K-12BERT: BERT for K-12 education

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\textbf{Abstract.} Online education platforms are powered by various NLP pipelines, which utilize models like BERT to aid in content curation. Since the inception of the pre-trained language models like BERT, there have also been many efforts toward adapting these pre-trained models to specific domains. However, there has not been a model specifically adapted for the education domain (particularly K-12) across subjects to the best of our knowledge. In this work, we propose to train a language model on a corpus of data curated by us across multiple subjects from various sources for K-12 education. We also evaluate our model, K-12BERT, on downstream tasks like hierarchical taxonomy tagging.

\textbf{Keywords:} AI in education · Language model · Domain adaption.

1 Introduction

The pre-trained language models like BERT\textsuperscript{4} have made considerable advancements in many NLP tasks. However, these models are trained on general domain text like Wikipedia and Book Corpus and are not adapted to the vocabulary of the target domain. Several works have addressed this by training domain-specific language models like PubMedBERT\textsuperscript{5}, SciBERT\textsuperscript{2}, BioBERT\textsuperscript{7} for biomedical NLP. Following their success over vanilla pre-trained models, several other works like TravelBERT\textsuperscript{9}, PatentBERT\textsuperscript{6}, FinBERT\textsuperscript{1} have adapted domain-specific pre-training for the respective domains. The domain-specific pre-training can be performed in two ways: the continued pre-training approach or pre-training from scratch. For instance, BioBERT and SciBERT demonstrate that when the corpus is small leveraging pre-trained models to continue training on domain-specific corpus leads to an increase in performance on downstream in-domain tasks. Additionally, works like PubMedBERT demonstrate that pre-training from scratch leads to gains on downstream tasks when in domain corpus is abundant.

In several instances, one might posit that the general domain text may overlap with the education vocabulary. However, the general domain text may contain advanced terms while lacking academic concepts, which are crucial for students to understand and achieve the learning objectives. This paper proposes to train the BERT model on a corpus of text collected from various sources for the
Table 1. Composition of our corpus.

| Source                          | Content            | # sentences |
|---------------------------------|--------------------|-------------|
| NCERT (India)                   | P, C, B, SS        | 15K         |
| Siyavulla.com (International)   | H, L               | 2K          |
| OpenStax.org (USA)              | P, C, B            | 4K          |
| Learncbse.in (India)            | P, C, B, SS        | 19K         |
| CK-12.org (USA)                 | P, C, B, L, H, E   | 14K         |
| KhanAcademy.org (USA)           | P, C, B, SS        | 282K        |
| Extramarks.com (India)          | P, C, B, H, SS     | 120K        |

K-12 education system across different geographic regions. We perform continued pre-training as the corpus is not abundant compared to other domains. In summary, the following are the core contributions of our work:

– We release a corpus for the K-12 education system as shown in Table 1.
– We perform continued pre-training of BERT on the K-12 corpus and evaluate on downstream tasks.
– Code and data are at https://github.com/ADS-AI/K12-Bert-AIED-2022

2 Methodology

2.1 Dataset

We curate our dataset from multiple online learning platforms that provide open access for research purposes. To the best of our knowledge, the dataset curated is the first of its kind due to the lack of a corpus of K-12 learning content suitable for language model training. Table 1 describes the details of the datasets collected. The data collected ranges across different regions like the USA, India, and South Africa to avoid regional bias in the dataset. The data collected is as follows:

– For NCERT (K-12) (India) we used pdfminer3, a python library for extracting information from NCERT PDFs4.
– For Siyavulla, OpenStax, LearnCBSE, CK-12 we systematically scraped the webpages which contained information and picked out the chunks which contained meaningful information. Then we used the HTML parser present with BeautifulSoup5 to break down the document into retrievable components and extract information from the paragraph tags.
– We accessed Khan Academy transcripts using the official API6. Khan academy transcripts had informal language, which added to the noise since they are made for an online video educational setup which was filtered out.

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3 https://pypi.org/project/pdfminer2/
4 https://ncert.nic.in/textbook.php
5 https://www.crummy.com/software/BeautifulSoup/bs4
6 https://github.com/Khan/khan-api
Table 2. Performance comparison (Recall@K) of K-12Bert with other baselines.

| Dataset | Model            | R@5 | R@10 | R@15 | R@20 |
|---------|------------------|-----|------|------|------|
| ARC     | BERT+USE         | 0.67| 0.81 | 0.86 | 0.89 |
|         | BERT+Sent_BERT   | 0.65| 0.77 | 0.84 | 0.88 |
|         | BERT+K-12Sent_BERT | 0.68| 0.81 | 0.87 | 0.90 |
|         | K-12Bert+USE     | 0.65| 0.78 | 0.85 | 0.88 |
|         | K-12Bert+Sent_BERT | 0.68| **0.82** | 0.87 | 0.90 |
|         | K-12Bert+K-12Sent_BERT | **0.68** | 0.81 | 0.86 | **0.90** |
| QC-Science | BERT+USE     | 0.86| 0.92 | 0.95 | 0.96 |
|         | BERT+Sent_BERT   | 0.85| 0.93 | 0.95 | 0.97 |
|         | BERT+K-12Sent_BERT | 0.88| **0.94** | 0.96 | 0.97 |
|         | K-12Bert+USE     | 0.84| 0.91 | 0.94 | 0.96 |
|         | K-12Bert+Sent_BERT | 0.88| 0.93 | 0.95 | 0.97 |
|         | K-12Bert+K-12Sent_BERT | 0.88| 0.94 | **0.96** | **0.97** |

– The Extramarks (EM) transcripts were made available by Extramarks in .docx format and had content in Hindi and English. We filtered out the text containing Roman Hindi characters by comparing their unicode values. Using pyenchant library, we run spellcheck on the words and maintain a count of approved words by the spell checker. Finally, we extract sentences that have more approved words than rejected words.

2.2 Continued pre-training

Due to the constraint on the data available in this domain, we decided to continue pre-training. For our current experiment, we do not update the existing vocabulary. Using the existing BERT vocabulary allows the model to capture diverse information and be well suited for education-related tasks. The data that we scraped had discontinuity in sentences due to the scraping mechanism, which is a downside for NSP (Next Sentence Prediction) objective. Hence, for training K-12Bert, we use only the MLM (Masked Language Modeling) objective. To make the training resource-efficient, we utilize training techniques like Gradient Checkpointing, Gradient Accumulation, and mixed-precision training, proven to save GPU memory and speed up training. We continue the pre-training for 10 epochs over a batch size of 32 and gradient accumulation step size of 4. This setup allowed us to train our setup over 2 GPUs of 16GB memory each. We performed extensive experiments by training our model over different combinations of curated datasets. We achieved the best performance when the model was trained over Siyavulla, OpenStax, LearnCBSE, Ck-12.org, and EM transcripts.

3 Results

To validate the training of K-12Bert we test it on the automated question tagging task for education domain. We evaluate our model on the task presented

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https://pypi.org/project/pyenchant/
of tagging learning content like questions to a hierarchical learning taxonomy of form subject - chapter - topic. We use the official code provided by the authors and replace the models and sentence encoder, keeping all other settings the same. The results of K-12Bert and previous best baselines are listed in Table 2. We use state of the art models for generating contextualized sentence embeddings like Universal Sentence Encoder (USE) and Sentence-BERT (SentBERT) to generate embeddings for the taxonomy. We noticed that K-12Bert + {USE, SentBERT} wasn’t performing as well as the vanilla BERT baseline. We believe the reason behind that could be since BERT, USE and SentBERT are trained on a general dataset, whereas K-12Bert is exposed to more data pertaining educational domain, the embeddings generated are farther away in the vector space. So, in order to validate our hypothesis, we trained K-12SentBERT, a sentence BERT model finetuned for educational domain. We see that with using K-12Bert with K-12SentBERT we were able to outperform the previous baselines by 2% for the QC-Science dataset and 1% for ARC. We strongly attribute these results to the domain specific training of the models.

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