HIGH SCHOOL EDITION
Journal of Student Research

Volume 12 Issue 3 (2023)

Is Artificial Intelligence Intelligent Enough to Read Human Sentiment?

Rayna Jindal

California High School

ABSTRACT

Sentiment analysis is the mining of text which extracts information from the source material and helps a business to understand the social sentiment of their service while monitoring online conversations. Sentiment analysis can apply in any social domain because opinions are central to human activities and prominent influencer of our behaviors. Our beliefs, perceptions of reality, and choices are conditioned by how others evaluate the world. Due to this, when humans need to make a decision, they often seek out the opinions of others. According to GlobalWebIndex, 54% of social media users use media reviews, and 71% are more likely to purchase services based on social media referrals. Therefore, Sentiment analysis is "opinion mining" because it's all about digging into the context of social posts to understand the opinions they reveal. Misleading information has a more substantial effect on society than before. Not only this, but cognitive bias is also systematic errors in thinking, usually inherited by cultural and personal experiences, that can lead to distortions of perceptions when making decisions. Consequently, sentiment analysis can provide you with a broader perspective prior to making a final decision. This research aims to use artificial intelligence techniques for an in-depth analysis of human sentiments. The use cases and dataset used for this research are:

- Stock Analysis using FinViz website
- Climate Change Analysis using Twitter
- Movie review using IMDB dataset

I used NLTK, Vader and Logistic regression machine-learning models and received approx 80% accuracy which shows us it is very promising that Machine Learning can help understand human sentiments and facilitates informed decision-making.

Introduction

Sentiment analysis can help companies understand how customers feel about a brand and identify which issues are urgent. Some of the benefits of Sentimental Analysis for organization are:

1. **Customer Service:** As today's customer service goes far beyond the traditional telephone support agent, it is challenging to maintain excellent customer relationships. 80% of customers would switch to a competitor after two or more bad experiences. The quicker you react, the better your chance of resolving the problem. Happy customers will market positive opinions about your brand. With Sentiment analysis, you can review customer feedback and responses and thus identify the negative comments and reasons why the customers have issues with your product.
2. **Marketing Campaigns:** Sentiment Analysis can help companies to boost their marketing strategy and can take a more agile approach. Marketers can study industry trends by analyzing sentiment toward new features or products on social media.

3. **Brand Monitoring:** With the help of Sentiment analysis techniques, you can easily monitor the industry through customers' eyes. It helps identify why your customers are unhappy and what they are complaining about. The thread of negative comment lists on top gives you ample time to react and listen to your customers.

But how can one do that? With the recent advances in deep learning, the creative use of advanced artificial intelligence techniques can be an effective tool for in-depth research to analyze text. Intent analysis helps in analyzing the user's intention behind a message and identifying whether it relates to an opinion, news, marketing, complaint, suggestion, appreciation, or query. But before that, what aspect of the brand a user is discussing is essential to understand. For example, Amazon may want to segregate messages related to late deliveries, promotion-related queries, product reviews, billing issues, etc.
On the other hand, Starbucks may want to segregate messages based on whether they relate to staff behavior, new coffee flavors, hygiene feedback, online orders, store name, location, etc.

To understand how sentiment analysis can be applied in our daily lives, let us delve into subjects that can affect our decisions and lives in different areas such as financially, relaxation, and awareness and highlight human contemporary feelings. The three topics selected for analysis are stocks, climate-change, and movies. Sentiment analysis on stocks gives insight into one's financial decision making. Similarly, climate-change analysis represents one's insight about critical awareness. Movies analysis represents one's insight about entertainment choices. Moreover, Sentiment Analysis is the most used text classification tool that analyzes any message and categorizes whether the sentiment associated with the message is positive, negative, or neutral.

Material and Methods

The use cases are divided into four sections, data generation, data formatting, sentiment analysis, and visualization.

Step 1: Data generation:

I. **Stock Analysis:** In order to get the sentiments of the people about a certain stock, FinViz is an extremely good place to collect headlines and reviews about different stocks. The data displayed on FinViz are collected from different sources such as Twitter, Bloomberg, Yahoo News, Reuters, and other popular media houses. Using FinViz APIs, we generate data about different stocks.

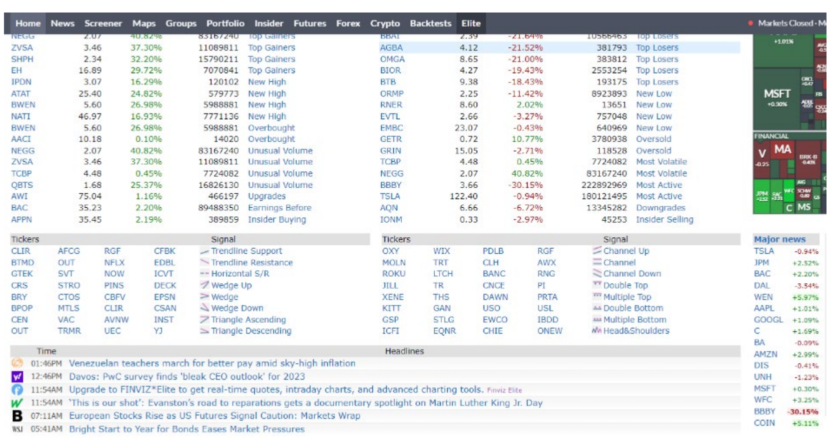

Figure 1: Finviz Sample Stock Data

II. **Climate Change Analysis:** The dataset is from Twitter data set with 44,000 reviews and divided into 4 classes (news, pro, neutral, and anti).

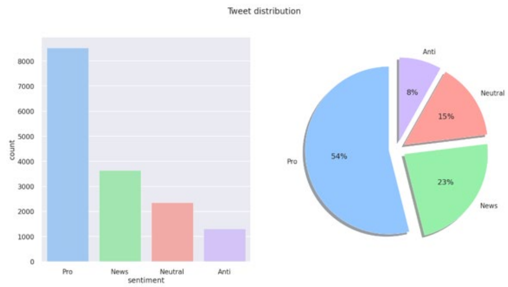

Figure 2: Tweet Distribution on Climate Change

III. **Movie Reviews:** The dataset is from IMDB the data set consists of 50,000 movie reviews. Since the sentiment of reviews is binary, an IMDB rating below 5 gets a sentiment value of 0, and a rating over 7 gets a sentiment score of 1. It was interesting to see how most of the data feedback was positive as shown in the graph.

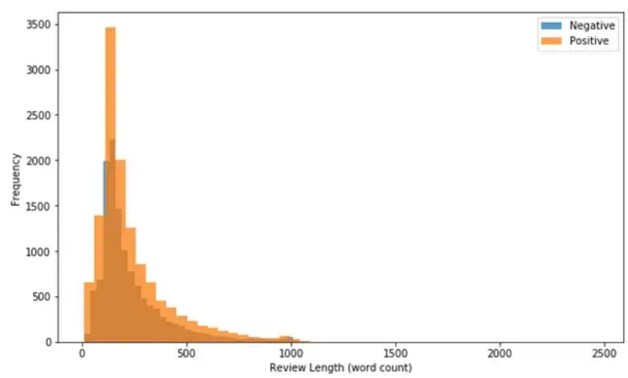

Figure 3: Word Frequency on Movies Reviews Data

Step 2 - Data formatting:

I. **Stock Analysis:** The data received from FinViz APIs are in a specific format. In order to pass this data into our Sentiment Analysis model, we have to clean and parse the stock data. We re-formatted the data in this structure <STOCK> <DATE> <TIME> <HEADLINE>, where stock is the name of the stock, and date and time are used to order data accordingly.

```
[['AMZN',
  'Jan-16-23',
  '01:27PM',
  "Jan-16-23 01:27PM2 FAANG Stocks to Buy in 2023 and 1 to Avoid: Here's Why Motley Fool"],
 ['AMZN',
  'Jan-16-23',
  '12:45PM',
  "12:45PMDavos: PwC survey finds 'bleak CEO outlook' for 2023 Yahoo Finance"],
 ['AMZN',
  'Jan-16-23',
  '11:36AM',
  '11:36AM2 Stocks to Benefit From Falling Inflation GuruFocus.com'],
 ['AMZN',
  'Jan-16-23',
  '11:29AM',
  '11:29AMBig Tech Stocks Could Rebound Big Time. Heres How. Barrons.com'],
 ['AMZN',
  'Jan-16-23',
  '10:34AM',
  '10:34AMAmazon Has a Partner for Enterprise Blockchain Tech. Its Crypto Token Has Soared. Barrons.com']]
```


Figure 4: Sample Formatted Data of Stocks

II. **Climate Change Analysis:** In the beginning, the data was unbalanced and many of the tweets fell under the pro category, especially tweets on the lengthier side. Look at the most frequently used words in tweets for each of the classes. For example, https is recurring which can imply that there are probably a lot of links being shared in tweets that could be about petitions, donations, or other external information regarding climate change. Hashtags are also a great way to see how a person feels about a certain topic or issue so examining the most popular hashtags in each class could be instructive. This will give a better idea of the material that is being delivered in each class.

III. **Movie Reviews:** The data from IMDB is divided into two whether the movie review was positive or negative. Pre-process the text to remove extra words, characters, punctuation, etc. and change all the letters to lowercase since machine learning models can't properly depict these types of texts.

Step 3 - Sentiment Analysis:

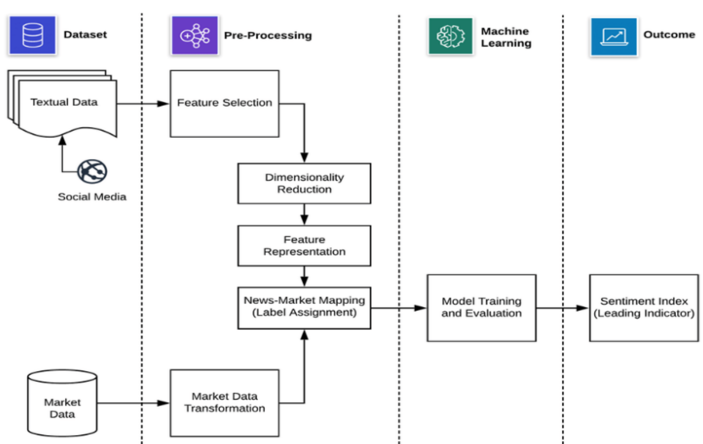

Figure 5: Sentiment Analysis Workflow

The Sentiment Analysis uses Natural Language Processing technique to classify data into different sentiments. The most basic categories are binary in nature, but in climate change cases, we have four different categories. Usually, sentiment analysis is performed using two types of approaches, rule-based approach, and automatic approach:

- Rule-based approach: In this approach, sentiments are determined using manually crafted rules such as tokenization, part-of-speech, tagging, lexicons, etc. Systems built using only this approach require extreme hyper tuning and maintenance for every slight change.
- Automatic approach: In this approach, the problem is treated as a classification problem in which different classification models are used to classify text into sentiments. In this approach, first divide data into training and testing sets, extract features from the data, apply different machine learning models on the extracted feature sets, then tag the sentiments on the results based on a set threshold for each tag.

In this approach, we can use a hybrid of both directions to eliminate some risks with Machine learning models. Setting rules for data parsing and formatting can eliminate the usual noise from data, which could generate preliminary results. After dividing data into training and testing sets, use the following different classification models:

- Random Forest: As its name implies, a random forest consists of many individual decision trees that operate as an ensemble. Each tree in the random forest spits out a class prediction, and the class with the most votes become model's prediction.
- K Nearest Neighbors: It is commonly known as KNN classifier which uses the principle of feature similarity for prediction. This essentially means it uses proximity of the new point and the point in the training set to determine the value of the new point.The proximity distance can be calculated using different methods such as Mahattan, Euclidian, Hamming distance, etc.
- Logistic regression is one of the most commonly used machine learning algorithms for binary classification problems. The purpose of logistic regression is to estimate the probabilities of events, including determining a relationship between features and the possibilities of particular outcomes.
- Linear SVC: This model uses plot for feature set by representing each feature as a dimension and assigning each row of features as a coordinate. To classify new data, decision boundaries are plotted for each class and based on tuned margin or hyperplance, new data can be easily classified into a class.

I. **Stock Analysis:** In this use case, we are using Valence Aware Dictionary and sEntiment Reasoner or VADER for short which uses lexicon and simple rule-based model for sentiment analysis. The primary benefits of using this model is that it does not require past training and it can optimally handles emoticons, punctuations, abbreviations, capitalizations, etc. These benefits reduce risk of generating inaccurate results from the social media texts.

II. **Climate Change Analysis:** In this use case, we will be using all five classification models described above to generate sentiments on the climate data. After gathering the results from these models, we would pick the model which generate the best accuracy. The usage of multiple models allows us to measure which model handles our social media data the best.

III. **Movie Reviews Analysis:** In this use, after formatting the data, we will be using multiple classification models described above to classify sentiments from the movie review data.

Step 4 - Visualization:

We use different plots and graphs to display the accuracy and sentiments achieved through different classification models for visualization.

Result

I. **Stock Analysis:** The goal of this research was to analyze stock sentiments using companies' latest news. From the below graph, we can get the stock sentiment score (positive, negative, neutral) followed by the mean score to make an unbiased decision.

	Stock	Date	Time	News	score	pos	neg	neu	sentiment_score
0	AMZN	Mar-08-23	03:46PM	Jeff Bezos Shows That Mega Yachts Arent Just f...	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound...	0.000	0.0	1.000	0.0000
1	AMZN	Mar-08-23	03:25PM	Southwest Airlines Taps Amazon Cloud Unit To O...	{'neg': 0.0, 'neu': 0.692, 'pos': 0.308, 'comp...	0.308	0.0	0.692	0.5994
2	AMZN	Mar-08-23	01:08PM	Roku Ropes In Stitch Fix's Dan Jedda As New CF...	{'neg': 0.0, 'neu': 0.754, 'pos': 0.246, 'comp...	0.246	0.0	0.754	0.5994
3	AMZN	Mar-08-23	11:50AM	Amazon (AMZN) to Launch NFT Marketplace & 15 C...	{'neg': 0.0, 'neu': 0.805, 'pos': 0.195, 'comp...	0.195	0.0	0.805	0.1779
4	AMZN	Mar-08-23	11:49AM	Can Roku Keep These Key Customers From Switching?	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound...	0.000	0.0	1.000	0.0000

Fig 6: Sentiment Score for Stock Ticker AMZN

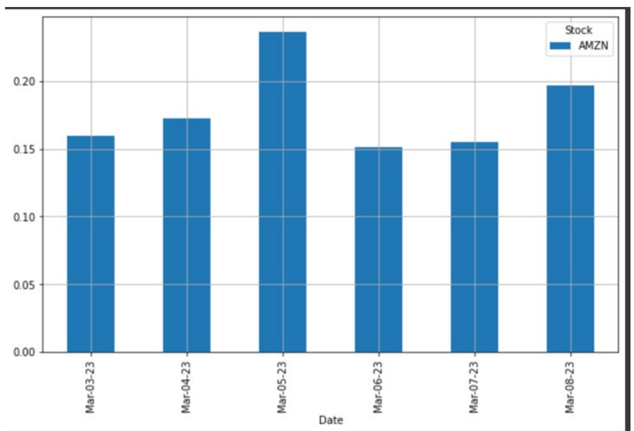

Fig 7: Mean Score for Stock Ticker AMZN

II. **Climate Change Analysis:** To achieve favorable outcomes, various Machine Learning models were compared. Below graphs demonstrate that the Linear Regression model achieved maximum accuracy of appx. 75% which is a promising outcome. This result provides assurance that machine learning can successfully extract impartial information from online reviews.

	precision	recall	f1-score
-1	0.72	0.51	0.59
0	0.59	0.49	0.53
1	0.77	0.87	0.81
2	0.77	0.73	0.75
accuracy			0.74
macro avg	0.71	0.65	0.67
weighted avg	0.73	0.74	0.73

Linear Regression Score

	precision	recall	f1-score
-1	0.51	0.38	0.44
0	0.47	0.42	0.44
1	0.71	0.77	0.74
2	0.62	0.61	0.62
accuracy			0.64
macro avg	0.58	0.55	0.56
weighted avg	0.63	0.64	0.63

Decision Tree Classifier

	precision	recall	f1-score
-1	0.83	0.38	0.52
0	0.66	0.39	0.49
1	0.71	0.92	0.80
2	0.79	0.68	0.73
accuracy			0.73
macro avg	0.75	0.60	0.64
weighted avg	0.73	0.73	0.71

Linear Support Vector Classification

	precision	recall	f1-score
-1	0.49	0.08	0.14
0	0.22	0.94	0.36
1	0.87	0.28	0.42
2	0.83	0.28	0.42
accuracy			0.37
macro avg	0.60	0.39	0.33
weighted avg	0.71	0.37	0.38

K Neighbors Classifier

Fig 8: Different ML Models with accuracy score

III. **Movie Review Analysis:** To obtain reliable outcomes in this result, the Linear Regression model was used. As illustrated in the graph below, the model exhibited an 89% accuracy rate, which is an encouraging outcome and gives us confidence that machine learning can effectively extract unbiased information from online reviews.

	precision	recall	f1-score
0	0.89	0.88	0.89
1	0.89	0.90	0.89
accuracy			0.89
macro avg	0.89	0.89	0.89
weighted avg	0.89	0.89	0.89

Fig 9: Sentiment response and the model accuracy score

Risk Associated with ML Models

The major problem with Machine Learning is the need for better data. While enhancing algorithms often consumes most of the developers' time in AI, good-quality data is essential for the algorithms to function as intended. Machine Learning requires considerable data to perform better than other techniques; otherwise, your analysis can be highly error prone. You may hear that "Garbage in, Garbage out" correctly fits when it comes to machine learning. Data may be limited to one region, race, country, population, etc. Therefore, you need help finding an imbalance in data that leads to poor accuracy of models. Secondly, a machine learning problem can implement various algorithms to find a solution. Running models with different algorithms and identifying the most accurate results is manual and tedious. The main goal of analyzing sentiment is to explore the reviews and examine the scores of sentiments. But these challenges become obstacles in analyzing the accurate meaning of sentiments and detecting the suitable sentiment polarity.

To eliminate some of these risks involved with the Machine Learning models, we are using existing training data to build our models. Moreover, the pre-built APIs are used to parse and format data eliminating linguistics challenges. Similarly, to achieve better accuracy, we have to set rigid manual rules for data formatting to avoid processing complex characters in the text. We are running our machine learning models using APIs on their servers, reducing the time to tune the parameters and results.

Conclusion

In this research, I used NLTK, Vader and Logistic regression machine-learning models for in-depth analysis of human sentiments by extracting unbiased information. I got approximately 80% accuracy which shows us it is very promising that Artificial Intelligent is intelligent enough to read human sentiments.
Based on the above analysis I can conclude that my hypothesis is correct and using ML we can better understand human sentiments and facilitates informed decision-making.

Future Research

- Machine Learning/NLP can be enhanced not only to read, but to understand the human sentiments
- It is possible to apply similar machine learning models for examining the effects of various phenomena, such as natural calamities, global issues, illnesses like COVID-19, on human sentiments.

References

Generanger. "The Math behind Linear SVC Classifier." *GeneRanger*, 2 Aug. 2018, https://xingewang.wordpress.com/2018/08/02/the-math-behind-linear-svc-classifier/.

S, Yang. "An Introduction to Naïve Bayes Classifier." *Medium*, Towards Data Science, 8 May 2020, https://towardsdatascience.com/introduction-to-na%C3%AFve-bayes-classifier-fa59e3e24aaf.

"What Is a Random Forest?" *TIBCO Software*, https://www.tibco.com/reference-center/what-is-a-random-forest.

Chaffey, Dave. "Global Social Media Statistics Research Summary 2022 [June 2022]." *Smart Insights*, 31 Aug. 2022, https://www.smartinsights.com/social-media-marketing/social-media-strategy/new-global-social-media-research/.

Oechsli, Matt. "How 95% of Decisions Are Made." *Oechsli*, 29 June 2021, https://www.oechsli.com/how-95-of-decisions-are-made#:~:text=Zaltman's%20research%20highlights%20the%20fact,with%20logic%20(conscious%20thinking).

Beer, Chris. "Social Browsers Engage with Brands." *GWI*, 30 Mar. 2021, https://blog.gwi.com/chart-of-the-day/social-browsers-brand/.

Ewing, Mike. "71% More Likely to Purchase Based on Social Media Referrals [Infographic]." HubSpot Blog, HubSpot, 28 June 2019, https://blog.hubspot.com/blog/tabid/6307/bid/30239/71-More-Likely-to-Purchase-Based-on-Social-Media-Referrals-Infographic.aspx.