```
In [1]: import os
        import pandas as pd
        import numpy as np
        import matplotlib
        import matplotlib.pyplot as plt
        %matplotlib inline
        import seaborn as sns
        sns.set(style='whitegrid')
        #from wordcloud import WordCloud
        import tensorflow as tf
        from sklearn.feature extraction.text import CountVectorizer, TfidfVectorizer
        from sklearn.model selection import train test split
        from sklearn.decomposition import PCA, TruncatedSVD
        from sklearn.metrics import classification report,confusion matrix
        from tensorflow.keras.preprocessing.text import Tokenizer
        from tensorflow.keras.preprocessing.sequence import pad_sequences
        from keras.models import Sequential
         from keras.layers import Embedding, LSTM,Dense, SpatialDropout1D, Dropout
        from keras.initializers import Constant
        # Reset individual options to default
        pd.reset_option('display.max_columns')
        pd.reset_option('display.max_rows')
        pd.reset_option('display.max_colwidth')
        # Set desired options
        pd.set_option('display.max_columns', 100)
        pd.set_option('display.max rows', 900)
        pd.set option('display.max colwidth', 200)
        import warnings
        warnings.filterwarnings("ignore")
        2024-07-30 10:23:35.795478: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register
        cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered 2024-07-30 10:23:35.795599: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register c
        uFFT factory: Attempting to register factory for plugin cuFFT when one has already been registered
        2024-07-30 10:23:35.964797: E external/local xla/xla/stream executor/cuda/cuda blas.cc:1515] Unable to register
        cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has already been registered
In [2]: train = pd.read_csv('/kaggle/input/sentiment-analysis-dataset/training.csv',header=None)
        validation = pd.read_csv('/kaggle/input/sentiment-analysis-dataset/validation.csv',header=None)
        train.columns=['Tweet ID','Entity','Sentiment','Tweet Content']
        validation.columns=['Tweet ID','Entity','Sentiment','Tweet Content']
        print("Training DataSet: \n")
        train = train.sample(2000)
        display(train.head())
        print("Validation DataSet: \n")
         #validation = validation.sample(1000)
        display(validation.head())
```

Training DataSet:

t Tweet	Sentiment	Entity	Tweet ID	
e <ur< th=""><th>Negative</th><th>MaddenNFL</th><th>7913</th><th>64883</th></ur<>	Negative	MaddenNFL	7913	64883
al .	Neutral	Google	4628	24633
Hey all hi @verizonfios If is my service a 563Mbps down\553Mbps up when I pay for 1Gig s services? Test is performed over a wired connection over CAT8 SFTP 40GB cables speedt	Negative	Verizon	11616	44337
Wife: "What did You do Last All Night? " Me: "Bombed a Few Legislative Buildings and a few People Meetings Me and You? " New Wife: " Stayed Up All Night Missing About	Irrelevant	Cyberpunk2077	3842	69136
Johnson & Johnson to Stop Selling Skin-Whitening Creams radio.com/articles/johns via @Rad	Neutral	johnson&johnson	7199	67722

Validation DataSet:

	Tweet ID	Entity	Sentiment	Tweet Content
0	3364	Facebook	Irrelevant	I mentioned on Facebook that I was struggling for motivation to go for a run the other day, which has been translated by Tom's great auntie as 'Hayley can't get out of bed' and told to his grandma
1	352	Amazon	Neutral	BBC News - Amazon boss Jeff Bezos rejects claims company acted like a 'drug dealer' bbc.co.uk/news/av/busine
2	8312	Microsoft	Negative	@Microsoft Why do I pay for WORD when it functions so poorly on my @SamsungUS Chromebook?
3	4371	CS-GO	Negative	CSGO matchmaking is so full of closet hacking, it's a truly awful game.
4	4433	Google	Neutral	Now the President is slapping Americans in the face that he really did commit an unlawful act after his acquittal! From Discover on Google vanityfair.com/news/2020/02/t

```
display(train.isnull().sum())
        print("***** 5)
        display(validation.isnull().sum())
                          0
        Tweet ID
        Entity
                          0
        Sentiment
                          0
        Tweet Content
                          0
        dtype: int64
         **********
        Tweet ID
                          0
        Entity
                          0
        Sentiment
                          Θ
        Tweet Content
                          0
        dtype: int64
In [4]: duplicates = train[train.duplicated(subset=['Entity', 'Sentiment', 'Tweet Content'], keep=False)]
        train = train.drop duplicates(subset=['Entity', 'Sentiment', 'Tweet Content'], keep='first')
        duplicates = validation[validation.duplicated(subset=['Entity', 'Sentiment', 'Tweet Content'], keep=False)]
        validation = validation.drop duplicates(subset=['Entity', 'Sentiment', 'Tweet Content'], keep='first')
In [5]: from tensorflow.keras.layers import Input, Dropout, Dense
        from tensorflow.keras.models import Model
        from tensorflow.keras.optimizers import Adam
        from tensorflow.keras.callbacks import EarlyStopping
        from tensorflow.keras.initializers import TruncatedNormal
        from tensorflow.keras.losses import CategoricalCrossentropy
         from tensorflow.keras.metrics import CategoricalAccuracy
        from tensorflow.keras.utils import to categorical
        import pandas as pd
        from sklearn.model selection import train test split
In [6]: !pip install plotly
        Requirement already satisfied: plotly in /opt/conda/lib/python3.10/site-packages (5.18.0)
Requirement already satisfied: tenacity>=6.2.0 in /opt/conda/lib/python3.10/site-packages (from plotly) (8.2.3)
        Requirement already satisfied: packaging in /opt/conda/lib/python3.10/site-packages (from plotly) (21.3)
        Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /opt/conda/lib/python3.10/site-packages (from packag
        ing->plotly) (3.1.1)
In [7]: import pandas as pd
        import plotly.graph_objects as go
        # Assuming you've already run the data preprocessing steps
        data = train[['Tweet Content', 'Sentiment']]
        # Set your model output as categorical and save in new label col
        data['Sentiment label'] = pd.Categorical(data['Sentiment'])
        # Transform your output to numeric
        data['Sentiment'] = data['Sentiment label'].cat.codes
        # Use the entire training data as data train
        data train = data
        # Use validation data as data test
        data_test = validation[['Tweet Content', 'Sentiment']]
        data_test['Sentiment_label'] = pd.Categorical(data_test['Sentiment'])
        data test['Sentiment'] = data test['Sentiment label'].cat.codes
         # Create a colorful table using Plotly
         fig = go.Figure(data=[go.Table(
             header=dict(
                 values=list(data_train.columns),
                 fill_color='paleturquoise',
                 align='left'
                 font=dict(color='black', size=12)
             cells=dict(
                 values=[data train[k].tolist()[:10] for k in data train.columns],
                 fill_color=[
                                   # Tweet Content
                      ['lightgreen' if s == 'Positive' else 'lightpink' if s == 'Negative'
                     else 'lightyellow' if s == 'Neutral' else 'lightgray' for s in data_train['Sentiment_label'][:10]
['lightgreen' if s == 'Positive' else 'lightpink' if s == 'Negative'
                       else 'lightyellow' if s == 'Neutral' else 'lightgray' for s in data train['Sentiment label'][:10]
                      'lavender' # Sentiment (numeric)
                 align='left'
                 font=dict(color='black', size=11)
             ))
        ])
        # Update the lavout
         fig.update_layout(
             title='First 10 Rows of Training Data',
```

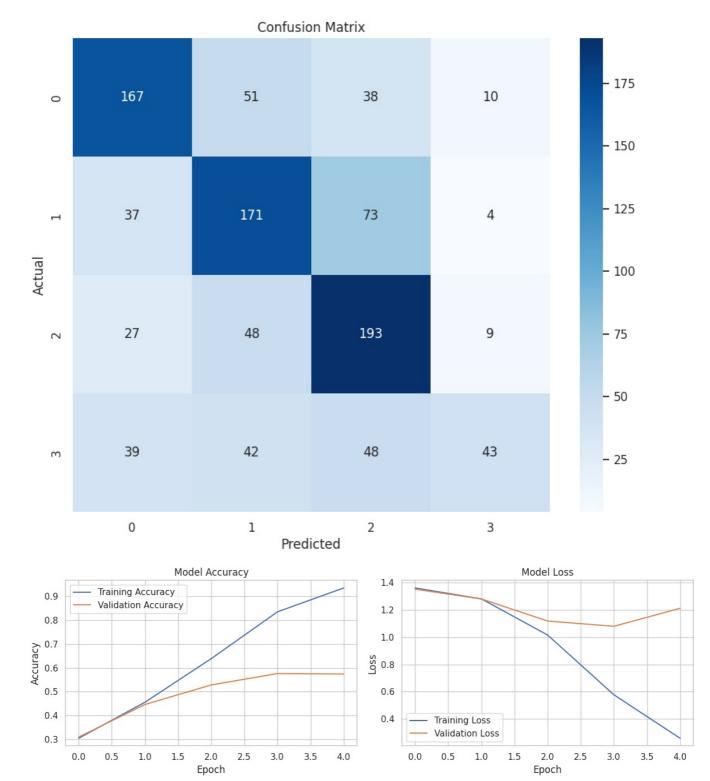
```
width=1000,
height=400,
)
fig.show()
```

```
In [8]: import plotly.graph objects as go
        # Create a colorful table using Plotly for the test data
        fig = go.Figure(data=[go.Table(
             header=dict(
                 values=list(data_test.columns),
                fill_color='paleturquoise',
align='left',
                 font=dict(color='black', size=12)
             cells=dict(
                 values=[data_test[k].tolist()[:5] for k in data_test.columns], # Show first 5 rows
                 fill_color=[
                     'lightcyan', # Tweet Content
['lightgreen' if s == 'Positive' else 'lightpink' if s == 'Negative'
                      else 'lightyellow' if s == 'Neutral' else 'lightgray' for s in data_test['Sentiment_label'][:5]],
                     ['lightgreen' if s == 'Positive' else 'lightpink' if s == 'Negative'
                      else 'lightyellow' if s == 'Neutral' else 'lightgray' for s in data test['Sentiment label'][:5]],
                     'lavender' # Sentiment (numeric)
                 align='left',
                 font=dict(color='black', size=11)
            ))
        ])
        # Update the layout
        fig.update_layout(
             title='First 5 Rows of Test Data',
            width=1000,
            height=300,
        # Show the figure
        fig.show()
        # If you want to save the figure as an HTML file, uncomment the following line:
        # fig.write_html("test_data_sample.html")
```

CNN

```
In [9]: %time
        import pandas as pd
        import numpy as np
        import tensorflow as tf
        from tensorflow.keras.preprocessing.text import Tokenizer
        from tensorflow.keras.preprocessing.sequence import pad sequences
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Embedding, Conv1D, GlobalMaxPooling1D, Dense, Dropout
from sklearn.metrics import confusion_matrix, classification_report
        import matplotlib.pyplot as plt
        import seaborn as sns
        # Ensure we're using GPU if available, otherwise use CPU
        gpus = tf.config.list physical devices('GPU')
        if gpus:
             try:
                 for gpu in gpus:
                     tf.config.experimental.set memory growth(gpu, True)
             except RuntimeError as e:
                 print(e)
        else:
            print("No GPU found. Using CPU.")
        # Extract text and labels
        train texts = data train["Tweet Content"].tolist()
        train_labels = data_train["Sentiment_label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
        # Convert labels to integers
        train_labels = train_labels.astype(int)
        test texts = data test["Tweet Content"].tolist()
        test labels = data test["Sentiment label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
        test_labels = test_labels.astype(int)
        # Preprocess text data
        max len = 100
        tokenizer = Tokenizer(num words=5000)
        tokenizer.fit on texts(train texts)
        train_sequences = tokenizer.texts_to_sequences(train_texts)
        test_sequences = tokenizer.texts_to_sequences(test_texts)
        train_padded = pad_sequences(train_sequences, maxlen=max_len, padding="post")
        test padded = pad sequences(test sequences, maxlen=max len, padding="post")
        # Create the model with CNN
        model = Sequential([
             Embedding(5000, 128, input_length=max_len),
             Conv1D(128, 5, activation='relu'),
             GlobalMaxPooling1D(),
            Dense(64, activation='relu'),
            Dropout (0.5)
            Dense(4, activation="softmax")
        ])
        # Compile the model
        model.compile(loss="sparse categorical crossentropy", optimizer="adam", metrics=["accuracy"])
        # Train the model
        epochs = 5
        batch size = 32
        history = model.fit(
             train_padded, train_labels,
             epochs=epochs,
```

```
batch size=batch size,
    validation_data=(test_padded, test_labels),
    verbose=1
# Make predictions
y pred = model.predict(test_padded)
y_pred_classes = np.argmax(y_pred, axis=1)
# Print classification report
print(classification report(test labels, y pred classes))
# Plot confusion matrix
cm = confusion matrix(test_labels, y pred classes)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
# Plot training history
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
Epoch 1/5
47/62
                          • 0s 2ms/step - accuracy: 0.2979 - loss: 1.3724
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1722335048.161148
                                   76 device_compiler.h:186] Compiled cluster using XLA! This line is logged a
t most once for the lifetime of the process.
                          - 10s 77ms/step - accuracy: 0.2992 - loss: 1.3696 - val accuracy: 0.3090 - val loss: 1
62/62
.3529
Epoch 2/5
                          - 0s 3ms/step - accuracy: 0.4457 - loss: 1.2935 - val_accuracy: 0.4460 - val_loss: 1.2
62/62
811
Epoch 3/5
62/62
                          – 0s 3ms/step - accuracy: 0.6291 - loss: 1.0683 - val_accuracy: 0.5280 - val loss: 1.1
191
Epoch 4/5
62/62
                          - 0s 3ms/step - accuracy: 0.8264 - loss: 0.6299 - val accuracy: 0.5760 - val loss: 1.0
803
Epoch 5/5
62/62
                          – 0s 3ms/step - accuracy: 0.9354 - loss: 0.2790 - val accuracy: 0.5740 - val loss: 1.2
126
                          - 1s 11ms/step
32/32
                           recall f1-score
              precision
                                               support
           0
                   0.62
                             0.63
                                        0.62
                                                   266
           1
                   0.55
                             0.60
                                        0.57
                                                   285
                   0.55
           2
                             0.70
                                                   277
                                        0.61
           3
                   0.65
                             0.25
                                       0.36
                                                   172
                                        0.57
                                                  1000
    accuracy
   macro avo
                   0.59
                             0.54
                                        0.54
                                                  1000
                             0.57
                                       0.56
                                                  1000
weighted avg
                   0.58
```



CPU times: user 11.6 s, sys: 1.35 s, total: 13 s Wall time: 14.2 s $\,$

Gated Recurrent Units (GRU)

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad sequences
from tensorflow.keras.models import Sequential
\textbf{from} \ \text{tensorflow}. \\ \text{keras.layers} \ \textbf{import} \ \text{Embedding}, \ \\ \text{Bidirectional}, \ \\ \text{GRU}, \ \\ \text{Dense}
from sklearn.metrics import confusion matrix, classification_report
import matplotlib.pyplot as plt
import seaborn as sns
# Ensure we're using GPU if available, otherwise use CPU
gpus = tf.config.list physical devices('GPU')
if gpus:
    try:
        for gpu in gpus:
             tf.config.experimental.set_memory_growth(gpu, True)
    except RuntimeError as e:
        print(e)
else:
    print("No GPU found. Using CPU.")
# Extract text and labels
train_texts = data_train["Tweet Content"].tolist()
train labels = data train["Sentiment label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
# Convert labels to integers
train_labels = train_labels.astype(int)
test texts = data test["Tweet Content"].tolist()
test_labels = data_test["Sentiment_label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
test_labels = test_labels.astype(int)
# Preprocess text data
max_len = 100
tokenizer = Tokenizer(num words=5000)
tokenizer.fit on texts(train texts)
train_sequences = tokenizer.texts_to_sequences(train_texts)
test_sequences = tokenizer.texts_to_sequences(test_texts)
train_padded = pad_sequences(train_sequences, maxlen=max_len, padding="post")
test_padded = pad_sequences(test_sequences, maxlen=max_len, padding="post")
# Create the model with BiGRU
model = Sequential([
    Embedding(5000, 128, input length=max len),
    Bidirectional(GRU(64, return sequences=True)),
    Bidirectional(GRU(32)),
    Dense(4, activation="softmax")
])
# Compile the model
model.compile(loss="sparse_categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
# Train the model
epochs = 5
batch_size = 32 # Add batch size
history = model.fit(
    train_padded, train_labels,
    epochs=epochs,
    batch_size=batch_size,
    validation data=(test padded, test labels),
    verbose=1
)
# Make predictions
y_pred = model.predict(test_padded)
y_pred_classes = np.argmax(y_pred, axis=1)
# Print classification report
print(classification report(test labels, y pred classes))
# Plot confusion matrix
cm = confusion_matrix(test_labels, y_pred_classes)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
# Plot training history
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

```
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
Epoch 1/5
62/62
                            - 7s 27ms/step - accuracy: 0.3275 - loss: 1.3633 - val_accuracy: 0.4510 - val_loss: 1.
3075
Epoch 2/5
62/62
                            - 1s 18ms/step - accuracy: 0.5775 - loss: 1.1264 - val_accuracy: 0.5100 - val_loss: 1.
2282
Epoch 3/5
62/62
                            - 1s 19ms/step - accuracy: 0.7510 - loss: 0.6151 - val_accuracy: 0.5060 - val_loss: 1.
3638
Epoch 4/5
62/62
                           - 1s 20ms/step - accuracy: 0.8704 - loss: 0.3772 - val accuracy: 0.5090 - val loss: 1.
6953
Epoch 5/5
62/62
                            - 1s 20ms/step - accuracy: 0.9151 - loss: 0.2492 - val_accuracy: 0.5240 - val_loss: 1.
7625
                            - 1s 16ms/step
32/32
               precision
                             recall f1-score
                                                  support
            0
                    0.59
                               0.58
                                          0.59
                                                      266
            1
                    0.54
                               0.56
                                          0.55
                                                      285
            2
                    0.55
                               0.53
                                          0.54
                                                      277
            3
                    0.36
                               0.36
                                          0.36
                                                      172
    accuracy
                                          0.52
                                                     1000
                    0.51
                               0.51
                                          0.51
                                                     1000
   macro avg
                    0.52
                               0.52
                                          0.52
                                                     1000
weighted avg
                                         Confusion Matrix
                                                                                                         - 160
                155
                                       61
                                                             21
                                                                                  29
   0
                                                                                                        - 140
                                                                                                        - 120
                 35
                                      161
                                                             56
                                                                                  33
                                                                                                        - 100
                                                                                                         - 80
                                       40
                                                            146
                                                                                   47
                 44
```

44

2

62

3

- 60

- 40

7

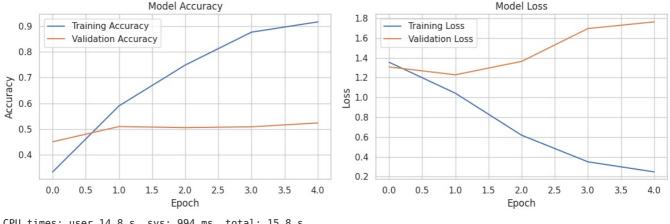
29

0

37

1

Predicted



CPU times: user 14.8 s, sys: 994 ms, total: 15.8 s Wall time: 14 s

RNN

```
In [11]: %time
         import pandas as pd
          import numpy as np
          import tensorflow as tf
          from tensorflow.keras.preprocessing.text import Tokenizer
          from tensorflow.keras.preprocessing.sequence import pad_sequences
          from tensorflow.keras.models import Sequential
          \textbf{from} \  \, \textbf{tensorflow}. \textbf{keras.layers} \  \, \textbf{import} \  \, \textbf{Embedding}, \  \, \textbf{SimpleRNN}, \  \, \textbf{Dense}
          from sklearn.metrics import confusion_matrix, classification_report
          import matplotlib.pyplot as plt
         import seaborn as sns
          # Ensure we're using GPU if available, otherwise use CPU
         gpus = tf.config.list physical devices('GPU')
          if gpus:
              try:
                  for gpu in gpus:
                       tf.config.experimental.set memory growth(gpu, True)
              except RuntimeError as e:
                  print(e)
         else:
              print("No GPU found. Using CPU.")
          # Extract text and labels
         train texts = data train["Tweet Content"].tolist()
         train_labels = data_train["Sentiment_label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
         # Convert labels to integers
         train_labels = train_labels.astype(int)
          test_texts = data_test["Tweet Content"].tolist()
         test_labels = data_test["Sentiment_label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
          test_labels = test_labels.astype(int)
          # Preprocess text data
         max len = 100
          tokenizer = Tokenizer(num words=5000)
          tokenizer.fit on texts(train texts)
          train_sequences = tokenizer.texts_to_sequences(train_texts)
          test_sequences = tokenizer.texts_to_sequences(test_texts)
          train padded = pad_sequences(train sequences, maxlen=max len, padding="post")
          test_padded = pad_sequences(test_sequences, maxlen=max_len, padding="post")
          # Create the model with RNN
         model = Sequential([
              Embedding(5000, 128, input_length=max_len),
              SimpleRNN(64, return_sequences=True),
              SimpleRNN(32),
              Dense(4, activation="softmax")
         ])
          # Compile the model
         model.compile(loss="sparse_categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
          # Train the model
         epochs = 5
```

```
batch size = 32
history = model.fit(
    train_padded, train_labels,
    epochs=epochs,
    batch size=batch size,
    validation_data=(test_padded, test_labels),
)
# Make predictions
y_pred = model.predict(test_padded)
y_pred_classes = np.argmax(y_pred, axis=1)
# Print classification report
print(classification report(test labels, y pred classes))
# Plot confusion matrix
cm = confusion matrix(test labels, y pred classes)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
# Plot training history
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
Epoch 1/5
                           8s 67ms/step - accuracy: 0.2899 - loss: 1.3887 - val accuracy: 0.2860 - val loss: 1.
62/62
3716
Epoch 2/5
                          - 1s 18ms/step - accuracy: 0.2835 - loss: 1.3795 - val accuracy: 0.2770 - val loss: 1.
62/62
3792
Epoch 3/5
62/62
                          - 1s 17ms/step - accuracy: 0.2826 - loss: 1.3699 - val accuracy: 0.2580 - val loss: 1.
3769
Epoch 4/5
62/62
                          - 1s 17ms/step - accuracy: 0.3448 - loss: 1.3540 - val_accuracy: 0.2660 - val loss: 1.
3985
Epoch 5/5
62/62
                          - 1s 17ms/step - accuracy: 0.3265 - loss: 1.3658 - val accuracy: 0.2850 - val loss: 1.
4062
32/32
                          - 1s 20ms/step
              precision
                           recall f1-score
                                               support
                              0.15
           0
                   0.25
                                        0.19
                                                   266
           1
                   0.32
                              0.25
                                        0.28
                                                   285
                   0.28
                              0.63
                                        0.39
                                                   277
           2
           3
                   0.00
                              0.00
                                        0.00
                                                   172
                                        0.28
                                                  1000
    accuracy
                              0.26
                   0.21
                                        0.21
                                                  1000
   macro avo
```

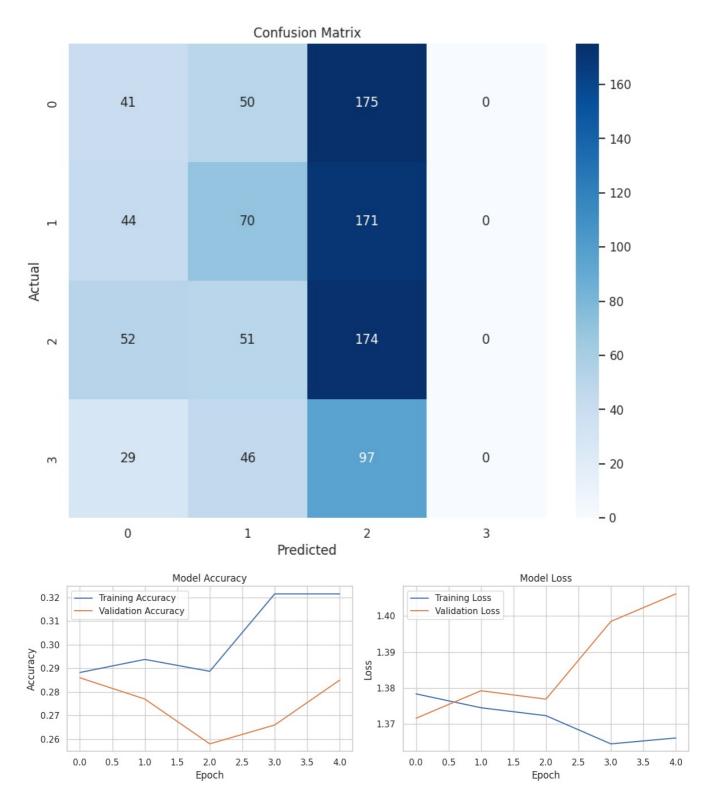
0.28

0.24

weighted avg

0.24

1000

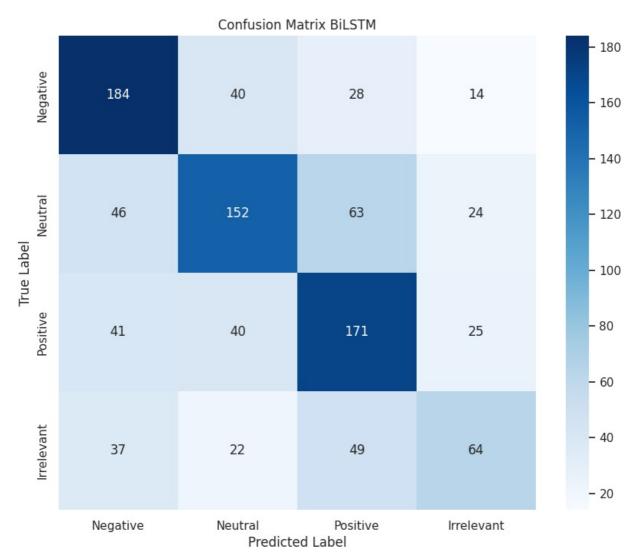


CPU times: user 14.7 s, sys: 740 ms, total: 15.4 s Wall time: 15.3 s $\,$

BiLSTM

```
import pandas as pd
import numpy as np
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad sequences
\textbf{from} \  \, \textbf{tensorflow}. \textbf{keras}. \textbf{models} \  \, \textbf{import} \  \, \textbf{Sequential}
\textbf{from} \ \text{tensorflow}. \\ \text{keras.layers} \ \textbf{import} \ \text{Embedding}, \ \\ \text{Bidirectional}, \ \\ \text{LSTM}, \ \\ \text{Dense}
from sklearn.metrics import confusion matrix, classification_report
import matplotlib.pyplot as plt
import seaborn as sns
# Extract text and labels
train_texts = data_train["Tweet Content"].tolist()
train_labels = data_train["Sentiment_label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
# Convert labels to integers (assuming numerical mapping)
train_labels = train_labels.astype(int) # Ensure labels are numerical
test texts = data test["Tweet Content"].tolist()
test_labels = data_test["Sentiment_label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
test_labels = test_labels.astype(int) # Ensure labels are numerical
# Preprocess text data
max_len = 100  # Adjust max sequence length as needed
tokenizer = Tokenizer(num words=5000) # Adjust vocabulary size as needed
tokenizer.fit on texts(train texts)
train_sequences = tokenizer.texts_to_sequences(train_texts)
test_sequences = tokenizer.texts_to_sequences(test_texts)
train padded = pad sequences(train sequences, maxlen=max len, padding="post")
test padded = pad sequences(test sequences, maxlen=max len, padding="post")
# Create the model with BiLSTM
model = Sequential()
model.add(Embedding(5000, 128, input_length=max_len)) # Embedding layer
model.add(Bidirectional(LSTM(64))) # Bidirectional LSTM layer with 64 units
model.add(Dense(4, activation="softmax")) # Output layer with softmax activation
# Compile the model
model.compile(loss="sparse categorical crossentropy", optimizer="adam", metrics=["accuracy"])
# Train the model
epochs = 5 # Adjust number of epochs as needed
history = model.fit(train padded, train_labels, epochs=epochs, validation data=(test padded, test labels))
# Make predictions
y_pred = model.predict(test_padded)
y_pred_classes = np.argmax(y_pred, axis=1)
# Plot training & validation accuracy values
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val loss'])
plt.title('Model Loss')
plt.ylabel('Loss'
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.tight_layout()
plt.show()
# Generate confusion matrix
cm = confusion matrix(test labels, y pred classes)
# Generate classification report
class_names = ["Negative", "Neutral", "Positive", "Irrelevant"] # Adjust if needed
cr = classification_report(test_labels, y_pred_classes, target_names=class_names)
print("Classification Report BiLSTM:")
print(cr)
# Make predictions
y_pred = model.predict(test_padded)
y pred classes = np.argmax(y pred, axis=1)
# Define class names
class names = ["Negative", "Neutral", "Positive", "Irrelevant"]
```

```
# Generate confusion matrix
cm = confusion_matrix(test_labels, y_pred_classes)
# Plot confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
plt.title('Confusion Matrix BiLSTM')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
# Evaluate the model (on validation data)
loss, accuracy = model.evaluate(test padded, test labels)
print("Test Accuracy BiLSTM:", accuracy)
Epoch 1/5
62/62
                            3s 18ms/step - accuracy: 0.2796 - loss: 1.3711 - val accuracy: 0.3130 - val loss: 1.
3292
Epoch 2/5
62/62
                             1s 11ms/step - accuracy: 0.4823 - loss: 1.2285 - val accuracy: 0.5410 - val loss: 1.
1484
Epoch 3/5
                            - 1s 11ms/step - accuracy: 0.7137 - loss: 0.7426 - val accuracy: 0.5420 - val loss: 1.
62/62
3064
Epoch 4/5
                           - 1s 11ms/step - accuracy: 0.8463 - loss: 0.4757 - val accuracy: 0.5490 - val loss: 1.
62/62
2401
Epoch 5/5
62/62
                           - 1s 11ms/step - accuracy: 0.9061 - loss: 0.2812 - val_accuracy: 0.5710 - val_loss: 1.
3985
32/32
                             0s 9ms/step
                          Model Accuracy
                                                                                         Model Loss
  0.9
                                                               1.4
            Train
                                                                         Train
            Test
                                                                         Test
  0.8
                                                               1.2
  0.7
                                                               1.0
Accuracy
                                                             0.8
  0.6
  0.5
                                                               0.6
  0.4
                                                               0.4
  0.3
       0.0
             0.5
                   1.0
                         1.5
                               2.0
                                     2.5
                                           3.0
                                                 3.5
                                                       4.0
                                                                    0.0
                                                                          0.5
                                                                                1.0
                                                                                      1.5
                                                                                            2.0
                                                                                                  2.5
                                                                                                        3.0
                                                                                                              3.5
                                                                                                                    4.0
                              Epoch
                                                                                           Epoch
Classification Report BiLSTM:
               precision
                             recall f1-score
                                                  support
                    0.60
                               0.69
                                          0.64
                                                      266
    Negative
                    0.60
                               0.53
                                          0.56
                                                      285
     Neutral
    Positive
                    0.55
                               0.62
                                          0.58
                                                      277
  Irrelevant
                    0.50
                               0.37
                                          0.43
                                                      172
    accuracy
                                          0.57
                                                     1000
                    0.56
                               0.55
                                          0.55
                                                     1000
   macro avg
weighted avg
                    0.57
                               0.57
                                          0.57
                                                     1000
32/32 •
                             0s 6ms/step
```



32/32 — **0s** 6ms/step - accuracy: 0.5755 - loss: 1.3273 Test Accuracy BiLSTM: 0.5709999799728394

CPU times: user 10.2 s, sys: 846 ms, total: 11 s

Wall time: 9.31 s

LSTM

```
In [13]: %time
```

```
import pandas as pd
import numpy as np
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
```

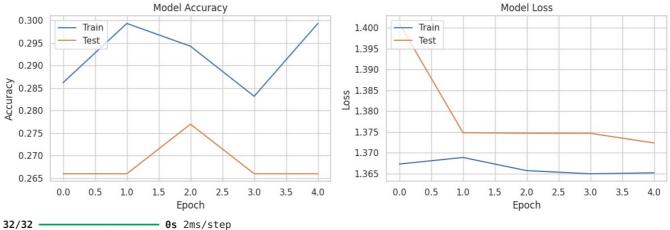
```
from sklearn.metrics import confusion matrix, classification report
         import matplotlib.pyplot as plt
         import seaborn as sns
         # Extract text and labels
         train_texts = data_train["Tweet Content"].tolist()
         train labels = data train["Sentiment label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
         # Convert labels to integers (assuming numerical mapping)
         train labels = train labels.astype(int) # Ensure labels are numerical
         test texts = data test["Tweet Content"].tolist()
         test_labels = data_test["Sentiment_label"].map({"Positive": 2, "Negative": 0, "Neutral": 1, "Irrelevant": 3})
         test_labels = test_labels.astype(int) # Ensure labels are numerical
         # Preprocess text data
         max len = 100 # Adjust max sequence length as needed
         tokenizer = Tokenizer(num words=5000) # Adjust vocabulary size as needed
         tokenizer.fit_on_texts(train_texts)
         train_sequences = tokenizer.texts_to_sequences(train_texts)
         test sequences = tokenizer.texts to sequences(test texts)
         train_padded = pad_sequences(train_sequences, maxlen=max_len, padding="post")
         test_padded = pad_sequences(test_sequences, maxlen=max_len, padding="post")
         # Create the model
         model = Sequential()
         model.add(Embedding(5000, 128, input_length=max_len)) # Embedding layer
         model.add(LSTM(64)) # LSTM layer with 64 units
         model.add(Dense(4, activation="softmax")) # Output layer with softmax activation
         # Compile the model
         model.compile(loss="sparse categorical crossentropy", optimizer="adam", metrics=["accuracy"])
         # Train the model
         epochs = 5 # Adjust number of epochs as needed
         history = model.fit(train padded, train labels, epochs=epochs, validation data=(test padded, test labels))
         # Make predictions
         y_pred = model.predict(test_padded)
         y_pred_classes = np.argmax(y_pred, axis=1)
         Epoch 1/5
         62/62
                                —— 2s 13ms/step - accuracy: 0.2687 - loss: 1.3725 - val accuracy: 0.2660 - val loss: 1.
         4010
         Epoch 2/5
         62/62
                                  — 1s 10ms/step - accuracy: 0.2906 - loss: 1.3779 - val accuracy: 0.2660 - val loss: 1.
         3748
         Epoch 3/5
         62/62
                                 —— 1s 9ms/step - accuracy: 0.3067 - loss: 1.3562 - val_accuracy: 0.2770 - val_loss: 1.3
         747
         Epoch 4/5
         62/62
                                  — 1s 8ms/step - accuracy: 0.2772 - loss: 1.3701 - val accuracy: 0.2660 - val loss: 1.3
         747
         Epoch 5/5
         62/62
                                   - 0s 8ms/step - accuracy: 0.3090 - loss: 1.3614 - val accuracy: 0.2660 - val loss: 1.3
         724
         32/32
                                   - 0s 6ms/step
         CPU times: user 5.56 s, sys: 292 ms, total: 5.85 s
         Wall time: 5.07 s
In [14]: # Plot training & validation accuracy values
         plt.figure(figsize=(12, 4))
         plt.subplot(1, 2, 1)
         plt.plot(history.history['accuracy'])
         plt.plot(history.history['val accuracy'])
         plt.title('Model Accuracy')
         plt.ylabel('Accuracy')
plt.xlabel('Epoch')
         plt.legend(['Train', 'Test'], loc='upper left')
         # Plot training & validation loss values
         plt.subplot(1, 2, 2)
         plt.plot(history.history['loss'])
         plt.plot(history.history['val_loss'])
         plt.title('Model Loss')
         plt.ylabel('Loss')
         plt.xlabel('Epoch')
         plt.legend(['Train', 'Test'], loc='upper left')
         plt.tight layout()
         plt.show()
         # Make predictions
         y_pred = model.predict(test_padded)
         y pred classes = np.argmax(y pred, axis=1)
         # Define class names
```

```
class_names = ["Negative", "Neutral", "Positive", "Irrelevant"]

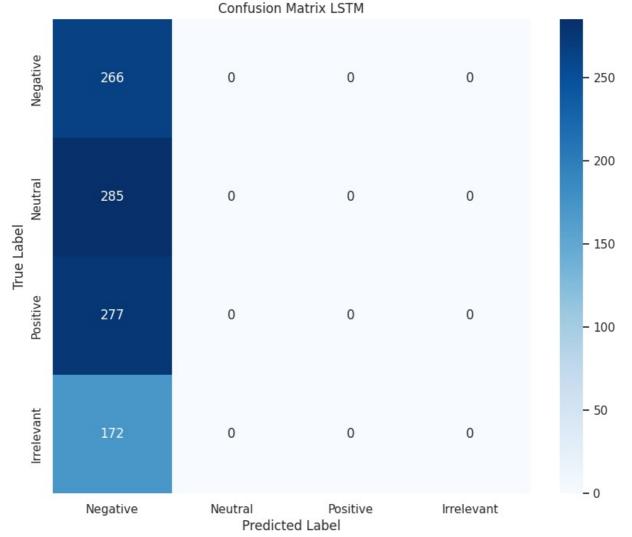
# Generate confusion matrix
cm = confusion_matrix(test_labels, y_pred_classes)

# Plot confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
plt.title('Confusion Matrix LSTM')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.xlabel('Predicted Label')
plt.show()

# Evaluate the model (on validation data)
loss, accuracy = model.evaluate(test_padded, test_labels)
print("Test Accuracy LSTM:", accuracy)
```







32/32 — **0s** 5ms/step - accuracy: 0.2743 - loss: 1.3666 Test Accuracy LSTM: 0.26600000262260437

```
In [15]: # Generate confusion matrix
cm = confusion_matrix(test_labels, y_pred_classes)

# Generate classification report
class_names = ["Negative", "Neutral", "Positive", "Irrelevant"] # Adjust if needed
```

```
cr = classification_report(test_labels, y_pred_classes, target_names=class_names)
print("Classification Report:")
print(cr)
Classification Report:
             precision
                          recall f1-score support
   Negative
                 0.27
                           1.00
                                     0.42
            0.00
0.00
    Neutral
                0.00
0.00
0.00
                           0.00
                                     0.00
                                                285
   Positive
                           0.00
                                     0.00
                                                277
  Irrelevant
                           0.00
                                     0.00
                                               172
                                     0.27
                                               1000
   accuracy
macro avg 0.07 0.25
weighted avg 0.07 0.27
                                     0.11
                                               1000
                                     0.11
                                               1000
```

https://www.kaggle.com/code/pythonafroz/neural-network-based-methods-nlp

In []:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js