NLP Analysis of Google Reviews for Saudi Arabian Sites

Artefact Data Science Assessment

Vishesh Chugh

Table of Contents

- Sentiment Analysis Methodology
 - o Overview
 - o Detailed Steps
 - Text Preprocessing
- Findings
 - o EDA & Insights
- Recommendations
 - o Key Strategies

Sentiment Analysis Methodology

Overview

<pre>print(df.shape) df.head(5)</pre>											
(10000, 7)											
	id	content	date	language	tags	title	ratings				
0	377380- 203583770957	من الاماكن الهاديه الجميله الممتعه فيالتسوق ت	2021-04- 11T06:45:00+00:00	ara	[{'value': 'c07bdfc8hb0r13sa7agg', 'sentiment'	Al Ahsa Mall by Arabian Centres	{'normalized': 100, 'raw': 5}				
1	377380- 203585579625	مساحة خضراء تتنفس فيها الهواء النقي المناظر	2021-04- 11T06:45:00+00:00	ara	[{'value': 'c07bdncbb64t6si78ssg', 'sentiment'	King Abdullah Park, Sea front	{'normalized': 100, 'raw': 5}				
2	377380- 203590496913	nice place	2021-04- 11T06:45:00+00:00	eng	[{'value': 'c0rlhqgcu1i938rekca0', 'sentiment'	Green Mountain Resort	{'normalized': 100, 'raw': 5]				
3	377380- 203589330972	پ جميل	2021-04- 11T06:45:00+00:00	ara	[{'value': 'c9ga0skbb64rs4ni6s7g', 'sentiment'	Waterfront Beach Royal Commission Yanbu	('normalized': 80, 'raw': 4				
4	377380- 203586632060	جميييل	2021-04- 11T06:45:00+00:00	ara	[{'value': 'c07bdncbb64t6si78ssg', 'sentiment'	Dammam Corniche	{'normalized': 100,				

- After removing duplicates (11 rows), we are left with 9989 reviews, out of which ~24% is
 English "content" or "title" & 76% is Arabic "content" or "title".
- To proceed with sentiment analysis there are multiple ways one can take to do this, some of them that I could think of (in increasing order of complexity & sophistication):
 - Use "ratings" column to generate sentiment (Higher rating -> positive sentiment;
 lower rating -> negative sentiment)
 - 2. **Translate Arabic text to English** and utilize various approaches such as lexicon-based sentiment analysis, pre-trained transformer models.
 - 3. Treat Arabic & English text separately, utilize CAMeL-Lab/camel_tools (very sophisticated library developed by NYU Abu Dhabi) to perform sentiment analysis on Arabic Text & lexicon-based/pre-trained for English
 Ref: https://github.com/CAMeL-Lab/camel_tools

Due to limited time, computational power & for ease of understanding the results & EDA. I finalized approach 2 mentioned above

Detailed Steps

• Utilized GoogleTranslator API to translate Arabic text to English.

```
from deep_translator import GoogleTranslator

name = 'المجميل'
name_translated = GoogleTranslator('ar', 'en').translate(name)
print(name_translated)

Beautiful*
```

• Used VADER (Valence Aware Dictionary for Sentiment Reasoning) model to generate sentiment (positive, negative, neutral) for the text.

VADER is a **lexicon and rule-based sentiment analysis** tool that is specifically attuned to sentiments expressed in social media

It is equipped with the following characteristics, which makes it easy to implement directly without any pre-processing:

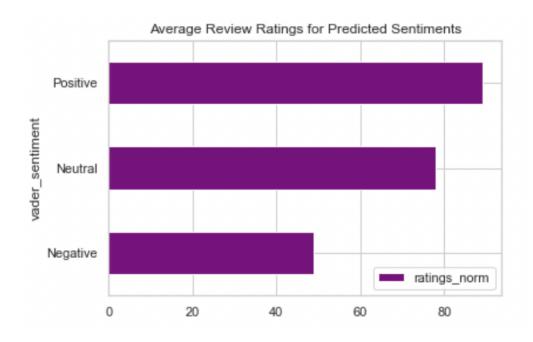
- o typical negations (e.g., "not good")
- o use of contractions as negations (e.g., "wasn't very good")
- conventional use of punctuation to signal increased sentiment intensity (e.g.,
 "Good!!!")
- conventional use of word-shape to signal emphasis (e.g., using ALL CAPS for words/phrases)
- using degree modifiers to alter sentiment intensity (e.g., intensity boosters such as "very" and intensity dampeners such as "kind of")
- understanding sentiment-laden initialisms and acronyms (for example: 'lol')
 Ref: github.com/cjhutto/vaderSentiment

```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
def sentiment_scores(sentence):
# Create a SentimentIntensityAnalyzer object.
sid_obj = SentimentIntensityAnalyzer()
sentiment_dict = sid_obj.polarity_scores(sentence)
# decide sentiment as positive, negative and neutral
if sentiment_dict['compound'] >= 0.05 :
    return "Positive"
elif sentiment_dict['compound'] <= - 0.05 :
    return "Negative"
else :
    return "Neutral"

sentiment_scores('A green space where you can breathe fresh air.')
'Positive'</pre>
```

'Negative'

sentiment_scores('food was not so great')



Insights

Average ratings (out of 100) seem in-line with the predicted sentiment using VADER. Positive sentiments have higher average rating as compared to Neutral & Negative sentiments.

Text Preprocessing

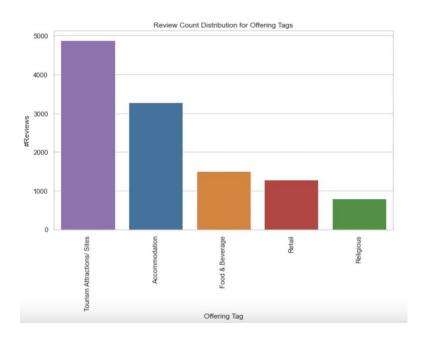
We apply the below string cleaning steps after prediction of sentiment for deeper insights:

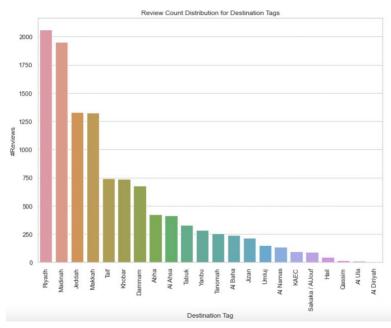
- Remove non-alphanumerics, URLs using regex
- Convert to lower-case
- Remove custom list of stop-words using nltk
- Tokenize the text & apply WordNetLemmatizer along with using POS tags as inputs

```
from nltk.corpus import wordnet
def get_wordnet_pos(treebank_tag):
    if treebank_tag.startswith('J'):
         return wordnet.ADJ
    elif treebank_tag.startswith('V'):
         return wordnet.VERB
     elif treebank_tag.startswith('N'):
         return wordnet.NOUN
     elif treebank_tag.startswith('R'):
         return wordnet.ADV
     else:
         return wordnet.NOUN
def clean_text(a):
    a_replaced = re.sub('[^A-Za-z0-9]+', ' ', a)
a_replaced = re.sub(r'w+:/{2}[dw-]+(.[dw-]+)*(?:(?:/[^s/]*))*', '', a_replaced)
     return a_replaced
w_tokenizer = tokenize.WhitespaceTokenizer()
lemmatizer = WordNetLemmatizer()
def lemmatize_text(text):
    return \ [lemmatizer.lemmatize(w,get\_wordnet\_pos(dict(nltk.pos\_tag([w]))[w])) \\
              for w in w_tokenizer.tokenize(clean_text(text.lower()))
if w not in stopwords.words('english') + ["google","translated"]]
df_nlp['review_lemmas'] = df_nlp['content_en'].apply(lambda x : lemmatize_text(x))
lemmatize_text('I am running, so exciting, loving it')
['run', 'excite', 'love']
```

Findings

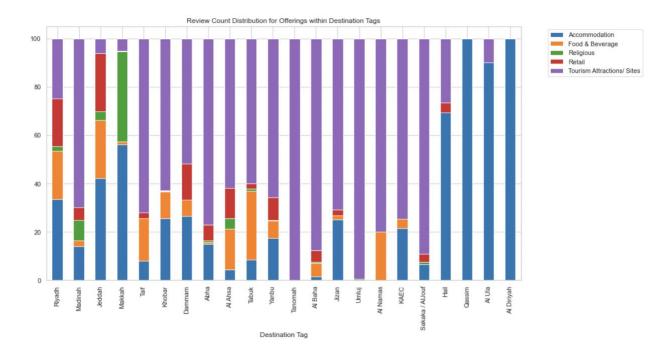
EDA & Insights





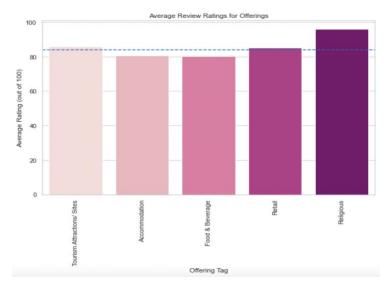
Insights

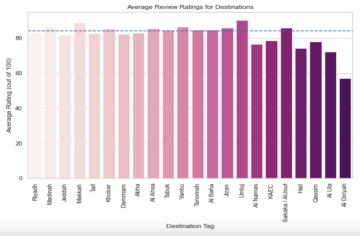
Using the mapping file to extract tags for each review. We see that maximum reviews are related to Tourism Attraction/Sites & Accommodation & from major cities like Riyadh & Madinah.



Insights

- Majority of Religious & Accommodation reviews come from Makkah, with almost negligible Retail and Food & Beverage reviews.
- Tourism Attraction being the dominant reviews overall, are found to be the least in Jeddah
 & Makkah.
- ~90% reviews in Jeddah come from Accommodation, Food & Beverage and Retail
- Madinah is dominated by Tourism Attraction reviews ~70%
- Riyadh consists of an approximately even distribution of Accommodation & Tourism
 Attraction and Food & Beverage & Retail reviews.





Insights

- Average overall rating in the dataset = 84 (blue dotted line), average rating for
 Religious tag is significantly higher than the overall average. Correspondingly, average rating for Makkah is also higher than the overall average since most of its reviews come from the Religious category.
- Average rating for Accommodation and Food & Beverage tags is lower than the
 overall average of the dataset. Correspondingly, average rating for Jeddah is
 marginally lower than the overall average since ~65% of its reviews are derived from
 Accommodation and Food & Beverage categories

Recommendations

Overall Key Strategies	Accommodation	Food & Beverage	Tourism	Religious	Retail
1	Deploy well trained reception staff for a smooth check-in/out experience Offer complementary welcome drinks	Keep a check on quality of service & experience provided without compromising on the taste	Deploy public facilities like bathrooms and maintain proper hygiene and cleanliness	Effective communication of mosque social etiquette for tourists, respecting tradition & culture	Efficient parking lot management for elevated end-to-end shopping experience
2	Keep a check on old room furniture, cleanliness & room service	Focus on proper functioning of air-conditioner, maintaining hygiene & cleanliness	Devise proper seating arrangement for tourists at public areas.		
3	A lot of tourists visit Makkah for religious purposes, positive accommodation experience is key for tourists	Better efficiency leading to lesser waiting time for customers			