Replication of DistilBERT evaluation results

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1 Introduction

Reproducible research is vital in machine learning for several reasons. Firstly, it enables the validation of results, when research can be consistently reproduced, it enhances the credibility of the original findings. Additionally, reproducibility supports benchmarking for comparing algorithms and models, allowing the machine learning community to identify the best-performing models. It also plays an important role in identifying errors and biases, such as coding mistakes or data handling issues, improving the reliability of the research.

The paper that we selected for this project, (Sanh et al, 2019)[1] "DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter", presents a method for training a more compact general-purpose language representation model called DistilBERT, which is a streamlined version of the larger BERT model (Bidirectional Encoder Representations from Transformers). Although BERT is highly effective for Natural Language Processing (NLP) tasks, its size and complexity can lead to slower inference times, particularly in on-the-edge or resource-constrained environments, potentially impacting user experience. This paper aims to pre-train the DistilBERT model to enhance inference performance by reducing both its size and inference time while maintaining accuracy. According to the paper, DistilBERT achieves a 40% reduction in model size, preserves 97% of BERT's language understanding capabilities, and improves processing speed by 60%.

The source files and collaborative work done on this project is available for review on GitHub[2].

2 Project Justification

In this project, we will not replicate the transfer learning or model training processes of DistilBERT. Instead, we aim to reproduce the evaluation metrics shown in Tables 1 and 2 on page 3 of the referenced research paper, across various datasets and downstream tasks. This will allow us to assess DistilBERT's performance both on the datasets from the paper and on some of our own datasets. The DistilBERT model is available for evaluation through Hugging Face's transformers library (Wolf et al., 2019). In the original research, DistilBERT was evaluated using three datasets: the GLUE (General Language Understanding and Evaluation)[3] benchmark, which includes nine sentence-pair language understanding tasks; IMDb (Internet Movie Database)[4], used for sentiment classification of user movie reviews; and SQuAD (Stanford Question Answering Dataset)[5], designed for question-answering based on a provided context.

[1] (Sanh et al, 2019): https://arxiv.org/pdf/1910.01108

[2] Project on GitHub: https://github.com/nadunchandrabahu/COMP8240-GroupM

[3] GLUE Benchmark: https://gluebenchmark.com/

[4] IMDb dataset: https://www.kaggle.com/datasets/lakshmi25npathi/imdb-dataset-of-50k-movie-reviews

[5] SQuAD v1.1 dataset: https://rajpurkar.github.io/SQuAD-explorer/

We will run some python code on Jupyter/Colab notebooks to make predictions on the data with the DistilBERT model and calculate various metrics: the average score across the nine GLUE benchmark tasks, test accuracy on the IMDb dataset, and the Exact Match (EM) and F1 score on the SQuAD task. These metrics are reported in Tables 1 and 2 of the research paper and it is the aim of this project to replicate these results. Each group member will also show the metrics using new data sources to perform similar NLP tasks with DistilBERT.

Table 1 below shows the scoring of DistilBERT evaluation on 9 GLUE benchmark tasks as shown in the research paper.

Table 1: BERT and DistilBERT results on GLUE tasks

	Metrics									
Model.Name	Score	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST.2	STS.B	WNLI
BERT-base	79.5	56.3	86.7	88.6	91.8	89.6	69.3	92.7	89	53.5
DistilBERT	77	51.3	82.2	87.5	89.2	88.5	59.9	91.3	86.9	56.3

Table 2 below shows the test accuracy of IMDb sentiment analysis tasks, and EM/F1 scores of the SQuAD question answering task as shown on the research paper.

Table 2: IMDb and SQuAD metrics

Model Name	IMDb	SQuAD	
	acc.	EM	F1
BERT-base	93.46	81.2	88.5
DistilBERT	92.82	77.7	85.8

3 Original Datasets

3.1 GLUE Benchmark

GLUE (General Language Understanding Evaluation) contains 9 tasks from sentiment understanding to inference to evaluate a Natural Language Program capability to comprehend and use linguistic effectively compared to a person with common knowledge.

The 9 tasks are divided on 3 group of tasks: Single-Sentence Tasks, Similarity and Paraphrase Tasks, and Inference Tasks.

3.1.1 Single-Sentence Tasks

CoLa testing linguistic acceptability determining whether a sentence is grammatically acceptable. It is taken from various piece of literature and its acceptability is manually marked by verified linguists *SST-2* testing sentiment understanding by making predictions whether a sentence is positive or negative. It is sourced from web movie reviews with binary classification.

3.1.2 Similarity and Paraprhase Tasks

MRPC testing paraphrase capability concerning the news. Microsoft Research designed this corpus from multiple news sources. It contain pair of sentences and the label will be judged whether they are similar or not

STS-B testing sentence similarity from a collection of sentences pair in the domain of news, forums, and image captions. It is a more fine-grained test when the label are annotated to a float score from 1 - 5. Hence, it uses regression and Pearson correlation coefficients to evaluate the performance not the usual classification test like the others

QQP testing paraphrase but this time concerning question. It comes from Quora site containing a pair of questions, the task here is for NLP model to predict whether the two questions are similar or not

3.1.3 Natural Language Inference Tasks

MNLI containing a premise-hypothesis pair about a wide sources of Fiction, Government Report, Telephone Conversation. The tasks is to test NLP about generalization to different types of text classified them to entailment, contradiction, or neutral

QNLI also testing a pair but this time question-answer pair. It comes from Stanford drawing Wikipedia site. The NLP model's task is to determine whether the answer entail or related to the question

WNLI a more challenging test with complex reasoning with data from fiction books which can be more ambiguous and require commonsense knowledge and context understanding. The NLP model in this test cannot simply use cues like pronouns to infer

RTE testing textual entailment.The test combines multiple versions of a challenge dataset (1,2,3,5 to be exact) coming from news article and Wikipedia. It contains two labels of entailment and not entailment ## IMDb dataset

3.2 SQuAD dataset

The research paper makes use of SQuAD v1.1 development set available on GitHub[6]. The dataset consists of 17968 question-answer combinations. Each question and answer is based on the provided context. There are multiple ground truth answers to the same question. We only need to extract the `context`, `question` and answer (`answer_text`) for the purpose of calculating Exact Match and F-Score.

```
## Columns of SQuAD devset:
##  ['answer_text', 'answer_start', 'question', 'context', 'subject']
```

3.3 SST-2 dataset

We decided to perform the analysis on a limited subset of the SST-2 training set in order to observe the performance of the model in a low-data scenario. It mimics situations which data is scarce, a condition that is often faced in real-world applications. Subset Size: It is important to note that our final training for feature selection was arrived at from the reduced training samples of the full 67,349 training examples, where we chose 8,000 samples of such examples randomly. This subset was randomly chosen in order to retain a wide representation. Label Distribution: This has been achieved to ensure that the subset we used in the training of the model has both positive and negative labels that are well balanced. The subset of the data was tokenized in the same way as the full dataset to keep all the data preparation procedures identical. A smaller subset was first used to approximate a scarce-resource scenario with which we could gauge whether DistilBERT generalizes well with limited training samples.

4 Replication of Evaluation on Datasets

We are able to access the DistilBERT model from 'transformers' library provided by HuggingFace. It is essential to have pyTorch installed before using the model to make predictions. The amount of time taken to make predictions depends on the size of the dataset, computational power and NLP task it tries to achieve.

[6]SQuAD v1.1 Dev set: https://github.com/rajpurkar/SQuAD-explorer/tree/master/dataset

4.1 GLUE Benchmark

The GLUE Benchmark reevaluation was initiated by Vu Anh Tai Ho using transformers library together with Trainer method to manage model training. The datasets are collected directly from HuggingFace's datasets library. Then tokenized using DistilBertTokenizerFast. The tokenize function are different in the 9 tests just because of the different format of label and features (some are called sentence1 and sentence2, some are called premise and hypothesis.

The pretrained-model I used are DistilBertForSequenceClassification for classification tasks and AutoModelForSequenceClassification for STS-B task. For simple training process, I use Training Arguments with settings about epochs, batch size, weight decays, or warmups steps.

The next task is to determine the metrics used to evaluate the performance of the models. In here I have to use two cases for STS-B tasks, as the labels are float number, I have to squeeze the predictions before pass them for pearson correlation coefficients computation in the metric loaded from datasets library. For other tasks, as label are ordinal value, I can use argmax to compute the accorded prediction used in the GLUE Benchmark (accuracy, F1 score, or Matthew's correlation)

Table 3: GLUE Benchmark Results

Task	Test_value	Orig_value	Differences
cola	0.43	0.51	0.08
sst2	0.86	0.91	0.05
mrpc	0.81	0.88	0.07
qqp	0.80	0.89	0.08
rte	0.52	0.60	0.08
wnli	0.37	0.56	0.20
stbs	0.87	0.87	0.00
mnli	0.67	0.82	0.15

For the most part, differences are less than 10% which is acceptable for using a auto model without much focusing into more complex architect like using Distilbert inside a neural network architecture with other Linear classification layer or dropout layer for regularization. However, the score on wnli and mnli which are inference tasks are not as good as the original paper, it might due to these model have more complicated reasoning and context dependence requirement. Therefore, it might require more complex fine tuning to get to better result.

4.2 SQuAD dataset

Evaluation of SQuAD (Stanford QUestion Answering Dataset) question answering task was performed by Nadun Chandrabahu and the Jupyter-notebook (SQuad-v1.1.ipynb) is available in the github repository.

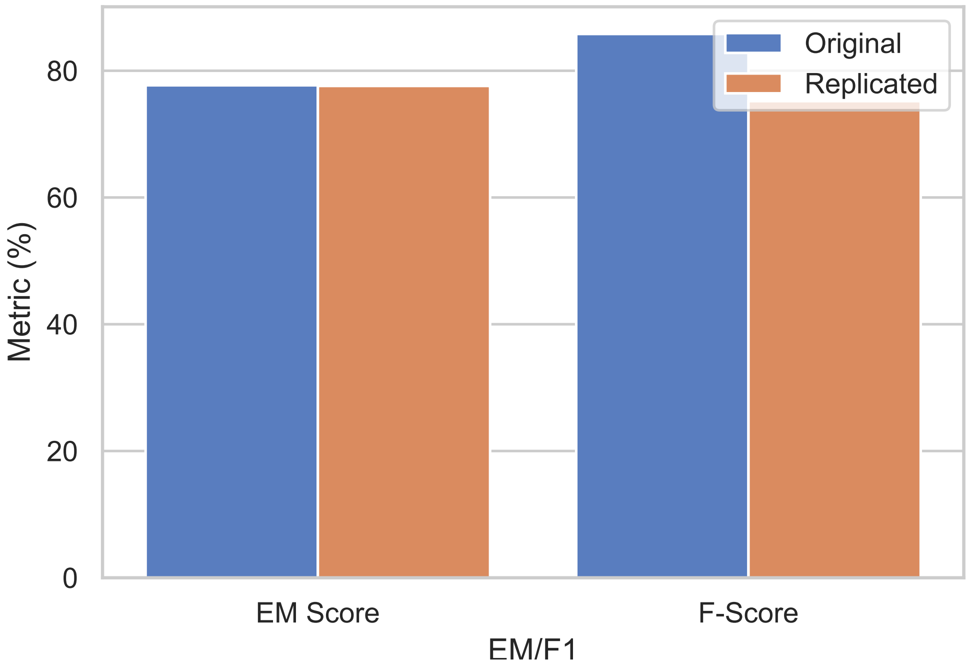
Using the DistilBERT model, predicted answers were obtained based on the context and question. The inference time was 44 minutes on an AMD Ryzen 5 CPU with 16GB RAM. The model prediction returns a score, start and answer. I made a new column called Exact match that is either 1 or 0 if the predicted answer is the exact same as the answer_text column. And I calculated the average score when the model predicted an exact match. I obtained a result of 77.6%, while the research paper reported an EM of 77.7%.

The F-Score was calculated by using the following formula.

The F-score is given by $F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$.

I used the f1_score function from Python's scikit-learn library to calculate the F-Score, as well as precision and recall, which rely on the counts of True Positives, False Positives, and False Negatives. True Positives occur when the predicted values match the ground truth exactly. False Positives arise when the prediction overlaps with the ground truth but is not fully correct, while False Negatives are predictions that do not align with any part of the ground truth. The results are visualized in figure 1 below.

Figure 1: Original & Replicated evaluation metrics



As shown in Figure 1, I obtained an F-Score of 75.2%, which is 10.6% lower than the 85.8% reported in the paper. This difference may stem from the inherent variability in calculating Precision and Recall, as the model's predictions can differ slightly with each run, significantly influencing Precision and Recall values, and hence the F-Score.

4.3 SST-2 dataset

Evaluation of SST-2 (Stanford Sentiment Treebank) task was performed by Muhammad Umer Bashir and the Jupyter-notebook code file is available in the github repository.

5 Evaluation on New Datasets

5.1 Nadun Chandrabahu

Evaluation of my new dataset McTest (Machine Comprehension Test)[7] (Richardson et al, 2013) with question answering task was performed and the Jupyter-notebook (own-dataset.ipynb) is available in the github repository.

The dataset includes 600 records of the following columns:

```
## Columns of McTest devset:
##  idx, question, story,
## properties, answer_options, answer, question_is_multiple
```

The dataset can be easily loaded into Python using the load_datasets method from the HuggingFace datasets library. I had to combine the above two columns `answer_options`, which is a dictionary of all the possible multiple choice answers and `answer`, which is the correct choice out of A, B, C, or D, into a new column called `answer_text` which would act as the ground truth label. The model predictions once again included a score,

[7]McTest Dataset: https://huggingface.co/datasets/sagnikrayc/mctest

start and `answer` (predicted answer) and the rest of the processing & evaluating of EM and F1 scores was carried out similar to how SQuAD task was evaluated.

I selected the McTest dataset due to it being another question-answering NLP task that is possible to be conducted using the DistilBERT model. Previously, we achieved an Exact Match (EM) score of 77.6% and an F1 score of 75.2% on the SQuAD question-answering task. I aimed to achieve similar results with this dataset. However, while I achieved an EM score of 76.1%, my F-Score was only 31.2%, this could be due to the ground truth labels in this dataset being formatted much differently to how DistilBERT makes predictions. As a solution, I could have manually curated the ground truth answers to be similar to the predictions made by DistilBERT.

5.2 Tai Ho

For my own datasets, I will test the capabilities of DistilBERT on the single-sentence tasks and similarity and paraphrase tasks with two datasets from HuggingFace.

5.2.1 Emotion Dataset

Table 4: Text Emotion Data

Text	Label
i didnt feel humiliated	sadness
i can go from feeling so hopeless to so damned hopeful just from being around someone who cares and is awake	sadness
im grabbing a minute to post i feel greedy wrong	anger
i am ever feeling nostalgic about the fireplace i will know that it is still on the property	love
i am feeling grouchy	anger
ive been feeling a little burdened lately wasnt sure why that was	sadness
ive been taking or milligrams or times recommended amount and ive fallen asleep a lot faster but i also feel like so funny	surprise

It contain single sentence describing simple human emotions and 6 labels including sadness, anger, fear, joy, love, and surprise [8]. The first three sadness, anger, and fear are formatted to negative and the last three joy, love, and surprise are formatted to positive. For the test, I formatted it to the SST-2 tokenize rule and metrics calculation to evaluate it on the pretrained DistilBERT model

5.2.2 PAWS dataset

Table 5: Sentence Pair Comparison Data

Sentence1	Sentence2	Label
In Paris , in October 1560 , he secretly met the English ambassador , Nicolas Throckmorton , asking him for a passport to return to England through Scotland .	In October 1560 , he secretly met with the English ambassador , Nicolas Throckmorton , in Paris , and asked him for a passport to return to Scotland through England .	0
The NBA season of 1975 – 76 was the 30th season of the National Basketball Association .	The 1975 – 76 season of the National Basketball Association was the 30th season of the NBA .	1

[8]Emotion Dataset: https://huggingface.co/datasets/dair-ai/emotion

Sentence1	Sentence2	Label
There are also specific discussions , public profile debates and project discussions .	There are also public discussions , profile specific discussions , and project discussions .	0
When comparable rates of flow can be maintained , the results are high .	The results are high when comparable flow rates can be maintained .	1

It from Google Research containing two sentence and a label of 0 and 1 determining whether the two sentences are equivalent or not [9]. I used labeled-final subset as it have both methods of acquiring similar sentences by Google: word swapping and back translations. It follows quite similar structure to other paraphrasing test so I can just use the MRPC format on it in terms of both tokenizer and metrics computation.

In terms of results, we can see similar trend to the GLUE benchmark replication. The emotion dataset as being only a single sentence with simple emotion expressions. That explains how it get quite high accuracy of 97.4%. But when the task get more complicated like PAWS, the model performs worse when only have accuracy of 51.9%.

Therefore, it hinted that there should be more tuning and considering adapting the DistillBERT model as the core feature extractor inside a neural network infrastructure could potentially increase its application and capability in terms of natural language understanding task.

Table 6: Emotion and PAWS Results

Task	Value
emotion	0.974
paws	0.519

5.3 Muhammed Umer Bashir

When measuring the performance of the DistilBERT model on the new subset of data, we concentrated on several metrics in addition to accuracy to get a better picture of model functioning.

• Accuracy: Measures the per cent likelihood of correct prediction. DistilBERT fine-tuning achieved approximately 92.75% validation accuracy in the current experiment, which is also near to the baseline accuracy. • Precision: Described as the actual positive (True positive) over total positive, which shows the percentage of the model's positive sentiment prediction accuracy. • Recall: Quantifies the model's capacity to detect positive sentiment cases; the ability is expressed as the ratio of correctly identified positive sentiment cases to the total number of actually positive cases. • F1 Score: A single value that amalgamates precision with recall meaning a high harmonic mean of precision and recall. The authors' model received a high F1 score, meaning that the identification of positive and negative sentiment classes was accurate. Epoch Training Loss Validation Loss Accuracy F1 Precision Recall 1 No Log 0.231639 0.903 0.918691 0.927505 0.910042 2 0.33800 0.242944 0.920 0.933194 0.931250 0.935146 3 0.172100 0.275485 0.927 0.939076 0.943038 0.935146 Table. 7 Classification Report of DistilBERT From the table.1 it can be observed that training loss reducing was observed in the model after the third epoch suggesting that the training was in proper progress. Instead, the validation loss marginally rose from 0.2316, the result at Epoch 1, to 0.2755, attained at Epoch 3. This rise of validation loss while the accuracy augmented, indicates a relatively small level of overfitting, a typical case in fine-tuning under small datasets. The last value of

[9]PAWS Dataset: https://huggingface.co/datasets/google-research-datasets/paws ## Thanushreyas Appaji

validation loss equals 0.2755, which is also low meaning that the values predicted by the model were close to true labels in validation set. Accuracy refers to number of correct predictions as a percentage of the number of prediction made. By epoch 3, the model was trained to a validation accuracy level of 92.75% which shows a good performance of the model in the classification between positive and negative sentiments. The high accuracy further justifies that DistilBERT is useful for sentiment analysis, even on simple binary classification. From 90.37% at Epoch 1 to 92.75% at Epoch 3, is attributed to the model's capacity to enhance its learning from the data across multiple epochs. The condition of f1-socre allows the selection of a fair measure in the circumstance in which it is possible to be desirable to balance between the precision and recall. An f1 score on the f1 scale of 0.9391 shows that the model worked as expected with similar efficiency rates for both positive and negative classes. Due to the fact that sentiment analysis usually determines weak distinctions between positive and negative values of the sentiment, high f1-score is needed for the model to be as proficient in the accurate definition of both the positive and negative sentiment. Accuracy is the ratio of all the actual positives that the model accurately flagged. With a recall of 0.9351, the model's recall accuracy was 93.5 percent for all actual positive instances. This is special for the applications where true positives detection is important and as many of them as possible should be detected. For example, in sentiment analysis, neglecting a large body of positive reviews may result in the wrong trend on overall sentiment and therefore different sentiments taken into consideration. The assessments such as accuracy, precision, recall, and f1-score imply the fact that DistilBERT yields a high performance in binary sentiment classification. The evaluation metrics show that the model is not only precisely accurate, but also impartial as in it does not over emphasize any class of sentiment. The small validation loss increase by Epoch 3 is matched with gradually improving accuracy and f1-score, at which point it is possible that the model is beginning to overfit, but its overall generalization capability is sound. This minor kind of overfitting can be reduced if need be using other techniques like early stopping or including a dropout layer.

Dataset Your Averaged Score DistilBERT Paper Score Remarks SST-2 0.9171 0.917 Matches paper score Table 8. Comparison of average score

6 Reflections

I, Nadun Chandrabahu, successfully replicated the evaluation results of DistilBERT on the SQuAD task, and explored the same metrics on McTest NLP question answering task. Although my EM scores were satisfactory, my F1 scores did not match up to expectations on both the SQuAD and MCTest question-answering tasks. This discrepancy may stem from an error in my method to F1 score calculation or could be due to the random errors in model predictions, which can notably impact the F1 score as True Positives, False Positives and False Negatives may be incorrectly counted.

Vu Anh Tai Ho (Tai), has finished reevaluate the DistilBERT model on GLUE task, as well as new datasets with single sentence tasks (emotion) and similarity tasks (PAWS). The finding is the pretrained models can work really well with simple single sentence task, however, when the tasks get complicated like more labels, more reasoning or context understanding requirement, the DistilBERT model performs worse than expected. However, given its purpose of being a lightweight model, its performances can be sufficient for initial analysing and testing before the comprehensive and exhaustive tasks that required more complex model

I, Muhammad Umer Bashir, here have this project showcased how DistilBERT remains performant even when the computations are optimized. Possible future work could take this study further by conducting the cross-domain experiment, or try using DistilBERT on other sentiment data sets, or by increasing the complexity of the SST-2 data set.

7 References

1. Sanh, V., Debut, L., Chaumond, J., & Wolf, T. (2019). DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. https://doi.org/10.48550/arXiv.1910.01108

2. Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Davison, J., Shleifer, S., Platen, P. V., M, C., Jernite, Y., Plu, J., Xu, C., Scao, T. L., Gugger, S., … Drame, M. (2021). HuggingFace's Transformers: State-of-the-art Natural Language Processing. Webology. https://doi.org/10.48550/arXiv.1910.03771

3. Richardson, M., Burges, C. J., & Renshaw, E. (2013). MCTest: A Challenge Dataset for the Open-Domain Machine Comprehension of Text. EMNLP. https://mattr1.github.io/mctest/MCTest_EMNLP2013.pdf

4. Zhang, Y., Baldridge, J., & He, L. (2019). PAWS: Paraphrase adversaries from word scrambling. In Proceedings of the North American Chapter of the Association for Computational Linguistics (NAACL).

5. Saravia, E., Liu, H.-C. T., Huang, Y.-H., Wu, J., & Chen, Y.-S. (2018). CARER: Contextualized affect representations for emotion recognition. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 3687-3697). Association for Computational Linguistics. https://doi.org/10.18653/v1/D18-1404