# MRP 2019: Cross-Framework Meaning Representation Parsing

http://mrp.nlpl.eu

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⋆ University of Colorado at Boulder, Department of Linguistics
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# 10,000-Meter Perspective: Parsing into Semantic Graphs

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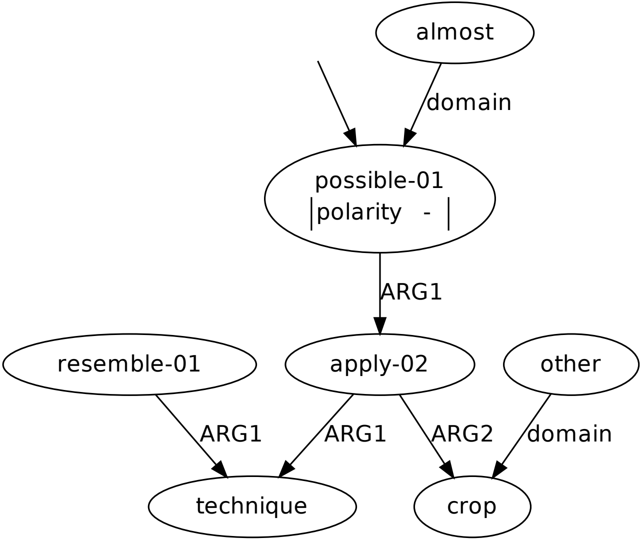

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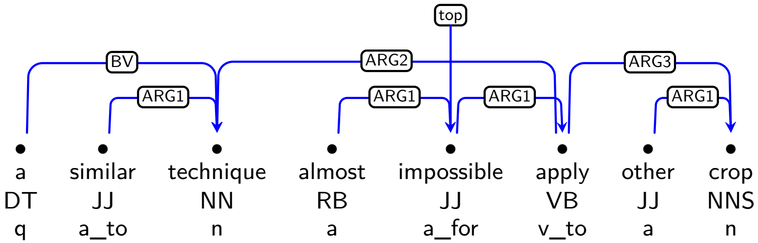

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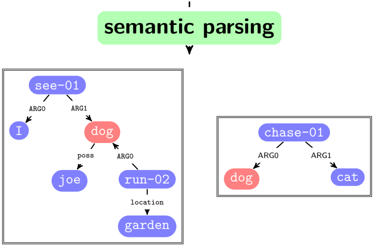

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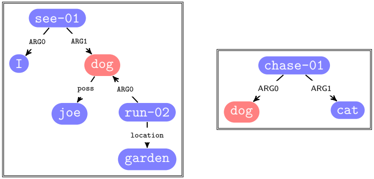
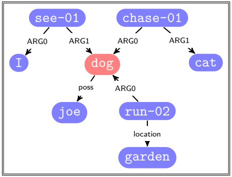
**semantic parsing**




**merge**



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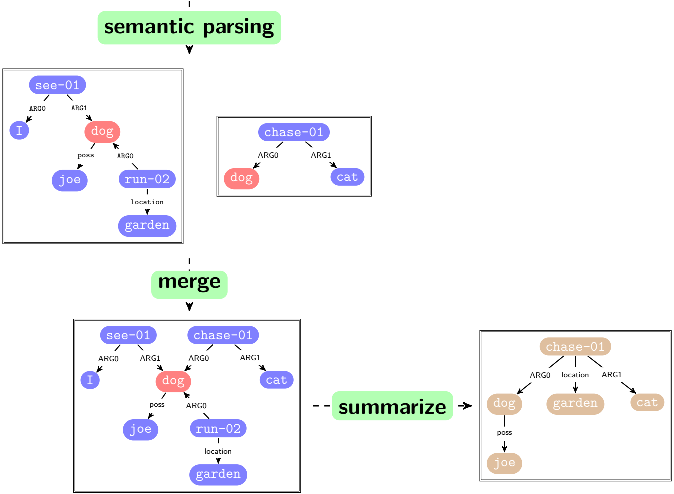

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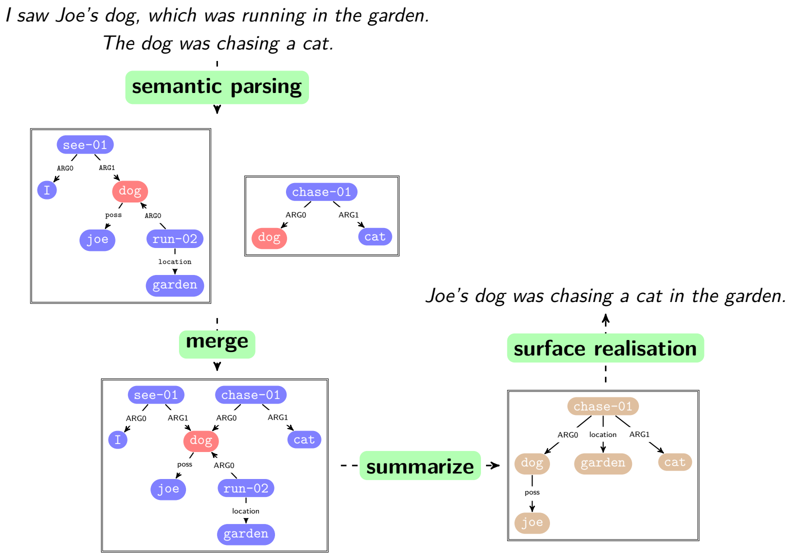

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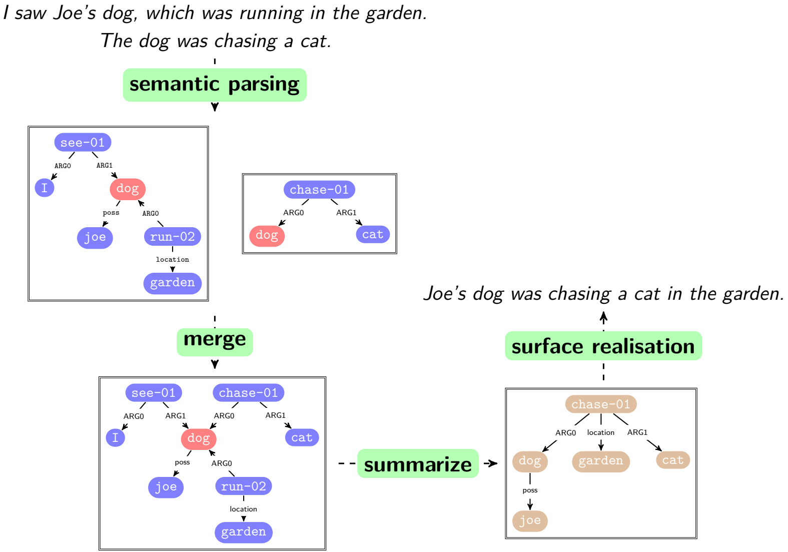


Hardy & Vlachos (2018): $2^+$ ROUGE points over strong encoder–decoder.

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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).

# Semi-Formally: Trees vs. Graphs

## Structural Wellformedness Conditions on Trees

- Unique root, connected, single parent, free of cycles; maybe: projective;

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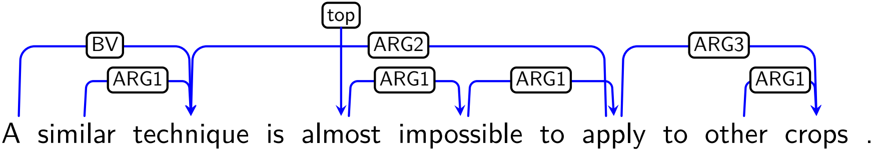

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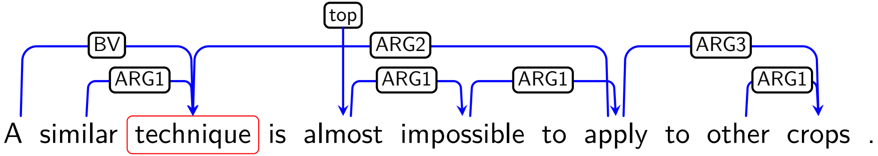


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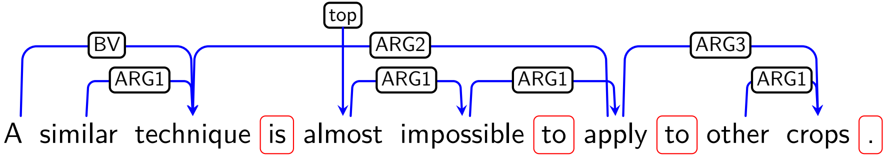


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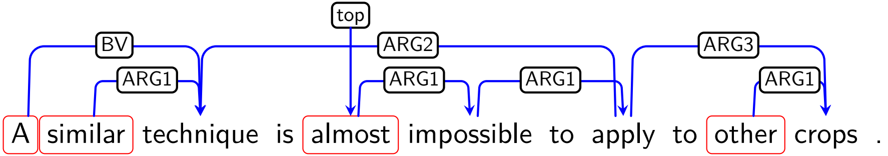


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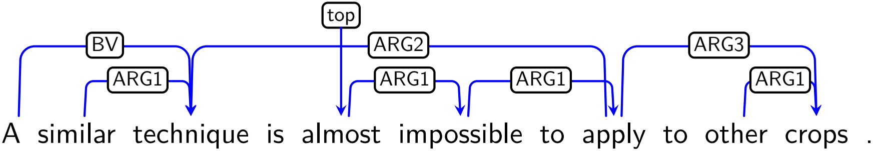


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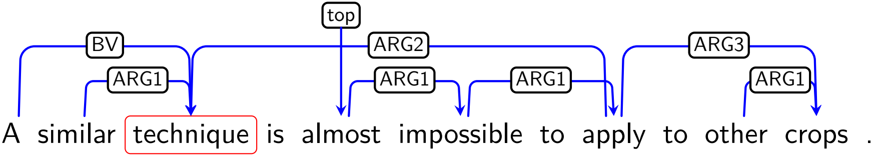


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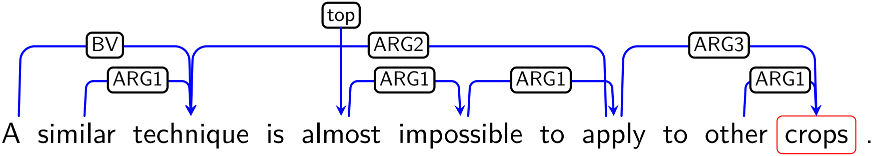


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- Cottage industry of parsers with output structures beyond rooted trees;
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- much framework-internal evolution: design reflects specific assumptions;

$\rightarrow$ evaluate across frameworks; learning from complementary knowledge.

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## Learning from Complementary Knowledge

- Cross-Framework Perspective: Seek commonality and complementarity.

# A Selection of Semantic Graphbanks

## Selection Criteria

- 'Full-sentence' semantics: all content-bearing units receive annotations;
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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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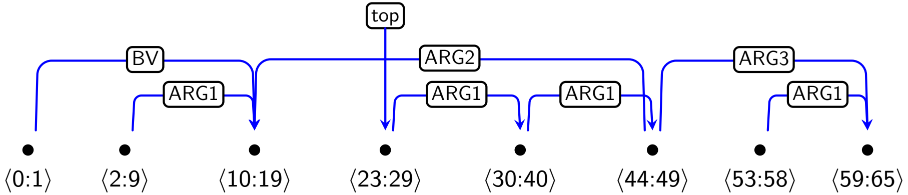

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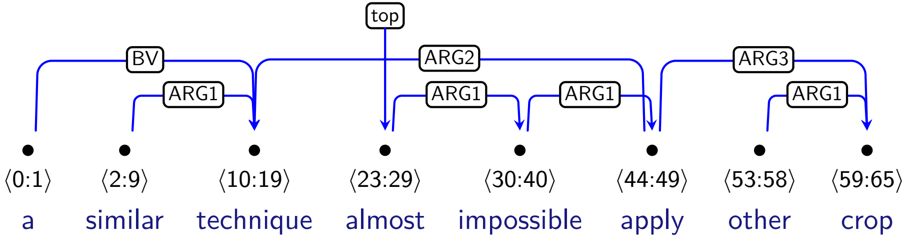

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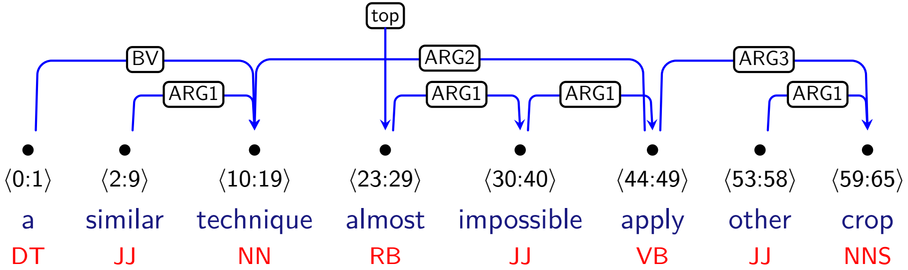

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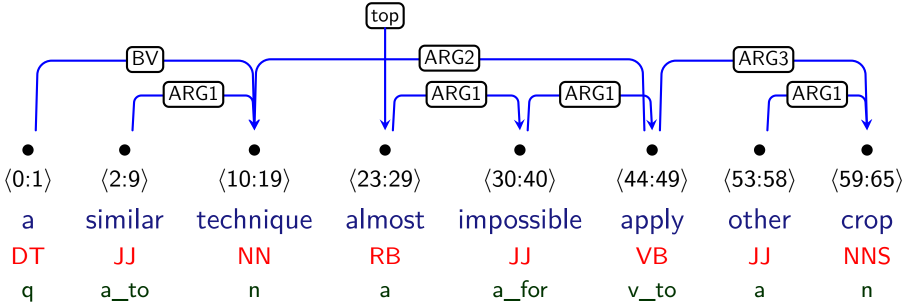

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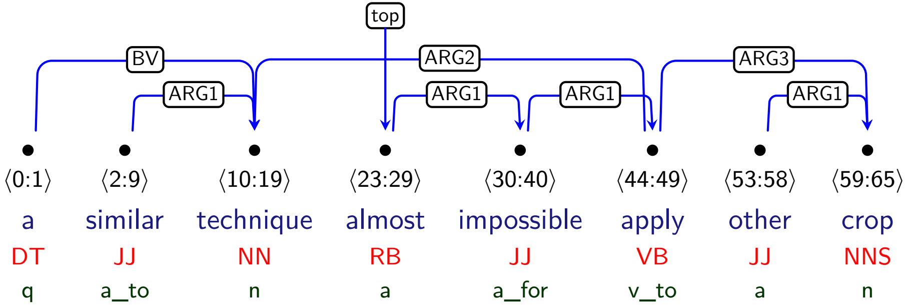

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- limited expressivity, e.g. no lexical decomposition, no covert meaning.

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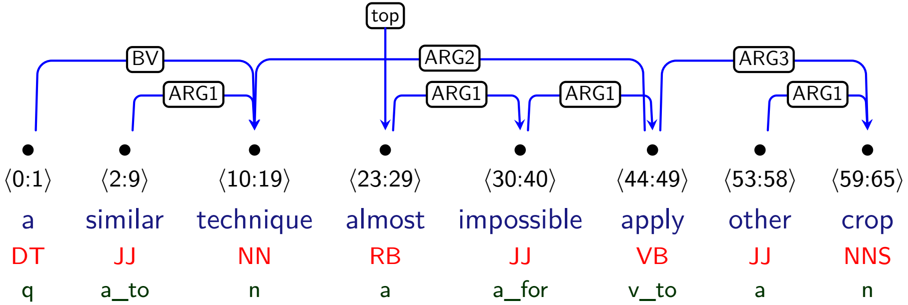

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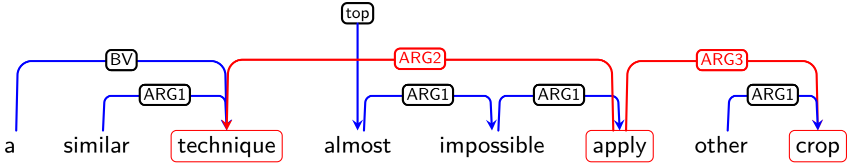

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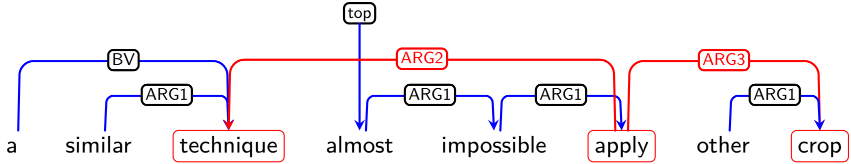
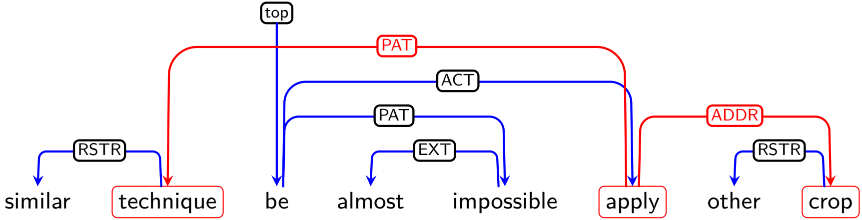



## PSD: Prague Semantic Dependencies (Hajič et al., 2012)

- Simplification from FGD tectogrammatical trees (Sgall et al., 1986).



### Break Free of Bi-Lexical Limitations (Oepen & Lønning, 2006)

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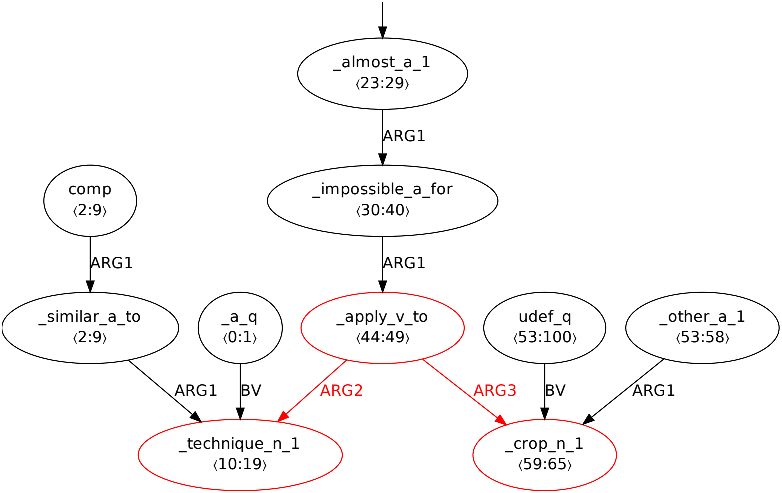


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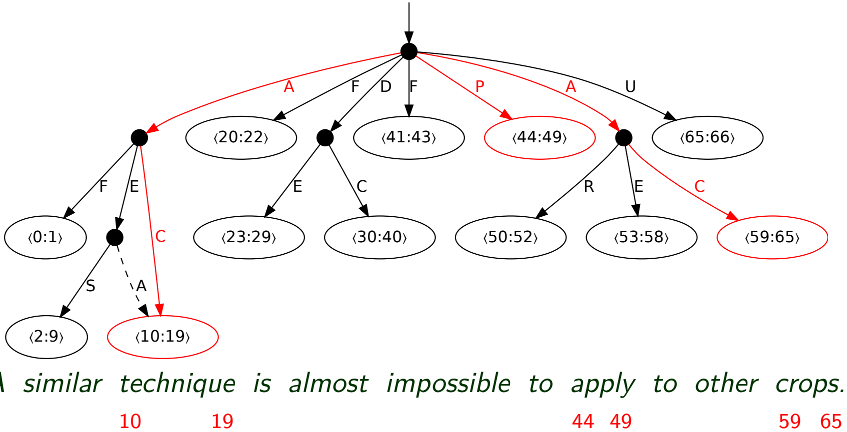
# (1) Universal Conceptual Cognitive Annotation (UCCA)

## Multi-Layered Design (Abend & Rappoport, 2013); Foundational Layer

- Tree backbone: semantic 'constituents' are scenes ('clauses') and units;



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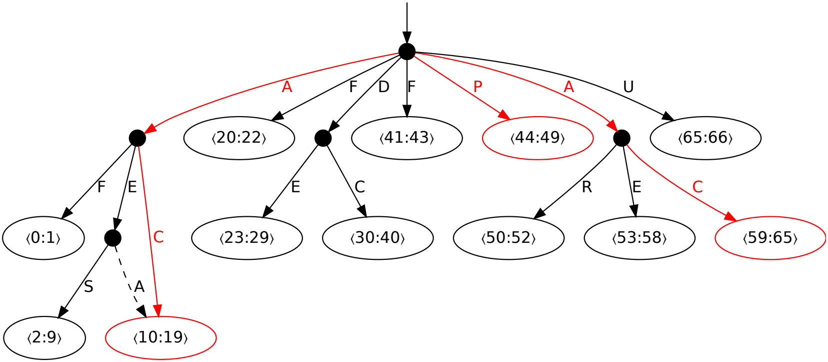


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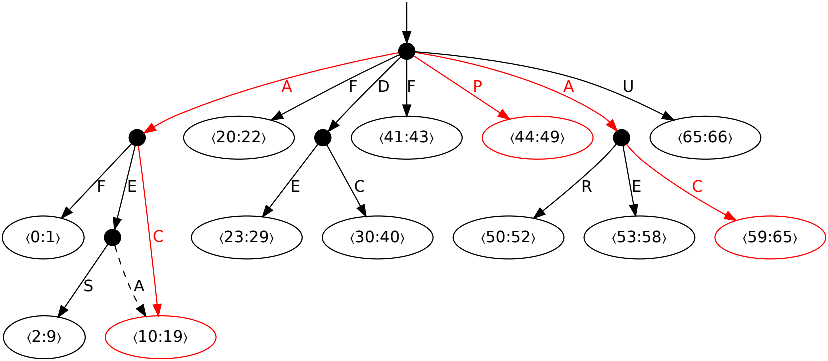
- complex units distinguish Center and Elaborator(s); allow remote edges.

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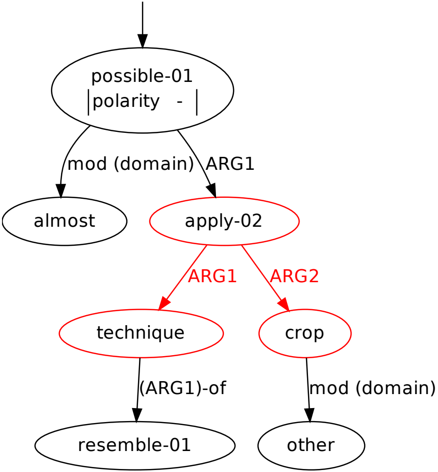
# (2) Abstract Meaning Representation (AMR)




**Banarescu et al. (2013)**

- Abstractly (if not linguistically) similar to EDS, but unanchored;
- verbal senses from PropBank$^{++}$;
- negation as node-local property;
- tree-like annotation: inversed edges normalized for evaluation;
- originally designed for (S)MT; various NLU applications to date.

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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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# Training and Evaluation Data in the Shared Task

| | | DM | PSD | EDS | UCCA | AMR |
|---|---|---|---|---|---|---|
| | Flavor | 0 | 0 | 1 | 1 | 2 |
| **train** | Text Type | newspaper | newspaper | newspaper | mixed | mixed |
| | Sentences | 35,656 | 35,656 | 35,656 | 6,572 | 56,240 |
| | Tokens | 802,717 | 802,717 | 802,717 | 138,268 | 1,000,217 |
| **test** | Text Type | mixed | mixed | mixed | mixed | mixed |
| | Sentences | 3,359 | 3,359 | 3,359 | 1,131 | 1,998 |
| | Tokens | 64,853 | 64,853 | 64,853 | 21,647 | 39,520 |

- DM, PSD, and ESD annotate the same text (Sections 00–20 of WSJ);
- UCCA: samples of EWT & Wikipedia; AMR: twelve different sources;

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|---|---|---|---|---|---|---|
| | Flavor | 0 | 0 | 1 | 1 | 2 |
| **train** | Text Type | newspaper | newspaper | newspaper | mixed | mixed |
| | Sentences | 35,656 | 35,656 | 35,656 | 6,572 | 56,240 |
| | Tokens | 802,717 | 802,717 | 802,717 | 138,268 | 1,000,217 |
| **test** | Text Type | mixed | mixed | mixed | mixed | mixed |
| | Sentences | 3,359 | 3,359 | 3,359 | 1,131 | 1,998 |
| | Tokens | 64,853 | 64,853 | 64,853 | 21,647 | 39,520 |

- DM, PSD, and ESD annotate the same text (Sections 00–20 of WSJ);
- UCCA: samples of EWT & Wikipedia; AMR: twelve different sources;
- linguistics: 100-item WSJ sample in all frameworks publicly available;

# Training and Evaluation Data in the Shared Task

| | | DM | PSD | EDS | UCCA | AMR |
|---|---|---|---|---|---|---|
| | Flavor | 0 | 0 | 1 | 1 | 2 |
| **train** | Text Type | newspaper | newspaper | newspaper | mixed | mixed |
| | Sentences | 35,656 | 35,656 | 35,656 | 6,572 | 56,240 |
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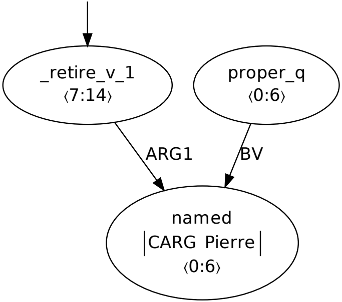
- UCCA: samples of EWT & Wikipedia; AMR: twelve different sources;
- linguistics: 100-item WSJ sample in all frameworks publicly available;
- evaluation: subset of 100 sentences from *The Little Prince* also public.

# Cross-Framework Evaluation: MRP Graph Similarity

- Break down graphs into types of information: per-type and overall $F_1$;



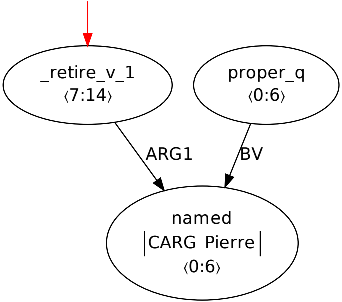

*Pierre retired.*

**Different Types of Semantic Graph 'Atoms'**

| | DM | PSD | EDS | UCCA | AMR |
|---|---|---|---|---|---|
| Top Nodes | ✓ | ✓ | ✓ | ✓ | ✓ |
| Labeled Edges | ✓ | ✓ | ✓ | ✓ | ✓ |
| Node Labels | ✓ | ✓ | ✓ | ✗ | ✓ |
| Node Properties | ✓ | ✓ | ✓ | ✗ | ✓ |
| Node Anchoring | ✓ | ✓ | ✓ | ✓ | ✗ |
| Edge Attributes | ✗ | ✗ | ✗ | ✓ | ✗ |

# Cross-Framework Evaluation: MRP Graph Similarity

- Break down graphs into types of information: per-type and overall $F_1$;
- tops

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# Cross-Framework Evaluation: MRP Graph Similarity

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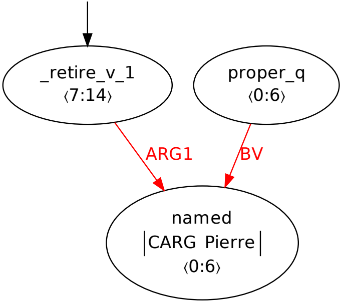
- tops and (labeled) edges;

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# Cross-Framework Evaluation: MRP Graph Similarity

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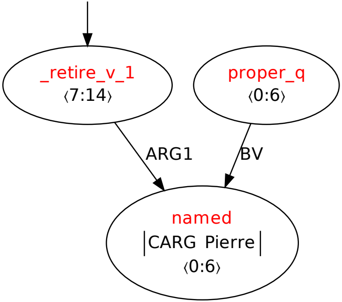


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# Cross-Framework Evaluation: MRP Graph Similarity

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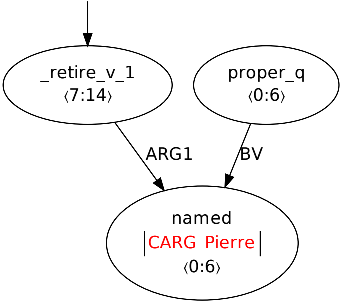


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| Edge Attributes | ✗ | ✗ | ✗ | ✓ | ✗ |

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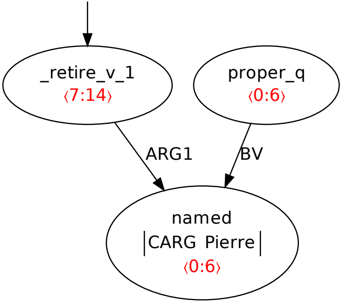


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# Cross-Framework Evaluation: MRP Graph Similarity

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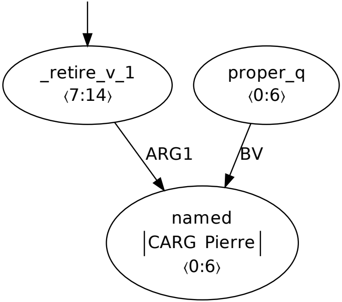


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# Cross-Framework Evaluation: MRP Graph Similarity

- Break down graphs into types of information: per-type and overall $F_1$;
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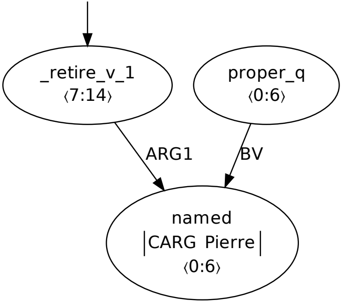
- requires node–node correspondences; search for overall maximum score;
- maximum common edge subgraph isomorphism (MCES) is NP-hard;

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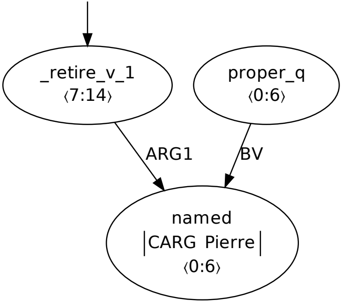
- tops and (labeled) edges; labels, properties, anchors, and attributes;
- requires node–node correspondences; search for overall maximum score;
- maximum common edge subgraph isomorphism (MCES) is NP-hard;

→ smart initialization, scheduling, and pruning yield strong approximation.

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# A Coarse Taxonomy of Parsing Approaches

| **Approach** | **Decomposes Graph to ...** |
|---|---|
| Factorization-based | Parts (edges/subgraphs) scored separately |
| Transition-based | Actions to build it incrementally |
| Composition-based | Derivation operations of a grammar |
| Translation-based | Linearized sequence of tokens |

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Generalize graph-based dependency parsers.

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| Translation-based | Linearized sequence of tokens |

Generalize transition-based dependency parsers.

# High-Level Overview of Submissions

| Teams | DM | PSD | EDS | UCCA | AMR | MTL | Approach |
|---|---|---|---|---|---|---|---|
| ERG[∦§†] | ✓ | ✗ | ✓ | ✗ | ✗ | ✗ | Composition |
| TUPA[§†] | ✓ | ✓ | ✓ | ✓ | ✓ | ✗/✓ | Transition |
| HIT-SCIR | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Transition |
| SJTU–NICT | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Factorization |
| SUDA–Alibaba | ✓ | ✓ | ✓ | ✓ | ✓ | (✓) | Factorization |
| Saarland | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Composition |
| Hitachi | ✓ | ✓ | ✓ | ✓ | ✓ | (✓) | Factorization |
| ÚFAL MRPipe | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Transition |
| ShanghaiTech | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | Factorization |
| Amazon | ✓ | ✓ | ✗ | ✗ | ✓ | ✗ | Factorization |
| JBNU | ✓ | ✓ | ✗ | ✓ | ✗ | ✗ | Factorization |
| SJTU | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition |
| ÚFAL–Oslo | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Transition |
| HKUST | ✓ | ✓ | ✗ | ✓ | ✗ | ? | |
| Bocharov | ✗ | ✗ | ✗ | ✗ | ✓ | ? | |
| Peking[∦] | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | Factorization |
| CUHK[§] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition |
| Anonymous[§] | ✗ | ✓ | ✗ | ✗ | ✗ | ? | |

# High-Level Overview of Submissions

| Teams | DM | PSD | EDS | UCCA | AMR | MTL | Approach |
|---|---|---|---|---|---|---|---|
| ERG[♯§†] | ✓ | ✗ | ✓ | ✗ | ✗ | ✗ | Composition |
| TUPA[§†] | ✓ | ✓ | ✓ | ✓ | ✓ | ✗/✓ | Transition |
| HIT-SCIR | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Transition |
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| SJTU | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition |
| ÚFAL–Oslo | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Transition |
| HKUST | ✓ | ✓ | ✗ | ✓ | ✗ | ? | |
| Bocharov | ✗ | ✗ | ✗ | ✗ | ✓ | ? | |
| Peking[♯] | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | Factorization |
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| ShanghaiTech | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ | Factorization |
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| JBNU | ✓ | ✓ | ✗ | ✓ | ✗ | ✗ | Factorization |
| SJTU | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition |
| ÚFAL–Oslo | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Transition |
| HKUST | ✓ | ✓ | ✗ | ✓ | ✗ | ? | |
| Bocharov | ✗ | ✗ | ✗ | ✗ | ✓ | ? | |
| Peking[∦] | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | Factorization |
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| Anonymous[§] | ✗ | ✓ | ✗ | ✗ | ✗ | ? | |

# High-Level Overview of Submissions

| Teams | DM | PSD | EDS | UCCA | AMR | MTL | Approach |
|---|---|---|---|---|---|---|---|
| ERG$^{\sharp\S\dagger}$ | ✓ | ✗ | ✓ | ✗ | ✗ | ✗ | Composition |
| TUPA$^{\S\dagger}$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗/✓ | Transition |
| HIT-SCIR | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Transition |
| SJTU–NICT | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Factorization |
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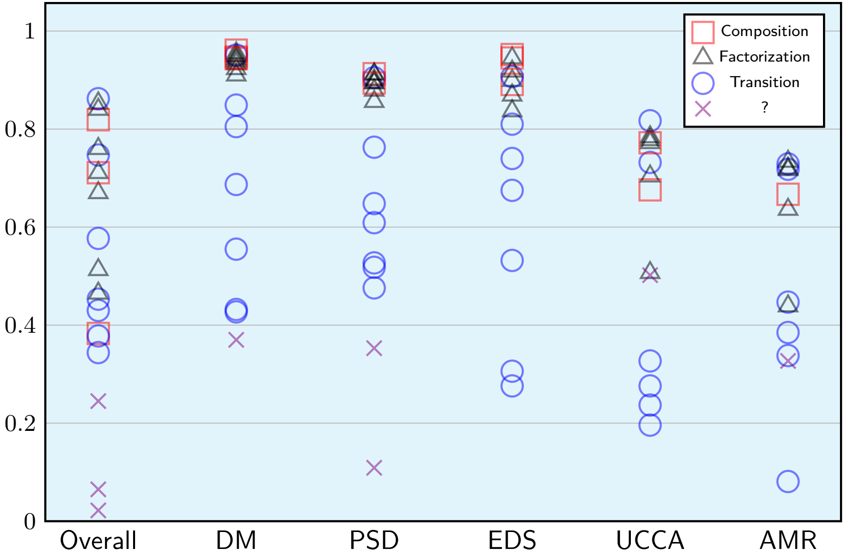
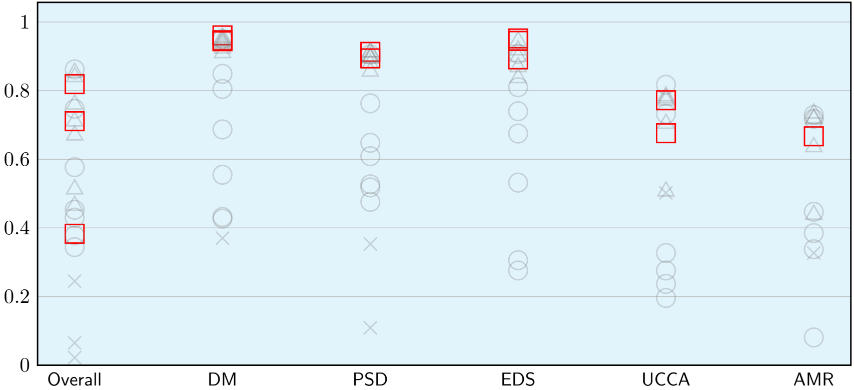
| JBNU | ✓ | ✓ | ✗ | ✓ | ✗ | ✗ | Factorization |
| SJTU | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition |
| ÚFAL–Oslo | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | Transition |
| HKUST | ✓ | ✓ | ✗ | ✓ | ✗ | ? | |
| Bocharov | ✗ | ✗ | ✗ | ✗ | ✓ | ? | |
| Peking$^{\sharp}$ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | Factorization |
| CUHK$^{\S}$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition |
| Anonymous$^{\S}$ | ✗ | ✓ | ✗ | ✗ | ✗ | ? | |

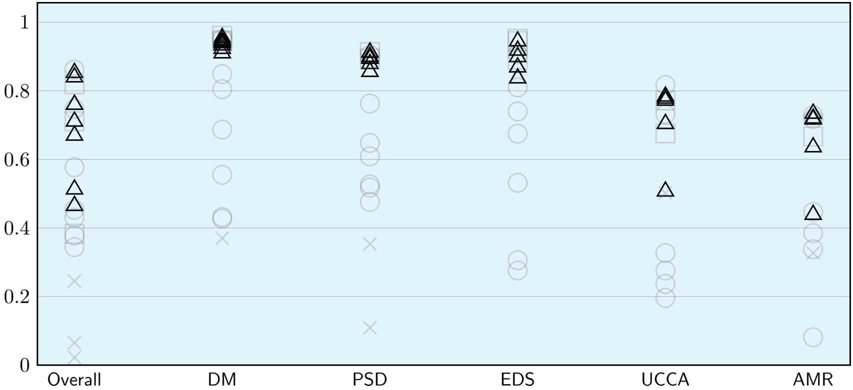
# Score Distributions





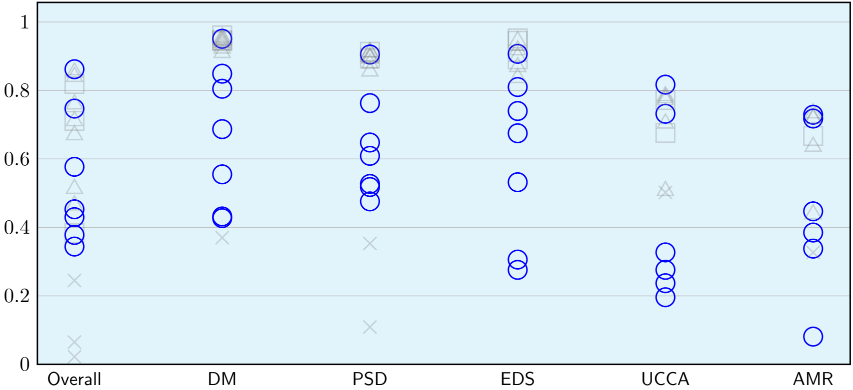

- Explicitly modeling the derivation process.
- A parser evaluates a derivation licensed by a symbolic system.

# Factorization-Based Approaches



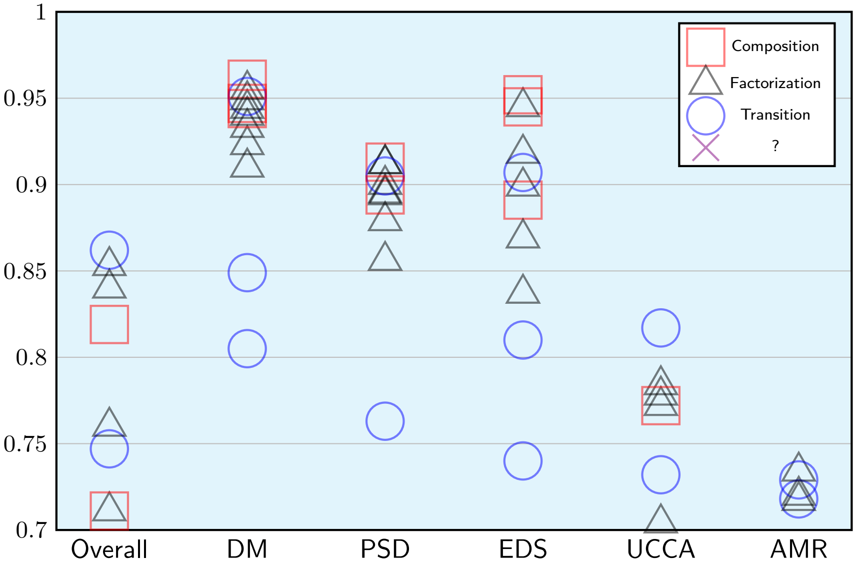

- Inspired by graph-based dependency parsers.
- Explicitly modeling the target structure.
- A parser evaluates factors of a candidate graph.

# Transition-Based Approaches




- Inspired by transition-based dependency parsers.
- Incremental (left-to-right, word-by-word).
- Partial parse constrains subsequent actions.
- Greedy/beam search to get a parse.

# Score Distributions: Zoom In

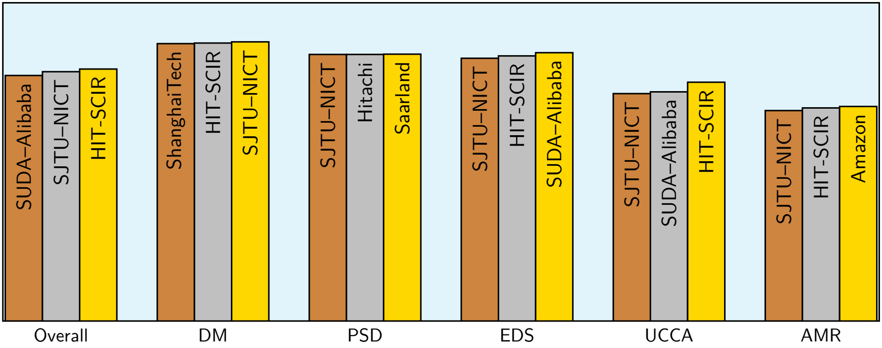


# State of the Art

Submissions from established top-performing teams:

- ShanghaiTech (DM, PSD)
- Peking (EDS)
- SUDA–Alibaba (UCCA)
- Saarland (AMR)

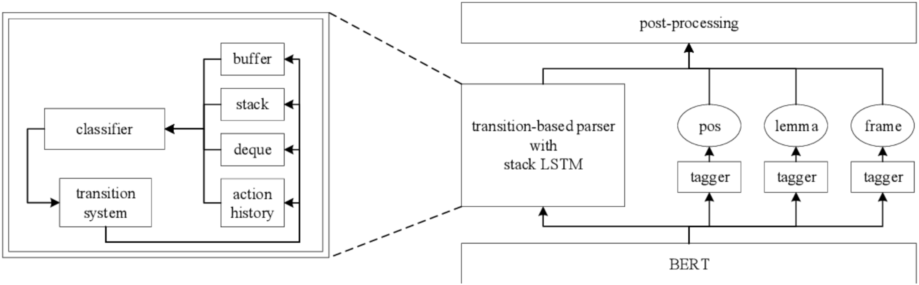
Outperformed in most cases!



# A Transition-based Parser

## HIT-SCIR at MRP 2019: A Unified Pipeline for Meaning Representation Parsing via Efficient Training and Effective Encoding

**Wanxiang Che, Longxu Dou, Yang Xu, Yuxuan Wang, Yijia Liu, Ting Liu**
Research Center for Social Computing and Information Retrieval
Harbin Institute of Technology, China
{car,lxdou,yxu,yxwang,yjliu,tliu}@ir.hit.edu.cn



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| DM & PSD | UCCA | EDS | AMR |
|---|---|---|---|
| Shift | Shift | Shift | Shift |
| Reduce | Reduce | Reduce | Reduce |
| Left-Edge | Left-Edge | Left-Edge | Left-Edge |
| Right-Edge | Right-Edge | Right-Edge | Right-Edge |
| Pass | Left-Remote | Drop | Drop |
| Finish | Right-Remote | Node-Start | Pass |
| | Node | Node-End | Merge |
| | Swap | Pass | Confirm |
| | Finish | Finish | Entity |
| | | | New |
| | | | Finish |

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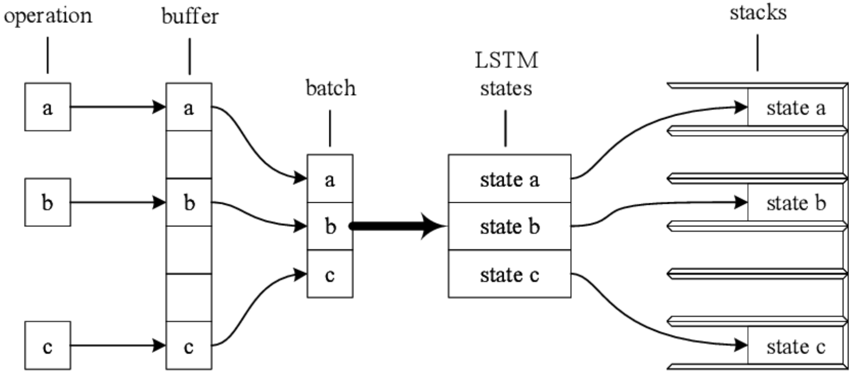

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Fine-tuning BERT

Narrows the gap between transition- and factorization-based

| | | | DM | | PAS | | PSD | |
|---|---|---|---|---|---|---|---|---|
| | Parser | Feature | id F | ood F | id F | ood F | id F | ood F |
| Wang et al. (2018b) | T | word2vec | 89.3 | 83.2 | 91.4 | 87.2 | 76.1 | 73.2 |
| Dozat and Manning (2018) | G | GloVe+char | 92.7 | 87.8 | 94.0 | 90.6 | 80.5 | 78.6 |
| HIT-SCIR | T | GloVe+char | 86.1 | 79.2 | 89.8 | 85.2 | 72.8 | 68.5 |
| AllenNLP | G | GloVe+char | 91.6 | 86.1 | 93.1 | 89.6 | 77.4 | 73.0 |
| HIT-SCIR | T | BERT | 92.9 | 89.2 | 94.4 | 92.4 | 81.6 | 81.0 |
| AllenNLP | G | BERT | 94.1 | 90.8 | 94.8 | 92.9 | 80.7 | 79.5 |

# Potential for Multitask/Transfer Learning?

## Deep Multitask Learning for Semantic Dependency Parsing

**Hao Peng**[*] **Sam Thomson**[†] **Noah A. Smith**[*]
[*]Paul G. Allen School of Computer Science & Engineering, University of Washington, Seattle, WA, USA
[†]School of Computer Science, Carnegie Mellon University, Pittsburgh, PA, USA
{hapeng,nasmith}@cs.washington.edu, sthomson@cs.cmu.edu

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†School of Computer Science, Carnegie Mellon University, Pittsburgh, PA, USA
{hapeng,nasmith}@cs.washington.edu, sthomson@cs.cmu.edu

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## Learning Joint Semantic Parsers from Disjoint Data

**Hao Peng♢** **Sam Thomson♣** **Swabha Swayamdipta♣** **Noah A. Smith♢**
♢ Paul G. Allen School of Computer Science & Engineering, University of Washington
♣ School of Computer Science, Carnegie Mellon University
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# Potential for Multitask/Transfer Learning?

**Deep Multitask Learning for Semantic Dependency Parsing**

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**Learning Joint Semantic Parsers from Disjoint Data**

**Hao Peng♢** **Sam Thomson♣** **Swabha Swayamdipta♣** **Noah A. Smith♢**
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**Compositional Semantic Parsing Across Graphbanks**

**Matthias Lindemann*** and **Jonas Groschwitz*** and **Alexander Koller**
Department of Language Science and Technology
Saarland University
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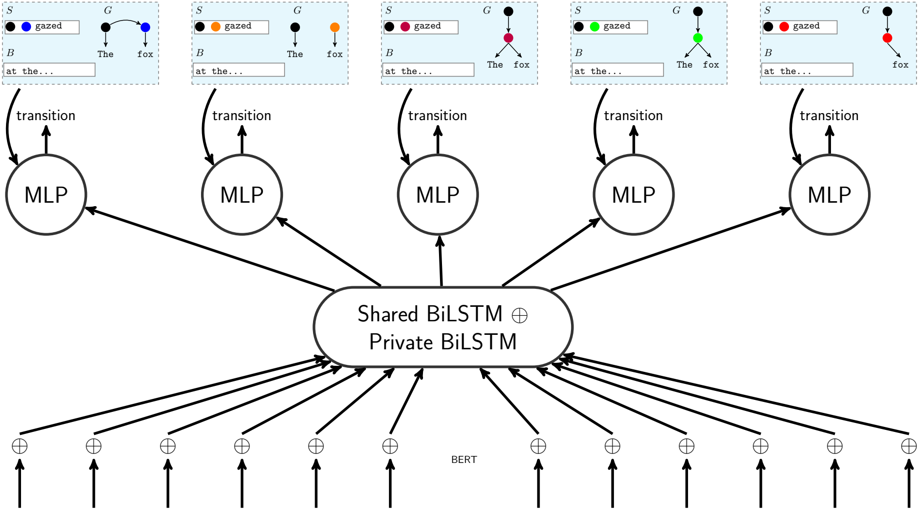
TUPA multitask: no improvement over single-task



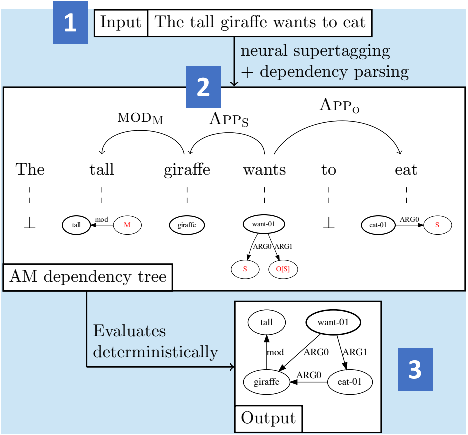
# Compositional Parsing Across All Graphbanks

## Saarland at MRP 2019

L. Donatelli, M. Fowlie, J. Groschwitz, A. Koller, M. Lindemann, M. Mina, P. Weißenhorn

- Compositional neural parser with competitive results across all MRP shared task graphbanks (only compositional parser to do so!)
  - 4th place overall
  - 1st on PSD
  - 1st *The Little Prince* subset
- Parser previously held SOTA on MRP graphbanks apart from UCCA at ACL 2019

# Apply-Modify (AM) Algebra and graph decomposition




**1** Sentence

**2** AM Dependency tree

**3** Graph

- Linguistically-motivated compositional structure
- Diverse meaning representations mapped to similar AM trees

# Interim Conclusions & Outlook

## Lessons Learned

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**Come Join Us, Team Up!**

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