Unsupervised Full Constituency Parsing with Neighboring Distribution Divergence

Letian Peng\textsuperscript{1,2,3,†}, Zuchao Li\textsuperscript{1,2,3,†}, and Hai Zhao\textsuperscript{1,2,3,*}

\textsuperscript{1}Department of Computer Science and Engineering, Shanghai Jiao Tong University
\textsuperscript{2}Key Laboratory of Shanghai Education Commission for Intelligent Interaction
and Cognitive Engineering, Shanghai Jiao Tong University, Shanghai, China
\textsuperscript{3}MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University
\{zxc-00,charlee\}@sjtu.edu.cn, zhaohai@cs.sjtu.edu.cn

Abstract

Unsupervised constituency parsing has been explored much but is still far from being solved. Conventional unsupervised constituency parser is only able to capture the unlabeled structure of sentences. Towards unsupervised full constituency parsing, we propose an unsupervised and training-free labeling procedure by exploiting the property of a recently introduced metric, Neighboring Distribution Divergence (NDD), which evaluates semantic similarity between sentences before and after editions. For implementation, we develop NDD into Dual POS-NDD (DP-NDD) and build "molds" to detect constituents and their labels in sentences. We show that DP-NDD not only labels constituents precisely but also inducts more accurate unlabeled constituency trees than all previous unsupervised methods with simpler rules. With two frameworks for labeled constituency trees inference, we set both the new state-of-the-art for unlabeled F1 and strong baselines for labeled F1. In contrast with the conventional predicting-and-evaluating scenario, our method acts as a plausible example to inversely apply evaluating metrics for prediction.

1 Introduction

Constituency parsing is a basic but crucial parsing task in natural language processing. Constituency parsers are required to build parsing trees for sentences which consist of spans representing constituents such as noun phrase and verb phrase. Parsed constituency trees can be applied to many downstream systems (Lee et al., 2013; Chen et al., 2015; Zhong et al., 2020).

Since the introduction of deep learning into natural language processing, supervised neural networks have achieved remarkable success in constituency parsing (Kitaev and Klein, 2018; Liu et al., 2018; Nguyen et al., 2020; Zhang et al., 2020b). Unfortunately, the need of large annotated datasets limits the performance of supervised systems on languages of low resources. As the result, many unsupervised systems have been proposed for constituency parsing (Drozdov et al., 2019; Kim et al., 2020; Shen et al., 2021; Sahay et al., 2021) by exploiting unlabeled corpus.

However, current unsupervised constituency parsing systems are still far from a real full procedure, especially for the reason that most of these systems only induct an unlabeled structure of the constituency tree. Towards the unsupervised full constituency parsing, we exploit a recently proposed metric, Neighboring Distribution Divergence (NDD) (Peng et al., 2021), to automatically detect and label constituents in sentences. NDD is a

\begin{itemize}
\item \textup{(Initial Sentences)}
\item The cat jumps into the hole.
\item The crow falls on the ground.
\item The cat jumps into the hole.
\item \textup{(Not Match)}
\item NDD = 1.04; POS-NDD = 0.01
\item NDD = 3.97; POS-NDD = 0.59
\item NDD = 13.22; POS-NDD = 8.33
\end{itemize}

Figure 1: Examples for substitution property of constituents among sentences. Neighboring Distribution Divergence performs well on detecting plausible substitutions.

\begin{itemize}
\item [NP] falls on the ground.
\item The crow.
\item The crow falls.
\item [VP]
\item [PP]
\end{itemize}

Figure 2: Molds constructed from examples in Figure 1.
Subterranean rose blooms in the sky

Pre-trained Language Model-based (PLM-based) (Devlin et al., 2019) metric and detects semantic changes caused by editions. We use NDD in a tricky way to adapt it to constituency parsing.

We first put forward the substitution property of constituents. As shown in Figure 1, if we substitute a constituent with another constituent with the same label, the edited sentence will still be plausible in syntax and semantics. Therefore, if the substitution by a span to an annotated constituent results in a plausible sentence, that span will be of high probability to be a constituent with the same label. Thus, metrics like perplexity may be able to detect successful substitutions. However, according to (Peng et al., 2021), perplexity lacks the capacity to provide reasonable comparison between sentences and has been prominently outperformed by NDD on most related tasks. So for the detecting metric, we instead use NDD which is able to detect very precise semantics similarity.

In practice, we construct very few detectors called "molds" as shown in Figure 2. We judge whether a span to be a constituent by fill it into the phrase mask ([NP], [VP], ...) and use NDD to detect the semantic similarity between the filled sentence and the initial sentence. If NDD is under a certain threshold, the span will be predicted to be a constituent.

To further boost the efficiency and performance of our method, we modify NDD into POS-NDD which only considers the likeliness of POS sequences since the initial NDD is too sensitive to precise semantic difference. Also, we use a dual detecting method which evaluates both the substitution to mold and substitution from mold to better link constituents with the same label together. We named our final metric Dual POS-NDD (DP-NDD).

We experiment on Penn Treebanks to construct labeled constituency trees and label predicted treebanks from other unsupervised constituency parsers. Results from our experiments verify DP-NDD to be capable of inducting labeled constituency trees and labeling unlabeled constituents. Based on DP-NDD molds, we introduce two novel frameworks for unsupervised constituency parsing. Our algorithm parses by following simple rules but results in remarkable results which outperform all previous unsupervised parsers on WSJ test dataset. Our algorithms set the first strong baseline in recent years for labeled F1 score. Our main contributions are concluded as follows:

- We propose an unsupervised method for full constituency parsing which involves constituent labeling.
- We introduce two novel frameworks for unsupervised constituency parsing, which set a new state-of-the-art for unlabeled F1 and strong baselines for labeled F1.
- We introduce variants of NDD, POS-NDD and DP-NDD which are less sensitive to semantic difference between sentences and perform well for constituent detecting.
We give a brief description for the NDD metric in \( \mathbb{V} \) with a span \( \mathbb{W} \). As we only use substitution for unsupervised \( \mathbb{W} \) NDD is capable of capturing precise semantics difference between the two distributions.

2 Neighboring Distribution Divergence

2.1 Background

We give a brief description for the NDD metric in this section as the background for further discussion. More details like motivation and explanation can be referred to (Peng et al., 2021).

Given an \( n \)-word sentence \( W = [w_1, w_2, \cdots, w_n] \), we use an edition \( E \) to convert \( W \) to an edited sentence \( W' = E(W) \). As we only use substitution for unsupervised constituency parsing, we limit \( E \) to a substituting operation which substitutes \( i \)-th to \( j \)-th word in \( W \) with a span \( V = [v_1, v_2, \cdots, v_m] \).

\[
W' = E(W) = [w_1, \cdots, w_{i-1}, v_1, \cdots, v_m, w_{j+1}, \cdots, w_n]
\]

Then we evaluate the semantic disturbance on the overlapped part \( [w_1, \cdots, w_{i-1}, w_{j+1}, \cdots, w_n] \) between the initial and edited sentences. For estimation, we use masked language model to get the distribution of predicted words for each masked position before and after the edition.

\[
W_i^{mask} = [w_1, \cdots, w_{i-1}, \text{[MASK]}, w_{i+1}, \cdots, w_n];
\]

\[
R = \text{PLM}(W_i^{mask}); d_i = \text{softmax}(R_i) \in \mathbb{R}^c
\]

We first mask the \( i \)-th word in \( W \) and use the PLM to predict the distribution \( d_i \) on the masked position. Here, \( d_i \) is a \( \mathbb{R}^c \) tensor which refers to the existence probability of the words in a \( c \)-word dictionary of the PLM. We do this for the overlapped part mentioned above both in \( W \) and \( W' \).

After we get the predicted distributions for \( W \) and \( W' \), we use KL divergence to calculate the difference between the two distributions.

\[
div_i = D_{KL}(d_i || d'_i) = \sum_{j=1}^{c} d_{ij} \log \left( \frac{d'_{ij}}{d_{ij}} \right)
\]

Finally, we integrate the divergence values together via a mean pooling layer.

\[
\text{NDD}(W, W') = \frac{\sum_{k \in [1, \ldots, n]} \text{div}_k}{n - (j - i + 1)}
\]

According to the cases in (Peng et al., 2021), NDD is capable of capturing precise semantics changes. We will show in Section 2.3 how to use modified NDD to construct molds for unsupervised constituency parsing.

2.2 POS-NDD

NDD performs well on supervising editions, but it might be too sensitive to some precise semantic difference. To adapt NDD to constituency parsing, we modify NDD’s calculating procedure to make it concentrate on the structural rather than semantic difference.

To do so, we gather the predicted words with the same POS together by summing up the existence probability of them. For implementation, we construct a word-to-POS matrix \( M \) as shown in Figure 3. \( M \) is a 2-dimension tensor of shape \( \mathbb{R}^{p \times c} \) where \( p \) is the number of POS classes and \( c \) is the scale of PLM’s dictionary. \( M \) is constructed following the rule as follows:

\[
M_{ij} = \begin{cases} 
0, & \text{if } j\text{-th word dictionary not in } i\text{-th POS class} \\
1, & \text{if } j\text{-th word dictionary in } i\text{-th POS class}
\end{cases}
\]

With \( M \), we gather the existence probability of words in the same POS class together and calculate the KL divergence for POS-NDD. The weighted sum in POS-NDD calculation is the same as in NDD.

\[
q_i = Md_i, q'_i = Md'_i
\]

\[
div_i^{pos} = D_{KL}(q_i || q_i) = \sum_{j=1}^{p} q_{ij} \log \left( \frac{q'_{ij}}{q_{ij}} \right)
\]

The comparison between the initial NDD and modified POS-NDD is presented in Table 1. In the first example, we edit the sentence while keeping both the semantics and structure unchanged. The edition results in rather low values for both NDD and POS-NDD. In the second example, our edition does not convert the sentence’s structure.
but result in difference semantics. Initial NDD is sensitive to this change as its value raises to nearly \( \times3 \). In contrast, POS-NDD is less likely to be affected by semantics and concentrates more on the sentence structure. The last example includes an edition which breaks the sentence’s structure as it substitutes a verb phrase by a probably noun phrase. As the value of POS-NDD raises to almost \( \times8 \), POS-NDD is verified to detect this anomaly.

2.3 NDD-based Dual Mold

Based on POS-NDD, we build “molds” which are able to discern constituents in sentences. Our mold is defined as a quaternion \((W, i, j, l)\) where \(W\) is an \(n\)-word sentence. \(i, j\) refers to the start and end position of the span for substitution. \(l\) refers to the constituent’s label. If we want to evaluate the probability of a span \(V[s : t]\) (words from \(s\)-th to \(t\)-th position in an \(m\)-word sentence \(V\)) to a constituent with the label \(l\), we will substitute \(W[i : j]\) with \(V[s : t]\) and calculate the POS-NDD between the sentence before and after the substitution.

\[
S_{s,t}^{l,tn} = \text{POS-NDD}(W, W')
W' = [w_1, \ldots, w_{i-1}, w_i, \ldots, w_t, w_{t+1}, \ldots, w_n]
\]

We call this score To-Mold score as it is obtained by substituting spans in molds. Likewise, we also have a From-Mold score which is obtained by substituting spans in sentences for parsing with spans in molds.

\[
S_{v,t}^{l,fm} = \text{POS-NDD}(V, V')
V' = [v_1, \ldots, v_{s-1}, v_s, \ldots, v_{t-1}, v_t, \ldots, v_m]
\]

We finally add To-Mold and From-Mold scores together for whole evaluation,

\[
S_{s,t}^l = S_{s,t}^{l,tn} + S_{s,t}^{l,fm}
\]

which forms a dual calculating procedure as shown in Figure 4. We thus name our method Dual POS-NDD. A lower DP-NDD score \(S\) refers to less disturbance in substituting to and by a constituent with label \(l\) and will thus reflects the likelihood of the span to be a constituent with the same label.

3 Constituency Tree Constructing

In this section, we will introduce two frameworks that we use in experiments to generate labeled constituency trees.

3.1 Labeled Span Generating

Labeled Span Generating (LSG) is to directly generate labeled spans with DP-NDD molds and then integrate spans with different labels together to construct the full labeled tree. Our LSG algorithm is much simpler than previous rules-based systems as it only requires 4 steps for constituency parsing.

- **Candidate Selection** We first use simple linguistic rules to sample some candidates for a constituent label. For a span \(V[s : t]\), we match the POS tags of \(V[s-1], V[s], V[t], V[t+1]\) to a POS list to roughly decide whether the span is a plausible candidate for constituent or not.

- **DP-NDD Scoring** We then use our Dual POS-NDD molds to score the sampled candidates as previously described. For some labels, there are multiple molds for evaluation as difference exists among constituents with the same label. We choose the minimal value of DP-NDD scores from the molds.

- **Conflict Removing** After scoring, we remove spans which conflict with previously parsed span. Conflicting spans are those overlapping with previous spans by \((s < s', s' < t, t < t')\) or \((s' < s, s < t', t' < t)\).

- **Filtering and Overlapping Removing** Finally, we filter the spans by only keeping the spans with DP-NDD scores under a certain threshold. Then, we remove spans overlapped with other spans of the same label. If \((s < s', s' < t, t < t')\) or \((s' < s, s < t', t' < t)\), we only keep the span with higher DP-NDD. But if \((s < s', t' < t)\) or \((s' < s, t < t')\), we add a tolerance factor to the algorithm to keep both spans if the difference between the two scores is lower than the tolerance.

We execute the 4 steps above for each label and finally integrate spans parsed from each iteration together to construct the whole labeled constituency tree.
3.2 Unlabeled Tree Labeling

Unlabeled Tree Labeling (ULT) is to first use a parsing algorithm to induct unlabeled treebanks from sentences, and then use DP-NDD molds to label the spans in the tree. Our UTL only annotates the edges in the tree with no changing in the tree structure. For each label, we use a mold to calculate the DP-NDD score. The span is labeled as label of the mold to minimize the DP-NDD. In practice, we maximize the exponential of negative DP-NDD.

\[ l_{s,t} = \arg\max \left( e^{-S_{l}(s,t)} \right) \]

We further refine the prediction by incorporating POS tags, we use the posterior probability collected before for approximation to induct the label of a span using the POS of start and end words.

\[ l_{s,t} = \arg\max \left( \alpha e^{-S_{l}(s,t)} \right) \]

\[ \alpha = p(\text{POS}(V[s])) p(\text{POS}(V[t])) \]

where we add \( \alpha \) as a modifier to incorporate POS-based probability into prediction.

4 Experiment

4.1 Data and Configuration

We experiment our parsing algorithm on Penn Treebank for Constituency Parsing. As our method is training-free, we only use the first 50 sentences in the development dataset to construct molds and we handcraft some simple molds. We do not use the training dataset and test our algorithm on the test dataset. We apply BERT-base-cased (Devlin et al., 2019) as the PLM for calculating DP-NDD. We also have two configurations for thresholds and tolerances in LSG. A strict configuration will produce fewer predicted spans and will thus result in higher labeled F1 scores while a loose configuration will in opposite result in higher unlabeled F1 scores. For ULT, we use DIORA+PP (Post-processing) (Drozdov et al., 2019) which is a strong baseline for unsupervised constituency parsing to induct the unlabeled treebanks. For probability approximation in POS-based refinement for UTL, we only use POS tags in development dataset. Specific molds, POS-based rules, thresholds and tolerances can be referred to Appendix A.

4.2 Main Result

Our main results and the comparison with previously reported results are shown in Table 2. We evaluate the models by unlabeled F1 for comparison with previous parsing methods. The performances of UTL and LSG are both reported to set baselines for those two frameworks.

From Table 2, our DP-NDD-based LSG algorithm, DP-NDD with a loose configuration, outperforms all previous unsupervised methods for constituency parsing and remarkably boosts the state-of-the-art unlabeled F1 score to upper than 60.0. Comparing with previous state-of-the-art methods consists of complex systems like post-processing with numerous linguistic rules, our algorithms are much simpler and of better scalability. We attribute this advance to the power of pre-trained language model which is able to cast constituents with high structural difference into near spaces in the latent space.

For labeled F1 score, our algorithms also reach significant performance. DP-NDD with a tight configuration reaches a strong performance of 54.5 which is even higher than most unlabeled F1 results from previous systems. Thus, we claim to successfully implement the first unsupervised full constituency parsing in recent years. Moreover, our

| Method               | UF1  | LF1* |
|----------------------|------|------|
| LB                   | 13.1 | -    |
| RB                   | 16.5 | -    |
| RL-SPINN (Choi et al., 2018) | 13.2 | -    |
| ST-Gumbel - GRU (Yogatama et al., 2017) | 22.8 | -    |
| PRPN (Shen et al., 2018a) | 38.3 | -    |
| BERT-base (Kim et al., 2020) | 42.3 | -    |
| ON-LSTM (Shen et al., 2019) | 47.7 | -    |
| XLNet-base (Kim et al., 2020) | 48.3 | -    |
| DIORA (Drozdov et al., 2019) | 48.9 | -    |
| Tree-T (Wang et al., 2019) | 49.5 | -    |
| StrctFormer (Shen et al., 2021) | 54.0 | -    |
| PRPN+PP              | 45.2 | -    |
| DIORA+PP             | 55.7 | -    |
| DIORA+PP+Aug (Sahay et al., 2021) | 58.3 | -    |
| Neural PCFG (Kim et al., 2019) | 50.8 | -    |
| Compound PCFG (Kim et al., 2019) | 55.2 | -    |
| 300D SPINN (Williams et al., 2018) | 59.6 | -    |
| (LSG) w/o NDD        | 32.5 | 25.7 |
| (ULTL) DIORA+PP      | 54.7 | 34.8 |
| (ULTL) DIORA+PP+POS  | 54.7 | 43.3 |
| (LSG) Tight DP-NDD   | 59.3 | 55.4 |
| (LSG) Loose DP-NDD   | 61.8 | 51.5 |

Table 2: Comparison on unlabeled and labeled F1 scores among methods for unsupervised constituency parsing on WSJ test dataset. PP: Post-processing heuristics. Aug: Rule-based Augmentation. *: Multiple edges are kept as constituents can have multiple labels.
Table 3: Performance of DP-NDD-based LSG algorithm on different labels. Unlabeled results (UR) are from loose DP-NPP and labeled (LP, LR, LF) results are from tight DP-NPP. Prop.: Proportion of labels in test treebanks.

| Label | UR   | LP   | LR   | LF1  | Prop. |
|-------|------|------|------|------|-------|
| NP    | 66.20| 68.49| 64.34| 66.35| 42.08%|
| VP    | 38.84| 53.54| 36.10| 43.12| 19.75%|
| ADJP  | 51.20| 14.97| 28.89| 19.72| 2.02% |
| ADVP  | 79.84| 47.37| 70.40| 56.63| 2.74% |
| PP    | 63.84| 66.37| 51.53| 58.02| 12.40%|

Table 4: Labeling performance of DP-NDD-based UTL algorithm on unlabeled golden edges in WSJ-10 treebanks. †: Refined by POS.

| Label | P   | R   | F1  | P†  | R†  | F1† |
|-------|-----|-----|-----|-----|-----|-----|
| NP    | 88.02| 86.70| 87.36| 91.34| 98.86| 94.95|
| VP    | 99.17| 50.70| 67.10| 98.52| 90.26| 94.21|
| ADJP  | 27.86| 75.88| 40.76| 91.33| 37.23| 52.90|
| ADVP  | 63.19| 55.74| 59.23| 93.93| 85.15| 89.32|
| PP    | 40.32| 82.57| 54.18| 84.30| 97.69| 90.50|

Method involves a much simpler PLM, BERT, than the highest baseline, xlnet, in (Kim et al., 2020), but reaches a much higher performance (13.5 unlabeled F1 score). Comparing with result of BERT-base in (Kim et al., 2020), unlabeled F1 score from DP-NDD is 19.5, which shows the high efficiency of DP-NDD-based method.

Comparing with UTL, LSG shows higher F1 scores in both unlabeled and labeled treebanks. We conclude from this phenomenon that using label-specific method (Our molds are for a certain label) can extract constituents better than parsing spans of different labels with a unified algorithm like in other PLM-based method (Kim et al., 2020; Shen et al., 2021). For UTL, incorporating POS benefits labeling in this framework much as this lifts the unlabeled F1 score to 8.5 higher.

We also launch an ablation study by removing DP-NDD scores from the LSG framework. LSG without DP-NDD returns all spans that satisfy the POS constraints. Without the guide of DP-NDD, the performance of LSG algorithm drops dramatically, even to half of the initial performance. We conclude from this phenomenon that our DP-NDD metric is essential for unsupervised full constituency parsing.

5 Analysis and Discussion

5.1 Label-specific Evaluation

We analyze the ability of our LSG algorithm for parsing edges of different labels in this section. We report unlabeled and labeled performance of LSG algorithm on different labels. Precision, recall and F1 score are all considered for labeled treebanks and only recall is evaluated for labeled treebanks.

As presented in Table 3, LSG performs well on extracting noun, adverb and preposition phrases. For these phrases, LSG leads to high results in unlabeled recalls and labeled F1 scores. We mainly attribute the success of LSG to the high performance in discerning noun phrases, which take 42.08% proportion of the constituents. LSG performs rather weaker for verb and adjective phrases as patterns of these phrases are more variable. Thereby, LSG will be more likely to confuse them with other phrases when trying to discern. This point will be elaborated in Section 5.3.

In contrast, phrases with regular patterns like adverb phrases and preposition phrases are more likely to be discerned successfully. This phenomenon can be attributed to the matching nature of our algorithm as less disturbance will be caused if a span is substituted by another span in a similar pattern. Take instances in Figure 1 for explanation, substituting into the hole with most preposition phrases will only result in subtle disturbance, i.e., in a warm autumn day, before the crashing. But verb phrase contain a variety of patterns like is so smart and to enjoy their lunch. Their substitution to the verb phrase jumps into the hole will cause much more disturbance. Thus, the selection of molds for verb phrases should be more carefully to cover the patterns of verb phrases. But this still remains another problem that these patterns may be confused with other phrases like labeling to enjoy their lunch to be a preposition phrase. Current structure-oriented LSG algorithm may not be able to offer a proper solution to this confusion, so we plan to leverage preciser semantics for a try in the future.

5.2 Labeling Performance

We analyze the labeling performance of our UTL algorithm in this section. To avoid parsing bias caused by parser chosen for constructing unlabeled constituency trees, we follow (Drozdov et al., 2019), we construct a WSJ-10 dataset by sampling sentences with length under 10 from train, development and test datasets. Then, constituents including noun, verb, adjective, adverb and preposition
phrases are filtered from these sentences. WSJ-10 contains 17935 golden constituents and we use UTL algorithm to label constituents.

We report the experiment results of UTL in Table 4. Without the refinement of POS information, UTL results in high precision and recall for labeling noun phrase, which verifies its capacity for discerning noun phrase’s patterns. Adjective phrase remains to be the most difficult constituent for parsing and other phrases are of the medium parsing difficulty. POS-based refinement works for all phrases by significantly improving the F1 score of noun, verb, adverb and preposition phrases to around 90.0 while still leaving the adjective phrase as a hard problem due to the difficulty in keeping recall and precision score for adjective phrase balanced.

5.3 Confusion in Constituent Discerning

Following the discussion of labeling performance, we further analyze factors that affect the constituent discerning procedure. We depict the confusion matrix in Figure 5. When POS is not used to help parsing, the most confusing labels are verb and adjective phrases. But the adjective phrase becomes prominently confusing when POS is taken into consideration, indicating that some adjective phrases have common POS patterns with noun phrases.

To go deeper for the factors behind the confusion in labeling, we construct disturbance matrices by sampling constituent pairs from WSJ and WSJ-10 datasets. We sample 2000 for each label pair and record the average POS-NDD caused by the substitution. Disturbance matrix is shown to be the direct reflection of pattern difference among constituents. Generally, self disturbance (disturbance between constituents of same labels) is lower than mutual disturbance (disturbance between constituents of different labels). Moreover, Phrases with more patterns like verb phrase have higher self disturbance. Referring to the confusion matrix without refinement, confusion appears when self disturbance is not enough lower than the mutual disturbance, i.e., VP-ADJP, VP-PP, ADVP-PP. The discerning difficulty leads to the drop in recall scores for verb and preposition phrases. For adjective phrases, its precision is affected to drop as some parts of noun phrases, which take a large proportion in constituents, are mislabeled as adjective phrases.

5.4 How about other tasks?

To verify the generalization of applying NDD for capturing labeled spans, we conduct experiments on named entity recognition, where all spans are noun phrases in constituency. We choose Conll-03 (Sang and Meulder, 2003) as the NER dataset. Conll-03 consists of named entities labeled in 4 types: [ORG], [PER], [MISC] and [PER]. We sample 2000 pairs of spans in the same way that we do in 5.3. We evaluate the average disturbance caused by substitute one span with another using both POS-NDD and the original NDD.

Figure 7 shows the disturbance matrix for NER. Comparing with constituents, substitution using named entity on average results in much lower POS-NDD since named entities are all noun phrases as mentioned before. Generally, self disturbance is lower than mutual disturbance, making it a plausible to label named entities with NDD. Com-
paring with POS-NDD, NDD captures preciser semantics changes as described before. NER experiment results also support that NDD generally perform better in discerning named entity, which share structural similarity with each other, especially for disturbance caused by substitution to [LOC].

Among labels, [PER] is the easiest for discerning as it differs the most from other labels. In contrast, [ORG] and [LOC] are likely to be confused with each other as they play similar roles in semantics. For instance, we may say a meeting took place in UN or a meeting took place in Paris, but a meeting took place in Jack is not semantically plausible. We conclude from the disturbance matrix the difficulty in entity labeling should be ranked as [ORG]>[MISC]>[LOC]>[PER].

6 Related Work

6.1 Unsupervised Constituency Parsing

Since the introduction of language models pre-trained on large corpus like BERT (Devlin et al., 2019), extracting constituents from those models raises as a new way for unsupervised constituency parsing (Kim et al., 2020; Shen et al., 2021). These methods try to extract constituents by calculating the syntactic distance (Shen et al., 2018b) which is supposed to reflect the information association among constituents according to (Shen et al., 2018a; Wang et al., 2019). The extraction of latent trees from PLMs has been studied on a variety of language models in (Kim et al., 2020), which provides rich posterior knowledge for completing unsupervised constituency parsing.

Models trained on masked language model put forward another framework for unsupervised parsing procedure. These models, like DIORA and its variants (Drozdov et al., 2019; Sahay et al., 2021), have been verified by experiment results to be efficient in discerning constituents from sentences. Unfortunately, these models fail to label the constituents after constructing an unlabeled treebanks from sentences. Our method differs from previous work by using constituency molds to match constituents and thus induct their labels. Instead of figuring out direct relationships among words, we allow neighboring words to supervise the structural disturbance caused by substitution. As the result, our method enables labeling on the constituency tree which implements the full unsupervised constituency parsing.

6.2 Neighboring Distribution Divergence

Neighboring distribution divergence (Peng et al., 2021) is initially proposed to detect semantic changes caused by editions like compression (Xu and Durrett, 2019) or rewriting (Liu et al., 2020). Their experiments on syntactic tree pruning and semantic predicate detection also show NDD to be aware of syntax and semantics. NDD is verified to have the capacity to detect predicates for semantic role labels by deleting or substituting words, which serves as our motivation to transfer this idea to unsupervised constituency parsing. We follow the idea in (Peng et al., 2021) and further adapt it to extract and label constituents.

In previous years, there are other works which focus on leveraging pre-trained models to produce metrics reflecting syntactic or semantic information. To evaluate the quality of text generation, BERTScore (Zhang et al., 2020a) matches representations from pre-trained language model of generated and golden sentences. Using pre-trained AMR parsers, (Opitz and Frank, 2021) offers a explainable metric, MF-Score, for AMR-to-sentence generation. MF-Score assigns scores by reconstructing the AMR graphs to compare them with the golden ones and thus evaluates semantic similarity better than conventional sequence matching metrics like BLEU and ROUGE. Encouraged by our success in applying NDD for parsing, we plan to further explore these pre-trained model-based automatic metrics for more tasks.

7 Conclusion

In this paper, we aim to explore an unsupervised full constituency parsing procedure which includes constituent labeling. We develop the recently proposed NDD metric into POS-NDD and exploit it by using dual mold to match constituents. Based on DP-NDD, we introduce two novel frameworks, labeled span generation and unlabeled tree labeling, which establish strong baselines for labeled constituency tree construction and set the new state-of-the-art for unlabeled F1 score. Further studies on constituents with NDD disclose the pattern variety of constituents with the same label and pattern similarity among constituents with different labels. Experiments on the NER dataset verify the generalization of our method to other tasks.
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A Detailed Configuration

Before we release our codes, you can re-implement the results in our experiments with the configuration setting in this section.

A.1 Mold

| W | i | j | l |
|---|---|---|---|
| Influential members of the House Ways and Means Committee introduced legislation that would restrict how the new savings-and-loan bailout agency can raise capital, creating another potential obstacle to the government’s sale of sick thrifts. | 16 | 20 | NP† |
| The complex financing plan in the S&L bailout law includes raising $30 billion from debt issued by the newly created RTC. | 1 | 4 | NP |
| Another $20 billion would be raised through Treasury bonds, which pay lower interest rates. | 5 | 16 | VP† |
| The bill intends to restrict the RTC to Treasury borrowings only, unless the agency receives specific congressional authorization. | 3 | 19 | VP |
| The complex financing plan in the S&L bailout law includes raising $30 billion from debt issued by the newly created RTC. | 17 | 22 | VP |
| But the RTC also requires “working” capital to maintain the bad assets of thrifts that are sold, until the assets can be sold separately. | 10 | 27 | VP |
| “Such agency ‘self-help’ borrowing is unauthorized and expensive, far more expensive than direct Treasury borrowing.” said Rep. Fortney Stark -LRB- D. , Calif. -RRB- , the bill’s chief sponsor. | 9 | 11 | ADJP† |
| “Such agency ‘self-help’ borrowing is unauthorized and expensive, far more expensive than direct Treasury borrowing” said Rep. Fortney Stark -LRB- D. , Calif. -RRB- , the bill’s chief sponsor. | 13 | 15 | ADJP |
| “To maintain that dialogue is absolutely crucial.” said Christopher Pedersen , senior vice president at Twenty-First Securities Corp. | 7 | 8 | ADJP |
| Many money managers and some traders had already left their offices early Friday afternoon on a warm autumn day – because the stock market was so quiet. | 8 | 8 | ADVP† |
| This country is fairly big. | 4 | 4 | ADVP |
| Therefore , we can exchange in the market. | 1 | 1 | ADVP |
| “To maintain that dialogue is absolutely crucial.” | 7 | 8 | ADVP |
| Once again -LCB- the specialists -RCB- were not able to handle the imbalances on the floor of the New York Stock Exchange, said Christopher Pedersen , senior vice president at Twenty-First Securities Corp. | 14 | 22 | PP† |
| Big investment banks refused to step up to the plate to support the beleaguered floor traders by buying big blocks of stock, traders say. | 17 | 22 | PP |
| Just days after the 1987 crash , major brokerage firms rushed out ads to calm investors. | 1 | 6 | PP |

Table 6: Molds for result reproduction (the rest). †: Used for UTL

Table 5 and 6 shows the molds we use for discerning constituents in LSG and labeling in UTL.

Table 5: Molds for result reproduction (from NP to PP). †: Used for UTL
A.2 POS Constraint

| Label | POS($V_i$) | POS($V_j$) | POS($V_{i-1}$) | POS($V_{j+1}$) | Max Len |
|-------|-------------|-------------|----------------|----------------|---------|
| NP    | NNP NNP PRP DT CD NN NNS JJ PRP PRPS S | NN NNS NNP NNP PRP CD POS | IN SOS VB | IN | VBD |
| VP    | VBD VB VBZ VBN VBVP TO VBG MD | NN NNS NNP CD RB VB VBN JJ VBD PRP | NN NNS NNP TO NNP RB MD | VBD VBZ VBP WDT VB VB IN RB VBN NN CC IN " DT | |
| ADJP  | JJ RB CD RBR JDR S | JJ NN NNS CD JRR | DT VBD VBZ VBP VB IN RB VBN NN CC | IN N NNS CC NNP | |
| ADVP  | IN | NN NNP NPS CD | | | |
| PP    | IN | NNP NPS CD | | | |
| QP    | S CD IN RB JRR | CD IN SOS TO VBD VBZ DT | IN N NNS | | |
| SBAR  | IN WDT PRP DT WRB WP TO | NN NNS NNP CD | NN VBD NNS VBP SOS VBD | | |
| S     | TO DT PRP NNP VBG NN NNS JJ VBD VBZ | NN NNP CD | IN VBD WDT VBZ VB IN RB VBN NN CC VBG WRB VBP WP | | |
| WHNP  | WDT WP WPS | WDT WP | NN NNS IN VBD VB VB CC | VBD VBZ VBP MD DT PRP NNP RB NNS JJ IN | |
| WHADVP | WRB | WRB | | | |
| PRN   | -LRB- | -LRB- | | | |
| PRT   | RP | RP | | | |

Table 7: POS and length constraints for result reproduction. **SOS**: Start of the sentence. **EOS**: End of the sentence. -: No constraint.

Table 7 shows our constraints for POS and max length. These constraints are inducted by statistical property and simple linguistic rules.

A.3 Threshold and Tolerance

| Label | Threshold (t) | Tolerance (t) | Threshold (l) | Tolerance (l) |
|-------|---------------|---------------|---------------|---------------|
| NP    | 2.0 | 0.15 | 1.4 | 0.10 |
| VP    | 0.8 | 0.15 | 2.0 | 0.05 |
| ADJP  | 0.2 | 0.04 | 0.6 | 0.10 |
| ADVP  | 0.8 | 0.03 | 0.8 | 0.03 |
| PP    | 0.2 | 0.10 | 0.4 | 0.12 |
| QP    | 0.2 | 0.03 | 0.2 | 0.03 |
| SBAR  | 0.2 | 0.01 | 2.2 | 0.10 |
| S     | 0.2 | 0.10 | 2.0 | 0.15 |
| WHNP  | 1.0 | 0.10 | 1.0 | 0.10 |
| WHADVP| 1.0 | 0.10 | 1.0 | 0.10 |
| PRN   | 1.0 | 0.10 | 1.0 | 0.10 |
| PRT   | 1.0 | 0.10 | 1.0 | 0.10 |

Table 8: Thresholds and tolerances for result reproduction. t: Tight configuration. l: Loose configuration.