A Morphology-Based Investigation of Positional Encodings

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Abstract

Contemporary deep learning models effectively handle languages with diverse morphology despite not being directly integrated into them. Morphology and word order are closely linked, with the latter incorporated into transformerbased models through positional encodings. This prompts a fundamental inquiry: Is there a correlation between the morphological complexity of a language and the utilization of positional encoding in pre-trained language models? In pursuit of an answer, we present the first study addressing this question, encompassing 22 languages and 5 downstream tasks. Our findings reveal that the importance of positional encoding diminishes with increasing morphological complexity in languages. Our study motivates the need for a deeper understanding of positional encoding, augmenting them to better reflect the different languages under consideration.

1 Introduction

Pre-trained language models (PLMs) (Devlin et al., 2018; Liu et al., 2019a; Radford et al., 2019; Raffel et al., 2020a; Brown et al., 2020) built upon transformers (Vaswani et al., 2017) have achieved ground-breaking results across a wide spectrum of language processing tasks such as natural language inference (Liu et al., 2019b), text classification (Raffel et al., 2020b), named entity recognition (Liu et al., 2019b), and part-of-speech tagging (Martin et al., 2020). However, only a few models take into account various linguistic aspects and theories in their design (Nzeyimana and Rubungo, 2022; Park et al., 2021). Morphology and word order of a language are closely related (Sapir, 1921; Comrie, 1989; Blake, 2001); the latter is incorporated into transformer-based models through positional encoding (PE) (Dufter et al., 2022). As language models are being developed for more languages which significantly differ in morphological typology, it

could be beneficial to construct language models that are sensitive to these linguistic nuances. Moreover, the enormous computational cost incurred during their training is a major challenge in the development of PLMs. Acquiring a deeper understanding of how various components of a PLM function in different languages can provide valuable insights regarding their necessity across languages. This motivates us to investigate the relation between positional encoding and morphology, which is essential for wider usage of PLMs across different languages. Our contributions are:

1. Performing the first study about the varying importance of positional encoding across languages with different morphological complexity.

Showing that the impact of PE diminishes as the morphological complexity of a language increases.
 Conducting exhaustive experiments covering 22 different languages across 9 language families and 5 diverse natural language processing tasks.

2 Related work

Positional Encoding (PE): Various methods have been proposed to incorporate position information in transformer models. Absolute positions in a sequence, represented by fixed (Vaswani et al., 2017) or trainable encodings (Gehring et al., 2017; Devlin et al., 2018; Radford et al., 2019; Lan et al., 2019), are typically added to input embeddings. Relative positions are encoded by directly adding position biases into the attention matrix (Shaw et al., 2018; Yang et al., 2019b; Raffel et al., 2020a; Huang et al., 2020; He et al., 2020; Press et al., 2021). Su et al. (2021) introduce rotary positional embeddings, employing a rotation matrix to encode both absolute and relative position information. Our study focuses on BERT models, which use learnable absolute PEs (Wang et al., 2020; Huang et al., 2020). We draw insights from linguistics theories and question the design choices for BERT-style



Figure 1: The figure illustrates the effect of word order on semantics for two languages: English (**left**) and Sanskrit (**right**). English is a morphologically poor language with SVO word order whereas Sanskrit is a morphologically rich language with no dominant word order (NODOM). Distorting the word order completely alters the meaning for English. However, for Sanskrit the meaning remains intact.

models that were designed with English in mind. Absence of Positional Information: Eliminating positional encoding results in a bag-of-words representation. Sinha et al. (2021) pre-train a RoBERTa model without positional embeddings and observe degraded performance on GLUE and PAWS tasks. Haviv et al. (2022); Le Scao et al. (2022) demonstrate that causal language models lacking explicit PE remain competitive with standard position-aware models. Additionally, Haviv et al. (2022) find that a pre-trained RoBERTa large model without PE exhibits higher perplexities than position-informed models. However, all these observations are limited to the English language.

Linguistic Information in BERT: Several works studied the linguistic knowledge encoded in PLMs such as BERT, focusing on different aspects of linguistics such as syntax (Goldberg, 2019; Jawahar et al., 2019), semantics (Ethayarajh, 2019) and morphology (Edmiston, 2020). Tenney et al. (2019); Puccetti et al. (2021) investigate the extent and organization of the linguistic information encoded in BERT. Gerz et al. (2018) investigate the connection between language modeling and linguistic typology across 50 different languages. However, they do not consider PLMs. Otmakhova et al. (2022) examine how various layers within a BERT model encode morphology and syntax.

3 The Relationship between Morphology and Word Order

In this section, we investigate the relationship between morphology and word order as outlined in different linguistic theories.

Linguistic theories : Morphological case mark-

ings serve a similar function as word order (Sapir, 1921; Blake, 2001). Several theories suggest that the presence of morphological case is necessary for free word order in a language (Comrie, 1989; Haspelmath, 1999). Either morphological case or structural position facilitates the unambiguous determination of grammatical role of the constituents of a sentence. The existence of morphological case reduces the need for fixed structural position in determination of the grammatical function of a word or phrase, allowing for variable word order. However, if morphological case is absent, fixed placement of words (and phrases) is necessary, exhibiting a fixed or rigid word order. In this work, we align our empirical study in accordance with the above theories that hints at the existence of a correlation between morphology and word order. Specifically, morphologically rich languages which tend to exhibit higher word-order flexibility as compared to morphologically poor languages¹.

3.1 Spectrum of Morphological Complexity

Through the lens of morphological typology (Haspelmath and Sims, 2013), we can categorize and cluster languages by studying their inherent morphological structures. At one extreme, we find languages such as Chinese and Vietnamese, which fall into the category of analytic languages and are morphologically poor. In these languages, it is

¹The theory regarding morphology and word order is a linguistically complex topic. Concurrent theories in the literature propose that there is no correlation between morphological complexity and word order. Müller (2002) demonstrates phenomena like scrambling and topic shift, where the change in word order does not necessarily require a high level of morphological complexity. However, this is beyond the scope of our study.

essential for words to maintain fixed positions in order to accurately convey grammatical relationships, resulting in a strict and invariant word order. On the other extreme, we find synthetic languages such as Sanskrit and Finnish, known for their rich morphology, where it's possible to rearrange the word order within a sentence without changing its meaning, as illustrated in Figure 1. However, most languages fall between these two extremes. Synthetic languages can be categorized into two main types. Agglutinative languages like Hungarian and Turkish tend to stick together multiple morphemes while fusional languages fuse several morphemes to express various grammatical features.

4 Methodology

In our work, we first quantify morphological complexity, and then systematically study the effect of removal of positional encodings during fine-tuning. Please refer to Section 3 for details on linguistic theories governing our study.

4.1 Quantifying Morphological Complexity

Following Kettunen (2014); Jayanthi and Pratapa (2021); Çöltekin and Rama (2023), we employ type-token ratio (TTR) as an empirical proxy of morphological complexity of a language. We use the many-to-many multilingual Flores-200 benchmark (Costa-jussà et al., 2022) to ensure information consistency across languages. As Chinese is an unsegmented language, we use character level ELMo model from the pywordseg library (Chuang, 2019) to split Chinese text into words. The remaining languages are space-delimited. Please refer to Appendix B for more details.

4.2 Morphology-based Investigation

To evaluate the impact of positional embeddings, we set them to 0, effectively nullifying its effect during fine-tuning. Our objective was to include multiple languages to ensure the generalizability of our findings. However, training language models from scratch (without positional encoding) for a large number of languages requires significant computational power and financial resources. Therefore, our primary focus was investigating the impact of nullifying positional encoding during fine-tuning.

We posit that for morphologically rich languages like Sanskrit, this would have minimal impact on downstream performance. For example, as depicted in Figure 1, the semantic meaning of a sentence in Sanskrit remains consistent even when the order of tokens is shuffled. However, this does not hold for morphologically poor languages.

5 Experimental Setup

To ensure the generalizability of our findings, we choose to perform a comprehensive study spanning different languages and tasks.

5.1 Tasks and Languages

As our work deals with the interplay of morphology and syntax in PLMs, we consider two sets of tasks:

a. Syntactic tasks: Part-of-speech (POS) tagging, Named Entity Recognition (NER), Dependency Parsing

b. Semantic tasks: Natural Language Inference (NLI), Paraphrasing

Factors considered in task and language selection include (1) availability of monolingual BERT-base model on HuggingFace Hub (Wolf et al., 2019), (2) availability of sufficient monolingual training data across different tasks, and (3) typological diversity. We aim to cover as many languages and language families as possible. Overall, we cover 22 languages distributed across 9 language families and one language isolate. We present an outline of the languages in Appendix A due to space constraints.

5.2 Datasets

Our study includes tasks from the XTREME benchmark (Hu et al., 2020), covering natural language inference (XNLI) (Conneau et al., 2018), paraphrasing (PAWS-X) (Yang et al., 2019a), and structure prediction tasks such as POS tagging and NER. We use the data from the Universal Dependencies v2.12 (Zeman et al., 2023) for the task of dependency parsing. The treebanks used for different languages are listed in Table 4 in Appendix.

5.3 Model Selection

In our research, we use monolingual pre-trained language models to prevent cross-lingual transfer from influencing our results. Given the availability of monolingual BERT models in various languages, we select BERT as the example PLM for our study. We consider BERT-base model for all languages to ensure that variations in model size and architecture do not influence the results. We consider fine-tuned BERT-base models with PE and without PE as the baseline and perturbed models, respectively.



Figure 2: Effect of Positional Encoding on NER task.



Figure 3: Effect of Positional Encoding on POS task.

5.4 Evalution Metrics

The metric used for different tasks is outlined in Table 1. For a given task, let m and n denote the metric scores for the baseline and perturbed models, respectively. We use the relative decrease in performance, calculated as (m-n)/m, as a quantitative measure of the importance of PE on the language. A higher value indicates a greater utilization of PE in effectively modeling the language.

5.5 Training and evaluation setup

For text classification tasks, we follow the generic pipeline. For dependency parsing, we implemented a biaffine parser by applying a biaffine attention layer directly on the output of BERT as described in Glavaš and Vulić (2021). As suggested in the XTREME benchmark, we have performed hyperparameter tuning on English validation data. However, since our goal is not to achieve the best absolute performance, we avoided conducting extensive hyperparameter tuning. More details are present in the Appendix E. Results are reported across 3 random trials of each experiment.

6 Results

In this section, we present the findings of our experiments on syntactic and semantic tasks. We also



Figure 4: Effect of Positional Encoding on Dependency Parsing.



Figure 5: Effect of Positional Encoding on XNLI.

conducted preliminary experiments on the GLUE benchmark, as discussed in Appendix D.

6.1 Results on Syntactic Tasks

Figures 2, 3 demonstrate the effect of removing positional encoding in NER, POS tagging tasks. For dependency parsing, figures 4 and 7 depict the effects on UAS and LAS scores, respectively.

a. Analytic languages like Chinese and Vietnamese, characterized by minimal or no morphology, exhibit the most significant decrease in performance when PE is removed. Moderately analytic languages like English and French follow.

b. In synthetic languages such as Hungarian, Finnish, and Turkish, known for their rich morphological systems, the function of morphology in encoding grammatical roles surpasses that of word order, resulting in a considerably smaller decrease in performance when PE is eliminated.

In the XTREME benchmark, different methods were employed for data annotation for POS tagging and NER datasets. While the former was human annotated, the latter was created through automatic annotation using weak supervision. Despite these disparities, the findings of the POS tagging and NER experiments are similar.



Figure 6: Effect of Positional Encoding on PAWS-X.

6.2 Results on Semantic Tasks

Natural language inference and paraphrasing tasks primarily involve understanding the semantic relationships and meaning between sentences or phrases. Syntax, including word order and grammatical rules, can influence the overall coherence and clarity of the expressions, but it is not the primary focus of these tasks.

The results depicted in Figures 5 and 6 illustrate the impact of nullifying PE in tasks related to natural language inference and paraphrasing. We notice a consistent pattern emerge in the graphs where morphologically poor languages are notably affected by the absence of positional encoding, while the impact is comparatively less for morphologically rich languages. However, in contrast to syntactic tasks, the variability in impact across different languages is less pronounced for semantic tasks.

Task (Metric)	Correlation
NER (F1)	-0.742
POS (F1)	-0.693
Dependency Parsing (UAS)	-0.882
Dependency Parsing (LAS)	-0.873
XNLI (Accuracy)	-0.773
PAWS-X (Accuracy)	-0.486

Table 1: Spearman correlation coefficient between morphological complexity of a language and relative decrease in performance across different tasks

In Table 1, we report the statistical correlation between the morphological complexity of a language and the relative decrease in performance across tasks, as determined by the Spearman Correlation Coefficient. A strong negative correlation is observed, indicating that higher morphological complexity is associated with a lower relative decrease in performance.

6.3 Analysis

We investigate the impact of removing positional encoding across languages in POS tagging and dependency parsing tasks. Both tasks depend on the interaction between morphology and word order to accurately interpret sentence structure.

For morphologically poor languages with relatively fixed word order, such as English and French, we observe increased ambiguity in distinguishing part-of-speech tags, particularly between nouns and pronouns, nouns and verbs, and adjectives and adverbs. In morphologically rich languages like Turkish, Finnish, and Arabic, the absence of positional encoding has minimal impact, as inflectional affixes marking features like number, tense, and person aid in correctly identifying the part of speech of a word.

Removing positional encoding has a more significant impact on dependency parsing than on POS tagging. In morphologically poor, fixed-word-order languages such as Chinese, English, and French, we observe a sharper decline in performance, with an increased tendency to misidentify subjects and objects. Parsers in these languages rely on word order to correctly assign modifiers to their heads, and without positional encoding, capturing headdependent relationships (e.g., between adjectives or adverbs and their heads) becomes more challenging. In contrast, morphologically rich languages experience a much smaller drop in UAS and LAS scores, as morphological case markers (e.g., nominative, accusative) help identify syntactic roles more effectively.

7 Conclusion

In this work, we demonstrate the interplay between positional encoding and morphology for morphologically diverse languages. We present the first study regarding the varying impact of positional encoding across languages with varying morphological complexity. We cover 22 different languages across 9 language families and 5 diverse natural language processing tasks for our investigation. Our results reveal that the importance of positional encoding diminishes as the morphological complexity of a language increases. Our study also emphasizes the need for a deeper understanding of positional encoding, augmenting them to better reflect the different languages under consideration.

Acknowledgements

We would like to thank our anonymous reviewers as well as the ARR, EMNLP action editors. Their insightful comments helped us improve the current version of the paper. The first author is grateful for the scholarship under the Prime Minister's Research Fellowship category at the Indian Institute of Technology Bombay.

Ethics Statement

All the experiments are conducted on openly available datasets and benchmarks with no ethical consideration.

Limitations

Our goal was to incorporate multiple languages to ensure the generalizability of our findings. However, the process of training language models from scratch (without positional encoding) for a large number of languages requires significant computational power and financial resources. We agree that pre-training without positional encoding would be a more holistic approach. However, due to limited computational resources, our primary focus was directed towards fine-tuning. However, we firmly believe that removing positional encoding in the pre-training phase would yield more pronounced results.

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A Details of Languages

We provide an overview of the languages included in our study in Table 2. Additionally, Table 4 presents the details of the treebanks used in the dependency parsing experiments.

B TTR-based Morphological Complexity

The TTR-based morphological complexity of different languages are listed in Table 3. For spacedelimited languages, we use the tokenizer from NLTK library for word segmentation.

C Additional Results

The effect of removing positional encoding in dependency parsing is examined by analyzing the relative decrease in UAS (Figure 4) and LAS scores (Figure 7).



Figure 7: Effect of Positional Encoding on Dependency Parsing (LAS).

D Results on GLUE tasks

In this section, we discuss the preliminary experiments conducted on the GLUE benchmark.

D.1 Impact of positional encoding

Removing positional encoding leads to a varied decrease in performance across different tasks, as evident in Table 5.

Sentence/Grammatical acceptability tasks: Positional encoding helps the model understand the hierarchical structure and dependencies between words, which is essential for determining the grammaticality of a sentence. As a result, in case of CoLA task, when positional encoding is removed,

Language (ISO code)	Language family	Hugging Face Model id	
Arabic (ar)	Afro-Asiatic	aubmindlab/bert-base-arabertv02	
Basque (eu)	Basque	orai-nlp/ElhBERTeu	
Bengali (bn)	Indo-European: Indo-Aryan	sagorsarker/bangla-bert-base	
Bulgarian (bg)	Indo-European: Slavic	usmiva/bert-web-bg	
Chinese (zh)	Sino-Tibetan	bert-base-chinese	
Dutch (nl)	Indo-European: Germanic	GroNLP/bert-base-dutch-cased	
English (en)	Indo-European: Germanic	bert-base-cased	
Finnish (fi)	Uralic	TurkuNLP/bert-base-finnish-cased-v1	
French (fr)	Indo-European: Romance	dbmdz/bert-base-french-europeana-cased	
German (de)	Indo-European: Germanic	dbmdz/bert-base-german-cased	
Greek (el)	Indo-European: Greek	nlpaueb/bert-base-greek-uncased-v1	
Hebrew (he)	Afro-Asiatic	onlplab/alephbert-base	
Hungarian (hu)	Uralic	SZTAKI-HLT/hubert-base-cc	
Indonesian (id)	Austronesian	indolem/indobert-base-uncased	
Italian (it)	Indo-European: Romance	dbmdz/bert-base-italian-cased	
Korean (ko)	Koreanic	kykim/bert-kor-base	
Portuguese (pt)	Indo-European: Romance	neuralmind/bert-base-portuguese-cased	
Russian (ru)	Indo-European: Slavic	DeepPavlov/rubert-base-cased	
Spanish (es)	Indo-European: Romance	dccuchile/bert-base-spanish-wwm-cased	
Swahili (sw)	Niger-Congo	flax-community/bert-base-uncased-swahili	
Turkish (tr)	Turkic	dbmdz/bert-base-turkish-cased	
Vietnamese (vi)	Austro-Asiatic	trituenhantaoio/bert-base-vietnamese-uncased	

Table 2: Overview of different languages

Language (ISO code)	FLORES-200 code	TTR
Arabic (ar)	arb_Arab	0.359
Basque (eu)	eus_Latn	0.324
Bengali (bn)	ben_Beng	0.292
Bulgarian (bg)	bul_Cyrl	0.268
Chinese (zh)	zho_Hans	0.17
Dutch (nl)	nld_Latn	0.207
English (en)	eng_Latn	0.194
Finnish (fi)	fin_Latn	0.428
French (fr)	fra_Latn	0.191
German (de)	deu_Latn	0.244
Greek (el)	ell_Grek	0.253
Hebrew (he)	heb_Hebr	0.364
Hungarian (hu)	hun_Latn	0.345
Indonesian (id)	ind_Latn	0.195
Italian (it)	ita_Latn	0.217
Korean (ko)	kor_Hang	0.465
Portuguese (pt)	por_Latn	0.205
Russian (ru)	rus_Cyrl	0.334
Spanish (es)	spa_Latn	0.192
Swahili (sw)	swh_Latn	0.212
Turkish (tr)	tur_Latn	0.376
Vietnamese (vi)	vie_Latn	0.077

Table 3: TTR-based morphological complexity of different languages

Language	Treebank
Chinese (zh)	UD_Chinese-GSD
Portuguese (pt)	UD_Portuguese-Bosque
Spanish (es)	UD_Spanish-GSD
English (en)	UD_English-GUM
French (fr)	UD_French-GSD
Italian (it)	UD_Italian-ISDT
Russian (ru)	UD_Russian-Taiga
German (de)	UD_German-GSD
Basque (eu)	UD_Basque-BDT
Finnish (fi)	UD_Finnish-FTB
Turkish (tr)	UD_Turkish-Penn

Table 4: Details of treebanks of different languages

Task	Dataset	With Positional Encoding				Without	Relative
		Unigram Permutation	Bigram Permutation	Trigram Permutation	Without Permutation	Positional Encoding	decrease
Sentence Acceptability	CoLA	4.4	12.3	16.8	59.1	23.8	59.7
Sentiment Analysis	SST-2	81.6	86.0	85.1	91.8	86.5	5.8
Paraphrasing / Sentence Similarity	MPRC	83.5	84.2	85.4	89.8	84.6	5.8
	QQP	75.6	79.1	80.8	87.1	85.8	1.5
	STS-B	85.2	87.1	86.6	89.0	86.6	2.7
Natural Language Inference	MNLI	68.3	74.8	76.5	83.6	79.7	4.7
	MNLI-MM	68.7	74.4	76.6	84.0	79.8	5.0
	QNLI	81.3	85.0	86.5	91.0	87.2	4.2
	RTE	58.1	61.5	61.8	64.5	62.8	2.6

Table 5: GLUE Results for English language: The evaluation metrics used for reporting the performance of QQP and MRPC tasks are F1 scores, while for the STS-B task, Spearman correlations are used, and accuracy scores are employed for the remaining tasks. The average and standard deviation are reported across 3 trails of the evaluation on the validation set. The relative decrease quantifies the decline in performance when positional encoding is excluded compared to when positional encoding was present. Additionally, we conducted experiments in which we removed positional encoding and perturbed the input to the model. Since the removal of positional encoding results in a bag of words model, we observed no noticeable change upon further distortion.

Task	learning rate	batch size	number of epochs
NER	2.00E-05	16	3
POS	3.00E-05	8	3
XNLI	3.00E-05	32	3
PAWS-X	3.00E-05	32	3

Table 6: Hyper-parameter details

the model struggles to identify grammatically acceptable sentences, leading to a notable decline of 59.7% in performance.

Paraphrasing and sentence similarity tasks: Models can effectively capture the similarity or relatedness between sentences by focusing on common signals present across sentences. These tasks primarily require understanding the underlying semantic meaning and contextual similarities between sentences rather than the syntactic structure. As a result, when positional encoding is removed, the relative decrease in performance is considerably smaller (5.8% for MRPC, 2.7% for STS-B, and 1.5% for QQP). This indicates that while positional encoding does provide some benefit in capturing the positional information within sentences, it is not very crucial for these tasks.

Natural language inference tasks: The removal of positional encoding leads to a relative decrease of 4.7% for MNLI, 5% for the mismatched version of MNLI, 4.2% for QNLI, and 2.6% for RTE. The decrease in performance is still relatively modest for these tasks. This highlights that positional encoding does not play a significant role in understanding the logical inference and entailment relationships between sentence pairs (Wang et al., 2020).

Even in the absence of positional encoding, the bag of words model gives considerably good performance for paraphrasing and natural language inference tasks. The results on GLUE benchmark serve as a driving force behind our investigation, where we aim to further test our hypothesis across morphologically diverse languages.

D.2 Impact of permutation:

In addition to studying the effect of positional encoding, we also conducted experiments to examine the impact of permutation on various GLUE tasks.

- Unigram permutation causes the most significant performance drop. However, as we increase the ngram order, which involves shuffling chunk of words instead of individual words, the decrease in performance is significantly less. This indicates that shuffling at higher ngram levels add less distortion and preserve the integrity of word order to a greater extent.
- The results also imply that lower order ngrams capture vocabulary match and is completely ignorant of word order whereas higher order ngrams capture word order and other dependen-

cies present in a sentence.

E Hyper-parameter details:

The hyper-parameter details used at the time of fine-tuning are outlined in Table 6. For dependency parsing, we have followed the hyper-parameter settings mentioned in Glavaš and Vulić (2021).