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()
```

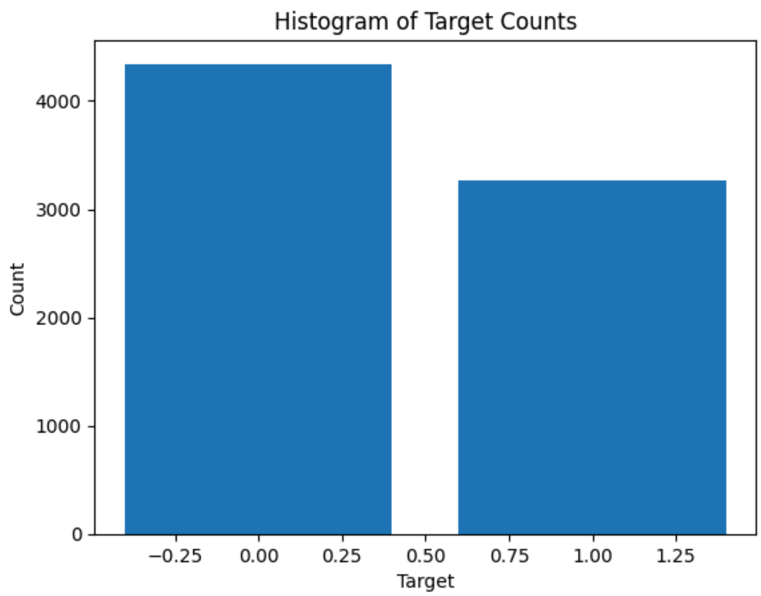
```
(7613, 5)
```

	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()
```

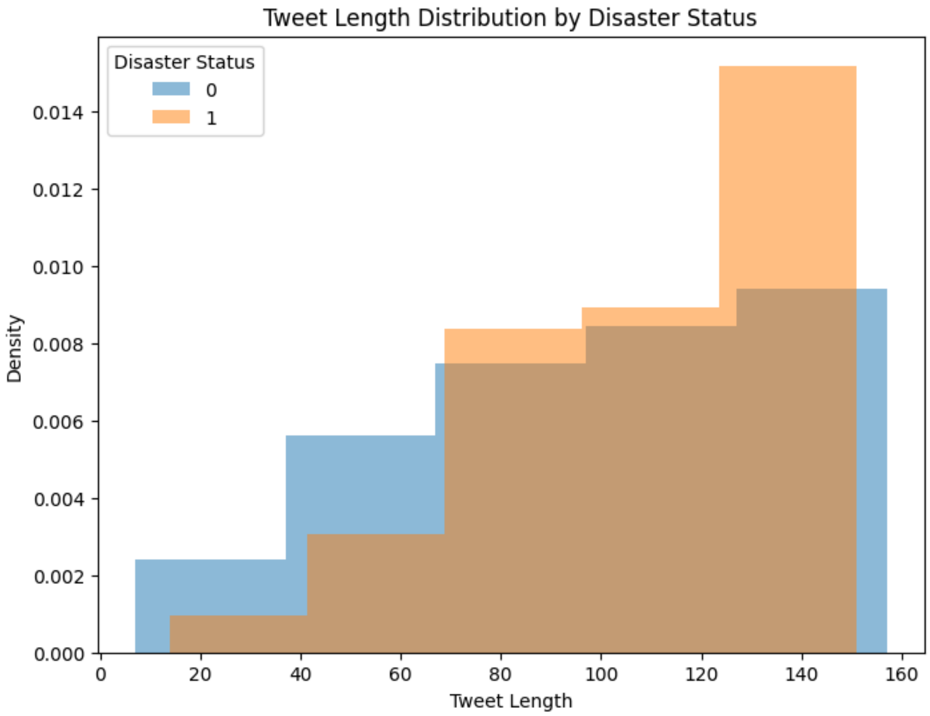



```
initial_df['text_len'] = initial_df["text"].apply(len)
```

```
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

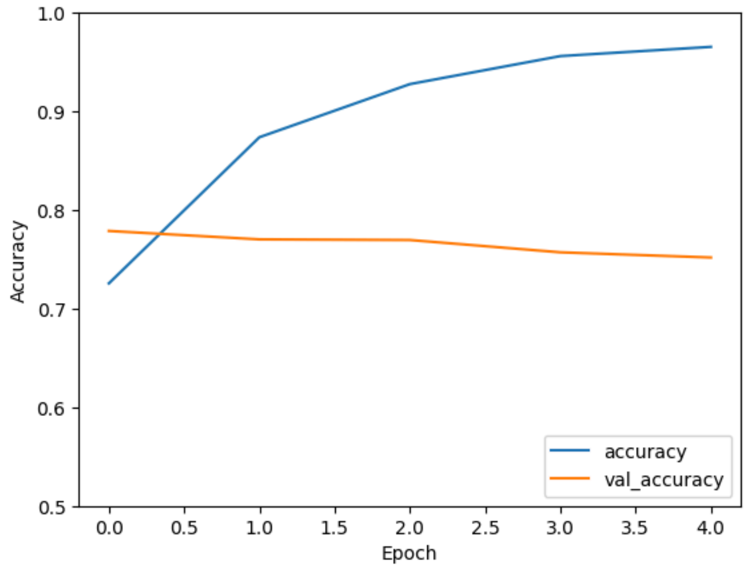
Total params: 431,489 (1.65 MB)
Trainable params: 431,489 (1.65 MB)
Non-trainable params: 0 (0.00 B)

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

Show hidden output

```
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

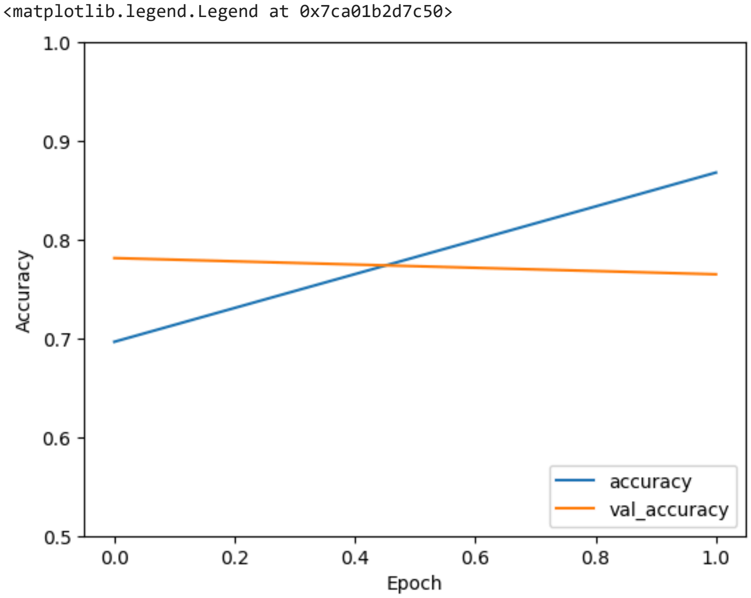
Total params: 694,145 (2.65 MB)
Trainable params: 694,145 (2.65 MB)
Non-trainable params: 0 (0.00 B)

```
# 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']
)
```

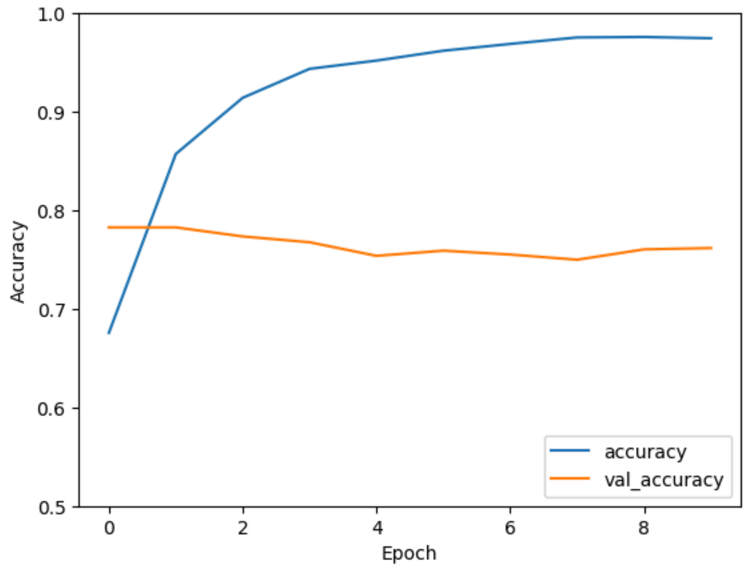
Show hidden output

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

Show hidden output

```
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']
```

```
)
```

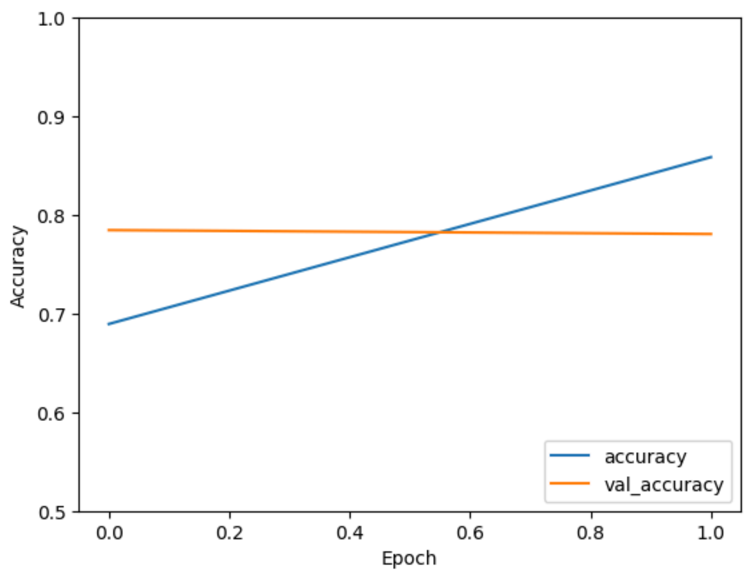
Show hidden output

```
# 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")
```

```
    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)
```

Show hidden output

```
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"))
```

Show hidden output

```
# 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()
```

Show hidden output

Results and Analysis

Overall, the various RNN architectures that I tried were not successful in this competition. Even with regularization and dropout, the models began to overfit after just a few epochs. I wonder if there are not enough records in the training set for the neural network to learn general patterns rather than just memorizing the answers for that specifi dataset.

The pretrained network was significantly more effective, even with just one training epoch on this specific task. The pretrained network begins with an ability to detect general language patterns, unlike the from-scratch recurrent models which all seem to be memorizing training-data-specific patterns that don't generalize particularly well.

Model	Best Validation Loss	Final Validation Loss	Test Score
Initial LSTM	0.5	0.69	0
GRU with Dropout	0.48	0.52	0
LSTM Regularization + Dropout	0.58	0.95	0
LSTM Regularization + Dropout with Early Stopping	0.55	0.55	0
Pretrained BERT Sequence Classifier	0.44	0.44	0.827

Conclusion

It was disappointing to have my efforts in making from-scratch networks be unsuccessful. I believe that I identified the right issue - overfitting - but the approaches that I took to fix it didn't end up helping. I think that's in part because the dataset is only about 10,000 examples. That's as small as it gets for deep learning techniques.

If I were to continue working on this problem, I'd put my next efforts into a more traditional NLP approach and spend more time preprocessing the texts. Another fruitful path might be to train the pretrained network over more epochs and/or compare other pretrained networks. Pretrained networks allow us to apply the learnings from much larger datasets to custom tasks like this and are an amazing innovation and a testament to the power of open source tools.

References

Hugging Face Text Classification guide: https://huggingface.co/docs/transformers/en/tasks/sequence_classification

BERT Classifier: https://huggingface.co/docs/transformers/en/model_doc/bert#transformers.BertForSequenceClassification

Tensorflow Embedding Layer: https://www.tensorflow.org/api_docs/python/tf/keras/layers/Embedding

```
# code placeholder
```

```
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)
```