BERTPlay - A semantic similarity checking project

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Abstract

In this project, we build and experiment with different deep learning models to predict the semantic similarity between two sentences. From our experiments, we have observed that the transformer based BERT models outperformed the LSTM network and also trained faster. Moreover, the BERT models that were finetuned with a Bi-directional LSTM gave a much better performance than the BERT model that was not finetuned to the specific task of semantic similarity recognition. We have developed two games, SemanticSimilarityGame and ReadingComprehensionGame, both of which are fun to play and a good way to learn English language.

Introduction

Semantic similarity checking is an important application, with usecases in the areas of language understanding, question answering and plagiarism detection. The reason we were drawn towards working on a semantic similarity based game was because it involved creating a novel way to learn language, and also provided us with an opportunity to tinker with various state of the art NLP models

Methodology

Semantic similarity prediction task requires a deep understanding of the language, and hence, we require complex models which create word embeddings based on the context in which it is used. We explore two of the most successful architectures in NLP: BERT, and a LSTM and compare their performance.

The common dataset used to train all the models is : Stanford Natural Language Inference (SNLI). We have also experimented with a BERT-large pre-trained on SQuAD (Stanford Question Answering Dataset)

First, we clean the SNLI dataset and divide it into train, validation and test data that can be used in the different models that we are testing. For each of the BERT models, we first create a BERT tokenizer that basically encodes the given sentence with the pre-trained BERT embeddings and adds the CLS, SEP embeddings to distinguish between the Sentence1 and Sentence2. Then, we load and train just the output layer (Dense) with the train data. In case we are finetuning, we train the model end-to-end, including the BERT. The model obtained from the above steps is then tested.

LSTM model is trained in a similar way, by encoding using word2vec, and then training the LSTM model built for 20 epochs.

We have used tensorflow for the output layer models, huggingface transformers library for the BERT models, and numpy and pandas for data cleaning.

We have used the colab notebook by Mohammed Merchant : https://colab.research.google.com/github/keras-team/keras-io/blob/master/examples/nlp/ipynb/semantic_similarity_with_bert.ipynb#scrollTo=w60qwFa1dWEB as a reference while creating our BERT models.

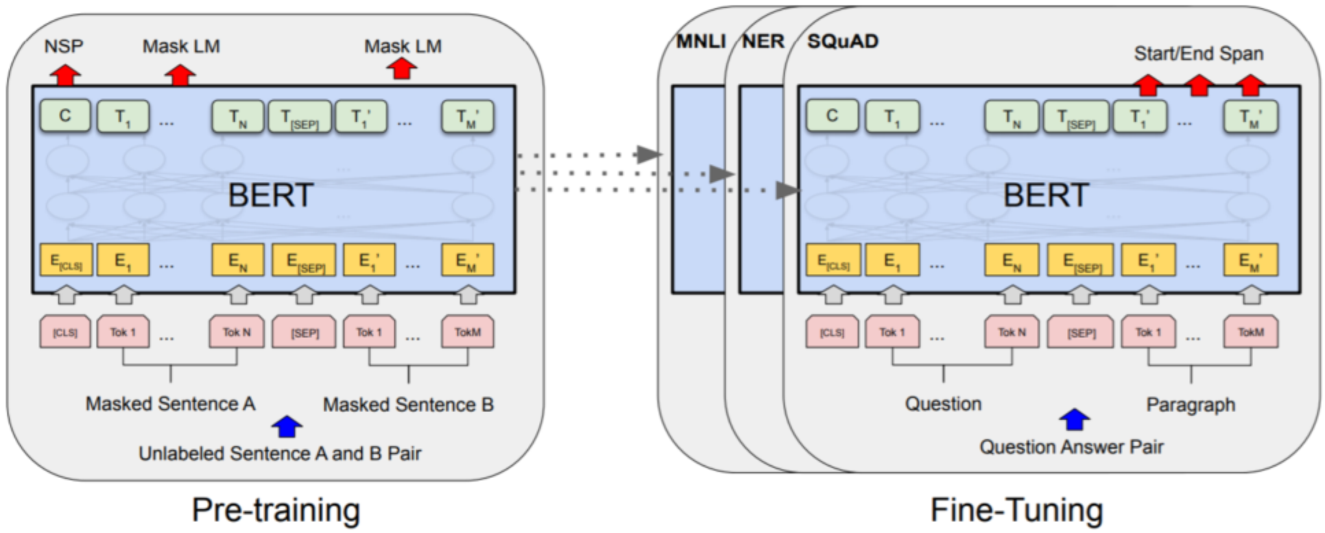
We have used the github code : https://gist.github.com/namakemono/4e2a37375edf7a5e849b0a499897dcbe to build our LSTM network

We have also optimized our models using the best optimizing strategies to get excellent results.

About BERT

BERT(Bidirectional Encoder Representations from Transformers) is a Transformer-based architecture used for Natural Language processing tasks. Prior to BERT, the state of the art NLP models used LSTM (Long Short Term Memory), which are a certain kind of recurrent neural networks that are slow and not completely bi-directional. This led to the invention of Transformers, that are relatively faster, and can accomodate context-aware word embeddings. BERT stacks a number of encoders to acheive excellent results in question answering, semantic similarity, text classification, etc.

Architecture of BERT



BERT is an encoder stack of transformer architecture. BERT-base has 12 layers in the Encoder stack while BERT-large has 24 layers in the Encoder stack. Bert-base has 110M parameters, while Bert-large has 340M parameters.

BERT trains on two unsupervised tasks simultaneously. These tasks are the Masked Language Model (MLM) and Next Sentence Prediction (NSP). For MLM, It takes in a sentence with random words filled with masks, and the goal is to understand these masked tokens and assign corresponding words by understanding bidirectional context within a sentence.

In the case of NSP, BERT takes in two sentences and returns if the second sentence follows from thefirst in a manner similar to a binary classification. More specifically, the inputs are fed in the form of pretrained embeddings. The BERT paper combines token embeddings, segment embeddings and position embeddings which are combined and fed as the input. The segment and position embedding are required for temporal understanding, and all these vectors are fed in simultaneously. This helps BERT understand context and thus, using these two BERT understands language in a deeper sense.

BERT Finetuning

Finetuning a BERT model is the task of training the pre-trained model of BERT with the specific problem in hand. This is generally done by training the output layer of our model separately (linear/ LSTM), and adding it to BERT and re-training the entire network.

In this project, we have tried using Linear and LSTM as the output layer.

Common Tasks (Run them before running any model)

1. Import the required libraries

```
!pip install transformers

import numpy as np
import pandas as pd
import tensorflow as tf
from transformers import BertForQuestionAnswering
from transformers import BertTokenizer
import transformers
```

```
Collecting transformers
  Downloading https://files.pythonhosted.org/packages/3a/83/e74092e7f24a08d751aa59b37a9
     |████████████████████████████████| 1.3MB 19.5MB/s
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Requirement already satisfied: dataclasses; python_version < "3.7" in /usr/local/lib/py
Requirement already satisfied: filelock in /usr/local/lib/python3.6/dist-packages (from
Collecting sacremoses
  Downloading https://files.pythonhosted.org/packages/7d/34/09d19aff26edcc8eb2a01bed8e9
     |████████████████████████████████| 890kB 46.0MB/s
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  Downloading https://files.pythonhosted.org/packages/4c/34/b39eb9994bc3c999270b69c9eea
     |████████████████████████████████| 2.9MB 53.3MB/s
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.6/dist-packages (fr
Requirement already satisfied: protobuf in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from tr
Collecting sentencepiece==0.1.91
  Downloading https://files.pythonhosted.org/packages/d4/a4/d0a884c4300004a78cca907a6ff
     |████████████████████████████████| 1.1MB 43.7MB/s
Requirement already satisfied: pyparsing>=2.0.2 in /usr/local/lib/python3.6/dist-packag
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Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/li
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.6/dist-packages (
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: setuptools in /usr/local/lib/python3.6/dist-packages (fr
Building wheels for collected packages: sacremoses
  Building wheel for sacremoses (setup.py) ... done
  Created wheel for sacremoses: filename=sacremoses-0.0.43-cp36-none-any.whl size=89325
  Stored in directory: /root/.cache/pip/wheels/29/3c/fd/7ce5c3f0666dab31a50123635e6fb5e
Successfully built sacremoses
Installing collected packages: sacremoses, tokenizers, sentencepiece, transformers
Successfully installed sacremoses-0.0.43 sentencepiece-0.1.91 tokenizers-0.9.3 transfor
```

2. Download the SNLI dataset

In this step, we download the SNLI dataset, extract it into the train, validation and test csv files

```
max_length = 128  # Maximum length of input sentence to the model.
batch_size = 32
epochs = 2

# Labels in our dataset.
labels = ["contradiction", "entailment", "neutral"]

!curl -LO https://raw.githubusercontent.com/MohamadMerchant/SNLI/master/data.tar.gz
!tar -xvzf data.tar.gz
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100 11.1M  100 11.1M    0     0  31.4M      0 --:--:-- --:--:-- --:--:-- 31.3M
SNLI_Corpus/
SNLI_Corpus/snli_1.0_dev.csv
SNLI_Corpus/snli_1.0_train.csv
SNLI_Corpus/snli_1.0_test.csv
```

3. Load the datasets into pandas dataframes

```
train_df = pd.read_csv("SNLI_Corpus/snli_1.0_train.csv", nrows=100000)
valid_df = pd.read_csv("SNLI_Corpus/snli_1.0_dev.csv")
test_df = pd.read_csv("SNLI_Corpus/snli_1.0_test.csv")

# Shape of the data
print(f"Total train samples : {train_df.shape[0]}")
print(f"Total validation samples: {valid_df.shape[0]}")
print(f"Total test samples: {valid_df.shape[0]}")

print(f"Sentence1: {train_df.loc[1, 'sentence1']}")
print(f"Sentence2: {train_df.loc[1, 'sentence2']}")
print(f"Similarity: {train_df.loc[1, 'similarity']}")
```

```
Total train samples : 100000
Total validation samples: 10000
Total test samples: 10000
Sentence1: A person on a horse jumps over a broken down airplane.
Sentence2: A person is at a diner, ordering an omelette.
Similarity: contradiction
```

4. Clean the data

```
print("Number of missing values")
```

```
print(train_df.isnull().sum())
train_df.dropna(axis=0, inplace=True)
print("Train Target Distribution")
print(train_df.similarity.value_counts())
print("Validation Target Distribution")
print(valid_df.similarity.value_counts())
```

```
Number of missing values
similarity    0
sentence1     0
sentence2     3
dtype: int64
Train Target Distribution
entailment       33384
contradiction    33310
neutral          33193
-                  110
Name: similarity, dtype: int64
Validation Target Distribution
entailment       3329
contradiction    3278
neutral          3235
-                 158
Name: similarity, dtype: int64
```

```
train_df = (
    train_df[train_df.similarity != "-"]
    .sample(frac=1.0, random_state=42)
    .reset_index(drop=True)
)
valid_df = (
    valid_df[valid_df.similarity != "-"]
    .sample(frac=1.0, random_state=42)
    .reset_index(drop=True)
)
```

5. Create labels for the train, validation and test datasets

```
train_df["label"] = train_df["similarity"].apply(
    lambda x: 0 if x == "contradiction" else 1 if x == "entailment" else 2
)
y_train = tf.keras.utils.to_categorical(train_df.label, num_classes=3)

valid_df["label"] = valid_df["similarity"].apply(
    lambda x: 0 if x == "contradiction" else 1 if x == "entailment" else 2
)
y_val = tf.keras.utils.to_categorical(valid_df.label, num_classes=3)

test_df["label"] = test_df["similarity"].apply(
    lambda x: 0 if x == "contradiction" else 1 if x == "entailment" else 2
```

```
)
y_test = tf.keras.utils.to_categorical(test_df.label, num_classes=3)
```

6. Sentence similarity verification method

```
def is_similar(sentence1, sentence2, model, tokenizer):
    '''
    Takes a sentence1 and checks if sentence2 is symantically similar to sentence1.
    '''
    sent = [sentence1,sentence2]

    encoded = tokenizer([sent], return_tensors='pt',add_special_tokens=True,
            max_length=max_length,
            return_attention_mask=True,
            return_token_type_ids=True,
            pad_to_max_length=True,
            )

    input_ids = np.array(encoded["input_ids"], dtype="int32")
    attention_masks = np.array(encoded["attention_mask"], dtype="int32")
    token_type_ids = np.array(encoded["token_type_ids"], dtype="int32")

    x_train = [input_ids, attention_masks, token_type_ids]
    # y_train = tf.keras.utils.to_categorical(train_df[0].label, num_classes=3)

    y_pred = np.array(model.predict(x_train))[0]
    print(y_pred)
    idx = np.argmax(y_pred)
    sentiment_labels = ["contradiction", "entailment", "neutral"]
    print(idx)
    print(sentiment_labels[idx])
    print(y_pred[idx])
```

Model 1 : Plain BERT(small)

1. Create BERT tokenizer

```
tokenizer = transformers.BertTokenizer.from_pretrained(
            "bert-base-uncased", do_lower_case=True
        )
```

2. Encode the train data using BERT tokenizer

```
max_length = 128

x_train = train_df[["sentence1", "sentence2"]].values.astype("str")

encoded = tokenizer(x_train[0:100000].tolist(), return_tensors='pt', add_special_tokens=True,
            max_length=max_length,
            return_attention_mask=True,
            return_token_type_ids=True,
            pad_to_max_length=True,
            )


#Embedding and stuff
input_ids = np.array(encoded["input_ids"], dtype="int32")
attention_masks = np.array(encoded["attention_mask"], dtype="int32")
token_type_ids = np.array(encoded["token_type_ids"], dtype="int32")

x_train = [input_ids, attention_masks, token_type_ids]
y_train = tf.keras.utils.to_categorical(train_df[0:100000].label, num_classes=3)


# Encoded token ids from BERT tokenizer.
input_ids = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="input_ids"
)
# Attention masks indicates to the model which tokens should be attended to.
attention_masks = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="attention_masks"
)
# Token type ids are binary masks identifying different sequences in the model.
token_type_ids = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="token_type_ids"
)


#Encode the validation set
encoded_valid = tokenizer(valid_df[["sentence1", "sentence2"]].values.astype("str").tolist(),
        add_special_tokens=True,
        max_length=max_length,
        return_attention_mask=True,
        return_token_type_ids=True,
        pad_to_max_length=True,
        )

input_ids_valid = np.array(encoded_valid["input_ids"], dtype="int32")
attention_masks_valid = np.array(encoded_valid["attention_mask"], dtype="int32")
token_type_ids_valid = np.array(encoded_valid["token_type_ids"], dtype="int32")
```

```
x_valid = [input_ids_valid, attention_masks_valid, token_type_ids_valid]
y_valid = tf.keras.utils.to_categorical(valid_df.label, num_classes=3)

valid_data = x_valid,y_valid
```

```
Truncation was not explicitly activated but `max_length` is provided a specific value,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:2022: Fu
  FutureWarning,
```

3. Load the BERT pre-trained model

```
# Loading pretrained BERT model.
bert_model = transformers.TFBertModel.from_pretrained("bert-base-uncased")

# Freeze the BERT model to reuse the pretrained features without modifying them.
bert_model.trainable = False

sequence_output, pooled_output = bert_model(
  input_ids, attention_mask=attention_masks, token_type_ids=token_type_ids
)

sequence_output = tf.keras.layers.Flatten()(sequence_output)
output = tf.keras.layers.Dense(3, activation="softmax")(sequence_output)
model = tf.keras.models.Model(
    inputs=[input_ids, attention_masks, token_type_ids], outputs=output
)

model = tf.keras.models.Model(
    inputs=[input_ids, attention_masks, token_type_ids], outputs=output
)

model.compile(
    optimizer=tf.keras.optimizers.Adam(),
    loss="categorical_crossentropy",
    metrics=["acc"],
)
model.summary()
```

Downloading: 100% 433/433 [00:00<00:00, 3.75kB/s]

Downloading: 100% 536M/536M [00:12<00:00, 43.5MB/s]

```
Some layers from the model checkpoint at bert-base-uncased were not used when initializ
- This IS expected if you are initializing TFBertModel from the checkpoint of a model t
- This IS NOT expected if you are initializing TFBertModel from the checkpoint of a mod
All the layers of TFBertModel were initialized from the model checkpoint at bert-base-u
If your task is similar to the task the model of the checkpoint was trained on, you can
Model: "functional_3"
________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
========================================================================================
input_ids (InputLayer)          [(None, 128)]        0
________________________________________________________________________________________
attention_masks (InputLayer)    [(None, 128)]        0
________________________________________________________________________________________
token_type_ids (InputLayer)     [(None, 128)]        0
________________________________________________________________________________________
tf_bert_model (TFBertModel)     ((None, 128, 768), ( 109482240   input_ids[0][0]
                                                                 attention_masks[0][0]
                                                                 token_type_ids[0][0]
```

4. Train the model

```
========================================================================================
```

```
training_history = model.fit(x_train,y_train,validation_data=valid_data,epochs=2,batch_size=1
```

```
Epoch 1/2
6243/6243 [==============================] - 1093s 175ms/step - loss: 4.1711 - acc: 0.5
Epoch 2/2
6243/6243 [==============================] - 1104s 177ms/step - loss: 4.3283 - acc: 0.5
```

5. Save the model (Optional)

```
model.save_weights('BERT_Plain.h5')
```

6. Verify the model performance

```
is_similar("Charlie went to the cycle shop on Sunday","Charlie was resting at home on Sunday'
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:2022: Fu
  FutureWarning,
[5.3576505e-01 2.0653822e-11 4.6423498e-01]
0
```

```
contradiction
0.53576505
```

7. Test the model

```
encoded = tokenizer(test_df[["sentence1", "sentence2"]].values.astype("str").tolist(), returr
        add_special_tokens=True,
        max_length=max_length,
        return_attention_mask=True,
        return_token_type_ids=True,
        pad_to_max_length=True,
        )

input_ids = np.array(encoded["input_ids"], dtype="int32")
attention_masks = np.array(encoded["attention_mask"], dtype="int32")
token_type_ids = np.array(encoded["token_type_ids"], dtype="int32")

x_test = [input_ids, attention_masks, token_type_ids]
y_test = tf.keras.utils.to_categorical(test_df.label, num_classes=3)

model.evaluate(x_test,y_test, verbose=1)
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:2022: Fu
  FutureWarning,
313/313 [==============================] - 89s 283ms/step - loss: 4.4134 - acc: 0.6278
[4.413364887237549, 0.6277999877929688]
```

8. Metrics

```
from sklearn import metrics
import matplotlib.pyplot as plt

y_pred = model.predict(x_test, verbose=1)

print("Confusion Matrix:\n")
print(metrics.confusion_matrix(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1)))


loss_train = training_history.history['loss']
loss_val = training_history.history['val_loss']
epochs = np.arange(1,3)
plt.plot(epochs, np.array(loss_train), 'g', label='Training loss')
plt.plot(epochs, np.array(loss_val), 'b', label='validation loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
```

```
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
313/313 [==============================] - 89s 284ms/step
Confusion Matrix:

[[2414  612  211]
 [ 475 2704  189]
 [1244  991 1160]]
```

Model 2 : LSTM

1. Create word embeddings

```
!wget -c "https://s3.amazonaws.com/dl4j-distribution/GoogleNews-vectors-negative300.bin.gz"
```

```
--2020-11-28 10:55:47--  https://s3.amazonaws.com/dl4j-distribution/GoogleNews-vectors-
Resolving s3.amazonaws.com (s3.amazonaws.com)... 52.216.139.53
Connecting to s3.amazonaws.com (s3.amazonaws.com)|52.216.139.53|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1647046227 (1.5G) [application/x-gzip]
Saving to: ‘GoogleNews-vectors-negative300.bin.gz’

GoogleNews-vectors- 100%[===================>]   1.53G  81.0MB/s    in 22s

2020-11-28 10:56:10 (70.0 MB/s) - ‘GoogleNews-vectors-negative300.bin.gz’ saved [164704
```

2. Create the model and run it

```
import numpy as np
import pandas as pd
from gensim.models import KeyedVectors
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.layers import Dense, Input, LSTM, Embedding, Dropout, Activation
from keras.layers.merge import concatenate
from keras.models import Model
from keras.layers.normalization import BatchNormalization
from keras.callbacks import EarlyStopping
from keras.utils import to_categorical

EMBEDDING_FILE  = 'GoogleNews-vectors-negative300.bin.gz'
TRAIN_DATA_FILE = "SNLI_Corpus/snli_1.0_train.csv"
TEST_DATA_FILE  = "SNLI_Corpus/snli_1.0_test.csv"
MAX_SEQUENCE_LENGTH = 30
MAX_NB_WORDS = 200000
EMBEDDING_DIM = 300
VALIDATION_SPLIT = 0.1
rate_drop_lstm = 0.15 + np.random.rand() * 0.25
rate_drop_dense = 0.15 + np.random.rand() * 0.25

def text_to_tokens(text):
    return text.lower()

def get_label_index_mapping():
    return {"neutral": 0, "contradiction": 1, "entailment": 2, "-": 3}

def create_embedding_matrix(word_index):
    nb_words = min(MAX_NB_WORDS, len(word_index))+1
    word2vec = KeyedVectors.load_word2vec_format(EMBEDDING_FILE, binary=True)
    embedding_matrix = np.zeros((nb_words, EMBEDDING_DIM))
    for word, i in word_index.items():
        if word in word2vec.vocab:
            embedding_matrix[i] = word2vec.word_vec(word)
    return embedding_matrix

def load_data():
    train_df = pd.read_csv(TRAIN_DATA_FILE, sep=",", usecols=["sentence1", "sentence2", "simi
    train_df.fillna("", inplace=True)
    sentence1 = train_df["sentence1"].apply(text_to_tokens)
    sentence2 = train_df["sentence2"].apply(text_to_tokens)
    y = train_df["similarity"].map(get_label_index_mapping())
    tokenizer = Tokenizer(num_words=MAX_NB_WORDS)
    tokenizer.fit_on_texts(sentence1 + sentence2)
    sequences1 = tokenizer.texts_to_sequences(sentence1)
    sequences2 = tokenizer.texts_to_sequences(sentence2)
    X1 = pad_sequences(sequences1, maxlen=MAX_SEQUENCE_LENGTH)
```

```
    X1 = pad_sequences(sequences1, maxlen=MAX_SEQUENCE_LENGTH)
    X2 = pad_sequences(sequences2, maxlen=MAX_SEQUENCE_LENGTH)
    perm = np.random.permutation(len(X1))
    num_train   = int(len(X1)*(1-VALIDATION_SPLIT))
    train_index = perm[:num_train]
    valid_index = perm[num_train:]
    X1_train    = X1[train_index]
    X2_train    = X2[train_index]
    y_train     = y[train_index]
    X1_valid    = X1[valid_index]
    X2_valid    = X2[valid_index]
    y_valid     = y[valid_index]
    return (X1_train, X2_train, y_train), (X1_valid, X2_valid, y_valid), tokenizer

def StaticEmbedding(embedding_matrix):
    input_dim, output_dim = embedding_matrix.shape
    return Embedding(input_dim,
            output_dim,
            weights=[embedding_matrix],
            input_length=MAX_SEQUENCE_LENGTH,
            trainable=False)

def entail(feat1, feat2, num_dense=300):
    x = concatenate([feat1, feat2])
    x = Dropout(rate_drop_dense)(x)
    x = BatchNormalization()(x)
    x = Dense(num_dense, activation="relu")(x)
    x = Dropout(rate_drop_dense)(x)
    x = BatchNormalization()(x)
    return x

def build_model(output_dim, embedding_matrix, num_lstm=300):
    sequence1_input = Input(shape=(MAX_SEQUENCE_LENGTH,), dtype='int32')
    sequence2_input = Input(shape=(MAX_SEQUENCE_LENGTH,), dtype='int32')

    # Embedding
    embed = StaticEmbedding(embedding_matrix)
    embedded_sequences1 = embed(sequence1_input)
    embedded_sequences2 = embed(sequence2_input)

    # Encoding
    encode = LSTM(num_lstm, dropout=rate_drop_lstm, recurrent_dropout=rate_drop_lstm)
    feat1 = encode(embedded_sequences1)
    feat2 = encode(embedded_sequences2)

    x = entail(feat1, feat2)
    preds = Dense(output_dim, activation='softmax')(x)
    model = Model(inputs=[sequence1_input, sequence2_input], outputs=preds)
    return model

def run():
    num_class = len(get_label_index_mapping())
```

```
    (X1_train, X2_train, y_train), (X1_valid, X2_valid, y_valid), tokenizer = load_data()
    Y_train, Y_valid = to_categorical(y_train, num_class), to_categorical(y_valid, num_class)
    embedding_matrix = create_embedding_matrix(tokenizer.word_index)
    model = build_model(output_dim=num_class, embedding_matrix=embedding_matrix)
    model.compile(loss='categorical_crossentropy', optimizer='nadam', metrics=['acc'])
    early_stopping = EarlyStopping(monitor='val_loss', patience=10)
    hist = model.fit([X1_train, X2_train], Y_train,
            validation_data=([X1_valid, X2_valid], Y_valid),
            epochs=20, batch_size=2048, shuffle=True,
            callbacks=[early_stopping])

if __name__ == "__main__":
    run()
```

```
WARNING:tensorflow:Layer lstm will not use cuDNN kernel since it doesn't meet the cuDNN
Epoch 1/20
242/242 [==============================] - 88s 363ms/step - loss: 1.0785 - acc: 0.5303
Epoch 2/20
242/242 [==============================] - 88s 365ms/step - loss: 0.8565 - acc: 0.6141
Epoch 3/20
242/242 [==============================] - 88s 365ms/step - loss: 0.8016 - acc: 0.6476
Epoch 4/20
242/242 [==============================] - 89s 367ms/step - loss: 0.7619 - acc: 0.6711
Epoch 5/20
242/242 [==============================] - 89s 369ms/step - loss: 0.7321 - acc: 0.6873
Epoch 6/20
242/242 [==============================] - 89s 368ms/step - loss: 0.7112 - acc: 0.6989
Epoch 7/20
242/242 [==============================] - 89s 367ms/step - loss: 0.6943 - acc: 0.7080
Epoch 8/20
242/242 [==============================] - 89s 368ms/step - loss: 0.6797 - acc: 0.7157
Epoch 9/20
242/242 [==============================] - 89s 369ms/step - loss: 0.6686 - acc: 0.7213
Epoch 10/20
242/242 [==============================] - 89s 368ms/step - loss: 0.6586 - acc: 0.7265
Epoch 11/20
242/242 [==============================] - 89s 367ms/step - loss: 0.6501 - acc: 0.7312
Epoch 12/20
242/242 [==============================] - 89s 369ms/step - loss: 0.6425 - acc: 0.7343
Epoch 13/20
242/242 [==============================] - 89s 369ms/step - loss: 0.6362 - acc: 0.7376
Epoch 14/20
242/242 [==============================] - 89s 369ms/step - loss: 0.6285 - acc: 0.7421
Epoch 15/20
242/242 [==============================] - 89s 368ms/step - loss: 0.6228 - acc: 0.7439
Epoch 16/20
242/242 [==============================] - 89s 367ms/step - loss: 0.6191 - acc: 0.7460
Epoch 17/20
242/242 [==============================] - 89s 367ms/step - loss: 0.6140 - acc: 0.7488
Epoch 18/20
242/242 [==============================] - 89s 368ms/step - loss: 0.6080 - acc: 0.7508
Epoch 19/20
242/242 [==============================] - 89s 369ms/step - loss: 0.6054 - acc: 0.7535
Epoch 20/20
242/242 [==============================] - 90s 370ms/step - loss: 0.6009 - acc: 0.7548
```

Model 3 : BERT-large pre-trained on SQuAD

1. Create BERT-large tokenizer

```
tokenizer_bl = BertTokenizer.from_pretrained('bert-large-uncased-whole-word-masking-finetunec
```

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2. Encode the train data using BERT-large tokenizer

```
max_length = 128

x_train = train_df[["sentence1", "sentence2"]].values.astype("str")

encoded = tokenizer_bl(x_train[0:100000].tolist(), return_tensors='pt', add_special_tokens=Tr
            max_length=max_length,
            return_attention_mask=True,
            return_token_type_ids=True,
            pad_to_max_length=True,
            )


#Embedding and stuff
input_ids = np.array(encoded["input_ids"], dtype="int32")
attention_masks = np.array(encoded["attention_mask"], dtype="int32")
token_type_ids = np.array(encoded["token_type_ids"], dtype="int32")

x_train = [input_ids, attention_masks, token_type_ids]
y_train = tf.keras.utils.to_categorical(train_df[0:100000].label, num_classes=3)


# Encoded token ids from BERT tokenizer.
input_ids = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="input_ids"
)
# Attention masks indicates to the model which tokens should be attended to.
attention_masks = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="attention_masks"
)
# Token type ids are binary masks identifying different sequences in the model.
token_type_ids = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="token_type_ids"
```

```
)


#Encode the validation set
encoded_valid = tokenizer_bl(valid_df[["sentence1", "sentence2"]].values.astype("str").tolist
        add_special_tokens=True,
        max_length=max_length,
        return_attention_mask=True,
        return_token_type_ids=True,
        pad_to_max_length=True,
        )

input_ids_valid = np.array(encoded_valid["input_ids"], dtype="int32")
attention_masks_valid = np.array(encoded_valid["attention_mask"], dtype="int32")
token_type_ids_valid = np.array(encoded_valid["token_type_ids"], dtype="int32")

x_valid = [input_ids_valid, attention_masks_valid, token_type_ids_valid]
y_valid = tf.keras.utils.to_categorical(valid_df.label, num_classes=3)

valid_data = x_valid,y_valid
```

```
Truncation was not explicitly activated but `max_length` is provided a specific value,
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:2022: Fu
  FutureWarning,
```

3. Load the BERT-large pre-trained model

```
# Loading pretrained BERT model.
bert_model = transformers.TFBertModel.from_pretrained("bert-large-uncased-whole-word-masking-

# Freeze the BERT model to reuse the pretrained features without modifying them.
bert_model.trainable = False

sequence_output, pooled_output = bert_model(
  input_ids, attention_mask=attention_masks, token_type_ids=token_type_ids
)

# Add trainable layers on top of frozen layers to adapt the pretrained features on the new da
bi_lstm = tf.keras.layers.Bidirectional(
tf.keras.layers.LSTM(64, return_sequences=True)
)(sequence_output)

# Applying hybrid pooling approach to bi_lstm sequence output.
avg_pool = tf.keras.layers.GlobalAveragePooling1D()(bi_lstm)
max_pool = tf.keras.layers.GlobalMaxPooling1D()(bi_lstm)
concat = tf.keras.layers.concatenate([avg_pool, max_pool])
dropout = tf.keras.layers.Dropout(0.3)(concat)
```

```
    output = tf.keras.layers.Dense(3, activation="softmax")(dropout)

    model_bl = tf.keras.models.Model(
        inputs=[input_ids, attention_masks, token_type_ids], outputs=output
    )

    model_bl.compile(
        optimizer=tf.keras.optimizers.Adam(),
        loss="categorical_crossentropy",
        metrics=["acc"],
    )
    model_bl.summary()
```

4. Train the model

```
training_history = model_bl.fit(x_train,y_train,validation_data=valid_data,epochs=2,batch_siz
```

```
Epoch 1/2
6243/6243 [==============================] - 3323s 532ms/step - loss: 0.7092 - acc: 0.6
Epoch 2/2
6243/6243 [==============================] - 3329s 533ms/step - loss: 0.6277 - acc: 0.7
```

5. Finetune the model

```
# Unfreeze the bert_model.
bert_model.trainable = True
# Recompile the model to make the change effective.
model_bl.compile(
    optimizer=tf.keras.optimizers.Adam(1e-5),
    loss="categorical_crossentropy",
    metrics=["accuracy"],
)
model_bl.summary()
```

```
finetuning_history = model_bl.fit(x_train,y_train, validation_data=valid_data, epochs=2,batch
```

Model: "functional_1"

Layer (type)	Output Shape	Param #	Connected to
input_ids (InputLayer)	[(None, 128)]	0	
attention_masks (InputLayer)	[(None, 128)]	0	
token_type_ids (InputLayer)	[(None, 128)]	0	
tf_bert_model (TFBertModel)	((None, 128, 1024),	335141888	input_ids[0][0] attention_masks[0][0] token_type_ids[0][0]
bidirectional (Bidirectional)	(None, 128, 128)	557568	tf_bert_model[0][0]
global_average_pooling1d (Globa	(None, 128)	0	bidirectional[0][0]
global_max_pooling1d (GlobalMax	(None, 128)	0	bidirectional[0][0]
concatenate (Concatenate)	(None, 256)	0	global_average_pooling global_max_pooling1d[0
dropout_73 (Dropout)	(None, 256)	0	concatenate[0][0]

```
dense (Dense)                   (None, 3)            771         dropout_73[0][0]
==================================================================================
Total params: 335,700,227
Trainable params: 335,700,227
Non-trainable params: 0

Epoch 1/2
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model/bert/pooler/den
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model/bert/pooler/den
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model/bert/pooler/den
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model/bert/pooler/den
6243/6243 [==============================] - 9002s 1s/step - loss: 0.4614 - accuracy: 0
Epoch 2/2
6243/6243 [==============================] - 8998s 1s/step - loss: 0.3380 - accuracy: 0
```

6. Save the model (Optional)

[ ] ↳ *1 cell hidden*

7. Verify the model performance

```
y to sample the region's exquisite wines.","Be sure to make time for a Tuscan wine-tasting ex
```

```
[0.01231802 0.7330076  0.2546743 ]
1
entailment
0.7330076
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:2022: Fu
  FutureWarning,
```

8. Test the model

```
encoded = tokenizer_bl(test_df[["sentence1", "sentence2"]].values.astype("str").tolist(), ret
        add_special_tokens=True,
        max_length=max_length,
        return_attention_mask=True,
        return_token_type_ids=True,
        pad_to_max_length=True,
        )

input_ids = np.array(encoded["input_ids"], dtype="int32")
attention_masks = np.array(encoded["attention_mask"], dtype="int32")
token_type_ids = np.array(encoded["token_type_ids"], dtype="int32")
```

```
x_test = [input_ids, attention_masks, token_type_ids]
y_test = tf.keras.utils.to_categorical(test_df.label, num_classes=3)

model_bl.evaluate(x_test,y_test, verbose=1)
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:2022: Fu
  FutureWarning,
313/313 [==============================] - 281s 898ms/step - loss: 0.3264 - accuracy: 0
[0.32644084095954895, 0.8827000260353088]
```

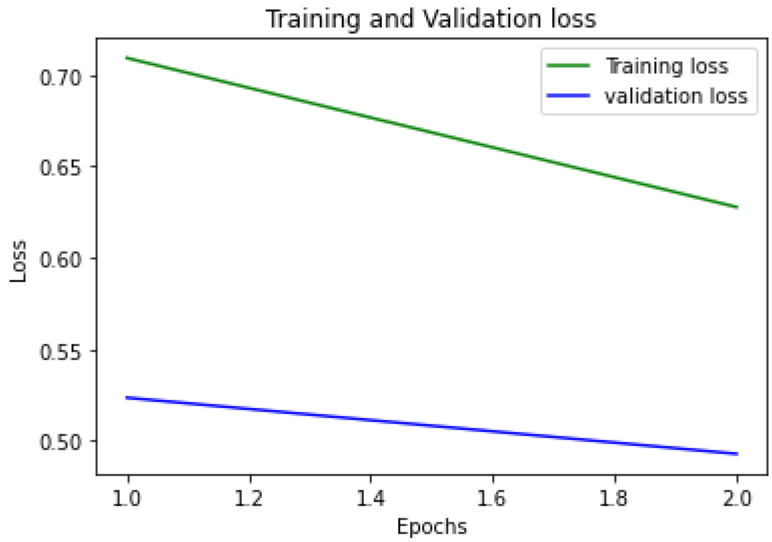
9. Metrics

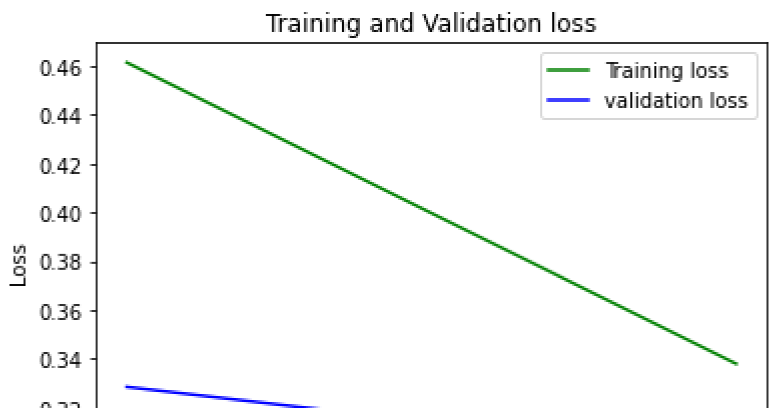
```
from sklearn import metrics
import matplotlib.pyplot as plt

y_pred = model_bl.predict(x_test, verbose=1)

print("Confusion Matrix:\n")
print(metrics.confusion_matrix(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1)))
```

```
loss_train = training_history.history['loss']
loss_val = training_history.history['val_loss']
epochs = np.arange(1,3)
plt.plot(epochs, np.array(loss_train), 'g', label='Training loss')
plt.plot(epochs, np.array(loss_val), 'b', label='validation loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
loss_train = finetuning_history.history['loss']
loss_val = finetuning_history.history['val_loss']
epochs = np.arange(1,3)
plt.plot(epochs, np.array(loss_train), 'g', label='Training loss')
plt.plot(epochs, np.array(loss_val), 'b', label='validation loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
313/313 [==============================] - 283s 903ms/step
Confusion Matrix:

[[2938   91  208]
 [  62 3058  248]
 [ 224  340 2831]]
```





Model 4 : Plain BERT(small) with Bi-Directional LSTM for finetuning

1. Create BERT tokenizer

```
tokenizer = transformers.BertTokenizer.from_pretrained(
            "bert-base-uncased", do_lower_case=True
        )
```

Downloading: 100% 232k/232k [00:00<00:00, 2.13MB/s]

2. Encode the train data using BERT tokenizer

```
max_length = 128

x_train = train_df[["sentence1", "sentence2"]].values.astype("str")

encoded = tokenizer(x_train[0:100000].tolist(), return_tensors='pt', add_special_tokens=True,
            max_length=max_length,
            return_attention_mask=True,
            return_token_type_ids=True,
            pad_to_max_length=True,
            )


#Embedding and stuff
input_ids = np.array(encoded["input_ids"], dtype="int32")
attention_masks = np.array(encoded["attention_mask"], dtype="int32")
token_type_ids = np.array(encoded["token_type_ids"], dtype="int32")

x_train = [input_ids, attention_masks, token_type_ids]
y_train = tf.keras.utils.to_categorical(train_df[0:100000].label, num_classes=3)


# Encoded token ids from BERT tokenizer.
input_ids = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="input_ids"
)
# Attention masks indicates to the model which tokens should be attended to.
attention_masks = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="attention_masks"
)
# Token type ids are binary masks identifying different sequences in the model.
token_type_ids = tf.keras.layers.Input(
    shape=(max_length,), dtype=tf.int32, name="token_type_ids"
)


#Encode the validation set
encoded_valid = tokenizer(valid_df[["sentence1", "sentence2"]].values.astype("str").tolist(),
        add_special_tokens=True,
        max_length=max_length,
        return_attention_mask=True,
        return_token_type_ids=True,
        pad_to_max_length=True,
        )

input_ids_valid = np.array(encoded_valid["input_ids"], dtype="int32")
attention_masks_valid = np.array(encoded_valid["attention_mask"], dtype="int32")
token_type_ids_valid = np.array(encoded_valid["token_type_ids"], dtype="int32")
```

```
x_valid = [input_ids_valid, attention_masks_valid, token_type_ids_valid]
y_valid = tf.keras.utils.to_categorical(valid_df.label, num_classes=3)

valid_data = x_valid,y_valid
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.py:2022: Fu
  FutureWarning,
```

3. Load the BERT pre-trained model

```
# Loading pretrained BERT model.
bert_model = transformers.TFBertModel.from_pretrained("bert-base-uncased")

# Freeze the BERT model to reuse the pretrained features without modifying them.
bert_model.trainable = False

sequence_output, pooled_output = bert_model(
  input_ids, attention_mask=attention_masks, token_type_ids=token_type_ids
)

# Add trainable layers on top of frozen layers to adapt the pretrained features on the new da
bi_lstm = tf.keras.layers.Bidirectional(
tf.keras.layers.LSTM(256, return_sequences=True)
)(sequence_output)

# Applying hybrid pooling approach to bi_lstm sequence output.
avg_pool = tf.keras.layers.GlobalAveragePooling1D()(bi_lstm)
max_pool = tf.keras.layers.GlobalMaxPooling1D()(bi_lstm)
concat = tf.keras.layers.concatenate([avg_pool, max_pool])
dropout = tf.keras.layers.Dropout(0.2)(concat)

output = tf.keras.layers.Dense(3, activation="softmax")(dropout)

model_ft = tf.keras.models.Model(
    inputs=[input_ids, attention_masks, token_type_ids], outputs=output
)

model_ft.compile(
    optimizer=tf.keras.optimizers.Adam(),
    loss="categorical_crossentropy",
    metrics=["acc"],
)
model_ft.summary()
```

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Downloading: 100% 536M/536M [00:22<00:00, 23.3MB/s]

```
Some layers from the model checkpoint at bert-base-uncased were not used when initializ
- This IS expected if you are initializing TFBertModel from the checkpoint of a model t
- This IS NOT expected if you are initializing TFBertModel from the checkpoint of a mod
All the layers of TFBertModel were initialized from the model checkpoint at bert-base-u
If your task is similar to the task the model of the checkpoint was trained on, you can
Model: "functional_3"
________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
========================================================================================
input_ids (InputLayer)          [(None, 128)]        0
________________________________________________________________________________________
attention_masks (InputLayer)    [(None, 128)]        0
________________________________________________________________________________________
token_type_ids (InputLayer)     [(None, 128)]        0
________________________________________________________________________________________
tf_bert_model_1 (TFBertModel)   ((None, 128, 768), ( 109482240   input_ids[0][0]
                                                                 attention_masks[0][0]
                                                                 token_type_ids[0][0]
________________________________________________________________________________________
bidirectional_1 (Bidirectional) (None, 128, 512)     2099200     tf_bert_model_1[0][0]
________________________________________________________________________________________
global_average_pooling1d_1 (Glo (None, 512)          0           bidirectional_1[0][0]
________________________________________________________________________________________
global_max_pooling1d_1 (GlobalM (None, 512)          0           bidirectional_1[0][0]
________________________________________________________________________________________
concatenate_1 (Concatenate)     (None, 1024)         0           global_average_pooling
                                                                 global_max_pooling1d_1
________________________________________________________________________________________
dropout_111 (Dropout)           (None, 1024)         0           concatenate_1[0][0]
________________________________________________________________________________________
dense_1 (Dense)                 (None, 3)            3075        dropout_111[0][0]
========================================================================================
Total params: 111,584,515
Trainable params: 2,102,275
```

4. Train the model

```
training_history = model_ft.fit(x_train,y_train,validation_data=valid_data,epochs=2,batch_siz
```

```
Epoch 1/2
6243/6243 [==============================] - 1228s 197ms/step - loss: 0.6517 - acc: 0.7
Epoch 2/2
6243/6243 [==============================] - 1222s 196ms/step - loss: 0.5699 - acc: 0.7
```

5. Finetune the model

```
# Unfreeze the bert_model.
bert_model.trainable = True
# Recompile the model to make the change effective.
model_ft.compile(
    optimizer=tf.keras.optimizers.Adam(1e-5),
    loss="categorical_crossentropy",
    metrics=["accuracy"],
)
model_ft.summary()

finetuning_history = model_ft.fit(x_train,y_train, validation_data=valid_data, epochs=2,batch
```

```
Model: "functional_3"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_ids (InputLayer)          [(None, 128)]        0
__________________________________________________________________________________________________
attention_masks (InputLayer)    [(None, 128)]        0
__________________________________________________________________________________________________
token_type_ids (InputLayer)     [(None, 128)]        0
__________________________________________________________________________________________________
tf_bert_model_1 (TFBertModel)   ((None, 128, 768), ( 109482240   input_ids[0][0]
                                                                 attention_masks[0][0]
                                                                 token_type_ids[0][0]
__________________________________________________________________________________________________
bidirectional_1 (Bidirectional) (None, 128, 512)     2099200     tf_bert_model_1[0][0]
__________________________________________________________________________________________________
global_average_pooling1d_1 (Glo (None, 512)          0           bidirectional_1[0][0]
__________________________________________________________________________________________________
global_max_pooling1d_1 (GlobalM (None, 512)          0           bidirectional_1[0][0]
__________________________________________________________________________________________________
concatenate_1 (Concatenate)     (None, 1024)         0           global_average_pooling
                                                                 global_max_pooling1d_1
__________________________________________________________________________________________________
dropout_111 (Dropout)           (None, 1024)         0           concatenate_1[0][0]
__________________________________________________________________________________________________
dense_1 (Dense)                 (None, 3)            3075        dropout_111[0][0]
==================================================================================================
Total params: 111,584,515
Trainable params: 111,584,515
Non-trainable params: 0
__________________________________________________________________________________________________
Epoch 1/2
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model_1/bert/pooler/d
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model_1/bert/pooler/d
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model_1/bert/pooler/d
WARNING:tensorflow:Gradients do not exist for variables ['tf_bert_model_1/bert/pooler/d
6243/6243 [==============================] - 3001s 481ms/step - loss: 0.4487 - accuracy
Epoch 2/2
4665/6243 [=====================>........] - ETA: 12:13 - loss: 0.3209 - accuracy: 0.88
```

6. Save the model (Optional)

```
model_ft.save_weights('BERT_Finetuned_Experiment1.h5')
```

7. Verify the model performance

```
is_similar("Charlie went to the cycle shop on Sunday","Charlie was resting at home on Sunday'
```

8. Test the model

```
encoded = tokenizer(test_df[["sentence1", "sentence2"]].values.astype("str").tolist(), returr
        add_special_tokens=True,
        max_length=max_length,
        return_attention_mask=True,
        return_token_type_ids=True,
        pad_to_max_length=True,
        )

input_ids = np.array(encoded["input_ids"], dtype="int32")
attention_masks = np.array(encoded["attention_mask"], dtype="int32")
token_type_ids = np.array(encoded["token_type_ids"], dtype="int32")

x_test = [input_ids, attention_masks, token_type_ids]
y_test = tf.keras.utils.to_categorical(test_df.label, num_classes=3)

model_ft.evaluate(x_test,y_test, verbose=1)
```

9. Metrics

```
from sklearn import metrics
import matplotlib.pyplot as plt

y_pred = model_ft.predict(x_test, verbose=1)

print("Confusion Matrix:\n")
print(metrics.confusion_matrix(np.argmax(y_test, axis=1), np.argmax(y_pred, axis=1)))


loss_train = training_history.history['loss']
loss_val = training_history.history['val_loss']
epochs = np.arange(1,3)
plt.plot(epochs, np.array(loss_train), 'g', label='Training loss')
```

```
plt.plot(epochs, np.array(loss_val), 'b', label='validation loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()


loss_train = finetuning_history.history['loss']
loss_val = finetuning_history.history['val_loss']
epochs = np.arange(1,2)
plt.plot(epochs, np.array(loss_train), 'g', label='Training loss')
plt.plot(epochs, np.array(loss_val), 'b', label='validation loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

Experiments

Experiment 1 : Plain Bert(Small) without finetuning

- Dense output layer
- bert-base-uncased tokenizer
- 100000 training examples

Results:

After Training:

```
loss: 4.1711 - acc: 0.5355
val_loss: 3.8692 - val_acc: 0.6167
```

Test data:

```
loss: 4.4134 - acc: 0.6278
```

We can see that this model performs poorly.

Experiment 2 : LSTM

- 20 epochs
- word2vec for embeddings
- 300 layers in the dense network

Results:

After Training:

```
loss: 0.6009 - acc: 0.7548
val_loss: 0.5742 - val_acc: 0.7664
```

We can see that the training and validation sets give bad results.

Experiment 3 : BERT-large pre-trained on SQuAD

- pre-trained on SQuAD
- 100000 training examples
- 64 node Bi-directional LSTM in output layer
- Dropout = 0.3

  Results:

  After Training:

  ```
  Epoch 1:
  loss: 0.7092 - acc: 0.6970
  val_loss: 0.5043 - val_acc: 0.8027

  Epoch 2:
  loss: 0.6277 - acc: 0.7438
  val_loss: 0.4929 - val_acc: 0.8092
  ```

After Finetuning:

```
Epoch 1:
loss: 0.4614 - accuracy: 0.8273
val_loss: 0.3286 - val_accuracy: 0.8795

Epoch 2:
loss: 0.3380 - accuracy: 0.8799
val_loss: 0.2995 - val_accuracy: 0.8916
```

Test data:

```
loss: 0.3264 - accuracy: 0.8827
```

Experiment 4 : Plain Bert(Small) with Bi-directional LSTM for finetuning

- 128 nodes in output LSTM layer
- dropout : 0.35

Results:

After Training:

```
loss: 0.5971 - acc: 0.7559
val_loss: 0.5043 - val_acc: 0.8027
```

After Finetuning:

```
loss: 0.4692 - accuracy: 0.8173
val_loss: 0.3623 - val_accuracy: 0.8683
```

Test data:

```
loss: 0.3819 - accuracy: 0.8587
```

Experiment 5 : Plain Bert(Small) with Bi-directional LSTM for finetuning

- 256 nodes in output LSTM layer
- Decreased dropout rate to 0.2

Results:

After Training:

```
Epoch 1:
loss: 0.6517 - acc: 0.7248
val_loss: 0.5049 - val_acc: 0.8002

Epoch 2:
loss: 0.5699 - acc: 0.7681
val_loss: 0.5088 - val_acc: 0.7995
```

After Finetuning:

```
Epoch 1:
loss: 0.4487 - accuracy: 0.8261
```

```
val_loss: 0.3707 - val_accuracy: 0.8625

Epoch 2:
loss: 0.3209 - accuracy: 0.8822
```

Conclusion

From the above experiments, we observed that the Experiment 3 : BERT-large pre-trained on SQuAD and finetuned with Bi-directional LSTM was performing the best, closely followed by Experiment 4 and 5 on Plain BERT(small) with Bidirectional LSTM for finetuning. From the training and validation set plots for these models, we could observe that the models are underfitting.

We have used the Model 4 in our two games (SemanticSimilarityGame.ipynb and ReadingComprehensionGame.ipynb) , and achieved a great gameplay experience.

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