# PharmBERT: A domain-specific BERT model for drug labels

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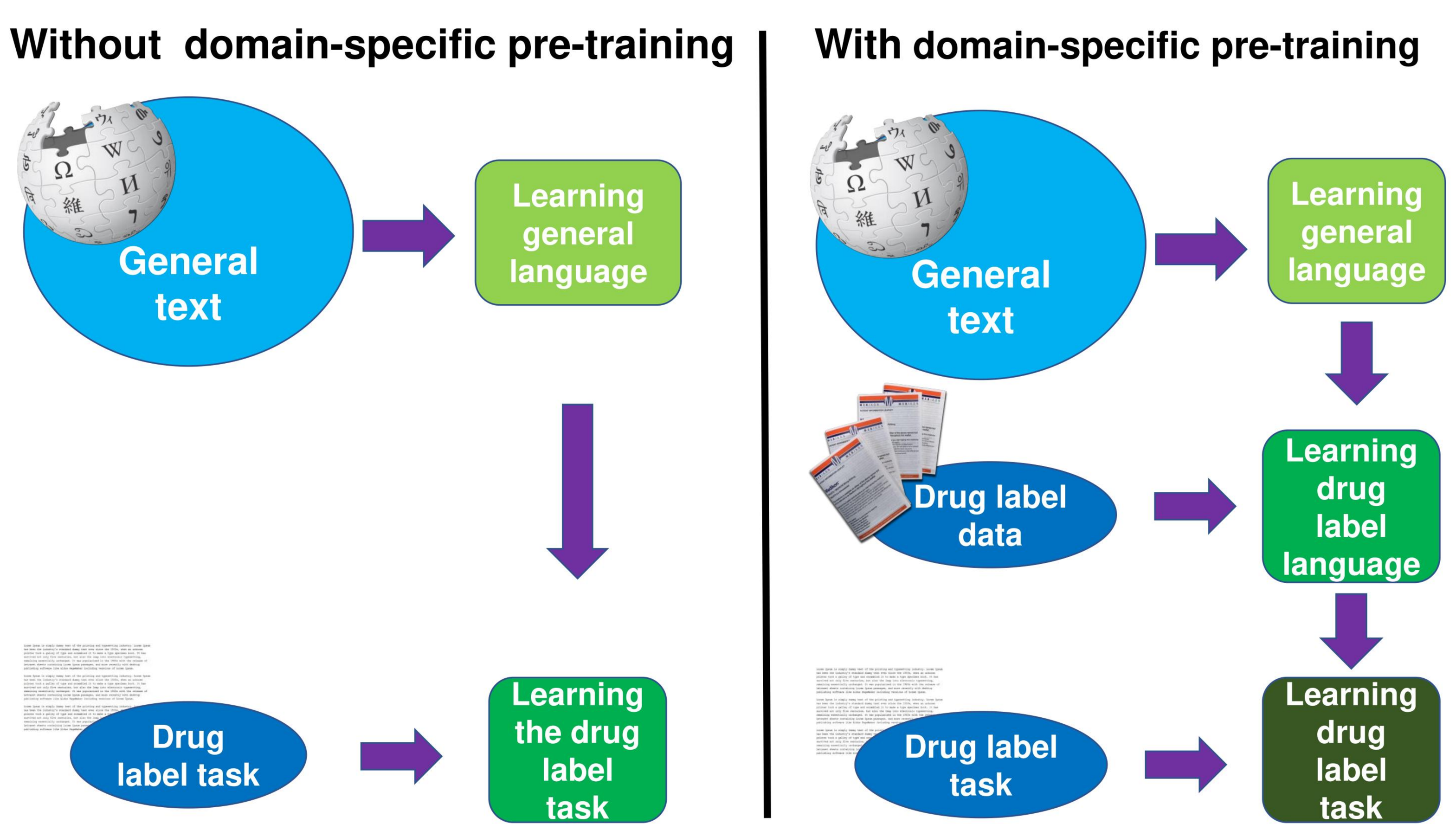
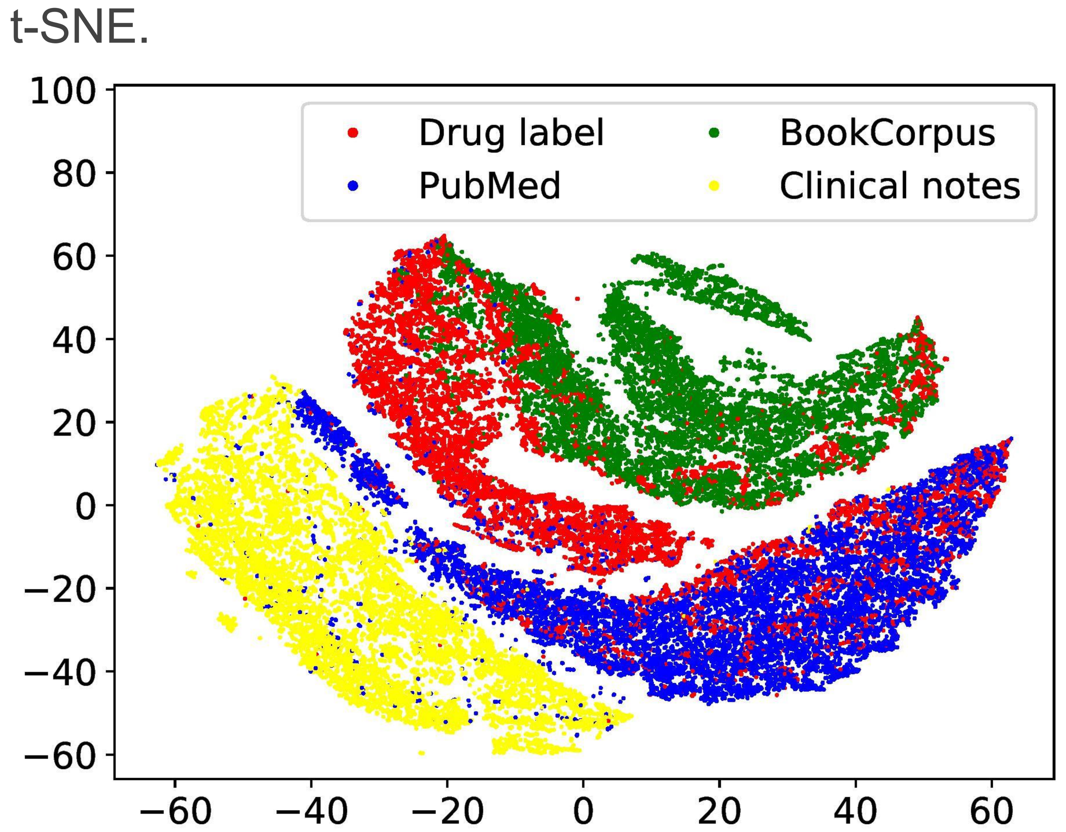
## Text domains in NLP

- NLP models are pre-trained on massive text corpora to learn the distribution of the words and then fine-tuned on a down-stream task.
- The distribution of the data on the domain of the down-stream task might be different from the pre-training domain.
- Further pre-training on the text from the target domain can help the model learn the distribution of the words in the target domain.

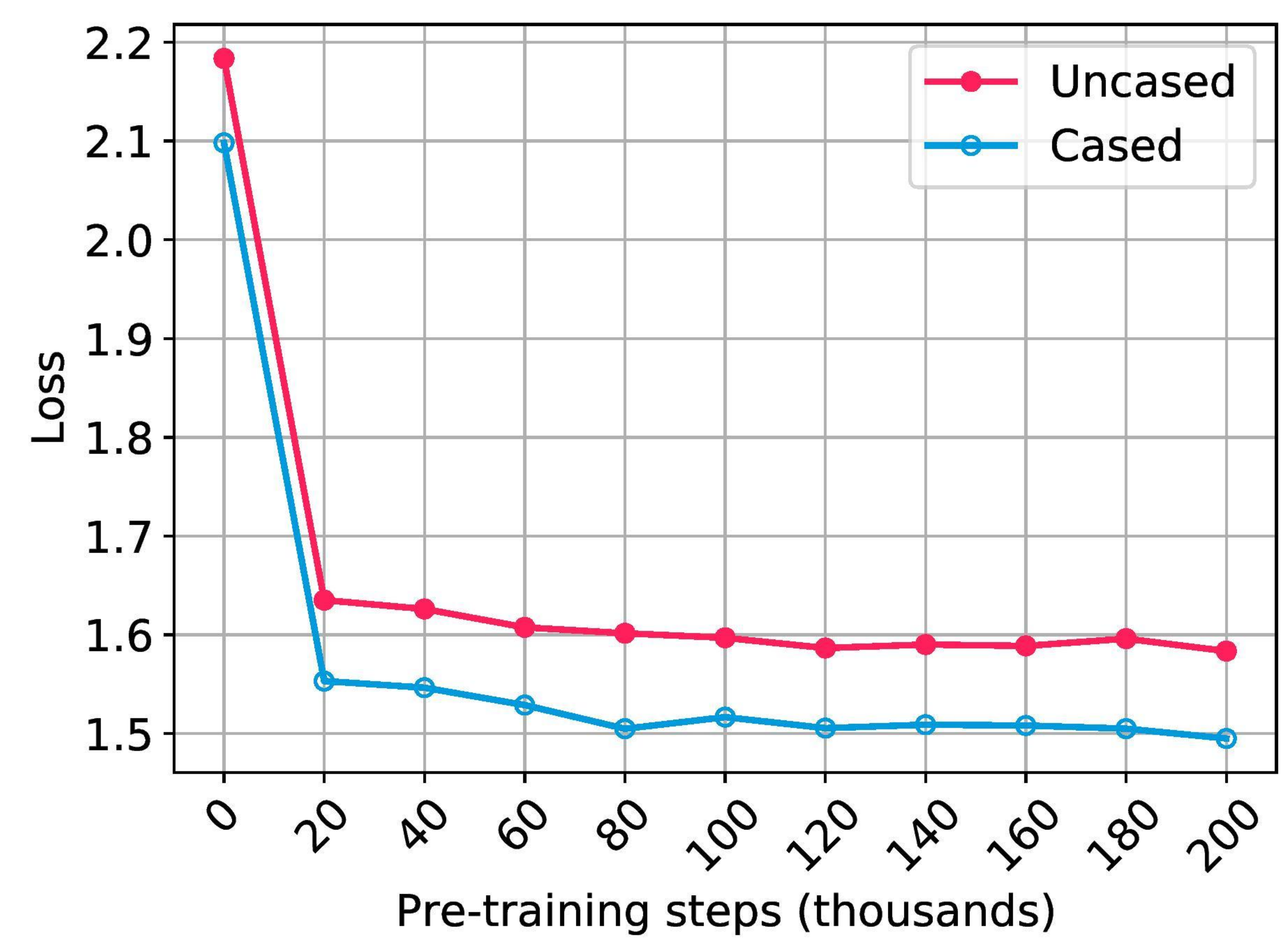



- Drug labels are the printed information, such as drug description, warnings and precautions, etc., included in the box of any medicine. We further pre-trained BERT on drug labels.
- Text samples of different domains cluster together in the embedding representations of BERT.
- We visualized the embeddings of the general BERT for text samples from different domains, namely, drug labels, general English (BookCorpus), clinical notes, and PubMed abstracts, using t-SNE.



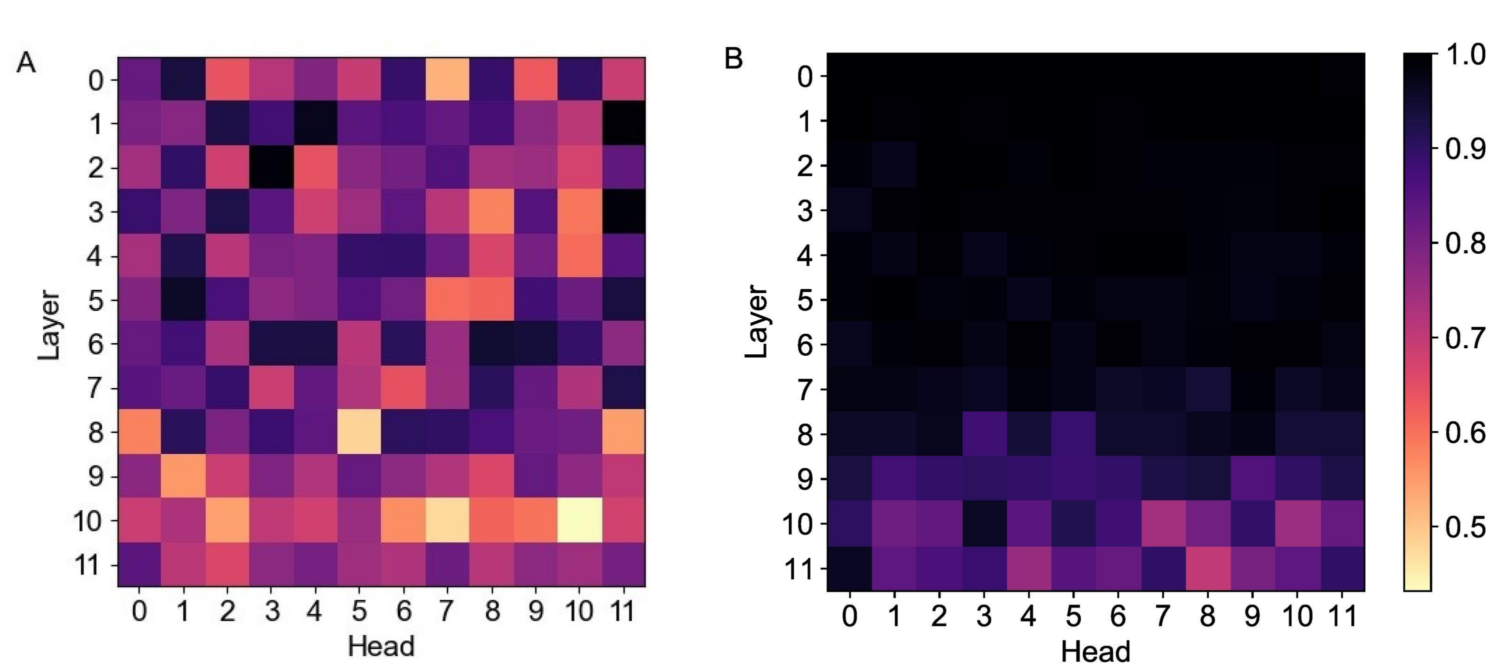

## Domain-specific pre-training

- PharmBERT was pre-trained using the data of DailyMed.
- 2 versions of PharmBERT: cased and uncased.
- Domain-specific pre-training decreased the loss of the masked language model on drug label text.




## How does the model change?

- Does the model change more during the domain-specific pre-training or during the fine-tuning? We compared the cosine similarity of attention heads.
- We compared pre-trained BERT vs. pre-trained PharmBERT (A) and pre-trained PharmBERT vs. fine-tuned PharmBERT (B).




## Testing PharmBERT on drug-label tasks

### ADME classification

- The FDA assessor must retrieve drug information of absorption, distribution, metabolism, and excretion (ADME) from the drug labeling for the PSG assessment, manually.
- We automated this process by fine-tuning the models for classifying pharmacokinetic text paragraphs into 5 topics, namely, absorption, distribution, metabolism, excretion (ADME) and other, based on their semantic meaning.

| Model | Mean F1 (Std Dev) |
|---|---|
| BERT-uncased | 0.9025 (0.0029) |
| PharmBERT-uncased | 0.9132 (0.0026) |
| BERT-cased | 0.9021 (0.0033) |
| PharmBERT-cased | **0.9165 (0.0036)** |
| BioBERT | 0.9116 (0.0019) |

### Adverse reaction detection

- The Center for Drug Evaluation and Research (CDER) in FDA is interested in detecting the adverse reactions of the drugs from drug labels automatically.
- The first task in 2017 Text Analysis Conference (TAC) was to extract adverse reactions and their related mentions from the drug labels.
- We fine-tuned the models for this classification task, where the goal is to assign each word to either an adverse reaction, a mention (severity, factor, drug class, negation, animal) or declare is as an ordinary word.

| Model | Mean F1 (Std Dev) |
|---|---|
| BERT-uncased | 0.8769 (0.0016) |
| PharmBERT-uncased | **0.8923 (0.0012)** |
| BERT-cased | 0.8700 (0.0017) |
| PharmBERT-cased | 0.8845 (0.0007) |
| BioBERT | 0.8897 (0.0009) |