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Data Science for MSc Cognitive Science
Aarhus University, May 2020

LARGE BERT VS. DISTILBERT: FIND THE RIGHT ANSWER

HTTPS://GITHUB.COM/MARISSALA/DATA-SCIENCE-BERT

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Students' individual contributions are marked with their initials in square brackets: [A] and [M]. Abstract, introduction and conclusion were written together.

ABSTRACT

In this paper the large version of BERT (Bidirectional Encoder Representations from Transformers by Google AI) is compared to its smaller knowledge-distilled version DistilBERT. Both models were fine-tuned to the SQuAD 1.1 task. The aim was to see how well these pre-made models perform on a new dataset that hasn't been part of their training nor fine-tuning data. For applications in the real world, it's ideal to find a model that doesn't take extra training and fine-tuning on large datasets to give accurate results with a small computational cost. To evaluate this, we compared the running time and performance of both models in a Question Answering task on the TweetQA dataset. GLEU and METEOR scores were used and optimized for automated performance evaluation. We found that DistilBERT ran 529% faster and reached around 87-90% of large BERTs performance, even though it was based on a smaller base-BERT. The possible applications and future model improvements are considered in the discussion.

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INTRODUCTION [A+M]

In 2018, Devlin et al. from the Google AI Language team released what is currently considered the state-of-the-art language model developed so far - BERT (Bidirectional Encoder Representations from Transformers). The model represents a stack of encoders from the Transformer neural net architecture proposed by Vaswani et al. (2017) with an additional output layer, that can be tailored to the language task at hand. Since its release date, Google AI's pre-trained version of BERT has been successfully fine-tuned to a variety of datasets and language tasks, surpassing other language models in performance.

BERT reaches high levels of accuracy, but it also takes a lot of computing power to fine-tune and run, since it has around 340M parameters. In evaluating a language model's performance, optimizing for accuracy of predictions is necessary. However, it also matters that the model can run on various devices without being restricted to the most powerful hardware, making model compression research an important domain in Data Science. As researchers explored different ways to compress BERT without undermining its performance, they published different compressed versions of BERT in a variety of sizes and with different tasks in mind.

Our focus is to compare a large BERT model to a knowledge-distilled version of BERT in a Question Answering task – a challenging language task less prominent in the literature on BERT. Both models would be tested on a new dataset that the models haven't been trained on previously. We are both interested in inference time and how well the results compare to each other and to the golden standard based on the appropriate evaluation metrics. Having an overview of how well the models handle a known task with an unknown dataset would give us an idea of how generalizable the models are and how much both would need to be improved.

Our prior expectation is that a compressed model would yield shorter inference time but worse performance than a larger model. Our main research question is to evaluate how close the performance of a compressed model can come to its larger counterpart, and whether that difference is justified by lower computational costs.

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THEORY

OVERVIEW OF BERT [A]

The original BERT by Devlin et al. (2018) was composed of 24 Encoder blocks from the Transformer architecture introduced by Vaswani et al. (2017). The Transformer architecture is described best in the original paper (Vaswani et al., 2017) and will not be included in this overview.

The standard input to BERT is a sequence of tokens, including special tokens marking start of the sequence and breaks between the sentences. All tokens of the sequence then undergo an embedding process shown in Figure 1, which is similar to input embedding stage in the original Transformers but also captures an additional segment embedding to track sentence affiliation.

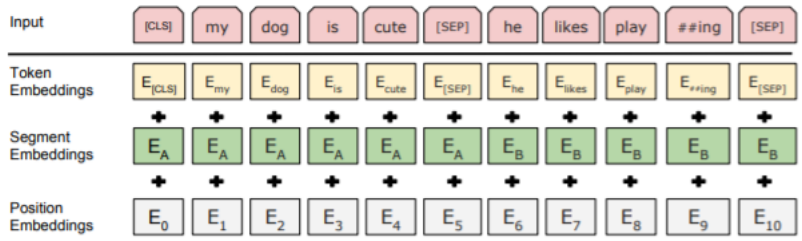

Figure 2: BERT input representation. The input embeddings are the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Figure 1. Input to BERT and summarization of its embeddings (image from Devlin et al. (2018)). Token (WordPiece embeddings), segment and position embeddings are summed together

Resulting input embeddings then flow through BERT's architecture, which according to the structural and qualitative analysis by Tenney et al. (2019) mimics a traditional NLP pipeline. There, earlier layers of the network seemed to conduct lower-level operations (e.g. part of speech tagging and parsing-like processes), while higher-level processes (e.g. assignment of semantic roles and coreference) seemed to be localised in later layers of BERT and were used by the model to revise lower-level decisions in case of ambiguity.

On top of the encoder stack, BERT's architecture ends with the final output layer. What this layer should look like depends on the particular language task at hand and is therefore defined for every task separately in the pre-training or fine-tuning process.

Unlike many unidirectional language models, BERT is pre-trained to produce a word's representation that captures its context in both directions. This is achieved by setting a 'masked language model' objective as the first part of the model's pre-training procedure. By randomly

masking 15% of tokens in the input sequence and training the model to guess those missing tokens, parameters on all levels of the model adjust to capture the token's context regardless whether it's on the right or on the left of the missing token (Devlin et al., 2018).

The second part of BERT's pre-training is the 'next sentence prediction task' performed simultaneously with the 'masking task'. This further adjusts model weights to also capture the relationship between two consequent sentences in the text. Just as masking, this task can be performed unsupervised, which allows pre-training on large and rich language corpora without imposing too many additional costs to the researcher. The original BERT was pre-trained on texts from BooksCorpus (800M words) and English Wikipedia (2,500M words).

The resulting pre-trained BERT can be used as a strong starting point for different language tasks regardless of their scale and domain (e.g. single word prediction, question answering, general language understanding) (Devlin et al., 2018).

While being faster than a convolutional or recurrent neural network of a similar size, the original large BERT by Devlin et al. (2018) is still considered to be a computationally expensive model with 340M parameters. The smaller version presented in the same paper was base BERT with 110M parameters. Both models scored well in a wide array of language tasks (see Table 1).

Table 1. Performance of large and base BERT on GLUE benchmark was better than in other models. Table from Devlin et al. (2018).

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$BERT_{BASE}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$BERT_{LARGE}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

MODEL COMPRESSION [A]

There are several ways trained neural net models can be compressed to gain an advantage in computational costs. When models are trained, they are usually over-parameterized because finding the appropriate parameters can be very difficult and it's hard to train an appropriately parameterized model using gradient descent (Gordon, 2020). Instead, a large model is compressed to a simpler one by removing its redundancies and thus bringing it closer to an appropriately parameterized model. In addition to a lessened computational cost, compressed

models tend to be more generalizable to noisy data and thus it makes sense to expect them to perform better on new data (Vijay, 2019).

Different types of model compression techniques focus on a different kind of property that differentiates a large model from a compressed one: redundancies such as many of the weights approximating 0 or some of the layers learning to do similar functions (Table 2).

Table 2. Types of model compression. Table from Gordon (2020).

Compression Method	**Redundancy**	**Why?**	**During Training**
Weight Pruning	Many zero weights	Unclear	Rigged Lottery
Weight Sharing	Different layers tend to perform similar functions	Images are locally coherent/compositional. So are sentences.	Convolutions, Recurrences, ALBERT
Quantization	Weights are low-precision	Unclear	XNOR Net, DoReFa-Net, ABC-Net
Matrix Factorization	Matrices are low rank	Dropout, Nuclear-norm regularization	ALBERT
Knowledge Distillation	Unclear	Unclear	BANs, Snapshot KD, Online KD

Table 2 illustrates various methods of model compression, which kinds of model redundancy they take advantage of and why. For knowledge distillation it is unclear which redundancy is used. We choose to focus on this methodology since it is interesting to study and experiment with a technique that performs well but the underlying reasons remain unclear.

KNOWLEDGE DISTILLATION [M]

Model compression in the form of knowledge distillation was originally proposed by Buciluǎ et al., (2006). However, mostly a more recent generalization of the topic published by Hinton et al. (2015) was used by Sanh et al. (2019) to distil base BERT into DistilBERT.

Knowledge distillation is a method where a smaller network (student) is taught by a larger network (teacher) about how to do what the trained network can do (Figure 2). In a supervised learning task, a deep neural net classifier model would be able to tell the difference between the categories and even if it makes mistakes, it makes likelier mistakes over less likely ones. Conceptually speaking, this kind of knowledge has been referred to as dark knowledge (Hinton

et al., 2015) and having a good grasp of it means that the model is good at generalizing, not just plainly classifying.

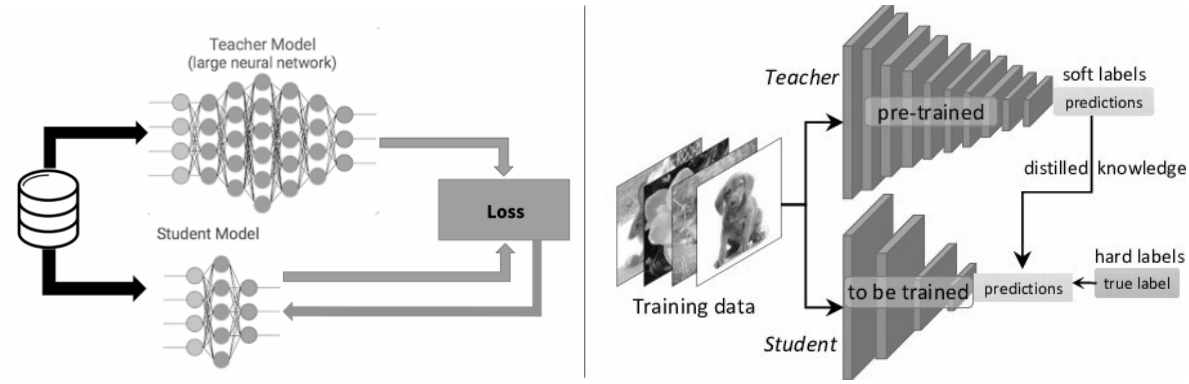

Figure 2. The interactions between a teacher model teaching the student model in a step-by-step fashion (Ganesh, 2019).

Machine learning algorithms use different loss functions to find out which answer is closest to the true label. In training of classification models, the categories are referred to as "hard targets" where the correct category is noted with 1 and the others with 0s such as [0, 1, 0, 0]. "Soft targets" represent the same categories as distribution of probabilities, such as [0.10, 0.60, 0.15, 0.15]. Usually deep neural networks are trained with a cross-entropy over the hard targets, but in the transfer of knowledge the student is instead trained with a cross-entropy of the soft targets retrieved from the teacher model. The training loss is then defined as:

$$L = -\sum_i t_i * log(s_i)$$

Where *t* is the logits from the teacher and *s* the logits of the student (Sanh et al., 2019). This is how deep knowledge can be practically transferred between the two models. Large models such as the teacher are good at generalizing due to their size and parameter amount. Transferring dark knowledge helps the student model be just as good at generalization compared to a model of the same size (Zhang, 2014).

The soft targets probability distributions are calculated with the following softmax activation function:

$$q_i = \frac{exp(z_i/T)}{\Sigma_j exp(z_j/T)}$$

Where q_i is the probability of a class, $z_i$are the logits for each class for every datapoint which are converted to probabilities using T as the temperature. At the time of training, a higher T

value, which results in softer distributions, is used in both the teacher and the student model because it allows for better deep knowledge understanding of the data. After training and during inference, *T* is set back to 1 (Sanh et al., 2019; Vijay, 2019).

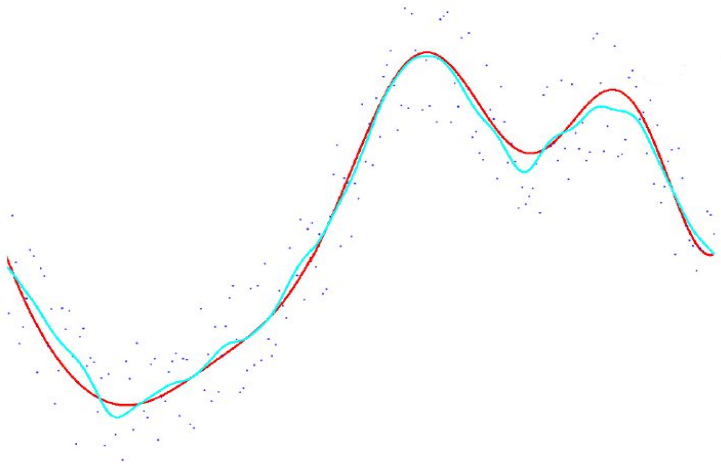

Figure 3. The teacher model (blue line) compared to the student model (red line) in generalizing on the complex dataset. Figure from Vijay (2019).

Figure 3 shows the teacher model (blue line) in comparison to the smoother student model (red line). The student model takes the geometric mean of all individual predictive distributions for the soft targets. High entropy (surprisal) in soft targets provides the training process with more information and less variance. This improves student model's ability to replicate the behavior of its teacher model in comparison to a small model that was directly trained on the same or smaller dataset. The compressed model can also use a higher learning rate and thus be fine-tuned faster than its teacher (Vijay, 2019).

KNOWLEDGE DISTILLED MODELS BY HUGGINGFACE [M]

HuggingFace has made several distilled models of BERT, the first one being DistilBERT (HuggingFace, 2020a; Sanh et al., 2019). DistilBERT has the same architecture as BERT but it has less layers, lacks the token-type embeddings and the pooler which is used for the next sentence prediction task. Because both BERT and DistilBERT have the same number of hidden layers, it was possible to initialize it's training by using a hidden layer from its teacher. This helps the model converge (as opposed to "the lottery ticket" hypothesis as described in Frankle & Carbin, 2019). DistilBERT was trained similarly to BERT on the same dataset with similarly large batch sizes and masking.

HuggingFace reports DistilBERT to have half the parameters of BERT base and yet based on the GLUE benchmark, it performs with 95% accuracy of the BERT base as seen in Table 3. Both base BERT and DistilBERT performed better than the GLUE baseline.

Table 3. Comparison of language models on different GLUE benchmark tests. Table from Sanh et al. (2019)

	Macro Score	CoLA	MNLI	MNLI-MM	MRPC		QNLI	QQP		RTE	SST-2	STS-B		WNLI
		mcc	acc	acc	acc	f1	acc	acc	f1	acc	acc	pearson	spearmanr	acc
GLUE BASELINE (ELMo + BiLSTMs)	68.7	44.1	68.6 (avg)		70.8	82.3	71.1	88.0	84.3	53.4	91.5	70.3	70.5	56.3
BERT base	78.0	55.8	83.7	84.1	86.3	90.5	91.1	90.9	87.7	68.6	92.1	89.0	88.6	43.7
DistilBERT	75.2	42.5	81.6	81.1	82.4	88.3	85.5	90.6	87.7	60.0	92.7	84.5	85.0	55.6

Table 4 shows that due to its much smaller size, DistilBERT is more than 60% faster than BERT, and 120% faster than ELMo + BiLSTM.

Table 4. Comparison of the language models in terms of parameters and inference time. Table from Sanh et al. (2019)

	Nb of parameters (millions)	Inference Time (s)
GLUE BASELINE (ELMo + BiLSTMs)	180	895
BERT base	110	668
DistilBERT	66	410

HuggingFace has made other distilled versions of BERT such as DistilmBERT for multilingual tasks and DistilRoBERTa which has been distilled from RoBERTa - another version of BERT. Different distilled models aim to address issues relevant for specific tasks, e.g. handling non-English datasets. These models are however not available in their fine-tuned form in HuggingFace's Transformers package.

BERT FOR QUESTION ANSWERING [A]

BERT can handle a wide variety of language tasks, but the one in the focus of this paper is the Question Answering (QA) task. In most cases the task is based on applying BERT to the Stanford Question Answering Dataset (SQuAD), where given a question and a prompt which includes the answer, the model is able to highlight the area in the prompt that corresponds to the answer to the question (McCormic, 2020; Figure 4).

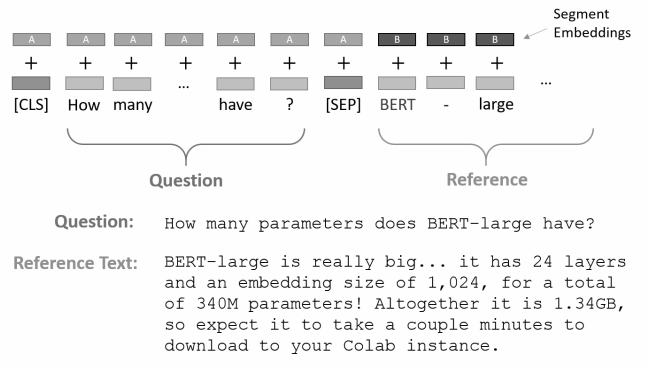

Figure 4. The premise on which BERT highlights the correct answer to a question in the reference text. Figure from McCormic (2020).

SQuAD 1.1. task's results presented Table 5 by Devlin et al. (2018) suggest that large and base BERT can be very successful in the QA task, given appropriate fine-tuning. As can be seen in Table 6 by Sanh et al. (2019), DistilBERT can perform almost as successfully as base BERT. Given that base BERT's performance is identical in both tables, we can estimate that DistilBERT was 96.9% as good as base BERT and 94.8% as good as large BERT.

Table 5. Comparison of language models to human performance on SQuAD 1.1. With additional fine-tuning on TriviaQA dataset, large BERT outperformed even human judgement. Table from Devlin et al. (2018).

System	Dev		Test	
	EM	F1	EM	F1
Top Leaderboard Systems (Dec 10th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
#2 Ensemble - QANet	-	-	84.5	90.5
Published				
BiDAF+ELMo (Single)	-	85.6	-	85.8
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
$BERT_{BASE}$ (Single)	80.8	88.5	-	-
$BERT_{LARGE}$ (Single)	84.1	90.9	-	-
$BERT_{LARGE}$ (Ensemble)	85.8	91.8	-	-
$BERT_{LARGE}$ (Sgl.+TriviaQA)	**84.2**	**91.1**	**85.1**	**91.8**
$BERT_{LARGE}$ (Ens.+TriviaQA)	**86.2**	**92.2**	**87.4**	**93.2**

Table 6. Comparison of DistilBERT to base BERT by performance on SQuAD 1.1. DistilBERT achieves close accuracy. Table from Sanh et al. (2019).

Model	IMDb (acc.)	SQuAD (EM/F1)
BERT-base	93.46	81.2/88.5
DistilBERT	92.82	77.7/85.8
DistilBERT (D)	-	79.1/86.9

This task was chosen by us because most BERT-related literature focuses on other tasks, since datasets for studying automated QA are not as abundant as classification and other kinds of NLP datasets. The QA task is especially interesting to use BERT on because BERTs architecture and training is optimizing towards bidirectional context cues which matters a lot for question answering and dialogue tasks.

AUTOMATED EVALUATION METRICS [M]

Language models are developed to solve language tasks as well as or better than humans, with large gains in speed. To properly measure performance of language models, it is necessary to carefully compare the different metrics that have been made for evaluation purposes. The evaluation of language models should be just as automated and approximate human levels of evaluation quality.

The field of machine translation (MT) has the most automated metrics developed so far. A good evaluation metric needs to fit with the task that it is used for, and when using an evaluation metric, one must be aware of its downsides and take them into consideration when inspecting the results.

In comparing the MT outputs, it's important that the meaning is translated from one language to another. This means that it matters to check for example grammar, synonyms, brevity of the output, word order. One of the first and most generally used metric was developed by IBM and is called the BLEU (bilingual evaluation understudy) (Papineni et al., 2002). BLEU is an intuitive measure of distance between the word matches of the translation to the reference texts. It's designed to work best on corpus-level, and on sentence-level analysis it might give inflated scores (Tatman, 2019). The scores are set from 0 to 1, where 1 signifies a perfect match between the human-made translation and the MT.

In the QA task, the correct answer that the models need to compare to, are given in a human-made text prompt. The models don't generate text themselves, meaning the outputs do not need to be checked for grammar nor synonyms. BLEU is a good fit here because it doesn't penalize for grammatical errors, but it does penalize for an answer being much longer or shorter than the reference. This is due to the way MT sometimes results in more words being produced (Papineni et al., 2002).

A general downside with BLEU is that in translation there are many ways to translate the same sentence, so having a high BLEU score does not entirely correlate with best translation. But in this task, the correct answers are only understandable in one way and the two models work based on highlighting the correct answer in the prompt text. This means that BLEU's main downside does not affect our results.

METEOR (Metric for Evaluation of Translation with Explicit Ordering) is another evaluation tool used to assess quality of MT. It is more complex than BLEU and is considered to approximate human judgement better since it also considers synonyms and uses a stemmer (Lavie & Agarwal, 2007). It weighs recall (matched unigrams divided by unigrams in reference) as more important than precision. METEOR is also adjusted to be used on sentence-level.

Given the nature of the QA task, BLEU and METEOR scores are good to use together since they are set on the same scale and might partially compensate for each other's drawbacks. Their performance should be evaluated within the context of the task to get a better sense of how well they describe the accuracies of the models.

HYPOTHESES AND THE RESEARCH QUESTION [A + M]

Thorough reports by Devlin et al. (2018) and Sanh et al. (2019) give us a good idea of BERT's and DistilBERT's QA performance on a standard dataset like SQuAD 1.1. Given that both models are openly available along with pre-trained and fine-tuned weights for the QA task, it is interesting to see how 'ready-to-use' they are on new data. Language models can make a difference in a variety of fields, where people working with the models would have an easier time if the models would be readily available and able to perform on similar levels as humans.

Question Answering task is a supervised learning problem, and often requires human workers to generate new question answering data (question-answer pairs based on a given prompt). Given how costly such data might be, it is important to see model's baseline performance before investing data into model fine-tuning. We want to understand the BERT's baseline performance with minimal computational and time costs. Baseline performance is considered to be using a pre-trained model on a new dataset which is different both from what BERT was originally trained on and what it was fine-tuned with. Since one of the goals of BERT is to be

generalizable across a variety of language tasks, we expect it to perform well even on a dataset it has never seen before.

BERT is computationally expensive to both train and fine-tune, and its inference time might be too long for tasks that need closer to real-time results. BERT is also large which means that it might be difficult to run on less powerful devices. Therefore, gauging whether DistilBERT can be successfully used instead of its larger counterpart is another focal point of this paper.

To summarize, our research question is two-fold:

1) How close can the baseline QA performance of a knowledge distilled model come to baseline performance of its much larger counterpart?
2) Can that difference in performance be justified by reduced computational costs?

Based on the presented theoretical overview, we state the following hypotheses of interest:

1) A knowledge distilled BERT will be at least 60% faster than the large model.
2) A knowledge distilled model will perform worse than the large model, with the difference in evaluation metric being at the very least 5%.
3) Judging from baseline performance on new data, a knowledge distilled BERT can be a better choice than a large BERT model if difference in performance does not exceed 15% while saving at least 60% of inference time.

We gave arbitrarily larger margins for acceptable performance difference to account for potential noisiness of a novel dataset.

METHODS

SELECTED MODELS [A]

As mentioned in the theoretical overview, a large selection of pre-trained versions of BERT can be found in the official documentation for Transformers by HuggingFace (2020)[1]. From that selection, out of models fine-tuned to Question Answering, we chose large BERT pre-

[1] HuggingFace documentation for Transformers (accessed 23.05.2020): https://huggingface.co/transformers/index.html

trained by Devlin et al. (2019) and DistilBERT distilled by Sanh et al. (2020). Our choice was motivated by the fact that DistilBERT is usually compared to its teacher – base BERT, and not the large BERT. We were interested in comparison between one of the lightest well-performing BERTs to one of the most expensive BERTs out there. The difference in model size between chosen models can be seen in Table 7.

Table 7. Model size comparison between large BERT and DistilBERT. (HuggingFace, 2020c)

	Large BERT	**DistilBERT**
Layers	24	6
Dimensions	1024	768
Attention Heads	16	12
Total parameters	340M	66M

Both large BERT by Devlin et al. (2019) and DistilBERT by Sanh et al. (2020) were pre-trained on texts from BooksCorpus (800M words) and English Wikipedia (2,500M words) and then further fine-tuned on the SQuAD task (Rajpurkar et al., 2016) for Question Answering.

To gauge baseline performance, we decided to run pre-trained models as they come on a new dataset without any additional fine-tuning.

DATASET [A]

The dataset we chose for this paper – TweetQA[2] – was developed by (Xiong et al., 2019) for automated social media-based question answering (SoMe QA). As pointed out by dataset's authors, SoMe QA is different from standard QA, as prompts are much shorter and noisier and questions may require understanding of Twitter metadata (e.g. usernames, hashtags, posting date). This motivated the dataset's authors to crowdsource question-answer pairs based on a selection of informational tweets scraped from CNN and NBC websites. The resulting dataset had 13,757 question-answer pairs, out of which 1,979 did not contain publicly available gold

[2] The TweetQA website with short demo of data and the download link (accessed 23.05.2020): https://tweetqa.github.io/

standard answers, as they were reserved as a test dataset for model evaluation in the ongoing competition at CodaLab[3].

In the original paper by Xiong et al. (2019), even after fine-tuning base BERT using the training part of the dataset, TweetQA task was more challenging for the model than standard question answering tasks, like the Wikipedia-based SQuAD task by Rajpurkar et al. (2016). Since our goal was to evaluate baseline performance of pre-trained BERT and DistilBERT in the TweetQA task, we utilised all parts of TweetQA dataset that already contained gold standard answers (merged 'training' and 'development' data, the total of 11,778 question-answer pairs). Short summary of the resulting dataset in comparison to the original dataset can be seen in Appendix 1.

MODEL APPLICATION PROCESS [A]

We decided to conduct data processing on a laptop with 2,3 GHz Intel Core i5 processor and 8 GB RAM, so the tracked processing time would reflect use of models on a personal computer without using GPU or any cloud computing services.

To apply the selected pre-trained models to the TweetQA dataset, we first loaded both models from the Transformers platform. Thorough documentation of the Transformers Python package and openly available OpenAI's pretrained model weights (HuggingFace, 2020b) allows easy access to pre-trained and fine-tuned models (see Code in Appendix 5). Model loading time was tracked for both models.

Since reference texts and questions need to be tokenized before being fed to the question answering model, we also load tokenizers for both models. Notably, even though DistilBERT model class has its own tokenizer called DistilBertTokenizer to be consistent with the rest of the package, it actually still uses standard BERT tokenizer in the backend (HuggingFace, 2020a). This means that both models use identical tokenizers, but they are fetched using different model-specific commands and thus their loading time will be tracked separately.

We then wrote a function that would conduct question answering using a specified model and track model's answer prediction and processing time for every question in the dataset.

[3] Competition at Codalab (accessed 23.05.2020): https://competitions.codalab.org/competitions/20307?secret_key=6684a0cf-9eac-4ac1-a648-213a3961e0fc

AUTOMATED EVALUATION METRICS SELECTION [M]

As BLEU performs best on corpus-level, Google developed their own adjusted form of BLEU which is better at assessing outputs on sentence-level - GLEU score (Wu et al., 2016). GLEU score is computed similarly to BLEU, recall is matching n-grams divided by total n-grams in the golden standard, and precision is the matching n-grams divided by total n-grams in the output. GLEU score is then calculated as the minimum of recall and precision.

To use METEOR score in a way that optimizes more towards the task at hand, the parameters in METEOR were adjusted according to suggestions made by Lavie & Agarwal (2007). They adjusted parameters to optimize for adequacy, fluency, and a sum of both. We chose the parameters that optimize both in order to remain conservative and try to reach a win-win scenario of output evaluation accuracy (see Appendix 2).

The parameter α controls relative weights for precision and recall. The new α defined in our evaluation is lower than the original which means it sets a smaller weight on precision. β controls the shape of penalty as a function of fragmentation, and γ is the relative weight for penalty of fragmentation. Fragmentation helps check whether the order of words is close to the true order. Both β and γ are lower than they were originally, meaning that the penalty is also lower than before (Lavie & Agarwal, 2007). Both GLEU and METEOR scores are calculated using the nltk package in Python.

In the analysis we computed GLEU and METEOR scores for every answer by BERT and DistilBERT models. Then 100 random samples were taken from the dataset and the performance of GLEU and METEOR scores were compared to our own human judgements. We scored the performance of the evaluation models based on which one gave a more accurate score compared to the other for both the results of BERT and DistilBERTs outputs. An example of manual scoring of the sample dataset is presented in Appendix 2.

There were 17 ties where both GLEU and METEOR succeeded or failed equally. Out of the 83 cases that were left, on 48 occasions (58%) the GLEU metric outperformed METEOR. This, however, was influenced by the fact that METEOR never gave a perfect 1 for a one-to-one correct answer whereas GLEU did. Crucially, METEOR failed to score 1-word responses that were exactly correct with a score of 1 and instead gave a 0. For answers that were longer than 3 words, the METEOR and GLEU scores were more comparable.

Based on evaluation results (see Appendix 4), the best compromise between the two metrics was to separate the dataset to evaluate short answers (up to 2 in length) with GLEU scores and long answers (greater than 2 in length) with METEOR scores. The short answers dataset is of length 7245 and the long answers dataset is much shorter - 3820 data points. The original data frame was split based on the lengths of the golden standard answers.

We would like to note some specifics of the dataset. In some cases, there were more than one correct answer options. For that reason, we were comparing model's answers to both gold standard options separately and only tracked the best match out of two. Data annotators were allowed to write answers in their own words, so in some cases it was not possible for the model to match the gold standard exactly and get a score of 1.

MEANS COMPARISON [A]

To evaluate whether the mean values of DistilBERT and BERT are significantly different, we conduct an independent t-test for every metric of interest: inference time, GLEU score and METEOR score.

SOFTWARE [M]

Model application, processing time tracking, and automated model evaluation were conducted in Python 3.8.3. using modules *transformers* (HuggingFace, 2020c), *PyTorch* (Paszke et al., 2019), *pandas* (McKinney, 2010), *nltk* (Bird et al., 2009), and *time* and *json* from the standard Python library.

Analysis and visualisation of processing times and evaluation metrics were conducted in R (R Core Team, 2019) using packages *tidyverse* (Wickham, 2017), *extrafont* (Winston Chang, 2014), and *rjson* (Couture-Beil, 2018).

RESULTS

MISSING ANSWERS [M]

After applying the models and receiving the outputs for BERT and DistilBERT, some of the questions were not answered by the models. The distilled model had missing answers for 446 questions, and the large model missed 303 questions. The models didn't answer questions when

the highest scored answer end token in the answer prompt was found to be before the answer beginning token. The missing values were excluded from the further analysis.

For the analysis, data was selected based on the questions that were answered by both models. Since there wasn't a perfect overlap, the size of the dataset got down to 11 065 rows.

LOADING AND INFERENCE TIME [A]

Tracked loading and inference time presented in Table 8 reveal that in total DistilBERT completed the TweetQA task 529% faster than the large BERT. DistilBERT was faster in everything, except the tokenizer loading time.

*Table 8. Summary of loading and inference time in **seconds** on the whole dataset including non-answered questions.*

	Model loading	**Tokenizer loading**	**Inference (avg. per question)**	**Inference (total)**	**Total (loading + inference)**
DistilBERT	2.030	1.297	0.080	906.613	909.940
BERT	12.132	0.595	0.419	4804.961	4817.238

From Figure 5 (top), it's visible that the distilled model's inference times accumulate much more around it's mean and have a smaller range of values compared to the large model's values which have a long tail towards higher values. We can also see that DistilBERT made most inferences in less than 0.25 seconds with the average of 0.080 seconds, and BERT – in less than 0.75 seconds with the average of 0.429. There was one outlier in larger BERT's answers which had the processing time of 114 sec/question, which we excluded from the analysis. Using an independent t-test, we found that the observed inference time of DistilBERT ($M = 0.080$, $SD = 0.101$) was significantly lower than inference time of large BERT ($M = 0.419$, $SD = 0.169$) $t(18776) = 183.91$, $p < .005$.

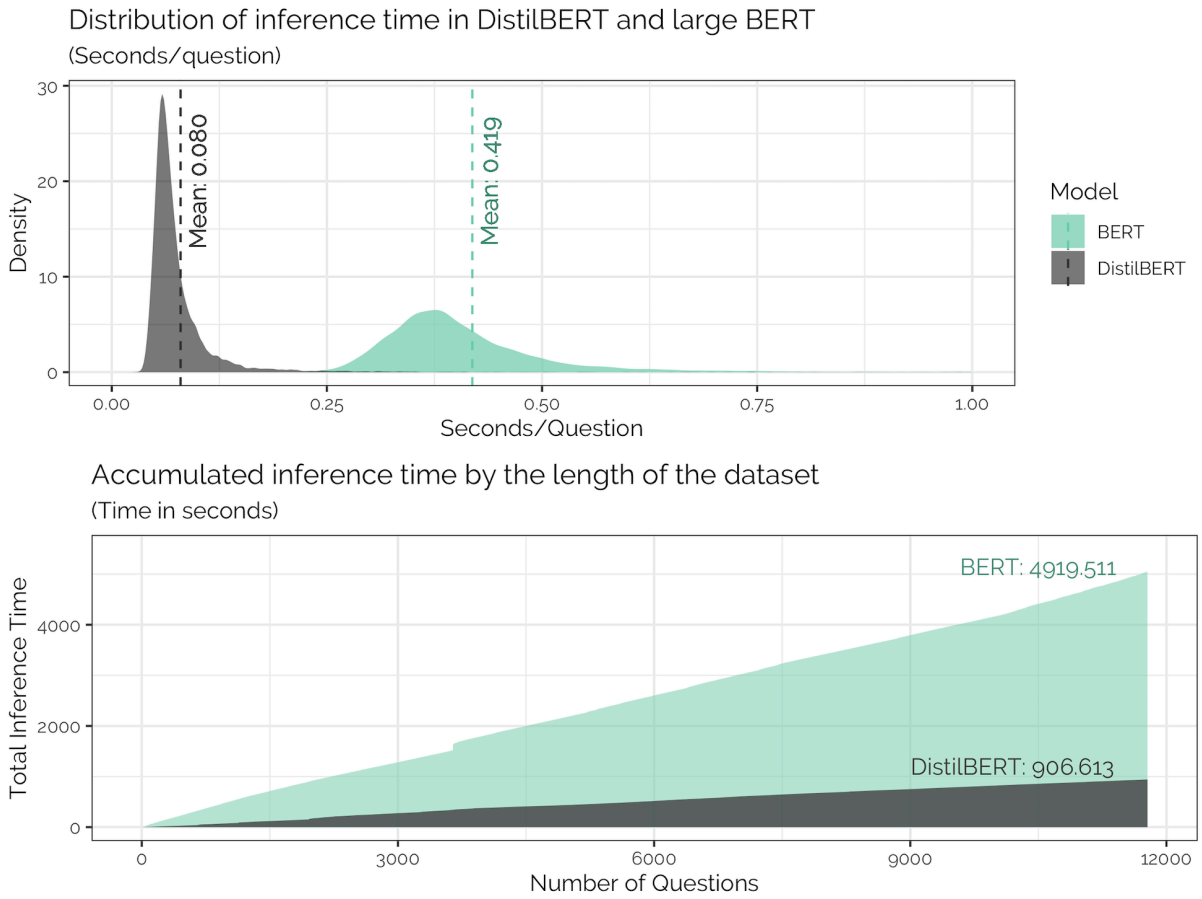

Figure 5. ***Top:*** *Distributions of inference time in DistilBERT and BERT (excl.118 observations that took longer than 1 sec).* ***Bottom:*** *Accumulated inference time in seconds by the number of questions in the dataset*

As can be seen in Figure 5 (bottom), along with the length of TweetQA dataset, the difference in accumulated processing time starts growing rapidly and by the end of the task exceeds an hour.

AUTOMATIC EVALUATION RESULTS [A+M]

GLEU scores presented in Figure 6 (top) were used to describe the performance on short answers which were less than 3 words in length. A score of 1 shows a one-to-one fit between the correct answer and the model's output and BERT receives more samples with such a score compared to DistilBERT. DistilBERT has more results which receive a score of 0 compared to BERT. Also, there is a larger difference between score 0 and 1 for BERT compared to DistilBERT. Interestingly, there are low GLEU scores around 0.75 and there is an extra small peak around 0.30.

Since the word lengths for GLUE scores are less than 3, we mostly expect to see the scores around 0 and 1 – either a fail or an exact match. The small peak can be explained by one word being missing, extra, or incorrect in a 2-word response. Issues with Twitter-specific data handling can also be a cause of the peculiarities in the distribution.

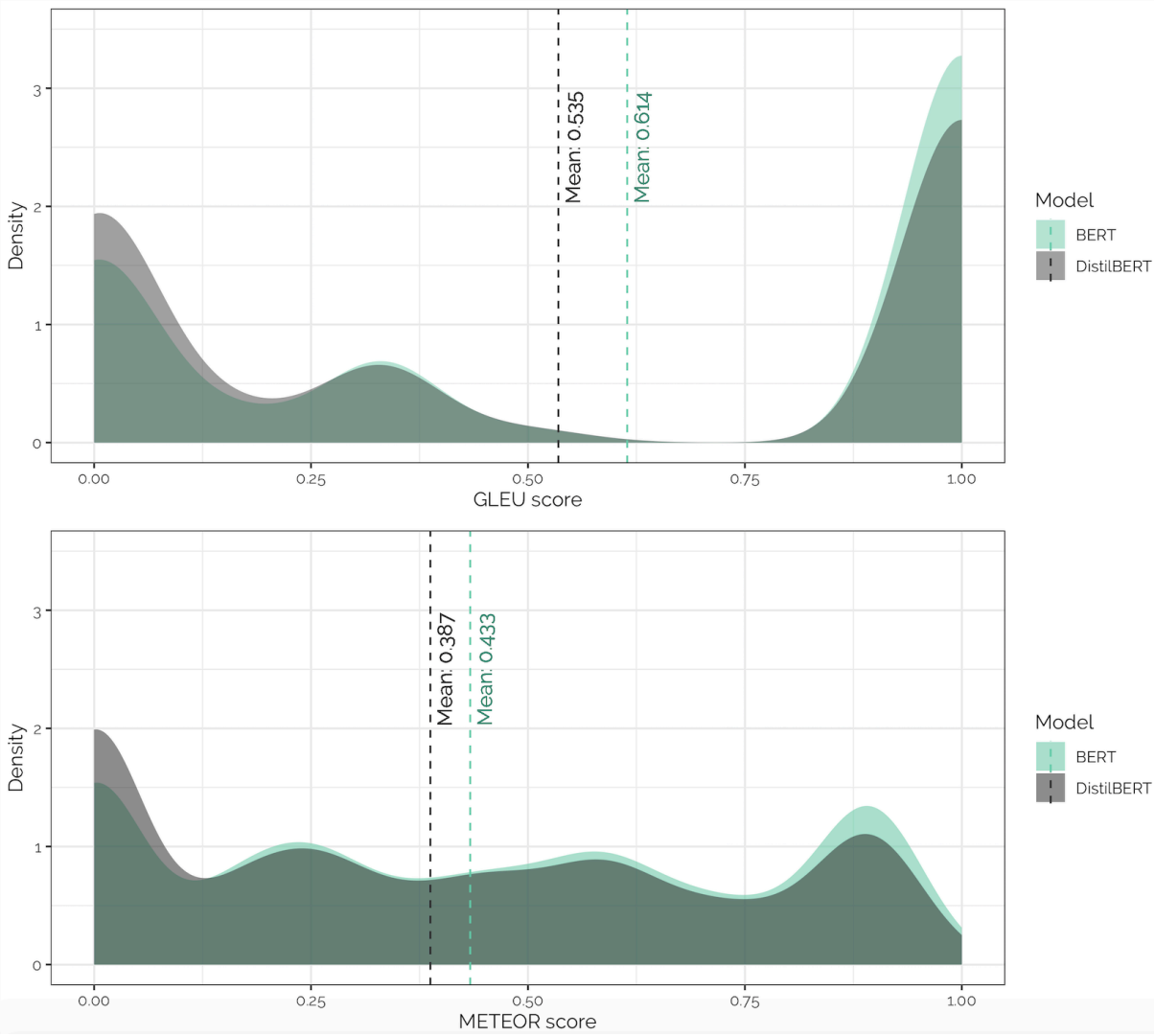

*Figure 6.**Top:** GLEU score distribution in questions with answers no longer than 2 words.*
***Bottom:** METEOR score distribution in questions with answers longer than or equal to 3 words*

METEOR scores were used to describe the performance of BERT and DistilBERT on answers that are longer than or equal to 3 words. Figure 6 (bottom) shows that there is a roughly equal distribution of METEOR scores in the limits of 0.2 and 0.8, with a peak around 0.8. BERT receives higher scores more often than DistilBERT and DistilBERT has more scores around 0.

The answers used for METEOR scores are equal to or longer than 3 words which means that there is naturally more variance in the accuracy of model outputs to the correct answers. This

is why the distribution is more uniform for the different scores between 0 and 1 compared to the GLEU scores.

Table 9. General statistics of GLEU and METEOR scores for both BERT and DestilBERT models.

	GLEU		METEOR	
	BERT	**DistilBert**	**BERT**	**DistilBERT**
Mean	**0.61**	0.53	**0.43**	0.39
Sd	0.45	0.46	0.33	0.33
Min	0.00	0.00	0.00	0.00
25%	0.04	0.00	0.15	0.00
50%	1.00	0.33	0.43	0.35
75%	1.00	1.00	0.72	0.67
Max	1.00	1.00	1.00	1.00

Overall, the average score for BERT is higher for both models, and the means of GLEU scores are generally higher than the scores of METEOR (Table 9). As is seen from the figures as well - the standard deviations are large but very similar for both models in the evaluation metrics.

On GLEU scores, DistilBERT can replicate 87% of BERT's accuracy, and 91% on METEOR score. BERT-base and DistilBERT which were fine-tuned to SQuAD as well and performance measured with the GLUE benchmark shows that DistilBERT reaches the performance of BERT-base of around 96% (Sanh et al., 2019).

Using an independent t-test, we found that in questions with shorter answers, GLEU scores for DistilBERT ($M = 0.53$, $SD = 0.46$) were significantly lower than GLEU scores for the large BERT ($M = 0.61$, $SD = 0.45$) $t(14477) = 10.526$, $p < .005$. We similarly found that in questions with longer answers, METEOR scores for DistilBERT ($M = 0.387$, $SD = 0.33$) were also significantly lower than METEOR scores of the large BERT ($M = 0.433$, $SD = 0.33$) $t(7637.8) = 6.145$, $p < .005$.

DISCUSSION

RESULTS IN RELATION TO HYPOTHESES [A+M]

To summarize our processing time results, on average both models took less than a second to answer a question, which makes the speed difference between the models barely noticeable on a single question example. However, processing time build-up across the whole data set shows that DestilBERT is about 529% faster than BERT, and in general is more consistent in its inference time, which exceeds our expectations stated in **Hypothesis 1**. This difference can save hours of time when working with big datasets and reflects how much lower DistilBERT's computational cost is in comparison to the large BERT. Such big difference in processing time as observed in our analysis is also an indicator of much lower computational cost, suggesting that DistilBERT would be a more appropriate choice for smaller devices.

The evaluation scores indicate that BERTs results are on average closer to the golden standard by 0.08 units for GLEU scores and 0.04 units for METEOR scores, compared to DistilBERTs results. BERT also tends to output missing answers less often than DistilBERT. DistilBERT still reaches around 87-90% of large BERTs performance, which is in line with our **Hypothesis 2**. Given what both of these models can do while not being specifically fine-tuned to Twitter data, it could be possible that both of the models are ready to be used in a system where they need to retrieve information from text prompts.

Based on these results we will try to answer whether the loss in accuracy is worth the gain in processing speed when it comes to DistilBERT. For making these comparisons, it's noteworthy that we compared the large BERT to the knowledge distilled version made from the base BERT. We are comparing one of the most computationally expensive models to one of the least expensive models - usually base BERT is compared to other compressed versions.

PROCESSING SPEED VS QUALITY OF PERFORMANCE [A+M]

The most difficult question is to evaluate whether it is worth losing in speed of processing but gaining in accuracy of performance when using BERT compared to DistilBERT. Based on arbitrary margins we stated in our **Hypothesis 3**, the observed difference is processing time justifies worse performance of DistilBERT. However, we argue that the trade-off between processing cost vs evaluation success depends on where the model is applied.

For a chatbot that can answer questions given a prompt (such as if it's connected to Wikipedia), the time constraint would be to infer an answer within what is considered to be a normal time

amount for answering a question. For this, BERT is probably more desirable over DistilBERT since the difference of time they take per answer is not that different, and in that case a more accurate model can be prioritized.

However, if a system needs to go through many texts to retrieve several answers quickly, such as finding the demographics information of participants in 2,000 research papers on autism for a meta-analysis, then the cumulative computational cost starts to matter. DistilBERT outperforms BERT by a large margin in that respect and with this case it might make more sense to build a DistilBERT-based model to retrieve relevant information. Another such example where DistilBERT is more advantageous would be a SoMe QA task, such as if the system is connected to Twitter API and needs to answer questions based on several tweets in real time.

These are just a few examples of QA applications, that show the nuance of choosing between the speed and the quality of performance.

LIMITATIONS AND CONSIDERATIONS

DATASET QUALITY [A]

The TweetQA dataset is both interesting and complex to use for this task. The correct answers were usually directly taken from the tweets, but sometimes they were rephrased in own words instead. Also, some but not all answers had several plausible answer options that were considered correct. This matters more for the evaluation metrics ability to score the models performance well and matters less for how the models will perform on the dataset. However, if this dataset is used for fine-tuning the model, it's unclear whether this would help make the model better or more confused at inferring answers that were not directly in the answer prompt.

Size-wise this dataset seems to be big enough for the metrics to be meaningful to compare performance between the models. For fine-tuning it might be smaller than is desired, given that a portion of it is necessary for testing.

EVALUATION IS COMPLICATED – AS WE'VE LEARNED [M]

As reviewed earlier, the metrics to compare text outputs by machines in NLP tasks is complicated and there are no good ways to date to quantify how well a machine-made text fits with a human made text.

In many papers that use both BLEU and METEOR scores to evaluate their results, they often get lower METEOR scores compared to BLEU scores, and the range at which they get the averages roughly matches the range reported in this paper (Dubey et al., 2019; Hadla et al., 2015). Even when the evaluation metrics themselves have issues in terms of validity, they are useful in showing which model is generally better than the other models. The scores shouldn't thus be taken as absolute values, such as a BLEU score of 0.5 meaning that the machine text is 50% correct compared to the reference. This is true even for the task and dataset used in our paper.

METEOR algorithm gave outputs that were larger than 1, even when we used optimized parameters, and additionally it failed to assign 1s to unigram one-to-one correct answers (when the correct answer is "blue" and both models produced "blue"). There were also some mismatches when the models' outputs said "cats" instead of "cat". In some cases, both should be considered as the right answer, but in others only one can be correct.

For these reasons we included a human evaluation process where we eyeballed the results of the evaluation metrics for both of the models and ended up splitting the data frame to two in order to get more accuracy out of the evaluation metrics. Even so, both GLEU and METEOR score still suffer from downsides and should be received with skepticism. For example, when a username was depicted written together, and the right answer wrote the name apart, neither metrics could evaluate the outputs of the model correctly.

Overall, even if the models perform better on this dataset, the metrics used to compare their results will need to be chosen with caution and approached by checking their quality via random sampling.

RECOMMENDATIONS FOR FUTURE RESEARCH [M]

Now that we have seen what the ready-made fine-tuned versions of BERT and DistilBERT can do, it would be interesting to test how much their performance would change if we were to fine-tune them on this dataset before testing them on a validation fraction of the same dataset. It's expected that the models would handle Twitter-specific data better. They could for example distinguish usernames, hashtags, and time stamps of the tweets. Having been trained on this kind of dataset would thus already improve the quality of the already good responses that the two models are giving.

As mentioned in theory, knowledge distilled models tend to be more generalized than their teacher models. This means a few things, for example they should be able to generalize to new data better than another model that was made to be smaller than the teacher and was trained on the same dataset. It also means that a higher learning rate can be used during fine-tuning - this would possibly speed up the fine-tuning process, providing DistilBERT with even bigger time-related gains.

The pre-training and fine-tuning of BERT has already been revised previously and a new model, RoBERTa (a Robustly Optimized BERT Pretraining Approach), has been published to have better baseline training in longer batch sizes and better tuned hyperparameters. HuggingFace has also made a distilled version of RoBERTa. It's possible that the best results would be achieved by fine-tuning these versions of BERT on this dataset and using the hyperparameter suggestions reported in their paper (Liu et al., 2019). The problem with RoBERTa compared to BERT is that a large part of its improved performance is due to it being trained on more data for longer. As far as machine learning models go, it's definitely good to optimize for accuracy in performance but ideally we'd have models that have more sophisticated structures and parameter settings which would make them able to generalize on smaller amounts of data. Thus, optimizing BERT and DistilBERT is a more interesting task when we do not simply increase batch size and training data set size, but instead try to optimize their structure and hyperparameters.

When Sanh et al. (2019) added another distillation step during fine-tuning of their DistilBERT, they reached a model performance of 98% of the BERT-base, compared to 96% that they had with just one step of model distillation. This would indicate even more that focusing on improving the distilled model with knowledge distillation methods would yield improved performance.

CONCLUSION [A+M]

In this paper we compared a pre-trained and fine-tuned large BERT to DistilBERT for Question Answering. We applied both models on the TweetQA dataset, a more challenging social media dataset. We evaluated the results with adjusted GLEU and METEOR scores on an answer-level basis and found that BERT outperformed DistilBERT based on both metrics, but the difference wasn't as large as we initially expected. In terms of processing time, DistilBERT took 529% less time than the large BERT. Even though per iteration the averages are quite similar (under 0.5 sec), in terms of cumulative costs on larger datasets DistilBERT definitely wins. Authors made a few suggestions on how this payoff between performance quality and speed could be used in different settings.

The next step is to fine-tune both models on Twitter dataset and see how much the evaluation scores change. Overall, it's important to focus on improving the existing models via their architecture and hyperparameter settings in order to improve performance. Using knowledge distillation during both pre-training and fine-tuning of DistilBERT already improves its performance, and thus other methods of model compression could be applied to further enhance its performance, e.g. using another language model as a second teacher network.

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APPENDIX 1. DATASET SUMMARY

	Original TweetQA	**Our subset of TweetQA**
# of question-answer pairs	13 757 10 692 (train) + 1086 (dev) +1979 (test)	11 778 (all used as test)
Average question length (# of words)	6.95	6.97
Average answer length (# of words in the longest answer option)	2.45	2.5

APPENDIX 2. METEOR PARAMETER VALUES

Table 10. Parameter values in the original METEOR algorithm and the adjusted values based on Lavie & Agarwal (2007)

	Original value	**Adjusted value**
α	0.90	0.81
β	3	0.83
γ	0.5	0.28

APPENDIX 3. MANUAL EVALUATION OF METRICS

Table 11. Fifteen examples from the random sample of 100 lines from the data set, the answers suggested by BERT and DistilBERT, the scores they received from METEOR and GLEU. The final column shows the judgement given by the authors of this paper – 0 shows that METEOR gives a more accurate score, and 1 means GLEU is better.

	BERT	DistilBERT	Gold_1	Gold_2	BERT_METEOR	DistilBERT_METEOR	BERT_GLEU	DistilBERT_GLEU	JUDGE
4936	his own	sean fennessey	he followed his own path.		0,380357477	0	0,214285714	0	0
3491	# restartlhc splash	restartlhc splash events	#restartlhc		0	0	0,333333333	0,166666667	1
10066	the office of the president	the president	office of the president		0,870068772	0,46546509	0,714285714	0,3	0
4760	sand bags	sand bags	sand bags		0,842491812	0,842491812	1	1	1
5200	nobel prize	nobel prize	a noble price		0	0	0	0	
2265	white hart lane	swansea city fc	white hart lane		0,88750133	0	1	0	1
3354	smiles	a 2003 in touch	she smiles		0,397790055	0	0,333333333	0	0
5832	sound check	sound check	a sound check		0,5996383	0,5996383	0,5	0,5	0
802	casting zoe saldana and darkening her skin	casting zoe saldana and darkening her skin	darkening skin	darkening zoe saldana's skin	0,488135593	0,488135593	0,136363636	0,136363636	0
7168	stopping the perpetrator	stopping the perpetrator and 2 - empowering the victims	stopping the perpetrator.		0,561661208	0,347826087	1	0,230769231	1
314	tom hiddleston	tom hiddleston	tom hiddleston	tim hiddleston	0,842491812	0,842491812	1	1	1
1249	pro - putin	pro - putin	putin.		0	0	0,333333333	0,333333333	1
2343	2022	2022	2022		0,72	0,72	1	1	1
6548	empire state building	empire state building	the empire state building.		0,44225292	0,44225292	0,6	0,6	1
3056	more affordable health care	what matters in long run is better , more affordable health care for americans	health care		0,707976313	0,393687763	0,3	0,065217391	0

APPENDIX 4. RESULTS OF METRIC EVALUATION

Gold Standard Length	GLEU correct	METEOR correct
Up to 2	**39**	21
Greater than 2	9	**13**
Up to 3	**42**	**26**
Greater than 3	6	8

APPENDIX 5. CODE

MODEL APPLICATION ON TWEETQA IN PYTHON

[https://github.com/marissala/data-science-bert/blob/master/twitterQA_bert_battle.py]

```
!pip install torch       # to access the pre-trained model weights
!pip install transformers # to access the models


# Import modules
import time
import json
import pandas as pd
import torch
from transformers import BertForQuestionAnswering
from transformers import DistilBertForQuestionAnswering
from transformers import BertTokenizer
from transformers import DistilBertTokenizer



# Import data: only dev and train since they have gold standard
# Data available at: https://tweetqa.github.io/
filenames = ["TweetQA_data/dev.json", "TweetQA_data/train.json"]

big_df = pd.DataFrame()
for file_name in filenames:
   with open(file_name, "r") as f:
       df = json.load(f)
   df = pd.DataFrame(df)
   # append data from every file to one large dataframe
   big_df = big_df.append(df, ignore_index=True)

# Load both models, track loading time, make a model list
start = time.time()
bert = BertForQuestionAnswering.from_pretrained('bert-large-uncased-whole-word-masking-finetuned-squad')
bert_time = time.time() - start

start = time.time()
distilbert = DistilBertForQuestionAnswering.from_pretrained('distilbert-base-uncased-distilled-squad')
distilbert_time = time.time() - start
```

```
# Write models into a dictionary to iterate over later
model_dict = {
   "L_BERT": bert,
   "DistilBERT": distilbert
}



# Write loading times down
model_loading_times = {
   "L_BERT": str(bert_time),
   "DistilBERT": str(distilbert_time)
}



# Define QA util functions for BERT and DistilBERT
def bert_QA(row):
   # Get tweet text to fetch answer from
   answer_text = row['Tweet']

   # Get question
   question = row['Question']
   # Start tracking time
   start = time.time()

   # Apply the tokenizer to the input text, treating them as a text-pair.
   input_ids = tokenizer.encode(question, answer_text)

   # Get start and end scores for answer selection
   start_scores, end_scores = model(torch.tensor([input_ids]))

   # Find the tokens with the highest 'start' and 'end' scores.
   answer_start = torch.argmax(start_scores)
   answer_end = torch.argmax(end_scores)
   ans_tokens = input_ids[answer_start:answer_end+1]
   answer_tokens = tokenizer.convert_ids_to_tokens(ans_tokens,
                                                   skip_special_tokens=True)
   # Combine the tokens in the answer and print it out.
   row[answer_id] = tokenizer.convert_tokens_to_string(answer_tokens)

   # track time from application of tokenizer to getting the answer
   row[time_id] = str(time.time() - start)
   return row



def distil_bert_QA(row):
   # Get tweet text to fetch answer from
```

```
    answer_text = row['Tweet']

    # Get question
    question = row['Question']
    # Start tracking time
    start = time.time()

    # Apply the tokenizer to the input text, treating them as a text-pair.
    encoding = tokenizer.encode_plus(question, answer_text)
    input_ids, att_mask = encoding["input_ids"], encoding["attention_mask"]

    # Get start and end scores for answer selection
    start_scores, end_scores = model(torch.tensor([input_ids]),
                                     attention_mask=torch.tensor([att_mask]))
    ans_tokens = input_ids[torch.argmax(start_scores) : torch.argmax(end_scores) + 1]
    answer_tokens = tokenizer.convert_ids_to_tokens(ans_tokens,
                                                    skip_special_tokens=True)

    # Combine the tokens in the answer and write it down
    row[answer_id] = tokenizer.convert_tokens_to_string(answer_tokens)
    # track time from application of tokenizer to getting the answer
    row[time_id] = str(time.time() - start)
    return row

# Apply models to the data, depending on model name load appropriate tokenizer
for m_name, model in model_dict.items():
    print(f"Running {m_name}")
    answer_id = f"{m_name}_answer"
    time_id = f"{m_name}_time"
    # choose tokenizer
    if m_name == "DistilBERT":
        tok_start = time.time()
        tokenizer = DistilBertTokenizer.from_pretrained('distilbert-base-uncased',
return_token_type_ids=True)
        distilbert_tok_time = time.time() - tok_start
        big_df = big_df.apply(distil_bert_QA, axis=1)
    else:
        tok_start = time.time()
        tokenizer = BertTokenizer.from_pretrained('bert-large-uncased-whole-word-masking-finetuned-
squad')
        bert_tok_time = time.time() - tok_start
        # Run BERT QA on data, track time
        big_df = big_df.apply(bert_QA, axis=1)
```

```
# Write tokenizer loading times down
tokenizer_loading_times = {
   "L_BERT": str(bert_tok_time),
   "DistilBERT": str(distilbert_tok_time)
}



# Write models' inference and inference time outputs down
big_df.to_csv('twitterQA_berts.csv')

with open('model_loading.txt', 'w') as file:
   file.write(json.dumps(model_loading_times))

with open('tokenizer_loading.txt', 'w') as file:
   file.write(json.dumps(tokenizer_loading_times))
```

INFERENCE EVALUATION: USING GLEU AND METEOR SCORES IN PYTHON

[https://github.com/marissala/data-science-bert/blob/master/Evaluation.ipynb]