Imperial College London

NLP for characterization of CT and X-Ray text reports

George Zhao, Yuting Xing, Bernard Hernandez

Named Entity Recognition

Named Entity Recognition (NER) in the clinical domain aims to identify clinically relevant concepts in the provider narrative text of electronic medical records (EMR), such as disorders, treatments, and body parts.

To help clinicians keep track of patients' status and organize information efficiently, we developed a method to extract entities of interest in reports of radiographic examinations(X-Ray, CT, etc.)

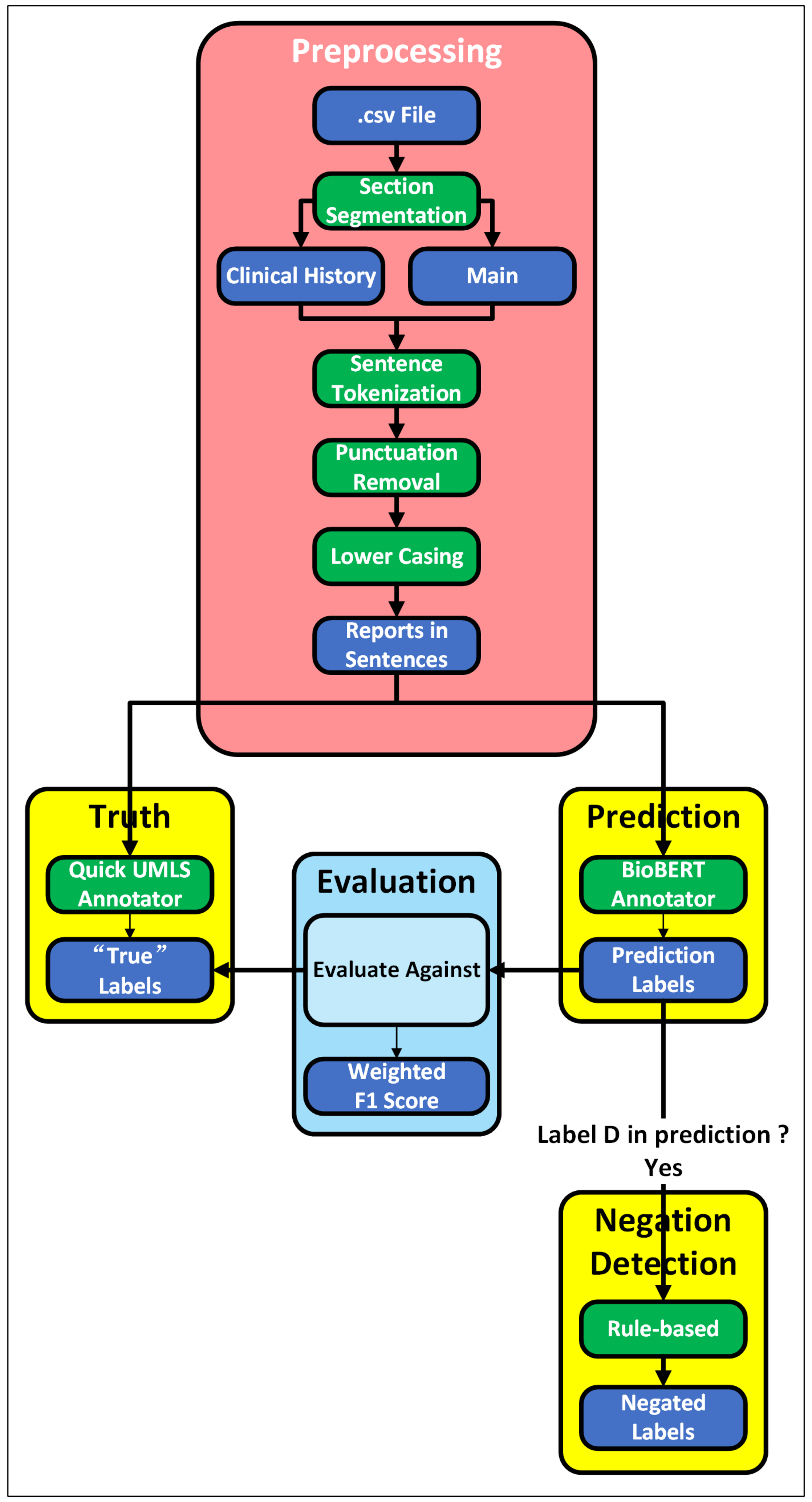
Features

- A volume of 1.35 GiB, which is 5% of the UMLS annotator.
- Customized labels and entity detection.
- Efficient use of contextual information.

Input and output

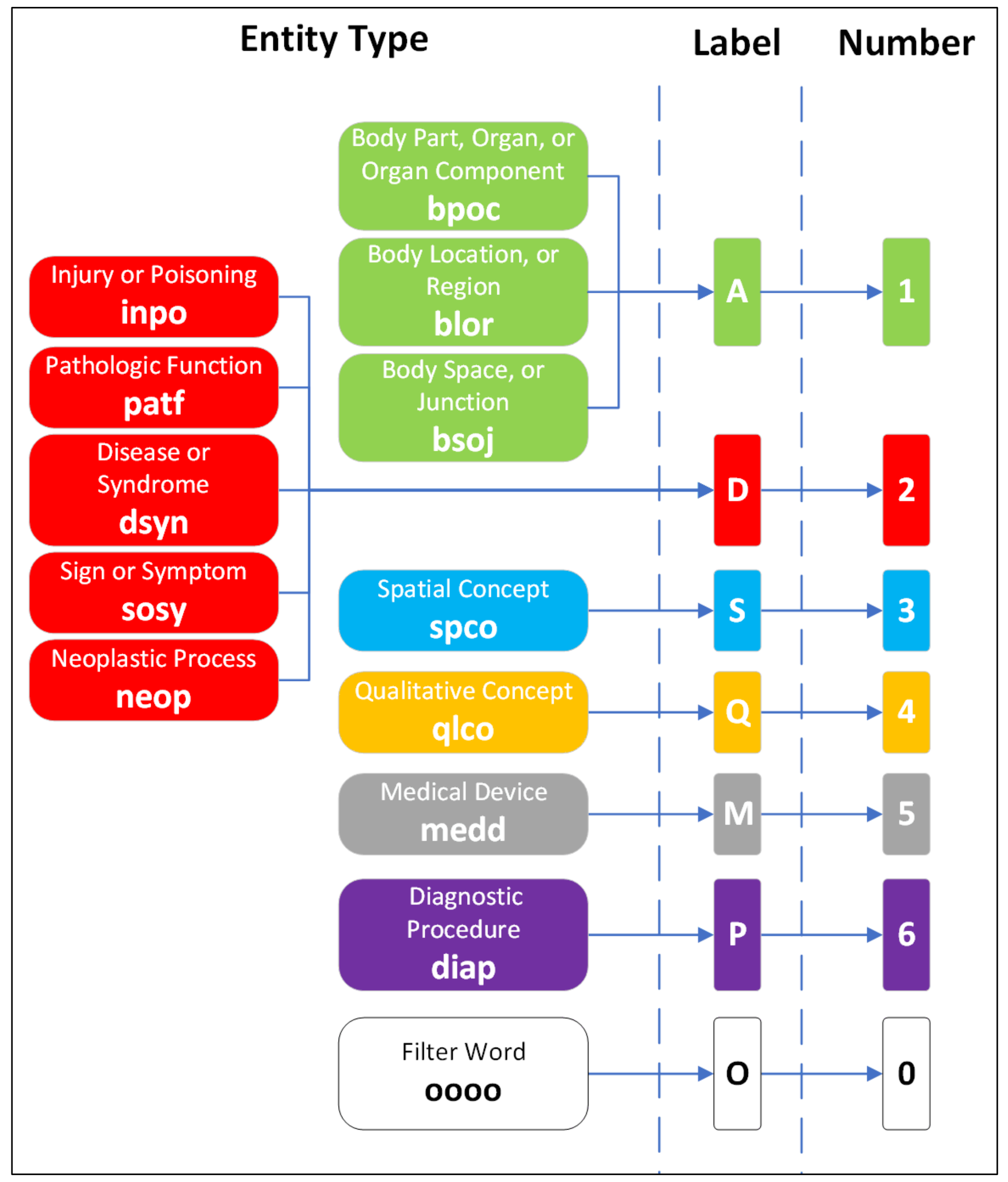
Text	Label
Clinical History:	
Sudden onset chest pain /cause.	QQDDO
Please rule out pneumothorax.	OOOD
Report:	
PA erect chest radiograph.	OOAP
No previous images for comparison.	OOOOO
The heart is not enlarged.	OAOOQ
The lungs and pleural spaces are clear.	OAOAAOQ
Specifically, no focal consolidation, collapse or effusion.	OOSQDOD
No pneumothorax.	OD
No acute bony abnormality identified.	OOOOQ

System Architecture



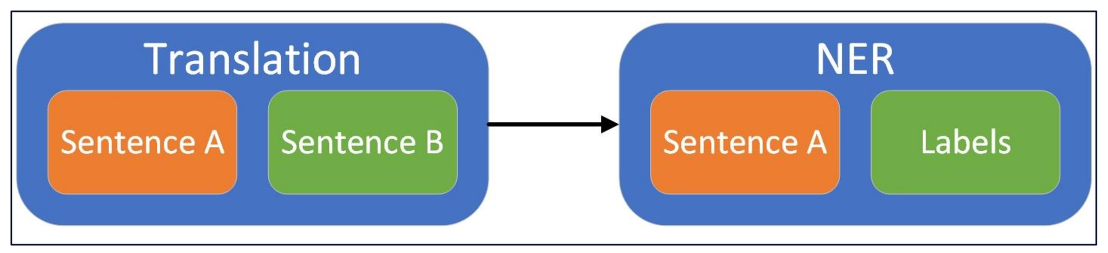
Annotation and Feature Selection

The data were annotated with QuickUMLS. Based on the statistics of entities in the data, several features are selected and merged into seven categories of labels.



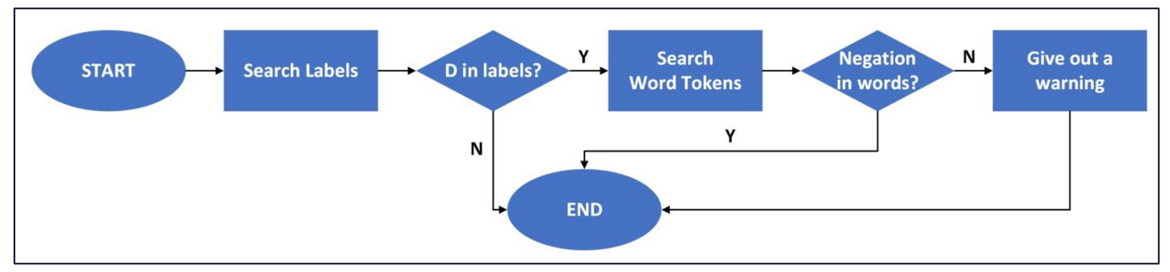
BioBERT and Fine-tuning

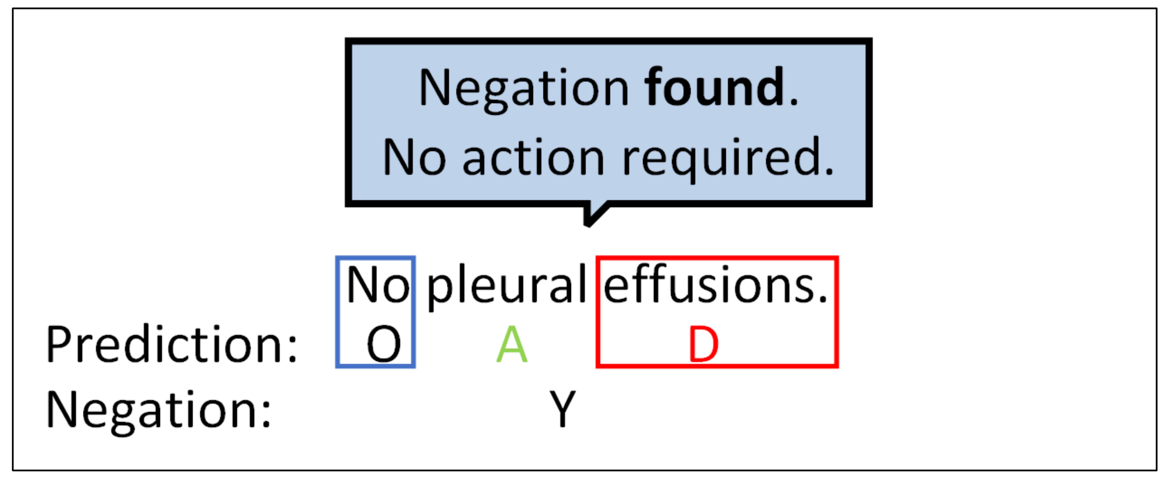
To improve the storage consumption (more than 21 GiB) of the UMLS database, correct the errors caused by QuickUMLS, and use the contextual information in reports, the annotation generated was than used for fine-tuning a BioBERT token classifier. BERT was originally created for generative tasks like machine translation, but it can be simply **fine-tunned** for NER tasks by changing the sequences generated from sentences to labels. After that, the BioBERT token classifier alone could carry out named entity recognition without the UMLS database.



Negation Detection

Among all the entities detected, the D class requires extensive attention, as it gives critical information on the patient's status. To take advantage of the rigorous style of clinical reports, we implemented a simple rule-based method to detect negations related to the class D.





Results

F1 Score				
Label	Precision	Recall	F1-score	Support
A	0.7816	0.9793	0.8693	3431
D	0.5429	0.8870	0.6735	2070
S	0.7215	0.9663	0.8261	3172
Q	0.5505	0.9360	0.6933	3080
M	0.6583	0.8155	0.7285	645
P	0.6407	0.9554	0.7670	672
Micro Average	0.6491	0.9420	0.7686	13070
Macro Average	0.6493	0.9232	0.7596	13070
Weighted Average	0.6614	0.9420	0.7741	13070

Strict Accuracy	
Unbalanced	0.8483
Balanced	0.9064