MRP 2019: Cross-Framework Meaning Representation Parsing

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Abstract

The 2019 Shared Task at the Conference for Computational Language Learning (CoNLL) was devoted to Meaning Representation Parsing (MRP) across frameworks. Five distinct approaches to the representation of sentence meaning in the form of directed graphs were represented in the training and evaluation data for the task, packaged in a uniform graph abstraction and serialization. The task received submissions from eighteen teams, of which five do not participate in the official ranking because they arrived after the closing deadline, and five do not participate in the official ranking because they arrived after the closing deadline, and involved one of the task co-organizers. All technical information regarding the task, including system submissions, official results, and links to supporting resources and software are available from the task web site at:

http://mrp.nlpl.eu

1 Background and Motivation

All things semantic are receiving heightened attention in recent years, and despite remarkable advances in vector-based (continuous and distributed) encodings of meaning, ‘classic’ (discrete and hierarchically structured) semantic representations will continue to play an important role in ‘making sense’ of natural language. While parsing has long been dominated by tree-structured target representations, there is now growing interest in general graphs as more expressive and arguably more adequate target structures for sentence-level analysis beyond surface syntax, and in particular for the representation of semantic structure.

The 2019 Conference on Computational Language Learning (CoNLL) hosts a shared task (or ‘system bake-off’) on Cross-Framework Meaning Representation Parsing (MRP 2019). The goal of the task is to advance data-driven parsing into graph-structured representations of sentence meaning. For the first time, this task combines formally and linguistically different approaches to meaning representation in graph form in a uniform training and evaluation setup. Participants were invited to develop parsing systems that support five distinct semantic graph frameworks (see §3 below)—which all encode core predicate–argument structure, among other things—in the same implementation. Ideally, these parsers predict sentence-level meaning representations in all frameworks in parallel. Architectures utilizing complementary knowledge sources (e.g., via parameter sharing) were encouraged, though not required. Learning from multiple flavors of meaning representation in tandem has hardly been explored (with notable exceptions, e.g., the parsers of Peng et al., 2017; Hershcovitch et al., 2018; or Stanovsky and Dagan, 2018).

Training and evaluation data were provided for all five frameworks. The task design aims to reduce framework-specific ‘balkanization’ in the field of meaning representation parsing. Its contributions include (a) a unifying formal model over different semantic graph banks (§2), (b) uniform representations and scoring (§4 and §6), (c) contrastive evaluation across frameworks (§5), and (d) increased cross-fertilization via transfer and multi-task learning (§7). Thus, the task engages the combined community of parser developers for graph-structured output representations, including from prior framework-specific tasks at the Semantic Evaluation (SemEval) exercises between 2014 and 2019 (Oepen et al., 2014, 2015; May, 2016; May and Priyadarshi, 2017; Hershcovitch et al., 2019). Owing to the scarcity of semantic anno-
tations across frameworks, the MRP 2019 shared task is regrettably limited to parsing English for the time being.

2 Definitions: Graphs and Flavors

Reflecting different traditions and communities, there is wide variation in how individual meaning representation frameworks think (and talk) about semantic graphs, down to the level of visual conventions used in rendering graph structures. The following paragraphs provide semi-formal definitions of core graph-theoretic concepts that can be meaningfully applied across the range of frameworks represented in the shared task.

Basic Terminology   Semantic graphs (across different frameworks) can be viewed as directed graphs or digraphs. A semantic digraph is a triple \((T, N, E)\) where \(N\) is a set of nodes and \(E \subseteq N \times N\) is a set of edges. The in- and out-degree of a node count the number of edges arriving at or leaving from the node, respectively. In contrast to the unique root node in trees, graphs can have multiple (structural) roots, which we define as nodes with in-degree zero. The majority of semantic graphs are structurally multi-rooted. Thus, we distinguish one or several nodes in each graph as top nodes, \(T \subseteq N\); the top(s) correspond(s) to the most central semantic entities in the graph, usually the main predication(s).

In a tree, every node except the root has in-degree one. In semantic graphs, nodes can have in-degree two or higher (indicating shared arguments), which constitutes a reentrancy in the graph. In contrast to trees, general digraphs may contain cycles, i.e. a directed path leading from a node to itself. Another central property of trees is that they are connected, meaning that there exists an undirected path between any pair of nodes. In contrast, semantic graphs need not generally be connected.

Finally, in some semantic graph frameworks there is a (total) linear order on the nodes, typically induced by the surface order of corresponding tokens. Such graphs are conventionally called bi-lexical dependencies and formally constitute ordered graphs. A natural way to visualize a bi-lexical dependency graph is to draw its edges as semicircles in the halfplane above the sentence. An ordered graph is called noncrossing if in such a drawing, the semicircles intersect only at their endpoints (this property is a natural generalization of projectivity as it is known from dependency trees).

A natural generalization of the noncrossing property, where one is allowed to also use the halfplane below the sentence for drawing edges is a property called pagelnumber two. Kuhlmann and Oepen (2016) provide additional definitions and a quantitative summary of various formal graph properties across frameworks.

Hierarchy of Formal Flavors   In the context of the shared task, we distinguish different flavors of semantic graphs based on the nature of the relationship they assume between the linguistic surface signal (typically a written sentence, i.e. a string) and the nodes of the graph. We refer to this relation as anchoring (of nodes onto sub-strings); other commonly used terms include alignment, correspondence, or lexicalization.

Flavor (0) is the strongest form of anchoring, obtained in bi-lexical dependency graphs, where graph nodes injectively correspond to surface lexical units (i.e. tokens or ‘words’). In such graphs, each node is directly linked to one specific token (conversely, there may be semantically empty tokens), and the nodes inherit the linear order of their corresponding tokens.

Flavor (1) includes a more general form of anchored semantic graphs, characterized by relaxing the correspondence between nodes and tokens, allowing arbitrary parts of the sentence (e.g. sub-token or multi-token sequences) as node anchors, as well as multiple nodes anchored to overlapping sub-strings. These graphs afford greater flexibility in the representation of meaning contributed by, for example, (derivational) affixes or phrasal constructions and facilitate lexical decomposition (e.g. of causatives or comparatives).

Finally, Flavor (2) semantic graphs do not consider the correspondence between nodes and the surface string as part of the representation of meaning (thus backgroundering notions of derivation and compositionality). Such semantic graphs are simply unanchored.

While different flavors refer to formally defined sub-classes of semantic graphs, we reserve the term framework for specific linguistic approaches to graph-based meaning representation (typically encoded in a particular graph flavor, of course).

3 Meaning Representation Frameworks

The shared task combines five frameworks for graph-based meaning representation, each with its specific formal and linguistic assumptions. This
A similar technique is almost impossible to apply to other crops, such as cotton, soybeans and rice.

The example exhibits some interesting linguistic complexity, including what is called a tough adjective (impossible), a scopal adverb (almost), a tripartite coordinate structure, and apposition. The example graphs in Figures 1 through 3 are presented in order of (arguably) increasing ‘abstraction’ from the surface string, i.e. ranging from ordered Flavor (0) to unanchored Flavor (2).

Two of the frameworks in the shared task present simplifications into bi-lexical semantic dependencies (i.e. lossy reductions) of independently developed syntactico-semantic annotations. These representations were first prepared for the Semantic Dependency Parsing (SDP) tasks at the 2014 and 2015 SemEval campaigns (Oepen et al., 2014, 2015). The SDP graph banks were originally released through the Linguistic Data Consortium (as catalogue entry LDC 2016T10); they comprise four distinct bi-lexical semantic dependency frameworks, from which the MRP 2019 shared task selects two (a) DELPH-IN MRS Bi-Lexical Dependencies (DM) and (b) Prague Semantic Dependencies (PSD).

DELPH-IN MRS Bi-Lexical Dependencies
The DM bi-lexical dependencies (Ivanova et al., 2012) originally derive from the underspecified logical forms computed by the English Resource Grammar (Flickinger et al., 2017; Copestake et al., 2005). These logical forms are not in and of themselves semantic graphs (in the sense of §2 above) and are often referred to as English Resource Semantics (ERS; Bender et al., 2015). The underlying grammar is rooted in the general linguistic theory of Head-Driven Phrase Structure Grammar (HPSG; Pollard and Sag, 1994).

Ivanova et al. (2012) propose a two-stage conversion from ERS into bi-lexical semantic dependency graphs, where ERS logical forms are first recast as Elementary Dependency Structures (EDS; Oepen and Lønning, 2006; see below) and then further simplified into pure bi-lexical semantic dependencies, dubbed DELPH-IN MRS Bi-Lexical Dependencies (or DM). As a Flavor (0) framework, graph nodes in DM are restricted to surface tokens. But DM graphs are neither lexically fully covering nor rooted trees, i.e. some tokens do not contribute to the graph, and for some nodes there are multiple incoming edges. In the example DM graph in Figure 1, technique semantically depends on the determiner (the quantificational locus), the modifier similar, and the predicate apply. Conversely, the predicative copula, infinitival to, and the vacu-
ous preposition marking the deep object of *apply* (in the top of Figure 1) are analyzed as not having a semantic contribution of their own. The top node in the DM graph is the degree adverb *almost*, reflecting the underlying logical form, where *almost* has operator-like status scoping over the full proposition.

In DM, edge labels predominantly indicate semantic argument positions (ARG1, ARG2, . . .) into the relation corresponding to their source node, but there are some more specialized edge labels too, like BV (bound variable) as a reflection of quantification in the underlying logic, conj and others for coordinate structures, and mwe to structurally tie together multi-token predicates. Node labels are tripartite, combining the lemmatized surface form with a part of speech (pos) and a framework-specific frame identifier. Together, these encode grammaticalized word sense distinctions, such as those between the nominal vs. verbal usages of *crop* or the distinct valency frames for three-place *apply* . . . to (e.g. paint, to the wall) vs. binary *apply for* (e.g. promotion).

**Prague Semantic Dependencies** Another instance of simplification from richer syntactico-semantic representations into Flavor (0) bi-lexical semantic dependencies is the reduction of *tectogrammatical trees* (or t-trees) from the linguistic school of Functional Generative Description (FGD: Sgall et al., 1986; Hajic et al., 2012) into what are called Prague Semantic Dependencies (or PSD). Miyao et al. (2014) sketch the nature of this conversion, which essentially collapses empty (or generated, in FGD terminology) t-tree nodes with corresponding surface nodes and forward-projects incoming dependencies onto all members of paratactic constructions, e.g. the appositive and coordinate structures in the bottom of Figure 1.

The PSD graph for our running example has many of the same dependency edges as the DM one (albeit using a different labeling scheme and inverse directionality in a few cases), but it analyzes the predicative copula as semantically contentful and does not treat *almost* as ‘scoping’ over the entire graph. The ADDR,m(ember) argument relation to the *apply* predicate has been recursively propagated to both elements of the apposition and to all members of the coordinate structure. Accordingly, edge labels in PSD are not in general functional, in the sense of allowing multiple outgoing edges from one node with the same label.

In FGD, role labels (called *functors*) ACT(or), PAT(ient), ADDR(ressee), ORIG(in), and EFF(ect) indicate ‘participant’ positions in an underlying valency frame and, thus, correspond more closely to the numbered argument positions in other frameworks than their names might suggest. The PSD annotations are grounded in a machine-readable valency lexicon (Ureová et al., 2016), and the frame values on verbal nodes in Figure 1 indicate specific verbal senses in the lexicon.

**Elementary Dependency Structures** Elementary Dependency Structures (EDS; Oepen and Lønning, 2006) encode English Resource Semantics in a variable-free semantic dependency graph—not limited to bi-lexical dependencies—where graph nodes correspond to logical predications and edges to labeled argument positions. The EDS conversion from underspecified logical forms to directed graphs discards partial information on semantic scope from the full ERS, which makes these graphs abstractly—if not linguistically—similar to Abstract Meaning Representation (see below).

Nodes in EDS are in principle independent of surface lexical units, but for each node there is an explicit, many-to-many anchoring onto sub-strings of the underlying sentence. Thus, EDS instantiates Flavor (1) in our hierarchy of different formal types of semantic graphs. Breaking free of the Flavor (0) one-to-one correspondence between graph nodes and surface lexical units enables EDS to more adequately represent, among other things, lexical decomposition (e.g. of comparatives), sublexical or construction semantics, and covert (e.g. elided) meaning contributions. All nodes in the example EDS in the top of Figure 2 make explicit their anchoring onto sub-strings of the underlying input, for example span ⟨2 : 9⟩ for *similar*.

In the EDS analysis for the running example, nodes representing covert quantifiers (e.g. on bare nominals, labeled udef,q3), the two-place *such as* relation, as well as the implicit conjunction relation (which reflects recursive decomposition of the coordinate structure

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2Accordingly, multiple instances of the same core participant role—as ADDR.m in Figure 1—will only occur with propagation of dependencies into paratactic constructions.

3In the EDS example in the top of Figure 2, all nodes corresponding to instances of bare ‘nominal’ meanings are bound by a covert quantificational predicate, including the group-forming implicit conj and and e nodes that represent the nested, binary-branching coordinate structure. This practice of uniform quantifier introduction in ERS is acknowledged as “particularly exuberant” by Steedman (2011, p. 21).
Figure 2: Semantic dependency graphs for the running example A similar technique is almost impossible to apply to other crops, such as cotton, soybeans and rice: Elementary Dependency Structures (EDS; top) and Universal Conceptual Cognitive Annotation (UCCA; bottom).

into binary predications) do not correspond to individual surface tokens (but are anchored on larger spans, overlapping with anchors from other nodes). Conversely, the two nodes associated with similar indicate lexical decomposition as a comparative predicate, where the second argument of the comp relation (the ‘point of reference’) remains unexpressed in Example (1).

### Universal Conceptual Cognitive Annotation

Universal Cognitive Conceptual Annotation (UCCA; Abend and Rappoport, 2013) is based on cognitive linguistic and typological theories, primarily Basic Linguistic Theory (Dixon, 2010/2012). The shared task targets the UCCA foundational layer, which focuses on argument structure phenomena (where predicates may be verbal, nominal, adjectival, or otherwise). This coarse-grained level of semantics has been shown to be preserved well across translations (Sulem et al., 2015). It has also been successfully used for improving text simplification (Sulem et al., 2018b), as well as to the evaluation of a number of text-to-text generation tasks (Birch et al., 2016; Sulem et al., 2018a; Choshen and Abend, 2018).

The basic unit of annotation is the scene, denoting a situation mentioned in the sentence, typically involving a predicate, participants, and potentially modifiers. Linguistically, UCCA adopts a notion of semantic constituency that transcends pure dependency graphs, in the sense of introducing separate, unlabeled nodes, called units. One or more labels are assigned to each edge. Formally, UCCA has a Type (1) flavor, where leaf (or terminal) nodes of the graph are anchored to possibly discontinuous sequences of surface sub-strings, while interior (or ‘phrasal’) graph nodes are formally unanchored.

The UCCA graph for the running example (see the bottom of Figure 2) includes a single scene, whose main relation is the Process (P) evoked by apply. It also contains a secondary relation labeled Adverbial (D), almost impossible, which is broken
Abstract Meaning Representation

Finally, the shared task includes Abstract Meaning Representation (AMR; Banerjee et al., 2013), which in the MRP hierarchy of different formal types of semantic graphs (see §2 above) is simply unanchored, i.e. represents Flavor (2). The AMR framework is independent of particular approaches to derivation and compositionality and, accordingly, does not make explicit how elements of the graph correspond to the surface utterance. Although most AMR parsing research presupposes a pre-processing step that ‘aligns’ graph nodes with (possibly discontinuous) sets of tokens in the underlying input, this anchoring is not part of the meaning representation proper.

At the same time, AMR frequently invokes lexical decomposition and normalization towards verbal senses, such that AMR graphs often appear to ‘abstract’ furthest from the surface signal. Since the first general release of an AMR graph bank in 2014, the framework has provided a popular target for data-driven meaning representation parsing and has been the subject of two consecutive tasks at SemEval 2016 and 2017 (May, 2016; May and Priyadarshi, 2017).

The AMR example graph in Figure 3 has a topology broadly comparable to EDS, with some notable differences. Similar to the UCCA example graph (and unlike EDS), the AMR representation of the coordinate structure is flat. Although most lemmas are linked to derivationally related forms in the sense lexicon, this is not universal, as seen by the nodes corresponding to similar and such as, which are labeled as resemble-01 and exemplify-01, respectively. These sense distinctions (primarily for verbal predicates) are grounded in the inventory of predicates from the PropBank lexicon (Kingsbury and Palmer, 2002; Hovy et al., 2006).

Role labels in AMR encode semantic argument positions, with the particular roles defined according to each PropBank sense, though the counting in AMR is zero-based such that the ARG1 and ARG2 roles in Figure 3 often correspond to ARG2 and ARG3, respectively, in the EDS of Figure 2. PropBank distinguishes such numbered arguments from non-core roles labeled from a general semantic inventory, such as frequency, duration, or domain.

Figure 3 also shows the use of inverted edges in AMR, for example ARG1-of and mod. These serve to allow annotators (and in principle also parsing systems) to view the graph as a tree-like structure (with occasional reentrancies) but are formally merely considered notational variants. Therefore, the MRP rendering of the AMR example graph also provides an unambiguous indication of the underlying, normalized graph: Edges with a label component shown in parentheses are to be reversed in normalization, e.g. representing an actual ARG0 edge from resemble-01 to technique or a domain edge from other to crop.

Given the non-compositionality of AMR annotation, AMR allows the introduction of semantic concepts which have no explicit lexicalization in the text, for example the et-cetera element in the coordinate structure in Figure 3. Conversely, like...
in the other frameworks (except UCCA), some surface tokens are analyzed as semantically vacuous. For example, parallel to the PSD graph in Figure 1, there is no meaning contribution annotated for the determiner *a* (let alone for covert determiners in bare nominals, as are made explicit as quantificational nodes in EDS).

### 4 Task Setup

The following paragraphs summarize the ‘logistics’ of the MRP 2019 shared task, including data and software provided to participants, the schedule, and rules of participation.

**Training and Evaluation Data** Table 1 summarizes the primary training and evaluation data provided to task participants. The DM and PSD data sets are annotations over the exact same selection of texts, which for the earlier SemEval tasks have been aligned at the sentence and token levels. As DM was originally derived from EDS, the EDS graphs also cover the same texts. The training data for these frameworks draws from a homogeneous source, WSJ Sections 00–20 from the PTB. As a common point of reference, a sample of 100 WSJ sentences annotated in all five frameworks is available for public download from the task web site (see §9 below).

UCCA training annotations are over web reviews from the English Web Treebank (LDC 2012T13), and from English Wikipedia articles on celebrities. While in principle UCCA structures are not confined to a single sentence (about 0.18 percent of edges cross sentence boundaries), in the MRP context passages are split to individual sentences, discarding inter-relations between them, to create a standard setting across the frameworks.

AMR annotations are drawn from a wide variety of texts, with the majority of sentences coming from on-line discussion forums. The training corpus also contains newswire, folktales, fiction, and Wikipedia articles.

Table 2 provides a quantitative side-by-side comparison of the training data, using some of the graph-theoretic properties discussed by Kuhlmann and Oepen (2016); see §2 for semi-formal definitions (the row indices in Table 2 correspond to the numbering used by Kuhlmann and Oepen, 2016). The table indicates clear differences among the frameworks. The underlying input strings for AMR (where text selection is more varied), for example, are shorter; and EDS and UCCA have many more nodes per token, on average, than the other frameworks—reflecting lexical decomposition and ‘phrasal’ grouping, respectively, as evident in Figure 2. In some respects, the PSD and UCCA graphs are more tree-like than graphs in the other frameworks, for example in their proportions of actual rooted trees, the frequencies of reentrant nodes, and the lower percentages of multi-rooted structures.

At the same time, PSD exhibits comparatively high average and maximal treewidth. Finally, the properties applicable to the ordered bi-lexical frameworks only are largely comparable, though PSD edges on average span over larger distances; propagation of dependencies into paratactic structures observed in Figure 1 may well contribute substantially to this quantitative difference.

Table 2: Quantitative summary of gold-standard training and evaluation data for the five frameworks.

| Flavor | DM | PSD | EDS | UCCA | AMR |
|--------|----|-----|-----|------|-----|
| 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 |
| COUNTS          | DM     | PSD    | EDS    | UCCA   | AMR⁻¹  |
|-----------------|--------|--------|--------|--------|--------|
| (02) Average Tokens per Graph | 22.51  | 22.51  | 22.51  | 21.03  | 17.78  |
| (03) Average Nodes per Token    | 0.77   | 0.64   | 1.29   | 1.37   | 0.65   |
| (04) Number of Edge Labels      | 59     | 90     | 10     | 15     | 101    |
| (05) % Rooted Trees             | 2.31   | 42.26  | 0.09   | 34.83  | 22.24  |
| (06) % Treewidth One            | 69.82  | 43.08  | 68.99  | 41.57  | 50.00  |
| (07) Average Treewidth          | 1.30   | 1.61   | 1.31   | 1.61   | 1.56   |
| (08) Maximal Treewidth          | 3      | 7      | 3      | 4      | 5      |
| (09) Average Edge Density       | 1.09   | 1.07   | 1.05   | 1.05   | 1.092  |
| (10) % Reentrant                | 27.43  | 11.41  | 32.78  | 4.98   | 19.89  |
| (11) % Cyclic                   | 0.00   | 0.00   | 0.12   | 0.00   | 0.38   |
| (12) % Not Connected            | 6.57   | 0.70   | 1.74   | 0.00   | 0.00   |
| (13) % Multi-Rooted             | 97.47  | 40.60  | 99.93  | 0.00   | 71.37  |
| ORDER                        |        |        |        |        |        |
| (15) Average Edge Length        | 2.684  | 3.320  | –      | –      | –      |
| (16) % Noncrossing             | 69.21  | 64.61  | –      | –      | –      |
| (17) % Pagename Two             | 99.59  | 98.08  | –      | –      | –      |

| FREENESS        |        |        |        |        |        |
|-----------------|--------|--------|--------|--------|--------|
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| (13) % Multi-Rooted             | 97.47 | 40.60  | 99.93  | 0.00   | 71.37  |

Table 2: Contrastive graph statistics for the MRP 2019 training data using a subset of the properties defined by Kuhlmann and Oepen (2016). Here, %g and %n indicate percentages of all graphs and nodes, respectively, in each framework; AMR⁻¹ refers to the normalized form of the graphs, with inverted edges reversed, as discussed in §3.

in all five frameworks. This subset of the evaluation data is available for download from the task site.

Because some of the semantic graph banks involved in the shared task had originally been released by the Linguistic Data Consortium (LDC), the training data was made available to task participants by the LDC under no-cost evaluation licenses. Upon completion of the competition, all task data (including system submissions and evaluation results) are being prepared for general release through the LDC, while those subsets that are copyright-free will also become available for direct, open-source download.

Additional Resources For reasons of comparability and fairness, the shared task constrained which additional data or pre-trained models (e.g., corpora, word embeddings, lexica, or other annotations) can be legitimately used besides the resources distributed by the task organizers. The overall goal was that all participants should in principle be able to use the same range of data. However, to keep such constraints to the minimum required, a ‘white-list’ of legitimate resources was compiled from nominations by participants (with a cut-off date six weeks before the end of the evaluation period). Thus, the task design reflects what is at times called a closed track, where participants are constrained in which additional data and pre-trained models can be used in system development.

At a technical level, training (and evaluation) data were distributed in two formats, (a) as sequences of ‘raw’ sentence strings and (b) in pre-tokenized, part-of-speech–tagged, lemmatized, and syntactically parsed form. For the latter, premium-quality English morpho-syntactic analyses were provided to participants, described in more detail below. These parser outputs are referred to as the MRP 2019 morpho-syntactic companion trees. Additional companion data available to participants includes automatically generated reference anchorings (commonly called ‘alignments’ in AMR parsing) for the AMR graphs in the training data, obtained from the JAMR and ISI tools of Flanigan et al. (2016) and Pourdamghani et al. (2014), respectively.

Companion Dependency Trees The optional morpho-syntactic trees were generated from the combination of a rule-based PTB-style tokenizer and a high-accuracy dependency parser trained on the union of (the majority of) available English syntactic treebanks. Notably, we applied an updated version of the converter by Schuster and Manning (2016) to the PTB annotations of the Brown Corpus (Francis and Kučera, 1982) and of the WSJ

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4Annotations of the full novel have long served as a common reference point for AMR, and gold-standard DM and EDS graphs could be converted from the ERS inter-annotator agreement study by Bender et al. (2015). For PSD and UCCA, the 100-sentence subset used for MRP evaluation has been annotated specifically for the shared task.

5See http://svn.nlpl.eu/mrp/2019/public/resources.txt for the full list of seventeen generally available third-party resources, including a broad range of large English corpora and distributed word representations.
Corpus, as well as to the PTB-style annotations of the GENIA Corpus (Tateisi et al., 2005). This conversion targets Universal Dependencies (UD; McDonald et al., 2013; Nivre, 2015) version 2.x, so that the resulting gold-standard annotations could be concatenated with the UD English Web Treebank (Silveira et al., 2014), for a total of 2.2 million tokens annotated with lemmas, Universal and PTB-style parts of speech, and UD labeled dependency trees.

We then trained the currently best-performing UDPipe architecture (Straka, 2018; Straka et al., 2019), which implements a joint part-of-speech tagger, lemmatizer, and dependency parser employing contextualized BERT embeddings. To avoid overlap of morpho-syntactic training data with the texts underlying the semantic graphs of the shared task, we performed five-fold jack-knifing on the WSJ and EWT corpora. For compatibility with the majority of the training data, the ‘raw’ input strings for the MRP semantic graphs were tokenized using the PTB-style REPP rules of Dridan and Oepen (2012) and input to UDPipe in pre-tokenized form. Whether as merely a source of state-of-the-art PTB-style parts of speech and a (syntactico-semantic) frame (or optionally combined with a (morpho-syntactic) part of speech, and UD labeled dependency trees.

The common interchange format for semantic graphs implements the abstract model of Kuhlmann and Oepen (2016) as a JSON-based serialization for graphs across frameworks. This format describes general directed graphs, with structured node and edge labels, and optional anchoring and ordering of nodes. JSON is easily manipulated in all programming languages and offers parser developers the option of ‘in situ’ augmentation of the graph representations from the task with system-specific additional information, e.g. by adding private properties to the JSON objects. The MRP interchange format is based on the JSON Lines format, where a stream of objects is serialized with line breaks as the separator character.

Each MRP graph is represented as a JSON object with top-level properties tops, nodes, and edges, reflecting the definitions in §2 above. Additionally, an input property on all graphs presents the ‘raw’ surface string corresponding to this graph; thus, parser inputs for the task are effectively assumed to be sentence-segmented but not pre-tokenized. Additional information about each graph is provided as properties id (a string), flavor (an integer in the range 0–2), framework (a string), version (a decimal number), and time (a string, encoding when the graph was serialized).

The nodes and edges values on graphs each are list-valued, but the order among list elements is only meaningful for the nodes of Flavor (0) graphs. Node objects have an obligatory id property (an integer) and optional properties called label, properties and values, as well as anchors. The label (a string) has a distinguished status in evaluation; the properties and values are both list-valued, such that elements between the lists correspond by position. Together, the two lists present a framework-specific, non-recursive attribute–value matrix (where duplicate properties are in principle allowed). The anchors list, if present, contains pairs of from-to sub-string indices into the input string of the graph. Finally, the edge objects in the top-level edges list all have two integer-valued properties: source and target, which encode the start and end nodes, respectively, to which the edge is incident. All
edges in the MRP collection further have a (string-valued) label property, although formally this is considered optional. Parallel to graph nodes, edges can carry framework-specific attributes and values lists; in MRP 2019, only the UCCA framework makes use of edge attributes, viz. a boolean remote flag (corresponding to dashed edges in the bottom of Figure 2).

Rules of Participation The shared task was first announced in early March 2019, the initial release of the unified training data became available in mid-April, and the evaluation period ran between July 8 and 25, 2019; during this period, teams obtained the unannotated input strings for the evaluation data and had available a little more than two weeks to prepare and submit parser outputs. Submission of semantic graphs for evaluation was through the online CodaLab infrastructure, which proved a suboptimal choice—in part due to limited transparency and customization options of the service, in part because technical problems on the CodaLab site caused the entire infrastructure to be unavailable for five days during the MRP evaluation period.

Teams were allowed to make repeated submissions, but only the most recent successful upload to CodaLab within the evaluation period was considered for the official, primary ranking of submissions. Task participants were encouraged to process all inputs using the same general parsing system, but—owing to inevitable fuzziness about what constitutes ‘one’ parser—this constraint was not formally enforced. Unlike in recent years of other CoNLL shared tasks, processing of the evaluation data was not tied to a uniform virtualization platform (such as TIRA; Potthast et al., 2014), because GPU computing resources are a prerequisite to modern, neural parsing architectures but are not currently available on such platforms.

5 Evaluation

For each of the individual frameworks, there are established ways of evaluating the quality of parser outputs in terms of graph similarity to gold-standard target representations called EDM (Dridan and Oepen, 2011), SMATCH (Cai and Knight, 2013), SDP (Oepen et al., 2014), and UCCA (Hershcovitch et al., 2019). There is broad similarity between the framework-specific evaluation metrics used to date, but also some subtle differences. Meaning representation parsing is commonly evaluated in terms of a graph similarity F1 score at the level of individual node–edge–node and node–property–value triples. Variations in extant metrics relate to among others, how node correspondences across two graphs are established, whether edge labels can optionally be ignored in triple comparison, and how top nodes (and other node properties, including anchoring) are evaluated.

Table 3: Different tuple types per framework.

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

Table 3: Different tuple types per framework.

In principle, one could further view unlabeled edges and their labels as two distinct pieces of information, but the task design shies away from such formal purity for both linguistic and practical reasons. First, it does not appear desirable to try and give credit for edges with incompatible labels (e.g. an ARG1 with an ARG3); and, second, it would make the search for node-to-node correspondences somewhat less tractable.
transitively the union of child anchors, in the case of UCCA) and allow many-to-many correspondences across the gold-standard and system graphs (Oepen et al., 2014; Hershcovich et al., 2019). Finally, as a Flavor (2) framework, nodes in AMR graphs are unanchored. Thus, node-to-node correspondences need to be established (as one-to-one equivalence classes of node identifiers), to maximize the set of shared tuples between each pair of graphs. Abstractly, this is an instance of the NP-hard maximum common edge subgraph isomorphism problem (where node-local tuples can be modeled as ‘pseudo-edges’ with globally unique target nodes). The standard SMATCH scorer for AMR approximates a solution through a hill-climbing search for high-scoring correspondences, with a fixed number of random restarts (Cai and Knight, 2013).

**Unified Evaluation** For the shared task, we have implemented a generalization of existing, framework-specific metrics, along the lines above. Our goal is for the unified MRP metric to (a) be applicable across different flavors of semantic graphs, (b) enable labeled and unlabeled variants, as much as possible, (c) not require corresponding node anchoring, but (d) minimize the impact of non-deterministic approximations, and (e) take advantage of anchoring information when available. The official MRP metric for the task is the average F1 score across frameworks over all tuple types.

The basic principle is that all information presented in the MRP graph representations is scored with equal weight, i.e. all applicable tuple types for each framework. There is no special status (or ‘primacy’) to anchoring in this scheme: Unlike the original SDP, EDM, and UCCA metrics, the MRP scorer searches for a correspondence relation between the gold-standard and system graphs that maximizes tuple overlap. Thus, the MRP approach is abstractly similar to SMATCH, but using a search algorithm that considers the full range of different tuple types and finds an exact solution in the majority of cases.\(^7\)

Anchoring (for all frameworks but AMR) in this scheme is treated on a par with node labels and properties, labeled edges, and edge attributes. Likewise, the pos and frame (or sense) node properties in DM and PSD are scored with equal weight as the node labels (which are lemmas for the bi-lexical semantic graphs), given that the three properties jointly determine the semantic predicate.

For AMR evaluation, there is an exception to the above principle that all information in MRP graphs be scored equally: The MRP encodings of AMR graphs preserve the tree-like topology used in AMR annotations, using ‘inverted’ edges with labels like ARG0-of (see §3 above). To make explicit which AMR edges actually are inverted, the MRP encoding in JSON provides an additional normal property, which is present only an inverted edges and provides the effective ‘base’ label (e.g. ARG0). AMR graphs are standardly evaluated in normalized form, i.e. with inverted edges restored to their ‘base’ directionality and label.

**Software Support** MRP scoring is implemented in the open-source mtool software (the Swiss Army Knife of Meaning Representation), which is hosted in a public Microsoft GitHub repository to stimulate community engagement.\(^8\) mtool implements a refinement of the maximum common edge subgraph (MCES) algorithm by McGregor (1982), initializing and scheduling candidate node-to-node correspondences based on pre-computed per-node rewards and upper bounds on adjacent edge correspondences.\(^9\) In addition to the cross-framework MRP metric, the tool also provides reference implementations of the SDP, EDM, SMATCH, and UCCA metrics, in the case of SDP and UCCA generalized to support character-based anchoring (rather than using token indices).

Value comparison in MRP evaluation is robust to ‘uninteresting’ variation, i.e. different encodings of essentially the same information. Specifically, literal values will always be compared as case-insensitive strings, such that for example 42 (an integer) and "42" (a string) are considered equivalent, as are "Pierre" and "pierre"; this applies to node and edge labels, node properties, and edge attributes. Anchor values are normalized for comparison into sets of non-whitespace character positions. For example, assuming the underlying

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\(^7\)The MRP scorer further avoids a few known implementation issues in SMATCH related to over-counting, incomplete normalization, and top nodes.

\(^8\)See https://github.com/cfmrp/mtool for access to the software and available documentation.

\(^9\)For the ordered DM and PSD graphs, an optimal initialization regarding node-local information can be efficiently computed, using an adaptation of the dynamic programming algorithm for minimum-edit–distance problems. For these graphs, scheduling of variant correspondences is further constrained to search for local variations first, i.e. alternate node–node pairings are considered in increasing node distance relative to the initial candidate correspondences.
Table 4: Overview of participating teams. The top and bottom blocks represent ‘unofficial’ submissions, which are not considered for the primary ranking because they used training data beyond the white-listed resources (indicated by the symbol “∦”), or were prepared by the task co-organizers as points of reference (“†”). The secondary ranking (see §6) considers all submissions by genuine task participants (excluding co-organizers), i.e. both the middle and bottom blocks (but not the ‘reference’ systems from the top block).

### 6 Submissions and Results

The task received submissions from sixteen teams, plus another two ‘reference’ submissions prepared by the task co-organizers (Hershcovich and Arviv, 2019; Oepen and Flickinger, 2019). These reference points are not considered in the overall ranking. Non-reference submissions are further subdivided into ‘official’ and ‘unofficial’ ones, where the latter are characterized by either arriving after the closing deadline (“§”), or using training data beyond the official resources provided (and white-listed) for the task; see §4 above.

Table 4 provides an inventory of participating teams, where the top block corresponds to reference submissions from the co-organizers, and the bottom block shows unofficial submissions by task participants. In two cases, participants discovered serialization or other technical issues in their submissions shortly after the closing date and provided corrected parser outputs (´UFAL MRPipe and ´UFAL–Oslo). The two submissions from the Peking team are considered unofficial because they incorporate EDS-specific training data beyond the white-listed resources for the shared task (see §4 above). And, finally, the Anonymous and CUHK submissions only became available a few days after the closing date of the evaluation period.

It is evident in Table 4 that some submissions are partial, in the sense of not providing parser outputs for all target frameworks. Albeit not the ultimate goal of the cross-framework shared task design, such partiality was explicitly allowed to lower the technical barrier to entry and make it possible to include framework-specific parsers in the comparison. Seven (of thirteen) of the official submissions, as well as the two TUPA baselines, provide semantic graphs for all five frameworks. Three highly-par-

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| Teams | DM | PSD | EDS | UCCA | AMR | MTL | Approach | Reference |
|-------|----|-----|-----|------|-----|-----|----------|----------|
| ERG§ | ✓  | ✓   | ✓   | ✓    | ✓   | ✓   | Composition | Oepen and Flickinger (2019) |
| TUPA | ✓  | ✓   | ✓   | ✓    | ✓   | ✓   | Transition  | Hershcovich and Arviv (2019) |
| TUPA | ✓  | ✓   | ✓   | ✓    | ✓   | ✓   | Transition  | Hershcovich and Arviv (2019) |
| HIT-SCIR | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Che et al. (2019) |
| SJTU–NICT | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Factorization | Li et al. (2019) |
| SUDA–Alibaba | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Factorization | Zhang et al. (2019c) |
| Saarland | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Composition | Donatelli et al. (2019) |
| Hitachi | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Factorization | Koreeda et al. (2019) |
| ÚFAL MRPipe | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Straka and Straková (2019) |
| ShanghaiTech | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Factorization | Wang et al. (2019) |
| Amazon | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Factorization | Cao et al. (2019) |
| JBN | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Factorization | Na et al. (2019) |
| SJTU | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Bai and Zhao (2019) |
| ÚFAL–Oslo | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Droganova et al. (2019) |
| HKUST | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Droganova et al. (2019) |
| Bocharov | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Droganova et al. (2019) |
| ÚFAL MRPipe | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Straka and Straková (2019) |
| Peking | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Factorization | Chen et al. (2019) |
| ÚFAL–Oslo | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Droganova et al. (2019) |
| CUHK | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Transition | Lai et al. (2019) |
| Anonymous | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Composition | Chen et al. (2019) |
| Peking | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Composition | Chen et al. (2019) |

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10In the case of the factorization-based Peking submission, the extra training data is limited to gold-standard tokenization from the original EDS annotations, which in hindsight could in principle have been white-listed.
tial submissions declined the invitation to submit a system description for publication in the shared task proceedings (and one team asked to remain anonymous), such that only limited information is available about these parsers, and they will not be considered in further detail in §7.

Finally, based on input by task participants, Table 4 also provides an indication of which submissions employed multi-task learning (MTL) and a high-level characterization of the overall parsing approach. The distinction between transition-, factorization-, and composition-based architectures follows Koller et al. (2019) and is discussed in more detail in §7 below. In some submissions there can of course be elements of more than one of these high-level architecture types. Also, not all of the teams who indicate the use of multi-task learning actually apply it across different semantic graph frameworks, but in some cases rather to multiple sub-tasks within the parsing architecture for a single framework.

The main task results are summarized in Table 6, showing average MRP scores across frameworks, broken down by the different component pieces (see §5 above). These cross-framework averages can only be meaningfully compared for parsers that support all five frameworks, indicated with italics in the table. The top-three submissions achieve performance levels in the mid-80s $F_1$ range, followed by a competitive middle field of complete submissions that perform comparably to the TUPA baselines and well above. Despite fundamental architectural differences, there are emergent patterns in the average performance levels for different graph elements. Except for the binary top property, node-local information (fine-grained labels and properties) tend to be harder to predict than labeled edges. Edge attributes are only present in UCCA, encoding a binary distinction between primary and remote edges, which none of the parsers appear to predict successfully.

The correlation between the primary ranking of the official submissions (by overall average MRP $F_1$) and per-framework ranks is indicated in Table 5. The top-performing HIT-SCIR submission performs best on only one of the five frameworks (UCCA), but achieves uniformly strong results across the board; the picture is similar for the second-ranked SJTU–NICT submission (which has the best performance on DM). For the other top-performing submissions, there is more variation across frameworks: SUDA–Alibaba is strongest on the Flavor (1) EDS and UCCA graphs, and Saarland and Hitachi rank first and second, respectively, on the PSD graphs, but are not among the top-three ranks for the other frameworks.

As indicated, Table 5 shows the primary ranking, and unofficial submissions are not included. The complete summary of quantitative results from the task (see §9 below) also provides a secondary ranking, considering all submissions (but not reference points) and excluding those entries that are superseded by others from the same team, viz. the earlier submissions from ÜFAL MRPipe and ÜFAL–Oslo and the EDS-only composition-based entry from Peking. In terms of secondary ranks, the unofficial ÜFAL MRPipe entry (correcting a minor bug in the original submission) would come in third overall (outranking SUDA–Alibaba), and the factorization-based Peking submission would take an overall seventh rank (outranking ShanghaiTech, and notably showing overall best performance for the EDS framework). Remaining secondary ranks are eleventh, thirteenth, and sixteenth, for ÜFAL–Oslo, CUHK, and Anonymous, respectively.

Table 5 also contrasts the ranking obtained from the official, cross-framework MRP metric in comparison to the pre-existing framework-specific metrics. For EDS, UCCA, and AMR there are only few
|     | Tops  | Labels | Properties | Anchors | Edges | Attributes | All   |
|-----|-------|--------|------------|---------|-------|------------|-------|
|     | P     | R      | F          | P       | R     | F          | P     |
| ERG | .36   | .36    | .36        | .39     | .39   | .39        | .39   |
|     | .38   | .36    | .37        | .37     | .37   | .37        | .37   |
|     | TUPA single | .65  | .60    | .59        | .76     | .664 | .41        | .58    |
|     | .76   | .68    | .71       | .66     | .677  | .43       | .61    |
|     | TUPA multi | .67  | .57    | .61        | .55     | .557 | .29        | .42    |
|     | .75   | .68    | .71       | .43     | .55   | .47       | .21    |

| HIT-SCIR |         | .91  | .90    | .70        | .70     | .709 | .78        | .77    |
| SJTU–NICT |         | .92  | .91    | .73        | .70     | .712 | .71       | .67    |
| SUDA–Alibaba |         | .88  | .84    | .69        | .70     | .695 | .68        | .68    |
| Saarlund |         | .89  | .90    | .72        | .72     | .723 | .61       | .586   |
| Hitachi   |         | .91  | .92    | .71        | .713    | .713 | .561      | .611   |
| ÓUFAL MRPipe |       | .83  | .71    | .75        | .75     | .754 | .75       | .75   |
| ShanghaiTech |       | .73  | .73    | .66        | .67     | .668 | .59        | .69    |
| Amazon   |         | .45  | .42    | .55        | .54     | .547 | .53       | .52    |
| BNU      |         | .49  | .47    | .32        | .53     | .526 | .45       | .49    |
| SJTU     |         | .56  | .56    | .35        | .35     | .353 | .37       | .36    |
| ÓUFAL–Oslo |        | .45  | .43    | .48        | .43     | .437 | .37       | .39    |
| HKUST    |         | .34  | .37    | .42        | .42     | .428 | .29       | .38    |
| Bocharov |         | .68  | .44    | .52        | .45     | .428 | .29       | .38    |

| Anonymous |         | .54  | .53    | .48        | .48     | .486 | .43       | .43    |
| Peking   |         | .57  | .56    | .33        | .33     | .333 | .34       | .37    |
| Peking   |         | .51  | .51    | .20        | .29     | .239 | .21       | .37    |
| Peking   |         | .53  | .54    | .18        | .20     | .222 | .19       | .38    |
| Peking   |         | .43  | .43    | .20        | .20     | .238 | .23       | .38    |

Table 6: Official results using the cross-framework MRPR metric, broken down by ‘atomic’ component pieces. For each component we report precision (P), recall (R), and F1 score (F). Entries are split into the same three blocks as in Table 4: references (top), official submissions (middle), and unofficial submissions (bottom). For each system, the first row shows MRPR scores on the full evaluation set, while the second shows results on the public 100-sentence subset sampled from The Little Prince. The official and unofficial submissions are sorted by overall average F1. Team names in italics indicate submissions that support all five frameworks.
and ‘local’ divergences in the rankings obtained from the different scoring approaches: In total, there are four instances of pairs of teams swapping specific results (the absolute per-framework scores in Table 7 suggest that such ‘fluctuation’ primarily reflects minor differences in performance). For DM and PSD, on the other hand, Table 5 reveals greater differences between the two ranks indicated in each cell: ShanghaiTech, for example, ranks much higher in the framework-specific SDP metric than in the official MRP ranks. These divergences likely reflect the more limited scope of the SDP approach to scoring, which essentially only considers labeled edges (and top nodes, as a pseudo-edge) but ignores node labels, properties, and anchors (which all used to be provided as part of the parser inputs in the original SDP parsing tasks; see § 3 above).

Finally, Tables 7 and 8 complement the breakdown of official results from the shared task with two per-framework views, using the official MRP metric and earlier framework-specific metrics, respectively. On both views, there are stark differences in overall parser accuracy across frameworks—ranging from the low-70s to mid-90s $F_1$ ranges—with mostly decreasing performance when moving from the bi-lexical Flavor (0) graphs to the unanchored Flavor (2) ones. Given the cross-framework MRP metric, these results become comparable for the first time (within the same parsing system at least, and assuming optimistically that it has been engineered and tuned at comparable effort levels for all frameworks). As such, it is tempting to interpret these differences as indicative of framework-specific parsing difficulty.

However, the volume, uniformity, and quality of available training data (and its similarity to evaluation data, in each framework) inevitably also must factor into such comparison; for example, gold-standard UCCA annotations count at less than one fifth the tokens of the other frameworks. Breaking down results further, viz. into component-wise per-framework scores (available through the task website; see § 9), suggests that scoring the more technical anchoring information at equal weight as the genuinely linguistic node and edge properties contributes to higher average MRP accuracies, in particular for the bi-lexical frameworks where anchors essentially encode tokenization. Ultimately, to put these differences into perspective more, contrastive, phenomena-oriented studies would likely be called for, as for example the comparison of parsing accuracies for EDS vs. AMR by Lin and Xue (2019).

7 Overview of Approaches

The participating systems in the shared task have approached this multi-meaning representation task in a variety of ways, which we characterize into three broad families of approaches: transition-, factorization-, or composition-based architectures.

Transition-Based Architectures In these parsing systems, the meaning representation graph is generated via a series of actions, in a process that is very similar to dependency tree parsing, with the difference being that the actions for graph parsing need to allow reentrancies, as well as (possibly) non-token nodes, labels, properties, and attributes. At any given point in the parsing process, a parser state, which typically consists of a stack that holds already processed elements in the input and a buffer for yet-to-be processed elements, needs to be maintained. Which action to take next is predicted by a classifier using a representation of the parser state as input. When this parsing procedure is complete, the sequence of parsing actions will be used to deterministically reconstitute the meaning representation graph.

This basic method allows variations in various aspects of the parsing process. First of all, the set of actions can vary from system to system. Apart from the standard actions used in syntactic dependency parsing such as SHIFT, LEFTARC, RIGHTARC, and REDUCE (Nivre, 2003; Yamada and Matsumoto, 2003), transition systems in meaning representation parsing also include actions to create reentrant edges, such as LEFTREMOTE and RIGHTREMOTE from the pre-task version of TUPA (Hershcovitch et al., 2017). It may also include actions to create abstract concepts that do not correspond to a word token in the input sentence, such as the NODE action from TUPA, and actions that allow the transition to skip a word token in the input when it does not have semantic content, such as the PASS action from HIT-SCIR. The transition set may also include actions that label the nodes or edges, such as LABEL in the version of TUPA used in the shared task. CUHK developed a transition-based parser with a general transition system suited for all five frameworks, by including a variable-arity RESOLVE action.
|     | DM | PSD | EDS | UCCA | AMR   |
|-----|----|-----|-----|------|-------|
|     | P  | R  | F  | P  | R  | F  | P  | R  | F  | P  | R  | F  | P  | R  | F  |
| ERG | .96 | .96 | .961 | .95 | .95 | .952 | .95 | .95 | .95 | .96 | .96 | .959 | .95 | .95 | .95 |
|     | .97 | .97 | .973 | .96 | .96 | .959 | .96 | .96 | .95 | .96 | .96 | .959 | .96 | .96 | .95 |
| TUPA single | .47 | .67 | .555 | .44 | .63 | .518 | .83 | .79 | .810 | .20 | .45 | .276 | .42 | .48 | .447 |
|     | .50 | .70 | .586 | .52 | .68 | .589 | .83 | .79 | .814 | .31 | .57 | .401 | .43 | .51 | .470 |
| TUPA multi | .31 | .69 | .427 | .45 | .63 | .526 | .74 | .74 | .740 | .17 | .38 | .236 | .29 | .41 | .338 |
|     | .28 | .68 | .395 | .47 | .65 | .545 | .74 | .76 | .748 | .34 | .52 | .410 | .45 | .42 | .434 |
| HIT-SCIR | .95 | .95 | .951 | .90 | .91 | .905 | .91 | .90 | .907 | .83 | .81 | .817 | .77 | .69 | .729 |
|     | .95 | .95 | .950 | .85 | .90 | .874 | .89 | .90 | .898 | .84 | .82 | .826 | .72 | .66 | .690 |
| SJTU–NICT | .91 | .93 | .923 | .85 | .86 | .856 | .92 | .92 | .918 | .81 | .76 | .784 | .73 | .70 | .717 |
| SUDA–Alibaba | .89 | .92 | .907 | .79 | .87 | .828 | .92 | .93 | .925 | .85 | .80 | .821 | .67 | .69 | .679 |
| Saarland | .95 | .95 | .947 | .91 | .91 | .913 | .90 | .88 | .891 | .71 | .65 | .675 | .70 | .63 | .667 |
| Hitachi | .91 | .91 | .910 | .91 | .91 | .912 | .84 | .84 | .837 | .72 | .68 | .704 | .47 | .41 | .439 |
| ÚFAL MRPipe | .91 | .79 | .850 | .87 | .68 | .763 | .82 | .57 | .674 | .76 | .71 | .732 | .77 | .67 | .718 |
|     | .91 | .80 | .854 | .82 | .60 | .691 | .77 | .57 | .651 | .78 | .71 | .741 | .74 | .67 | .707 |
| ShanghaiTech | .95 | .94 | .949 | .90 | .89 | .895 | .86 | .88 | .869 | .86 | .88 | .869 | .86 | .88 | .869 |
|     | .94 | .94 | .943 | .83 | .88 | .852 | .86 | .89 | .875 | .86 | .89 | .875 | .86 | .89 | .875 |
| Amazon | .92 | .92 | .921 | .85 | .91 | .879 | .84 | .85 | .867 | .86 | .88 | .867 | .86 | .88 | .867 |
| JBNU | .92 | .94 | .940 | .88 | .88 | .879 | .86 | .88 | .867 | .86 | .88 | .867 | .86 | .88 | .867 |
|     | .36 | .53 | .431 | .48 | .48 | .476 | .75 | .41 | .532 | .31 | .35 | .327 | .40 | .37 | .385 |
| SJTU | .35 | .53 | .419 | .48 | .48 | .476 | .74 | .44 | .553 | .31 | .40 | .350 | .46 | .42 | .441 |
| ÚFAL–Oslo | .72 | .91 | .805 | .48 | .83 | .609 | .27 | .35 | .306 | .86 | .88 | .888 | .86 | .88 | .888 |
| HKUST | .34 | .41 | .370 | .28 | .48 | .353 | .52 | .52 | .520 | .52 | .52 | .520 | .52 | .52 | .520 |
| Bocharov | .32 | .42 | .364 | .26 | .48 | .334 | .61 | .58 | .592 | .58 | .59 | .592 | .58 | .59 | .592 |
|     | .37 | .29 | .327 | .28 | .44 | .342 | .28 | .44 | .342 | .28 | .44 | .342 | .28 | .44 | .342 |

Table 7: Per-framework results using the official MRP metric. For each framework we report precision (P), recall (R), and $F_1$ score (F). Entries are split and sorted into the same three blocks as in Tables 4 and 6, and again the two rows per submission correspond to the full evaluation data and the Little Prince subset.
|                  | DM |       |       | PSD |       |       | EDS |       |       | UCCA |       |       | AMR |       |       |
|------------------|----|-------|-------|-----|-------|-------|-----|-------|-------|------|-------|-------|-----|-------|-------|
|                  | P  |       |       | R   |       |       | F   |       |       | P    |       |       | R   |       |       |
| ERG              | .91| .91   | .912  | –   | –     | –     | .93 | .92   | .926  | –    | –    | –     | –   | –     | –     |
| TUPA single      | .65| .69   | .670  | .51 | .60   | .552  | .77 | .71   | .741  | .28  | .19  | .224  | .41 | .47   | .438  |
| TUPA multi       | .66| .71   | .690  | .55 | .63   | .585  | .77 | .72   | .744  | .32  | .25  | .284  | .42 | .49   | .451  |
| HIT-SCIR         | .87| .91   | .898  | .76 | .76   | .760  | .90 | .89   | .893  | .66  | .62  | .639  | .73 | .70   | .713  |
| SJTU–NICT        | .93| .92   | .924  | .82 | .81   | .817  | .93 | .83   | .877  | .63  | .59  | .609  | .75 | .68   | .714  |
| SUDA–Alibaba     | .89| .91   | .895  | .75 | .77   | .759  | .90 | .91   | .903  | .69  | .63  | .662  | .71 | .69   | .696  |
| Saarland         | .90| .91   | .906  | .80 | .80   | .796  | .80 | .78   | .794  | .34  | .31  | .324  | .70 | .63   | .661  |
| Hitachi          | .91| .93   | .919  | .80 | .82   | .808  | .78 | .78   | .783  | .39  | .37  | .381  | .46 | .40   | .425  |
| ÚFAL MRPipe      | .80| .70   | .745  | .69 | .52   | .594  | .73 | .49   | .587  | .42  | .38  | .396  | .77 | .67   | .716  |
| ShanghaiTech     | .81| .72   | .749  | .68 | .45   | .539  | .67 | .48   | .560  | .48  | .42  | .445  | .74 | .67   | .700  |
| Amazon           | .87| .86   | .866  | .76 | .72   | .742  | –   | –     | –     | –    | .75  | .71   | .73  | .70   | .704  |
| JBU              | .92| .90   | .912  | .80 | .80   | .800  | –   | –     | –     | .19  | .17  | .177  | –   | –     | –     |
| SJTU             | .93| .92   | .926  | .81 | .81   | .815  | –   | –     | –     | .34  | .31  | .325  | –   | –     | –     |
| SJTU             | .51| .30   | .379  | .49 | .26   | .340  | .66 | .33   | .435  | .05  | .04  | .045  | .39 | .36   | .373  |
| ÚFAL–Oslo        | .90| .86   | .880  | .81 | .73   | .769  | .14 | .21   | .168  | –    | –    | –     | –   | –     | –     |
| HKUST            | .33| .27   | .297  | .45 | .36   | .398  | –   | –     | –     | .21  | .20  | .203  | –   | –     | –     |
| Bocharov         | –  | –     | –     | –   | –     | –     | –   | –     | –     | –    | .35  | .28   | .314 | –    | –     |
| ÚFAL MRPipe      | .87| .90   | .881  | .76 | .79   | .775  | .87 | .85   | .859  | .42  | .38  | .396  | .77 | .67   | .716  |
| Peking           | .87| .91   | .893  | .77 | .80   | .782  | .87 | .87   | .869  | .48  | .41  | .442  | .73 | .67   | .699  |
| Peking           | .92| .92   | .924  | .81 | .80   | .808  | .93 | .91   | .919  | .63  | .61  | .620  | –   | –     | –     |
| ÚFAL–Oslo        | .93| .93   | .925  | .80 | .80   | .797  | .90 | .91   | .906  | .67  | .62  | .640  | –   | –     | –     |
| CUHK             | .90| .86   | .880  | .81 | .73   | .769  | .14 | .21   | .168  | –    | .002 | .56   | .26  | .351  | –     |
| Anonymous        | –  | –     | –     | –   | –     | –     | –   | –     | –     | .10  | .09  | .060  | –   | –     | –     |
| Peking           | –  | –     | –     | –   | –     | –     | –   | .88   | .88   | .879 | –    | –     | –   | –     | –     |
| Anonymous        | –  | –     | –     | –   | –     | –     | –   | .88   | .90   | .890 | –    | –     | –   | –     | –     |

Table 8: Results using the framework-specific (labeled) metrics: SDP (for DM and PSD), EDM (for EDS), UCCA, and SMTACH (for AMR); see §5 above. For each framework (and its metric) we report precision (P), recall (R), and F₁ score (F). Entries are split and sorted into the same three blocks as in Tables 4 and 6, and again the two rows per submission correspond to the full evaluation data and the Little Prince subset.
Second, the classifier used to predict the action for any given state can also vary a great deal. For example, the HIT-SCIR system aggregates information from the action history, the stack, the list, and the buffer with a stack LSTM and then predicts the action by taking a softmax over the output of the LSTM. The CUHK system uses a regular LSTM to aggregate information from the stack, the sequence of words before the current word token, and the sequence of words after the current token, and then predict the action with a softmax. The TUPA system uses a BiLSTM with an MLP and softmax layer, with the BiLSTM running over the sequence of input tokens.

**Factorization-Based Architectures** These parsing models for meaning representation also have their roots in syntactic dependency parsing (where they are often called graph-based; McDonald and Pereira, 2006). Given a set of nodes, the basic idea of the factorization-based approach is to find the graph that has the highest score among all possible graphs. In the case of dependency parsing, the goal is to find the Maximum Spanning Tree, and this has been extended to meaning representation parsing, where the goal is to find the Maximum Spanning Connected Subgraphs (Flanigan et al., 2014). To make the computation of the score of a graph practical, the typical strategy is to factorize the score of a graph into the sum of the scores of its subgraphs, and in the case of first-order factorization, into the sum of the scores of its nodes and edges. A popular choice for predicting the edge is to feed the output of an LSTM encoder to a biaffine classifier to predict if an edge exists between a pair of nodes as well as the label of the edge (SJTU–NICT, SUDA–Alibaba, Hitachi, and JBN). With slight variations as to the input to the LSTM encoder. Due to the difference in anchoring between the nodes in the graph and the word tokens in the sentence, the way to identify nodes also differs from framework to framework. ÚFAL–Oslo used the factorization-based NeurboParser (Peng et al., 2017) for DM and PSD, and for EDS they simply submitted graphs identical to the DM ones. They also used the factorization-based JAMR (Flanigan et al., 2014, 2016) for AMR, and further adjusted JAMR to support UCCA graphs, by converting UCCA to the standard AMR serialization.

**Composition-Based Architectures** Finally, this approach to meaning representation parsing emphasizes the principle of compositionality in meaning construction and assumes an explicit inventory of operations that combine pieces of meaning into larger fragments. Typically grounded in some kind of formal derivation process, composition-based architectures associate meaning fragments with lexical items (leaf nodes in the derivation) and apply a designated composition operation for each step in the derivation. What differentiates composition-based approaches from transition-based or factorization-based ones is that the derivations are licensed by some form of ‘grammar’ (explicit or implicit), where illegitimate derivations can be ruled out by the structural constraints over the lexical items and the rules of derivation. The MRP shared task attracted two (and a half) composition-based systems, the Apply-Modify (AM) algebra based system from Saarland and the Peking parser based on Synchronous Hyperedge Replacement Grammar (SHRG) for EDS. For composition-based approaches, the extraction of lexical items from a sentence is a crucial component of the system. In the case of the Saarland parser, the lexical items are produced by a BiLSTM-based supertagger, and the best derivation is selected in a tree dependency parsing process where the edge between a head and its argument or modifier is labeled with the derivation operation. In the case of the Peking system, the SHRG rules are extracted with a context-free parser, and the derivation is scored by a sum of the scores of its subgraphs.

**Other Approaches** The transition-, factorization-, and composition-based systems represent the main approaches in the shared task, but there are a few systems that stretch the dividing lines of this categorization. When parsing the UCCA framework, a number of systems—e.g. SJTU–NICT, SUDA–Alibaba, and Amazon—adopt an approach where ‘remote’ (reentrancy) edges are first removed to create constituent tree structures to train standard constituent tree parsers using neural network–based models, and then in a postprocessing stage, the remote edges are added back with a separate classifier, following Jiang et al. (2019).

The MRPipe system could be said to define its own category. It differs from transition-based systems in that it does not use the typical actions
used in transition-based systems and it also does not maintain a typical parser state. It also differs from factorization-based systems in that it builds the meaning representation iteratively, while in a factorization-based systems all possible graphs are (conceptually) enumerated at once and the focus is on finding the graph with the highest score.

**Anchoring** One difference among the five meaning representation frameworks covered in the shared task is the correspondence relation between the concepts (graph nodes) and word tokens in the sentence (see §2). In Flavors (0) and (1) (DM, PSD, EDS, and UCCA), this alignment is explicit, while in Flavor (2) AMRs there is no explicit anchoring. How to tackle anchoring in the parsing system has a significant impact on parser performance. Some of the participating systems follow early approaches in AMR parsing and use a separate ‘alignment’ model to provide hard anchorings and then proceed with the rest of the parsing process (e.g. the HIT-SCIR system) assuming the alignments are already in place. Other submissions use a soft alignment component that is trained jointly with other components of their systems. For example, the Amazon and the SUDA–Alibaba parsers jointly model anchoring, node detection, and edge detection, adopting the approach of Lyu and Titov (2018), while the SJTU–NICT system uses a sequence-to-sequence model with a pointer-generator network to predict the concepts in AMR, following Zhang et al. (2019a). That sequence-to-sequence model is trained jointly with other components of their system.

**Cross-Framework Architecture Design** One question that the co-organizers would like to help answer through the shared task is to what degree the same general architecture can be used to effectively parse all five meaning representation frameworks. The answer to this question is tentatively in the affirmative. The HIT-SCIR and TUPA systems use a transition-based system to parse all five meaning representations, with the caveat that the transitions for the five meaning representations vary in the actions that are used. The CUHK parser, on the other hand, uses a uniform transition set for all frameworks. The Saarland system uses the same AM algebra composition system to parse all five meaning representations, but has to do a considerable amount of pre-processing to convert the meaning representations into well-formed terms of the AM algebra (accordingly, some of the pre-processing effects need to be undone in post-processing). The MRPipe system adopts an approach in which the meaning representation graph is built up iteratively with two operations, ADDNODES and ADD EDGES, and applies this model successfully to all five meaning representations. Other participating systems adopt the strategy of using the model that they consider to be the most appropriate for a particular flavor of meaning representation. For example, the SJTU–NICT submission uses a factorization-based model for DM, PSD, and EDS parsing, but uses a constituent tree parsing approach for UCCA, as it is not obvious how a factorization-based model would be extended to also handle UCCA parsing. The Amazon system uses a factorization-based model for DM, PSD, and AMR while adopting a constituent tree parsing approach for UCCA and EDS. The SUDA–Alibaba system also adopts a constituent tree parsing approach to UCCA, similar to Jiang et al. (2019).

**Benefits of Multi-Task Learning** Another research question the shared task seeks to advance is whether and how multi-task learning (MTL) helps with multi-framework meaning representation parsing. The term, in fact, seems to be applied somewhat variably in the system descriptions. In one sense, it is equated with traditional joint learning, where different components of the SUDA–Alibaba system are trained jointly by combining their objectives. The sense of the term that was intended by the organizers is whether pooling the training data for all five frameworks in a multi-task learning framework can improve the parser performance of one particular framework. A number of participating systems attempted MTL in the latter sense, and the results are mixed and not definitive. The MTL version of the TUPA system performs much worse than its single-task version, but this might be attributed to inadequate training strategies and incomplete tuning. The Hitachi systems (in a post-competition experiment) show MTL results that are slightly better than single framework results, but the difference is probably not statistically significant.

8 On the State of the Art

Prior to the shared task, various methods have been proposed for semantic graph parsing, including transition-, factorization-, and composition-based, as well as sequence-to-sequence systems. Existing
parsers also diverge in terms of their assumptions regarding the syntax–semantics interface, some parsing raw text directly to meaning representation graphs, and some producing the graphs from or in parallel with syntactic derivations.

While some meaning representations have parsers for languages other than English (Oepen et al., 2015; Wang et al., 2018; Damonte and Cohen, 2018; Hershcovich et al., 2019), we limit the discussion here to the state of the art in English meaning representation parsing, as has been the focus of the current shared task.

DM and PSD were both among the representations targeted in two SemEval shared tasks on Semantic Dependency Parsing (Oepen et al., 2014, 2015), where the winning system (Kanerva et al., 2015) utilized SVM-based sequence labeling. The runner-up (Du et al., 2014, 2015) used an ensemble based on factorization-based weighted tree approximation. More recently, Peng et al. (2017, 2018a,b) improved upon previous approaches by using a neural factorization-based multi-task system, sharing parameters between representations and applying joint inference. Stanovsky and Dagan (2018) linearized the bi-lexical graphs and modeled the parsing task as a sequence-to-sequence problem. They also used multi-task learning, adapting multilingual machine translation algorithms to ‘translate’ between text and meaning representations, outperforming the previous best results on PSD. Lindemann et al. (2019) trained a composition-based parser on DM, PAS, PSD, AMR and EDS, using the Apply–Modify algebra, on which the Saarland submission to the shared task is based. They employed multi-task training with all tackled semantic frameworks and UD, establishing the state of the art on all graph banks but AMR 2017.

AMR has been a challenging target representation for parsing, due to the fact that AMRs are Flavor (2), unanchored graphs. AMR parsing was pioneered by Flanigan et al. (2014), who performed alignment as a preprocessing step during training. They developed their own rule-based alignment method, complemented by Pourdamghani et al. (2014), who adapted methods from machine translation. Some transition-based AMR parsers also perform rule-based alignment (Damonte et al., 2017; Damonte and Cohen, 2018; Ballesteros and Al-Onaizan, 2017; Naseem et al., 2019), while others derive AMRs from syntactic dependencies by applying transitions (Wang et al., 2015; Wang and Xue, 2017). The latter approach reached the best performance (Wang et al., 2016; Nguyen and Nguyen, 2017) in two SemEval shared tasks on AMR parsing (May, 2016; May and Priyadarshi, 2017), where in the former it performed as well as a novel character-level neural translation based AMR parser (Barzdins and Gosko, 2016). Composition-based AMR parsers include Artzi et al. (2015), who combined CCG grammar induction with AMR parsing. Sequence-to-sequence attention-based approaches (Konstas et al., 2017; van Noord and Bos, 2017) use techniques from machine translation to directly generate (linearized) graphs from text. Lyu and Titov (2018) parsed AMR using a joint probabilistic model with latent alignments, avoiding cascading errors due to alignment inaccuracies and outperforming previous approaches. The factorization-based parser by Zhang et al. (2019a,b) uses an attention-based architecture, but derives target graphs directly instead of a linearization, also treating alignment as a latent variable with a copy mechanism. Their parser additionally supports UCCA and SDP, and establishes the state-of-the-art in AMR parsing, though without using multi-task training across frameworks.

UCCA parsing was first tackled by Hershcovich et al. (2017), who used a neural transition-based parser. Hershcovich et al. (2018) further showed that multi-task learning with AMR, DM, and UD as auxiliary tasks improves UCCA parsing performance. UCCA also recently featured in a SemEval shared task (Hershcovich et al., 2019), where the composition-based best system (Jiang et al., 2019) outperformed the transition-based baseline by treating the task as constituency tree parsing with the recovery of remote edges as a postprocessing task.

EDS, being a result of automatic conversion from English Resource Semantics (Bender et al., 2015), can be derived by any ERG parser (e.g. Callmeier, 2002; Packard, 2012). Buys and Blunsom (2017) were the first to build a purely data-driven EDS parser, combining graph linearization with a custom transition system. Chen et al. (2018) established the state of the art on data-driven EDS parsing, using a neural SHRG-based, ERG-guided parser. Their comparison on in-domain WSJ evaluation data showed parsing accuracies on par or in excess of the full, grammar-based ACE parser of Packard (2012).

While some shared task submissions are based on existing systems that have been specifically im-
proved, direct comparison to previously published results is impossible: Our definition of the SDP task, for example, is different from Oepen et al. (2014, 2015); prior EDS work has mostly tested on WSJ only; the UCCA annotations have been revised and extended; we are using a new, forthcoming version of AMRbank; and gold-standard tokenization is not provided for any of the frameworks. Also, even some of our framework-specific metrics are not exactly what was used previously: We have made SDP and UCCA character-based (for increased robustness to tokenization mismatches), and we un-invert edges more thoroughly in AMR graphs before calling SMATCH for scoring. However, overall performance levels and general trends observed in §6 appear consistent with recent developments in the field: By and large, the transition-, factorization-, and composition-based approaches all can yield competitive parsers, where cross-framework multi-task learning sometimes helps but only slightly so. While general methods for meaning representation graph parsing are clearly beneficial, there is yet progress to be made (so far) in sharing information between parsers for different frameworks and making better use of their overlap.

9 Reflections and Outlook

The MRP 2019 shared task was a first step in a new direction, aiming to more closely (inter)relate the representations and parsing approaches across a diverse range of semantic graph frameworks. Despite new uniformity in packaging and evaluation, cumulative overall complexity and inherent technical and linguistic diversity of the frameworks deemed participation in the competition a demanding challenge. The problem attracted broad interest: Some 140 individuals have subscribed to the shared task mailing list, and 38 teams obtained the training data package from the LDC (of these, sixteen submitted parser outputs for evaluation). In a post-evaluation questionnaire and through informal communication, several prospective participants have indicated that they had started to work towards a system submission but in the end simply ran out of time for the official evaluation period.

Possibly related to the high technological barrier to participation is the comparatively low proportion of submissions that successfully utilize multi-task learning (across frameworks). Even though some of the participating teams have previously applied multi-task learning for semantic graph parsing, it appears some may have shied away from increased training times and tuning effort and instead had to focus their work on developing strong end-to-end parsers for individual frameworks. As task co-organizers, we remain committed to enabling continued research along these lines, and we will ultimately make all training and evaluation data generally available. In the interim, however, we are delighted (and a little frightened) to confirm that CoNLL has invited us to orchestrate a follow-up shared task on Cross-Framework Meaning Representation Parsing in 2020.

Deciding on the task parameters for MRP 2020 will be a balancing act between keeping overall complexity manageable, in particular for ‘newcomer’ participants, and pushing further in the direction of learning from complementary knowledge sources. Above all, the mid- to long-term goals of the cross-framework meaning representation initiative are to advance our understanding of degrees of complementarity among the various frameworks. Current plans foresee inclusion of one additional framework, viz. a graph-based encoding of the Discourse Representation Structures of Basile et al. (2012). Further, we plan on refining and extending the available training data (in particular for UCCA) and will put greater focus on the systematic exploration of variant evaluation perspectives, for example scoring at the level of larger sub-graphs in the spirit of the ‘complete predications’ metric of Oepen et al. (2015), or ‘semantic n-grams’ along the lines of the SemBleu proposal by Song and Gildea (2019). Aiming for increased linguistic diversity, it will of course also be tempting to seek to include meaning representations for additional languages. For each of the frameworks involved (six in total for MRP 2020), gold-standard annotations are in principle available for at least one language besides English, but in most cases these would be different languages for each framework. Thus, it remains yet to be decided how best to balance cross-linguistic and multi-task perspectives on the MRP problem.

All technical information regarding the MRP 2019 shared task, including system submissions, detailed official results, and links to supporting resources and software are available from the task web site at: http://mrp.nlpl.eu
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