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# A Majority Voting Strategy of a SciBERT-based Ensemble Models for Detecting Entities in the Astrophysics Literature (Shared Task)

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## Abstract

Detecting Entities in the Astrophysics Literature (DEAL) is a proposed shared task in the scope of the first Workshop on Information Extraction from Scientific Publications (WIESP) at ACL-IJCNLP 2022. It aims to propose systems identifying astrophysical named entities. This article presents our system based on a majority voting strategy of an ensemble composed of 32 SciBERT models. The system we propose is ranked second and outperforms the baseline provided by the organisers by achieving an F1 score of 0.7993 and a Matthews Correlation Coefficient (MCC) score of 0.8978 in the testing phase.

## 1 Introduction

Astronomy and astrophysics consist of observing and studying various cosmic phenomena such as tidal disruption events, gamma-ray bursts, and many other messengers such as neutrinos and gravitational waves (Neronov, 2019; Abbott et al., 2016). Missions and observations performed by astronomical facilities worldwide significantly increase the number of astrophysics papers. Most published papers are freely available and accessible through the Astrophysics Data System (ADS<sup>1</sup>), where researchers can search and access more than 15 million records covering astronomy, astrophysics, and general physics publications. However, some domain keywords can be easily confused when searching for articles in the literature. For instance, "Planck" can refer to the person, the mission, the constant, or several institutions. One approach for this word sense disambiguation problem would be automatically recognised entities. Named Entity Recognition (NER) consists of recognising mentions of entities from text belonging to predefined semantic types: person, location or organisation (Yadav and Bethard, 2018). It is, therefore, an es-

<sup>1</sup><https://ui.adsabs.harvard.edu/>

sential technique to extract relevant information from unstructured human-written data.

Detecting Entities in the Astrophysics Literature (DEAL) is a shared task that tackles the challenge of developing a system that identifies named entities in the astrophysics literature (Grèzes et al., 2022). The shared task was organised in two stages: validation and test. Evaluation metrics used were both the CoNLL-2000 shared task seqeval<sup>2</sup> F1-Score at the entity level and scikit-learn's Matthews correlation coefficient (MCC<sup>3</sup>) method at the token level. Organisers provided the NER system's baseline (see Table 3 in Appendix) using astroBERT (Grèzes et al., 2021), a deep contextual language model pre-trained on 395 499 publications (3 819 322 591 tokens, 16GB on disk) from the ADS database. The model astroBERT is not available yet, but preliminary results are exposed in the companion paper.

As part of this shared task, we used and explored an ensemble of contextual Pre-Trained Language Models (PLTMs) for NER purposes.

The paper is organised as follows: Section 2 briefly presents existing methods and approaches for named entity recognition in astrophysics and other scientific domain. Section 3 provides information about the corpus. Section 4 describes our system as well as the experimental setup. Section 5 presents our results.

## 2 Strategies for Entities Detection

### 2.1 State-of-the-Art Methods

The use of neural networks constitutes the current state-of-the-art in many tasks of NLP, including NER. Indeed, for a few years, word embeddings and the combination of two algorithms: bi-

<sup>2</sup><https://github.com/chakki-works/seqeval>

<sup>3</sup>[https://scikit-learn.org/stable/modules/generated/sklearn.metrics.matthews\\_corrcoef.html](https://scikit-learn.org/stable/modules/generated/sklearn.metrics.matthews_corrcoef.html)



## 4.2 Setup

**Internal Training and Validation Data** Since we were limited to 15 daily submissions (and 100 in total) for the validation phase, we decided to create our internal validation set by splitting the original training set and conducting several experiments. Thus, our internal training set consists of 1653 annotated documents (542 550 tokens), and the internal development set comprises 100 documents (30 582 tokens).

**Entities Filtering** Among the defined categories, two were difficult to interpret (`TextGarbage` and `EntityOfFutureInterest`). Moreover, their low distribution in the training corpus did not make the system efficient in predicting these classes. These two reasons led us to remove them from the fine-tuning phase. Deleting these classes did not impact the overall performance since the evaluation metric was based on the micro F1-score.

**Sliding Window for Long Sequences** We used `BertTokenizerFast`, one of BERT’s tokenizers. During the fine-tuning stage, Transformer-based models segment original tokens into subwords (or word pieces), extending thus an original sequence of  $N$  tokens into a sequence of length  $N + n_{subwords}$ , where  $n_{subwords}$  is the number of sub-words generated by the tokenizer. This extension can exceed the size of 512, the limit sequence length that a Transformer-based model can handle. The standard way to deal with this is to apply a sliding window across the input sequence, where each window contains a passage of tokens that fit in the model’s context.

## 4.3 Hyper-Parameters Tuning

When we started our experiments, we wanted to know the optimal combination of hyper-parameters. To do so, we proceeded to a grid search by varying two hyper-parameters: the learning rate  $\alpha$  ( $[1.10^{-5}, 2.10^{-5}, 5.10^{-5}]$ ) and the training batch size ( $[4, 8, 16]$ ), representing a total of nine combinations. In order to ensure reliable results regarding the impact of hyper-parameters, each combination of hyper-parameters was used five times with five different seeds randomly chosen ( $[0, 123, 762, 5000, 6822]$ ). We fine-tuned all models on 15 epochs using our internal training corpus and evaluated them on the internal validation set at each epoch. On average, one epoch lasts approximately 170 seconds. The ranking of the nine

combinations is in Table 4 (appendix).

## 4.4 Ensemble Strategy

In our study, we wanted to test the influence of an ensemble approach composed of several NER classifiers. Therefore, we conducted experiments comparing the performance of a single system to an ensemble of multiple systems. We used the different models fine-tuned during the grid search to design our ensemble. We wonder two main questions:

- Which different models should we use, and how many models should be included in the system?
- What method should we use to combine the predictions of the different models in our ensemble?

Regarding the first question, we first rank the combinations of the models by performances according to their hyper-parameters during the grid search stage (Table 4, appendix). Then, we proceeded by adding models progressively to the ensemble.

Regarding the second question, related studies showed that there are mainly two approaches: the first consists of a soft strategy, where each model returns its predicted probabilities, and the class label is obtained by applying the argmax function to the sum of all probabilities (Schneider et al., 2022). The second is a majority voting strategy where the system selects the majority class of the class labels predicted by each classifier (Dang et al., 2020). We opted for the majority voting strategy.

## 5 Results on Official Sets

The official validation and test corpora results (Table 2) show that an ensemble composed of classifiers leads to a higher F1 score.

To determine the number of models to include in our ensemble, we progressively formed an ensemble consisting of the five models of the first performant combination (C2), then added the five models of the second performant combination (C5) and so on. We notice that the performance decreases beyond a certain number of models. Our ensemble comprises the first six combinations that gave the best results during the grid search. This represents 30 models (6 combinations \* 5 models / combination). A last submission in the validation phase

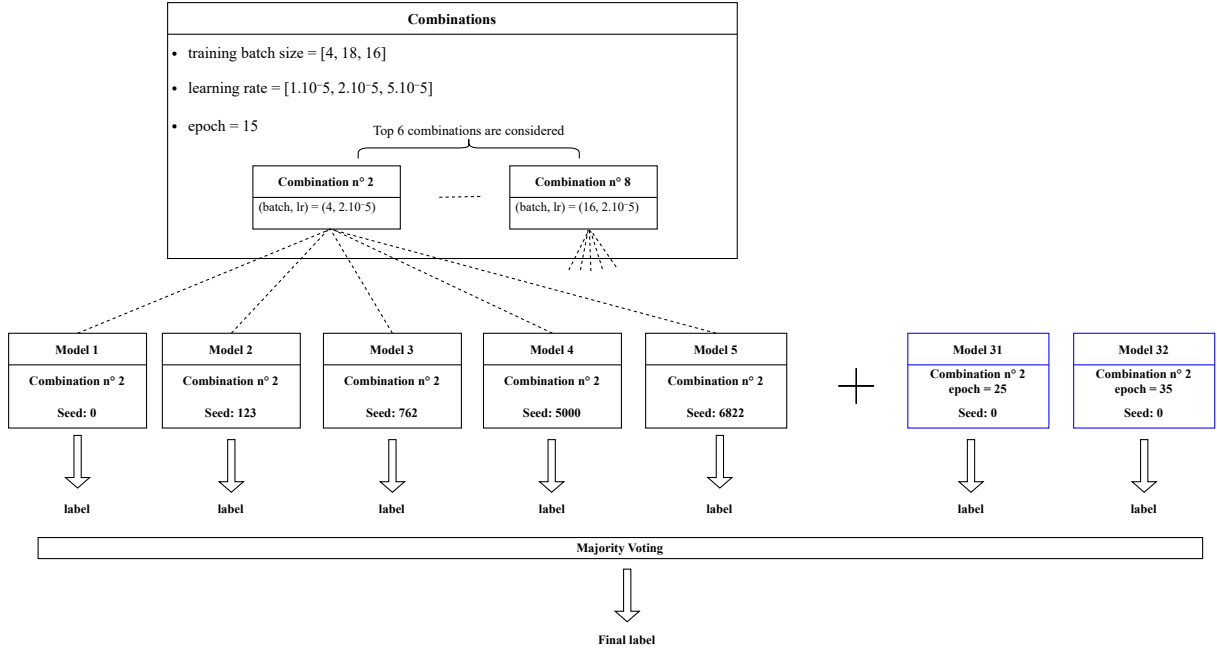


Figure 2: Final architecture of our NER ensemble based on a majority voting strategy.

| Ensemble                              | Validation |        |               |        |    | Test   |        |               |        |   |
|---------------------------------------|------------|--------|---------------|--------|----|--------|--------|---------------|--------|---|
|                                       | P          | R      | F1            | MCC    | s  | P      | R      | F1            | MCC    | s |
| Single system                         | 0.7751     | 0.8284 | 0.8009        | 0.9025 | 4  | 0.7990 | 0.7957 | 0.7973        | 0.8968 | 1 |
| $\sum_{i=1}^6 S_i$                    | 0.8140     | 0.8366 | 0.8251        | 0.9132 | 17 | 0.8008 | 0.7966 | 0.7988        | 0.8974 | 2 |
| $\sum_{i=1}^6 S_i + 2 \text{ models}$ | 0.8145     | 0.8383 | <b>0.8262</b> | 0.9140 | 24 | 0.8013 | 0.7972 | <b>0.7993</b> | 0.8978 | 4 |

Table 2: Results on official validation and test sets with the corresponding submission number (s) on the Codalab platform. Metrics used are Precision (P), Recall (R), F1-score and MCC.

(s=24) showed us that adding two additional models from combination n°2 (fine-tuned on a few additional epochs) increases the F1 score. Ultimately, our ensemble consists of 32 models. Figure 2 illustrates our architecture.

## 6 Conclusion

This shared task aimed to tackle the challenge of detecting entities in the astrophysics literature by proposing a NER system. We exposed in this paper our approach, which first consists of identifying the different hyper-parameters combination giving the highest F1-score. To do so, we proceeded to do a grid search on our internal training and validation sets. In the second stage, we built an ensemble of classifiers based on the top 6 combinations identified during the grid search. Our submissions on the official validation and test sets show that adopting a majority voting strategy of an ensemble of SciBERT-based classifiers gives better results than a single model approach. Finally, we ranked sec-

ond, achieving an F1 score of 0.7993 and an MCC coefficient of 0.8978 using an ensemble of 32 SciBERT models.

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## A Appendix

| Model     | P             | R             | F1            | MCC           |
|-----------|---------------|---------------|---------------|---------------|
| random    | 0.119         | 0.0274        | 0.0166        | 0.1089        |
| BERT      | 0.4779        | 0.4697        | 0.4738        | 0.7405        |
| SciBERT   | 0.5457        | 0.5741        | 0.5595        | 0.8016        |
| astroBERT | <b>0.5511</b> | <b>0.6080</b> | <b>0.5781</b> | <b>0.8104</b> |

Table 3: Baseline scores for the DEAL shared task. Metrics used are Precision (P), Recall (R), F1-score and MCC.

| Rank | Comb. | Designation | Hyp.-params.             |
|------|-------|-------------|--------------------------|
| 1    | C2    | S1          | (4, 2.10 <sup>5</sup> )  |
| 2    | C5    | S2          | (8, 2.10 <sup>5</sup> )  |
| 3    | C9    | S3          | (16, 5.10 <sup>5</sup> ) |
| 4    | C6    | S4          | (5, 5.10 <sup>5</sup> )  |
| 5    | C1    | S5          | (4, 1.10 <sup>5</sup> )  |
| 6    | C8    | S6          | (16, 2.10 <sup>5</sup> ) |
| 7    | C3    | S7          | (4, 5.10 <sup>5</sup> )  |
| 8    | C4    | S8          | (8, 1.10 <sup>5</sup> )  |
| 9    | C7    | S9          | (16, 1.10 <sup>5</sup> ) |

Table 4: Grid search: ranking of the combination (Comb.) giving the best results. After having ranked the different combinations, we denote by  $S_i$  the set of five models (having the same hyper-parameters) ranked in position  $i$

| Category                | Definition  | Example   |
|-------------------------|---|---|
| Person                  | A named person or their initials  | Andrea M. Ghez, Ghez A.   |
| Organization            | A named organization that is not an observatory.                                      | NASA, University of Toledo                                      |
| Location                | A named location on Earth.  | Canada  |
| Observatory             | A, often similarly located, group of telescopes.                                      | Keck Observatory, Fermi   |
| Telescope               | A "bucket" to catch light.  | Hubble Space Telescope, Discovery Channel Telescope             |
| Instrument              | A device, often, but not always, placed on a telescope, to make a measurement.        | Infrared Array Camera, NIRCam                                   |
| Survey                  | An organized search of the sky often dedicated to large scale science projects.       | 2MASS, SDSS   |
| Mission                 | A spacecraft that is not a telescope or observatory that carries multiple instruments | WIND  |
| CelestialObject         | A named object in the sky   | ONC, Andromeda galaxy   |
| CelestialRegion         | A defined region projected onto the sky, or celestial coordinates.                    | GOODS field, l=2, b=15  |
| CelestialObjectRegion   | Named area on/in a celestial body.  | Inner galaxy  |
| Wavelength              | Portion of the electromagnetic spectrum   | 656.46 nm, H-alpha  |
| ObservationalTechniques | Methods/techniques for observation  | Spectroscopic, helioseismic                                     |
| Model                   | Mathematical/Physical model   | Gaussian, Keplerian   |
| Software                | Software, IT tool   | NuSTAR, healpy, numpy   |
| ComputingFacility       | Server, cluster for computation   | Supercomputer, GPU  |
| Dataset                 | Astronomical catalogues   | 3FGL catalog  |
| Database                | A curated set of data   | Simbad database   |
| Archive                 | A curated collection of the literature or data.                                       | NASA ADS, MAST  |
| Identifier              | A unique identifier for data, images, etc.  | ALMA 123.12345  |
| Citation                | A reference to previous work in the literature.                                       | Allen et al. 2012   |
| Collaboration           | Name of collaboration   | Fermi LAT Collaboration   |
| Event                   | A conference, workshop or other event that often brings scientists together.          | Protostars and Planets VI                                       |
| Grant                   | An allocation of money and/or time for a research project.                            | grant No. 12345, ADAP grant 12345                               |
| Fellowship              | A grant focused towards students and/or early career researchers.                     | Hubble Fellowship   |
| Formula                 | Mathematical formula or equations.  | $F = Gm_1m_2/r^2, z = 2.3$                                      |
| Tag                     | A HTML tag.   | <bold>  |
| TextGarbage             | Incorrect text, often multiple punctuation marks with no inner text.                  | ,,,   |
| EntityOfFutureInterest  | A general catch all for things that may be worth thinking about in the future.        | Earth-like, Solar-like  |
| URL                     | A link to a website.  | <a href="https://www.astropy.org/">https://www.astropy.org/</a> |

Table 5: Classification of the named entities in the annotation guideline. The HuggingFace repository containing the annotated data and the annotation guide is only accessible to participants of the shared task. Thus, we have reproduced the same list of named entities with their definition.