

Universal Decompositional Semantic Parsing

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Abstract

We introduce a transductive model for parsing into Universal Decompositional Semantics (UDS) representations, which jointly learns to map natural language utterances into UDS graph structures and annotate the graph with decompositional semantic attribute scores. We also introduce a strong pipeline model for parsing into the UDS graph structure, and show that our transductive parser performs comparably while additionally performing attribute prediction. By analyzing the attribute prediction errors, we find the model captures natural relationships between attribute groups.

1 Introduction

A structured account of compositional meaning has been longstanding goal for both natural language understanding and computational semantics. To this end, a number of efforts have focused on encoding semantic relationships and attributes in a semantic graph—e.g. Abstract Meaning Representation (AMR; [Banarescu et al., 2013](#)), Universal Conceptual Cognitive Annotation (UCCA; [Abend and Rappoport, 2013](#)), and Semantic Dependency Parsing (SDP; [Oepen et al., 2014, 2015, 2016](#)).

In these formalisms, semantic information is typically encoded discretely, using nominal category labels for nodes and edges. This categorical encoding can make such formalisms brittle when presented with non-prototypical instances, and leads to challenges in coping with changing label ontologies and new datasets ([White et al., 2019](#)). Furthermore, they are difficult to annotate, often requiring trained linguists and large annotation manuals.

The Decompositional Semantics framework presents an alternative to categorical formalisms that encodes semantic information in a feature-based scheme—using continuous scales rather than categorical labels. Starting with a feature-based semantic role representation rooted in [Dowty 1991](#)'s

(1991) proto-role theory ([Reisinger et al., 2015; White et al., 2016](#)), this framework has expanded to cover a wide variety of phenomena: event factuality ([Rudinger et al., 2018b](#)), genericity ([Govindarajan et al., 2019](#)), entity types ([White et al., 2016](#)), and temporal relations ([Vashishtha et al., 2019](#)).

While this rich array of annotation types has been separately modeled, no system yet exists for its joint prediction, which has only recently been made feasible by the introduction of Universal Decompositional Semantics v1.0 (UDS1.0). Presented by [White et al. \(2019\)](#), UDS1.0 normalizes all of these annotations, and incorporates them as node- and edge-level attributes in a single semantic graph whose structure is deterministically extracted from Universal Dependencies (UD; [Nivre et al., 2015](#)) syntactic parses via the PredPatt tool ([White et al., 2016; Zhang et al., 2017](#)).¹ An example graph can be seen in [Fig. 1](#).

We present the first joint UDS parser, which learns to extract both graph structures and attributes from natural language input. This parser is a sequence-to-graph transductive model which takes as input a sentence and outputs a UDS graph complete with node- and edge-level annotations.

In contrast to the traditional semantic parsing paradigm, which shares its roots with syntactic parsing and rests on the assumption that the nodes in the graph correspond to tokens in the input—i.e. the graph is *lexicalized*—the *parsing-as-transduction* paradigm treats parsing as a sequence-to-graph problem. Rather than generating one sequence conditional on another sequence (sequence-to-sequence), we generate the nodes in a graph conditional on an input sequence, dynamically adding their edges during generation. As in sequence-to-sequence modeling, the supports of the input and output distributions—i.e. the input and output

¹Available at <http://decomp.io>.

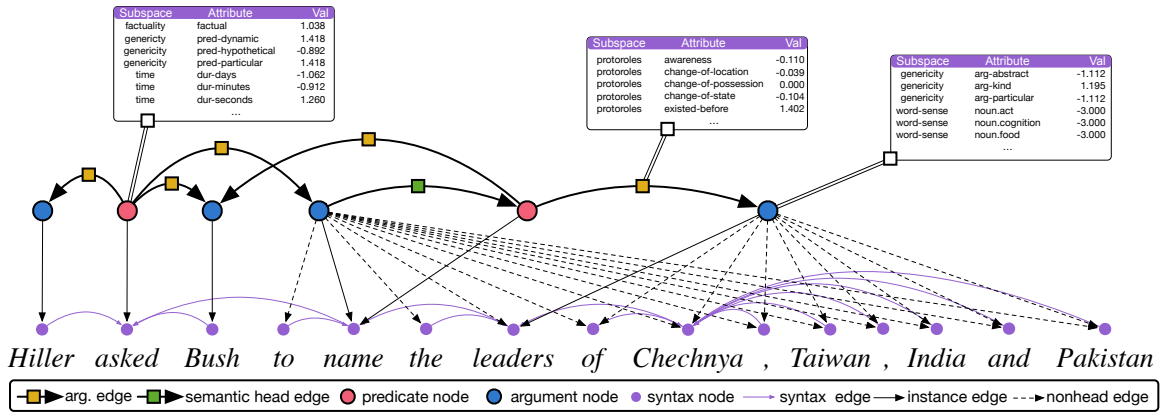


Figure 1: The UDS graph structure. Semantic subgraph is outlined in black while the syntactic subgraph is annotated in pink. Node and edge attribute annotations are shown via annotations on argument and attribute edges.

vocabularies—are not constrained to be identical.

This has two benefits: first, post-hoc methods of obtaining alignments between input sequences and graphs—common especially in AMR parsing—are no longer required; and second, we are able to produce semantic graphs from arbitrary input vocabularies—allowing for future extensions to cross-lingual parsing (Zhang et al., 2018). The parsing-as-transduction paradigm thus lends itself perfectly to UDS parsing, since the UDS protocol allows non-lexicalized (as well as cross-lingual) graphs, and these graphs may have nodes with multiple parents—i.e. re-entrant nodes—which pose problems for traditional tree-based methods but are handled natively by the transductive paradigm.

We compare our end-to-end transductive parser against a strong pipeline system, finding that the parser slightly outperforms the pipeline while additionally learning to produce decompositional attribute scores. Our results are reflected in the UDS1.0 leaderboard at <http://decomp.io/leaderboards/>.

2 Related Work

Datasets Reisinger et al. (2015) introduce the Decompositional Semantics framework in the context of a corpus-based verification of Dowty’s seminal proto-role theory of semantic roles. This work was substantially expanded by White et al. (2016), who annotate for semantic proto-roles (SPR), word-sense, and temporal properties on top of semantic graphs extracted from English Web Treebank (EWT; Bies et al., 2012) UD parses using PredPatt (White et al., 2016; Zhang et al., 2017).

White et al.’s EWT annotations are modeled by Teichert et al. (2017), who present a CRF-based multi-label classifier for proto-role labelling, and

Rudinger et al. (2018a), who make use of an event-driven neural model. More recently, the annotation coverage for the same EWT data was expanded by Vashishtha et al. (2019) who annotate and model fine-grained temporal distinctions, and Govindarajan et al. (2019), who add annotations and models for genericity—i.e. the degree of generality of events and entities in linguistic expressions.

All of these efforts coalesce in White et al. (2019), which presents the first unified Decompositional Semantics-aligned dataset—Universal Decompositional Semantics v1.0 (UDS1.0)—containing all properties annotated on top of EWT parses with standardized train, validation, and testing splits and a native reader and query interface.

Parsing In most work on decompositional semantics, models are tasked with learning to predict attribute values, but not the structure of the graph. Zhang et al. (2018) develop the first model for performing both graph parsing and UDS attribute prediction in a cross-lingual setting, where Chinese input sentences were transduced into UDS graphs derived from UD parses of the input’s English translation. This represents the first application of the parsing-as-transduction paradigm to a subset of UDS data as well as the introduction of a novel graph evaluation metric, S which we describe in further detail in Section 5. In contrast to the end-to-end approach presented here, Zhang et al. take a pipeline approach to parsing.

Andreas et al. (2013) recast semantic parsing in a tree formalism as a sequence-to-sequence problem. Parsing-as-transduction, which extends this approach to directed acyclic graphs, has proven to be applicable in a variety of settings: Zhang et al. (2019a) use it to achieve state-of-the-art re-

sults in AMR parsing. These results are improved upon and shown to generalize to two other semantic formalisms (UCCA and SDP) by Zhang et al. (2019b), which set new state-of-the-art benchmarks for AMR and UCCA. The former result was subsequently surpassed by Cai and Lam (2020), which applies a similar transductive approach, while the latter was surpassed by Jiang et al. (2019).

Having both been subjects of SemEval tasks (May, 2016; May and Priyadarshi, 2017; Oepen et al., 2019; Hershovich et al., 2019), there are a number of contrasting methods for both AMR and UCCA parsing. These include transition-based parsing system for AMR (Wang et al., 2018; Goodman et al., 2016; Damonte et al., 2017; Balles-teros and Al-Onaizan, 2017) and for UCCA (Hershovich et al., 2017). In a similar vein to Zhang et al. (2019b), Hershovich et al. (2018a) convert multiple formalisms into a unified formalism and use multitask learning for improved UCCA parsing; however, the latter does so at a loss to performance on the other formalisms, while Zhang et al. achieve state-of-the-art results in AMR and UCCA simultaneously. UCCA has also been shown to transfer to syntactic parsing: by converting UD parse trees into a format resembling UCCA, Hershovich et al. (2018b) are able to apply a UCCA parser to both standard UD parses as well as enhanced UD parses, which contain re-entrant nodes.

3 Data

The UDS1.0 dataset is built on top of the UD-EWT data with three layers of annotations: UD parses, PredPatt graph structure, and decompositional semantic annotations on the edge and node level. In addition to specifying the syntactic head and head relation of every token in the input, UD parses include lexical features, such as word form, word lemma, and part-of-speech (POS) tag. This forms the *syntactic graph*, which is lexicalized (each token is tied to a node in the graph). From these pieces of information, PredPatt outputs a set of predicates and their arguments.

Each predicate and argument is tied via an *instance edge* to a particular node in the syntactic graph. Because both predicates and arguments can consist of multi-word spans, there can be multiple instance edges leaving a semantic node. The *semantic graph* contains edges between predicates and arguments; in the case of clausal embedding, there can also be argument-argument edges. UDS1.0

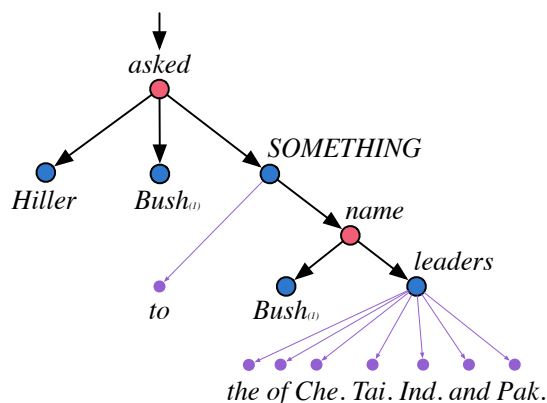


Figure 2: Arborescence for graphs with object control.

includes “performative” speaker/author and addressee nodes, which model discourse properties of the sentence. These nodes are structural placeholders for future discourse-level annotations; as these properties have not yet been annotated, we have opted to remove them from the graphs.²

The crowdsourced decompositional annotations tied to the semantic subgraph can be divided into node-level annotations and edge-level annotations. On the node level, annotations were collected for factuality, genericity, time, and entity type. Edge-level annotations are in the space of semantic protocols, which are designed to provide a nuanced higher-dimensional substrate for notions of agency and patienthood. These are summarized in Table 1, where purple indicates a high attribute score, while orange indicates a low score. For further details on attribute types and data annotation, see White et al. (2019) and the references therein.

Arborescence Recall that the lowest level of the UDS graph (Fig. 1) is a syntactic dependency parse. Modeling this level is out of scope for this work, as we are interesting in modeling the semantic structure and attributes. In order to train a parsing-as-transduction model, an arborescence—a hierarchical tree structure which has only edge and node annotations—is required. From the full UDS graph, we construct the arborescence by:

- (a) Assigning each semantic node a lexical label; this label is taken from the syntactic head that the semantic node dominates. The only exception to this is in the case of embedded clauses, where an argument node dominates an embedded predicate. Here, we follow PredPatt, assigning the label “SOMETHING” to the embedded argument (c.f. Fig. 2).

²Since these placeholder nodes are currently added deterministically, recovering them is also a deterministic operation.

Annotation	Description	Examples
Factuality	Factuality inferences represent how likely (or unlikely) a listener thinks a scenario is to have occurred.	Jo left (3), Jo didn't leave (-3), Jo thought that Cole had left (-1)
Genericity	Genericity refers to inferences about the generality of events or event participants.	<i>Ex. property: genericity-pred-particular:</i> Amy ate oats for breakfast today (3), Amy ate oats for breakfast every day (-3)
Time	Temporal inferences pertain to the duration of events.	<i>Ex. property: time-dur-minutes:</i> Tom left (-3), Tom was singing (3)
Word Sense	UDS decomposes word sense, allowing multiple senses to apply to a given node.	<i>Ex. property: supersense.person:</i> Sandy led Rufus by a leash (-3), Sandy led Rufus by a leash (3)
Semantic Proto-Roles	SPR properties are edge-level annotations that capture fine-grained semantic relations between predicates and arguments.	<i>Ex. property: volition:.</i> Derek broke his arm (-3), Derek broke the wishbone (3)

Table 1: Type descriptions and illustrative sentences for UDS properties predicted in this work. Example ratings in parentheses, bolding indicates the salient predicate/argument/edge. See White et al. (2019) for further details.

- (b) Retaining all edges between semantic nodes as “argument” edges, duplicating nodes in cases of re-entrancy (e.g. “*Bush*₍₁₎” in Fig. 2).
- (c) Converting the deep syntactic structure into a shallow representation, where we introduce “non-head” edges from the syntactic head (attached to a semantic node) to each node it dominates, and remove all other syntax-semantics edges. This effectively linearizes the yield of each semantic node (see Fig. 2).

4 Model

Our model is based on the transductive broad-coverage parsing model presented in Zhang et al. (2019b), which can be consulted for further details on the encoder, decoder, and pointer-generator modules. The original parser is composed of six major modules: the encoder, the decoder embedding module, the target node module, the target label module, the head module, and the relation module. In this work we introduce two new modules: the node attribute module and the edge attribute module, as well a loss function for attributes.

Encoder The encoder module takes a concatenation of multiple input features: GloVe token embeddings (Pennington et al., 2014), POS tag embeddings, character CNN embeddings, and BERT (Devlin et al., 2019) contextual embeddings (mean-pooled over subwords). These representations are passed through a stacked bidirectional LSTM encoder, which has the following definition:

$$\mathbf{s}_t^l = \begin{bmatrix} \overrightarrow{\mathbf{s}}_t^l \\ \overleftarrow{\mathbf{s}}_t^l \end{bmatrix} = \begin{bmatrix} \overrightarrow{\text{LSTM}}(\mathbf{s}_t^{l-1}, \mathbf{s}_{t-1}^t) \\ \overleftarrow{\text{LSTM}}(\mathbf{s}_t^{l-1}, \mathbf{s}_{t+1}^t) \end{bmatrix}$$

where arrows denote the LSTM direction, t denotes the timestep, and l denotes the layer of the stack.

Decoder embedding module In order to generate new semantic nodes and relationships, a method of embedding categorical semantic information is required. More formally, a semantic relation is given by a tuple $\langle u_i, d_i^u, r_i, v_i, d_i^v \rangle$, where u_i denotes the “head” token of index i and v_i denotes the token at index i . Note that these tokens are the labels of nodes in the arborescence (see Fig 2.) d_i^u and d_i^v are the indices of u_i and v_i , while r_i is the relationship type between v_i and u_i . The decoder embedding module embeds these categorical variables into real space, producing a tuple of vectors $\langle \mathbf{u}_i, \mathbf{d}_i^u, \mathbf{r}_i, \mathbf{v}_i, \mathbf{d}_i^v \rangle$. For node labels \mathbf{u}_i and \mathbf{v}_i , we take the concatenation of GloVe and CharCNN features. \mathbf{r}_i , \mathbf{d}_i^v and \mathbf{d}_i^u are randomly initialized.

Target Node Module From the continuous embedding of a semantic relation $\langle \mathbf{u}_i, \mathbf{d}_i^u, \mathbf{r}_i, \mathbf{v}_i, \mathbf{d}_i^v \rangle$ we want to obtain a latent node representation \mathbf{z}_i . We initialize the hidden states of the 0th layer and the hidden states of the 0th state in each layer to

$$\begin{aligned} \mathbf{h}_i^0 &= [\mathbf{v}_i; \mathbf{d}_i^v] \\ \mathbf{h}_0^1 &= [\overleftarrow{\mathbf{s}}_1^l; \overrightarrow{\mathbf{s}}_n^l] \end{aligned}$$

respectively. Further, let \mathbf{c}_i be a context vector over encoder states $\mathbf{s}_{1:n}^l$, defined as

$$\begin{aligned} \mathbf{a}_i^{(\text{enc})} &= \text{softmax}(\text{MLP}^{(\text{enc})}([\mathbf{h}_i^l; \mathbf{s}_{1:n}^l])) \\ \mathbf{c}_i &= \mathbf{a}_i^T \mathbf{s}_{1:n}^l \end{aligned}$$

Let \mathbf{h}_i^l and \mathbf{z}_i be defined as follows:

$$\begin{aligned} \mathbf{z}_i &= \text{MLP}^{(\text{relation})}([\mathbf{h}_i^l; \mathbf{c}_i; \mathbf{r}_i; \mathbf{u}_i; \mathbf{d}_i^u]) \\ \mathbf{h}_i^l &= \text{LSTM}(\mathbf{h}_i^{l-1}, \mathbf{h}_{i-1}^l) \end{aligned}$$

where \mathbf{z}_i can be thought as a representation of node i in the graph, conditioned on previous nodes (via \mathbf{h}_i^l as well as the input text via \mathbf{c}_i , the graph token (via \mathbf{u}_i and \mathbf{d}_i^u) and the relation type (via r_i).

Using this representation \mathbf{z}_i , Zhang et al. (2019b) introduce an extended pointer-generator network (See et al., 2017) which computes the distribution over the next node label v_{i+1} :

$$\begin{aligned} [p_{\text{gen}}, p_{\text{enc}}, p_{\text{dec}}] &= \text{softmax}(\text{MLP}^{(\text{switch})}(\mathbf{z}_i)) \\ \mathbf{a}_i^{\text{dec}} &= \text{softmax}(\text{MLP}^{\text{dec}}([\mathbf{z}_{1:i}])) \\ \mathbf{p}_i^{(\text{vocab})} &= \text{softmax}(\text{MLP}^{(\text{vocab})}(\mathbf{z}_i)) \\ \mathbf{P}(v_{i+1}) &= p_{\text{gen}}\mathbf{p}_i^{(\text{vocab})} \oplus p_{\text{enc}}\mathbf{a}_i^{(\text{enc})} \oplus p_{\text{dec}}\mathbf{a}_i^{(\text{dec})} \end{aligned}$$

From this last equation, we have that the generation of a new node is decomposed into three options: (1) generate a new node from a vocabulary of node labels, (2) copy a node label directly from the input sequence (lexicalization), or (3) copy a node label from a previously generated node (re-entrancy).

Parsing modules To obtain a parse from the node states $\mathbf{h}_{1:n}$, a head node and relation type must be assigned to each node $1 : n$. In order to assign a head node, we instantiate two multi-layer perceptrons (MLPs): $\text{MLP}^{(\text{start})}$ and $\text{MLP}^{(\text{end})}$, where (start) denotes the starting node of the edge and (end) denotes its target. Using these MLPs, for node $i + 1$ we obtain

$$\begin{aligned} \mathbf{h}_{i+1}^{(\text{start})} &= \text{MLP}^{(\text{start})}(\mathbf{h}_{i+1}^l) \\ \mathbf{h}_{1:i}^{(\text{end})} &= \text{MLP}^{(\text{end})}(\mathbf{h}_{1:i}^l) \\ \mathbf{P}(u_{i+1}) &= \text{softmax}(\text{BIAFFINE}(\mathbf{h}_{i+1}^{(\text{start})}, \mathbf{h}_{1:i}^{(\text{end})})) \end{aligned}$$

The next relationship r_{i+1} is computed in a similar fashion, also using two MLPs:

$$\begin{aligned} \mathbf{h}_{i+1}^{(\text{rel-src})} &= \text{MLP}^{(\text{rel-src})}(\mathbf{h}_j^l) \\ \mathbf{h}_{i+1}^{(\text{rel-tgt})} &= \text{MLP}^{(\text{rel-tgt})}(\mathbf{h}_{i+1}^l) \\ \mathbf{P}(r_{i+1}) &= \text{softmax}(\text{BILINEAR}(\mathbf{h}_{i+1}^{(\text{rel-src})}, \mathbf{h}_{i+1}^{(\text{rel-tgt})})) \end{aligned}$$

where j is the index of the head assigned to the node indexed by $i + 1$.³

³BIAFFINE is defined in Dozat and Manning (2016). $\text{BILINEAR}(x_1, x_2) = x_1Ax_2 + b$ where A and b are learned parameters.

Node attribute module As noted in previous UDS projects, an important step in decompositional attribute annotation is determining whether a property applies in a given context. For example, factuality typically applies only to predicate nodes. Since all nodes (predicate and argument) are treated identically w.r.t. their semantic relations \mathbf{z}_i , this work introduces a two-fold node attribute model, which predicts whether a property j applies to a node i via a binary mask α_i^j as well as its value ν_i^j . This module defines α_i^j and ν_i^j as follows:

$$\begin{aligned} \mathbf{P}(\alpha_i^j) &= \text{sigmoid}(\text{MLP}^{(\text{node-mask})}(\mathbf{z}_i)) \\ \nu_i^j &= \text{MLP}^{(\text{node-attr})}(\mathbf{z}_i) \end{aligned}$$

Edge attribute module As in the case of node attributes, edge attributes do not apply in all cases. Therefore, a similar bifurcation strategy is pursued with edge attribute prediction: we predict a binary attribute mask $\beta_{s,e}^j$ for attribute j on edge $s \rightarrow e$ as well as an attribute value $\lambda_{s,e}^j$. These are given by:

$$\begin{aligned} \mathbf{m}_{s,e}^{(\text{mask})} &= \text{BILINEAR}^{(\text{mask})}(\mathbf{h}_s^l, \mathbf{h}_e^l) \\ \mathbf{m}_{s,e}^{(\text{attr})} &= \text{BILINEAR}^{(\text{attr})}(\mathbf{h}_s^l, \mathbf{h}_e^l) \\ \mathbf{P}(\beta_{s,e}^j) &= \text{sigmoid}(\text{MLP}^{(\text{edge-mask})}(\mathbf{m}_{s,e}^{(\text{mask})})) \\ \lambda_{s,e}^j &= \text{MLP}^{(\text{edge-attr})}(\mathbf{m}_{s,e}^{(\text{attr})}) \end{aligned}$$

Training The nodes in the graph are linearized in a pre-order traversal over the arborescence, which ensures that at prediction time, we have seen the potential antecedent of a node for target-side copying (e.g. *Bush*₍₁₎ in Fig. 2), determining the order of semantic nodes in the graph. The syntactic children of these nodes are presented in the order they appear in the text. The loss functions for the node, head, and relation prediction modules are cross-entropy loss, while for the masks α and β binary cross-entropy loss is used, since each position in the mask is a separate classification decision. The loss function used for K attributes $\nu^{1:K}$ on N nodes/edges is given by:

$$\begin{aligned} \tau(x) &= \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases} \\ \mathcal{L}_{\text{MSE}}(\nu, \nu^*) &= \frac{1}{NK} \sum_{i=1}^N \sum_{j=1}^K c_i^j (\nu_i^j - \nu_i^{j*})^2 \end{aligned}$$

$$\mathcal{L}_{\text{BCE}}(\nu, \nu^*) = \frac{1}{NK} \sum_{i=1}^N \sum_{j=1}^K \left(\tau(\nu_i^{j*}) \log(\tau(\nu_i^j)) + (1 - \tau(\nu_i^{j*})) \log(1 - \tau(\nu_i^j)) \right)$$

$$\mathcal{L}(\nu, \nu^*) = \gamma \frac{2 * \mathcal{L}_{\text{MSE}}(\nu, \nu^*) * \mathcal{L}_{\text{BCE}}(\nu, \nu^*)}{\mathcal{L}_{\text{MSE}}(\nu, \nu^*) + \mathcal{L}_{\text{BCE}}(\nu, \nu^*)}$$

where γ is a scaling factor, c_i^j is the annotator confidence for annotation j on token i , ν is the set of predicted attributes, and ν^* is the set of true attributes. Note that inclusion of the confidence mask c_i^j means the model only incurs loss on attributes annotated for a given node, since $c_i^j = 0$ when an annotation is missing (i.e. no MSE loss is incurred for attributes which do not apply to a node or edge); in the “binary” experimental setting, we replace c_i^j with $\tau(c_i^j)$, removing the weighting but still masking out loss on un-annotated nodes. Also note that in the case of edges, the form of the loss is identical, but ν is replaced by λ , and α by β .

This loss encourages the predicted attribute ν_i^j value to be close in value to the true value ν_i^{j*} via the mean-squared error criterion while concomitantly encouraging the predicted and reference values to share a sign via the thresholded cross-entropy criterion. Both node and edge attribute models are trained to predict attribute values independently, and that parameters are shared across attributes. This is central to our analysis in §7.

Following Zhang et al. (2019b) we train the structural parsing modules with coverage loss (See et al., 2017). All models were trained to convergence using the Adam optimizer (Kingma and Ba, 2014) with a learning rate of 0.001.

5 Experiments

Pipeline Model Recall from Section 3 that the semantic graph structure in UDS graphs is deterministically generated from PredPatt, which takes as input a UD parse and outputs a semantic graph structure. This leads to a strong pipeline model for the graph structure alone: running a high-performing UD parser—the Stanford UD parser (Chen and Manning, 2014)—and passing its output through PredPatt to create a structure.⁴ For this baseline,

⁴This structure is missing the core decompositional attributes but has both predicate and argument nodes. Additionally, the pipeline model fails to capture nominal heads of copular predicates (e.g. *Jo is a doctor*), which are not returned by PredPatt but are added to the dataset as a preprocessing step in the genericity annotation task.

Method	P	R	F1
Pipeline	84.83	75.22	79.74
Parser	83.52	77.92	80.62
Parser (binary)	84.97	78.52	81.62

Table 2: Test set S score precision, recall, and F1.

the only source of error is the UD parsing model, which for English performs very highly.

S Metric For evaluating the quality of output graph structures, Smatch (Cai and Knight, 2013), a hill-climbing approach to approximating the optimal matching between variables in two graphs, is commonly used. While Smatch can match categorical variables such as those found in meaning representations like AMR, it lacks a matching function for continuous variables such as decompositional attributes. To remedy this, Zhang et al. (2018) introduce the S metric, an extension to Smatch that allows for attribute matching.

Using hill-climbing, we are able to match instance and attribute nodes and edges; instance nodes are matched via string match, while attribute similarity is given by $1 - \left(\frac{\nu_i - \nu_j}{\omega}\right)^2$ where $\omega = 6$ is the maximum possible difference between attributes, which are bounded on $[-3, 3]$.⁵

6 Results

Table 5 shows the Pearson’s correlation coefficient (ρ) and the F1 score computed on binarized responses for each node and edge attribute under the “oracle” decoding setting, where a gold graph structure is provided to the model. An asterisk denotes that $p < 0.05$, where p is determined by a Student’s t-test. F1 scores are obtained by binarizing continuous attribute predictions into positive and negative, following from the original UDS motivation found in Dowty (1991), where binary proto-role features were introduced. The binarization threshold was tuned per attribute on the validation set.

The baseline column in Table 5 shows the binarized F1 score for the baseline attribute model, given by predicting the median attribute value for each attribute type at each position. Pearson’s ρ is undefined for this approach, as the variance of the predicted distribution is 0. The thresholds were similarly tuned on validation data for this baseline.

Table 2 shows S metric (c.f. §5) precision, recall, and F1 score as computed on full arborescences

⁵This function was found to produce more matches on UDS1.0 than the $e^{-\text{MAE}}$ function used by Zhang et al. (2018).

with both semantics and syntax nodes. Our parser slightly outperforms the pipeline, with higher performance in the “binary” setting, where we exclude annotator confidence from the loss.

Table 3 shows precision, recall, and F1 score on semantics nodes alone. The first parser setting (syntax) reflects a parsing model trained on full graphs, and evaluated only on the semantic subgraphs of the produced graphs. The second parser (semantics) is directly trained on semantic subgraphs, with no syntactic nodes in the training graphs. The full parser performs comparably to the pipeline, while the parser trained specifically on semantics-only graphs outperforms the pipeline. However, the mean attribute ρ of the syntactic parser (0.3433) exceeded that of the semantics-only parser (0.3151).

Method	P	R	F1
Pipeline	84.72	88.51	86.57
Parser (syntax)	89.02	83.67	86.26
Parser (syntax, binary)	89.74	86.00	87.83
Parser (semantics)	91.28	87.23	89.21
Parser (sem., binary)	91.10	84.59	87.73

Table 3: Test set S score precision, recall, and F1 on semantics nodes only, where (syntax) denotes a parser trained to predict full graphs (semantics nodes with non-head edges to syntax nodes) while (semantics) denotes model trained on semantics-only subgraphs.

Table 4 gives the S metric results on full graphs predicted by the model, including attribute matching. The pipeline model is unable to perform this task because it predicts structure alone, without attributes. We see that training the parser with shared MLP and BILINEAR modules (i.e. $\text{MLP}^{\text{(mask)}} = \text{MLP}^{\text{(attr)}}$ and $\text{BILINEAR}^{\text{(mask)}} = \text{BILINEAR}^{\text{(attr)}}$) for both the attribute mask and attribute value heavily degrades the performance, while removing annotator confidence increases it slightly.

7 Analysis

Table 2 suggests that the structural quality of the parses obtained by the parsing model presented here is slightly superior to that of pipeline model’s parses, with Table 3 indicating that the semantic component of the graph can be parsed significantly more accurately by our model. Taken together with Table 5, we can conclude that the model is able to learn to jointly predict the graph structure and attributes. This is further reinforced by Table 4. Note that the numbers reported in Tables 2 and 4 are not directly comparable, as the scores in Table 4

Method	P	R	F1
Shared	79.52	32.48	46.12
Separate	83.46	82.27	82.86
Separate (binary)	84.19	84.19	84.19

Table 4: Test set precision, recall, and F1 computed via S score with attributes (syntactic nodes included)

Property	Pearson’s ρ (model)	F1 (baseline)	F1 (model)	
node-level generativity	factuality-factual	0.6479*	75.15	84.46
	arg-abstract	0.3392*	40.04	48.05
	arg-kind	0.2145*	67.61	67.54
	arg-particular	0.3347*	83.10	84.62
	pred-dynamic	0.2469*	72.49	71.19
	pred-hypothetical	0.3442*	44.16	50.21
	pred-particular	0.1887*	77.47	78.16
	dur-centuries	0.1336*	10.14	12.30
	dur-days	0.1802*	68.72	68.21
	dur-decades	0.2383*	29.89	34.19
	dur-forever	0.2524*	37.93	38.58
	dur-hours	0.2227*	73.66	73.61
	dur-instant	0.1761*	55.98	51.90
	dur-minutes	0.3409*	86.28	87.05
	dur-months	0.3204*	63.25	64.42
	dur-seconds	0.2751*	65.33	64.75
	dur-weeks	0.2475*	54.02	55.41
	dur-years	0.4239*	65.03	66.19
node-level time	supersense-noun.tops	0.4660*	7.34	40.00
	supersense-noun.act	0.6007*	27.37	56.39
	supersense-noun.animal	0.3773*	5.60	25.64
	supersense-noun.artifact	0.5617*	23.12	52.79
	supersense-noun.attribute	0.4505*	10.81	29.27
	supersense-noun.body	0.4543*	1.53	42.86
	supersense-noun.cognition	0.5692*	21.17	50.56
	supersense-noun.communication	0.6182*	30.60	62.12
	supersense-noun.event	0.4233*	5.80	33.61
	supersense-noun.feeling	0.2404*	2.74	5.45
	supersense-noun.food	0.6773*	7.15	67.72
	supersense-noun.group	0.5650*	15.57	55.22
	supersense-noun.location	0.5118*	7.81	55.64
	supersense-noun.motive	0.3447*	0.62	50.00
	supersense-noun.object	0.2276*	2.04	19.05
	supersense-noun.person	0.6091*	15.74	61.25
	supersense-noun.phenomenon	0.2955*	2.04	8.85
	supersense-noun.plant	0.0358	0.21	13.33
	supersense-noun.possession	0.5247*	6.67	47.62
	supersense-noun.process	0.1292*	1.13	3.96
	supersense-noun.quantity	0.4403*	4.92	36.11
	supersense-noun.relation	0.2089*	2.34	11.94
	supersense-noun.shape	0.0659*	0.31	1.55
	supersense-noun.state	0.4877*	11.36	36.17
	supersense-noun.substance	0.2411*	1.43	3.64
	supersense-noun.time	0.5175*	10.99	51.43
	awareness	0.6715*	68.20	81.99
	change-of-location	0.1061*	38.98	36.90
	change-of-possession	0.0452	14.93	20.00
	change-of-state	0.0448	42.59	37.21
	change-of-state-continuous	0.0793	31.47	27.69
	existed-after	0.3910*	93.33	95.58
existed-before	0.4802*	91.60	92.31	
existed-during	0.3247*	98.31	98.61	
instigation	0.3820*	74.48	76.77	
partitive	0.0213	31.91	34.64	
sentient	0.6494*	64.67	82.81	
volition	0.5501*	63.79	79.86	
was-for-benefit	0.2389*	59.87	62.11	
was-used	0.1608*	86.64	89.00	
macro-average	0.3433	37.20	50.66	

Table 5: Pearson’s ρ , baseline F1, and model F1 for each UDS attribute given gold test-set graph structures.

incorporate the matching scores between attributes.

Table 3 shows that a parser trained on semantic subgraphs better recovers the subgraphs than a parser trained on full graphs whose outputs are

postprocessed to remove syntactic nodes. However, the fact that the parser trained on full graphs achieves a higher Pearson’s ρ score indicates that the inclusion of syntactic nodes may provide additional information for predicting UDS attributes.

In examining instances with an S score below 50, we observe two trends: the input sentences are often ungrammatical, and for 63.82% (on the validation set) the model predicts no output nodes.

While the pipeline system does well on modeling semantic graph structure, it is by its definition unable to perform attribute parsing. In contrast, the results presented in Tables 4 and 5 show that the parser can jointly learn to produce semantic graphs and annotate them with attributes.

Finally, we find that while weighting the loss with the confidence scores has a small benefit in the semantics-only setting, it hurts overall attribute and structure prediction performance. This may be due to the relatively small size of the UDS dataset, which makes a strategy that is effectively weakening the loss signal at training time less effective.⁶

Figs. 3a-3c show the correlational strength coefficient between the true and predicted attributes under a forced decode of the graph structure. It is defined over property types indices j, k with predicted attribute values ν_i^j and true values ν_i^{j*} as:

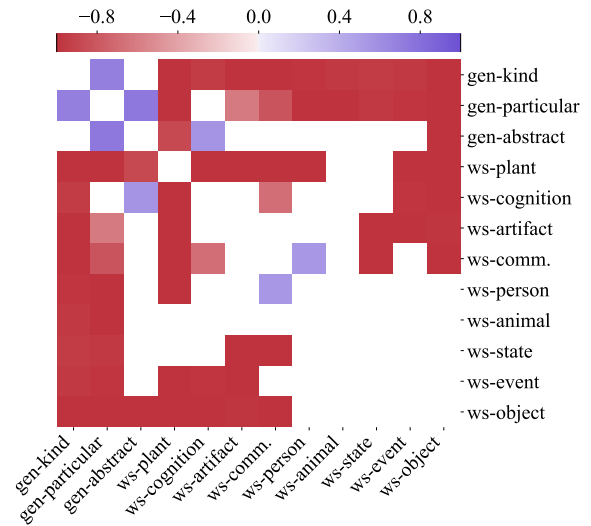
$$\psi(j, k) = \tanh\left(1 - \frac{|\text{corr}(\nu^j - \nu^{j*}, \nu^k - \nu^{k*})|}{|\text{corr}(\nu^{j*}, \nu^{k*})|}\right)$$

where $\text{corr}(\nu^{j*}, \nu^{k*})$ is Pearson’s correlation coefficient. Further details are given in Appendix A.

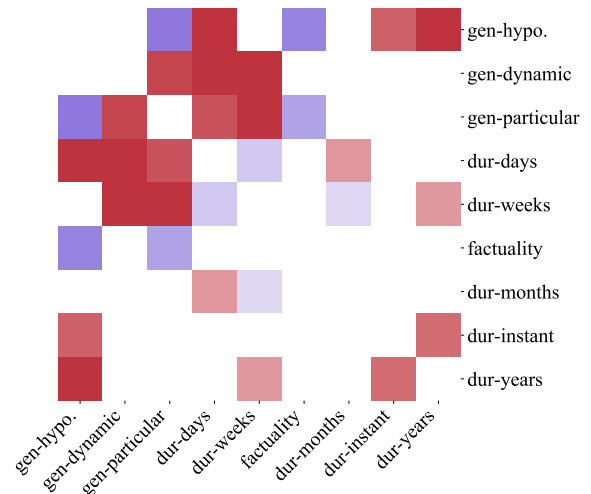
$\psi(i, j)$ reflects how well the model captures the strength of the correlations (either positive or negative) between two attribute types in the dataset: a positive value indicates that the model captures the correlation to some extent, with values closer to 1 implying better performance; a value of 0 indicates that the model does not capture the correlation at all, or that no significant interaction was present; a negative value indicates that the model makes systematic mistakes while predicting the two variables, e.g. when the model under-predicts the value of property i , it also under-predicts property j ’s value. A Bonferroni-corrected non-parametric bootstrap test (1000 replicants) was used for significance testing, with failing pairs being said to not be reliably different from 0 correlation.

Fig. 3a shows the model typically systematically under- or over-predicts the values for pairs

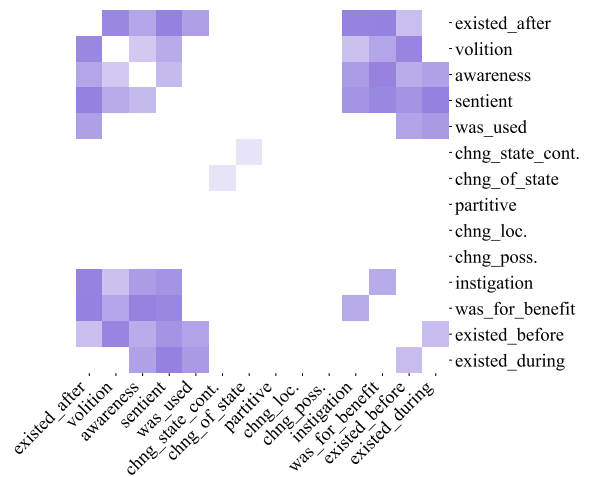
⁶All confidences are on $[0, 1]$



(a) ψ between argument-node attribute pairs. Subset of word-senses used for readability.



(b) ψ between predicate-node attribute pairs. Subset of time attributes used for readability.



(c) ψ between all edge attribute pairs.

Figure 3: ψ heatmaps for UDS1.0 attribute pairs of argument-node attributes, with most ψ values close to -1. However, we do see positive correlations between some of the genericity annotations,

Sentences	Property	(A)	Ours (A)	(B)	Ours (B)	(C)	Ours (C)
(A) She was untrained and, in one botched job, <i>killed</i> a client.	awareness	3	3.04	1	3.69	5	3.68
	volition	2	2.92	1	3.45	5	3.44
(B) The antibody then <i>kills</i> the cell.	instigation	5	3.08	5	3.39	5	3.37
(C) An assassin in Colombia <i>killed</i> a federal judge on a Medellin street.	sentience	5	2.99	1	3.71	5	3.70
	existed-after	5	3.57	2	3.79	5	3.78

Table 6: Comparison of gold properties from Reisinger et al. (2015) (on an ordinal scale from 1 to 5, with 3 as “neutral”) and predicted properties (mapped to [1, 5]) for sentences involving the predicate “kills”.

as well as between *genericity-arg-abstract*, which rates how conceptually abstract an argument is, and the *cognition* wordsense, which applies to abstract terms such as “doubts” and “thoughts”.

In Fig. 3b, we again observe several negative ψ values; however, some positive correlations can be seen between certain time properties, such as *duration-days*, *duration-weeks*, and *duration-months*, as well as more strongly positive ψ ’s between certain genericity annotations. The positive ψ between *factuality* and *genericity-hypothetical* indicates the model has captured the commonalities between predicates with these annotations.

In contrast to the node attributes, Fig. 3c shows stronger results for edge attribute prediction, with all significant ψ ’s being positive, and related attributes falling into clusters (e.g. *volition*, *awareness*, *sentience*, or the *existed* attributes)

Qualitative examples Table 6 lists three sentences from Reisinger et al. (2015) along with a relevant subset of their original SPR properties and values; the scale in Reisinger et al. was ordinal from 1-5, with 1 corresponding to “very unlikely,” 5 to “very likely,” and 3 to “neutral.” Our model’s predictions for the same sentences and properties are given as well, mapped onto [1, 5]. We first note that the structural component of the model is sufficiently strong that the correct predicate-argument edges were extracted during parsing, allowing for a direct comparison between the annotations by Reisinger et al. and the parser’s predictions. We see that while for sentence (C), the model captures at least the correct direction of the protorole annotations, it overgeneralizes these results to (B), where a more nuanced analysis is required. For (A), we see that on most attributes the model captures the desired binary direction of the inferences, but that it fails on *sentience*. Overall, the model’s predictions are weaker than the desired output, even when the prediction is on the correct side of the midpoint, 3. This might help explain the disparity between Pearson and F1 scores in Table 5, and represents

a direction for future work. Note that to obtain attributes for (A) and (B), the threshold for the masks β was dropped; ideally, this would not be required.

8 Conclusion

The scalar valued, multi-attribute nature of UDS provides for a distinct structured prediction problem as compared to other existing representations. We have demonstrated how a transductive parsing paradigm that has achieved state-of-the-art results on other representations can be adapted to UDS1.0 structures and attributes, and have provided procedures for analysis, with the fine-grained nature of UDS allowing for investigating novel correlations and aspects of meaning. While UDS structures and various attribute types have been modeled separately (Vashishtha et al., 2019; Govindarajan et al., 2019; White et al., 2016; Rudinger et al., 2018a,b; Zhang et al., 2018), this work represents the first time all of these attributes and structures have been modeled jointly, and establishes a baseline for future efforts on UDS1.0.

We envision future efforts exploring the interactions between improving the underlying graph-structure prediction and ever-better correlations to human judgements on individual properties.

9 Acknowledgements

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References

Omri Abend and Ari Rappoport. 2013. Universal Conceptual Cognitive Annotation (UCCA). In *Proceedings of the 51st Annual Meeting of the Association*

- for *Computational Linguistics (Volume 1: Long Papers)*, pages 228–238, Sofia, Bulgaria. Association for Computational Linguistics.
- Jacob Andreas, Andreas Vlachos, and Stephen Clark. 2013. Semantic parsing as machine translation. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 47–52.
- Miguel Ballesteros and Yaser Al-Onaizan. 2017. **AMR parsing using stack-LSTMs**. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1269–1275, Copenhagen, Denmark. Association for Computational Linguistics.
- Laura Banarescu, Claire Bonial, Shu Cai, Madalina Georgescu, Kira Griffitt, Ulf Hermjakob, Kevin Knight, Philipp Koehn, Martha Palmer, and Nathan Schneider. 2013. Abstract meaning representation for sembanking. In *Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse*, pages 178–186.
- Ann Bies, Justin Mott, Colin Warner, and Seth Kulick. 2012. English web treebank. *Linguistic Data Consortium, Philadelphia, PA*.
- Deng Cai and Wai Lam. 2020. Amr parsing via graph-sequence iterative inference. *arXiv preprint arXiv:2004.05572*.
- Shu Cai and Kevin Knight. 2013. Smatch: an evaluation metric for semantic feature structures. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 748–752, Sofia, Bulgaria. Association for Computational Linguistics.
- Danqi Chen and Christopher Manning. 2014. A fast and accurate dependency parser using neural networks. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 740–750.
- Marco Damonte, Shay B. Cohen, and Giorgio Satta. 2017. **An incremental parser for abstract meaning representation**. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 536–546. Association for Computational Linguistics.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- David Dowty. 1991. Thematic proto-roles and argument selection. *Language*, 67(3):547–619.
- Timothy Dozat and Christopher D Manning. 2016. Deep biaffine attention for neural dependency parsing. *arXiv preprint arXiv:1611.01734*.
- James Goodman, Andreas Vlachos, and Jason Naradowsky. 2016. **Ucl+sheffield at semeval-2016 task 8: Imitation learning for amr parsing with an alpha-bound**. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 1167–1172. Association for Computational Linguistics.
- Venkata Govindarajan, Benjamin Van Durme, and Aaron Steven White. 2019. Decomposing Generalization: Models of Generic, Habitual, and Episodic Statements. *Transactions of the Association for Computational Linguistics*, 7:501–517.
- Daniel Hershcovich, Omri Abend, and Ari Rappoport. 2017. **A transition-based directed acyclic graph parser for UCCA**. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1127–1138, Vancouver, Canada. Association for Computational Linguistics.
- Daniel Hershcovich, Omri Abend, and Ari Rappoport. 2018a. **Multitask parsing across semantic representations**. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 373–385, Melbourne, Australia. Association for Computational Linguistics.
- Daniel Hershcovich, Omri Abend, and Ari Rappoport. 2018b. Universal dependency parsing with a general transition-based dag parser. In *Proceedings of the CoNLL 2018 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies*, pages 103–112.
- Daniel Hershcovich, Zohar Aizenbud, Leshem Choshen, Elior Sulem, Ari Rappoport, and Omri Abend. 2019. **SemEval-2019 task 1: Cross-lingual semantic parsing with UCCA**. In *Proceedings of the 13th International Workshop on Semantic Evaluation*, pages 1–10, Minneapolis, Minnesota, USA. Association for Computational Linguistics.
- Wei Jiang, Zhenghua Li, Yu Zhang, and Min Zhang. 2019. Hlt@ suda at semeval 2019 task 1: Ucca graph parsing as constituent tree parsing. *arXiv preprint arXiv:1903.04153*.
- Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.
- Jonathan May. 2016. **SemEval-2016 task 8: Meaning representation parsing**. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 1063–1073, San Diego, California. Association for Computational Linguistics.

- Jonathan May and Jay Priyadarshi. 2017. *SemEval-2017 task 9: Abstract meaning representation parsing and generation*. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pages 536–545, Vancouver, Canada. Association for Computational Linguistics.
- Joakim Nivre, Zeljko Agic, Maria Jesus Aranzabe, Masayuki Asahara, Aitziber Atutxa, Miguel Ballesteros, John Bauer, Kepa Bengoetxea, Riyaz Ahmad Bhat, Cristina Bosco, Sam Bowman, Giuseppe G. A. Celano, Miriam Connor, Marie-Catherine de Marneffe, Arantza Diaz de Ilarraza, Kaja Dobrovoljc, Timothy Dozat, Tomaž Erjavec, Richárd Farkas, Jennifer Foster, Daniel Galbraith, Filip Ginter, Iakes Goenaga, Koldo Gojenola, Yoav Goldberg, Berta Gonzales, Bruno Guillaume, Jan Hajič, Dag Haug, Radu Ion, Elena Irimia, Anders Johannsen, Hiroshi Kanayama, Jenna Kanerva, Simon Krek, Veronika Laippala, Alessandro Lenci, Nikola Ljubešić, Teresa Lynn, Christopher Manning, Cătălina Măranduc, David Mareček, Héctor Martínez Alonso, Jan Mašek, Yuji Matsumoto, Ryan McDonald, Anna Missilä, Verginica Mititelu, Yusuke Miyao, Simonetta Montemagni, Shunsuke Mori, Hanna Nurmi, Petya Osenova, Lilja Øvrelid, Elena Pascual, Marco Passarotti, Cené-Augusto Perez, Slav Petrov, Jussi Piitulainen, Barbara Plank, Martin Popel, Prokopis Prokopidis, Sampo Pyysalo, Loganathan Ramasamy, Rudolf Rosa, Shadi Saleh, Sebastian Schuster, Wolfgang Seeker, Mojgan Seraji, Natalia Silveira, Maria Simi, Radu Simionescu, Katalin Simkó, Kiril Simov, Aaron Smith, Jan Štěpánek, Alane Suhr, Zolt Szántó, Takaaki Tanaka, Reut Tsarfaty, Sumire Uematsu, Larraitz Uria, Viktor Varga, Veronika Vincze, Zdeněk Žabokrtský, Daniel Zeman, and Hanzhi Zhu. 2015. Universal Dependencies 1.2. <http://universaldependencies.github.io/docs/>.
- Stephan Oepen, Omri Abend, Jan Hajic, Daniel Herscovich, Marco Kuhlmann, Tim O’Gorman, Nianwen Xue, Jayeol Chun, Milan Straka, and Zdenka Urešová. 2019. Mrp 2019: Cross-framework meaning representation parsing. In *Proceedings of the Shared Task on Cross-Framework Meaning Representation Parsing at the 2019 Conference on Natural Language Learning*, pages 1–27.
- Stephan Oepen, Marco Kuhlmann, Yusuke Miyao, Daniel Zeman, Silvie Cinková, Dan Flickinger, Jan Hajic, Angelina Ivanova, and Zdenka Uresova. 2016. Towards comparability of linguistic graph banks for semantic parsing. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016)*, pages 3991–3995.
- Stephan Oepen, Marco Kuhlmann, Yusuke Miyao, Daniel Zeman, Silvie Cinková, Dan Flickinger, Jan Hajič, and Zdeňka Urešová. 2015. SemEval 2015 task 18: Broad-coverage semantic dependency parsing. In *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, pages 915–926, Denver, Colorado. Association for Computational Linguistics.
- Stephan Oepen, Marco Kuhlmann, Yusuke Miyao, Daniel Zeman, Dan Flickinger, Jan Hajič, Angelina Ivanova, and Yi Zhang. 2014. SemEval 2014 task 8: Broad-coverage semantic dependency parsing. In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, pages 63–72, Dublin, Ireland. Association for Computational Linguistics.
- Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543.
- Drew Reisinger, Rachel Rudinger, Francis Ferraro, Craig Harman, Kyle Rawlins, and Benjamin Van Durme. 2015. Semantic Proto-Roles. *Transactions of the Association for Computational Linguistics*, 3:475–488.
- Rachel Rudinger, Adam Teichert, Ryan Culkin, Sheng Zhang, and Benjamin Van Durme. 2018a. Neural-davidsonian semantic proto-role labeling. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 944–955, Brussels, Belgium. Association for Computational Linguistics.
- Rachel Rudinger, Aaron Steven White, and Benjamin Van Durme. 2018b. Neural Models of Factuality. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 731–744, New Orleans, Louisiana. Association for Computational Linguistics.
- Abigail See, Peter J Liu, and Christopher D Manning. 2017. Get to the point: Summarization with pointer-generator networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1073–1083.
- Adam Teichert, Adam Poliak, Benjamin Van Durme, and Matthew R Gormley. 2017. Semantic proto-role labeling. In *Thirty-First AAAI Conference on Artificial Intelligence*.
- Siddharth Vashishtha, Benjamin Van Durme, and Aaron Steven White. 2019. Fine-Grained Temporal Relation Extraction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2906–2919, Florence, Italy. Association for Computational Linguistics.
- Yuxuan Wang, Wanxiang Che, Jiang Guo, and Ting Liu. 2018. A neural transition-based approach for semantic dependency graph parsing. In *AAAI Conference on Artificial Intelligence*.
- Aaron Steven White, Drew Reisinger, Keisuke Sakaguchi, Tim Vieira, Sheng Zhang, Rachel Rudinger,

- Kyle Rawlins, and Benjamin Van Durme. 2016. Universal decompositional semantics on universal dependencies. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1713–1723, Austin, TX. Association for Computational Linguistics.
- Aaron Steven White, Elias Stengel-Eskin, Siddharth Vashishtha, Venkata Govindarajan, Dee Ann Reisinger, Tim Vieira, Keisuke Sakaguchi, Sheng Zhang, Francis Ferraro, Rachel Rudinger, et al. 2019. The universal decompositional semantics dataset and decomp toolkit. *arXiv preprint arXiv:1909.13851*.
- Sheng Zhang, Xutai Ma, Kevin Duh, and Benjamin Van Durme. 2019a. AMR parsing as sequence-to-graph transduction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 80–94, Florence, Italy. Association for Computational Linguistics.
- Sheng Zhang, Xutai Ma, Kevin Duh, and Benjamin Van Durme. 2019b. Broad-coverage semantic parsing as transduction. *arXiv preprint arXiv:1909.02607*.
- Sheng Zhang, Xutai Ma, Rachel Rudinger, Kevin Duh, and Benjamin Van Durme. 2018. Cross-lingual decompositional semantic parsing. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1664–1675, Brussels, Belgium. Association for Computational Linguistics.
- Sheng Zhang, Rachel Rudinger, and Benjamin Van Durme. 2017. An Evaluation of PredPatt and Open IE via Stage 1 Semantic Role Labeling. In *IWCS 2017 — 12th International Conference on Computational Semantics — Short papers*.

A Derivation of ψ

The metric used in visualizations Fig. 3a-3c is given by:

$$\psi(j, k) = \tanh\left(1 - \frac{|\text{corr}(\nu^j - \nu^{j*}, \nu^k - \nu^{k*})|}{|\text{corr}(\nu^{j*}, \nu^{k*})|}\right)$$

where $\text{corr}(\nu^j - \nu^{j*}, \nu^k - \nu^{k*})$ and $\text{corr}(\nu^{j*}, \nu^{k*})$ are defined as follows:

$$\begin{aligned}\bar{\nu}^j &= \frac{1}{N} \sum_{i=1}^N \nu_i^j \\ O_j &= \frac{1}{N} \sum_{i=1}^N (\nu_i^j - \nu_i^{j*})^2 \\ \text{corr}(\nu^j - \nu^{j*}, \nu^k - \nu^{k*}) &= \frac{\frac{1}{N} \sum_{i=1}^N ((\nu_i^{j*} - \nu_i^j)(\nu_i^{k*} - \nu_i^k))}{\sqrt{O_j} \sqrt{O_k}} \\ E_j &= \frac{1}{N} \sum_{i=1}^N (\nu_i^{j*} - \bar{\nu}^{j*})^2 \\ \text{corr}(\nu^{j*}, \nu^{k*}) &= \frac{\frac{1}{N} \sum_{i=1}^N ((\nu_i^{j*} - \bar{\nu}^{j*})(\nu_i^{k*} - \bar{\nu}^{k*}))}{\sqrt{E_j} \sqrt{E_k}}\end{aligned}$$

Note that by this definition, ψ is effectively a ratio of Pearson correlations, where the denominator is exactly the Pearson correlation between ν^{j*} and ν^{k*} .