An ELECTRA Model for Latin Token Tagging Tasks

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Abstract
This report describes the KU Leuven / Brepols-CTLO submission to EvaLatin 2022. We present the results of our current small Latin ELECTRA model, which will be expanded to a larger model in the future. For the lemmatization task, we combine a neural token-tagging approach with the in-house rule-based lemma lists from Brepols’ ReFlex software. The results are decent, but suffer from inconsistencies between Brepols’ and EvaLatin’s definitions of a lemma. For POS-tagging, the results come up just short from the first place in this competition, mainly struggling with proper nouns. For morphological tagging, there is much more room for improvement. Here, the constraints added to our Multiclass Multilabel model were often not tight enough, causing missing morphological features. We will further investigate why the combination of the different morphological features, which perform fine on their own, leads to issues.

Keywords: ELECTRA, lemmatization, POS-tagging, morphological tagging, morphological features, token tagging

1. Introduction
This short report describes the systems developed by the KU Leuven / Brepols-CTLO team for the EvaLatin 2022 Evaluation Campaign. The first section will describe the language model that is used in all three tasks. Subsequently, the three tasks (lemmatization, POS-tagging and morphological tagging) are discussed, each divided in subsections concerning the followed methodology, the results and a discussion of these results.

2. Language Model
We pretrained a custom Latin ELECTRA-model, using Brepols’ Library of Latin Texts as training data (160M tokens). ELECTRA models maintain the same basic computational architecture as BERT models (Devlin et al., 2018). While they are computationally less expensive, they nevertheless achieve better results, due to a more efficient training approach. This makes them particularly suited to training models with comparatively less amounts of data. In the future, we will train a larger Latin ELECTRA model with more training data, continuing the pioneering work of Bamman and Burns’ Latin-BERT (Bamman and Burns, 2020).

3. Lemmatization
3.1. Methodology
For the lemmatization task, we combined a rule-based gazetteer approach (in which handcrafted rules provide lists of possible word forms for each lemma) with a neural token tagging task. Using a rule-based approach, Brepols provided a system (ReFlex) that generates all possible forms for each lemma in their database. As a first step in our lemmatization system, ReFlex returns for each token in the lemmatization task the corresponding lemmata. If there is only one possibility, no further action is needed. Otherwise, we predict the POS-tag of the token as described in the next section, and use this POS-tag to resolve the existing ambiguity, returning the lemma with the matching POS-tag. For the remaining ambiguous tokens, we had to make a pragmatic decision, as it is not feasible to train a separate classifier for each of the remaining tokens. Therefore, we trained one classifier on choosing the right lemma out of the list of possible lemmata that ReFlex returned, using the Huggingface Transformers implementation of ElectraForTokenClassification. For example, if ReFlex returned 3 possible lemmata for a token, e.g. two nouns and a verb, we would assign them the labels n1, n2 and v1 respectively. The task of the classifier consists of predicting which label is needed in the current context, and thus returning the right lemma. This is not an optimal solution, as there is no linguistic reason why a certain lemma would be first or second in the ReFlex list. However, this approach is needed to make a decision between, for example, two or three nouns, as the disambiguation based on the POS-tag is impossible in this scenario. Based on the validation data, our approach was successful concerning nouns, but fails when faced with multiple verbs as possible lemmata. Lastly, a few manual rules were written based on a run on validation data, for example converting abbreviated praenomina to their spelled out counterparts.

1In the future, our pretrained Latin ELECTRA-model will be uploaded to Huggingface Transformers.
2See Brepols’ Library of Latin Texts.
3For this specific implementation, see ElectraForTokenClassification on Huggingface Transformers.
In the same vein, ReFlex returned the original adjecti-
tive when processing an adjectival adverb, while the
EvaLatin dataset expects the adjectival adverb itself as
the predicted lemma. We adopted the following rule to
circumvent this problem: if the POS-tag is ADV, Re-
Flex does not return its normal lemma, but the associ-
adverted adverb.

3.2. Results
The results of the lemmatization task are described in
Table 1.

| KU Leuven / Brepols-CTLO closed | LEMMATIZATION |
|---------------------------------|---------------|
| Ab Urbe Condita (classical)     | 85.44         |
| Metamorphoseon (cross-genre)    | 87.22         |
| Naturalis Historia (cross-genre)| 85.75         |
| De Latinae Linguae Reparatione (cross-time) | 84.60 |

Table 1: Results of the lemmatization task

3.3. Discussion
While it is clear that our system performs worse than
our competitors [Sprugnoli et al., 2022], this can be
at least partly attributed to differences in defining a
lemma. As mentioned in the previous section, we had
to implement manual rules to make sure that the Re-
Flex lemmata were consistent with EvaLatin lemmata.
This was done based on frequent mistakes while tag-
gging a validation dataset (20% of the provided training
dataset). However, due to time constraints, it was not
feasible to remove all these inconsistencies. It comes
apparent, for example, that EvaLatin prefers the plu-
ral form as a lemma for demonyms such as Allobroges,
Samnites, Romani, while ReFlex resorts to the singu-
lar Allobrox, Samnis and Romanus. A second prob-
lem are the so-called deponent verbs, where EvaLatin
prefers the passive form as a lemma, while ReFlex re-
turns the active form, even if this form is only attested
once (otherwise, ReFlex also gives the passive form).
Likewise, EvaLatin takes fio (“I become”) as a separate
lemma, while ReFlex considers it the passive form of
facio (“I make”). Thirdly, ReFlex will always return
the original verb when faced with adjectival participles
such as iatus (“angered”), tatus (“guarded”) and ex-
cellens (“towering”), while EvaLatin chooses the ad-
jective in these cases. Finally, the relative pronoun quis
was consistently tagged as qui, while the ablative quo
(with lemma qui in EvaLatin) was tagged as quo by ReFlex as if it were an adverb (“where”). These rela-
tive pronoun errors make up 6.3 % of the lemmatiza-
tion errors, which is a significant amount. In the future,
we will take the frequency of a lemma into account, to
avoid situations in which a very common word such as
cum (“with”, “when”) is lemmatized as an infrequent
lemma Cous (“of Cos”, “Coan”).

4. POS-tagging
4.1. Methodology
Our POS-tagging system is very straightforward: we
trained a Huggingface Transformers ElectraForToken-
Classification model on the provided datasets. Based
on our own previous experiments with inflectional lan-
guages, we decided to make one modification. As most
modern language models do, ELECTRA models make
use of a subword tokenizer, which processes frequent
forms as one token and splits less common forms into
smaller subwords, e.g. amat (“he/she loves”) is tok-
ened as amat, while amabamini (“you were loved”) be-
comes ama #bam #ini. Thus, an important step con-
sists of determining on which subword of the complete
word the actual token tagging will take place. Usually,
a tagger uses the embedding of the first subword, or
the average of all the subwords. Our system uses the
last subword of a token, as crucial morphological in-
formation is stored in the last part of the word, because
Latin is an inflectional language [Acs et al., 2021]. In
the future, we will further experiment with other, more
advanced subword pooling techniques, as discussed in
Acs et al. [Acs et al. (2021)].

4.2. Results
The results of the POS-tagging task are described in
Table 2.

| KU Leuven / Brepols-CTLO closed | POS-TAGGING |
|---------------------------------|-------------|
| Ab Urbe Condita (classical)     | 96.33       |
| Metamorphoseon (cross-genre)    | 94.66       |
| Naturalis Historia (cross-genre)| 89.96       |
| De Latinae Linguae Reparatione (cross-time) | 92.11 |

Table 2: Results of the POS-tagging task

4.3. Discussion
The results show that our system performs well, com-
ing just short of the results of our competitors in the
EvaLatin campaign. In 52.7 % of the mistakes on the
test set, PROPN is either the gold label that gets a
different tag, or PROPN is wrongly predicted instead
of the correct tag. Many of the latter are geographical
adjectives such as Romanus that can also be used
as nouns. Furthermore, less frequent words with non-
Latin roots such as psittachoras (a certain kind of tree)
are often tagged as PROPN as well, probably because of the similarity with Greek personal names. This type of words is especially frequent in Pliny, describing various plants etc. Secondly, the aforementioned problem concerning the distinction between adjectives and participles (and thus, verbs) explains some mistakes in this task as well.

5. Morphological tagging

5.1. Methodology

Rather than predicting all the features at once, which causes issues of data sparsity on the one hand, and a large amount of labels on the other hand, we trained a separate classifier for each of the morphological features defined in the dataset. Next, we calculated the probability of the full morphological tag as the product of the probabilities of the individual features: e.g. \( P(\text{Case}=\text{Gen}—\text{InflClass}=\text{IndEurO}—\text{Number}=\text{Sing}) \) is defined as \( P(\text{Case}=\text{Gen}) \times P(\text{InflClass}=\text{IndEurO}) \times P(\text{Number}=\text{Sing}) \). This is similar to the approach used by RFTagger (Schmid and Laws, 2008) and is defined by Tkachenko and Sirts (2018) as the Multiclass Multilabel model. For this, we used the same architecture as discussed before in the POS-tagging section. Afterwards, we combine the predicted labels into one tag. Rather than taking a naive approach (taking the highest-scoring prediction for each feature and combining them, without constraints), which can lead to impossible combinations (such as adjectives receiving a mood feature), we predefine a set of possible combinations of tags, which act as constraints on the output of our system. These tag combinations are mostly based on POS-tags (e.g. interjections do not have any morphological features), but are sometimes more fine-grained, particularly for verbs as there are different rules needed to distinguish, for example, finite verbs and participles. Combining this approach with a lexicon of tags that occur in the training data ensures that no impossible predictions are formed.

5.2. Results

The results of the morphological tagging task are described in Table 3.

| KU Leuven / Brepols-CTLO closed | MORPHOLOGICAL TAGGING |
|---------------------------------|------------------------|
| Ab Urbe Condita (classical)     | 69.91                  |
| Metamorphoseon (cross-genre)    | 63.06                  |
| Naturalis Historia (cross-genre)| 58.04                  |
| De Latinae Linguae Reparatione (cross-time) | 60.09 |

Table 3: Results of the morphological tagging task

5.3. Discussion

The results of this task are rather disappointing. A big part in this is played by exceptions, which we will illustrate with an example. In the test data, we find instances of the word *opus*, with only InflClass=IndEurInd as a morphological feature. This is an exception to the usual morphological features of a noun, which involve an InflClass, a Case and a Number. However, to accommodate our ruleset in such a way that the exceptions are handled as well, we have to allow nouns to only have a IndEurInd feature. As such, our constraint-based system is weakened by these few exceptions, leading to mistakes where the Number feature for example, is mistakenly omitted. Furthermore, morphologically identical features, such as the nominative and accusative for neuter words, have considerably more errors than features that are morphologically different. This is already apparent while training the data: on the validation data we see that there are 317 nominatives falsely tagged as accusatives, compared to only 17 falsely tagged datives and 34 genitives (8786 nominatives received the right tag). Currently, we are looking into better ways of combining the different tags, as our separate morphological feature classifiers are performing considerably better than the sum of their parts.

6. Conclusion

In this report, we described the first steps in using an ELECTRA model for Latin token tagging tasks. In the future, we will train a larger model on the one hand, and refine our system on the other hand, especially with regards to the morphological tagging task.

7. Acknowledgements

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