A Comparative Analysis of Knowledge-Intensive and Data-Intensive Semantic Parsers

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We present a phenomenon-oriented comparative analysis of the two dominant approaches in task-independent semantic parsing: classic, knowledge-intensive and neural, data-intensive models. To reflect state-of-the-art neural NLP technologies, we introduce a new target structure-centric parser that can produce semantic graphs much more accurately than previous data-driven parsers. We then show that, in spite of comparable performance overall, knowledge- and data-intensive models produce different types of errors, in a way that can be explained by their theoretical properties. This analysis leads to new directions for parser development.

1. Introduction

The recent study of task-independent semantic parsing has shifted from the knowledge-intensive approach to the data-intensive approach. Early attempts in semantic parsing leverage explicitly expressed symbolic rules in a deep grammar formalism, e.g., Combinatory Categorial Grammar (CCG, Steedman (1996, 2000)) and Head-driven Phrase Structure Grammar (HPSG, Pollard and Sag (1994a)), to model the syntactico-semantic composition process (Bos et al. 2004; Callmeier 2000). Then, statistical machine learning technologies, especially structured prediction models, are employed to enhance deep grammar-driven parsers (Clark and Curran 2007; Miyao and Tsujii 2008; Zhang, Oepen, and Carroll 2007). Recently, various deep learning models together with vector-based embeddings induced from large-scale raw texts have been making advances significantly (Dozat and Manning 2018; Chen, Sun, and Wan 2018).

The numerical improvements brought by neural networks have typically come at the cost of our understanding of the systems. It is still unclear as to what extent we can expect supervised training or pre-trained embeddings to induce the implicit linguistic knowledge and thus help semantic parsing. In this paper, we take a step back and analyze the recent progress of semantic parsing through a comparative analysis of the knowledge-intensive and data-intensive paradigms. Our analysis is based on a fine-grained construction-focused evaluation and sheds light on the kinds of strengths each type of parser exhibits. In particular, we utilize linguistically-informed datasets based on previous work (Bender et al. 2011) and our own creation, covering a rich set of linguistic phenomena related to various lexical, phrasal and non-local dependency constructions.

To reflect the state-of-the-art deep learning technologies that are already available for data-intensive parsing, we design and implement a new system for string-to-
Figure 1
An example of EDS graph. Some concepts are surface relations, meaning that they are related to a single lexical unit, e.g. _the_q or _introduce_v_to, while others are abstract relations representing grammatical meanings, e.g. compound_name (multiword expression), parq_d (passive) and loc_nonsp (temporal). ERS corpus provides alignment between concept nodes and surface strings, e.g. <0:1> that is associated to _the_q indicates that this concept is signaled by the first word.

Figure 2
An example of EDS graph to represent complicate phenomena like right node raising and raising/control constructions.

conceptual graph parsing (Kuhlmann and Oepen 2016). Figure 1 and 2 are two examples to illustrate the representations. This parser learns to produce conceptual graphs for sentences from an annotated corpus and does not assume the existence of a grammar that explicitly defines syntactico-semantic patterns. The core engine is score functions that use contextualized word and concept embeddings to discriminate good parses from bad for a given sentence, regardless of its semantic composition process.

To evaluate the effectiveness of the new parser, we conduct experiments on English Resource Semantics (ERS; Flickinger, Bender, and Oepen 2014b,a) annotations. Our
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... parser achieves an accuracy of 95.05 for Elementary Dependency Structure (EDS; Oepen and Lønning 2006) in terms of SMATCH, which is 8.05 point improvement over the best transition-based model (Buys and Blunsom 2017), 4.19 point improvement over the SHRG parser (Chen, Sun, and Wan 2018), and 0.45 point improvement over the knowledge-intensive ACE parser. We take it as a reflection that the models induced from large-scale data by neural networks have a strong coherence with linguistic knowledge.

By comparing the newly created data-intensive parser with ACE, we find several non-obvious facts: (1) The data-intensive parser is good at capturing local information at the lexical level even when the training data is rather small; (2) the data-intensive parser performs better on some peripheral phenomena but may suffer from data sparsity; (3) the knowledge-intensive parser produces more coherent semantic structures, which may have a great impact on advanced natural language understanding tasks, such as textual inference; (4) it is difficult for both parsers to find long-distance dependencies and their performance varies across phenomena. There is no apriori restriction that a data-intensive approach must remove all explicitly defined grammatical rules, or a knowledge-intensive approach cannot be augmented by data-based technologies. Our comparative analysis appears highly relevant, in that these insights may be explored further to design new computational models with improved performance.

2. Background

2.1 Graph-Based Meaning Representations

Considerable NLP research has been devoted to the transformation of natural language utterances into a desired linguistically-motivated semantic representation. Such a representation can be understood as a class of discrete structures that describe lexical, syntactic, semantic, pragmatic as well as many other aspects of the phenomenon of human language. In this domain, graph-based representations provide a lightweight yet effective way to encode rich semantic information of natural language sentences and have been receiving heightened attention in recent years (Kuhlmann and Oepen 2016). Popular frameworks under this umbrella includes Semantic Dependency Graphs (SDG; Clark, Hockenmaier, and Steedman 2002; Ivanova et al. 2012; Oepen et al. 2014, 2015), Abstract Meaning Representation (AMR; Banarescu et al. 2013), Graph-based Representations for ERS (Oepen and Lønning 2006; Copestake 2009), and Universal Conceptual Cognitive Annotation (UCCA; Abend and Rappoport 2013).

2.2 Parsing to Semantic Graphs

Parsing to the graph-based representations has been extensively studied recently (Du, Sun, and Wan 2015; Zhang et al. 2016; Cao et al. 2017; Peng, Thomson, and Smith 2017; Flanigan et al. 2014; Artzi, Lee, and Zettlemoyer 2015; Peng, Song, and Gildea 2015; Buys and Blunsom 2017; Hershcovich, Abend, and Rappoport 2017; Konstas et al. 2017; Chen, Sun, and Wan 2018). Work in this area can be divided into two types, according to how information about the mapping between natural language utterances and target graphs is formalized, acquired and utilized. In the first type of approach, a semantic graph is derived according to a set of lexical and syntactico-semantic rule,
which extensively encode explicit linguistic knowledge. Usually, such rules are governed by a well-defined grammar formalism, e.g., Combinatory Categorial Grammar, Head-driven Phrase Structure Grammar, and Hyperedge Replacement Grammar, and exploit compositionality (Callmeier 2000; Bos et al. 2004; Artzi, Lee, and Zettlemoyer 2015; Peng, Song, and Gildea 2015; Groschwitz et al. 2018; Chen, Sun, and Wan 2018). In this paper, we call it the knowledge-intensive approach.

The other type of approach explicitly models the target semantic structures. It may associate each basic part with a target graph score, and casts parsing as the search for the graphs with the highest sum of partial scores (Flanigan et al. 2014; Cao et al. 2017). To search for the highest-scoring semantic graphs involves a combinatorial optimization problem, which is usually resolved by dynamic programming. The essential computational module in this architecture is the score function, which is usually induced based on moderate-sized annotated sentences. Various deep learning models together with vector-based encodings induced from large-scale raw texts have been making advances in shaping a score function significantly (Dozat and Manning 2018). In this paper, we call it the data-intensive approach.

2.3 English Resource Semantics

ERS is the semantic annotation associated to English Resource Grammar (ERG; Flickinger 2000), an open-source, domain-independent, linguistically precise and broad-coverage grammar of English, which encapsulates the linguistic knowledge required to produce many of the types of compositional meaning annotations. The ERG is an implementation of the grammatical theory of Head-driven Phrase Structure Grammar (HPSG; Pollard and Sag 1994b). ERG is a resource grammar that can be used for both parsing and generation. Development of the ERG begins in 1993, and after continuously evolving through a series of projects, it allows the grammatical analysis of most running test across domains and genres.

In the most recent stable release, viz. version ‘1214’, the ERG contains 225 syntactic rules and 70 lexical rules for derivation and inflection. The hand-built lexicon of the ERG contains 39,000 lemmata, instantiating 975 leaf lexical types providing part-of-speech and valence constraints, which aims at providing complete coverage of function words and open-class words with ‘non-standard’ syntactic properties (e.g. argument structure). The ERG also supports light-weight named entity recognition and an unknown word mechanism, allowing the grammar to derive full syntactico-semantic analyses for 85-95% of all utterances in real corpora such as newspaper text, the English Wikipedia, or bio-medical academic paper (Flickinger, Oepen, and Ytrestøl 2010; Flickinger, Zhang, and Kordoni 2012; Adolphs et al. 2008). For more than 20 years of development, ERS has shown their advantages of explicit formalization and large scalability (Copestake and Flickinger 2000).

The Minimal Recursion Semantics (MRS; Copestake et al. 2005)) is the associated semantic representation employed by the ERG. MRS is based on the first order language family with generalized quantifiers. ERS can also be expressed as other semantic graphs, including SDG (Ivanova et al. 2012), EDS (Oepen and Lønning 2006) and Dependency-based Minimal Recursion Semantics (DMRS; Copestake 2009). In this paper, we illustrate our models using the EDS format².

² http://moin.delph-in.net/EdsTop
The graphs in Figure 1 and 2 are examples of EDS graph. Figure 2 further shows EDS does have the ability to represent more complicated linguistic phenomena such as the right node raising and raising/control constructions. The semantic structure is a directed graph where nodes labeled with semantic predicates/relations related to a constituent of the sentence, and arcs are labeled with semantic arguments roles. By linking concepts with lexical units, this EDS graph can be reduced to a SDG, as shown in Figure 3. In these forms, relation is the predicate name of an elementary predication from the MRS, and role is an argument label such as ARG1.

Figure 3
The standard SDG that is converted from the EDS in Figure 1.

The drug was introduced in West Germany this year.

2.4 Analyzing Neural Networks for NLP

What the representations are that the neural network learns and how can we explore that? Concerns of this question have led to the interpretability of the system being an active area of research. Related work tries to answer these questions by: (1) investigating specific components of the architectures (Karpathy, Johnson, and Fei-Fei 2015; Radford, Jozefowicz, and Sutskever 2017; Qian, Qiu, and Huang 2016; Bau et al. 2018), (2) testing models on specific tasks, including part-of-speech tagging (Blevins, Levy, and Zettlemoyer 2018; Belinkov et al. 2017; Shi, Padhi, and Knight 2016), semantic role labeling (Tenney et al. 2019), word sense disambiguation (Peters et al. 2018a), coreference (Peters et al. 2018b), etc., and (3) building linguistically-informed dataset for evaluation (Linzen, Dupoux, and Goldberg 2016; Isabelle, Cherry, and Foster 2017; Burchardt et al. 2017; Sennrich 2017; Isabelle and Kuhn 2018; Warstadt, Singh, and Bowman 2018; Wang et al. 2018).

In this paper, we try to probe this question by applying the models built on the state-of-the-art technologies to the string-to-conceptual graph parsing task, and utilizing linguistically-informed datasets based on previous work (Bender et al. 2011) and our own creation.

3. A Knowledge-Intensive Parser

There are two main existing knowledge-intensive parsers with unification-based grammars for the English Resource Grammar, namely PET system (Callmeier 2000) and ACE system. PET is an efficient open-source parser for unification grammars. Coupled
with ERG, it is able to produce HPSG-style syntactico-semantic derivations and MRS-style semantic representations in logic forms. Similar to PET, ACE is another industrial strength implementation of the typed feature structure formalism. We choose to use ACE in this work given the fact that, comparing to PET’s parsing performance, ACE is significantly faster in certain common configurations. Coupled with ERG, it serves as a valid companion to study our problem: comparing knowledge- and data-intensive approaches.

4. A Data-Intensive Parser

To empirically analyze data-intensive parsing technologies, we design, implement and evaluate a new target structure–centric parser for ERS graphs, trained on (string, graph) pairs without explicitly incorporating linguistic knowledge. The string-to-graph parsing is formulated as a problem of finding Maximum Subgraph for a graph class \( G \) of a sentence \( s = l_1, \ldots, l_m \): Given a graph \( G = (V, A) \) related to \( s \), the goal is to search for a subset \( A' \subseteq A \) with maximum total score such that the induced subgraph \( G' = (V, A') \) belongs to \( G \). Formally, we have the following optimization problem:

\[
\arg \max_{G^* \in \mathcal{G}(s, G)} \sum_{p \in \text{FACTORIZE}(G^*)} \text{SCORE}_{\text{part}}(s, p)
\]

where \( \mathcal{G}(s, G) \) denotes the set of all graphs belong to \( \mathcal{G} \) and compatible with \( s \) and \( G \). This view matches a classic solution to the structured prediction which captures elemental and structural information through part-wise factorization. To evaluate the goodness of a semantic graph is to calculate the sum of local scores assigned to those parts.

We consider two basic factors, i.e., single concepts and single dependencies. Formally, we use the following objective function:

\[
\sum_{n \in \text{NODE}(G)} \text{SC}_n(s, n) + \sum_{(p, a) \in \text{ARC}(G)} \text{SC}_a(s, p, a)
\]

Our parser adopt a two-step architecture to produce EDS graphs: (1) it identifies the concept nodes based on contextualized word embeddings by solving a simplified optimization problem, viz. \( \max \sum_{n \in \text{NODE}(G)} \text{SC}_n(s, n) \); (2) it identifies the dependencies between concepts based on concept embeddings by solving another optimization problem, viz. \( \max \sum_{(p, a) \in \text{ARC}(G)} \text{SC}_a(s, p, a) \). Particularly, our architecture is a pipeline: single best prediction of the first step is utilized as the input for the second step.

4.1 Concept Identification

Usually, the nodes in a conceptual graph have a strong correspondence to surface lexical units, viz. tokens, in a sentence. Take the graph in Figure 1 for example, the generalized quantifier \( \_\text{the}_q \) corresponds to \( \text{the} \) and the property concept \( \_\text{drug}_n_1 \) corresponds to \( \text{drug} \). Because the concepts are highly lexicalized, it is reasonable to employ a sequence labeler to predict concepts that are triggered by tokens.

Nodes may be aligned with arbitrary parts of the sentence, including sub-token or multi-token sequences, which affords more flexibility in the representation of meaning contributed by derivational morphemes (e.g., \( \text{par}_d \) that indicates a passive con-
struction) or phrasal constructions (e.g., compound\_name that indicates a multiword expression). To handle these types of concepts by a word-based sequence labeler, we align them to words based on their span information and a small set of heuristic rules. Take Figure 4 for example, we align parg\_d to the word where -ed is attached to, and compound\_name to the first word of the compound.

Figure 4
An example for illustrating concept identification. The “N” row presents the results of lexicalization. The “S” row presents the gold supertags assigned to tokens which are utilized to train a sequence labeling based concept identifier.

|   | The | drug | was | introduced | in | West | Germany | this | year |
|---|-----|------|-----|------------|----|------|---------|------|------|
| N | _the_q | _drug_n_i | ∅   | _introduce_v_to | parg\_d | _in_p | named    | proper_q | named | _this_q_dem | _year_n_i | loc\_nonsp |
| S | *q | *n_i | ∅   | *v_to | parg\_d | *p | named    | proper_q | named | *q_dem | *n_i | loc\_nonsp |

The concept predicate may contain the lexical part aligning to the surface predicate, which leads to a serious data sparseness problem for training. To deal with this problem, we delexicalize lexical predicates as described in Buys and Blunsom (2017): replacing the lemma part by a placeholder “*”. Figure 4 shows a complete example. In summary, the concept identification problem is formulated as a supertagging problem:

$$\sum_{n \in \text{NODE}(G)} \text{SC}_n(s, n) \approx \max_{1 \leq i \leq m} \text{SC}_{sd}(s, i, s_t)$$

Our parser applies a neural sequence labeling model to predicts concepts. In particular, a BiLSTM model is utilized to capture words’ contextual information and another softmax layer for classification. Usually words and POS-tags are needed to be transformed into continuous and dense representation in neural models. Inspired by Costa-jussà and Fonollosa (2016), we use word embedding of two granularities in our model: character based and word based, for low frequency and high frequency words (the words appear more than $k$ times in the training data) respectively. A character based model can capture rich affix information of low frequency words for better word representations. The word based embedding uses a common lookup-table mechanism. The character based word embedding $w_i$ is implemented by extracting features with bidirectional LSTM from character embeddings $c_1, \ldots, c_n$.

Contextualized representation models such as CoVe (McCann et al. 2017), ELMo (Peters et al. 2018a), OpenAI GPT (Radford et al. 2018) and BERT (Devlin et al. 2018) have recently achieved the state-of-the-art results on downstream NLP models across many domains. In this paper, we use pretrained ELMo embedding $e_i$ to capture richer contextual information for word representation. The concatenation of word embedding $w_i$, ELMo embedding and POS-tag embedding $t_i$ of each word in a specific sentence is used as the input of bi-LSTMs to extract context related feature vectors $r_i$ for each position $i$. Finally we use $r_i$ as input of a softmax layer to get the probability $\text{SC}_{sd}(s, i, s_t)$. 


\[ a_i = w_i \oplus e_i \oplus t_i \]
\[ r_1 : r_m = \text{BiLSTM}(a_1 : a_m) \]
\[ \text{SC}_{st}(s, i, st_i) = \text{softmax}(r_i) \]

### 4.2 Dependency Identification

Given a set of concept nodes \( N \) which are predicted by our concept identifier, the semantic dependency identification problem is formalized as the following optimization problem:

\[
\hat{G} = \arg \max_{G \in \mathcal{G}(N)} \sum_{(p,a) \in \text{ARC}(G)} \text{SC}_a(s, N, p, a)
\]

where \( \mathcal{G}(N) \) denotes the set of all possible graphs that take \( N \) as their vertex set. Following the factorization principle, we measure a graph using a sum of local scores.

In order to effectively learn a local score function, viz. \( \text{SC}_a \), we represent concepts with the concatenation of two embeddings: textual and conceptual embeddings.

\[ c_i = r_i \oplus n_i \]

To represent two concept nodes’ textual information, we use stacked BiLSTMs that are similar to the proposed structure of our concept identifier to get \( r_i \). Besides contextual information, we also need to transform a concept into a dense vector \( n_i \). Similar to word embedding and POS-tag embedding, we also use a common lookup-table mechanism and let our parser automatically induce conceptual embeddings from semantic annotations.

We calculate scores for all directional arcs between two concepts in the graph, which can be scored with a non-linear transformation from the two feature vectors of each concept pair:

\[ \text{SC}_a(s, N, p, a) = W_2 \cdot \delta(W_1 \cdot (c_p \oplus c_a) + b) \]

Similar to unlabeled arcs, we also use MLP to get each arc’s scores for all labels, and select the max one as its label.

For training, we use a margin-based approach to compute loss from the gold graph \( G^* \) and the best prediction \( \hat{G} \) under the current model and decoder. We define the loss term as:

\[
\max(0, \Delta(G^*, \hat{G}) - \text{SCORE}(G^*) + \text{SCORE}(\hat{G}))
\]

The margin objective \( \Delta \) measures the similarity between the gold graph \( G^* \) and the prediction \( \hat{G} \). Following Peng, Thomson, and Smith (2017)’s approach, we define \( \Delta \) as weighted Hamming to trade off between precision and recall.

Inspired by the maximum spanning connected subgraph algorithm proposed by Flanigan et al. (2014), we also consider using an additional constraint to restrict the
generated graph to be connected. The algorithm is simple and effective: generating a maximum spanning tree (MST) firstly, and then adding all arcs with positive local scores. During the training, our dependency identifier ignores this constraint.

4.3 Evaluation

We conduct experiments on DeepBank v1.1 that corresponds to ERG version 1214, and adopt the standard data split. The pyDelphin\(^5\) library and the jigsaw tool\(^6\) are leveraged to extract EDS graphs and to separate punctuations from their attached words respectively. The TensorFlow ELMo model\(^7\) is trained on the 1B Word Benchmark for pre-trained feature, and we use the same pre-trained word embedding introduced in Kiperwasser and Goldberg (2016). DyNet2.0\(^8\) is utilized to implement the neural models. The automatic batch technique (Neubig, Goldberg, and Dyer 2017) in DyNet is applied to perform mini-batch gradient descent training, where the batch size equals to 32.

Different models are tested to explore the contribution of BiLSTM and ELMo, including (1) ELMo* using BiLSTM and ELMo features, (2) ELMo using only ELMo features, (3) W2V using BiLSTM and word2vec features (Mikolov et al. 2013) and (4) Random using BiLSTM and random embedding initialization.

4.3.1 Results on Concept Identification. Since we predict concepts by composing them together as a supertag, there are two strategies for evaluating concept identification: the accuracy of supertag (viz. concept set) prediction and concept prediction. For the former, we just take “∅” as a unique tag and compare each word’s predicted supertag as a whole part; for the latter, we ignore the empty concepts, such as was in Figure 1. We can see that the ELMo* model performs better than the others. Empirically speaking, the numeric performance of concept prediction is better than the supertag prediction. The results are illustrated in Table 1.

| Supertag | Concept | |
|----------|---------|---|
| Accuracy | Percision | Recall | F-Score |
| Random | 92.74 | 95.13 | 94.60 | 94.87 |
| W2V | 94.51 | 96.68 | 96.11 | 96.39 |
| ELMo | 92.34 | 95.73 | 95.16 | 95.45 |
| ELMo* | 95.38 | 97.31 | 96.77 | 97.04 |

4.3.2 Results on Dependency Identification. In dependency identification step, we train the parsing model on sentences with golden concepts and alignment. Both unlabeled and labeled results are reported. Since golden concepts are used, the accuracy will be

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5 www.github.com/delph-in/pydelphin
6 www.coli.uni-saarland.de/~yzhang/files/jigsaw.jar
7 www.github.com/allenai/bilm-tf
8 www.github.com/clab/dynet
obviously much higher than the total system with predicted concepts. Nevertheless, the numbers here serve as a good reflection of the goodness of our models. We can see that the ELMo model is much lower than the others, indicating that BiLSTM layers are much more important for dependency identification. Table 2 shows the results. The measure for comparing two dependency graphs is the precision/recall of concept tokens which are defined as \((c_h, c_d, l)\) tuples, where \(c_h\) is the functor concept, \(c_d\) is the dependent concept and \(l\) is their dependency relation. Labeled precision/recall (LP/LR) is the ratio of tuples correctly identified by the automatic generator, while unlabeled precision/recall (UP/UR) is the ratio regardless of \(l\). F-score (LF/UF) is a harmonic mean of precision and recall.

Table 2
Accuracy of dependency identification on development data.

| Model  | UP     | UR     | UF     | LP     | LR     | LF     |
|--------|--------|--------|--------|--------|--------|--------|
| Random | 94.47  | 95.95  | 95.21  | 94.25  | 95.57  | 94.98  |
| W2V    | 94.91  | 96.3   | 95.6   | 94.72  | 96.12  | 95.42  |
| ELMo   | 88.97  | 92.95  | 90.92  | 88.44  | 92.40  | 90.38  |
| ELMo*  | 96.00  | 96.99  | 96.49  | 95.80  | 96.79  | 96.29  |

4.3.3 Results for Graph Identification. As for the overall evaluation, we report parsing accuracy in terms of SMATCH (Cai and Knight 2013) that considers both nodes and relations, which was initially used for evaluating AMR parsers. The Smatch metric (Cai and Knight 2013), proposed for evaluating AMR graphs, also measures graph overlap, but does not rely on sentence alignments to determine the correspondences between graph nodes. SMATCH is computed by performing inference over graph alignments to estimate the maximum F-score obtainable from a one-to-one matching between the predicted and gold graph nodes. Considering the difference between AMR graph and EDS graph, we implement our own tool for the disconnected graph, and calculate the scores in Table 3. The ELMo*’s concept and arc score are obviously higher than the others, while ELMo’s arc prediction yields the lowest SMATCH score.

Table 3
Accuracy of the whole graphs on the development data. Concept and Arc in the table header are the F-Score of concept and arc mapping for highest smatch score. Smatch is the Smatch score of each model.

| Model  | Concept | Arc     | SMATCH |
|--------|---------|---------|--------|
| Random | 94.69   | 91.25   | 92.95  |
| W2V    | 96.07   | 92.41   | 94.22  |
| ELMo   | 95.06   | 86.75   | 90.82  |
| ELMo*  | 96.71   | 93.86   | 95.27  |

We compare our system with the ERG-guided ACE parser, the data-driven parser introduced in Buys and Blunsom (2017) and SHRG parser in Chen, Sun, and Wan (2018).
on the test data. As ACE parser fails to parse some sentences (more than 1%)\(^9\), the outputs of the whole data and the successfully parsed part are evaluated separately. For the other parsers, the results on the whole data and those ACE parsed data are very similar (less than 0.05% lower), so we just show the results on the whole data for brevity. The numbers of ACE and Buys and Blunsom’s are different from the results as they reported due to the different SMATCH evaluation tools. Our ELMo\(^*\) model achieves an accuracy of 95.05, which is significantly better than existing parsers, demonstrating the effectiveness of this parsing architecture.

Table 4

| Model                  | Node | Arc  | SMATCH  |
|------------------------|------|------|---------|
| ACE\(_1\)              | 95.51| 91.90| 93.69   |
| ACE\(_2\)              | 96.42| 92.84| 94.61   |
| Buys and Blunsom (2017)| 89.06| 84.96| 87.00   |
| Chen, Sun, and Wan (2018)| 94.51| 87.29| 90.86   |
| W2V                    | 95.65| 91.97| 93.78   |
| ELMo                   | 94.74| 86.64| 90.60   |
| ELMo\(^*\)             | 96.42| 93.73| 95.05   |

5. Linguistic Phenomena in Question

Most benchmark datasets in NLP are drawn from text corpora, reflecting a natural frequency distribution of language phenomena. Such datasets are usually not sufficient for evaluating and analyzing neural models in many advanced NLP tasks, since they may fail to capture a wide range of complex and low-frequency phenomena (Kuhnle and Copestake 2018; Belinkov and Glass 2018). Therefore, an extensive suite of unit-tests should be considered to evaluate models on their ability to handle specific linguistic phenomena.

In this section, we discuss several important linguistic phenomena for evaluating semantic parsers, including lexical constructions, predicate–argument structures, phrase constructions, and non-local dependencies (Fillmore, Kay, and O’connor 1988; Kay and Fillmore 1999; Michaelis and Lambrecht 1996; Hilpert 2014), which diverge from the common average-case evaluation but critical for understanding natural language (Goldberg 2003). The phenomena and the corresponding examples are summarized in Table 5.

5.1 Lexical Constructions: Multiword Expression

Multiword Expressions (MWEs) are lexical items made up of multiple lexemes that undergo idiosyncratic constraints and therefore offer a certain degree of idiomaticity.

\(^9\) Note that the DeepBank data already removes a considerable portion (c.a. 11%) of sentences.
Table 5
Definitions and examples of the linguistic phenomena for evaluation.

| Definition | Head | Examples |
|------------|------|----------|
| as: basic predicate-argument structures | core predicate | Mike gave them to a new bureaucracy. |
| comp: compound/named entity | head word in compound or last name | Donald Trump withdrew his $7.54 billion offer. |
| vpart: verb-particle constructions | (B) verb+particle | The pass helped set up Donny's two companies. |
| ditr: ditransitive construction | core predicate | Sally baked her sister a cake. |
| causemo: cause motion construction | core predicate | The audience laughed Bob off the office. |
| passive: passive verb construction | Passive verb | The paper was accepted by the reviewer. |
| way: way construction | core predicate | Frank dug his way out of prison. |
| itexpl: expletive it | it-subject taking verb | It is suggested that the flight was canceled. |
| ned: adj/Noun2+Noun1-ed | (A) head noun (B) Noun1-ed | The light colored glazes have softening effects. |
| argadj: interleaved arg/adj | (A) selecting verb (B) selecting verb | The story shows, through flashbacks, the different histories. |
| barerel: bare relatives (flat-less) | (B) grapped predicate in relative | They took over the lead (that) brooklyn has held. |
| tough: tough adjectives | (A) tough adjective (B) grapped predicate in to-VP | Original copies are very hard to find. |
| rnr: right node raising | (A) verb/prep2 (B) verb/prep1 | Humboldt supported and worked with other scientists. |
| absol: absolutes | (A) absolutive predicate (B) main clause predicate | It consisted of 4 games each team facing other teams twice. |
| vger: verbal gerunds | (A) selecting head (B) gerund | Asking for the help from the school prompts an announcement. |
| control: raising/control constructions | (A) "upstairs" verb (B) "downstairs" verb | They managed to house and feed the poor. |

MWEs cover a wide range of linguistic phenomena including fixed and semi-fixed expressions, phrasal verbs, named entities.

Although MWEs can lead to various categorization schemes and its definitions observed in the literature tend to stress different aspects, in this paper we mainly focus on **compound** and **multiword named entity**. Roughly speaking, a compound is a
lexeme formed by the juxtaposition of adjacent lexemes. Compounds can be subdivided according to their syntactic function. Thus, nominal compounds are headed by a noun (e.g., bank robbery) or a nominalized verb (e.g., cigarette smoking) and verbal compounds are head by a verb (e.g., London-based). Multiword named entity is a multiword linguistic expression that rigidly designates an entity in the world, typically including persons, organizations, and location (e.g., International Business Machines).

5.2 Basic Argument Structure

The term “argument structure” refers to a relationship that holds between a predicate denoting an activity, state, or event and the respective participants, which are called arguments. Argument structure is often referred to as valency (Tesnière 2018). A verb can attract a certain number of arguments, just as the valency of an atom determines the number of bonds it can engage in (Ágel and Fischer 2009).

Valency is first and foremost a characteristic of verbs, but the concept can also be applied to adjectives and nouns. For instance, the adjective certain can form a bond with a that-clause in the sentence I am certain that he left or an infinitival clause (John is certain to win the election). Nouns such as fact can bond to that-clause as well: the fact that he left. We view all these valency relations as basic argument structures.

5.3 Phrasal Constructions

In the past two decades, the constructivist perspective to syntax is more and more popular. For example, Goldberg (1995) argued that argument structure cannot be wholly explained in terms of lexical entries alone, and syntactic constructions also lead hearers to understand some meanings. Though this perspective is very controversial, we think the related phenomena are relevant to computational semantics. To test a parser’s adaptation ability to handle peripheral phenomena, we evaluate the performance on several valency-increasing and decreasing constructions, including the ditransitive construction, cause motion construction, way construction and passive.

Ditransitive construction. The ditransitive construction links a verb with three arguments — a subject and two objects. Whereas English verbs like give, send, offer conventionally include two objects in their argument structure, the same cannot be said of other verbs that occur with the ditransitive construction.

(1) Sally baked her sister a cake.

The above sentence means that Sally produced a cake so that her sister could willingly receive it. We can posit the ditransitive construction as a symbolic unit that carries meaning and that is responsible for the observed increase in the valency of bake. In general, the ditransitive construction conveys, as its basic sense, the meaning of a transfer between an intentional agent and a willing recipient (indirect object).

Cause motion construction. The cause motion construction can also change the number of arguments with which a verb combines and yield an additional meaning. For example, in the sentence (2), the event structure of laugh specifies someone who is laughing and the unusually added argument leads to a new motion event in which both the agent and the goal are specified.
Way construction. This construction specifies the lexical element way and a possessive determiner in its form. For example, in (3), the construction evokes a scenario in which an agent moves along a path that is difficult to navigate, thus adds up two arguments in the process — the way argument and a path/goal argument that is different from the cause motion construction.

Passive. The passive construction with be is most often discussed as the marked counterpart of active sentences with transitive verbs. For example, in (4) the subject of the active (the reviewer) appears in the corresponding passive sentences as an oblique object marked with the preposition by, and it is possible to omit this argument in the passive. It is this type of omission that justifies categorizing the passive as a valency-decreasing construction.

5.4 BFOZ’s Ten Constructions

Bender et al. (2011) proposed a selection of ten challenging linguistic phenomena, each of which consists of 100 examples from English Wikipedia and occurs with reasonably high frequency in running text. Their selection (hereafter BFOZ) considers lexical (e.g., vpart), phrasal (e.g., ned) as well as non-local (e.g., rnr) constructions. The definitions and examples of the linguistic phenomena are outlined in Table 5, which considers representative local and non-local dependencies. Refer to their paper for more information.

In some phenomena, there are might be subtypes A and B, corresponding to different arcs in the structure. It is noted that the number of “A” and the number of “B” are not necessarily equal, as illustrated in the example of control in the table. Some sentences contain more than one instance of the phenomenon they illustrate and multiple sets of dependencies are recorded. In total, the evaluation data consists of 2,127 dependency triples for the 1,000 sentences.

6. Evaluation and Analysis

To investigate the type of representations manipulated by different parsers, in this section we evaluate the ACE parser and our parser regarding the linguistic phenomena discussed in Section 5.

6.1 Lexical Construction

MRS uses the abstract predicate compound to denote compounds as well as lightweight named entities. The edge labeled with ARG1 denotes the root of the compound structure and thus can help to distinguish the type of the compound (nominal or verbal compounds), and the nodes in named entities are labeled as named-relation. The head words of the compound in the test set can be other types such as adjectives, due to their data sparsity in the test data, we just omit this part. The results are illustrated in Table 6.
Table 6
Accuracy of lexical constructions.

| Type                      | Example        | #    | ACE  | W2V  | ELMo | ELMo* |
|---------------------------|----------------|------|------|------|------|-------|
| Compound                  |                | 2266 | 80.58| 87.56| 84.33| 89.67 |
| Nominal w/nominalization  | flag burning   | 22   | 85.71| 90.91| 81.82| 90.91 |
| Nominal w/noun            | pilot union    | 1044 | 85.28| 89.27| 88.51| 90.04 |
| Verbal                    | state-owned    | 23   | 40.91| 82.61| 47.83| 65.22 |
| Named Entity              | Donald Trump   | 1153 | 82.92| 86.93| 82.74| 90.55 |

From the table we find that, ELMo* performs much better than ACE, especially for the named entity recognition (the total number of verbal compounds in the test set is rather small and does not affect the overall performance too much). It is noted that even the pure ELMo alone can achieve fairly good results, indicating that those pre-trained embedding-based models are good at capturing local semantic information such as compound constructions and named entities.

6.2 Basic Argument Structure

The detailed performances on the 1474 test data in terms of basic argument structure are shown in Table 7. In MRS, different senses of a predicate are distinguished by optional sense labels. Usually, the verb with its basic sense will be assigned the sense label as _v_1 (e.g., _look_v_1), while verb particle construction is handled semantically by having the verb contribute a relation particular to the combination (e.g., _look_v_up). In the evaluation, we also categorize the verb into basic verbs and verb particle constructions, and show the detailed performance.

Table 7
Accuracies on basic argument structure over the 1474 test data. The accuracies are based on complete match, i.e., the predicates, arguments (nodes, edges and the edge labels in the graph) should be all correctly parsed to their gold standard graphs.

| Type           | #       | ACE  | W2V  | ELMo | ELMo* |
|----------------|---------|------|------|------|-------|
| Overall        | 7108    | 86.98| 81.44| 74.56| 84.70 |
| Total verb     | 4176    | 85.34| 77.59| 69.08| 81.81 |
| Basic verb     | 2354    | 85.79| 80.76| 73.70| 83.90 |
| ARG1           | 1683    | 90.25| 87.17| 80.45| 89.07 |
| ARG2           | 1995    | 90.48| 84.96| 81.95| 87.85 |
| ARG3           | 195     | 82.63| 58.46| 55.90| 72.31 |
| Verb-particle  | 1761    | 84.69| 73.31| 62.86| 78.99 |
| ARG1           | 1545    | 89.57| 80.45| 75.15| 84.72 |
| ARG2           | 923     | 86.27| 78.80| 68.42| 82.73 |
| ARG3           | 122     | 81.88| 58.44| 47.40| 73.38 |
| Total noun     | 394     | 92.41| 87.56| 72.34| 90.61 |
| Total adjective| 2538    | 89.27| 87.31| 84.48| 89.05 |
As can be observed from the table, the overall performance of ELMo* is relatively worse than the one of ACE, and this is mainly due to the relatively low accuracy of verb particle constructions and ARG3. As for pure ELMo model, this issue will be exacerbated. The verb particle construction emphasizes combinations, and ARG3 often denotes long distances cross words within the sentence, while pure ELMo (without LSTM) is weak in capturing such information.

6.3 Phrasal Construction

For each valency increasing construction (ditransitive construction, cause motion construction and way construction) introduced in Section 5.3, we manually select 100 sentences from Linguee\(^\text{10}\), a web service that provides access to large amounts of appropriate bilingual sentence pairs found online. The paired sentences identified undergo automatic quality evaluation by a human-trained machine learning algorithm that estimates the quality of those sentences. In order to form the gold standard for the subsequent evaluation, we then ask a senior linguistic student who is familiar with ERG to annotate the argument structure of those sentences. The annotation format is based on dependency triples, identifying the head words and dependents by the surface form of the head words in the sentence suffixed with a number indicating the word position.

As for the valency decreasing construction, viz. the passive construction, MRS gives special treatment to passive verbs, identified by the abstract node parg_d. Similar to previous evaluation, we test the parsing accuracies on parg_d over the 1474 test data. The results of phrasal constructions are shown in Table 8.

| Type         | #   | ACE     | W2V     | ELMo    | ELMo*   |
|--------------|-----|---------|---------|---------|---------|
| Ditransitive | 100 | 87.36   | 90.00   | 88.00   | **93.00** |
| ARG1         | 98  | **97.65** | 95.92   | 94.90   | 96.94   |
| ARG2         | 100 | **100.00** | 99.00   | 98.00   | 99.00   |
| ARG3         | 100 | 87.36   | 94.00   | 93.00   | **95.00** |
| Cause motion | 100 | 41.11   | 27.00   | 32.00   | **55.00** |
| ARG1         | 94  | 91.86   | 90.43   | 75.53   | **93.62** |
| ARG2         | 100 | **100.00** | 99.00   | 97.00   | 99.00   |
| ARG3         | 100 | 43.33   | 30.00   | 45.00   | **60.00** |
| Way          | 100 | 7.14    | 0.00    | 3.00    | 4.00    |
| ARG1         | 94  | 81.25   | 86.46   | 79.17   | **88.54** |
| ARG2         | 100 | 61.22   | 96.00   | 59.00   | **99.00** |
| ARG3         | 100 | **9.18** | 1.00    | 4.00    | 7.00    |
| Passive      | 522 | **85.12** | 82.57   | 76.05   | 84.87   |

The results are shown in Table 8, from which we find that all the parsers perform worse on the way construction, while on the other valency increasing constructions,
ELMo* yields the best results. The performances on the three constructions are mainly affected by the performances on ARG3, where ELMo* performs relatively better on ditransitive and cause motion constructions. Interestingly, it is a contrast to the results on ARG3 in basic argument constructions.

It is possible that the parsers run across a variety of cases where a predicate appeared to be in an atypical context: none of the senses listed in the lexicon provided the appropriate role label choices for novel arguments encountered. The issue can be addressed by either adding many individual senses for every predicate compatible with a particular construction, as what rule-based parser has done, or learning the construction pattern from the training data, as what data-driven parser has done.

The latter option clearly had a practical advantage of requiring far less time-consuming manual expansion of the lexicon while may also suffer from data sparsity. The annotated MRS data provides considerably wide coverage for the most frequent and predictably patterned linguistic phenomena, while sometimes fails to include some of the rarer structures found in the long tail of language. According to our statistics, the cause motion and way constructions are very sparse in the training data – appearing 12 and 0 times respectively in the 35,314 sentences, which severely limits the prediction on these constructions.

Table 9
Recall of individual dependencies on Bender et al.’s ten constructions.

| Phenomena | Arc | ACE1 | ACE2 | Rand | W2V | ELMo | ELMo* | ∆+W2V | ∆+ELMo | ∆+LSTM |
|-----------|-----|------|------|------|-----|------|-------|--------|---------|---------|
| vpart     | 3.8 | 79   | 81   | 71   | 69  | 46   | 85    | -2     | +14     | +39     |
| itexpl    | -   | 91   | 91   | 52   | 48  | 63   | 74    | -4     | +23     | +11     |
| ned_A     | 2.7 | 63   | 72   | 78   | 83  | 79   | 88    | +5     | +10     | +9      |
| ned_B     | 1   | 81   | 93   | 75   | 79  | 47   | 83    | +4     | +7      | +35     |
| argadj_A  | 1.6 | 78   | 84   | 74   | 75  | 69   | 76    | +1     | +3      | +8      |
| argadj_B  | 6.3 | 50   | 53   | 39   | 47  | 43   | 56    | +8     | +17     | +13     |
| barere1   | 3.4 | 60   | 67   | 70   | 72  | 73   | 75    | +2     | +6      | +3      |
| tough_A   | 2.2 | 88   | 90   | 91   | 90  | 86   | 86    | -1     | -5      | -4      |
| tough_B   | 6.4 | 83   | 85   | 68   | 70  | 47   | 83    | +2     | +16     | +37     |
| rnr_A     | 2.8 | 69   | 76   | 75   | 72  | 77   | 73    | -3     | -2      | -4      |
| rnr_B     | 6.2 | 43   | 47   | 17   | 17  | 10   | 32    | +1     | +16     | +22     |
| absol_A   | 1.8 | 61   | 68   | 81   | 83  | 73   | 92    | +3     | +11     | +18     |
| absol_B   | 9.5 | 6    | 7    | 3    | 3   | 3    | 3     | 0      | 0       | 0       |
| vger_A    | 1.9 | 56   | 62   | 69   | 62  | 61   | 69    | -7     | 0       | +8      |
| vger_B    | 2.4 | 80   | 88   | 88   | 89  | 79   | 84    | +2     | -4      | +5      |
| control_A | 3   | 90   | 91   | 83   | 87  | 82   | 92    | +4     | +8      | +9      |
| control_B | 4.8 | 87   | 89   | 89   | 88  | 63   | 91    | -1     | +2      | +28     |

6.4 BFOZ’s Ten Constructions

While the annotated style for those 10 linguistic phenomena introduced in Bender et al. (2011) is not the same as the one of MRS, We were able to associate our parser-specific results with the manually-annotated target non-local dependencies, and Table 9 shows the results.

All the parser perform markedly worse on the dependencies of rnr(B), absol(B) and argadj(B), which have very long average distances of dependencies. Each of the parsers attempts with some success to analyze each of these phenomena, but they vary
across phenomena. Comparing pure ELMO and ELMO*, we can observe that in most cases, ELMO* outperforms pure ELMO especially for long-distance dependencies such as tough(B), vpart and control(B), indicating that LSTM features helps to capture distant information to some extent. Similar to the conclusion drawn in 6.1, in general, compared with ACE, ELMO is good at capturing relatively local dependencies that have short distances, e.g., absol(A), vger(A) and ned(A).

Figure 5
Performances of compound (compound), named entity (ner) and basic argument (arg) on development set when down-sampling the training data size

Figure 6
Performances of valency-increasing constructions (valency) and passive (passive) on development set when down-sampling the training data size

6.5 Down-sampling Data Size

Our next experiment examines this effect in a more controlled environment by down-sampling the training data and observing the performances on the development set. The results are shown in Figure 5 and Figure 6, where we test the overall performance for lexical (compound and named entities), basic argument and phrasal (valency-increasing and passive) constructions.

As can be seen from Figure 5, adding training data cannot help the parser predict valency-increasing constructions that much. When it comes to local constructions (lexical construction), even rather small training data can lead to relatively high per-
formance, especially for the light-weight named entity recognition, and the learning curve of the basic argument structures also serves as another complementary reflection. From Figure 6, we also find that due to the low frequency of the valency-increasing constructions in the data, the performance will stay low as the training data grows.

7. Conclusion

In this work, we have presented a thorough study of the difference in errors made between systems that leverage different methods to express the mapping between string and meaning representation. To achieve that, we employed a construction focused parser evaluation methodology as an alternative to the exclusive focus on incremental improvements in overall accuracy measures such as SMATCH. We have shown that knowledge- and data-intensive make different types of errors and such differences can be quantified with respect to linguistic constructions. Our analysis provides insights that may lead to better semantic parsing models in the future.

References

Abend, Omri 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, Association for Computational Linguistics, Sofia, Bulgaria.

Adolphs, Peter, Stephan Oepen, Ulrich Callmeier, Berthold Crysmann, Dan Flickinger, and Bernd Kiefer. 2008. Some fine points of hybrid natural language parsing. In LREC, Citeseer.

Ágel, Vilmos and Klaus Fischer. 2009. Dependency grammar and valency theory. In The Oxford Handbook of Linguistic Analysis.

Artzi, Yoav, Kenton Lee, and Luke Zettlemoyer. 2015. Broad-coverage ccg semantic parsing with amr. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1699–1710, Association for Computational Linguistics, Lisbon, Portugal.

Banarescu, Laura, 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, Association for Computational Linguistics, Sofia, Bulgaria.

Bau, Anthony, Yonatan Belinkov, Hassan Sajjad, Nadir Durrani, Fahim Dalvi, and James Glass. 2018. Identifying and controlling important neurons in neural machine translation. arXiv preprint arXiv:1811.01157.

Belinkov, Yonatan and James Glass. 2018. Analysis methods in neural language processing: A survey. arXiv preprint arXiv:1812.08951.

Belinkov, Yonatan, Lluís Márquez, Hassan Sajjad, Nadir Durrani, Fahim Dalvi, and James Glass. 2017. Evaluating layers of representation in neural machine translation on part-of-speech and semantic tagging tasks. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), volume 1, pages 1–10.

Bender, Emily M., Dan Flickinger, Stephan Oepen, and Yi Zhang. 2011. Parser evaluation over local and non-local deep dependencies in a large corpus. In Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, pages 397–408, Association for Computational Linguistics, Edinburgh, Scotland, UK.

Blevins, Terra, Omer Levy, and Luke Zettlemoyer. 2018. Deep rnns encode soft hierarchical syntax. arXiv preprint arXiv:1805.04218.

Bos, Johan, Stephen Clark, Mark Steedman, James R. Curran, and Julia Hockenmaier. 2004. Wide-coverage semantic representations from a CCG parser. In Proceedings of Coling 2004, pages 1240–1246, COLING, Geneva, Switzerland.

Burchardt, Aljoscha, Vivien Macketanz, Jon Dehdati, Georg Heigold, Jan-Thorsten Peter, and Philip Williams. 2017. A linguistic evaluation of rule-based, phrase-based, and neural mt engines. The Prague Bulletin of Mathematical Linguistics, 108(1):159–170.
Oepen, Stephan, Marco Kuhlmann, Yusuke Miyao, Daniel Zeman, Silvie Cinková, Dan Flickinger, Jan Hajic, and Zdenka Uresová. 2015. Semeval 2015 task 18: Broad-coverage semantic dependency parsing. In Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015).

Oepen, Stephan, Marco Kuhlmann, Yusuke Miyao, Daniel Zeman, Dan Flickinger, Jan Hajic, 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, Association for Computational Linguistics and Dublin City University, Dublin, Ireland.

Oepen, Stephan and Jan Tore Lønning. 2006. Discriminant-based mrs banking. In Proceedings of the Fifth International Conference on Language Resources and Evaluation (LREC-2006), European Language Resources Association (ELRA), Genoa, Italy. ACL Anthology Identifier: L06-1214.

Peng, Hao, Sam Thomson, and Noah A. Smith. 2017. Deep multitask learning for semantic dependency parsing. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 2037–2048, Association for Computational Linguistics, Vancouver, Canada.

Peng, Xiaochang, Linfeng Song, and Daniel Gildea. 2015. A Synchronous Hyperedge Replacement Grammar based approach for AMR parsing. In Proceedings of the Nineteenth Conference on Computational Natural Language Learning, pages 32–41, Association for Computational Linguistics, Beijing, China.

Peters, Matthew, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018a. Deep contextualized word representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), volume 1, pages 2227–2237.

Peters, Matthew, Mark Neumann, Luke Zettlemoyer, and Wen-tau Yih. 2018b. Dissecting contextual word embeddings: Architecture and representation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1499–1509.

Pollard, Carl and Ivan A. Sag. 1994a. Head-Driven Phrase Structure Grammar. The University of Chicago Press, Chicago.

Pollard, Carl and Ivan A Sag. 1994b. Head-driven phrase structure grammar. University of Chicago Press.

Qian, Peng, Xipeng Qiu, and Xuanjing Huang. 2016. Analyzing linguistic knowledge in sequential model of sentence. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 826–835.

Radford, Alec, Rafal Jozefowicz, and Ilya Sutskever. 2017. Learning to generate reviews and discovering sentiment. arXiv preprint arXiv:1704.01444.

Radford, Alec, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training. URL https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/languageunsupervised/language-understanding-paper.pdf.

Sennrich, Rico. 2017. How grammatical is character-level neural machine translation? assessing mt quality with contrastive translation pairs. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, volume 2, pages 376–382.

Shi, Xing, Inkit Padhi, and Kevin Knight. 2016. Does string-based neural mt learn source syntax? In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1526–1534.

Steedman, M. 1996. Surface Structure and Interpretation. Mit Press.

Steedman, Mark. 2000. The syntactic process. MIT Press, Cambridge, MA, USA.

Tenney, Ian, Patrick Xia, Berlin Chen, Alex Wang, Adam Poliak, R Thomas McCoy, Najoung Kim, Benjamin Van Durme, Samuel R Bowman, Dipanjan Das, et al. 2019. What do you learn from context? probing for sentence structure in contextualized word representations. arXiv preprint arXiv:1905.06316.

Tesnière, Lucien. 2018. Elements of structural syntax. John Benjamins Publishing Company.

Wang, Alex, Amapreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2018. Glue: A multi-task benchmark and analysis platform for natural language understanding. arXiv preprint arXiv:1804.07461.
Warstadt, Alex, Amanpreet Singh, and Samuel R Bowman. 2018. Neural network acceptability judgments. arXiv preprint arXiv:1805.12471.

Zhang, Xun, Yantao Du, Weiwei Sun, and Xiaojun Wan. 2016. Transition-based parsing for deep dependency structures. Computational Linguistics, 42(3):353–389.

Zhang, Yi, Stephan Oepen, and John Carroll. 2007. Efficiency in unification-based n-best parsing. In Proceedings of the Tenth International Conference on Parsing Technologies, pages 48–59, Association for Computational Linguistics, Prague, Czech Republic.
