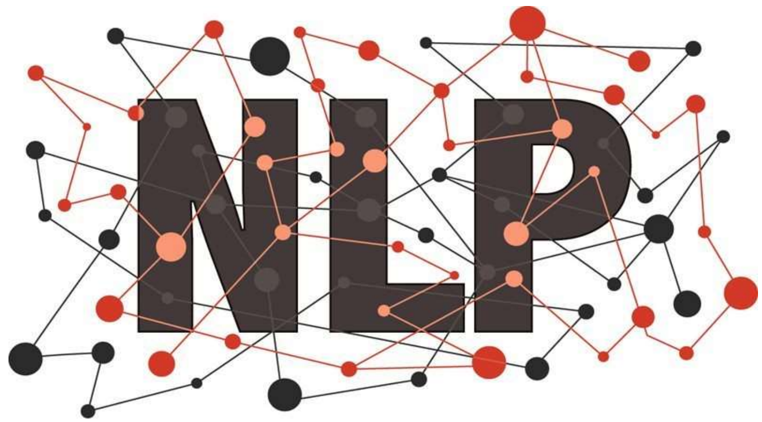

Text Sentiment Analysis

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Overview

- The aim of this project:
- Explore and analyze reviews from multiple web sites like Amazon and Yelp business reviews.
- Identify the relationship between the sentiment of the reviewer's comment and their rating .
- Analyze the text with VALDER scoring and the RoBERTa Pretrained Model and compare model performance over example review.
- Directly predicting the star rating from the text review.
- Using our Models to make predictions on new data scraped from Yelp to perform Sentiment Analysis.

Dataset① Reviews.csv

- 568,454 data samples
- 10 variables (5 num, 5 cat)

column_name	counts	unique_value_pct	nan_pct	data_type
Id	568454	100.000000	0.000000	int64
ProductId	74258	13.060000	0.000000	object
UserId	256059	45.040000	0.000000	object
ProfileName	218416	38.420000	0.000000	object
HelpfulnessNumerator	231	0.040000	0.000000	int64
HelpfulnessDenominator	234	0.040000	0.000000	int64
Score	5	0.000000	0.000000	int64
Time	3168	0.560000	0.000000	int64
Summary	295742	52.030000	0.000000	object
Text	393579	69.240000	0.000000	object

Score	Summary	Text
5	Good Quality Dog Food	I have bought several of the Vitality canned dog food products and have found them all to be of good quality. The product looks more like a stew than a processed meat and it smells better. My Labrador is finicky and she appreciates this product better than most.
1	Not as Advertised	Product arrived labeled as Jumbo Salted Peanuts...the peanuts were actually small sized unsalted. Not sure if this was an error or if the vendor intended to represent the product as "Jumbo".
4	"Delight" says it all	This is a confection that has been around a few centuries. It is a light, pillowy citrus gelatin with nuts - in this case Filberts. And it is cut into tiny squares and then liberally coated with powdered sugar. And it is a tiny mouthful of heaven. Not too chewy, and very flavorful. I highly recommend this yummy treat. If you are familiar with the story of C.S. Lewis' "The Lion, The Witch, and The Wardrobe" - this is the treat that seduces Edmund into selling out his Brother and Sisters to the Witch.
2	Cough Medicine	If you are looking for the secret ingredient in Robitussin I believe I have found it. I got this in addition to the Root Beer Extract I ordered (which was good) and made some cherry soda. The flavor is very medicinal.
5	Great taffy	Great taffy at a great price. There was a wide assortment of yummy taffy. Delivery was very quick. If your a taffy lover, this is a deal.

- Reviews.csv – Selected Columns(head5)

Data Processing

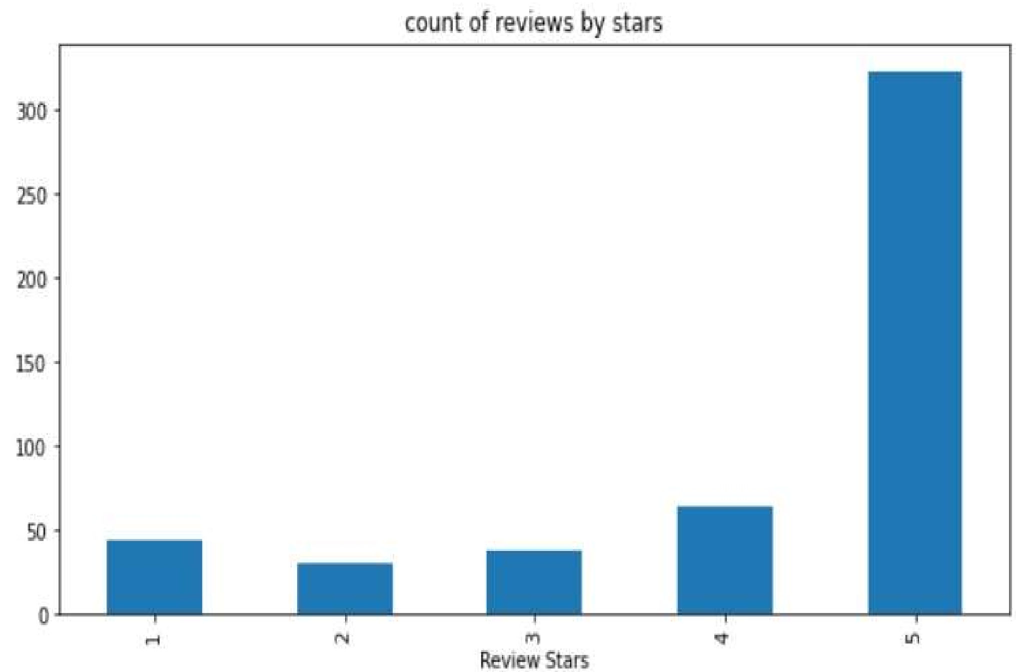
Steps	Action	Variable Names	Detail Explanation	Dataset Name
Step 1	Downsample the data to 500 sample	All variables	Drow a random sample of rows (Sample size = 500)	data from 'Reviews.csv'
Step 2	New Variable Creation	Summary, Text, review_text	Combine the summary / heading and text description	sample_data
Step 3	Drop variable	Summary, Text	Remove the original columns	sample_data
Step 4	Reset Index	All variables	Reset the Dataframe Index and drop the old index	sample_data

Score	review_text
1	Sprayed orange grease all over the inside of the microwave The pop-up bowl sounds like a great idea, but evidently they rushed it to market before all the bugs were out. The first bag I cooked was fine, except the instructions for opening the bag are far from clear, and even after you figure out how to do it it's a lot of trouble and makes a big mess. But the second bag evidently sprang a leak - it sprayed bright orange grease all over the inside of my microwave, even into the tiny vent holes inside the top and side. I always watch popcorn carefully while it pops, but I could not see the grease spray until after it was done and I opened the door. Cleaning it all out was a horrible ordeal, and I'm sure everything I cook in the microwave will come out smelling like popcorn grease for weeks. They released this product too soon. It needs serious redesign. I will not buy it again.
3	Had higher expectations It is a naturally sweetened soda with Stevia, but I expect more robust flavor simular to Dr. Pepper. I wouldn't even say it is close to Dr. Pepper. I was disappointed, especially when I love the "Cola" flavor of Zevia so much.
5	Everything is as it should be I ordered these nuts...for both my own personal consumption...and my two African Greys Scaredy Bird and Reggie. I believe I can speak for all of us in saying that the nuts arrived on time and in delectable condition. They were fresh....and arrived not broken or damaged in any way. Diamond Nuts..has a high reputation with me---and they continue to prove their worth..by sending out a excellent product ! I do --highly recommend this company--and this product !
5	So Happy I found this; Product is Fabulous I decided to stop using sweet n' low for obvious reasons. I hated the cost of buying the boxes of Splenda in my locale grocery, as it was so expensive. When I googled Splenda and found this I was elated and ordered it right away. I will order a second for my home upstate shortly, as I certainly cannot transport this box in an efficient manner and I need it in my City location.
5	Great tea, very satisfying Nice mellow tea for all occassions. I'm an ex-coffee drinker searching for an alternative and this product fit nicely. It's smooth, very satisfying. Nice product.

- Sample Data from Reviews.csv - Sample(500, head5)

Key Findings

The overall distribution of reviews seems to be more positive, then there is a slight spike in the 1 star negative reviews, meaning the data is mostly very polar.



Count of reviews by stars

Great Price, Not what I was hoping for though. There's the original Tang. There's the fruition Tang that was around from 2008 to 2010, which had extra vitamins (B,D,A, etc.) and replaced half the sugar with zero calorie sweeteners. But tang has gone back to a flavor more similar to the original with full sugar content. I was hoping for the fruition version, which other reviewers received.

['Great', 'Price', ',', 'Not', 'what', 'I', 'was', 'hoping']

Use the NLTK's word tokenizer to smartly split the sentence into tokens which can be used to understand the language by a computer

- Basic NLTK (word_tokenize) – On the 51th row of the sample reviews

Great Price, Not what I was hoping for though. There's the original Tang. There's the fruition Tang that was around from 2008 to 2010, which had extra vitamins (B,D,A, etc.) and replaced half the sugar with zero calorie sweeteners. But tang has gone back to a flavor more similar to the original with full sugar content. I was hoping for the fruition version, which other reviewers received.

[('Great', 'NNP'),
('Price', 'NNP'),
(',', ','),
('Not', 'RB'),
('what', 'WP'),
('I', 'PRP'),
('was', 'VBD'),
('hoping', 'VBG'),
('for', 'IN'),
('though', 'IN')]

Find a part of the speech for each of the token words with NLTK. Each word will get a part of the speech value associated with it and it is represented by codes like NN for singular nouns

- Basic NLTK (pos_tag) – On the 51th row of the sample reviews

Modeling & Analysis

VADER: Valence Aware Dictionary and Sentiment Reasoner

We are starting by using the NLTK's **SentimentIntensityAnalyzer** to get the **negative** (neg), **neutral** (neu) and **positive** (pos) scores for the text.

Approach:

- Uses a "bag of words" approach
- Stop words are removed - words like (is, the, am, etc.)
- Each word is scored and combined to a total score to get the overall sentiment score of the text.

Limitations:

- Does not account for relationships between words, which is an important part of human speech.

Basic NLTK – VADER Sentiment Scoring

```
# Initializing a Sentiment Analyzer Model
Sia = SentimentIntensityAnalyzer()
```

```
#example of using sentiment analyzer on a positive sentence
sia.polarity_scores('I am so happy! Today is such a great day and I love ML.')
```

```
{'neg': 0.0, 'neu': 0.389, 'pos': 0.611, 'compound': 0.9272}
```

```
#on the other hand sentiment analyzer on a negetive example
sia.polarity_scores('This is the worst thing ever, I would never buy something this bad.')
```

```
{'neg': 0.451, 'neu': 0.549, 'pos': 0.0, 'compound': -0.8491}
```

```
#It can also work well on some confusing sentences - to give a overall slightly positive rating for this sentence.
sia.polarity_scores('hey, I hate you, just kidding you know I love you!')
```

```
{'neg': 0.237, 'neu': 0.385, 'pos': 0.378, 'compound': 0.2942}
```

- BASIC NLTK – Examples of using sentiment analyzer on sentences

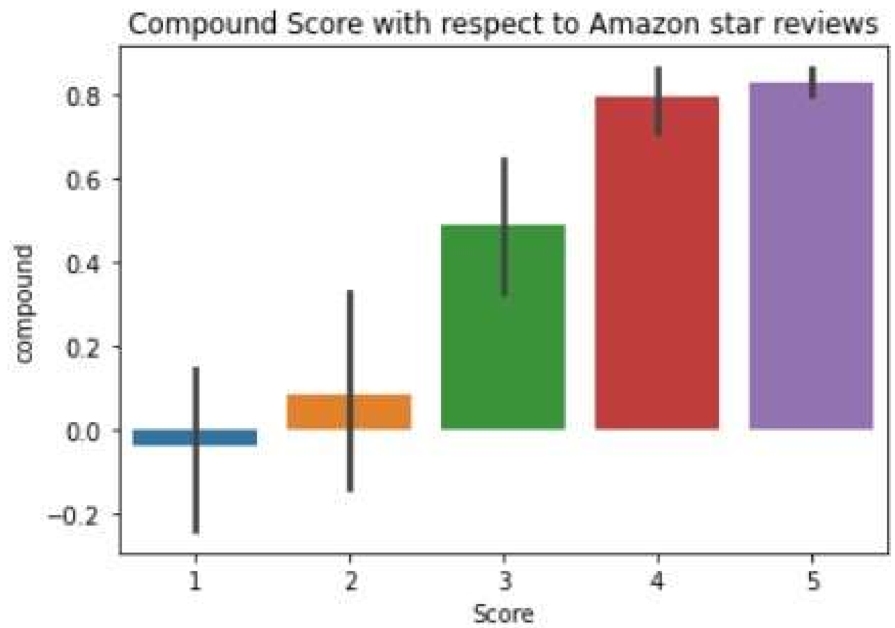
Observations:
We are successfully able to identify the overall sentiment of the text with compound score which varies between 1 (for positive) and -1 (for negative).

neg	neu	pos	compound	Score	review_text
0.070000	0.800000	0.130000	0.842200	1	Sprayed orange grease all over the inside of the microwave The pop-up bowl sounds like a great idea, but evidently they rushed it to market before all the bugs were out. The first bag I cooked was fine, except the instructions for opening the bag are far from clear, and even after you figure out how to do it it's a lot of trouble and makes a big mess. But the second bag evidently sprang a leak - it sprayed bright orange grease all over the inside of my microwave, even into the tiny vent holes inside the top and side. I always watch popcorn carefully while it pops, but I could not see the grease spray until after it was done and I opened the door. Cleaning it all out was a horrible ordeal, and I'm sure everything I cook in the microwave will come out smelling like popcorn grease for weeks. They released this product too soon. It needs serious redesign. I will not buy it again.
0.082000	0.727000	0.192000	0.765500	3	Had higher expectations It is a naturally sweetened soda with Stevia, but I expect more robust flavor simular to Dr. Pepper. I wouldn't even say it is close to Dr. Pepper. I was disappointed, especially when I love the "Cola" flavor of Zevia so much.
0.025000	0.807000	0.168000	0.923800	5	Everything is as it should be I ordered these nuts...for both my own personal consumption...and my two African Greys Scaredy Bird and Reggie. I believe I can speak for all of us in saying that the nuts arrived on time and in delectable condition. They were fresh....and arrived not broken or damaged in any way. Diamond Nuts..has a high reputation with me---and they continue to prove their worth..by sending out a excellent product ! I do --highly recommend this company--and this product !
0.092000	0.693000	0.214000	0.906100	5	So Happy I found this; Product is Fabulous I decided to stop using sweet n' low for obvious reasons. I hated the cost of buying the boxes of Splenda in my locale grocery, as it was so expensive. When I googled Splenda and found this I was elated and ordered it right away. I will order a second for my home upstate shortly, as I certainly cannot transport this box in an efficient manner and I need it in my City location.
0.000000	0.497000	0.503000	0.969200	5	Great tea, very satisfying Nice mellow tea for all occassions. I'm an ex-coffee drinker searching for an alternative and this product fit nicely. It's smooth, very satisfying. Nice product.

- BASIC NLTK – Results of using sentiment analyzer on the sentences in the reviews.

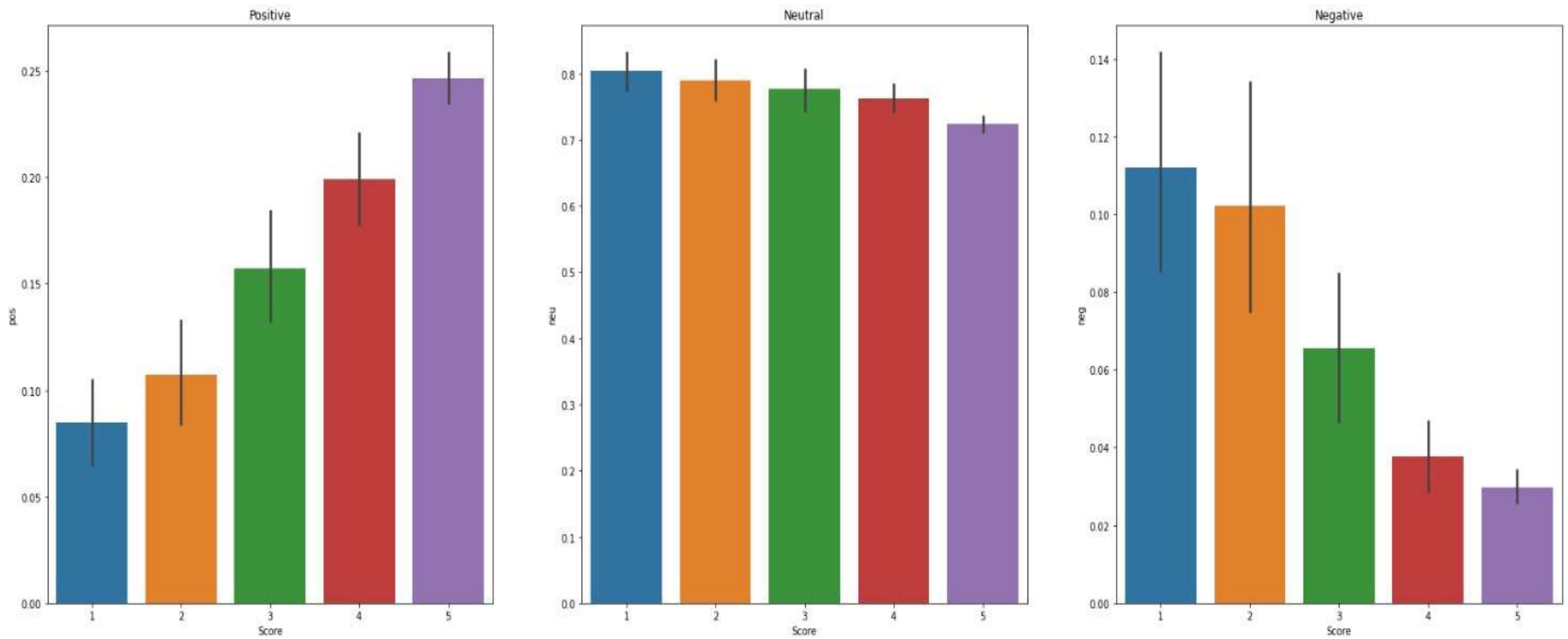
- One way to see if our model is working as expected, is to check an assumption.
- We can assume that the reviews our model classifies as more positive has higher star review and the ones predicted to be more negative have a lower star review associated with them.
- If this is true then, we can rely on text sentiment analysis to indicate how our users feel about products overall.

Observation: The assumption seems to be right because higher star reviews have a high compound score associated with them.



▪ BASIC NLTK – How to measure effectiveness?

Taking a look at each component of sentiment analysis (pos, neu and neg) with respect to the star reviews



▪ BASIC NLTK – Components of Sentiment Analysis vs star reviews

Observations:

- Positive score is higher as star reviews are higher
- Neutral score do not vary much across different star reviews
- Negative score decreases with lower star reviews

We can conclude that our sentiment analysis score is related to the star reviews given by the users

Limitations:

- This way of analyzing text with **VADER** does not consider the relationship between the words and the context in which they are used. We can improve upon that by using the state of the art Transformer based **BERT** model which can understand and learn context and make better predictions on overall sentiment.

- Basic NLTK – VADER Sentiment Scoring observations and limitations

- Now let's try the RoBERTa model trained on large samples of data (with hundred Millions+ examples)
- This Transformer model accounts for the words but also their context related to the other words in the text
  - For instance, sentences with negative words in it but actually just sarcastic.
  - Or ironic sentences with positive words but overall negative sentiment.

We are essentially using transfer learning by using pretrained weights of a model created for analyzing the sentiments of tweets to perform reviews of sentiment analysis.

RoBERTa Pretrained Model

```
#VADER Results on example
print(example)
sia.polarity_scores(example)
```

```
Great Price, Not what I was hoping for though. There's the original Tang. There's the fruition Tang that was around from 2008 to 2010, which had extra vitamins (B,D,A, etc.) and replaced half the sugar wi
th zero calorie sweeteners. But tang has gone back to a flavor more similar to the original with full sugar content. I was hoping for the fruition version, which other reviewers received.
{'neg': 0.064, 'neu': 0.815, 'pos': 0.12, 'compound': 0.6169}
```

```
scores = output[0][0].detach().numpy()
scores = softmax(scores)
scores_dict = {
    'roberta_pos': scores[0],
    'roberta_neu': scores[1],
    'roberta_neg': scores[2],
}
scores_dict
```

```
{'roberta_pos': 0.09246168, 'roberta_neu': 0.5420258, 'roberta_neg': 0.3655125}
```

- Comparing RoBERTa and VADER Performances on our example

```
print(f"User's actual given star review on the example is: {df['Score'][50]}")
```

```
User's actual given star review on the example is: 4
```

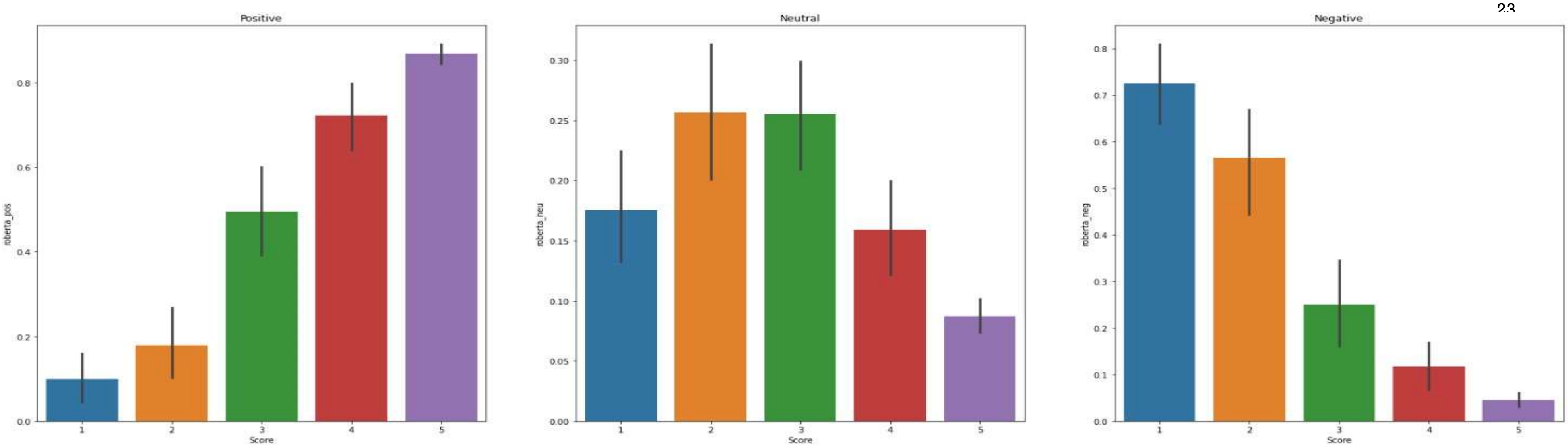
Observation:

The RoBERTa Model seems to better understand the context, and give a more appropriate score for the given example. The user starts with a positive comment but actually have some complaints about the products. We can confirm from user's given rating that the overall sentiment and review is still positive.

- Comparing RoBERTa and VADER Performance on our example

roberta_neg	roberta_neu	roberta_pos	vader_neg	vader_neu	vader_pos	vader_compound	Score	review_text
0.655937	0.270591	0.073472	0.064000	0.805000	0.132000	0.726900	1	Sprayed orange grease all over the inside of the microwave The pop-up bowl sounds like a great idea, but evidently they rushed it to market before all the bugs were out. The first bag I cooked was fine, except the instructions for opening the bag are far from clear, and even after you figure out how to do it it's a lot of trouble and makes a big mess. But the second bag evidently sprang a leak - it sprayed bright orange grease all over the inside of my microwave, even into the tiny vent holes inside the top and side. I always watch popcorn carefully while it pops, but I could not see the grease spray until after it was done and I opened the door. Cleaning it all out was a horrible ordeal, and I'm sure everything I cook in the microwave will come out smelling like popcorn grease for weeks. They released this product too soon. It needs serious redesign. I will not buy it again.
0.555764	0.328938	0.115297	0.082000	0.727000	0.192000	0.765500	3	Had higher expectations It is a naturally sweetened soda with Stevia, but I expect more robust flavor simular to Dr. Pepper. I wouldn't even say it is close to Dr. Pepper. I was disappointed, especially when I love the "Cola" flavor of Zevia so much.
0.002329	0.030420	0.967251	0.025000	0.807000	0.168000	0.919400	5	Everything is as it should be I ordered these nuts...for both my own personal consumption...and my two African Greys Scaredy Bird and Reggie. I believe I can speak for all of us in saying that the nuts arrived on time and in delectable condition. They were fresh....and arrived not broken or damaged in any way. Diamond Nuts..has a high reputation with me---and they continue to prove their worth..by sending out a excellent product ! I do --highly recommend this company--and this product !
0.090271	0.174114	0.735615	0.092000	0.693000	0.214000	0.906100	5	So Happy I found this; Product is Fabulous I decided to stop using sweet n' low for obvious reasons. I hated the cost of buying the boxes of Splenda in my locale grocery, as it was so expensive. When I googled Splenda and found this I was elated and ordered it right away. I will order a second for my home upstate shortly, as I certainly cannot transport this box in an efficient manner and I need it in my City location.
0.002495	0.013362	0.984142	0.000000	0.497000	0.503000	0.969200	5	Great tea, very satisfying Nice mellow tea for all occassions. I'm an ex-coffee drinker searching for an alternative and this product fit nicely. It's smooth, very satisfying. Nice product.

- Run RoBERTa model over all the review examples



Observation:
With the roBERTa model the trend seems to be even more precise. When positive score increases the star rating increases and with lower star reviews negative sentiment decreases drastically. Thus, we can get a better idea of how the users are feeling with text sentiment predictions using the RoBERTa Model.

- Plot of RoBERTa model results over all the review examples

Which are the examples that our models classifies as having a positive sentiment but it actually has a low star rating?

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

```
"YUCH! Impressed,as always,with Amazon's expedient delivery. I perused customer reviews before ordering and felt comfortable with my choice (I was going to get the Emeril Bourbon Street blend , which I lo
ve) as reviewers gave this a great rating. I find it strong but bitter as opposed to strong and rich. Would not recommend this blend to anyone. No negatives to Amazon but wonder who could find this a plea
surable coffee."
```

We can see this is a confusing statement as the user praises Amazon's service but is actually disappointed by the product, and our VADER model was not able to make that distinction.

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

```
"YUCH! Impressed,as always,with Amazon's expedient delivery. I perused customer reviews before ordering and felt comfortable with my choice (I was going to get the Emeril Bourbon Street blend , which I lo
ve) as reviewers gave this a great rating. I find it strong but bitter as opposed to strong and rich. Would not recommend this blend to anyone. No negatives to Amazon but wonder who could find this a plea
surable coffee."
```

RoBERTa model also got the same review wrong

Review Examples: Positive Sentiment Prediction but low star review

Which are the examples that our models classifies as having a negative sentiment but it actually has a high star rating?

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

```
"Miss those nuts Really enjoy those Redskins. Realy disappointment that Planters discontinued those big cans. Now I have to buy small ones frequently. Let's get them back."
```

The sentence does contain words like disappointment and user does want some changes in product but overall, the user has a positive sentiment towards the product.

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

```
"price warp Exceptional coffee, but now priced out of my league.  This is the most totally unreasonable price hike I've seen in a long while--anywhere for anything."
```

In the text review, the user expresses disagreement with change in product price, so our model classified it as a negative sentiment but the user's overall sentiment towards the product is positive.

- Review Examples: Negative Sentiment Prediction but high star review

Finally, let's use the **BERT** based model from hugging face 🤗 to classify the text between 1 to 5 star rating depending on the sentiment of the comment.

- Instead of just predicting if the review is positive or not, we can get a more quantitative result in form of a rating.

```
#Load the model
ratings_model_name = 'nlptown/bert-base-multilingual-uncased-sentiment'
ratings_tokenizer = AutoTokenizer.from_pretrained(ratings_model_name)
ratings_model  = AutoModelForSequenceClassification.from_pretrained(ratings_model_name)
```

```
tokenizer_config.json: 100%   39.0/39.0 [00:00<00:00, 161B/s]
config.json: 100%   953/953 [00:00<00:00, 27.7kB/s]
vocab.txt: 100%   872k/872k [00:00<00:00, 1.57MB/s]
special_tokens_map.json: 100%   112/112 [00:00<00:00, 1.04kB/s]
pytorch_model.bin: 100%   669M/669M [00:45<00:00, 14.7MB/s]
```

- BERT Model: Directly predicting the star rating from the text review

```
print("Example review:", example)
print("\nActual Rating:", df['Score'][50])
```

```
Example review: Great Price, Not what I was hoping for though. There's the original Tang. There's the fruition Tang that was around from 2008 to 2010, which had extra vitamins (B,D,A, etc.) and replaced h
alf the sugar with zero calorie sweeteners. But tang has gone back to a flavor more similar to the original with full sugar content. I was hoping for the fruition version, which other reviewers received.

Actual Rating: 4
```

Actual Star Rating is: 4.

```
ratings_output = ratings_model(**ratings_encoded_text)
```

```
ratings_output.logits[0].detach().numpy()
```

```
array([-1.4275525,  0.7332723,  1.8107648,  0.8325193, -1.6171392],
      dtype=float32)
```

```
#we have to add one as indexing starts from 0 but star ratings are from 1 to 5
ratings_pred = np.argmax(ratings_output.logits[0].detach().numpy()) + 1
print("Predicted Star rating:", ratings_pred)
```

```
Predicted Star rating: 3
```

Predicted Star rating is: 3

- BERT Model: Directly predicting the star rating from the example

- We can exactly predict the rating of review with ~70% accuracy and can predict the rating very closely (just one more or less) with 95% accuracy.

- We can now say the model works considerably well and can be used to understand the users sentiments over new products and services in the future or we can use it to analyze some other existing products or businesses.

rating	Score	review_text
2	1	Sprayed orange grease all over the inside of the microwave The pop-up bowl sounds like a great idea, but evidently they rushed it to market before all the bugs were out. The first bag I cooked was fine, except the instructions for opening the bag are far from clear, and even after you figure out how to do it it's a lot of trouble and makes a big mess. But the second bag evidently sprang a leak - it sprayed bright orange grease all over the inside of my microwave, even into the tiny vent holes inside the top and side. I always watch popcorn carefully while it pops, but I could not see the grease spray until after it was done and I opened the door. Cleaning it all out was a horrible ordeal, and I'm sure everything I cook in the microwave will come out smelling like popcorn grease for weeks. They released this product too soon. It needs serious redesign. I will not buy it again.
3	3	Had higher expectations It is a naturally sweetened soda with Stevia, but I expect more robust flavor simular to Dr. Pepper. I wouldn't even say it is close to Dr. Pepper. I was disappointed, especially when I love the "Cola" flavor of Zevia so much.
5	5	Everything is as it should be I ordered these nuts...for both my own personal consumption...and my two African Greys Scaredy Bird and Reggie. I believe I can speak for all of us in saying that the nuts arrived on time and in delectable condition. They were fresh....and arrived not broken or damaged in any way. Diamond Nuts..has a high reputation with me---and they continue to prove their worth..by sending out a excellent product ! I do --highly recommend this company--and this product !
5	5	So Happy I found this; Product is Fabulous I decided to stop using sweet n' low for obvious reasons. I hated the cost of buying the boxes of Splenda in my locale grocery, as it was so expensive. When I googled Splenda and found this I was elated and ordered it right away. I will order a second for my home upstate shortly, as I certainly cannot transport this box in an efficient manner and I need it in my City location.
5	5	Great tea, very satisfying Nice mellow tea for all occassions. I'm an ex-coffee drinker searching for an alternative and this product fit nicely. It's smooth, very satisfying. Nice product.

```
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(ratings_df['rating'], ratings_df['Score'])
accuracy
```

```
0.692
```

```
one_off_accuracy = np.where(abs(ratings_df['rating'] - ratings_df['Score']) <= 1, 1, 0).sum() / ratings_df.shape[0]
one_off_accuracy
```

```
0.95
```

BERT Model: Make prediction for all reviews

- We have selected a restaurant business on Yelp and collected some reviews from the customers to see if this is a place where people like to eat or NOT. We could do a similar test for any business and collect data from multiple sources like twitter, reddit, YouTube, Facebook, Instagram and more.

```
reviews[:2]
```

```
["Seated without a booking on a super busy Saturday night. Lovely, warm, and Theo right hostess also looked after our table and went out of her way to give detailed ingredients in every dish to avoid alle
rgies for one of us. And the food was great! Guacamole made right at our table, everything prepared with our allergies in mind, and great dish recommendations. We'd been visiting Sydney for about a week f
rom Melbourne, and this was by far our best dining experience. I'd definitely return here in the future.",
 'The food was decent not great..  We had the guacamole which was bland and came with some type of plantain chips.. The chicken and steak tacos were good.. But the service was poor. We had a waitress with
an attitude. She seemed upset whenever we asked for anything.  She would walk by and just stick up her hand and say " just wait ".  She spilled the ingredients to make the guacamole all over the table but
never apologized. The waitress didn\'t come by at all, not even once to check on us.. I will not go back. Suggest you find a Mexican restaurant that really wants your business..']
```

review_text
Seated without a booking on a super busy Saturday night. Lovely, warm, and Theo right hostess also looked after our table and went out of her way to give detailed ingredients in every dish to avoid allergies for one of us. And the food was great! Guacamole made right at our table, everything prepared with our allergies in mind, and great dish recommendations. We'd been visiting Sydney for about a week from Melbourne, and this was by far our best dining experience. I'd definitely return here in the future.
The food was decent not great.. We had the guacamole which was bland and came with some type of plantain chips.. The chicken and steak tacos were good.. But the service was poor. We had a waitress with an attitude. She seemed upset whenever we asked for anything. She would walk by and just stick up her hand and say " just wait ". She spilled the ingredients to make the guacamole all over the table but never apologized. The waitress didn't come by at all, not even once to check on us.. I will not go back. Suggest you find a Mexican restaurant that really wants your business..
Food was okay, guacamole was below average. Service was awful. Waitress acted like she was missing the Finals in The Australian Open. In such a hurry she spilled the fixings for the less than average guac. Took less than a minute to take our order but it wasn't fast enough for her. Felt like we were intruding on her screen time. The food was fair. Prices were way too high for the level of mediocrity in the food. Average food, lousy service Wouldn't recommend this place
The food and service here was really good. It was more like tapas food than Mexican food! The drinks were amazing too!
Visiting from Texas and decided to give this restaurant a try. We were pleasantly surprised. While the margaritas are more like martinis, the food was excellent. More like a tapas, Mexican fusion. Great way to try different plates.The real treat was Chelsea, our waitress. Took the time to explain the menu and offer suggestions. Always smiling and very pleasant. Best service we have had in Sydney!

- BERT Model: Using Model to make predictions on new data scraped from Yelp to perform Sentiment Analysis

- We can perform a sentiment analysis over these text reviews
- Using RoBERTa model to get different component scores (pos, neu and neg) and BERT to predict numerical star ratings

roberta_neg	roberta_neu	roberta_pos	rating	review_text
0.655937	0.270591	0.073472	2.000000	Seated without a booking on a super busy Saturday night. Lovely, warm, and Theo right hostess also looked after our table and went out of her way to give detailed ingredients in every dish to avoid allergies for one of us. And the food was great! Guacamole made right at our table, everything prepared with our allergies in mind, and great dish recommendations. We'd been visiting Sydney for about a week from Melbourne, and this was by far our best dining experience. I'd definitely return here in the future.
0.555764	0.328938	0.115297	3.000000	The food was decent not great.. We had the guacamole which was bland and came with some type of plantain chips.. The chicken and steak tacos were good.. But the service was poor. We had a waitress with an attitude. She seemed upset whenever we asked for anything. She would walk by and just stick up her hand and say " just wait ". She spilled the ingredients to make the guacamole all over the table but never apologized. The waitress didn't come by at all, not even once to check on us.. I will not go back. Suggest you find a Mexican restaurant that really wants your business..
0.002329	0.030420	0.967251	5.000000	Food was okay, guacamole was below average. Service was awful. Waitress acted like she was missing the Finals in The Australian Open. In such a hurry she spilled the fixings for the less than average guac. Took less than a minute to take our order but it wasn't fast enough for her. Felt like we were intruding on her screen time. The food was fair. Prices were way too high for the level of mediocrity in the food. Average food, lousy service Wouldn't recommend this place
0.090271	0.174114	0.735615	5.000000	The food and service here was really good. It was more like tapas food than Mexican food! The drinks were amazing too!
0.002495	0.013362	0.984142	5.000000	Visiting from Texas and decided to give this restaurant a try. We were pleasantly surprised. While the margaritas are more like martinis, the food was excellent. More like a tapas, Mexican fusion. Great way to try different plates.The real treat was Chelsea, our waitress. Took the time to explain the menu and offer suggestions. Always smiling and very pleasant. Best service we have had in Sydney!

```
yelp_results_df.rating.mean()
```

```
4.026
```

BERT Model: Yelp Data prediction results

VADER, RoBERTa and BERT Models Evaluation

VADER

- **SentimentIntensityAnalyzer** to get the negative (neg), neutral (neu) and positive (pos) scores for the text

RoBERTa

- **RoBERTa Transformer model** accounts for the words but also their context related to other words

BERT

- **BERT based model** directly classify the text between 1 to 5 star rating depending on the sentiment of the comment.

Model evaluation

VADER

- Does not account for relationships between words, which is an important part of human speech.

RoBERTa

- The RoBERTta Model does seem to better understand the context and give an overall more appropriate score for the given example.

BERT

- We can exactly predict the rating of review with ~70% accuracy and can predict the rating very closely (just one more or less) with 95% accuracy.

Conclusion

Conclusion

Using text reviews we predicted that the restaurant has an overall rating of approximately 4, and we confirm that our model can give us a good idea about sentiment towards any business with just text reviews because the actual rating of the restaurant is 4.5 and we were able to closely predict that with just a small sample of reviews. We could improve our prediction by analyzing all the reviews.

How is all of this useful?

We can use hundreds of thousands of online comments and text reviews posted by people on social media about any particular product, movie, service, business or Ad campaign to understand the overall feeling of public towards that. We can use this approach to better select and market our products and make data driven decisions. My recommendation will be to use the **RoBERTa** model to better understand the context and obtain an appropriate score, then use the **BERT** model to predict the rating of reviews with high accuracy .

This can help us deliver better services and increase profit margins among other things.

Conclusion and Recommendation

Appendix

```python
#function to perform sentiment analysis for any given text and also predict the numerical rating out of 5
def predict_sentiment_and_rating(text):
    #making sentiment predictions using roberta model (positive, neutral and negative)
    roberta_result = polarity_scores_roberta(text)

    #making star prediction using bert model (stars / score out of 5)
    bert_result = rating_prediction_bert(text)

    #combine both results
    result = roberta_result.copy()
    result.update(bert_result)

    return result
```

- Function for making predictions

- We can use this function in the future to make predictions on any review to analyze the sentiment of the user and learn their opinion quantitatively

- This function can also be used to deploy a simple web app that works for a single review at a time or a batch of multiple reviews.

```
predict_sentiment_and_rating("Oh I love this place this is the most amazing thing ever. It great every time I go there.")
```

```
{'roberta_neg': 0.0026398143,
 'roberta_neu': 0.004872264,
 'roberta_pos': 0.9924879,
 'rating': 5}
```

```
predict_sentiment_and_rating("No I am not a fan of this, not recommended at all.")
```

```
{'roberta_neg': 0.970489,
 'roberta_neu': 0.026750673,
 'roberta_pos': 0.0027602962,
 'rating': 1}
```

Predictions Examples using our Custom Predictions Function