A Novel Metric for Evaluating Semantics Preservation

Letian Peng1,2,3,†, Zuchao Li1,2,3,†, and Hai Zhao1,2,3∗

1Department of Computer Science and Engineering, Shanghai Jiao Tong University
2Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, Shanghai Jiao Tong University, Shanghai, China
3MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University

{zxc-00,charlee}@sjtu.edu.cn, zhaohai@cs.sjtu.edu.cn

Abstract

In this paper, we leverage pre-trained language models (PLMs) to precisely evaluate the semantics preservation of edition process on sentences. Our metric, Neighbor Distribution Divergence (NDD), evaluates the disturbance on predicted distribution of neighboring words from mask language model (MLM). NDD is capable of detecting precise changes in semantics which are easily ignored by text similarity. By exploiting the property of NDD, we implement a unsupervised and even training-free algorithm for extractive sentence compression. We show that our NDD-based algorithm outperforms previous perplexity-based unsupervised algorithm by a large margin. For further exploration on interpretability, we evaluate NDD by pruning on syntactic dependency treebanks and apply NDD for predicate detection as well.

1 Introduction

Sentence editions, like deletion and replacement (Liu et al., 2020; Huang et al., 2021; Xu and Durrett, 2019a), are widely used in natural language processing (NLP) to complete generative tasks in an extractive procedure. Many such tasks require model to maintain most semantics, including text compression and rewriting. However, metrics for semantics comparison remain insufficient. Perplexity emphasizes more on structural integrity rather than semantics and text similarity is not precise enough for a satisfying performance.

As the two cases in Figure 1, we execute an edition (replacement) for each sentence. In the first case, we keep the semantics almost unchanged while in the second case, the replacement from river into town obvious leads to a semantics change, especially for the meaning of bank. However, conventional cosine similarity fails to capture the semantics shifting in the second case as it predicts a similarity close to the first case.

Thus, we introduce our novel metric, Neighbor Distribution Divergence, to precisely detect the semantics changes caused by text edition. NDD evaluates based on pre-trained language models like BERT(Devlin et al., 2019). NDD is designed based on the assumption that changes in semantics can be reflected by predicted distribution changes of neighboring words. For instance, when we use masked language model to predict the masked bank in The man sits beside the bank of the river., words like source or surface will more likely be predicted. If we replace river by bank, which leads to a semantics change, the probability of words like center or college to be predicted will become higher. In contrast, if river is replaced by lake, source be surface will still be predicted with high confidence, which indicates the edition preserves the initial semantics.

In Specific, NDD predicts distributions of masked neighboring words before and after the edition. Then these distributions are calculated by the KL divergence function and summed up to get the final metric. A higher NDD indicates greater change in semantics of a sentence. As shown in

Figure 1: Comparison on semantic change detection between conventional text similarity and Neighboring Distribution Divergence.

— Corresponding author. † These authors made equal contribution. This work was supported by Key Projects of National Natural Science Foundation of China (U1836222 and 61733011).
We implement a NDD-based training-free algorithm which performance significantly better than previous perplexity-based algorithm on unsupervised text compression.

Our further experiments on syntactic and semantic treebanks show NDD’s awareness of syntax and semantics.

2 Neighboring Distribution Divergence

In this section, we give an elaborate description of the procedure to calculate the NDD metric. In NDD, distribution refers to the predicted probability distributions in MLM, divergence refers to the KL divergence of the predicted distributions before and after the edition, and neighboring means that more attention will be paid to words near the edited spans. NDD directly reflects the semantic disturbance on other unedited words caused by the edition.

Given a sentence $W$ with $n$ words $W = [w_1, w_2, \cdots, w_n]$, an editing operation $E$ is used to convert the sentence to an edited one. For formula simplification, we suppose $E$ to be a replacement for discussion. Suppose that $E$ replaces a span $[w_i, w_{i+1}, \cdots, w_j]$ in $W$ with a span $V = [v_1, v_2, \cdots, v_k]$, then the new sentence will be $W' = [w_1, \cdots, w_{i-1}, v_1, \cdots, v_k, w_{j+1}, \cdots, w_n]$. Then we calculate predicted distribution divergence on those neighboring words...
[\{w_1, \ldots, w_{i-1}, w_{i+1}, \ldots, w_n\}] of the edition. We use MLM-based prediction as depicted in Figure 2.

For a sentence \(W\), we predict the MLM-based distribution on \(i\)-th position as follows.

\[
W_m = [w_1, \ldots, w_{i-1}, [\text{MASK}], w_{i+1}, \ldots, w_n]; \\
R = \text{PLM}(W_m); d = \text{softmax}(R_i) \in \mathbb{R}^c
\]

We first mask the word on \(i\)-th position and then apply PLM for prediction on that position. Finally a softmax function is used to get the probability distribution \(D\) where \(d_j\) refers to the appearance possibility of \(j\)-th word in the \(c\)-word dictionary on \(i\)-th position. We summarize this distribution predicting process with a function \(\text{MLM}(\cdot)\) where \(\text{MLM}(W, i) = d\).

Then we go back to the discussion of text edition. For the edition \(E\), we use \(\text{MLM}(\cdot)\) to predict the distribution \(D = [d_1, \ldots, d_{i-1}, d_{j+1}, \ldots, d_n]\) of neighboring words in the unedited sentence \(W\). We calculate another distribution \(D'\) for neighboring words in the edited sentence \(W'\).

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

\[
div = D_{KL}(d' || d) = \sum_{i=1}^{c} d'_i \log(\frac{d'_i}{d_i})
\]

Here we use \(D\) from the unedited sentence as the observed distribution and \(D'\) from the edited sentence for approximation. After we get the divergence \(\text{div}\) between each pair in \(D\) and \(D'\), we use a weighted sum for the final NDD score.

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

where \(a_k\) is the distance weight which can be designed as \(\mu_{\min}(k-i, k-j)|\mu \leq 1.0\). Distance weight is added for scaling for that more divergence will be detected on words closer to edited spans. In latter experiments, this weight will be re-designed for specific tasks, but generally, words closer to edited spans will be assigned higher weights.

So why is NDD capable to capture precise semantics changes? First, NDD uses predicted distributions to represent words rather than just the word itself. As shown in Figure 2, the disturbance on semantics is not just detected by existing words like \(\text{be and mine}\), but is detected by all words in the dictionary as well. Moreover, this procedure enables PLM to evaluate semantic disturbance on unknown words much better. For instance, if a PLM meets an unknown word like \textit{Okinawa}, it will use it as an \([\text{UNK}]\) token to calculate the perplexity. In contrast, we replace evaluation directly on real words by evaluating on appearance likelihood. Thus, the PLM will be able to know this word to have like 10\% probability to be \textit{place}, 20\% probability to be \textit{region}, etc. from the surrounding words. Finally, NDD compares the semantics between sentences before and after edition, which is unlikely to be implemented using perplexity. Perplexity can only be used to evaluate the fluency of the edited sentence while NDD is also able to detect whether the semantics has been preserved.

### 3 Evaluating Precise Semantic Similarity

Following the discussion in the introduction, we use cases to further explore the ability of our model to capture precise semantics changes using several examples. As in Table 1, we edit the initial sentence \"I am walking in the cold rain\." with a series of replacement. We keep syntactic structure of the sentence unchanged and replace some words by other words with the same POS. Thus, the difference between the initial and edited sentences is majorly the semantics.

| Sentence                        | PPL | NDD | Cos.Sim. |
|---------------------------------|-----|-----|----------|
| I am walking in the cold rain.  | 5.99| 0.00| 1.000    |
| I am walking in the cold rain.  | 10.10| 0.81| 0.995    |
| I am walking in the freezing rain.| 5.63| 0.97| 0.997    |
| I am walking in the Heavy rain. | 5.30| 1.82| 0.994    |
| I am walking in the hot rain.   | 14.77| 3.17| 0.995    |
| I am walking in the cold snow.  | 5.37| 2.46| 0.996    |
| I am walking in the cold night. | 6.18| 3.52| 0.991    |
| I am walking in the cold sunshine.| 8.59| 4.73| 0.994    |
| I am running in the cold rain.  | 11.86| 0.66| 0.990    |
| I am wandering in the cold rain.| 16.89| 0.89| 0.982    |
| I am swimming in the cold rain. | 14.84| 3.29| 0.986    |
| He is walking in the cold rain. | 10.32| 4.72| 0.980    |
| He is walking in the cold rain. | 105.55| 13.04| 0.991    |
| He is walking in the cold rain. | 13.95| 7.22| 0.980    |

Table 1: Cases for detection of NDD on very precise semantics changes. The initial sentence is \"I am walking in the cold rain.\"

This issue is overcome in NDD as we use predicted results, NDD correctly scores the semantics changes and even named entities much better. As the re-before, NDD can understand low-frequency words distributions rather than real words. As described is semantically closer to walking lead to a higher perplexity, even though wandering ability of words, the low-frequency wandering will be classified to be similar. NDD is able to preserve semantics much better by changing from cold into cool and freezing keeps the most semantics while changing into hot leads to the opposite and even implausible semantics. NDD reflects the difference of semantics between these edited results and assigns a much higher score to the cold-to-hot case. Moreover, in the medium case where the aspect for description is changed to heavy, NDD remarkably assigns a medium score to this case, showing its high discerning capability.

In the last case group, we change the tense and subject of the sentence. NDD is shown to be fairly sensitive to tenses and subjects. This property can be used to retain those critical properties during editions. NDD is also able to detect syntactic faults like the combination of He am and can thus be used for fault preventing.

From these cases we can also see why perplexity and cosine similarity is incapable of detecting precise semantics changes as NDD. In Table 1, cosine similarity cannot detect subtle semantics changes and even syntactic faults. We attribute this to the high reliance on word representations for sentence represents as sentences with many words overlapped will be classified to be similar.

For perplexity, the first problem with it is that this metric evaluates a single sentence rather than a pair of sentences. Thus, perplexity can only estimate the plausibility of sentences instead of semantic relationships. Perplexity will thus guide editions to transform sentences into more syntactically plausible versions. As shown in Table 1, edited results with lower perplexity may change semantics like cold-to-heavy and rain-to-snow. Our NDD is able to preserve semantics much better by suggesting changing cold to cool and changing walking to running or wandering.

Another reason is that perplexity can easily be misguided by low-frequency words. In the walking-to-wandering case, the resulted perplexity is even higher than the walking-to-swimming case. Since perplexity is scored based on existence probability of words, the low-frequency wandering will lead to a higher perplexity, even though wandering is semantically closer to walking than swimming. This issue is overcome in NDD as we use predicted distributions rather than real words. As described before, NDD can understand low-frequency words and even named entities much better. As the result, NDD correctly scores the semantics changes caused by replacement on walking.

4 Unsupervised Text Compression

To show the advantages of NDD in application, we implement an unsupervised algorithm for text compression guided by NDD.

4.1 Span Searching

Given a sentence \( W \), we try every span \( W_{ij} = [w_i, \cdots, w_j] \) with length under a certain limit \( L_{max} \) for deletion. Then we use NDD to score the semantics changes caused by the deletions.

\[
S_{ij} = \text{NDD}(W, W'_{ij})
\]

\[
W'_{ij} = [w_1, \cdots, w_{i-1}, w_{j+1}, \cdots, w_n]
\]

where all words in \( W' \) are used as neighboring words for metric calculating. We select spans with NDD under a certain limit \( NDD_{max} \) as the candidates for the next processing step.

4.2 Overlapped Span Selection

As overlapping often occurs in the spans from searching, we apply a simple selective algorithm to filter the candidate spans. Specifically, we compare each overlapped span pairs, in which two spans contain some common words. For each pair, we delete the span with lower NDD score and keep the other span for next round of comparison. This process iterates until there is no overlapped span in candidates.

4.3 Other Details

As following the distance weights described before are imbalanced for words near the start and end of a sentence. In practice, we use a modified balanced weights for distance.

\[
a_k = \mu_{\text{min}}(|k-i|,|k-j|)
\]

\[
a'_k = a_k + a_{n' - k} \mu^{n'}
\]

\[
n' = n - (j - i + 1)
\]

The main effect of this modification is to let words near the two side to be detected twice for their disturbance on neighboring words. With the help of this modification, we overcome the weight imbalance issue and thus avoid incorrect deletions.

Furthermore, we add another weight \( b_k \) to encourage our algorithm to delete latter words in the sentence as it is less common to use these words for summary. We modify the weighted sum as follows.

\[
W_{ij} = [w_1, \cdots, w_{i-1}, w_{j+1}, \cdots, w_n]
\]
We use the evaluation dataset with 10,000 sentence pairs for performance evaluating. We use BERT-base-cased which has been specialized for the MLM task as the PLM. We set \( L_{\text{max}} \) to 9 and \( NDD_{\text{max}} \) to 1.0 for span filtering. For weighting, we set \( \mu \) and \( \nu \) both to 0.9. We choose BLEU (Papineni et al., 2002) and F1 score as metrics for evaluation and comparison because precision is more critical than recall (Returning the whole unedited sentence will result in a high recall) in extractive compression.

### 4.4 Experiment

#### Dataset and Configuration

To compare our algorithm with the previous unsupervised sentence compression algorithm, we conduct our experiments on the Google dataset (Filippova et al., 2015). We use the evaluation dataset with 10,000 sentence pairs for performance evaluating. We use BERT-base-cased which has been specialized for the MLM task as the PLM. We set \( L_{\text{max}} \) to 9 and \( NDD_{\text{max}} \) to 1.0 for span filtering. For weighting, we set \( \mu \) and \( \nu \) both to 0.9. We choose BLEU (Papineni et al., 2002) and F1 score as metrics for evaluation and comparison because precision is more critical than recall (Returning the whole unedited sentence will result in a high recall) in extractive compression.

#### Results

Our results are shown in Table 2: Results for sentence compression on the Google dataset, we compare our algorithm with other unsupervised algorithms. Underlines mean the improvement to be significant \((p < 0.05)\) considering the highest baseline. *: Re-implementation

| Method                  | F1  | B1  | B2  | B3  | B4  | B5  |
|-------------------------|-----|-----|-----|-----|-----|-----|
| (Unsupervised)          |     |     |     |     |     |     |
| Unedited                | 63.2| 44.8| 34.9| 28.3| 23.5| 32.9|
| Random                  | 45.7| 43.0| 25.4| 16.2| 10.4| 23.8|
| PPL-based (Niu et al., 2019) | 50.0|     |     |     |     |     |
| PPL-based*              | 52.3| 45.9| 35.5| 19.9| 14.7| 29.0|
| NDD-based (ours)        | 67.4| 54.8| 39.3| 30.5| 23.7| 37.3|
| (Supervised)            |     |     |     |     |     |     |
| (Filippova et al., 2015)| 82.0|     |     |     |     |     |
| (Kamigaito et al., 2018)| 85.1|     |     |     |     |     |
| (Zhan et al., 2018)     | 85.8|     |     |     |     |     |
| (Kamigaito and Okumura, 2020) | 85.5|     |     |     |     |     |

Table 2: Results for sentence compression on the Google dataset, we compare our algorithm with other unsupervised algorithms. Underlines mean the improvement to be significant \((p < 0.05)\) considering the highest baseline. *: Re-implementation

\[ b_k = \nu^k \]

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

### 4.5 Compression Cases

#### Real Effect vs. Automatic Metrics

As the compressed results for sentences can be various, automatic metrics might not be able to fully reflect the compressing ability of our algorithm. Also, as our compression follows a training-free procedure, the compressed results might not be in the same style as the annotated golden ones like the first instances in Table 3. Both our compressed and the golden result keep the main point that the speed limit will be 70 mphs, preserving the semantics of the whole sentence. However, the golden compression tends to keep some auxiliary information like the location on highways in Illinois and the time next year. In contrast, NDD-based compression tends to remove those unimportant information and prevent...
A US$5 million fish feed mill with an installed capacity of 24,000 metric tonnes has been inaugurated at Prampram, near Tema, to help boost the aquaculture sector of the country.

We further analyze our metric and algorithm on compression until we get a fully satisfying output. We also implement algorithm for other languages to verify the cross-lingual capability of NDD-based compression.

Compress compression and fluency while removing unimportant and auxiliary components at the same time.

Outputs from Compression Iterations We present the intermediate outputs of our algorithm in Table 4. NDD-based text compression is shown to be capable of detect and remove auxiliary components like locations or adjective spans in the sentence for example. Also, the syntactic integrity and initial semantics are preserved in each iteration of our algorithm. There is an advantage over supervised methods as output in each iteration is still a plausible compression for the initial sentence. We can thus set some proper thresholds and iterate the compression until we get a fully satisfying output.

Compression on Other Languages We also implement algorithm for other languages to verify the cross-lingual capability of NDD-based compressing. Cases in Table 5 show our algorithm to be pretty well-performed on compression of other languages.

5 Syntactic Dependency Tree Pruning

We further analyze our metric and algorithm on upstream tasks. To show that NDD understands semantics, we first verify NDD’s awareness of syntax since semantics is highly dependent on syntax. In this section, we continue experimenting on the mentioned compression algorithm to use it to prune syntactic dependency treebanks and then analyze the distribution of pruned nodes. If the pruned nodes mostly play subordinated roles in the tree, our algorithm can be better convinced to compress sentences with the awareness of syntax.

We first give an example for the syntactic dependency treebank in Figure 3, the depths of nodes in the tree are also annotated. In the dependency tree, deeper nodes like the and early contain less semantic information and should be more likely to be pruned in a well-performed compression algorithm. Also, pruning subtrees of the dependency tree is less likely to hinder the syntactic integrity of the sentence. For instance, pruning the subtree since the early 1970s will still preserve the syntactic structure of the rest components That would be the lowest level.

Therefore, we introduce two metrics to evaluate the pruning ability for words and spans. The first one is Depth-n, which evaluates the proportion in all pruned words of words in a depth n of the dependency tree. The second one is Subtree-n, which refers to the proportion of spans which are also subtrees of dependency trees in pruned n-gram spans. Higher Depth-n for larger n and lower Depth-n for smaller n indicates better preservation of the syntactic structure. Higher Subtree-n indicates the pruned spans result in less damage to the syntactic integrity.

We experiment on the test data of PTB-3.0 dataset (Marcus et al., 1993). We randomize our
algorithm as before for a fair comparison with the same compressing rate. For our algorithm in different configuration, we implement a corresponding randomized algorithm for preciser comparison. As in Table 6, the awareness of syntax is verified for both node and span pruning. First, the proportion of nodes in shallower levels (depth=1 ~ 3) pruned by our algorithm are smaller than all the corresponding proportion when pruned nodes are randomized. NDD-based pruning is more likely to prune deeper nodes (depth≥ 4) in the syntactic dependency tree. Also, the proportion of subtrees in spans pruned by NDD-based algorithm is significantly larger (30 ~ 50) than the randomized correspondents. Thus, we conclude that NDD is able to guide the compressing algorithm to detect subordinated components in syntax dependency treebanks even though the PLM has never been trained on any syntactic datasets.

For comparison among different configurations, a lower $NDD_{max}$ will lead both node and span pruning to improve. This is natural as the lower threshold will only allow the algorithm to prune components with little disturbance to semantics. For $L_{max}$, when $NDD_{max}$ is low, a higher $L_{max}$ will improve the node pruning by pruning more auxiliary components in deeper levels. For instance, long spans like since the early 1970s in Figure 3 might not be detected when $L_{max}$ is low. But for a higher $NDD_{max}$, $L_{max}$ will lead to higher proportion of subtrees in pruned spans as higher $L_{max}$ may allow longer spans which are not subtrees to be pruned.

6 Predicate Detection

As pruning on the syntax dependency treebanks shows our NDD to have the understanding of syntax, we further explore the discerning ability of NDD for semantic components on large datasets. We choose to experiment on the semantic role labeling (SRL) dataset for predicate detection. In the experiment, words in the sentence are edited by deletion or replacement and semantics changes caused by these editions are evaluated using NDD. As predicates are semantically related to more components (augments) in the sentence, higher NDD refers to higher probability of an edited word to be a predicate. Thus, we evaluate the predicate detecting ability following with the words ranking task. We rank the probability of words to be predicates and use ranking metrics mean average precision (mAP) and area under curve (AUC) for evaluation.

We conduct our experiments on Conll09 SRL datasets (Hajic et al., 2009). To test the generalizing ability of our method, we experiment on both in-domain (ID) and out-of-domain (OOD) English (ENG) datasets. Another Spanish (SPA) dataset is also involved for cross-language evaluation. We edit each word in the sentence in three ways: (a) Directly delete the word, (b) Replace the word with a mask token, (c) Replace the word with a certain word (a for ENG-ID, that for ENG-OOD and el for SPA). We apply SpanBERT-base-cased (Joshi et al., 2020) and BERT-base-spanish-cased (Cañete et al., 2020) as PLMs. For comparison, we also implement a PPL-based algorithm which likewise uses perplexity to determine predicates.

Our main results are presented in Table 7, showing that PPL might not be a proper metric to detect predicates as AUCs that result from PPL-based algorithm are around 40 ~ 60 and mAPs are generally poor. In contrast, NDD-based algorithm produces much better results and outperforms PPL-based algorithm by 10 ~ 20 scores on both AUC and mAP metrics, which is a remarkably significant margin and verifies NDD to be much more capable in understanding semantics. We also ensemble
Table 7: Evaluation on ability of metrics to detect predicates in sentences. *We use a for replacement in ENG-ID, that in ENG-OOD and el in SPA, those words empirically perform well for predicate detection.

| Edition          | ENG-ID | ENG-OOD | SPA   |
|------------------|--------|---------|-------|
|                  | mAP    | AUC     | mAP   | AUC   |
| (NDD-based)      |        |         |       |
| Delete           | 52.1   | 75.8    | 80.7  | 77.0  |
| Replace by mask  | 48.2   | 74.6    | 80.2  | 76.3  |
| Replace by word* | 51.6   | 77.2    | 78.5  | 77.5  |
| Ensemble         | 54.3   | 80.0    | 83.8  | 83.0  |
| (PPL-based)      |        |         |       |
| Delete           | 36.8   | 56.8    | 60.4  | 54.5  |
| Replace by mask  | 35.9   | 56.7    | 33.1  | 25.1  |

The three editions by using the product of three predicted probabilities. The ensembled algorithm leads to further improvement and lifts AUC, mAP to higher than 80.0, 50.0 respectively, even making it a plausible way to detect predicates following an unsupervised procedure.

Comparison among editions shows that direct deletion will lead to the better performance than other editions evaluated by AUC. Replacing with a certain word perform better on ENG-ID and SPA when we evaluate algorithms with the mAP. Thus, we conclude that deleting predicates causes the greatest disturbance on other components (augments) in the sentence and makes the disturbance more prominent for our algorithm to detect. Also, as a, that and el may empirically outperform other words when being used to detect predicates, those words with low semantic meanings might be advisable choices for predicate detection using word replacement.

7 Related Works

Text similarity and perplexity are metrics which can be used for many downstream tasks (Park et al., 2020; Lakshmi and Baskar, 2021; Nguyen-Son et al., 2021; Campos et al., 2018; Neishabouri and Desmarais, 2020; Lee et al., 2021). Unfortunately, these metrics are not precise enough to detect semantics changes. Conventional text similarity is highly relied on its each word component for cosine function to calculate. Perplexity can evaluate the fluency of sentences, but still not capable of detecting semantic difference between sentences. Also, recent study (Kuribayashi et al., 2021) shows that low perplexity does not directly refer to a human-like sentence. Therefore, we should consider again how to evaluate subtle text difference like semantic shift caused by an edition on the text.

Therefore, we assume PLM like BERT (Devlin et al., 2019) to be a chance for some changes. Recently, PLM-based metrics like BERT score has been verified by experiments to evaluate text generation better (Zhang et al., 2020). Instead of matching words exactly, BERT score compute pairwise cosine similarity between words in texts and use greedy matching for the final scoring. Our NDD also puts real words aside but uses distributions predicted from MLM to represent words. We use KL divergence to estimate the semantic difference between texts.

Sentence compression is currently dominated by supervised methods (Malireddy et al., 2020; Nguyen et al., 2020; Nóbrega et al., 2020) and highly relies on syntactic dependency trees (Le et al., 2019; Xu and Durrett, 2019b; Wang and Chen, 2019; Kamigaito and Okumura, 2020). Unsupervised methods have been explored to extract sentences from documents to represent the key points (Jang and Kang, 2021). But the performance on pruning components in sentences is still far from satisfaction. (Niu et al., 2019) explores evaluating the perplexity of outputs after compression. However, such metric is not able to detect semantics changes in editions and thus cannot preserve the semantics. As our proposed NDD metric is aware of semantics, we show it plausible to compress sentences following an unsupervised procedure.

Annotated data from parsing tasks like syntactic dependency parsing (Dozat and Manning, 2017; Li et al., 2020b) and semantic role labeling (Li et al., 2020a,c) can reflect model’s awareness of those internal relationships between words in sentences. Experiments show our NDD to perform well on detecting those relationships. Thus, we may explore unsupervised procedures for those tasks based on NDD in the future.

8 Conclusion

In this paper, we propose a novel metric, neighboring distribution divergence, to evaluate very precise semantics changes caused by editions. We implement an unsupervised and training-free algorithm for text compression and find that NDD-based algorithm outperforms PPL-based algorithm by a large margin. Also, NDD-based text compression can still produce highly semantics-preserved outputs even when human-annotated data cause automatic metrics to be biased. We further explore for whether NDD has a real awareness of semantics...
and verify our hypothesis as NDD perform well for both syntactic dependency treebank pruning and predicate detection in semantic role labeling. Experiments show NDD to have the potential to realize an unsupervised predicate detection.

References

José Ramom Pichel Campos, Pablo Gamallo, and Iñaki Alegría. 2018. Measuring language distance among historical varieties using perplexity. Application to European Portuguese. In Proceedings of the Fifth Workshop on NLP for Similar Languages, Varieties and Dialects, VarDial@COLING 2018, Santa Fe, New Mexico, USA, August 20, 2018, pages 145–155. Association for Computational Linguistics.

José Cañete, Gabriel Chaperon, Rodrigo Fuentes, Jou-Hui Ho, Hojin Kang, and Jorge Pérez. 2020. Spanish pre-trained bert model and evaluation data. In PML4DC at ICLR 2020.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2–7, 2019, Volume 1 (Long and Short Papers), pages 4171–4186. Association for Computational Linguistics.

Timothy Dozat and Christopher D. Manning. 2017. Deep biaffine attention for neural dependency parsing. In 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings. OpenReview.net.

Katja Filipova, Enrique Alfonseca, Carlos A. Colmenares, Lukasz Kaiser, and Oriol Vinyals. 2015. Sentence compression by deletion with lstms. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015, pages 360–368. The Association for Computational Linguistics.

Jan Hajic, Massimiliano Ciaramita, Richard Johanson, Daisuke Kawahara, Maria Antônia Martl, Luís Márquez, Adam Meyers, Joakim Nivre, Sebastian Padó, Jan Stepánek, Pavel Stránský, Mihai Surdeanu, Nianwen Xue, and Yi Zhang. 2009. The conll-2009 shared task: Syntactic and semantic dependencies in multiple languages. In Proceedings of the Thirteenth Conference on Computational Natural Language Learning: Shared Task, CoNLL 2009, Boulder, Colorado, USA, June 4, 2009, pages 1–18. ACL.

Mengzuo Huang, Feng Li, Wuhe Zou, and Weidong Zhang. 2021. SARG: A novel semi-autoregressive generator for multi-turn incomplete utterance restoration. In Thirty-Fifth AAAI Conference on Artificial Intelligence, AAAI 2021, Thirty-Third Conference on Innovative Applications of Artificial Intelligence, IAAI 2021, The Eleventh Symposium on Educational Advances in Artificial Intelligence, EAAI 2021, Virtual Event, February 2-9, 2021, pages 13055–13063. AAAI Press.

Myeongjun Jang and Pilsung Kang. 2021. Learning-free unsupervised extractive summarization model. IEEE Access. 9:14358–14368.

Mandar Joshi, Danqi Chen, Yinhui Liu, Daniel S. Weld, Luke Zettlemoyer, and Omer Levy. 2020. Spanbert: Improving pre-training by representing and predicting spans. Trans. Assoc. Comput. Linguistics, 8:64–77.

Hidetaka Kamigaito, Katsuhiko Hayashi, Tsutomu Hirao, and Masaaki Nagata. 2018. Higher-order syntactic attention network for longer sentence compression. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers), pages 1716–1726. Association for Computational Linguistics.

Hidetaka Kamigaito and Manabu Okumura. 2020. Syntactically look-ahead attention network for sentence compression. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020, pages 8050–8057. AAAI Press.

Tatsuki Kuribayashi, Yohei Oseki, Takumi Ito, Ryo Yoshida, Masayuki Asahara, and Kentaro Inui. 2021. Lower perplexity is not always human-like. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021, pages 5203–5217. Association for Computational Linguistics.

R. Lakshmi and S. Baskar. 2021. Efficient text document clustering with new similarity measures. Int. J. Bus. Intell. Data Min., 18(1):49–72.

Hoa T. Le, Christophe Cerasara, and Claire Gardent. 2019. RL extraction of syntax-based chunks for sentence compression. In Artificial Neural Networks and Machine Learning - ICANN 2019, Text and Time Series - 28th International Conference on Artificial Neural Networks, Munich, Germany, September 17-19, 2019, Proceedings, Part IV, volume 11730 of Lecture Notes in Computer Science, pages 337–347. Springer.
Nayeon Lee, Yejin Bang, Andrea Madotto, and Pascale Fung. 2021. Towards few-shot fact-checking via perplexity. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6–11, 2021, pages 1971–1981. Association for Computational Linguistics.

Tao Li, Parth Anand Jawale, Martha Palmer, and Vivek Srikumar. 2020a. Structured tuning for semantic role labeling. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020, pages 8402–8412. Association for Computational Linguistics.

Zuchao Li, Hai Zhao, and Kevin Parnow. 2020b. Global greedy dependency parsing. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020, pages 8319–8326. AAAI Press.

Zuchao Li, Hai Zhao, Rui Wang, and Kevin Parnow. 2020c. High-order semantic role labeling. In Findings of the Association for Computational Linguistics: EMNLP 2020, Online Event, 16–20 November 2020, volume EMNLP 2020 of Findings of ACL, pages 1134–1151. Association for Computational Linguistics.

Qian Liu, Bei Chen, Jian-Guang Lou, Bin Zhou, and Dongmei Zhang. 2020. Incomplete utterance rewriting as semantic segmentation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16–20, 2020, pages 2846–2857. Association for Computational Linguistics.

Chanakya Malireddy, Tirth Maniar, and Manish Shri-vastava. 2020. SCAR: sentence compression using autoencoders for reconstruction. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop, ACL 2020, Online, July 5-10, 2020, pages 88–94. Association for Computational Linguistics.

Mitchell P. Marcus, Beatrice Santorini, and Mary Ann Marcinkiewicz. 1993. Building a large annotated corpus of english: The penn treebank. Comput. Linguistics, 19(2):313–330.

Asana Neishabouri and Michel C. Desmarais. 2020. Reliability of perplexity to find number of latent topics. In Proceedings of the Thirty-Third International Florida Artificial Intelligence Research Society Conference, Originally to be held in North Miami Beach, Florida, USA, May 17-20, 2020, pages 246–251. AAAI Press.

Thi-Trang Nguyen, Huu-Hoang Nguyen, and Kiem-Hieu Nguyen. 2020. A study on seq2seq for sentence compression in vietnamese. In Proceedings of the 34th Pacific Asia Conference on Language, Information and Computation, PACLIC 2020, Hanoi, Vietnam, October 24-26, 2020, pages 488–495. Association for Computational Linguistics.

Hoang-Quoc Nguyen-Son, Tran Thao Phuong, Seira Hidano, Ishita Gupta, and Shinsaku Kiyomoto. 2021. Machine translated text detection through text similarity with round-trip translation. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021, pages 5792–5797. Association for Computational Linguistics.

Tong Niu, Caiming Xiong, and Richard Socher. 2019. Deleter: Leveraging BERT to perform unsupervised successive text compression. CoRR, abs/1909.03223.

Fernando António Asevedo Nóbrega, Alípio M. Jorge, Pavel Brazdil, and Thiago A. S. Pardo. 2020. Sentence compression for portuguese. In Computational Processing of the Portuguese Language - 14th International Conference, PROPOR 2020, Evora, Portugal, March 2–4, 2020, Proceedings, volume 12037 of Lecture Notes in Computer Science, pages 270–280. Springer.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Kwang-Il Park, June Seok Hong, and Wooju Kim. 2020. A methodology combining cosine similarity with classifier for text classification. Appl. Artif. Intell., 34(5):396–411.

Yifan Wang and Guang Chen. 2019. Improving a syntactic graph convolution network for sentence compression. In Chinese Computational Linguistics - 18th China National Conference, CCL 2019, Kunming, China, October 18-20, 2019, Proceedings, volume 11856 of Lecture Notes in Computer Science, pages 131–142. Springer.

Jiacheng Xu and Greg Durrett. 2019a. Neural extractive text summarization with syntactic compression. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 3290–3301. Association for Computational Linguistics.

Jiacheng Xu and Greg Durrett. 2019b. Neural extractive text summarization with syntactic compression. In Proceedings of the 2019 Conference on
Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. BERTscore: Evaluating text generation with BERT. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net.

Yang Zhao, Zhiyuan Luo, and Akiko Aizawa. 2018. A language model based evaluator for sentence compression. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 2: Short Papers, pages 170–175. Association for Computational Linguistics.