Schema-Free Dependency Parsing via Sequence Generation

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Abstract

Dependency parsing aims to extract syntactic dependency structure or semantic dependency structure for sentences. Existing methods suffer the drawbacks of lacking universality or highly relying on the auxiliary decoder. To remedy these drawbacks, we propose to achieve universal and schema-free Dependency Parsing (DP) via Sequence Generation (SG) DPSG by utilizing only the pre-trained language model (PLM) without any auxiliary structures or parsing algorithms. We first explore different serialization designing strategies for converting parsing structures into sequences. Then we design dependency units and concatenate these units into the sequence for DPSG. Thanks to the high flexibility of the sequence generation, our DPSG can achieve both syntactic DP and semantic DP using a single model. By concatenating the prefix to indicate the specific schema with the sequence, our DPSG can even accomplish multi-schemata parsing. The effectiveness of our DPSG is demonstrated by the experiments on widely used DP benchmarks, i.e., PTB, CODT, SDP15, and SemEval16. DPSG achieves comparable results with the first-tier methods on all the benchmarks and even the state-of-the-art (SOTA) performance in CODT and SemEval16. This paper demonstrates our DPSG has the potential to be a new parsing paradigm. We will release our codes upon acceptance.

1 Introduction

Dependency Parsing (DP), which aims to extract the structural information beneath sentences, is fundamental in understanding natural languages. It benefits a wide range of Natural Language Processing (NLP) applications, such as machine translation (Bugliarello and Okazaki, 2020), question answering (Teney et al., 2017), and information retrieval (Chandurkar and Bansal, 2017). As shown in Figure 1, dependency parsing predicts for each word the existence and dependency relation with other words according to a pre-defined schema. Such dependency structure is represented in tree or directed acyclic graph, which can be converted into flattened sequence, as presented in this paper.

The field of dependency parsing develops three main categories of paradigms: graph-based methods (Dozat and Manning, 2017), transition-based methods (Ma et al., 2018), and sequence-based methods (Li et al., 2018). While prospering with these methods, dependency parsing shows three trends now. 1) New Schema. Recent works extend dependency parsing from syntactic DP (SyDP) to semantic DP (SeDP) with many new schemata (Oepen et al., 2014; Che et al., 2012). 2) Cross-Domain. Corpora from different domains facilitate the research on cross-domain dependency parsing (Peng et al., 2019; Li et al., 2019). 3) PLM. With the development of pre-trained language models (PLMs), researchers manage to enable PLMs...
on dependency task and successfully achieve the new state-of-the-art (SOTA) results (Fernández-González and Gómez-Rodríguez, 2020; Gan et al., 2021). However, there are still two main issues.

Lacking Universality. Although there are many successful parsers, most of them are schema-specific and have limitations, e.g., sequence-based parsers (Vacareanu et al., 2020) are only suitable for SyDP. Thus, these methods require re-training before being adapted to another schema.

Relying on Extra Decoder. Previous parsers usually produce the parsing results employing an extra decoding module, such as a biaffine network for score calculation (Dozat and Manning, 2017) and a neural transducer for decision making (Zhang et al., 2019). These modules cannot be pre-trained and learn the dependency relation merely from the training corpora. Thus, only part of these models generalizes to sentences of different domains.

To address these issues, we propose schema-free Dependency Parsing via Sequence Generation (DPSG). The core idea is to find a unified unambiguous serialized representation for both syntactic and semantic dependency structures. Then an encoder-decoder PLM is learned to generate the parsing results following the serialized representation, without the need for an additional decoder. That is, our parser can achieve its function using one original PLM (without any modification), and thus is entirely pre-trained. Furthermore, by adding a prefix to the serialized representation, DPSG provides a principled way to pack different schemata into a single model.

In particular, DPSG consists of three key components. The Serializer is responsible for converting between the dependency structure and the serialized representation. The Positional Prompt pattern provides supplementary word position information in the input sentence to facilitate the sequence generation process. The encoder-decoder PLM with added special tokens performs the parsing task via sequence generation. The main advantages of DPSG comparing with previous paradigms are summarized in Table 1. Our DPSG accomplishes DP for different schemata, unifies multiple schemata without training multiple models, and transfers the overall model to different domains.

We conduct experiments on 4 popular DP benchmarks: PTB, CODT, SDP15, and SemEval16. DPSG performs generally well on different DP. It significantly outperforms the baselines on cross-domain (CODT) and Chinese SeDP (SemEval16) corpora, and achieves comparable results on the other two benchmarks, which further shows that our DPSG has the potential to be a new paradigm for dependency parsing.

| Paradigms | SyDP | SeDP | Multi-Schema | Unsupervised Cross-Domain |
|-----------|------|------|--------------|------------------------|
| Transition | ●    | ●    | ○            | ●                      |
| Graph     | ●    | ○    | ○            | ●                      |
| Sequence  | ●    | ○    | ○            | ●                      |
| DPSG      | ●    | ●    | ●            | ●                      |

Table 1: Summary of the previous parsing paradigms and DPSG. ● means “can be directly used in this scenario”, ○ means “can be used in this scenario after modification”, ◌ means “can partially generalize to this scenario”, and ○ means “cannot be used in this scenario”.

2 Preliminaries

We formally introduce the dependency parsing task and the encoder-decoder PLM, and the corresponding notations. This paper uses bold lower case letters, blackboard letters, and bold upper case letters to denote sequences, sets, and functions, respectively. Elements in the sequence and the sets are enclosed in parentheses and braces, respectively.

2.1 Dependency Parsing

A pre-defined dependency schema is a set of relations $\mathbb{R}$. Dependency parsing takes a sentence $x = (w_1, w_2, ..., w_n)$ as input, where $w_i$ is the $i$th word in the sentence. It outputs the set of dependency pairs $y = (p_1, p_2, ..., p_n)$, where $p_i = \{(r^j_i, h^j_i)\}$ denotes the dependency pair of the $i$th word $w_i$. We use $h^j_i$ and $r^j_i$ to denote the $j$th head word of $w_i$ and their relation. POS($w$) denotes the position of the specific word $w$ in the input sentence.

Syntactic Dependency Parsing (SyDP) analyses the grammatical dependency relations. The parsing result of SyDP is a tree structure called the syntactic parsing tree. In the SyDP, each non-root word has exactly one head word, which means $|p_i| = 1$ if $w_i$ is the not root word.

Semantic Dependency Parsing (SeDP) focuses on representing the deep-semantic relation between words. Each word in SeDP is allowed to have multiple (even no) head words. This leads to the result of SeDP being a directed acyclic graph called Semantic Dependency Graph. Fig-
Figure 2: This figure shows the overall framework of DPSG. The PSD semantic dependency structure of “Ms. Haag plays Elianti.” is converted into the serialized representation by the Serializer. The Positional Prompt module injects positional information into the input sentence, and the PLM is responsible for generating the results.

3.1 Serializer for Dependency Structure

The Serializer \( S : (x, y) \mapsto t \) is a function that maps sentence \( x \) and its corresponding dependency pairs \( y \) into a serialized representation \( t \), which servers as the target output to fine-tune the language model. The Inverse Serializer \( S^{-1} : (x, o) \mapsto y \) converts the output \( o \) of the PLM into dependency pairs to meet the output requirement of the DP task.

Specifically, the Serializer \( S \) decomposes dependency pairs, \( \{(h_i^j, r_i^j)\} \in y \), into smaller dependency units by scattering the dependent word \( w_i \) into each of its head word, which forms the following triplets set: \( \{(w_i, r_i^j, h_i^j)\} \). Then, it replaces each relation \( r_i^j \) with a special token

\[
\text{REL}(r_i^j) \in \mathbb{R}, \text{where } \mathbb{R} \text{ is a set of special tokens for all different relations.}
\]

The head word \( h_i^j \) is substituted by its position in the input sentence \( x \), denoted as POS\( (h_i^j) \). The target serialized representation \( t = S(x) \) concatenates all the dependency units with split token [SPT] as the following:

\[
\text{[SPT] } w_i \text{ [REL}(r_i^j)\text{] POS}(h_i^j) \text{ [SPT]... }
\]

The Inverse Serializer \( S^{-1} \) restores the dependency structure from the serialized representation by substituting the special token [REL\( (r_i^j)\)] with the original relation and indexing the head with its position POS\( (h_i^j) \) in the input sentence \( x \).

1Brackets indicate special tokens out of vocabulary \( V \).
There are two issues in the Serializer designing: *Word Ambiguity*. It is highly possible to have words, especially function words, appear multiple times in one sentence, e.g., there are more than 72% sentences in Penn Treebank (Marcus et al., 1993) have repeated words. We take two measures for word disambiguation in a dependency unit: (1) To disambiguate head word, the Serializer represents the head word by its position, rather than the word itself; (2) To disambiguate dependent word, the Serializer arranges dependency units by order of the dependent word in the input sentence x, rather than topological ordering or depth/breadth first search ordering of the dependency graph. The Inverse Serializer scans x and o simultaneously so as to refer the corresponding dependent word to x.

**Isolated Words.** There are dependency schemata allowing for isolated words which have neither head words nor dependency relations with other words, e.g., the period mark in the SeDP results shown in Figure 1. Note that the isolated words are different from the root word, as the root word is the head word of itself. One direct solution is to remove the isolated words from the serialized representation. However, this will result in inconsistencies between x and t, which complicates the word disambiguation. Thus, We use special token [NO] to denote such isolation relation and word no to represent the position of the virtual head word.

### 3.2 Positional Prompt for Input Sentence

As Section 3.1 mentions, representing the head words by their positions is an important scheme for head word disambiguation. However, PLMs are less skilled at numerical reasoning (Geva et al., 2020). We also empirically find it difficult for the PLM to learn the positional information of each word from scratch. Thus, we inject Positional Prompt (PP) for each word, which converts the positional encoding problem into generating the position number in the input, rather than counting for each word.

In particular, given the input sentence x, the positional prompt is the position number of each word w_i wrapped with two special tokens [PID] and [SPT]. [PID] marks the beginning of the position number and prevents the tokenization algorithms from falsely taking the position prompt as part of the previous word. [SPT] separates the position number from the next word. They also provide word segmentation information for some languages, such as Chinese. After the conversion, we have the input sequence in the following form:

\[ s = w_1 [\text{PID}] 1 [\text{SPT}] w_2 [\text{PID}] 2 [\text{SPT}] \cdots \]

For brevity, we denote the above process as a function \( PP : x \mapsto s \) that maps input sentence into sequence with positional prompt.

### 3.3 PLM for Sequence Generation

Both Serializer and Positional Prompt introduce special tokens that are out of the original vocabulary \( V \), including the relation tokens in \( R \), the separation tokens [PID], [SPT], and the special relation token [NO]. Before training, these tokens are added to the vocabulary, and their corresponding embeddings are randomly initialized from the same distribution as other tokens. As we should notice, these special tokens are expected to undertake different semantics. PLM thus treats them as trainable variables and learns their semantics during training.

With all the three components of DPSG, input sentence is first converted into sequence with positional prompt: \( s = PP(x) \). The sequence is further fed into the PLM and get the sequence output with the maximum probability: \( o = PLM(s) \). The final predicted dependency structure is recovered via the Inverse Serializer: \( y' = S^{-1}(o) \).

The training objective aims to maximize the likelihood of the ground truth dependency structure. To do so, we take the serialized dependency structure as the target and minimize the auto-regressive language model loss. We can further enhance the unsupervised cross-domain capacity of DPSG with intermediate fine-tuning (IFT) (Pruksachatkun et al., 2020; Chang and Lu, 2021). Before training on the dependency parsing, the intermediate fine-tuning uses the unlabeled sentences in the target domain and continues to train the PLM in source domain.

### 4 Experiments

#### 4.1 Evaluation Setups

##### 4.1.1 Datasets

We evaluate DPSG on the following 4 widely used benchmarks for both SyDP and SeDP. We show more details about datasets in Appendix A.

- **Penn Treebank** (PTB) (Marcus et al., 1993) is the most proverbial benchmark for SyDP.
- **Chinese Open Dependency Treebank** (CODT) (Li et al., 2019) aims to evaluate the cross-domain
SyDP capacity of the parser. It includes a balanced corpus (BC) for training, and three other corpora gathering from different domains for testing: product blogs (PB), popular novel “Zhu Xian” (ZX), and product comments (PC).

- **BroadCoverage Semantic Dependency Parsing** dataset (SDP15) [Oepen et al., 2014] annotates English SyDP sentences with three different schemata, named as DM, PAS, and PSD. It provides both in-domain (ID) and out-of-domain (OOD) evaluation datasets. The schema of SDP15 allows for isolated words.

- **Chinese semantic Dependency Parsing** dataset (SDP16) [Che et al., 2012] is a Chinese SyDP benchmark. The sentences are gathered from News (NEWS) and textbook (TEXT). The schema of SemEval16 allows for multiple head words but does not have isolated words.

### 4.1.2 Evaluation Metrics

Following the conventions, we use unlabeled attachment score (UAS) and labeled attachment score (LAS) for SyDP. We use labeled attachment F1 Score (LF) on SDP15 of SeDP. For SeDP on SemEval16, we use unlabeled attachment F1 (UF) and labeled attachment F1 (LF). All the results are presented in percentages (%).

### 4.1.3 Implementations

We use T5-base [Raffel et al., 2020] and mT5-base [Xue et al., 2021] as the backbone PLM for English dependency parsing and Chinese dependency parsing, respectively. In particular, we use their V1.1 checkpoints, which are only pre-trained on unlabeled sentences, so as to keep the PLM unbiased. In order to focus on the parsing capability of PLM itself, we do not use additional information, such as part-of-speech (pos) tagging and character embedding [Wang and Tu, 2020; Gan et al., 2021].

The PLM is implemented with Huggingface Transformers [Wolf et al., 2020]. The learning rate is $4 \times 10^{-5}$, weight decay is $1 \times 10^{-5}$. The optimizer is AdamW [Loshchilov and Hutter, 2019]. We conduct all the experiments on Tesla V100.

### 4.2 Baselines

We divide baselines into three main categories based on their domain of expertise. Note that almost all baselines use the additional lexical-level feature (including pos tagging, character-level embedding, and other pre-trained word embeddings), which is different from our DPSG. We supplement more details about baselines in Appendix B.

- **In-domain SyDP.** *Biaffine* [Dozat and Manning, 2017], *StackPTR* [Ma et al., 2018], and *CRF2O* [Zhang et al., 2020] introduce specially designed parsing modules without PLM. *CVT* [Clark et al., 2018], *MP2O* [Wang and Tu, 2020], and *MRC* [Gan et al., 2021] are recently proposed PLM-based dependency parser. SeqNMT [Li et al., 2018], SeqViable [Strzyz et al., 2019], and PaT [Vacareanu et al., 2020] cast dependency parsing as sequence labeling task, which is closely related to our sequence generation method.

- **Unsupervised Cross-domain SyDP.** Peng et al. (2019) and Li et al. (2019) modify the *Biaffine* for the unsupervised cross-domain DP. SSADP [Lin et al., 2021] relies on extra domain adaptation steps. In the PLM era, Li et al. (2019) propose *ELMo-Biaffine* with IFT on unlabeled target domain data.

- **SeDP.** Dozat and Manning (2018) modify *Biaffine* for SeDP. BS-IT [Wang et al., 2018] is a transition-based semantic dependency parser with incremental Tree-LSTM. HIT-SCIR [Che et al., 2019] solves the SeDP with a BERT based pipeline. BERT+Flair$^2$ [He and D. Choi, 2020] augments the Biaffine model with BERT and Flair [Akbik et al., 2018] embedding. *Pointer* [Fernández-González and Gómez-Rodríguez, 2020] combines transition-based parser with Pointer Network. It is also augmented with a Convolutional Neural Network (CNN) encoder for the character-level feature.

### 4.3 Main Results

#### 4.3.1 DPSG is Schema-Free

The schema-free characteristics of DPSG are reflected by the following two perspectives.

- **Towards Specific Schema.** DPSG obtains the SOTA performance on both CODT in Table 5 and SemEval16 in Table 3, and achieves the first-tier even among methods used additional lexical-level features on PTB in Table 2 and SDP15 in Table 4. For in-domain SyDP in Table 2, DPSG outperforms all the previous sequence-based methods, and performs slightly lower than MRC, which uses contextual interactive pos tagging, by 0.45% in LAS.

For SeDP in Table 3, DPSG outperforms BERT +Flair to a large margin on SemEval16, achieves 3.55% performances gain on NEWS, and 1.95% performance gain on TEXT with regard to LF.

$^2$They use different pre-processing scripts on SDP15, thus are not comparable with DPSG and other baselines on SDP15.
1.49% in ID evaluation of the PAS schema, 0.05% schema-specific model is most obvious on PAS. It most the same performance with Pointer in ID eval-
in ID evaluation of the DM schema, and achieves al-
DPSG (Multi) in Table 4 outperforms Pointer by
for PTB, it performs worse than DPSG in Table 2.

As DPSG (Multi) uses less training data
training set of PTB, which also appear in the test set
input text to distinguish different schemata. To pre-
PTB and SDP15 by concatenating a prefix to the
search space of our generation model.
other schemata (Peng et al., 2017), which increases
in that PSD has much more relation labels than the
gap in the PSD schema of SDP15. This is caused
serve that DPSG and the Pointer have the largest
code the character-level embeddings. We also ob-
than Pointer, which applies additional CNN to en-
HIT-SCIR on SDP15 (Table 4), but sightly lower
CDP, 82.20.

Table 4: Experimental results on SDP15 in terms of LF. DPSG (Multi) means the parameters are optimized in the combination of PTB and current SeDP dataset. † means the model utilizing PLM.

| Features Method (PLM) | UAS | LAS |
|-----------------------|-----|-----|
| Char                  | CRF2O | 96.14 | 94.49 |
| POS                   | Biaffine | 95.74 | 94.08 |
| POS                   | StackPTR | 95.87 | 94.19 |
| Char+POS              | MP2O (BERT-large) | 96.91 | 95.34 |
| POS                   | MRC (RoBERTa-large) | 97.24 | 95.49 |
| POS                   | CVT (CVT) | 96.60 | 95.00 |
| POS                   | SeqNMT | 92.08 | 94.11 |
| POS                   | SeqViable | 93.67 | 91.72 |
| POS                   | PaT (BERT-base) | 95.87 | 94.66 |
| -                     | DPSG (T5-base) | 96.48 | 95.04 |
| -                     | DPSG (Multi) | 96.25 | 94.85 |

Table 3: Experimental results on SemEval16.

DPSG also outperforms the PLM-based pipeline
HIT-SCIR on SDP15 (Table 4), but sightly lower
than Pointer, which applies additional CNN to en-
encode the character-level embeddings. We also ob-
serve that DPSG and the Pointer have the largest
gap in the PSD schema of SDP15. This is caused
in that PSD has much more relation labels than the
other schemata (Peng et al., 2017), which increases
the search space of our generation model.

Towards Multi-Schemata. Furthermore, we
design the multi-schemata experiment. We mix
PTB and SDP15 by concatenating a prefix to the
input text to distinguish different schemata. To pre-
dant leakage, we filter out sentences from the
training set of PTB, which also appear in the test set
of SDP15. As DPSG (Multi) uses less training data
for PTB, it performs worse than DPSG in Table 2.
DPSG (Multi) in Table 4 outperforms Pointer by
1.49% in ID evaluation of the PAS schema, 0.05%
in ID evaluation of the DM schema, and achieves al-
most the same performance with Pointer in ID eval-
uation of the PSD schema. The improvement over
schema-specific model is most obvious on PAS. It
could be because the PAS schema is more similar
to the syntax schema (Peng et al., 2017), thus it
benefits more from PTB. This multi-schemata
approach also provides a new method to explore the
inner connection between SyDP and SeDP.

4.3.2 Unsupervised Cross-domain
Table 5 demonstrates the outstanding transferability
of DPSG. We implement DPSG with and without
IFT on the target domain. DPSG with IFT achieves
the new SOTA, with a boosting of 5.06%, 7.21%
and 10.49% in terms of LAS on PB, ZK, and PC,
compared to ELMo with IFT. DPSG is completely
trained during IFT. While the additional biaffine
module of ELMo cannot benefit from the unlabeled
sentences from the target domain.

5 Analysis
This section studies whether there is better imple-
mentation for DPSG. We are particularly interested
in: 1) the designing of the Serializer, 2) the effect
of the introduced special tokens, and 3) the choice
of the PLM model. We use PTB as the benchmark
and compare DPSG introduced in Section 3 with
many other possible choices. The results of these
exploratory experiments are shown in Table 6.

5.1 Serializer Designing
Tree, as the well-studied data structure for syntac-
tic dependency parsing, has several other serializa-
tion methods to be converted into serialized repre-
We introduce special tokens that are useful. As expansion strategy in Section 3.1 eases the learning complexity of the PLM, the serialization representation proposed in Section 3.2 has smaller generation space than reconstruction, which indicates that our Serializer provides a better serialized representation for the PLM to generate. This is because our Serializer guarantees the dependency units in the output have the same order of the words in the input sentences, while Prufer sequence and bracket tree do not preserve the order. Thus, our proposed DPSG expands the input sentence to generate the output sequence, while Prufer sequence and bracket tree based DPSG reconstruct the syntax dependency structure. As expansion strategy has smaller generation space than reconstruction, the serialization representation proposed in Section 3.1 eases the learning complexity of the PLM, and further brings better performance.

### 5.2 Special Tokens Designing

We further investigate whether the additionally introduced special tokens are useful.

**Relation Tokens.** There are two different ways to represent the dependency relations in the serialized representation: adding a special token for each dependency relation, or mapping each dependency relation to one token in the original vocabulary with the closest meaning, e.g., `conj` → `conjunct`. Experimental results using word mapping is denoted as DPSG<sub>rel</sub> in Table 6. DPSG<sub>rel</sub> is inferior to the corresponding method with special relation tokens.

| Category   | Model           | UAS  | LAS  | UAS  | LAS  | UAS  | LAS  | UAS  | LAS  |
|------------|-----------------|------|------|------|------|------|------|------|------|
| w/o PLM    | Biaffine        | 67.75| 60.95| 69.41| 61.55| 39.95| 26.96| 59.04| 49.82|
|            | SSADP           | 68.55| 61.59| 70.82| 63.61| 41.10| 27.67| 60.16| 50.96|
| w/ PLM     | ELMo-Biaffine w/ IFT | 77.15| 71.54| 74.68| 67.51| 53.04| 39.48| 68.29| 59.51|
|            | DPSG w/o IFT    | 78.86| 73.28| 75.74| 69.42| 54.00| 41.98| 69.53| 61.56|
|            | DPSG w/ IFT     | 81.74| 76.60| 80.73| 74.77| 62.44| 49.97| 74.97| 67.11|

### Table 5: Results on CODT for unsupervised cross-domain SyDP.

| Metric | DPSG | Prufer | Bracket |
|--------|------|--------|---------|
| UAS    | 96.48| 85.53 | 95.37  |
| LAS    | 95.04| 83.72 | 93.70  |

### Table 6: Results on PTB for exploratory experiment.

![Figure 3: Prufer sequence and Bracket Tree sequence of the same sentence “Ms. Haag plays Elianti.”](image-url)
than DPSG, which indicates that the special tokens for relations are important. The reason is that if we use the tokens in the original vocabulary, they interfere with their original meanings as the word. Special tokens disentangle the dependency relation from the words that could appear in the sentence.

**Positional Prompt.** We are also particularly interested in the effectiveness of the positional prompts. We conduct experiments where the positional prompt is removed and send the original input sentence to the PLM. The result is denoted as DPSG\textsubscript{pos} in Table 6. DPSG\textsubscript{pos} undermines the performance of DPSG because it requires the PLM to perform numerical reasoning, that is, to count for the position of each head word.

5.3 Model Choosing

Both BART and T5 are widely used encoder-decoder PLMs. We try BART-base as the backbone PLM in DPSG. Table 6 shows that BART undermines the performance. In addition, BART has a significant performance drop after achieving the best performance, as shown in Appendix E.

5.4 Legality

There are two different legalities in DPSG. **Formation Legality** focus on whether the sequence has the correct formation (see Section 3.1) and **Structural Legality** focus on the legality of the corresponding parsing structure. The statistics on PTB show that the formation legality of DPSG is 100\%, and the structure legality of DPSG is 99.7\%, which is acceptable in practical usage.

6 Related Work

6.1 Syntactic Dependency Parsing

**In-domain SyDP.** Transition-based methods and graph-based methods are widely used in SyDP. Dozat and Manning (2017) introduce bi-affine attention into the graph-based methods. Ma et al. (2018) adopt pointer network to alleviate the drawback of local information in transition-based methods. Zhang et al. (2020) improve the CRF to capture second-order information.

There are also researches using sequence to sequence methods for SyDP. Li et al. (2018) use BiLSTM to predict the labeling of positions and relations of dependency parsing. Strzyz et al. (2019) improve Li et al. (2018)’s method and explore more representation of predicated labeling sequence of dependency parsing. Vacareanu et al. (2020) use BERT to augment the sequence labeling methods.

**Unsupervised Cross-domain SyDP.** The labeling of parsing data requires a wealth of linguistics knowledge and this limitation facilitates the research of unsupervised cross-domain DP. Yu et al. (2015) introduce pseudo-labeling unsupervised cross-domain SyDP via self-training. Li et al. (2019) propose a cross-domain datasets CODT for SyDP and build baselines for unsupervised cross-domain SyDP. Lin et al. (2021) introduce feature-based domain adaptation method in this field.

6.2 Semantic Dependency Parsing

Buys and Blunsom (2017) accomplish the first transition-based parser for Minimal Recursion Semantics (MRS). Zhang et al. (2016) present two novel transition-systems to generate arbitrary directed graphs in an incremental manner. Dozat and Manning (2018) modify the Biaffine (Dozat and Manning, 2017) for SeDP. However, due to the words in SeDP may have multiple-head, there is not sequence-based method for SeDP now.

6.3 Probing in Language Model

The research of exploring whether PLM can learn the linguistic features during the pre-training process, especially syntax knowledge, attracts some attention. Hewitt and Manning (2019) map the distance between word embedding in PLM into the distance in syntax tree and construct a syntax tree without relation label. Clark et al. (2019) design a structural probe to detect the ability of attention heads to express dobj (direct object) dependency relation. Their results prove the syntax knowledge can also be found in the attention maps.

7 Conclusion

This paper proposes DPSG—a schema-free dependency parsing method. By serializing the parsing structure to a flattened sequence, PLM can directly generate the parsing results in serialized representation. DPSG not only achieves good results in each different schema, but also performs surprisingly well on unsupervised cross-domain DP. The multi-schemata experiments also suggest that DPSG is capable of investigating the inner connection between different schemata dependency parsing. The exploratory experiments and analyses demonstrate the rationality of the designing of DPSG. Considering the unity, indirectness, and effectiveness of
DPSG, we believe it has the potential to become a new paradigm for dependency parsing.
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Table 7: Data statistics of PTB.

| Domain | Train Set | Dev Set | Test Set |
|--------|-----------|---------|----------|
| BC     | 16.3K     | 1K      | 2K       |
| PB     | 5.1K      | 1.3K    | 2.6K     |
| PC     | 6.6K      | 1.3K    | 2.6K     |
| ZX     | 1.6K      | 0.5K    | 1.1K     |

Table 8: Data statistics of CODT.

Table 9: Data statistics of SDP15.

| Domain | Train Set | ID Test Set | OOD Test Set |
|--------|-----------|-------------|--------------|
| DM     | 35,656    | 1,140       | 1,849        |
| PAS    | 35,656    | 1,140       | 1,849        |
| PSD    | 35,656    | 1,140       | 1,849        |

Table 10: Data statistics of SemEval16.

A Dataset Statistics

The details about the statistics of datasets used in this paper are shown on Table 7, Table 8, Table 9 and Table 10.

B More Details on Baseline

Baselines for in-domain SyDP.

* Biaffine: Dozat and Manning (2017) adopt bi-affine attention mechanism into the graph-based method of dependency parsing.

* StackPTR: Ma et al. (2018) introduce the pointer network into the transition-based methods of dependency parsing.

* CRF: Zhang et al. (2020) improve the CRF to capture more high-order information in dependency parsing.

* SeqNMT: Li et al. (2018) use an Encoder-Decoder architecture to achieve the Seq2Seq dependency parsing by sequence tagging. The BPE segmentation from Neural Machine Translation (NMT) and character embedding from AllenNLP (Gardner et al., 2018) are applied to argument their model.

* SeqViable: Strzyz et al. (2019) explore four encodings of dependency trees and improve the performance comparing with Li et al. (2018).

* PaT: Vacareanu et al. (2020) use a simple tagging structure over BERT-base to achieve sequence labeling of dependency parsing.

+ CVT: Clark et al. (2018) propose another pre-train method named cross-view training, which can be used in many sequence constructing task including SyDP. The best results of CVT is achieved by the multi-task pre-training of SyDP and part-of-speech tagging.

MP2O: Wang and Tu (2020) use message passing GNN based on BERT to capture second-order information in SyDP.

MRC: Gan et al. (2021) use span-based method to construct the edges at the subtree level. The Machine Reading Comprehension (MRC) is applied to link the different span. RoBERTa-large (Liu et al., 2019) is applied to enhance the representation of parser.

Baselines for cross-domain SyDP.

* Biaffine: Peng et al. (2019); Li et al. (2019) use Biaffine trained on source domain and test on target domain as the baseline of unsupervised cross-domain SyDP.

* SSADP: Lin et al. (2021) use both semantic and structural feature to achieve the domain adaptation of unsupervised cross-domain parsing.

ELMo: Li et al. (2019) use ELMo with intermediate fine-tuning in unlabeled text of target domain to achieve the SOTA on unsupervised cross-domain SyDP.

Baselines for SeDP.

* Biaffine: Dozat and Manning (2018) transfer the Biaffine model from SyDP to SeDP.

* BS-IT: Wang et al. (2018) use graph-based method for SeDP.

* HIT-SCIR: Che et al. (2019) propose a BERT-based pipeline model for SeDP.

* BERT+Flair: He and D. Choi (2020) use BERT and flair embedding (Akbik et al., 2018) to argument their modified Biaffine.

3* means model without PLM
4* means sequence-based methods
5+ means model utilizing PLM
C Construction of Prufer Sequence

C.1 Prufer Sequence

The principle of construction is deleting the leaf node with minimum index and adding the index of its farther node into the prufer sequence. This process is repeated more times until there are only two nodes left in the tree.

C.2 Prufer for Parsing Tree

The arc in parsing tree is directed and thus is a rooted tree. When all the son nodes with smaller index are deleted, the root node will be treated as a leaf node then deleted in the next step. To address this problem, we add a virtual node with the maximum index and build a arc from virtual node to the real root. This virtual root force the root node always being a leaf node in the whole construction of prufer sequence. The overall construction process as shown on Figure 4 (a)~(f).

D Construction of Bracket Tree

The Bracket Tree uses Bracket to indicate levels of nodes. All the nodes belonging to the same level are wrapped in the same pair of brackets. The process of construction is shown on Figure 5.
E Comparison between T5 and BART

Figure 6 shows the UAS comparison on dev sets of PTB between the T5 and BART in first 30 epochs. After the first two epochs, the performance of T5 raise rapidly and can better maintain performance in the later stages of training. Although BART achieves a better performance in the first two round, but there is not much room for performance improvement. To make matters worse, it can be clearly seen that after achieving the best performance, BART is very unstable, and even a significant performance drop has occurred.