Introduction

Nowadays high-performing natural language models gained much relevance. In this project, we used three different pre-trained LLMs in order to classify opinions as positive or negative. The LLMs utilized in our study include:

- Distilbert
- Mistral
- Gemma

Our GitHub repository contains all the code and explanations for every decision we have made.

DistilBERT Fine-Tuning

Introduction

Distilbert as mentioned in paper is smaller variant of Bert with 66 million parameters. It was found that it's possible to reduce size of BERT model by 40% while retraining 97% of its language understanding capabilities and being 60% faster.

Architecture

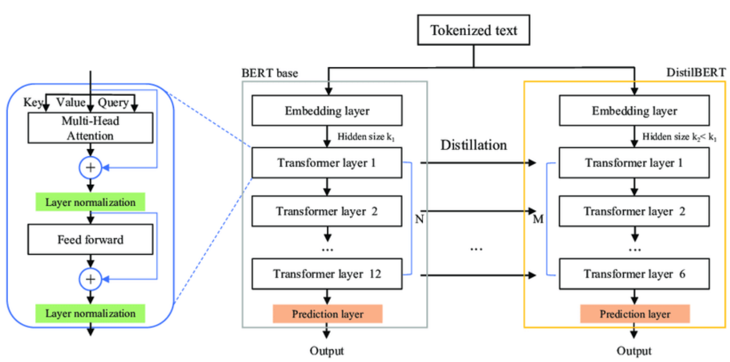


Figure 1: Architecture

DistilBERT really a stripped down version of BERT. Instead of 12 transformer layers it contains 6 transformer layers. The overall structure:

- Embedding Layer: Token Embeddings, Position Embeddings
- Transformer Layers: Each transformer layer contains
  - Multi-Head self-attention
  - Feed-Forward Neural Network
  - Layer Normalization
  - Residual Connections

Fine Tuning

Dataset: IMDB 50k movie review. Train set is 70%, validation set is 10% and Test set is 20% of entire dataset split.

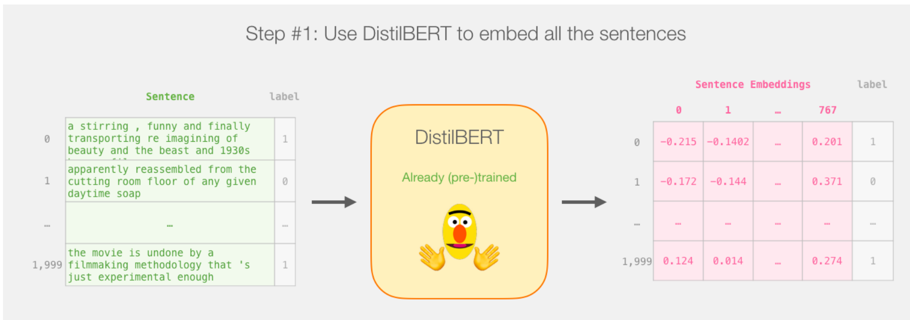


Figure 2: embedding

Fine Tuning Scikit Version The input text is tokenized into `input_ids` and `attention_mask` and passed through the DistilBERT model to get the `last_hidden_states`

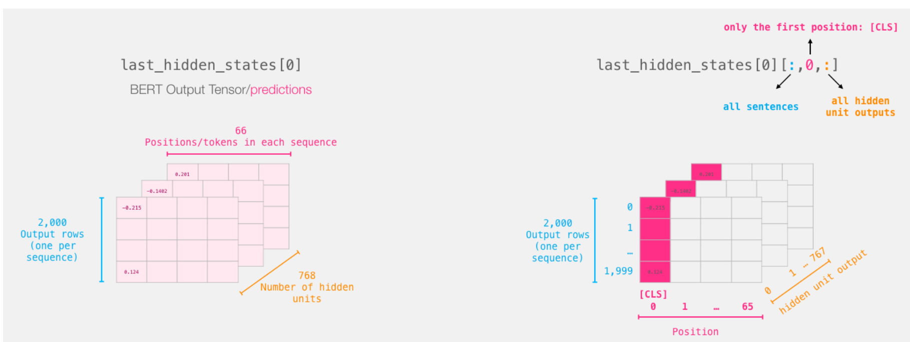


Figure 3: embedding

Feature Extraction

```
with torch.no_grad():
    last_hidden_states = model(input_ids, attention_mask=attention_mask)

features = last_hidden_states[0][:,0,:].numpy()
```

```
Tokenized input:
[
    [CLS] I love this movie [SEP],
    [CLS] This film was terrible [SEP]
```

```
]

last_hidden_states:
[
    [h_CLS_1, h_I, h_love, h_this, h_movie, h_SEP_1],
    [h_CLS_2, h_This, h_film, h_was, h_terrible, h_SEP_2]
]


Selected `[CLS]` token hidden states:
[
    h_CLS_1,  # Contains contextual information from "I love this movie."
    h_CLS_2   # Contains contextual information from "This film was terrible."
]
```

Self-attention layers ensure that h_CLS_1 and h_CLS_2 (the hidden states for the [CLS] token) contain information from all other tokens in their respective sentences.

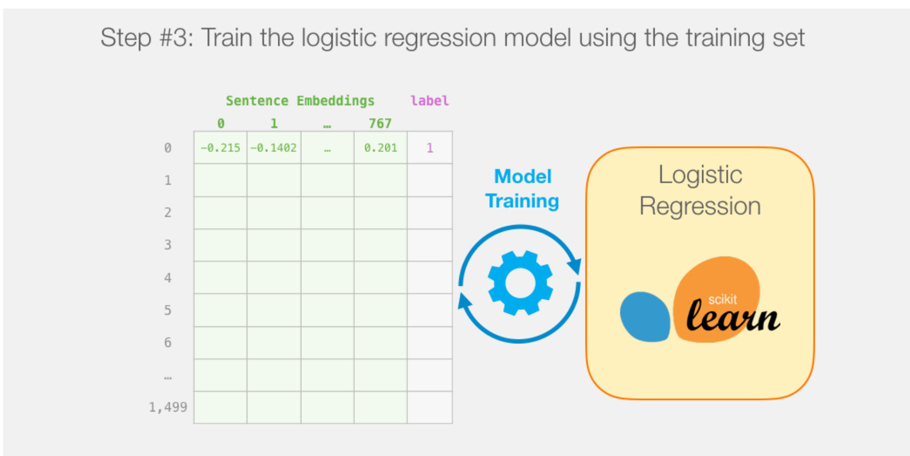


Figure 4: training_process

Training: Summarize important aspects of the code.

1. Learning Rate: Graphs show a decreased learning rate, it is common in training as it shows model is converging by doing smaller updates to the weights as training progresses
2. Global Step: This indicates the number of batches the has been trained on. It increase with each batch processed
3. Gradient Norm: A slight decrease in gradient norm suggests that the updates to the model's weights are becoming more stable as training goes on

4. Epoch: It just means that the model is seeing the data repeatedly, and with each pass(epoch), it's learning more about dataset
5. Loss: The declining loss means model's prediction are getting closer to the actual labels, which the model is learning effectively.

Train loop:

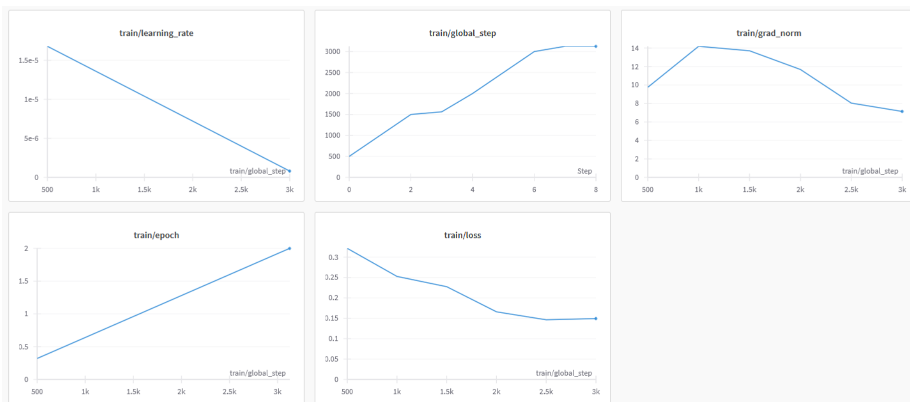


Figure 5: train_loop

Test loop:

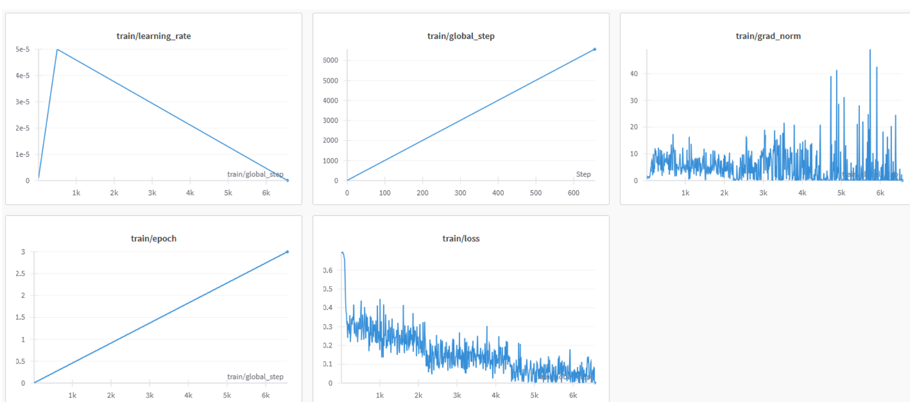


Figure 6: trainer

Results

Method	Accuracy
Training loop	93.82%
HuggingFace Trainer	93.56%

Method	Accuracy

Mistral Fine-Tuning

Introduction

Mistral is an open-source model owned by the company Mistral AI. It was published with the a paper and it is famous due to its performance and efficiency. Compared to the Llama model, Mistral surpasses the first version of Llama in all evaluated benchmarks. With the second version of Llama, Mistral is better in mathematics and code generation.

We build a notebook based on a public notebook. In relation with Mistral version, we used the version Mistral-7B-Instruct-v0.2.

Architecture

Mistral is based on Transformers Architecture.

The parameters of Mistral architecture are:

Parameter	Value	Explanation
dim	4096	Dimensionality of the model's embeddings and hidden states. This defines the size of the vectors used throughout the model.
n_layers	32	Number of transformer blocks in the model.
head_dim	128	Dimensionality of each attention head.
hidden_dim	14336	Dimensionality of the feed-forward layer within each transformer block.
n_heads	32	Number of attention heads in the multi-head attention mechanism.
n_kv_heads	8	Number of key-value heads used in attention.
window_size	4096	Size of the local context window used in models with attention mechanisms that restrict the range of attention to a local context.

Parameter	Value	Explanation
context_len	8192	Maximum length of the input sequences.
vocab_size	32000	How many unique tokens (words, subwords, or characters) the model can represent.

Sliding Window Attention (SWA) The sliding window attention pattern employs a fixed-size window attention surrounding each token. This means that each position in a layer can attend to hidden states from the previous layer within a range of 4096 tokens behind it and up to itself.

Rolling Buffer Cache: Fixed cache size.

Pre-fill and Chunking: Devide the prompt into smaller pieces and then work with those pieces instead of the all prompt.

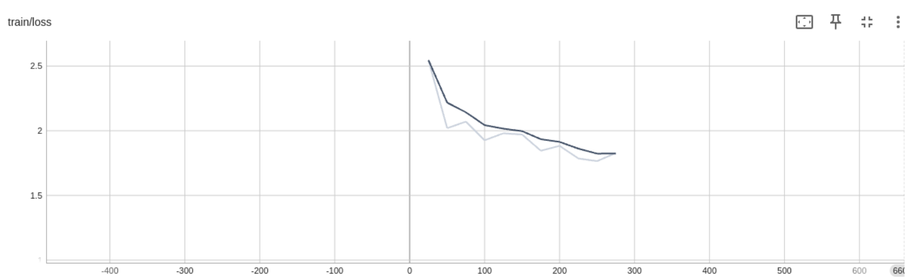
Fine Tuning

Dataset: IMDB movie review, 300 cases for training, 100 cases for evaluating and 2500 cases for testing. The data is balanced.

Training For tune Mistral we have used the library Supervised Fine-tuning Trainer, as known as SFTT instead of the normal Trainer.

- More appropriated to text classification problems.
- Our dataset is not that large.
- The training process is faster.
- Uses less memory.

Epoch	Training Loss	Validation Loss
1	2.019900	2.116099
2	1.980300	2.124171
3	1.883400	2.153847
4	1.827500	2.167378



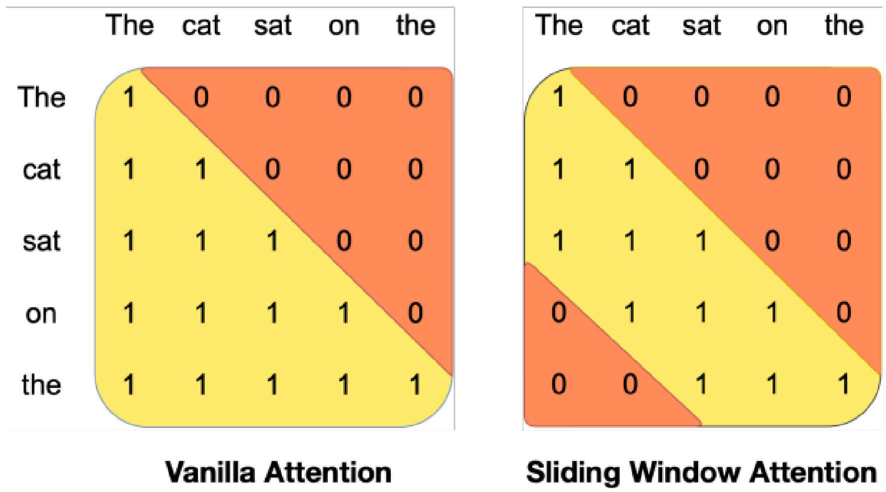


Figure 7: swa

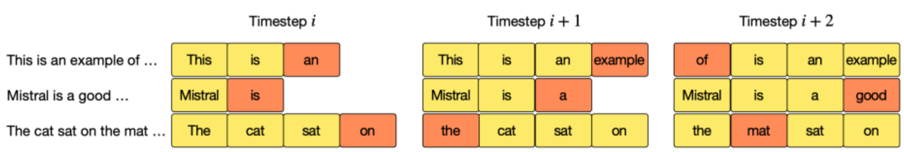


Figure 8: fixed_cache

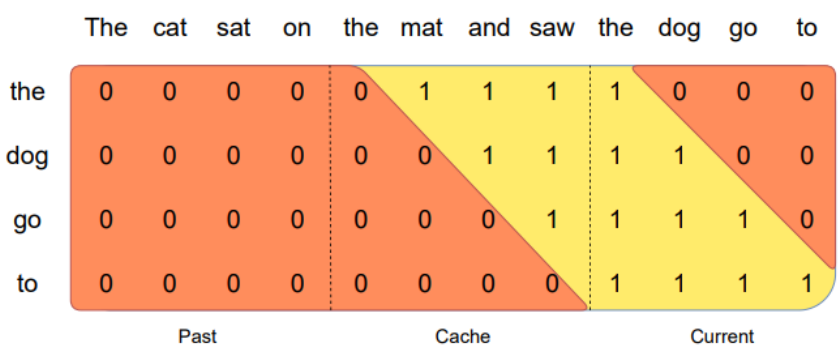
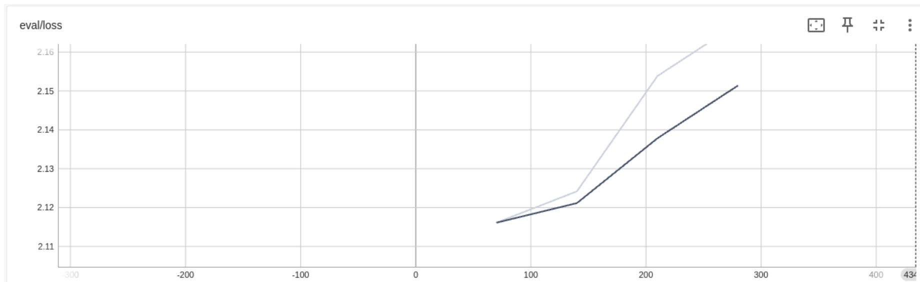


Figure 9: prefillchunking



Results

Stage	Metric	Value
Original	Accuracy	63.0%
Original	Accuracy for negative reviews	98.0%
Original	Accuracy for positive reviews	28.0%
Tuned	Accuracy	96.0%
Tuned	Accuracy for negative reviews	97.4%
Tuned	Accuracy for positive reviews	94.6%

Gemma Zero Shot Learning

The Gemma directory contains four Jupyter notebooks used to explore the Gemma model's text classification capabilities.

Initially, we aimed to fine-tune this model, just like we did with *Mistral* and *Distilbert*. Sadly, that was not feasible because every attempt ended up consuming all available resources in both Kaggle and Google Colab.

So, we focused on implementing Zero Shot Learning to test the model's performance in this task. We successfully managed to implement this type of classification. After doing so, we attempted to implement both One Shot classification and Few Shot classification.

These attempts led to failure, as once again, we consumed all the resources.

However, we still want to provide the code for all our attempts. We will not go into as much detail as we did for the other two models, since we can consider this to be an extra that improves the overall work.

Model Architecture

The Gemma model is based on Transformers Architecture. It comes in two varients with either 2B or 7B parameters and they has the following values:

Parameter	2B	7B
d_model	2048	3072
Layers	18	28
Feedforward hidden dims	32768	49152
Num Heads	8	16
Num of KV heads	1	16
Head size	256	256
Vocab size	256128	256128

These models also have a fair few enhancements such as:

- **Multi-Query Attention**: The 7B model utilizes multi-head attention, whereas the 2B model employs multi-query attention with `num_kv_heads = 1`. Ablation studies indicate that multi-query attention performs effectively at smaller scales.
- **RoPE Embeddings**: Instead of absolute positional embeddings, rotary positional embeddings are employed in each layer. Moreover, embeddings are shared across inputs and outputs to minimize model size.
- **GeGLU Activations**: Conventional ReLU activation function is replaced with the GeGLU activation function, providing improved performance.
- **RMSNorm**: Stabilize trainings, RMSNorm is applied to the input of each transformer sub-layer, including both the attention and feedforward layers.

The parameters can be split into embedding and non-embedding in the following manner:

Model	Embedding Parameters	Non-embedding Parameters
2B	524,550,144	1,981,884,416
7B	786,825,216	7,751,248,896

These models inherit a large vocabulary from the Gemini framework, comprising 256,000 entries handling multiple languages, which results in larger embedding parameter counts compared to models limited to fewer languages.

Code Explanation

We kept some code blocks that are not particularly relevant, such as some pip installs that ended up not being utilized in the final version. Yet, these would be necessary for the failed fine-tuning. We also kept under comments a function that can be used to clear resources on Google Colab.

Three of our notebooks implement Zero Shot Learning. These notebooks contain the exact same content, but we created them to prove the randomness in zero-shot learning as results vary on each execution. Then we have a notebook that contains the same basic code with the code needed for One Shot and Few Shot classification added to it. We kept the output that showcases the error.

To sum up what we did, we basically load the dataset and utilizing the pipeline abstraction from transformers library we can simply run the model for zero shot classification for two labels. This generates two values one for each label, we then just pick the label with the highest value and compare to the reference values.

Results

Execution	Accuracy	Recall	Precision
#1	0.49	0.49	0.48
#2	0.62	0.62	0.62
#3	0.60	0.60	0.71

Conclusions

Unsurprisingly, Mistral was the best in terms of performance. This outcome was anticipated, given Mistral's superior pre-training compared to Distilbert, and the absence of specific tuning for Gemma.

Our journey has been truly fulfilling, marked by the exploration of diverse models and methodologies, each offering unique insights into the realm of natural language processing.

References

1. Mistral 7B, Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, William El Sayed, 2023. arXiv eprint: 2310.06825, primary class: cs.CL.

2. Gemma Team, Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, Pouya Tafti, Léonard Hussenot, Pier Giuseppe Sessa, Aakanksha Chowdhery, Adam Roberts, Aditya Barua, Alex Botev, Alex Castro-Ros, Ambrose Slone, Amélie Héliou, Andrea Tacchetti, Anna Bulanova, Antonia Paterson, Beth Tsai, Bobak Shahriari, Charline Le Lan, Christopher A. Choquette-Choo, Clément Crepy, Daniel Cer, Daphne Ippolito, David Reid, Elena Buchatskaya, Eric Ni, Eric Noland, Geng Yan,

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3. Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. "DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter." arXiv preprint arXiv:1910.01108, 2020.