

Evaluation of Named Entity Recognition in Latin using an Unsupervised Model

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Abstract

Tackling the challenges of Named Entity Recognition (NER) in Latin using an unsupervised approach revealed that tokenization strategies and contextual embeddings from a pre-trained model such as BERT are better suited for these tasks and that the an ensemble of models being used plays a significant role in the final results. Clustering has proved to be the most straight-forward model to group entities together but a more intricate pipeline lead to a significantly better result, achieving an averaged macro F1 score of 0.90 for the binary clustering, 0.43 for the multi-class clustering, and 0.41 for the neural network.

1 Introduction

As international students, the probability of sharing a common language outside of English is not high, however, during our studies we came to the realization that some of us share knowledge in one such language, Latin. Due to Latin being a low resource language, but still widely used in fields such as medicine and theology, it is a perfect language to use as a foundation for developing NER methods for less resourced languages, and a stepping stone towards even less resourced languages, such as Old Norse.

As there is no past research on unsupervised NER for Latin, only on other low resource languages, such as the paper titled *Zero-Resource Cross-Lingual Named Entity Recognition*¹ (Bari et al., 2019), we would like to contribute to the field of Natural Language Processing (NLP) by developing unsupervised NER methods that can be applied not only to Latin, but to other low resource languages as well in the future.

As such we chose to build upon a past research, titled *Challenges and Solutions for Latin Named*

*Entity Recognition*² (Erdmann et al., 2016), which tackles the problem of NER in Latin using a supervised and semi-supervised model. Our dataset is based on the one used in the original paper, following the same structure, with some additional specifications for clarity.

2 Dataset

The dataset from the original paper named 3 works of literature, Caesar’s *De Bello Gallico* (BG), Pliny the Younger’s *Epistulae* (EP), and Ovid’s *Ars Amatoria* (AA). We have received the full dataset in its entirety, as large text files, in IOB format, with tags GEO-B, GEO-I, GRP-B, GRP-I, PRS-B, PRS-I, O. While all the literature was scrambled in large combined files, we have had to separate them in different files to process in accordance to which literature it is. Next we have done some Exploratory Data Analysis (EDA), and after thorough investigation, we have found that there is a slight inconsistency in the original paper regarding the dataset, and that of which we have received. As mentioned, the entirety of BG, and parts of EP and AA were annotated, however, parts of Caesar’s *De Bello Civili* (BC) were also annotated within the dataset, but left unmentioned in the original paper. Below is a table¹ of the token counts from the original paper and our investigation.

| | Original | Ours |
|----|----------|--------|
| EP | 18,676 | 18,676 |
| AA | 17,562 | 17,564 |
| BG | 58,891 | 58,889 |
| BC | 0 | 4,836 |

Table 1: Token counts from the original paper and ours

As we can see, the token counts do closely match between the original paper and our investigation,

¹Original paper: <https://arxiv.org/abs/1911.09812>

²Original paper: <https://aclanthology.org/W16-4012/>

with slight differences, likely due to manual splitting of the dataset, so there is a negligible inconsistency on our end, however *BC* is an outlier, which has a token count of 0 in the original paper, and 4,836 in our investigation, as it is not mentioned in the original paper.

To have an initial understanding of the expectations of our models, we must understand the distribution of the dataset, namely the amount of *Named entities (NE)* and *Non-Named entities (Non NE)* in the dataset. As shown in Figure 1 and Figure 2, we can see that there is a significant imbalance in the dataset, with only about 5.5% and 3.3% of the tokens being NE.

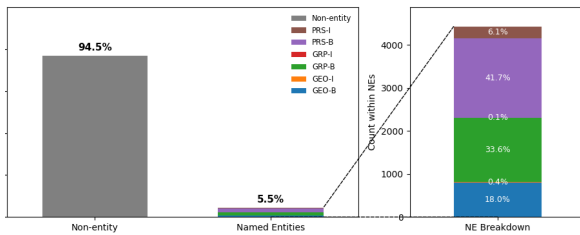


Figure 1: Distribution of data for *BG*, *BC*, and *AA* combined, used for one of the training folds.

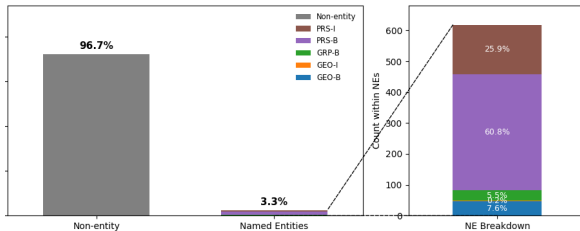


Figure 2: Distribution of data for *EP*, used for one of the testing folds.

3 Methodology

Once we had the dataset split into training and testing files, we started with tokenizing the words, and researching approaches on how to handle the tokens, embeddings, and labels, without having supervision over the original entity information that were available. Afterwards we have implemented several approaches in training a model, namely Binary and Multi-Class Clustering, and a Neural Network.

3.1 Embeddings

Our initial approach was to vectorize tokens using a basic Word2Vec method from the Gensim library. However, this produced unacceptably low results

with clustering as the model was not able to separate entities from non-entities in a meaningful way. So we moved on to a more powerful method: using contextual word embeddings from a pretrained Bidirectional encoder representations from transformers (BERT) model, specifically bert-base-multilingual-cased. This model was trained on a large corpus of multilingual text, including Latin, and is capable of generating high-quality embeddings for words in context.

We used the Hugging Face Transformers library to load the model and generate embeddings for our tokens. We extracted the embeddings from the last hidden layer of the model. Since BERT works on subword level, we combined the embeddings of the subwords that compose a token by averaging the subwords embeddings. This approach has been shown to work well in practice and allows us to obtain a single embedding for each token. We discussed the options of using subwords embeddings for clustering and switching to the word level later on, but this led to unnecessary complications of the pipeline, for example, by introducing the necessity of handling scenarios when embeddings of one word end up in different clusters.

3.2 Clustering

Once we had the word level embeddings, we applied KMeans Clustering to automatically group the tokens into clusters. Kmeans was the most straightforward choice for the task. One of the challenges we faced was the choice of K - number of clusters. We tried several methods to determine the optimal number of clusters, including the *Elbow Method* and *Silhouette Score*. The elbow method suggested that big values of K are better, up to the point that number of clusters was close to the number of tokens. Silhouette score also was not very helpful, since bigger score didn't correspond to better evaluation scores afterwards. We approached the problem with the simplest and most straightforward method: trial and error. First we started with a binary classification, where we had two clusters: one for NE and one for Non NE. For this we settled on a value of K = 7.500, due to the silhouette score having the highest value, 0.1, at around that number of clusters. Where we then passed the clusters classified as NE to another kmeans clustering, where we had 207 clusters for the different types of NE.

We used the KMeans implementation from the scikit-learn library, which provides a simple

and efficient way to perform KMeans clustering. After clustering we labelled each cluster by taking the most frequent token’s label in the cluster. We had a short discussion on whether this makes the model semi-supervised, but concluded that it does not: the label data is only used after clustering, and does not influence how the clusters are formed. Then we evaluated the clusters as a baseline for our model. We used the macro F1 score to measure the performance of the multi-class clustering, and got an average macro F1 score of 0,43, and 0,90 for the binary clustering, due to Capitalization, which lines up with the high results from the original paper.

3.3 Neural Network

Next we reconstructed the model using a Neural Network (NN). We used a lightweight NN consisting of two linear layers with GELU Activation and LayerNorm, mapping contextual BERT embeddings to entity class logits. The network is trained using pseudo-labels derived from the initial clustering, which makes the inherently supervised neural network **unsupervised**.

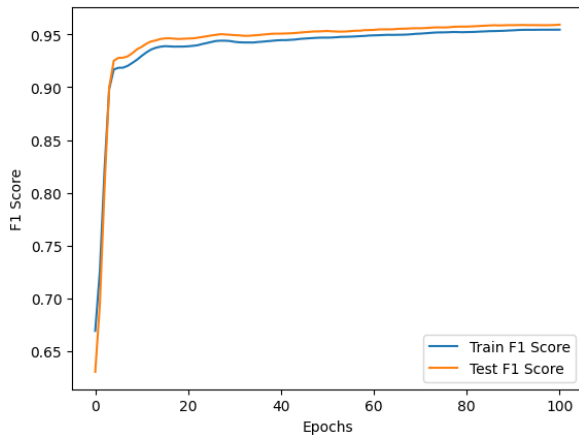


Figure 3: Rate of change of the F1 score with increasing number of epochs.

We used Pytorch to implement and train the model. The choice of the number of epochs was based on the rate of change of the F1 score, which we observed in most cases to not significantly increase after 10 epochs, and plateau after 30 epochs. As shown in Figure 3, which is what we chose.

4 Results

We have stayed true to the original paper and used the same train and test sets, indicated in Table 2, and have used the same evaluation metrics, indicated in Table 3. Given the state of the original

dataset, it is unclear whether *BC* was part of the original train set, so we have included it in our train set, as it was present in the original dataset even though not explicitly mentioned, and all 8 books of *BG* were included as those are part of the mentioned train set.

| | Test Set | In or Out-of-domain |
|--------|----------|---------------------|
| Fold 1 | Piny | Out |
| Fold 2 | Ovid | Out |
| Fold 3 | Caesar | In |

Table 2: Train and Test Sets for each fold

To have a detailed overview of the results, we have included a classification report for each fold and each model in Table 3, which includes the precision, recall, and macro F1 score for each fold and each model, namely Binary Clustering, Multi-Class Clustering, and Neural Network. While we understand that the modern standard score for NER is the Span F1 score, we have used the word F1 score for the sake of consistency with the original paper, as there is no mention of specificity of the type of F1 score used.

| | Prec. | Rec. | M. F1 |
|-------------------------------|-------|------|-------|
| <i>Binary Clustering</i> | | | |
| Fold 1 | 0.90 | 0.91 | 0.91 |
| Fold 2 | 0.86 | 0.78 | 0.82 |
| Fold 3 | 0.98 | 0.98 | 0.98 |
| <i>Multi-Class Clustering</i> | | | |
| Fold 1 | 0.41 | 0.43 | 0.41 |
| Fold 2 | 0.38 | 0.34 | 0.35 |
| Fold 3 | 0.56 | 0.53 | 0.54 |
| <i>Neural Network</i> | | | |
| Fold 1 | 0.33 | 0.52 | 0.39 |
| Fold 2 | 0.29 | 0.42 | 0.32 |
| Fold 3 | 0.48 | 0.60 | 0.53 |

Table 3: Classification report, showing Precision, Recall, and Macro F1 for each fold and each model

These results suggest a match in our expectations, that binary clustering performs extraordinarily well, aligning with the results of past research having an F1 score of 0.99 for the in-domain test set, however once we dive deeper into being able to distinguish between different named entities, the results are much lower. Additionally, the Neural Network does not provide any improvement over the multi-class clustering, however, we must note that the purpose of the Neural Network is to generalise

on unseen data, and not to specifically outperform the multi-class clustering.

There are a few key points worthy of mention, that may not be initially obvious. Fold 3 represents the In Domain datasets, which have higher chance of performing better, as per our observation, the training and testing datasets mention the same entities more often, resulting in a better fit. Finally, some entities are better detected, which the results table also does not show. The entities that we found to be better detected, were GEO-B, GRP-B, PRS-B, with F1 scores on average of around 0.6 to 0.8 for each entity.

5 Future Work

As our results are not very promising, it gives us a glimpse into the mysteries of the Latin language, and the challenges of NER within it. We plan to explore some aspects of this field as there is a lot of room for improvement, and a lot more to discover.

To start, we would like to explore having a much larger dataset to work with, and observe how results improve with the proportion of data. Next, we would like to explore different capitalizations of the language, and observe how results change, as we suspect that the capitalization played a significant role in the performance of the model. Finally, considering an ensemble method of different models may prove to be the most effective approach, as it has been observed so far, and we would like to explore the limits of this approach and benefits of it.

Limitations

Due to the size of the dataset and the complexity of the task, we were not able to train a more capable model. A comparable evaluation of NER using an unsupervised model within the English language has been shown to achieve high results, indicating that the size and distribution of the dataset is a significant factor in the performance of the model, even more so than the choice of model.

Having a discrepancy between the original dataset wordcount and what we have received, based on the original splits, having to manually split the dataset has made our work substantially longer than expected, as we had to manually separate the dataset up into new files. Using the help of the original source of the dataset, we managed to find and split it appropriately, at a significant cost of time.

Due to the limitations of time, we were not able to explore more methods of approach and tinker extensively with the hyperparameters of the model.

A Appendix

Group contributions are as follows:

- Mykyta: Initial EDA to identify distribution of NE's and non NE's, observations on inconsistencies in the dataset, implementation of binary pipeline and of the Neural Network.
- Wenzel: Implementation of the Multi-Class Clustering method, multi-class classification, training the models, and reporting the results.
- Gabriel: Collaborating with previous papers authors, obtaining the dataset, EDA, splitting up dataset into train and test sets, implementing initial Word2Vec and Tokenization methods.

We feel these contributions are fair and equal, and reflect the work done by each of us.

We have used chatbots, in the form of spellcheckers after writing our paper to make sure we are formulating our sentences in an appropriate manner, and autocompletion in our code to speed up the development process.

All of our code is available on GitHub³. As the dataset shared was not disclosed to be public, it is left out of the repository.

³Github Repository: <https://github.com/GabrielCirciu/Latin-NER-NLP>

References

- M Saiful Bari, Shafiq Joty, and Prathyusha Jwalapuram. 2019. [Zero-resource cross-lingual named entity recognition](#). *Preprint*, arXiv:1911.09812.
- Alexander Erdmann, Christopher Brown, Brian Joseph, Mark Janse, Petra Ajaka, Micha Elsner, and Marie-Catherine de Marneffe. 2016. [Challenges and solutions for Latin named entity recognition](#). In *Proceedings of the Workshop on Language Technology Resources and Tools for Digital Humanities (LT4DH)*, pages 85–93, Osaka, Japan. The COLING 2016 Organizing Committee.