

## Documentation

### Course Project: Text Classification – Sarcasm Detection

**Problem:** Detection of sarcasm from tweets. I got set of training list of tweets and the context for each tweet. using the state of art text classification practices I need to generate a model to solve the problem.

**Approach:** Using Tensorflow2 and Keras deep learning API with Pretrained BERT to generate a model.

**Results:** I have tried multiple models with various combination with BERT,LSTM and finally following model gave me better results.

Below are a validation results for 500 tweets, Validated from the generated trained model(Note: results varies by training epochs).

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| SARCASM      | 0.79      | 0.80   | 0.80     | 250     |
| NOT_SARCASM  | 0.80      | 0.79   | 0.80     | 250     |
| -----        |           |        |          |         |
| accuracy     |           |        | 0.80     | 500     |
| macro avg    | 0.80      | 0.80   | 0.80     | 500     |
| weighted avg | 0.80      | 0.80   | 0.80     | 500     |

#### BERT (Bidirectional Encoder Representations from Transformers):

BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications. It was wildly successful on a variety of tasks in NLP (natural language processing). They compute vector-space representations of natural language that are suitable for use in deep learning models. The BERT family of models uses the Transformer encoder architecture to process each token of input text in the full context of all tokens before and after, hence the name: Bidirectional Encoder Representations from Transformers. More details are available at <https://github.com/google-research/bert>  
In our model I used L=12 hidden layers (i.e., Transformer blocks), a hidden size of H=768, and A=12 attention heads. Available at

[https://storage.googleapis.com/bert\\_models/2018\\_10\\_18/uncased\\_L-12\\_H-768\\_A-12.zip](https://storage.googleapis.com/bert_models/2018_10_18/uncased_L-12_H-768_A-12.zip)

Using the BERT model created a training model:

```
def create_model(max_seq_len, bert_file):

    with tf.io.gfile.GFile(bert_config, "r") as reader:
        bc = StockBertConfig.from_json_string(reader.read())
        bert_params = map_stock_config_to_params(bc)
        bert_params.adapter_size = None
        bert = BertModelLayer.from_params(bert_params, name="bert")

    input_ids = keras.layers.Input(shape=(max_seq_len, ), dtype='int32', name="input_ids")
    bert_output = bert(input_ids)

    cls_out = keras.layers.Lambda(lambda seq: seq[:, 0, :])(bert_output)
    cls_out = keras.layers.Dropout(0.5)(cls_out)
    logits = keras.layers.Dense(units=250, activation="tanh")(cls_out)
    logits = keras.layers.Dropout(0.5)(logits)
    logits = keras.layers.Dense(units=2, activation="sigmoid")(logits)

    model = keras.Model(inputs=input_ids, outputs=logits)

    model.build(input_shape=(None, max_seq_len))
    model.summary()
    load_stock_weights(bert, bert_file)

    return model
```

Summary of model:

Model: "functional\_3"

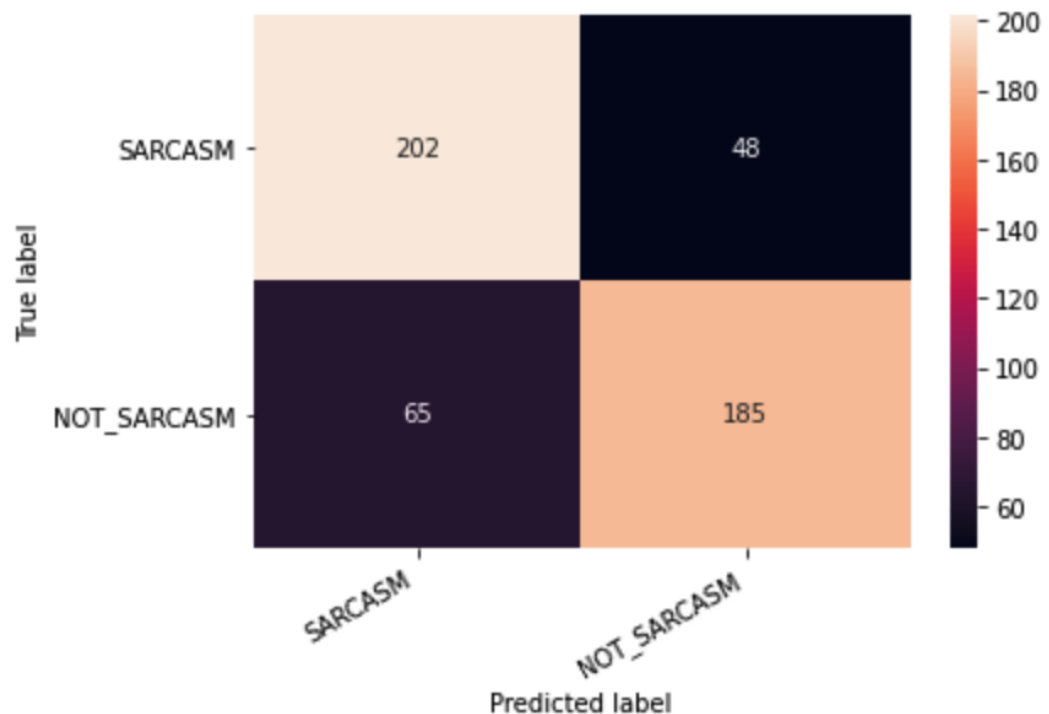
| Layer (type)                  | Output Shape    | Param #   |
|-------------------------------|-----------------|-----------|
| input_ids (InputLayer)        | [(None, 85)]    | 0         |
| bert (BertModelLayer)         | (None, 85, 768) | 108890112 |
| lambda_1 (Lambda)             | (None, 768)     | 0         |
| dropout_2 (Dropout)           | (None, 768)     | 0         |
| dense_2 (Dense)               | (None, 250)     | 192250    |
| dropout_3 (Dropout)           | (None, 250)     | 0         |
| dense_3 (Dense)               | (None, 2)       | 502       |
| Total params: 109,082,864     |                 |           |
| Trainable params: 109,082,864 |                 |           |
| Non-trainable params: 0       |                 |           |

Classification Report:

```
[ ] print(classification_report(data.test_y, y_pred, target_names=classes))
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| SARCASM      | 0.76      | 0.81   | 0.78     | 250     |
| NOT_SARCASM  | 0.79      | 0.74   | 0.77     | 250     |
| accuracy     |           |        | 0.77     | 500     |
| macro avg    | 0.78      | 0.77   | 0.77     | 500     |
| weighted avg | 0.78      | 0.77   | 0.77     | 500     |

Confusion Matrix:



With this model, we can clearly see the accuracy after the training reached 77 percentage. I got the similar results for various fine-tuning efforts. As part of finetuning I have updated the training learning rate of optimizer and epsilon also tried other activation logics for layers in the models.

## Other Model: BERT + LSTM

```
def create_model_lstm(max_seq_len, bert_file):

    with tf.io.gfile.GFile(bert_config, "r") as reader:
        bc = StockBertConfig.from_json_string(reader.read())
        bert_params = map_stock_config_to_params(bc)
        bert_params.adapter_size = None
        bert = BertModelLayer.from_params(bert_params, name="bert")

    input_ids = keras.layers.Input(shape=(max_seq_len, ), dtype='int32', name="input_ids")
    bert_output = bert(input_ids)
    lstm = keras.layers.LSTM(units=768, return_sequences=True, name="LSTM")(bert_output)
    print("bert shape", bert_output.shape)

    cls_out = keras.layers.Lambda(lambda seq: seq[:, 0, :])(lstm)
    cls_out = keras.layers.Dropout(0.5)(cls_out)
    logits = keras.layers.Dense(units=768, activation="tanh")(cls_out)
    logits = keras.layers.Dropout(0.5)(logits)
    logits = keras.layers.Dense(units=len(classes), activation="softmax")(logits)

    model = keras.Model(inputs=input_ids, outputs=logits)
    model.build(input_shape=(None, max_seq_len))
    model.summary()
    load_stock_weights(bert, bert_file)

    return model
```

```
[17] model = create_model_lstm(data.max_seq_len, bert_file)
```

```
bert shape (None, 70, 768)
Model: "functional_3"
```

| Layer (type)                  | Output Shape    | Param #   |
|-------------------------------|-----------------|-----------|
| =====                         |                 |           |
| input_ids (InputLayer)        | [(None, 70)]    | 0         |
| -----                         |                 |           |
| bert (BertModelLayer)         | (None, 70, 768) | 108890112 |
| -----                         |                 |           |
| LSTM (LSTM)                   | (None, 70, 768) | 4721664   |
| -----                         |                 |           |
| lambda (Lambda)               | (None, 768)     | 0         |
| -----                         |                 |           |
| dropout (Dropout)             | (None, 768)     | 0         |
| -----                         |                 |           |
| dense (Dense)                 | (None, 768)     | 590592    |
| -----                         |                 |           |
| dropout_1 (Dropout)           | (None, 768)     | 0         |
| -----                         |                 |           |
| dense_1 (Dense)               | (None, 2)       | 1538      |
| =====                         |                 |           |
| Total params: 114,203,906     |                 |           |
| Trainable params: 114,203,906 |                 |           |
| Non-trainable params: 0       |                 |           |

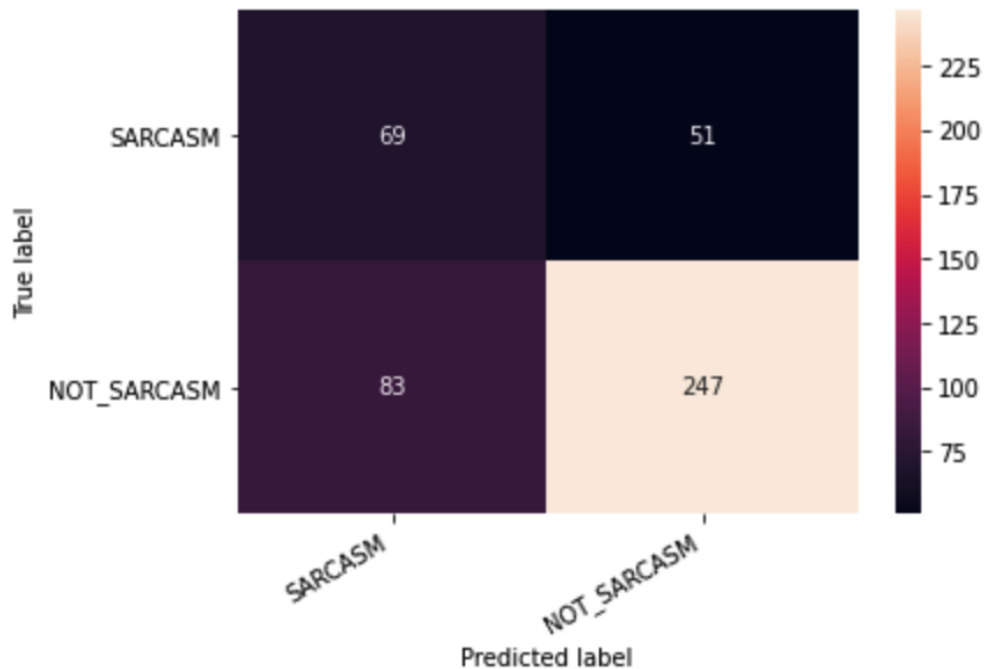
```
Done loading 196 BERT weights from: model/uncased_L-12_H-768_A-12/bert_model.ckpt into <
Unused weights from checkpoint:
bert/embeddings/token_type_embeddings
bert/pooler/dense/bias
bert/pooler/dense/kernel
cls/predictions/output_bias
cls/predictions/transform/LayerNorm/beta
cls/predictions/transform/LayerNorm/gamma
cls/predictions/transform/dense/bias
cls/predictions/transform/dense/kernel
cls/seq_relationship/output_bias
cls/seq_relationship/output_weights
```

### Classification Report:

```
print(classification_report(data.test_y, y_pred, target_names=classes))
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| SARCASM      | 0.45      | 0.57   | 0.51     | 120     |
| NOT_SARCASM  | 0.83      | 0.75   | 0.79     | 330     |
| accuracy     |           |        | 0.70     | 450     |
| macro avg    | 0.64      | 0.66   | 0.65     | 450     |
| weighted avg | 0.73      | 0.70   | 0.71     | 450     |

### Confusion Matrix:



Clearly the LSTM model doesn't do as expected. The accuracy doesn't reached the limit set for the competition.

### Resources:

- <https://github.com/google-research/bert>
- [https://www.tensorflow.org/tutorials/text/classify\\_text\\_with\\_bert](https://www.tensorflow.org/tutorials/text/classify_text_with_bert)
- <https://towardsdatascience.com/bert-for-dummies-step-by-step-tutorial-fb90890ffe03>
- <https://medium.com/atheros/text-classification-with-transformers-in-tensorflow-2-bert-2f4f16eff5ad>