NER for acknowledgements
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Abstract

Named Entity Recognition (NER) is a crucial task in Natural Language Processing (NLP), aimed at identifying and classifying named entities in text. In this paper, we present our project's goal and methodology, which revolves around developing and evaluating NER models for recognizing and classifying entities in scientific acknowledgements. We build upon the work of Smirnova and Mayr (1) and train NER models using Flair Embeddings, BERT and XLNet models. According to our hypotheses, the described project showed that advanced deep-learning models perform better than basic machine learning techniques. Moreover, a small dataset does not perform well during learning, however, if increased by a silver set of even lower quality, the model's performance increases significantly. The final improvement in the models after using the silver set was most noticeable with the smallest original set, when it increased the F1 score from 0 to 51%. In other cases, the score also increased but not so dramatically. Flair Embeddings proved to be the fastest learner and achiever of all models taken for experimentation. However, models using transformers are very promising but a lot of computing power is needed to train them. Our research can contribute to the development of NLP and scientific text analysis.

Keywords: Named Entity Recognition (NER), Natural Language Processing (NLP), acknowledgements

1 Introduction

Named entity recognition is a fundamental task in natural language processing (NLP), the aim of which is to identify and classify named entities into predefined categories such as people, organisations and many others. In a variety of fields such as healthcare, finance, law and science, the correct recognition of these entities is crucial for making meaningful inferences, facilitating information retrieval and enhancing text comprehensibility. Incorrect or incomplete recognition of units can lead to misinformation, misinterpretations and impede accurate decision-making.

Acknowledgments in scientific papers are a section where authors express gratitude and recognition to individuals, organizations, or funding sources that contributed to the research but may not be directly involved in the writing or analysis. This section typically appears near the end of the paper, before the references. Authors use acknowledgments to appreciate the support, guidance, technical assistance, or financial assistance received during the course of the study. It is a way for researchers to acknowledge the collaborative nature of scientific endeavors and show appreciation for those who played a role in the project's success. Importance of this section in papers been growing for some time (2).

The aim of our project is to develop and evaluate named entity recognition (NER) models for identifying and classifying entities in acknowledgements. The plan was to build our work on the foundations of the paper written by Smirnova and Mayr (1) by training the models presented in the paper on the provided data and conducting their own evaluation. In addition, we wanted to try a different approach and compare what results LLM models can achieve and create a silver set, a corpus of articles with automatic annotations provided by our new trained models.

1.1 Research questions

- What techniques and models in the field of NLP are most effective for recognising named individuals in a specific area?

- How does the performance of NER models change with different types and amounts of training data?

- Can the use of different text normalisation techniques, such as lemmatization or stop word removal, improve the effectiveness of NER models in identifying entities in scientific acknowledgement texts?

- Can preparing a silver-set and further training models on it improve their effectiveness?

- Which types of entities are the most difficult to classify?

1.2 Hypotheses

- Deep learning models, especially those using transform architectures, will outperform traditional machine learning approaches in recognising named entities, especially for complex and context-dependent entities.

- Increasing the size and diversity of the training dataset will improve the accuracy and generality of NER models, providing better recognition of actors

- The use of text normalisation techniques, such as lemmatization or stop word removal, combined with NER models, leads to improved accuracy and precision in the identification of entities in scientific acknowledgement texts.

- Preparing a silver-set and further training models on it will improve performance.

- Proper names of corporations, especially with specific words, will be the most difficult to recognise.

1.3 Significance of the project

In our project, we used advanced NER models, especially those based on transformers, using the Flair library. We focused on the identification and classification of entities in scientific acknowledgements, which is a significant challenge in the field of natural language processing (NLP). With the growth of scientific data, understanding the implicit relationships and collaborations of scientists in acknowledgements becomes particularly important. Our research in this specific area of NLP is crucial to improve the identification of relationships between scientists and to assess the impact of financial and technical support on research outcomes.
We expect our findings to have a significant impact on the development of the field of NLP and scientific text analysis. By identifying key individuals in scientific acknowledgements and analysing their interrelationships, our findings may facilitate the understanding of key figures in the field of science. In addition, our research can influence the way scientists collaborate, enabling a more efficient and organised exchange of knowledge. This combination of advanced NER technologies with the analysis of acknowledgements a step towards novel solutions in natural language processing and scientific research.

2 Related works

As the number of articles containing an acknowledgement section has been growing for a few years now (2), researchers have begun to look at methods to exploit the information they contain. Smirnova and Mayr (1) developed this theme in their work using tools from the Flair library (5). However, a few years earlier Wu, Jian & Wang, Pei & Wei, Xin & Rajtmajer, Sarah & Giles, C. & Griffin, Christopher in their paper (3) have created a system to extract acknowledgment entities from articles in the database CORD-19 and classifies extraction results from open source NER packages that recognize people and organizations. This work has achieved a giant step compared to the initial work, which began with manual extraction of information. In such a way (4) Blaise Cronin, Gail McKenzie, Lourdes Rubio, and Sherrill Weaver-Wozniak extracted a total of 9561 peer interactive communication (PIC) names from a total of 4200 research sociology articles.

What is equally important as the selected model is to pay attention to the quality of the dataset on which the training is based. Creating new one, however, is not easy and most often requires extensive domain knowledge. For the NER problem, the CoNLL-2003 (8) dataset is most often used as a benchmark. The dataset comprises four types of named entities: person, location, organisation, and miscellaneous. However, it does not meet all the needs we want to include in our work.

2.1 Dataset

Therefore, based on Smirnova and Mayr (1) example, we used their base dataset. It recognizes 6 types of entities:

1. funding agency,
2. grant number,
3. individuals,
4. university,
5. corporation,
6. miscellaneous.

The dataset has been divided in 4 different subsets, called corpora, that differed in size. First corpus contained 832 training samples, second - 12621, third - 26981, and the last one - 36213. The differences in corpora sizes would significantly affect results obtained (more on that in section 4).

As for the first classification task (entity/no entity), the division was quite even - 42.6% of words were entities, and 57.4% of words were not. Regardless of the corpus, the most popular entity types in acknowledgements were funding agency (FUND), grant number (GRNB) and individual (IND) (see: Figure 1). This will also have impact on the results.

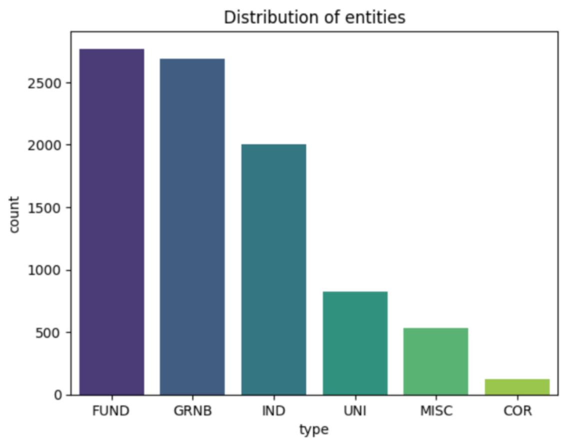

Figure 1: Distribution of entities appearances in corpora

When it comes to differentiation both within and between entity types, we checked cosine similarity

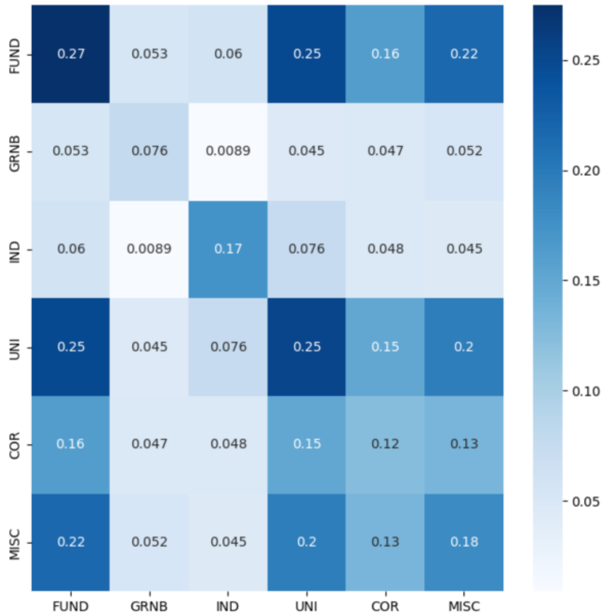

Figure 2: Cosine similarity between words wrt. entity type

between words by creating a vector embeddings of each (see: figure 2. As we can see, words in given entity group are not so similar to each other (maximum value in the cosine similarity matrix is 0.27), but it appears that the words within given group are more similar to each other than to words from other groups (although the differences in many cases are not significant). This is mostly because use of common words share between some of the groups. For instance, the word *of* is among top 5 most frequent words in three out of six entities groups. This makes the entity recognition task harder, as models need to evaluate the context of all entity and not by just looking at single words.

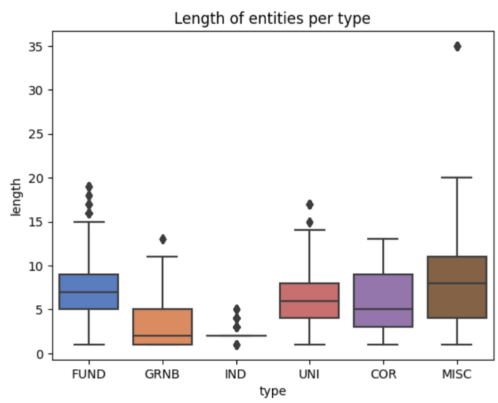

Figure 3: Distribution of length of entities wrt. type

Speaking of words within a given entity, we also checked the average length of given entity to see whether this may become a clue for the model (see: Figure 3). Not suprisingly individuals have on average two words (name and surname). The remaining entity types have similar distributions, with funding agency and miscellaneous having the longest tails.

3 Approach & research methodology

3.1 Models

We built our work upon three different models that are considered to be state-of-the-art solutions for namedy entity recognition task.

3.1.1 Flair Embeddings

NER model with Flair Embeddings is a method which create contextual word embeddings for text data (6). Unlike traditional word embeddings like Word2Vec or GloVe, Flair Embeddings consider the surrounding words and the context in which a word appears. It thus gives different embeddings for the same word depending on it's surrounding text. This is achieved through the use of two-way Long Short-Term Memory (LSTM) models, enabling Flair to capture complex relationships between words, which makes it particularly useful for tasks like named entity recognition, part-of-speech tagging, sentiment analysis, and other sequence labeling tasks, where the meaning of a word can vary depending on its context.

3.1.2 BERT

Apart from Flair Embeddings, Smirnowa and Mayr in their work used also another Flair model, this time the one based on transformers approach (1). In our work, we tried with different transformer-based model, BERT (Bidirectional Encoder Representations from Transformers) (10). This model use attention mechanism, which is a way for a model to assign weight to input features based on their importance to some task. Before feeding word sequences into BERT, 15% of the words in each sequence are replaced with a mask token. The model then attempts to predict the original value of the masked words, based on the context provided by the other, non-masked, words in the sequence.

3.1.3 XLNet

Lastly, we proposed a different language model, XLNet (7). Introduced in 2020, it also belongs to the family of transformer-based models. XLNet combines the best of both worlds by utilizing autoregressive modeling (like in traditional language models) and autoencoder modeling. It maximizes the likelihood of predicting the next word in a sequence while considering all possible permutations of the input sequence. It aims to capture bidirectional context effectively, leading to improved performance on a wide range of NLP tasks, including named entity recognition. For the purpose of the project we used two versions of XLNet - base (the lighter version) and large. Large, although obtaining better results, trained very long compared to the other methods, therefore base was also used in order to compare the time/results tradeoff. More on that in section 4.

3.2 Evaluation methods

Named entity recognition is a task that can be divided into two steps - extracting entities from plain text and providing a category for given entity. This can be considered as two classification tasks - first 0-1 classification (entity, no entity) and then multiclass classification (entity A, entity B, etc.). Similarily to Smyrnova and Mayr's approach, we can treat this two classification tasks as one - if we consider no entity as a separate class in multiclass classification.

Therefore, we evaluated the models performance with F1 score, as it's a very good metric for multiclass classification task.

3.3 Silver set

One of the research questions was about the impact of adding new data on the model results. Because of specific setup of the dataset, we were not able to find anywhere in the Internet yet another dataset to enlarge our training set. Instead, we decided to enrich gold standard set provided by Smyrnova, with a silver standard set. The key difference is that goal standard is made or approved by some domain expert, while silver standard set allows automatic or semi-automatic ways to create labels, in this example labels of entities for text in acknowledgement sections.

Therefore, our plan was first to train a model based on a gold standard set provided. Additionally, we manually collected acknowledgement sections of 243 papers from science domain. Next in line, our plan was to create labels for those 243 acknowledgement sections based on predictions from the model we trained before. Lastly, we wanted to verify the hypothesis that having more data (even not only in gold standard, but also in silver) can be benefitial in terms of model's efficiency. This is described in more detail in section 4.

3.4 Equipment and devices

Due to the use of models requiring high computing resources, we were not able to carry out experiments and model fine-tuning processes on our own hardware. Instead, all work was carried out on a dedicated project in the Google Cloud Platform. There, we set up a virtual machine (16 vCPUs, 64 GB RAM) with the Jupyter Notebook environment.

4 Experiments and Results

The goal of the first set of experiments was to train the Flair Embeddings model on different corpora and compare the results. As mentioned in section 3, corpus 1 contains the least data, while corpus 4 the most. Each corpus has been split to training, validation and test set. The setup is shown on Figure 4. The general conclusion is - smaller the corpus used for training, the worse the results of the model. The F1 score of the Flair Embeddings for each corpus is as follows:

Corpus	F1 Score
Corpus 1	0%
Corpus 2	81%
Corpus 3	83%
Corpus 4	83%

Table 1: F1 Scores for Each Corpus

As the amount of data in the corpus increases, the model achieves a better result. However, for corpus 3 and 4 there is no significant difference in the model performance.

Flair Embeddings model trained on corpus 4 was then used to create the silver standard corpus. The intention was to select the model trained on the most numerous corpus in order to create a silver corpus of the best possible quality. This can also be seen on Figure 4.

The goal of second set of experiments was to see how silver standard set affects the results. For two different corpora we trained the model with and without silver standard set. The silver set was

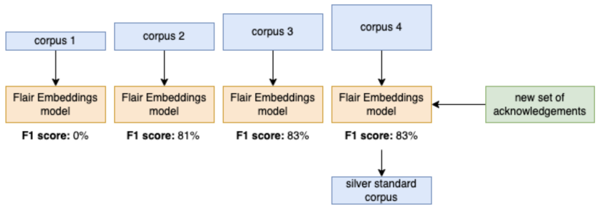

Figure 4: Flair Embeddings trainings setup

added to the train set of given corpus, the validation and test sets remained the same for each corpus. For corpus 1, we used Flair Embeddings model, while for corpus 4 - XLNet-large. The setup and results are shown on Figure 5.

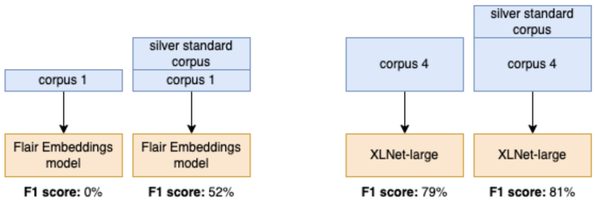

Figure 5: Comparison of the effectiveness of models trained directly on the corpus vs. trained on the corpus combined with the silver set

The use of the silver standard set in training models significantly improves results. For corpus 1, the model finally started to learn. F1 score increased from 0% to 52%. For corpus 4, there was also an increase from 79% to 81%.

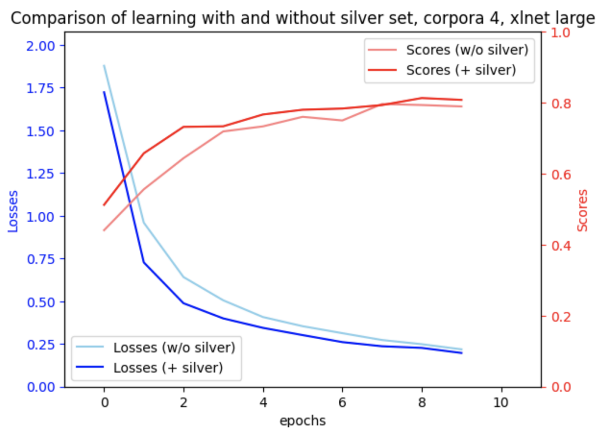

Figure 6: Training history of models with and without silver set

The results of training history (both losses and F1 scores) can be seen on Figure 6. As we can see, the training with silver set gives better results starting from the very first epoch.

The third set of experiments was performed in order to compare the performance of the Flair Embedding model wrt. entities. The worst results were always recorded for the classes *Miscellaneous* and *Corporation*; this is due to the fact that these are the two least numerous classes (compare with Figure 1). The results are shown in Figure 7. Flair Embedings trained directly on corpus 1 is not included in the graph, as its F1 score was 0.

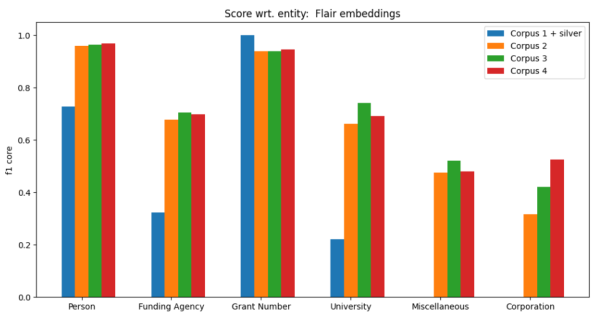

Figure 7: Flair embeddinds model f1-scores for individual classes

Fourth set of experiments shows a comparison of different models, Flair Embeddings, XLNet-large, XLnet-base and BERT on the same corpus 4. The results can be found on Figure 8. As we can see, the best result was achieved by the Flair Embeddings model (F1 score 83%). XLNet-base achieved 80%, BERT 79% and XLNet-large 77%.

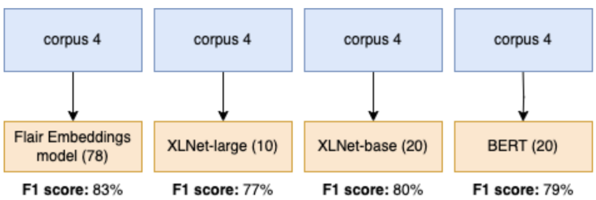

Figure 8: FLair Embeddings, XLNet-large, XLnet-base and BERT scores on corpus no. 4.

However, it should be noted that from above results we cannot make any conclusions, as they are biased by the different number of epochs. The original intention was to train the models on the same number of 20 epochs. However, XLNet-Large is a more complex model, requires more computational resources and takes longer to train, which is why it was trained on 10 epochs. The FLair Embeddings model, on the other hand, is the lightest model with very fast training, so the number of epochs was chosen as the number after which the model did not improve in the next iteration (the learning rate decreased from 0.1 to 0.00001 by a order of magnitude after 3 epochs without improvement. For this experiment, the last epoch was 78th one. The scores history while training can be found on Figure 9 and losses history are on Figure 10.

Figure 9: F1 Score training history

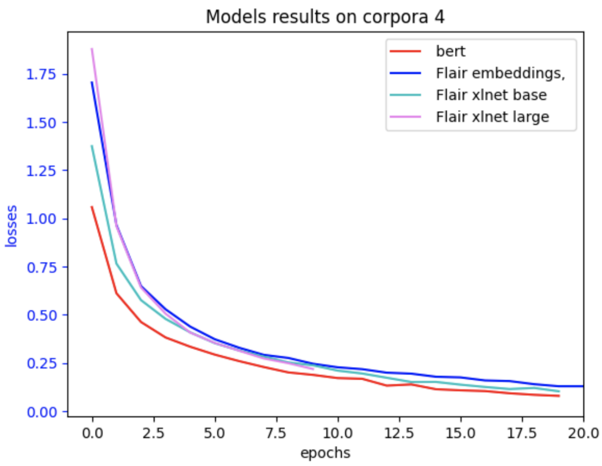

Figure 10: Losses training history

As we can see, the XLNet-large stops after 10th epoch, while Flair Embeddings run further than 20 epochs but still we are able to see that the latter one, although in the end achieving the highest result, definitely learns the slowest. On the other hand, on 10th epoch XLNet-large obtained the highest F1 score on validation set. This may be a hint that if given a required amount of time, this model may outperform the others. It's also worth to notice that BERT always had the lowest loss out of all four models.

Lastly, 5th experiment shows the results of the models from the perspective of specific entities on corpsus 4. The worst results usually occur again for the classes the least populated classes (see Figure 11). The comparison also includes separately the XLNet-large models trained on corpus 4 with and without silver standard set. As we can see, XLNet-large model with silver standard included in training performs the best when it comes to *Funding agency* and *Corporation* classes, while performing a bit poorer than others in *Grant number*.

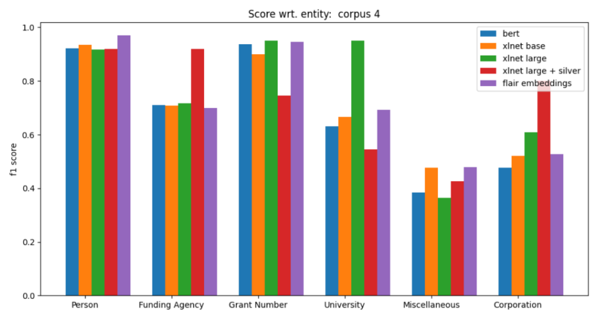

Figure 11: Models f1-scores for individual classes on corpora no. 4

5 Discussion on your results

We are quite satisfied with our work and the results we received. We believe that we have achieved most of the initial objectives of the project and can answer the reaserch questions posed:

- What techniques and models in the field of NLP are most effective for recognising named individuals in a specific area?

  All the models we tested achieved good results, both transformer-based (BERT and XLnet) and from the flair library. It seems to us that XLnet large trained on more epochs would achieve the best results.

- How does the performance of NER models change with different types and amounts of training data?

  As expected, the more data, the better training process. By adding our silver standard set we not only improved decreasing of loss function, but also improved F1 score on test set.

- Can the use of different text normalisation techniques, such as lemmatization or stop word removal, improve the effectiveness of NER models in identifying entities in scientific acknowledgement texts?

  Because of our lack of knowledge about NLP data preprocessing, we thought that such techniques can improve model performance. However, after the research we made, it turned out that these techniques are not used in NER task, because in English language those words are in their proper noun form. Additionally, removing stop words can also affect the model, because in some entity types stop words are important (e.g. grant number). Finally, they can interfere the context of sentences and as the models can understand the context, it's better to leave them in original form.

- Can preparing a silver-set and further training models on it improve their effectiveness?

  Yes, definitely. Although silver standard is not as precise as gold standard (which requires domain expert), it still can improve effectiveness of the model (taking into account around 80% F1 score). This is a very good news as we can first train model on relatively small amount of gold standard data and then based on this generate huge amount of silver standard data, which then can be used to train a better model. That approach may be beneficial when we don't have a domain expert or he/she is unable to manually label vast amount of data.

- Which types of entities are the most difficult to classify?

  Not surprisingly, the hardest class is miscellaneous which contains all the entities not classified to any other class. Models had also struggles with corporations but this is mostly because the least amount of examples in the training data.

6 Conclusions and future work

Considering the wide field of this work and our current results, we plan to continue working on this topic. The results obtained are satisfactory, however, large models such as XLnet-large have not been trained (due to limited equipment and time) on the optimal number of epochs. Therefore, our first step will be to train this model on a better virtual machine and re-evaluate the results, also with the silver-set.

In order to increase the accuracy of the models, it is worth considering how to improve the effectiveness of the worst classes. According to the current results, these entities are: Miscellaneous and Corporation. This may be due to the fact that the least data was found for these classes. Taking this into account, our next step will be to try to balance the training dataset and see if the results are better. In addition, we should check which units were misclassified most often and do more work to identify them better.

In the results obtained, the improved performance of the model on the combined dataset with the silver set is evident. In order to avoid manually extracting acknowledgements from scientific articles, it is planned to develop a code that, with the help of an API, automatically reads them and processes them into a file ready for model learning.

The culmination of this work will be the creation of a user interface to load a custom acknowledeldgemtns section and it will be returned with recognised and classified entities.

Contribution	Contributors
Research	All
EDA	Deregowski, Jamroży
Initial models training	Janus, Gruszkowska
Creating silver set	Gruszkowska, Jamroży
Final models	Janus, Deregowski
Evaluation	All

Table 2: Contribution Table

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