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Exercise notebook code and output

All work files, including report and notebook are located here in GitHub
https://github.com/mramsundar/IITM-Graded-Projects/tree/b85e06634a085b93155c455db2371c45ddf3ad2b/Week%2031
Notebook file direct link
https://github.com/mramsundar/IITM-Graded-Projects/blob/b85e06634a085b93155c455db2371c45ddf3ad2b/Week%2031/tweet_anaysis.ipynb
PDF of the notebook
https://github.com/mramsundar/IITM-Graded-Projects/blob/b85e06634a085b93155c455db2371c45ddf3ad2b/Week%2031/tweet_anaysis.pdf

Documentation

1. My approach started with defining a set of global constants, that could be then reused in multiple places across the notebook.

```
In [3]: @dataclass
class Config:
    DATA_PATH: str = "twitter_training.csv"
    RANDOM_SEED: int = 28
    SPACY_MODEL: str = "en_core_web_sm"
    TEXT_VECTOR_MAX_TOKENS:int = 5000
    TEXT_VECTOR_OUTPUT_MODE: str = "int"
    TEXT_VECTOR_OUTPUT_SEQUENCE_LENGTH:int =300
    TEXT_VECTOR_EMBEDDING_DIMENSION:int = 64 # Recommended value for tweets and short texts
    VECTORIZER: Any = None
    TOTAL_EPOCHS: int = 10
    BATCH_SIZE: int = 254
    EARLY_STOPPING_PATIENCE: int = 5
    LSTM_UNITS: int = 64 # Keeping the embedding dimension size in mind
    HIDDEN_UNITS: int = 32
    DROPOUT_RATE: float = 0.2
```

```
GlobalConfig = Config()


def set_global_seed(seed_value: int) -> None:
    os.environ['PYTHONHASHSEED'] = str(seed_value)
    random.seed(seed_value)
    tf.random.set_seed(seed_value)
    np.random.seed(seed_value)

set_global_seed(GlobalConfig.RANDOM_SEED)
```

2. Dataset was then loaded and basic cleanup process started, including setting headers, removing duplicates

```
def load_and_setup_data() -> pd.DataFrame:
    df = pd.read_csv(GlobalConfig.DATA_PATH)
    # First column appers to be some sort file or sequence number and the second appears to be the source
    # Those two columns do not have any impact on sentiment analysis
    # Take the last two columns
    df = df.iloc[:, -2:]
    # Swap columns 1 and 2
    df = df[[df.columns[1], df.columns[0]]]
    # Setup column names
    df.columns = ["tweet", "sentiment"]
    # Remove empty rows
    df = df.dropna()
    # Remove where sentiment is "Irrelevant"
    df = df[df["sentiment"] != "Irrelevant"]
    # Remove diuplicate rows
    df = df.drop_duplicates()
    # Look for tweets where the same tweet is classified as a different sentiment
    # Take the first occurence - this will get us clean data and will not mislead the classifier later during train
    df = df.drop_duplicates(subset=["tweet"], keep="first")
    return df
```

```
df = load_and_setup_data()
```

3. Since this is a sentiment analysis project, the next step was to take what is essential from the tweets. SpaCy was used to lemmatize the text

```
df = load_and_setup_data()


# Just keep the essentials, remove named entities, parsing and sentence segmentation for speed
nlp = spacy.load(GlobalConfig.SPACY_MODEL, disable=["ner", "parser", "senter"])


def clean_and_pre_process(texts: list[str]) -> list[str]:
    # Standard regex patterns for cleaning tweets
    url_pattern = re.compile(r"http\S+|www\S+|https\S+")
    twitter_handle_pattern = re.compile(r"\@\w+|\#")
    non_alpha_pattern = re.compile(r"[^a-zA-Z\s]")

    cleaned_texts: list[str] = []
    for text in texts:
        text = url_pattern.sub("", text)
        text = twitter_handle_pattern.sub("", text)
        text = non_alpha_pattern.sub("", text)
        cleaned_texts.append(text.strip().lower())

    # Use spaCy's nlp.pipe for efficient processing of multiple texts
    docs = nlp.pipe(cleaned_texts, batch_size=2000, n_process=-1)

    final_texts: list[str] = []
    for doc in tqdm(docs, total=len(cleaned_texts)):
        # This is a key line - we are lemmatizing, removing stop words, punctuation and single character tokens
        tokens = [token.lemma_ for token in doc if not token.is_stop and not token.is_punct and len(token.lemma_) >
        final_texts.append(" ".join(tokens))

    return final_texts


df["sanitized_tweet"] = clean_and_pre_process(df["tweet"].tolist())
df.head()
```

```
100%|██████████| 57296/57296 [00:17<00:00, 3188.16it/s]
```

4. Next is feature engineering. We transformed the cleaned-up tweet into a sequence of integers. These would later be converted into embeddings when we construct our RNN

```
def create_tokenized_words(df: pd.DataFrame) -> tuple[pd.DataFrame, Any]:
    texts = df["sanitized_tweet"].values
    vectorizer = tf.keras.layers.TextVectorization(
        max_tokens=GlobalConfig.TEXT_VECTOR_MAX_TOKENS,
        output_mode=GlobalConfig.TEXT_VECTOR_OUTPUT_MODE,
        output_sequence_length=GlobalConfig.TEXT_VECTOR_OUTPUT_SEQUENCE_LENGTH
    )
    vectorizer.adapt(texts)
    # Convert text to integer sequences - which will then be fed into the embedding layer
    tfidf_vectors = vectorizer(texts)
    # add the tokenized words as a new column
    df["sanitized_tweet_vector"] = list(tfidf_vectors.numpy())
    return (df, vectorizer)

df, GlobalConfig.VECTORIZER = create_tokenized_words(df)
df.head()
```

```
imizer for device_type GPU is enabled.
```

Out[5]:

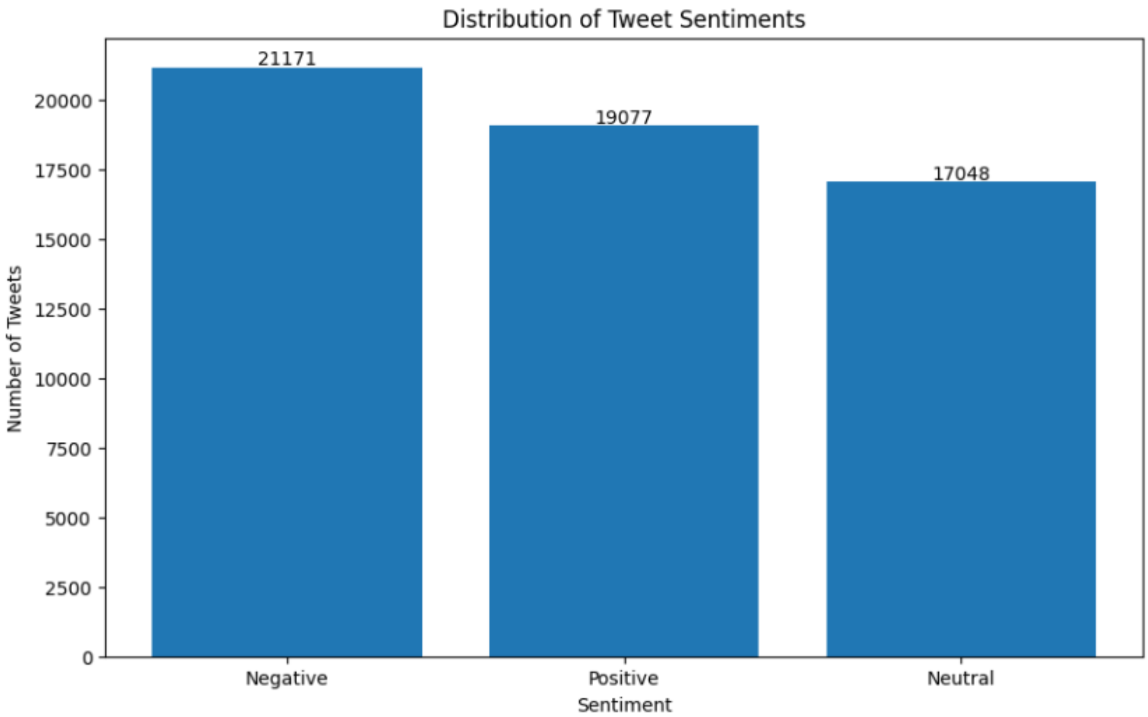
	tweet	sentiment	sanitized_tweet	sanitized_tweet_vector
0	I am coming to the borders and I will kill you...	Positive	come border kill	[30, 1496, 82, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
1	im getting on borderlands and i will kill you ...	Positive	get borderland kill	[7, 50, 82, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
2	im coming on borderlands and i will murder you...	Positive	come borderland murder	[30, 50, 1111, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
3	im getting on borderlands 2 and i will murder ...	Positive	get borderland murder	[7, 50, 1111, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
4	im getting into borderlands and i can murder y...	Positive	get borderland murder	[7, 50, 1111, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...

5. During EDA, it was observed that the sentiments were fairly well distributed

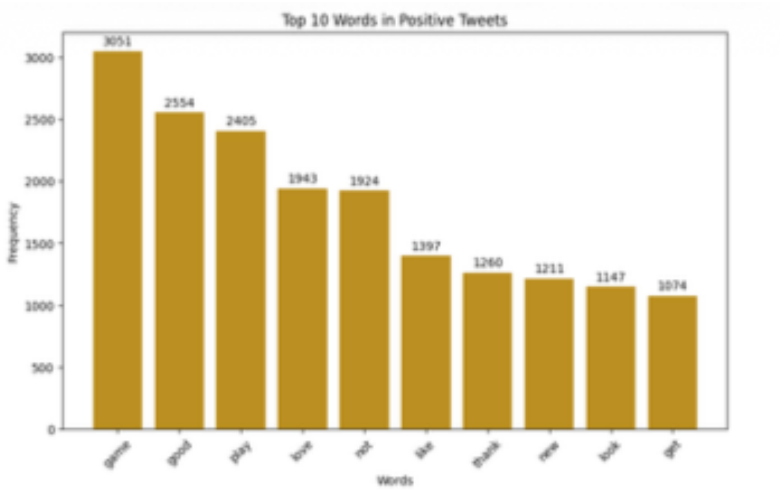
2.1 Basic Statistics

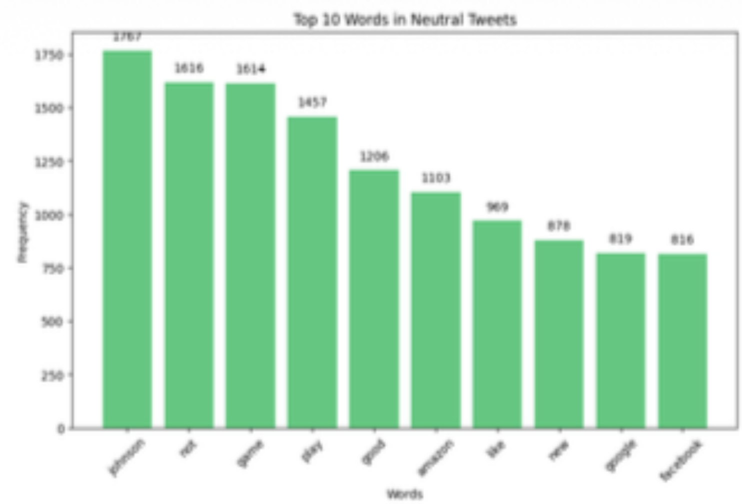
```
# Explore the distribution of tweet sentiments (e.g., how many positive, negative, and neutral tweets are there?)
# Plot a simple bar chart
sentiment_counts = df["sentiment"].value_counts()
plt.figure(figsize=(10, 6))
plt.bar(sentiment_counts.index, sentiment_counts.values.tolist())
# Add total counts on top of each bar
for i, count in enumerate(sentiment_counts.values):
    plt.text(i, count + 100, str(count), ha="center")
plt.xlabel("Sentiment")
plt.ylabel("Number of Tweets")
```

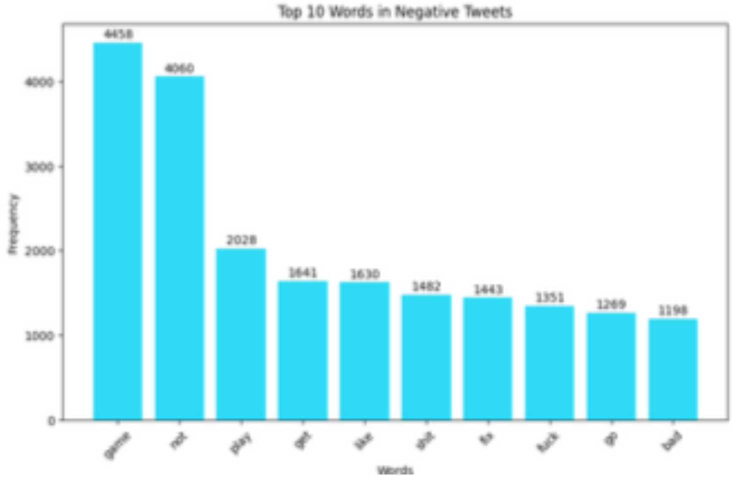
```
plt.title("Distribution of Tweet Sentiments")
plt.show()
```



6. Bar charts with word frequencies and word clouds were created next


Top 10 Words in Positive Tweets
Frequency
Words
0
500
1000
1500
2000
2500
3000
3051
2554
2405
1943
1924
1397
1260
1211
1147
1074
game
good
play
love
not
like
thank
new
look
get


Top 10 Words in Neutral Tweets
Frequency
Words
0
250
500
750
1000
1250
1500
1750
1767
1616
1614
1457
1206
1103
969
878
819
816
johnson
not
game
play
good
amazon
like
new
google
facebook


Top 10 Words in Negative Tweets
Frequency
Words
0
1000
2000
3000
4000
4458
4060
2028
1641
1630
1482
1443
1351
1269
1198
game
not
play
get
like
shit
fix
fuck
go
bad

7. Word clouds

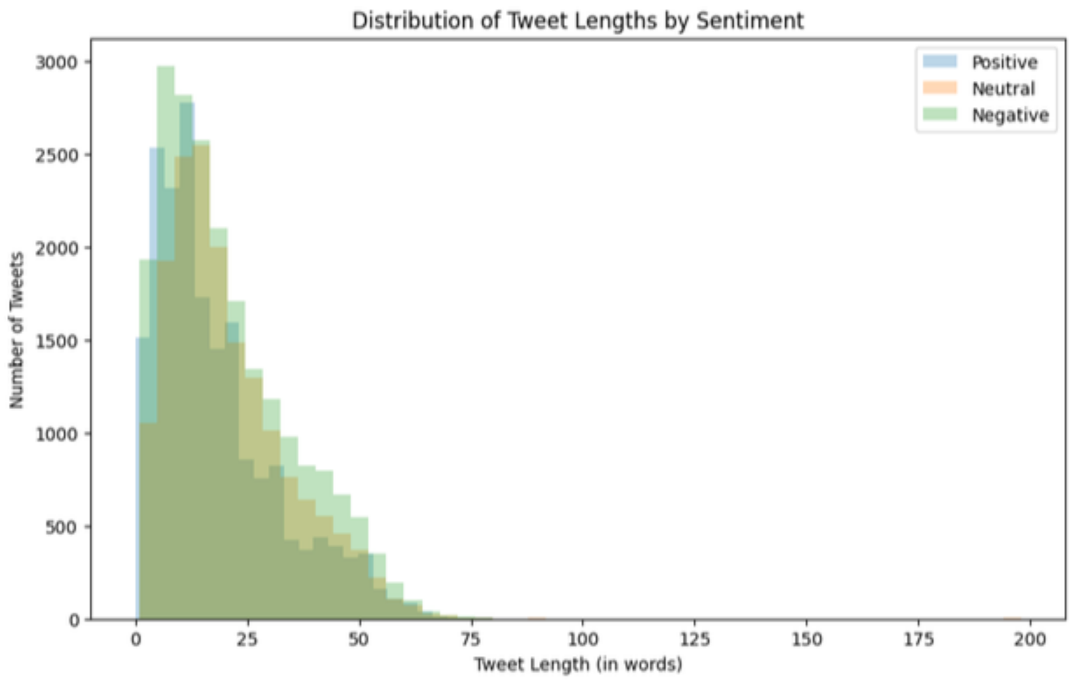
```
In [8]: def create_wordcloud() -> None:
            # Wordcloud for positive and negative tweets
            for sentiment in ["Positive", "Negative"]:
                subset = df[df["sentiment"] == sentiment]
                all_words = " ".join(subset["sanitized_tweet"])
                wordcloud = WordCloud(width=1000, height=400, background_color="white").generate(all_words)

                plt.figure(figsize=(10, 10))
                plt.imshow(wordcloud, interpolation="bilinear")
                plt.axis("off")
                plt.title(f"Word Cloud for {sentiment} Tweets")
                plt.show()

        create_wordcloud()
```

Word Cloud for Positive Tweets

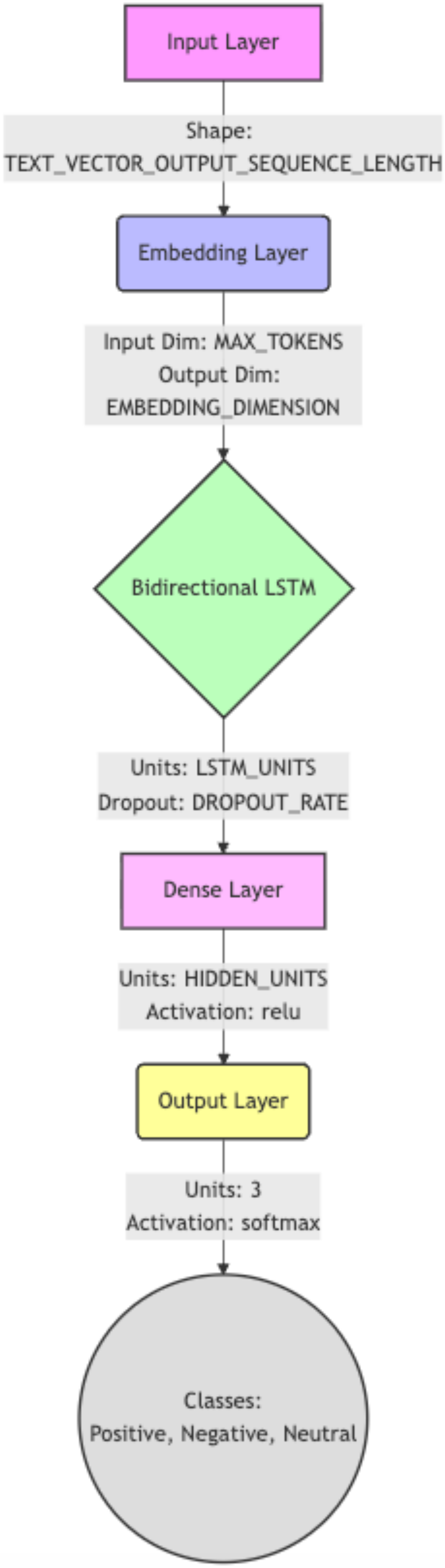
Word Cloud for Negative Tweets

8. Last step of EDA was to look at the relationship between tweet length and the sentiment. It was observed that there is no obvious relationship

```
In [9]: def show_relationship_between_tweet_length_and_sentiment() -> None:
            # Relationthip between tweet length and sentiment
            df["tweet_length"] = df["tweet"].apply(lambda x: len(x.split()))
            plt.figure(figsize=(10, 6))
            for sentiment in sentiment_categories:
                subset = df[df["sentiment"] == sentiment]
                plt.hist(subset["tweet_length"], bins=50, alpha=0.3, label=sentiment)
            plt.xlabel("Tweet Length (in words)")
            plt.ylabel("Number of Tweets")
            plt.title("Distribution of Tweet Lengths by Sentiment")
            plt.legend()
            plt.show()

        show_relationship_between_tweet_length_and_sentiment()
```



9. The following is the RNN model architecture (created in Mermaid format based on the Python code) with ~400K trainable parameters



Input Layer
Shape: TEXT_VECTOR_OUTPUT_SEQUENCE_LENGTH
Embedding Layer
Input Dim: MAX_TOKENS
Output Dim: EMBEDDING_DIMENSION
Bidirectional LSTM
Units: LSTM_UNITS
Dropout: DROPOUT_RATE
Dense Layer
Units: HIDDEN_UNITS
Activation: relu
Output Layer
Units: 3
Activation: softmax
Classes: Positive, Negative, Neutral

10. Model code

```
]: def build_rnn_model() -> keras.Model:
    model = keras.Sequential()

    #Input layer - same as output sequence length of text vectorization
    model.add(keras.Input(shape=(GlobalConfig.TEXT_VECTOR_OUTPUT_SEQUENCE_LENGTH,)))

    # Embedding layer
    model.add(
        keras.layers.Embedding(
            input_dim=GlobalConfig.TEXT_VECTOR_MAX_TOKENS,
            output_dim=GlobalConfig.TEXT_VECTOR_EMBEDDING_DIMENSION
        )
    )

    # LSTM Layer for analyzing sequences
    model.add(keras.layers.Bidirectional(
        keras.layers.LSTM(GlobalConfig.LSTM_UNITS, dropout=GlobalConfig.DROPOUT_RATE)
    ))

    # Fully connected hidden layer
    model.add(keras.layers.Dense(GlobalConfig.HIDDEN_UNITS, activation="relu"))

    # Output layer set to 3 classes - positive, negative, neutral
    model.add(keras.layers.Dense(3, activation="softmax"))

    model.compile(loss="sparse_categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
    return model
```

```
model = build_rnn_model()
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 300, 64)           320000

 bidirectional (Bidirection  (None, 128)               66048
 al)

 dense (Dense)               (None, 32)                4128

 dense_1 (Dense)             (None, 3)                 99

=================================================================
Total params: 390275 (1.49 MB)
Trainable params: 390275 (1.49 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

11. Before model evaluation, final data preparation was implemented to map sentiments into integers and getting X and y values

```python
# Add an extra column "sentiment_label" with numerical labels - encoding
def prepare_data_for_model(df: pd.DataFrame) -> pd.DataFrame:
    label_mapping = {"Negative": 0, "Neutral": 1, "Positive": 2}
    df["sentiment_label"] = df["sentiment"].map(label_mapping)
    return df

df = prepare_data_for_model(df)

def get_features_and_targets(df: pd.DataFrame) -> tuple[np.ndarray, np.ndarray]:
    X = np.array(list(df["sanitized_tweet_vector"].values))
    y = df["sentiment_label"].to_numpy(dtype=np.int32)
    return X, y

X, y = get_features_and_targets(df)


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=GlobalConfig.RANDOM_SEED, str

# Stop training if validation loss does not improve for certain number of epochs
early_stopping = keras.callbacks.EarlyStopping(monitor="val_loss", patience=GlobalConfig.EARLY_STOPPING_PATIENCE, r

history = model.fit(
    X_train,
    y_train,
    validation_split=0.2,
    epochs=GlobalConfig.TOTAL_EPOCHS,
    batch_size=GlobalConfig.BATCH_SIZE,
    callbacks=[early_stopping, TqdmCallback(verbose=1)], #TqdmCallback for progress bar
    verbose=0

)
```

```
100%|██████████| 10/10 [01:35<00:00,  9.55s/epoch, loss=0.285, accuracy=0.895, val_loss=0.562, val_accuracy=0.817]
```

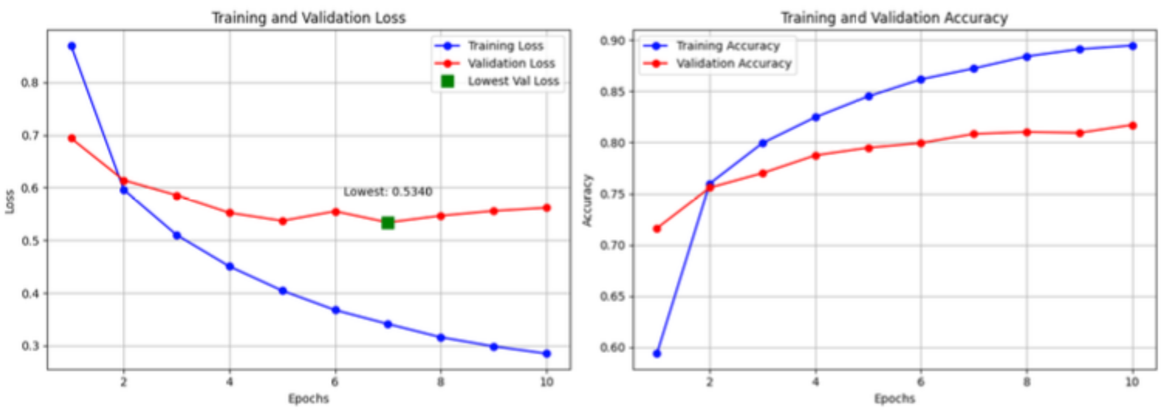
12. Key points on model training
    a. Early stopping was implemented to ensure model does not overfit
    b. 10 Epochs were chosen based on industry standard practices for twitter sentiment analysis recommendations
    c. ~82% val_accuracy was obtained after this round of training
13. Model evaluation was done by analyzing training and validation loss on the one hand and training and validation accuracy on the other. Through this, Epoch 7 was identified as the right number as it gave the lowest validation loss

3.3 Evaluation

```
def plot_training_history(history):
    metrics = history.history
```

```
    # Get key metrics
    loss = metrics["loss"]
    val_loss = metrics["val_loss"]
    accuracy = metrics["accuracy"]
    val_accuracy = metrics["val_accuracy"]
    epochs = range(1, len(loss) + 1)

    min_val_loss = min(val_loss)
    min_val_loss_epoch = val_loss.index(min_val_loss) + 1

    plt.figure(figsize=(14, 5))
    plt.subplot(1, 2, 1)
    plt.plot(epochs, loss, "bo-", label="Training Loss") #bo- Blue line with o markers and - line
    plt.plot(epochs, val_loss, "ro-", label="Validation Loss")


    plt.plot(min_val_loss_epoch, min_val_loss, 'gs', markersize=10, label='Lowest Val Loss') # Green Square
    plt.annotate(
        f"Lowest: {min_val_loss:.4f}",
        xy=(min_val_loss_epoch, min_val_loss),
        xytext=(min_val_loss_epoch, min_val_loss + 0.05), # Offset text slightly up
        horizontalalignment='center'
    )

    plt.title("Training and Validation Loss")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.grid(True)

    plt.subplot(1, 2, 2)
    plt.plot(epochs, accuracy, "bo-", label="Training Accuracy")
    plt.plot(epochs, val_accuracy, "ro-", label="Validation Accuracy")
    plt.title("Training and Validation Accuracy")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.grid(True)

    plt.tight_layout()
    plt.show()
```

```
plot_training_history(history)
```



14. To make things more interesting, we went ahead and completed all 10 Epochs and performed a what-if analysis

```
model_unrestricted = build_rnn_model()

# We are trying to do two things below - do not stop training early and train for full number of epochs and then do
print(f"Starting unrestricted training for {GlobalConfig.TOTAL_EPOCHS} epochs ...")
history_unrestricted = model_unrestricted.fit(
    X_train,
    y_train,
    validation_split=0.2,
    epochs=GlobalConfig.TOTAL_EPOCHS,
    batch_size=GlobalConfig.BATCH_SIZE,
    callbacks=[TqdmCallback(verbose=1)],
    verbose=0
)
```

```
Starting unrestricted training for 10 epochs ...
100%|██████████| 10/10 [01:35<00:00,  9.60s/epoch, loss=0.277, accuracy=0.897, val_loss=0.537, val_accuracy=0.824]
```

```
def plot_what_if_analysis_for_unrestricted_training(history):
    val_loss = history_unrestricted.history["val_loss"]
    epochs = range(1, len(val_loss) + 1)

    # Find the epoch where val_loss was minimum (Best Model)
    best_epoch_index = val_loss.index(min(val_loss))
    best_epoch = best_epoch_index + 1
    best_loss = val_loss[best_epoch_index]

    plt.figure(figsize=(10, 8))

    # Plot the curve
    plt.plot(epochs, val_loss, "r-o", label="Validation Loss", linewidth=2)

    # Vertical line at the Best Epoch
    plt.axvline(x=best_epoch, color="green", linestyle="--", label=f"Ideal Stop (Epoch {best_epoch})")

    # Shade the Overfitting Zone (What happened after)
    if best_epoch < len(epochs):
        plt.axvspan(best_epoch, len(epochs), color="red", alpha=0.1, label="Overfitting / Wasted Compute")

        # Add annotation arrow
        plt.annotate(
            "Loss increases here\n(Model gets worse)",
            xy=(len(epochs), val_loss[-1]),
            xytext=(best_epoch + 2, max(val_loss) * 0.95)
        )

    plt.title("What-If Analysis: Training Without Early Stopping")
    plt.xlabel("Epochs")
    plt.ylabel("Validation Loss")
    plt.legend()
    plt.grid(True)
    plt.show()

# Run the plot
plot_what_if_analysis_for_unrestricted_training(history_unrestricted)
```

15. This also confirmed our earlier finding that beyond Epoch 7, our returns were diminishing

16. Model Cross Validation was then performed to find out how model behaves for un-seen data outside the validation dataset. This also yielded ~83% validation accuracy – further attesting the fact that our training is very solid

3.4 Model Improvement

In [ ]:
```
# Evaluate the model to see if our model is performing well on unseen test data through fold cross validation
def do_model_cross_validation() -> None:
    skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=GlobalConfig.RANDOM_SEED)
    fold_no = 1
    accuracies = []

    for train_index, val_index in skf.split(X, y):
        X_train_fold, X_val_fold = X[train_index], X[val_index]
        y_train_fold, y_val_fold = y[train_index], y[val_index]

        model_cv = build_rnn_model()

        history_cv = model_cv.fit(
            X_train_fold,
            y_train_fold,
            validation_data=(X_val_fold, y_val_fold),
            epochs=GlobalConfig.TOTAL_EPOCHS,
            batch_size=GlobalConfig.BATCH_SIZE,
            callbacks=[early_stopping],
            verbose=0
        )

        scores = model_cv.evaluate(X_val_fold, y_val_fold, verbose=0)
        print(f"Fold {fold_no} - Validation Accuracy: {scores[1]*100:.2f}%")
        accuracies.append(scores[1] * 100)
        fold_no += 1

    print(f"Average Validation Accuracy across folds: {np.mean(accuracies):.2f}% ± {np.std(accuracies):.2f}%")

do_model_cross_validation()
```

```
Fold 1 - Validation Accuracy: 83.90%
Fold 2 - Validation Accuracy: 83.70%
Fold 3 - Validation Accuracy: 83.20%
Fold 4 - Validation Accuracy: 82.98%
Fold 5 - Validation Accuracy: 83.34%
Average Validation Accuracy across folds: 83.42% ± 0.33%
```

17. For tuning the hyper parameters, Grid Search was performed next to determine the right combination of LSTM, Hidden layer units and Dropout rates. 64 was kept as the embedding dimension, the LSTM and hidden layer units to align with industry standard recommendations in this space. 0.2 was identified as the optimal dropout rate yielding ~81% accuracy

```python
def do_model_grid_search(lstm_units_list: list[int], hidden_units_list: list[int], dropout_list: list[float]) -> No
    best_accuracy = 0.0
    best_params = {}
    # Loop through all possible combinations
    for lstm_unit in lstm_units_list:
        for hidden_unit in hidden_units_list:
            for dropout in dropout_list:
                print(f"Training model with {lstm_unit} lstm units, {hidden_unit} hidden units, and {dropout} dropo
                model_gs = keras.Sequential()
                model_gs.add(keras.Input(shape=(GlobalConfig.TEXT_VECTOR_OUTPUT_SEQUENCE_LENGTH,)))
                model_gs.add(
                    keras.layers.Embedding(
                        input_dim=GlobalConfig.TEXT_VECTOR_MAX_TOKENS,
                        output_dim=GlobalConfig.TEXT_VECTOR_EMBEDDING_DIMENSION
                    )
                )
                model_gs.add(keras.layers.Bidirectional(
                    keras.layers.LSTM(lstm_unit, dropout=dropout)
                ))
                model_gs.add(keras.layers.Dense(hidden_unit, activation="relu"))

                model_gs.add(keras.layers.Dense(3, activation="softmax"))
                model_gs.compile(loss="sparse_categorical_crossentropy", optimizer="adam", metrics=["accuracy"])

                history_gs = model_gs.fit(
                    X_train,
                    y_train,
                    validation_split=0.2,
                    epochs=10,
                    batch_size=GlobalConfig.BATCH_SIZE,
                    callbacks=[early_stopping],
                    verbose=0
                )
                # Capture scores and get best accuracy
```

```python
                scores = model_gs.evaluate(X_test, y_test, verbose=0)
                accuracy = scores[1] * 100
                print(f"Test Accuracy: {accuracy:.2f}%")

                if accuracy > best_accuracy:
                    best_accuracy = accuracy
                    best_params = {"lstm unit": lstm_unit, "hidden unit": hidden_unit, "dropout": dropout}

    print(f"Best Test Accuracy: {best_accuracy:.2f}% with parameters: {best_params}")

do_model_grid_search(lstm_units_list=[64], hidden_units_list=[64] ,dropout_list=[0.0, 0.2, 0.3])
```

```
Training model with 64 lstm units, 64 hidden units, and 0.0 dropout...
Test Accuracy: 79.48%
Training model with 64 lstm units, 64 hidden units, and 0.2 dropout...
Test Accuracy: 81.02%
Training model with 64 lstm units, 64 hidden units, and 0.3 dropout...
Test Accuracy: 80.99%
Best Test Accuracy: 81.02% with parameters: {'lstm unit': 64, 'hidden unit': 64, 'dropout': 0.2}
```

18. A benchmark test was performed with twitter data from NTLK to test our model strength. The outcome of the test was moderate at best. This indicates that our training data is fairly domain specific and needs to be utilizing transfer learning by taking into consideration a wider vocabulary

Benchmarking our Model with external data and making the case for transfer learning

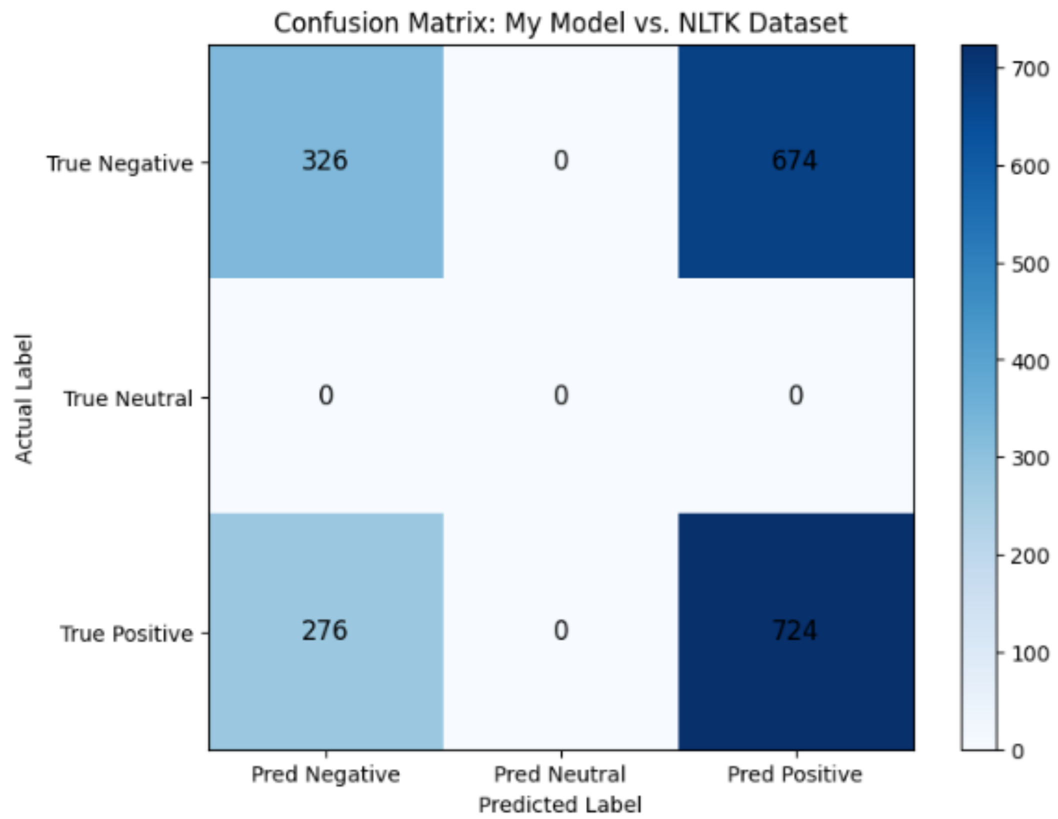
```
5]: def quick_cleanse(text: str) -> str:
    if not isinstance(text, str):
        return ""
    text = html.unescape(text)
    text = text.lower()
    text = re.sub(r"http\S+|www\S+|https\S+", "", text, flags=re.MULTILINE)
    text = re.sub(r"@\w+", "", text)
    text = re.sub(r"#", "", text)
    text = re.sub(r"[^a-zA-Z\s]", "", text)
    text = re.sub(r"\s+", " ", text).strip()
    return text


def benchmark_model():
```

```
    print("Downloading NLTK Twitter dataset...")
    nltk.download("twitter_samples", quiet=True)
    raw_pos = [quick_cleanse(t) for t in twitter_samples.strings("positive_tweets.json")[:1000]]
    raw_neg = [quick_cleanse(t) for t in twitter_samples.strings("negative_tweets.json")[:1000]]

    X_benchmark_text = raw_pos + raw_neg
    y_benchmark_true = np.array([2] * 1000 + [0] * 1000)


    print(f"Vectorizing {len(X_benchmark_text)} tweets...")
    X_benchmark_vectors = GlobalConfig.VECTORIZER(X_benchmark_text) # Reusing the saved vectorizer

    # 5. Predict with Your Model
    print("Running predictions...")
    y_pred_probs = model.predict(X_benchmark_vectors, verbose=0)
    y_pred_probs[:, 1] = -1 # No neutral class in benchmark dataset
    y_pred_classes = np.argmax(y_pred_probs, axis=1)


    print("\n" + "="*40)
    print(" EXTERNAL DATASET BENCHMARK RESULTS")
    print("="*40)

    print(classification_report(
        y_benchmark_true,
        y_pred_classes,
        labels=[0, 1, 2],
        target_names=["Negative", "Neutral", "Positive"]
    ))


    cm = confusion_matrix(y_benchmark_true, y_pred_classes, labels=[0, 1, 2])

    fig, ax = plt.subplots(figsize=(8, 6))
    cax = ax.matshow(cm, cmap="Blues")
    fig.colorbar(cax)


    ax.set_xticklabels([""] + ["Pred Negative", "Pred Neutral", "Pred Positive"])
    ax.set_yticklabels([""] + ["True Negative", "True Neutral", "True Positive"])
```

```
    ax.xaxis.set_ticks_position("bottom")


    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, str(cm[i, j]), va="center", ha="center", color="black", fontsize=12)

    plt.title("Confusion Matrix: My Model vs. NLTK Dataset")
    plt.xlabel("Predicted Label")
    plt.ylabel("Actual Label")
    plt.show()


benchmark_model()
```

Downloading NLTK Twitter dataset

```
========================================
 EXTERNAL DATASET BENCHMARK RESULTS
========================================
              precision    recall  f1-score   support

    Negative       0.54      0.33      0.41      1000
     Neutral       0.00      0.00      0.00         0
    Positive       0.52      0.72      0.60      1000

    accuracy                           0.53      2000
   macro avg       0.35      0.35      0.34      2000
weighted avg       0.53      0.53      0.51      2000
```



Obsevations

- Our accuracy with random tweets is as good as a coin toss
- This indicates that our vocabulary from twitter_training.csv is limited
- We could use a model like GloVe embeddings through transfer learning method

19. Finally, a quick test with sample tweets were performed and the model performed as expected

```
def manual_test_samples() -> pd.DataFrame:
    sample_tweets = [
        "I absolutely love the new features!",
        "The service was terrible and I am very disappointed.",
        "It was okay, nothing special but not bad either.",
        "Can anyone help me with this issue? I'm stuck."
    ]
    label_mapping = {"Negative": 0, "Neutral": 1, "Positive": 2}
    index_to_label = {v: k for k, v in label_mapping.items()}
    processed_samples = GlobalConfig.VECTORIZER(sample_tweets)
    predictions = model.predict(processed_samples)
    predicted_indices = np.argmax(predictions, axis=1)
    predicted_labels = [index_to_label[idx] for idx in predicted_indices]
    results_df = pd.DataFrame({
        "Tweet": sample_tweets,
        "Prediction": predicted_labels,
        "Confidence": np.max(predictions, axis=1)
    })

    return results_df

results_df = manual_test_samples()
display(results_df)
```

✓ 0.0s

```
1/1 [==============================] - 0s 21ms/step
```

	Tweet	Prediction	Confidence
0	I absolutely love the new features!	Positive	0.837939
1	The service was terrible and I am very disappo...	Negative	0.963436
2	It was okay, nothing special but not bad either.	Neutral	0.723399
3	Can anyone help me with this issue? I'm stuck.	Negative	0.918900

Presentation

Presentation is located here in GitHub - https://github.com/mramsundar/IITM-Graded-Projects/blob/c623766d58d22acec56bc2c02f906e3c3aaf0634/Week%2031/Week%2031%20Summary%20Presentation.pdf