

In this notebook we will be doing some sentiment analysis in python using two different techniques:

1. VADER (Valence Aware Dictionary and sEntiment Reasoner) - Bag of words approach
2. Roberta Pretrained Model from 🤗
3. Huggingface Pipeline

✓ Step 0. Read in Data and NLTK Basics

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
plt.style.use('ggplot')
```

```
import nltk
nltk.download('punkt_tab')
nltk.download('averaged_perceptron_tagger_eng')
nltk.download('maxent_ne_chunker_tab')
nltk.download('words')
nltk.download('vader_lexicon')
```

```
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data] Package punkt_tab is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger_eng to
[nltk_data] /root/nltk_data...
[nltk_data] Package averaged_perceptron_tagger_eng is already up-to-
[nltk_data] date!
[nltk_data] Downloading package maxent_ne_chunker_tab to
[nltk_data] /root/nltk_data...
[nltk_data] Package maxent_ne_chunker_tab is already up-to-date!
[nltk_data] Downloading package words to /root/nltk_data...
[nltk_data] Package words is already up-to-date!
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
True
```

```
df = pd.read_csv('/content/Reviews.csv')
```

```
df.shape
```

```
(142748, 10)
```

```
# scaling down the dataset
```

```
df = df.head(500)
```

```
df.shape
```

```
(500, 10)
```

```
df.head()
```

```
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data] Package punkt_tab is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger_eng to
[nltk_data] /root/nltk_data...
[nltk_data] Package averaged_perceptron_tagger_eng is already up-to-
[nltk_data] date!
[nltk_data] Downloading package maxent_ne_chunker_tab to
[nltk_data] /root/nltk_data...
[nltk_data] Package maxent_ne_chunker_tab is already up-to-date!
[nltk_data] Downloading package words to /root/nltk_data...
[nltk_data] Package words is already up-to-date!
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
True
```

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1.0	1.0	5.0	1.303862e+09	Good Quality Dog Food

✓ Quick EDA

```
ax = df['Score'].value_counts().sort_index().plot(kind='bar',
          title='Count of Reviews by Stars',
          figsize=(10,5))
ax.set_xlabel('Review Stars')
plt.show()
```



✓ Basic NLTK

```
example = df['Text'][50]
print(example)
```



This oatmeal is not good. Its mushy, soft, I don't like it. Quaker Oats is the way to go.

```
nltk.word_tokenize(example)
```



```
['This',
 'oatmeal',
 'is',
 'not',
 'good',
 '.',
 'Its',
 'mushy',
 ',',
 'soft',
 ',',
 'I',
 'do',
 "n't",
 'like',
 'it',
 '.']
```

```
'Quaker',
'Oats',
'is',
'the',
'way',
'to',
'go',
'.'
```

```
tokens = nltk.word_tokenize(example)
tokens[:10]
```

```
↪ ['This', 'oatmeal', 'is', 'not', 'good', '.', 'Its', 'mushy', ',', 'soft']
```

```
# part of speech tagging
nltk.pos_tag(tokens)
```

```
↪ [('This', 'DT'),
 ('oatmeal', 'NN'),
 ('is', 'VBZ'),
 ('not', 'RB'),
 ('good', 'JJ'),
 ('.', '.'),
 ('Its', 'PRP$'),
 ('mushy', 'NN'),
 (',', ','),
 ('soft', 'JJ'),
 (',', ','),
 ('I', 'PRP'),
 ('do', 'VBP'),
 ("n't", 'RB'),
 ('like', 'VB'),
 ('it', 'PRP'),
 ('.', '.'),
 ('Quaker', 'NNP'),
 ('Oats', 'NNPS'),
 ('is', 'VBZ'),
 ('the', 'DT'),
 ('way', 'NN'),
 ('to', 'TO'),
 ('go', 'VB'),
 ('.', '.')]

```

```
tagged = nltk.pos_tag(tokens)
tagged[:10]
```

```
↪ [('This', 'DT'),
 ('oatmeal', 'NN'),
 ('is', 'VBZ'),
 ('not', 'RB'),
 ('good', 'JJ'),
 ('.', '.'),
 ('Its', 'PRP$'),
 ('mushy', 'NN'),
 (',', ','),
 ('soft', 'JJ')]
```

```
entities = nltk.chunk.ne_chunk(tagged)
entities.pprint()
```

```
↪ (S
  This/DT
  oatmeal/NN
  is/VBZ
  not/RB
  good/JJ
  ./
  Its/PRP$
  mushy/NN
  ,/,
  soft/JJ
  ,/,
  I/PRP
  do/VBP
  n't/RB
  like/VB
  it/PRP
  ./
  (ORGANIZATION Quaker/NNP Oats/NNPS)
  is/VBZ
  the/DT
  way/NN
  to/TO
  go/VB

```

./.)

✓ Step 1. VADER Seniment Scoring

We will use NLTK's `SentimentIntensityAnalyzer` to get the neg/neu/pos scores of the text.

- This uses a "bag of words" approach:
 1. Stop words are removed
 2. each word is scored and combined to a total score.

```
from nltk.sentiment import SentimentIntensityAnalyzer
from tqdm.notebook import tqdm
```

```
sia = SentimentIntensityAnalyzer()
```

```
sia.polarity_scores('I am so happy!')
```

```
{'neg': 0.0, 'neu': 0.318, 'pos': 0.682, 'compound': 0.6468}
```

```
sia.polarity_scores('This is the worst thing ever.')
```

```
{'neg': 0.451, 'neu': 0.549, 'pos': 0.0, 'compound': -0.6249}
```

```
sia.polarity_scores(example)
```

```
{'neg': 0.22, 'neu': 0.78, 'pos': 0.0, 'compound': -0.5448}
```

```
# run the polarity score on the entire dataset
```

```
res = {}
```

```
for i, row in tqdm(df.iterrows(),total=len(df)):
```

```
    text = row['Text']
```

```
    myid = row['Id']
```

```
    res[myid] = sia.polarity_scores(text)
```

```
100% 500/500 [00:00<00:00, 1654.36it/s]
```

```
vaders = pd.DataFrame(res).T
```

```
vaders = vaders.reset_index().rename(columns={'index':'Id'})
```

```
vaders = vaders.merge(df,how='left')
```

```
# sentiment scores and metadata
```

```
vaders.head()
```

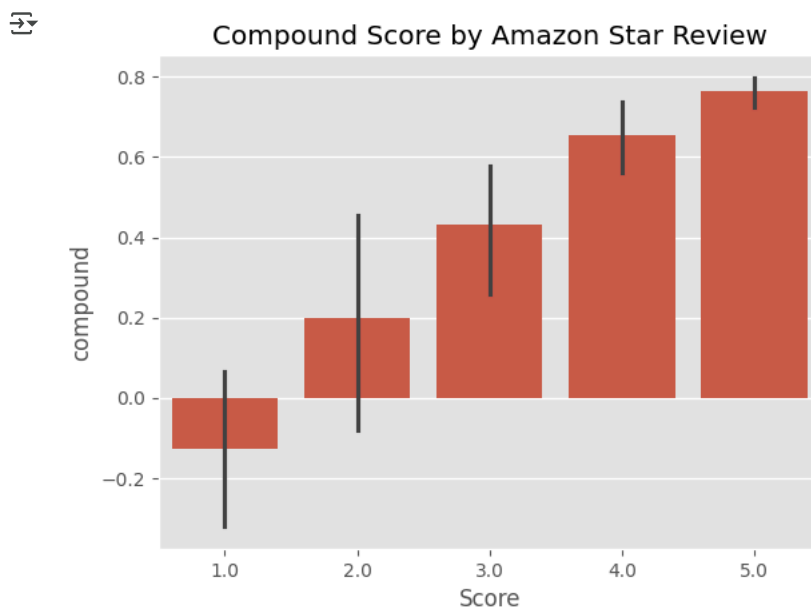
```

Id    neg    neu    pos  compound  ProductId  UserId  ProfileName  HelpfulnessNumerator  HelpfulnessDenominator  Score
0  1  0.000  0.695  0.305    0.9441  B001E4KFG0  A3SGXH7AUHU8GW  delmartian                1.0                1.0        5

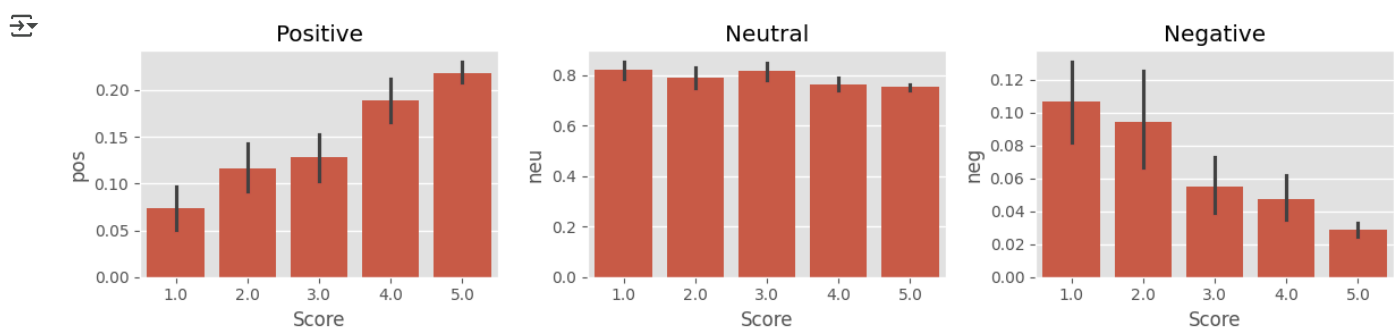
```

✓ Plot VADER results

```
ax = sns.barplot(data=vaders,x='Score',y='compound')
ax.set_title('Compound Score by Amazon Star Review')
plt.show()
```



```
fig,axis = plt.subplots(1,3,figsize=(12,3))
sns.barplot(data=vaders,x='Score',y='pos',ax=axis[0])
sns.barplot(data=vaders,x='Score',y='neu',ax=axis[1])
sns.barplot(data=vaders,x='Score',y='neg',ax=axis[2])
axis[0].set_title('Positive')
axis[1].set_title('Neutral')
axis[2].set_title('Negative')
plt.tight_layout()
plt.show()
```



✓ Step 3. Roberta Pretrained Model

- Use a model trained of a large corpus of data.
- Transformer model accounts for the words but also the context related to other words.

```
from transformers import AutoTokenizer
from transformers import AutoModelForSequenceClassification
from scipy.special import softmax
```

```
MODEL = f"cardiffnlp/twitter-roberta-base-sentiment"
tokenizer = AutoTokenizer.from_pretrained(MODEL)
model = AutoModelForSequenceClassification.from_pretrained(MODEL)
```

```
config.json: 100% 747/747 [00:00<00:00, 76.3kB/s]
vocab.json: 100% 899k/899k [00:00<00:00, 12.6MB/s]
merges.txt: 100% 456k/456k [00:00<00:00, 12.7MB/s]
special_tokens_map.json: 100% 150/150 [00:00<00:00, 16.5kB/s]
pytorch_model.bin: 100% 499M/499M [00:06<00:00, 74.5MB/s]
```

```
# vader result on example
print(example)
sia.polarity_scores(example)
```

```
This oatmeal is not good. Its mushy, soft, I don't like it. Quaker Oats is the way to go.
{'neg': 0.22, 'neu': 0.78, 'pos': 0.0, 'compound': -0.5448}
```

```
# run for roberta model
encoded_text = tokenizer(example, return_tensors='pt')
output = model(**encoded_text)
scores = output[0][0].detach().numpy()
scores = softmax(scores)
scores_dict = {
    'roberta_neg' : scores[0],
    'roberta_neu' : scores[1],
    'roberta_pos' : scores[2]
}
print(scores_dict)
```

```
{'roberta_neg': 0.97635514, 'roberta_neu': 0.020687466, 'roberta_pos': 0.002957372}
```

```
def polarity_scores_roberta(example):
    encoded_text = tokenizer(example, return_tensors='pt')
    output = model(**encoded_text)
    scores = output[0][0].detach().numpy()
    scores = softmax(scores)
    scores_dict = {
        'roberta_neg' : scores[0],
        'roberta_neu' : scores[1],
        'roberta_pos' : scores[2]
    }
    return scores_dict
```

```
res = {}
for i, row in tqdm(df.iterrows(), total=len(df)):
    try:
        text = row['Text']
        myid = row['Id']
        vader_result = sia.polarity_scores(text)
        vader_result_rename = {}
        for key, value in vader_result.items():
            vader_result_rename[f"vader_{key}"] = value
        roberta_result = polarity_scores_roberta(text)
        both = {**vader_result_rename, **roberta_result}
        res[myid] = both
    except RuntimeError:
        print(f'Broke for id {myid}')
```

```
100% 500/500 [02:00<00:00, 3.85it/s]
Broke for id 83
Broke for id 187
```

```
results_df = pd.DataFrame(res).T
results_df = results_df.reset_index().rename(columns={'index': 'Id'})
results_df = results_df.merge(df, how='left')
```

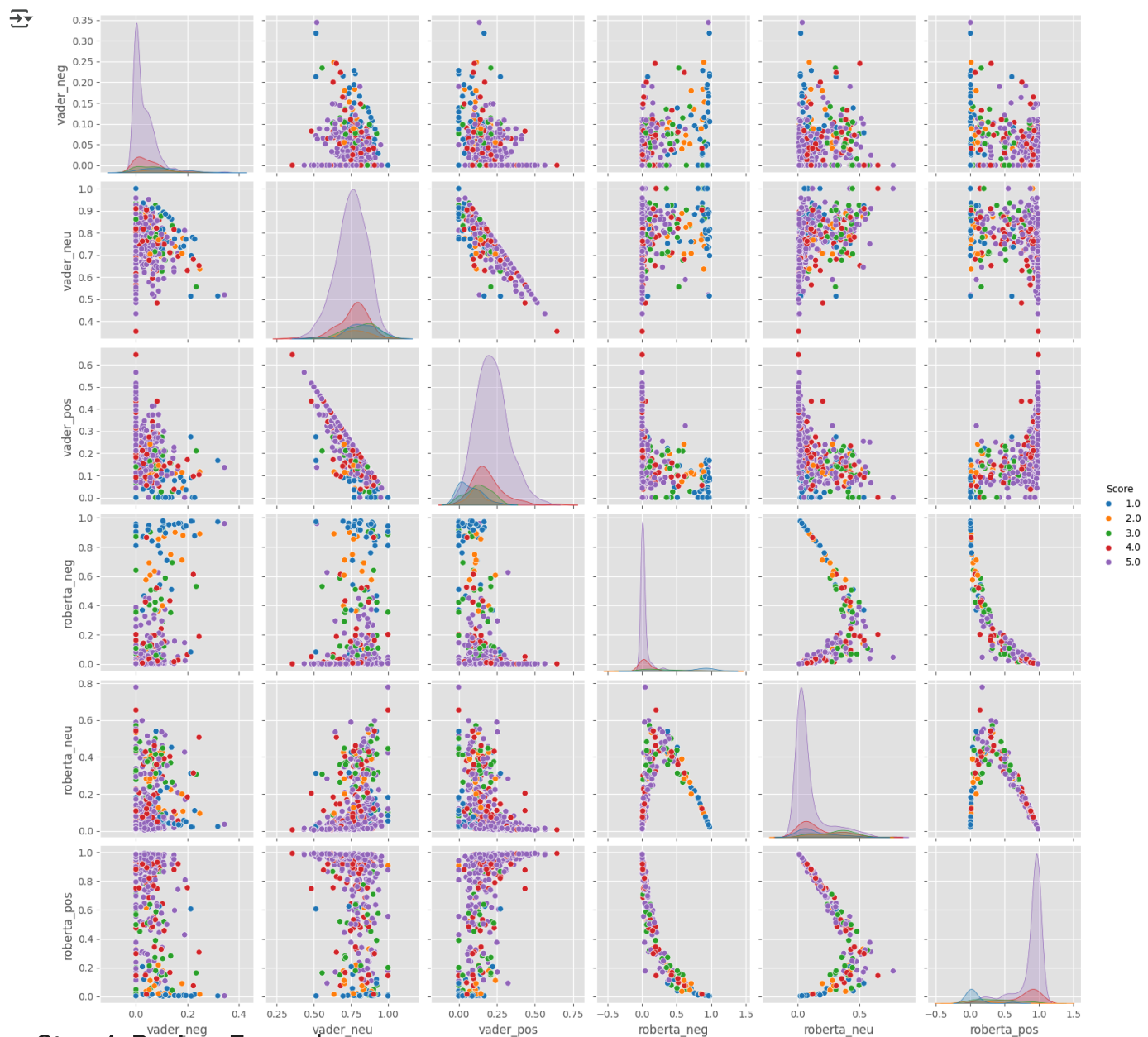
▼ Compare Scores between models

```
results_df.columns
```

```
Index(['Id', 'vader_neg', 'vader_neu', 'vader_pos', 'vader_compound',  
      'roberta_neg', 'roberta_neu', 'roberta_pos', 'ProductId', 'UserId',  
      'ProfileName', 'HelpfulnessNumerator', 'HelpfulnessDenominator',  
      'Score', 'Time', 'Summary', 'Text'],  
      dtype='object')
```

```
sns.pairplot(data=results_df,  
            vars=['vader_neg', 'vader_neu', 'vader_pos',  
                  'roberta_neg', 'roberta_neu', 'roberta_pos'],  
            hue='Score',  
            palette='tab10')
```

```
plt.show()
```



▼ Step 4: Review Examples:

- Positive 1-Star and Negative 5-Star Reviews

Lets look at some examples where the model scoring and review score differ the most.

```
results_df.query('Score == 1').sort_values('roberta_pos', ascending=False)['Text'].values[0]
```

```
'I felt energized within five minutes, but it lasted for about 45 minutes. I paid $3.99 for this drink. I could have just drunk a c
```

```
results_df.query('Score == 1').sort_values('vader_pos', ascending=False)['Text'].values[0]
```

```
↵ 'So we cancelled the order. It was cancelled without any problem. That is a positive note...'
```

```
results_df.query('Score == 5').sort_values('roberta_neg', ascending=False)['Text'].values[0]
```

```
↵ 'this was sooooo delicious but too bad i ate em too fast and gained 2 pds! my fault'
```

```
results_df.query('Score == 5').sort_values('vader_neg', ascending=False)['Text'].values[0]
```

```
↵ 'this was sooooo delicious but too bad i ate em too fast and gained 2 pds! my fault'
```

✓ Extra: The Transformers Pipeline

- Quick & easy way to run sentiment predictions

```
from transformers import pipeline
sent_pipeline = pipeline("sentiment-analysis")
```

```
↵ No model was supplied, defaulted to distilbert/distilbert-base-uncased-finetuned-sst-2-english and revision 714eb0f (https://huggingface.co/distilbert/distilbert-base-uncased-finetuned-sst-2-english)
Using a pipeline without specifying a model name and revision in production is not recommended.
```

config.json: 100%	629/629 [00:00<00:00, 70.5kB/s]
model.safetensors: 100%	268M/268M [00:04<00:00, 34.2MB/s]
tokenizer_config.json: 100%	48.0/48.0 [00:00<00:00, 5.46kB/s]
vocab.txt: 100%	232k/232k [00:00<00:00, 5.07MB/s]
Device set to use cpu	

```
sent_pipeline('I love sentiment analysis!')
```

```
↵ [{'label': 'POSITIVE', 'score': 0.9997853636741638}]
```

```
sent_pipeline('Make sure to like and subscribe!')
```

```
↵ [{'label': 'POSITIVE', 'score': 0.9991742968559265}]
```

```
sent_pipeline('booo')
```

```
↵ [{'label': 'NEGATIVE', 'score': 0.9936267137527466}]
```