Week 4: NLP Disaster Tweets Kaggle Mini-Project

Loading the required modules below.

In [370…

```
import numpy as np
import pandas as pd
import re
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
import tensorflow_datasets as tfds
from collections import Counter

import keras
from keras import layers
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
```

Brief description of the problem and data (5 pts)

Briefly describe the challenge problem and NLP. Describe the size, dimension, structure, etc., of the data.

This data set consists of tweets (text) and the training portion is labeled based on if the tweet is about a disaster or not. The objective is to create a model that can predict if a tweet is about a disaster or not. We will be using NLP tecnhiques, namely Long Short-Term Memory architecture, to classify the text/tweet.

The data comes in csv-files. Training data has 7613 entries (6961 after removing duplicates). In addition to the text and the target label, the training set has id, location and keyword which are ignored in this work. The split between the two label is fairly even, 57/43. Testing data has 3236 entries. The tweets have different amount of words, up to 31 words. More basic information about the data is printed in the code below.

In [371…

```
def count_words(df):
    for i, row in df.iterrows():
        df.loc[i, 'word_count'] = len(row.text.split())
        txt = df.loc[i, 'text']
        txt = re.sub(r'https?://\S+|www.\S+', '', txt) # Remove URLs
        txt = re.sub(r'[^a-z0-9A-Z\s]', '', txt) # Remove numbers
        # txt = txt.lower()
        df.loc[i, 'text'] = txt
    df['word_count'] = df['word_count'].astype(int)
    all_text = ' '.join(df.text)
    unique_words = len(set(all_text.split()))
```

```
    return unique_words

train_df = pd.read_csv('train.csv')
test_df = pd.read_csv('test.csv')

train_unique_words = count_words(train_df)
test_unique_words = count_words(test_df)

all_text = ' '.join(((pd.concat([train_df,test_df], axis=0)).text.values))
all_unique_words = len(set(all_text.split()))


print('\n' + 40*'*' + ' Train dataset ' + 40*'*')
train_df.info()
print('\nNumerical statistics:\n', train_df.describe())
print('\n', train_df.head(4), '\n')
# print('\n', train_df.tail(3))
print('Number of duplicated rows:', np.sum(train_df.duplicated()))
print('Number of duplicated texts:', np.sum(train_df.duplicated(subset='text')))
print('Longest tweet has', np.max(train_df.word_count), 'words.')
print('Unique words in the dataset:', train_unique_words)
print('Target values:', pd.unique(train_df.target))
y_split = round(100 * np.sum(train_df.target == 1)/len(train_df.target))
print('Target split: \n1 (disaster) =', y_split, '%\n0 (not disaster) =', 100-y_spl
sns.countplot(train_df, x='target')
plt.title('Target label split')
plt.show()

print('\n' + 40*'*' + ' Test dataset ' + 40*'*')
test_df.info()
print('\nNumerical statistics:\n', test_df.describe())
print('\n', test_df.head(4), '\n')
# print('\n', test_df.tail(3))
print('Number of duplicated rows:', np.sum(test_df.duplicated()))
print('Number of duplicated texts:', np.sum(test_df.duplicated(subset='text')))
print('Longest tweet has', np.max(test_df.word_count), 'words.')
print('Unique words in the dataset:', test_unique_words)
```

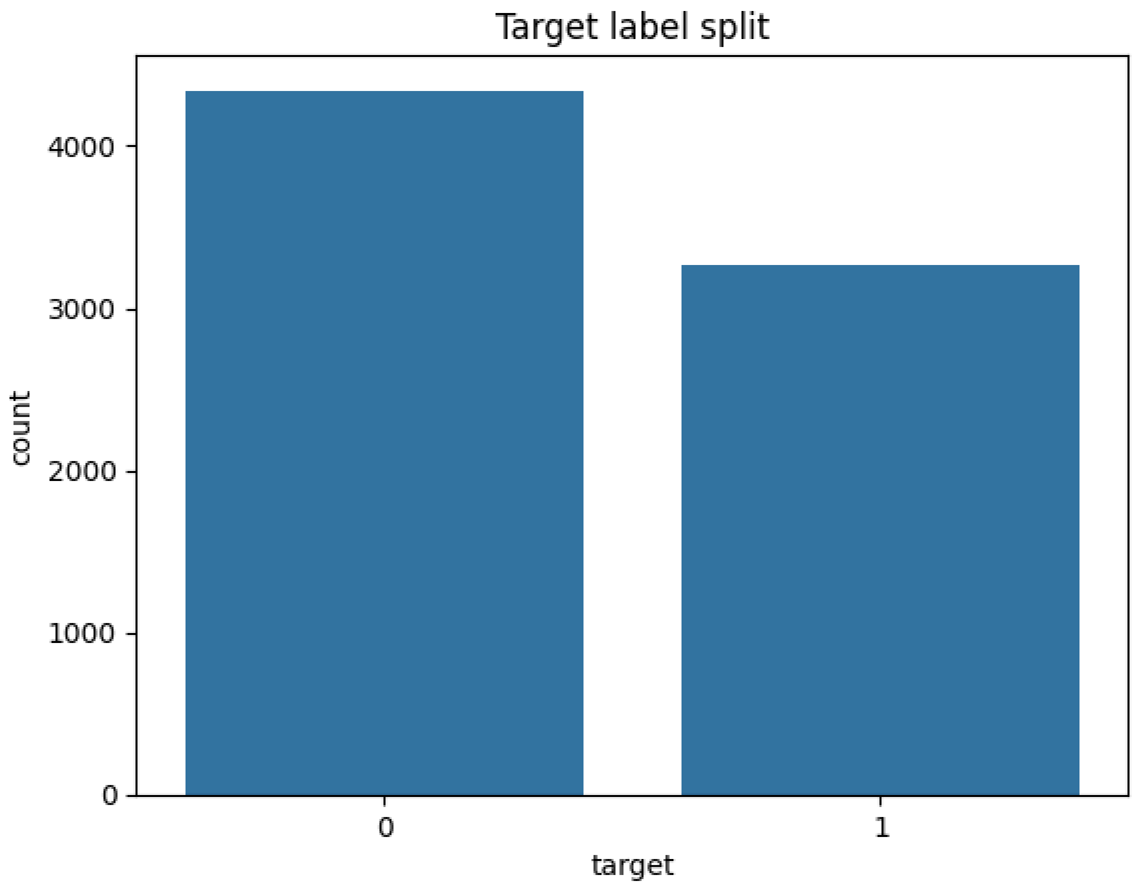
```
**************************************** Train dataset *****************************
***********
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          7613 non-null   int64 
 1   keyword     7552 non-null   object
 2   location    5080 non-null   object
 3   text        7613 non-null   object
 4   target      7613 non-null   int64 
 5   word_count  7613 non-null   int64 
dtypes: int64(3), object(3)
memory usage: 357.0+ KB

Numerical statistics:
                 id      target   word_count
count   7613.000000  7613.00000  7613.000000
mean    5441.934848     0.42966    14.903586
std     3137.116090     0.49506     5.732604
min        1.000000     0.00000     1.000000
25%     2734.000000     0.00000    11.000000
50%     5408.000000     0.00000    15.000000
75%     8146.000000     1.00000    19.000000
max    10873.000000     1.00000    31.000000

    id keyword location                                               text  \
0   1     NaN      NaN  Our Deeds are the Reason of this earthquake Ma...
1   4     NaN      NaN             Forest fire near La Ronge Sask Canada
2   5     NaN      NaN  All residents asked to shelter in place are be...
3   6     NaN      NaN  13000 people receive wildfires evacuation orde...

   target  word_count
0       1          13
1       1           7
2       1          22
3       1           8

Number of duplicated rows: 0
Number of duplicated texts: 652
Longest tweet has 31 words.
Unique words in the dataset: 21891
Target values: [1 0]
Target split:
1 (disaster) = 43 %
0 (not disaster) = 57 %
```


Target label split
count
4000
3000
2000
1000
0
0
1
target

```
**************************************** Test dataset ******************************
**********
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3263 entries, 0 to 3262
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          3263 non-null   int64 
 1   keyword     3237 non-null   object
 2   location    2158 non-null   object
 3   text        3263 non-null   object
 4   word_count  3263 non-null   int64 
dtypes: int64(2), object(3)
memory usage: 127.6+ KB

Numerical statistics:
                 id   word_count
count   3263.000000  3263.000000
mean    5427.152927    14.965369
std     3146.427221     5.783576
min        0.000000     1.000000
25%     2683.000000    11.000000
50%     5500.000000    15.000000
75%     8176.000000    19.000000
max    10875.000000    31.000000

    id keyword location                                               text  \
0   0     NaN      NaN                 Just happened a terrible car crash   
1   2     NaN      NaN  Heard about earthquake is different cities sta...   
2   3     NaN      NaN  there is a forest fire at spot pond geese are ...   
3   9     NaN      NaN              Apocalypse lighting Spokane wildfires   

   word_count  
0           6  
1           9  
2          19  
3           4  

Number of duplicated rows: 0
Number of duplicated texts: 157
Longest tweet has 31 words.
Unique words in the dataset: 12889
```

Exploratory Data Analysis (EDA) — Inspect, Visualize and Clean the Data (15 pts)

Show a few visualizations like histograms. Describe any data cleaning procedures. Based on your EDA, what is your plan of analysis?

Checking the general structure of the data. Check and remove potential duplicates from the training set.

In [372…

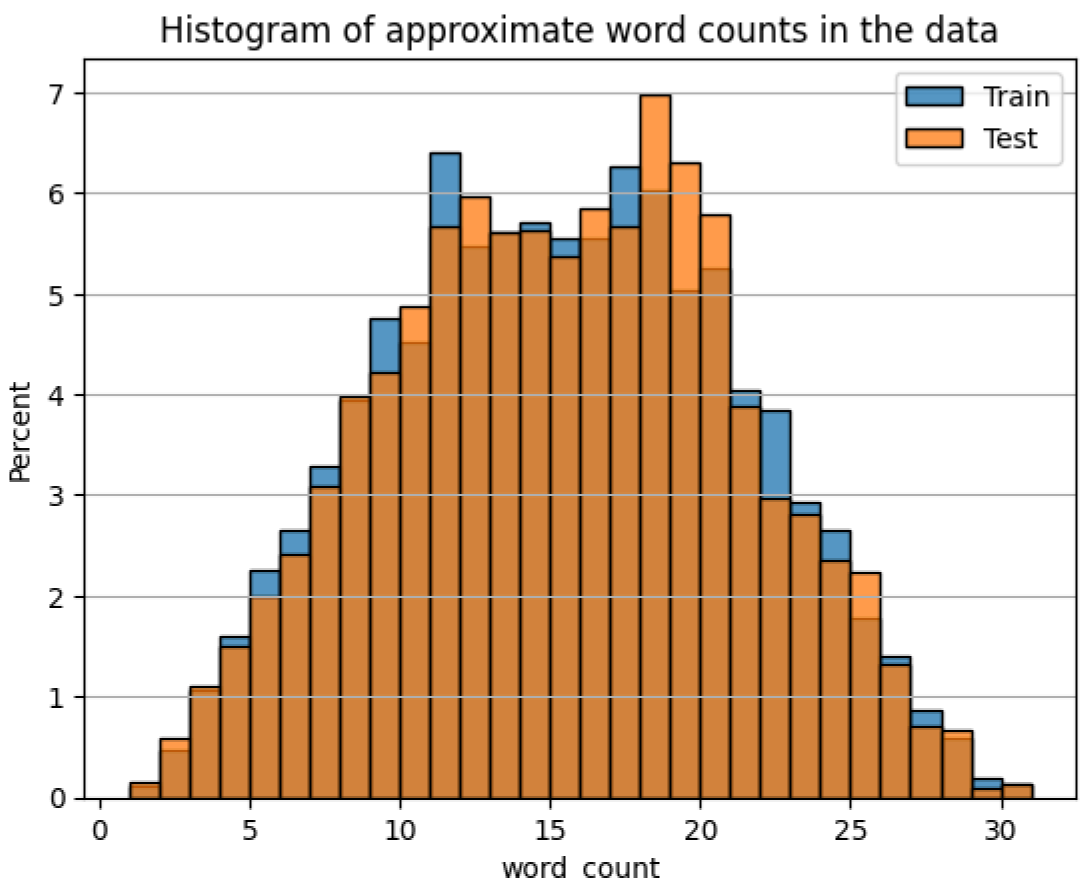
```
print('Size with duplicated texts:', len(train_df))
train_df.drop_duplicates(subset='text', inplace=True)
print('Size without duplicated texts:', len(train_df))
```

```
Size with duplicated texts: 7613
Size without duplicated texts: 6961
```

Checking the distribution of word counts in each tweet. Distibutions seem identical in the training and testing sets.

In [373…

```
sns.histplot(train_df, x='word_count', bins=30, stat='percent')
sns.histplot(test_df, x='word_count', bins=30, stat='percent')
plt.grid(axis='y')
plt.title('Histogram of approximate word counts in the data')
plt.legend(['Train','Test'])
plt.show()
```



In [374…

```
all_text = pd.concat([train_df,test_df], axis=0).text.values
```

Model Architecture (25 pts)

Describe your model architecture and reasoning for why you believe that specific architecture would be suitable for this problem.

Since we did not learn NLP-specific techniques such as word embeddings in the lectures, we recommend looking at Kaggle tutorials, discussion boards, and code examples posted for this challenge. You can use any resources needed, but make sure you "demonstrate" you understood by including explanations in your own words. Also importantly, please have a reference list at the end of the report.

There are many methods to process texts to matrix form (word embedding), including TF-IDF, GloVe, Word2Vec, etc. Pick a strategy and process the raw texts to word embedding. Briefly explain the method(s) and how they work in your own words.

Build and train your sequential neural network model (You may use any RNN family neural network, including advanced architectures LSTM, GRU, bidirectional RNN, etc.).

Using a word tokenization below to map the words. The resulting matrix is also padded to the length of the longest tweet, 31 words.

A few examples from training and testing data are shown.

Text to matrix

In [403…

```
max_features = 5000
```

In [404…

```
my_vectorizer = keras.layers.TextVectorization(
    max_tokens=max_features,
    standardize="lower_and_strip_punctuation",
    split="whitespace",
    ngrams=1,
    output_mode="int",
    output_sequence_length=None,
    pad_to_max_tokens=True,
    vocabulary=None,
    idf_weights=None,
    sparse=False,
    ragged=False,
    encoding="utf-8",
    name=None,
)
my_vectorizer.adapt(train_df['text'])
x_train = my_vectorizer(train_df['text'])
x_test = my_vectorizer(test_df['text'])
y_train = train_df.target

def check_vector(vect, text):
    print('Shape:', vect.shape)
    print('Min and max:', np.min(vect), np.max(vect))
    for txt, vec in zip(text[0:3], vect[0:3]):
        print(txt, '\n', vec[0:15])

print('Training:')
check_vector(x_train, train_df['text'])
print()
```

```
print('Testing:')
check_vector(x_test, test_df['text'])
```

```
Training:
Shape: (6961, 31)
Min and max: 0 4999
Our Deeds are the Reason of this earthquake May ALLAH Forgive us all
 tf.Tensor(
[ 101    1   22    2  735    6   18  219  135 1904    1   65   38    0
    0], shape=(15,), dtype=int64)
Forest fire near La Ronge Sask Canada
 tf.Tensor(
[ 186   42  193  713    1    1 1289    0    0    0    0    0    0    0
    0], shape=(15,), dtype=int64)
All residents asked to shelter in place are being notified by officers No other evac
uation or shelter in place orders are expected
 tf.Tensor(
[  38 1605 1539    4 1974    5  605   22  123    1   19 1620   40  323
  236], shape=(15,), dtype=int64)

Testing:
Shape: (3263, 31)
Min and max: 0 4998
Just happened a terrible car crash
 tf.Tensor(
[  27  787    3 1738  133   98    0    0    0    0    0    0    0    0
    0], shape=(15,), dtype=int64)
Heard about earthquake is different cities stay safe everyone
 tf.Tensor(
[ 382   51  219    9 1030 2530  501 1769  196    0    0    0    0    0
    0], shape=(15,), dtype=int64)
there is a forest fire at spot pond geese are fleeing across the street I cannot sav
e them all
 tf.Tensor(
[  70    9    3  186   42   17  937 2798    1   22    1  764    2  648
    7], shape=(15,), dtype=int64)
```

Also a TF-IDF matrix is created. TF-IDF stands for Term Frequency - Inverse Document Frequency. For each given word, term frequency is the number of times the word appears in the texts and Document Frequency is the number of documents the word appears in. TF-IDF does not take account the word order so I believe it is not be useful for RNN models.

In [377…

```
tfidf_vectorizer = TfidfVectorizer(max_features=max_features)
tfidf_vectors = tfidf_vectorizer.fit_transform(train_df['text'])
tfidf_vectors.shape
```

Out[377…

```
(6961, 5000)
```

Model building

LSTM 1 - Long Short Term Memory network

Basic LSTM with two RNN layers.

In [378…

```
# Input for variable-length sequences of integers
inputs = keras.Input(shape=(None,), dtype="int32")
# Embed each integer in a 128-dimensional vector
x = layers.Embedding(max_features, 128)(inputs)
# Add 2 LSTMs
# x = layers.LSTM(128, return_sequences=True)(x)
x = layers.LSTM(128, return_sequences=True)(x)
x = layers.LSTM(128)(x)
# Add a classifier
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.summary()
model_name = 'LSTM'
```

Model: "functional_33"

Layer (type)	Output Shape	Param #
input_layer_47 (InputLayer)	(None, None)	0
embedding_36 (Embedding)	(None, None, 128)	640,000
lstm_49 (LSTM)	(None, None, 128)	131,584
lstm_50 (LSTM)	(None, 128)	131,584
dense_36 (Dense)	(None, 1)	129

Total params: 903,297 (3.45 MB)

Trainable params: 903,297 (3.45 MB)

Non-trainable params: 0 (0.00 B)

LSTM 2 - Long Short Term Memory network

Two-layer LSTM with added dropout function.

In [405…

```
## Source: https://www.kaggle.com/code/anmolstha/disaster-tweets-simple-rnn-impleme

# We need sequential model to process sequence of text data
model = keras.models.Sequential()

# Embedding(input_dimension, output_dimension,embeddings_initializer = initialize t
embedding= layers.Embedding(max_features, 128)#, trainable=False)
# Adding Embedding Layer
model.add(embedding)

# Drops 40% of entire row
model.add(layers.SpatialDropout1D(0.4))

# Recurrent Layer LSTM(dimensionality of the output space, dropout = 20%, recurrent
model.add(layers.LSTM(128, dropout=0.2, recurrent_dropout=0.2, return_sequences=Tru
model.add(layers.LSTM(128, dropout=0.2, recurrent_dropout=0.2))
```

```
# Decide what we are going to output Dense(units, activation function)
model.add(layers.Dense(1, activation='sigmoid'))

model.summary()
model_name = 'LSTM-dropout'
```

Model: "sequential_14"

Layer (type)	Output Shape	Param #
embedding_42 (Embedding)	?	0 (unbuilt)
spatial_dropout1d_14 (SpatialDropout1D)	?	0
lstm_59 (LSTM)	?	0 (unbuilt)
lstm_60 (LSTM)	?	0 (unbuilt)
dense_42 (Dense)	?	0 (unbuilt)

Total params: 0 (0.00 B)

Trainable params: 0 (0.00 B)

Non-trainable params: 0 (0.00 B)

LSTM with TF-IDF input

LSTM combined with neural network layer using TF-IFD.

In [368…

```
# Define input layers
input_seq = keras.layers.Input(shape=(x_train.shape[1],))
input_tfidf = keras.layers.Input(shape=(tfidf_vectors.shape[1],))

# Embedding and LSTM layers
embedding = keras.layers.Embedding(input_dim=10000, output_dim=64)(input_seq)
lstm = keras.layers.LSTM(64, dropout=0.2, recurrent_dropout=0.2)(embedding)

# Concatenate LSTM output and TF-IDF vectors
concatenated = keras.layers.Concatenate()([lstm, input_tfidf])

# Add dropout and dense layers
dropout = keras.layers.Dropout(0.5)(concatenated)
dense = keras.layers.Dense(1, activation='sigmoid')(dropout)

# Define the model
model = keras.models.Model(inputs=[input_seq, input_tfidf], outputs=dense)
model_name = 'LSTM-TF-IDF'
```

Bi-directional LSTM

RNN that takes account the words in both directions, forward and backward.

In [318…

```
# Input for variable-length sequences of integers
inputs = keras.Input(shape=(None,), dtype="int32")
# Embed each integer in a 128-dimensional vector
x = layers.Embedding(max_features, 128)(inputs)
# Add 2 bidirectional LSTMs
x = layers.Bidirectional(layers.LSTM(128, return_sequences=True))(x)
x = layers.Bidirectional(layers.LSTM(128))(x)
# Add a classifier
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.summary()
model_name = 'LSTM-bidirectional'
```

Model: "functional_27"

Layer (type)	Output Shape	Param #
input_layer_39 (InputLayer)	(None, None)	0
embedding_30 (Embedding)	(None, None, 128)	1,280,000
bidirectional (Bidirectional)	(None, None, 256)	263,168
bidirectional_1 (Bidirectional)	(None, 256)	394,240
dense_30 (Dense)	(None, 1)	257

Total params: 1,937,665 (7.39 MB)

Trainable params: 1,937,665 (7.39 MB)

Non-trainable params: 0 (0.00 B)

GRU

Gated Recurrent Unit that can memorize or forget words but does not have output gate and thus has less amount of parameters.

In [410…

```
# Input for variable-length sequences of integers
inputs = keras.Input(shape=(None,), dtype="int32")
# Embed each integer in a 128-dimensional vector
x = layers.Embedding(max_features, 256)(inputs)
# Add 2 GRUs
x = layers.GRU(256, return_sequences=True)(x)
x = layers.GRU(256)(x)
# Add a classifier
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.summary()
model_name = 'GRU'
```

Model: "functional_40"

Layer (type)	Output Shape	Param #
input_layer_54 (InputLayer)	(None, None)	0
embedding_43 (Embedding)	(None, None, 256)	1,280,000
gru_14 (GRU)	(None, None, 256)	394,752
gru_15 (GRU)	(None, 256)	394,752
dense_43 (Dense)	(None, 1)	257

Total params: 2,069,761 (7.90 MB)

Trainable params: 2,069,761 (7.90 MB)

Non-trainable params: 0 (0.00 B)

Model training

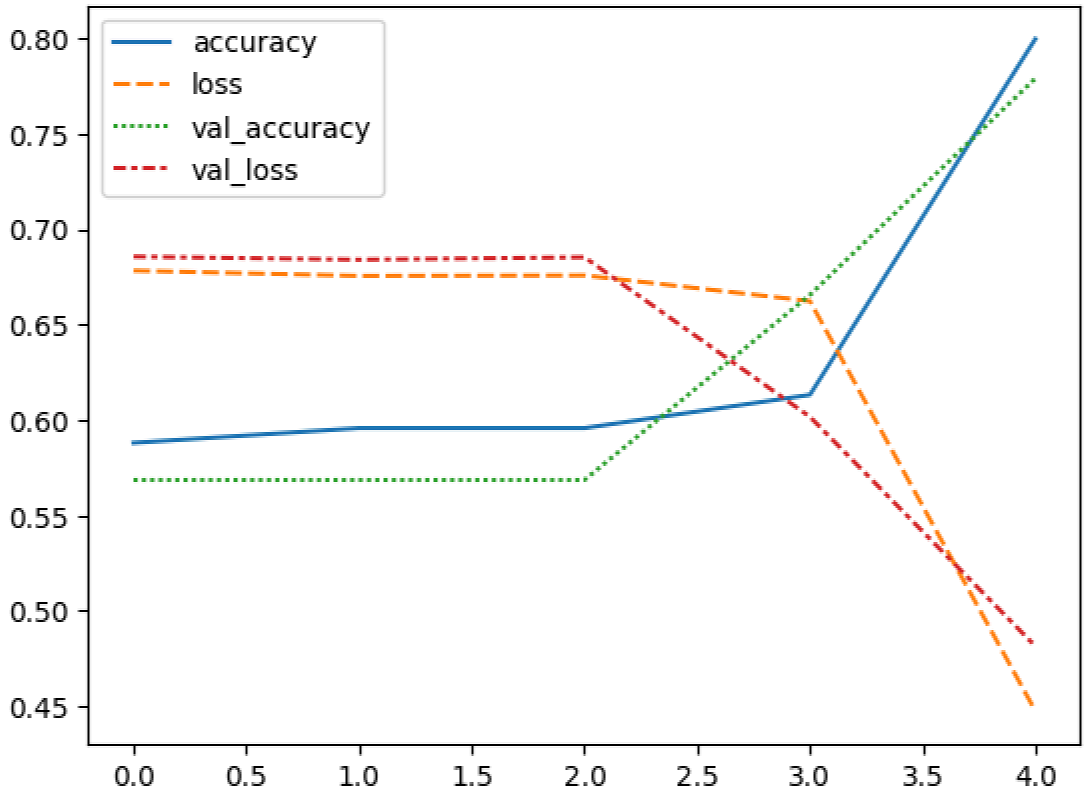
Baseline settings

- Size of vocalbury: 10k
- Number of units in layers: 128

In [411…

```
print('Building model', model_name)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=1e-4), loss="binary_cro
history = model.fit(x_train, y_train, batch_size=32, epochs=5, validation_split=0.2
sns.lineplot(history.history)
plt.show()
```

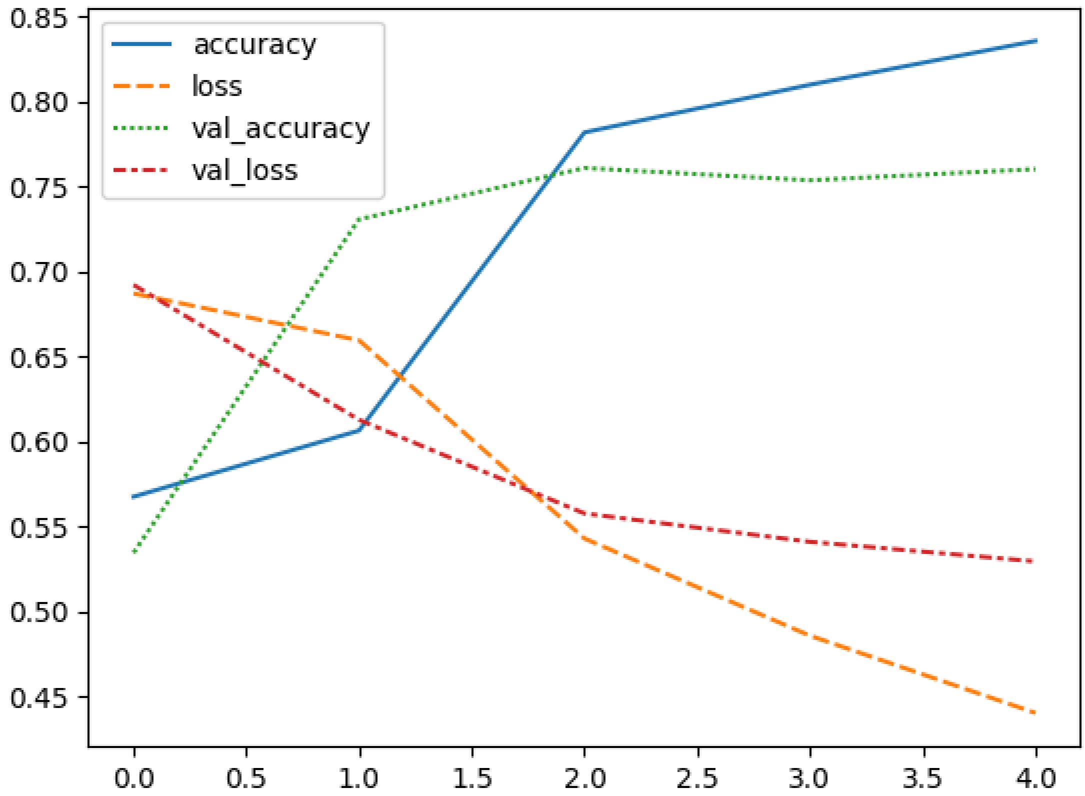
```
Building model GRU
Epoch 1/5
174/174 ━━━━━━━━━━━━━━━━━━━━ 11s 47ms/step - accuracy: 0.5715 - loss: 0.6815 - val_a
ccuracy: 0.5686 - val_loss: 0.6856
Epoch 2/5
174/174 ━━━━━━━━━━━━━━━━━━━━ 9s 50ms/step - accuracy: 0.6015 - loss: 0.6735 - val_ac
curacy: 0.5686 - val_loss: 0.6840
Epoch 3/5
174/174 ━━━━━━━━━━━━━━━━━━━━ 7s 42ms/step - accuracy: 0.6008 - loss: 0.6746 - val_ac
curacy: 0.5686 - val_loss: 0.6852
Epoch 4/5
174/174 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - accuracy: 0.5890 - loss: 0.6762 - val_a
ccuracy: 0.6655 - val_loss: 0.6017
Epoch 5/5
174/174 ━━━━━━━━━━━━━━━━━━━━ 8s 43ms/step - accuracy: 0.7770 - loss: 0.4775 - val_ac
curacy: 0.7789 - val_loss: 0.4815
```



In [369…

```
print('Building model', model_name)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=1e-4), loss='binary_cro
history = model.fit([x_train, tfidf_vectors], y_train, batch_size=32, epochs=5, val
sns.lineplot(history.history)
plt.show()
```

```
Building model LSTM-TF-IDF
Epoch 1/5
191/191 ━━━━━━━━━━━━━━━━━━━━ 8s 14ms/step - accuracy: 0.5521 - loss: 0.6907 - val_ac
curacy: 0.5345 - val_loss: 0.6922
Epoch 2/5
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.5766 - loss: 0.6765 - val_ac
curacy: 0.7308 - val_loss: 0.6127
Epoch 3/5
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.7753 - loss: 0.5589 - val_ac
curacy: 0.7610 - val_loss: 0.5576
Epoch 4/5
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.8098 - loss: 0.4896 - val_ac
curacy: 0.7538 - val_loss: 0.5409
Epoch 5/5
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 13ms/step - accuracy: 0.8386 - loss: 0.4410 - val_ac
curacy: 0.7603 - val_loss: 0.5294
```



Save benchmarking

In [412…

```
comparison_df = pd.DataFrame(history.history)
comparison_df['model'] = model_name
comparison_df['DoE'] = 'Baseline'
comparison_df.to_csv('model_comparison.csv', index=False, header=False, mode='a')
```

Results and Analysis (35 pts)

Run hyperparameter tuning, try different architectures for comparison, apply techniques to improve training or performance, and discuss what helped.

Includes results with tables and figures. There is an analysis of why or why not something worked well, troubleshooting, and a hyperparameter optimization procedure summary.

Below is a list of some of the parameters amd hyperparameters explored.

- Feature size: 1k, 5k, 10k, 20k
- LSTM vs bi-directional LSTM vs LSTM with TF-IDF vs GRU
- 1 layer vs 2 layers vs 3 layers
- Number of units, dimensionality: 64, 128, 256

Feature size around 5k to 10k seemed to work best. All the models worked pretty good. Bi-directional LSTM and GRU worked slightly better. In general, two layers was enough and the larger the dimensionality the better, however the difference was not big.

In [423…

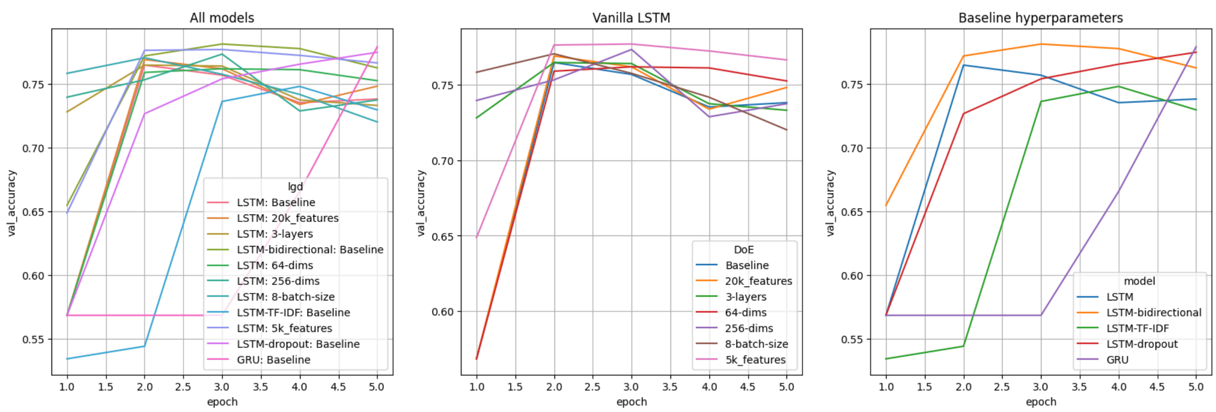
```
plt.figure(figsize=(20, 6))

ax = plt.subplot(1, 3, 1)
sns.lineplot(comparison_df, x='epoch', y='val_accuracy', hue='lgd')
plt.grid()
plt.title('All models')

ax = plt.subplot(1, 3, 2)
comparison_df = pd.read_csv('model_comparison.csv')
comparison_df['epoch'] = [i+1 for i in range(5)] * 11
comparison_df['lgd'] = comparison_df['model'] + ': ' + comparison_df['DoE']
sns.lineplot(comparison_df.loc[comparison_df.model=='LSTM'], x='epoch', y='val_accu
plt.grid()
plt.title('Vanilla LSTM')

ax = plt.subplot(1, 3, 3)
sns.lineplot(comparison_df.loc[comparison_df.DoE=='Baseline'], x='epoch', y='val_ac
plt.grid()
plt.title('Baseline hyperparameters')
plt.show()

['LSTM: 5k-features', 'GRU: 256-dims']
print('Top-5 models:')
(comparison_df.sort_values('val_accuracy', ascending=False)[0:5])
```




```
Top-5 models:
```

Out[423…

	accuracy	loss	val_accuracy	val_loss	model	DoE	epoch	lg
17	0.858836	0.343805	0.781048	0.487795	LSTM-bidirectional	Baseline	3	LSTM bidirectiona Baselin
54	0.799569	0.447570	0.778894	0.481525	GRU	Baseline	5	GRU Baselin
18	0.899246	0.263863	0.777459	0.505856	LSTM-bidirectional	Baseline	4	LSTM bidirectiona Baselin
42	0.844007	0.362775	0.776756	0.462070	LSTM	5k_features	3	LSTM 5k_feature
41	0.794417	0.452031	0.776100	0.475283	LSTM	5k_features	2	LSTM 5k_feature

Check that training accuracy can be reproduced

In [381…

```
predictions = model.predict(x_train, verbose=False)
pred_label = np.round(predictions,0)
accu = []
for pred, act in zip(pred_label, y_train):
    accu.append(pred==act)
np.mean(accu)
```

Out[381…

```
np.float64(0.8711392041373366)
```

Submission

Code for predicting test data and saving it into a csv file.

In [382…

```
predictions = model.predict(x_test, verbose=False)
pred_label = np.round(predictions,0)
```

In [383…

```
test_df.id
print(x_test[0])
print(test_df.iloc[0])

submission_df = pd.DataFrame(test_df.id)
submission_df['target'] = pred_label.astype('int')
submission_df.head(5)
submission_df.to_csv('submission_3.csv', index=False)
```

```
tf.Tensor(
[  27  787    3 1738  133   98    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0], shape=(31,), dtype=int64)
id                                              0
keyword                                       NaN
location                                      NaN
text           Just happened a terrible car crash
word_count                                      6
Name: 0, dtype: object
```

Conclusion (15 pts)

Discuss and interpret results as well as learnings and takeaways. What did and did not help improve the performance of your models? What improvements could you try in the future?

Improvements could be to stratify the training data to even out the label values, trying different activation functions and further cleaning the text..

In the end, most of the models performed with similar accuracy which suggest that more work on the text cleaning and processing could be beneficial. Some of the models could have benefitted having more epochs to train since the validation accuracy did not quite saturate yet.

Sources

https://keras.io/examples/nlp/bidirectional_lstm_imdb/

https://www.kaggle.com/code/anmolstha/disaster-tweets-simple-rnn-implementation

https://keras.io/examples/nlp/text_classification_from_scratch/