Saarland at MRP 2019:
Compositional parsing across all graphbanks

Lucia Donatelli, Meaghan Fowlie*, Jonas Groschwitz, Alexander Koller, Matthias Lindemann, Mario Mina, Pia Weißenhorn
Department of Language Science and Technology, Saarland University
* Department of Linguistics, Utrecht University
{donatelli|jonasg|koller|mlinde|mariom|piaw}@coli.uni-saarland.de
m.fowlie@uu.nl

Abstract
We describe the Saarland University submission to the shared task on Cross-Framework Meaning Representation Parsing (MRP) at the 2019 Conference on Computational Natural Language Learning (CoNLL).

1 Introduction
In this paper, we describe the semantic parser submitted by Saarland University to the MRP shared task (Oepen et al., 2019). This task consists in learning to accurately map English sentences to graph-based meaning representations across five different graphbanks.

There has been substantial previous work on graph parsing for each of the graphbanks in MRP, including DM and PSD (Peng et al., 2017; Dozat and Manning, 2018), EDS (Buys and Blunsom, 2017; Chen et al., 2018), AMR (Flanigan et al., 2014; Buys and Blunsom, 2017; Lyu and Titov; Zhang et al., 2019), and UCCA (Hershcovich et al., 2017, 2018; Jiang et al., 2019). One advantage of our parser is that it works accurately across all graphbanks at the same time.

Instead of learning to map directly from sentences to graphs, our parser learns to map sentences to AM dependency trees. Each AM dependency tree consists of a graph for the lexical meaning of each token in the sentence, along with a dependency tree that specifies the words that fill each semantic role of a given predicate. An AM dependency tree can be deterministically evaluated to a graph via the AM Algebra (Groschwitz et al., 2017).

In earlier work, we showed how to accurately predict AM dependency trees for AMR using a neural dependency parser and supertagger (Groschwitz et al., 2018). We extended this parser from AMR to the DM, PAS, PSD, and EDS graphbanks and obtained state-of-the-art results across all of these graphbanks (Lindemann et al., 2019); we will call this system the ACL-19 parser throughout this paper. Earlier semantic parsers were only available for one or two families of closely related graphbanks; our system was the first to parse accurately across a range of different graphbanks. We took this parser as the starting point of our MRP submission; we explain the minor tweaks that were needed for the MRP flavors of DM, PSD, EDS, and AMR in Section 3.

The one MRP graphbank which was not directly supported by the ACL-19 parser is UCCA (Abend and Rappoport, 2013). We thus implemented heuristics for converting UCCA annotations into AM dependency graphs. Certain design decisions in UCCA made this more difficult than for the other graphbanks; we worked around some of these in preprocessing. We describe the details in Section 4.

We present detailed evaluation results in Section 5. We also describe a few post-deadline improvements, which bring our parser up to an MRP f-score of 71.6 on AMR and 70.1 on UCCA.

2 AM dependency parsing
We start by describing the ACL-19 parser (Lindemann et al., 2019). This parser is trained to map sentences into AM dependency trees, which are then deterministically evaluated to graphs in the AM algebra.

2.1 AM Algebra
The Apply-Modify Algebra (AM algebra; Groschwitz et al. (2017)) builds graphs from graph
frags called annotated s-graphs, or as-graphs. Figures 1a–1d show as-graphs from which the AMR in Fig. 3c for the sentence “the tall giraffe wants to eat” can be built. An as-graph is a labeled, directed graph, some of whose nodes have been marked as sources. Every as-graph used in AM dependency parsing has one special root source node, indicated with a bold outline. We mark the other sources with red labels (e.g. S and O); these are nodes at which the root source node of another as-graph will be inserted.

The AM algebra defines two operations for combining as-graphs: Apply, which combines a head with a semantic argument, and Modify, which combines a head with a modifier. Fig. 2a shows a term using these operations that evaluates to the AMR in Fig. 3c.

The result of the Apply-O operation APPO (GWant, Geat) is shown in Fig. 3a, where the root of the argument Geat is inserted into the O-source of the head GWant. The annotation “[S]” at this O-source means that the O-argument must still have an S-source, as is the case for Geat. When two graphs that share a source name are combined, the shared sources automatically merge, creating a re-entrancy. In our example this occurs for the S-source, creating a shared subject slot for GWant and Geat.

Fig. 3b shows the result of the Modify-M operation MODM (Ggiraffe, Gtall). The M-source of the modifier Gtall is merged with the root of the head Ggiraffe, which has the effect of adding the modifier to Ggiraffe; the operation leaves the root of Ggiraffe where it was. Modify is defined only when it adds no new sources to the head.

Finally, the APPS operation at the root of the term combines the two graphs we built so far, plugging the graph for “tall giraffe” into the S source of the combined want-eat graph. This yields the full graph in Fig. 3c. From a linguistic perspective, a term over the AM algebra serves as a compositional derivation (Montague, 1973) of the graph to which it evaluates.

For this last operation, too, a restriction applies: if a source has no annotation, like the S-source in Fig. 3a, the graph inserted there must have no remaining non-root sources (as is the case here). Thus, both Apply and Modify have restrictions on when they can be used. A term over the AM algebra that satisfies all these restrictions is called well-typed.

2.2 AM Dependency Parsing

Note that in a term over the AM algebra, such as in Fig. 2a, the root source of the resulting graph is always inherited from the left child; i.e. the left child is always the head. For example, after APPO (GWant, Geat), the head is still GWant. We can track the heads through the term, as indicated by the colors in the example term. This allows us to read terms over the AM algebra as AM dependency trees in the following manner. Each operation between two graphs is encoded as a dependency edge from the head to the argument (or modifier respectively), and the edge is labeled with the relevant operation. By aligning the graph fragments to the words in the sentence, we get a dependency tree over the sentence. As a result, the term in Fig. 2a can be unambiguously encoded as the dependency tree in Fig. 2b (Groschwitz et al., 2018).

We can now perform AM dependency parsing by training models for the following two tasks: (i) a supertagger to predict the as-graphs for the individual word tokens (such as GWant) and (ii) a dependency parser to predict the dependency tree. Together, these two components predict an AM dependency tree, which then evaluates to a graph in the AM algebra as explained above.

Both of these tasks can be performed by neural models with high accuracy. We train a BiLSTM to predict a supertag for each token and use the dependency parser of Kiperwasser and Goldberg (2016) to predict dependency trees. To ensure that we obtain well-typed AM dependency trees, we use the fixed-tree decoder algorithm of Groschwitz et al. (2018).

2.3 Decomposition

To train the neural supertagging and dependency models, we need AM dependency trees for the training set. However, the available graphbanks contain only sentences with their graph annotations. Thus we have to decompose the graphs in each graphbank into the corresponding AM dependency trees. We do this with handwritten heuristics, which we
Figure 2: Compositional derivation of the example AMR graph in Fig. 3c.

Figure 3: As-graphs to which the AM term in Fig. 2a and some of its subterms evaluate.

Figure 4: PSD graph (left) for The tall giraffe wants to eat and its AM dependency tree (right).

Figure 5: EDS graph (left) for The tall giraffe wants to eat and its AM dependency tree (right).
defined for AMR in Groschwitz et al. (2018) and for DM, PAS, PSD, and EDS in Lindemann et al. (2019). The decomposition heuristics perform the following three steps:

1. **align** graph nodes to words (not necessary for graphbanks with annotated alignments between tokens and nodes),

2. **group edges** with nodes, splitting the graph into disjoint aligned fragments,

3. **assign sources** and type annotations to the argument/modification slots of each graph fragment.

These steps define the supertags, and the dependency edges follow from there. Empirically, given an assignment of supertags to tokens, there is never more than one dependency tree which evaluates to the correct graph.

While the AM algebra was originally designed for AMR, the ACL-19 parser extends it to DM, PAS, PSD and EDS as well. In fact, as the AM algebra adds a layer of abstraction on top of the original graphs, using the same parser for all graphbanks becomes easy. Conceptually, we only need a different set of graph fragment supertags for each graphbank.

The decomposition heuristics for PSD and EDS are illustrated in Fig. 4 (PSD) and Fig. 5 (EDS), both for the same sentence “the tall giraffe wants to eat” whose AMR analysis we discussed in Fig. 2b. The examples show that structural differences in the graphbanks can lead to different AM dependencies: for example, the article “the” is part of the EDS graph but not of the PSD and AMR graphs. Overall, however, the AM dependency trees are much more uniform than the underlying graphs.

In Step 2, we group argument edges with the relevant head and modifying edges with the modifier. This yields consistent supertags: for example, “giraffe” can be assigned the same supertag regardless of whether and how many times it is modified. Our heuristics form these groups based only on the edge labels. For example, in AMR, DM and EDS, we group all ‘ARGx’ labels with their source node. In AMR, we group ‘mod’ edges with their target node (the modifier), and do the same with ‘RSTR’ edges in PSD.

The source names are loosely inspired by (deep) syntactic relations; for example, we use the source name S for the endpoints of ‘ARG0’ edges in AMR, ‘ACT-arg’ edges in PSD, and ‘ARG1’ edges in EDS, because these edge labels all correspond to “deep subjects”. We also add variants of source assignments to account for e.g. passive. The source annotations are obtained by matching certain patterns in the final graph. For example, the [S] annotation in $G_{\text{want}}$ in Figure 3 is added because of the triangle structure in the final graph. Details of these heuristics can be found in Lindemann et al. (2019).

3 Changes to the ACL-19 parser

For the DM, PSD, EDS, and AMR parts of the shared task, we used the ACL-19 parser with the following minor modifications.

3.1 Decomposition heuristics

We did not change any edge attachment or source naming heuristics, but focused on complying with the rules of the shared task and accommodating changes in the graphbanks.

**EDS** While the ACL-19 parser only dealt with connected EDS graphs, the training corpus of the shared task also contains disconnected graphs. We handle this in the same manner as we handle disconnected graphs in DM and PSD: by introducing an additional node that has a child in each of the disconnected components. This child is chosen as the node being anchored in the highest node in a UD dependency analysis. Along with this node, we introduce a corresponding additional artificial token to the end of the sentence.

Because our decomposition heuristics require a full alignment between tokens and nodes, but the EDS annotations can anchor arbitrary subgraphs in arbitrary substrings, we have to translate EDS anchorings into node-token alignments. We refine our method from the ACL-19 paper in two ways. First, we align implicit conjunctions to punctuation in their anchoring span, instead of their left-most child. Second, we include a special treatment of comparisons in subordinated clauses, where a subord node is grouped with a comp node, even though they are not immediately connected. This is illustrated in Fig. 6. The ACL-19 heuristic would have tried to group hard a for and subord into one supertag, which makes it impossible to decompose the EDS graph into an AM dependency tree, because this supertag would have to have two root sources: hard a for the modification with comp too, and subord for the application to
Friends told her she was pushing too hard.

**EDS** Since EDS nodes can be anchored in entire phrases but our parser only provides anchoring for tokens to subgraphs, we applied our ACL-19 heuristics to restore such non-trivial anchorings. Where this failed, we marked the node to be anchored in the entire sentence. The ACL-19 parser deleted unanchored subgraphs for evaluation with EDM (Dridan and Oepen, 2011).

**AMR** We fixed a postprocessing bug which occasionally resulted in invalid labels in the graph, originating from our procedure for handling rare words.

### 3.2 Pre- and postprocessing

Unlike earlier versions of the graphbanks and their evaluation metrics, the MRP shared task makes a clear distinction between edges (which link two nodes) and attributes (which attach an atomic value to a node). For instance, information such as polarity and the parts of a named entity are represented as attributes in MRP-style AMR, and parsers are penalized for confusing edges with attributes.

Because our parser uses as-graphs internally, which have node and edge labels but no attributes, we encode attributes into as-graphs. For most graphbanks, we encode attribute information in the node labels and unpack them again in postprocessing. For AMR, we found a considerable amount of noise in the distinction of edges and attributes in the data. We therefore chose to read attributes as edges and restore the distinction heuristically in postprocessing (see appendix).

**EDS** The revised heuristic instead groups *subord* and *comp_too* into one supertag, which then contains a source node into which *hard_a_for* can be inserted via Apply.

**AMR** The aligner we developed for the ACL-19 parser makes non-trivial use of WordNet in order to link tokens to nodes with semantically related labels. Since WordNet was not on the white list of allowed resources, we had to replace it by ConceptNet (Speer et al., 2017). We found that this decreased the dev-set accuracy of our parser by more than a point, possibly because ConceptNet does not distinguish between word senses and thus offers a much larger variety of “hypernyms” than WordNet does.

For the shared task, we extended the AM dependency parser to UCCA. This was harder than expected. Unlike the other graphbanks, UCCA takes a phrase-structure-like perspective on semantic graphs, in which one terminal node can recursively be the head of several non-terminal nodes (see Fig. 7a). This introduces two challenges for our decomposition heuristic.

First, semantic arguments and modifiers can attach to nodes at any level of the “phrase structure”. The graph in Fig. 7a predicates that “office” is an (A)rgument of “success”; these nodes only come together at the root of the UCCA graph. At the same time, the (F)unction word “a” modifies “success” at a lower level of the graph. The obvious decomposition heuristic, which would put the “success” leaf and all the nodes that dominate it into the same supertag, would fail because both of these nodes would have to be root sources, which is not allowed.

Second, under such a decomposition heuristic, the correct supertag for a given word depends on the circumstances. The unmodified word “office” should simply correspond to an as-graph with a single node labeled “office”. However, in a sentence where “office” is modified, the correct as-graph consists of “office” with an extra parent node, which is linked to the “office” leaf node with a (C)enter edge (see Fig. 7a). Modifier edges can then attach to this new parent node. This increases lexical ambiguity for our parser, which now has to predict the correct supertag for a word from a larger class of possible supertags.
We address these issues in preprocessing, which we explain below. Edge attachment and source naming heuristics are in the appendix.

4.1 C-edge contraction

We tackle the second problem by contracting C-edges. Whenever we observe a C-edge in the training data, we delete the C-edge and replace its origin node (a nonterminal node) with the node to which the C-edge points (see Fig. 7b). As an exception, we do not contract C-edges for the conjuncts of a coordination, i.e. those C-edges that have a sister C-edge. This decreases the number of nonterminals in the UCCA graph, reduces lexical ambiguity, and increases the proportion of UCCA training graphs which we can decompose.

At test time, the parser predicts UCCA graphs with contracted C-edges, as in Fig. 7b. We uncontract these by creating an outgoing C-edge from all non-leaf nodes that have node labels, changing these nodes into nonterminal nodes. At uncontraction time, we keep the outgoing edges attached to the nonterminal node.

4.2 Edge raising

C-edge contraction is insufficient to completely solve the first problem. For instance, in Fig. 7b, the as-graph for “success” still has two nodes at which other graphs attach: the U and F edge attach to the “success” node with Modify operations, and the “was” node attaches to a non-terminal node with Modify as well. As above, this means that both “success” and this non-terminal node must be root-sources, which is not allowed.

In order to ensure that only one root-source node is required, we flatten the as-graph for “success” by raising the edges out of the lower node to the upper node, as illustrated in Fig. 7c. This means that all modifiers attach to the same node, which becomes the root-source. We train the semantic parser on these flattened UCCA graphs, and then lower the edges again in postprocessing.

Our objective when applying edge lowering on the graph is to redistribute the edges we had previously raised as they were before pre-processing. The initial idea was to make use of the edge labels and only allow lowering an edge from an upper to a lower node if they are connected by another edge with a specific label; however, we found instances where there were multiple outgoing edges with the same label, which resulted in an ambiguity regarding along which edge to lower. Thus, when we raised an edge from the lower node to the upper node, we also marked the edge that connects them with “-r” (for “raised”), and then lowered along the marked edge.

However, we encountered examples where edge lowering was still ambiguous. We found this to occur when edges were raised from multiple lower nodes to the same upper node, resulting in multiple outgoing edges of that upper node bearing the -r mark. Consequently, we had no way of determining which raised edge belonged to which lower node. To remedy this problem, we added a subindex on each of the raised edges indicating the edge over which we had raised the node (see Figure 7c for the subindices). This means for post-processing only lower a given edge to a node through another edge if the label of the former edge matched the subindex of the latter edge. For example, in Fig. 7c, we can only lower the edges with the labels U_p and F_p through another edge with the label P, which in this case implies that we can only lower these edges to the node “success”. This procedure results in unambiguous lowering in most cases.

The edge raising and lowering procedure was not part of the submitted system. However, it is part of the improved system.

4.3 H-edge removal

An H-edge represents a scene evoked by a Process or State. These edges are normally outgoing edges

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Figure 7: Fragment of UCCA graph of the sentence *A Few Good Men was released in 1992 and was a box office success*
of the top node in UCCA. If an H-edge appears in a
given graph, it is either unique or accompanied by
other H-edges representing multiple parallel scenes
and an L-edge to link these scenes, i.e. from the
top node there is a single outgoing H-edge in the
former case and multiple outgoing H-edges as well
as one or more L-edges in the latter. In order to
simplify our decomposition heuristics, we remove
the H-edge in former case and add it again in post-
processing, and only include heuristics for the latter
case, rather than distinguish between the two cases.

4.4 Remote edges
We found that removing remote edges drastically
helps decomposability. Since this gives us more
training data, we decided to remove them and
thereby improved decomposability from 34% to
47% in the submitted system.

4.5 Node-token alignments
The UCCA annotation aligns the leaf nodes of the
UCCA graph with the tokens in the string; our
parser requires an alignment of all nodes with their
corresponding tokens. We project the aligned to-
kens upwards from the leaf nodes using a simple set
of head percolation rules (see appendix for details).

4.6 Tops
We mark nodes with no incoming edges as top
nodes. In an improved version, when more than
one top is found, rather than include all of them,
we select an arbitrary one.

5 Evaluation
5.1 Experimental setup
We trained one single-task model per graphbank
and made use of a concatenation of BERT (Devlin
et al., 2019) and Elmo (Peters et al., 2018) embed-
dings, without any finetuning. We tweaked some
hyperparameters of the neural network compared
to the ACL-19 parser (see appendix for details).

For DM, PSD and EDS, we use the usual
train/dev split. We take a random sample of 3% of
graphs as development data for AMR and 20% for
UCCA since there is much less training data.

During parsing, we use the fixed-tree decoder
described in Groschwitz et al. (2018) with the six
highest-scoring supertags per token. Because the
search for a well-typed AM dependency tree is
NP-complete, we set a timeout for each graphbank;
when the parsing time for a single sentence exceeds
a certain limit, we back off to a smaller number of
supertags per token and restart parsing. We used
a timeout of 30 minutes for DM, PSD and EDS, a
timeout of 5 minutes for UCCA and 15 minutes for
AMR. We ensured that every sentence was parsed
using at least the highest scoring supertag.

In the ACL-19 parser, we used named entity
tags as additional input to the neural network for
all graphbanks. Here, we only do so for AMR,
whose graphs contain very detailed named entity
information. We use the Illinois Named Entity
Tagger (Ratinov and Roth, 2009). We make use
of the tokenization, POS tags and lemmas pro-
vided in the MRP companion data. Our code is
publicly available at https://github.com/coli-saar/am-parser.

5.2 Results
Table 1 ("submitted") shows the official results of
our parser in the shared task. Our parser achieved
the highest accuracy on PSD and did very well on
DM and EDS. It did much worse on AMR than we
expected based on earlier results (Lindemann et al.,
2019).

Table 2 shows a more detailed evaluation of
the system on the development sets. First, we ob-
serve that not all graphs in the development sets
can be decomposed by the heuristics described
above. This is especially striking for EDS (which
frequently requires graphs with multiple sources,
see the discussion in Lindemann et al. (2019)) and
UCCA, where the edge contraction and raising
heuristics were still insufficient to decompose all
graphs. The distinction between decomposable and
non-decomposable graphs also has a clear effect
on development f-score: the f-scores on the decom-
posable subset of each devset are noticeably higher
than on the full devset.

Second, we report the accuracy of the two com-
ponent parts of our parser: dependency parsing
reported as UAS and LAS) and supertagging (re-
ported as 1-best and 6-best supertagging accu-
rracy). It is noticeable that the errors in some graph-
banks (e.g. PSD) are dominated by the supertagger,
whereas others are hard for the dependency parser
(e.g. UCCA). For most graphbanks, low supertag-
ing accuracy goes together with a large supertag set,
and low dependency accuracy with a large set
of edge labels. For UCCA, accuracy is low across
the board, which may be because the decomposable
part of the UCCA training set is so small (47%).
### Table 1: Results of a single run on official test set (MRP cross-framework f-score).

|           | DM | PSD | EDS | UCCA | AMR | Average |
|-----------|----|-----|-----|------|-----|---------|
| Submitted | 94.7 | 91.3 | 89.1 | 67.6 | 66.7 | 81.9    |
| Improved  | 94.7 | 91.3 | 89.1 | 70.1 | 71.0 | 83.2    |
| Improved + WordNet/Stanford | 94.7 | 91.3 | 89.1 | 70.1 | 71.6 | 83.4    |

### Table 2: Detailed dev set results of the submitted system. All rows except the first and third are based on the decomposable subsets. The last section contains statistics about the decomposed training set.

|                                      | DM     | PSD    | EDS    | UCCA   | AMR    | Average |
|--------------------------------------|--------|--------|--------|--------|--------|---------|
| F-score, complete                    | 96.6   | 92.7   | 91.1   | 65.6   | 72.0   | 83.6    |
| F-score, decomposable                | 96.9   | 92.8   | 92.0   | 74.6   | 73.5   | 86.0    |
| Decomposability                      | 93.2   | 97.2   | 82.0   | 48.6   | 91.3   | 82.5    |
| UAS                                  | 95.4   | 95.7   | 94.6   | 74.7   | 75.2   | 87.1    |
| LAS                                  | 94.6   | 91.8   | 93.4   | 68.1   | 69.2   | 83.4    |
| Supertagging Accuracy (1-best)       | 96.6   | 88.6   | 93.9   | 74.5   | 75.2   | 85.8    |
| Supertagging Accuracy (6-best)       | 99.8   | 98.8   | 99.2   | 94.2   | 94.2   | 97.2    |
| Number supertags                     | 424    | 1566   | 2739   | 298    | 4705   | 1946.4  |
| Number edge labels                   | 32     | 42     | 34     | 22     | 48     | 35.6    |

### 5.3 Improvements

After the shared task submission deadline, we implemented some further improvements.

**AMR** We fixed a bug in the post-processing of named entities, which improved the MRP f-score by 0.5 points on the dev set and by 4.3 points on the test set (“improved” in table 1).

We also analyzed the impact of switching out WordNet and the Stanford NER tagger for their whitelisted replacements, ConceptNet and the Illinois NER tagger. As Table 3 shows, the use of the whitelisted resources decreased the AMR devset accuracy by almost 1.5 points. This illustrates the impact of these low-level resources on the evaluation results. Interestingly, this translates only to an improvement of 0.6 points on the test set (“Improved + WordNet/Stanford” in table 1).

We leave an investigation why the magnitude of these improvements differs so much between dev set and test set for future work.

**UCCA** In contrast to the submitted version, we employed edge raising and lowering and used the improved version of the top handling (see 4.6). We also fixed a bug in the node-token alignments. Overall, this resulted in 85% of the training set being decomposable as opposed to 47% in the submitted system. The results are reported in row two

### Table 3: Comparison of MRP f-scores on our AMR development set for different NE recognizers and lexical databases, includes bugfix.

| NER tool | Stanford | Illinois |
|----------|----------|----------|
| WordNet  | 73.9     | 72.7     |
| ConceptNet | 73.7     | 72.5     |

### 6 Conclusion

In this paper, we have described the Saarland University submission to the MRP shared task. Our system is mostly based on our compositional neural graph parser, which had already worked very well across all MRP graphbanks except for UCCA.

We found that extending the parser to UCCA was a challenge due to the radically different graph structures that UCCA uses. We aim to improve the accuracy of our parser on UCCA in future work.

One challenge our system faces is that nontrivial quantities of training data cannot be decomposed by the heuristics we used. It therefore wastes a lot of training data, especially for UCCA. In future work, we will look into better decomposition heuristics, and also into variants of the AM algebra which support multiple root-sources per as-graph.
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