NLP Disaster Tweets

The goal of this Kaggle project is to differentiate tweets that are describing a disaster versus those that aren't. The Kaggle competition is available here: https://www.kaggle.com/competitions/nlp-getting-started

The dataset includes approximately 10,000 tweets. Each row contains the text of the tweet, an often-empty column with the location, and the target field which is what we're trying to predict and indicates whether the tweet was about a disaster or not.

Project code for this project available here: https://github.com/blockee/cu-deep/tree/main/disaster

Setup and Data Reading

```
import pandas as pd
from sklearn.model_selection import train_test_split

import tensorflow as tf

import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.callbacks import EarlyStopping
import matplotlib.pyplot as plt


import torch
from torch.utils.data import Dataset, DataLoader
from transformers import BertTokenizer, BertForSequenceClassification, Trainer, TrainingArguments


def pandas_to_dataset(df, text_column, target_column, batch_size=64):
  """Converts a Pandas DataFrame with one text input column + target column
   to a TensorFlow Dataset."""

  texts = df[text_column].values

  if target_column is None:
    dataset = tf.data.Dataset.from_tensor_slices((texts))
  else:
    labels = df[target_column].astype(int).values
    dataset = tf.data.Dataset.from_tensor_slices((texts, labels))

  dataset = dataset.batch(batch_size)
  return dataset


initial_df = pd.read_csv('/content/train.csv')
test_df = pd.read_csv('/content/test.csv')
print(initial_df.shape)
initial_df.head()
```

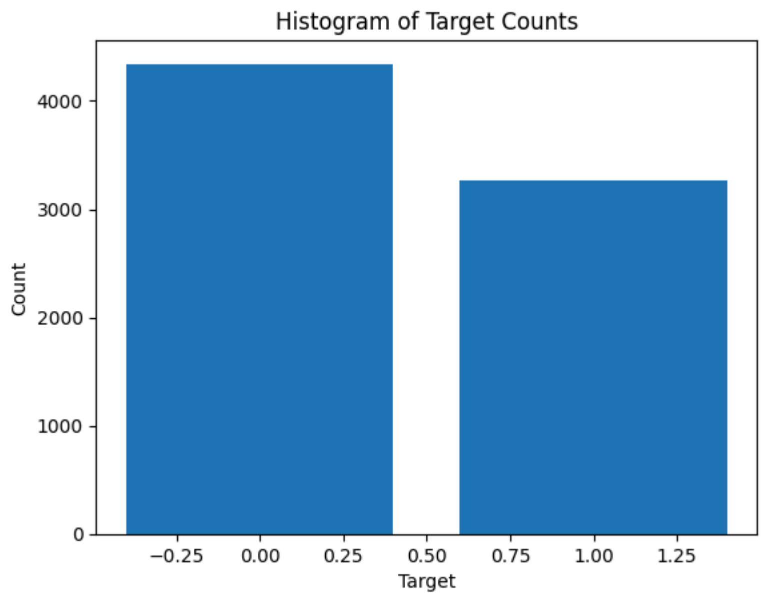
```
(7613, 5)
```

	id	keyword	location	text	target
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M...	1
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1
2	5	NaN	NaN	All residents asked to 'shelter in place' are ...	1
3	6	NaN	NaN	13,000 people receive #wildfires evacuation or...	1
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as ...	1

Exploratory Data Analysis

```
category_counts = initial_df['target'].value_counts()
# Create the histogram
plt.bar(category_counts.index, category_counts.values)
# Add labels and title
plt.xlabel('Target')
plt.ylabel('Count')
plt.title('Histogram of Target Counts')
```

```
# Show the plot
plt.show()
```

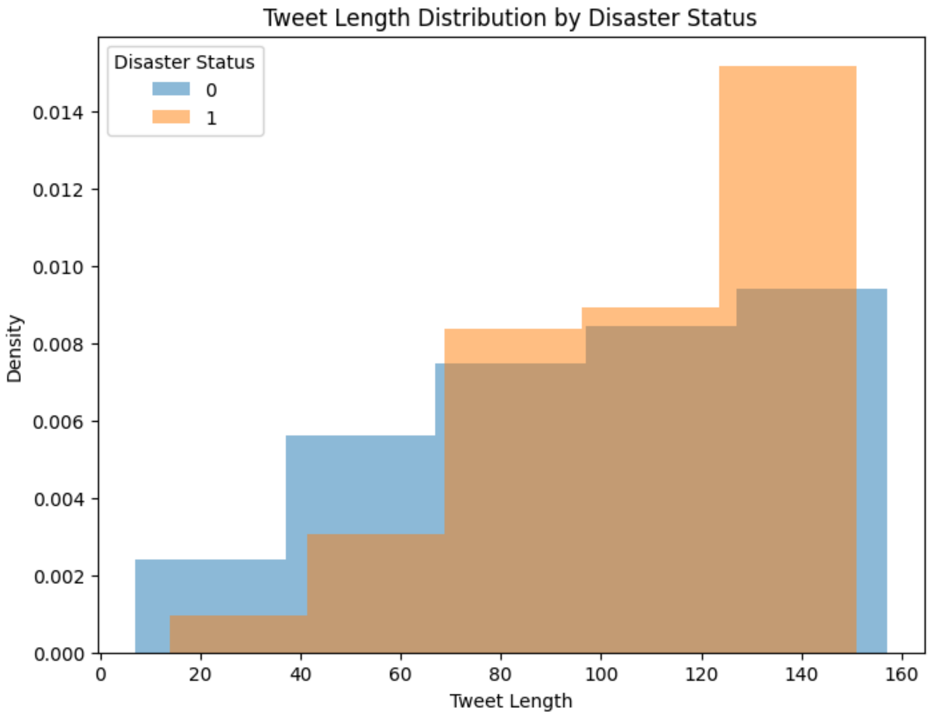



```
initial_df['text_len'] = initial_df["text"].apply(len)
```

```
initial_df.describe()
```

	id	target	text_len
count	7613.000000	7613.00000	7613.000000
mean	5441.934848	0.42966	101.037436
std	3137.116090	0.49506	33.781325
min	1.000000	0.00000	7.000000
25%	2734.000000	0.00000	78.000000
50%	5408.000000	0.00000	107.000000
75%	8146.000000	1.00000	133.000000
max	10873.000000	1.00000	157.000000

```
grouped = initial_df.groupby('target')
# Plot histograms for each category
plt.figure(figsize=(8, 6))
for name, group in grouped:
  plt.hist(group['text_len'], bins=5, alpha=0.5, label=name, density=True)
plt.xlabel('Tweet Length')
plt.ylabel('Density')
plt.title('Tweet Length Distribution by Disaster Status')
plt.legend(title='Disaster Status')
plt.show()
```



Tweets about disasters do tend to be longer than non-disaster tweets and there's a slight imbalance in the dataset but nothing that requires extra measures in my opinion - especially considering that we don't have very much training data to begin with. I wouldn't want to downsample and lose training examples.

Dataset Prep and Initial Model Creation

```
train_df, valid_df = train_test_split(initial_df, test_size=0.2, random_state=121, stratify=initial_df.target)

print(train_df.shape)
print(valid_df.shape)
```

```
(6090, 5)
(1523, 5)
```

```
train_tf = pandas_to_dataset(train_df, 'text', 'target')
valid_tf = pandas_to_dataset(valid_df, 'text', 'target')
test_tf = pandas_to_dataset(test_df, 'text', None)
```

```
example, label = next(iter(train_tf))
print('Text:\n', example.numpy()[0])
print('\nLabel: ', label.numpy()[0])
```

```
Text:
 b'Julie + R is the apocalypse version of Romeo + Juliet #warmbodies'

Label:  0
```

```
encoder = tf.keras.layers.TextVectorization(max_tokens=10000)
encoder.adapt(train_tf.map(lambda text, _: text))

# Extracting the vocabulary from the TextVectorization layer.
vocabulary = np.array(encoder.get_vocabulary())

# Encoding a test example and decoding it back.
original_text = example.numpy()[0]
encoded_text = encoder(original_text).numpy()
decoded_text = ' '.join(vocabulary[encoded_text])

print('original: ', original_text)
print('encoded: ', encoded_text)
print('decoded: ', decoded_text)
```

```
original:  b'Julie + R is the apocalypse version of Romeo + Juliet #warmbodies'
encoded:  [3426  897    9    2  650 1154    6 8363    1 6426]
decoded:  julie r is the apocalypse version of romeo [UNK] warmbodies
```

```
len(encoder.get_vocabulary())
```

```
10000
```

I've decided to create a straightforward LSTM model to set the baseline for this task. The dataset is fairly small so I want to start with a simple model architecture. The memory component of the LSTM layers are well-suited to the task of putting words in context with one another to determine whether or not the text pertains to a disaster.

```
# Creating the model
model = tf.keras.Sequential([
  tf.keras.Input(shape=(1,), dtype=tf.string),
  encoder,
  tf.keras.layers.Embedding(
    len(encoder.get_vocabulary()), 64, mask_zero=True),
  tf.keras.layers.Bidirectional(
    tf.keras.layers.LSTM(64, return_sequences=True)),
  tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32)),
  tf.keras.layers.Dense(64, activation='relu'),
  tf.keras.layers.Dense(1, activation = 'sigmoid')
])

# Summary of the model
model.summary()

# Compile the model
model.compile(
  loss=tf.keras.losses.BinaryCrossentropy(),
  optimizer=tf.keras.optimizers.Adam(),
  metrics=['accuracy']
)
```

Model: "sequential_16"

Layer (type)	Output Shape	Param #
text_vectorization_5 (TextVectorization)	(None, None)	0
embedding_16 (Embedding)	(None, None, 64)	320,000
bidirectional_12 (Bidirectional)	(None, None, 128)	66,048
bidirectional_13 (Bidirectional)	(None, 64)	41,216
dense_32 (Dense)	(None, 64)	4,160
dense_33 (Dense)	(None, 1)	65

Total params: 431,489 (1.65 MB)
Trainable params: 431,489 (1.65 MB)
Non-trainable params: 0 (0.00 B)

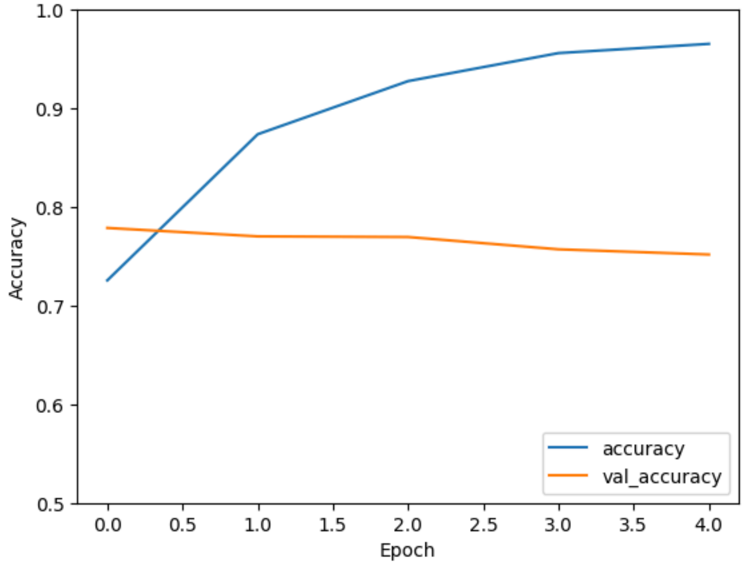
```
# Training the model and validating it on test set
history = model.fit(
    train_tf,
    epochs=5,
    validation_data=valid_tf,
)
```

```
Epoch 1/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 23s 126ms/step - accuracy: 0.6336 - loss: 0.6239 - val_accuracy: 0.7669 - val_loss: 0.5034
Epoch 2/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 10s 106ms/step - accuracy: 0.8485 - loss: 0.3699 - val_accuracy: 0.7669 - val_loss: 0.5153
Epoch 3/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 12s 123ms/step - accuracy: 0.8937 - loss: 0.2744 - val_accuracy: 0.7577 - val_loss: 0.6293
Epoch 4/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 12s 120ms/step - accuracy: 0.9221 - loss: 0.2150 - val_accuracy: 0.7577 - val_loss: 0.7288
Epoch 5/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 11s 115ms/step - accuracy: 0.9400 - loss: 0.1706 - val_accuracy: 0.7485 - val_loss: 0.6917
```

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
```

```
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x7ca01b565b90>
```




```
test_pred = model.predict(test_tf)
test_pred = test_pred.reshape(-1)
test_pred.shape
```

```
51/51 ━━━━━━━━━━━━━━━━━━━━ 4s 63ms/step
(3263,)
```

```
test_pred
```

```
array([0.56881297, 0.13576531, 0.994531  , ..., 0.97534287, 0.9398776 ,
       0.9872991 ], dtype=float32)
```

```
test_df['target'] = test_pred
submit_df = test_df[['id', 'target']]
submit_df = submit_df.round()
submit_df.to_csv('/content/submission-initial.csv', index=False)
```

Simpler GRU Model with Dropout

The first model I tried quickly overfit the data wo I'm adding in a dropout layer after the dense layer and also trying Gated Recurrent Units rather than LSTM units. GRU is a simpler architecture and is appropriate when the task doesn't require memory for long sequences. Given that we're working with tweets, that seems appropriate.

```
# Creating the model
model = tf.keras.Sequential([
    tf.keras.Input(shape=(1,), dtype=tf.string),
  encoder,
    tf.keras.layers.Embedding(
        len(encoder.get_vocabulary()), 64, mask_zero=True),
    tf.keras.layers.GRU(units=64, return_sequences=True),
    tf.keras.layers.GRU(units=64),
    tf.keras.layers.Dense(64, activation='relu'),
  tf.keras.layers.Dropout(0.35),
    tf.keras.layers.Dense(1, activation = 'sigmoid')
])

# Summary of the model
model.summary()

# Adding Early Stopping
callback = EarlyStopping(monitor='val_accuracy',
                         patience=0,
```

```
        verbose=0,
        mode='auto',
        baseline=None,
        restore_best_weights=True
    )

    # Compile the model
    model.compile(
        loss=tf.keras.losses.BinaryCrossentropy(),
        optimizer=tf.keras.optimizers.Adam(),
        metrics=['accuracy']
    )
```

Model: "sequential_14"

Layer (type)	Output Shape	Param #
text_vectorization_3 (TextVectorization)	(None, None)	0
embedding_14 (Embedding)	(None, None, 64)	640,000
gru_14 (GRU)	(None, None, 64)	24,960
gru_15 (GRU)	(None, 64)	24,960
dense_28 (Dense)	(None, 64)	4,160
dropout_3 (Dropout)	(None, 64)	0
dense_29 (Dense)	(None, 1)	65

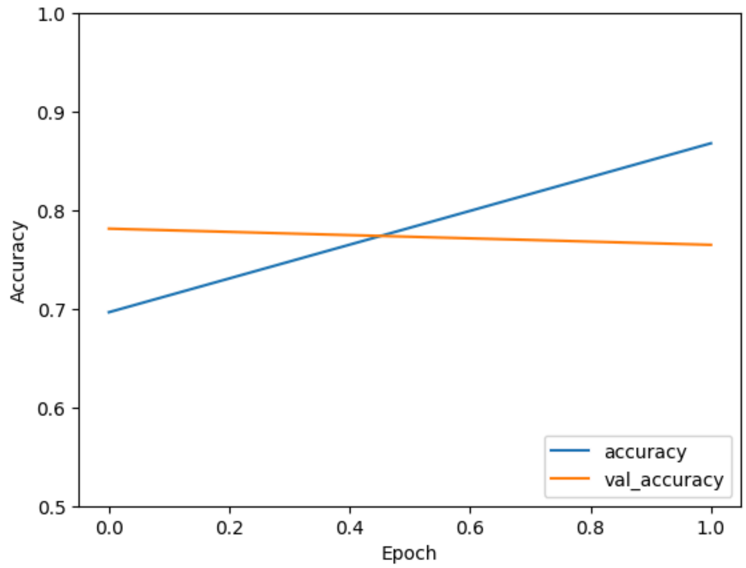
Total params: 694,145 (2.65 MB)
Trainable params: 694,145 (2.65 MB)
Non-trainable params: 0 (0.00 B)

```
# Training the model and validating it on test set
history = model.fit(
    train_tf,
    epochs=5,
    validation_data=valid_tf,
  callbacks=[callback]
)
```

```
Epoch 1/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 15s 93ms/step - accuracy: 0.6109 - loss: 0.6494 - val_accuracy: 0.7807 - val_loss: 0.4831
Epoch 2/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 7s 70ms/step - accuracy: 0.8496 - loss: 0.3718 - val_accuracy: 0.7708 - val_loss: 0.5240
```

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x7ca01b2d7c50>
```




```
test_pred = model.predict(test_tf)
test_pred = test_pred.reshape(-1)
test_pred.shape
```

```
51/51 ━━━━━━━━━━━━━━━━━━━━ 3s 41ms/step
(3263,)
```

```
test_df['target'] = test_pred
submit_df = test_df[['id', 'target']]
submit_df = submit_df.round()
submit_df.to_csv('/content/submission-gru-early.csv', index=False)
```

I added early stopping in anticipation of some overfitting and that was the case again. This model also didn't pass the scoring threshold.

Adding Regularization and Dropout

In an effort to reduce overfitting, I've added regularization to the dense layer and added dropout and recurrent dropout to the bidirectional layers.

```
model = tf.keras.Sequential([
    tf.keras.Input(shape=(1,), dtype=tf.string),
    encoder,
    tf.keras.layers.Embedding(len(encoder.get_vocabulary()), 64, mask_zero=True),

    tf.keras.layers.Bidirectional(
        tf.keras.layers.LSTM(64, return_sequences=True, dropout=0.3, recurrent_dropout=0.2)),

    tf.keras.layers.Bidirectional(
        tf.keras.layers.LSTM(32, dropout=0.3, recurrent_dropout=0.2)),

    tf.keras.layers.Dense(64, activation='relu',
                          kernel_regularizer=tf.keras.regularizers.l2(0.01)),

    tf.keras.layers.Dropout(0.4),
    tf.keras.layers.Dense(1, activation='sigmoid')
])


# Summary of the model
model.summary()

# Compile the model
model.compile(
    loss=tf.keras.losses.BinaryCrossentropy(),
    optimizer=tf.keras.optimizers.Adam(),
```

```
    metrics=['accuracy']
)
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
text_vectorization (TextVectorization)	(None, None)	0
embedding_1 (Embedding)	(None, None, 64)	640,000
bidirectional (Bidirectional)	(None, None, 128)	66,048
bidirectional_1 (Bidirectional)	(None, 64)	41,216
dense_2 (Dense)	(None, 64)	4,160
dropout_1 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 1)	65

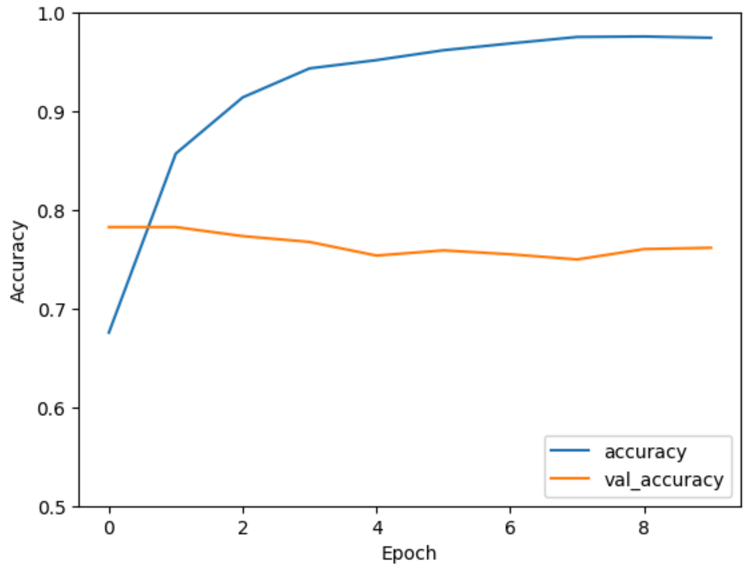
```
Total params: 751,489 (2.87 MB)
Trainable params: 751,489 (2.87 MB)
Non-trainable params: 0 (0.00 B)
```

```
history = model.fit(
    train_tf,
    epochs=10,
    validation_data=valid_tf,
)
```

```
Epoch 1/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 40s 260ms/step - accuracy: 0.5985 - loss: 1.1418 - val_accuracy: 0.7827 - val_loss: 0.6673
Epoch 2/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 23s 235ms/step - accuracy: 0.8387 - loss: 0.5431 - val_accuracy: 0.7827 - val_loss: 0.5818
Epoch 3/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 22s 229ms/step - accuracy: 0.9049 - loss: 0.3054 - val_accuracy: 0.7735 - val_loss: 0.6175
Epoch 4/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 22s 229ms/step - accuracy: 0.9381 - loss: 0.2058 - val_accuracy: 0.7676 - val_loss: 0.7005
Epoch 5/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 22s 231ms/step - accuracy: 0.9511 - loss: 0.1688 - val_accuracy: 0.7538 - val_loss: 0.7056
Epoch 6/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 23s 239ms/step - accuracy: 0.9627 - loss: 0.1297 - val_accuracy: 0.7590 - val_loss: 0.7524
Epoch 7/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 22s 234ms/step - accuracy: 0.9688 - loss: 0.1097 - val_accuracy: 0.7551 - val_loss: 0.8599
Epoch 8/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 23s 234ms/step - accuracy: 0.9760 - loss: 0.0865 - val_accuracy: 0.7498 - val_loss: 0.8943
Epoch 9/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 22s 229ms/step - accuracy: 0.9766 - loss: 0.0843 - val_accuracy: 0.7603 - val_loss: 0.9213
Epoch 10/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 22s 227ms/step - accuracy: 0.9764 - loss: 0.0751 - val_accuracy: 0.7617 - val_loss: 0.9525
```

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x7aab5d39f2d0>
```




```
test_pred = model.predict(test_tf)
test_pred = test_pred.reshape(-1)
test_pred.shape
```

```
51/51 ━━━━━━━━━━━━━━━━━━━━ 6s 83ms/step
(3263,)
```

```
test_df['target'] = test_pred
submit_df = test_df[['id', 'target']]
submit_df = submit_df.round()
submit_df.to_csv('/content/submission-reg-dropout.csv', index=False)
```

Regularization and Dropout with Early Stopping

```
model = tf.keras.Sequential([
    tf.keras.Input(shape=(1,), dtype=tf.string),
    encoder,
    tf.keras.layers.Embedding(len(encoder.get_vocabulary()), 64, mask_zero=True),

    tf.keras.layers.Bidirectional(
        tf.keras.layers.LSTM(64, return_sequences=True, dropout=0.3, recurrent_dropout=0.2)),

    tf.keras.layers.Bidirectional(
        tf.keras.layers.LSTM(32, dropout=0.3, recurrent_dropout=0.2)),

    tf.keras.layers.Dense(64, activation='relu',
                          kernel_regularizer=tf.keras.regularizers.l2(0.01)),

    tf.keras.layers.Dropout(0.4),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

# Summary of the model
model.summary()

# Adding Early Stopping
callback = EarlyStopping(monitor='val_accuracy',
                         patience=0,
    verbose=0,
    mode='auto',
    baseline=None,
    restore_best_weights=True
)

# Compile the model
model.compile(
    loss=tf.keras.losses.BinaryCrossentropy(),
    optimizer=tf.keras.optimizers.Adam(),
```

```
    metrics=['accuracy']
)
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
text_vectorization (TextVectorization)	(None, None)	0
embedding_2 (Embedding)	(None, None, 64)	640,000
bidirectional_2 (Bidirectional)	(None, None, 128)	66,048
bidirectional_3 (Bidirectional)	(None, 64)	41,216
dense_4 (Dense)	(None, 64)	4,160
dropout_2 (Dropout)	(None, 64)	0
dense_5 (Dense)	(None, 1)	65

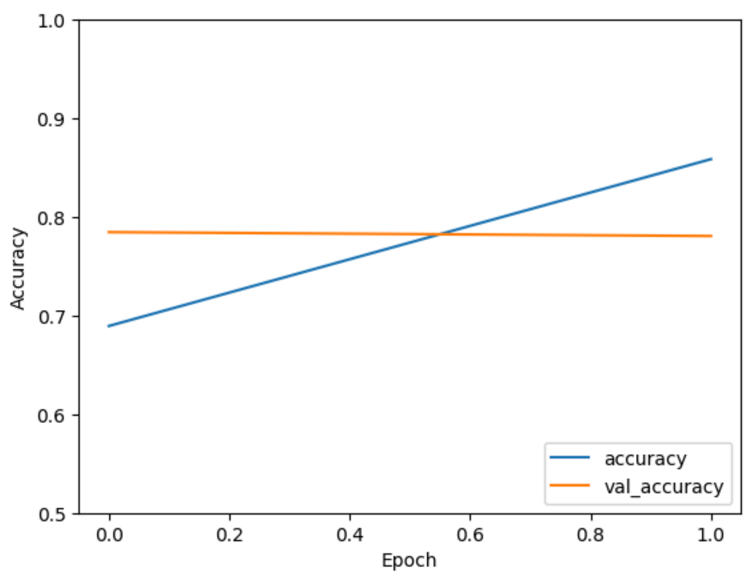
Total params: 751,489 (2.87 MB)
Trainable params: 751,489 (2.87 MB)
Non-trainable params: 0 (0.00 B)

```
# Training the model and validating it on test set
history = model.fit(
    train_tf,
    epochs=5,
    validation_data=valid_tf,
  callbacks=[callback]
)
```

```
Epoch 1/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 39s 255ms/step - accuracy: 0.6128 - loss: 1.1299 - val_accuracy: 0.7846 - val_loss: 0.6582
Epoch 2/5
96/96 ━━━━━━━━━━━━━━━━━━━━ 23s 238ms/step - accuracy: 0.8413 - loss: 0.5190 - val_accuracy: 0.7807 - val_loss: 0.5476
```

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5, 1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x7aaca1968b90>
```




```
test_pred = model.predict(test_tf)
test_pred = test_pred.reshape(-1)
test_pred.shape
```

```
51/51 ━━━━━━━━━━━━━━━━━━━━ 6s 85ms/step
(3263,)
```

```
test_df['target'] = test_pred
submit_df = test_df[['id', 'target']]
submit_df = submit_df.round()
submit_df.to_csv('/content/submission-reg-dropout-early.csv', index=False)
```

Pretrained Network Approach

The various iterations of recurrent neural networks that I've created and trained have all failed to beat the scoring threshold for this task, unfortunately. Here, I go with a different approach and use a pretrained network for the task. Below, I bring the "BertForSequenceClassification" model into the environment and train it for just one epoch on this classification task.

```
# Initialize tokenizer
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

def tokenize_data(df, tokenizer):
    return tokenizer(df['text'].tolist(), padding=True, truncation=True, max_length=128, return_tensors="pt")

# Encode the data
train_encodings = tokenize_data(train_df, tokenizer)
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it as secre
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
tokenizer_config.json: 100%    48.0/48.0 [00:00<00:00, 649B/s]
vocab.txt: 100%    232k/232k [00:00<00:00, 1.37MB/s]
tokenizer.json: 100%    466k/466k [00:00<00:00, 6.54MB/s]
config.json: 100%    570/570 [00:00<00:00, 19.0kB/s]
```

```
class TweetDataset(Dataset):
    def __init__(self, encodings, labels=None):
        self.encodings = encodings
        self.labels = labels

    def __getitem__(self, idx):
        item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
        if self.labels is not None:
            item['labels'] = torch.tensor(self.labels[idx])
        return item

    def __len__(self):
        return len(self.encodings['input_ids'])
```

```
training_args = TrainingArguments(
    output_dir='./results',
    num_train_epochs=1,
    per_device_train_batch_size=32,
    per_device_eval_batch_size=64,
    warmup_steps=500,
    weight_decay=0.01,
    logging_dir='./logs',
    logging_steps=50,
    evaluation_strategy="epoch"
)
```

```
model = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=2)
model.to(torch.device("cuda" if torch.cuda.is_available() else "cpu"))
```

```
Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncased and are newly initiali
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
BertForSequenceClassification(
  (bert): BertModel(
    (embeddings): BertEmbeddings(
      (word_embeddings): Embedding(30522, 768, padding_idx=0)
      (position_embeddings): Embedding(512, 768)
      (token_type_embeddings): Embedding(2, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
```

```
    )
    (encoder): BertEncoder(
      (layer): ModuleList(
        (0-11): 12 x BertLayer(
          (attention): BertAttention(
            (self): BertSdpaSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
            (dense): Linear(in_features=768, out_features=3072, bias=True)
            (intermediate_act_fn): GELUActivation()
          )
          (output): BertOutput(
            (dense): Linear(in_features=3072, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
      )
    )
    (pooler): BertPooler(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (activation): Tanh()
    )
  )
  (dropout): Dropout(p=0.1, inplace=False)
  (classifier): Linear(in_features=768, out_features=2, bias=True)
)
```

```
# Tokenize both training and validation data
train_encodings = tokenize_data(train_df, tokenizer)
val_encodings = tokenize_data(valid_df, tokenizer)

# Create datasets
train_dataset = TweetDataset(train_encodings, train_df['target'].values)
val_dataset = TweetDataset(val_encodings, valid_df['target'].values)
```

```
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=val_dataset,  # Adding the validation dataset here
    compute_metrics=lambda p: {'accuracy': (np.argmax(p.predictions, axis=1) == p.label_ids).mean()}
)
```

```
trainer.train()
```

```
<ipython-input-11-ec98418e07fc>:7: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach()
  item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
```

[191/191 1:34:56, Epoch 1/1]

Epoch	Training Loss	Validation Loss	Accuracy
1	0.473400	0.439386	0.813526

```
<ipython-input-11-ec98418e07fc>:7: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach()
  item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
TrainOutput(global_step=191, training_loss=0.5455501416590826, metrics={'train_runtime': 5738.2009, 'train_samples_per_second': 1.061,
'train_steps_per_second': 0.033, 'total_flos': 262884944296800.0, 'train_loss': 0.5455501416590826, 'epoch': 1.0})
```

```
test_encodings = tokenize_data(test_df, tokenizer)
test_dataset = TweetDataset(test_encodings)
predictions = trainer.predict(test_dataset)
predicted_labels = np.argmax(predictions.predictions, axis=1)

# Create a submission DataFrame
submission = pd.DataFrame({
    'id': test_df['id'],
```

```
    'target': predicted_labels
})
```

```
<ipython-input-11-ec98418e07fc>:7: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach()
  item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
```

```
submission.to_csv('pretrained-submission.csv', index=False)
```