Investigating Transformers for Automatic Short Answer Grading

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Abstract. Recent advancements in the field of deep learning for natural language processing made it possible to use novel deep learning architectures, such as the Transformer, for increasingly complex natural language processing tasks. Combined with novel unsupervised pre-training tasks such as masked language modeling, sentence ordering or next sentence prediction, those natural language processing models became even more accurate. In this work, we experiment with fine-tuning different pre-trained Transformer based architectures. We train the newest and most powerful, according to the glue benchmark, transformers on the SemEval-2013 dataset. We also explore the impact of transfer learning a model fine-tuned on the MNLI dataset to the SemEval-2013 dataset on generalization and performance. We report up to 13% absolute improvement in macro-average-F1 over state-of-the-art results. We show that models trained with knowledge distillation are feasible for use in short answer grading. Furthermore, we compare multilingual models on a machine-translated version of the SemEval-2013 dataset.

Keywords: Self-attention · Transfer learning · Short answer grading

1 Introduction

Online tutoring platforms enable students to learn individually and independently. To provide the users with individual feedback on their answers, the answers have to be graded. In large tutoring platforms, there are an abundant number of domains and questions. This makes building a general system for short answer grading challenging, since domain-related knowledge is frequently needed to evaluate an answer. Additionally, the increasing accuracy of short answer grading systems makes it feasible to employ them in examinations. In this scenario it is desirable to achieve the maximum possible accuracy, with a relatively high computational budget, while in case of tutoring a less computational intensive model is desirable to keep costs down and increase responsiveness. In this work, we experiment with fine-tuning the most common transformer models and explore the following questions:

Does the size of the Transformer matter for short answer grading? How well do multilingual Transformers perform? How well do multilingual Transformers generalize to another language? Are there better pre-training tasks for short answer grading? Does knowledge distillation work for short answer grading?

The field of short answer grading can mainly be categorized into two classes of approaches. The first ones represent the traditional approaches, based on hand-crafted features [14,15] and the second ones are deep learning based approaches [1,8,13,16,18,21]. One of the core constraints of short answer grading remained the limited availability of labeled domain-relevant training data. This issue was mitigated by transfer learning from models pre-trained using unsupervised pre-training tasks, as shown by Sung et al. [21] outperforming previous approaches by about twelve percent. In this study, we aim to extend upon the insights provided by Sung et al. [21].

2   Experiments

We evaluate our proposed approach on the SemEval-2013 [5] dataset. The dataset consists of questions, reference answers, student answers and three-way labels, represenenting the CORRECT, INCORRECT and CONTRADICTORY class. We translate it with the winning method from Wmt19 [2]. For further information see Sung et al. [21]. We also perform transfer learning from a model previously fine-tuned on the MNLI [22] dataset.[1]

For training and later comparison we utilize a variety of models, including BERT [4], RoBERTa [11], AlBERT [10], XLM [9] and XLMRoBERTa [3]. We also include distilled models of BERT and RoBERTa in the study [19]. Furthermore we include a RoBERTa based model previously fine-tuned on the MNLI dataset.

For fine tuning we add a classification layer on top of every model. We use the AdamW [12] optimizer, with a learning rate of 2e−5 and a linear learning rate schedule with warm up. For large transformers we extend the number of epochs to 24, but we also observe notable results with 12 epochs or less. We train using a single NVIDIA 2080ti GPU (11 GB) with a batch size of 16, utilizing gradient accumulation. Larger batches did not seem to improve the results. To fit large transformers into the GPU memory we use a combination of gradient accumulation and mixed precision with 16 bit floating point numbers, provided by NVIDIAs apex library[2]. We implement our experiments using huggingfaces transformer library [23]. We will release our training code on GitHub[3]. To ensure comparability, all of the presented models where trained with the same code, setup and hyper parameters (Table 1).

3   Results and Analysis

Does the size of the Transformer matter for short answer grading?
Large models demonstrate a significant improvement compared to Base models.

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[1] https://www.nyu.edu/projects/bowman/multinli/.
[2] https://github.com/NVIDIA/apex.
[3] https://github.com/28Smiles/SAS-AIED2020.

Table 1. Results on the SciEntsBank Dataset of SemEval 2013. Accuracy (Acc), macro-average-F1 (M-F1), and weighted-average-F1 (W-F1) are reported in percentage.

	Languages Trained	English									German								
		Unseen answer			Unseen question			Unseen domain			Unseen answer			Unseen question			Unseen domain		
		Acc	M-F1	W-F1	Acc	M-F1	W-F1	Acc	M-F1	W-F1	Acc	M-F1	W-F1	Acc	M-F1	W-F1	Acc	M-F1	W-F1
Baseline [5]	en	55.6	40.5	52.3	54.0	39.0	52.0	57.7	41.6	55.4	-	-	-	-	-	-	-	-	-
ETS [6]	en	72.0	64.7	70.8	58.3	39.3	53.7	54.3	33.3	46.1	-	-	-	-	-	-	-	-	-
SOFTCAR [7]	en	65.9	55.5	64.7	65.2	46.9	63.4	63.7	48.6	62.0	-	-	-	-	-	-	-	-	-
MEAD [17]	en	-	42.9	55.4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Graph [17]	en	-	43.8	56.7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Sultan et al. [20]	en	60.4	44.4	57.0	64.3	45.5	61.5	62.7	45.2	60.3	-	-	-	-	-	-	-	-	-
Saha et al. [18]	en	71.8	66.6	71.4	61.4	49.1	62.8	63.2	47.9	61.2	-	-	-	-	-	-	-	-	-
Marvaniya et al. [13]	en	-	63.6	71.9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Sung et al. [21]	en	75.9	72.0	75.8	65.3	57.5	64.8	63.8	57.9	63.4	-	-	-	-	-	-	-	-	-
BERTDISTILL	en	69.2	67.2	69.2	56.6	54.7	56.6	61.4	49.7	61.4	38.8	26.2	38.8	33.7	21.5	33.7	51.7	29.5	51.7
BERTBASE	en	72.8	70.6	72.8	57.3	56.0	57.3	63.4	54.6	63.4	45.0	37.0	45.0	40.5	32.9	40.5	59.0	41.7	59.0
BERTLARGE	en	75.8	75.0	75.8	63.4	62.4	63.4	67.7	62.8	67.7	50.2	40.5	50.2	43.7	35.5	43.7	57.7	42.2	57.7
RoBERTaDISTILL	en	74.8	73.2	74.8	56.9	55.2	56.9	65.1	55.6	65.1	48.0	40.4	48.0	44.1	36.7	44.1	58.2	40.2	58.2
RoBERTaBASE	en	74.5	73.2	74.5	63.2	61.7	63.2	65.3	62.5	65.3	47.8	38.1	47.8	43.5	35.1	43.5	60.6	43.2	60.6
RoBERTaLARGE	en	76.7	75.5	76.7	64.1	62.7	64.1	66.8	65.6	66.8	48.8	40.4	48.8	42.7	34.7	42.7	61.5	48.2	61.5
RoBERTaLARGE	de	41.2	19.4	41.2	47.7	21.5	47.7	42.0	19.7	42.0	41.2	19.4	41.2	47.7	21.5	47.7	42.0	19.7	42.0
RoBERTaLARGE	en, de	76.1	74.9	76.1	63.0	61.9	63.0	65.6	63.3	65.6	73.9	72.3	73.9	58.9	57.3	58.9	61.9	56.3	61.9
RoBERTaLARGE.MNLI	en	78.8	78.3	78.8	**66.4**	**65.7**	**66.4**	**71.8**	**70.8**	**71.8**	52.6	49.3	52.6	46.1	42.5	46.1	60.1	51.9	60.1
RoBERTaLARGE.MNLI	de	62.6	59.1	62.6	55.1	51.5	55.1	66.5	66.8	66.5	74.9	74.0	74.9	**60.8**	**59.0**	**60.8**	62.5	57.2	62.5
RoBERTaLARGE.MNLI	en, de	**79.7**	**79.1**	**79.7**	66.3	65.3	66.3	69.4	69.1	69.4	**76.0**	**75.0**	**76.0**	59.6	58.4	59.6	**64.9**	**59.2**	**64.9**
AlBERTBASE	en	72.6	71.4	72.6	57.6	55.2	57.6	60.1	52.3	60.1	37.0	31.5	37.0	30.0	24.9	30.0	40.6	31.8	40.6
AlBERTLARGE	en	71.3	70.1	71.3	58.1	56.8	58.1	65.3	60.7	65.3	45.0	42.1	45.0	38.7	34.9	38.7	58.1	46.0	58.1
XLMMLM-TLM-XNLI	en	72.6	71.2	72.6	57.6	55.5	57.6	56.3	44.8	56.3	48.0	47.4	48.0	43.7	43.3	43.7	47.7	41.5	47.7
XLMMLM-TLM-XNLI	de	57.0	54.8	57.0	43.7	41.9	43.7	56.4	41.2	56.4	68.8	66.5	68.8	54.0	51.6	54.0	55.8	44.8	55.8
XLMMLM-TLM-XNLI	en, de	64.8	62.2	64.8	52.1	49.2	52.1	48.6	35.7	48.6	63.8	61.2	63.8	51.8	49.7	51.8	48.1	33.8	48.1
XLMRoBERTaBASE	en	75.4	73.8	75.4	59.9	57.9	59.9	62.6	54.4	62.6	64.2	60.6	64.2	52.7	48.3	52.7	60.1	49.5	60.1
XLMRoBERTaBASE	de	69.0	67.4	69.0	53.6	51.9	53.6	62.3	51.9	62.3	73.4	71.7	73.4	56.9	55.6	56.9	60.8	49.7	60.8
XLMRoBERTaBASE	en, de	74.1	72.4	74.1	59.1	57.5	59.1	60.1	48.1	60.1	73.1	71.3	73.1	56.1	54.6	56.1	59.4	46.5	59.4

The improvement arises most likely due to the increased capacity of the model, as more parameters allow the model to retain more information of the pre-training data.

How well do multilingual Transformers perform? The *XLM* [9] based models do not perform well in this study. The *RoBERTa* based models (*XLM-RoBERTa*) seem to generalize better than their predecessors. *XLMRoBERTa* performs similarly to the base *RoBERTa* model, falling behind in the unseen questions and unseen domains category. Subsequent investigations could include fine-tuning the large variant on MNLI and SciEntsBank. Due to GPU memory constraints, we were not capable to train the large variant of this model.

How well do multilingual Transformers generalize to another language? The models with multilingual pre-training show stronger generalization across languages than their English counterparts. We are able to observe that the score of the multilingual model increases across languages it was never fine-tuned on, while the monolingual model does not generalize.

Are there better pre-training tasks for short answer grading? Transfer learning a model from MNLI yields a significant improvement over the same version of the model not fine-tuned on MNLI. It improves the models ability to generalise to a separate domain. The models capabilities on the german version of the dataset are also increased, despite the usage of a monolingual model. The reason for this behavior should be further investigated.

Does knowledge distillation work for short answer grading? The usage of models pre-trained with knowledge distillation yields a slightly lower score. However, since the model is 40% smaller, a maximum decrease in performance of about 2% to the previous state of the art may be acceptable for scenarios where computational resources are limited.

4 Conclusion and Future Work

In this paper we demonstrate that large Transformer-based pre-trained models achieve state of the art results in short answer grading. We were able to show that models trained on the MNLI dataset are capable of transferring knowledge to the task of short answer grading. Moreover, we were able to increase a models overall score, by training it on multiple languages. We show that the skills developed by a model trained on MNLI improve generalization across languages. It is also shown, that cross lingual training improves scores on SemEval2013. We show that knowledge distillation allows for good performance, while keeping computational costs low. This is crucial in evaluating answers from many users, like in online tutoring platforms.

Future research should investigate the impact of context on the classification. Including the question or its source may help the model grade answers, which were not considered during the reference answer creation.

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