Demystifying Neural Language Models’ Insensitivity to Word-Order

Louis Clouâtre\textsuperscript{1,3} Prasanna Parthasarathi\textsuperscript{2,3} Amal Zouaq\textsuperscript{1} and Sarath Chandar \textsuperscript{1,3,4}
\textsuperscript{1} Polytechnique Montréal
\textsuperscript{2} School of Computer Science, McGill University
\textsuperscript{3} Quebec Artificial Intelligence Institute (Mila)
\textsuperscript{4} Canada CIFAR AI Chair

Abstract

Recent research analyzing the sensitivity of natural language understanding models to word-order perturbations have shown that the state-of-the-art models in several language tasks may have a unique way to understand the text that could seldom be explained with conventional syntax and semantics. In this paper, we investigate the insensitivity of natural language models to word-order by quantifying perturbations and analysing their effect on neural models’ performance on language understanding tasks in GLUE benchmark. Towards that end, we propose two metrics — the \textit{Direct Neighbour Displacement} (DND) and the \textit{Index Displacement Count} (IDC) — that score the local and global ordering of tokens in the perturbed texts and observe that perturbation functions found in prior literature affect only the global ordering while the local ordering remains relatively unperturbed. We propose perturbations at the granularity of sub-words and characters to study the correlation between DND, IDC and the performance of neural language models on natural language tasks. We find that neural language models — pretrained and non-pretrained Transformers, LSTMs, and Convolutional architectures — require local ordering more so than the global ordering of tokens. The proposed metrics and the suite of perturbations allow a systematic way to study the (in)sensitivity of neural language understanding models to varying degree of perturbations.

1 Introduction

Large pretrained (PT) models have become an inevitability in modern Natural Language Processing (NLP) applications (Vaswani et al., 2017; Devlin et al., 2018; Radford et al., 2019; Liu et al., 2019c; Lewis et al., 2020; Brown et al., 2020; Peters et al., 2018; Howard and Ruder, 2018). Pretraining techniques such as Masked Language Modeling (MLM) and Causal Language Modeling (CLM) have aided in making the best use of language statistics learned from large corpora to achieve improved performance on several NLP benchmarks (Socher et al., 2013; Bar Haim et al., 2006; Dagan et al., 2006; Dolan and Brockett, 2005; Agirre et al., 2007; Wang et al., 2019b,a; Warstadt et al., 2018; Williams et al., 2018; Rajpurkar et al., 2016b; Giampiccolo et al., 2007; Bentivogli et al., 2009; Levesque et al., 2011; Rajpurkar et al., 2016a, 2018). With the increase in applications of these large models also came a growing interest in evaluating the way these models learn to solve natural language tasks.

Research has shown that large models do have an understanding of well-formed English syntax in recurrent neural networks, convolutional neural networks, and in large PT Transformers (Gulordava et al., 2018; Zhang and Bowman, 2018; Chrupała and Alishahi, 2019; Lin et al., 2019a; Belinkov and Glass, 2019; Liu et al., 2019a; Jawahar et al., 2019; Rogers et al., 2020). More recent studies, however, take a critical stance with experiments suggesting that models may be insensitive to word-order perturbations. Pham et al. (2020); Sinha et al. (2021, 2020); Gupta et al. (2021); O’Connor and Andreas (2021) show that shuffled word-order have little to no impact during training or inference with neural language models. While, some research show that models learn some abstract notion of syntax, further probing into their insensitivity to the perturbation of syntax is necessary. Specifically, \textit{What are the underlying mechanisms causing those unintuitive, or unnatural (Sinha et al., 2020), results from neural models} is still a largely unanswered question.

Recent research exploring the sensitivity to syntax of pretrained models have mostly been applying perturbations to text through perturbing the order of words. Perturbations applied and quantified at this granularity of text offer only a limited understanding to the learning dynamics of the large architec-
The scholar is typesetting.

scholar typesetting is The.

schotyp eset Thelar tingis.

chlorse Thn ypsitetning es.

Figure 1: Perturbations applied at different granularities of text are shown: (from top to bottom) original text, word-level perturbed text, subword-level perturbed text, and character-level perturbed text.

Analysing perturbations at a finer granularity such as subwords (Bojanowski et al., 2017) or characters (Gao et al., 2018; Ebrahimi et al., 2017), may provide a deeper insight into the insensitivity of neural models. Consider Figure 1, which shows an unperturbed sentence, a word-level perturbed sentence, a subword-level perturbed sentence, and a character-level perturbed sentence. An average reader may find it possible to parse and infer the meaning up to the word-level perturbed sentence, but would have issues inferring any meaning from subword and character-level perturbed text.

In this paper, we define two types of structure in text, global which relates to the absolute position of characters, and local, which relates to the relative position of characters to their immediate neighbors. We observe from experiments in the paper that most perturbations proposed and analyzed in the literature often perturb the global structures well with different reordering of words, while the amount of disturbance to the local structure remains limited, thus preserving most of the local structure. We hypothesize that the local structure enables understanding in natural language tasks and effectively perturbing this structure aids in analyzing the sensitivity of neural models in language tasks. We, hence, propose two new metrics, the Index Displacement Count metric (IDC) and the Direct Neighbour Displacement metric (DND), to measure the amount of perturbation to the global and local structures of text respectively.

Our contributions are as follows:

- We propose two metrics, IDC (global) and DND (local), to measure the perturbations on global and local structures of text.
- We show that the performance of neural models – Transformers and others – to perturbed input has a strong correlation with the proposed DND metric.
- We observe that DND has a strong correlation with GLUE scores across different architectures, suggesting that neural language understanding models generally are sensitive to distortions in local structures moreso than global structures.
- We show that commonly used lexical perturbations distort the global structures and seldom affect the local structures explaining the insensitivity of large models to such perturbations.
- We show that DND has a weak correlation to other metrics – BLEU, Levenshtein – indicating that the common metrics used for evaluation do not measure the dimension captured by DND.
- We find that the lack of correlation to performance of non-pretrained Transformers to IDC is useful in detecting when models do not make use of the positional information present in text, defaulting to bag-of-word models.

2 Related Work

Importance of syntax Discussions on semantics (Culbertson and Adger, 2014; Futrell et al., 2020) agree on specific orders of words to be necessary for comprehending the text. Psycholinguistic research (Hale, 2017) corroborates this through evaluating sentence comprehension mechanisms of humans. Hence, interpreting language as a bag-of-words could limit the expressions conveyed through the word-orders (Harris, 1954; Le and Mikolov, 2014) and understanding syntax becomes an essential artifact.

Prior works have explored the relationship between neural models and syntax. Goldberg (2019); Hewitt and Manning (2019) both show that BERT (Devlin et al., 2018) models have some syntactic capacity. Lin et al. (2019b) show that BERT represents information hierarchically and conclude that BERT models linguistically relevant aspects in

1 Structure here relates to the organization of characters in the text.

2 There is a wordplay in the naming of the metrics. IDC: standing for I Don’t Care and DND: Do Not Disturb in internet slang is used to identify the metric the neural models cares the most about in language tasks and the one it does not.

3 Preference to a specific word-order over the other and the preference complying with the choices of an average human speaking that language.
a hierarchical structure. Tenney et al. (2019); Liu et al. (2019b) show that the contextual embeddings that BERT outputs contain syntactic information that could be used in downstream tasks.

While it seems that syntax is both important, and to an extent, understood by the recent family of PT models, it is unclear how much use they make of it. Glavaš and Vulić (2020) showed that pretraining BERT on syntax does not seem to improve downstream performance much. Warstadt et al. (2020) showed that while models such as BERT do understand syntax, they often prefer not to use that information to solve tasks. Ettinger (2020); Pham et al. (2019); Sinha et al. (2020); Gupta et al. (2021) show that large language models are insensitive to minor perturbations highlighting the lack of syntactic knowledge used in syntax rich NLP tasks. Sinha et al. (2021) show that pretraining models on perturbed inputs still obtain reasonable results on downstream tasks, showing that models that have never been trained on well-formed syntax can obtain results that are close to their peers.

While syntactic information seems vital to language, and large PT models seem to be at least aware of syntax, the lack of sensitivity of neural models to perturbation of syntax motivates further probing.

**Text Similarity Metrics** Several popular similarity metrics can be used to measure perturbations. Metrics like BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004) will treat text as a sequence of words, from which a measure of overlap is computed. The Levenshtein distance (Levenshtein, 1966; Yujian and Bo, 2007), or the edit distance, measures the minimum amount of single character edits (insertions, deletions or substitutions) necessary to match two strings together. Parthasarathi et al. (2021) observed that learned metrics like BERT-Score (Zhang et al., 2019) and BLEURT (Sellam et al., 2020) are often unaffected by minor perturbations in text which limits their usefulness in measuring perturbations. Sinha et al. (2020) propose a POS mini-tree overlap score to interpret the results of the perturbation analysis. The score computes the part-of-speech (PoS) tags neighborhood for every word and estimates an average overlap in the neighborhood for all the tokens before and after applying the perturbation. The authors, however, find that the working range of the proposed metric to be small and explain the effect only for PT Transformer architectures.

**Text Perturbations** Several different types of reordering perturbation functions and schemes have been explored to understand and study the (in)sensitivity of neural architectures to word-order. The class of perturbation analysis could broadly be split into three categories that involves – deletion, paraphrase injection and/or reordering of tokens. Sankar et al. (2019) explore utterance and word-level perturbations applied to generative dialogue models to highlight their insensitivity to the order of conversational history. On natural language classification tasks, Pham et al. (2020) define n-grams for different values of n and shuffle them to highlight the insensitivity of pretrained models. They show that shuffling larger n-grams have a lesser effect than shuffling smaller n-grams, hinting that preserving more local structure causes less degradation in performances. Studying textual entailment tasks, Sinha et al. (2020) perform perturbations on the position of the words, with a criteria that no word remains in its initial position.

Hsieh et al. (2019) propose a suite of adversarial attacks that replace one word in the input to cause a model to flip its correct prediction. Gupta et al. (2021) combine several types of destructive transformations — such as sorting, reversing, shuffling words — towards removing all informative signal in a text. Along similar lines, Wang et al. (2019c) inject noise by reordering articles or deleting minimally towards injecting artificial noise to measure the robustness of pretrained language models. Character-level perturbations that perform minimal flips to cause a degenerate response have been explored by Ebrahimi et al. (2017); Gao et al. (2018). Gao et al. (2018) quantify the perturbation in Levenshtein distance and draw a correlation to the model’s performance. This work is closely related to our own. We, however, demonstrate that our proposed metric is a much more robust explanation of the degradation in performance of models than the Levenshtein distance.

Although the recent literature on perturbation analysis in PT language models was able to observe the extremes — sensitivity and insensitivity, understanding the attributes of text to which PT models and others are sensitive to requires a detailed study. We speculate that the perturbation analyses done at the granularity of sub-words and characters is necessary for properly probing the neural models’ insensitivity to word-order phenomenon. Likewise, a generic score quantifying the amount of perturba-
We define two metrics — the *D* with respect to the position of the *c* would imply that characters in the perturbed text have moved 30% of the text length on average. The values of *IDC* will lie in the range $[0,0.5]$, where 0.5 would be obtained by reversing a text at the character level.

### 3.1 IDC

Let a string, $x_i = (c_i)_k$, be denoted by a sequence of characters $c_0, \ldots, c_k$, where $k$ is the length of the string in characters and $p^i$ denote the positions of characters in $x_i$. Let $\eta(\cdot)$ be a perturbation operation.

$$x'_i \leftarrow \eta(x_i),$$

where $x'_i$ denote the perturbed string with positions of the characters specified by $p'^i$.

$$\text{IDC} \leftarrow \frac{1}{k^2} \sum_{j=1}^{k} \left\| p'^i(j) - p^i(j) \right\|_1 \tag{2}$$

The denominator $k^2$ normalizes the average by the length of the text $k$. Intuitively, an IDC of 0.3 would imply that characters in the perturbed text have moved 30% of the text length on average. The values of IDC will lie in the range $[0,0.5]$, where 0.5 would be obtained by reversing a text at the character level.

### 3.2 DND

For every $c_j$, let $\mathcal{N}^x(c_j,R)$ indicate the relative position of the right neighbor (R) of character $c_j$ with respect to the position of $c_j$ in string $x_i$. Then, DND is computed as a summation over an indicator variable that indicates when the neighbor to the right of $c_i$ has shifted to a different position in $x'_i$.

$$\text{DND} \leftarrow \frac{1}{k-1} \sum_{j=1}^{k-1} \left[ \mathcal{N}^x(c_j,R) \neq \mathcal{N}'^x(c_j,R) \right] \tag{3}$$

DND measures the amount of distortions that happened to the local neighborhood of every character. Intuitively, a DND of 0.3 would imply that 30% of characters in the perturbed text are no longer followed by their immediate neighbouring character in the unperturbed text. The values of DND will lie in the range $[0,1]$, where 1 can be obtained by removing every single neighborhood relation.

### 4 Perturbation Functions

Towards conducting a detailed analysis on the effect of perturbations on performance of neural language models, we define three granularities of perturbation functions — *word-level*, *subword-level* and *character-level*. The subwords are taken from the RoBERTa-Base vocabulary. We define the perturbation functions as generic operations that can be applied across the different levels of granularity. Pseudo-code and examples for all perturbations are shown in Appendix B.

**Full-shuffling** randomly shuffles the position of every word, sub-word, or character, according to the level it is applied to. This transformation should cause a great amount of perturbation to the *global* and *local* structure for the specific granularity.

**Phrase shuffling** creates chunks of contiguous tokens of variable length and shuffles the phrases of word, subword, or characters. This perturbation has, on average, the same impact as the full shuffling on the *global* structure as the absolute positions of characters tend to change just as much as full shuffling while having a lesser impact on the *local* structure.

Unlike the full-shuffling operation, phrase shuffling uses a parameter $\rho$ that controls the average size of the randomly defined contiguous chunks.
The scholar is typesetting.
is typesetting lar.

Figure 3: Subword-level phrase shuffling. The perturbed sentence has an IDC of 0.35 and a DND of 0.19. This example can be compared with Figure 2 in that the two have the same DND scores but different IDC scores.

of tokens. To randomly define our phrases, we traverse the text sequentially on the desired granularity. The entire text is assumed as a single large phrase and is truncated at a token with probability $\rho$ into smaller phrases.

The lower the value of $\rho$ is, the longer, on average, the phrases are, thus preserving more of the local structure while destroying roughly the same amount of global structure. In the extreme case with $\rho = 1.0$, phrase shuffling will be equivalent to full shuffling as phrases will all be one token long.

**Neighbour flip perturbations** flip tokens of the chosen granularity with the immediate right neighbor with probability, $\rho$. This function has, on average, a smaller impact on the global structure, as the absolute positions of tokens do not change much but can have an arbitrary large effect on disturbing the local structure.

The perturbation is applied by traversing the string from left-to-right on the desired granularity and, with a probability $\rho$, switching the current attended token with the following token. The lower the $\rho$ is, the less perturbation happens, thus preserving more of the local structure. This transformation never has a large impact on the global metric, thus letting us isolate the impact of perturbations to the different structures.

**Models** We experiment on neural architectures with different inductive biases — BiLSTMs (Schuster and Paliwal, 1997), ConvNets, PT Transformers (RoBERTa-Base and BART-Base), and a Non-Pretrained (NPT) Transformer (RoBERTa-Base architecture). We also experiment with different tokenization schemes, using byte-pair encoding as well as character-level tokenization. All training, finetuning and evaluation are done on the perturbed version of the dataset. The tokenization for PT Transformer models use their corresponding vocabulary, while NPT models use RoBERTa-Base vocabulary and the character-level models use exclusively characters as vocabulary.

The primary objectives of the experiments are to: (1) understand if different degrees of perturbations affect the models alike, (2) verify if correlation exists between the performance across different NLU tasks and the amount of perturbation measured by DND and IDC, (3) investigate the different perturbation operations used in the literature and their distribution on our proposed metrics, and (4) understand if the pretraining of models is important to the studied phenomenon.

---

6The hyperparameters used for the perturbation functions are detailed in Appendix A.

7The training details can be found in Appendix A. Code to reproduce the results is available in GitHub.
6 Analysis

6.1 Correlation with other metrics
Towards estimating the relationship the proposed metrics — IDC and DND — have with the existing metrics — BLEU and Levenshtein —, we compute pairwise \( \rho \)-correlation among the metrics averaged across all samples in the GLUE validation set in Figure 5\(^8\). Specifically, for every sample in the validation set of the tasks, we perturb them using the different perturbation functions and compute their scores with the different metrics.

Figure 5: Correlation matrix between the different metrics on the GLUE tasks shows that the proposed two metrics have no correlation between them, suggesting that the two indeed measure orthogonal components of the perturbed texts. Further, DND has a moderate to weak correlation with BLEU and Levenshtein distance suggesting that DND measures a different component that is not measured by the other metrics.

We observe that IDC and DND are uncorrelated suggesting that the metrics measure different aspects of the perturbations. Further, we observe that DND only has a weak correlation with BLEU and Levenshtein, indicating that DND measures a previously unmeasured dimension of the structure and similarity in texts.

6.2 Comparison of Perturbation Functions
We populate an assorted list of perturbation functions analyzed by Parthasarathi et al. (2021) that can be applied to examples in GLUE tasks. The 16 different word-level perturbations are categorized as PoS-Tag perturbations, Dependency Tree perturbations, and Random shuffles that include perturbing with different traversal orders of dependency tree — Pre-Order, Post-Order or In-Order —, swapping verbs, adverbs, nouns in a text, reversing sentences among other perturbations.

We perturb the samples across GLUE tasks for every perturbation function, compute the scores with the metrics and compare with the perturbations defined in § 4. The distribution of scores measured by BLEU and Levenshtein covers the entire range of values for most of the word-level functions (shown in Figure 14). While the distribution of scores computed by DND for the different perturbations functions shown in Figure 6 indicates that the word-level and subword-level perturbations have a limited impact on the local structure.

No surprise but, we found BLEU to be uninterpretable when the perturbations were done at character or subword level rendering it ineffective for our study. Although Levenshtein does better in that regard, we observe DND metric to strongly correlate with model performance on perturbed samples (in §6.3). The analysis provides a reasonable explanation to the insensitivity observed due to word-level perturbations studied in the literature (Sinha et al., 2020; Pham et al., 2020; Gupta et al., 2021).

6.3 IDC/DND vs GLUE tasks
We compute the average GLUE score of different models on validation data perturbed with different functions to cover the range of DND score as shown in Figure 8. We observe the general trend to be that the proposed DND metric has a strong correlation with neural models’ loss in performance on the GLUE benchmark tasks (Figure 7). By computing a correlation between the performance of the different models on the perturbed samples and a measure of perturbation as estimated by the different metrics (Figure 13), we see that the correlation with DND holds for every single architecture and setting tested. On the other hand, IDC is only weakly correlated with performance decay. This implies that local structure, moreso than global structure, is necessary for models to understand text. The Levenshtein distance and the BLEU metric both hold some explanatory power, but do not show a monotonically increasing or decreasing performance which limits the usefulness of those measures. For example, A model being evaluated on a perturbed text with a DND of 0.5 can be assumed to have much lower performance than on a per-

\(^8\)For every correlation, we inverted the value of DND, IDC, and the Levenshtein distance by subtracting the value from 1 to make the comparison of the different correlations more straightforward. They are a measure of perturbation and not similarity and are therefore inversely correlated to the GLUE score.
Figure 6: We analyse different perturbations discussed in the literature with the proposed metrics — IDC and DND. The two plots show the distribution of the scores defined by the metrics over $\in [0, 1]$. In (a), one can observe the distribution of scores for different word-level perturbations that they mostly impact IDC and the distribution of DND remains roughly in the range $\in [0, 0.2]$. In (b), the proposed perturbation operations on character granularity impact the full range of possible DND values. Note: W = Word-level, S = Subword-level, C = Character-level. FS = Full Shuffle, NF = Neighbour Flip, PS = Phrase Shuffle.

Figure 7: Plotted are the relation between the different choices of metrics measuring the amount of perturbation and the performance of PT RoBERTa-Base model finetuned and tested on the perturbed data. The plots highlight that the proposed DND metric has a stronger correlation to the GLUE score of model to perturbed sample than the other metrics. Similar trends can be observed in all of our tested models shown later in the paper.
Figure 8: Comparison of different neural architectures’ performances with different level of perturbation as measured by DND.

Figure 8: Comparison of different neural architectures’ performances with different level of perturbation as measured by DND.

6.4 Model specific analysis

The loss in performance of models in GLUE tasks shows a greater degree of correlation with the DND metric than any other metric, as shown in Figure 13. We found our results to be consistent across PT Transformers, NPT Transformers, ConvNets, and BiLSTMs. This indicates that our results generalize to neural language models across different inductive biases, pretrained or not-pretrained, and to the different pretraining techniques.

6.4.1 Pretrained vs Non-Pretrained

Unsurprisingly, PT Transformers outperform every NPT variant across all types of perturbations, as shown in Figure 8. The PT RoBERTa and BART model have a comparable level of degradation across the different perturbations, shown in Figure 9, despite the different pretraining schemes used.

All NPT models also exhibit a strong correlation between the DND metric and their degradation in performance on the GLUE tasks, which indicates that the insensitivity to word-order is not an artifact of pretraining. In contrast with PT models, NPT models have very low correlations between all metrics and performance on the RTE task. This is explained by the fact that most NPT models do not obtain significantly above chance-level performance on the RTE task. As the performance quickly degrades to chance-level once any perturbation is applied, it is hard to measure correlations between the metrics and the task performance.

6.4.2 NPT Transformer and Positional Embeddings

Interestingly, the NPT Transformer, as shown in Figure 10, has a close to zero correlation between its performance and IDC metric, which other Non-Transformer models do not mirror. As the IDC metric measures the changes in absolute position of tokens, the IDC metric being completely uncorrelated with performance implies that the absolute position of tokens has little to no impact on the performance of NPT Transformers. We hypothesize that learning the positional embeddings require much more data than is present in a single NLU task, leading the NPT model to essentially act as bag-of-words model.

Towards studying this, we conduct an ablation study on the impact of positional embeddings with NPT and PT Transformers. To do this, we freeze the weights of the positional embeddings to 0, making them have no contribution on the overall output of the model. As we are interested in the marginal utility of positional embeddings with relation to
Figure 9: Correlation matrices between perturbations measured by different metrics and the performance on GLUE Tasks of PT Transformers. This highlights that across different pretraining settings, DND remains very strongly correlated with downstream performance.

Figure 10: Correlation matrices between perturbations measured by different metrics and the performance on GLUE Tasks of different NPT architectures. This highlights that across different architecture settings, the DND correlation remains very strongly correlated with downstream performance.

Figure 11: Correlation matrices between perturbations measured by different metrics and the performance on GLUE Tasks of ConvNets and BiLSTMs using only characters as tokens. The results showcase the correlation of the proposed metrics on character-models, thereby removing tokenization as a confounder.
NPT Transformers, we report the difference in performance between the model that does not have access to those embeddings and the model that does ($\Delta$ GLUE Score). Without positional embeddings, a model has no information on the relative position of inputs and is forced to use only a bag-of-words level of information from the input text. In Figure 12, we can see a drop in performance of at most 1%, consistent across all levels of perturbations, for the NPT Transformer. This suggests that NPT Transformers barely make any use of the positional embeddings on those tasks.

The positional embeddings of PT models, however, seem strongly impacted by perturbations, suggesting that they make heavy use of the positional embeddings. We see that the impact of those embeddings degrades monotonically with perturbation on the local structure and is somewhat correlated with perturbation on the global structure, which is not observed with the NPT Transformer.

6.5 Character-Level Experimentation

Figure 13: Plot shows the correlation between the models’ performance to perturbed samples on the different GLUE tasks and the perturbation quantified by the different metrics. The higher the value the better the explainability of the metric; suggests that DND is a better proxy to the performance of model to a perturbed example.
As the results presented from experiments so far use subword tokenization, it is possible that the local perturbations being directly correlated with performance decay could be caused by the perturbation to the vocabulary. Towards removing tokenization as a confounding factor for the observed phenomenon, we train character-level BiLSTMs and ConvNets to evaluate whether the correlations with the DND metric hold without multi-character vocabulary. Results shown in Figure 13 demonstrate that DND remains as good of an explanation of the decay in performance of models with character-level tokenization, as with models using a vocabulary of subwords. This result allows generalizing the correlation to neural models beyond the choice of tokenization.

7 Discussion

Tokenization Our results on the importance of local structure could bear some implications for tokenization. Recent research trends (Xu et al., 2021; Clark et al., 2021) look at alternatives and improvements to BPE. The current research appears to be pushing towards smaller vocabulary at finer granularity, even exploring simple byte-level representations (Xue et al., 2021; Tay et al., 2021).

Through our DND metric, we find that local clumps of characters contain the most essential structural information required to solve several NLU problems. As a large part of the complexity of NLU seems to be contained within the meaning of the specific order of clumps of characters, by having more of that local structure fixed through tokenization, it is possible to inject additional inductive biases into the model. The perturbation analysis discussed in the paper could be used for better construction of vocabulary with improved heuristics.

Local, Global, and Bag-of-Words Our results on the relative importance of local structure in relation to global structure hint at the possibility that much of the tested NLU tasks can be solved with a bag-of-words formulation. Intuitively, local structure mainly relates to building meaningful words from the characters of a text whereas the global structure relates to the general order and word-level syntax being maintained. From our experiments, we observe that as long as the local structure is roughly maintained, a majority of NLU tasks can be solved without requiring the global structure. This correlates with similar findings by O’Connor and Andreas (2021). In essence, the structure required to build words seems to be necessary, but much of NLU can be solved with the information of which words (or subwords) are present in the text, without regard to their relative positions. This adds further credibility to similar research that attempts to understand the success of Transformers in NLP through hypothesizing that the global attention makes the architectures particularly apt at reflecting over a set of items, like a bag-of-words.

8 Conclusion

In this work, we propose the Direct Neighbour Displacement metric and the Index Displacement Count metric — that score the local and global structure of tokens in the perturbed texts. The results provide a way to quantify perturbations to better understand the inner workings of neural language understanding models. Reflecting on our results, we observe that perturbations on a local level, as measured by DND, explains the (in) sensitivity of pretrained language models to perturbations at different granularities on a variety of natural language understanding tasks. Although the paper primarily focuses on the effects of perturbations on English texts, extending the study to neural models on other languages could be beneficial. Especially, studying whether perturbations have a similar effect on other languages could help in deepening our understanding of cross-language tasks, like machine translation.

---

As character sequences are much longer than subword sequences for the same text and memory usage of transformer models scale quadratically with sequence length, we were not able to run our study on a character-level Transformer.
Acknowledgements

We thank Saujas Vaduguru for the useful comments and discussions on early drafts. This research was supported by Apogée Canada, Canada First Research Excellence Fund program and École Polytechnique Startup Fund PIED. SC is supported by a Canada CIFAR AI Chair and an NSERC Discovery Grant.

References

Eneko Agirre, Lluís M’arquez, and Richard Wicentowski, editors. 2007. Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007). Association for Computational Linguistics, Prague, Czech Republic.

Roy Bar Haim, Ido Dagan, Bill Dolan, Lisa Ferro, Danilo Giampiccolo, Bernardo Magnini, and Idan Szpektor. 2006. The second PASCAL recognising textual entailment challenge. In Proceedings of the Second PASCAL Challenges Workshop on Recognising Textual Entailment.

Yonatan Belinkov and James Glass. 2019. Analysis methods in neural language processing: A survey. Transactions of the Association for Computational Linguistics, 7:49–72.

Luisa Bentivogli, Ido Dagan, Hoa Trang Dang, Danilo Giampiccolo, and Bernardo Magnini. 2009. The fifth PASCAL recognising textual entailment challenge. In TACL.

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics, 5:135–146.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. arXiv preprint arXiv:2005.14165.

Grzegorz Chrupała and Afra Alishahi. 2019. Correlating neural and symbolic representations of language. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2952–2962, Florence, Italy. Association for Computational Linguistics.

Jonathan H Clark, Dan Garrette, Iulia Turc, and John Wiecing. 2021. Canine: Pre-training an efficient tokenization-free encoder for language representation. arXiv preprint arXiv:2103.06874.

Ronan Collobert and Jason Weston. 2008. A unified architecture for natural language processing: Deep neural networks with multitask learning. In Proceedings of the 25th International Conference on Machine Learning, ICML ’08, page 160–167, New York, NY, USA. Association for Computing Machinery.

Jennifer Culbertson and David Adger. 2014. Language learners privilege structured meaning over surface frequency. Proceedings of the National Academy of Sciences, 111(16):5842–5847.

Ido Dagan, Oren Glickman, and Bernardo Magnini. 2006. The PASCAL recognising textual entailment challenge. In Machine learning challenges. evaluating predictive uncertainty, visual object classification, and recognising textual entailment, pages 177–190. Springer.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: pre-training of deep bidirectional transformers for language understanding. CoRR, abs/1810.04805.

William B Dolan and Chris Brockett. 2005. Automatically constructing a corpus of sentential paraphrases. In Proceedings of the International Workshop on Paraphrasing.

Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejing Dou. 2017. Hotflip: White-box adversarial examples for text classification. arXiv preprint arXiv:1712.06751.

Allyson Ettinger. 2020. What BERT is not: Lessons from a new suite of psycholinguistic diagnostics for language models. Transactions of the Association for Computational Linguistics, 8:34–48.

Richard Futrell, Roger P Levy, and Edward Gibson. 2020. Dependency locality as an explanatory principle for word order. Language, 96(2):371–412.

Ji Gao, Jack Lanchantin, Mary Lou Soffa, and Yanjun Qi. 2018. Black-box generation of adversarial text sequences to evade deep learning classifiers. In 2018 IEEE Security and Privacy Workshops (SPW), pages 50–56. IEEE.

Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and Bill Dolan. 2007. The third PASCAL recognising textual entailment challenge. In Proceedings of the ACL-PASCAL workshop on textual entailment and paraphrasing, pages 1–9. Association for Computational Linguistics.

Goran Glavaš and Ivan Vulić. 2020. Is supervised syntactic parsing beneficial for language understanding? an empirical investigation.

Yoav Goldberg. 2019. Assessing bert’s syntactic abilities. CoRR, abs/1901.05287.

Kristina Gulordava, Piotr Bojanowski, Edouard Grave, Tal Linzen, and Marco Baroni. 2018. Colorless green recurrent networks dream hierarchically. arXiv preprint arXiv:1803.11138.
Ashim Gupta, Giorgi Kvernadze, and Vivek Srikanth. 2021. Bert & family eat word salad: Experiments with text understanding. arXiv preprint arXiv:2101.03453.

John Hale. 2017. Models of human sentence comprehension in computational psycholinguistics. Oxford Research Encyclopedia of Linguistics.

Zellig S Harris. 1954. Distributional structure. Word, 10(2-3):146–162.

John Hewitt and Christopher D. Manning. 2019. A structural probe for finding syntax in word representations. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4129–4138, Minneapolis, Minnesota. Association for Computational Linguistics.

Jeremy Howard and Sebastian Ruder. 2018. Fine-tuned language models for text classification. CoRR, abs/1801.06146.

Yu-Lun Hsieh, Minhao Cheng, Da-Cheng Juan, Wei Wei, Wen-Lian Hsu, and Cho-Jui Hsieh. 2019. On the robustness of self-attentive models. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1520–1529, Florence, Italy. Association for Computational Linguistics.

Ganesh Jawahar, Benoît Sagot, and Djamé Seddah. 2019. What does BERT learn about the structure of language? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3651–3657, Florence, Italy. Association for Computational Linguistics.

Quoc Le and Tomas Mikolov. 2014. Distributed representations of sentences and documents. In International conference on machine learning, pages 1188–1196. PMLR.

V. I. Levenshtein. 1966. Binary Codes Capable of Correcting Deletions, Insertions and Reversals. Soviet Physics Doklady, 10:707.

Hector J Levesque, Ernest Davis, and Leora Morgenstern. 2011. The Winograd schema challenge. In AAAI Spring Symposium: Logical Formalizations of Commonsense Reasoning, volume 46, page 47.

Mike Lewis, Yinjie Lin, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880, Online. Association for Computational Linguistics.

Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In Text summarization branches out, pages 74–81.

Yongjie Lin, Yi Chern Tan, and Robert Frank. 2019a. Open sesame: Getting inside BERT’s linguistic knowledge. In Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 241–253, Florence, Italy. Association for Computational Linguistics.

Yongjie Lin, Yi Chern Tan, and Robert Frank. 2019b. Open sesame: Getting inside BERT’s linguistic knowledge. In Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 241–253, Florence, Italy. Association for Computational Linguistics.

Nelson F Liu, Matt Gardner, Yonatan Belinkov, Matthew E Peters, and Noah A Smith. 2019a. Linguistic knowledge and transferability of contextual representations. arXiv preprint arXiv:1903.08855.

Nelson F. Liu, Matt Gardner, Yonatan Belinkov, Matthew E. Peters, and Noah A. Smith. 2019b. Linguistic knowledge and transferability of contextual representations. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1073–1094, Minneapolis, Minnesota. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019c. Roberta: A robustly optimized bert pretraining approach. ArXiv, abs/1907.11692.

Joe O’Connor and Jacob Andreas. 2021. What context features can transformer language models use? arXiv preprint arXiv:2106.08367.

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.

Prasanna Parthasarathi, Koustuv Sinha, Joelle Pineau, and Adina Williams. 2021. Sometimes we want translationese. arXiv preprint arXiv:2104.07623.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. PyTorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d Alchê-Buc, E. Fox, and R. Garnett, editors, Advances in Neural Information Processing Systems 32, pages 8024–8035. Curran Associates, Inc.

Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke
Ngoc-Quan Pham, Jan Niehues, Thanh-Le Ha, and Alexander Waibel. 2019. Improving zero-shot translation with language-independent constraints. In Proceedings of the Fourth Conference on Machine Translation (Volume 1: Research Papers), pages 13–23, Florence, Italy. Association for Computational Linguistics.

Thang M Pham, Trung Bui, Long Mai, and Anh Nguyen. 2020. Out of order: How important is the sequential order of words in a sentence in natural language understanding tasks? arXiv preprint arXiv:2012.15180.

Alec Radford, Jeffrey Wu, Rewon Child, David Lan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9.

Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. Know what you don’t know: Unanswerable questions for squad. CoRR, abs/1806.03822.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016a. Squad: 100,000+ questions for machine comprehension of text. CoRR, abs/1606.05250.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016b. SQaD: 100,000+ questions for machine comprehension of text. In Proceedings of EMNLP. Association for Computational Linguistics.

Anna Rogers, Olga Kovaleva, and Anna Rumshisky. 2020. A primer in bertology: What we know about how bert works. Transactions of the Association for Computational Linguistics, 8:842–866.

Chinnadhurai Sankar, Sandeep Subramanian, Chris Pal, Sarath Chandar, and Yoshua Bengio. 2019. Do neural dialog systems use the conversation history effectively? an empirical study. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 32–37, Florence, Italy. Association for Computational Linguistics.

Mike Schuster and Kuldip K. Paliwal. 1997. Bidirectional recurrent neural networks. IEEE Trans. Signal Process., 45(11):2673–2681.

Thibault Sellam, Dipanjan Das, and Ankur Parikh. 2020. BLEURT: Learning robust metrics for text generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7881–7892, Online. Association for Computational Linguistics.

Koustuv Sinha, Robin Jia, Diewuke Hupkes, Joelle Pineau, Adina Williams, and Douwe Kiela. 2021. Masked language modeling and the distributional hypothesis: Order word matters pre-training for little. arXiv preprint arXiv:2104.06644.

Koustuv Sinha, Prasanna Parthasarathi, Joelle Pineau, and Adina Williams. 2020. Unnatural language inference. arXiv preprint arXiv:2101.00010.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of EMNLP, pages 1631–1642.

Yi Tay, Vinh Q Tran, Sebastian Ruder, Jai Gupta, Hyung Won Chung, Dara Bahri, Zhen Qin, Simon Baumgartner, Cong Yu, and Donald Metzler. 2021. Charformer: Fast character transformers via gradient-based subword tokenization. arXiv preprint arXiv:2106.12672.

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

Ke Tran, Arianna Bisazza, and Christof Monz. 2018. The importance of being recurrent for modeling hierarchical structure. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4731–4736, Brussels, Belgium. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. CoRR, abs/1706.03762.

Alex Wang, Yada Prukachatkat, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019a. Superglue: A stickier benchmark for general-purpose language understanding systems. CoRR, abs/1905.00537.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019b. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019.

Hai Wang, Dian Yu, Kai Sun, Jianshu Chen, and Dong Yu. 2019c. Improving pre-trained multilingual model with vocabulary expansion. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 316–327, Hong Kong, China. Association for Computational Linguistics.

Alex Warstadt, Amanpreet Singh, and Samuel R. Bowman. 2018. Neural network acceptability judgments. arXiv preprint 1805.12471.

Alex Warstadt, Yian Zhang, Xiaocheng Li, Haokun Liu, and Samuel R. Bowman. 2020. Learning which features matter: RoBERTa acquires a preference for
linguistic generalizations (eventually). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 217–235, Online. Association for Computational Linguistics.

Adina Williams, Nikita Nangia, and Samuel R. Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of NAACL-HLT*.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R’emi Louf, Morgan Funtowicz, and Jamie Brew. 2019. Huggingface’s transformers: State-of-the-art natural language processing. *ArXiv*, abs/1910.03771.

Jingjing Xu, Hao Zhou, Chun Gan, Zaixiang Zheng, and Lei Li. 2021. Vocabulary learning via optimal transport for neural machine translation. In *Proceedings of the Association for Computational Linguistics*.

Linting Xue, Aditya Barua, Noah Constant, Rami Al-Rfou, Sharan Narang, Mihir Kale, Adam Roberts, and Colin Raffel. 2021. Bt5: Towards a token-free future with pre-trained byte-to-byte models. *arXiv preprint arXiv:2105.13626*.

Li Yujian and Liu Bo. 2007. A normalized levenshtein distance metric. *IEEE transactions on pattern analysis and machine intelligence*, 29(6):1091–1095.

Kelly Zhang and Samuel Bowman. 2018. Language modeling teaches you more than translation does: Lessons learned through auxiliary syntactic task analysis. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 359–361.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q Weinberger, and Yoav Artzi. 2019. Bertscore: Evaluating text generation with bert. *arXiv preprint arXiv:1904.09675*.

Han Zhao, Zhendong Lu, and Pascal Poupart. 2015. Self-adaptive hierarchical sentence model. *CoRR*, abs/1504.05070.
A  Experiment Details

Model Hyperparameters  The results in the paper are averaged over five experiments run for 5 random seeds. Early stopping was performed after 2 full epochs not resulting in better results on the validation set. All models had similar model sizes, containing between 100 million and 130 million parameters. The ConvNet architecture is the one described in Collobert and Weston (2008) and the BiLSTM architecture is the one described in Zhao et al. (2015). Both use the same hidden size, dropout and word embedding size as the RoBERTa-Base model. Pretrained models used a learning rate of 2e-5, a batch size of 32, a maximum of 3 epochs and a weight decay of 0.1. Non pretrained models used a learning rate of 1e-4, a batch size of 128, and a weight decay of 0.06, as described in Liu et al. (2019c). Experiments using characters as input used a maximum sequence length of 2048 inputs. All other experiments used a maximum sequence length of 512. The Winograd Schema Challenge (WNLI) task was omitted from all experiments.

Perturbations  Subword-level perturbations were all done with the RoBERTa-Base vocabulary. On all level of granularity, we perform experiments with the full shuffling, the n-gram shuffling with ρ = 0.66 and the neighbour flip perturbation with ρ = 0.5. As the word-level and subword-level perturbations do not permit a sufficient exploration of DND, we populate the continuum of our metric with several more character-level perturbations by testing different values of ρ for both the n-gram shuffling and the neighbour flip perturbation. Experiments are run with following values of ρ for n-gram shuffling: {0.5, 0.4, 0.3, 0.2, 0.15}, and for neighbour flip perturbation: {0.4, 0.3, 0.2, 0.15, 0.1}.

B  Pseudocode for Metric and Perturbations

Function IDC(X_p):
    \begin{align*}
    X_p^{len} &\leftarrow X_p.length(); \\
    IDC_{list} &\leftarrow list(); \\
    \text{for } i &\leftarrow 0 \text{ and } i \leq X_p^{len} do \\
    \quad \text{abs_distortion} &\leftarrow \text{abs}(1-X_p[i]); \\
    \quad IDC_{list}.append(abs\_distortion); \\
    \text{end}
    \end{align*}

    IDC_{agg} &\leftarrow IDC_{list}.mean(); \\
    IDC &\leftarrow \frac{IDC_{agg}}{X_p^{len}};
    \end{align*}

return

Algorithm 1: Pseudocode to compute IDC metric.

Function DND(X_p):
    \begin{align*}
    X_p^{len} &\leftarrow X_p.length(); \\
    DND_{list} &\leftarrow list(); \\
    \text{for } i &\leftarrow 0 \text{ and } i \leq X_p^{len} do \\
    \quad \text{if } X_p[i] = X_p[i+1] \text{ then} \\
    \quad \quad DND_{list}.append(0); \\
    \quad \text{else} \\
    \quad \quad DND_{list}.append(1); \\
    \text{end}
    \end{align*}

    DND_{agg} &\leftarrow DND_{list}.sum(); \\
    DND &\leftarrow \frac{DND_{agg}}{X_p^{len}};
    \end{align*}

return

Algorithm 2: Pseudocode to compute DND metric.

Function PhrasePerturbation(ρ → 0.5, text → list):
    \begin{align*}
    \text{all\_phrases} &\leftarrow list(); \\
    \text{phrase} &\leftarrow list(text[0]) \\
    \text{for } \text{token} \text{ in } text[1:] do \\
    \quad p &\sim \text{Unif }([0, 1]); \\
    \quad \text{if } p < ρ \text{ then} \\
    \quad \quad \text{all\_phrases}.append(phrase); \\
    \quad \quad \text{phrase} &\leftarrow list(\text{token}); \\
    \quad \text{else} \\
    \quad \quad \text{phrase} &\leftarrow [\text{phrase}, \text{token}]; \\
    \text{end}
    \end{align*}

    \text{all\_phrases}.append(phrase); \\
    \text{perturbed\_text} &\leftarrow \text{.join}(\text{shuffle(all\_phrases)})
    \end{align*}

return perturbed\_text

Algorithm 3: Pseudocode for PhraseShuffle.

Function NeighborFlip(ρ → 0.5, text → list):
    \begin{align*}
    \text{perturbed\_tokens} &\leftarrow list(); \\
    \text{held\_token} &\leftarrow list(text[0]) \\
    \text{for } \text{token} \text{ in } text[1:] do \\
    \quad p &\sim \text{Unif }([0, 1]); \\
    \quad \text{if } p < ρ \text{ then} \\
    \quad \quad \text{perturbed\_tokens}.append(\text{held\_token}); \\
    \quad \quad \text{held\_token} &\leftarrow list(\text{token}); \\
    \quad \text{else} \\
    \quad \quad \text{perturbed\_tokens} &\leftarrow [\text{perturbed\_tokens}, \text{token}]; \\
    \text{end}
    \end{align*}

    \text{perturbed\_tokens}.append(\text{held\_token}); \\
    \text{perturbed\_text} &\leftarrow \text{.join}(\text{perturbed\_tokens})
    \end{align*}

return perturbed\_text

Algorithm 4: Pseudocode for NeighborFlip.
Listing 1: A few example of perturbations as well as the calculation steps to obtain both the IDC and DND metrics.

```plaintext
# Original order
X = "Th i s ' ' i s ' ' a ' ' t e s t"
F_X = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13]

# Simple splitting along the middle
X' = "a ' ' t e s t T h i s ' ' i s ' '"
P_X' = [8, 9, 10, 11, 12, 13, 0, 1, 2, 3, 4, 5, 6, 7]
IDC_list = [8, 8, 8, 8, 8, 8, 6, 6, 6, 6, 6, 6, 6, 6]
IDC_mean = 6.85
IDC = 0.49
DND_list = [0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]
DND_sum = 1
DND = 0.08

# Shuffling of the words randomly
X' = "t e s t i s ' ' a ' ' T h i s ' '"
P_X' = [10, 11, 12, 13, 5, 6, 7, 8, 9, 0, 1, 2, 3, 4]
IDC_list = [10, 10, 10, 10, 1, 1, 1, 1, 9, 9, 9, 9, 9, 9]
IDC_mean = 6.42
IDC = 0.46
DND_list = [0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0]
DND_sum = 2
DND = 0.15

# Flipping neighbouring characters randomly
X' = "h T i ' ' i s ' ' s a ' ' t s e t"
P_X' = [1, 0, 2, 4, 5, 3, 7, 6, 8, 9, 10, 12, 11, 13]
IDC_list = [1, 1, 0, 1, 1, 2, 1, 1, 0, 0, 1, 1, 0, 0]
IDC_mean = 0.71
IDC = 0.05
DND_list = [1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1]
DND_sum = 10
DND = 0.76
```

Figure 14: The distribution highlights that although the different word-level perturbations seem to cover the spectrum of possible scores, the perturbations do not seem to perturb the local ordering as effectively measured by DND.
E Reproducibility Checklist

As per the prescribed Reproducibility Checklist, we provide the information of the following:

- **A clear description of the mathematical setting, algorithm and/or model:** We provide details of models used in §5 and §B for detailing pseudocodes for both the metrics and the different perturbations proposed in the paper.

- **Submission of source code:** Source code for the perturbations, metrics and models is provided in GitHub. The training code was adapted from the excellent Wolf et al. (2019) github.

- **Description of the computing infrastructure used:** We used up to 20 NVIDIA V100 32 GB at a time to run all experiments. All models where trained and evaluated on 1 NVIDIA V100 32 GB GPUs for every seed of every model.

- **Average runtime for each approach:** The approximate training time for fine-tuning varies between 4-8 hours and the inferencing on standard validation sets was about an hour.

- **Explanation of evaluation metrics used, with links to code:** We add necessary citations for the metrics considered in the paper and also provide codes to reproduce them.

- **Relevant statistics of the datasets used:** We provide the statistics of the datasets used in 5.

- **Explanation of any data that were excluded, and all pre-processing steps:** The details for omitting WNLI data from GLUE benchmark are provided in §A.

- **Link to downloadable version of data:** The data sets used in the paper are from public repositories. Links to the paper that proposes the data sets is included in §5.