t-classification2-cs4395-sxv180047

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1 Text Classification and Analysis using Deep Learning

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Section: CS 4395.001

*** Before executing this notebook, ensure all necessary libraries/modules are installed. Simply run the notebook from top to bottom.** The dataset is used to solve a multi-class classification problem, classifying emails as fraud, commerical spam, phishing, or none (false-positive). This dataset is dervied from Kaggle, and is called "Phishing Email Data by Type." In this notebook, we will try to train our model using various algorithms, such as a simple sequential model, Recurrent Neural Network (RNN), and a Convolutional Neural Network (CNN), to be able to predict whether a given email message is fraud, commerical spam, phishing, or none (false-positive). The dataset has 3 columns: 'Subject', 'Text', and 'Type.'The 'Text' column holds the entire email message. The subject of the emails is also another attribute in the dataset, however, in this notebook we will only be using the "Text" and "Type" columns. We will vectorize the "Text" column to derive the features for the model and the "Type" will represent our target class. This project builds on the previous 'Text Classification using Naive Bayes, Logistic Regression, and Neural Network' notebook and uses the same dataset. Here is the link to the dataset: https://www.kaggle.com/datasets/charlottehall/phishing-email-data-by-type

1. Import Libraries and Preprocessing

[59]:
```
# import libraries
import pandas as pd
import seaborn as sns
import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction import text
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk import word_tokenize
from nltk.stem import WordNetLemmatizer
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, confusion_matrix
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

[60]:
```
# get a text classification dataset (hosted on a public url via github)
data_url = "https://raw.githubusercontent.com/shreyavala/
↪nlp_text_classification_data/main/phishing_data_by_type.csv"
df=pd.read_csv(data_url)
df
```

[60]:
```
                                              Subject  \
0          URGENT BUSINESS ASSISTANCE AND PARTNERSHIP
1                 URGENT ASSISTANCE /RELATIONSHIP (P)
2                                      GOOD DAY TO YOU
3                                     from Mrs.Johnson
4                                         Co-Operation
..                                                 …
154                 These Bags Just Arrived For Spring
155  POTUS Comes to Broadway this April! Get Ticket…
156                        Let’s talk about Bridgerton!
157                     MONDAY MIX: All eyes on Ukraine
158  The DOTD is back on with 15% off a lightning-f…

                                                 Text             Type
0    URGENT BUSINESS ASSISTANCE AND PARTNERSHIP.\n\…            Fraud
1    Dear Friend,\n\nI am Mr. Ben Suleman a custom …            Fraud
2    FROM HIS ROYAL MAJESTY (HRM) CROWN RULER OF EL…            Fraud
3    Goodday Dear\n\n\nI know this mail will come t…            Fraud
4    FROM MR. GODWIN AKWESI\nTEL: +233 208216645\nF…            Fraud
..                                                 …              …
154  Bags so perfect-you'll never want to be withou…  Commercial Spam
155  INAUGURAL BROADWAY PERFORMANCE APRIL 14\r\nA N…  Commercial Spam
156  GET THE BEST OF EVERYTHING IN THE APP\n\nSTARB…  Commercial Spam
157  Hi!\n \nSpring forward with our newest noPac c…  Commercial Spam
158  Hi,  | PLAYER MEMBER | 0 Points\n\nEarn And Sa…  Commercial Spam

[159 rows x 3 columns]
```

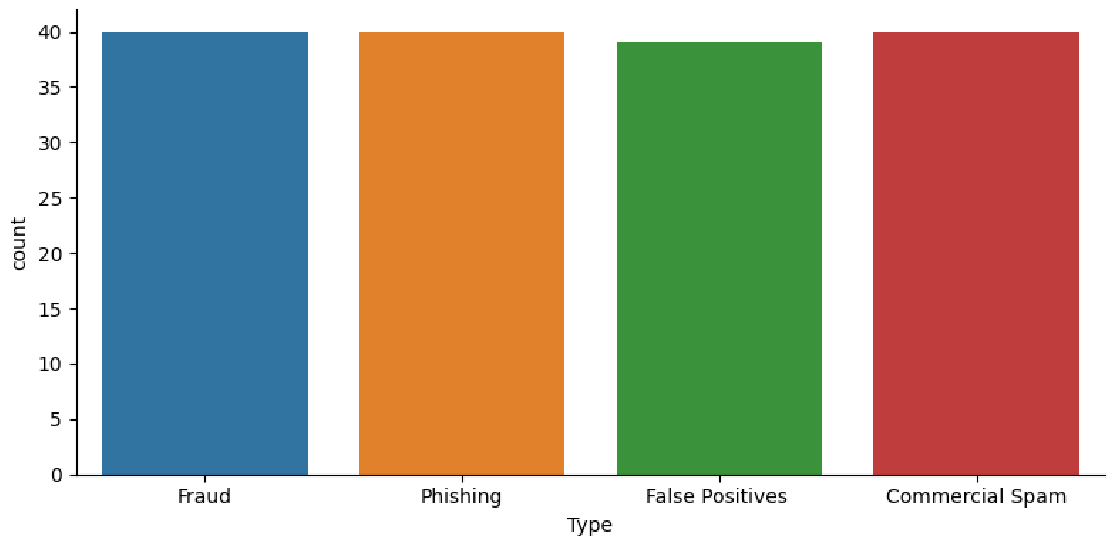
[61]:
```
print("Shape(Rows, Columns): ",df.shape)
```

```
Shape(Rows, Columns):  (159, 3)
```

[62]:
```
# creates a graph showing the distribution of the target classes

sns.catplot(data=df, kind='count', x='Type', height=4, aspect=2)
```

[62]: <seaborn.axisgrid.FacetGrid at 0x7fb1ae149970>



From this distribution we can see that the classes are fairly balanced. There is a proportional number of instances between Fraud, Phishing, False Positives, and Commerical Spam emails. We do not need to undersample or oversample any class in this dataset. This dataset it relatively small, with 159 instances and 3 attributes.

[63]:
```
# preprocess the 'Text' column (lowercase, remove punctuation and numbers)
df['Text'] = df['Text'].str.lower() # lower
df['Text'] = df['Text'].str.replace('[^\w\s]','') # remove punctuation
df['Text'] = df['Text'].str.replace('\n','') # remove newlines
df['Text'] = df['Text'].str.replace('\t','') # remove tabs
df['Text'] = df['Text'].str.replace('\d+', '') # remove numbers
df
```

```
<ipython-input-63-a91182193439>:3: FutureWarning: The default value of regex
will change from True to False in a future version.
  df['Text'] = df['Text'].str.replace('[^\w\s]','') # remove punctuation
<ipython-input-63-a91182193439>:6: FutureWarning: The default value of regex
will change from True to False in a future version.
  df['Text'] = df['Text'].str.replace('\d+', '') # remove numbers
```

[63]:
```
                                            Subject  \
0          URGENT BUSINESS ASSISTANCE AND PARTNERSHIP
1                   URGENT ASSISTANCE /RELATIONSHIP (P)
```

```
2                                       GOOD DAY TO YOU
3                                      from Mrs.Johnson
4                                          Co-Operation
..                                                  ...
154                  These Bags Just Arrived For Spring
155  POTUS Comes to Broadway this April! Get Ticket...
156                        Let's talk about Bridgerton!
157                     MONDAY MIX: All eyes on Ukraine
158  The DOTD is back on with 15% off a lightning-f...

                                                  Text             Type
0    urgent business assistance and partnershipdear...            Fraud
1    dear friendi am mr ben suleman a custom office...            Fraud
2    from his royal majesty hrm crown ruler of elem...            Fraud
3    goodday deari know this mail will come to you ...            Fraud
4    from mr godwin akwesitel  fax  before i introd...            Fraud
..                                                 ...              ...
154  bags so perfectyoull never want to be without ...  Commercial Spam
155  inaugural broadway performance april \ra new c...  Commercial Spam
156  get the best of everything in the appstarbucks...  Commercial Spam
157  hi spring forward with our newest nopac course...  Commercial Spam
158  hi   player member   pointsearn and save moreb...  Commercial Spam

[159 rows x 3 columns]
```

[64]:

```python
# use tf-idf vectorization to extract features (tf-idf frequencies) and
↪preprocess by lemmatization
class LemmaTokenizer:
     def __init__(self):
         self.wnl = WordNetLemmatizer()
     def __call__(self, doc):
         return [self.wnl.lemmatize(t) for t in word_tokenize(doc)]

vectorizer = TfidfVectorizer(stop_words =
↪'english',tokenizer=LemmaTokenizer(),min_df=3) # intitialize a tf-idf
↪vectorizer (with stopwords removal and lemmatization)

vectorized_data = vectorizer.fit_transform(df['Text'].values.astype('U')) #
↪tell the vectorizer to read our data

# construct a dataframe with vectorized words (dataframe will be large)
df_vectorized= pd.DataFrame(vectorized_data.toarray(), columns=vectorizer.
↪get_feature_names_out())
df_vectorized.head()
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/feature_extraction/text.py:528:
UserWarning: The parameter 'token_pattern' will not be used since 'tokenizer' is
```

```
not None'
  warnings.warn(
/usr/local/lib/python3.9/dist-packages/sklearn/feature_extraction/text.py:409:
UserWarning: Your stop_words may be inconsistent with your preprocessing.
Tokenizing the stop words generated tokens ['ha', 'le', 'u', 'wa'] not in
stop_words.
  warnings.warn(
```

[64]:

```
    abacha  abandoned  abidjan  able    abroad  academic    accept  accepted  \
0  0.00000        0.0      0.0   0.0  0.000000       0.0  0.000000       0.0
1  0.14028        0.0      0.0   0.0  0.000000       0.0  0.000000       0.0
2  0.00000        0.0      0.0   0.0  0.070671       0.0  0.000000       0.0
3  0.00000        0.0      0.0   0.0  0.200996       0.0  0.000000       0.0
4  0.00000        0.0      0.0   0.0  0.000000       0.0  0.068949       0.0

   access  accordance  …     youas      youi  youll  young  youre  youth  \
0     0.0         0.0  …  0.000000  0.000000    0.0    0.0    0.0    0.0
1     0.0         0.0  …  0.000000  0.000000    0.0    0.0    0.0    0.0
2     0.0         0.0  …  0.000000  0.000000    0.0    0.0    0.0    0.0
3     0.0         0.0  …  0.000000  0.000000    0.0    0.0    0.0    0.0
4     0.0         0.0  …  0.083368  0.065382    0.0    0.0    0.0    0.0

   youtube  youve  zip
0      0.0    0.0  0.0   0.0
1      0.0    0.0  0.0   0.0
2      0.0    0.0  0.0   0.0
3      0.0    0.0  0.0   0.0
4      0.0    0.0  0.0   0.0

[5 rows x 1251 columns]
```

2. Train/Test Split w/ Encoding

[65]:

```python
# train/test split with encoding
from sklearn.preprocessing import LabelEncoder

X = df_vectorized  # drop any other columns/features deemed unecessary for the X
y = df["Type"] # target class

# add an encoder for the target class, categorical -> numerical
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)
print(y_encoded)

# split train/test
x_train, x_test, y_train_encoded, y_test_encoded = train_test_split(X,
 ↪y_encoded,test_size = 0.25,random_state = 42) # split data into 75% train,
 ↪25% test
```

```
print("X shape: ", x_train.shape, x_test.shape)
print("y shape: ", y_train_encoded.shape, y_test_encoded.shape)
```

```
[2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
 3 3 3 3 3 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 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 0 0 0
 0 0 0 0 0 0 0 0 0 0 0]
X shape:  (119, 1251) (40, 1251)
y shape:  (119,) (40,)
```

3. Run and Evaluate Sequential, RNN, CNN

[66]:
```
# import libraries for deep learning models
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras import layers, models
from tensorflow.keras.layers import Dropout, Embedding, LSTM, Dense
from keras import regularizers
```

A. Sequential Model

[67]:
```
# build and fit the model
vocab_size = len(vectorizer.vocabulary_)

model = models.Sequential()
model.add(layers.Dense(32, input_dim=vocab_size, kernel_initializer='normal',␣
 ↪activation='relu'))
model.add(layers.Dense(4, activation='softmax',kernel_initializer='normal')) #␣
 ↪use softmax bc we have 4 target classes
```

[68]:
```
# compile
model.
 ↪compile(optimizer='adam',loss='sparse_categorical_crossentropy',metrics=['accuracy'])
```

[69]:
```
model.fit(x_train, y_train_encoded, epochs=50, batch_size=32,␣
 ↪validation_split=0.1)
```

```
Epoch 1/50
4/4 [==============================] - 1s 74ms/step - loss: 1.3857 - accuracy:
0.2710 - val_loss: 1.3851 - val_accuracy: 0.2500
Epoch 2/50
4/4 [==============================] - 0s 13ms/step - loss: 1.3772 - accuracy:
0.5140 - val_loss: 1.3833 - val_accuracy: 0.4167
Epoch 3/50
4/4 [==============================] - 0s 15ms/step - loss: 1.3695 - accuracy:
0.6449 - val_loss: 1.3811 - val_accuracy: 0.4167
```

```
Epoch 4/50
4/4 [==============================] - 0s 21ms/step - loss: 1.3604 - accuracy:
0.7664 - val_loss: 1.3783 - val_accuracy: 0.4167
Epoch 5/50
4/4 [==============================] - 0s 20ms/step - loss: 1.3497 - accuracy:
0.8224 - val_loss: 1.3743 - val_accuracy: 0.4167
Epoch 6/50
4/4 [==============================] - 0s 14ms/step - loss: 1.3375 - accuracy:
0.8692 - val_loss: 1.3695 - val_accuracy: 0.4167
Epoch 7/50
4/4 [==============================] - 0s 15ms/step - loss: 1.3223 - accuracy:
0.8879 - val_loss: 1.3629 - val_accuracy: 0.4167
Epoch 8/50
4/4 [==============================] - 0s 13ms/step - loss: 1.3049 - accuracy:
0.8879 - val_loss: 1.3557 - val_accuracy: 0.4167
Epoch 9/50
4/4 [==============================] - 0s 15ms/step - loss: 1.2847 - accuracy:
0.9159 - val_loss: 1.3472 - val_accuracy: 0.5000
Epoch 10/50
4/4 [==============================] - 0s 19ms/step - loss: 1.2632 - accuracy:
0.9252 - val_loss: 1.3376 - val_accuracy: 0.5000
Epoch 11/50
4/4 [==============================] - 0s 19ms/step - loss: 1.2379 - accuracy:
0.9252 - val_loss: 1.3266 - val_accuracy: 0.5000
Epoch 12/50
4/4 [==============================] - 0s 20ms/step - loss: 1.2110 - accuracy:
0.9252 - val_loss: 1.3155 - val_accuracy: 0.5000
Epoch 13/50
4/4 [==============================] - 0s 13ms/step - loss: 1.1808 - accuracy:
0.9346 - val_loss: 1.3038 - val_accuracy: 0.5000
Epoch 14/50
4/4 [==============================] - 0s 15ms/step - loss: 1.1487 - accuracy:
0.9626 - val_loss: 1.2911 - val_accuracy: 0.5000
Epoch 15/50
4/4 [==============================] - 0s 13ms/step - loss: 1.1149 - accuracy:
0.9626 - val_loss: 1.2773 - val_accuracy: 0.5000
Epoch 16/50
4/4 [==============================] - 0s 12ms/step - loss: 1.0787 - accuracy:
0.9813 - val_loss: 1.2620 - val_accuracy: 0.5000
Epoch 17/50
4/4 [==============================] - 0s 15ms/step - loss: 1.0418 - accuracy:
0.9907 - val_loss: 1.2453 - val_accuracy: 0.5833
Epoch 18/50
4/4 [==============================] - 0s 19ms/step - loss: 1.0027 - accuracy:
0.9907 - val_loss: 1.2290 - val_accuracy: 0.5833
Epoch 19/50
4/4 [==============================] - 0s 13ms/step - loss: 0.9623 - accuracy:
0.9907 - val_loss: 1.2111 - val_accuracy: 0.5833
```

```
Epoch 20/50
4/4 [==============================] - 0s 15ms/step - loss: 0.9218 - accuracy:
0.9907 - val_loss: 1.1927 - val_accuracy: 0.6667
Epoch 21/50
4/4 [==============================] - 0s 14ms/step - loss: 0.8807 - accuracy:
0.9907 - val_loss: 1.1742 - val_accuracy: 0.6667
Epoch 22/50
4/4 [==============================] - 0s 19ms/step - loss: 0.8398 - accuracy:
0.9907 - val_loss: 1.1570 - val_accuracy: 0.6667
Epoch 23/50
4/4 [==============================] - 0s 13ms/step - loss: 0.7996 - accuracy:
0.9907 - val_loss: 1.1409 - val_accuracy: 0.6667
Epoch 24/50
4/4 [==============================] - 0s 13ms/step - loss: 0.7601 - accuracy:
0.9907 - val_loss: 1.1222 - val_accuracy: 0.6667
Epoch 25/50
4/4 [==============================] - 0s 16ms/step - loss: 0.7211 - accuracy:
0.9907 - val_loss: 1.1030 - val_accuracy: 0.6667
Epoch 26/50
4/4 [==============================] - 0s 14ms/step - loss: 0.6829 - accuracy:
0.9907 - val_loss: 1.0856 - val_accuracy: 0.6667
Epoch 27/50
4/4 [==============================] - 0s 21ms/step - loss: 0.6463 - accuracy:
0.9907 - val_loss: 1.0693 - val_accuracy: 0.6667
Epoch 28/50
4/4 [==============================] - 0s 14ms/step - loss: 0.6106 - accuracy:
0.9907 - val_loss: 1.0545 - val_accuracy: 0.6667
Epoch 29/50
4/4 [==============================] - 0s 19ms/step - loss: 0.5770 - accuracy:
1.0000 - val_loss: 1.0400 - val_accuracy: 0.7500
Epoch 30/50
4/4 [==============================] - 0s 14ms/step - loss: 0.5438 - accuracy:
1.0000 - val_loss: 1.0253 - val_accuracy: 0.7500
Epoch 31/50
4/4 [==============================] - 0s 21ms/step - loss: 0.5128 - accuracy:
1.0000 - val_loss: 1.0111 - val_accuracy: 0.7500
Epoch 32/50
4/4 [==============================] - 0s 14ms/step - loss: 0.4832 - accuracy:
1.0000 - val_loss: 0.9970 - val_accuracy: 0.7500
Epoch 33/50
4/4 [==============================] - 0s 20ms/step - loss: 0.4547 - accuracy:
1.0000 - val_loss: 0.9844 - val_accuracy: 0.7500
Epoch 34/50
4/4 [==============================] - 0s 14ms/step - loss: 0.4282 - accuracy:
1.0000 - val_loss: 0.9713 - val_accuracy: 0.7500
Epoch 35/50
4/4 [==============================] - 0s 17ms/step - loss: 0.4032 - accuracy:
1.0000 - val_loss: 0.9580 - val_accuracy: 0.7500
```

```
Epoch 36/50
4/4 [==============================] - 0s 13ms/step - loss: 0.3793 - accuracy:
1.0000 - val_loss: 0.9461 - val_accuracy: 0.7500
Epoch 37/50
4/4 [==============================] - 0s 13ms/step - loss: 0.3563 - accuracy:
1.0000 - val_loss: 0.9351 - val_accuracy: 0.7500
Epoch 38/50
4/4 [==============================] - 0s 14ms/step - loss: 0.3350 - accuracy:
1.0000 - val_loss: 0.9237 - val_accuracy: 0.7500
Epoch 39/50
4/4 [==============================] - 0s 12ms/step - loss: 0.3147 - accuracy:
1.0000 - val_loss: 0.9137 - val_accuracy: 0.7500
Epoch 40/50
4/4 [==============================] - 0s 20ms/step - loss: 0.2963 - accuracy:
1.0000 - val_loss: 0.9042 - val_accuracy: 0.7500
Epoch 41/50
4/4 [==============================] - 0s 13ms/step - loss: 0.2782 - accuracy:
1.0000 - val_loss: 0.8947 - val_accuracy: 0.7500
Epoch 42/50
4/4 [==============================] - 0s 15ms/step - loss: 0.2616 - accuracy:
1.0000 - val_loss: 0.8872 - val_accuracy: 0.7500
Epoch 43/50
4/4 [==============================] - 0s 14ms/step - loss: 0.2465 - accuracy:
1.0000 - val_loss: 0.8806 - val_accuracy: 0.7500
Epoch 44/50
4/4 [==============================] - 0s 13ms/step - loss: 0.2322 - accuracy:
1.0000 - val_loss: 0.8719 - val_accuracy: 0.7500
Epoch 45/50
4/4 [==============================] - 0s 19ms/step - loss: 0.2190 - accuracy:
1.0000 - val_loss: 0.8652 - val_accuracy: 0.7500
Epoch 46/50
4/4 [==============================] - 0s 13ms/step - loss: 0.2070 - accuracy:
1.0000 - val_loss: 0.8590 - val_accuracy: 0.7500
Epoch 47/50
4/4 [==============================] - 0s 14ms/step - loss: 0.1955 - accuracy:
1.0000 - val_loss: 0.8539 - val_accuracy: 0.7500
Epoch 48/50
4/4 [==============================] - 0s 15ms/step - loss: 0.1851 - accuracy:
1.0000 - val_loss: 0.8487 - val_accuracy: 0.7500
Epoch 49/50
4/4 [==============================] - 0s 14ms/step - loss: 0.1752 - accuracy:
1.0000 - val_loss: 0.8435 - val_accuracy: 0.7500
Epoch 50/50
4/4 [==============================] - 0s 13ms/step - loss: 0.1663 - accuracy:
1.0000 - val_loss: 0.8389 - val_accuracy: 0.7500
```

```
[69]: <keras.callbacks.History at 0x7fb1aafe0520>
```

[70]:
```
# predict
import numpy as np
y_test_pred = model.predict(x_test)
y_test_pred = np.argmax(y_test_pred, axis=1) # get the correct, encoded labels

y_test_pred
```

```
2/2 [==============================] - 0s 8ms/step
```

[70]:
```
array([0, 1, 0, 3, 1, 2, 0, 3, 1, 0, 2, 1, 2, 3, 2, 2, 0, 1, 1, 2, 1, 2,
       2, 2, 2, 0, 1, 0, 0, 0, 0, 3, 3, 0, 2, 1, 3, 3, 0, 1])
```

[71]:
```
print('accuracy score: ', accuracy_score(y_test_encoded, y_test_pred))
print('precision score: ', precision_score(y_test_encoded, y_test_pred, average␣
 ↪= 'macro')) # macro because we have equal classes
print('recall score: ', recall_score(y_test_encoded, y_test_pred, average =␣
 ↪'macro'))
print('f1 score: ', f1_score(y_test_encoded, y_test_pred, average = 'macro'))
```

```
accuracy score:  0.85
precision score:  0.8625
recall score:  0.8636363636363636
f1 score:  0.8459789712986643
```

B. RNN

[72]:
```
# add padding and re-split train/test
from tensorflow.keras.preprocessing.sequence import pad_sequences
max_len = 100 # max length of sequences
X = pad_sequences(df_vectorized.values.tolist(), maxlen=max_len,␣
 ↪padding='post', truncating='post')
print(X.shape)

# re-add encoding
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)
print(y_encoded)

x_train, x_test, y_train_encoded, y_test_encoded = train_test_split(X,␣
 ↪y_encoded,test_size = 0.25,random_state = 42) # split data into 75% train, 2
```

```
(159, 100)
[2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
 3 3 3 3 3 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 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 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0]
```

[73]:
```
# build a Sequential model with Embedding and SimpleRNN layers and embedding
import tensorflow_hub as hub
dropout_rate = 0.2  # might help overfitting
vocab_size = len(vectorizer.vocabulary_)
model2 = models.Sequential()
model2.add(layers.Embedding(vocab_size, 64))
model2.add(layers.SimpleRNN(32))
model2.add(Dropout(dropout_rate))
model2.add(layers.Dense(4, activation='softmax'))
```

[74]:
```
# compile model
model2.compile(loss='sparse_categorical_crossentropy', optimizer='rmsprop',␣
↪metrics=['accuracy'])
```

[75]:
```
# fit and train
model2.fit(x_train, y_train_encoded, epochs=10, batch_size=32,␣
↪validation_split=0.1)
```

```
Epoch 1/10
4/4 [==============================] - 2s 133ms/step - loss: 1.3996 - accuracy:
0.2150 - val_loss: 1.4010 - val_accuracy: 0.1667
Epoch 2/10
4/4 [==============================] - 0s 35ms/step - loss: 1.3975 - accuracy:
0.2523 - val_loss: 1.4062 - val_accuracy: 0.1667
Epoch 3/10
4/4 [==============================] - 0s 35ms/step - loss: 1.3908 - accuracy:
0.2430 - val_loss: 1.3890 - val_accuracy: 0.1667
Epoch 4/10
4/4 [==============================] - 0s 39ms/step - loss: 1.3934 - accuracy:
0.2243 - val_loss: 1.4077 - val_accuracy: 0.1667
Epoch 5/10
4/4 [==============================] - 0s 34ms/step - loss: 1.4006 - accuracy:
0.2617 - val_loss: 1.4084 - val_accuracy: 0.1667
Epoch 6/10
4/4 [==============================] - 0s 39ms/step - loss: 1.3923 - accuracy:
0.2897 - val_loss: 1.3934 - val_accuracy: 0.1667
Epoch 7/10
4/4 [==============================] - 0s 40ms/step - loss: 1.3942 - accuracy:
0.2523 - val_loss: 1.3877 - val_accuracy: 0.1667
Epoch 8/10
4/4 [==============================] - 0s 40ms/step - loss: 1.3923 - accuracy:
0.2056 - val_loss: 1.4083 - val_accuracy: 0.1667
Epoch 9/10
4/4 [==============================] - 0s 41ms/step - loss: 1.3951 - accuracy:
0.2336 - val_loss: 1.4039 - val_accuracy: 0.1667
Epoch 10/10
4/4 [==============================] - 0s 36ms/step - loss: 1.3950 - accuracy:
```

```
0.2617 - val_loss: 1.4115 - val_accuracy: 0.1667
```

[75]: <keras.callbacks.History at 0x7fb1a487a460>

[76]:
```
# predict
import numpy as np
y_test_pred = model2.predict(x_test)
y_test_pred = np.argmax(y_test_pred, axis=1) # get the correct, encoded labels

y_test_pred
```

```
2/2 [==============================] - 0s 11ms/step
```

[76]:
```
array([3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3])
```

[77]:
```
# print classification report
from sklearn.metrics import classification_report
print(classification_report(y_test_encoded, y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        11
           1       0.00      0.00      0.00         7
           2       0.00      0.00      0.00        11
           3       0.28      1.00      0.43        11

    accuracy                           0.28        40
   macro avg       0.07      0.25      0.11        40
weighted avg       0.08      0.28      0.12        40

/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
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/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

C. CNN

[78]:
```
# build a Sequential model 1D convnet
model3 = models.Sequential()
vocab_size = len(vectorizer.vocabulary_)
model3.add(layers.Embedding(vocab_size, output_dim = 128, input_length=max_len))
model3.add(layers.Conv1D(32, 7, activation='relu',␣
 ↪kernel_regularizer=regularizers.l2(0.01)))
model3.add(layers.MaxPooling1D(5))
model3.add(layers.Conv1D(32, 7, activation='relu',␣
 ↪kernel_regularizer=regularizers.l2(0.01)))
model3.add(layers.GlobalMaxPooling1D())
model3.add(layers.Dense(4, activation = 'softmax'))
```

[79]:
```
# compile
model3.compile(optimizer=tf.keras.optimizers.RMSprop(learning_rate=0.01),␣
 ↪loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

[80]:
```
# fit and train
model3.fit(x_train, y_train_encoded, epochs=50, batch_size=32,␣
 ↪validation_split=0.1)
```

```
Epoch 1/50
4/4 [==============================] - 1s 99ms/step - loss: 1.8098 - accuracy:
0.2243 - val_loss: 1.4515 - val_accuracy: 0.1667
Epoch 2/50
4/4 [==============================] - 0s 34ms/step - loss: 1.4204 - accuracy:
0.2336 - val_loss: 1.4043 - val_accuracy: 0.1667
Epoch 3/50
4/4 [==============================] - 0s 40ms/step - loss: 1.3942 - accuracy:
0.2523 - val_loss: 1.3929 - val_accuracy: 0.1667
Epoch 4/50
4/4 [==============================] - 0s 42ms/step - loss: 1.3912 - accuracy:
0.1963 - val_loss: 1.3951 - val_accuracy: 0.1667
Epoch 5/50
4/4 [==============================] - 0s 39ms/step - loss: 1.3892 - accuracy:
0.2056 - val_loss: 1.3945 - val_accuracy: 0.1667
Epoch 6/50
4/4 [==============================] - 0s 36ms/step - loss: 1.3893 - accuracy:
0.1869 - val_loss: 1.3984 - val_accuracy: 0.1667
Epoch 7/50
4/4 [==============================] - 0s 36ms/step - loss: 1.3884 - accuracy:
0.2243 - val_loss: 1.4006 - val_accuracy: 0.1667
Epoch 8/50
4/4 [==============================] - 0s 34ms/step - loss: 1.3877 - accuracy:
0.2523 - val_loss: 1.4045 - val_accuracy: 0.1667
Epoch 9/50
4/4 [==============================] - 0s 50ms/step - loss: 1.3870 - accuracy:
0.2523 - val_loss: 1.4047 - val_accuracy: 0.1667
```

```
Epoch 10/50
4/4 [==============================] - 0s 55ms/step - loss: 1.3876 - accuracy:
0.2243 - val_loss: 1.3987 - val_accuracy: 0.1667
Epoch 11/50
4/4 [==============================] - 0s 37ms/step - loss: 1.3877 - accuracy:
0.1589 - val_loss: 1.4000 - val_accuracy: 0.1667
Epoch 12/50
4/4 [==============================] - 0s 34ms/step - loss: 1.3870 - accuracy:
0.2150 - val_loss: 1.4018 - val_accuracy: 0.1667
Epoch 13/50
4/4 [==============================] - 0s 37ms/step - loss: 1.3873 - accuracy:
0.1963 - val_loss: 1.4017 - val_accuracy: 0.1667
Epoch 14/50
4/4 [==============================] - 0s 37ms/step - loss: 1.3871 - accuracy:
0.2523 - val_loss: 1.3978 - val_accuracy: 0.1667
Epoch 15/50
4/4 [==============================] - 0s 39ms/step - loss: 1.3876 - accuracy:
0.2523 - val_loss: 1.3945 - val_accuracy: 0.1667
Epoch 16/50
4/4 [==============================] - 0s 38ms/step - loss: 1.3874 - accuracy:
0.2523 - val_loss: 1.3935 - val_accuracy: 0.1667
Epoch 17/50
4/4 [==============================] - 0s 39ms/step - loss: 1.3872 - accuracy:
0.2430 - val_loss: 1.3931 - val_accuracy: 0.1667
Epoch 18/50
4/4 [==============================] - 0s 37ms/step - loss: 1.3867 - accuracy:
0.2150 - val_loss: 1.3916 - val_accuracy: 0.1667
Epoch 19/50
4/4 [==============================] - 0s 34ms/step - loss: 1.3878 - accuracy:
0.2150 - val_loss: 1.3945 - val_accuracy: 0.1667
Epoch 20/50
4/4 [==============================] - 0s 33ms/step - loss: 1.3874 - accuracy:
0.2523 - val_loss: 1.3967 - val_accuracy: 0.1667
Epoch 21/50
4/4 [==============================] - 0s 38ms/step - loss: 1.3881 - accuracy:
0.2150 - val_loss: 1.3987 - val_accuracy: 0.1667
Epoch 22/50
4/4 [==============================] - 0s 31ms/step - loss: 1.3875 - accuracy:
0.1776 - val_loss: 1.3948 - val_accuracy: 0.1667
Epoch 23/50
4/4 [==============================] - 0s 31ms/step - loss: 1.3879 - accuracy:
0.2243 - val_loss: 1.3918 - val_accuracy: 0.1667
Epoch 24/50
4/4 [==============================] - 0s 34ms/step - loss: 1.3871 - accuracy:
0.2430 - val_loss: 1.3966 - val_accuracy: 0.1667
Epoch 25/50
4/4 [==============================] - 0s 38ms/step - loss: 1.3871 - accuracy:
0.2056 - val_loss: 1.3955 - val_accuracy: 0.1667
```

```
Epoch 26/50
4/4 [==============================] - 0s 32ms/step - loss: 1.3872 - accuracy:
0.2430 - val_loss: 1.3953 - val_accuracy: 0.1667
Epoch 27/50
4/4 [==============================] - 0s 33ms/step - loss: 1.3877 - accuracy:
0.2523 - val_loss: 1.3946 - val_accuracy: 0.1667
Epoch 28/50
4/4 [==============================] - 0s 34ms/step - loss: 1.3865 - accuracy:
0.2430 - val_loss: 1.3938 - val_accuracy: 0.1667
Epoch 29/50
4/4 [==============================] - 0s 34ms/step - loss: 1.3871 - accuracy:
0.2523 - val_loss: 1.3906 - val_accuracy: 0.1667
Epoch 30/50
4/4 [==============================] - 0s 32ms/step - loss: 1.3869 - accuracy:
0.2523 - val_loss: 1.3904 - val_accuracy: 0.1667
Epoch 31/50
4/4 [==============================] - 0s 39ms/step - loss: 1.3870 - accuracy:
0.2243 - val_loss: 1.3935 - val_accuracy: 0.1667
Epoch 32/50
4/4 [==============================] - 0s 30ms/step - loss: 1.3868 - accuracy:
0.2523 - val_loss: 1.3925 - val_accuracy: 0.1667
Epoch 33/50
4/4 [==============================] - 0s 37ms/step - loss: 1.3874 - accuracy:
0.2523 - val_loss: 1.3892 - val_accuracy: 0.1667
Epoch 34/50
4/4 [==============================] - 0s 33ms/step - loss: 1.3886 - accuracy:
0.1963 - val_loss: 1.3923 - val_accuracy: 0.1667
Epoch 35/50
4/4 [==============================] - 0s 38ms/step - loss: 1.3884 - accuracy:
0.2523 - val_loss: 1.3893 - val_accuracy: 0.1667
Epoch 36/50
4/4 [==============================] - 0s 36ms/step - loss: 1.3871 - accuracy:
0.2523 - val_loss: 1.3914 - val_accuracy: 0.1667
Epoch 37/50
4/4 [==============================] - 0s 46ms/step - loss: 1.3867 - accuracy:
0.2056 - val_loss: 1.3958 - val_accuracy: 0.1667
Epoch 38/50
4/4 [==============================] - 0s 55ms/step - loss: 1.3878 - accuracy:
0.2523 - val_loss: 1.3986 - val_accuracy: 0.1667
Epoch 39/50
4/4 [==============================] - 0s 66ms/step - loss: 1.3871 - accuracy:
0.2056 - val_loss: 1.3971 - val_accuracy: 0.1667
Epoch 40/50
4/4 [==============================] - 0s 59ms/step - loss: 1.3875 - accuracy:
0.2150 - val_loss: 1.3960 - val_accuracy: 0.1667
Epoch 41/50
4/4 [==============================] - 0s 55ms/step - loss: 1.3867 - accuracy:
0.2523 - val_loss: 1.3948 - val_accuracy: 0.1667
```

```
Epoch 42/50
4/4 [==============================] - 0s 51ms/step - loss: 1.3873 - accuracy:
0.2523 - val_loss: 1.3968 - val_accuracy: 0.1667
Epoch 43/50
4/4 [==============================] - 0s 55ms/step - loss: 1.3871 - accuracy:
0.2523 - val_loss: 1.3993 - val_accuracy: 0.1667
Epoch 44/50
4/4 [==============================] - 0s 51ms/step - loss: 1.3870 - accuracy:
0.2523 - val_loss: 1.3943 - val_accuracy: 0.1667
Epoch 45/50
4/4 [==============================] - 0s 52ms/step - loss: 1.3876 - accuracy:
0.2523 - val_loss: 1.3965 - val_accuracy: 0.1667
Epoch 46/50
4/4 [==============================] - 0s 56ms/step - loss: 1.3871 - accuracy:
0.2336 - val_loss: 1.3952 - val_accuracy: 0.1667
Epoch 47/50
4/4 [==============================] - 0s 51ms/step - loss: 1.3874 - accuracy:
0.2523 - val_loss: 1.3914 - val_accuracy: 0.1667
Epoch 48/50
4/4 [==============================] - 0s 58ms/step - loss: 1.3879 - accuracy:
0.1776 - val_loss: 1.3882 - val_accuracy: 0.1667
Epoch 49/50
4/4 [==============================] - 0s 50ms/step - loss: 1.3871 - accuracy:
0.2523 - val_loss: 1.3909 - val_accuracy: 0.1667
Epoch 50/50
4/4 [==============================] - 0s 52ms/step - loss: 1.3875 - accuracy:
0.1963 - val_loss: 1.3910 - val_accuracy: 0.1667
```

[80]:
```
<keras.callbacks.History at 0x7fb1a4c29b50>
```

[81]:
```
# predict
y_test_pred = model3.predict(x_test)
y_test_pred = np.argmax(y_test_pred, axis=1) # get the correct, encoded labels

y_test_pred
```

```
2/2 [==============================] - 0s 7ms/step
```

[81]:
```
array([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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

[82]:
```
# print classification report
from sklearn.metrics import classification_report
print(classification_report(y_test_encoded, y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.28      1.00      0.43        11
```

```
           1       0.00      0.00      0.00         7
           2       0.00      0.00      0.00        11
           3       0.00      0.00      0.00        11

    accuracy                           0.28        40
   macro avg       0.07      0.25      0.11        40
weighted avg       0.08      0.28      0.12        40

/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
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0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
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/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

1.0.1 4. Analysis

Running Deep Learning on a small dataset produced interesting results which make sense. The dataset used was very small, and overal performed extremely poor using RNN and CNN. However, when using a simple sequential model, the accuracy was fairly high, over 80%, this also includes precision, recall, and F1 for all the 4 target classes.

The simple sequential model performed very well given our small, balanced dataset. This is probably due to the fact that it is less likely to overfit/overlearn the small data. There are less hyper-parameters to tune and it is therefore less likely to overfit and overlearn during training. I learned that for simple datasets, deep learning does not provide good results.

For RNN and CNNs, a large about data is required. We have 159 instances and 4 classes, so it is expected to perform poorly. Even though I added padding and tried L2 regularization, the RNN and CNN both still predicted the same class for all instances in the test sets, resulting in accuracies less than 30%. It seems like both RNN and CNN overfitted to a point when it performed very badly on the test data. Additionally, there are too many hyper-parameters to adjust, leading to overlearning during training. I should have used a dataset with more training examples. For the CNN, I saw that changing the learning rate from 1e-4 or 0.01 helped the loss actually decrease. The variances in recall and precision are probably due to the fact that the model was unable to train on sufficient data for that class. Both RNN and CNN were good at detecting/classifying for one class whether an email was fraud/spam/phishing, but it has a low precision, which means that even though it may have said an email is fraud/spam/phishing, it is not likely that is actually is. It is good at detecting positive cases in general but not reliable.