Cross-Genre Learning for Old English Poetry POS Tagging

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Abstract

Poetry has always distinguished itself from other literary genres in many ways, including grammatically and syntactically. These differences are evident not only in modern literature but also in earlier stages. Linguistic analysis tools struggle to address these differences. This paper focuses on the dichotomy between Old English poetry and prose, specifically in the context of the POS tagging task. Two annotated corpora representing each genre were analyzed to show that there are several types of structural differences between Old English poetry and prose. For POS tagging, we conduct experiments on both a detailed tag set with over 200 tags and a mapping to the UPOS tag set with 17 tags. We establish a baseline and conduct two cross-genre experiments to investigate the effect of different proportions of prose and poetry data. Across both tag sets, our results indicate that if the divergence between two genres is substantial, simply increasing the quantity of training data from the support genre does not necessarily improve prediction accuracy. However, incorporating even a small amount of target data can lead to better performance compared to excluding it entirely. This study not only highlights the linguistic differences between Old English poetry and prose but also emphasizes the importance of developing effective NLP tools for underrepresented historical languages across all genres.

1 Introduction

Poetry has always stood apart from other genres, and poetic language differs from other genres on several levels, including those of syntax and grammar. There is a tendency to use incomplete sentences, omit finite verbs, or deviate from standard word order. These choices appear to be motivated by the desire to emphasize specific connections of words or trigger specific emotions in the reader (Nofal, 2011). The adoption of different constructions across genres is a phenomenon that shapes not only modern literary traditions but also those of the past. This is the case of Old English poetry, which has been the focus of studies highlighting its structural, syntactical, and grammatical differences from Old English prose. The dichotomy between the two genres lies in several aspects; for instance, significant emphasis is placed on the types of clauses—whether principal or subordinate—employed in the poems (Mitchell, 1985). Being able to recognize the characteristics of each genre is essential to properly analyze a text.

Linguistic analysis is essential for examining and identifying the characteristics of different genres. Several tools have been developed to ease this process, such as Part-of-Speech (POS) tagging tools, which have benefited from significant technological advancements and improvements over time. The development of these tools has also a few shortcomings. It has been shown that modern POS taggers struggle to shift between different genres and offer accurate predictions (Arai, 2021). One possible reason for this limitation is the uneven distribution of data across genres within the corpora. The solutions proposed often involve the addition of new or synthetic data to help refine the performance of these tools (Arai, 2021). These practices are more easily implemented in a high-resource language setting. However, this is not always a suitable approach for older languages that typically have less data. In addition to limited data resources, some languages, such as Old English, have been comparatively underrepresented in POS-tagging research. Old English poetry, in particular, is even less represented in this body of research. Addressing the issue of domain shift between genres in support tools for modern languages is essential for reliable tools with all texts; equally important is the focus on older languages, which form the bedrock of human history, offering insights into interactions between past civilizations and helping to preserve our cultural heritage (van Gelderen, 2014). In addi-

tion, old languages are a topic of interest for many scholars and students who need to have tools with accurate performance as a support for their studies.

This paper explores POS-tagging for Old English poetry and investigates cross-genre learning to address the challenge of domain shift. To do that, two corpora with Old English poetry and prose have been used to establish a baseline for this task. Two experiments were then conducted to investigate the impact of mixing poetry and prose training data in different proportions. Because of the high number of labels in the original tag sets and the slight differences between the tag sets of the two corpora, we have also converted the labels used by both corpora to the Universal Dependencies UPOS tag set (de Marneffe et al., 2021). The paper will present the results for both the original tag sets and the UPOS tag set. Section 2 will present an overview of the related work. Section 3 will present the datasets, the POS mapping, and a series of structural analyses to investigate further the differences between the two genres. Experimental setups will be presented in Section 4. Section 5 will present and analyze the results. Conclusions will be discussed together with future work suggestions in Section 6.

2 Related Work

Specific studies on POS tagging tools for Old English poetry appear to be lacking, with only one known POS tagger currently available for Old English. The tagger is part of the CLTK library (Johnson et al., 2021), and has been trained on the available texts from the ISWOC Treebank (Bech and Eide, 2014). While the tool provides several model options, their accuracy remains uncertain.

While there is a lack of studies in this particular area, as noted, there are several studies that explore domain shift issues in POS taggers for historical English. Rayson et al. (2007) highlighted the low performance of existing Modern English POS taggers on Early Modern English datasets. Their study showed that handling orthographic variations increases accuracy. In the same year, Moon and Baldridge (2007) investigated ways to implement a POS Tagger for historical languages based on existing resources from their modern varieties. They used Modern English resources to tag Middle English data using alignments on parallel Biblical texts. The results were promising, but the accuracy of the manually annotated training set was not outperformed. Domain adaptation techniques were the focus of Yang and Eisenstein (2016) who evaluated several methods for the task of POS tagging for Early Modern and Modern British English texts. The combination of FEMA, domain adaptation algorithm designed for sequence labeling problems, and normalization techniques, improved the performances. A few years later, Karimov (2018) focused his attention on Middle English corpora and historical texts. To handle the irregular word order in older English, he applied a moving-average method to generate multidimensional vectors, capturing both character composition and weighted positions. Arai (2021) addresses the domain shift problem for Modern English poetry. Since existing POS taggers' performances became worse when subjected to poetry data, data augmentation techniques were implemented to face the problem.

3 Data and Tag Sets

The paper aims to establish a baseline for Old English poetry POS taggers and investigate cross-genre learning scenarios. Two corpora were used to train the models:

- the York-Helsinki Parsed Corpus of Old English Poetry (YCOEP) (University of Oxford, 2001): selection of poetic texts from the Old English section of the Helsinki Corpus of English Texts.
- the York Toronto Helsinki Parsed Corpus of Old English (YCOE) (University of Oxford, 2003): syntactically annotated corpus with all the major Old English prose works.

3.1 POS Mapping

Both YCOE and YCOEP datasets contain a substantial number of POS tags: 196 in the poetry dataset and 289 in the prose dataset. This extensive number of labels offers highly detailed linguistic information (i.e. grammatical features, inflectional features, morphological features); at the same time, it can pose significant challenges for both manual annotation and automated processing. A further complication arises from the inconsistencies between the two tag sets: despite originating from the same project (University of Oxford, 2003) and describing the same language variety, only 171 labels are common to both datasets. Our analysis revealed that the differences can be related to:

- potential spelling errors in the tags;

- discrepancies in linguistic categorization, such as the distinction between comparative and superlative use, which is present in the prose but missing in the poetry; this affects adjectives, adverbs, and quantifiers;
- missing tags, such as *MAN*, present in the YCOE dataset, but not in the YCOEP, is frequently used as a pronoun;
- inconsistencies in tag naming conventions, such as proper nouns labeled as *NPR* in the poetry dataset and as *NR* in the prose one.

The large number of tags and the discrepancies between the two tag sets may negatively impact the performance of the models. For this reason, and to facilitate the structural analysis, both YCOE and YCOEP tag sets were mapped to the Universal Dependencies UPOS tag set (de Marneffe et al., 2021), a widely adopted and standardized POS framework. We will report results for both the original and the UPOS tag set. The YCOE documentation (University of Oxford, 2001) was adopted as the primary reference for both datasets since the official documentation for the poetry dataset is missing. Table 5, in Appendix A, presents the complete mapping from the original tag sets to the UD categories. For the majority of the tags, the conversion to UPOS was straightforward, but a subset of Old English labels required specific rules for the conversion.

Prepositions, a closed class in both Old and Modern English, exhibit diverse syntactic behaviors in the original annotation scheme, leading to multiple tags. When prepositions are used with a complement, they are tagged as such and mapped to the UD category *ADP* (adposition). When no complement is present, they are annotated as adverbs or adverbial particles, and accordingly mapped to the UD category *ADV* (adverb). Furthermore, certain prepositions appear to be able to function also as subordinate conjunctions, which can complicate the effort to extract a clean closed class. For this reason, only complementizers and the word *'whether'* were mapped to the UD category *SCONJ* (subordinating conjunction).

Participles also pose a conversion challenge. Although they often function adjectivally, neither the YCOE nor the YCOEP tags them as *ADJ*. However, the case is a fully productive category in Old English that can be applied to nouns, adjectives, quantifiers, determiners, numbers, and participles (University of Oxford, 2001). For this reason, when participles display a case, instead of the corresponding participle tag, they will be tagged as *ADJ*.

The original tag set has specific labels for auxiliaries; however, *be* and *have* are always tagged as verbs, even when they function as auxiliaries. To more accurately reflect their syntactic role, we introduced a rule-based refinement: *be* and *have* will be labeled as *AUX* (auxiliary) when (i) followed by another verb, or (ii) followed by a subject (noun, proper noun, or pronoun) and another verb. Future work will aim to identify additional syntactic environments in which *be* and *have* fulfill auxiliary functions but are not annotated as such.

Some POS tags, particularly for verbs, adverbs, and quantifiers, include additional markers such as *RP+* or *NEG+*, respectively indicating the presence of adverbial particles or contracted negative forms. In such cases, the suffix tags are removed, and the token is assigned its core POS tag.

The UPOS mapping led a decrease in the number of POS tags from over 200 to 17. By adopting this conversion, datasets, and POS tags are more easily comparable and can be used to train the models. However, the conversion loses the linguistic granularity that was part of the original tag set such as grammatical features (i.e. case, gender, number, etc.).

3.2 Structural Analysis of the Genres

To assess the structural differences between Old English poetry and prose, we conducted a series of analyses on POS tag distributions using data from the UPOS-mapped versions of the YCOE (prose) and YCOEP (poetry) corpora. The size of the samples used, 5668 sentences, corresponds to the training and development sets employed in the training of the baseline models.

We began by analyzing the frequency of each POS tag. Figure 1 shows a comparison between the frequencies of each tag for both poetry and prose. For both genres, nouns, punctuation, and verbs are the most common tags. Nouns are much more frequent in the poetry compared to the prose, with a difference of approximately 10%. Punctuation is similarly more frequent in poetry, while verbs have similar frequencies. The distribution of the POS tags suggests that, in the poetry, the frequency of content words is higher than that of function words. Prose also shows this behavior, but the gap appears to be smaller. We also extracted the sentence-level POS tag sequences across the two corpora: there are 4814 unique sequences in the poetry and 5195

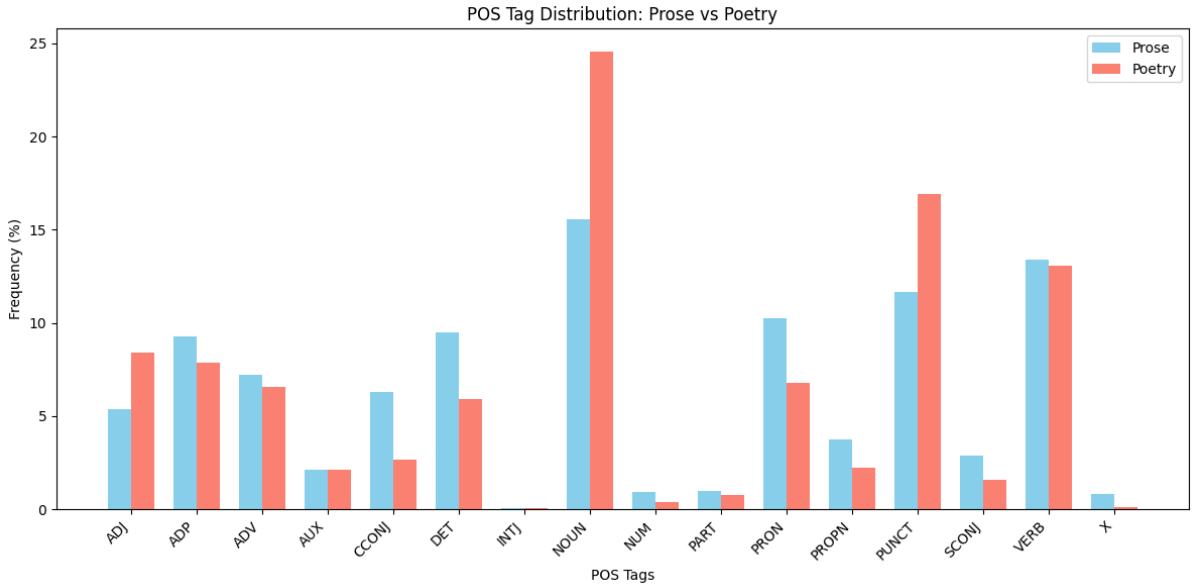

Figure 1: Distribution of POS tag frequencies in samples from the UPOS mapped versions of the YCOEP (poetry) and YCOE (prose) datasets.

in the prose. Notably, only 90 are shared by both genres. This low number of overlaps between the two datasets highlights the substantial structural difference between Old English poetry and prose, and the importance of considering it when training models.

A closer look at these differences is given in Table 6, in Appendix A, which displays, for both genres, the ten most common bigrams and trigrams, along with their probabilities. Among the bigrams, only five are common to both corpora. These shared bigrams have higher probabilities in the poetry data except for ('DET', 'NOUN'), which rank as the second most frequent pair in the prose data. Another interesting bigram is ('NOUN', 'NOUN'), which is present only in the poetry data and has one of the highest probabilities. Nouns and punctuation are the most frequent elements in the poetry bigrams: appearing respectively in eight and four pairs. In prose, the most common are verbs and nouns present in five and four bigrams. The high frequencies of these tags are not a surprise if we consider the POS tags distribution presented in Figure 1. This also supports the supposition about the higher frequency of content words in the poetry.

Regarding trigrams, only two are shared between the datasets, and as for the bigrams, these common combinations have higher probabilities in the poetry data. Also, in this case, nouns, punctuation, and verbs have higher frequencies. In the poetry results, nouns are present in each trigram. Punctuation tags increase, appearing seven times. The distribution of the POS tags in the poetic trigrams seems to indicate the presence of more fragmented constructions. The prose sample, on the other hand, shows an increasing number of trigrams with nouns and a consistent amount of verbs. Even with the poetic trigrams, we can observe a stronger presence of content words. Functional words are more present in the trigrams, but not at the same level as in the prose ones.

To further investigate the genre differences, we

UniGram Model		
Genre	**Poetry Test Set**	**Prose Test Set**
Poetry	9.603	12.353
Prose	10.352	11.377
BiGram Model		
Genre	**Poetry Test Set**	**Prose Test Set**
Poetry	9.093	11.349
Prose	10.464	9.866
TriGram Model		
Genre	**Poetry Test Set**	**Prose Test Set**
Poetry	7.428	9.5
Prose	8.862	7.994

Table 1: Perplexity Scores for N-Gram Models on samples from the UPOS mapped versions of the YCOEP (poetry) and YCOE (prose) datasets. The Genre column indicates the genre of the training data. Poetry and Prose Test Set display the perplexity score of the model computed on the corresponding test test.

calculated the perplexity scores for unigrams, bigrams and trigrams of two poetry and prose test sets with two models: one trained only with poetry data and one only with prose data. All the models were implemented using the Language Model module from the Natural Language Toolkit (NLTK) (Bird et al., 2009). Laplace smoothing was used to ensure non-zero probabilities for unseen sequences. Perplexity was computed using the NLTK's built-in function. The results are presented in Table 1.

As expected, both models exhibited lower perplexity scores when evaluated on their own test set, and higher scores when evaluated on the other genre. A general trend across all models is the decrease in perplexity with increasing n-gram size: as more context is incorporated, the predicting abilities of the models improve. In addition, the difference between the in-genre and out-of-genre training increases with n-gram size. This indicates that the differences between the two genres are more pronounced with higher-order n-grams, being consistent with observations about structural differences between poetry and prose (Nofal, 2011; Mitchell, 1985). These findings highlight the importance of taking into account these variations when developing NLP tools.

4 Experimental Setup

The poetry dataset, YCOEP, contains 6299 sentences. For the baseline model, the poetry data were divided into training set (80%), development set (10%), and test set (10%). This resulted in 5039 sentences for training, 629 for development, and 631 for test sets. To create a comparable dataset for the prose genre, a subset of the YCOE corpus was selected: a sample of 5668 sentences—matching the combined size of the poetry training and development sets. We did not include the test set in the prose sample because all the models were tested on the poetry test set from the original split.

In our first experiment, we investigated the models' performances in a scenario of limited target genre data combined with a greater amount of support data. In this experiment, the same data used to train the poetry-only baseline model were used as target genre data. The support data consisted of progressively larger subsets of prose data, up to the full prose dataset consisting of 109,703 lines. The prose data was always only divided into a training set (90%) and a development set (10%).

Our second experiment was designed with two primary objectives: (i) to determine the minimum amount of target genre data required to maintain acceptable model performance, and (ii) to examine the impact of progressively reducing the amount of target genre data while keeping the quantity of support genre data constant. In this experiment, the prose data used to train the baseline models was used as support genre data. The amount of poetry data was progressively decreased until it reached 57 sentences; the data were divided into a training set (90%) and a development set (10%).

All models were trained with MaChAmp, a toolkit for multi-task learning and fine-tuning offering a wide variety of tasks. It offers an easy configuration, especially for dealing with multiple datasets, together with a wide range of NLP tasks (i.e., POS tagging, text classification, etc.). It utilizes a shared pre-trained encoder, which is fine-tuned during training. Each task is equipped with its decoder (van der Goot et al., 2021). For our experiments, we employed the *seq* task type, for which MaChAmp applies a greedy softmax classification layer over the contextualized token embeddings provided by the encoder. All the models were based on multilingual BERT, the default language model in MaChAmp, and trained with default hyperparameters. Each model was trained for 20 epochs with three different random seeds. The evaluation was performed exclusively on the poetry test set from the original data split. For each seed, we computed accuracy and macro F1 score across all tags; the results will report the average performance over the three seeds.

5 Results

Tables 2, 3, and 4 present the results respectively for the baseline models, the first and the second experiments, for both tag sets.

5.1 Baseline

Table 2 reports the results obtained from the baseline models. The first model (*poe*) was trained only on poetry data, and despite relying on the smallest dataset, it showed strong performance with both tag sets. By reducing the number of tags from 200 to 17, both accuracy and F1 score values increase. This approach helps reduce the number of rare classes leading to more informative results, but at the same time, a deeper level of linguistic information is lost.

The second model (*pro*) was trained solely on

	OG Tag Set		UPOS Tag Set	
Genre	**Acc.**	**F1**	**Acc.**	**F1**
poe (5668)	0.909	0.708	0.961	0.944
pro (5668)	0.762	0.464	0.879	0.840
poe, pro (11,336)	0.917	0.707	0.966	0.948

Table 2: Results for baseline POS taggers trained the Original (OG) tag set and the Universal Dependencies (UD) tag set. The data belong to either poetry, prose genres, or a combination of both.

prose data and evaluated on poetry data. Compared to the first model, the performances across both tag sets, drop significantly. With the original tag set, model accuracy declines from 90% to 76%, accompanied by a decrease in F1 score from 70% to 46%. The same trend is observed with the UPOS tag set, although the decline is less pronounced. This behavior can be explained by the different syntactical structures of the two genres. As it has been shown in section 3.2, the distribution of the POS tags in the prose differs significantly from the poetry one; these differences are so broad that the model is not able to learn to correctly predict the poetry POS tags.

The third model (*poe, pro*) is trained with data from both genres, which results in the largest dataset (11,336 sentences) among the three. This model has better performances than the second, but not compared to the first: the second model is outperformed because of the presence of the target genre which is missing from the second model. Compared to the first model, there is only a marginal improvement in accuracy and almost no change in the F1 score. One might expect to have higher results with a larger dataset, but this is not the case. Even with the same amount of target and support data, the differences between the two genres are too broad for the model to learn information suitable to tag data from the target genre.

5.2 Limited Target Data and Increasing Support Data Scenario

The first experiment involves a constant amount of poetry (5668 lines) combined with progressively larger subsets of prose data, up to the full prose dataset consisting of 109,703 lines. The results of the experiment are presented in Table 3.

Consistent with the findings from Table 2, the UPOS tag set has higher scores than the original one, especially for what concerns the F1 score. Accuracy also improves, but the difference is notably smaller than the one observed for the other measure.

	OG Tag Set		UPOS Tag Set	
Size	**Acc.**	**F1**	**Acc.**	**F1**
0	*0.909*	*0.708*	*0.961*	*0.944*
1417	0.916	0.705	0.963	0.945
2834	0.916	0.698	0.964	0.946
5668	*0.917*	*0.707*	*0.966*	*0.948*
11,336	0.919	0.692	0.966	0.948
22,672	0.917	0.680	0.969	0.953
34,008	0.921	0.676	0.970	0.952
45,344	0.920	0.676	0.969	0.949
56,680	0.920	0.697	0.969	0.945
68,016	0.923	0.684	0.969	0.945
79,352	0.921	0.684	0.970	0.942
90,688	0.921	0.672	0.969	0.944
109,703	0.921	0.688	0.970	0.942

Table 3: Results for the first experiment. In this experiment, the amount of poetry is consistent (5668 lines) while the amount of prose increases systematically. The Size column indicates the amount of prose added to the dataset. *Italic* is used to indicate the baseline results.

With both tag sets, independently of the amount of prose data, the accuracy increases slightly compared to the poetry-only model (i.e. size 0 model). The F1 score is more or less consistent with the UPOS tag set, but it declines more with the original tag set. As for the baseline models, we might expect outperforming results as the dataset size increases, but this is not happening. Even the last model, trained with the largest dataset (109,703 lines) has either lower results than the baseline (OG tag set) or almost the same values (UPOS). These results suggest that indiscriminately increasing training data is not a universally effective strategy: the intrinsic differences between the two genres could be too diverse for the model to learn properly the patterns.

Interestingly, the models trained with smaller subsets of prose data—comprising 1417, 2834, and 5668 lines—have slightly higher results than those trained with larger amounts of prose. This finding could signal that a limited quantity of support data could contribute to the training of the model. It could be the case that selecting a smaller quantity of data with similar patterns to the target genre, could refine the predictions without overwhelming the target genre's patterns. Future studies will focus

	OG Tag Set		UPOS Tag Set	
Size	**Acc.**	**F1**	**Acc.**	**F1**
5668	*0.917*	*0.707*	*0.966*	*0.948*
4534	0.913	0.676	0.964	0.947
3779	0.908	0.661	0.961	0.939
2834	0.897	0.626	0.957	0.934
1889	0.883	0.598	0.949	0.930
945	0.857	0.554	0.936	0.924
472	0.824	0.519	0.919	0.907
227	0.802	0.491	0.904	0.891
113	0.784	0.482	0.893	0.878
57	0.775	0.471	0.889	0.867
0	*0.762*	*0.464*	*0.879*	*0.840*

Table 4: Results for the second experiment. The amount of prose data is set to 5668 lines, while the amount of poetry decreases. The Size column indicates the amount of poetry for each model. *Italic* is used to indicate the baseline results.

on this finding.

5.3 Decreasing Target Data and Consistent Support Data Scenario

Table 4 presents the results for the second experiment: the amount of prose data remains constant (5668 lines), while the amount of poetry data is progressively reduced across models.

For both tag sets, accuracy, and F1 score values decline as the size of the poetry data decreases. The decline is more pronounced with the OG tag set, especially for the F1 score, which drops by 23% points compared to the 70% of the *poe, pro* baseline model. This progressive decline is again an indication of the differences between the two genres. When the proportion of target data decreases, the model has fewer genre-specific patterns to learn from; thus, the model struggles to predict unseen patterns. However, it is noteworthy that even the model trained with the smallest amount of poetry data—only 57 lines—achieves slightly better performances than the baseline model trained with only prose data (i.e. size 0 model). This finding emphasizes the importance of the target genre in the training data. Even in a minimal amount, the target genre can improve the performance of the model, suggesting that the specific features of a genre cannot be learned even from large quantities of out-of-genre data.

6 Conclusions and Future Work

The study explores the differences between Old English poetry and prose, focusing on the POS tagging task. Two datasets, YCOE and YCOEP, were mapped to the UPOS tag set and used to establish a baseline and conduct two cross-genre experiments. Additionally, a series of analyses of the distributions of the POS tags within the sentences of both datasets have been conducted to investigate the differences between the two genres.

Baseline results demonstrated that when the differences between target and support genres are too wide, the model struggles to correctly predict the target POS tags. This limitation was also present when the training data included the same amount of target and support data, suggesting that quantity cannot account for genre-specific patterns in the data.

The first experiment involved a constant amount of target data combined with an increasing amount of support data. Results showed that indiscriminately enlarging the training data is not always an effective solution. If the divergence between the two genres is substantial, selecting the largest amount of support data could simply lead to the same performance as the absence of the support data. Conversely, selecting a smaller and more controlled amount of support data could result in more refined performances.

The second experiment fixed the amount of support data while gradually decreasing the target data. As expected, the performance of the models declined as the target data was reduced: the model had fewer genre-specific instances to learn from, so it was unable to correctly predict unseen target data. However, even a minimal amount of target data can result in better performance compared to the complete absence of the genre itself.

These findings highlight the necessity of developing linguistic analysis tools able to handle a wide range of genres with equal proficiency. Moreover, this study contributes to the development of more robust NLP tools for underrepresented historical languages and supports broader efforts to preserve and analyze linguistic heritage.

Future research will focus on selecting small support datasets that mirror the sentence-level POS tag sequences in the target data. Since this paper explores only data concatenation for combining data from different genres, future work will investigate more advanced methods such as treebank

embeddings (Stymne et al., 2018). In future works, we aim to investigate further ways to deal with historical, low-resource languages. Additional underrepresented historical languages and other tasks relevant to the linguistic analyses will also be taken into consideration.

7 Limitations

This study offers insight into the linguistic differences between Old English poetry and prose, and how these differences can affect linguistic analysis tools, such as POS taggers. In doing so, it also encounters some limitations.

Firstly, Old English is a morphologically rich language, and the granularity of the original tag sets reflects this complexity. As a result, losing linguistic information when converting these detailed tags to UPOS is inevitable. While we made an effort to map the original tags in a reliable way, there may still be conversion errors influencing the UPOS quality. Additionally, the study relies solely on combining data from different genres as a method of concatenation; future work will investigate alternative approaches.

Secondly, the models were trained with MaChAmp default hyperparameter settings. A more focused investigation into hyperparameter optimization could influence the models' performances, especially given the unique characteristics of Old English poetic data.

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A Appendix

POS Mapping and Tag Distributions

Table 5 presents the tag set conversion scheme. The POS and UPOS columns denote the name of the label and its corresponding Universal POS tag, while the YCOEP and YCOE columns list the corresponding tags according to our conversion. Table 6 reports the ten most common bigrams and trigrams for each genre, along with their probabilities, based on a representative sample of the datasets.

Table 5: Mapping of YCOEP and YCOE to UPOS.

POS	UPOS	YCOEP	YCOE
Adjective	ADJ	VBN^D, WADJ^N, ADJ^G, VAG^N, WADJ^D, VAG^D, VBN^G, VBN^A, ADJ^A, ADJ^N, ADJ^I, BEN^N, ADJ^D, ADJ, VAG^A, WADJ^A, ADJP-NOM, VAG^G, VBN^N	HVN^N, ADJ, ADJS^A, VAG^I, WADJ^G, ADJS, ADJR^N, MAG^G, ADJ^A, HAG^A, WADJ^D, VAG^N, ADJR^I, WADJ^I, HAG^N, WADJ^N, VAG^A, ADJR, ADJ^D, BEN^D, WADJ^A, VAG^D, VBN^I, VBN^N, VBN^D, BEN^A, BEN^G, ADJ^N, ADJS^G, ADJS^D, ADJ^I, VBN^A, ADJR^G, ADJ^G, ADJS^N, ADJR^D, WADJ, VAG^G, VBN^G, ADJR^A, BEN^N
Adposition	ADP	P	P21, P22, PP, P+D^I, P
Adverb	ADV	RP, ADV^D, WADV^D, RP-1, ADV^L, ADV, WADV^DX, ADV^DX, WADV^L, WADV^T, WADV-1, WADV, ADV^T, ADVP	ADV^T22, WADV^D, ADV, ADVR^D, ADVP, ADVP-LOC, ADVS^T, ADV^T21, RP-1, ADVS^L, ADV22, ADV+P, RP-4, RPX, ADV^L, ADV^D, ADV^T, ADVS, ADVR, WADV^T, WADVP-LOC-1, ADVR^L, P+ADV, WADV^L, WADV, RP, WADV+P, ADVR^T, ADV21, ADVP-TMP
Auxiliary	AUX	AXDS, AXP, MDI, AXPS, MDPS, AXI, MDPI, AXN, MDDI, MDD, AXDI, AXPI, MD, AXD, MDP, AX, MDDS	MD, AXG, MDDI, AXDS, AXDI, MDPS, MDP, AXI, MDD, AXP, AXPS, AXD, AXPI, MD^D, MDDS, MDI, MDPI, AX
Coordinating Conjunction	CCONJ	CONJ	CONJ
Determiner	DET	Q^G, Q^I, D^G, D^D, Q, Q^A, D^I, D^N, D^A, Q^N, Q^D	Q^D, QS^A, D, QR^N, Q+Q^N, D^N, QR^A, QS^D, D^G, D^A, Q, Q+N^A, Q^G, QR^G, Q21, D^D, Q+N^G, QR^D, D^I, Q^N, Q+Q^A, QS^G, Q+N^N, Q^A, Q^I, Q22, QR, QP-NOM, QS, QS^N
Interjection	INTJ	INTJ	INTJ
Noun	NOUN	NP-ACC-SBJ, N^G, NP-ACC, NP-DAT, N^D, N^I, N^N, NP-NOM, N^A, NP-DAT-PRN-1, NP-DAT-ADT	NP-ACC, N^G, NP-NOM-x, N^A, N^N, NP-GEN, NP, N, NP-SBJ, NP-NOM, N^I, N^D
Numeral	NUM	NUM^A, NUM^G, NUM^I, NUM, NUM^D, NUM^N	NUM^D, NUM^G, NUM^A, NUM^N, NUM, NUM^I
Particle	PART	TO, UTP, FP, NEG, FP-5	TO, FP, NEG, UTP
Pronoun	PRON	PRO$ ^G, WPRO^A, PRO^A, PRO$, PRO^D, WPRO, PRO^N, PRO$ ^N, PRO^I, WPRO^D, PRO$ ^A, PRO$ ^D, MAN^N, PRO^G, MAN^A, PRO$ ^I, WPRO^G, WPRO^N, WPRO^I	PRO^D, PRO, WPRO, PRO^G, WPRO^N, PRO$ ^N, WPRO^D, MAN^N, PRO$ ^A, PRO$ ^D, PRO^N, WPRO^G, PRO^A, WPRO^I, PRO$ ^G, WPRO^A, PRO$, PRO$ ^I
Proper Noun	PROPN	NPR, NPR^N, NPR^G, NPR^D, NPR^A	NR^N, NR, NR^G, NR^A, NR^D
Punctuation	PUNCT	, .	, .
Subordinating Conjunction	SCONJ	WNP-ACC-2, WNP-NOM-2, WNP-ACC-3, WNP-NOM-1, WQ, C, WNP-NOM-6	C, WNP-NOM-2, WQ-1, WNP-ACC-1, WNP-ACC-3, CP-REL, WQ, WNP-ACC-2, WNP-NOM-1
Verb	VERB	BE, VBD, VBN, VBPI, VAG, VBDI, BEDS, HVPS, HVD, HVPI, BED, VB, VBPS, VBDS, HVP, VBPH, BEDI, HVI, HV, VB^D, VB-3, BEPS, HVDI, BEI, BEP, BEPI, VBI, VB^A, BEN, VBP	BAG, HV^D, VBD, HVDI, VB, HVN, VBP, HVPS, HV, HVD, VBDS, BEDI, HVP, VBPH, BE, BEDS, BEI, BEPS, VBN, VAG, BEPH, BE^D, BED, BEN, HVI, HVDS, BEPI, HVPI, HAG, VB^D, VBPS, VBPI, VBDI, VBI, BEP
Other	X	FW, UNKNOWN	XX, FW, UNKNOWN
Symbol	SYM	-	-

Poetry			
BiGram	**Prob.**	**TriGram**	**Prob.**
('NOUN', 'PUNCT')	7.44%	('NOUN', 'VERB', 'PUNCT')	3.56%
('VERB', 'PUNCT')	5.67%	('ADJ', 'NOUN', 'PUNCT')	2.07%
('NOUN', 'VERB')	5.59%	('NOUN', 'NOUN', 'PUNCT')	2.03%
('ADP', 'NOUN')	4.66%	('ADP', 'NOUN', 'PUNCT')	1.78%
('NOUN', 'NOUN')	4.59%	('NOUN', 'PUNCT', 'NOUN')	1.41%
('ADJ', 'NOUN')	3.65%	('NOUN', 'ADJ', 'PUNCT')	1.40%
('PUNCT', 'NOUN')	3.36%	('NOUN', 'ADP', 'NOUN')	1.23%
('DET', 'NOUN')	2.44%	('VERB', 'PUNCT', 'NOUN')	1.16%
('NOUN', 'ADJ')	2.42%	('NOUN', 'NOUN', 'VERB')	1.15%
('ADJ', 'PUNCT')	2.39%	('ADP', 'NOUN', 'NOUN')	1.08%
Prose			
BiGram	**Prob.**	**TriGram**	**Prob.**
('NOUN', 'PUNCT')	4.99%	('ADP', 'DET', 'NOUN')	1.72%
('DET', 'NOUN')	4.96%	('DET', 'ADJ', 'NOUN')	1.45%
('VERB', 'PUNCT')	3.95%	('NOUN', 'VERB', 'PUNCT')	1.29%
('PRON', 'VERB')	3.10%	('DET', 'NOUN', 'PUNCT')	1.10%
('NOUN', 'VERB')	3.00%	('ADJ', 'NOUN', 'PUNCT')	1.10%
('ADJ', 'NOUN')	2.91%	('DET', 'NOUN', 'VERB')	1.09%
('ADP', 'DET')	2.89%	('VERB', 'DET', 'NOUN')	0.95%
('ADV', 'VERB')	2.42%	('ADP', 'PRON', 'NOUN')	0.85%
('ADP', 'PRON')	2.35%	('VERB', 'ADP', 'DET')	0.76%
('VERB', 'ADP')	2.29%	('PRON', 'VERB', 'PUNCT')	0.75%

Table 6: Ten most frequent bigrams and trigrams with probabilities of representative samples from YCOEP and YCOE.