SENTIMENT ANALYSIS PROJECT REPORT PHASE-5

Introduction

The main idea of this article is to help you all understand the concept of Sentiment Analysis Deep Learning & NLP. Let's try to understand this with the help of a case. *Anirudh owns an e-commerce company-Universal for the past 1 year and he was very happy as more and more new customers were coming to purchase through his platform. One day he came to know that one of his friends was not satisfied with the product he purchased through his platform. He purchased a foldable geared cycle and the parts required for assembly were missing. He saw few negative reviews by other customers but he purchased from Anirudh as he was his friend. After listening to* his friend, Anirudh decided to deploy a machine-learning algorithm to categorize user reviews and their sentiments so that his team can understand their customers better and provide the products and services without any inconvenience to the customers.

Goal: To know what users are saying about products and services. It can help in future decision-making.

Objective: 1. To compile and Tag past data of User Reviews.

2. Use of NLP and Deep Learning to classify the Reviews and find out the Polarity/Sentiment.

His Team labelled the past User Review data. They were reading the Reviews and Classifying them into one or more categories.

1 indicates the presence of that category. For Example, First Review is talking about ***usability and its polarity/sentiment is negative as the user is***

complaining(indicated by 0) whereas the second review is talking about ***features and Functionality having a positive Polarity/Sentiment***(***indicated by 1***)

Id	Review	Components	Delivery and Customer Support	Design and Aesthetics	D
0	For some reason everybody complains and I'm complaining now about my toilet that I just boughtFor some reason it's not ceiling from the tank to the pedestal I can't get it sealed without cracking the toilet support design for some reason I'm very unhappy with his toilet never buy American standard again	0	0	0	
1	I like everything about it, great choice of spray patterns, it puts out a large volume of water out of my 1" pipes	0	0	0	

Anant is the Data Scientist in the company. Now it's his time to be in the playground. He is using Jupyter Notebook for the model building.

Getting Familiar with Data

Importing Core Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt                      # For Plotting
import seaborn as sns                                # For Plotting
from sklearn.metrics import log_loss                 # For Model Evaluation
```

```
6 from sklearn.model_selection import RepeatedKFold      #
For Cross-Validation
```

Reading data

```
data = pd.read_csv("/content/train.csv")
data.head()                          # First 5 rows
```

	Id	Review	Components	Delivery and Customer Support	Design and Aesthetics	Dimensions	Features
0	0	For some reason everybody complains and I'm co...	0	0	0	0	0
1	1	I like everything about it, great choice of sp...	0	0	0	0	1
2	2	Excellent ceiling fan brace. Easy to install a...	0	0	0	0	0
3	3	Work great easy to use . No issues at all with...	0	0	0	0	0
4	4	I would recommend this product because it is p...	0	0	0	0	0

Observation: By looking at the data, it is clear that it has multiclass(12 classes). It is called a multiclass problem. Apart from multiclass a review can have >=1 category. For Example, Id-1 has 2 categories, Features & Functionality. Categories are not mutually exclusive which is called multilabel. By combining both, we can say that it is a multiclass, multilabel challenge.

```
data.columns            # List of columns in the dataframe
```

```
... Index(['Id', 'Review', 'Components', 'Delivery and Customer Support',
       'Design and Aesthetics', 'Dimensions', 'Features', 'Functionality',
       'Installation', 'Material', 'Price', 'Quality', 'Usability',
       'Polarity'],
      dtype='object')
```

```
data.isnull().sum()
```

```
Id                               0
Review                           0
Components                       0
Delivery and Customer Support    0
Design and Aesthetics            0
Dimensions                       0
Features                         0
Functionality                    0
Installation                     0
Material                         0
Price                            0
Quality                          0
Usability                        0
Polarity                         0
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6136 entries, 0 to 6135
Data columns (total 14 columns):
 #   Column                        Non-Null Count  Dtype 
---  ------                        --------------  ----- 
 0   Id                            6136 non-null   int64 
 1   Review                        6136 non-null   object
 2   Components                    6136 non-null   int64 
 3   Delivery and Customer Support 6136 non-null   int64 
 4   Design and Aesthetics         6136 non-null   int64 
 5   Dimensions                    6136 non-null   int64 
 6   Features                      6136 non-null   int64 
 7   Functionality                 6136 non-null   int64 
 8   Installation                  6136 non-null   int64 
 9   Material                      6136 non-null   int64 
 10  Price                         6136 non-null   int64 
 11  Quality                       6136 non-null   int64 
 12  Usability                     6136 non-null   int64 
 13  Polarity                      6136 non-null   int64 
dtypes: int64(13), object(1)
memory usage: 671.2+ KB
```

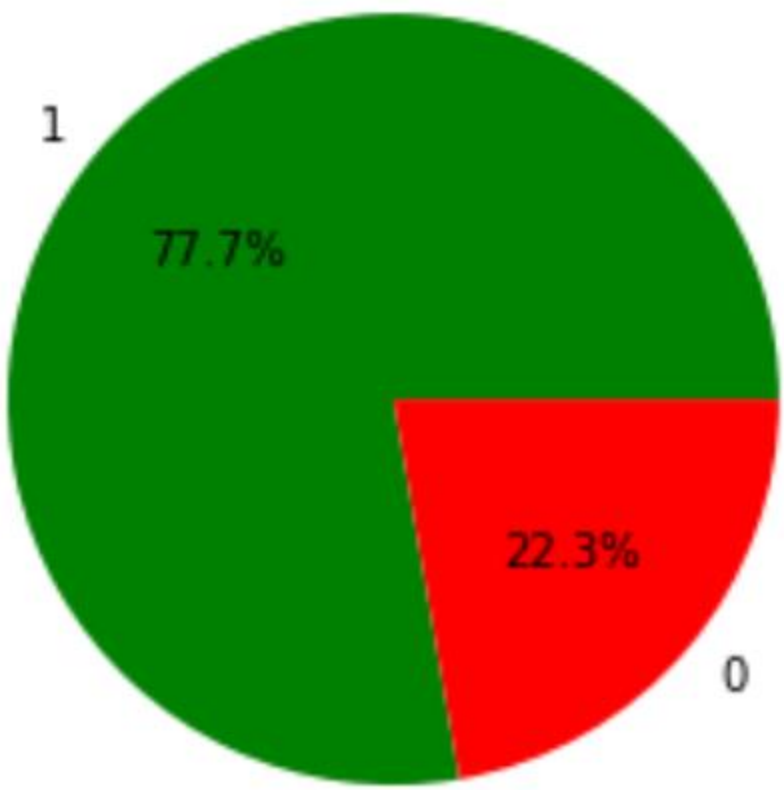
```
data.shape
```

```
(6136, 14)
```

Exploratory Data Analysis (EDA)

What % of users are talking negatively about the product/services?

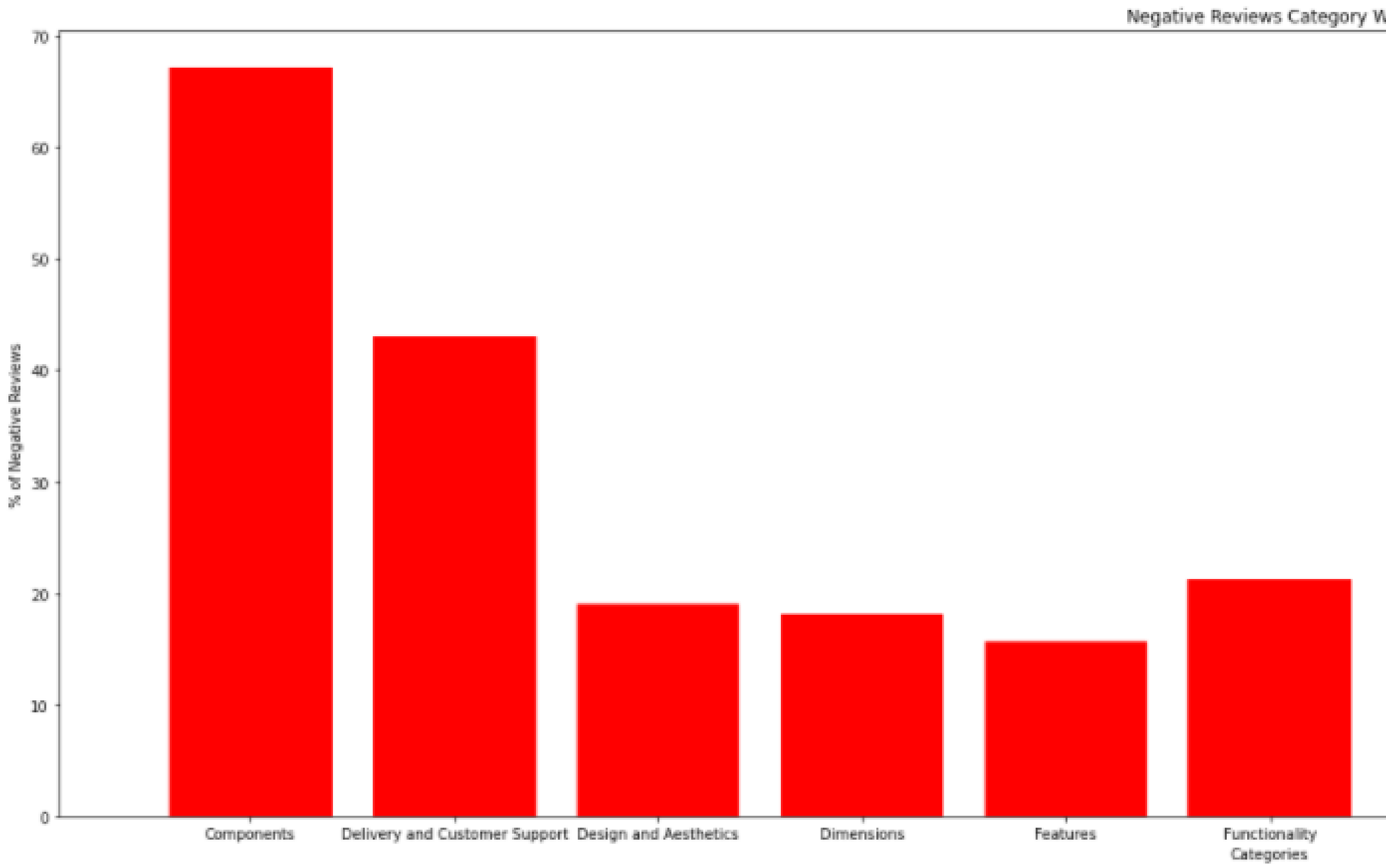
```
sentiment_count = data.Polarity.value_counts()

sentiment_type = data.Polarity.value_counts().index            #
1- Positive   0- Negative

plt.pie(sentiment_count,lablels=sentiment_type,
autopct='1.1f%%',colors=['green', 'red'])
```



Observation: 22.3 % of users are giving negative reviews. In simple terms, only 1 out 5 users are giving negative reviews.

Out of total Reviews in different categories, What % of reviews are negative in different categories?

```
col = ['Components', 'Delivery and Customer Support',
       'Design and Aesthetics', 'Dimensions', 'Features',
'Functionality',
       'Installation', 'Material', 'Price', 'Quality', 'Usability']
negative_category=[]
for i in col:
    k = ((data[i].sum()-
data[data[i]==1]['Polarity'].sum())/data[i].sum())*100
    negative_category.append(k)
fig = plt.figure(figsize = (30, 10))
plt.bar(col,negative_category,color ='red')
plt.xlabel("Categories")
plt.ylabel("% of Negative Reviews")
plt.title("Negative Reviews Category Wise")
plt.show()
```



Observation: Out of total reviews in different categories, Users are giving the highest % of negative reviews for the Component Category. This is followed by Material, Delivery, and Customer Support.

Text Preprocessing in NLP

Before we feed our data as input to the machine learning algorithm, it's important to prepare the data in such a way that it reduces the time for processing, takes less memory space, and gives the highest metric evaluation.

Lower Casing & De contraction

The lower casing is removing capitalization from words so that it is treated the same. For example, Look & look are considered different as the first one is capitalized.

```
import re
def clean_text(text):
    text = text.lower()
    text = re.sub(r"what's", "what is ", text)
    text = re.sub(r"'s", " ", text)
    text = re.sub(r"'ve", " have ", text)
    text = re.sub(r"can't", "can not ", text)
    text = re.sub(r"n't", " not ", text)
    text = re.sub(r"i'm", "i am ", text)
    text = re.sub(r"'re", " are ", text)
    text = re.sub(r"'d", " would ", text)
    text = re.sub(r"'ll", " will ", text)
    text = text.strip(' ')

    return text
```

data[‘Review’] = data[‘Review’].map(lambda com : clean_text(com))

data[‘Review’][0]

```
'for some reason everybody complains and i am complaining now about my toilet that i just bou
can not get it sealed without cracking the toilet support design for some reason i am very ur
```

Stop Words Removal

Stop words are used for grammatical flow and connecting sentences. For example, I ,are, my, me etc. It does not convey any meaning. If we get rid of stop words, we

can reduce the size of our data without information loss. NLTK library is used here to remove stop words.

```
!pip install nltk
import nltk
from nltk.corpus import stopwords
stop_words = stopwords.words('english')
data['Review'] = data['Review'].apply(lambda x: ' '.join([word for
word in x.split() if word not in (stop_words)]))
data['Review'][0]
```

```
'reason everybody complains complaining toilet boughtfor reason ceiling tank pedestal get sea
never buy american standard'
```

```
y = np.array(data[[ 'Components', 'Delivery and Customer Support',
       'Design and Aesthetics', 'Dimensions', 'Features',
'Functionality',
       'Installation', 'Material', 'Price', 'Quality',
'Usability','Polarity']])
X = data['Review']
X.head(5)


X.shapes
```

```
(6136,)
```

Feature Matrix through TF-IDF

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(min_df=20,ngram_range=(1,4),
max_features=250)
vectorizer.fit(X)
X = vectorizer.transform(X)  # Taking X as input and converting
into feature matrix(numerical values)
X = X.todense()
```

Deep Learning in Picture

Deep learning attempts to mimic the human brain, and analysis with deep learning fetches fruitful results when we implement it in our model. In deep learning, there are at least three hidden layers. Each unit that takes, processes or outputs the data is called a neuron just like we have in our brain. Based on the work these neurons do, deep learning neurons are divided into input, hidden & output layers. More Hidden layers mean a more complex model!

```
!pip install tensorflow
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Dropout
from tensorflow.keras.initializers import RandomNormal
def get_model(n_inputs, n_outputs):
  batch_size = 256
  hidden_units = 64
  dropout = 0.2

  model = Sequential()
  model.add(Dense(hidden_units, 
input_dim=n_inputs,activation='relu',
          kernel_initializer='he_uniform'))
  model.add(Dropout(dropout))
  model.add(Dense(64,activation='relu',
          kernel_initializer='he_uniform'))
  model.add(Dropout(dropout))
  model.add(Dense(n_outputs))
  model.add(Activation('sigmoid'))
  model.compile(loss='binary_crossentropy', optimizer='adam')
  return model
import tensorflow as tf
```

```python
def evaluate_model(X,y):
  results_test = []
  results_train =[]
  callback = tf.keras.callbacks.EarlyStopping(monitor='loss',
patience=5,min_delta = 0.05)
  n_inputs, n_outputs = X.shape[1], y.shape[1]
  cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
  for train_ix,test_ix in cv.split(X):
    X_train, X_test = X[train_ix], X[test_ix]
    y_train,y_test = y[train_ix],y[test_ix]
    model = get_model(n_inputs, n_outputs)
    model.fit(X_train,y_train,verbose = 0,epochs = 50,callbacks =
callback)
    yhat_train = model.predict(X_train)
    yhat_test = model.predict(X_test)
    train_log_loss = log_loss(y_train, yhat_train)
    test_log_loss = log_loss(y_test,yhat_test)
    results_train.append(train_log_loss)
    results_test.append(test_log_loss)
  return results_train,results_test,model
results_train,results_test,model = evaluate_model(X, y)
print(results_train)
print(results_test)
```

```
[3.5139198823818822, 3.505231494258729, 3.4783167782543534, 3.492847705914982, 3.4851307805
3.520050463600045, 3.479009317257429, 3.4819550845166214, 3.4870210044876644, 3.426046772285
3.4839328269358023, 3.4496328771740288, 3.473185864038578, 3.409536043203937, 3.387313297674
3.4336210431093237, 3.388879736370688, 3.4979578228655575, 3.5123577021114984, 3.486905565558
[3.705203401925898, 3.561822240729285, 3.672187381973096, 3.756914945592321, 3.6663835101096
3.6634419265812412, 3.6727915209813764, 3.728755685085194, 3.6561066618959757, 3.7805267660
3.813879993864218, 3.829266992469013, 3.74797056763635, 3.596130327581387, 3.764390825351597
3.611410211613978, 3.772000024246859, 3.619896247861436, 3.679787778154283, 3.837101425082
```

Training and Validation Score

```
print(sum(results_train)/len(results_train)
print(sum(results_test)/len(results_test)
```

Training Log Loss = 3.45

Cross-Validation Log Loss = 3.69

Its time to test on current User Reviews

```
test_data = pd.read_csv("/content/test.csv")
test_data.head(5)
```

	Id	Review	Components	Delivery and Customer Support	Design and Aesthetics	Dimensions	Features
0	0	Made of very thin cheap metal broke on very fi...	NaN	NaN	NaN	NaN	NaN
1	1	As good as the brand names, no jams or misfire...	NaN	NaN	NaN	NaN	NaN
2	2	unit was easy to use, with understandable in s...	NaN	NaN	NaN	NaN	NaN
3	3	I am the new family plumber. Works well. No pr...	NaN	NaN	NaN	NaN	NaN
4	4	Seems to be holding up well.	NaN	NaN	NaN	NaN	NaN

Preprocessing

```
test_data['Review'] = test_data['Review'].map(lambda com :
clean_text(com))
test_data['Review'] = test_data['Review'].apply(lambda x: '
'.join([word for word in x.split() if word not in (stop_words)]))
test_vectorised_data = vectorizer.transform(test_data['Review'] )
test_vectorised_data = test_vectorised_data.todense()
```

Prediction on Test Data

```
prediction_on_test_data = model.predict(test_vectorised_data)
df_test = pd.DataFrame(prediction_on_test_data, columns =
['Components', 'Delivery and Customer Support',
       'Design and Aesthetics', 'Dimensions', 'Features',
'Functionality',
       'Installation', 'Material', 'Price', 'Quality', 'Usability',
       'Polarity'])
df_test
```

	Components	Delivery and Customer Support	Design and Aesthetics	Dimensions	Features	Func
0	0.202828	0.094082	0.041671	0.028449	0.027827	
1	0.020624	0.028530	0.008319	0.044094	0.019136	
2	0.004376	0.000356	0.007200	0.019483	0.022487	
3	0.019462	0.012524	0.005593	0.008895	0.040877	
4	0.018546	0.041017	0.043874	0.107526	0.036558	
...	...	...	...	...	...	
2626	0.022171	0.009481	0.046267	0.046757	0.034359	
2627	0.051097	0.072741	0.089164	0.139320	0.033380	
2628	0.011313	0.046942	0.009325	0.027490	0.012047	
2629	0.029497	0.025951	0.349195	0.111933	0.029618	
2630	0.035730	0.005115	0.023342	0.029309	0.041107	

2631 rows × 12 columns

Conclusion

Let's check a few Reviews classification and Polarity Suggested by our Model

Review: Made of very thin cheap metal broke on the very first crimp. Had to rush to a local hardware store spend 60 more on another because the water was shut off in my home.Did not return because using the case for the new one.

Our Model is categorizing it as Quality- 0.86 and Polarity/Sentiment-0.06(Negative)

Review: As good as the brand names, no jams or misfires on my Paslode fuel cell nailer or on my Banks (HF) nailer.

Our Model is categorizing it as Functionality- 0.79 and Polarity/Sentiment-0.88(Positive)

Different departments now can take actions based on negative reviews in their bucket.

Thus from the above article, it has been lucidly explained as to how we can categorise user reviews and and study the sentiment analysis with Deep Learning & NLP.

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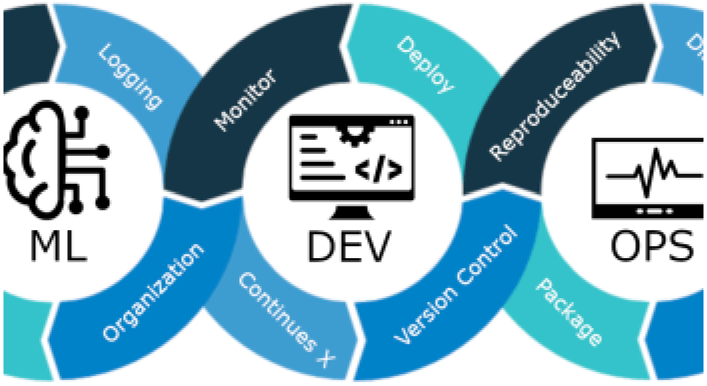

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