رواد مصر الرقمية

Customer Sentiment and Trend Analysis

Supervisor: Basma Reda

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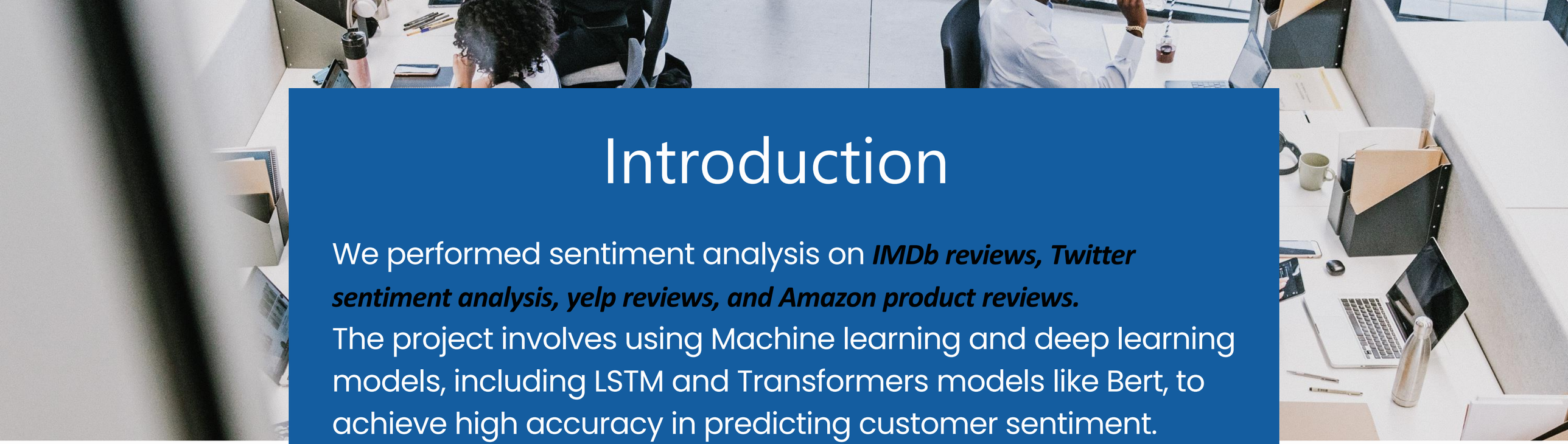


Introduction

We performed sentiment analysis on ***IMDb reviews, Twitter sentiment analysis, yelp reviews, and Amazon product reviews.***
The project involves using Machine learning and deep learning models, including LSTM and Transformers models like Bert, to achieve high accuracy in predicting customer sentiment. Additionally, we implemented platforms like HuggingFace, MLFlow, and Streamlit for model optimization, tracking, and deployment

Team Members

- Mohamed Mostafa Abdelhamed
- Moaz Mohamed Tawfik
- Mohamed Talaat Abo Elftouh
- Mohamed Alaa Elsayad
- Amr Khaled Mostafa
- Mahmoud Mohammed Abdelmawgoud

Datasets

Amazon Product Reviews

Total Records: 568,454
Available Fields: Id, ProductId, UserId, ProfileName, HelpfulnessNumerator, HelpfulnessDenomenator, Score, Time, Summary, Text

Yelp Review

Number of rows: 700,000
The Yelp reviews dataset consists of reviews from Yelp. It is extracted from the Yelp Dataset Challenge 2015 data.

IMDB Reviews

Total Records: 50K
This is a dataset for binary sentiment classification containing substantially more data than previous benchmark datasets. We provide a set of 25,000 highly polar movie reviews for training and 25,000 for testing.

Twitter sentiment

This is the sentiment140 dataset. It contains **1,600,000 tweets** extracted using the twitter api . The tweets have been annotated (0 = negative, 4 = positive) and they can be used to detect sentiment .

Yelp Review

The Yelp reviews dataset consists of reviews from Yelp.
It is extracted from the Yelp Dataset Challenge 2015 data.

Data Fields

- 'text': The review texts are escaped using double quotes ("), and any internal double quote is escaped by 2 double quotes (""). New lines are escaped by a backslash followed with an "n" character, that is "\n".
- 'label': Corresponds to the score associated with the review (between 1 and 5).

Data Splits

The Yelp reviews full-star dataset is constructed by randomly taking 130,000 training samples and 10,000 testing samples for each review star from 1 to 5. In total, there are 650,000 training samples and 50,000 testing samples.

	label	text
0	4	dr. goldberg offers everything i look for in a...
1	1	Unfortunately, the frustration of being Dr. Go...
2	3	Been going to Dr. Goldberg for over 10 years. ...
3	3	Got a letter in the mail last week that said D...
4	0	I don't know what Dr. Goldberg was like before...
...	...	...
649995	4	I had a sprinkler that was gushing... pipe bro...
649996	0	Phone calls always go to voicemail and message...
649997	0	Looks like all of the good reviews have gone t...
649998	4	I was able to once again rely on Yelp to provi...
649999	0	I have been using this company for 11 months. ...

650000 rows × 2 columns

Yelp Review

To convert Yelp ratings into categorical values like "Positive," "Negative," and "Neutral," you could define rules based on the rating scale (often from 0 to 4). Here's a common way to categorize these ratings:

- **Ratings 3 and 4: Positive**
- **Rating 2: Neutral**
- **Ratings 0 and 1: Negative**

	label	text
0	4	dr. goldberg offers everything i look for in a...
1	1	Unfortunately, the frustration of being Dr. Go...
2	3	Been going to Dr. Goldberg for over 10 years. ...
3	3	Got a letter in the mail last week that said D...
4	0	I don't know what Dr. Goldberg was like before...
...	...	...
649995	4	I had a sprinkler that was gushing... pipe bro...
649996	0	Phone calls always go to voicemail and message...
649997	0	Looks like all of the good reviews have gone t...
649998	4	I was able to once again rely on Yelp to provi...
649999	0	I have been using this company for 11 months. ...

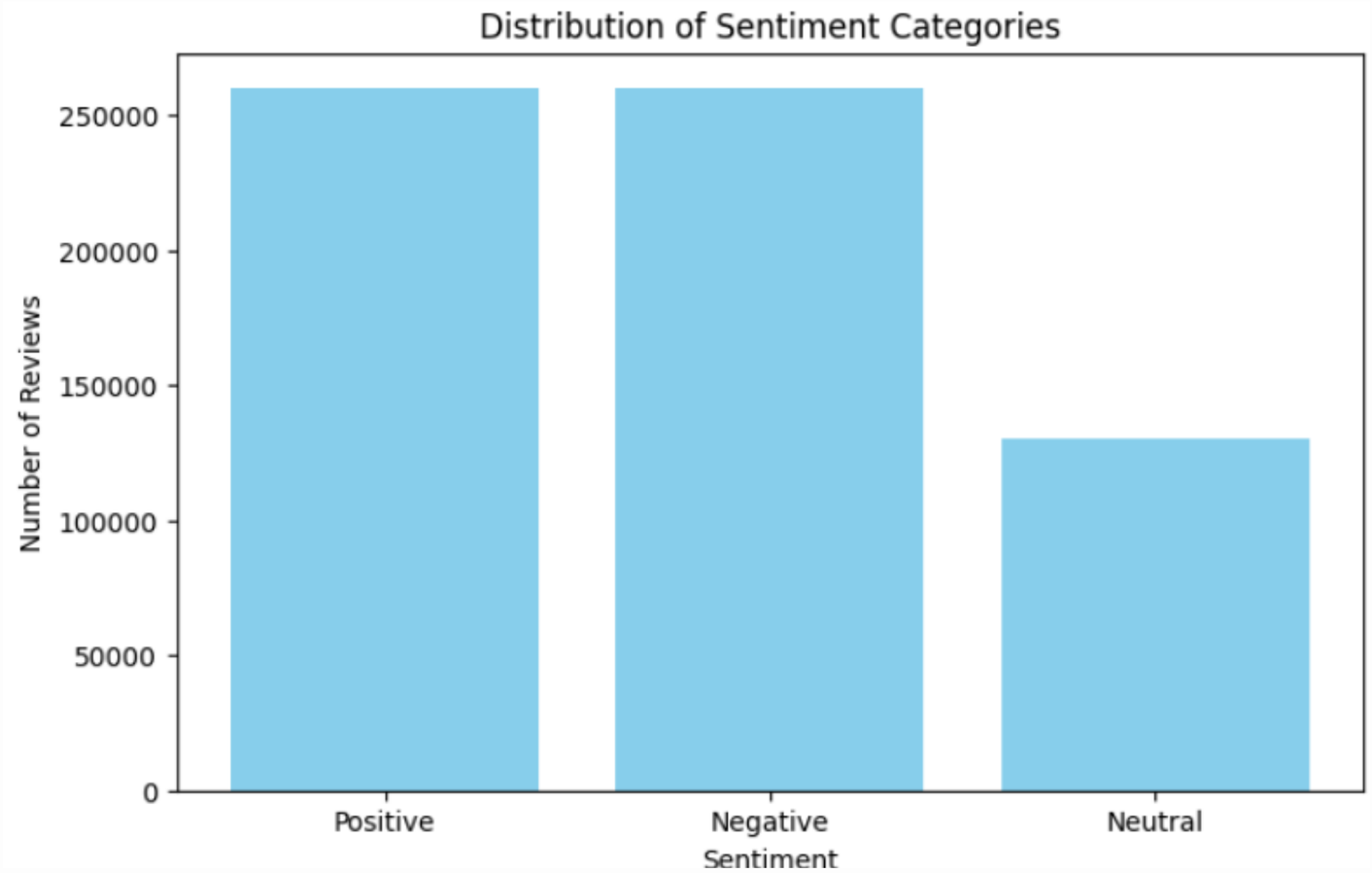
650000 rows × 2 columns

	text	sentiment
0	dr. goldberg offers everything i look for in a...	Positive
1	Unfortunately, the frustration of being Dr. Go...	Negative
2	Been going to Dr. Goldberg for over 10 years. ...	Positive
3	Got a letter in the mail last week that said D...	Positive
4	I don't know what Dr. Goldberg was like before...	Negative
...	...	...
649995	I had a sprinkler that was gushing... pipe bro...	Positive
649996	Phone calls always go to voicemail and message...	Negative
649997	Looks like all of the good reviews have gone t...	Negative
649998	I was able to once again rely on Yelp to provi...	Positive
649999	I have been using this company for 11 months. ...	Negative

650000 rows × 2 columns

Yelp Review

visualize the distribution of reviews (Positive, Neutral, Negative)



Preprocessing and Cleaning Data

	text	sentiment
0	dr. goldberg offers everything i look for in a...	Positive
1	Unfortunately, the frustration of being Dr. Go...	Negative
2	Been going to Dr. Goldberg for over 10 years. ...	Positive
3	Got a letter in the mail last week that said D...	Positive
4	I don't know what Dr. Goldberg was like before...	Negative
...	...	...
649995	I had a sprinkler that was gushing... pipe bro...	Positive
649996	Phone calls always go to voicemail and message...	Negative
649997	Looks like all of the good reviews have gone t...	Negative
649998	I was able to once again rely on Yelp to provi...	Positive
649999	I have been using this company for 11 months. ...	Negative

650000 rows × 2 columns

Using nltk and regular expression

	text	sentiment
0	dr goldberg offers everything look general pra...	Positive
1	unfortunately frustration dr goldberg patient ...	Negative
2	going dr goldberg years think one st patients ...	Positive
3	got letter mail last week said dr goldberg mov...	Positive
4	know dr goldberg like moving arizona let tell ...	Negative
...	...	...
649995	sprinkler gushing pipe broken way ground turne...	Positive
649996	phone calls always go voicemail messages retur...	Negative
649997	looks like good reviews gone head place jason ...	Negative
649998	able rely yelp provide needed response leaking...	Positive
649999	using company months ryan would come every wee...	Negative

650000 rows × 2 columns

Yelp Review

Process The Dataset

```
new_data.isnull().sum()
```

```
text         48
sentiment     0
dtype: int64
```

```
new_data.duplicated().sum()
```

```
590
```

	text	sentiment
0	dr goldberg offers everything look general pra...	Positive
1	unfortunately frustration dr goldberg patient ...	Negative
2	going dr goldberg years think one st patients ...	Positive
3	got letter mail last week said dr goldberg mov...	Positive
4	know dr goldberg like moving arizona let tell ...	Negative
...	...	...
649995	sprinkler gushing pipe broken way ground turne...	Positive
649996	phone calls always go voicemail messages retur...	Negative
649997	looks like good reviews gone head place jason ...	Negative
649998	able rely yelp provide needed response leaking...	Positive
649999	using company months ryan would come every wee...	Negative

649407 rows × 2 columns

usage to take 40,000 samples from each class

```
sentiment

Positive     40000

Negative     40000

Neutral      40000

Name: count, dtype: int64
```

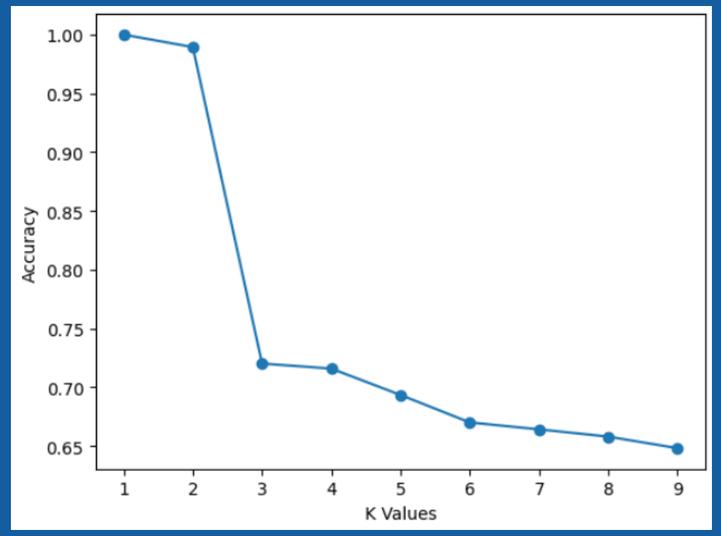
	text	sentiment
417633	bestie recently bought jeep wanted go mini roa...	Positive
488716	charlotte wake get face food halcyon amazing s...	Positive
122370	husband found engagement ring years ago shoppi...	Positive
294942	perfect mocha yesterday special whole milk cho...	Positive
108228	never realy go always shop fry redbox used mon...	Positive
...	...	...
516943	went yesterday place wanted go closed handy dr...	Neutral
140162	stopped something different looked menu online...	Neutral
41391	sticker shock n nthree us ate really enjoyed s...	Neutral
195385	cute french setting turkey despite adding grav...	Neutral
390601	ak chin bless n nit sneeze throat clear new na...	Neutral

120000 rows × 2 columns

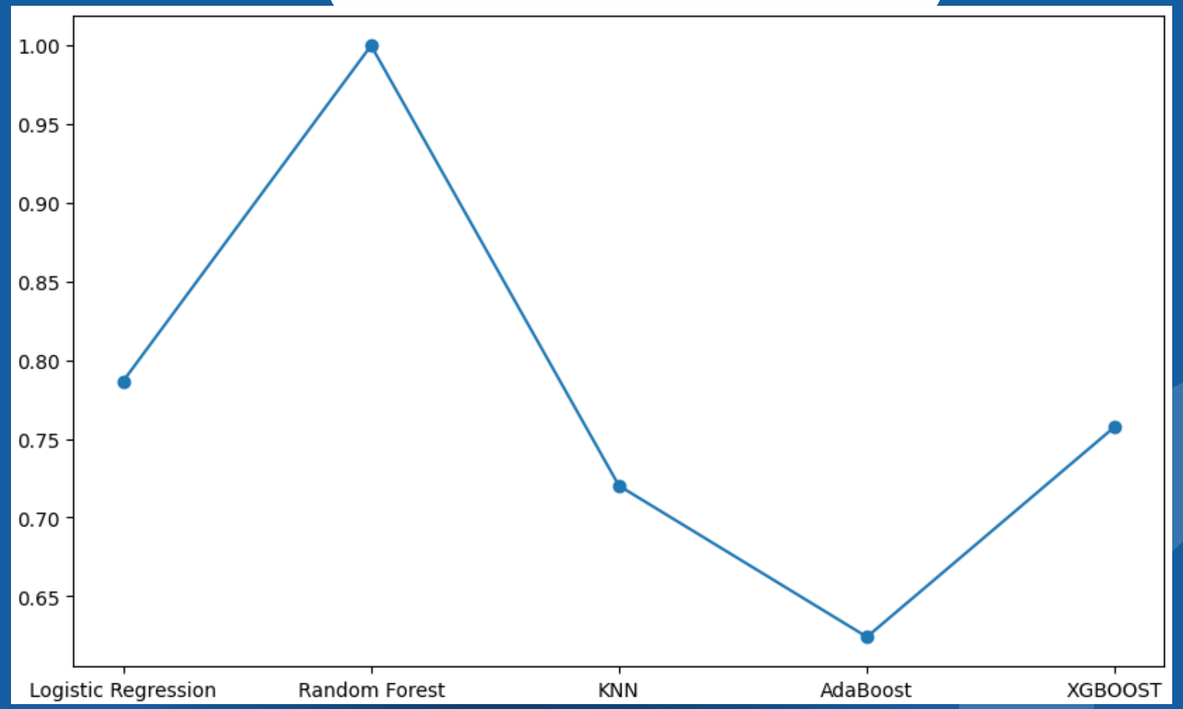
Machine Learning models

Use Cleaning Data and Use TF-IDF

KNN



	Model	Test Scores
0	Logistic Regression	0.786700
1	Random Forest	0.999933
2	KNN	0.720200
3	AdaBoost	0.624133
4	XGBOOST	0.757733



Deep Learning Model

- Apply Labelecnoder on "sentiment" Column
- Tokenize The Text

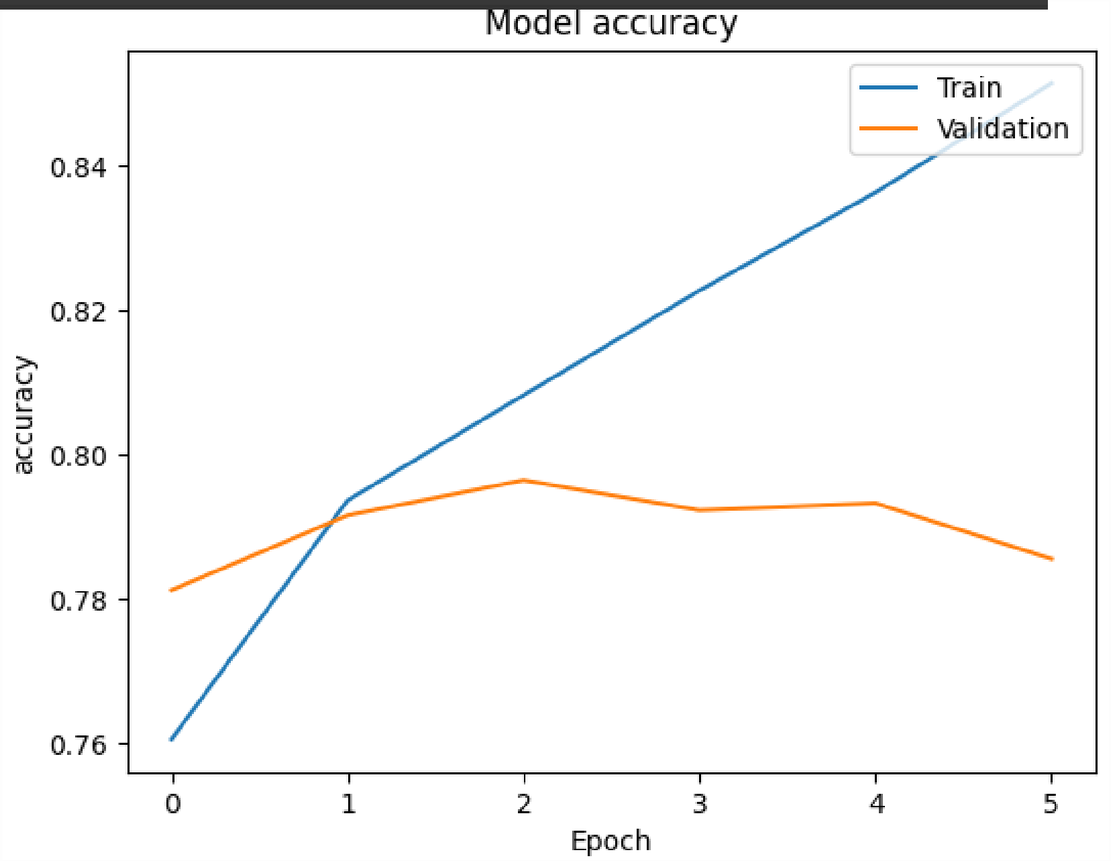
```
The 10 most repeated words are: ['n', 'food', 'good', 'place', 'like', 'get', 'one', 'time', 'would', 'great']
```

Build The LSTM Model

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	?	0 (unbuilt)
bidirectional (Bidirectional)	?	0 (unbuilt)
dropout (Dropout)	?	0 (unbuilt)
bidirectional_1 (Bidirectional)	?	0 (unbuilt)
dropout_1 (Dropout)	?	0 (unbuilt)
dense (Dense)	?	0 (unbuilt)
dense_1 (Dense)	?	0 (unbuilt)

Total params: 0 (0.00 B)
Trainable params: 0 (0.00 B)
Non-trainable params: 0 (0.00 B)

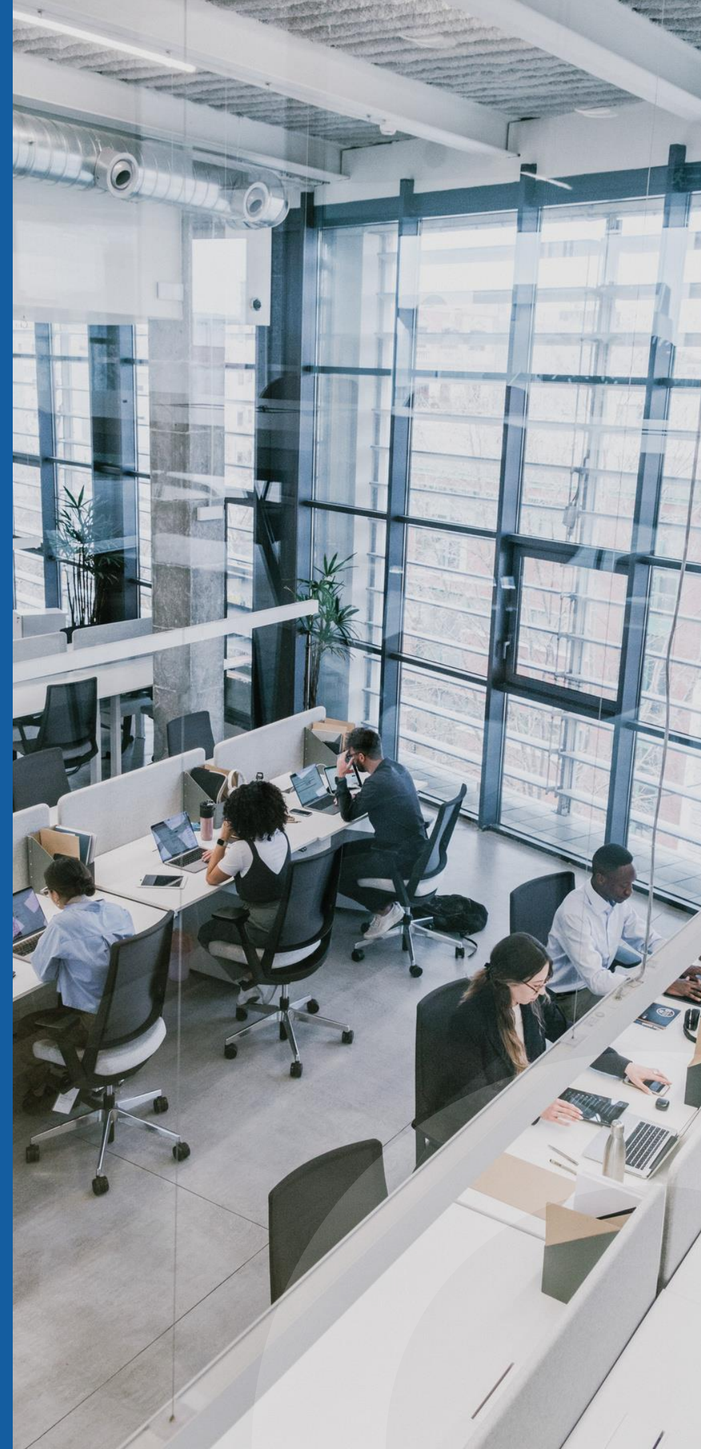


We can See From This Plot The Overfitting

IMDB Reviews

This is a dataset for binary sentiment classification containing substantially more data than previous benchmark datasets. We provide a set of 25,000 highly polar movie reviews for training and 25,000 for testing. So, predict the number of positive and negative reviews using either classification or deep learning algorithms.

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. The...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive



Importing Dataset & Preprocessing

```
print('Number Of Duplications is :', df.duplicated().sum())
df.drop_duplicates(inplace=True)
```

```
Number Of Duplications is : 418
```

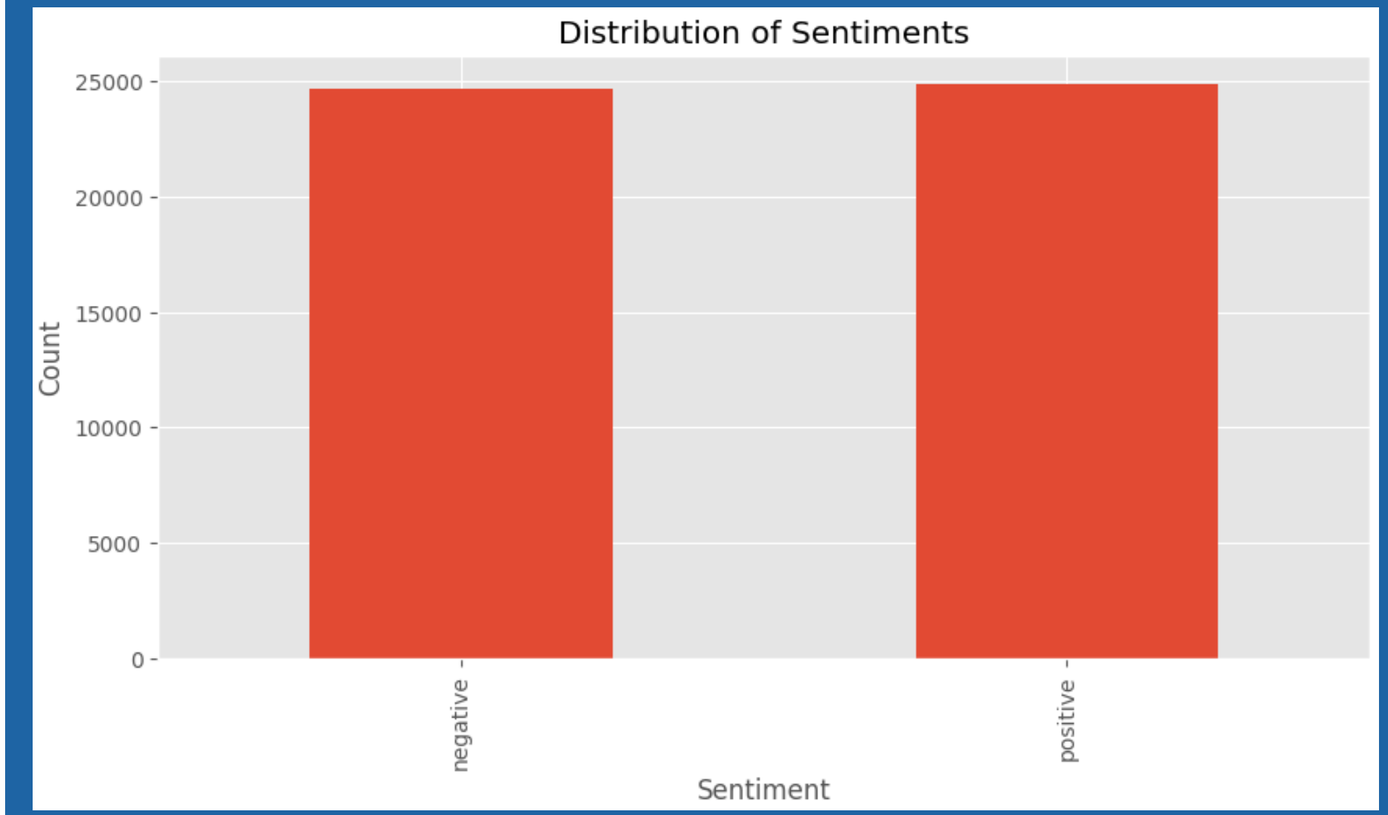
```
df.isna().sum()
```

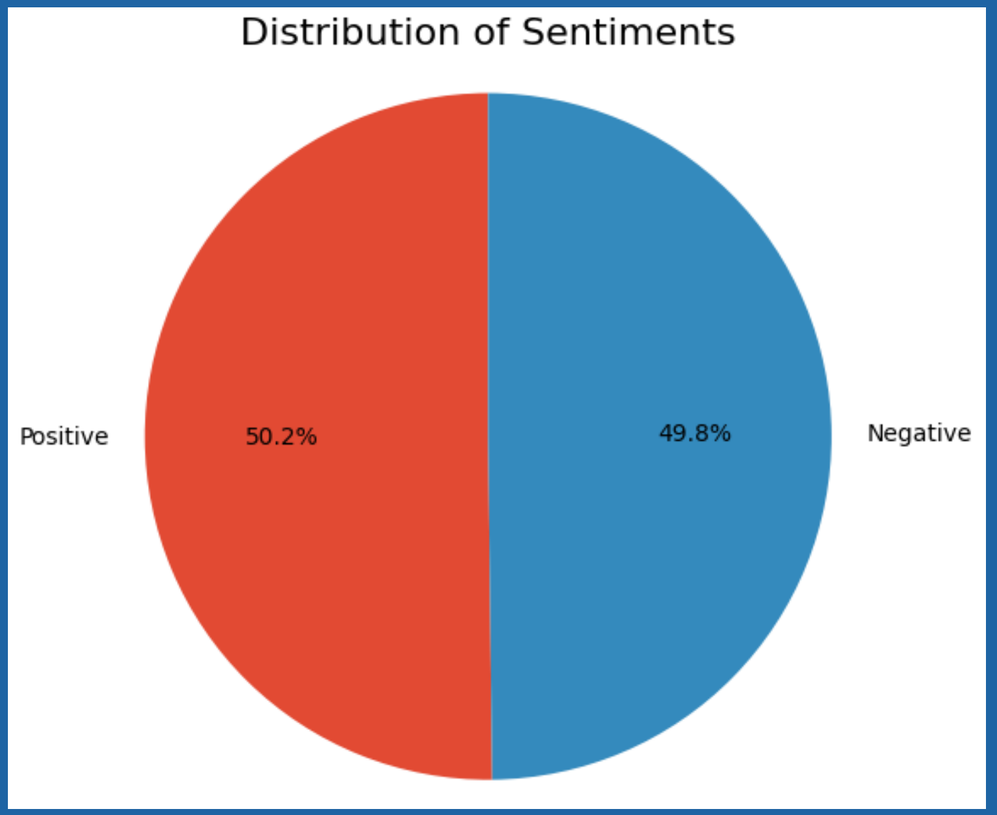
```
review       0
sentiment    0
dtype: int64
```

```
df["review"][40]
```

```
"It had all the clichés of movies of this type and no substance. The plot went nowhere and at the end of the movie I felt like a sucker for watching it. The production was good; however, the script and acting were B-movie quality. The casting was poor because there were good actors mixed in with crumby actors. The good actors didn't hold their own nor did they lift up the others. <br /><br />This movie is not worthy of more words, but I will say more to meet the minimum requirement of ten lines. James Wood and Cuba Gooding, Jr. play caricatures of themselves in other movies. <br /><br />If you are looking for mindless entertainment, I still wouldn't recommend this movie."
```

Importing Dataset & Preprocessing





balanced data

After Cleaning

```
df["review"][40]
```

```
"It had all the clichés of movies of this type and no substance. The plot went nowhere and at the end of the movie I felt like a sucker for watching it. The production was good; however, the script and acting were B-movie quality. The casting was poor because there were good actors mixed in with crumby actors. The good actors didn't hold their own nor did they lift up the others. <br /><br />This movie is not worthy of more words, but I will say more to meet the minimum requirement of ten lines. James Wood and Cuba Gooding, Jr. play caricatures of themselves in other movies. <br /><br />If you are looking for mindless entertainment, I still wouldn't recommend this movie."
```

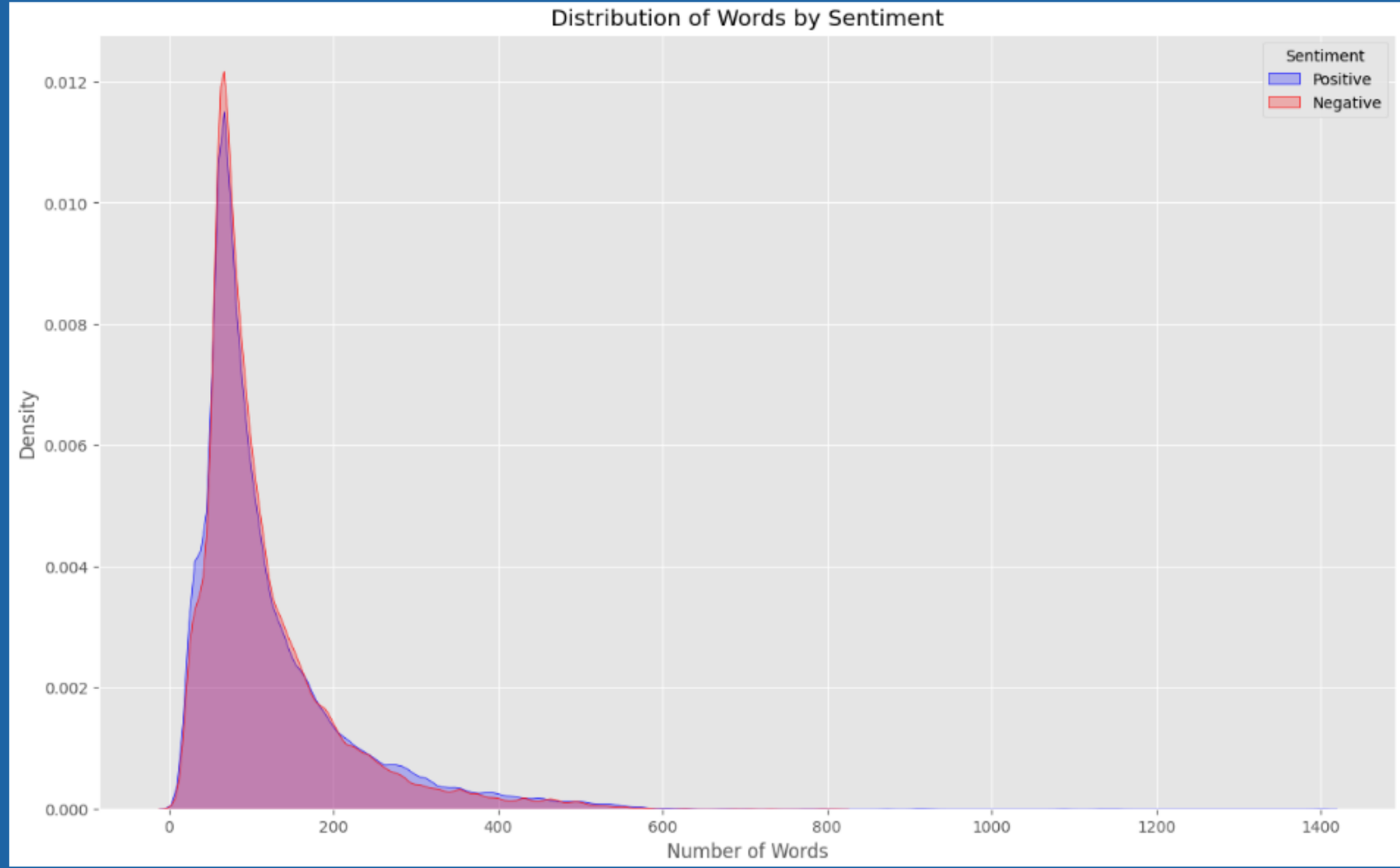
```
df['review'][40]
```

```
'clich movies type substance plot went nowhere end movie felt like sucker watching production good however script acting movie quality casting poor good actors mixed crumby actors good actors hold lift others movie worthy words say meet minimum requirement ten lines james wood cuba gooding jr play caricatures movies looking mindless entertainment still recommend movie'
```

convert labels into integers. convert them into integers by replacing "positive" --> 1 and negative --> 0

	review	sentiment	word_length
0	one reviewers mentioned watching oz episode ho...	1	162
1	wonderful little production filming technique ...	1	86
2	thought wonderful way spend time hot summer we...	1	84
3	basically family little boy jake thinks zombie...	0	64
4	petter mattei love time money visually stunnin...	1	125

Plot KDE
for Positive and Negative sentiment

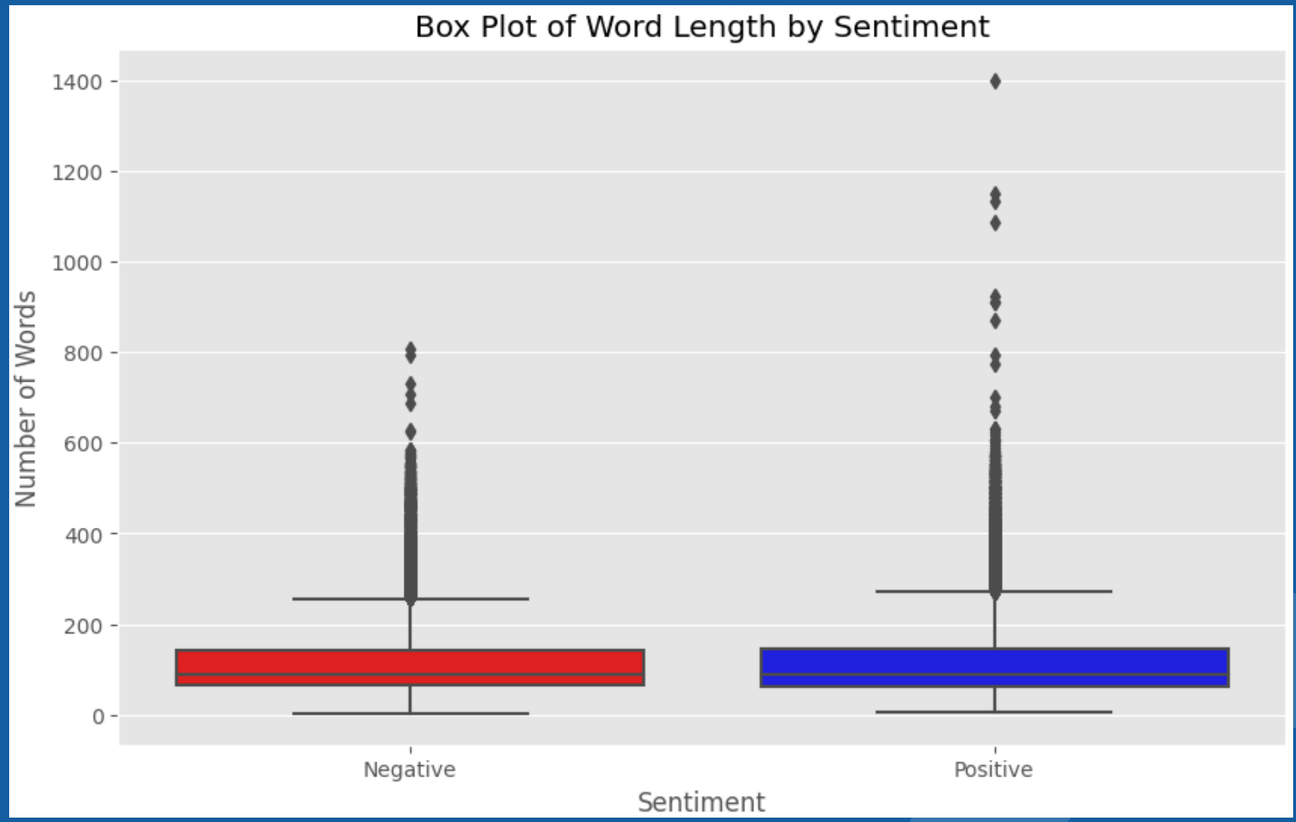


Average review length

```
average_length = df.groupby('sentiment')['word_length'].mean()
print("Average review length:")
print(average_length)
```

```
Average review length:
sentiment
0    116.133128
1    119.834392
Name: word_length, dtype: float64
```

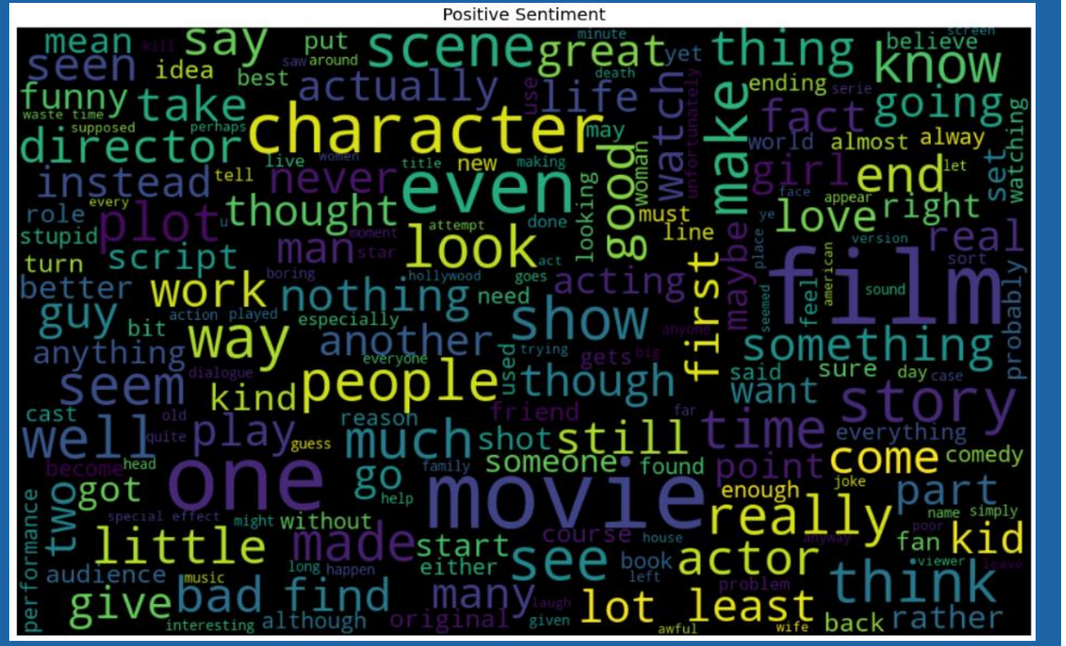
Number of Words



Combine all reviews labeled with sentiment

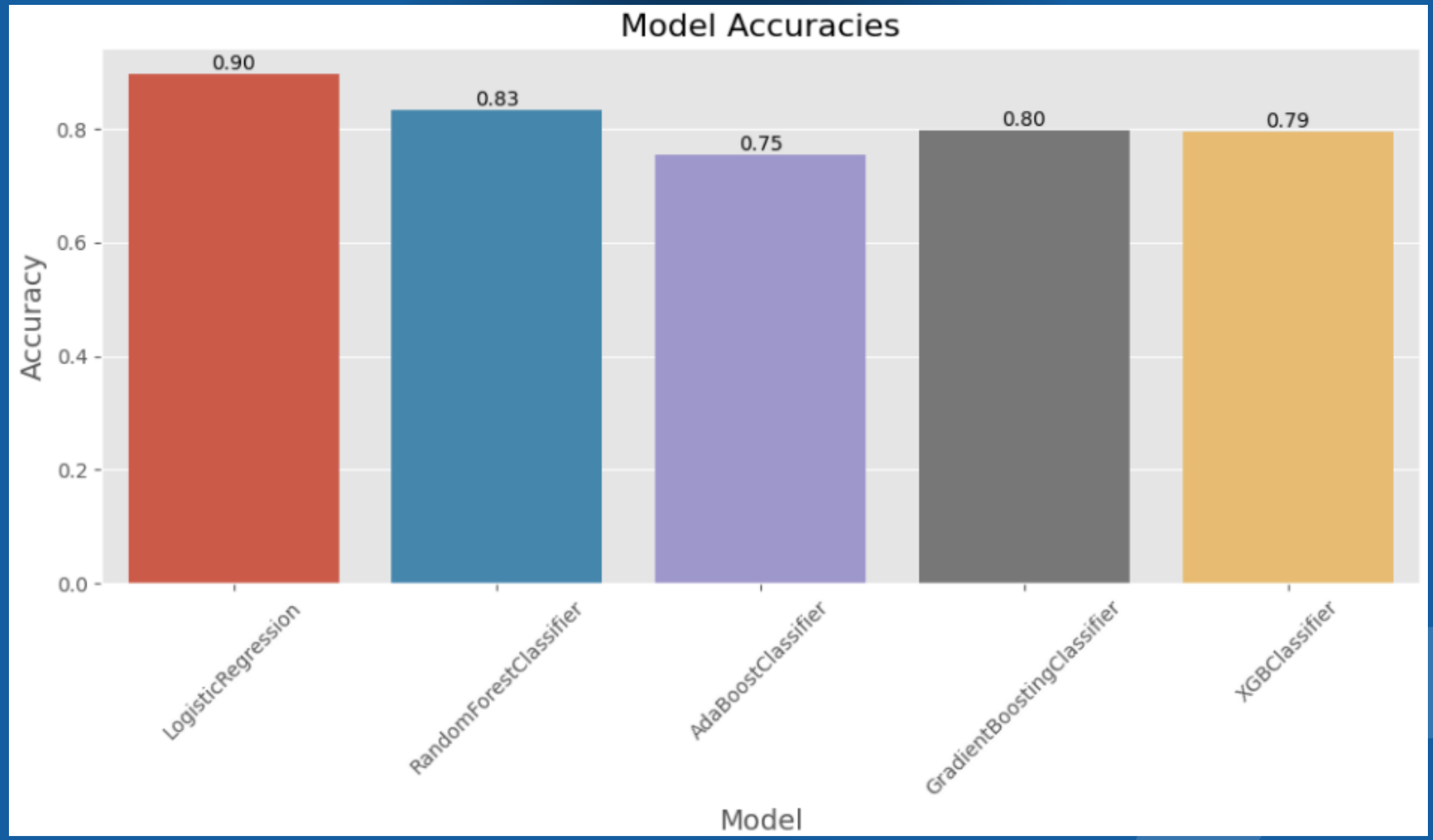
(Negative sentiment)

(Positive sentiment)



Machine Learning models

	Model	Test Scores
0	LogisticRegression	0.896844
1	RandomForestClassifier	0.833619
2	AdaBoostClassifier	0.754361
3	GradientBoostingClassifier	0.797419
4	XGBClassifier	0.794293



Deep Learning Model

LSTM With Glove Embedding

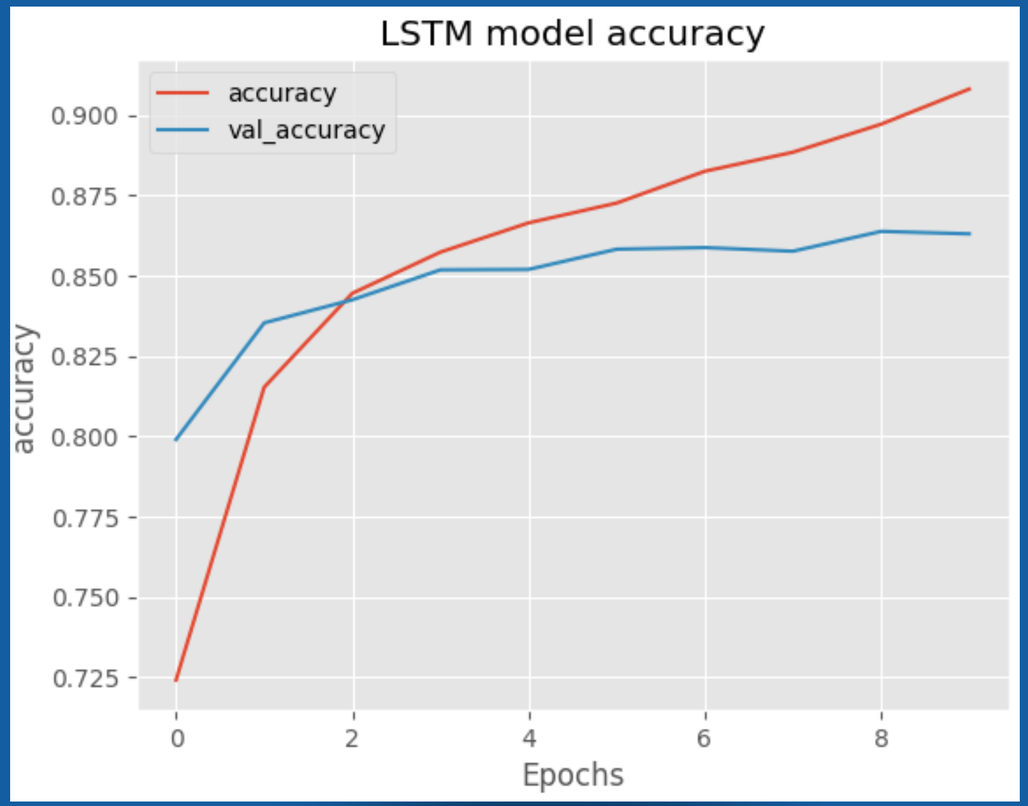
Model: "sequential"

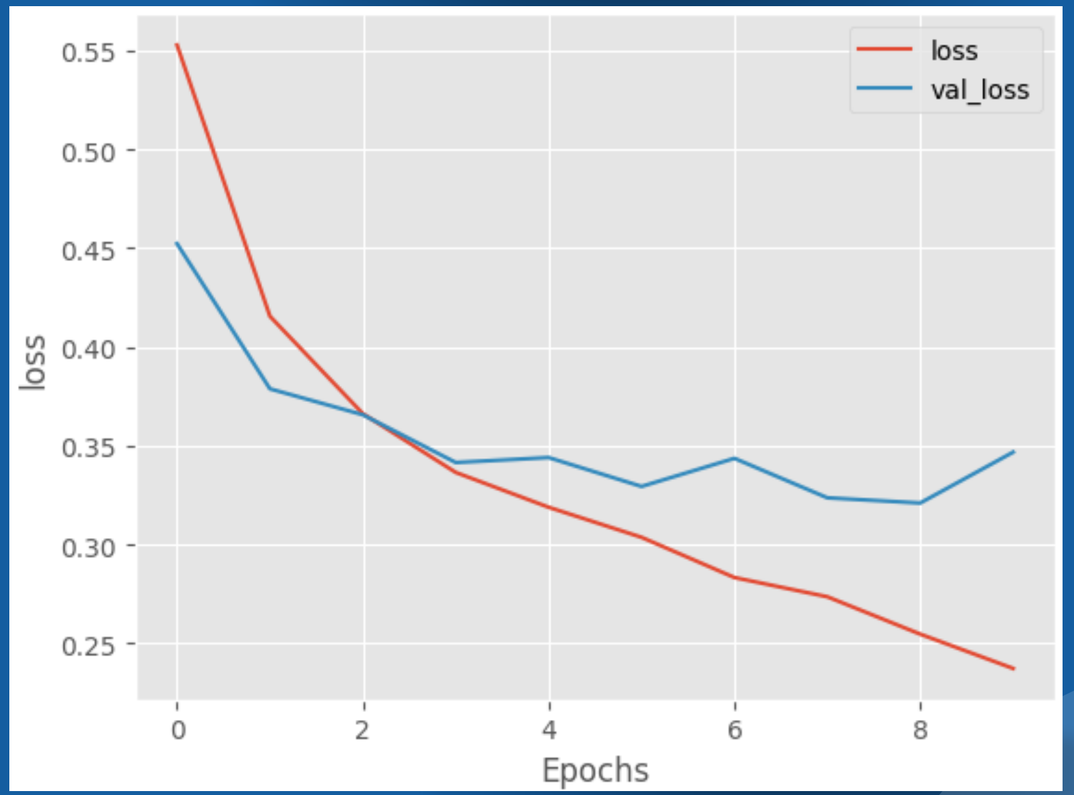
Layer (type)	Output Shape	Param #
embedding (Embedding)	?	10,124,600
lstm (LSTM)	?	0 (unbuilt)
dense (Dense)	?	0 (unbuilt)

Total params: 10,124,600 (38.62 MB)
Trainable params: 0 (0.00 B)
Non-trainable params: 10,124,600 (38.62 MB)

Deep Learning Model

model accuracy





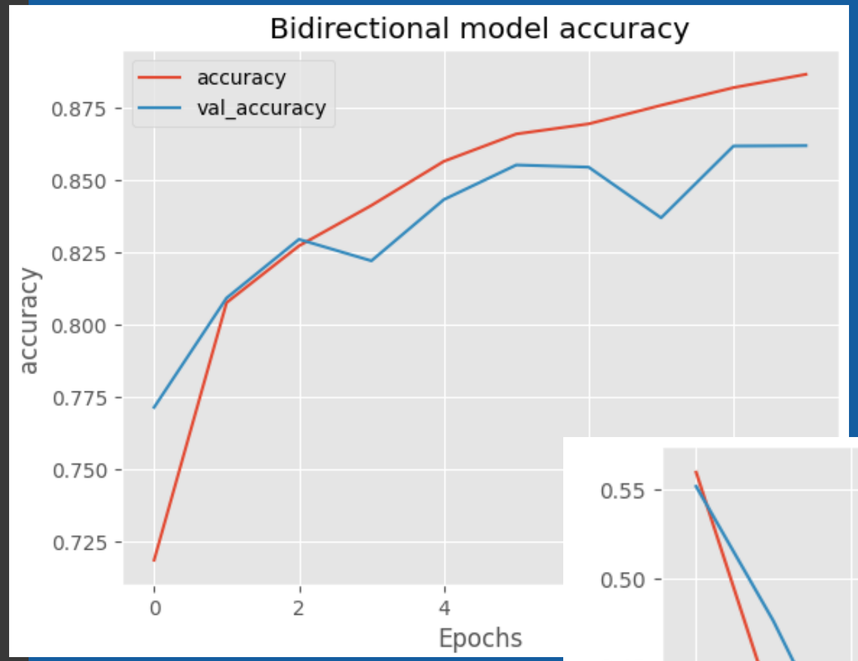
Bidirectional LSTM

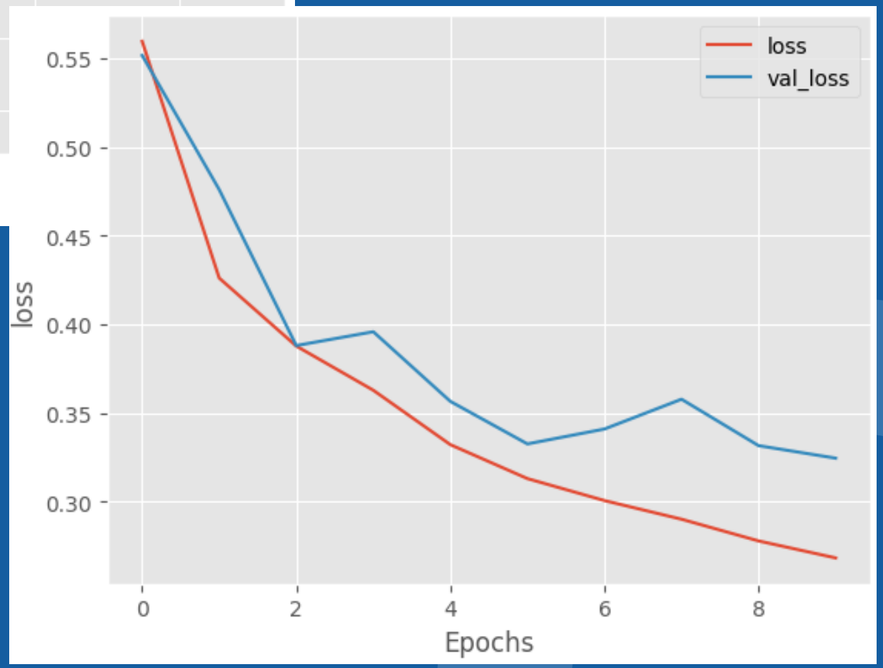
Model: "sequential_10"

Layer (type)	Output Shape	Param #
embedding_8 (Embedding)	?	10,124,600
bidirectional_14 (Bidirectional)	?	0 (unbuilt)
dropout_20 (Dropout)	?	0 (unbuilt)
bidirectional_15 (Bidirectional)	?	0 (unbuilt)
dropout_21 (Dropout)	?	0 (unbuilt)
dense_23 (Dense)	?	0 (unbuilt)
batch_normalization_12 (BatchNormalization)	?	0 (unbuilt)
dense_24 (Dense)	?	0 (unbuilt)

Total params: 10,124,600 (38.62 MB)
Trainable params: 0 (0.00 B)
Non-trainable params: 10,124,600 (38.62 MB)

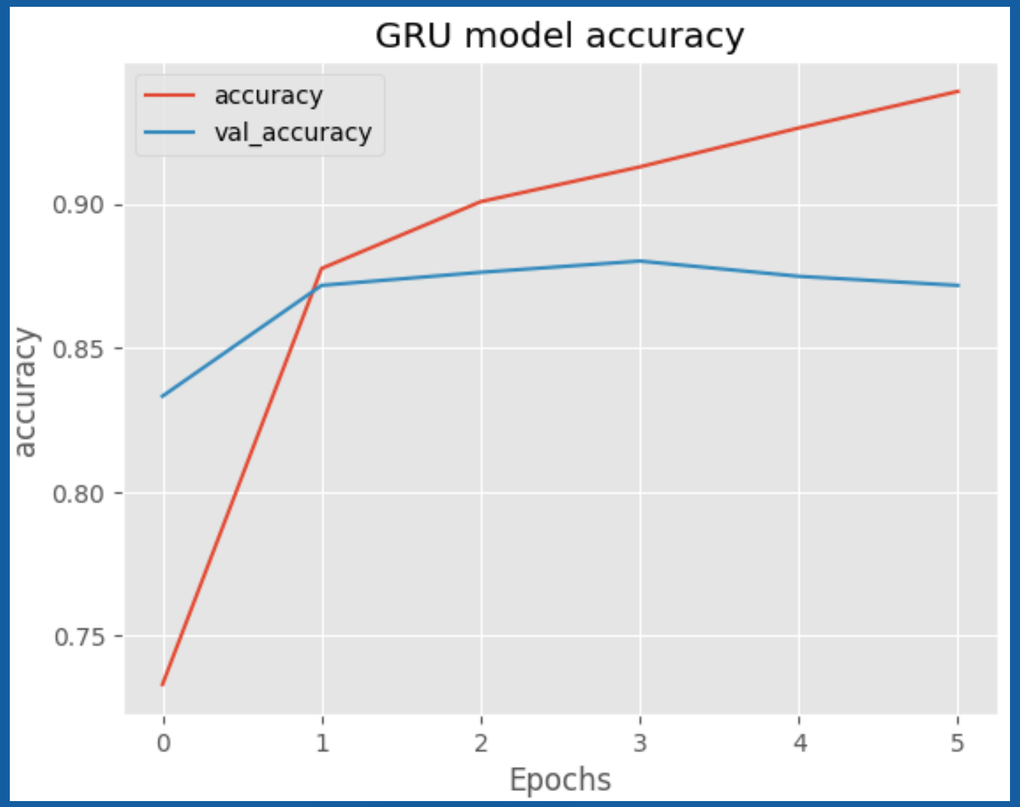
model accuracy

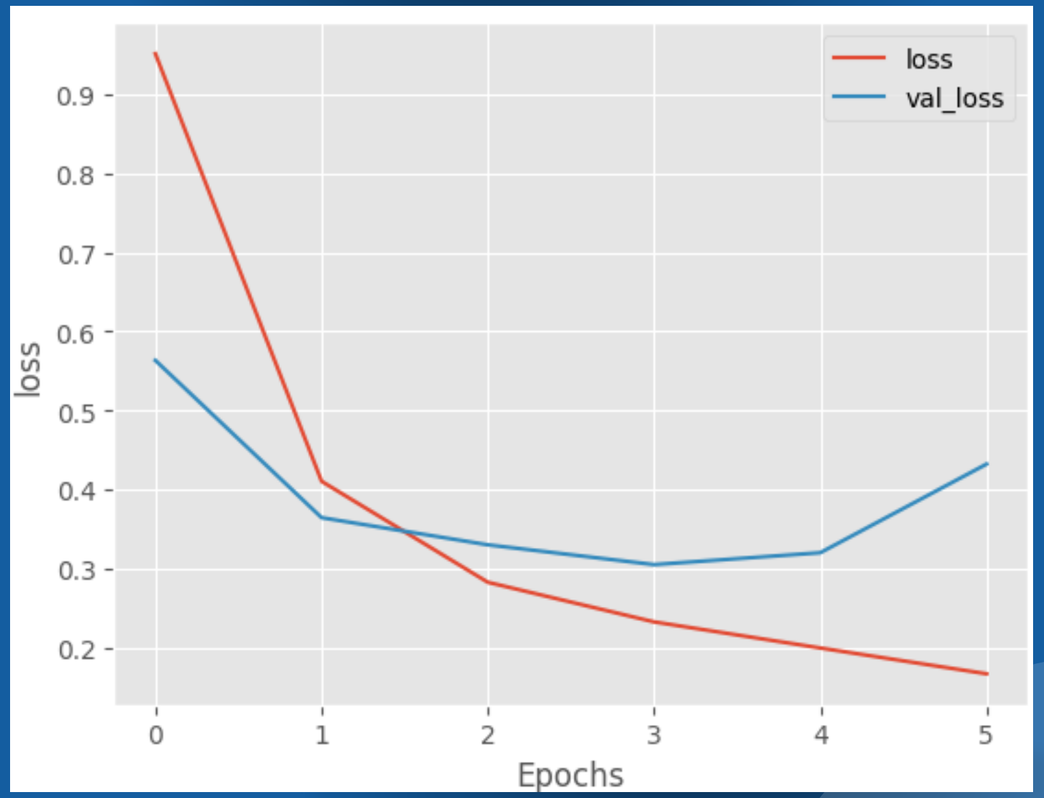




Bidirectional GRU

model accuracy





Make Predictions

```
instance =df['review'][70]
print(instance)
```

```
caddyshack two good movie compared original cant stack robert stack horrible replaceme
```

```
# Convert the input text instance to a sequence of integers using the tokenizer
instance = tokenizer.texts_to_sequences(instance)

# Flatten the list of sequences into a single list
flat_list = []
for sublist in instance:
    for item in sublist:
        flat_list.append(item)

# Wrap the flat list in another list to create a 2D array (required for padding)
flat_list = [flat_list]

# Pad the sequences to ensure uniform input size for the model
instance = pad_sequences(flat_list, padding='post', maxlen=max_len)

# Use the model to predict the sentiment of the processed instance
model
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 369ms/step
array([[0.90760624]], dtype=float32)
```

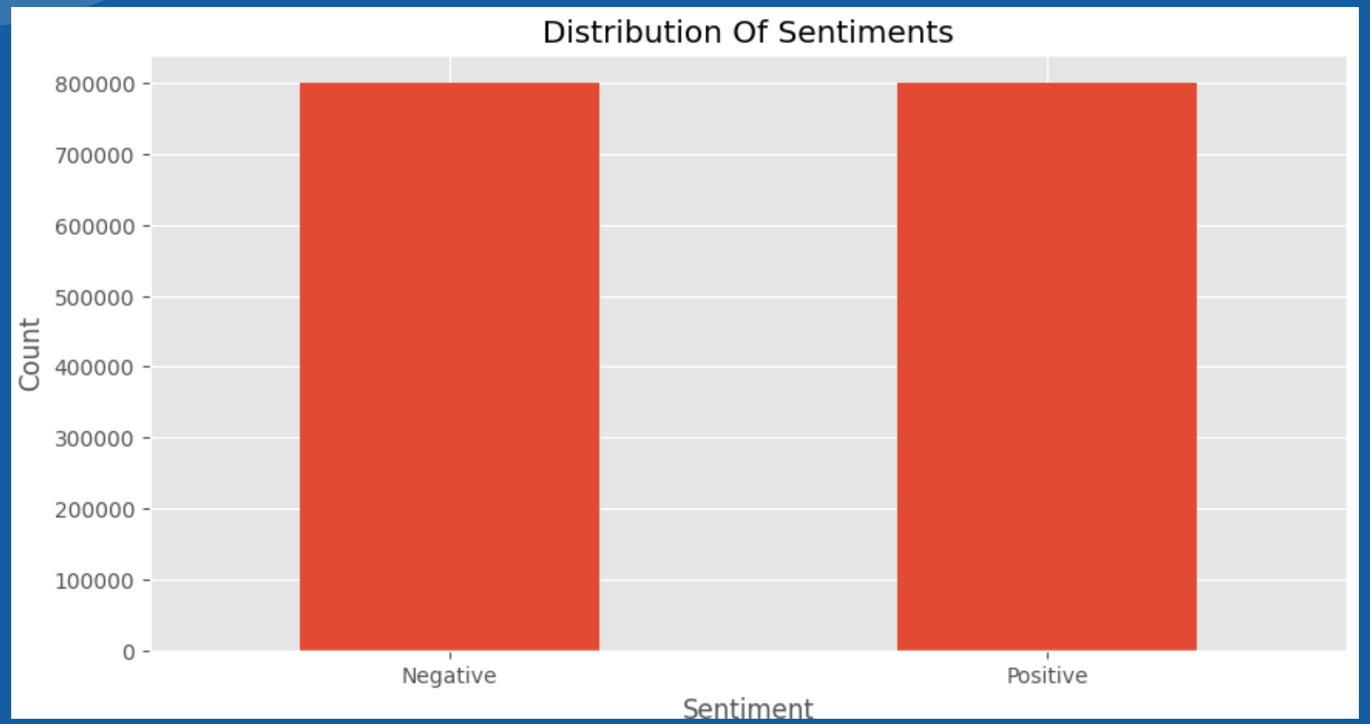
Twitter sentiment

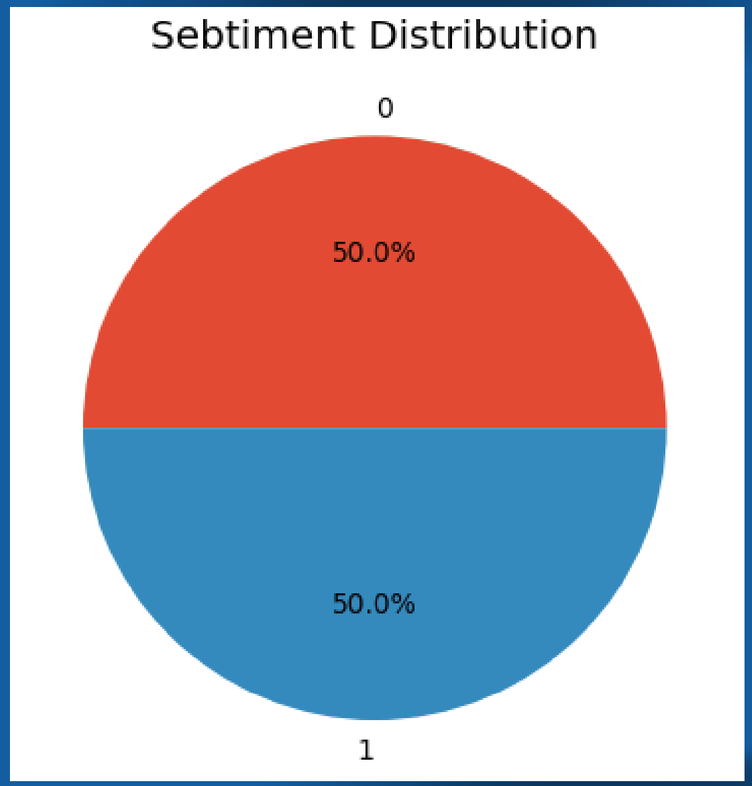
This is the sentiment140 dataset. It contains 1,600,000 tweets extracted using the twitter api . The tweets have been annotated (0 = negative, 4 = positive) and they can be used to detect sentiment .

	sentiment	Id	Date	Query	User_id	text
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....

Twitter sentiment

Plot the distribution of sentiments





Twitter sentiment

implement a balanced sampling strategy by randomly selecting 75 ,000 reviews from each Class . This approach ensures equal representation across all Classes , which facilitates more accurate sentiment . Additionally, by reducing the dataset size, we also decrease training time, making the model training process more efficient.

```
sentiment
0    75000
1    75000
```

Convert to Lowercase: Convert the entire text to lowercase, To standardize the text so that words are treated equally regardless of their case.

Remove Special Characters, Usernames, and Hyperlinks: To eliminate unwanted characters that do not contribute to the meaning of the text..

Remove Stopwords: Filter out common stopwords,that do not add significant meaning to the text.

Lemmatize the Text: Convert words to their base forms.

Joining Tokens: To reconstruct the processed text from the list of lemmatized tokens.

performs preprocessing on the string

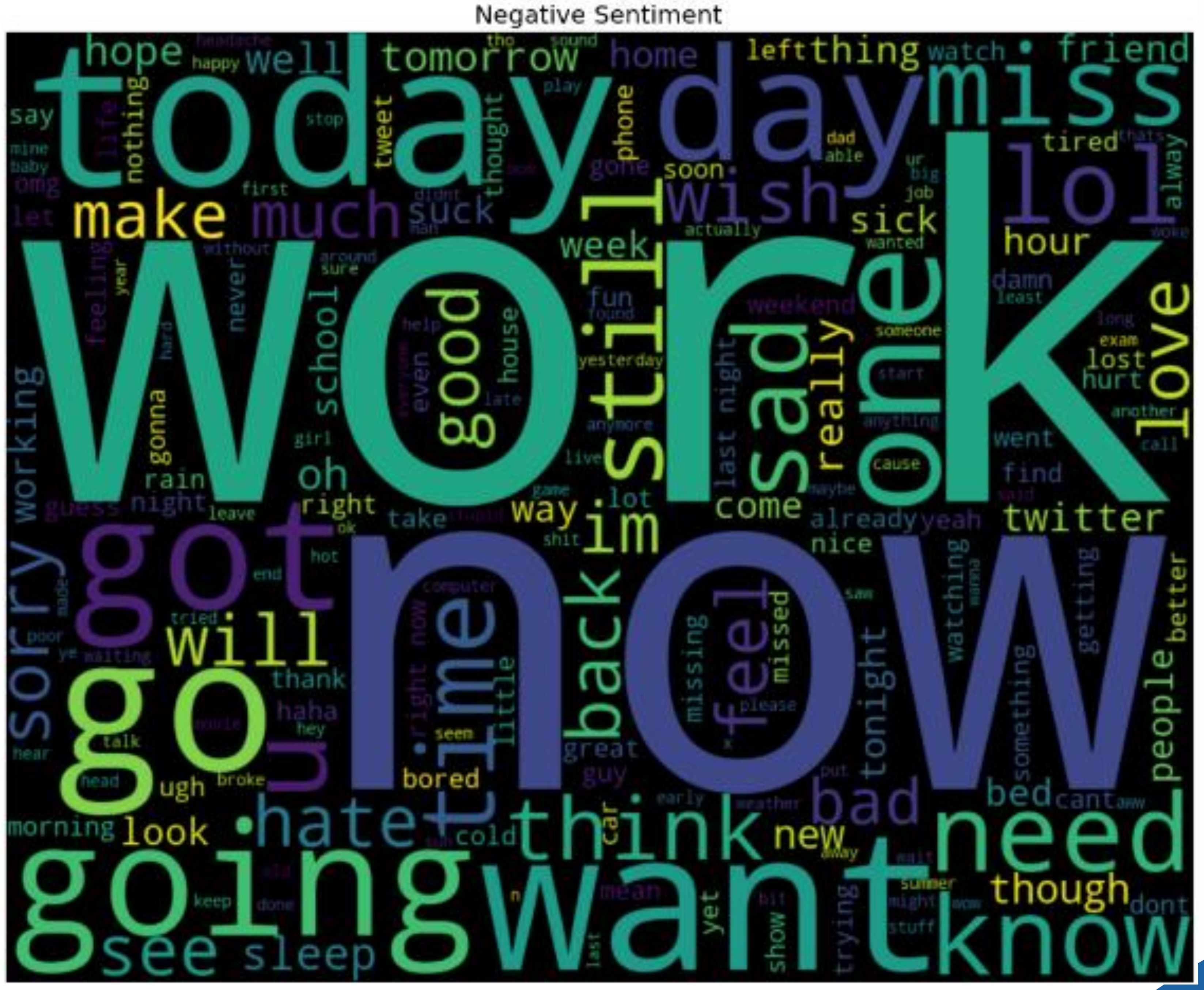
Apply the preprocessing function to the DataFrame

```
lemmatizer = WordNetLemmatizer()
stop_words = set(stopwords.words('english'))
def preprocess_text(tweet):
    url_pattern = re.compile(r"(?:\@|https?\://)\S+|[^\w\s#]")
    repeat_pattern = re.compile(r"(.)\1{2,}")
    tweet = BeautifulSoup(tweet, 'html.parser').get_text()
    tweet = tweet.lower()
    tweet = url_pattern.sub('', tweet)
    tokens = word_tokenize(tweet)
    expanded_words = [repeat_pattern.sub(r"\1\1", word) for word in tokens]
    expanded_words = [re.sub(r"[^\w\s]", "", word) for
                      word in expanded_words if word.strip()]
    expanded_words = [word for word in expanded_words if not re.search(r'\d', word)]
    lemmatized_tokens = [lemmatizer.lemmatize(word) for word in
                         expanded_words if word not in stop_words and len(word) > 1]
    processed_tweet = ' '.join(lemmatized_tokens)
    return processed_tweet
```

after perprocessing

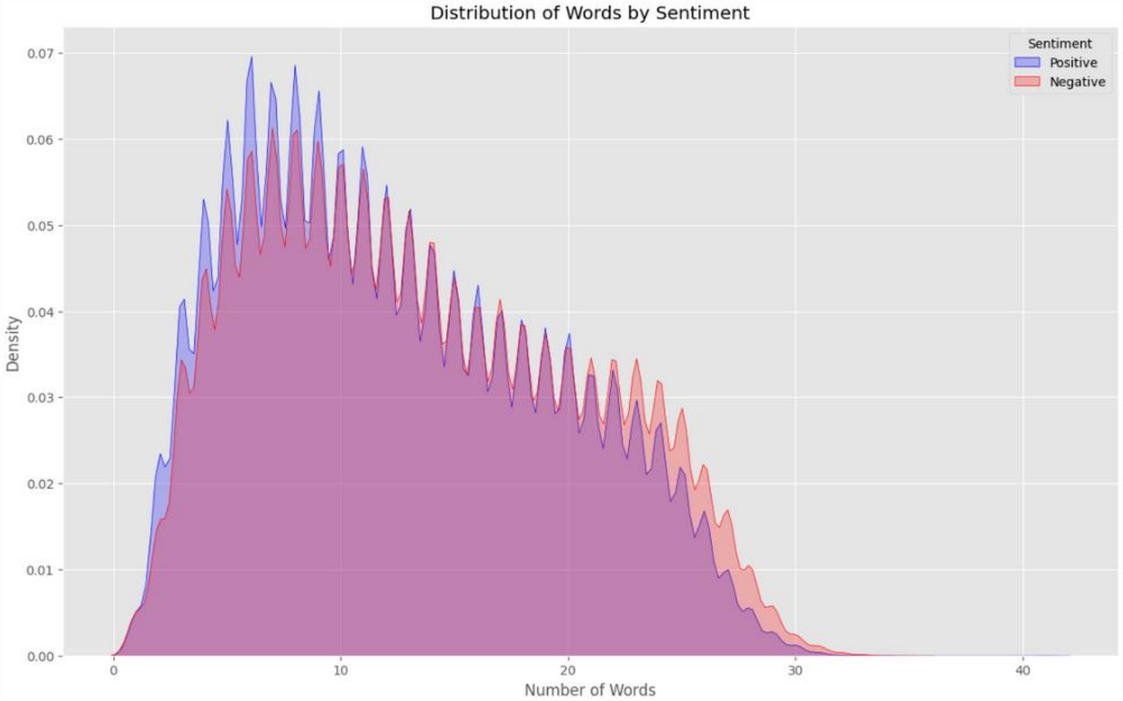
	sentiment	text
12934	0	OMG Transformers comes out tonite I'm tryin...
76182	1	Listening to Sia calming me down About to get ...
26739	0	Leanne0710 they horny kittys have been followi...
128613	1	got to level 10 on tetris it's school tomorrow...
73170	0	just for back from track practise and fricken ...
95052	1	dreamhampton Yes by far To this day before I g...
63971	0	I'm not sure if this is working told you I do...
45379	0	i miss youu tooo kblovesyouu you just called m...
97710	1	campusrock war cool, ja schon
57052	0	LouiseMayes Oh really, this nice weather is le...

word cloud for positive and negative sentiment

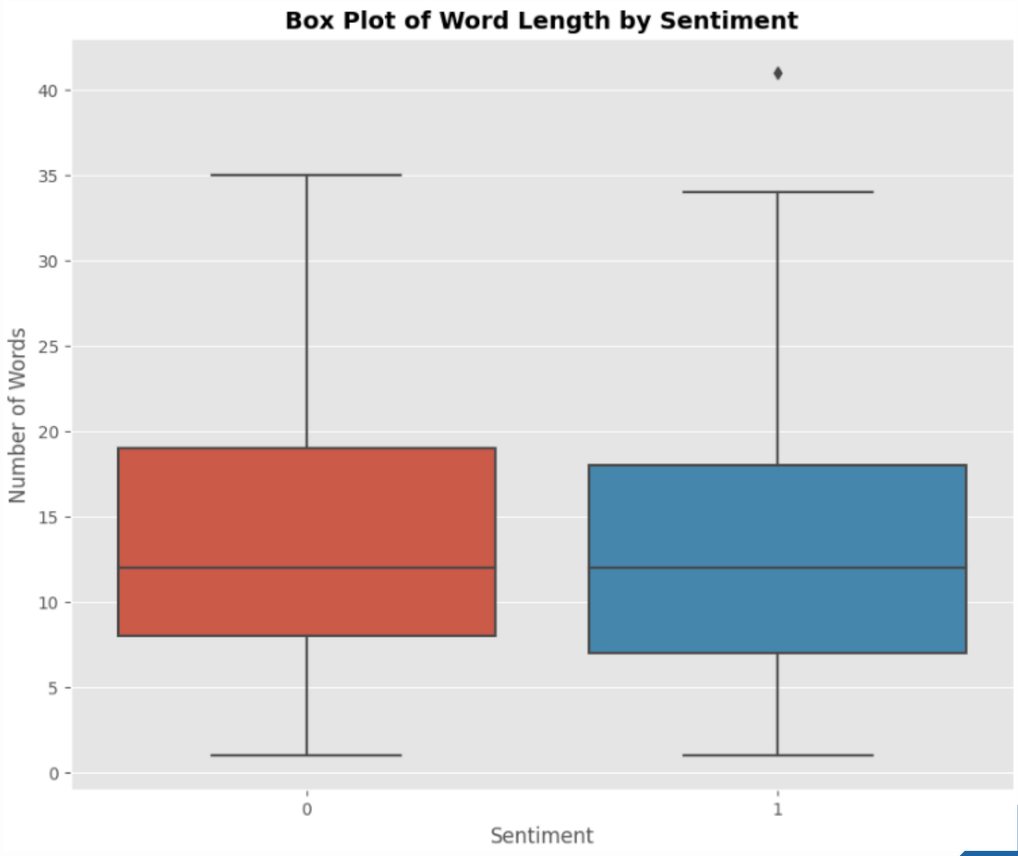


Visualization

KDE for Negative and positive sentiment



Create a box plot for word length distribution by sentiment



Twitter sentiment

- Preprocessing steps

- **Splitting the data into train, validation, and test sets**
- **One-Hot Encoding**
- **TF-IDF Vectorization**
- **Tokenization and Padding**

- Deep learning Model

- Load GloVe embeddings
- Create embedding matrix
- Initialize the model
- Embedding layer (converts text to dense vector representations)
- Bidirectional LSTM layer

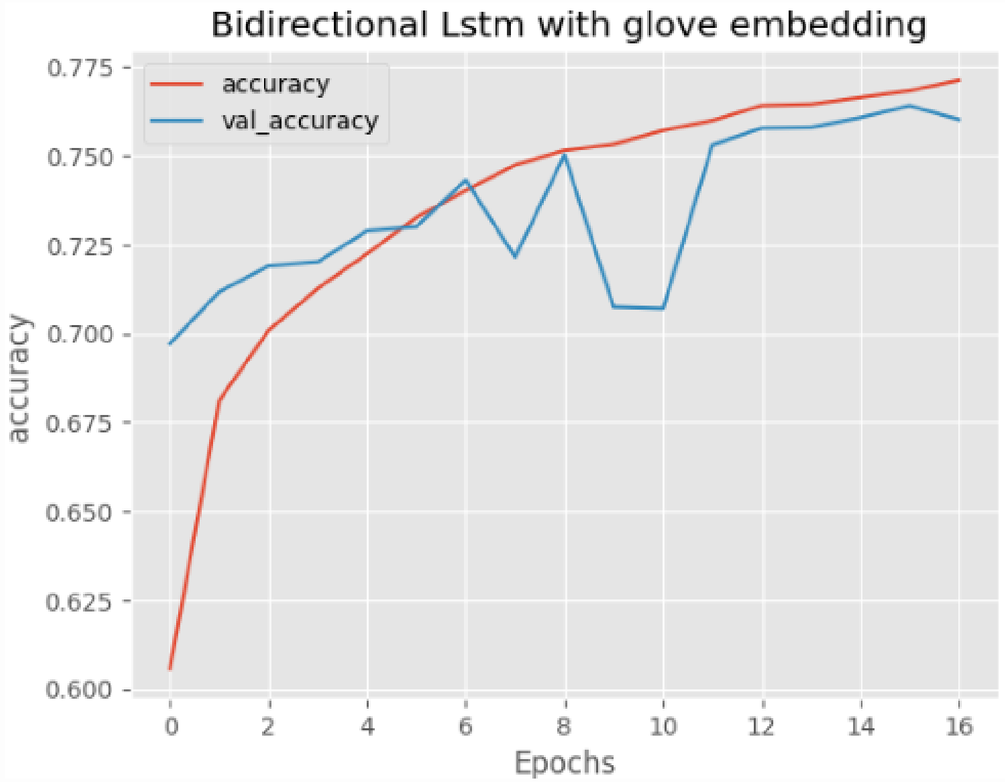
Model: "sequential"

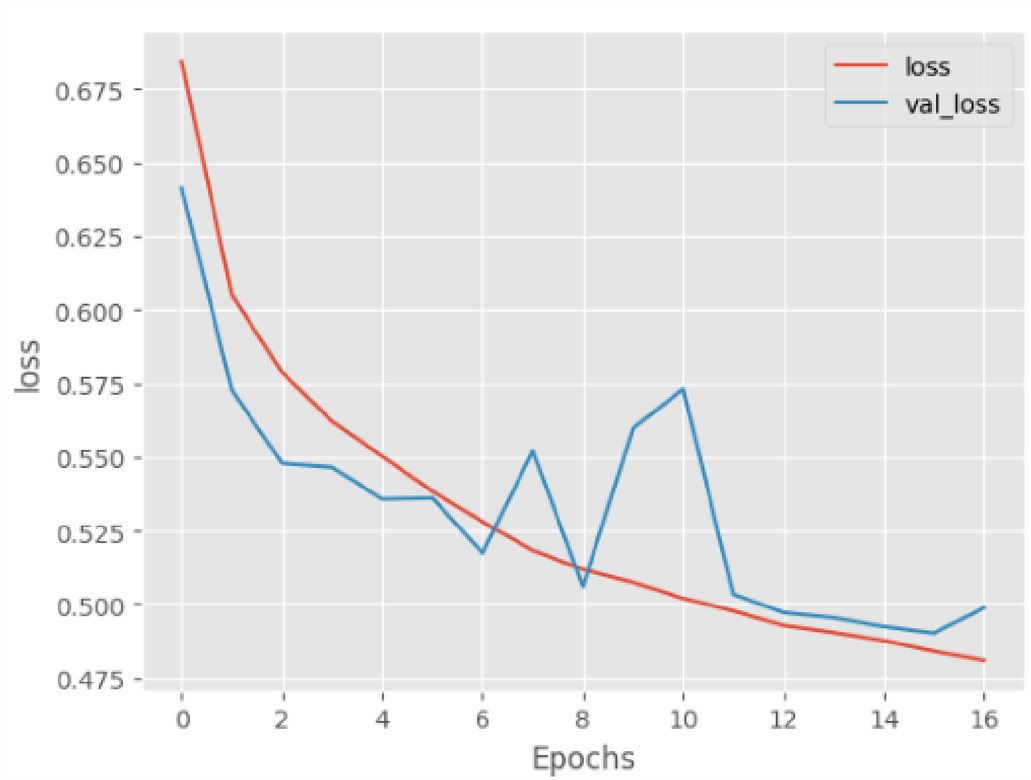
Layer (type)	Output Shape	Param #
embedding (Embedding)	?	1,000,000
bidirectional (Bidirectional)	?	0 (unbuilt)
dropout (Dropout)	?	0 (unbuilt)
bidirectional_1 (Bidirectional)	?	0 (unbuilt)
dropout_1 (Dropout)	?	0 (unbuilt)
bidirectional_2 (Bidirectional)	?	0 (unbuilt)
dropout_2 (Dropout)	?	0 (unbuilt)
dense (Dense)	?	0 (unbuilt)
batch_normalization (BatchNormalization)	?	0 (unbuilt)
dense_1 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)
Trainable params: 0 (0.00 B)
Non-trainable params: 1,000,000 (3.81 MB)

Twitter sentiment

Plot training and validation accuracy





Twitter sentiment

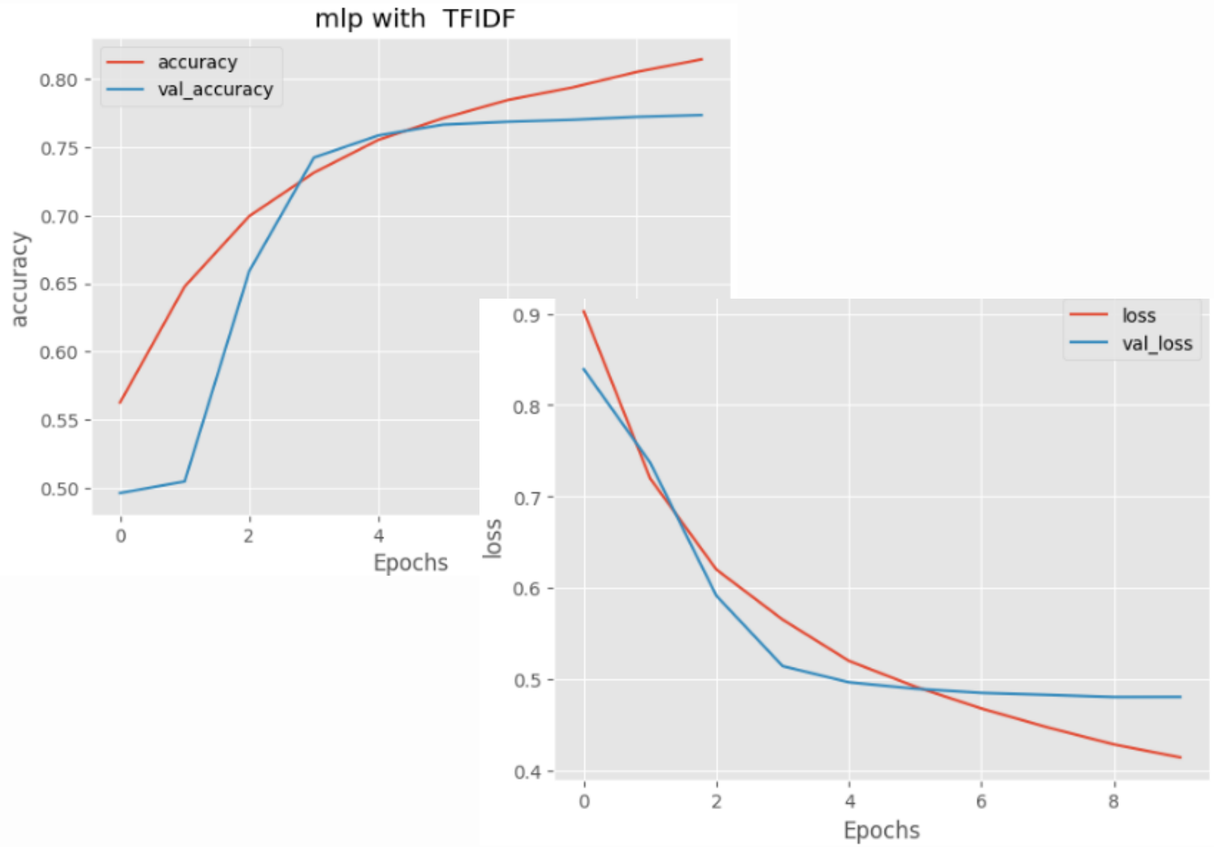
Define the MLP model with TF-IDF

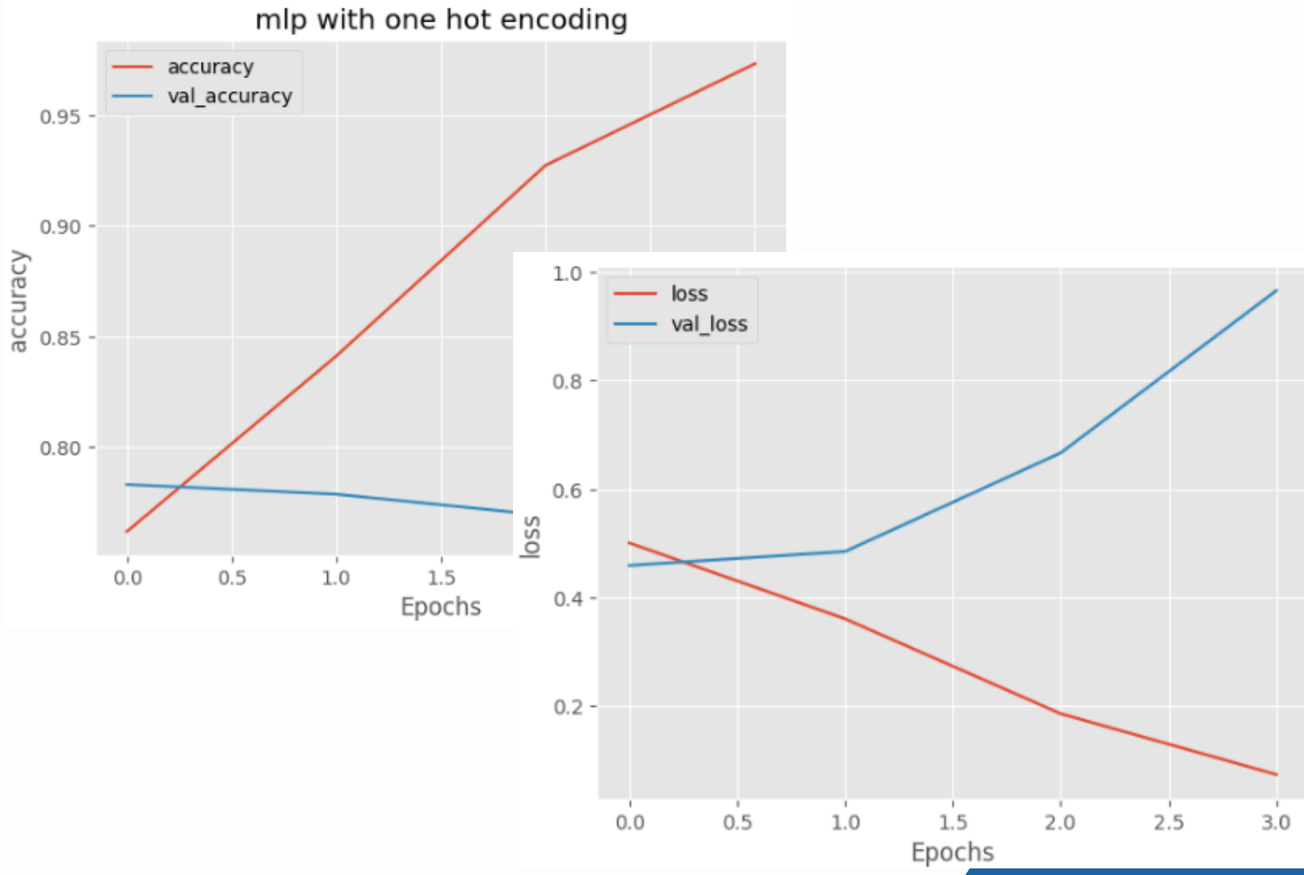
```
Training Loss: 0.3477531969547272
Training Accuracy: 0.8496285676956177
Validation Loss: 0.48063763976097107
Validation Accuracy: 0.7675555348396301
```

MLP model with one hot encoding

```
Training Loss: 0.3713001608848572
Training Accuracy: 0.8438857197761536
Validation Loss: 0.4552420675754547
Validation Accuracy: 0.7828888893127441
```

Plot training and validation accuracy



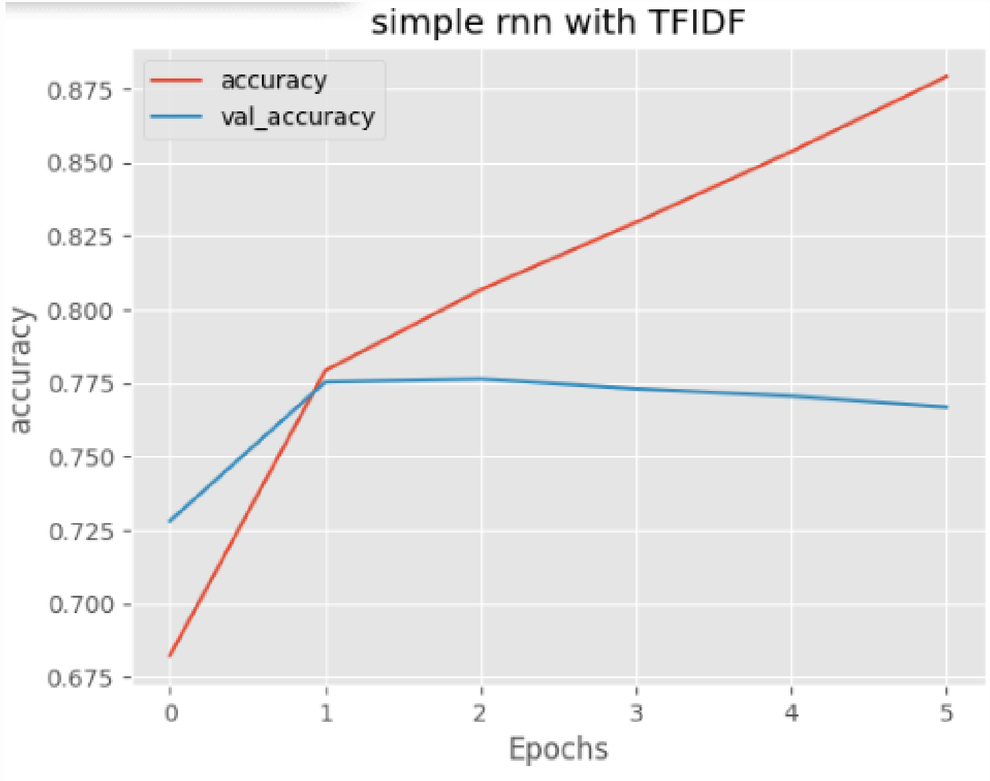


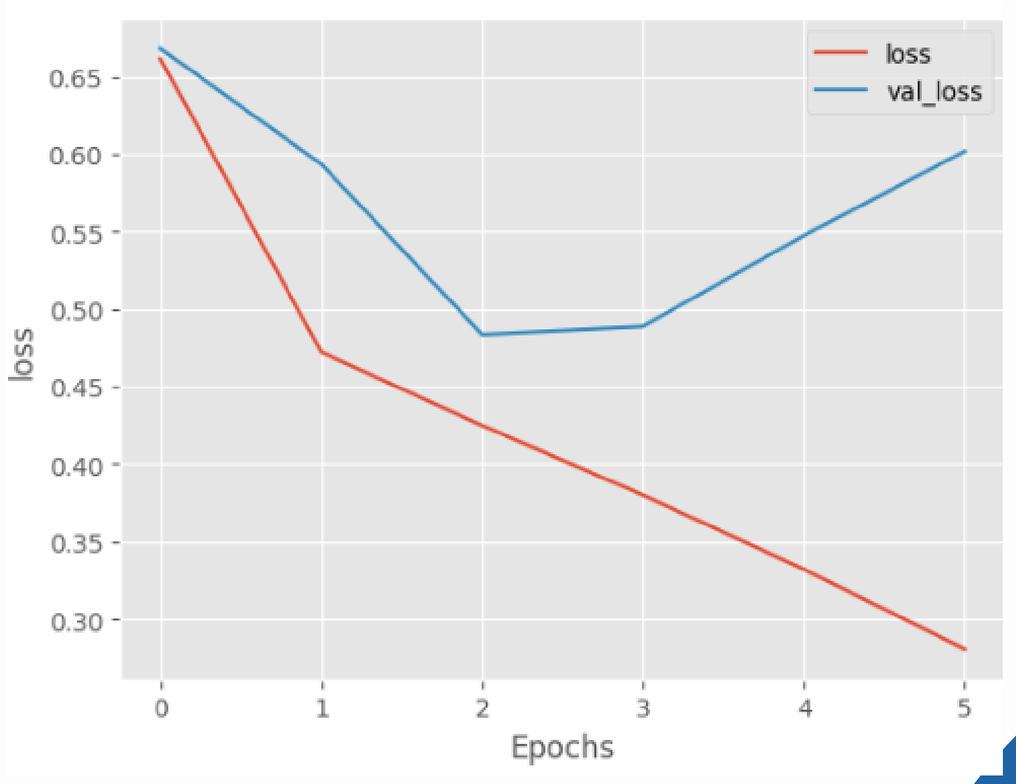
Twitter sentiment

simple RNN with TF-IDF

```
Training Loss: 0.3924139142036438
Training Accuracy: 0.8541333079338074
Validation Loss: 0.4823756814002991
Validation Accuracy: 0.7724888920783997
```

Plot training and validation accuracy





Twitter sentiment

DL Models

LSTM Model

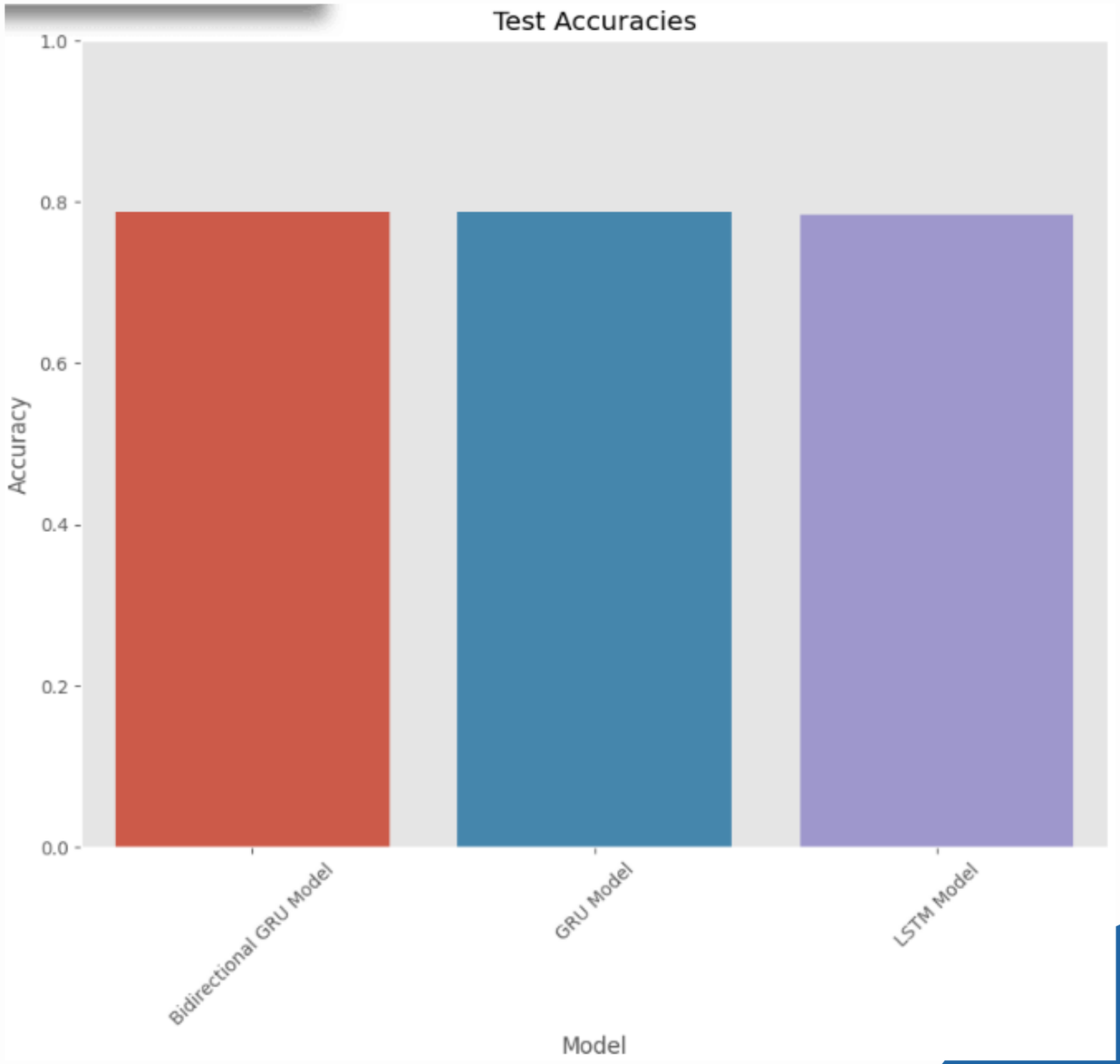
- Training Accuracy for LSTM Model: 0.8350
- Test Accuracy for LSTM Model: 0.7844

GRU Model

- Training Accuracy for GRU Model: 0.8302
- Test Accuracy for GRU Model: 0.7866

Bidirectional GRU Model

- Training Accuracy for Bidirectional GRU Model: 0.8495
- Test Accuracy for Bidirectional GRU Model: 0.7876



BERT Tokenization

BERT tokenization is used to convert the raw text into numerical inputs that can be fed into the BERT model. It tokenized the text and performs some preprocessing to prepare the text for the model's input format.
Batch Encoding: The batch_encode_plus function is used to tokenize and encode the training, validation, and test sets:

- 1- Padding: Ensures all sequences are the same length.
- 2- Truncation: Cuts off sequences that exceed the maximum length.
- 3- Tensor Conversion: Outputs are returned as TensorFlow tensors for compatibility with TensorFlow models.

Twitter sentiment using Bert

BERT

- Test Loss: 0.426111668348312 4
- Test Accuracy: 0.8358666896820068

DistilBERT

- Test Loss: 0.401414424180984 5
- Test Accuracy: 0.829200029373169

RoBERTa

- Test Loss: 0.3660981655120849 6
- Test Accuracy: 0.8709333539009094

ALBERT

- Test Loss: 0.4147121012210846
- Test Accuracy: 0.833644449710846

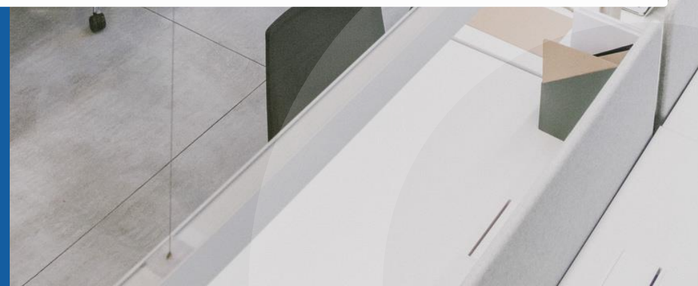
```
Model: "tf_bert_for_sequence_classification_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bert (TFBertMainLayer)      multiple                  109482240

 dropout_171 (Dropout)       multiple                  0

 classifier (Dense)          multiple                  1538

=================================================================
Total params: 109483778 (417.65 MB)
Trainable params: 109483778 (417.65 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
Model: "tf_distil_bert_for_sequence_classification_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 distilbert (TFDistilBertMa  multiple                  66362880
 inLayer)

 pre_classifier (Dense)      multiple                  590592

 classifier (Dense)          multiple                  1538

 dropout_191 (Dropout)       multiple                  0

=================================================================
Total params: 66955010 (255.41 MB)
Trainable params: 66955010 (255.41 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Amazon Product Reviews

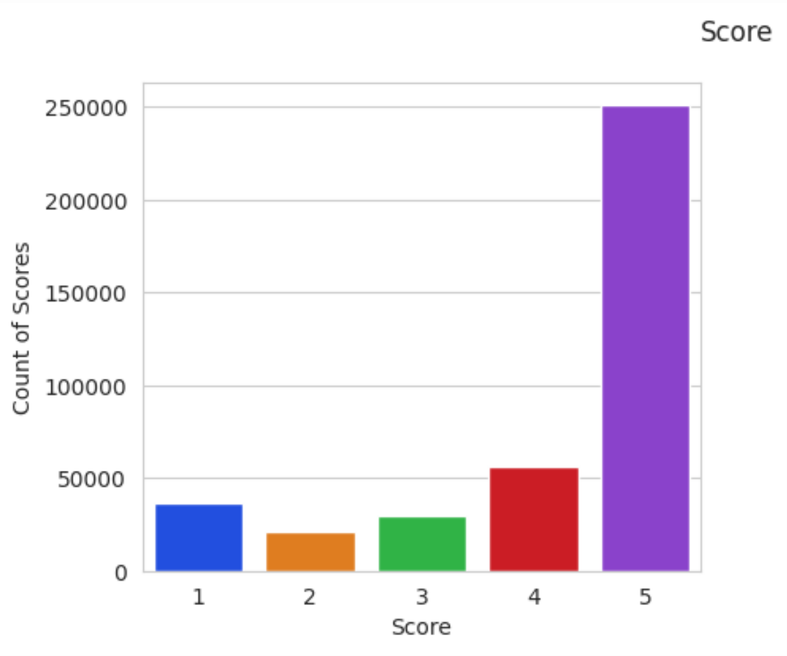
This dataset contains more than 568k consumer reviews on different amazon products.

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned dog food products and have found them all to be of ...
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanuts...the peanuts were actually small sized unsalted...
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a few centuries. It is a light, pillowy citrus gelati...
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine	If you are looking for the secret ingredient in Robitussin I believe I have found it. I got thi...
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy	Great taffy at a great price. There was a wide assortment of yummy taffy. Delivery was very qu...

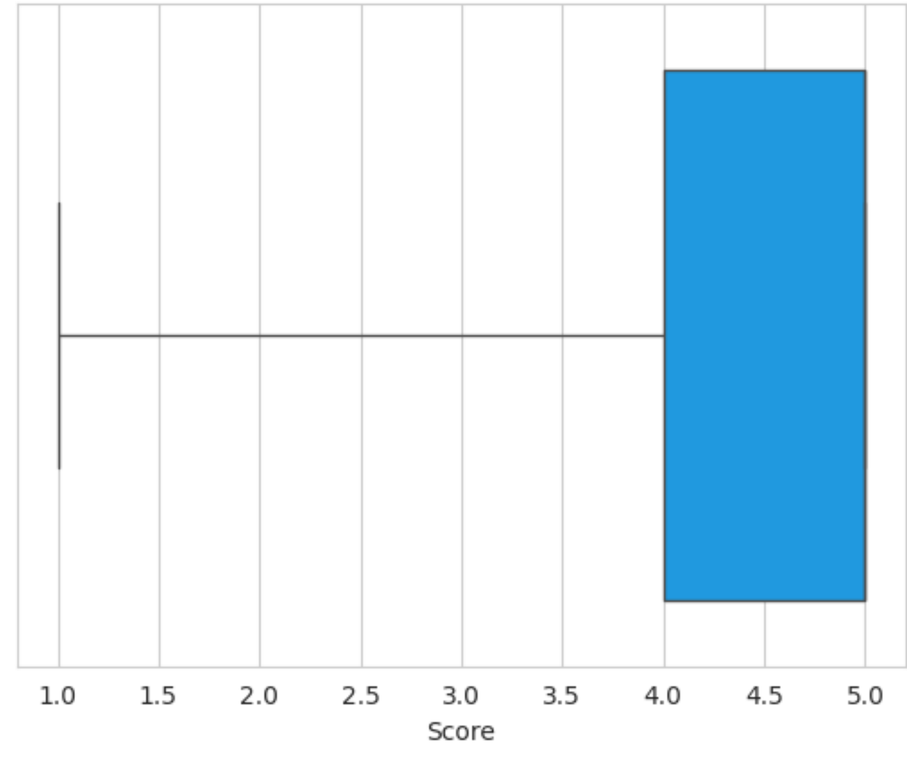


Data Exploration

These graph showing how many reviews get a specific score

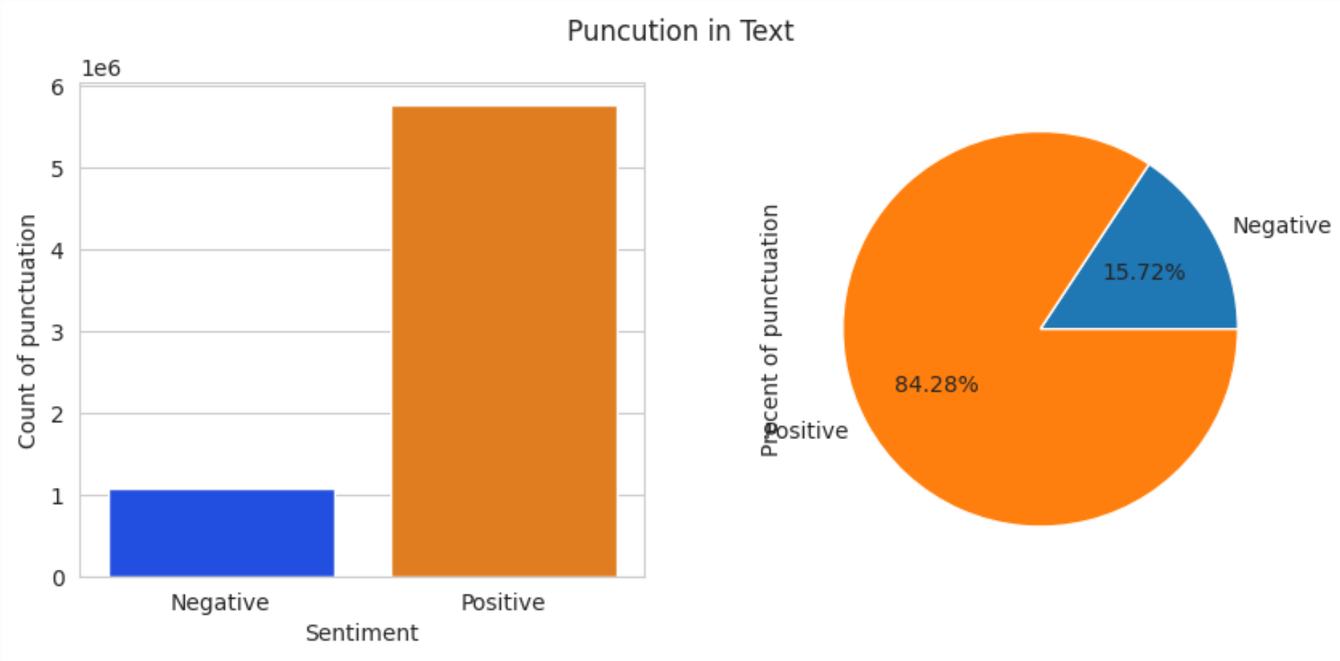


Box-Plot gives the concentration data distribution

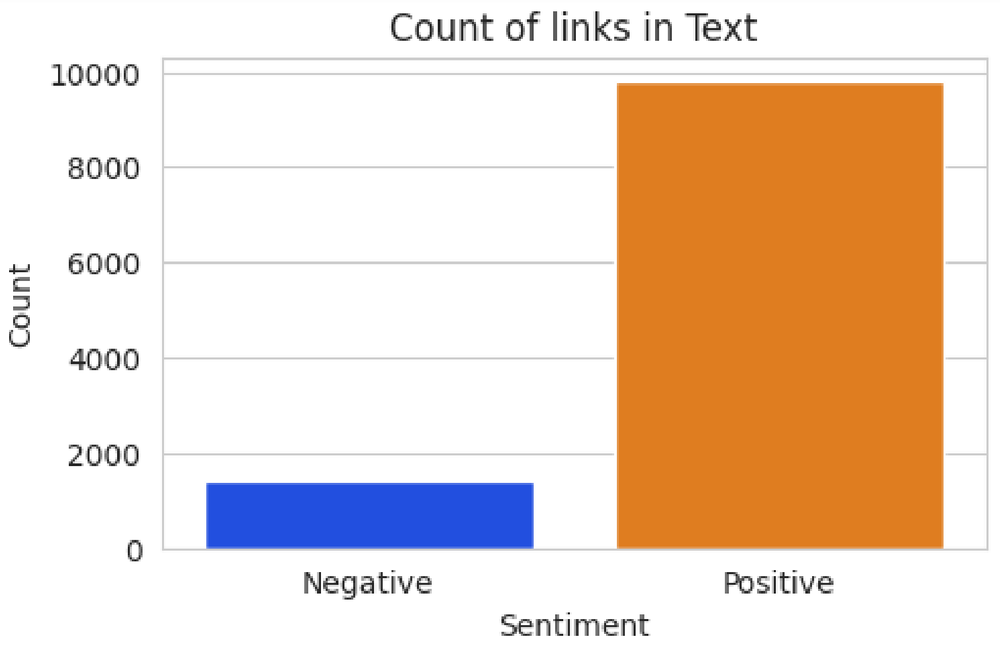


Data Exploration

Punctuation in text



Calculate count of links



Data Cleaning

Removing Duplicates of the Data

```
# Display duplicated rows and their counts
duplicated_data = data[data[["Text","Score"]].duplicated(keep=False)] # Changed Score to Score
duplicated_counts = duplicated_data[["Text","Score"]].value_counts() # Changed Score to Score
duplicated_counts
```

```
# Drop duplicates based on 'Text' and 'Score' columns
data = data.drop_duplicates(subset=["Text", "Score"])
```

Dropping null values

```
unique_products = len(data["ProductId"].unique())
print(f"Number of Unique Product IDs: {unique_products}")
```

Number of Unique Product IDs: 67563

Data Cleaning

Removing Unnecessary Columns and Data Sampling :

- to **reduce processing time and make it work for slow systems too. You can take all the 568k records if your system is efficient enough**

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 568454 entries, 0 to 568453
Data columns (total 10 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   Id                      568454 non-null  int64
 1   ProductId               568454 non-null  object
 2   UserId                  568454 non-null  object
 3   ProfileName             568428 non-null  object
 4   HelpfulnessNumerator    568454 non-null  int64
 5   HelpfulnessDenominator  568454 non-null  int64
 6   Score                   568454 non-null  int64
 7   Time                    568454 non-null  int64
 8   Summary                 568427 non-null  object
 9   Text                    568454 non-null  object
dtypes: int64(5), object(5)
memory usage: 43.4+ MB
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 568454 entries, 0 to 568453
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   ProductId  568454 non-null  object
 1   Score      568454 non-null  int64
 2   Time       568454 non-null  int64
 3   Text       568454 non-null  object
dtypes: int64(2), object(2)
memory usage: 17.3+ MB
```

```
Score
1    12500
2    12500
3     8500
4     8500
5     8500
```

rating	count
1	25500
0	25000

EDA

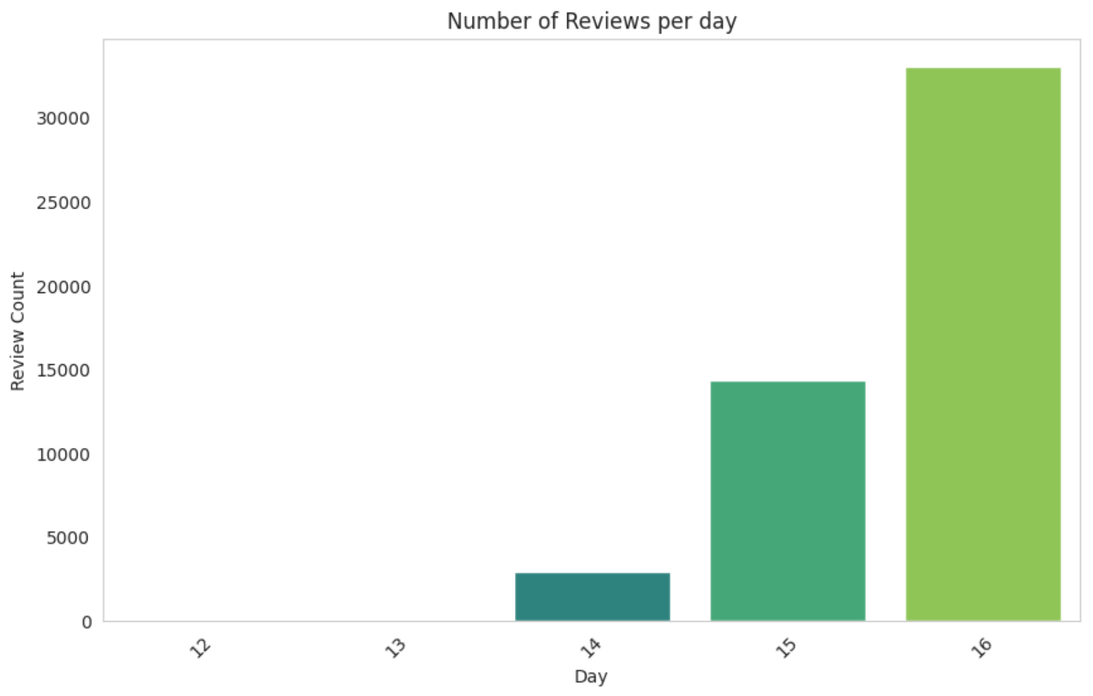
WordCloud of Positive and Negative Reviews

common words - Top 8

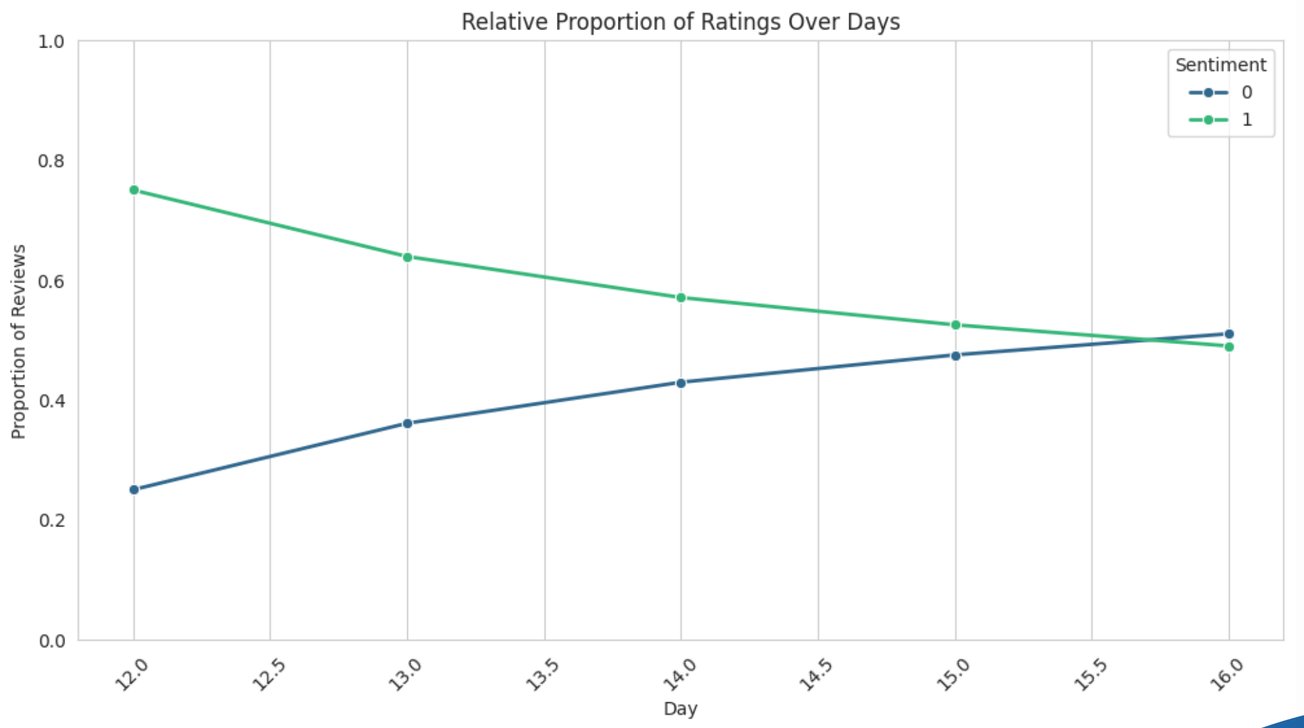
```
Positive :
[('br', 375500), ('br br', 150429), ('like', 143241), ('good', 124033), ('great', 108981), ('just', 100612), ('taste', 97969),

Negative :
[('br', 69945), ('like', 30301), ('br br', 27916), ('product', 24984), ('taste', 22602), ('just', 18809), ('good', 14768), ('c
```

Reviews Trend Analysis

Number of reviews for each Day



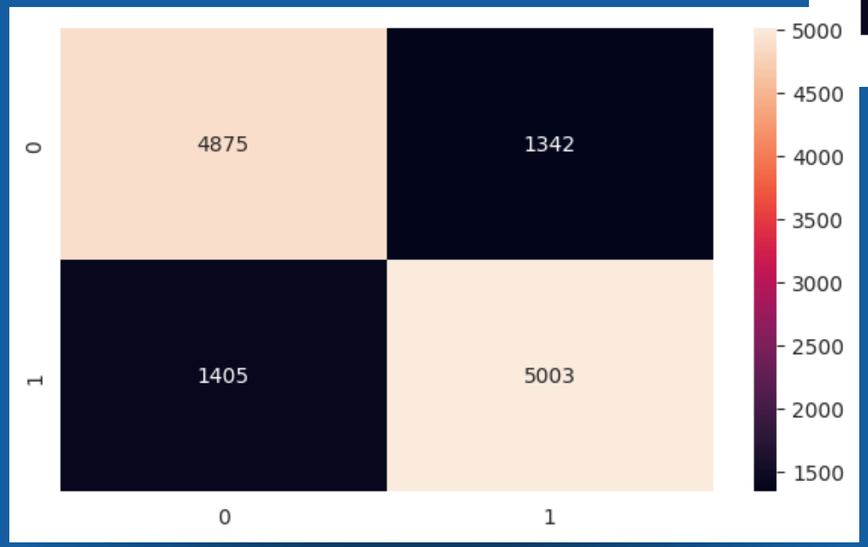
Line Chart

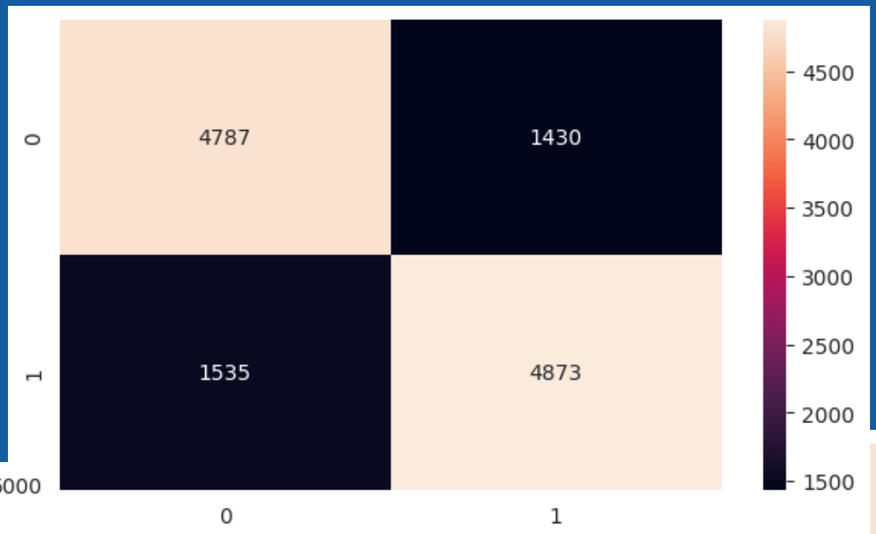


Models Training - TFIDF

Confusion matrix

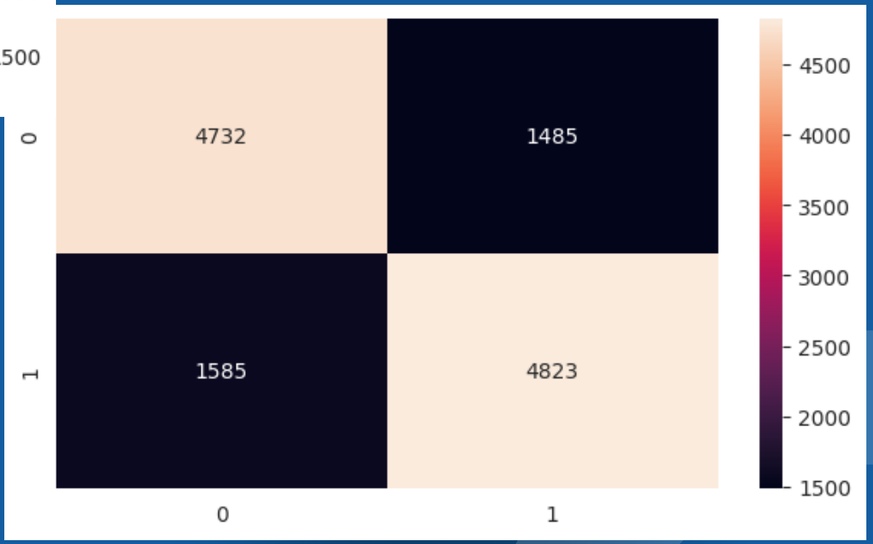
Classifier: Logistic_Regression
Train Accuracy: 0.8374125412541255
Test Accuracy: 0.7824158415841584





Classifier: Random_Forest
Train Accuracy: 1.0
Test Accuracy: 0.7651485148514852

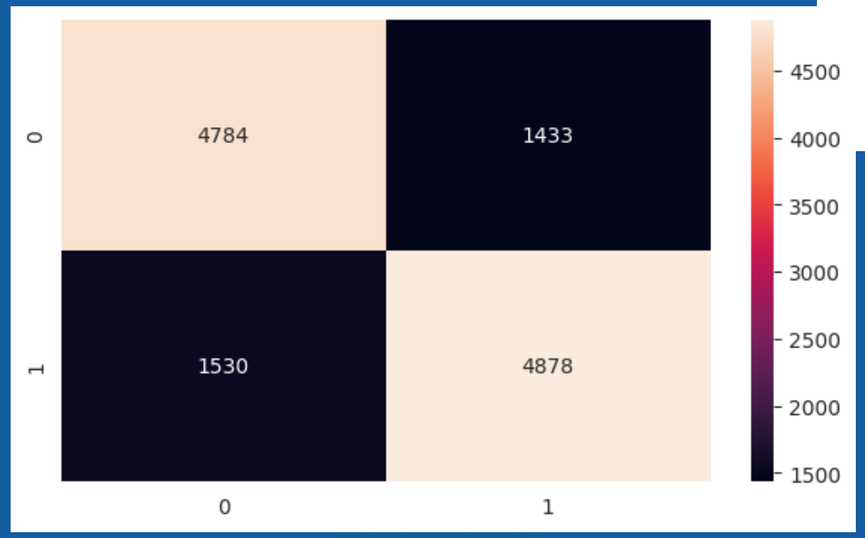
Classifier: XGBoost
Train Accuracy: 0.8538613861386138
Test Accuracy: 0.7568316831683168

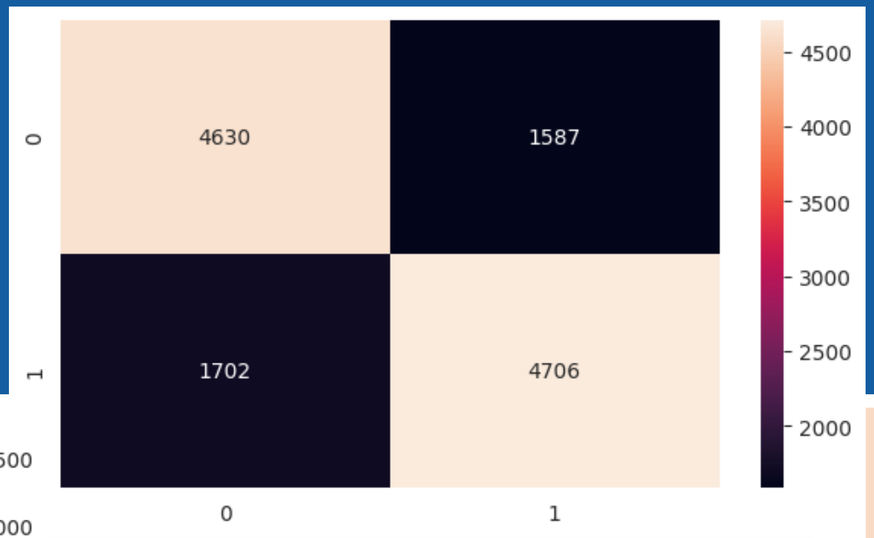


Models Training - Word2Vec

Confusion matrix

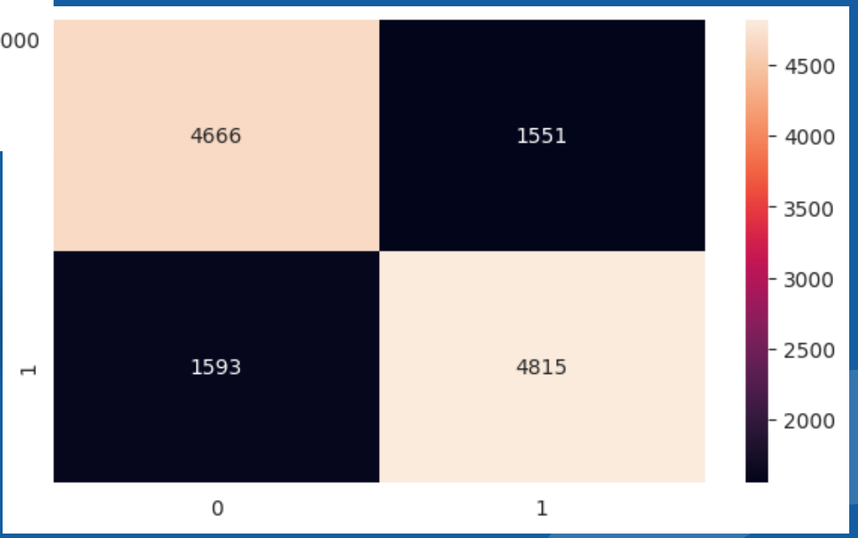
Classifier: Logistic_Regression
Train Accuracy: 0.7661782178217822
Test Accuracy: 0.7653069306930693





Classifier: Random_Forest
Train Accuracy: 1.0
Test Accuracy: 0.7394851485148515

Classifier: XGBoost
Train Accuracy: 0.9372937293729373
Test Accuracy: 0.750970297029703

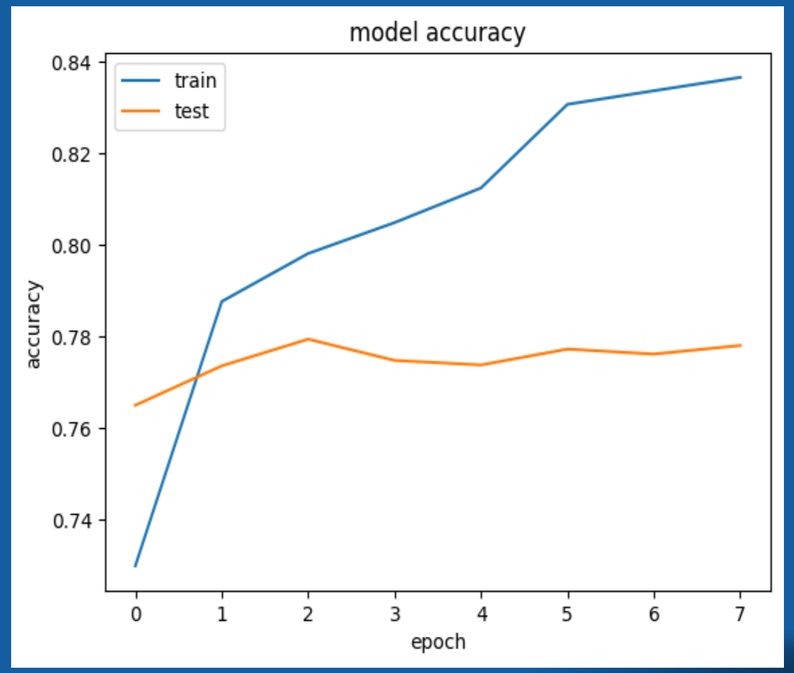


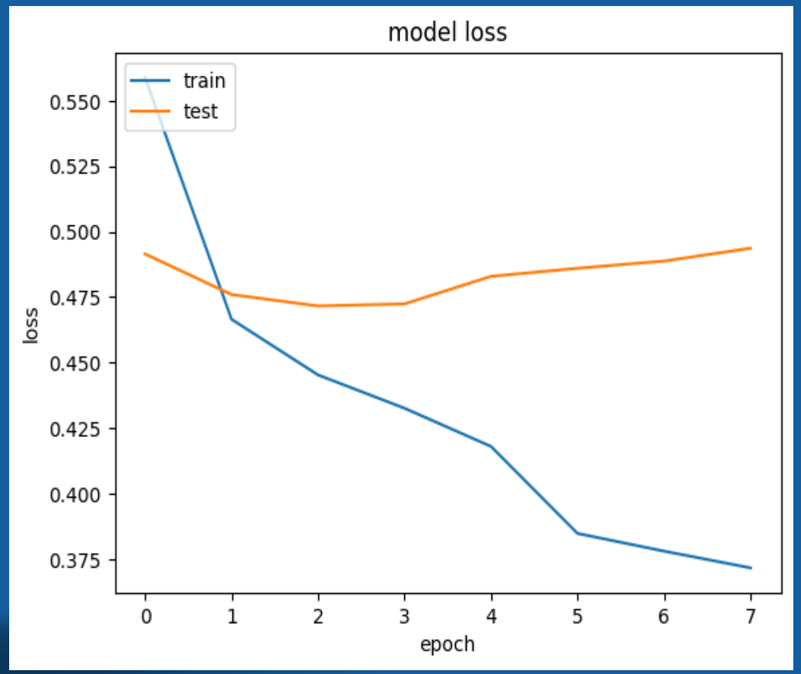
Models Training - LSTM

```
model=Sequential()
model.add(Embedding(input_dim=voca_size,output_dim=embedding_size,input_length=max_len))
model.add(LSTM(256,recurrent_dropout=0.3,dropout=0.3))
model.add(Dropout(0.5))
model.add(Dense(1,activation='sigmoid',kernel_regularizer=regularizers.l2(0.01)))
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 150, 200)          400000

 lstm (LSTM)                 (None, 256)               467968

 dropout (Dropout)           (None, 256)               0

 dense (Dense)               (None, 1)                 257

=================================================================
```

Model Accuracy - LSTM






```
Final Test Accuracy: 77.94%
Final Train Accuracy: 83.69%
```

Models Training & Accuracy - DistilBert

[7575/7575 28:23, Epoch 3/3]

Epoch	Training Loss	Validation Loss	Accuracy	F1
1	0.064600	0.697429	0.870495	0.870500
2	0.033100	0.741822	0.871287	0.871284
3	0.031400	0.870741	0.874851	0.874857

8]:
```
TrainOutput(global_step=7575, training_loss=0.04511223522349946, metrics={'train_runtime': 1703.
9447, 'train_samples_per_second': 71.129, 'train_steps_per_second': 4.446, 'total_flos': 8027524
358553600.0, 'train_loss': 0.04511223522349946, 'epoch': 3.0})
```

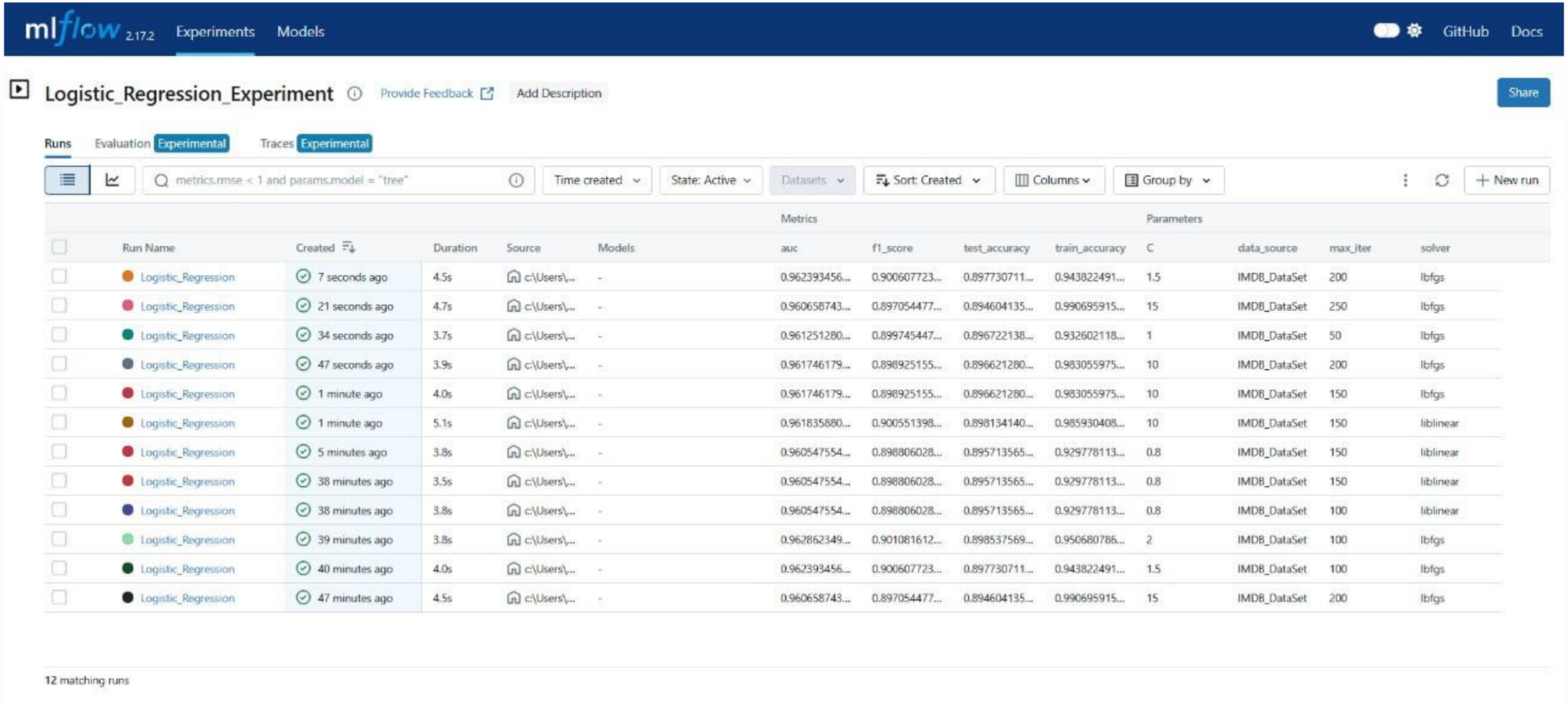
+ Code + Markdown

3]:
```
# Save the model
model.save_pretrained('./DistilBert_Model')
```

MLOPS

IMDB MLflow

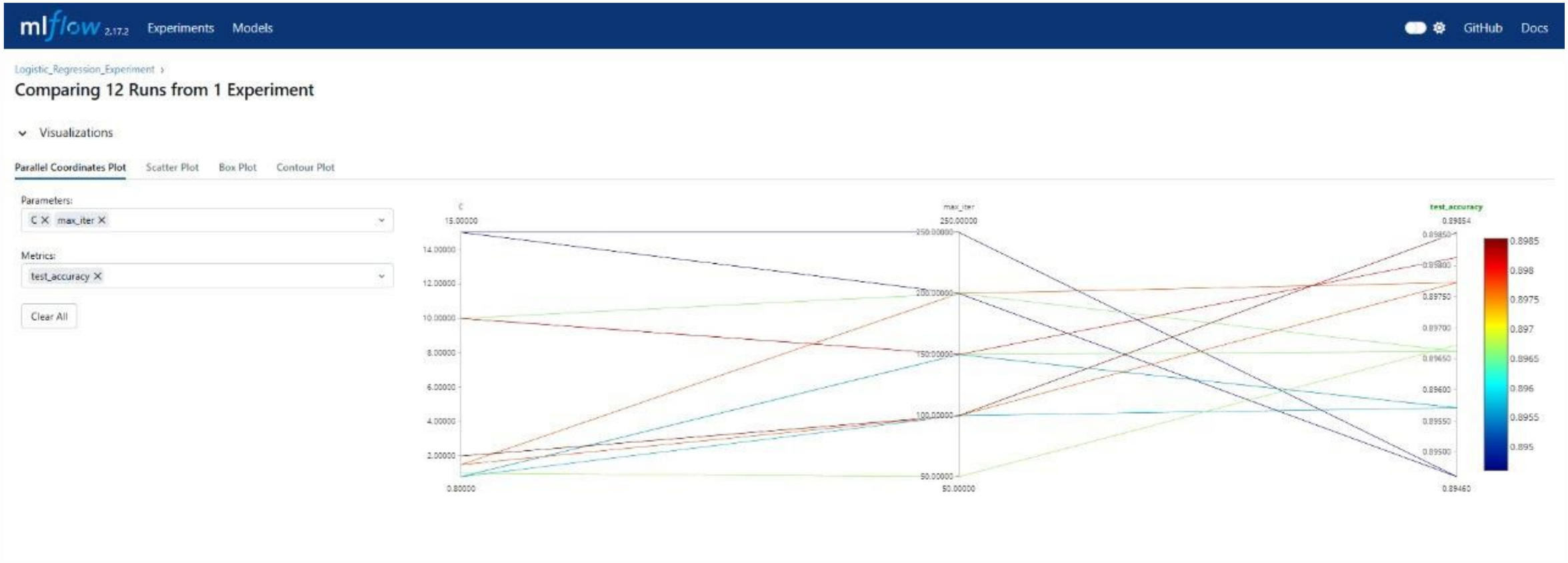
Logistic Regression EXPERIMENT



MLOPS

IMDB MLflow

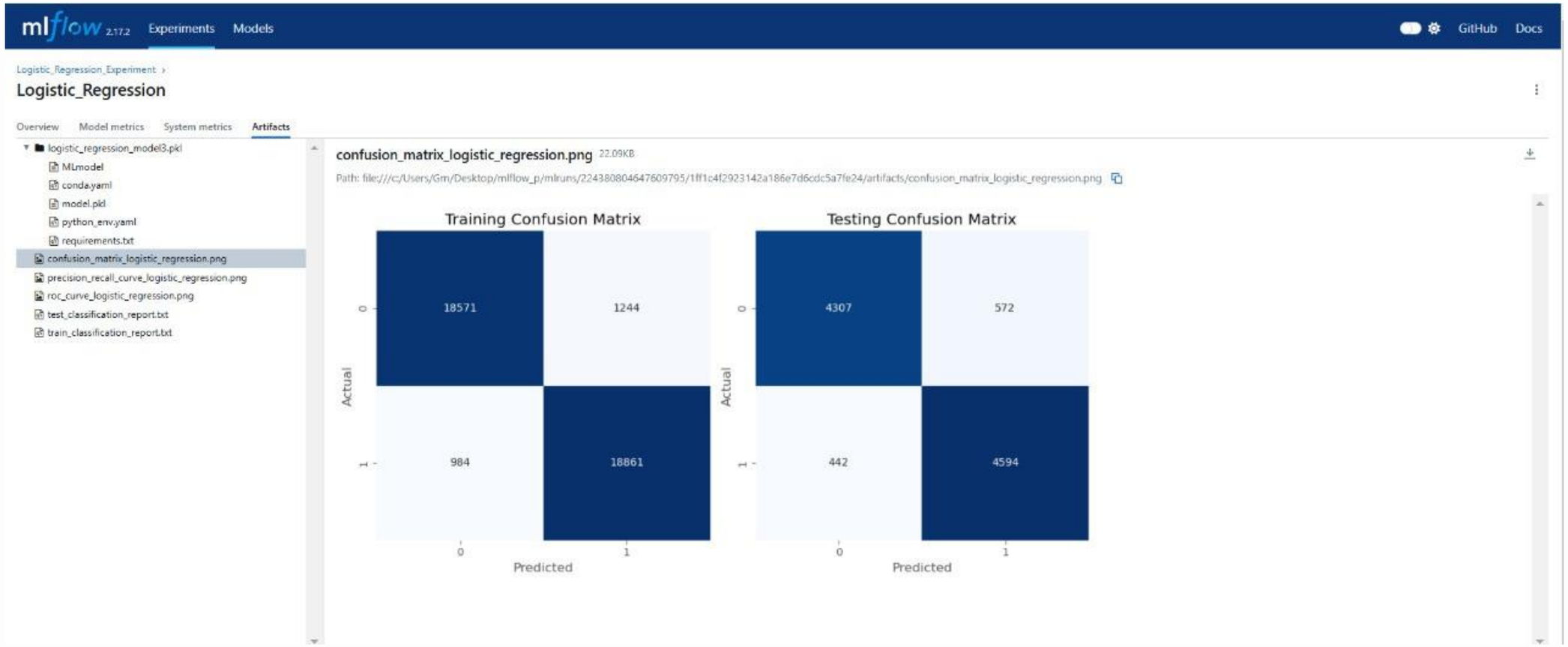
Logistic Regression Comparing Runs



MLOPS

IMDB MLflow

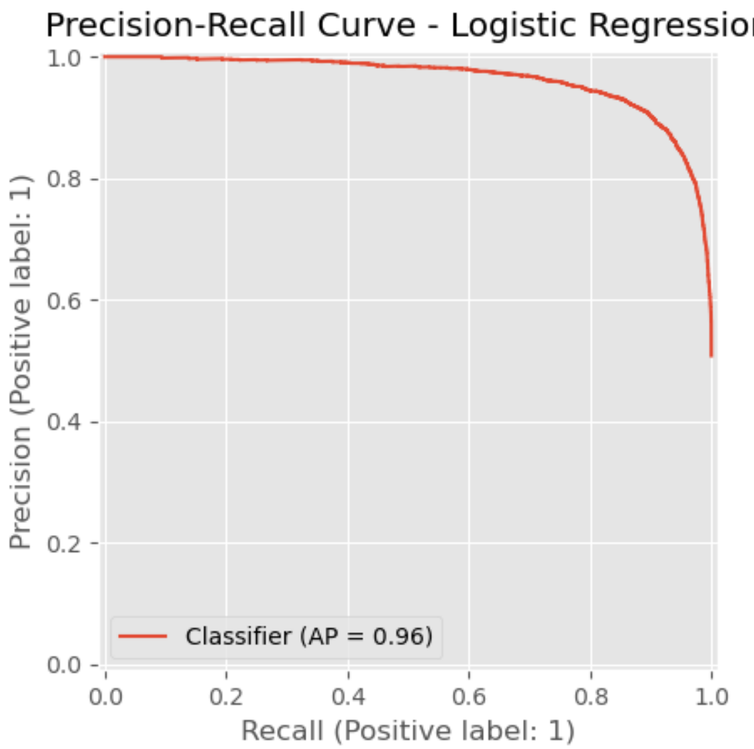
Logistic Regression Confusion Matrix



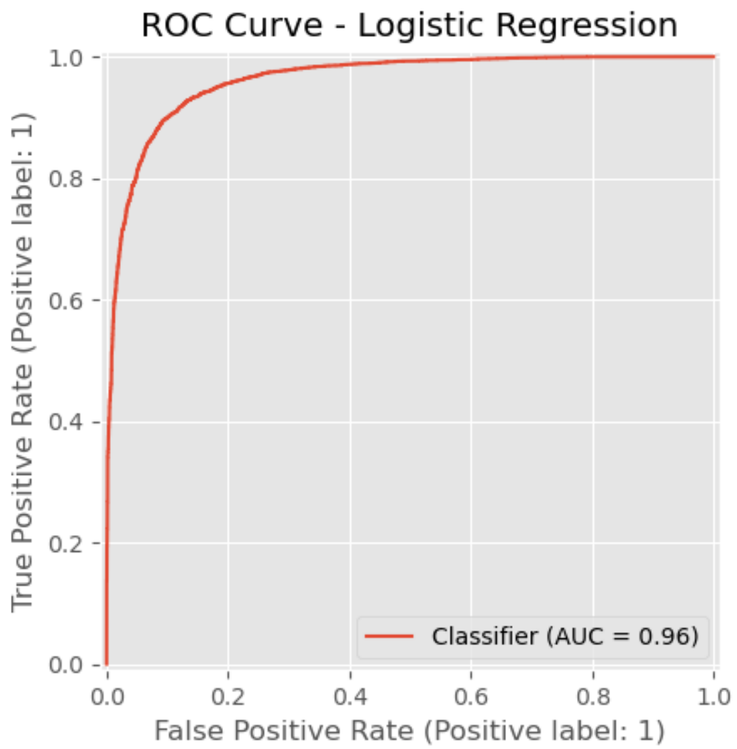
MLOPS

IMDB MLflow

Logistic Regression
Precision Recall Curve



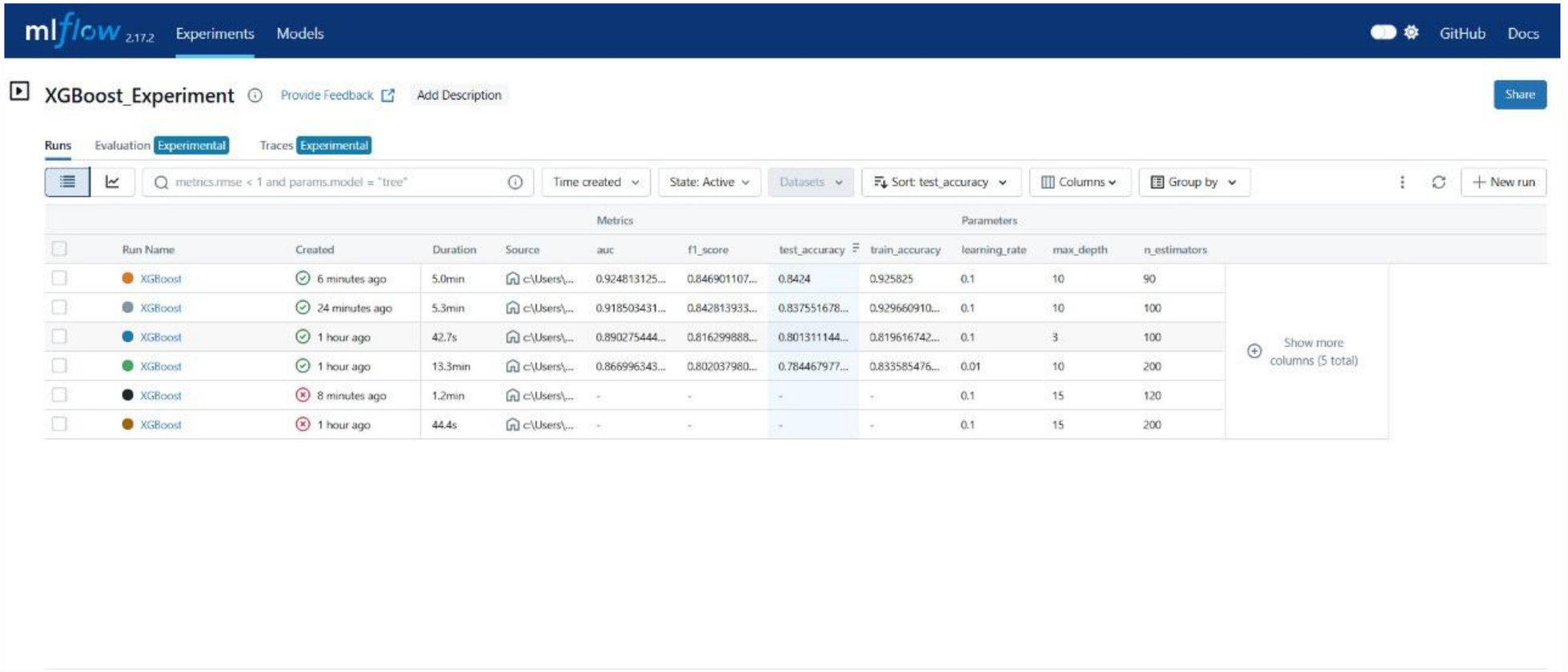
Logistic Regression
ROC Curve



MLOPS

IMDB MLflow

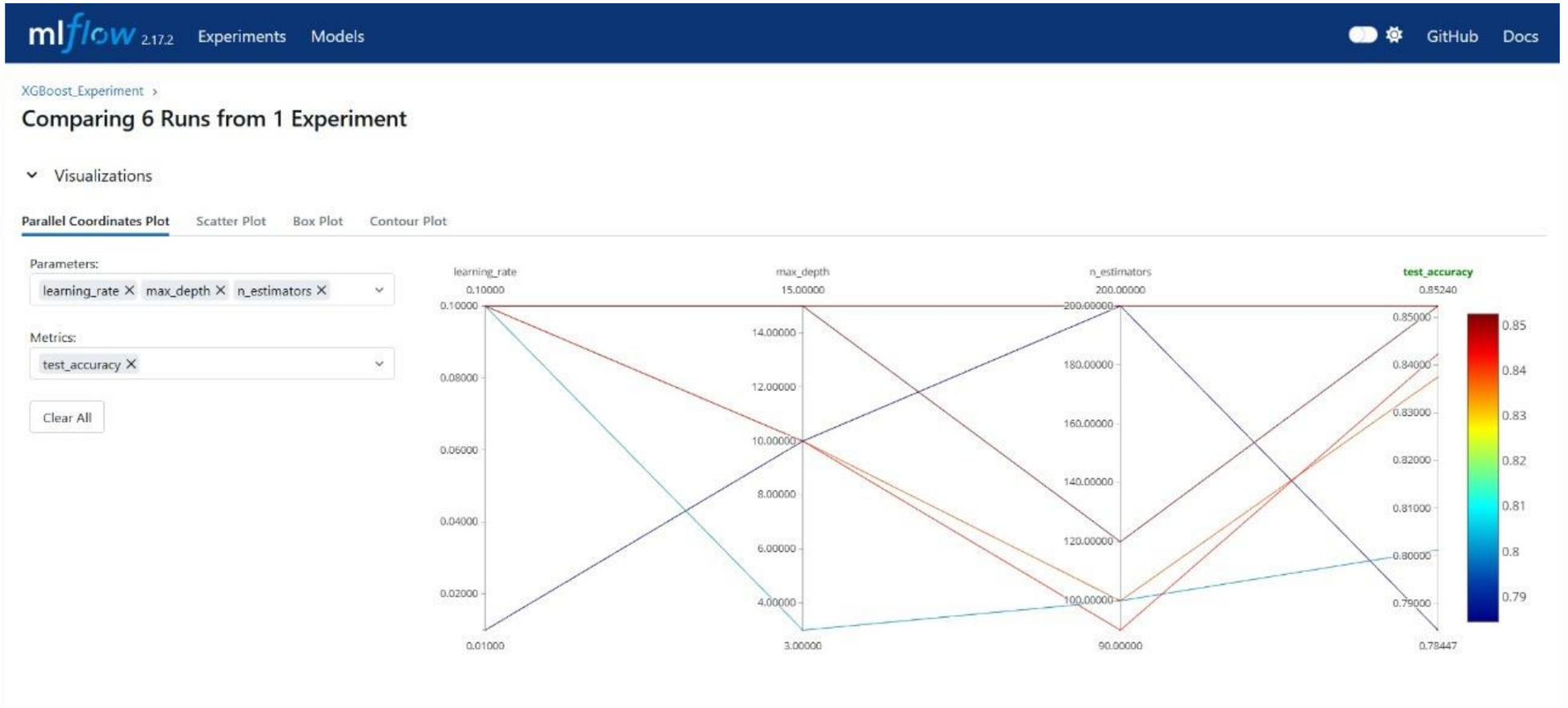
XGBoost Experiment



MLOPS

IMDB MLflow

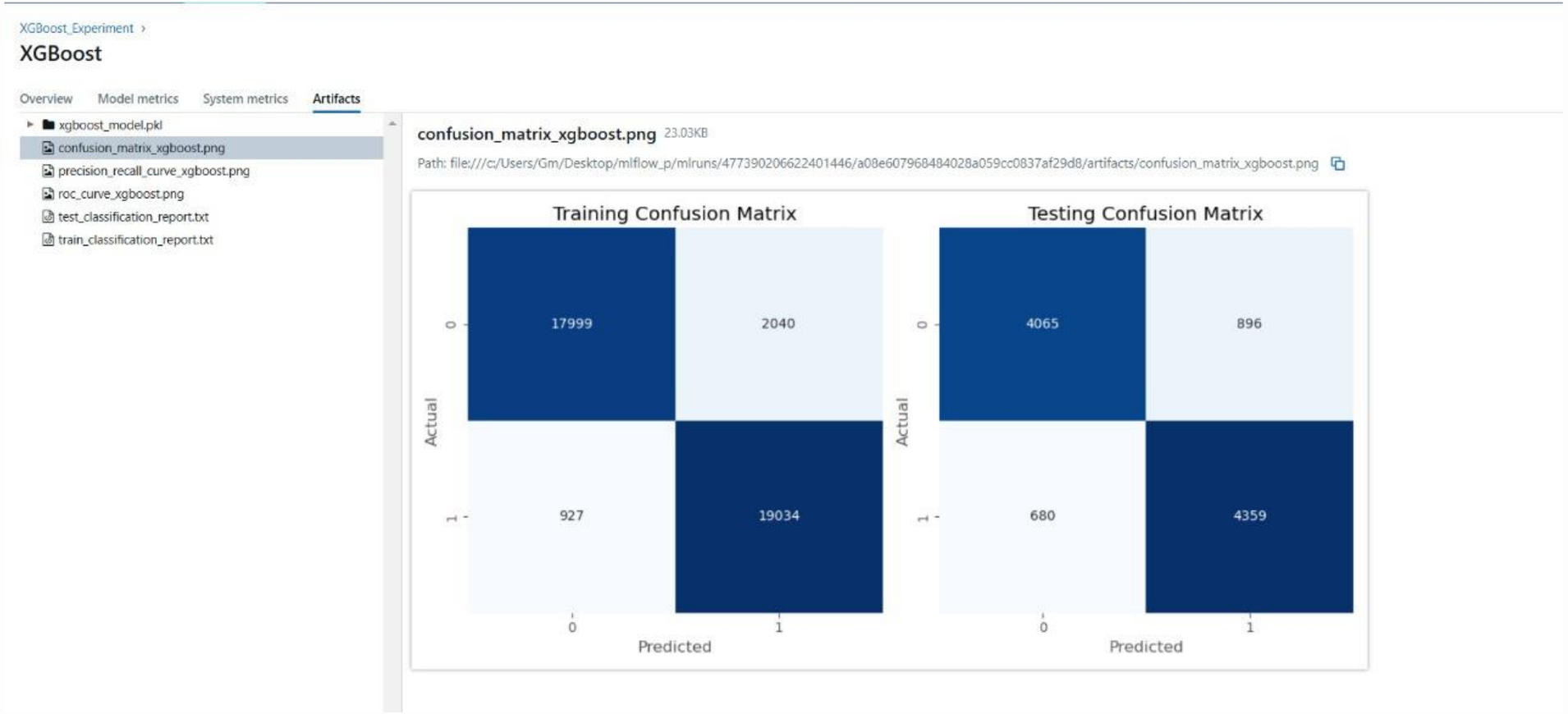
XGBoost Comparing runs



MLOPS

IMDB MLflow

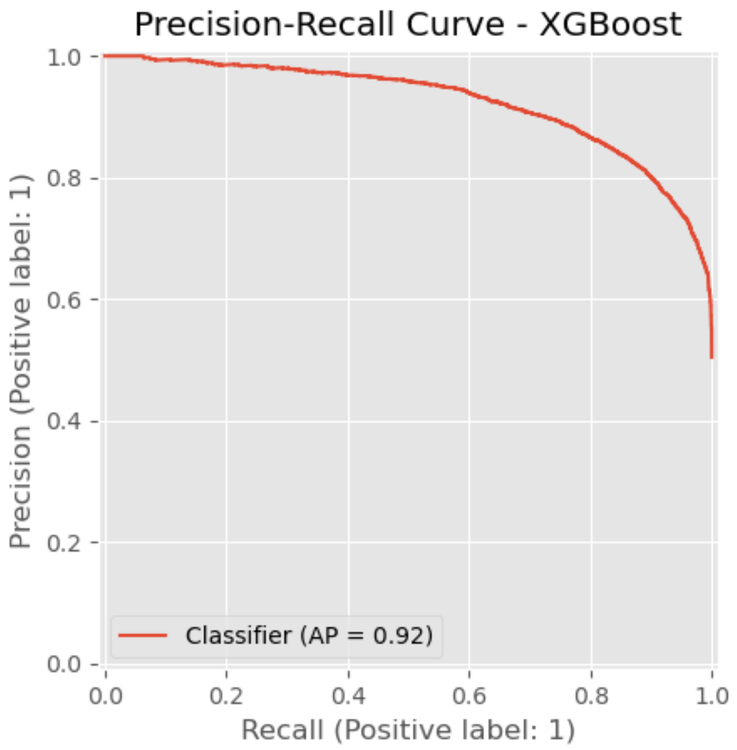
XGBoost Confusion Matrix



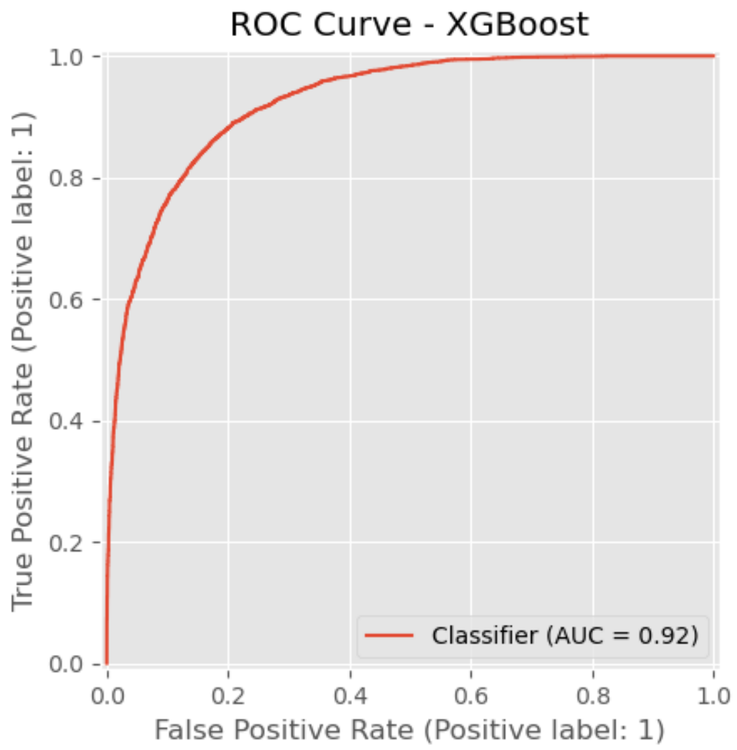
MLOPS

IMDB MLflow

XGBoost Precision Recall Curve



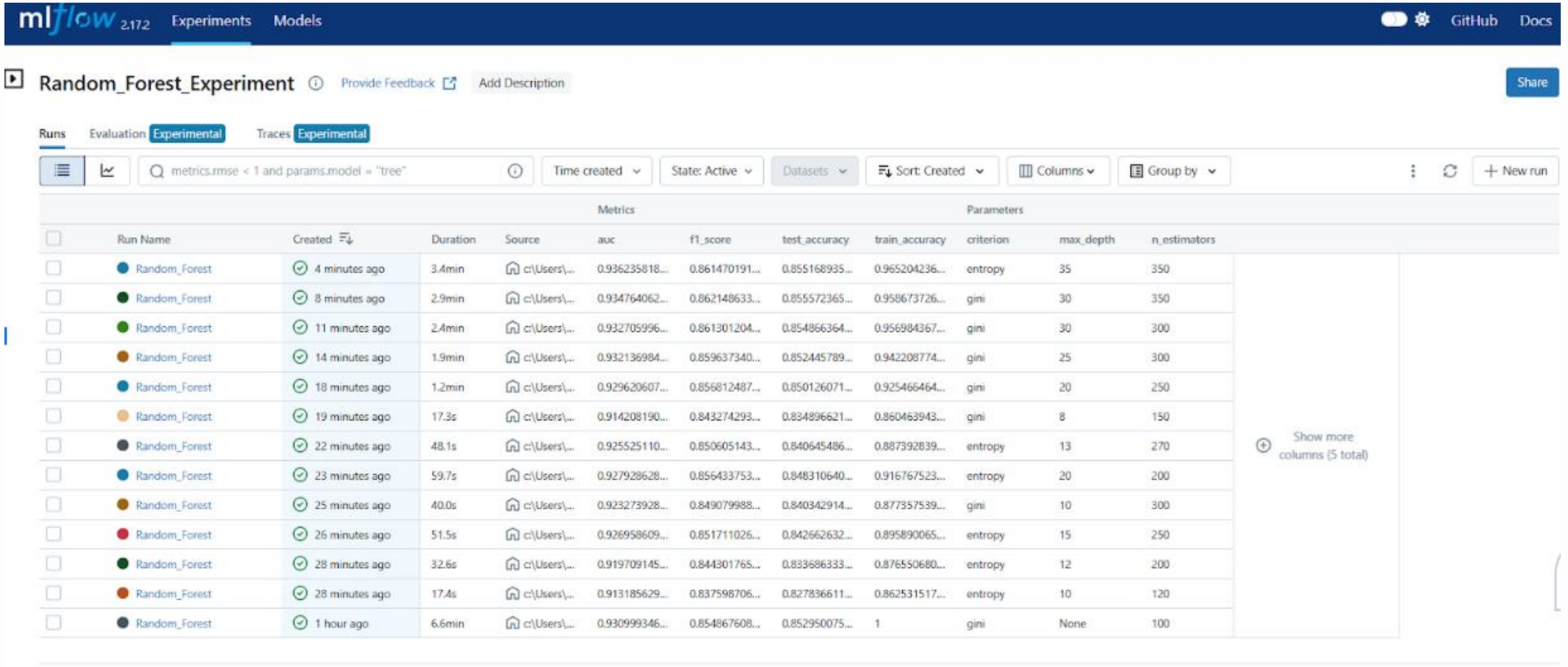
XGBoost ROC



MLOPS

IMDB MLflow

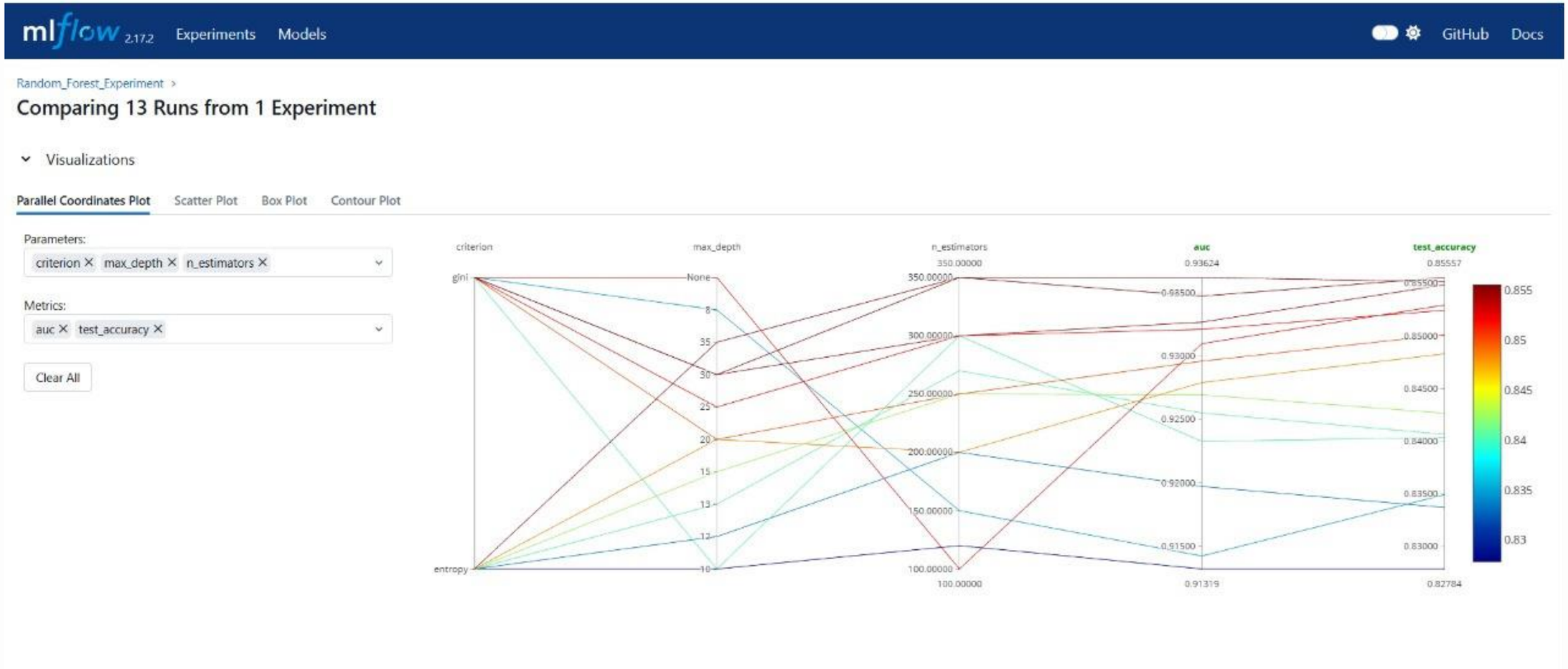
Random Forest Experiment



MLOPS

IMDB MLflow

Random Forest Comparing Runs



MLOPS

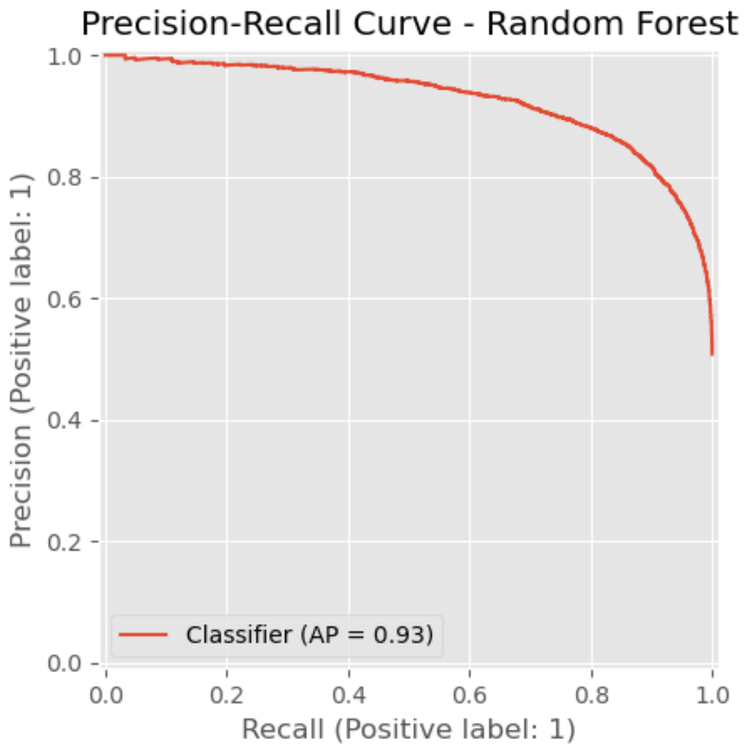
IMDB MLflow

Random Forest Confusion matrix

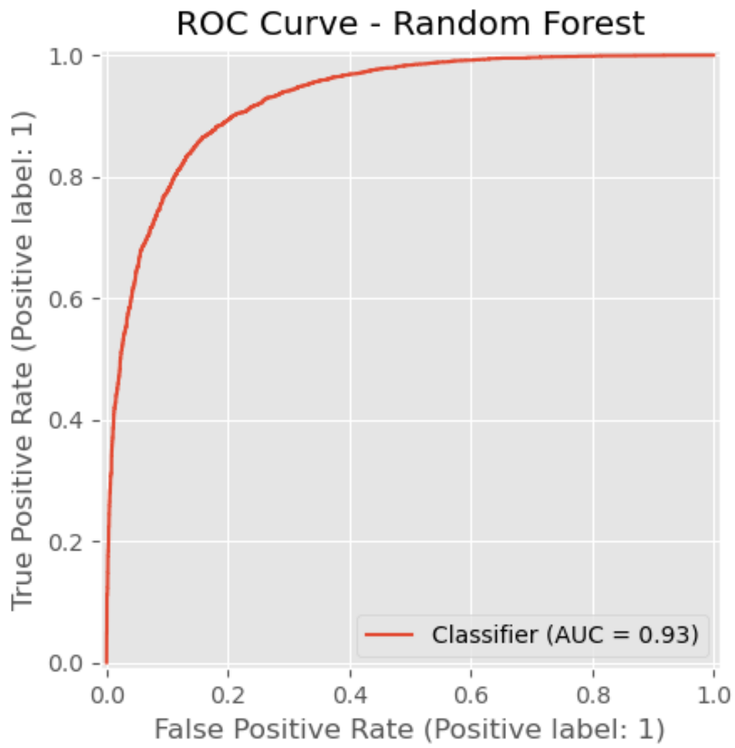
MLOPS

IMDB MLflow

Random Forest Precision Recall Curve



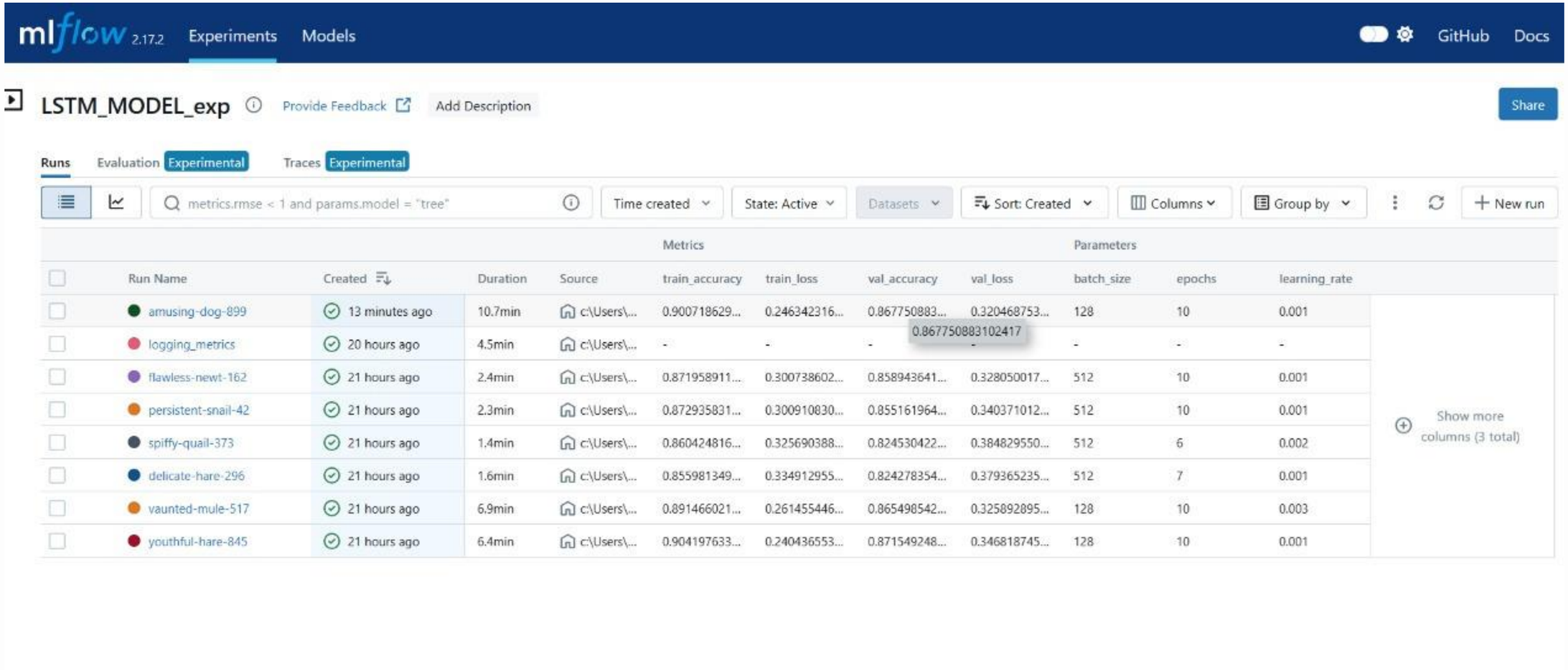
Random Forest Roc Curve



MLOPS

IMDB MLflow

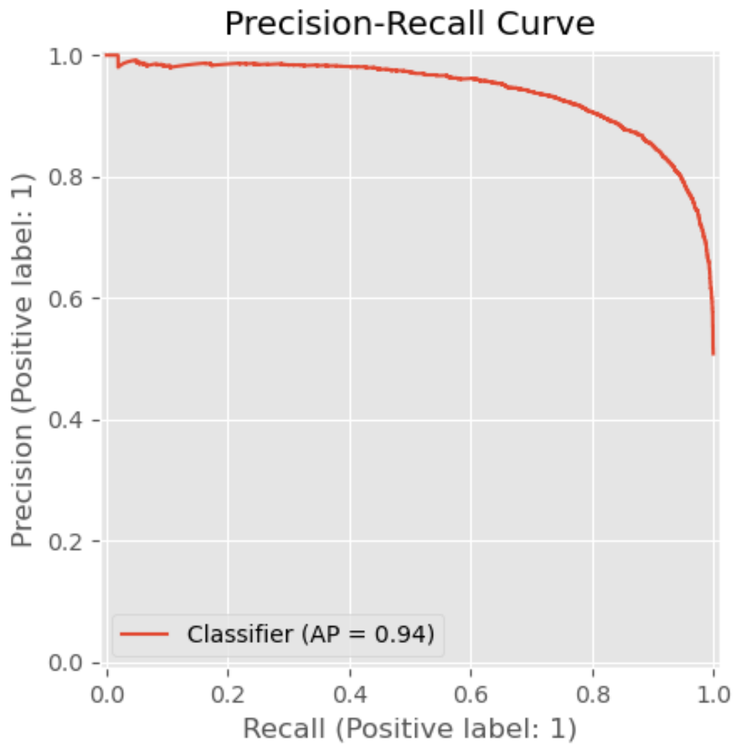
LSTM EXPRESSION



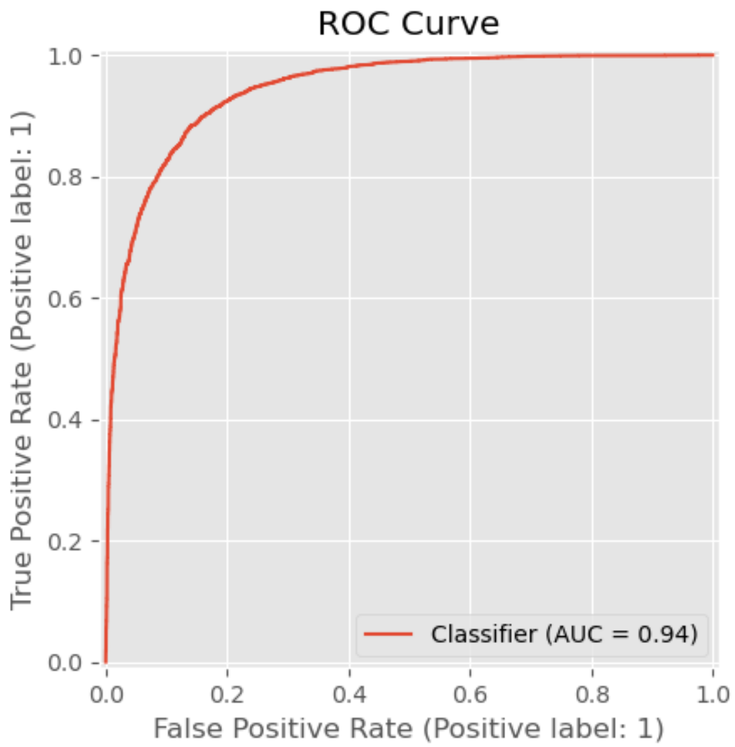
MLOPS

IMDB MLflow

LSTM Precision recall curve



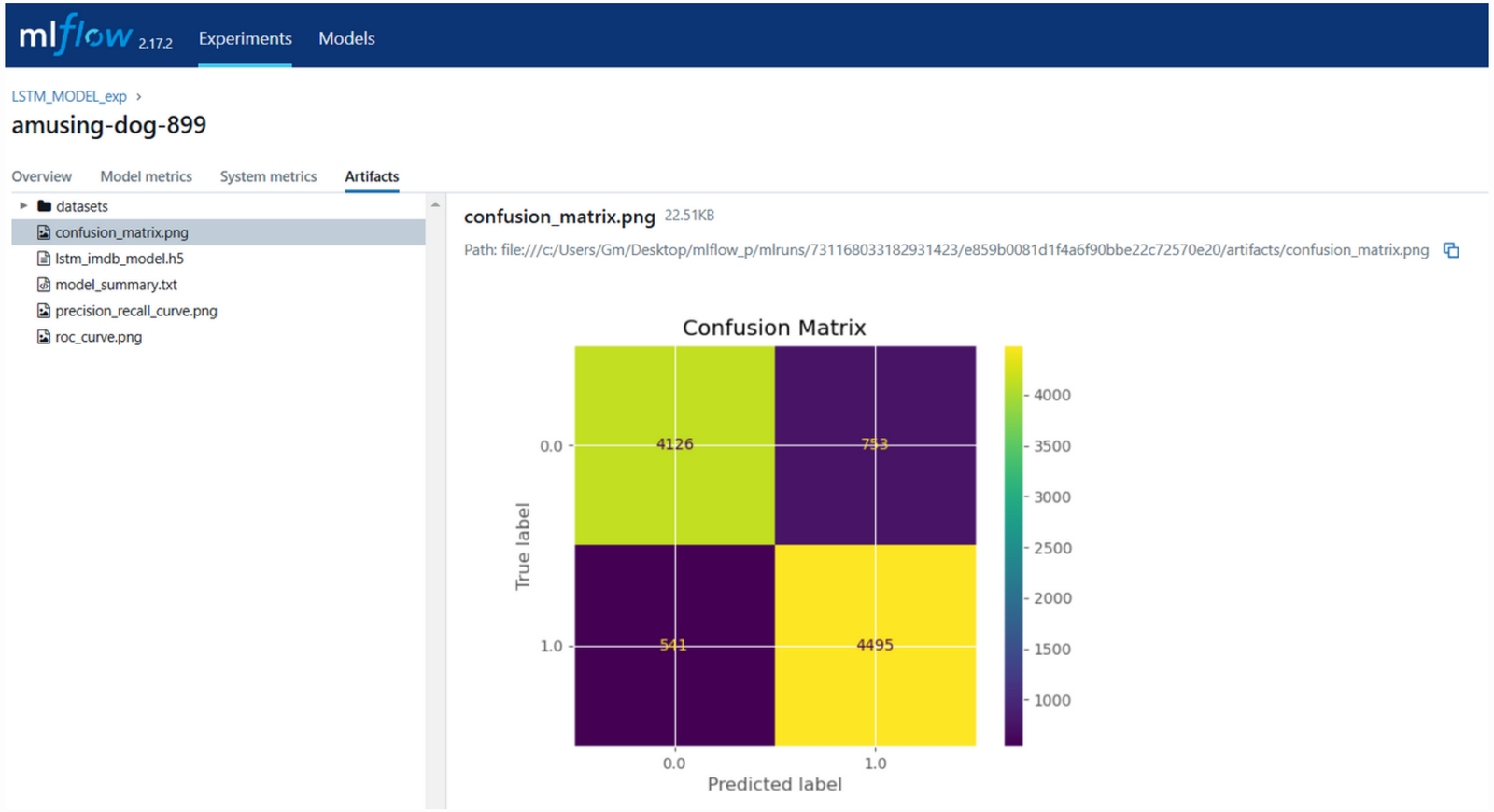
LSTM ROC Curve



MLOPS

IMDB MLflow

LSTM Confusion matrix



Model Deployment On Azure ML

After we finished training our models and achieved good results, we used multiple platforms like: Azure ML , streamlit , Github, MLFlow and DagsHub to version and deploy our model and automate lifecycle of our ML model and to make our system more reliable and scalable and maintainable.
During MLOps to train and validate multiple versions of a model to ensure accurate tracking and comparison.

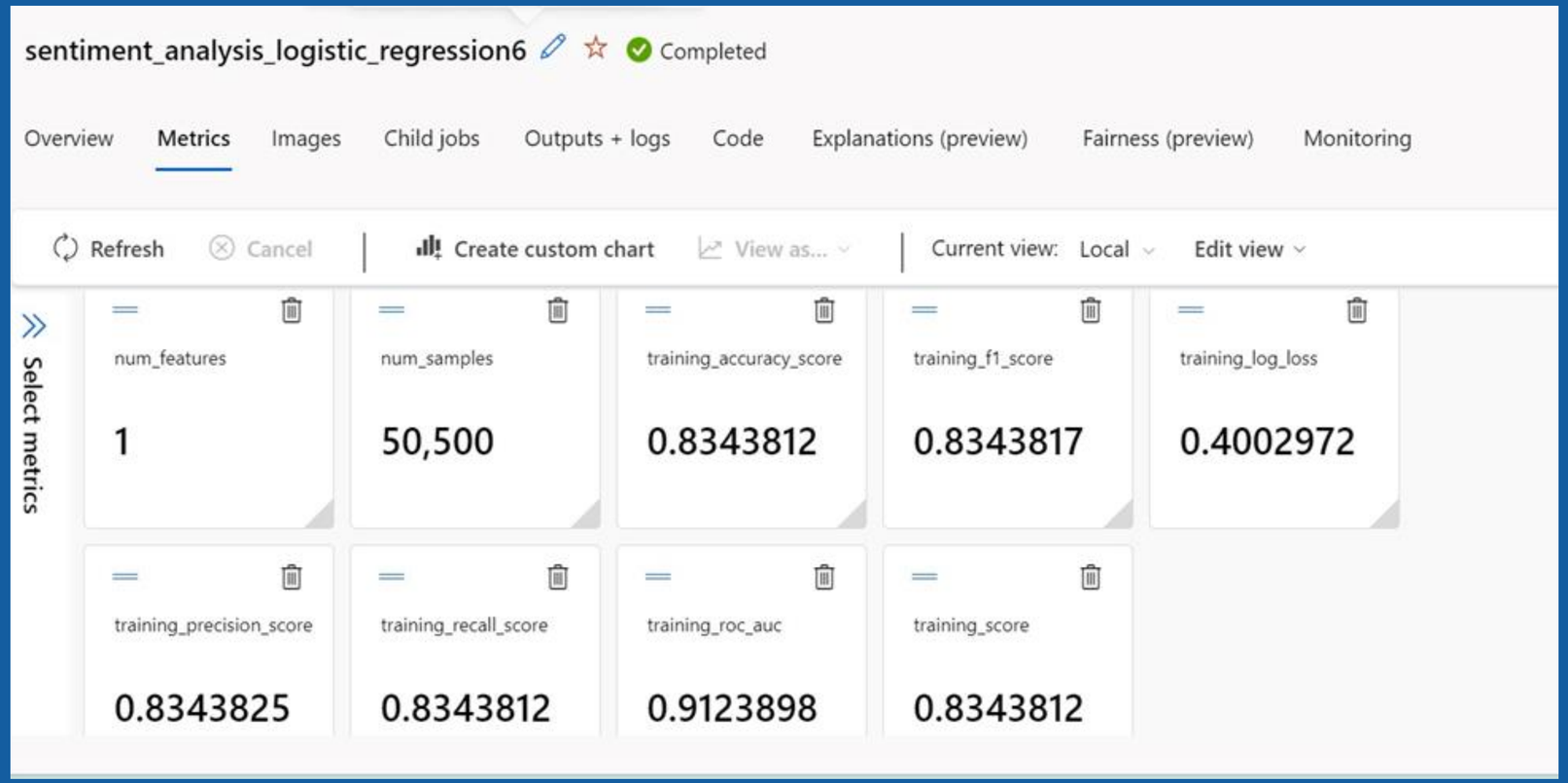
- **Here are the steps that we have taken to deploy our model on Azure ML:**

1. **Create training and registering the model as MLFlow model.**
2. **Create Azure ML job.**
3. **Create a new Batch endpoint.**
4. **Deploy the model to the endpoint with the latest version of your model.**

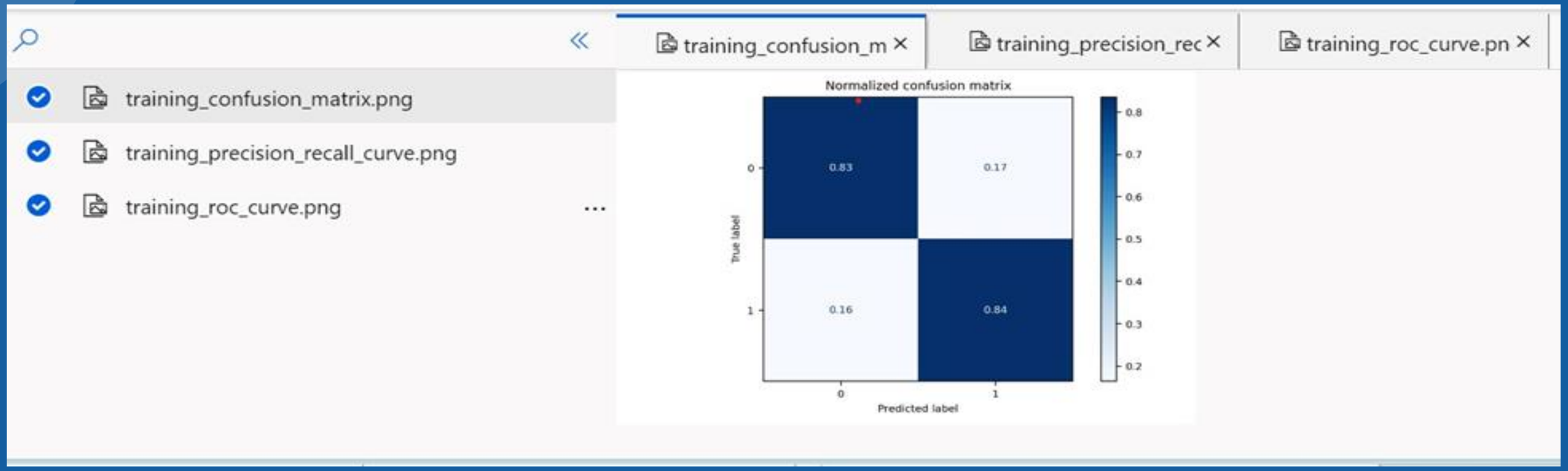
Training ML FLOW Model Results on Azure ML Job

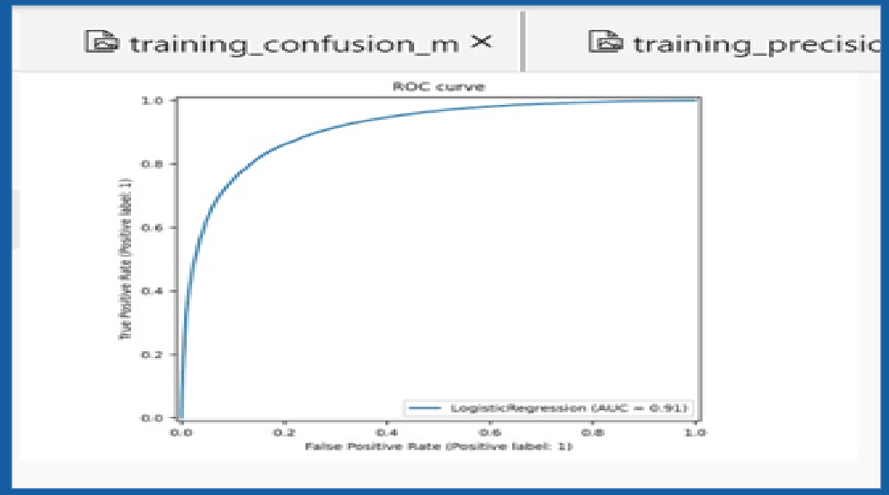
We have finished our model on Amazon products data and trained our Logistic Regression model and deployed our model after making sure that it achieves high accuracy on Azure and Streamlit and these some of the results we have achieved after making our customer sentiment and trend analysis machine learning model

· The following photo shows the model and its Accuracy metrics on Azure ML Job



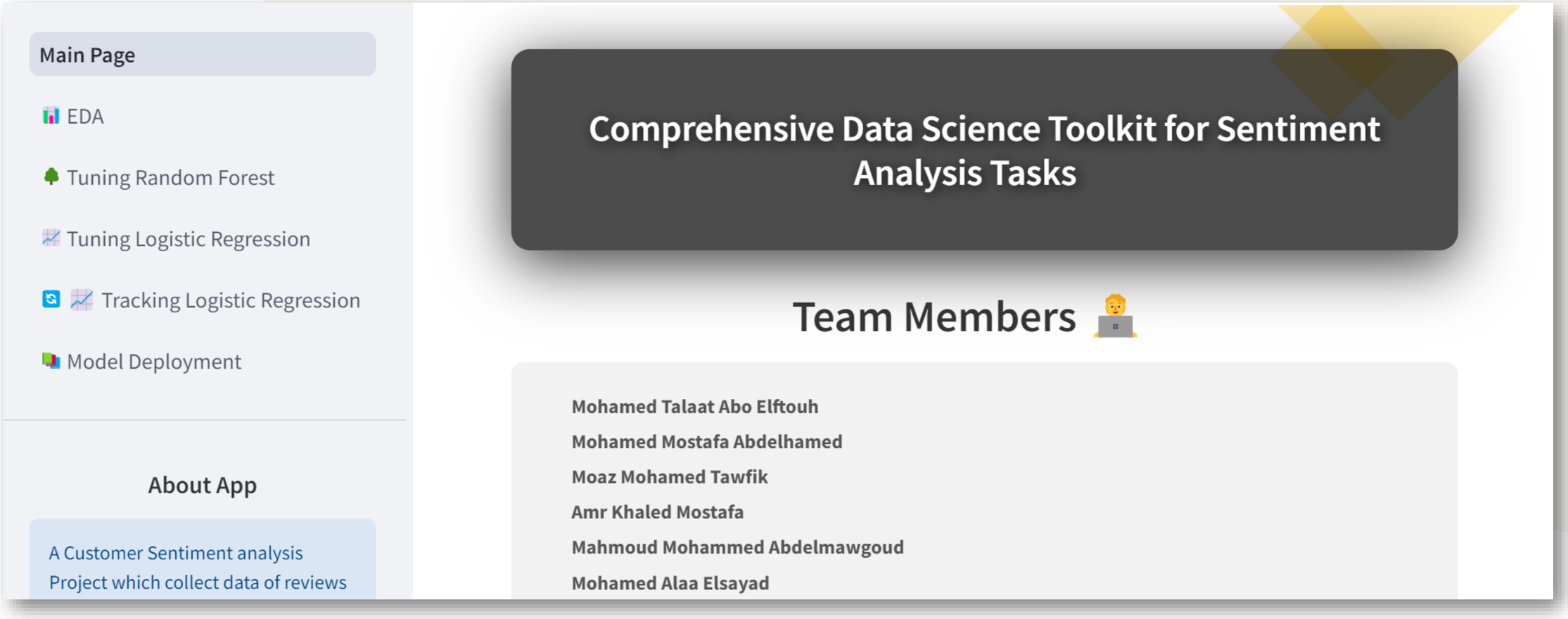
· Training confusion matrix and ROC curve of azure ML Job





Streamlit Deployment

- **Also, we deployed our model on streamlit and Azure web Service and created Comprehensive Data Science Toolkit for EDA ,Sentiment Analysis and MLFlow Tracking.**



Streamlit EDA

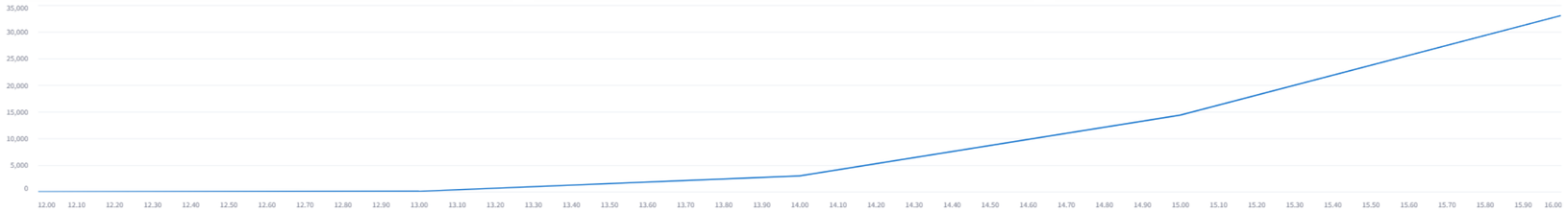
Customer Reviews EDA 📊

Discover insights and trends from customer reviews

Reviews Metrics

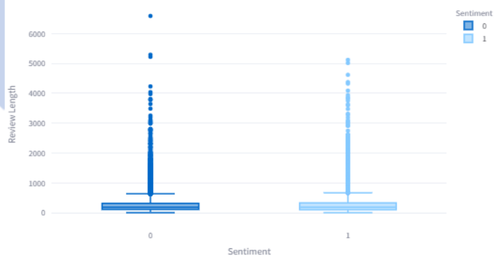
Total Reviews	Total Positive Reviews	Total Negative Reviews
50500	25500	25000

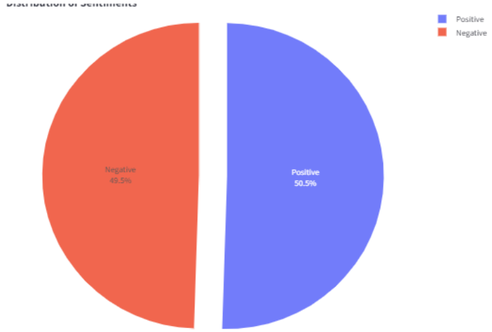
Total Number of Reviews per Day



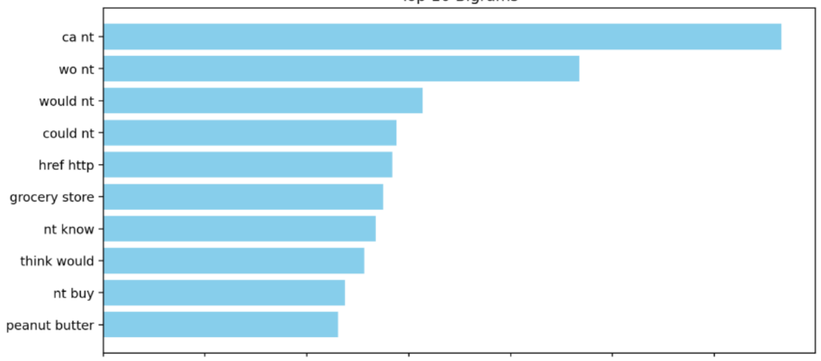
Average Ratings per Day - Trend Analysis

Review Length by Sentiment

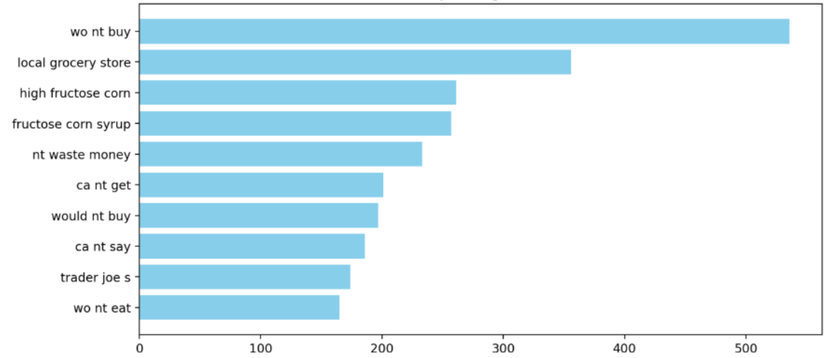




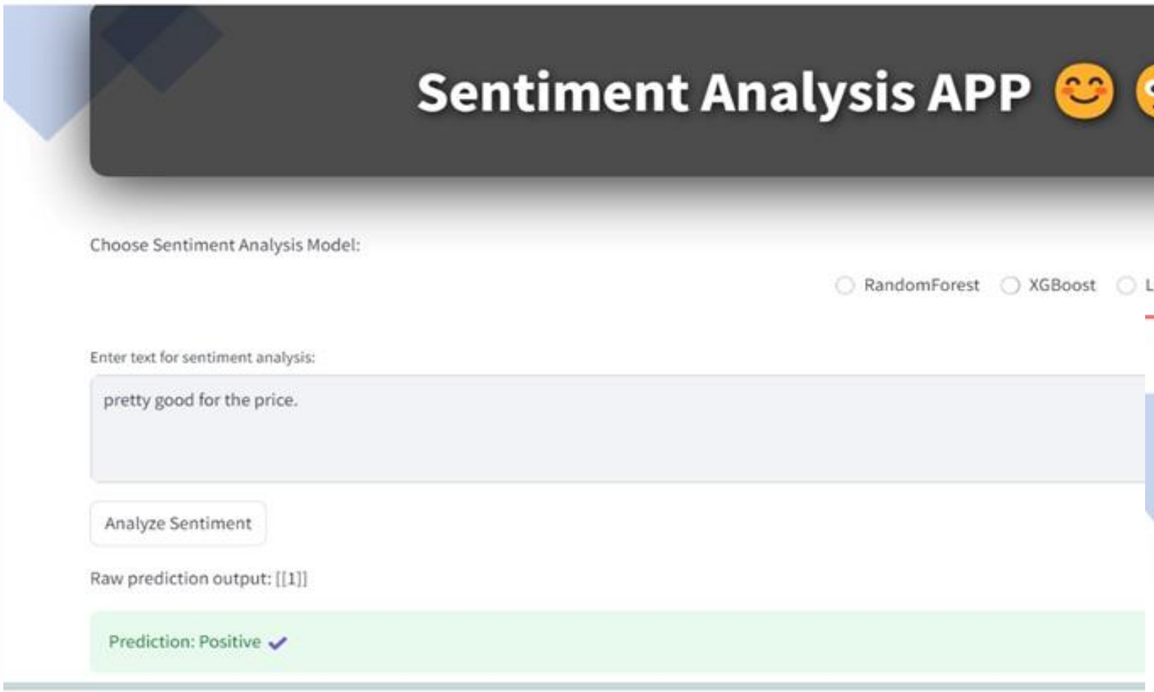
Top 10 Bigrams



Top 10 Bigrams

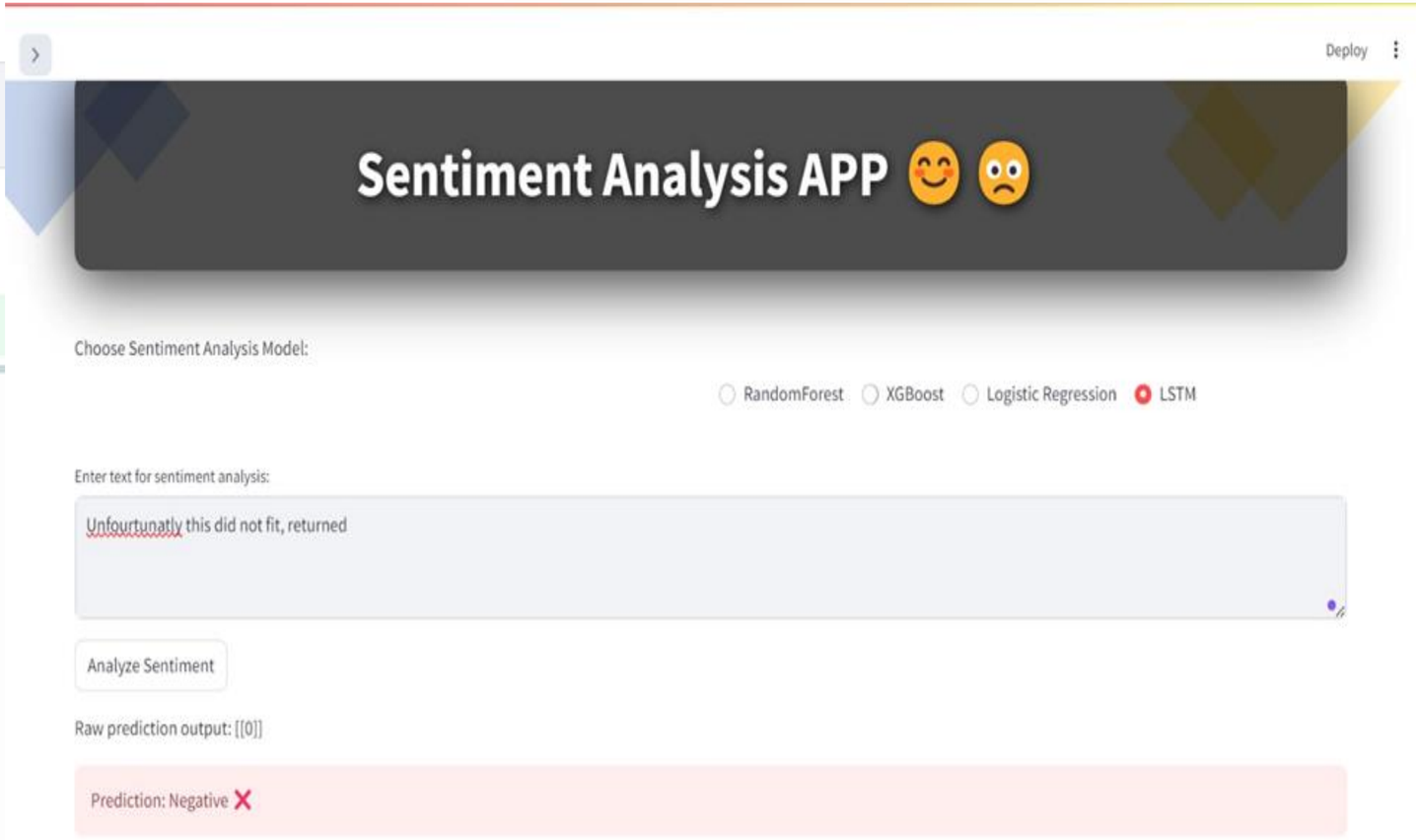


Real-Time Sentiment Analysis Result

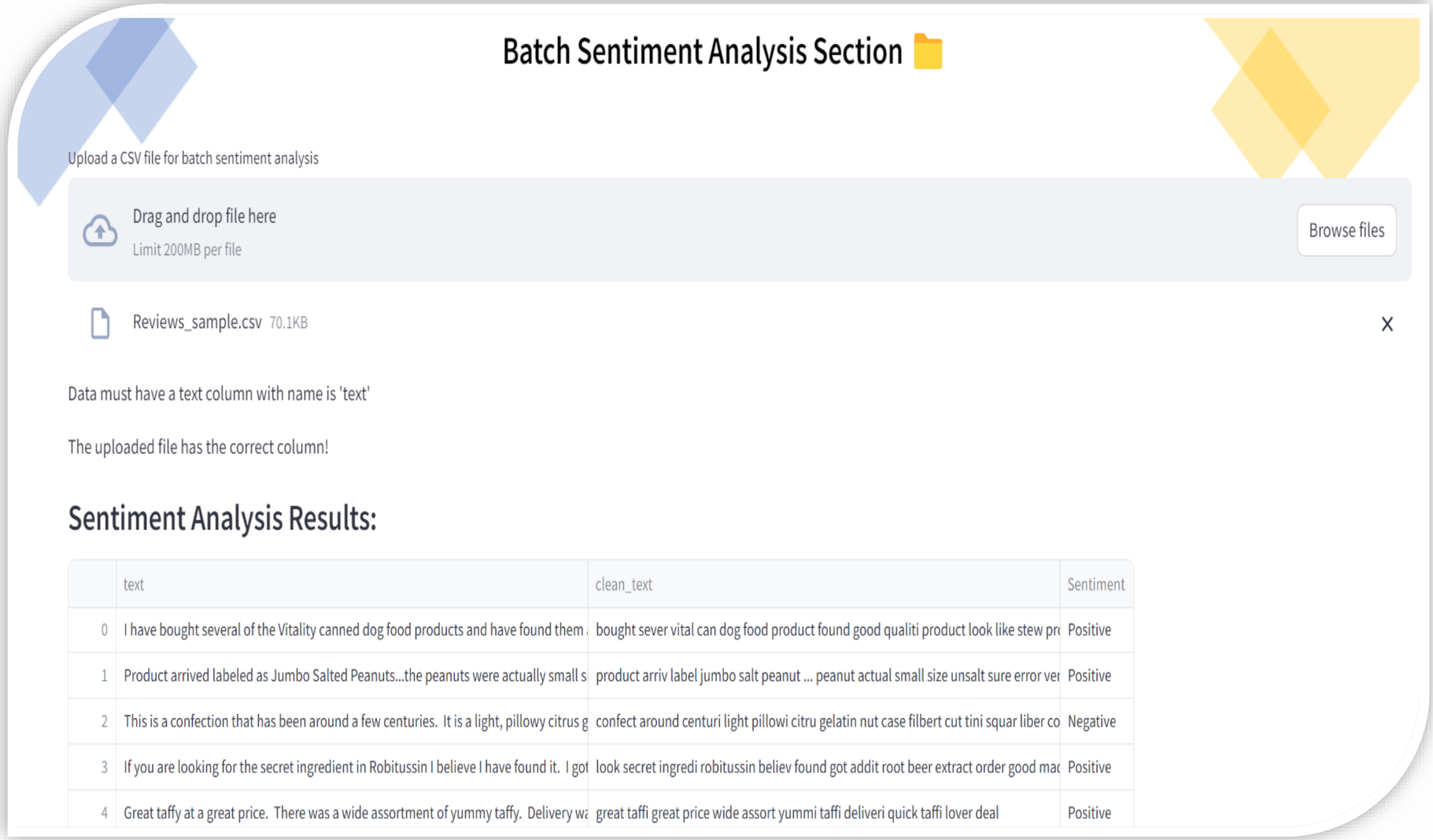


TRY IT

https://depisentimentanalysisapp-11-6-2024.streamlit.app/



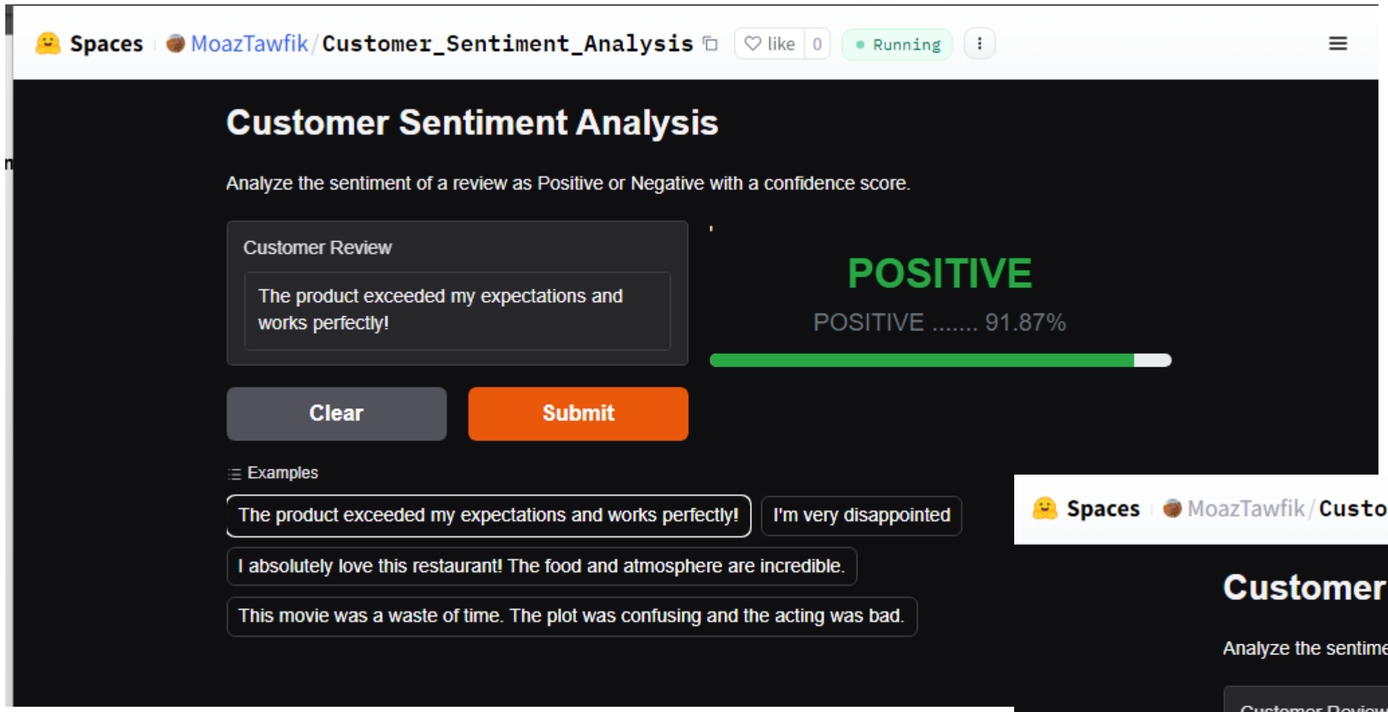
Batch Sentiment Analysis Result

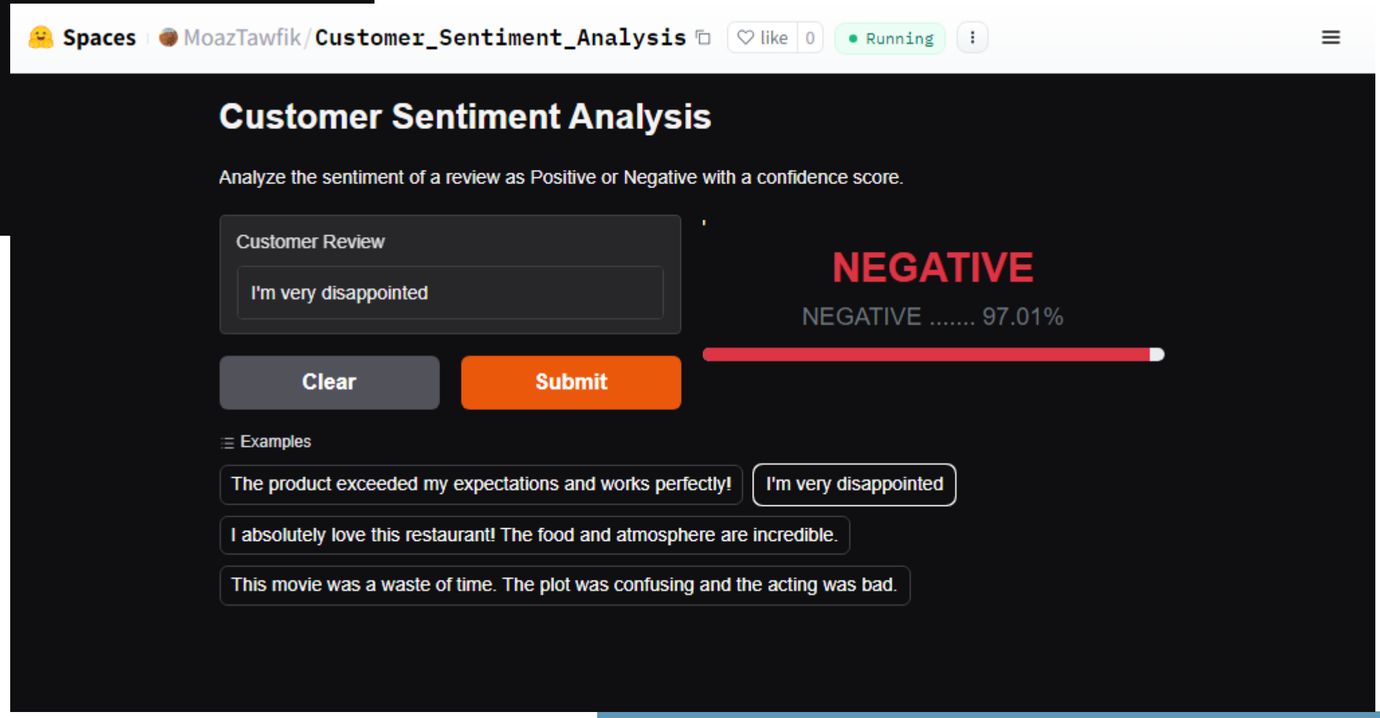


TRY IT

https://depisentimentanalysisapp-11-6-2024.streamlit.app/

· **Our sentiment analysis model on HuggingFace**





https://huggingface.co/spaces/MoazTawfik/Customer_Sentiment_Analysis

رواد مصر الرقمية

Resource Page

Hugging Face

kaggle

رواد مصر الرقمية

THANK YOU!