



Improving Biomedical Named Entity Recognition using custom NER models

W266 – Christine Bakan, Emerald Swei, Viola Pu
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01.

INTRODUCTION

Why does biomedical NER matter?

- Accurate NER can lead to faster knowledge discovery in the biomedical research space.

Our Experiment:

- Custom layered models on top of BERT/BioBERT
- Transfer learning

Evaluation metrics:

- Precision, Recall, F-1 score



02.

DATASETS

Datasets	Entity Type	Containing
NCBI Disease	Disease	793 PubMed abstracts
BioCreative II Gene Mention (GM)	Gene	20,000 sentences
BioCreative V Chemical Disease Relation (CDR)	Chemical, Disease	1,500 PubMed articles
Biomedical expert-labeled PubMed dataset (Private)	Disease, Gene, Chemical	661 PubMed Abstracts

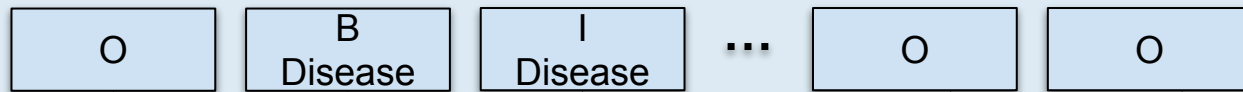
	tokens	ner_tags
[4, Discussion, Cardiovascular, diseases, are, closely, linked, to, hypertension, .]		[0, 0, 1, 2, 0, 0, 0, 0, 0, 0]
[Furthermore, ,, the, numbers, of, CD14*CD163*CD206*, M2, monocyte, not, only, increased, in, the, three, subgroups, of, IMN, but, also, shared, the, same, changes, in, trend, with, disease, progression, .]		[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
[These, mice, display, a, complex, phenotype, ,, with, increased, activation, of, the, thiazide, -, sensitive, Na*, -, Cl-, cotransporter, (NCC), ,, and, polyuria, due, to, a, loss, of, aquaporin, -, 2, (AQP2), .]		[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 5, 0, 0, 5, 0, 5, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 3, 4, 4, 0, 0]



03.

MODEL ARCHITECTURE

predicted
labels

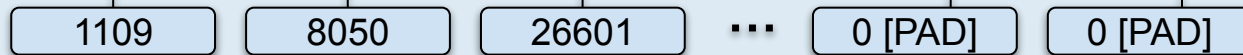


Conditional Random Fields Layer

Bidirectional-LSTM Layer

BERT

tokenized
input



BERT Tokenizer

example
input
sentence

The adenomatous polyposis coli (APC) tumour-suppressor protein controls the Wnt signalling pathway by forming a complex with glycogen synthase kinase 3beta (GSK-3beta), axin/conductin and betacatenin.



04.

MODELS & RESULTS

Results from training & evaluating on BC5CDR Dataset

MODEL	PRECISION	RECALL	F-1 SCORE
BERT <i>large-NER</i>	88.04	90.41	89.18
BioBERT	87.66	91.76	89.65
BERT+CRF	88.55	90.42	89.47
BioBERT+CRF	89.63	91.14	90.38
BERT+BiLSTM+CRF (768)	88.12	89.61	88.85
BioBERT+BiLSTM+CRF (888)	90.86	89.64	90.24



04.

MODELS & RESULTS

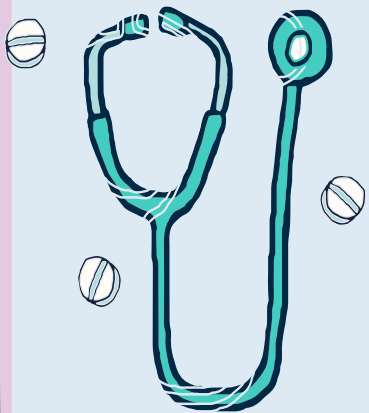
Transfer Learning Results evaluating on NCBI Data

MODEL	Dataset	PRECISION	RECALL	F-1 SCORE
BioBERT	NCBI	80.76	90.02	85.14
BioBERT	Custom Labeled PubMed + NCBI	83.79	89.21	86.42



05.

INTERPRETATION



- BioBERT consistently outperforms BERT_{large-NER}
- Adding BiLSTM and CRF layers in general improve the model performance, but the number of BiLSTM units need to be fine-tuned depending on the dataset
- The best-performing custom model varies across datasets
- Value-add of transfer learning





Thank You



03.

TECHNIQUES

BERT

BERT (BERT-Large-NER) to establish our general use baseline

BioBERT, a variation of BERT pre-trained on biomedical data

BioBERT

BiLSTM

Bidirectional LSTM as a layer between BERT/BioBERT and CRF

Conditional Random Fields as the output layer for our custom models

CRF

