.5	10.6
PMB (all)	8	10.0	9.53
PMB (test only)	6	6.60	2.08

Table 3: Sentence length across (sub-)corpora

¹Available here: <https://github.com/Universal-NLU/DRASTIC>

Sentence length in the PMB and DRASTIC

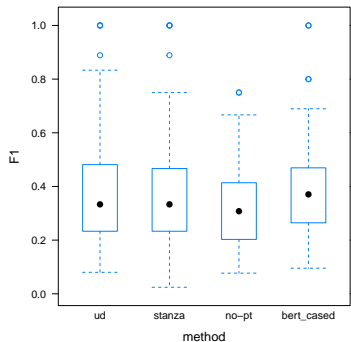


Performance on DRASTIC

- The advantage of neural networks drops off almost entirely!

(cf. Yao & Koller 2022; Donatelli & Koller 2023)

- The best neural parser from the PMB experiments achieves an F1 score of only **36.2** on the DRASTIC texts.



- Rule-based systems scale better than stochastic models.
- The neural nets often struggle with complex sentences involving negation and other scopal operators.

(4) *While the impact of a translation may be close to the original, there can be no identity in detail.*

Correct: $\Diamond[\dots] \wedge \neg\Diamond[\dots]$

ML: $\Diamond\Diamond\neg[\dots]$

Robustness – coverage

- The lambda calculus, like other rule-based approaches, is brittle.
 - If there is a type clash, the result is undefined.
- There are still many instances our rules don't cover.
- We do not want a failure in one place to cause the whole proof to fail.
- In many cases, even if we don't know what the meaning of some subconstituent is, we do know *what type* it should be.
 - For example, we consistently treat arguments as event modifiers; and we know that conjuncts should have the type of their head.
- So we can provide a default “placeholder” semantics of the correct type in case the computation fails.

Example

Dvořák's own style has been described as "the fullest recreation of a national idiom with that of the symphonic tradition, absorbing folk influences and finding effective ways of using them".

e y z u x t

Name(x, 'dvořák')

poss(y, x)

own(z)

Attribute(y, z)

style(y)

describe(e)

time(t)

TPR(t, 'now')

Time(e, t)

nsubj-pass(e, y)

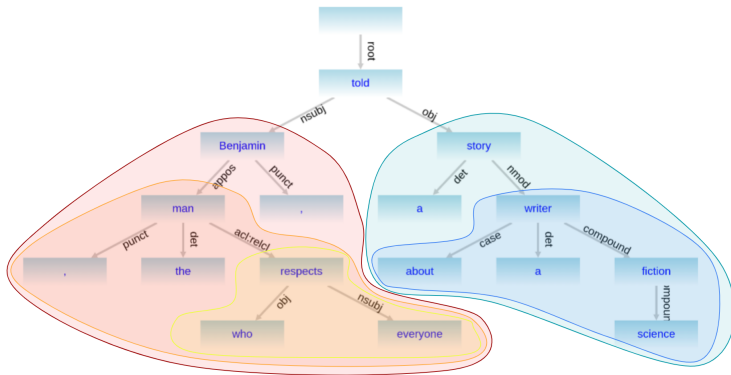
obl(e, u)

DUMMY(u)

Multistage proving

- We achieve this by ‘chopping’ the UD tree and processing the Glue proof for each part separately.

Benjamin, the man everyone respects, told a story about a science fiction writer



- This helps constrain both spurious and unattested ambiguities. (Findlay & Haug 2022)

- The rules are much more likely to miss things out than put extraneous things in.
- By contrast, the ML systems, as always, are prone to 'hallucinations'.
 - teenager, what teenager?
 - female YouTube
- The rules will consistently get names right (they just lift the lemmas); the ML output goes very wrong here.
 - E.g. (*Jenna*) *Marbles* rendered as 'georgia strawberry', 'marau', 'margis', 'name', etc.
 - Evidence that models overfit to peculiarities of the PMB training data? (e.g. at least 15% of the sentences across the PMB subsets contain the name *Tom* ...)

Summing up

- The syntactic scaffolding of Universal Dependencies provides a suitable basis for building semantic representations.
- One key advantage is that UD parsers are available for many languages, whereas richer syntactic parsers are not.
 - We can provide (at least skeletal) semantic representations for all these languages.
- Neural approaches apparently outperform rule-based systems, **but** DRS parsing is not as easy as the PMB test set would lead us to believe.
- Definitely a role for rule-based systems:
 - increased robustness when it comes to length and complexity
 - more reliable when it comes to systematic correspondences (e.g. names)
 - more theoretically illuminating

References i

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Natural language inference

- **Natural language inference:** an in-demand NLP task – given a text, what follows?
 - Especially important for question-answering systems.
- Modern computational approaches treat NLI as a classification problem over sentence pairs, without explicit modelling of semantic structure.

(e.g. Bowman et al. 2015; Jiang & de Marneffe 2019)

- Results can be good, but seem often to rely on quirks of the datasets to extract incorrect generalisations that are effective, but brittle and easily misled (e.g. by passivisation).

(McCoy et al. 2019)

Natural Language Inference

- NLI can be straightforward given an suitable logical representation of the premise:

(5) Before John left, Mary slept.
 \Rightarrow John left.

(6) $leave(e_1, j) \wedge sleep(e_2, m) \wedge before(e_2, e_1)$

(7) $A \wedge B \vdash A$

(8) If Mary shouted, John ran.
 \nRightarrow Mary shouted.

(9) $shout(m) \rightarrow run(j)$

(10) $A \rightarrow B \nvdash A$

- At the same time, purely logical entailments are rare – we often need access to e.g. lexical information.

(Bos & Markert 2005)

Post-processing

- Output of rule-system is underspecified; language-specific information added when available, such as
 - Translation of UD relations to thematic roles

Jim loves Naomi.

<i>e x y</i>		<i>e x y</i>
<i>person(x)</i>	\Rightarrow	<i>person(x)</i>
<i>Name(x, 'Jim')</i>		<i>Name(x, 'Jim')</i>
<i>person(y)</i>		<i>person(y)</i>
<i>Name(x, 'Naomi')</i>		<i>Name(x, 'Naomi')</i>
<i>love(e)</i>		<i>love(e)</i>
nsubj(e, x)		Experiencer(e, x)
obj(e, y)		Source(e, y)

- Also (to come):
 - Idioms/multiword expressions
 - Anaphora resolution

More challenging constructions

- Relativization: many languages have no overt indication of the gap site
 - we generate possible gap sites
- Control: no subject vs. object control distinction
 - underspecified relation
- Coordination: collapse of first conjunct and coordination as a whole, always assumes like function coordination