Sentiment Analysis of IMDb's Avengers:Endgame Reviews

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How Many of you are Marvel fans here ?

Did you watch the Avengers : Endgame Movie ?

How was the Movie ?

OBJECTIVES

- **Analyze Sentiment**: Determine the overall sentiment of IMDb reviews (positive, negative) for Avengers Endgame.
- **Evaluate Models:** Compare the performance of machine learning models (Logistic Regression, SVM, Random Forest) in sentiment analysis.
- **Provide Insights**: Extract actionable insights from sentiment analysis to aid filmmakers, producers, and distributors.

REVIEWS

★ 10/10

Epic Ending
eandros-77451 26 April 2019

Thank you Marvel, End Game is an ending that give me speechless.

★ 8/10

Huge fan left underwhelmed!!!
james-84287 30 April 2019

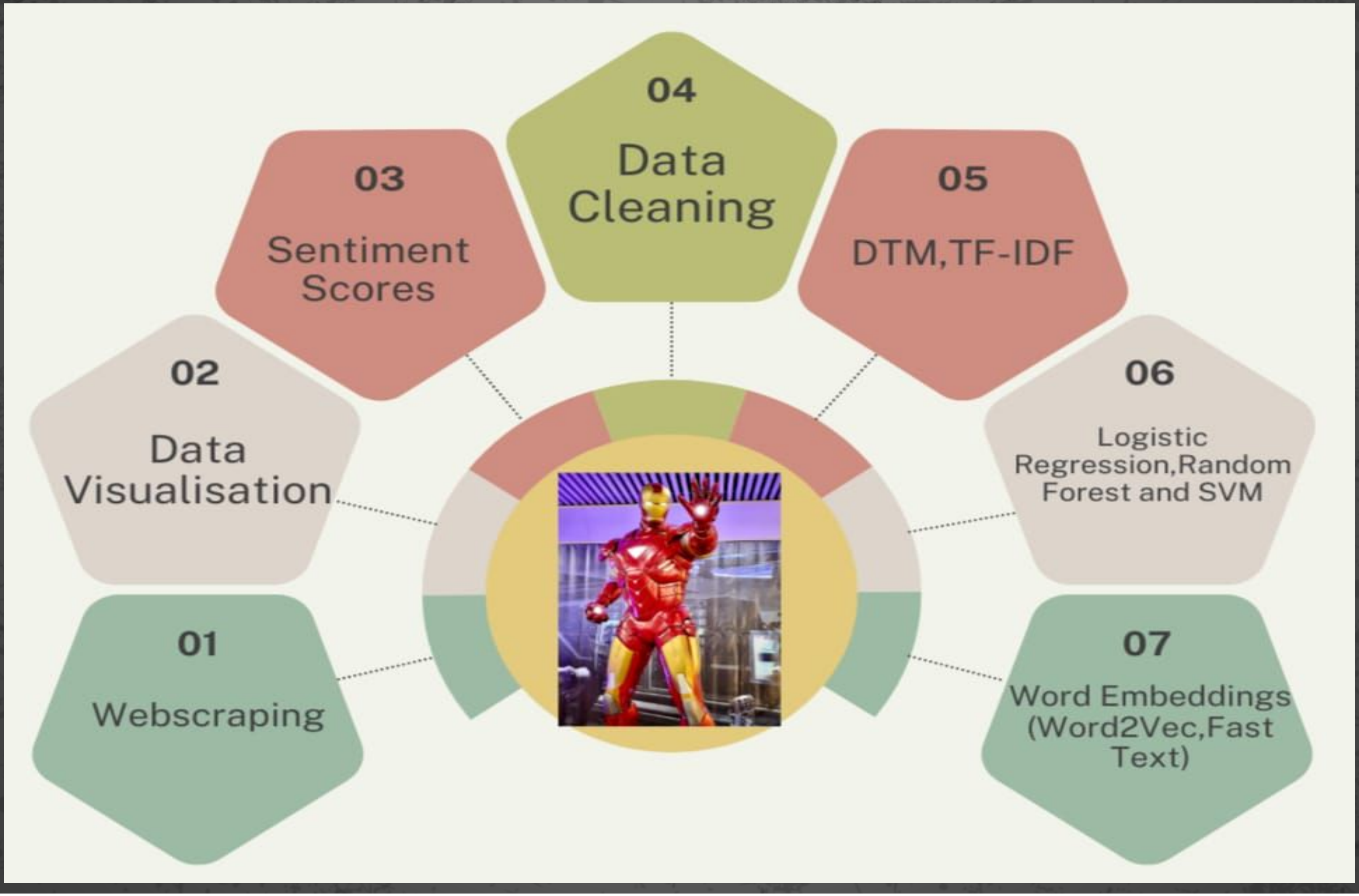
I went in with the highest expectations and came out underwhelmed and disappointed. its nowhere near as good as infinity war !!!

★ 1/10

One of the most overrated films of all time
moudekerk-82980 20 May 2019

Acting extremely sub-par, terrible story, and a cheap piece of non directional fan service.

WORKFLOW



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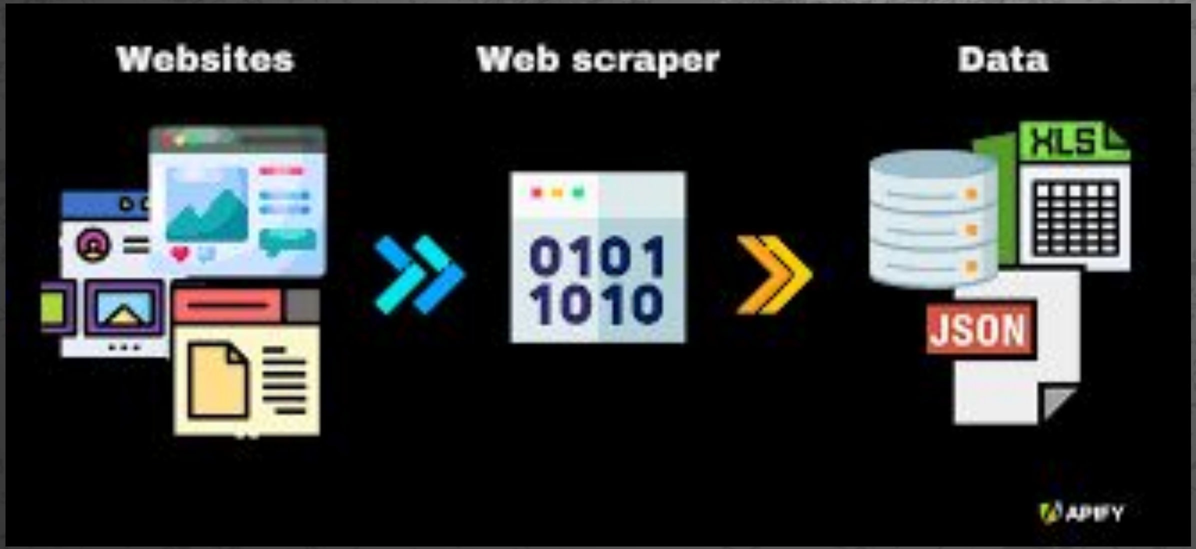
WEB SCRAPING

Web scraping is the automated process of extracting structured data from web pages, specifically designed for our project to gather IMDb reviews and ratings for the movie 'Avengers: Endgame' from the IMDb website.



1. Installing Python Libraries

```
[1]  !pip install selenium
     !pip install scrapy
     !pip install fake_useragent
```

2. Creating and Configuring Selenium WebDriver

```python
#all reviews and ratings
import pandas as pd
from selenium import webdriver
from selenium.webdriver.common.by import By
from selenium.webdriver.support.ui import WebDriverWait
from selenium.webdriver.support import expected_conditions as EC

# Set up Chrome WebDriver
chrome_options = webdriver.ChromeOptions()
chrome_options.add_argument('--headless')
chrome_options.add_argument('--no-sandbox')
chrome_options.add_argument('--disable-dev-shm-usage')
driver = webdriver.Chrome(options=chrome_options)

# IMDb URL for Avengers: Endgame reviews
url = 'https://www.imdb.com/title/tt4154796/reviews?spoiler=hide&sort=curated&dir=desc&ratingFilter=0'
driver.get(url)
```

3. Function to click "Load More" button until all reviews are loaded

```python
# Wait for the reviews to load
wait = WebDriverWait(driver, 10)
wait.until(EC.presence_of_element_located((By.CLASS_NAME, 'lister-list')))

# Function to click "Load More" button until all reviews are loaded
def load_all_reviews():
    while True:
        try:
            load_more_button = driver.find_element(By.CLASS_NAME, 'ipl-load-more__button')
            driver.execute_script("arguments[0].scrollIntoView();", load_more_button)
            load_more_button.click()
            wait.until(EC.invisibility_of_element_located((By.CLASS_NAME, 'ipl-load-more__load-indicator')))
        except Exception as e:
            break
```

4. Extracting and Printing all reviews and ratings

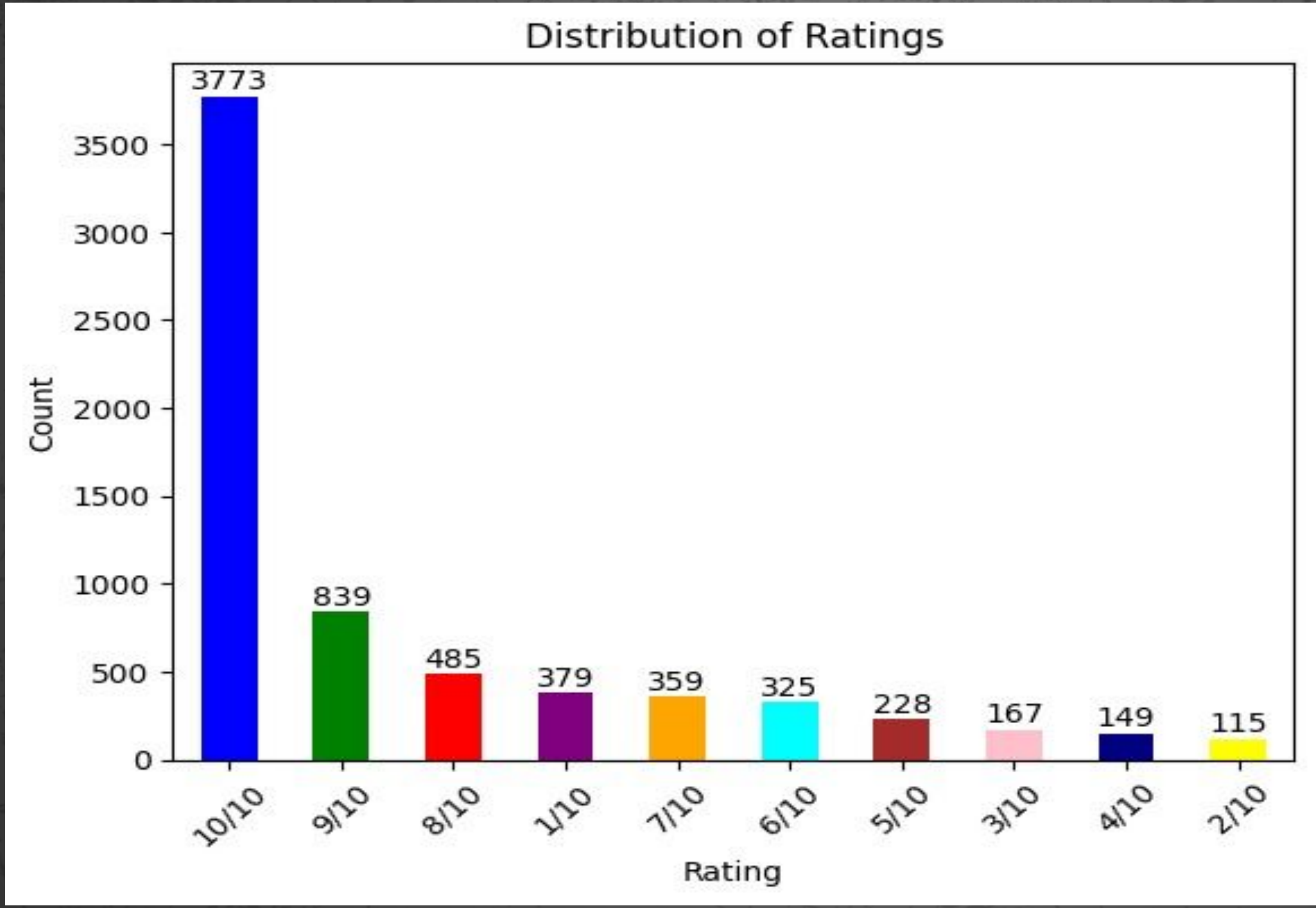
```python
# Function to extract ratings and reviews
def extract_data():
    rating_elements = driver.find_elements(By.CLASS_NAME, 'ipl-ratings-bar')
    review_elements = driver.find_elements(By.CLASS_NAME, 'text')

    data = []
    for rating_element, review_element in zip(rating_elements, review_elements):
        rating = rating_element.text.strip().split('\n')[0]
        review = review_element.text.strip()
        data.append({'Rating': rating if rating else None, 'Review': review if review else None})
        print(f"Rating: {rating if rating else 'None'}")
        print(f"Review: {review if review else 'None'}\n")
    return data
```

5. Saving the Data to Excel File

```
[ ]  # Extract text content from review elements
     from google.colab import drive
     drive.mount('/content/drive')

     import pandas as pd

     # Create a DataFrame to store the ratings and reviews
     ratings_reviews_df = pd.DataFrame(all_data)

     # Save DataFrame to Excel with ratings and reviews in different columns
     output_file = "/content/drive/MyDrive/Final Project/Reviews.xlsx"
     ratings_reviews_df.to_excel(output_file, index=False)
```

```
Mounted at /content/drive
  Rating                                             Review
0   7/10  But its a pretty good film. A bit of a mess in...
1  10/10  This film is an emotional rollercoaster with s...
2  10/10  First review from me. This film deserves it. A...
3  10/10  Thank you Marvel, End Game is an ending that g...
4  10/10  After watching Infinity war, I was looking for...
```

DATA VISUALISATION



WORD CLOUD

A word cloud is a visual representation of text data where words are displayed in varying sizes based on their frequency or importance within the text.

SENTIMENT SCORES

- Sentiment scores are numerical values(0,1) assigned to text data to quantify and categorize the sentiment or emotion expressed within the text.

- Sentiment scores can be calculated using tools like SentimentIntensityAnalyzer() and polarity_scores() from the NLTK package

- However, for our project,sentiment scores are derived from the rating given by users.

- Ratings greater than 7 are considered positive (1) and ratings less than or equal to 7 are considered negative (0).

```
[ ]  import pandas as pd

     # Load the data from the Excel file
     input_file = "/content/drive/MyDrive/Final Project/Reviews.xlsx"
     ratings_reviews_df = pd.read_excel(input_file)

     # Function to calculate sentiment score based on ratings
     def calculate_sentiment(rating):
         # Extract the numerical part of the rating (e.g., "7/10" -> 7)
         rating_value = float(rating.split('/')[0])
         # Calculate sentiment score
         sentiment_score = 1 if rating_value > 7 else 0
         return sentiment_score
```

	Rating	Review	Sentiment
0	7/10	But its a pretty good film. A bit of a mess in...	0
1	10/10	This film is an emotional rollercoaster with s...	1
2	10/10	First review from me. This film deserves it. A...	1
3	10/10	Thank you Marvel, End Game is an ending that g...	1
4	10/10	After watching Infinity war, I was looking for...	1
...	...	...	...
6814	5/10	Great expectations.. But just a good film. And...	0
6815	5/10	Ugh. This three hour opus did not need to be t...	0
6816	5/10	This movie is so horrible I don't know why Mar...	0
6817	5/10	I really don't get the hype around this mess. ...	0
6818	5/10	They spent a lot of time in this film trying t...	0

DATA LOADING

```
import pandas as pd

training = pd.read_excel("/content/drive/MyDrive/Final Project/Reviews-1S.xlsx", header=0)

y_train = training['Sentiment']
x_train = training.drop(["Sentiment","Rating"], axis=1)
```

- “y_train” represents the target variable containing ‘sentiment score’ column.

- “x_train” contains the input features ‘Review’ and ‘Sentiment score’ excluding the 'Rating' column which is just used for assigning sentiment scores.

DATA CLEANING

```
[ ]  # Data pre-processing

     import nltk
     import numpy as np
     import matplotlib.pyplot as plt

     # Import list of stopwords from library NLTK
     from nltk.corpus import stopwords
     nltk.download('stopwords')
```

1. Removing Stopwords

```
[ ]  # Remove Stopwords

     stopwords_list = stopwords.words("english")
     print(f'List of stopwords:\n{stopwords_list}\n')

     # We remove negation words in list of stopwords
     no_stopwords = ["not","don't",'aren','don','ain',"aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "has
                     'ma', 'mightn', "mightn't", 'mustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren
                     "won't", 'wouldn', "wouldn't"]
     for no_stopword in no_stopwords:
         stopwords_list.remove(no_stopword)

     print(f'Final list of stopwords:\n{stopwords_list}')
```

2. Lemmatize Reviews

```
# Lemmatize reviews

# Import Lemmatizer from NLTK
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')

lemmatizer = WordNetLemmatizer()

# function that receive a list of words and do lemmatization:
def lemma_stem_text(words_list):
    # Lemmatizer
    text = [lemmatizer.lemmatize(token.lower()) for token in words_list]
    text = [lemmatizer.lemmatize(token.lower(), "v") for token in text ]
    return text
```

```
#Negative Contractions

# create a function to change negative contractions
import re
re_negation = re.compile("n't ") # specify a pattern you want to find in a string

# function that receive a sequence of words and return the same sequence transforming
# abbreviated negations to the standard form.
def negation_abbreviated_to_standard(sent):
    sent = re_negation.sub(" not ", sent)
    return sent
```

3. Negative Contractions

Function for cleaning reviews

```python
def review_to_words(raw_review):
    # 1. Remove HTML tags
    review_text = BeautifulSoup(raw_review).get_text()

    # 2. Transform abbreviated negations to the standard form.
    review_text = negation_abbreviated_to_standard(review_text)

    # 3. Remove non-letters and non-numbers
    tokenizer = RegexpTokenizer(r'\w+')
    words = tokenizer.tokenize(review_text)

    # 4. Remove stop words
    meaningful_words = [w for w in words if w.lower() not in stopwords_list]

    # 5. Apply lemmatization function
    lemma_words = lemma_stem_text(meaningful_words)

    # 6. Join the words back into one string separated by space, and return the result.
    return( " ".join(lemma_words))

    # 7. Handling Short Words
    tokens = [word for word in tokens if len(word) >= 3]

    # 8. Handling Rare Words
    word_counts = Counter(tokens)
    common_words = set(word for word, count in word_counts.items() if count > 5)
    tokens = [word for word in tokens if word in common_words]

    # 9. # Drop rows with NaN values in the 'Reviews' column
    training.dropna(subset=['Review'], inplace=True)
```

DOCUMENT TERM MATRIX(DTM)

- A document-term matrix or term-document matrix is a matrix that describes the frequency of terms (words) that occur in a collection of documents.
- In a document-term matrix,rows correspond to documents in the collection, columns correspond to terms
- The CountVectorizer function(imported from sklearn library) creates a matrix representation of text data by counting the frequency of each word (unigrams and bigrams).

```
# Initialize CountVectorizer
c = CountVectorizer(stop_words='english', lowercase=True, token_pattern=r'\w+', ngram_range=(1, 2))
```

TF-IDF

- TFIDF measures the importance of a word by both term frequency and how many times the word appears in all documents.
- TFIDF is defined as the product of two statistics:term frequency tf(w,d) and inverse document frequency idf(w).

$$tf(w,d) = \frac{f_{w,d}}{\text{number of words in d}} = \frac{f_{w,d}}{\sum_{w'} f_{w',d}}$$

$$idf(w) = \log\left(\frac{N}{df(w)}\right), \quad tfidf(w,d) = tf(w,d) \times idf(w)$$

where f(w,d) is the frequency of word w in document d, N is the total number of documents and $df(w)$ is the number of documents that contain term w.

- The TfidfVectorizer function (imported from the sklearn library) transforms text data into a TF-IDF matrix representation, assigning weights to words based on their frequency in individual documents and their rarity across all documents. The parameters min_df=0.5 and max_df=0.90 control the inclusion of words based on their document frequency, while ngram_range = (1,2) specifies that both unigrams and bigrams should be considered in the vectorization process.

```
# Define some hyperparameters of encoded
vectorizer = TfidfVectorizer(min_df=0.5, max_df=0.90,ngram_range = (1,2))
```

Train-Test Split

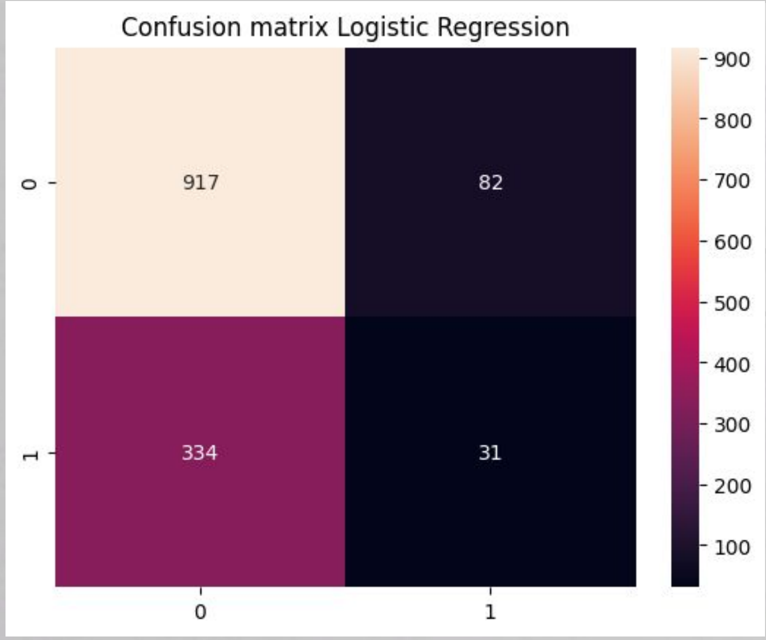
- Splitting the data into training and testing sets is a crucial step in machine learning model to assess the model's performance on unseen data; In our project, we divided into 80% training and 20% testing sets.

- The random_state parameter is set to 42 in the train_test_split function to ensure reproducibility, allowing for consistent results across different runs of the code.

LOGISTIC REGRESSION

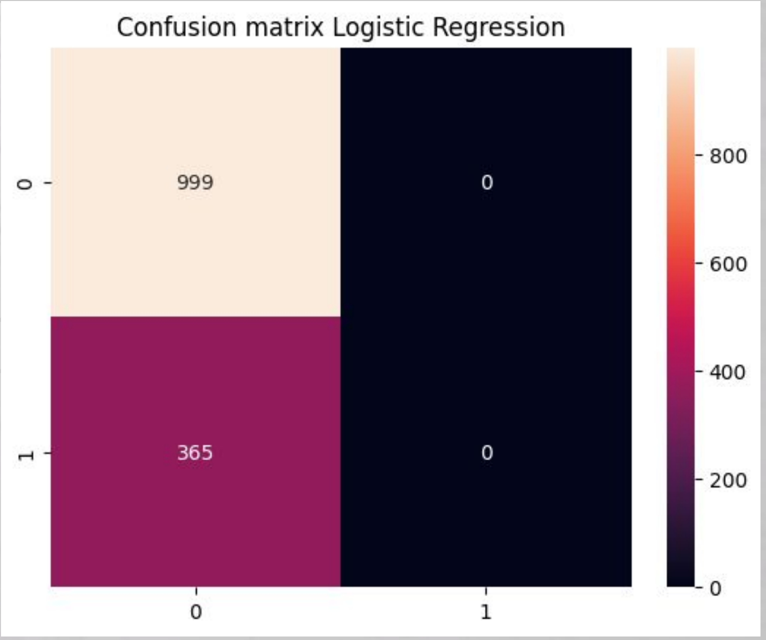
DTM

- **ACCURACY :** 0.7
- **PRECISION :** 0.733
- **RECALL SCORE :** 0.918
- **F1 SCORE :** 0.815



TF-IDF

- **ACCURACY :** 0.7416
- **PRECISION :** 0.754
- **RECALL SCORE :** 1
- **F1 SCORE :** 0.857



RANDOM FOREST

DTM

- **ACCURACY :** 0.73
- **PRECISION :** 0.732
- **RECALL SCORE :** 0.994
- **F1 SCORE :** 0.843

TF-IDF

- **ACCURACY :** 0.748
- **PRECISION :** 0.7612
- **RECALL SCORE :** 1
- **F1 SCORE :** 0.864

SVM

DTM

- **ACCURACY :** 0.731
- **PRECISION :** 0.732
- **RECALL SCORE :** 0.998
- **F1 SCORE :** 0.845

TF-IDF

- **ACCURACY :** 0.7425
- **PRECISION :** 0.757
- **RECALL SCORE :** 1
- **F1 SCORE :** 0.859

WORD EMBEDDINGS

Word2Vec :

- Word2Vec : method for generating word embeddings, its a dense vector representations of words that capture their semantic meanings. These embeddings can then be used as features in NLP tasks.
- In our project, we're using the skip-gram model [i.e given a target word, the model aims to predict the context words] within Word2Vec model.

- We then train Word2Vec model using gensim package with the following specifications: a vector size of 150 dimensions, a window size of 10 words, a minimum count of 3 occurrences for words, and employing 10 worker threads for efficient training.

```
model = gensim.models.Word2Vec(tokenized_reviews,vector_size=150,window=10,min_count=3,workers=10)
```

- We choose to train our Word2Vec model for 10 epochs.

```
model.train(tokenized_reviews, total_examples=len(tokenized_reviews), epochs=10)
```

```
similar_words = word2vec_model.wv.most_similar('great', topn=5)
print(similar_words)
```

```
[('fantastic', 0.9186002612113953), ('amaze', 0.9070403575897217), ('excellent', 0.9013640284538269), ('deliver', 0.8921491503715515), ('brilliant', 0.8832753300666809)]
```

```
[54] similar_words = word2vec_model.wv.most_similar('thanos', topn=5)
print(similar_words)
```

```
[('snap', 0.9181135892868042), ('brolin', 0.8936883211135864), ('josh', 0.8878936171531677), ('catastrophic', 0.8855810761451721), ('undo', 0.8682962656021118)]
```

The similarity score ranges between -1 and 1, where higher scores indicate greater similarity.

```
# Find the odd word out
odd_one_out = word2vec_model.wv.doesnt_match(["film", "thor", "ironman"])

# Print the odd word out
print(odd_one_out)
```

```
film
```

```
similarity_score = word2vec_model.wv.similarity(w1="love", w2="3000")

# Print the similarity score
print(similarity_score)
```

```
0.9523064
```

FastText :

- FastText, developed by Facebook AI Research (FAIR), is an extension of Word2Vec it is faster and also it enhance its efficiency and effectiveness by incorporating subword information and in handling out-of-vocabulary words..

- We created a FastText model, configuring it with a vector size of 100 dimensions, a window size of 5 words, a minimum count of 1 occurrence for words, and employing 4 worker threads for training efficiency.

```
model = FastText(sentences=tokenized_reviews, vector_size=100, window=5, min_count=1, workers=4)
```

- We choose to train our FastText model with 10 epochs.

```
#Training the model
model.train(sentences, total_examples=model.corpus_count, epochs=10)
```

```
[75] vocabulary = model.wv.index_to_key
     print('uniform' in vocabulary)

     False
```

```
vocabulary = model.wv.index_to_key
print('3000' in vocabulary)

True
```

```
[65] # Calculate similarity between two words
     similarity = model.wv.similarity("great", "amazing")
     print("Similarity between 'great' and 'amazing':", similarity)

     Similarity between 'great' and 'amazing': 0.90961784
```

```
[66] # Calculate similarity between two words
     similarity = model.wv.similarity("action", "adventure")
     print("Similarity between 'action' and 'adventure':", similarity)

     Similarity between 'action' and 'adventure': 0.6749082
```

Limitations

- The use of simple sentiment scoring (positive or negative) based solely on user ratings might overlook sentiments expressed in the reviews.
- The project's accuracy is influenced mainly due to unbalanced data, potentially leading to biased predictions.

FUTURE SCOPE

- Implementing Transformer models like BERT and GPT to enhance our sentiment analysis capabilities, leveraging their advanced language understanding for more accurate sentiment classification.

- Enhancing sentiment analysis to detect sarcasm, irony, or mixed feelings for a deeper understanding of user reviews.

- Expanding the project to analyze sentiments in multiple languages for a broader reach.

References

- https://www.imdb.com/title/tt4154796/reviews?spoiler=hide&sort=curated&dir=desc&ratingFilter=0
- https://kavita-ganesan.com/gensim-word2vec-tutorial-starter-code/
- https://www.analyticsvidhya.com/blog/2023/01/introduction-to-fasttext-embeddings-and-its-implication/


Thank You!