Project 2 - IMDB Review Classification

Objectives:

- ➔ Task 1: Explore TfidfVectorizer
- ➔ Task 2: Explore Word2Vector Model glove-twitter-25
- ➔ Task 3: Explore distilbert-base-uncased
- ➔ Task 4: Compare the model's classification abilities using IMDB dataset

Data:

- IMDB: https://huggingface.co/datasets/imdb
- Large Movie Review Dataset. This is a dataset for binary sentiment classification containing substantially more data than previous benchmark datasets. We provide a set of 25,000 highly polar movie reviews for training, and 25,000 for testing. There is additional unlabeled data for use as well.

Implementation:

Libraries

- Torch - neural network optimization
- TfidfVectorizer- used for data parsing and processing
- gensim - Word2Vec
- Transformers - used to load pretrained models

Hyperparameters

- Batch Size = 100 batches (250 entries per batch)
- Epoch = 10
- Test Size= 200 randomize entries
- Learning Rate= 0.01

Algorithm and Code

The comparison code is divided into three main python files each containing the classifications model used for testing. In addition, there are additional utilizing functions for testing the models used across all of the testing.

Results:

Summary:

Model	Accuracy	Recall	F1
Word2Vec	0.56	0.0112	0.022
Bert	0.81	0.78	0.804
Tfid	0.735	0.72	0.746

Task 1 Results:

TfidfVectorizer

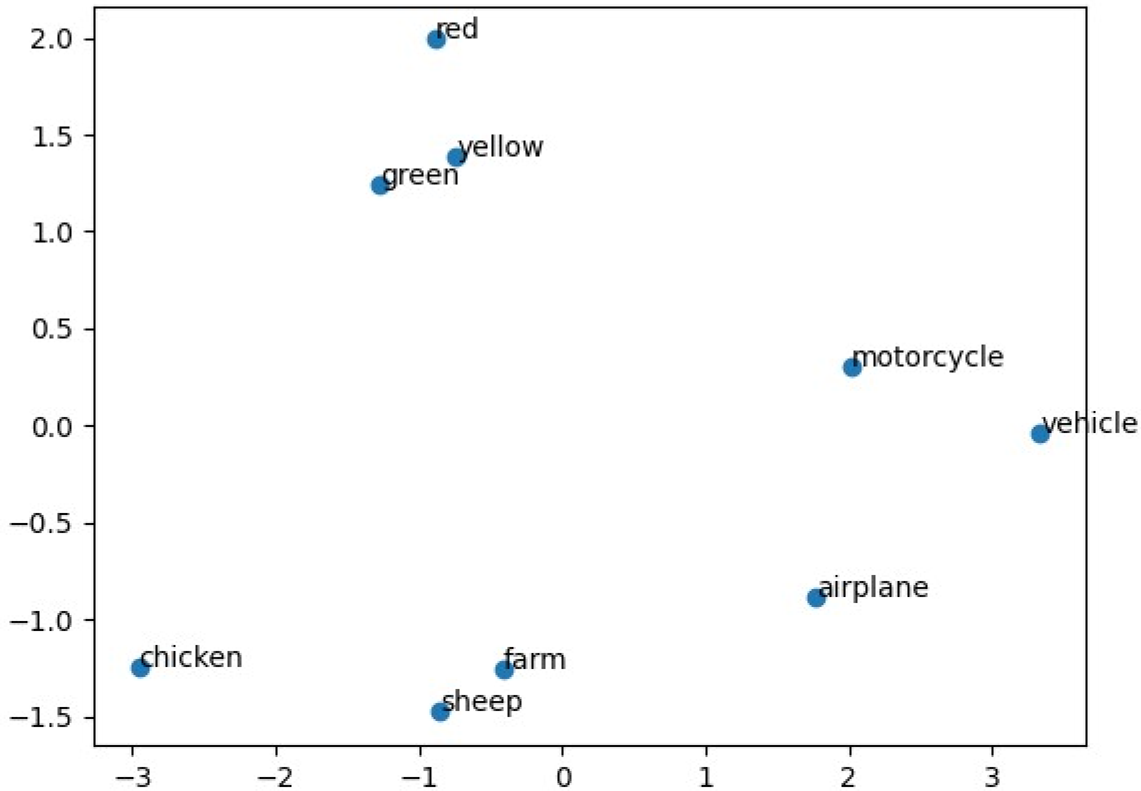
Vocab Size = 74849
ID for ”ambitious" = 2977
feature vector sum = 2.294023319093611

Task 2 Results:

Word2Vector
Similarity between computer and laptop = 0.8352675
Similarity between computer and fruit = 0.45673344
Similarity between fruit and banana = 0.8357839

Distance between france and paris 0.11305677890777588
Distance between canada and paris 0.28165972232818604
Distance between brazil and paris 0.3328576683998108

Closest words to ”boat” = ['cabin', 'truck', 'pool', 'plane', 'flying', 'balloon', 'roof', 'rides', 'backyard', 'cab']



Task 3 Results:

Bert
Vocab Size = 30522
Hidden Size = 768

Bert uses a tokenizer to preprocess text inputs into a format that can be effectively processed by the mode. This allows the model to go beyond the syntax of the language and further break down meaning by breaking down words and its meaning. It also allows for a more predictable input handling.

['natural', 'language', 'processing', 'is', 'fun', '!']
[101, 3019, 2653, 6364, 2003, 4569, 999, 102]

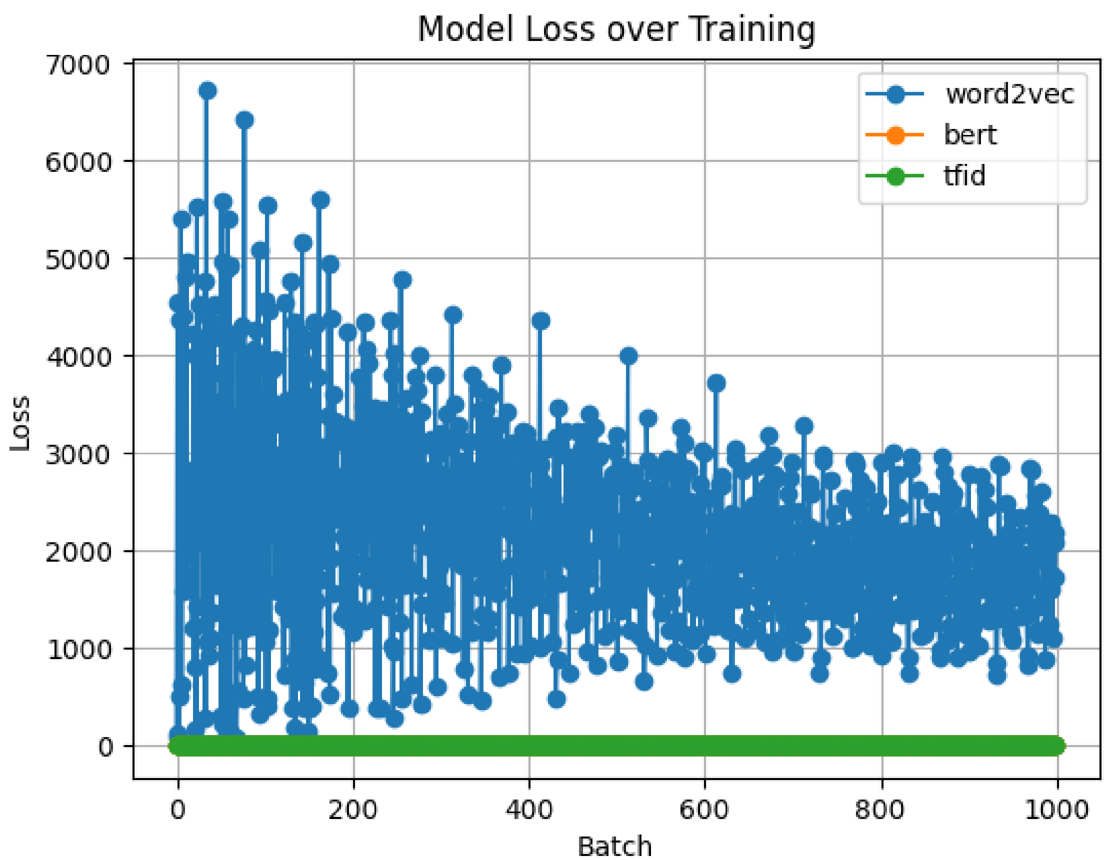
What is input ID: Input IDs are numerical representations of tokenized input sequences in BERT, mapping each token to a unique integer ID through a pre-trained tokenizer. They form the basis of the input data, converting text into a format suitable for processing by the model.

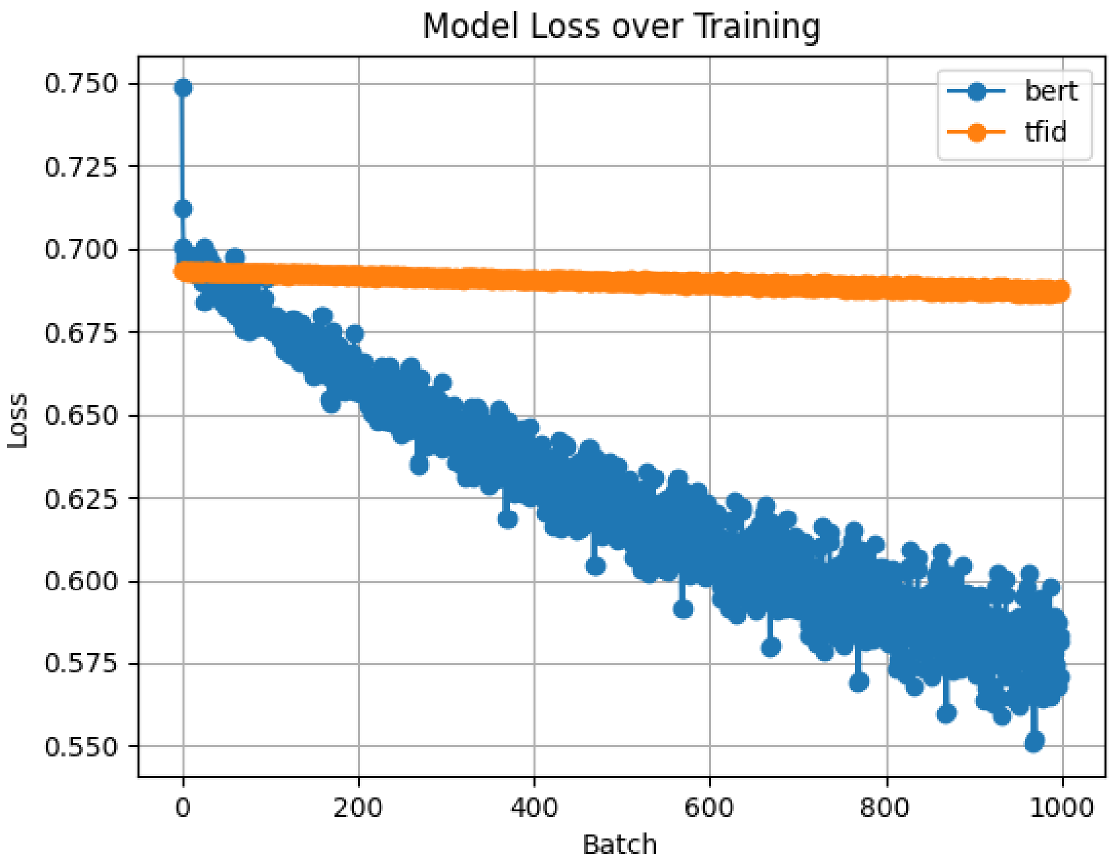
Why Do we use an attention Mask? The attention mask in BERT is a binary tensor indicating which tokens should be attended to (with a value of 1) and which ones should be ignored (with a value of 0).

Task 4 Results:

Model Classification for “The Dark Knight was a masterpiece! The plot, cast, and everything were absolutely sick!”

Bert = 1
Word2Vec = 1
Tfid = 1





IMDB Dataset Classification Testing
Epoch [1/10] [Batch 1/100], Loss: 126.4317
Epoch [1/10] [Batch 51/100], Loss: 303.9315
Epoch [1/10] [Batch 100/100], Loss: 2457.9600
Epoch [2/10] [Batch 1/100], Loss: 1063.0090
Epoch [2/10] [Batch 51/100], Loss: 158.5443
Epoch [2/10] [Batch 100/100], Loss: 3251.4592
Epoch [3/10] [Batch 1/100], Loss: 3205.6118
Epoch [3/10] [Batch 51/100], Loss: 2592.6526
Epoch [3/10] [Batch 100/100], Loss: 3203.9482
Epoch [4/10] [Batch 1/100], Loss: 3109.8796
Epoch [4/10] [Batch 51/100], Loss: 1921.8265
Epoch [4/10] [Batch 100/100], Loss: 3086.6624
Epoch [5/10] [Batch 1/100], Loss: 3060.0234
Epoch [5/10] [Batch 51/100], Loss: 1256.3806
Epoch [5/10] [Batch 100/100], Loss: 2674.9924
Epoch [6/10] [Batch 1/100], Loss: 3182.2952
Epoch [6/10] [Batch 51/100], Loss: 1371.8215
Epoch [6/10] [Batch 100/100], Loss: 2558.4595

Epoch [7/10] [Batch 1/100], Loss: 3014.4380
Epoch [7/10] [Batch 51/100], Loss: 1304.4070
Epoch [7/10] [Batch 100/100], Loss: 2402.4958
Epoch [8/10] [Batch 1/100], Loss: 2914.2891
Epoch [8/10] [Batch 51/100], Loss: 1341.7588
Epoch [8/10] [Batch 100/100], Loss: 2219.8572
Epoch [9/10] [Batch 1/100], Loss: 2917.6953
Epoch [9/10] [Batch 51/100], Loss: 1149.2812
Epoch [9/10] [Batch 100/100], Loss: 2177.4436
Epoch [10/10] [Batch 1/100], Loss: 2779.9236
Epoch [10/10] [Batch 51/100], Loss: 1082.4510
Epoch [10/10] [Batch 100/100], Loss: 2097.5608
Sum= 1
Accuracy 0.56
Precision: (1.0,)
Recall: 0.011235955056179775
F1 Score: 0.022222222222222223
We strongly recommend passing in an `attention_mask` since your input_ids may be padded. See https://huggingface.co/docs/transformers/troubleshooting#incorrect-output-when-padding-tokens-arent-masked.
Epoch [1/10] [Batch 1/100], Loss: 0.7485
Epoch [1/10] [Batch 51/100], Loss: 0.6834
Epoch [1/10] [Batch 100/100], Loss: 0.6799
Epoch [2/10] [Batch 1/100], Loss: 0.6762
Epoch [2/10] [Batch 51/100], Loss: 0.6628
Epoch [2/10] [Batch 100/100], Loss: 0.6640
Epoch [3/10] [Batch 1/100], Loss: 0.6582
Epoch [3/10] [Batch 51/100], Loss: 0.6464
Epoch [3/10] [Batch 100/100], Loss: 0.6498
Epoch [4/10] [Batch 1/100], Loss: 0.6425
Epoch [4/10] [Batch 51/100], Loss: 0.6325
Epoch [4/10] [Batch 100/100], Loss: 0.6370
Epoch [5/10] [Batch 1/100], Loss: 0.6285
Epoch [5/10] [Batch 51/100], Loss: 0.6204
Epoch [5/10] [Batch 100/100], Loss: 0.6255
Epoch [6/10] [Batch 1/100], Loss: 0.6159
Epoch [6/10] [Batch 51/100], Loss: 0.6097
Epoch [6/10] [Batch 100/100], Loss: 0.6150
Epoch [7/10] [Batch 1/100], Loss: 0.6044
Epoch [7/10] [Batch 51/100], Loss: 0.6001
Epoch [7/10] [Batch 100/100], Loss: 0.6054
Epoch [8/10] [Batch 1/100], Loss: 0.5939
Epoch [8/10] [Batch 51/100], Loss: 0.5915
Epoch [8/10] [Batch 100/100], Loss: 0.5967

Epoch [9/10] [Batch 1/100], Loss: 0.5843
Epoch [9/10] [Batch 51/100], Loss: 0.5836
Epoch [9/10] [Batch 100/100], Loss: 0.5887
Epoch [10/10] [Batch 1/100], Loss: 0.5754
Epoch [10/10] [Batch 51/100], Loss: 0.5764
Epoch [10/10] [Batch 100/100], Loss: 0.5813
Sum= 94
Accuracy 0.81
Precision: (0.8297872340425532,)
Recall: 0.78
F1 Score: 0.8041237113402062
Epoch [1/10] [Batch 1/100], Loss: 0.6931
Epoch [1/10] [Batch 51/100], Loss: 0.6928
Epoch [1/10] [Batch 100/100], Loss: 0.6926
Epoch [2/10] [Batch 1/100], Loss: 0.6925
Epoch [2/10] [Batch 51/100], Loss: 0.6920
Epoch [2/10] [Batch 100/100], Loss: 0.6919
Epoch [3/10] [Batch 1/100], Loss: 0.6918
Epoch [3/10] [Batch 51/100], Loss: 0.6913
Epoch [3/10] [Batch 100/100], Loss: 0.6912
Epoch [4/10] [Batch 1/100], Loss: 0.6912
Epoch [4/10] [Batch 51/100], Loss: 0.6906
Epoch [4/10] [Batch 100/100], Loss: 0.6906
Epoch [5/10] [Batch 1/100], Loss: 0.6906
Epoch [5/10] [Batch 51/100], Loss: 0.6899
Epoch [5/10] [Batch 100/100], Loss: 0.6899
Epoch [6/10] [Batch 1/100], Loss: 0.6899
Epoch [6/10] [Batch 51/100], Loss: 0.6892
Epoch [6/10] [Batch 100/100], Loss: 0.6893
Epoch [7/10] [Batch 1/100], Loss: 0.6893
Epoch [7/10] [Batch 51/100], Loss: 0.6885
Epoch [7/10] [Batch 100/100], Loss: 0.6886
Epoch [8/10] [Batch 1/100], Loss: 0.6887
Epoch [8/10] [Batch 51/100], Loss: 0.6878
Epoch [8/10] [Batch 100/100], Loss: 0.6879
Epoch [9/10] [Batch 1/100], Loss: 0.6881
Epoch [9/10] [Batch 51/100], Loss: 0.6871
Epoch [9/10] [Batch 100/100], Loss: 0.6873
Epoch [10/10] [Batch 1/100], Loss: 0.6874
Epoch [10/10] [Batch 51/100], Loss: 0.6864
Epoch [10/10] [Batch 100/100], Loss: 0.6866
Sum= 108
Accuracy 0.735
Precision: (0.7222222222222222,)

Recall: 0.7722772277227723
F1 Score: 0.7464114832535885