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Sequential Sentence Classification for Medical Health Records

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Machine Learning for Health Care FS21 - Project 3
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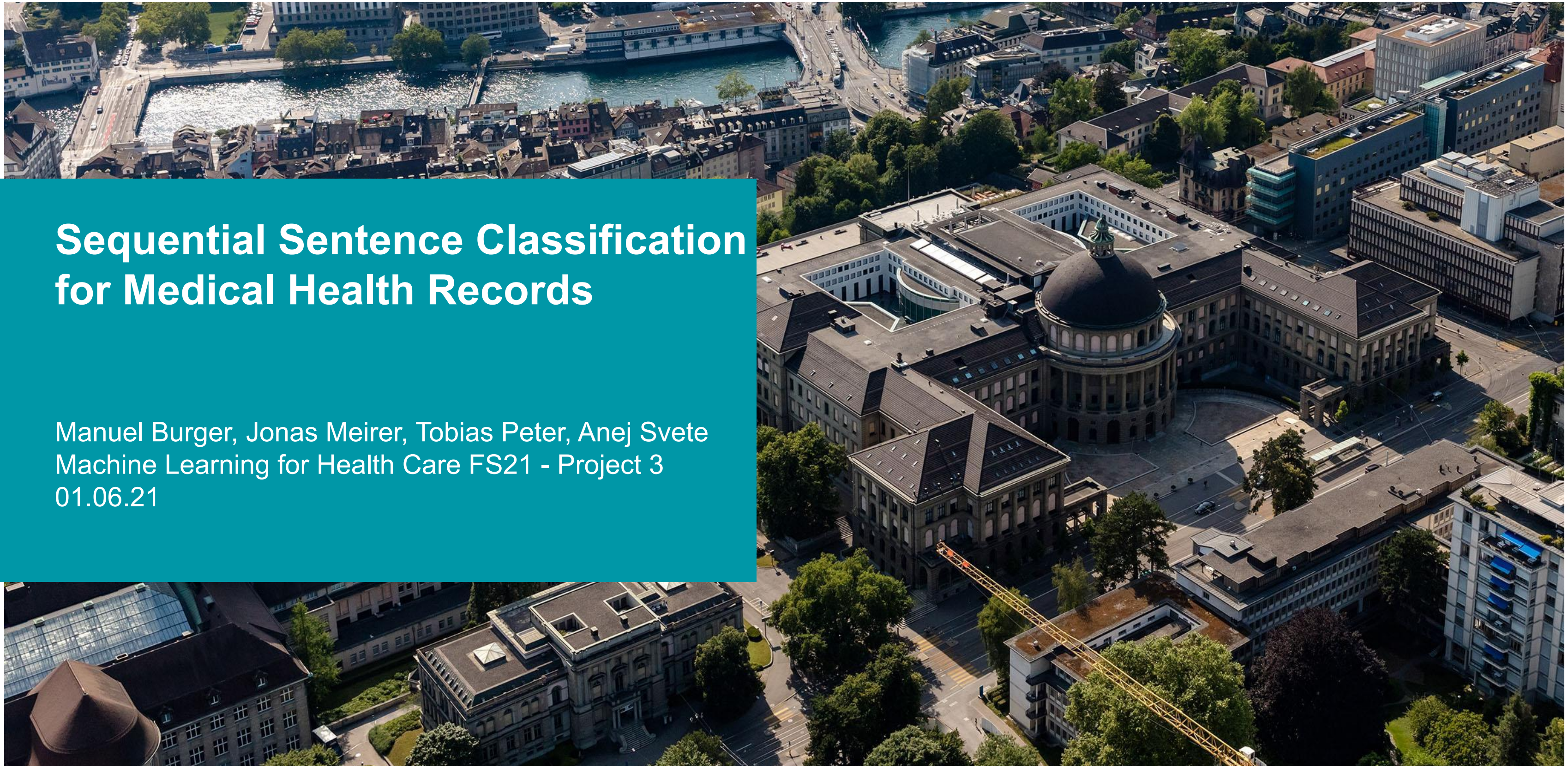
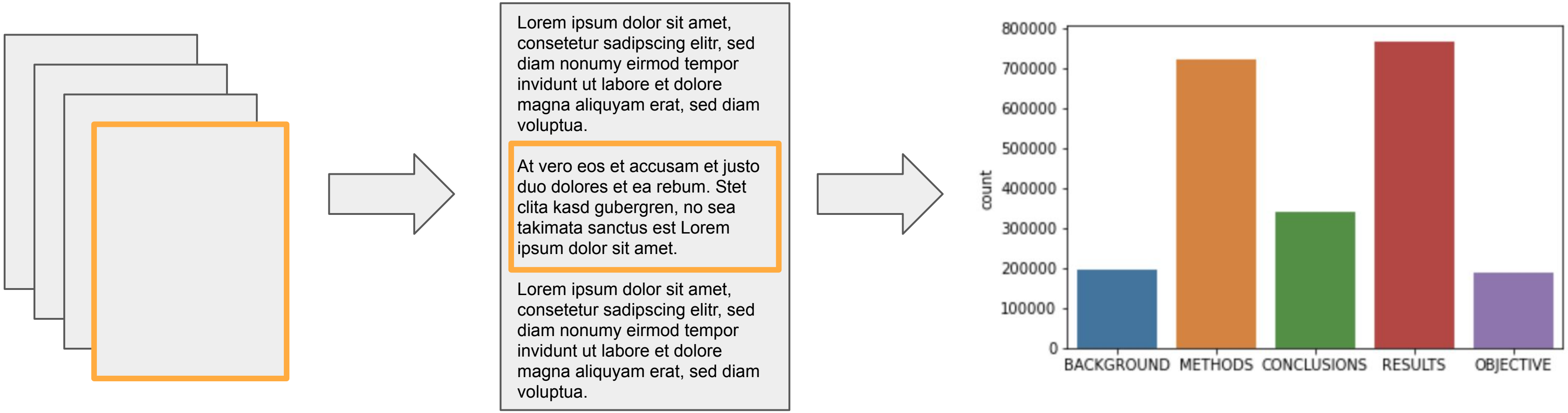


Outline

- Task Overview
- Word Embeddings (Word2Vec, FastText)
- Keras Text Vectorization and LSTM
- Transfomers
- Hierarchical modelling with Transformer and RNN
- Conclusion

Task Overview

- Sentence classification on PubMed 200k RCT dataset



Word Embeddings

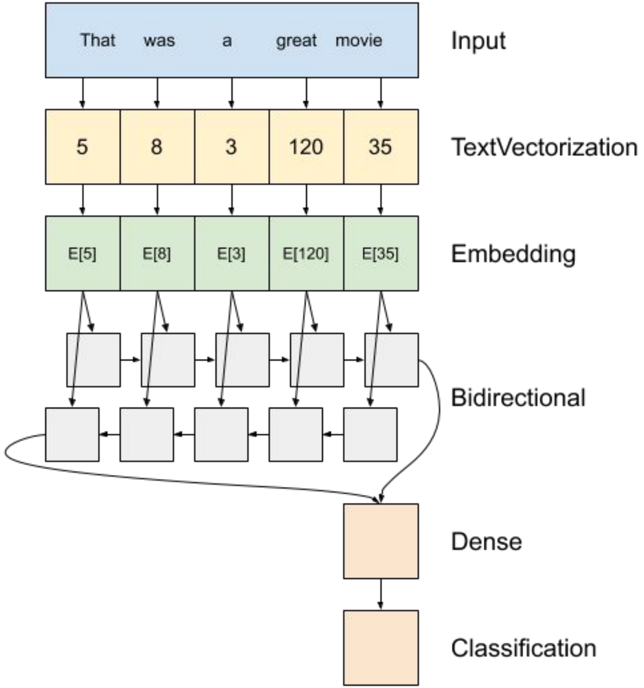
1. Trained Word2Vec as well as fastText.
2. Hyperparameter search (e.g. dimension, min. count) in combination with LogReg & XGBoost Classifier
   → embedding dimension of 250/300
3. W2V & fastText yielded similar performance:
   - With LogReg both slightly worse than Tf-idf
   - XGBoost yields only additional 3 pp over LogReg
4. fastText's *supervised* algorithm (indeed a very fast off-the-shelf baseline) with 0.85 F1-score.
5. MLP: concatenated W2V mean embeddings of neighboring sentences (3 on each side) of the same abstract for additional context:
   - highest F1-score (0.87) with mean embeddings.

Results with Mean Embeddings

F1-score	LogReg	XGB
W2V	0.76	0.79
fastText	0.75	0.78
Tf-idf	0.77	-

fastText supervised	0.85
MLP	**0.87**

Keras Text Vectorization and LSTM



Text Vectorization

```
vectorize_layer = TextVectorization(max_tokens=VOCAB_SIZE,
                                    output_mode='int',
                                    ngrams=1,
                                    output_sequence_length=MAX_SEQUENCE_LENGTH)
vectorize_layer.adapt(X_train)
```

Model Setup

```
model = Sequential()

model.add(Input(shape=(1,), dtype=tf.string))

model.add(vectorize_layer)

model.add(Embedding(VOCAB_SIZE, EMBEDDING_SIZE, trainable=True))

model.add(Bidirectional(LSTM(EMBEDDING_SIZE,
                             dropout=0.4,
                             recurrent_dropout=0.25,
                             return_sequences=True)))

model.add(Bidirectional(LSTM(EMBEDDING_SIZE,
                             dropout=0.4,
                             recurrent_dropout=0.25)))

model.add(BatchNormalization())
model.add(Dense(256, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.3))
model.add(Dense(256, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.3))

model.add(Dense(256, activation='relu'))
model.add(Dense(N_CLASSES, activation='softmax'))
```

Notes:

- Does not work well with preprocessed sentences
- Performance Boost (micro-F1) from 87% to 90%

Transformers

- **Transformers** are current state-of-the-art models across various tasks
  - **BERT-based** models known to perform best for tasks like classification
- The large models are **pre-trained on enormous corpora** and then **fine-tuned for any task of interest**
  - In our case, that was sentence classification
- The **Huggingface () library** provides numerous implementations and pre-trained models
- They can **take into account the word/sentence context** and provide a **richer representation than raw word embeddings**

Raw sentence

Based on the findings, we conclude...

Model-dependent tokenization

[1, 2007, 312, 0, 281, 2987, 482, ...]

magic

(109 million parameters)

[0.821, 0.127, 1.928, 0.216, 2.167, ...]

A Classifier head

Prediction

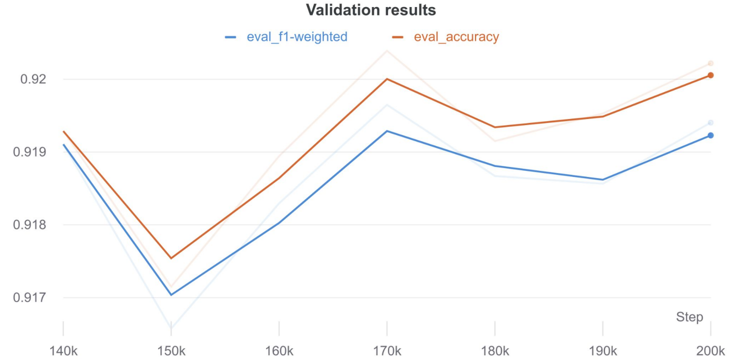
Transformers

Base model

- We used a pure BERT model **pre-trained on a corpus of full PubMed texts [3]** and added a **classifier head**
  - It "knows" the vocabulary well
  - It performed better than a model trained on unrelated text

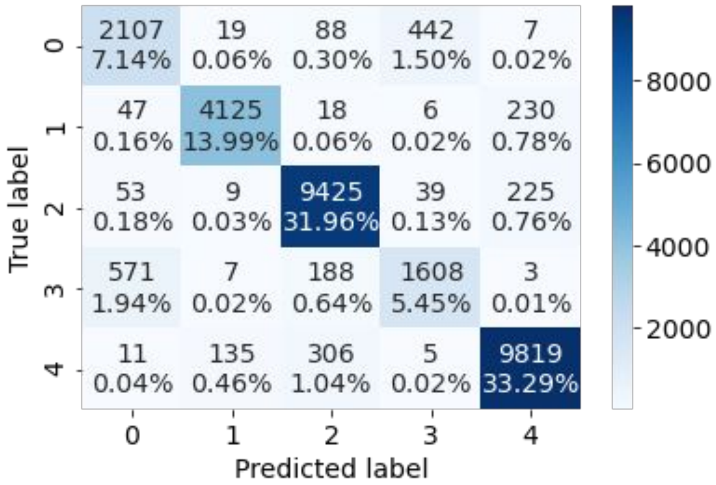
Fine-tuning

- The default tokenizer was used on sentences with context window of size 3
  - Sequence length was capped at 96
  - The special way the library performs tokenization is beneficial
- The **whole model** was fine tuned for **2 epochs** on our training data
  - That takes around 12 hours!
  - Small step size (5e-5), weight decay (0.01) on the whole model



Test set performance

Model	F1 micro	F1 weighted
Plain BERT model	0.918	0.918



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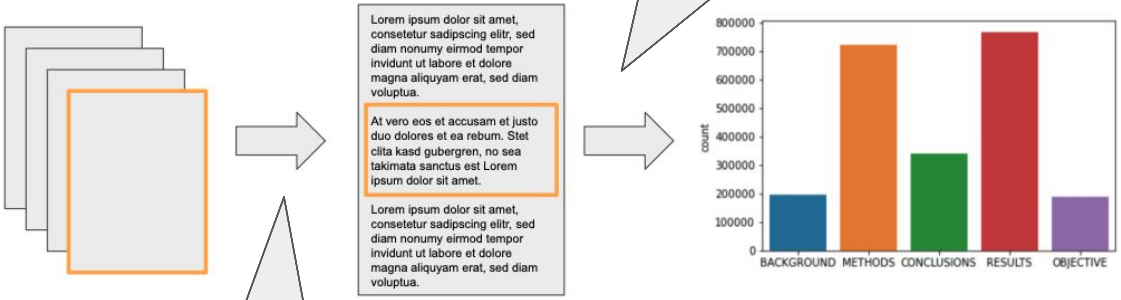
Hierarchical modelling

Classification per sentence



Sentences follow a global structure within an abstract

Inspired by Jin et al. [1] **"Hierarchical Neural Networks for Sequential Sentence Classification in Medical Scientific Abstracts"**

Hierarchical modelling

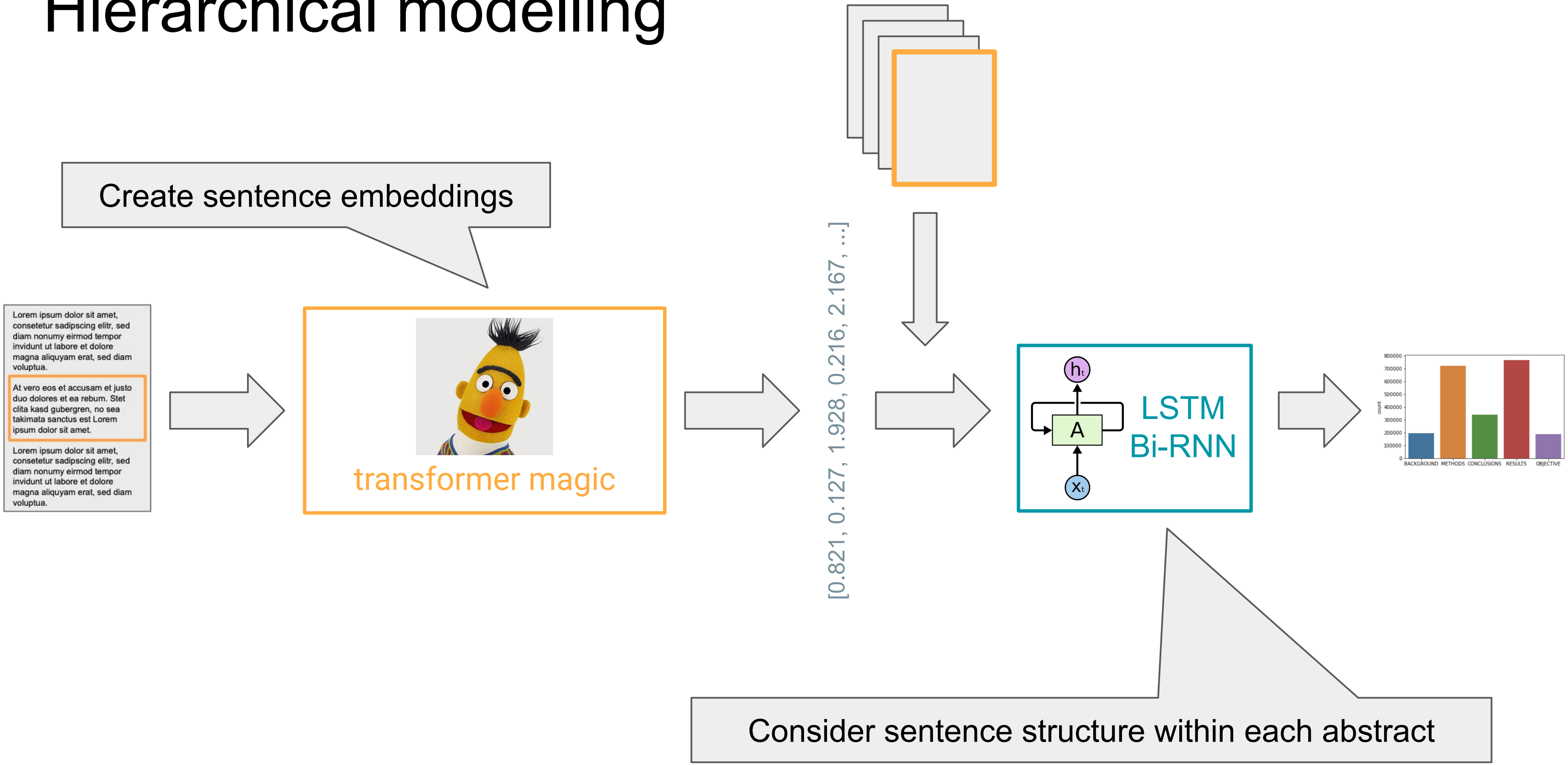
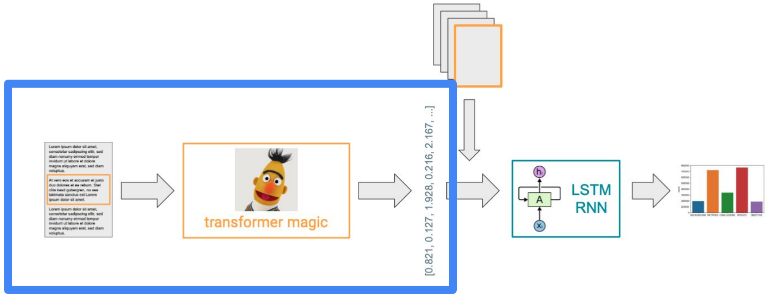


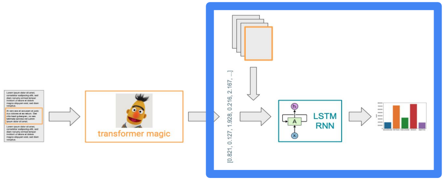
Image Source RNN: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

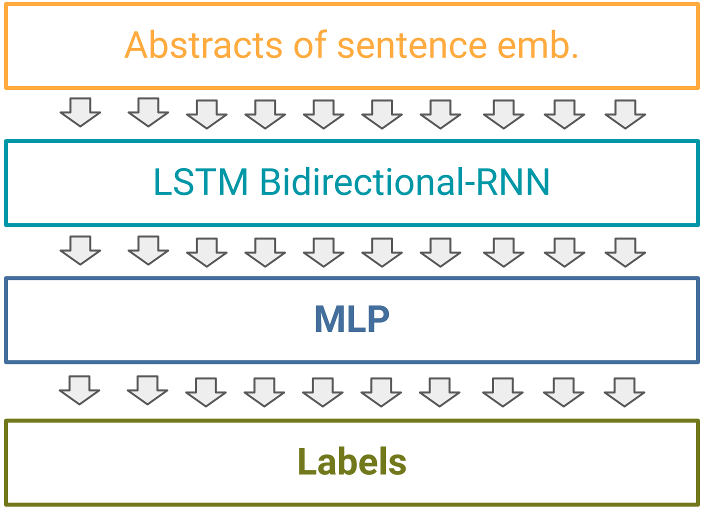
Hierarchical modelling



- BERT language model
- Pretrained on PubMed text data
- Fine-tune complete model to task
  - Attach dense head
  - Train for single epoch
- Predict sentence embeddings for full dataset
  - Averaged token embedding

Hierarchical modelling





- For each abstract:
  - Create sequence of sentence embeddings
  - 0-pad to longest abstract (embedding and label)
- Feed dataset of abstracts through RNN
- Feed each RNN hidden state through an MLP
  - Predict seq. of final class label on hidden state
  - Post-Process: cut-back seq., impute labels

F1 Score: 0.94366 (SOTA)

Conclusion

- Incremental performance improvement through models
- Exploit problem structure and create respective inductive bias

- Improvements:
  - End-to-end training of hierarchical approach
  - Jin et al.:
    - Labelling noise
    - Unsupervised data

Model	F1-Score
Tf-idf (LR)	0.77
W2V (XGB)	0.79
fastText (XGB)	0.78
fastText (supervised)	0.85
MLP	0.87
RNN	0.90
Transformer	0.92
Hierarchical Model	0.944
Jin et al.	0.939

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Thank you for your attention!

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References

[1] Jin, Di and Szolovits, Peter. **Hierarchical Neural Networks for Sequential Sentence Classification in Medical Scientific Abstracts** (2018). https://www.aclweb.org/anthology/D18-1349

[2] Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova. **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding** (2019). https://www.aclweb.org/anthology/N19-1423

[3] Liu, Nigel. **Self-Alignment Pretraining for Biomedical Entity Representations**. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (pp. 4228–4238). Association for Computational Linguistics, 2021.