Graph-Based Meaning Representations:

Design and Processing



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Stephan Oepen University of Oslo oe@ifi.uio.no Weiwei Sun Peking University ws@pku.edu.cn I reached into that funny little pocket that is high up on my dress.

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- ▶ What types of information are at play in reasoning about entailment?
- ▶ Who did what to whom, when and where? Reference, veridicality, etc.

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- Logical inference or distributional approximation, both need structure.

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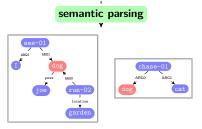


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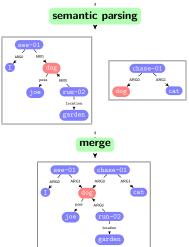
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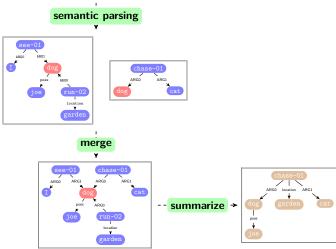
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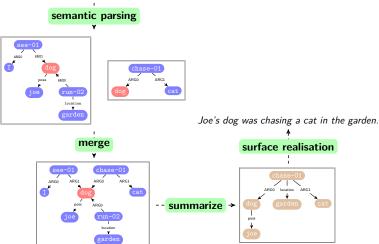
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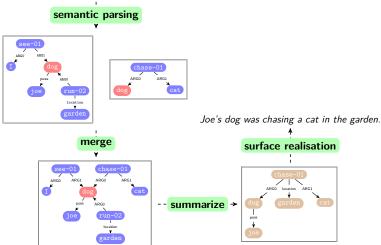
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Hardy & Vlachos (2018): 2⁺ ROUGE points over strong encoder–decoder.

High-Level Goals of the Tutorial



Graph-Based Representations of Meaning

- ► Vast, complex landscape of representing natural language meaning;
- diverse linguistic traditions, modeling assumptions, levels of ambition;
- ▶ some differences are superficial (e.g. terminology), others run deeper;
- $\,\rightarrow\,$ clarify concepts and vocabulary; high-level survey of selected resources.

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Parsing into Graph-Structured Representations

- Cottage industry of parsers with output structures beyond rooted trees;
- distinct techniques, e.g. based on transitions, composition, 'translation';
- ▶ much framework-internal evolution: design reflects specific assumptions;
- $\rightarrow\,$ tease apart sub-tasks and families of approaches; review representatives.

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Community Fragmentation and 'Balkanization'

► Cross-Framework Perspective: Seek commonality and complementarity.

Outline: Our Game Plan



- (1) & (2) Foundations: Linguistic & Formal (0:30)
- ▶ Introduce various 'facets' (or layers) of meaning; common terminology.
- (3) Graph-Based Meaning Banks (0:45)
- Selective and terse review of five English corpora with semantic graphs;
- ▶ highlight distinct design decisions and goals; contrast across schools.
- (4) Parsing into Semantic Graphs (1:00)
- ► Factorization-, composition-, transition-, translation-based techniques;
- ▶ graph similarity evaluation; cross-framework and cross-lingual parsing.
- (5) & (6) Outlook: Using Semantic Graphs (0:15)
 - ► Example use cases: summarization, entity linking, machine translation.

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(Some) Time for Questions at the End of Each Block; Please Introduce Yourself (Name & Affiliation).

Foundations: Semantics



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Abrams gave a book to Browne.
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- ► Superficially different linguistic forms can describe the same situation;
- ▶ hold true under the same circumstances; can substitute for each other;
- → close paraphrases: convey the 'same meaning' (in unmarked contexts).



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Common Distinction in Linguistic Semantics—Challenging to Make Precise

He wants to be seen by her. vs. He wants her to see him.



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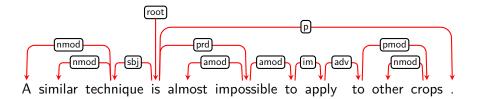


Sherlock saw the suspect with the binoculars.



Syntactic Trees vs. Semantic Graphs [WSJ #0209013]

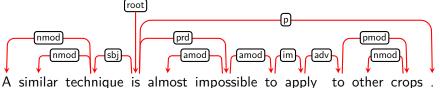




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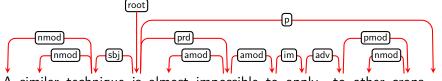
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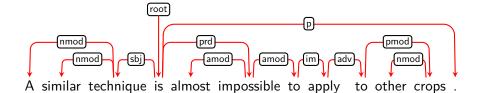


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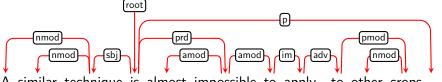
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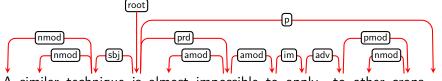


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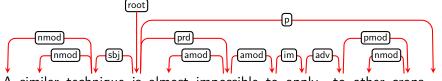


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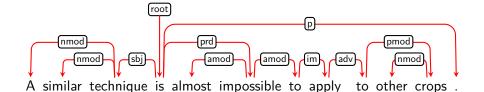
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Different Desiderata (and Levels of Abstraction)

► Grammaticality (e.g. subject—verb agreement) vs. relational structure.



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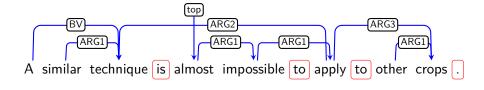
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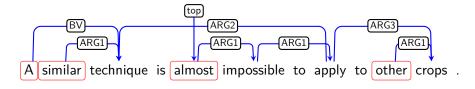
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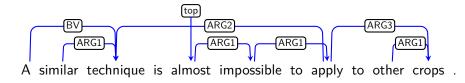
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- \rightarrow massive growth in modeling and algorithmic complexity (NP-complete).



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- ► Heads license and govern, e.g. verbs, relational nouns, prepositions;
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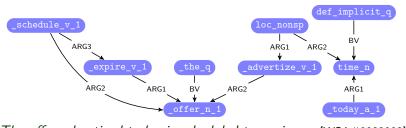
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▶ Prepositions *on* or *in* as two-place relations, e.g. temporal or locative.

Reflections on Predicate-Argument Structure



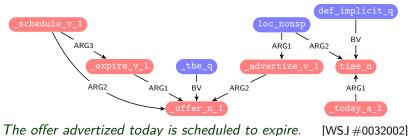
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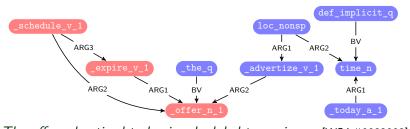


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\mathsf{offer'}(x) \land \mathsf{schedule'}(\_, x, \mathsf{expire'}(x))
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The offer advertized today is scheduled to expire.

[WSJ #0032002]

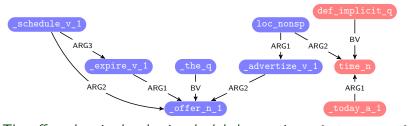
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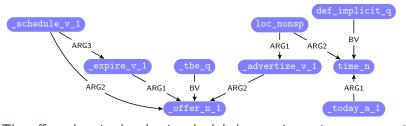
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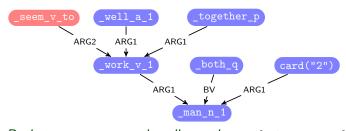


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Mismatches between Syntax and Semantics

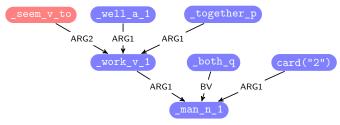




- Both men seem to work well together. [WSJ#0109043]
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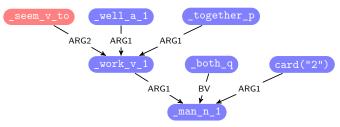




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- ► consider close paraphrase: *It seems that both men work well together.*
- expletive it subject is not referential, hence no semantic contribution;
- ▶ about two dozen subject raising verbs in broad-coverage English lexicon.

Example Design Decisions: Copula Constructions

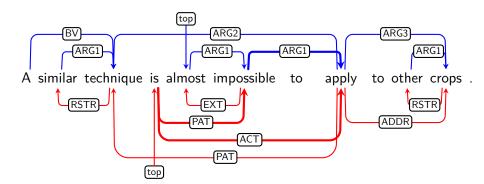


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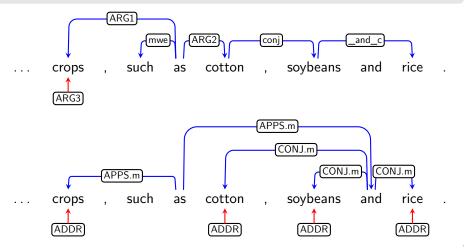


- ► There is much variation in analysis of individual linguistic phenomena;
- specific semantic framework requires many interacting design decisions;
- divergent views already at the level of which words are content-bearing;
- ▶ for example, the predicative copula: the fierce dog vs. the dog is fierce.



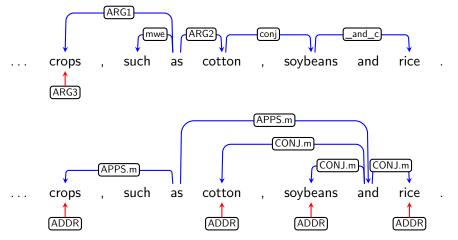
Example Design Decisions: Coordination

- ▶ No less frequent: coordinate structures (sometimes called parataxis);
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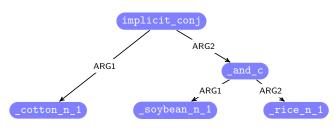
- ► No less frequent: coordinate structures (sometimes called parataxis);
- ▶ different types: Abrams arrived and ate vs. Abrams and Brown arrived.
- ▶ intuitively, a kind of 'grouping'; how to represent the group as a whole?



Further Variations on Coordination



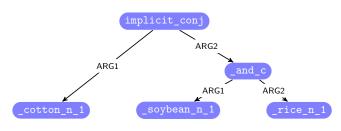
cotton, soybeans, and rice

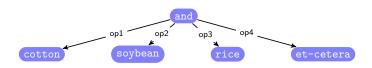


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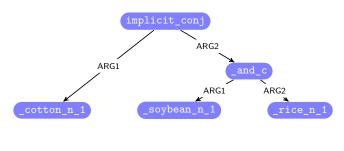


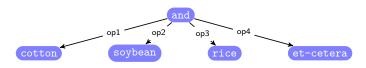


Further Variations on Coordination



cotton, soybeans, and rice





Popel et al. (2013): nine distinct syntactico-semantic dependency patterns.

Background: Partial Predicate–Argument Structures



- ► Predicate—argument structure with strong focus on verbal predicates;
- ▶ large, manually annotated corpora available (for multiple languages), e.g. Framenet (Baker et al., 1998), PropBank (Palmer et al., 2005);

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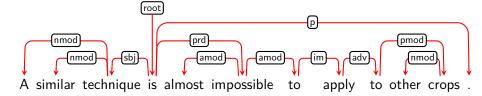


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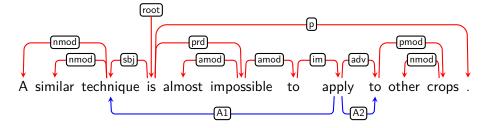
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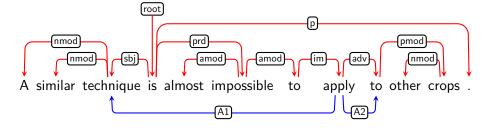


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Since Late 1990s, Semantic Role Labeling (SRL)

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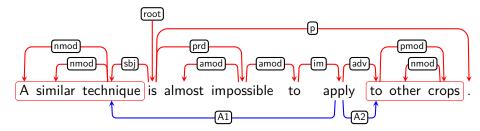
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- Several (semantic) predicate—argument relations remain unannotated;
- ► conversion to bilexical dependency graphs, head selection from syntax.

Beyond Predicate-Argument Structure



Many NL expressions add <u>logical structure</u> on top of the predicate—argument structure.

Negation

- ► John does not eat cookies.
- John said that Mary does not like cookies. vs. John did not say that Mary likes cookies.

Quantification

- Every boy likes cookies.
- Every boy ate a cookie.
- ► All funny jokes are short. vs. All short jokes are funny.
- Israel stood still as eight soldiers from all branches of the military carried the coffin to the burial ground.

FraCaS: An Early 'Meaning Bank'



Fracas #074

- P1 All/most Europeans can travel freely within Europe.
- Q Can all/most Europeans who reside outside of Europe travel freely within Europe?
- H All/most Europeans who reside outside of Europe can travel freely within Europe.
- ► EU project on computational semantics in the mid-1990s.
- ► Collected 346 (non-)entailment sentence tuples.
- ► Also annotated with popular semantic representations of the time (predicate logic, DRT, etc.); but the annotations were lost.

Presupposition and Focus



Certain semantic phenomena supply meaning beyond the truth conditions of the sentence.

Presupposition

- ► A presupposition of a sentence is a piece of meaning that survives even if the sentence is negated, embedded, etc.
- Today I took my cat to the vet. Today I didn't take my cat to the vet. Did you take your cat to the vet today?

Focus

- ► A focused phrase implicitly evokes alternatives of which the predication is false.
- ► YOUR children don't hate school.

 Your CHILDREN don't hate school. . . .

Word Senses



The words in a sentence may be ambiguous with respect to their <u>senses</u>. The semantic annotation may or may not choose to disambiguate.

Senses of *plant* in Wordnet

- ▶ plant-1: works, industrial plant (buildings for carrying on industrial labor) "they built a large plant to manufacture automobiles"
- plant-2: flora, plant life ((botany) a living organism lacking the power of locomotion)

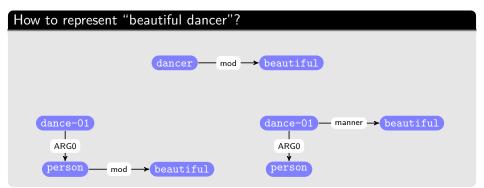
Senses of keep in Propbank

- keep.01(ARG0:Keeper, ARG1:thing-kept): "The Herald kept its old-time Hearst readership."
- keep.02(ARG0:causer-of-continued-action, ARG1:continued-entity, ARG2:continued-state-or-action): "The captain kept the crew loyal."

Lexical Decomposition



The meanings of individual words can have internal structure, which the semantic annotation may or may not represent.



Anaphoric Coreference



The meaning of an anaphoric expression depends on the context in which it occurs (within the sentence; across sentences).

Examples

- ► John kicked his ball.
- ► He wants her to see him.

Summary: Facets of Linguistic Meaning



- ► Predicate—argument structure
- Quantification and Scope
- Presupposition and focus
- ► Word sense differentiation
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- ► Anaphoric coreference
- ► Grounding (in world; in picture; in Wikipedia; ...)
- Tense and aspect
- ► Information structure
- ► Discourse structure
- ► ... and many others ...

Compositionality





(Example by Jan van Eijck)

The Principle of Compositionality

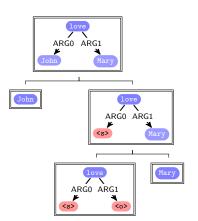
The meaning of an expression is a function of the meanings of its parts and of the way they are syntactically combined. B. Partee

Compositionality



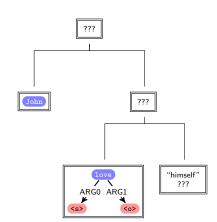
Not all semantic phenomena lend themselves easily to a compositional analysis.

Predicate—argument structure "John loves Mary."



Coreference

"John loves himself."



Foundations: Basic Graph Theory



$$\mathbb{G} = \langle N, E, T \rangle$$

- ▶ \mathbb{G} is a directed graph: N is set of nodes; $E \subseteq N \times N$ is set of edges;
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- ▶ **G** is connected if there is an undirected path between all pairs of nodes;
- ▶ \mathbb{G} is a tree if |T| = 1 and there is a unique path to all other nodes.

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Zero-Arity Predicates vs. Constants

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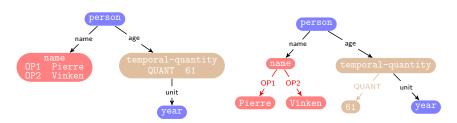
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- ▶ anchoring central in parsing, explicit or latent; aka 'alignment' for AMR;
- ► relevant to at least some downstream tasks; should impact evaluation.

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Overview: A Selection of Graphbanks



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(With Apologies to) Non-Graph or Non-Meaning Banks

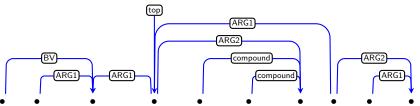
- ▶ PropBank (Palmer et al., 2005), Framenet (Baker et al., 1998), ...;
- ► Groningen Parallel Meaning Bank: GMB, PMB (Basile et al., 2012);
- ► Universal Decompositional Semantics (White et al., 2016);
- ► Enhanced Universal Dependencies (Schuster & Manning, 2016);
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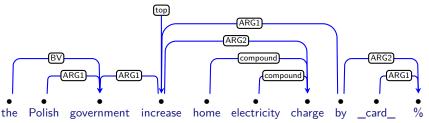


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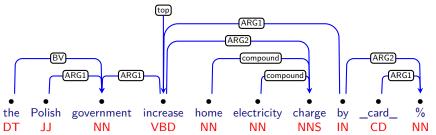


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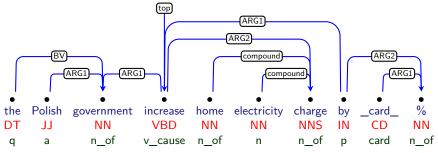


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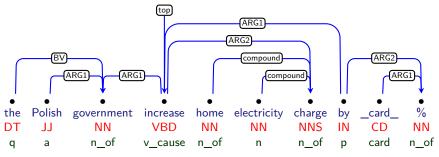


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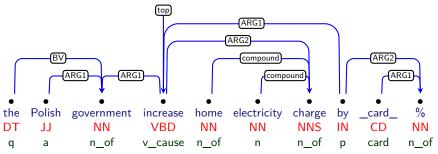


Arguably Basicest: Bilexical Semantic Dependencies



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- ▶ nodes limited to surface lexical units (words): lemmas, PoS, and frames;
- edges encode argument roles and maybe some construction semantics;
- ▶ limited expressivity, e.g. no lexical decomposition, no covert meaning.

The Polish government increased home electricity charges by 150%. [WSJ#0037059]



The Semantic Dependency Parsing Tasks (SDP)



Background

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- Sentence- and token-align annotations; simplify into bilexical digraphs;
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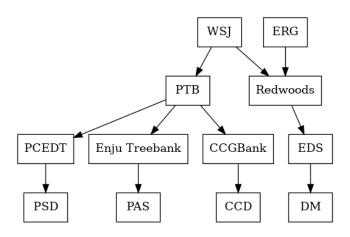
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More Recently (http://sdp.delph-in.net)

Release as LDC2016T10 with fourth framework; 'standard' benchmark.

Bilexical Semantic Dependencies: English Genealogy

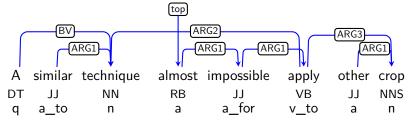




DELPH-IN MRS Bi-Lexical Dependencies (DM)



A similar technique is almost impossible to apply to other crops.



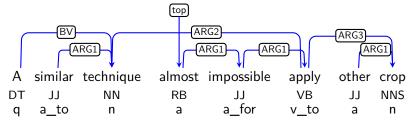
Ivanova et al. (2012)

- Simplification from underspecified logical forms (ERS; coming right up);
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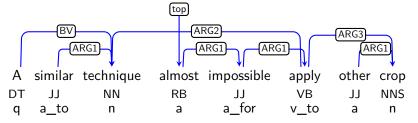
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- typically, unique top node; quantifiers have special 'bound variable' role.



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- ► Hand-designed computational grammar for English in HPSG framework;
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- ► Grammar-based annotation: select 'correct' reading from parse forest;
- efficient selection based on minimal discriminants; re-use across releases;



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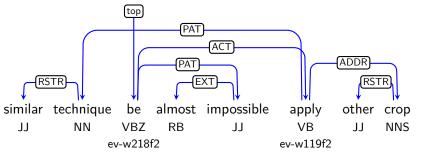
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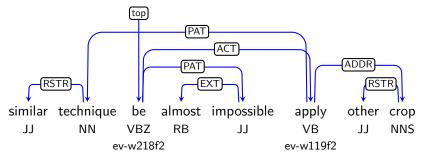
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- record full HPSG derivation; export into various graph-based formats.

A similar technique is almost impossible to apply to other crops.



Simplification of multi-layer dependency annotation (coming right up);

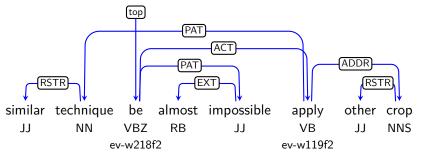
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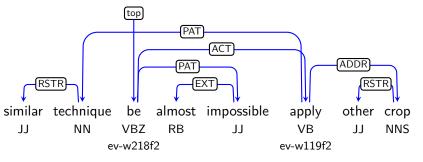


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- ▶ simple determiners (a, the) treated as not content-bearning (in PSD).

Background: Functional Generative Description



Linguistic Theory (Sgall et al., 1986)

- ► Charles University in Prague, since 1960s; (Petr Sgall; 1926–2019);
- ▶ layered dependencies, e.g. morphological, analytical, tectogrammatical;
- ▶ nodes are interlinked across layers; simple feature structures on nodes;
- tectogrammatical layer: predicate—argument structure, verb senses, coreference, ellipsis, information structure, discourse connectives, . . .
- ► formally, always rooted trees; 'generated' nodes and explicit coreference.

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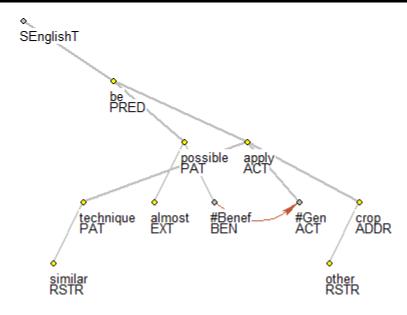
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Large-Scale Annotations (Böhmová et al., 2003; Hajič et al., 2012)

- ► Prague Dependency Treebank (PDT) 3.5: 800,000 tokens of Czech;
- ► Prague Czech–English Dependency Treebank (PCEDT) 2.0: PTB WSJ;
- ▶ since mid-1990s, several person decades of annotation; still on-going;
- ▶ pre-SDP, some use in morpho-syntactic parsing and machine translation.

Background: Underlying Tectogrammatical Tree





http://ufal.mff.cuni.cz/pedt2.0/introduction.html

Background: Tectogrammatical Valency Frames



apply² ACT(sub) PAT(obj1;ving) ADDR(to[objpp;ving])

- Mr. Bologna said the sale would allow Gen-Probe to speed up the development of new technology, and to more quickly apply existing technology to an array of diagnostic products.
- The gains are to be applied *trace* to fourth quarter or first-quarter results.

Corpus example(s):

Close [X]

pedt Saudi Arabia ← ACT, for its part, has vowed *-2 to enact a copyright law compatible with international standards and *-2 to apply the PAT law PAT to ADDR computer software ADDR as well as to ADDR literary works ADDR, Mrs. Hills said *T*-1.

pedt It PAT was later applied to ADDR other new-car programs ADDR, ADDR including those that *T*-1 produced the Ford Thunderbird and Mercury Cougar.

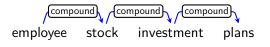
pedt A PAT similar technique PAT is almost impossible 0 * to apply *T*-1 to ADDR other crops ADDR, such as cotton ADDR, soybeans ADDR and rice ADDR.

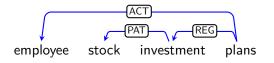
pedt Armstrong expects *-1 to close the sale of the color unit in late
November and the carpet sale in December, with the PAT gains PAT to be applied *-4 to ADDR fourth quarter or first-quarter results ADDR.

pedt *-1 Using small electrical shocks←PAT applied * to ADDR her feet ADDR, they were able *-1 to monitor sensory nerves.

DM vs. PSD: Sentence vs. Speaker Meaning?







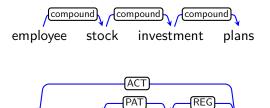
Diverging Ambitions

- ▶ Meaning determined by linguistic signal alone vs. by utterance context;
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DM vs. PSD: Sentence vs. Speaker Meaning?

emplovee





investment

plans

Diverging Ambitions

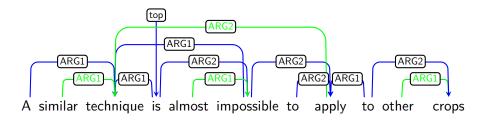
▶ Meaning determined by linguistic signal alone vs. by utterance context;

stock

- ▶ internal bracketing arguably grammaticized, but not role interpretation;
- ▶ investment and plan as deverbal: PSD valency frames parallel to verbs;
- ▶ never mind disagreement in bracketing (both structures are defensible).

Other Bilexical 'Semantic' Dependencies (1 of 2)



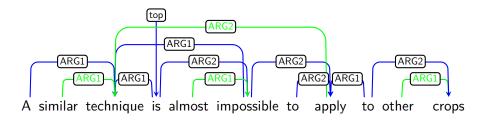


PAS: Enju Predicate–Argument Structures (Miyao, 2006)

- Similar in pedigree to DM: derived compositionally by lage-scale HPSG;
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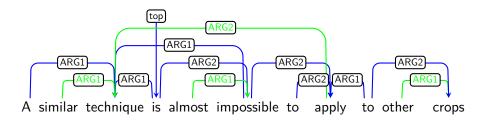


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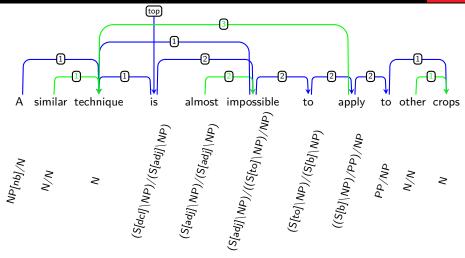




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- ► Enju Parser was early broad-coverage engine for semantic dependencies.

Other Bilexical 'Semantic' Dependencies (2 of 2)



CCD: CCG Word-Word Dependencies (Hockenmaier & Steedman, 2007)

- ► CCG categories as 'frame' identifiers; edge labels for argument position;
- ► more 'deep syntax' than semantics, but functor—argument directionality.

Pairwise Similarity (Unlabeled Dependency F₁)



	Directed			Undirected		
	DM	PAS	PSD	DM	PAS	PSD
DM	_	.6425	.2612	_	.6719	.5675
PAS	.6688	_	.2963	.6993	_	.5490
PSD	.2636	.2963	_	.5743	.5630	_

(Upper Right Diagonals: Including punctuation; Lower Left: Ignoring It)

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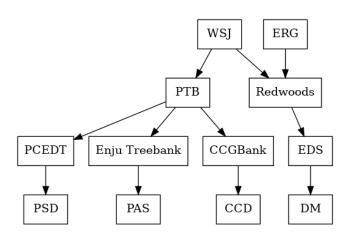
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- ▶ DM and PAS structurally much closer to each other than either to PSD;
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- directionality of dependencies as one of the key sources of divergence.

Bilexical Semantic Dependencies: English Genealogy





Moving On: Elementary Dependency Structures (EDS)

Limitations in Bi-Lexical Semantic Dependencies

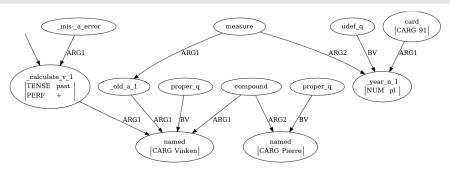
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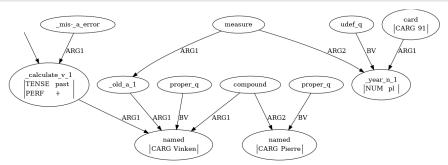


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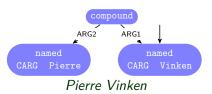
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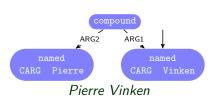
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- ► ERS without variables (Oepen et al., 2002; Oepen & Lønning, 2006);
- ▶ like DM, nodes encode n-ary predications, edges (expressed) arguments;
- ► Flavor (1): arbitrary (overlapping) sub-strings carry pieces of meaning.







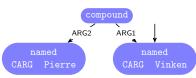


Named Entities

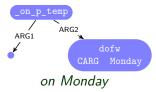
- Underspecified structure in names;
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Michelle and Barack Obama





Pierre Vinken

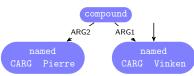


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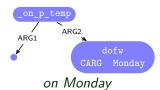
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- Predicates: distinct two-place relation;
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before and during the meeting





Pierre Vinken



on Monday



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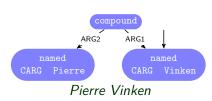
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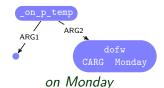
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before and during the meeting

Literal Numbers

- syntax yields arithmetic expressions;
- trivial 'downstream' normalization.

ten two twenty thousand







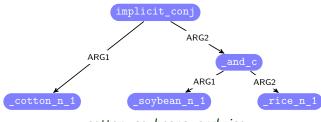


She cheerfully took a steaming-hot bath.



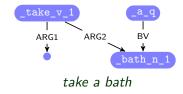


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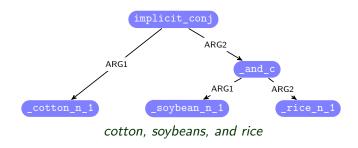


cotton, soybeans, and rice





She cheerfully took a steaming-hot bath.



She arrived, ate, and slept.



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Limitations

- ► Grammar-based annotation: no 'correct' analysis in 5–15 % of inputs;
- ▶ limited resources for other languages (German, Japanese, Spanish, ...);
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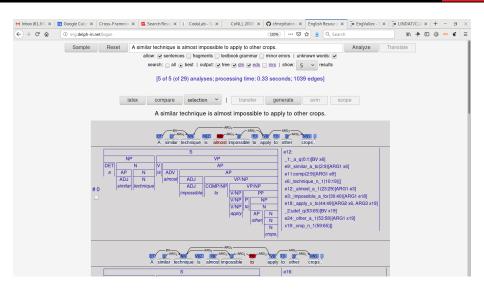
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Dependency Minimal Recursion Semantics (DMRS)

- ► Recall: Original ERSs contain partial, underspecified scope information;
- ► Copestake (2009) monotonically extends EDS with scopal 'overlays'.

Background: English Resource Semantics On-Line





http://erg.delph-in.net/

Abstract Meaning Representation (AMR)



- ► Goals:
 - ► Capture predicate—argument structure of a sentence.
 - Nodes annotated with lexically decomposed predicates, using PropBank senses.
 - ▶ Different sentences with same meaning should have the same AMR.
 - ► Use for NLU, NLG, machine translation.
- First large-scale hand-annotated sembank:
 - ► "Little Prince" pilot annotation, ~1500 sentences
 - ► AMRBank v1 (LDC2014T12), ~13k sentences
 - ► AMRBank v2 (LDC2017T10), ~40k sentences, includes v1
 - ► ISI, since 2013 (Banarescu et al., 2013)
- ▶ Inter-annotator agreement: Typical Smatch scores of 70–80.

Predicate-Argument Structure in AMR

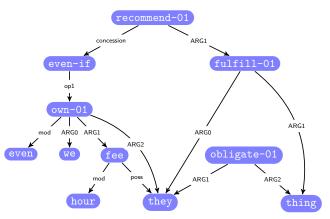




The boy wants to sleep.

More Complex AMRs



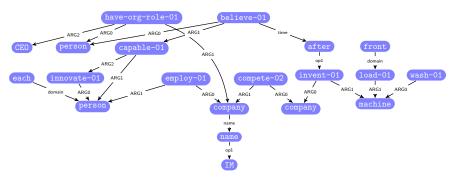


Even if we owed their hourly fees, they still should fulfill their obligations. (AMR2015 #34, simplified)

- (a) implicit arguments
- (b) raising-style argument passing
- (c) lexical decomposition
- (d) coreference

(Even) More Complex AMRs





After its competitor invented the front loading washing machine, the CEO of the IM company believed that each of its employees had the ability for innovation. (AMR2015 #1, simplified)

- (a) lexical decomposition (c) coreference
- (b) named entities (d) quantification (?)

'Inverse Edges' in AMRs



Standard string format for AMRs is Penman-style:

```
want-01

ARGO ARGI

boy - ARGO — sleep-01
```

```
The boy wants to sleep.

(w / want-01
:ARG0 (b / boy)
:ARG1 (s / sleep-01 :ARG0 b))
```

String representation is based on DFS traversal of AMR, which sometimes traverses edges backwards. Represent with "label-of" edges:

```
snore-01 sleep-01
```

```
The man who sleeps snores.

(sn / snore-01
:ARGO (m / man
:ARGO-of (sl / sleep-01)))
```

"label-of" edges are primarily artifacts of the string encoding. Some people interpret them as linguistically meaningful.

Limitations of AMR



Coreference

- ► Coreference-based edges indistinguishable from others.
- Linguistically, coreference is very different than e.g. control, namely noncompositional.
- ► Challenge for composition-based semantic parsers.

Expressive Capacity

- Operators such as quantifiers and modal verbs have scope. This is hard to represent when the MR is not a tree.
- ► People are stil trying.
- ► AMR has no model theory. "Man" and "every" are the same type of node label. If "man" refers to a set of men in the world, what's an "every"?

Universal Conceptual Cognitive Annotation (UCCA)



▶ Goals:

- ► Capture predicate—argument structure of a sentence, in a way that abstracts over syntactic details.
- ► Inspired by typological principles (Basic Linguistic Theory).
- ▶ Make annotation as intuitive as possible, also cross-linguistically.

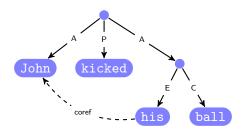
► Basic ideas:

- Backbone of UCCA graph is a tree with the tokens as leaves and additional internal nodes, connected by a small set of semantic relations.
- Additional remote edges represent argument sharing.
- ► Multiple annotation layers, e.g. pred-arg structure vs. coreference.
- ► Annotations of "20000 Miles under the Sea" available in English, French, German; also web texts annotated.
- ► Hebrew University, since 2013 (Abend & Rappoport, 2013)
- ► Inter-annotator agreement: around 80 f-score.

UCCA Terminology

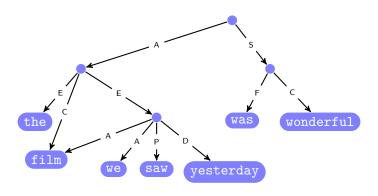
- ► A <u>scene</u> is a description of a single action or state. Sentences can contain multiple scenes. UCCA annotations distinguish between "processes" and "states".
- ▶ Scenes can have <u>participants</u> (\approx arguments) and <u>adverbials/times</u> (\approx modifiers).
- ▶ Below the clause level, distinguish <u>centers</u> from their <u>elaborators</u> and combine them with connectors.

UCCA: Basic Example



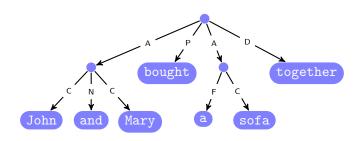
John kicked his ball.

UCCA: Argument sharing



The film we saw yesterday was wonderful.

UCCA: Coordination



John and Mary bought a sofa together.

Limitations of UCCA

- Less well-studied approach than the others; may change with MRP Shared Task at CoNLL 2019.
- ▶ Does not distinguish different argument roles.
- Modification of a head causes major changes to graph structure; may be challenging for accurate parsing.

Graphbank Statistics (Kuhlmann & Oepen, 2016)

			DM	PSD	EDS	UCCA	AMR^{-1}
(n	(01)	number of graphs	35,656	35,656	35,656	6,572	56,240
nţ	(01)	number of tokens	802,717	802,717	802,717	138,268	1,000,217
counts	(02)	average number of tokens	22.51	22.51	22.51	21.03	17,78
U	(03)	average nodes per token	0.77	0.64	1.37	1.29	0.65
	(04)	number of edge labels	59	90	15	10	101
	(05)	$%_g$ trees	2.31	42.26	34.83	0.09	22.24
	(06)	$%_g$ treewidth one	69.82	43.08	41.57	68.99	50.00
	(07)	average treewidth	1.30	1.61	1.61	1.31	1.56
Ś	(80)	maximal treewidth	3	7	4	3	5
nes	(09)	average edge density	1.019	1.073	1.053	1.015	1.092
treeness	(10)	$%_{n}$ reentrant	27.43	11.41	4.98	32.78	19.89
₽	(11)	$%_g$ cyclic	0.00	0.00	0.00	0.12	0.38
	(12)	$%_g$ not connected	6.57	0.70	0.00	1.74	0.00
	(13)	$%_g$ multi-rooted	97.47	40.60	0.00	99.93	71.37
	(14)	percentage non-top roots	44.94	4.34	0.00	54.85	20.09
<u>_</u>	(15)	average edge length	2.684	3.320	_	_	_
order	(16)	$%_g$ noncrossing	69.21	64.61	_	_	_
5	(17)	$% {}_{g}$ pagenumber two	99.59	98.08	_	_	_

Parallel Meaning Bank



```
x1
person.n.01(x1)

x2 e1 t1
time.n.08(t1)
t1 = now
peel.v.01(e1)
Time(e1, t1)
Source(e1, x2)
Agent(e1, x1)
banana.n.02(x2)
```

A person is not peeling a banana.

- Groningen Parallel Meaning Bank: 6k sentences in English, plus smaller corpora in DE, IT, NL (Basile et al., 2012; Abzianidze et al., 2017).
- ► First version: automatically annotated with Discourse Representation Structures (DRT) using Boxer.
- ► Iteratively hand-corrected, e.g. through game-based crowdsourcing.

Facets of Meaning in the Graphbanks



Type of Information	DM	PSD	EDS	DMRS	UCCA	AMR	PMB
Predicates-Arguments	+	+	++	++	+	++	++
Sense Differentiation	+	++	+	+	_	++	++
Scope & Quantification	±	_	±	+	_	_	+
Presupposition & Focus	_	_	_	_	_	_	+
Anaphoric Coreference	_	_	_	_	_	+/-	+
Grounding	_	_	_	_	_	\pm	_

.

Facets of Meaning in the Graphbanks



Type of Information	DM	PSD	EDS	DMRS	UCCA	AMR	PMB
Predicates-Arguments	+	+	++	++	+	++	++
Sense Differentiation	+	++	+	+	_	++	++
Scope & Quantification	土	_	±	+	_	_2	+
Presupposition & Focus	_	_	_	_	_	_	+
Anaphoric Coreference	_	_1	_	_	_3	+/-	+
Grounding	_	_	_	_	_	\pm	_

Represented in base resource, but not graphbank: 1) Hajič et al. (2018). Ongoing activities: 2) Pustejovsky et al. (2019), 3) Prange et al. (2019).

Facets of Natural Language Meaning



- ► Natural-language meaning has many facets.
- ► Each annotation scheme for semantics only captures some of these facets.
- ► Tradeoffs:
 - ► information captured by annotation
 - ► annotation effort
 - ► inter-annotator agreement

Multilingual Resources



We focus here on graphbanks for English corpora. We know of a handful of multilingual graphbanks:

framework	languages	corpora
AMR	ZH	Chinese AMRBank, 10k sentences https://www.cs.brandeis.edu/~clp/camr/camr. (Li et al., 2016)
AMR	IT, ES, DE, ZH	AMR projected across parallel corpora (Damonte & Cohen, 2018)
UCCA	FR, DE	20k Leagues under the Sea http://www.cs.huji.ac.il/~oabend/ucca.html
DRT	EN, DE, IT, NL	Groningen Parallel Meaning Bank https://pmb.let.rug.nl/ (Abzianidze et al., 2017)

Semantic

Parsing

Approaches

Parsing to Flavor (0) Graphs



Flavor	Name	Example	Type of Anchoring
0	bilexical	SDP	nodes are sub-set of surface tokens
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Parsing to Flavor (0) graphs

- ► Nodes = tokens
- ► The goal is to predict labeled edges



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The drug was introduced in West Germany this year



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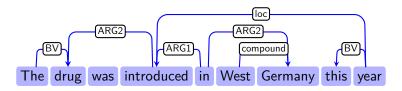
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Semantic Parsing is Making Rapid Progress

	D	М	PAS		PSD	
	id	ood	id	ood	id	ood
Du et al. (2015) (close)	89.1	81.8	91.3	87.2	75.7	73.3
H. Peng et al. (2017) +Multitask learning Dozat & Manning (2018)	89.4 90.4 93.7	84.5 85.3 88.9	92.2 92.7 94.0	88.3 89.0 90.8	77.6 78.5 81.0	75.3 76.4 79.4
Lindemann et al. (2019) +Multitask learning	93.9 94.1	90.3 90.5	94.5 94.7	92.5 92.8	82.0 82.1	81.5 81.6

Accuracy of edge prediction

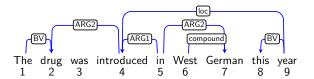
 $(\mathsf{id} = \mathsf{in} \; \mathsf{domain} \; \mathsf{test} \; \mathsf{set}; \; \mathsf{ood} = \mathsf{out} \; \mathsf{of} \; \mathsf{domain} \; \mathsf{test} \; \mathsf{set})$

Semantic Parsing is Making Rapid Progress



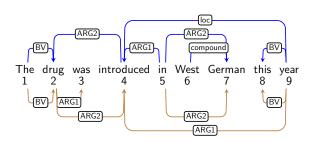
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Quantifying graph similarity is challenging. What do these numbers mean?



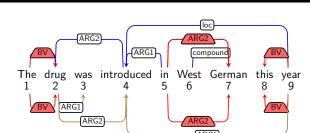
$$E_{\mathsf{gold}} = \{(1, 2, \mathsf{bv}), (2, 4, \mathsf{arg1}), \cdots\}$$

$$|E_{\mathsf{gold}}| = 7$$



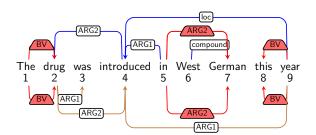
$$\begin{split} E_{\mathsf{gold}} &= \{(1,2,\mathsf{bv}), (2,4,\mathsf{arg1}), \cdots\} \\ E_{\mathsf{system}} &= \{(1,2,\mathsf{bv}), (2,3,\mathsf{arg1}), \cdots\} \end{split} \qquad \begin{aligned} |E_{\mathsf{gold}}| &= 7 \\ |E_{\mathsf{system}}| &= 6 \end{aligned}$$

Oepen et al. (2014, 2015)



$$\begin{split} E_{\mathsf{gold}} &= \{ (1, 2, \mathsf{bv}), (2, 4, \mathsf{arg1}), \cdots \} & |E_{\mathsf{gold}}| = 7 \\ E_{\mathsf{system}} &= \{ (1, 2, \mathsf{bv}), (2, 3, \mathsf{arg1}), \cdots \} & |E_{\mathsf{system}}| = 6 \\ E_{\mathsf{match}} &= E_{\mathsf{gold}} \cap E_{\mathsf{system}} = \{ (1, 2, \mathsf{bv}), (5, 7, \mathsf{arg1}), \cdots \} & |E_{\mathsf{match}}| = 3 \end{split}$$

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$$\begin{array}{c|cccc} \text{Precision} & \text{Recall} & \text{F-score} \\ \hline \frac{|E_{\mathsf{match}}|}{|E_{\mathsf{system}}|} = 0.43 & \frac{|E_{\mathsf{match}}|}{|E_{\mathsf{gold}}|} = 0.5 & \frac{2*|E_{\mathsf{match}}|}{|E_{\mathsf{gold}}|+|E_{\mathsf{system}}|} = 0.46 \\ \hline \end{array}$$

Oepen et al. (2014, 2015)

Magic Numbers Again

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Modern graph parsers are cool!

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► We need to predict labeled nodes

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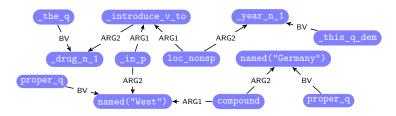
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► We need to predict labeled nodes and labeled edges



Semantic Parsing is Making Rapid Progress



	ED	S	AMR 2015	AMR 2017
	Smatch F	EDM_na	Smatch F	Smatch F
Groschwitz et al. (2018)	-	-	70.2	71.0
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Accuracy of node and edge prediction

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 $_{ ext{the}}$ q $\langle 0,1
angle$

 $\boxed{\texttt{_want_v_to}\langle 2, 3\rangle}$

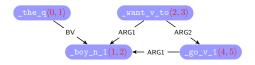
 $\boxed{\texttt{_boy_n_1}\langle 1,2\rangle}$

 $\left(\operatorname{go_v_1}\langle 4,5 \rangle \right)$

$$V_{\mathrm{gold}} = \{ \left(\left\langle 0,1 \right\rangle, _\mathtt{the}_\mathtt{q} \right), \cdots \} \text{, } |V_{\mathrm{gold}}| = 4$$



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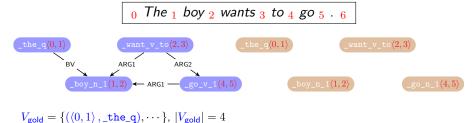


 $_0$ The $_1$ boy $_2$ wants $_3$ to $_4$ go $_5$. $_6$

$$\begin{array}{c|c} \text{the} _q \langle 0, 1 \rangle & \text{want} _v_to \langle 2, 3 \rangle \\ \text{BV} & \text{ARG1} & \text{ARG2} \\ \hline _boy_n_1 \langle 1, 2 \rangle & \longleftarrow \text{ARG1} & \longleftarrow _go_v_1 \langle 4, 5 \rangle \\ \end{array}$$

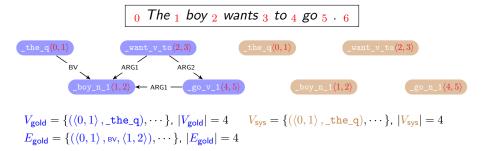
$$\begin{split} V_{\mathsf{gold}} &= \{(\langle 0, 1 \rangle\,, _\mathsf{the}_\mathsf{q}), \cdots \}, \ |V_{\mathsf{gold}}| = 4 \\ E_{\mathsf{gold}} &= \{(\langle 0, 1 \rangle\,, \mathsf{BV}, \langle 1, 2 \rangle), \cdots \}, \ |E_{\mathsf{gold}}| = 4 \end{split}$$



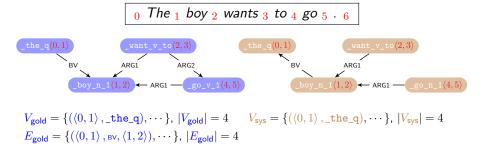


$$\begin{split} & \mathbf{\mathcal{E}_{gold}} = \{(\langle 0,1\rangle, \text{\tiny ELQ}), \cdots\}, \ |\mathbf{\mathcal{V}_{gold}}| = 4\\ & E_{gold} = \{(\langle 0,1\rangle, \text{\tiny BV}, \langle 1,2\rangle), \cdots\}, \ |E_{gold}| = 4 \end{split}$$













 $V_{\mathsf{match}} = V_{\mathsf{gold}} \cap V_{\mathsf{sys}} = \{(\langle 1, 2 \rangle, \mathtt{boy_n_1}), \dots\} \mid V_{\mathsf{match}} \mid = 3$ $E_{\mathsf{match}} = E_{\mathsf{gold}} \cap E_{\mathsf{sys}} = \{(\langle 2, 3 \rangle, \mathtt{ARGI}, \langle 1, 2 \rangle, \dots\} \mid E_{\mathsf{match}} \mid = 2$



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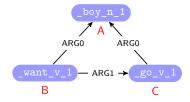
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Dridan & Oepen (2011)

 $boy_n_1\langle 1,2\rangle \leftarrow ARG1 - go n 1\langle 4,5\rangle$

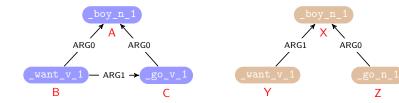


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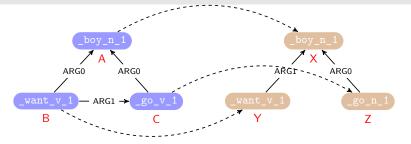


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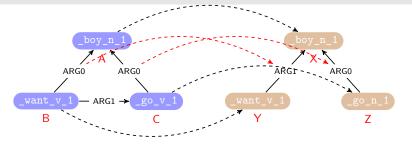
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Assume an alignment: $A \leftrightarrow X \ \& \ B \leftrightarrow Y \ \& \ C \leftrightarrow Z$



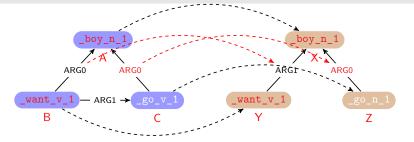
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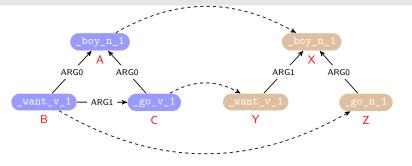
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EDM_n	EDM_a	EDM_na
$\frac{2*2}{3+3} = 0.67$	$\frac{2*1}{3+2} = 0.40$	$\frac{2*3}{6+5} = 0.55$



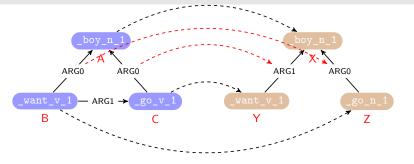
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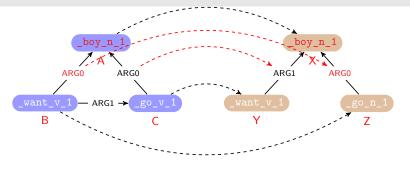
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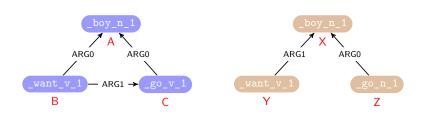


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EDM _n	EDM_a	EDM_{na}
$\frac{2*1}{3+3} = 0.33$	$\frac{2*1}{3+2} = 0.40$	$\frac{2*2}{6+5} = 0.36$

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$$\operatorname{SMATCH}(G_g, G_s) = \max_{a \in \mathcal{A}(G_q, G_s)} \operatorname{EDM}_{\mathsf{na}}(a)$$

 $\mathcal{A}(G_g,G_s)$ denotes the set of all plausible alignments between G_g and G_s Cai & Knight (2013)

Magic Numbers Again

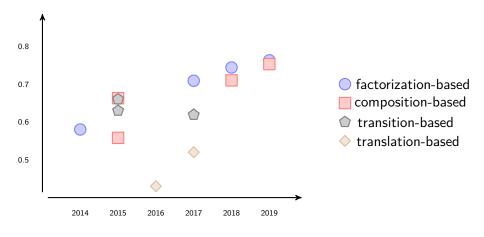


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Modern graph parsers are cool!

Graph Parsing is Making Rapid Progress



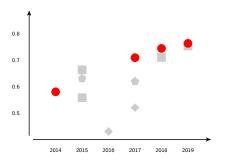


AMR parsing accuracies reported in Flanigan et al. (2014); Foland & Martin (2017); Lyu & Titov (2018); S. Zhang et al. (2019);

X. Peng et al. (2015); Artzi et al. (2015); Groschwitz et al. (2018); Lindemann et al. (2019); Barzdins & Gosko (2016); X. Peng et al. (2017); Konstas et al. (2017); Wang et al. (2015b, 2015a); Buys & Blunsom (2017)

Factorization-Based Approaches



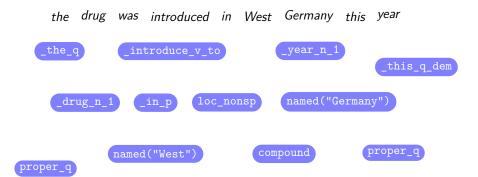


- ► Inspired by the successful design of graph-based dependency parsers. Very early work: McDonald & Pereira (2006).
- ► Explicitly modeling the target structure.
- ► A parser knows how to evaluate the *goodness* of a candidate graph.
- ► A parser knows how to find the *best* graph from an extremely large set.

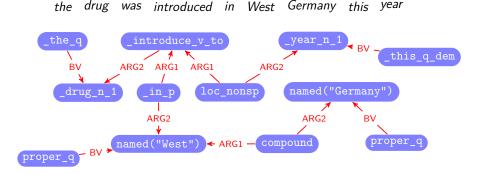


the drug was introduced in West Germany this year













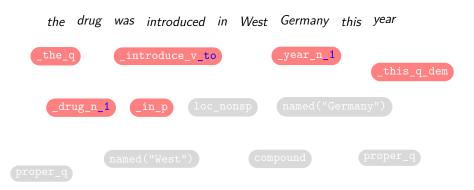
Task 1: Concept Identification



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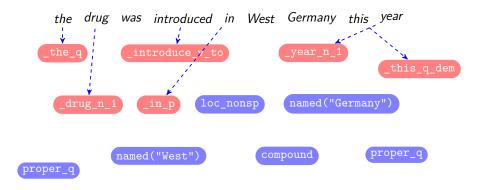
Task 1: Concept Identification



Task 1: Concept Identification

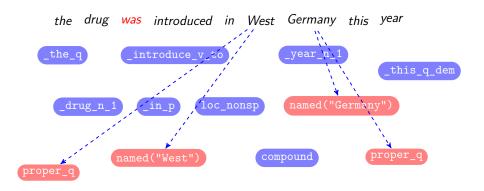


Task 1: Concept Identification



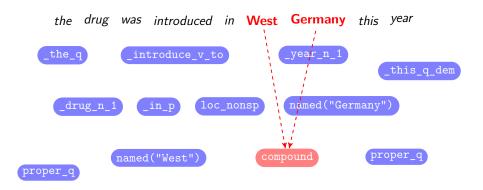
Task 0: Concept-to-word Alignment

Task 1: Concept Identification



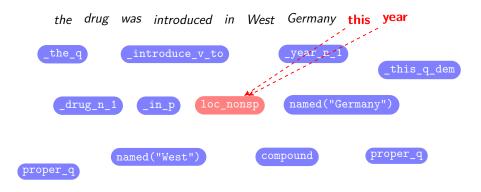
Task 0: Concept-to-word Alignment

Task 1: Concept Identification



Task 0: Concept-to-word Alignment

Task 1: Concept Identification



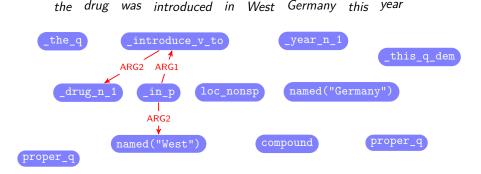
Task 0: Concept-to-word Alignment

Task 1: Concept Identification



- **Task 0**: Concept-to-word Alignment
- Task 1: Concept Identification
- Task 2: Relation Detection





- **Task 0**: Concept-to-word Alignment
- Task 1: Concept Identification
- Task 2: Relation Detection

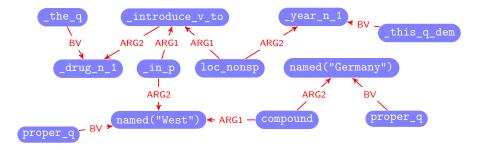


the drug was introduced in West Germany this year ARG1 ARG2 _drug_n_1 _in_p ARG2 named("West") ← ARG1 — compound

- Task 0: Concept-to-word Alignment
- Task 1: Concept Identification
- Task 2: Relation Detection



the drug was introduced in West Germany this year



- Task 0: Concept-to-word Alignment
- Task 1: Concept Identification
- Task 2: Relation Detection

- ► Concept Identification (CI): predicting nodes
- ► Relation Detection (RD): linking nodes
- ► Concept-to-word alignment: finding concept-word correspondences

	Alignment	Concept Identification	Relation Detection
Flavor (0)			✓
Flavor (1)		✓	✓
Flavor (2)	✓	✓	✓

- ► Concept Identification (CI): predicting nodes
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	Alignment	Concept Identification	Relation Detection
Flavor (0)			✓
Flavor (1)		✓	✓
Flavor (2)	✓	✓	✓

As a Structured Prediction Problem



Maximum Subgraph Parsing

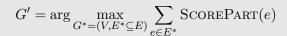
- ▶ Start from a directed graph G = (V, E) that corresponds to $x = w_0, \dots w_{n-1}$ and a score function that evaluates the *goodness* of a graph.
- ▶ Search for a subgraph $G' = (V, E' \subseteq E)$ that maximizes the score function:

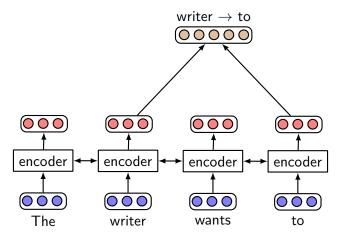
$$G' = \arg \max_{G^* = (V, E^* \subseteq E)} Score(G^*)$$

First-order factorization

$$G' = \arg\max_{G^* = (V, E^* \subseteq E)} \sum_{e \in E^*} \text{ScorePart}(e)$$

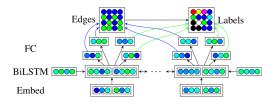
M. Kuhlmann and P. Jonsson. 2015. Parsing to Noncrossing Dependency Graphs.





H. Peng et al. (2017); Chen, Huang, et al. (2018); Dozat & Manning





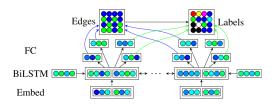
Concatenate word and POS tag embeddings.

$$\mathbf{x}_i = \mathbf{e}_i^{\mathsf{word}} \oplus \mathbf{e}_i^{\mathsf{tag}}$$

Then BiLSTM them:

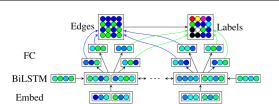
$$\mathbf{r}_1, \mathbf{r}_2, ..., \mathbf{r}_n = \text{BiLSTM}(\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n)$$

T. Dozat and C. Manning. 2018. Simpler but More Accurate Semantic Dependency Parsing.



A word can be either a predicate or an argument. **Distinguish its** grammartical/semantic function:

$$\begin{array}{ccc} \mathbf{h}_i^{\mathsf{edge-head}} & = & {}_{\mathsf{FNN}}\mathsf{edge-head}(\mathbf{r}_i) \\ \\ \mathbf{h}_i^{\mathsf{edge-dep}} & = & {}_{\mathsf{FNN}}\mathsf{edge-dep}(\mathbf{r}_i) \\ \\ \mathsf{SCOREEDGE}(s,i,j) & = & \mathsf{BIAFFINE}^{\mathsf{edge}}(\mathbf{h}_i^{\mathsf{edge-head}}, \mathbf{h}_j^{\mathsf{edge-dep}}) \end{array}$$



A word can be either a predicate or an argument. **Distinguish its** grammartical/semantic function:

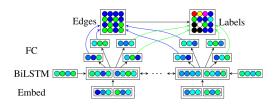
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FNN and BIAFFINE functions are popular

BIAFFINE
$$(\mathbf{x}_1, \mathbf{x}_2) = \mathbf{x}_1^{\top} \mathbf{U} \mathbf{x}_2 + \mathbf{W}(\mathbf{x}_1 \oplus \mathbf{x}_2) + \mathbf{b}$$

FNN $(\mathbf{x}) = \text{ReLU}(\mathbf{W}\mathbf{x} + \mathbf{b})$





If $\text{ScoreEdge}(s,i,j) \geq 0$, then take $i \rightarrow j$ as an edge.

Select a label for $i \rightarrow j$ according to

$$\begin{array}{lll} {\rm ScoreLabel}({i,j}) & = & {\rm Biaffine}^{\sf label}(\mathbf{h}_i^{\sf label-head}, \mathbf{h}_j^{\sf label-dep}) \\ & \mathbf{h}_i^{\sf label-head} & = & {\rm FNN}^{\sf label-head}(\mathbf{r}_i) \\ & \mathbf{h}_i^{\sf label-dep} & = & {\rm FNN}^{\sf label-dep}(\mathbf{r}_i) \\ \end{array}$$

Structure validation



Parsing to dependency trees

$$G' = \arg\max_{T^* = \mathcal{T}(G)} \sum_{e \in E^*} \text{ScorePart}(e)$$

Constraints on syntactic graphs: $\forall T' = (V, E') \in \mathcal{T}(G)$

- $ightharpoonup E' \subseteq E$
- ightharpoonup T' is a directed tree.

Constraints on semantic graphs

- ▶ Pagenumber-1 (= noncrossing): $O(n^3)$
- ► Pagenumber-2: NP-hard
- ▶ Pagenumber-2 and 1-endpoint-crossing and ...: $O(n^4)$

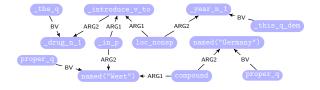
Kuhlmann & Jonsson (2015); Cao et al. (2017a, 2017b)

- ► Concept Identification (CI): predicting nodes
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	Alignment	Concept Identification	Relation Detection
Flavor (0)			✓
Flavor (1)		✓	✓
Flavor (2)	✓	✓	✓

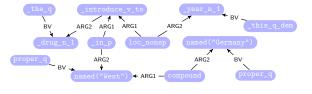


Flavor	Name	Example	Type of Anchoring
1	anchored	EDS	free node-sub-string correspondences
2	unanchored	AMR	no sub-string correspondences annotated





Flavor	Name	Example	Type of Anchoring
1	anchored	EDS	free node-sub-string correspondences
2	unanchored	AMR	no sub-string correspondences annotated



The	dr	ıg /	was	introduced	in		West	-	Germany	-	this	year
_the_q	_drug	_n_1	Ø	_introduce_v_to	_in_p	•	named("W") proper_q	•	named("G") proper_q		_this_q_dem	_year_n_1
							com	рот	und		loc_n	onsp



The	drug	was	introduced		in		West		Germany	this		year
_the_q	_drug_n_1	Ø	_introduce_v_to	1	_in_p		named("W") proper_q		named("G") proper_q	_this_q_	dem	_year_n_1
				Ī		Ī	comp	01	ind	(loc_no	onsp

Almost Sequence Labeling

- ► Some nodes are linked to sub-words.
- Some nodes are linked to multiple words.

- ▶ Preprocessing: every node is assigned to a single word
- ► Chunking: joint segmentation and tagging
 - **B**-x: begin of x
 - ightharpoonup I-x: inside x
- Lightweight phrase-structure parsing (UCCA)



The	drug	was	introduced		in	West	Germany	this	year
_the_q	_drug_n_1	Ø	_introduce_v_to	1	_in_p	named("W") proper_q	named("G") proper_q	_this_q_dem	_year_n_1
						compound			loc_nonsp

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The	drug	was	introduced	in	West	Germany	this	year
_the_q	_drug_n_1	Ø	_introduce_v_to	_in_p	named("W") proper_q	<pre>named("G") proper_q</pre>	_this_q_dem	_year_n_1
					B-compound	[I-compound]	B-loc_nonsp	[I-loc_nonsp

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The	drug	was	introduced		in		West		Germany	this		year
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						Ī	com	po	und	loc_n	on	sp

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Neural Tagging

Almost Sequence Labeling

- ▶ Preprocessing: every node is assigned to a single word
- ► Chunking: joint segmentation and tagging

Challenge

Like POS tagging but with thousands of labels.

Delexicalization

The	drug	introduced	in	West	Germany	this	year
_the_q	rug_n_1	_introduce_v_to	_in_p	named("W") compound proper_q	named("G") proper_q	_this_q_dem	_year_n_1 loc_nonsp

Neural Tagging



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The	drug	introduced	in	West	Germany	this	year
_the_q	_drug_n_1	_introduce_v_to	_in_p	named("W") compound proper_q	named("G") proper_q	_this_q_dem	_year_n_1 loc_nonsp
*_q	*_n_1	*_v_to	*_p	named compound proper_q	named proper_q	*_q_dem	*_n_1 loc_nonsp



Solution

- ► Pretraining: ELMo, BERT, etc.
- ► Word encoder: LSTM, Transformer, etc.
- Classification





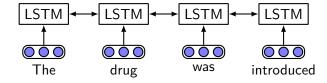






Solution

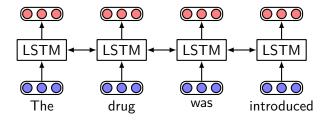
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Solution

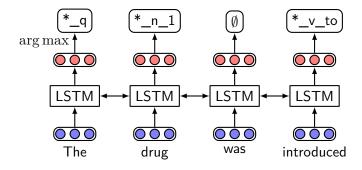
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Solution

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Sub-Tasks

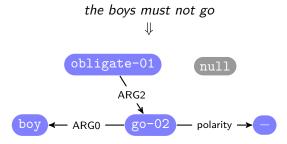
-

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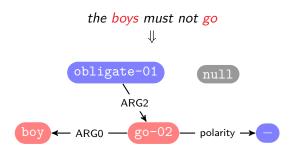
	Alignment	Concept Identification	Relation Detection	
Flavor (0)			✓	
Flavor (1)		✓	✓	
Flavor (2)	~	✓	✓	

Transition- and composition-based approaches also need concept-to-word alignments.









No annotations for concept-to-word alignment

- ► Heuristic rules (Flanigan et al., 2014)
- ► Linearize graphs and reuse word alignment tools, e.g. GIZA++ and BerkeleyAligner, etc. (Pourdamghani et al., 2014)
- ► Consider all possible alignments (Lyu & Titov, 2018)



the boys must not go

obligate-01

go-02

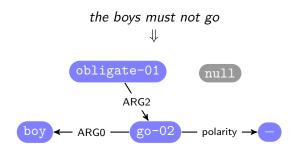
boy



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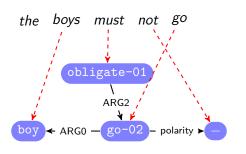
the boys must not go

$$P_{\theta,\phi}(\mathbf{c},R|\mathbf{w}) = \sum_{\mathbf{a}} P(\mathbf{a}) P_{\theta}(\mathbf{c}|\mathbf{a},\mathbf{w}) P_{\phi}(R|\mathbf{a},\mathbf{w},\mathbf{c})$$

- 1. the concept identification model: $P_{\theta}(\mathbf{c}|\mathbf{a},\mathbf{w})$
- 2. the relation identification model: $P_{\phi}(R|\mathbf{a}, \mathbf{w}, \mathbf{c})$
- 3. the alignment model: $P(\mathbf{a})$ ($Q_{\psi}(\mathbf{a}|\mathbf{c}, R, \mathbf{w})$)

C. Lyu and I. Titov. 2018. AMR Parsing as Graph Prediction with Latent Alignment



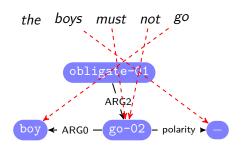


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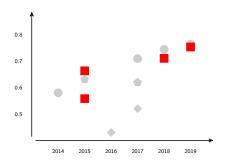
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C. Lyu and I. Titov. 2018. AMR Parsing as Graph Prediction with Latent Alignment

Composition-Based Approaches

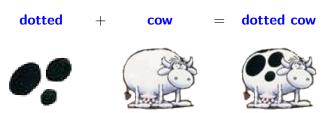




- ► Inspired by *old school*, rule-based approaches.
- Explicitly modeling the syntactico-semantic derivation process.
- ▶ A parser knows how to evaluate the *goodness* of a derivation process.
- ► A parser knows how to find the *best* derivation from a large set of derivations that are licensed by a symbolic *system*.

Reminder: Compositionality





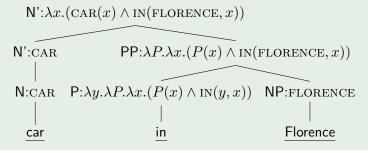
(Example from Jan van Eijck)

The Principle of Compositionality

The meaning of an expression is a function of the meanings of its parts and of the way they are syntactically combined. B. Partee

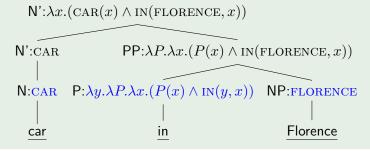


Tree construction + Lexical interpretation \Rightarrow Meaning representation



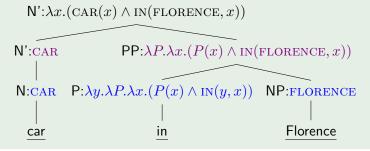


Tree construction + Lexical interpretation \Rightarrow Meaning representation



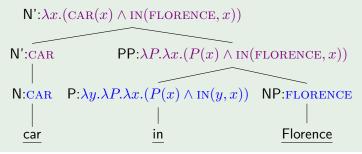


Tree construction + Lexical interpretation \Rightarrow Meaning representation





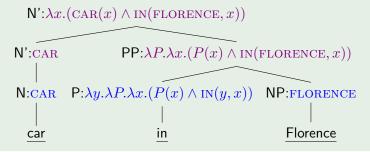
Tree construction + Lexical interpretation \Rightarrow Meaning representation





Tree construction + Lexical interpretation \Rightarrow Meaning representation

Using λ Expressions



Manipulating Graphs

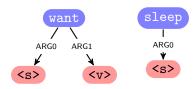
- ► Graph algebra (AM algebra)
- Graph grammar (hyperedge replacement grammar)



S-Graph

An s-graph is a graph in which nodes (called sources) are marked with "public names".

Examples



- "root" source
- want
- sleep

- other sources
- ► <s> (for "subjects")
- ► <v> (for "verb complements")



The writer wants to sleep soundly

AM algebra provides a systematic way to construct graphs

- term (=tree of operation symbols)
- ► value (=s-graph)

Two operations for combining s-graphs:

- ► Apply (=head+complement)
- ▶ Modify (=head+modifier)

Groschwitz et al. (2017)



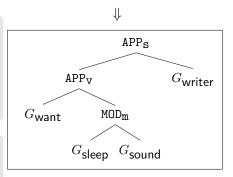
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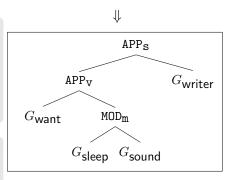
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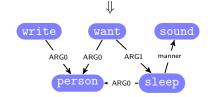
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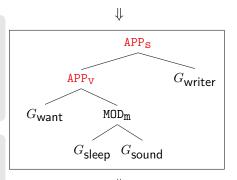
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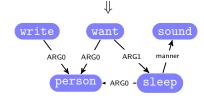
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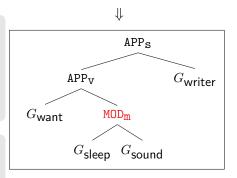
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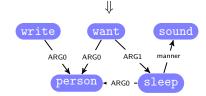
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Groschwitz et al. (2017)

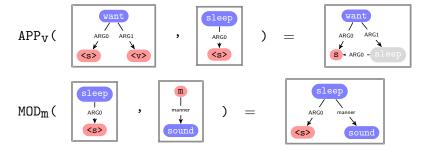




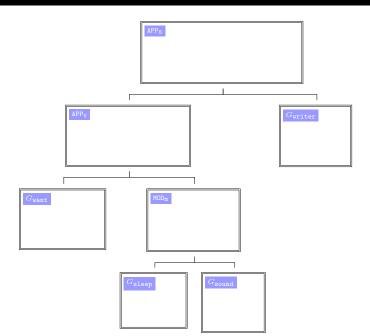


Two operations for combining s-graphs:

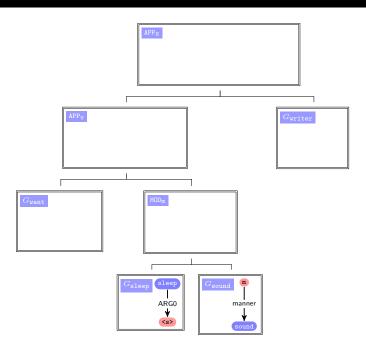
Apply (=head+complement), Modify (=head+modifier)



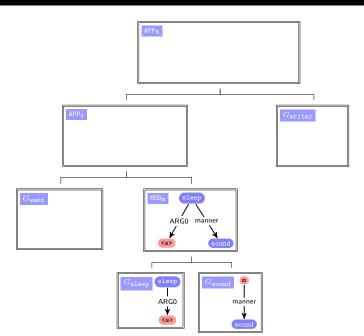
J. Groschwitz, M. Fowlie, M. Johnson and A. Koller. 2017. A constrained graph algebra for semantic parsing with AMRs.



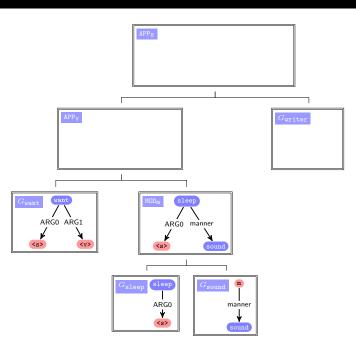




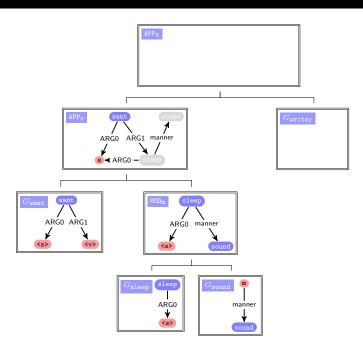




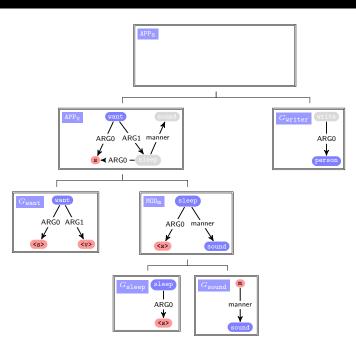




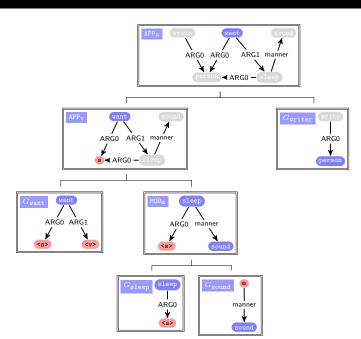










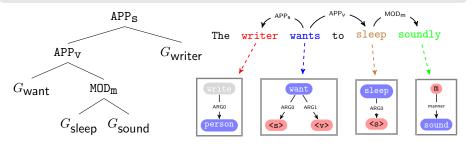




AM Algebra-Based Parsing



Tree construction + Lexical interpretation \Rightarrow Meaning representation



- ► J. Groschwitz, M. Lindemann, M. Fowlie, M. Johnson, and A. Koller. 2018. AMR dependency parsing with a typed semantic algebra.
- M. Lindemann, J. Groschwitz and A. Koller. 2019. Compositional Semantic Parsing Across Graphbanks.

AM Algebra-Based Parsing

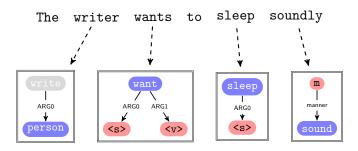


Tree construction + Lexical interpretation \Rightarrow Meaning representation

- ► A supertagger predicts graphs for words.
- ► A dependency parser predicts APP and MOD edges.
- ► At test time, compute highest-scoring well-typed AM dependency tree for input sentence.

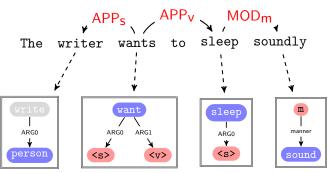


- ► A supertagger predicts graphs for words.
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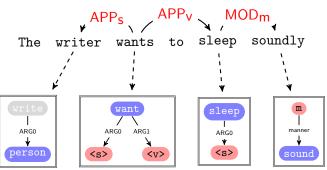


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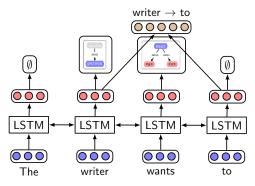


- ► A supertagger predicts graphs for words.
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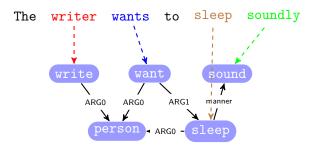


The writer wants to sleep soundly



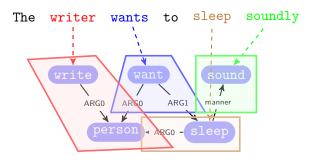
Decompose graph into parts based on concept-to-word alignment.





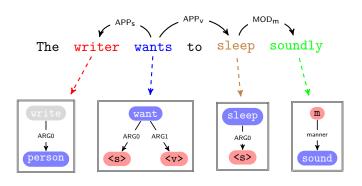
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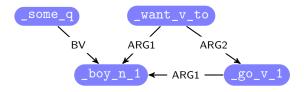
Decompose graph into parts based on concept-to-word alignment.





Training data = supertags + AM dependency tree

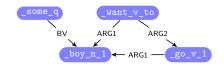
Hypergraph

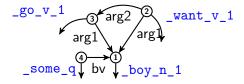


A graph consists of:

- ► A set of nodes.
- ► A set of edges connecting two nodes.

Hypergraph





A hypergraph adds:

- ► Hyperedges connecting any number of nodes.
- ► A single node can be treated as an edge.



↓s

- ► Terminal vs. non-terminal hyperedges
- ► Non-terminal hyperedges are utilized to control a derivation process.
- ► A derivation starts from a non-terminal hyperedge .



$$\mathring{\downarrow} \mathsf{S} \ \stackrel{\gamma_1}{\Longrightarrow} \ \overset{\mathsf{arg1}}{\overset{\mathsf{VP}}{\longrightarrow}} \ \overset{\mathsf{nrg1}}{\overset{\mathsf{NP}}{\longrightarrow}} \ \mathsf{NP}$$

- ► Terminal vs. non-terminal hyperedges
- ► Non-terminal hyperedges are utilized to control a derivation process.
- ► A derivation starts from a non-terminal hyperedge .
- ► In a derivation step, we substitute a non-terminal hyperedge with a hypergraph .



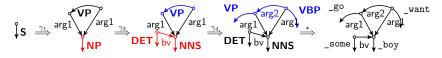
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- ► Terminal vs. non-terminal hyperedges
- ► Non-terminal hyperedges are utilized to control a derivation process.
- ► A derivation starts from a non-terminal hyperedge .
- ► In a derivation step, we substitute a non-terminal hyperedge with a hypergraph .
- ► We repeat until all edges are terminal ones.

Drewes et al. (1997)





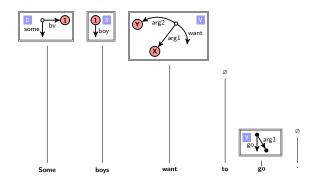
- Terminal vs. non-terminal hyperedges (symbols)
- ► Non-terminal hyperedges (symbols) are utilized to control a derivation process.
- ► A derivation starts from a non-terminal hyperedge (symbol).
- ► In a derivation step, we substitute a non-terminal hyperedge (symbols) with a hypergraph (a sequence of symbols).
- ► We repeat until all edges (symbols) are terminal ones.

Drewes et al. (1997)

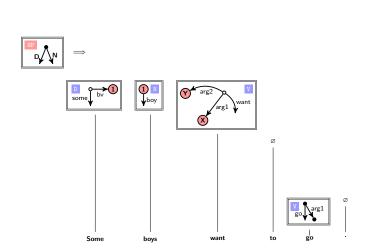


Some boys want to go ·

108

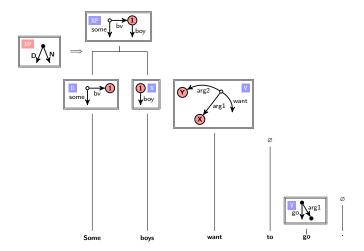


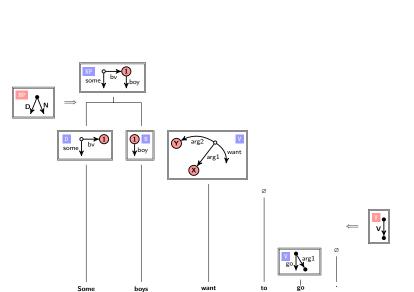






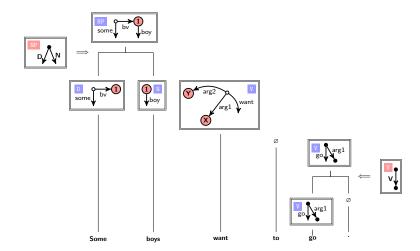




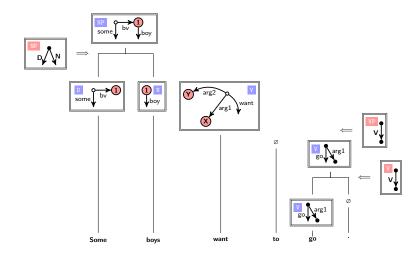




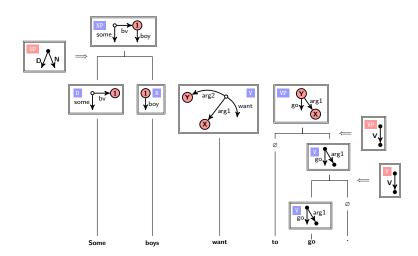




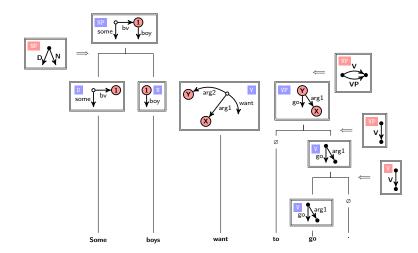




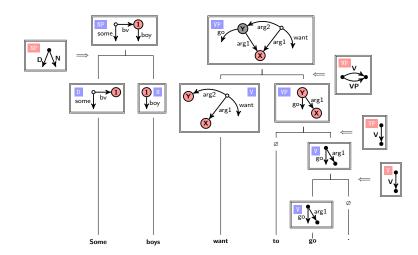




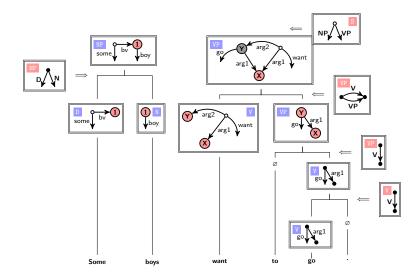




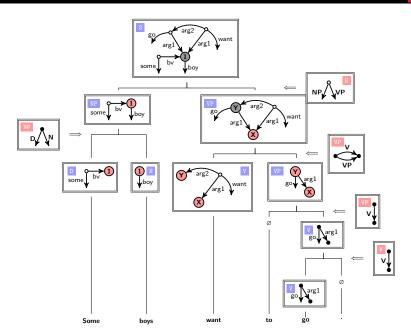










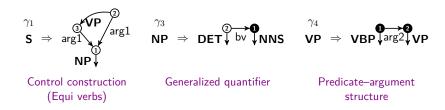


HRGs Can be Linguistically Meaningful

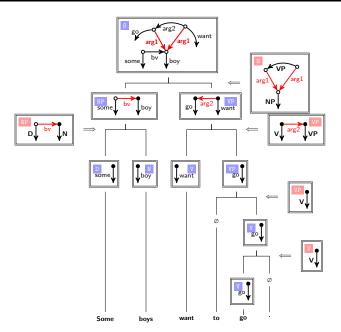




Rules



Construction Semantics (Revisited)

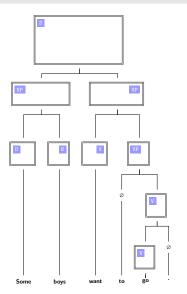






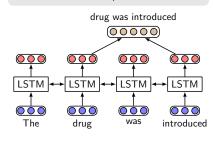


Tree construction + Semantic interpretation ⇒ Meaning representation



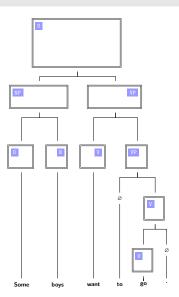
Syntactic parsing

- Word representation: LSTM/Transformer
- Phrase representation: LSTM-minus/Transformer



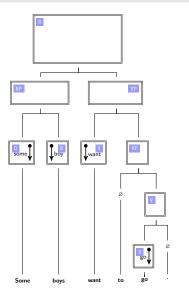


Tree construction + Semantic interpretation ⇒ Meaning representation





Tree construction + Semantic interpretation ⇒ Meaning representation

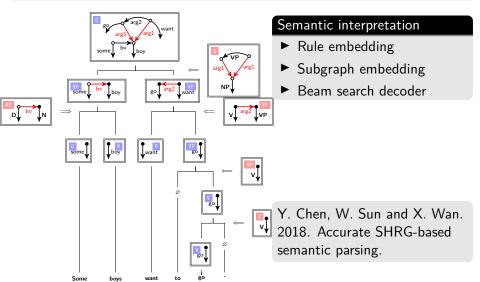


Semantic interpretation

- ► Rule embedding
- ► Subgraph embedding
- Beam search decoder

Y. Chen, W. Sun and X. Wan. 2018. Accurate SHRG-based semantic parsing.





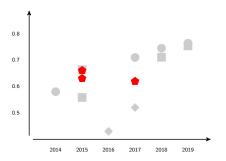
Magic Numbers



	DM		PAS		PSD		EDS		AMR	
	id	ood	id	ood	id	ood	${\sf Smatch}$	EDM_{na}	${\sf Smatch}$	Smatch
Groschwitz et al. (2018)	-	-	-	-	-	-	-	-	70.2	71.0
Lyu & Titov (2018)	-	-	-	-	-	-	-	-	73.7	74.4
S. Zhang et al. (2019)	-	-	-	-	-	-	-	-	-	76.3
H. Peng et al. (2017)	89.4	84.5	92.2	88.3	77.6	75.3	-	-	-	-
+Multitask learning	90.4	85.3	92.7	89.0	78.5	76.4	-	-	-	-
Dozat & Manning (2018)	93.7	88.9	94.0	90.8	81.0	79.4	-	-	-	-
Buys & Blunsom (2017)	-	-	-	-	-	-	85.5	85.9	60.1	-
Chen, Sun, & Wan (2018)	-	-	-	-	-	-	90.9	90.4	-	-
Lindemann et al. (2019) +Multitask learning	93.9 94.1	90.3 90.5	94.5 94.7	92.5 92.8	82.0 82.1	81.5 81.6	90.1 90.4	84.9 85.2	74.3 74.5	75.3 75.3

Transition-Based Approaches





- ► Inspired by the successful design of transition-based dependency parsers.
 - Very early work: Sagae & Tsujii (2008).
- ► Psycholinguistically motivated: Left-to-right, word-by-word
- Partially parsed results (parsing states) constrain parsing of subsequent words
- ► Greedy search to get a *good* parse.



- A transition system for parsing is a quadruple $S = (C, T, c_s, C_t)$, where
- $1. \ C$ is a set of configurations, each of which represents a parser state.
- 2. T is a set of transitions, each of which represents a parsing action,
- 3. c_s initializes S by mapping a sentence x to a particular configuration,
- 4. $C_t \subseteq C$ is a set of terminal configurations.

Deterministic parsing

PARSE
$$(x = (w_0, w_1, \dots, w_n))$$

1 $c \leftarrow c_s(x)$

- 2 while $c \notin C_t$
- c = Act(c, GetTransition(c))
- 4 return G_c

Sagae & Tsujii (2008); Wang et al. (2015c, 2015a); X. Zhang et al. (2016); Buys & Blunsom (2017); Gildea et al. (2018); Sun et al. (2019)



Partial analysis

Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ► Reduce

Stack

Buffer

[Some, boys, want, to, go]

Transition Init(_some_q)

>replace Some in the buffer with _some_q



Partial analysis

_some_q

Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
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Stack

Buffer

[_some_q, boys, want, to, go]

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Partial analysis

_some_q

Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- Reduce

Stack

Buffer

 $[\underline{some}_q, boys, want, to, go]$

Transition Shift(_boy_n_1)

⊳move <u>_some_q</u> from the buffer to the stack;



Partial analysis

_some_q

Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ► Reduce

Stack [_some_q]

Buffer

[_boy_n_1, want, to, go]

```
Transition Shift(_boy_n_1)
```

bys in the buffer with _boy_n_1



Partial analysis

_some_q

_boy_n_1

Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ► Reduce

Stack [_some_q]

Buffer

[_boy_n_1, want, to, go]

Transition Right-Arc(BV)

⊳link _some_q and _boy_n_1



Partial analysis



Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ▶ Reduce

Stack [_some_q]

Buffer

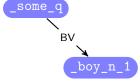
[_boy_n_1, want, to, go]

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⊳link _some_q and _boy_n_1



Partial analysis



Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ▶ Reduce

Stack [_some_q]

Buffer

[_boy_n_1, want, to, go]

Transition Reduce

⊳remove <u>some</u>q from the stack



Partial analysis



Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ▶ Reduce

Stack [] Buffer

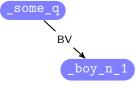
[_boy_n_1, want, to, go]

Transition Reduce

⊳remove <u>some</u>q from the stack



Partial analysis



Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ► Reduce

Stack []

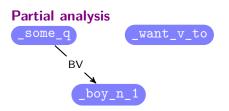
Buffer

 $[_boy_n_1$, want, to, go]

```
Transition Shift(_want_v_to)
```

⊳move _boy_n_1 from the buffer to stack;





Transition

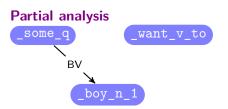
- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ► Reduce

```
Stack Buffer [_want_v_to, to, go]
```

```
Transition
Shift(_want_v_to) 

⊳then replace want in the buffer with _want_v_to
```





Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ► Reduce

```
Stack [_boy_n_1]
```

Buffer [_want_v_to, to, go]

```
Transition Left-Arc(ARG1)
```

⊳link _boy_n_1 and _want_v_to



Partial analysis _some_q _bv ARG1 _boy_n_1

Transition

- ► Shift (CI)
- ► Left-Arc (RD)
- ► Right-Arc (RD)
- ► Reduce

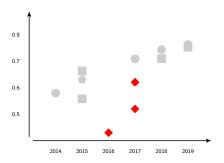
```
Stack Buffer [_want_v_to, to, go]
```

Transition Left-Arc(ARG1)

⊳link _boy_n_1 and _want_v_to

Translation-Based Approaches

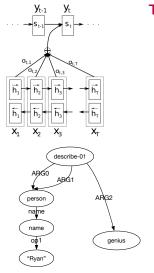




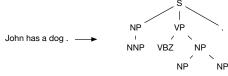
- ► Inspired by neural machine translation.
- Semantic graph as a foreign language.
- ► A parser knows how to linearize a graph.
- ▶ Data augmentation has been shown very helpful, partially reflecting the data-hungry nature of seq2seq models.

Sequence-to-Sequence Models for Parsing





Tree as a foreign language



John has a dog . → (S (NP NNP)NP (VP VBZ (NP DT NN)NP)VP .)S

Graph as a foreign language

-TOP-(describe-01 ARGO(person name(name op1("Ryan")op1)name)ARGO ARG1(person -RET-)ARG1 ARG2(genius)ARG2)-TOP-

Many variants

X. Peng et al. (2017); Konstas et al. (2017); Wang et al. (2015b, 2015a); Buys & Blunsom (2017)

Integrated with Other Approaches



Translation + Transition-Based Approach

- Using a sequence-to-sequence model
- ► The input sequence is the sequence of input words
- ► The output sequence is a sequence of transitions that leads to an output graph

X. Peng et al. (2018)

Translation + Factorization-Based Approach

- ► Identifying concepts with a sequence-to-sequence model
- ► Linking nodes with a factorization model

S. Zhang et al. (2018)

Cross-Framework Parsing



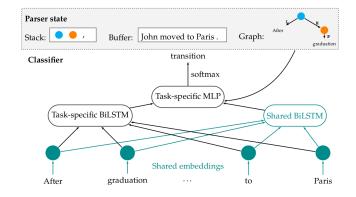
- ► State-of-the-art graph parsers rely on large-scale, manually annotated graphbanks.
- ► Multiple heterogeneous graphbanks EXIST!
- ?> Can we get a better parser by integrating heterogeneous graphbanks?
- 1. Heterogeneous annotations are (similar but) different.
 - ► Different projects, different linguistic theories, different representation formalisms, different annotation schemes, etc.
 - → Reducing approximation errors
- 2. Heterogeneous annotations are (different but) similar.
 - ► Similar high-level linguistic principles.
 - \rightarrow Reducing estimation errors

Multitask Learning for Semantic Parsing



Freda (Daumé III, 2007)

Hal Daumé III. 2007. Frustratingly easy domain adaptation.



D. Hershcovich, O. Abend and A. Rappoport. 2018. Multitask Parsing Across Semantic Representations

Magic Numbers



Improving a Transition-Based Parser for UCCA (Hershcovich et al., 2018)

	In-Do	omain	Out-of-Domain			
	Primary	Romote	e Primary Romo			
Single	73.6	51.5	69	26.7		
+AMR	73.7	49.9	69.5	27.5		
+DM	74.8	53.9	70.7	25.9		
+UD	74.1	50.8	69.7	28.7		

Improving a Factorization-Based Parser for Many Graphbanks (Lindemann et al., 2019)

	DM		PAS		PSD		EDS	AMR
	id	ood	id	ood	id	ood	EDM_{na}	Smatch
Single (GloVe) +MTL	90.4 91.2	84.3 85.7			78.1 78.9	74.5 76.2	82.5 83.3	69.2 70.4
Single (BERT) +MTL	93.9 94.1	90.3 90.5			82.0 82.1	81.5 81.6	84.9 85.2	74.3 74.5

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Cross-lingual parsing

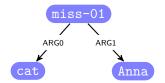


Multilingual Parsing

- ► SemEval 2016: Chinese Semantic Dependency Parsing
- SemEval 2019: Cross-lingual semantic parsing with UCCA
 * English, German, French
- One single parsing architecture for many languages

Cross-lingual parsing

- ▶ Mapping a string of \mathcal{L}_A to a graph of \mathcal{L}_B
- ▶ Motivation: Don't create a graphbank for \mathcal{L}_A .



EN: Anna's cat is missing her

DE: Anna fehlt ihrem Kater

Using

Semantic

Structure

Applications of Semantic Graphs



- Using semantic graphs in applications may improve accuracy:
 - ► Semantic graphs abstract over surface variation.
 - ► Easier to generalize over graphs than over sentences.
 - ▶ ... if semantic parsing is accurate enough.
- Typical applications:
 - ► machine translation Jones et al. (2012)
 - ▶ entity linking / KB population Reddy et al. (2014); Pan et al. (2015)
 - ► summarization Liu et al. (2015); Hardy & Vlachos (2018)

-

- Original motivation for AMR: semantics-based SMT.
- ▶ Initial work of Jones et al. (2012) yielded results that were promising at the time.
- Steamrolled by end-to-end neural methods for MT.

Example

-

- Original motivation for AMR: semantics-based SMT.
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- Steamrolled by end-to-end neural methods for MT.

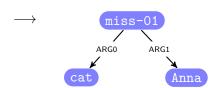
Example

DE: Anna fehlt ihrem Kater

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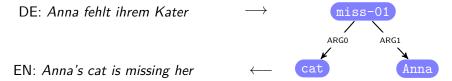
Example

DE: Anna fehlt ihrem Kater



- Original motivation for AMR: semantics-based SMT.
- ▶ Initial work of Jones et al. (2012) yielded results that were promising at the time.
- ► Steamrolled by end-to-end neural methods for MT.

Example





Task: Map entities in text to entities in a knowledge base (KB).



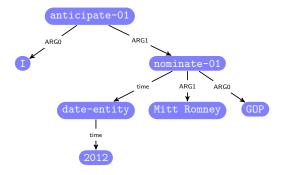
Task: Map entities in text to entities in a knowledge base (KB).

I am cautiously anticipating the GOP nominee in 2012 not to be Mitt Romney.



Task: Map entities in text to entities in a knowledge base (KB).

I am cautiously anticipating the GOP nominee in 2012 not to be Mitt Romney.





Task: Map entities in text to entities in a knowledge base (KB).

I am cautiously anticipating the GOP nominee in 2012 not to be Mitt Romney.

Romney was the Governor of Massachusetts ...

Romney is the great-great-grandson of a Mormon pioneer Republican candidates like Romney, Paul, and Johnson ...

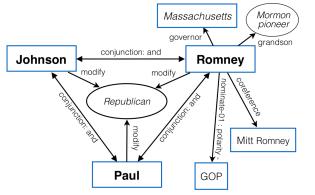


Task: Map entities in text to entities in a knowledge base (KB).

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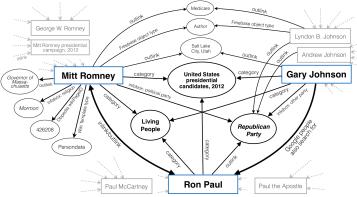


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Entity Linking: Evaluation

-

Evaluation on corpus with 1600 entity mentions, manually annotated with AMRs and entity links.

approach	news	forums	total
non-graph SOTA	93.1	87.4	91.0
"collaborator", human AMR	93.7	86.9	91.1
"collaborator", JAMR	90.2	85.7	88.5
"combined", human AMR	94.3	88.3	92.1

Pan et al. (2015)

Abstractive Summarization

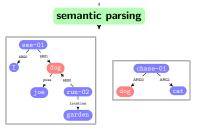


I saw Joe's dog, which was running in the garden.
The dog was chasing a cat.

Liu et al. (2015); Hardy & Vlachos (2018)

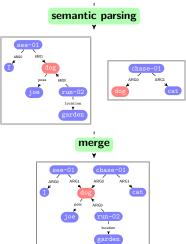


I saw Joe's dog, which was running in the garden.





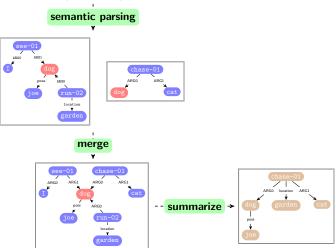
I saw Joe's dog, which was running in the garden.



Liu et al. (2015); Hardy & Vlachos (2018)



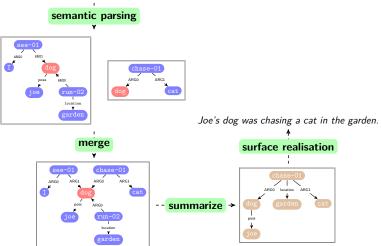
I saw Joe's dog, which was running in the garden.



Liu et al. (2015); Hardy & Vlachos (2018)



I saw Joe's dog, which was running in the garden.



Liu et al. (2015); Hardy & Vlachos (2018)

Abstractive Summarization: Evaluation



Evaluation on Proxy Report section of AMRBank LCD2017T10.

AMRs	NLG model	Rouge-1	Rouge-2	Rouge-L
gold	amr2seq + LM	40.4	20.3	31.4
	amr2seq	38.9	12.9	27.0
	amr2bow (Liu et al.)	39.6	6.2	22.1
RIGA	amr2seq + LM	42.3	21.2	33.6
	amr2seq	37.8	10.7	26.9
_	OpenNMT	36.1	19.2	31.1

Hardy & Vlachos (2018)

Conclusions Outlook

Conclusion



Semantic graph parsing: a success story

- ► Capture semantic information that is not explicit in syntactic parses.
- ► Parsers getting increasingly accurate.
- ► Graphs seem useful in applications.
- ► Look out for graph parsing papers throughout ACL 2019.

Differences between graphbanks are substantial

- ► Anchoring of nodes in tokens (flavors 0–2).
- ► Capture different facets of meaning.
- Different design choices.

Outlook



Cross-Framework Semantic Parsing

- ► Most graph parsers work only for one flavor of graphbank.
- ► To what degree do they generalize across frameworks?
- ► Check out CoNLL 2019 Shared Task on Cross-Framework Meaning Representation Parsing (MRP, http://mrp.nlpl.eu/).

Facets of Meaning

- ► Many facets of meaning are not represented by graphbanks.
- What facets are relevant for what applications?
- ► Push graphbanks so they can be represented, or switch to different meaning representations.
- Check out the ACL 2019 Workshop on Designing Meaning Representations (https://www.cs.brandeis.edu/~clp/dmr/).

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Tim O'Gorman, Martha Palmer, and Nianwen Xue;
The Chinese Student; and others.

All errors, mistakes, and oversights are, of course, our own responsibility.

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There might still be time for questions.

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