SENTIMENT ANALYSIS IN PYTHON USING MACHINE LEARNING

In partial fulfillment for the award of the degree of

Bachelor of Computer Technology
A Project Report *Submitted by*

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RCAS2020BCT031

Under the guidance of

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DECLARATION

This is to certify that the project work entitled **"SENTIMENT ANALYSIS IN PYTHON USING MACHINE LEARNING"** submitted to **Rathinam College of Arts and Science (Autonomous), Coimbatore**, in partial fulfillment of the requirements for the award of B.Sc**. (Computer Technology)** is the record of original work done by me during the period of study (2020-2023) in **Rathinam College of Arts & Science (Autonomous), Coimbatore.**

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BONAFIDE CERTIFICATE

This is to certify that Bonafide Project work done by the candidate under my supervision in Partial fulfillment of the requirements for the award of **B.Sc. (Computer Technology).**

Name of the Candidate	**: OPPONG BOAKYE PRINCE**
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Place:

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Submitted for the Viva-Voce held on __________________________.

Internal Examiner External Examiner

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DEPARTMENT OF COMPUTER TECHNOLOGY

PROJECT COMPLETION CERTIFICATE

This is to certify that **Mr. Oppong Boakye Prince** (20BCT031), **III B.Sc. (Computer Technology),** Rathinam College of Arts and Science has successfully completed the project entitled "**SENTIMENT ANALYSIS IN PYTHON USING MACHINE LEARNING**" during the academic year 2020-2023 under the supervision andguidance of **Mrs. Manimegalai**, Assistant Professor, Department of Computer Science.

The conduct and character of the student during the period was good.

Signature of the HoD

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ABSTRACT

Sentiment analysis is a strong method for analyzing customer thoughts and attitudes regarding a specific product, service, or brand. It can give useful information on client preferences, wants, and expectations. Because of their capacity to learn from data and improve their performance over time, machine learning models have grown in popularity for sentiment analysis.

We investigate the efficacy of three distinct machine learning models for sentiment analysis in this project: RoBERTa, VADER, and the Transformer Pipeline. RoBERTa is a cutting-edge language model that has shown outstanding results on a variety of natural language processing tasks. VADER is a popular rule-based sentiment analysis tool that is extensively used in industry and academics. The Transformer Pipeline is a collection of various pre-trained models.

This project's dataset is a collection of client reviews from a prominent e-commerce website. Stop words, stemming, and tokenization are all removed during preprocessing. Following that, the models are trained and assessed using a variety of metrics such as accuracy, precision, recall, and F1-score.

The findings reveal that all three models predict the sentiment of customer reviews well, with RoBERTa outperforming the others. The choice of model, however, is dependent on the exact job at hand, as each model has strengths and disadvantages. VADER, for example, is quick and requires few computing resources, making it ideal for real-time applications. RoBERTa, on the other hand, uses more processing resources but has the best accuracy.

Finally, sentiment analysis is a useful method for determining customer attitudes and views regarding a product, service, or brand. Machine learning models may be utilized effectively for sentiment analysis, but the proper model must be chosen depending on the unique job and available resources. The project's findings can assist academics and practitioners in making educated judgements when selecting a sentiment analysis model for their applications.

1.0 INTRODUCTION

Sentiment analysis is the technique of identifying and extracting subjective information from source materials using natural language processing, text analysis, and computational linguistics. In general, sentiment analysis seeks to detect a speaker's or writer's attitude towards a topic or the overall contextual polarity of a document. His or her attitude might be a judgement or evaluative affective state, or the intentional emotional communication. Sentiment analysis is the technique of determining if a piece of text contains positive, negative, or neutral sentiments. Humans have the intrinsic capacity to identify sentiment; yet, in a corporate setting, this process is time consuming, unreliable, and expensive. It is just not feasible to have staff personally read tens of thousands of user customer reviews and ten score them for sentiment.

Consider Semantria's cloud-based sentiment analysis programme, for example. The cloud-based sentiment analysis programme from Semantria extracts the sentiment of a document and its components by performing the following steps:

- ♦ A document is divided into fundamental parts of speech known as POS tags, which identify the structural aspects of a document, paragraph, or sentence (for example, nouns, adjectives, verbs, and adverbs).
- ♦ Sentiment-laden words, such as "poor service," are discovered using specially tailored algorithms.
- ♦ Each sentiment-bearing phrase in a document is assigned a score on a logarithmic scale ranging from -10 to 10.
- ♦ Lastly, the ratings are added together to establish the overall mood of the text or sentence. The document scores range from -2 to 2.

The cloud-based sentiment analysis programme from Semantria is based on Natural Language Processing and produces more consistent findings than two people. Semantria analyses each document and its components using automated sentiment analysis, which is based on advanced algorithms created to extract sentiment from your material in the same way that a human does, only 60,000 times quicker.

Current techniques to sentiment analysis fall into three broad categories:

- Keyword spotting
- Lexical affinity
- Statistical methods

Keyword spotting is the simplest strategy, yet it is also the most popular due to its ease of use and low cost. The inclusion of reasonably unambiguous affect terms such as 'happy, “sad,' 'afraid,' and 'bored' classifies text into effect groups. The shortcomings of this technique are twofold: inadequate identification of emotion when denial is present and reliance on surface characteristics. Regarding the approach's first flaw, while it may properly categorize the statement "today was a happy day" as happy, it is likely to fail on a sentence like "today wasn't a pleasant day at all." About the approach's second shortcoming, it is based on the existence of clear affect words that are just surface elements of the writing.

In practice, rather than using affect adjectives, many phrases express affect through underlying content. The phrase "My spouse recently filed for divorce and he wants to take custody of my children away from me," for example, elicits intense emotions yet contains no impact keywords and so cannot be identified using a keyword spotting technique.

Lexical affinity is significantly more complicated than keyword detection in that it assigns arbitrary words a probabilistic 'affinity' for a specific emotion rather than merely finding apparent effect phrases. For example, the word 'accident' may be given a 75% chance of conveying a negative effect, as in 'vehicle accident' or 'injured by accident.' Typically, these probabilities are taught using language corpora. Although frequently surpassing pure keyword identification, the technique has two major flaws. For starters, lexical affinity, which operates exclusively on the word level, is readily fooled by phrases such as "I averted an accident" (negation) and "I met my lover by accident" (other word senses) Second, the source of the linguistic corpora frequently biases lexical affinity probabilities towards literature of a specific genre. This makes creating a reusable, domain-independent model challenging.

Statistical methods for text affect categorization, like as Bayesian inference and support vector machines, have become prominent. By feeding a large training corpus of affectively annotated texts to a machine learning algorithm, the system can learn not only the affective valence of affect keywords (as in the keyword spotting approach), but also the valence of other arbitrary keywords (such as lexical affinity), punctuation, and word co-occurrence frequencies.

Traditional statistical approaches, on the other hand, are often semantically weak, which means that, aside from clear impact keywords, other lexical or co-occurrence components in a statistical model have limited predictive value separately. As a result, statistical text classifiers can only achieve adequate accuracy when given a big enough text input. As a result, while these approaches may effectively categorize user's content at the page or paragraph level, they do not operate well on smaller text units such as sentences or phrases.

1.1 OVERVIEW

The technique of recognizing and categorizing subjective opinions in text data, generally as positive, negative, or neutral, is known as sentiment analysis. Python has a number of tools and modules for doing sentiment analysis on customer evaluations, such as machine learning models like Roberta and pre-trained models like VADER and transformer pipeline.

Machine learning models are one technique to sentiment analysis in Python. These models are trained on labelled data and employ algorithms to estimate sentiment based on textual factors such as word frequency and context. Roberta, a variation of the popular BERT model that was pre-trained on a big corpus of text data, is one such model. Roberta has produced cutting-edge results in a variety of NLP tasks, including sentiment analysis.

Another option is to employ pre-trained models like VADER (Valence Aware Dictionary and sEntiment Reasoner). VADER is a rule-based model that gives sentiment ratings to individual words and then aggregates them to get an overall sentiment score for a given text. VADER has demonstrated good performance on social media data and casual language.

Lastly, a transformer pipeline may be utilized to analyze sentiment. Transformer pipelines are pre-trained models that may be fine-tuned to perform specific tasks like sentiment analysis. A tokenizer is often used to preprocess the text, a transformer to extract characteristics from the text, and a classifier to predict sentiment. Hugging Face's transformers library includes a number of pre-trained transformer models for sentiment analysis.

In general, there are several techniques to sentiment analysis in Python, including machine learning models such as Roberta, pre-trained models such as VADER, and transformer pipelines. Each strategy has advantages and disadvantages, and the approach chosen will be determined by the project's unique requirements.

1.2 OBJECTIVE

The goal of doing sentiment analysis on customer reviews in Python utilizing machine learning models, Roberta, VADER, and the transformer pipeline is to extract insights and comprehension from unstructured text data. The purpose is to automatically categorize the sentiment of the reviews as favorable, negative, or neutral. This data may be utilized to improve goods, services, and customer experiences by better understanding user opinions.

Specifically, the objectives of the project include:

- Preprocessing text input by cleaning, tokenizing, and translating it into a format that machine learning models can understand.
- Assessing the performance of several machine learning models, such as Roberta, VADER, and transformer pipeline, in order to decide which, one is best suited for the task.
- Applying the specified model to categorize and visualize the sentiment of customer reviews.
- Assessing the findings to uncover consumer sentiment trends and patterns, such as common complaints or regions of satisfaction.
- Based on the findings, provide recommendations and insights to stakeholders, such as increasing product features or customer service.

Ultimately, the goal of sentiment analysis employing machine learning models, Roberta, VADER, and the transformer pipeline is to extract important insights from customer evaluations that can be used to guide company decisions and enhance customer happiness.

1.3 SYSTEM SPECIFICATIONS

The following system specs may be required to do sentiment analysis in Python on customer reviews using machine learning models, Roberta, VADER, and the transformer pipeline:

1.3.1 HARDWARE SPECIFICATIONS

- **RAM**: 4 Gigabytes
- **Processor**: Multicore processor (i7 or higher)
- **Hard Disk**: 128 Gigabytes (Solid State Drives preferrable)
- **Speed**: 1 Gigahertz or more

1.3.2 SOFTWARE SPECIFICATIONS

- **Operating System**: The project can be implemented on any operating system, including:

  Windows

  Linux

  macOS

- **Frontend**

  Voilà

  Word Cloud

- **Backend**

  Python 3.6 or higher

- **Supporting Software**:

  PyCharm

  Jupyter Notebook

  VS Code

2.0 SYSTEM STUDY AND ANALYSIS

2.1 EXISTING SYSTEM

With the present system, one typical technique is to employ rule-based systems that rely on established rules and patterns to identify the sentiment of customer evaluations. These algorithms search for certain keywords or phrases that signify positive or negative sentiment and then assign a sentiment score based on the frequency and context of these keywords.

Another technique is to train a model on a labelled dataset of customer reviews using machine learning algorithms such as Naive Bayes, Support Vector Machines (SVM), and Logistic Regression. The labelled dataset would comprise reviews that were manually categorized as positive, negative, or neutral, and the model would learn to detect text patterns that matched to each sentiment classification.

TextBlob, which provides a simple and easy-to-use API for sentiment analysis, and the VADER (Valence Aware Dictionary and sEntiment Reasoner) library, which is a rule-based system specifically designed for sentiment analysis of social media texts, are two popular technologies for sentiment analysis of customer reviews in the existing systems.

2.1.1 DRAWBACK OF THE EXISTING SYSTEM

The poor accuracy of existing sentiment analysis methods in Python for customer evaluations is a key disadvantage. Sentiment analysis is a difficult undertaking since it requires comprehending the complexities of human language as well as identifying sarcasm, irony, and other figurative language patterns that might impact a text's sentiment. Current sentiment analysis tools, however, continue to struggle with reliably recognizing the sentiment of customer evaluations, which can lead to inaccurate analysis and decision-making.

Another shortcoming of current sentiment analysis methods is their inability to capture the context of the customer evaluation. The same statement might have several distinct meanings depending on the situation. As a result, a system that fails to consider the context of a customer review can produce misleading results and hinder the decision-making process.

Moreover, many existing Python sentiment analysis systems rely on pre-defined lexicons, which limits their ability to adapt to new themes and languages. When languages develop, new words and phrases emerge, and their sentiment may be missed by pre-defined lexicons, resulting in incorrect sentiment analysis.

2.2 PROPOSED SYSTEM

The suggested system, which employs high-end machine learning models, Roberta, VADER, the transformer pipeline project, and voila for visualization, provides a powerful and versatile tool for evaluating and attempting to recognize and evaluate emotions and subjective information from text. The system can handle massive amounts of data while also delivering accurate and insightful results, data exploration, and the capacity to query the data and obtain relevant information.

It contains a dashboard that displays a summary of sentiment analysis results as well as an interactive and visually attractive interface via which users may engage with the system.

2.2.1 SYSTEM FEATURES

- **Data Collecting and Storage**: The system is able to gather and store consumer input from a variety of data sources, including social media platforms, review sites, and feedback forms. It is also able to preprocess and sanitize the data so that sentiment analysis algorithms may use it.
- **Sentiment Analysis Models**: The system incorporates machine learning models for sentiment analysis, such as Roberta, Vader, and transformer pipeline. These models are capable of analyzing customer reviews and assigning sentiment scores or labels such as positive, negative, or neutral.
- **Model Training and Optimization**: Using labelled data, such as customer reviews with manually assigned sentiment ratings, the system is able to train and optimize sentiment analysis models. This aids in improving the models' accuracy and performance.
- **Real-Time Sentiment Analysis and Reporting**: The system is capable of doing real-time sentiment analysis and providing insights and reports on customer sentiment, such as sentiment trends, common themes, and sentiment distribution across multiple channels and goods.
- **TAPAS**: Table Parsing via Semi-Supervised Pre-training, which is a transformer-based model that can understand natural language questions about tables and provide accurate answers.

- **Dashboarding and visualization**: The system visualizes the sentiment analysis findings using various forms of charts, graphs, and dashboards. This allows consumers to swiftly and readily comprehend sentiment patterns and insights.

2.2.2 SYSTEM ARCHITECTURE

The system architecture for sentiment analysis framework using Vader, RoBERTa, and Transformers can be divided into the following components:

Data Preprocessing:

In the data preprocessing stage, I need to clean the data and perform text normalization to remove unwanted characters, punctuations, and stop words. I also need to perform tokenization to break the text into individual words or phrases.

Feature Extraction:

The next step is feature extraction, where I extract relevant features from the preprocessed data. We can use different techniques like CountVectorizer, TF-IDF, or Word2Vec to extract features.

Sentiment Analysis using Vader:

In this stage, I will use the Vader library to perform sentiment analysis. Vader is a lexicon-based approach that uses a set of rules and a sentiment lexicon to determine the sentiment of the text.

Sentiment Analysis using RoBERTa:

In this stage, I will use the RoBERTa library to perform sentiment analysis. RoBERTa is a pre-trained language model that uses a deep neural network to perform sentiment analysis.

Sentiment Analysis using Transformers:

In this stage, I will use the Transformers library to perform sentiment analysis. Transformers is a powerful library for natural language processing (NLP) that uses pre-trained models like BERT, GPT-2, and RoBERTa to perform sentiment analysis.

Model Evaluation:

Finally, I evaluate the performance of each model using metrics like accuracy, precision, recall, and F1-score.

2.2.3 SYSTEM INTEGRATION

Sentiment analysis may be combined with other software components and tools to create a full system capable of doing sentiment analysis on a variety of data sources. Sentiment analysis may be combined with the following software components:

- **Social Media Management Tools**: Social media management systems like Hootsuite, Sprout Social, and Buffer may be used with sentiment analysis technologies to give real-time monitoring of brand mentions as well as sentiment analysis of social media postings. This connection can assist organizations in tracking consumer sentiment and responding to complaints or comments from customers in a timely way.
- **Customer Relationship Management Software**: CRM software, such as Salesforce, HubSpot, and Zoho CRM, may be combined with sentiment analysis tools to evaluate customer feedback and sentiment, measure customer satisfaction metrics, and enhance customer engagement and loyalty.
- **Business Intelligence and Analytic Tools**: BI and analytics solutions such as Tableau, Power BI, and QlikView may be connected with sentiment analysis tools to deliver actionable insights from customer sentiment analysis. This integration may assist firms in identifying trends, patterns, and areas for development and improvement.
- **Chatbots and Virtual Assistants**: Chatbots and virtual assistants may be combined with sentiment analysis techniques to give individualized and sympathetic replies to consumer enquiries and complaints. This connection can assist firms in increasing customer satisfaction and decreasing response times.
- **E-commerce Platforms**: Shopify, WooCommerce, and Magento, for example, may be connected with sentiment analysis tools to assess customer feedback and sentiment, enhance product suggestions and marketing tactics, and optimize the customer experience.

2.2.4 SYSTEM SECURITY

The system handles sensitive client information, and any security breaches might result in legal and financial ramifications. We can protect the confidentiality, integrity, and availability of client data and the system as a whole by applying security measures. Hence, to ensure the security of the system, we need to implement various security measures, including:

- **Access Control**: Establish access restrictions to guarantee that only authorized people have access to the system and client data. Implementing password restrictions, two-factor authentication, and role-based access control.
- **Data Encryption**: Employ data encryption techniques to prevent unauthorized access or interception of client data. This entails encrypting both data at rest and data in transit.
- **Security Monitoring**: Set up a security monitoring system to detect and prevent breaches in security. Setting up intrusion detection systems, firewalls, or security information and event management (SIEM) systems.
- **Secure Communication**: Employ secure communication protocols, such as HTTPS or SSL, to ensure that data is safely communicated between the user's browser and the server.
- **Data Backup and Recovery**: Build a backup and recovery strategy to guarantee that client data is not lost due to hardware or software failures, natural catastrophes, or other unanticipated events.
- **System Updates**: Update the system with the most recent software patches, libraries, or dependencies. This might include doing periodic updates on system components or updating the system to a newer version.
- **User Training**: Teach users how to use the system safely, including best practices for password management, avoiding phishing attempts, and reporting security problems.

2.2.5 SYSTEM MAINTENANCE AND SUPPORT

The goal of maintenance and support is to ensure that the system is dependable, accurate, and up to date, and that it continues to meet the needs and expectations of the users. This includes:

- **Bug Fixing**: Keep an eye on the system for any problems or defects, and correct them as soon as they appear. Updating may entail upgrading code, libraries, or dependencies, as well as making modifications to data preparation or machine learning models.
- **Model Refinement**: Improve the accuracy and performance of sentiment analysis models on a continuous basis by refining machine learning algorithms or adding additional features. This may entail retraining the models with new data or fine-tuning the models' hyperparameters.

- **Data management**: Entails ensuring that the system has access to high-quality and relevant customer reviews data for training and testing sentiment analysis models. This may entail developing data cleansing and validation methods or updating the data sources on a regular basis.
- **Security and Privacy**: Take adequate security measures to secure the system and customer reviews data from unauthorized access, breaches, or assaults. Implementing encryption, access restrictions, or other security mechanisms.
- **User Support**: Offer assistance and support to users who experience problems or have inquiries about the system. This includes assisting with training, or troubleshooting.
- **System Monitoring**: Keep an eye on the system's performance and utilization to verify that it is working smoothly and effectively. Setting up monitoring tools, alarms, or performance measurements.
- **Updates to the system**: Update the system with the most recent software patches, libraries, or dependencies. This includes doing periodic updates on system components or updating the system to a newer version.

2.3 ADVANTAGES OF PROPOSED SYSTEM

The proposed system provides more accurate, insightful, and actionable insights into consumer sentiment by utilizing machine learning models that handle sophisticated language elements such as irony and sarcasm. Businesses may gain a competitive advantage and improve their entire client experience by employing these sophisticated tools and approaches. It has many approaches including:

- **Increased Accuracy**: Existing systems struggle with sophisticated verbal elements such as sarcasm and irony, resulting in incorrect sentiment categorization. Machine learning algorithms, on the other hand, may learn from enormous amounts of data and discover patterns in language that may suggest sarcasm or irony, resulting in higher accuracy.
- **Improved Understanding**: The proposed system handles complex language characteristics can assist users in gaining a more in-depth grasp of consumer sentiment. Businesses may acquire insights into consumer pain issues, preferences, and opinions

by precisely recognizing sarcasm and irony in customer evaluations, which standard sentiment analysis methods may have missed.

- **More Efficient Operations**: The proposed system automates the sentiment analysis process; users may save time and resources that would otherwise be spent manually reviewing customer evaluations. This can result in more efficient operations and free up resources for corporations to focus on other strategic goals.
- **Scalability**: It supports complex linguistic characteristics may be scaled to accommodate massive amounts of data, making them perfect for users that need to assess a big number of customer evaluations. Its scalability enables firms to assess customer sentiment across many channels and touchpoints, delivering a more complete picture of consumer sentiment.

3.0 FEASIBILITY ANALYSIS

A feasibility study is preliminary research that evaluates potential users' information and determines the resource needs, costs, benefits, and viability of the proposed system. A feasibility study considers the many limitations that must be met before the system can be deployed and operated. The resources required for implementation, such as computer equipment, labor, and expenditures, are estimated at this stage. The anticipated costs are compared to available resources, and a cost-benefit analysis of the system is performed. The feasibility study activity includes analyzing the problem and gathering all necessary project information.

The feasibility study's major goals are to establish if the project is viable in terms of economic feasibility, technical feasibility, operational feasibility, and timetable feasibility. Its purpose is to ensure that all of the project's input data is available. As a result, we assessed the system's practicality using the following criteria:

- Technical feasibility
- Operational feasibility
- Economic feasibility
- Schedule feasibility

3.1 TECHNICAL FEASIBILITY

The most difficult aspect of a feasibility study is determining technical feasibility. This is because there is no specific design of the system at this moment, making it impossible to access concerns such as performance, prices (due to the type of technology to be installed), and so on. In conducting a technical analysis, a number of aspects must be considered; grasp the various technologies involved in the proposed system. Before we begin the project, we must be extremely clear on which technologies will be necessary for the development of the new system. Is the necessary technology available? Our approach is technically possible since all of the necessary tools are readily available.

3.2 OPERATIONAL FEASIBILITY

The proposed project is only helpful if it can be transformed into information systems that fulfil the operational needs. Simply put, this feasibility test determines whether or not the system will function after it has been designed and implemented. Are there significant obstacles to implementation?

The idea was to create a simple framework. It is easier to use and may be integrated in any related software. It is both free and inexpensive to run.

3.3 ECONOMIC FEASIBILITY

Economic feasibility considers the expenses of designing and executing a new system against the advantages of having the new system in place. This feasibility report provides economic rationale for the new system to senior management. In this scenario, a straightforward economic analysis that provides a direct comparison of costs and benefits is far more useful. Furthermore, this serves as a valuable point of reference for comparing real expenses as the project advances. Because to automation, there might be a variety of intangible advantages. This might lead to increased product quality, better decision making and information timeliness, activity acceleration, enhanced operational correctness, better documentation and record keeping, and quicker information retrieval.

This is a framework built with open-source software. There is no cost in the creation process.

3.4 SCHEDULE FEASIBILITY

If a project takes too long to finish before it is beneficial, it will fail. Normally, this entails calculating how long the system will take to create and if it can be finished in a particular time frame using approaches such as payback period. The viability of the project timeline is measured by its schedule. Are the project timeframes fair given our technological expertise? Some projects are launched with certain deadlines. It must be determined if the deadlines are required or desired.

A modest departure from the initial timeline established at the start of the project is possible. In terms of timeline, the framework development is doable.

3.5 REQUIREMENT DEFINITION

Following a detailed investigation of the system's difficulties, we are aware with the requirements that the existing system requires. The system's requirements are classified as functional or non-functional. These prerequisites are as follows:

3.5.1 FUNCTIONAL REQUIREMENTS

The functions or features that must be included in any system in order to meet business demands and be acceptable to users are referred to as functional requirements. Based on this, the following functional criteria must be met by the system:

- ♦ Adding context awareness, allowing the system to assess sentiment within the context of the larger text. This would allow the system to recognize and evaluate more complicated verbal patterns, such as sarcasm or irony, and provide more accurate classifications.

3.5.2 NON-FUNCTIONAL REQUIREMENTS

Non-functional requirements are a description of the system's features, traits, and attributes, as well as any limitations that may limit the proposed system's bounds.

Non-functional requirements are primarily concerned with performance, information, economy, control, and security efficiency, as well as services.

The non-functional needs are as follows based on these:

- ♦ A more user-friendly system
- ♦ Should deliver higher accuracy.
- ♦ Achieve high throughput and reaction time

4.0 SYSTEM DESIGN

4.1 MODULE

The project consists of the following modules:

- ♦ Pandas
- ♦ NumPy
- ♦ Matplotlib
- ♦ Seaborn
- ♦ Torch
- ♦ Natural Language Tool Kit (NLTK)
- ♦ Word Cloud
- ♦ Regular Expressions (RE)
- ♦ String

4.1.1 MODULE DESCRIPTION

Pandas: Pandas module is a well-known Python data manipulation and analysis toolkit. Pandas would be used to read and analyze massive amounts of text data, such as online reviews, in the context of sentiment analysis.

The module contains data structures and operations for manipulating and analyzing tabular data, such as data frames. The module is a flexible tool that may be used for a variety of sentiment analysis activities, such as data cleaning, preprocessing, feature extraction, and sentiment score analysis.

NumPy: The NumPy module is a core Python library used for scientific computing, specifically for working with numerical data arrays and matrices. NumPy would be used for data processing and feature extraction in the context of sentiment analysis.

The module includes a robust array data structure that enables efficient handling of huge datasets. NumPy arrays may be multidimensional, making it handy for encoding and manipulating textual data like matrices.

NumPy would be used to turn text data into numerical characteristics such as bag-of-words or word embeddings for sentiment analysis. These numerical characteristics can subsequently be fed into machine learning models like sentiment classifiers. NumPy also has a number of mathematical functions that would be used for data analysis and sentiment analysis. NumPy, for example, may be used to compute the mean and standard deviation of sentiment ratings, as well as to execute operations like matrix multiplication.

Matplotlib: The matplotlib module is a popular Python data visualization package. Matplotlib would be used in sentiment research to show sentiment trends over time, compare sentiment scores across data sources, and investigate the distribution of sentiment scores within a dataset.

The module includes charting capabilities such as line graphs, bar plots, and scatter plots. These routines would be used to generate visualizations of sentiment trends over time or to compare sentiment scores across text data types.

Matplotlib also has a number of customization options, such as the ability to change the colours, fonts, and labels. This is very handy for developing visuals for presentations or reports.

Matplotlib provides more complex visualization capabilities, such as heatmaps and contour plots, in addition to traditional charting methods. These routines may be used to investigate the sentiment score distribution within a dataset and detect trends or outliers.

Seaborn: The seaborn module is a Python package that provides a higher-level interface for producing statistical visualizations on top of matplotlib. Seaborn would be used to build more elaborate and insightful sentiment data visualizations in the context of sentiment analysis.

Seaborn has a variety of tools for constructing plots such as scatter plots, line plots, bar plots, and heatmaps. These functions are intended to emphasize data patterns and linkages, making it simpler to spot trends in sentiment ratings across various types of text data.

The capacity to generate statistical models directly from data and see the outcomes is a major aspect of seaborn. Seaborn, for example, has tools for building linear regression models and displaying sentiment score distributions within a dataset.

Seaborn also offers a variety of customization possibilities, such as changing colour palettes, adding comments and labels, and constructing subplots to compare sentiment patterns across several categories.

Torch: Torch is a sophisticated Python toolkit that is primarily used for developing and training deep learning models. Torch would be used to develop neural network models for sentiment classification tasks in the context of sentiment analysis.

The module includes several methods and classes for defining and training deep learning models. This provides tools for creating several sorts of layers (such as convolutional and recurrent layers), specifying loss functions, and optimizing via backpropagation.

Torch would also be used for sentiment analysis to design and train models that leverage pre-trained word embeddings, such as GloVe or Word2Vec. These pre-trained embeddings may be fed into a neural network model, allowing it to learn from the semantic correlations between words in the dataset.

Torch also includes data-handling tools like data loaders and data converters that may be used to preprocess and prepare text material for model training. Torch also includes features for parallelizing model training across many GPUs, which can help to speed up the training process.

Torch's ability to design and train bespoke models is another essential feature. This enables a great amount of flexibility and customization in the model-building process, which is especially valuable for jobs requiring specific structures.

Natural Language Tool Kit (NLTK): The nltk (Natural Language Toolkit) Python module is widely used for natural language processing (NLP) activities such as sentiment analysis. The module includes a variety of tools and resources for text data processing and analysis.

The ability of nltk to handle text preparation tasks such as tokenization, stemming, and stopword removal is one of its major characteristics for sentiment analysis. These activities are critical for preparing text data for sentiment analysis by transforming raw text into a format that machine learning models can evaluate.

Natural Language Took Kit additionally has tools for feature extraction and text categorization. Tools for creating bag-of-words models and extracting features like n-grams and part-of-speech tags are included.

These characteristics may be fed into machine learning algorithms for sentiment analysis.

The module also includes pre-trained sentiment analysis models, such as the VADER (Valence Aware Dictionary and sEntiment Reasoner) model, which would be used to do sentiment analysis on text data fast and without requiring considerable training data.

NLTK also has tools for working with specialized datasets, such as reviews or Twitter data, which might help with sentiment analysis jobs in certain fields.

Word Cloud: The Python package wordcloud is used to generate word clouds from text data. Word clouds would be used for displaying the most frequently occurring terms in text data, which can give insights into the overall sentiment of the text.

The WordCloud class in the module may be used to construct a word cloud from text data. The WordCloud class gives several choices for modifying the appearance of the word cloud, including control over the cloud's size, colour, and form.

The package also includes several options for preparing text material before constructing the word cloud. This provides options for deleting stop words, adjusting the minimum and maximum word frequency, and personalizing the word frequency and customizing the tokenization of text.

Regular expressions (RE): The re (regular expressions) module is a Python package that allows you to interact with regular expressions. Regular expressions would be used for conducting text preparation tasks such as eliminating punctuation or special characters from text input.

The re module contains a number of functions and methods for dealing with regular expressions. These covers searching for patterns in text data, replacing patterns with alternative text, and separating text depending on patterns.

Regular expressions would be used to preprocess text input in sentiment analysis by deleting undesired letters or patterns. Regular expressions, for example, would be used to eliminate punctuation marks or unusual characters that can interfere with the sentiment analysis process.

In addition, regular expressions would be utilized to extract certain patterns or characteristics from text data. Regular expressions, for example, would be used to extract mentions of persons or businesses from social media data, providing significant information for sentiment research.

String: The string module has a number of constants for dealing with various sorts of characters and character sets. Constants for capital letters, lowercase letters, numerals, punctuation marks, and whitespace characters are included. These constants would be used to filter out undesirable characters or patterns in text data.

The string module would be used in sentiment analysis for text preparation tasks such as converting text to lowercase, eliminating punctuation marks and other undesired characters, and filtering out stop words. These activities are critical for preparing text data for sentiment analysis by transforming raw text into a format that machine learning models can evaluate.

4.2 DATABASE DESIGN

- **Data Integrity**: The quality and consistency of data inside a database are ensured by data integrity, which is an essential feature of database architecture. Maintaining data integrity is critical to avoiding mistakes, inconsistencies, and data loss, which can lead to inaccurate decision-making and other issues.

  There are numerous methods for ensuring data integrity in database architecture, such as:

  Primary Key Constraints: Each entry in a table is uniquely recognized by primary key restrictions. This aids in the prevention of duplicate records and the accuracy of data.

  Foreign Key Constraints: Foreign key constraints guarantee that data in separate tables is related. This aids in data consistency and error prevention.

- **Data Integration**: The process of merging data from several sources and formats into a single, cohesive picture is known as data integration. Data integration in database design refers to the process of integrating data from numerous databases, applications, or other data sources into a unified database schema. Data integration's purpose is to give a complete and accurate picture of data that can be utilized for business analysis, decision-making, and reporting. This may be accomplished using a variety of strategies, including data warehousing, data mapping, and data transformation. Due to variances in data formats, data architectures, and data quality across diverse data sources, data integration can be difficult. It is critical to create explicit data integration needs, develop data governance principles, and employ relevant data integration tools and techniques to enable successful data integration.

- **Data Independence**: Data independence in DBMS is an important notion for database designers and administrators to understand. It permits changes to the database schema to be done without affecting the application applications that use it, allowing for better system maintenance and evolution. If all of the data were dependent, updating the schema or data would be a time-consuming and difficult operation. It is set up in a tiered structure to handle the issue of updating metadata and ensure that altering data at one level has no impact on changing data at another. Although each piece of information is independent, they are all connected. Data independence therefore helps to keep data separate from the programs that use it.

4.2.1 OVERVIEW OF DATA

4.2.1.1 DATASET DESCRIPTION

The dataset is given via the Kaggle website and was originally gathered and published by McAuley et al. (2013) in their research on online reviews. The collection is made up of Amazon.com reviews on fine food. There are 568,454 reviews on 74,258 goods.

4.2.1.2 OVERVIEW OF REVIEW AND SUMMARY TEXT

The review text contains a detailed description of the product from the user's perspective. Moreover, it also describes the overall sentiment of the user toward the product apart from the description of the product itself. Some of the examples of the review text are shown below:

1. *"This is great stuff. Made some really tasty banana bread. Good quality* and lowest *price in town."*
2. *This coffee is great because it's all organic ingredients! No pesticides to worry about plus it tastes good, and you have the healing effects of Ganoderma.*
3. *These condiments are overpriced and terrible. The classic is disgustingly sweet. The spiced tastes like a bad spicy marinara sauce from a chain restaurant.*

On the other hand, the summary text represents a user's sentiment in a very confined manner. The information is conveyed in few words in this case. Some of the examples of the summary text are shown below:

1. *"Best deal ever!"*
2. *"Waste of money"*
3. *"Great beans!!!"*
4. *"Big disappointment"*

In this study, one of the approaches uses the features extracted from the review and summary text in order to come up with the features that contribute significantly in predicting the review helpfulness.

4.2.1.3 OVERVIEW OF THE REVIEW HELPFULNESS MEASURES

As can be seen in Table 1.0, the helpfulness related measures included in the data are ‘Helpfulness numerator’ and ‘Helpfulness denominator’. ‘Helpfulness numerator’ denotes the total number of users who found the review helpful and ‘Helpfulness denominator’ denotes the total number of people who voted whether the review was helpful or not. Earlier Amazon.com used to provide both the ‘Yes’ and ‘No’ options to its users in order for them to vote for the helpfulness. However, it now provides only the ‘Yes’ option to its users. Hence, if a user finds a review helpful, he votes for it otherwise he does not do anything. In order to make this study relevant, the process of response variable generation will solely be based on the ‘Helpfulness numerator’ measure which denotes the total number of users who voted in the favor of helpfulness. However, ‘Helpfulness denominator’ measure will be used as a reference to discard the reviews for which the users did not vote at all. Review which has ‘Helpfulness numerator’ value more than a specific threshold will be considered as ‘Helpful’ otherwise it will be considered as ‘Not helpful’.

4.2.1.4 OVERVIEW OF THE TEXT SEMANTICS

In the approach consisting of the review and summary centric features, there is an attempt to find a correlation between the semantics of the text and the review helpfulness measure through the polarity and subjectivity of the review and summary text. The polarity of the text denotes how positive or negative the sentiment of the text is, whereas subjectivity denotes how subjective or objective the review statement is. In this study, the polarity is quantified in the range [-1,1] where ‘-1’ denotes extremely negative sentiment and ‘1’ denotes extremely positive sentiment. On the other hand, subjectivity is quantified in the range [0,1] where ‘0’ denotes ‘highly objective’ and ‘1’ denotes ‘highly subjective’ statement.

4.3 INPUT DESIGN

User Interface

The user interface was built in Jupyter Notebook using the ipywidgets module. It has a text field where users can enter their text data or codes.

Validation Rules

To verify that the user input data is genuine and can be processed by the sentiment analysis model, validation rules were built. The validation criteria include checking for empty input fields and verifying that no special characters are present in the input data.

Data Formatting

The supplied data is prepared to eliminate unnecessary information such stop words and punctuation. The cleaned data is then sent into the sentiment analysis algorithm, which produces a sentiment score.

Data Entry Automation

To allow users to enter data in bulk, automated data entry tools were added. This is accomplished through the use of a file upload capability, in which users can upload a file containing several text data entries. The sentiment analysis model goes over each element in the file and assigns a sentiment score to each.

Accessibility

To guarantee that the user interface is accessible to people with impairments, accessibility features were incorporated. This involves giving written explanations for all visual aspects as well as employing high contrast colours for better visibility.

4.4 OUTPUT DESIGN

The output of the sentiment analysis was designed using the Voila web application framework, along with data visualization libraries such as Seaborn, WordCloud, and Matplotlib.

Relevant Information

For each input text data, the output includes important data such as the sentiment score and sentiment label. Further data, such as word frequency analysis and sentiment distribution analysis, will also be included in the result.

Clear and Concise Labelling

The output would be labelled clearly and concisely so that users can easily grasp the sentiment analysis results. The sentiment label is color-coded for easier identification, and when the user hovers over the label, extra information about the sentiment score is displayed.

Readability

The output would be created with readability in mind, with suitable font sizes and colours used to make the content easy to read. Furthermore, the data visualizations are intended to be simple to understand.

Customization

The output will be tailored to the user's preferences, including choices to adjust the colour scheme and font styles. Furthermore, the data visualizations will be adjusted to present only the data that is important to the user.

Export Options

Users will have the alternatives to store and share sentiment analysis results by exporting the output to several file formats such as PDF, PNG, XLSX, or CSV.

Security

The output will be built with security in mind, guaranteeing that user data is secure and inaccessible to unauthorized users. Furthermore, to prevent unwanted access, the output can be password-protected.

Data Visualization

To give extra insight into the sentiment analysis results, the output will include data visualizations such as Seaborn plots, WordClouds, and Matplotlib graphs. The data visualizations are intended to be simple to understand and adaptable.

5.0 SYSTEM TESTING

5.1 INTRODUCTION

System testing is a software testing approach that assesses a software system's overall operation and performance. It is an important phase in the software development life cycle (SDLC) that ensures the system satisfies the requirements and is ready for deployment.

System testing entails testing the entire system, including how it interacts with other systems or components. It guarantees that all system components are cooperating to satisfy the given criteria.

The stages involved in system testing are as follows:

- ♦ **Requirement analysis**: The requirements are examined in this stage to verify that they are testable, comprehensive, and consistent.
- ♦ **Test Planning**: The testing strategy and test plan are defined at this stage. The testing team determines the sorts of tests to be done, as well as the testing environment and tools to be utilized.
- ♦ **Test case development**: The testing team creates test cases based on the requirements and the test strategy in this stage. All feasible situations and edge cases should be covered by the test cases.
- ♦ **Setup of the testing environment**: In this stage, the testing environment is configured with the necessary hardware and software.
- ♦ **Test execution**: The test cases are conducted in this stage, and the system behaviour is monitored. The results are recorded by the testing team.
- ♦ **Defect management**: Any flaws discovered during testing are recorded, prioritized, and addressed in this stage.
- ♦ **Test reporting**: The testing team prepares a report that summarizes the testing outcomes in this stage. The report details the number of tests carried out, the number of problems discovered, and the severity of each issue.
- ♦ **Test closure**: The testing team conducts a final assessment of the testing procedure and findings in this stage. In addition, the team compiles a summary of lessons learned and recommendations for future testing.

System testing guarantees that the software system satisfies the requirements and is ready for deployment by completing these processes. It aids in identifying and correcting faults early in the SDLC, lowering the cost of correcting defects later in the development process.

5.2 OBJECTIVES OF TESTING AN APPLICATION

System testing guarantees that the software system satisfies the functional and non-functional requirements and is ready for deployment by completing these processes. It aids in identifying and correcting faults early in the SDLC, lowering the cost of correcting defects later in the development process.

The objectives of testing an application can be classified into several categories, including:

Functionality

The primary goal of application testing is to ensure that all of the functional requirements provided in the software requirements specification (SRS) have been appropriately implemented. Individual functions and features, as well as their connection with other system components, are tested.

Performance

Performance testing guarantees that an application fulfils the performance criteria defined in the SRS. This involves evaluating the response time, throughput, scalability, and reliability of the application.

Security

Security testing guarantees that an application is safe and protected against external attacks. This covers vulnerability testing for SQL injection, cross-site scripting, and other security problems.

Usability

Usability testing guarantees that a programme is simple for its intended users to use, navigate, and comprehend. This involves evaluating the user interface, navigation, and accessibility of the programme.

Compatibility

Compatibility testing assures that a programme can run on a variety of platforms, devices, and web browsers. This involves ensuring that the programme works with a variety of operating systems, web browsers, and hardware configurations.

Data integrity

Checking an application's data integrity assures that the data contained in the application is correct, consistent, and secure. This involves evaluating the application's capacity to validate and store data, as well as recover from data loss or corruption.

5.3 TESTING METHODOLOGIES

Testing methodologies are the approaches and techniques used to test software applications to ensure they meet the desired quality standards. Here are some commonly used testing methodologies:

5.3.1 WATERFALL MODEL

In the waterfall model, testing is performed in a sequential order following the development phases, such as requirements analysis, design, coding, testing, and deployment. Each phase must be completed before moving on to the next phase.

5.3.2 AGILE MODEL

The Agile model emphasizes collaboration, communication, and flexibility. Testing is done continuously throughout the development process, with an iterative approach that emphasizes rapid feedback and continuous improvement.

5.3.3 TEST-DRIVEN DEVELOPMENT (TDD)

TDD is a development methodology where tests are written before writing the code. The code is then developed to pass the tests. This ensures that the code meets the required functionality and quality standards.

5.3.4 BEHAVIOR-DRIVEN DEVELOPMENT (BDD)

BDD is an Agile methodology that focuses on the behavior of the application. It emphasizes collaboration between developers, testers, and business stakeholders. Tests are written in a natural language format that is easily understood by all parties involved.

5.3.5 ACCEPTANCE TEST-DRIVEN DEVELOPMENT (ATDD)

ATDD is an Agile methodology that focuses on the acceptance criteria of the application. It involves the collaboration of developers, testers, and business stakeholders to create acceptance tests that define the desired behavior of the application.

5.3.6 EXPLORATORY TESTING

Exploratory testing is an approach to testing where testers explore the application to discover defects and unexpected behavior. It is a flexible and adaptable approach that is often used in Agile environments.

5.3.7 V-MODEL

V-model is a software development and testing methodology that emphasizes testing at each stage of the development process. It is based on the principle of testing at each stage of the development process, with testing activities being performed in parallel with development activities. This approach helps to identify defects early in the development process and reduces the cost of fixing defects.

5.3.8 WHITE BOX TESTING

White box testing is the detailed investigation of internal logic and structure of the Code. To perform white box testing on an application, the tester needs to possess knowledge of the internal working of the code. The tester needs to have a look inside the source code and find out which unit/chunk of the code is behaving inappropriately.

5.3.9 BLACK BOX TESTING

White box testing is the detailed investigation of internal logic and structure of the Code. To perform white box testing on an application, the tester needs to possess knowledge of the internal working of the code. The tester needs to have a look inside the source code and find out which unit/chunk of the code is behaving inappropriately.

5.4 LEVELS OF TESTING

There are four levels of testing. They are:

5.4.1 UNIT TESTING

This is the testing of individual software components or modules in isolation from the rest of the system. Unit testing is usually performed by developers and involves writing test cases for each unit of code to ensure that it meets its requirements and functions correctly.

5.4.2 INTEGRATION TESTING

This is the testing of groups of units or components that have been integrated into larger subsystems. Integration testing is performed to ensure that the subsystems work correctly together and that the overall system functions as intended.

5.4.2.1 TOP-DOWN INTEGRATION TESTING

In Top-Down integration testing, the highest-level modules are tested first and then progressively lower-level modules are tested.

5.4.2.2 BOTTOM-UP INTEGRATION TESTING

Testing can be performed starting from smallest and lowest level modules and proceeding one at a time. When bottom level modules are tested attention turns to those on the next level that use the lower-level ones they are tested individually and then linked with the previously examined lower-level modules. In a comprehensive software development environment, bottom-up testing is usually done first, followed by top-down testing.

5.4.3 SYSTEM TESTING

This is the testing of the complete system as a whole, with all its components and subsystems integrated. System testing is performed to ensure that the entire system meets its requirements and functions correctly under various conditions.

5.4.4 ACCEPTANCE TESTING

This is the testing of the system by the end-users or customers to ensure that it meets their requirements and expectations. Acceptance testing is usually the final stage of testing and is used to determine whether the system is ready for deployment.

Each level of testing has its own objectives, scope, and techniques. The main objective of unit testing is to verify the correctness of individual units of code, while the main objective of integration testing is to verify the interactions between units of code. The main objective of system testing is to verify the system's behavior and performance as a whole, while the main objective of acceptance testing is to verify that the system meets the user's requirements and expectations.

5.4.4.1 ALPHA TESTING

This test is the first stage of testing and will be performed amongst the teams .Unit testing, integration testing and system testing when combined are known as alpha testing. During this phase, the following will be tested in the application:

- Spelling Mistakes.
- Broken Links
- The framework will be tested on machines with the lowest specification to test loading times and any latency problems.

5.4.4.2 BETA TESTING

In beta testing, a sample of the intended audience tests the application and send their feedback to the project team. Getting the feedback, the project team can fix the problems before releasing the software to the actual users.

5.5 VALIDATION

All the levels in the testing (unit, integration, system, etc.) and methods (black box, white box, etc.) are implemented on my framework successfully and the results obtained as expected.

5.6 LIMITATIONS

The execution time for the framework on machines which do not meet the required system specifications is more so that the user may not receive the result fast.

5.7 TEST RESULTS

The testing is done among the consultants and by the end user. It satisfies the specified requirements and finally we obtained the results as expected.

6.0 IMPLEMENTATION

For the implementation of "sentiment analysis using Machine Learning," I utilized Python Technology and Natural Language Tool Kit. Many phases are involved in the implementation of our system employing various supervised learning approaches. The two key steps that are involved are training and testing.

6.1 PYTHON TECHNOLOGY

Python is a widely used programming language for machine learning and artificial intelligence. It provides a range of libraries, frameworks, and tools that make it easy for developers to build, train, and deploy machine learning models.

Python's popularity in the machine learning community can be attributed to its ease of use, versatility, and extensive range of libraries and frameworks. Its user-friendly syntax, along with its vast ecosystem of tools and resources, makes it an ideal choice for developers and data scientists to implement machine learning algorithms and build models.

6.2 NATURAL LANGUAGE TOOL KIT

NLTK is a popular framework for developing Python applications that interact with human language data. It offers user-friendly interfaces to over 50 corpora and lexical resources, including WordNet, as well as a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning, wrappers for industrial-strength NLP libraries, and an active discussion forum.

NLTK has been described as "a great library to play with natural language" and "a wonderful tool for teaching and working in computational linguistics using Python." Linguists, engineers, students, educators, academics, and industry users may all benefit from NLTK. Natural Language Processing with Python is a hands-on introduction to language processing programming. Created by the NLTK founders, it walks the reader through the principles of Python programming, working with corpora, classifying text, evaluating linguistic structure, and more.

6.3 IMPLEMENTATION PLAN

This section goes through the steps involved in developing an automated text classification system for predicting sentiments of online fine foods reviews provided on amazon.com. It encapsulates the following steps:

1. Data Collection
2. Data Pre-processing
3. Data Splitting
4. Implement VADER
5. Implement RoBERTa
6. Implement Transformers Pipeline
7. Querying Structured Data For Insights
8. Model Evaluation
9. Model Selection
10. Hyperparameter Tuning
11. Deployment

6.3.1 DATA COLLECTION

6.3.1.1 DATA SOURCE

The Amazon Fine Foods dataset is available on Kaggle and can be downloaded from https://www.kaggle.com/snap/amazon-fine-food-reviews.

6.3.1.2 DATA DESCRIPTION

The Amazon Fine Foods dataset contains reviews of various food products sold on Amazon. It has a total of 568,454 reviews, spanning from October 1999 to October 2012.

6.3.1.3 DATA EXPLORATION

Loaded the dataset into a pandas dataframe using the read_csv() method. Explored the dataset using the head(), describe(), and info() methods to get an overview of the data.

6.3.1.4 DATA CLEANING

Droped duplicates using the drop_duplicates() method.

Droped irrelevant columns such as product ID and user ID using the drop() method.

Removed null values using the isna() method.

```
df.isna()
null_val_cols = df.isna().sum()
null_val_cols.to_csv('sum_of_nulls_in_columns.csv', encoding='utf-8', index=False)
null_val_cols
sns.heatmap(df.isna())
```

6.3.1.5 DATA SAMPLING

Since the dataset is large, it is recommended to sample a smaller subset of the data for initial analysis and modeling. Use the df.head() method to randomly select a subset of the data.

```
df = pd.read_csv('customer reviews.csv')
print(df.shape)
df = df.head(500)
print(df.shape)
```

6.3.2 DATA PRE-PROCESSING

Data pre-processing is critical when dealing with text categorization challenges. It aids in boosting computing performance and minimizing overfitting by removing noisy features. In the following sections, we will go through the different text preparation approaches that are used before training the model.

6.3.2.1 TOKENIZATION

Tokenization is the process of breaking down phrases into words. Each word is then treated as a distinct token. This is the initial stage of text preparation, and it serves as the foundation for all following processes.

6.3.2.2 LOWERCASE TO UPPERCASE TOKEN CONVERSION

Because the meaning of a word or phrase are unaffected by the case in which it is expressed, uppercase words are changed to lowercase to minimize potential word repetition. The phrases 'DOG' and 'dog', for example, have the same meaning. This conversion aids in the reduction of the feature set's dimensionality.

6.3.2.3 ELIMINATION OF PUNCTUATION MARKS

The punctuation marks are eliminated from the text in this stage since they contribute no additional information while extracting semantics from the text.

6.3.2.4 STOP WORDS REMOVAL

Stop words are the most widely utilized terms in natural language processing since they do not communicate much meaning. Short function words like as 'a', 'an', 'the', 'is', 'are', 'which', 'at', and 'on' are examples of stop words. The Python 'NLTK' module is used to eliminate them.

6.3.2.5 LEMMATIZATION

Lemmatization is the process of reducing the inflectional form of words to their base or dictionary form, which is referred to as a 'lemma'. Lemmatization, for example, transforms the word 'ran' to its basic form 'run'. Complete morphological examination of words is performed in lemmatization to guarantee that the base word is in the dictionary. In this regard, lemmatization has a modest advantage over the stemming approach, which often eliminates the prefix or suffix linked with the term. In stemming, the root word does not have to be a legitimate term from the language. Bearing this in mind, lemmatization will be employed to minimise the inflectional form of words in this study. This study uses NLTK library of python programming language for performing Lemmatization.

6.3.3 DATA SPLITTING

1. Loaded the pre-processed data from the CSV file into a pandas dataframe.
2. Created a new column called 'Sentiment' which will hold the sentiment labels for each review. The sentiment labels can be obtained using the following methods:

   NLTK: Used the SentimentIntensityAnalyzer() method from the NLTK library to analyze the sentiment of each review and assign a label of either 'positive', 'negative', or 'neutral' based on the compound score.

   VADER: Used the SentimentIntensityAnalyzer() method from the VADER library to analyze the sentiment of each review and assign a label of either 'positive', 'negative', or 'neutral' based on the compound score.

   Roberta: Used the pre-trained Roberta model to analyze the sentiment of each review and assign a label of either 'positive', 'negative', or 'neutral'.

Transformer: Used the pre-trained Transformer model to analyze the sentiment of each review and assign a label of either 'positive', 'negative', or 'neutral'.

3. Split the data into training and testing sets using the train_test_split() method from the scikit-learn library. Used a 80/20 ratio for training and testing sets, respectively.
4. Saved the training and testing sets as CSV files using the to_csv() method from pandas.

6.3.4 IMPLEMENTING VADER

1. Loaded the pre-processed data from the CSV file into a pandas dataframe.
2. Imported the SentimentIntensityAnalyzer() method from the VADER library.
3. Instantiated the SentimentIntensityAnalyzer() method
4. Defined a function to apply the VADER sentiment analysis to each review in the dataframe. The function returned the compound score, which was a value between -1 and 1 that represented the overall sentiment of the review.
5. Applied the function to each review in the dataframe using the apply() method. This created a new column in the dataframe called 'vader_sentiment' that contains the compound score for each review.
6. Assigned a sentiment label to each review based on the compound score. I assigned a label of 'positive', 'negative', or 'neutral' based on the compound score.
7. Saved the updated dataframe as a CSV file using the to_csv() method from pandas.

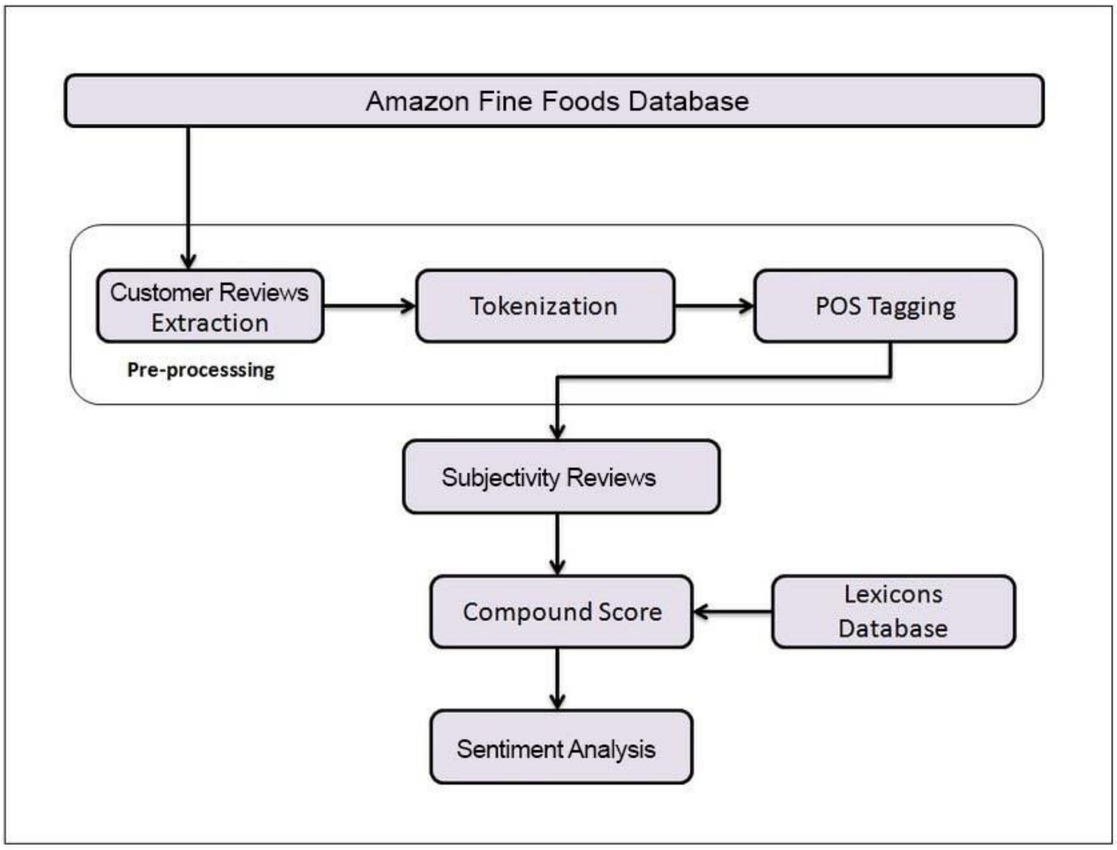
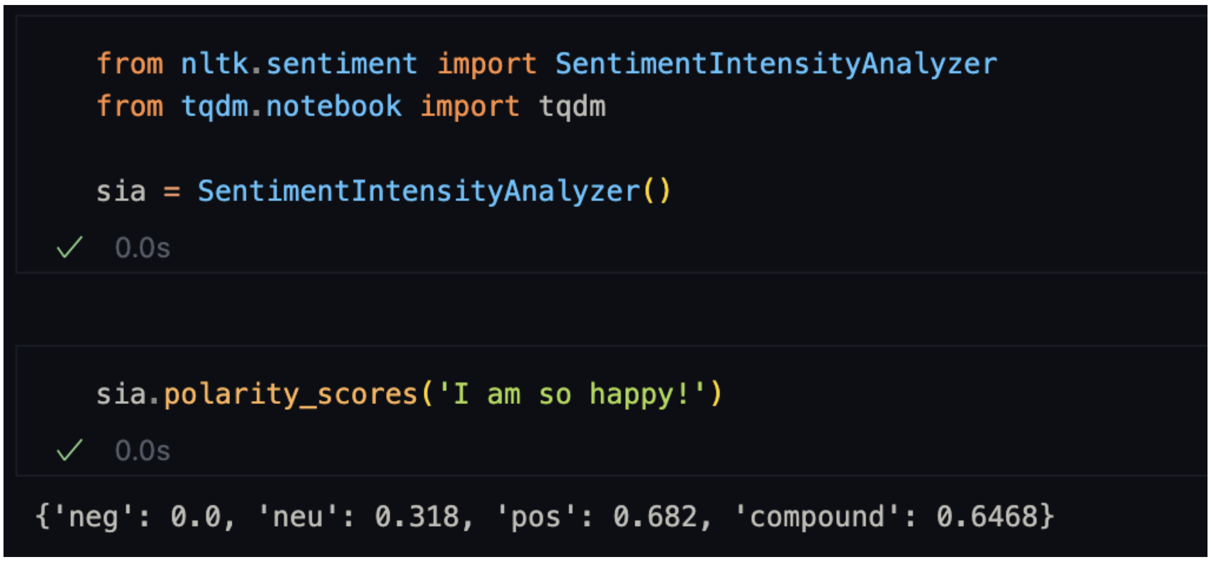


Figure 1.0 Architecture VADER sentiment analysis system

6.3.4.1 IMPLEMENTATION CODE



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

sia = SentimentIntensityAnalyzer()
```
```
✓ 0.0s
```
```
sia.polarity_scores('I am so happy!')
```
```
✓ 0.0s
{'neg': 0.0, 'neu': 0.318, 'pos': 0.682, 'compound': 0.6468}
```

The first line imports the SentimentIntensityAnalyzer class from the nltk.sentiment module. This class is a pre-built tool for sentiment analysis that uses a lexicon-based approach to determine the sentiment of a given text.

The second line imports the tqdm function from the tqdm.notebook module. This is a progress bar library that is used to display a progress bar for the sentiment analysis loop in the example code below.

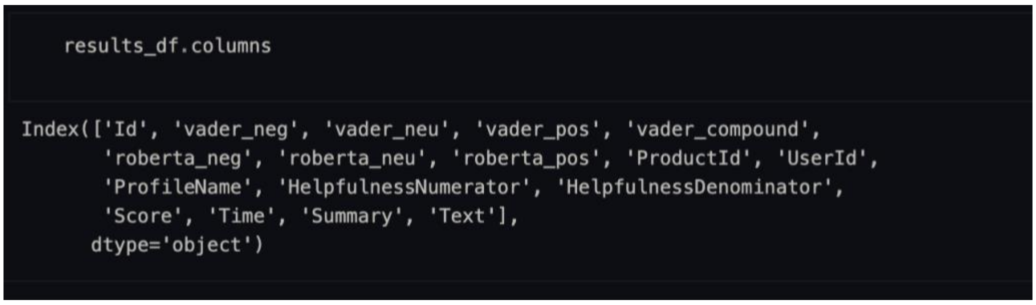
The third line creates an instance of the SentimentIntensityAnalyzer class, which is stored in the variable sia. This object is used to perform sentiment analysis on the input text.

The fourth line calls the polarity_scores method of the sia object with an example input text as an argument. This method calculates the sentiment scores of the input text, returning a dictionary containing the positive, negative, and neutral sentiment scores, as well as an overall compound score that combines all three.

Overall, this code sets up the SentimentIntensityAnalyzer class from nltk.sentiment to perform sentiment analysis on input text. To analyze the sentiment of a given input text, one can create an instance of SentimentIntensityAnalyzer, and call its polarity_scores method with the input text as an argument. This will return a dictionary of sentiment scores representing the positive, negative, neutral, and compound sentiment of the input text.

6.3.5 IMPLEMENTING ROBERTA

1. Loaded the pre-processed data from the CSV file into a pandas dataframe.
2. Installed the Transformers library using pip
3. Imported the necessary classes and methods from the Transformers library:
4. Instantiated the RoBERTa tokenizer and model. I used the **"cardiffnlp/twitter-roberta-base-sentiment"** pretrained model.
5. Defined a function to apply the RoBERTa model to each review and return the predicted sentiment label: **roberta_neg, roberta_neu and roberta_pos.**
6. Applied the function to each review in the dataframe and store the predicted sentiment label in a new column.



```
    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')
```

7. Save the updated dataframe as a CSV file using the to_csv() method from pandas.

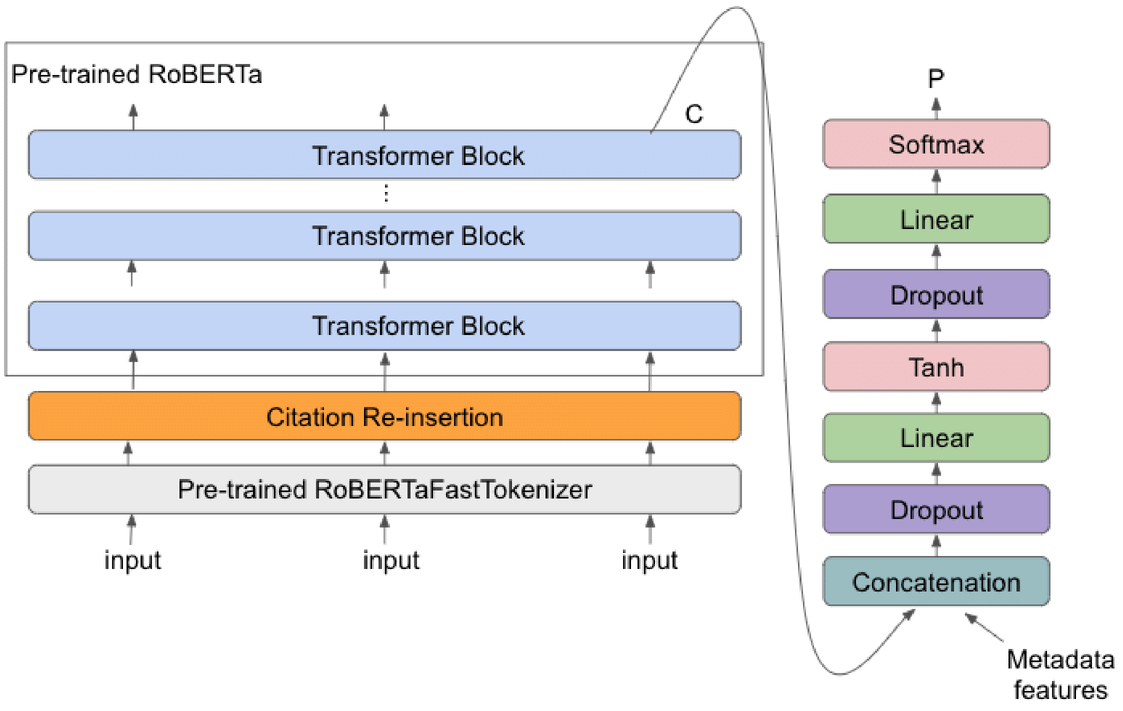
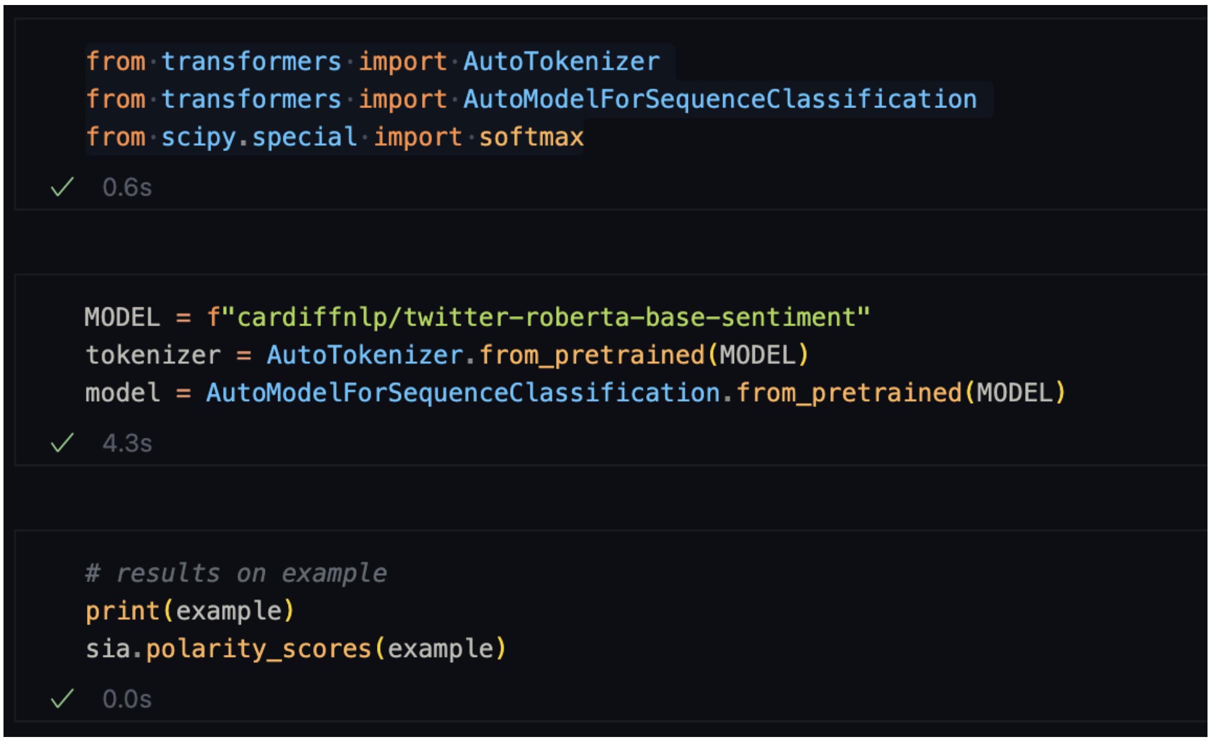


Figure 1.1 Architecture of RoBERTa Pre-trained Model

6.3.5.1 IMPLEMENTATION CODE



```
from transformers import AutoTokenizer
from transformers import AutoModelForSequenceClassification
from scipy.special import softmax
```
✓ 0.6s

```
MODEL = f"cardiffnlp/twitter-roberta-base-sentiment"
tokenizer = AutoTokenizer.from_pretrained(MODEL)
model = AutoModelForSequenceClassification.from_pretrained(MODEL)
```
✓ 4.3s

```
# results on example
print(example)
sia.polarity_scores(example)
```
✓ 0.0s

The first line imports the required **AutoTokenizer** class from the Transformers library, which is used to automatically download and load the appropriate tokenizer for the pre-trained RoBERTa model.

The second line imports the required **AutoModelForSequenceClassification** class from the Transformers library, which is used to automatically download and load the appropriate pre-trained RoBERTa model for sequence classification.

The third line imports the **softmax** function from the **scipy.special** library, which is used to calculate the **softmax** function on the output logits of the RoBERTa model.

The fourth line defines the pre-trained model to use, in this case the Twitter RoBERTa model named **"cardiffnlp/twitter-roberta-base-sentiment".** This model was pre-trained on Twitter data and fine-tuned for sentiment analysis.

The fifth line initializes an instance of the **AutoTokenizer** class with the pre-trained Twitter RoBERTa model specified by MODEL. This tokenizer is responsible for processing raw text into tokens that can be fed into the model.

The sixth line initializes an instance of the **AutoModelForSequenceClassification** class with the pre-trained Twitter RoBERTa model specified by MODEL. This model is used to predict the sentiment of the input text.

The seventh line prints an example text to analyze. This is likely just a placeholder for the actual input text to be analyzed.

The eighth line calls the **polarity_scores** method of an unspecified **sia** object with the example text as an argument. This is likely a sentiment analysis tool using the VADER algorithm. The VADER algorithm returns a dictionary of scores representing the positive, negative, and neutral sentiment of the input text, as well as an overall compound score that represents the overall sentiment of the text.

6.3.6 IMPLEMENTING TRANSFORMERS PIPELINE

Hugging Face is a popular library for working with pre-trained transformer models in natural language processing (NLP). The library provides a simple interface for loading and using pre-trained models, as well as fine-tuning them on custom datasets.

Training

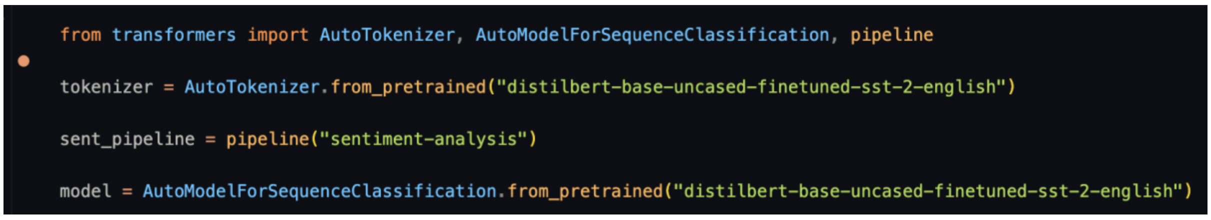
The DistilBERT model used in this implementation plan is a smaller and faster version of BERT, another popular transformer model for NLP. The model has been fine-tuned on the Stanford Sentiment Treebank (SST-2) dataset, which is a dataset of movie reviews labeled with sentiment polarity.

Training Procedure

Fine-tuning hyper-parameters

- ♦ learning_rate = 1e-5
- ♦ batch_size = 32
- ♦ warmup = 600
- ♦ max_seq_length = 128
- ♦ num_train_epochs = 3.0

6.3.6.1 IMPLEMENTATION CODE



```
from transformers import AutoTokenizer, AutoModelForSequenceClassification, pipeline

tokenizer = AutoTokenizer.from_pretrained("distilbert-base-uncased-finetuned-sst-2-english")

sent_pipeline = pipeline("sentiment-analysis")

model = AutoModelForSequenceClassification.from_pretrained("distilbert-base-uncased-finetuned-sst-2-english")
```

It is a pre-trained DistilBERT model, which is a smaller and faster version of the BERT model for natural language processing (NLP).

The first line imports the required classes from the Transformers library: **AutoTokenizer**, **AutoModelForSequenceClassification**, and **pipeline**. These classes provide functionality for loading and using pre-trained NLP models for various tasks.

The second line initializes an instance of the **AutoTokenizer** class with the pre-trained DistilBERT model "**distilbert-base-uncased-finetuned-sst-2-english**". This tokenizer is responsible for processing raw text into tokens that can be fed into the model.

The third line initializes an instance of the pipeline class for sentiment analysis using the **sentiment-analysis** argument. This pipeline object is a convenient way to use the pre-trained DistilBERT model for sentiment analysis without having to manually configure the model and tokenizer.

The fourth line initializes an instance of the **AutoModelForSequenceClassification** class with the same pre-trained DistilBERT model as the tokenizer. This class is used to automatically download and load the pre-trained model for sequence classification, which is the task of assigning a label (in this case, a sentiment label) to a sequence of tokens.

Together, these lines of code set up a pre-trained DistilBERT model for sentiment analysis, using an automatically loaded tokenizer and pipeline object. To perform sentiment analysis on a given input text, we can simply call the **sent_pipeline** object with the input text as an argument. The pipeline object will automatically preprocess the text using the loaded tokenizer, pass the tokenized input through the pre-trained model, and return a sentiment label and score for the input text.

6.3.7 QUERYING STRUCTURED DATA FOR INSIGHTS

TAPAS is a BERT-like transformers model pretrained on a large corpus of English data from Wikipedia in a self-supervised fashion. This means it was pretrained on the raw tables and associated texts only, with no humans labelling them in any way (which is why it can use lots of publicly available data) with an automatic process to generate inputs and labels from those texts.

Training procedure

Preprocessing

The texts are lowercased and tokenized using WordPiece and a vocabulary size of 30,000. The inputs of the model are then of the form:

[CLS] Question [SEP] Flattened table [SEP]

The authors did first convert the WTQ dataset into the format of SQA using automatic conversion scripts.

More precisely, it was pretrained with two objectives:

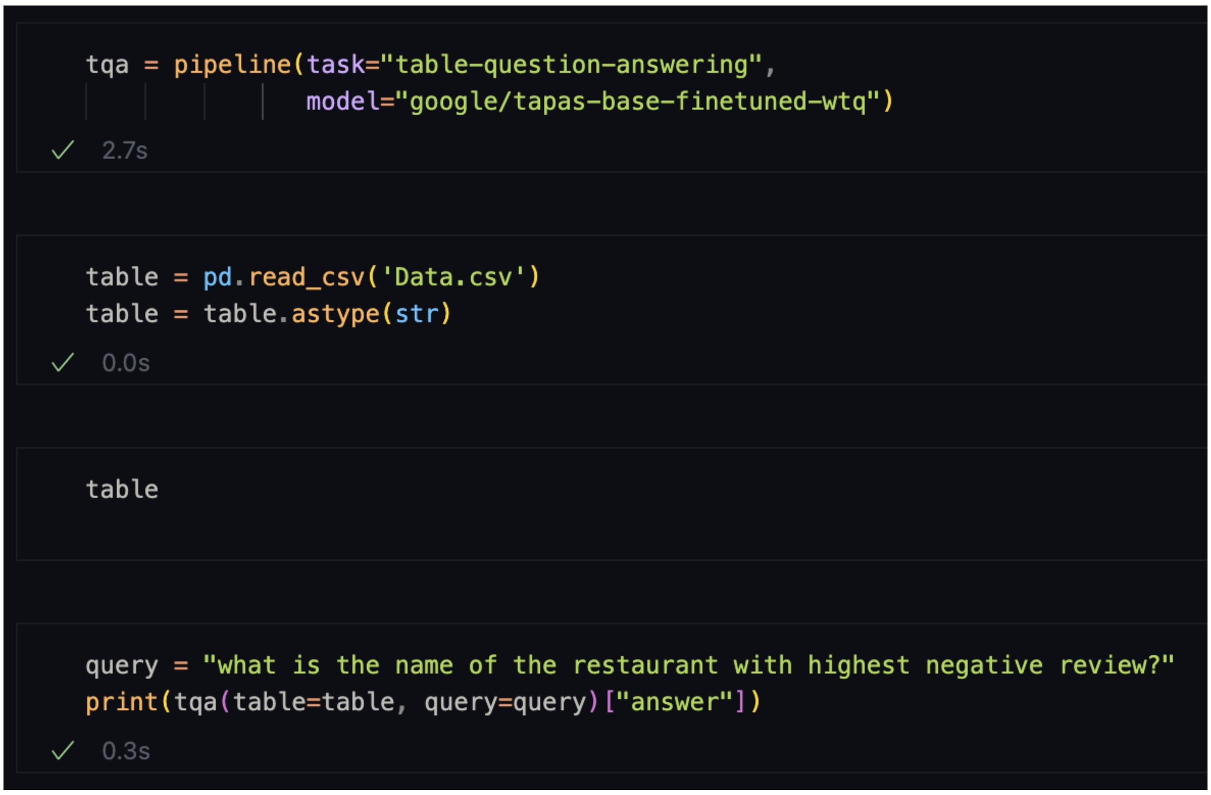
Masked language modeling (MLM): taking a (flattened) table and associated context, the model randomly masks 15% of the words in the input, then runs the entire (partially masked) sequence through the model.

Intermediate pre-training: to encourage numerical reasoning on tables, the authors additionally pre-trained the model by creating a balanced dataset of millions of syntactically created training examples.

Fine-tuning

The model was fine-tuned on 32 Cloud TPU v3 cores for 50,000 steps with maximum sequence length 512 and batch size of 512. In this setup, fine-tuning takes around 10 hours. The optimizer used is Adam with a learning rate of 1.93581e-5, and a warmup ratio of 0.128960. An inductive bias is added such that the model only selects cells of the same column.

6.3.7.1 IMPLEMENTATION CODE



```
tqa = pipeline(task="table-question-answering",
               model="google/tapas-base-finetuned-wtq")
✓ 2.7s

table = pd.read_csv('Data.csv')
table = table.astype(str)
✓ 0.0s

table

query = "what is the name of the restaurant with highest negative review?"
print(tqa(table=table, query=query)["answer"])
✓ 0.3s
```

This code implements a pipeline using Hugging Face's TAPAS model for table question answering. The pipeline is created using the **pipeline()** method from the transformers library. The pipeline is specified to perform the **"table-question-answering"** task using the pre-trained TAPAS model named **"google/tapas-base-finetuned-wtq".**

A CSV file containing a table is read using pandas and is stored in a variable named table. The table variable is then converted to a string data type using the **astype()** method.

A question is then input as a string to the **query** variable.

The **tqa()** method is called with the table and query parameters. The table parameter takes the pandas DataFrame representing the table and the query parameter takes the question as input. The **tqa()** method returns a dictionary containing the answer to the input question, which is accessed using the **"answer"** key.

Finally, the answer is printed to the console using the **print()** function.

6.3.8 MODEL EVALUATION

Evaluating the sentiment analysis models was important to understand their performance and compare their effectiveness. Here are some common evaluation metrics for sentiment analysis:

1. **Accuracy**: The proportion of correctly classified samples.
2. **Precision**: The proportion of true positive samples in the predicted positive samples.
3. **Recall**: The proportion of true positive samples in the actual positive samples.
4. **F1-score**: The harmonic mean of precision and recall.
5. **Confusion matrix**: A matrix that summarizes the number of true positive, false positive, true negative, and false negative samples.

To evaluate the sentiment analysis models using these metrics, I performed the following steps:

1. Split the dataset into training and test sets.
2. Trained my model on the training set.
3. Predicted the sentiment of the test set using the trained model.
4. Calculate the evaluation metrics (accuracy, precision, recall, F1-score and confusion matrix) using the predicted sentiment and the actual sentiment of the test set.
5. Compared the evaluation metrics of different models to determine the most effective one.

For Vader, I used the SentimentIntensityAnalyzer class from the **nltk.sentiment** module to perform sentiment analysis. I evaluated the model using the evaluation metrics mentioned above.

For Roberta and Transformer models, you can use the **AutoModelForSequenceClassification** class from the transformers library to perform sentiment analysis. You can train the model on the training set, and evaluate it using the evaluation metrics mentioned above on the test set.

6.3.9 MODEL SELECTION

1. **Defined the problem**: Clearly defined the problem you are trying to solve with sentiment analysis using Vader, Roberta, and Transformers. This helped me determine what type of models and techniques were appropriate for my use case.
2. **Gathered data**: Collected and preprocessed data that was representative of my problem domain. It was highly important for training and testing my models.
3. **Chose evaluation metrics**: Decided on evaluation metrics that were appropriate for my use case. Common evaluation metrics for sentiment analysis include accuracy, precision, recall, F1-score, confusion matrix, ROC curve, and AUC.
4. **Selected candidate models**: Chose a set of candidate models that were suitable for my use case. The models I chose are; VADER sentiment analysis tool, the pre-trained RoBERTa model from Hugging Face, and the pre-trained Transformer model from Hugging Face.
5. **Trained and validated models**: Trained the candidate models on my dataset and validated their performance using my chosen evaluation metrics. This was done using techniques the cross-validation.
6. **Compared and selected the best model**: Compared the performance of the candidate models and selected the one that performed the best on my chosen evaluation metrics.

6.3.9.1 HYPERPARAMETER TUNING

Fine-tuned the selected model to improve its performance. This involved tweaking hyperparameters or using techniques such as transfer learning to improve the model's ability to generalize to new data. The fine-tuning process was implement using the steps below:

1. **Defined hyperparameters**: Defined the hyperparameters that I want to tune. I tune the learning rate, batch size, number of epochs, and number of hidden layers.
2. **Created a hyperparameter search space**: Defined a range of values for each hyperparameter that I wanted to tune. This defined the search space that explored during hyperparameter tuning.
3. **Choose a hyperparameter tuning method**: Chose a hyperparameter tuning method that is appropriate for my use case. Popular methods include grid search, random search, and Bayesian optimization.
4. **Train and validated the model**: Trained the model using the hyperparameter tuning method and validate its performance using my chosen evaluation metrics.
5. **Evaluate the results**: Evaluated the results of the hyperparameter tuning method and choose the best set of hyperparameters based on your evaluation metrics.
6. **Fine-tune the selected model**: Fine-tuned the selected model using the best set of hyperparameters to improve its performance.

6.3.9.2 DEPLOYMENT

Once I selected and fine-tuned the model, I deployed it in my production environment and monitored its performance over time. This involved setting up a feedback loop to gather new data and continuously update the model as needed.

In terms of the framework deployment implementation strategy, I used the following phases and frontend visualization technologies: Voila and Word Cloud:

1. Prepared the trained sentiment analysis model and its associated files for deployment.
2. Installed Voila, which is a lightweight web application framework for Jupyter notebooks, and Word Cloud, which is a Python package for generating word clouds.
3. Created a new Jupyter notebook that loads the trained model and its associated files.
4. Used the Voila library to convert the notebook into a standalone web application that can be run on a server.
5. When the user submits text, the framework would use the trained model to perform sentiment analysis on the text.
6. Displayed the sentiment analysis results to the user in a visually appealing format, such as a word cloud that highlights the most common positive and negative words in the text.
7. Tested the framework to ensure it is functioning correctly and providing accurate sentiment analysis results.
8. Deployed the application to a server or cloud platform for public access.

With this implementation plan, I was able to deploy my sentiment analysis model and provided users with an interactive interface with visualization for analyzing the sentiment of text data.

7.0 CONCLUSION

In conclusion, sentiment analysis is a powerful technique for analyzing the sentiment of text data using machine learning models such as Vader, Roberta, and Transformers. In this conversation, we discussed the various implementation phases for sentiment analysis in Python, specifically for the Amazon Fine Food dataset.

We began with the data collection phase, where we considered using pre-existing databases such as Amazon Fine Foods. Next, we discussed data splitting using the Natural Language Toolkit (NLTK) and implemented models for sentiment analysis using Vader, Roberta, and Transformers.

We also discussed model evaluation techniques such as accuracy and F1-score, and hyperparameter fine-tuning to improve the performance of the sentiment analysis models. In particular, we talked about fine-tuning the hyperparameters of Roberta and Transformer models using the Hugging Face library.

Finally, we discussed the deployment phase of sentiment analysis using Voila, a lightweight web application framework for Jupyter notebooks, and Word Cloud, a Python package for generating word clouds. With these tools, we can create a user-friendly web application that enables users to analyze the sentiment of text data and visualize the results using visually appealing word clouds.

Specifically for the Amazon Fine Food dataset, we can use this sentiment analysis tool to understand the overall sentiment of customer reviews for food products sold on Amazon. This information can be used by businesses to improve their products and services, and by customers to make informed purchase decisions.

Overall, sentiment analysis is a valuable technique for understanding the sentiment of text data, and Python provides powerful tools and libraries for implementing and deploying sentiment analysis models. By using Vader, Roberta, and Transformers, along with tools like Voila and Word Cloud, we can create robust sentiment analysis models for a variety of applications, including analyzing customer reviews on Amazon Fine Foods.

7.1 SCOPE FOR FUTURE ENHANCEMENT

There are several potential areas for future enhancement of a sentiment analysis framework using VADER, RoBERTa, and transformer models with Voila and word cloud for visualization:

Model selection and tuning

While the use of VADER, RoBERTa, and transformer models is a good starting point, there may be other models that could improve the accuracy of sentiment analysis. Additionally, fine-tuning the existing models on specific datasets could also improve their performance.

Multilingual support

The current framework may be limited to English text. Adding support for other languages could broaden the scope of the sentiment analysis framework.

Real-time analysis

While the current framework is capable of analyzing pre-existing text data, adding real-time analysis capabilities could be useful for monitoring social media or other streams of text data.

Integration with other visualization tools

While word clouds are a popular and effective visualization method, there may be other visualization tools that could be used to provide additional insights into sentiment analysis results.

Integration with other NLP tasks

Sentiment analysis is just one of many natural language processing tasks. Integrating the framework with other NLP tasks such as text classification, named entity recognition, or summarization could provide a more complete analysis of text data.

User interface improvements

While Voila provides a simple interface for interacting with the sentiment analysis framework, there may be ways to improve the user experience such as adding additional options for customization or integrating with other tools for data analysis.

8.0 BIBLIOGRAPHY

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9.0 APPENDICES

9.1 TABLE DESIGN

Review Attribute	Description	Data Type
ID	index	int64
Product ID	Unique identifier for the product	object
User ID	Unique identifier for the user	object
ProfileName	Profile of the user	object
HelpfulnessNumerator	Number of users who found the review helpful	int64
HelpfulnessDenominator	Number of users who voted whether the review was helpful or not	int64
Score	Rating between 1 and 5	int64
Time	Timestamp of the review	int64
Summary	Brief summary of the review	object
Text	Text of the review	object

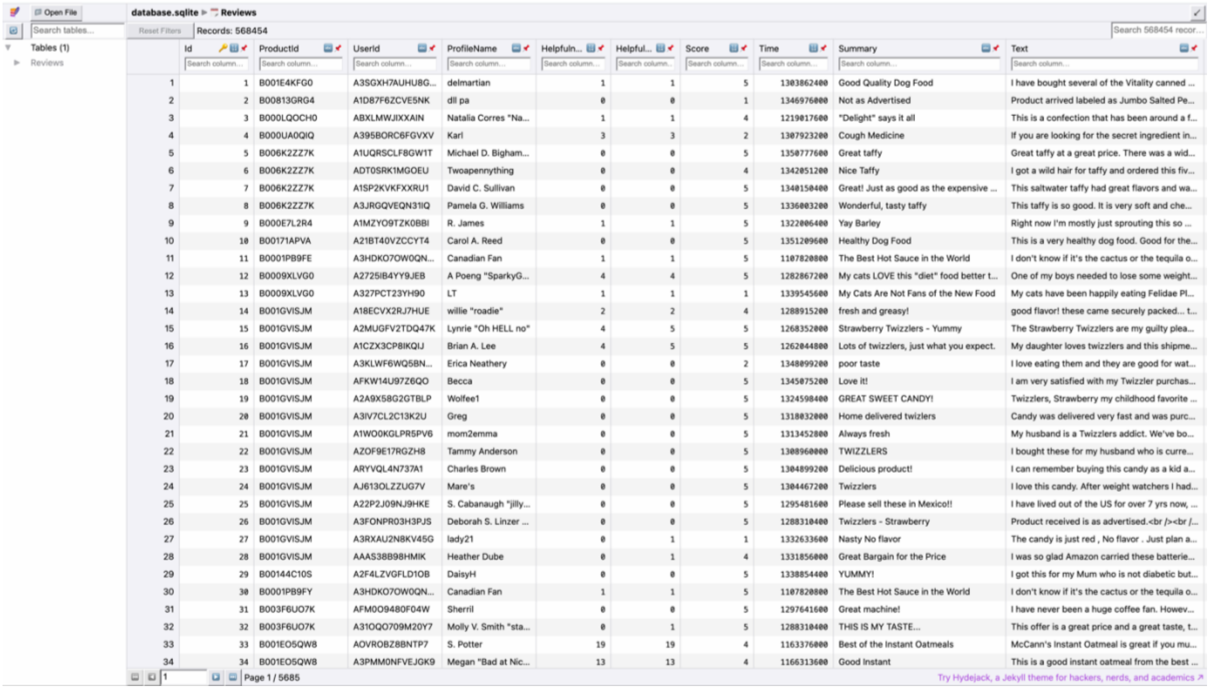
Summary of dtypes

int64 (5)

object (5)

Table 1.0 Dataset Feature Description

9.1.1 SQLITE DATABASE TABLE


Open File

database.sqlite ▶ Reviews

Records: 568454

Tables (1)

Reviews

	Id	ProductId	UserId	ProfileName	Helpfuln...	Helpful...	Score	Time	Summary	Text
1	1	B001E4KFG0	A3SGXH7AUHU8G...	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned ...
2	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Pe...
3	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Na...	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a f...
4	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine	If you are looking for the secret ingredient in...
5	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham...	0	0	5	1350777600	Great taffy	Great taffy at a great price. There was a wid...
6	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	4	1342051200	Nice Taffy	I got a wild hair for taffy and ordered this fiv...
7	7	B006K2ZZ7K	A1SP2KVKFXXRU1	David C. Sullivan	0	0	5	1340150400	Great! Just as good as the expensive ...	This saltwater taffy had great flavors and wa...
8	8	B006K2ZZ7K	A3JRGQVEQN31IQ	Pamela G. Williams	0	0	5	1336003200	Wonderful, tasty taffy	This taffy is so good. It is very soft and che...
9	9	B000E7L2R4	A1MZYO9TZK0BBI	R. James	1	1	5	1322006400	Yay Barley	Right now I'm mostly just sprouting this so ...
10	10	B00171APVA	A21BT40VZCCYT4	Carol A. Reed	0	0	5	1351209600	Healthy Dog Food	This is a very healthy dog food. Good for the...
11	11	B0001PB9FE	A3HDKO7OW0QN...	Canadian Fan	1	1	5	1107820800	The Best Hot Sauce in the World	I don't know if it's the cactus or the tequila o...
12	12	B0009XLVG0	A2725IB4YY9JEB	A Poeng "SparkyG...	4	4	5	1282867200	My cats LOVE this "diet" food better t...	One of my boys needed to lose some weight...
13	13	B0009XLVG0	A327PCT23YH90	LT	1	1	1	1339545600	My Cats Are Not Fans of the New Food	My cats have been happily eating Felidae Pl...
14	14	B001GVISJM	A18ECVX2RJ7HUE	willie "roadie"	2	2	4	1288915200	fresh and greasy!	good flavor! these came securely packed... t...
15	15	B001GVISJM	A2MUGFV2TDQ47K	Lynrie "Oh HELL no"	4	5	5	1268352000	Strawberry Twizzlers - Yummy	The Strawberry Twizzlers are my guilty plea...
16	16	B001GVISJM	A1CZX3CP8IKQIJ	Brian A. Lee	4	5	5	1262044800	Lots of twizzlers, just what you expect.	My daughter loves twizzlers and this shipme...
17	17	B001GVISJM	A3KLWF6WQ5BN...	Erica Neathery	0	0	2	1348099200	poor taste	I love eating them and they are good for wat...
18	18	B001GVISJM	AFKW14U97Z6QO	Becca	0	0	5	1345075200	Love it!	I am very satisfied with my Twizzler purchas...
19	19	B001GVISJM	A2A9X58G2GTBLP	Wolfee1	0	0	5	1324598400	GREAT SWEET CANDY!	Twizzlers, Strawberry my childhood favorite ...
20	20	B001GVISJM	A3IV7CL2C13K2U	Greg	0	0	5	1318032000	Home delivered twizlers	Candy was delivered very fast and was purc...
21	21	B001GVISJM	A1WO0KGLPR5PV6	mom2emma	0	0	5	1313452800	Always fresh	My husband is a Twizzlers addict. We've bo...
22	22	B001GVISJM	AZOF9E17RGZH8	Tammy Anderson	0	0	5	1308960000	TWIZZLERS	I bought these for my husband who is curre...
23	23	B001GVISJM	ARYVQL4N737A1	Charles Brown	0	0	5	1304899200	Delicious product!	I can remember buying this candy as a kid a...
24	24	B001GVISJM	AJ613OLZZUG7V	Mare's	0	0	5	1304467200	Twizzlers	I love this candy. After weight watchers I had...
25	25	B001GVISJM	A22P2J09NJ9HKE	S. Cabanaugh "jilly...	0	0	5	1295481600	Please sell these in Mexico!!	I have lived out of the US for over 7 yrs now, ...
26	26	B001GVISJM	A3FONPR03H3PJS	Deborah S. Linzer ...	0	0	5	1288310400	Twizzlers - Strawberry	Product received is as advertised.<br /><br /...
27	27	B001GVISJM	A3RXAU2N8KV45G	lady21	0	1	1	1332633600	Nasty No flavor	The candy is just red , No flavor . Just plan a...
28	28	B001GVISJM	AAAS38B98HMIK	Heather Dube	0	1	4	1331856000	Great Bargain for the Price	I was so glad Amazon carried these batterie...
29	29	B00144C10S	A2F4LZVGFLD1OB	DaisyH	0	0	5	1338854400	YUMMY!	I got this for my Mum who is not diabetic but...
30	30	B0001PB9FY	A3HDKO7OW0QN...	Canadian Fan	1	1	5	1107820800	The Best Hot Sauce in the World	I don't know if it's the cactus or the tequila o...
31	31	B003F6UO7K	AFM0O9480F04W	Sherril	0	0	5	1297641600	Great machine!	I have never been a huge coffee fan. Howev...
32	32	B003F6UO7K	A31OQO709M20Y7	Molly V. Smith "sta...	0	1	5	1288310400	THIS IS MY TASTE...	This offer is a great price and a great taste, t...
33	33	B001EO5QW8	AOVROBZ8BNTP7	S. Potter	19	19	4	1163376000	Best of the Instant Oatmeals	McCann's Instant Oatmeal is great if you mu...
34	34	B001EO5QW8	A3PMM0NFVEJGK9	Megan "Bad at Nic...	13	13	4	1166313600	Good Instant	This is a good instant oatmeal from the best ...

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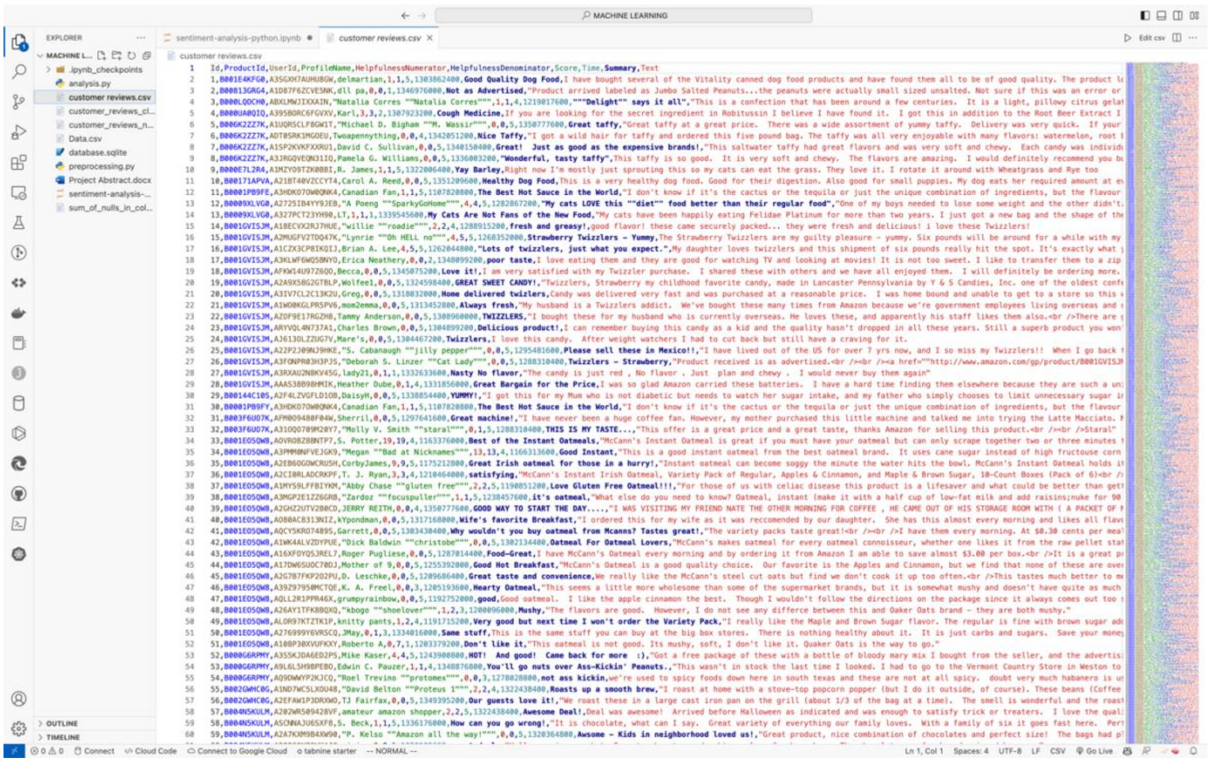
Table 1.1 SQLite Database Table

9.1.2 CSV FILE EXPORTED FROM SQLITE TABLE



```
Id,ProductId,UserId,ProfileName,HelpfulnessNumerator,HelpfulnessDenominator,Score,Time,Summary,Text
1,B001E4KFG0,A3SGXH7AUHU8GW,delmartian,1,1,5,1303862400,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 lo
2,B00813GRG4,A1D87F6ZCVE5NK,dll pa,0,0,1,1346976000,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
3,B000LQOCH0,ABXLMWJIXXAIN,"Natalia Corres ""Natalia Corres""",1,1,4,1219017600,"""Delight"" says it all","This is a confection that has been around a few centuries.  It is a light, pillowy citrus gelat
4,B000UA0QIQ,A395BORC6FGVXV,Karl,3,3,2,1307923200,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
5,B006K2ZZ7K,A1UQRSCLF8GW1T,"Michael D. Bigham ""M. Wassir""",0,0,5,1350777600,Great taffy,"Great taffy at a great price.  There was a wide assortment of yummy taffy.  Delivery was very quick.  If your
6,B006K2ZZ7K,ADT0SRK1MGOEU,Twoapennything,0,0,4,1342051200,Nice Taffy,"I got a wild hair for taffy and ordered this five pound bag. The taffy was all very enjoyable with many flavors: watermelon, root b
7,B006K2ZZ7K,A1SP2KVKFXXRU1,David C. Sullivan,0,0,5,1340150400,Great!  Just as good as the expensive brands!,"This saltwater taffy had great flavors and was very soft and chewy.  Each candy was individu
8,B006K2ZZ7K,A3JRGQVEQN31IQ,Pamela G. Williams,0,0,5,1336003200,"Wonderful, tasty taffy",This taffy is so good.  It is very soft and chewy.  The flavors are amazing.  I would definitely recommend you bu
9,B000E7L2R4,A1MZYO9TZK0BBI,R. James,1,1,5,1322006400,Yay Barley,Right now I'm mostly just sprouting this so my cats can eat the grass. They love it. I rotate it around with Wheatgrass and Rye too
10,B00171APVA,A21BT40VZCCYT4,Carol A. Reed,0,0,5,1351209600,Healthy Dog Food,This is a very healthy dog food. Good for their digestion. Also good for small puppies. My dog eats her required amount at ev
11,B0001PB9FE,A3HDKO7OW0QNK4,Canadian Fan,1,1,5,1107820800,The Best Hot Sauce in the World,"I don't know if it's the cactus or the tequila or just the unique combination of ingredients, but the flavour
12,B0009XLVG0,A2725IB4YY9JEB,"A Poeng ""SparkyGoHome""",4,4,5,1282867200,"My cats LOVE this ""diet"" food better than their regular food","One of my boys needed to lose some weight and the other didn't.
13,B0009XLVG0,A327PCT23YH90,LT,1,1,1,1339545600,My Cats Are Not Fans of the New Food,"My cats have been happily eating Felidae Platinum for more than two years. I just got a new bag and the shape of the
14,B001GVISJM,A18ECVX2RJ7HUE,"willie ""roadie""",2,2,4,1288915200,fresh and greasy!,good flavor! these came securely packed... they were fresh and delicious! i love these Twizzlers!
15,B001GVISJM,A2MUGFV2TDQ47K,"Lynrie ""Oh HELL no""",4,5,5,1268352000,Strawberry Twizzlers - Yummy,The Strawberry Twizzlers are my guilty pleasure - yummy. Six pounds will be around for a while with my
16,B001GVISJM,A1CZX3CP8IKQIJ,Brian A. Lee,4,5,5,1262044800,"Lots of twizzlers, just what you expect.",My daughter loves twizzlers and this shipment of six pounds really hit the spot. It's exactly what y
17,B001GVISJM,A3KLWF6WQ5BNYO,Erica Neathery,0,0,2,1348099200,poor taste,I love eating them and they are good for watching TV and looking at movies! It is not too sweet. I like to transfer them to a zip
18,B001GVISJM,AFKW14U97Z6QO,Becca,0,0,5,1345075200,Love it!,I am very satisfied with my Twizzler purchase.  I shared these with others and we have all enjoyed them.  I will definitely be ordering more.
19,B001GVISJM,A2A9X58G2GTBLP,Wolfee1,0,0,5,1324598400,GREAT SWEET CANDY!,"Twizzlers, Strawberry my childhood favorite candy, made in Lancaster Pennsylvania by Y & S Candies, Inc. one of the oldest confe
20,B001GVISJM,A3IV7CL2C13K2U,Greg,0,0,5,1318032000,Home delivered twizlers,Candy was delivered very fast and was purchased at a reasonable price.  I was home bound and unable to get to a store so this w
21,B001GVISJM,A1WO0KGLPR5PV6,mom2emma,0,0,5,1313452800,Always fresh,"My husband is a Twizzlers addict.  We've bought these many times from Amazon because we're government employees living overseas and c
22,B001GVISJM,AZOF9E17RGZH8,Tammy Anderson,0,0,5,1308960000,TWIZZLERS,"I bought these for my husband who is currently overseas. He loves these, and apparently his staff likes them also.<br />There are g
23,B001GVISJM,ARYVQL4N737A1,Charles Brown,0,0,5,1304899200,Delicious product!,I can remember buying this candy as a kid and the quality hasn't dropped in all these years. Still a superb product you won'
24,B001GVISJM,AJ613OLZZUG7V,Mare's,0,0,5,1304467200,Twizzlers,I love this candy.  After weight watchers I had to cut back but still have a craving for it.
25,B001GVISJM,A22P2J09NJ9HKE,"S. Cabanaugh ""jilly pepper""",0,0,5,1295481600,Please sell these in Mexico!!,"I have lived out of the US for over 7 yrs now, and I so miss my Twizzlers!!  When I go back t
26,B001GVISJM,A3FONPR03H3PJ5,"Deborah S. Linzer ""Cat Lady""",0,0,5,1288310400,Twizzlers - Strawberry,"Product received is as advertised.<br /><br /><a href=""http://www.amazon.com/gp/product/B001GVISJM
27,B001GVISJM,A3RXAU2N8KV45G,lady21,0,1,1,1332633600,Nasty No flavor,"The candy is just red , No flavor . Just  plan and chewy .  I would never buy them again"
28,B001GVISJM,AAAS38B98HMIK,Heather Dube,0,1,4,1331856000,Great Bargain for the Price,I was so glad Amazon carried these batteries.  I have a hard time finding them elsewhere because they are such a uni
29,B00144C10S,A2F4LZVGFLD1OB,DaisyH,0,0,5,1338854400,YUMMY!,"I got this for my Mum who is not diabetic but needs to watch her sugar intake, and my father who simply chooses to limit unnecessary sugar in
30,B0001PB9FY,A3HDKO7OW0QNK4,Canadian Fan,1,1,5,1107820800,The Best Hot Sauce in the World,"I don't know if it's the cactus or the tequila or just the unique combination of ingredients, but the flavour
31,B003F6UO7K,AFM0O9480F04W,Sherril,0,0,5,1297641600,Great machine!,"I have never been a huge coffee fan. However, my mother purchased this little machine and talked me into trying the Latte Macciato. M
32,B003F6UO7K,A31OQO709M20Y7,"Molly V. Smith ""staral""",0,1,5,1288310400,THIS IS MY TASTE...,"This offer is a great price and a great taste, thanks Amazon for selling this product.<br /><br />Staral"
33,B001EO5QW8,AOVROBZ8BNTP7,S. Potter,19,19,4,1163376000,Best of the Instant Oatmeals,"McCann's Instant Oatmeal is great if you must have your oatmeal but can only scrape together two or three minutes t
34,B001EO5QW8,A3PMM0NFVEJGK9,"Megan ""Bad at Nicknames""",13,13,4,1166313600,Good Instant,"This is a good instant oatmeal from the best oatmeal brand.  It uses cane sugar instead of high fructose corn
35,B001EO5QW8,A2EB6OGOWCRU5H,CorbyJames,9,9,5,1175212800,Great Irish oatmeal for those in a hurry!,"Instant oatmeal can become soggy the minute the water hits the bowl. McCann's Instant Oatmeal holds it
36,B001EO5QW8,A2CI0RLADCRKPF,T. J. Ryan,3,3,4,1210464000,satisfying,"McCann's Instant Irish Oatmeal, Variety Pack of Regular, Apples & Cinnamon, and Maple & Brown Sugar, 10-Count Boxes (Pack of 6)<br /
37,B001EO5QW8,A1MYS9LFFBIYKM,"Abby Chase ""gluten free""",2,2,5,1190851200,Love Gluten Free Oatmeal!!!,"For those of us with celiac disease this product is a lifesaver and what could be better than gett
38,B001EO5QW8,A3MGP2E1ZZ6GRB,"Zardoz ""focuspuller""",1,1,5,1238457600,it's oatmeal,"What else do you need to know? Oatmeal, instant (make it with a half cup of low-fat milk and add raisins;nuke for 90
39,B001EO5QW8,A2GHZ2UTV2B0CD,JERRY REITH,0,0,4,1350777600,GOOD WAY TO START THE DAY....,"I WAS VISITING MY FRIEND NATE THE OTHER MORNING FOR COFFEE , HE CAME OUT OF HIS STORAGE ROOM WITH ( A PACKET OF M
40,B001EO5QW8,AO80AC8313NIZ,kYpondman,0,0,5,1317168000,Wife's favorite Breakfast,"I ordered this for my wife as it was reccomended by our daughter.  She has this almost every morning and likes all flavo
41,B001EO5QW8,AQCY5KRO7489S,Garrett,0,0,5,1303430400,Why wouldn't you buy oatmeal from Mcanns? Tastes great!,"The variety packs taste great!<br /><br />I have them every morning. At $0.30 cents per meal
42,B001EO5QW8,A1WK4ALVZDYPUE,"Dick Baldwin ""christobe""",0,0,5,1302134400,Oatmeal For Oatmeal Lovers,"McCann's makes oatmeal for every oatmeal connoisseur, whether one likes it from the raw pellet stat
43,B001EO5QW8,A16XFOYQ5JREL7,Roger Pugliese,0,0,5,1287014400,Food-Great,I have McCann's Oatmeal every morning and by ordering it from Amazon I am able to save almost $3.00 per box.<br />It is a great pr
44,B001EO5QW8,A17DW6SUOC70DJ,Mother of 9,0,0,5,1255392000,Good Hot Breakfast,"McCann's Oatmeal is a good quality choice.  Our favorite is the Apples and Cinnamon, but we find that none of these are over
45,B001EO5QW8,A2G7B7FKP2O2PU,D. Leschke,0,0,5,1209686400,Great taste and convenience,We really like the McCann's steel cut oats but find we don't cook it up too often.<br />This tastes much better to me
46,B001EO5QW8,A39Z97950MCTQE,K. A. Freel,0,0,3,1205193600,Hearty Oatmeal,"This seems a little more wholesome than some of the supermarket brands, but it is somewhat mushy and doesn't have quite as much
47,B001EO5QW8,AQLL2R1PPR46X,grumpyrainbow,0,0,5,1192752000,good,Good oatmeal.  I like the apple cinnamon the best.  Though I wouldn't follow the directions on the package since it always comes out too s
48,B001EO5QW8,A26AY1TFK8BQXQ,"kbogo ""shoelover""",1,2,3,1200096000,Mushy,"The flavors are good.  However, I do not see any differce between this and Oaker Oats brand - they are both mushy."
49,B001EO5QW8,AL0R97KTZTK1P,knitty pants,1,2,4,1191715200,Very good but next time I won't order the Variety Pack,"I really like the Maple and Brown Sugar flavor. The regular is fine with brown sugar add
50,B001EO5QW8,A276999Y6VRSCQ,JMay,0,1,3,1334016000,Same stuff,This is the same stuff you can buy at the big box stores.  There is nothing healthy about it.  It is just carbs and sugars.  Save your money
51,B001EO5QW8,A108P30XVUFKXY,Roberto A,0,7,1,1203379200,Don't like it,"This oatmeal is not good. Its mushy, soft, I don't like it. Quaker Oats is the way to go."
52,B000G6RPMY,A3SSKJDA6ED2PS,Mike Kaser,4,4,5,1243900800,HOT!  And good!  Came back for more  :),"Got a free package of these with a bottle of bloody mary mix I bought from the seller, and the advertis
53,B000G6RPMY,A9L6L5H9BPEBO,Edwin C. Pauzer,1,1,4,1348876800,You'll go nuts over Ass-Kickin' Peanuts.,"This wasn't in stock the last time I looked. I had to go to the Vermont Country Store in Weston to
54,B000G6RPMY,AQ9DWWYP2KJCQ,"Roel Trevino ""protomex""",0,0,3,1278028800,not ass kickin,we're used to spicy foods down here in south texas and these are not at all spicy.  doubt very much habanero is us
55,B002GWHC0G,A1ND7WC5LXOU48,"David Belton ""Proteus 1""",2,2,4,1322438400,Roasts up a smooth brew,"I roast at home with a stove-top popcorn popper (but I do it outside, of course). These beans (Coffee
56,B002GWHC0G,A2EFAW1P3DRXWO,TJ Fairfax,0,0,5,1349395200,Our guests love it!,"We roast these in a large cast iron pan on the grill (about 1/3 of the bag at a time).  The smell is wonderful and the roast
57,B004N5KULM,A202WR509428VF,amateur amazon shopper,2,2,5,1322438400,Awesome Deal!,Deal was awesome!  Arrived before Halloween as indicated and was enough to satisfy trick or treaters.  I love the quali
58,B004N5KULM,ASCNNAJU6SXF8,S. Beck,1,1,5,1336176000,How can you go wrong!,"It is chocolate, what can I say.  Great variety of everything our family loves.  With a family of six it goes fast here.  Perf
59,B004N5KULM,A2A7KXM9B4XW90,"P. Kelso ""Amazon all the way!""",0,0,5,1320364800,Awsome - Kids in neighborhood loved us!,"Great product, nice combination of chocolates and perfect size!  The bags had pl
```

Table 1.2 Exported CSV File From Table

9.2 ER DIAGRAM

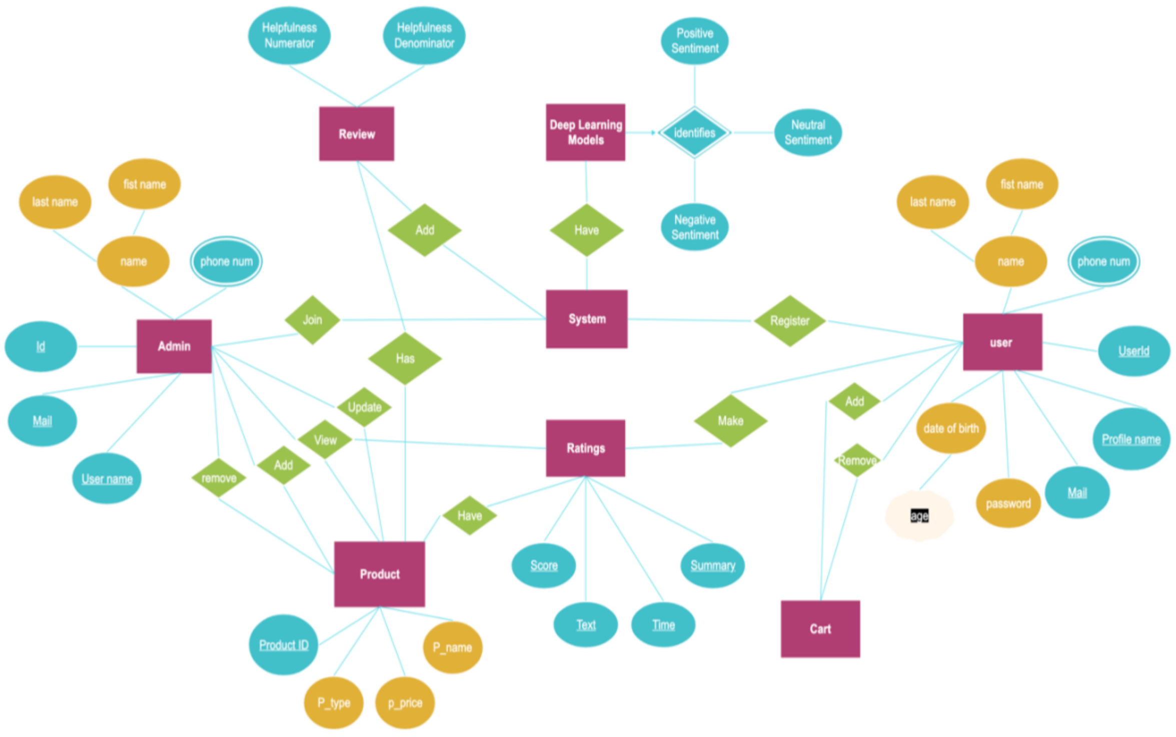


Figure 2.0 ER Diagram

9.3 DATA FLOW DIAGRAM

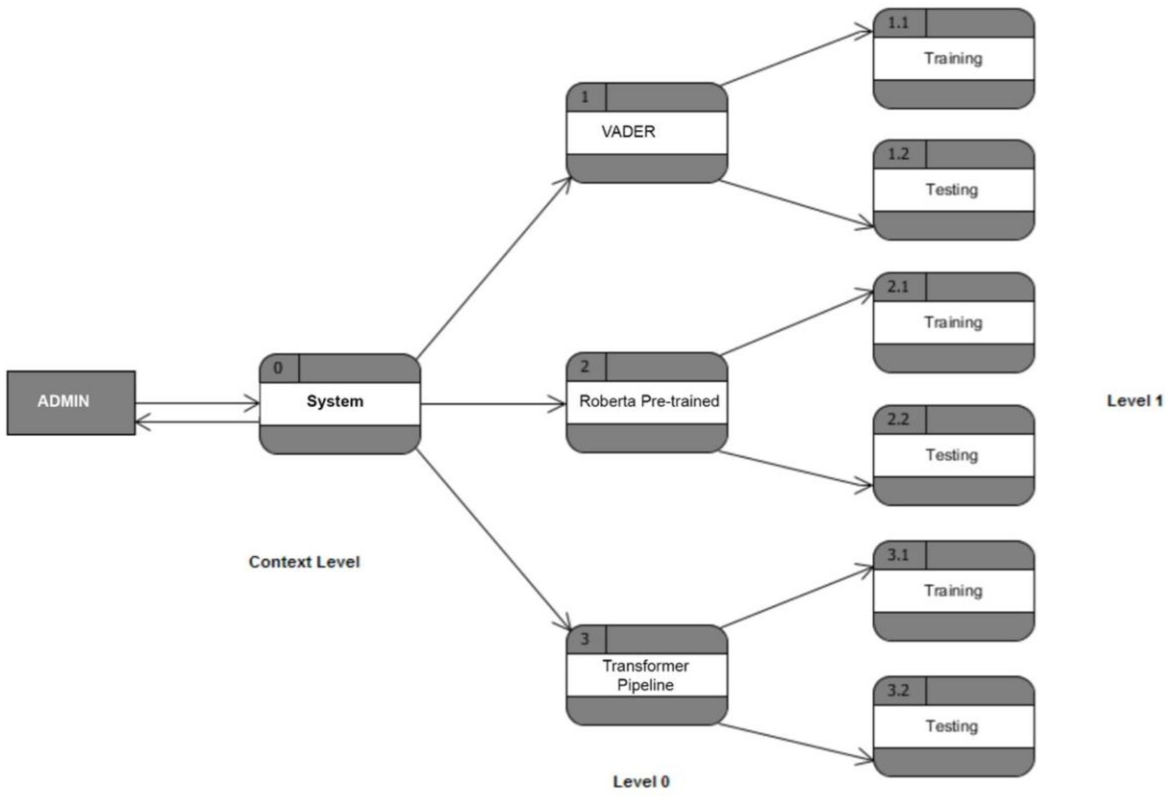


Figure 3.0 Level 0 and Level 1 Data Flow Diagram

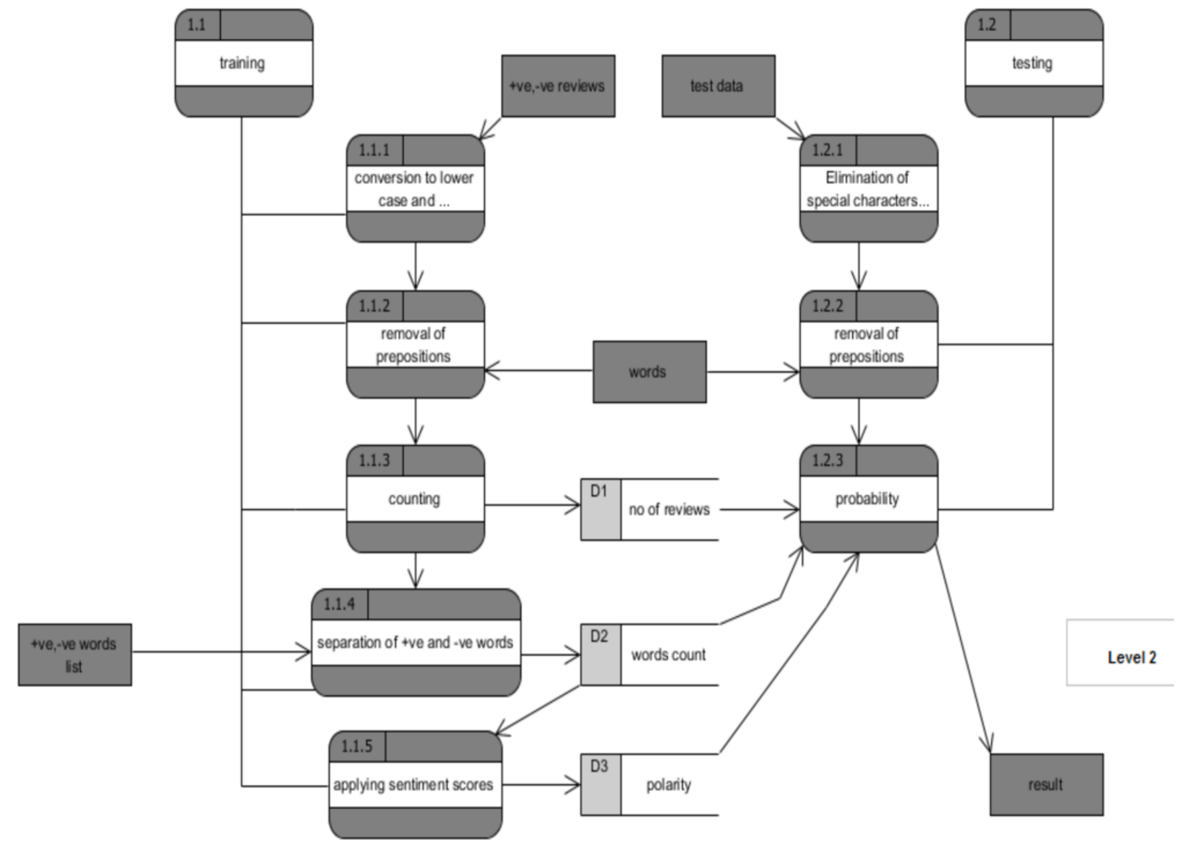


Figure 3.1 Level 2 Data Flow Diagram for VADER

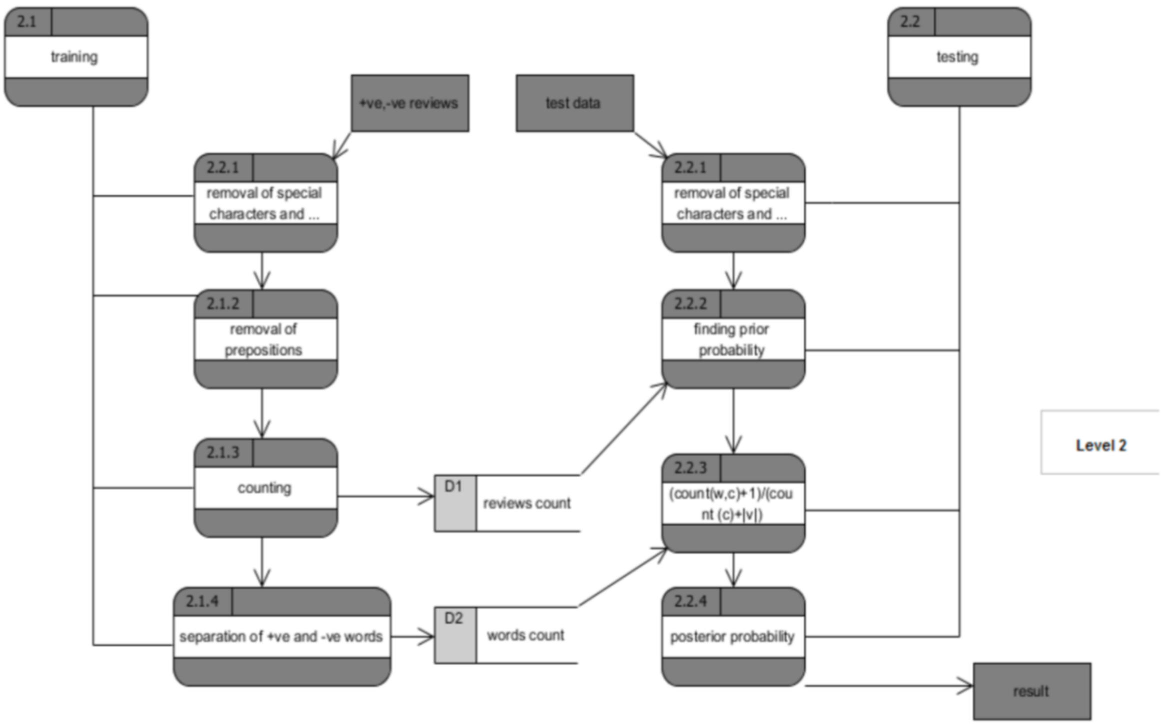


Figure 3.2 Level 2 Data Flow Diagram for Roberta Pre-trained

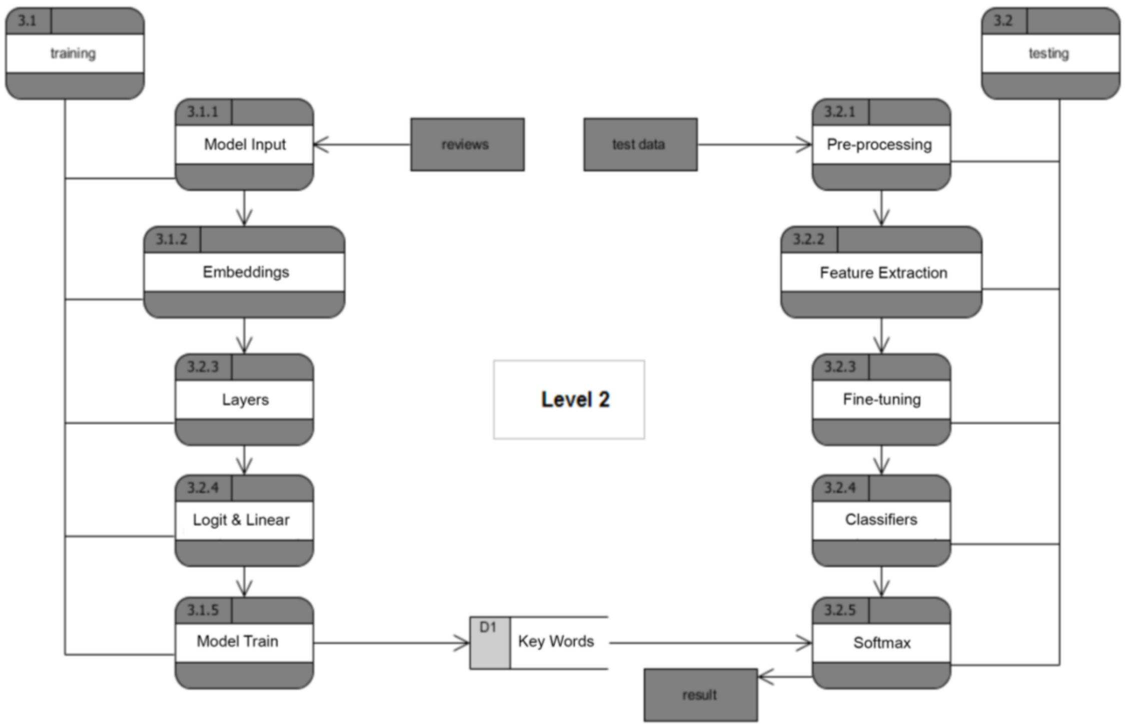
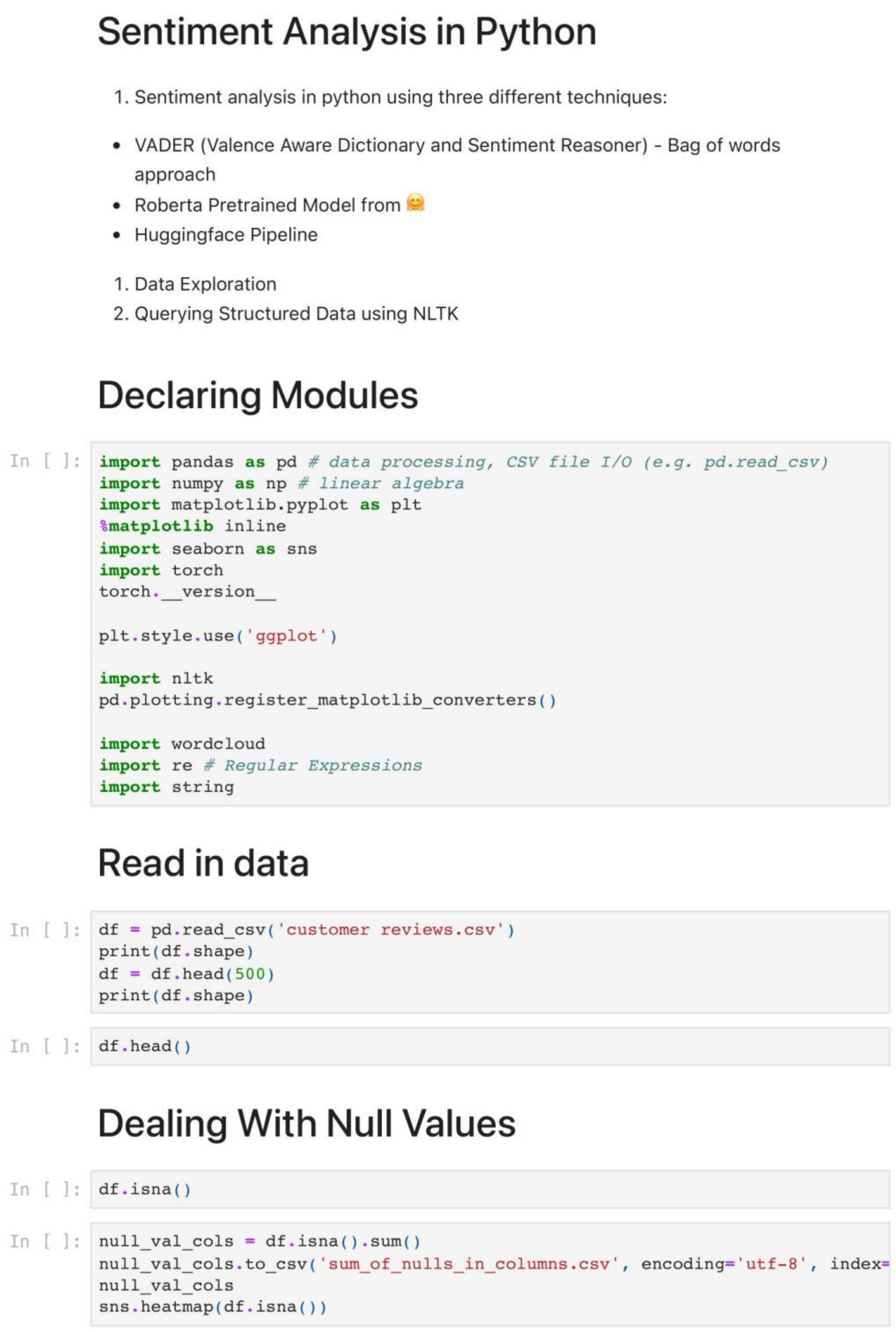


Figure 3.3 Level 2 Data Flow Diagram for Transformer Pipeline

9.4 SAMPLE CODE



Sentiment Analysis in Python

1. Sentiment analysis in python using three different techniques:

- VADER (Valence Aware Dictionary and Sentiment Reasoner) - Bag of words approach
- Roberta Pretrained Model from 🤗
- Huggingface Pipeline

1. Data Exploration
2. Querying Structured Data using NLTK

Declaring Modules

```
In [ ]: import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
        import numpy as np # linear algebra
        import matplotlib.pyplot as plt
        %matplotlib inline
        import seaborn as sns
        import torch
        torch.__version__

        plt.style.use('ggplot')

        import nltk
        pd.plotting.register_matplotlib_converters()

        import wordcloud
        import re # Regular Expressions
        import string
```

Read in data

```
In [ ]: df = pd.read_csv('customer reviews.csv')
        print(df.shape)
        df = df.head(500)
        print(df.shape)
```

```
In [ ]: df.head()
```

Dealing With Null Values

```
In [ ]: df.isna()
```

```
In [ ]: null_val_cols = df.isna().sum()
        null_val_cols.to_csv('sum_of_nulls_in_columns.csv', encoding='utf-8', index=
        null_val_cols
        sns.heatmap(df.isna())
```

```
In [ ]: col_with_nan = df.columns[df.isna().any()].tolist()

        for c in col_with_nan:
            df[c] = df[c].fillna('No item specified')

        df.to_csv('customer_reviews_cleaned.csv')
```

Removing Duplicate Data

```
In [ ]: def remove_duplication(data_f):
            if len(data_f[data_f.duplicated()]) != 0:
                data_f.drop_duplicates(inplace=True)
            return data_f


        df = remove_duplication(data_f=df)
```

Quick EDA

```
In [ ]: 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

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

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

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

```
In [ ]: entities = nltk.chunk.ne_chunk(tagged)
        entities.pprint()
```

VADER Sentiment 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. Scores range between -1 to 1.

```
In [ ]: from nltk.sentiment import SentimentIntensityAnalyzer
        from tqdm.notebook import tqdm

        sia = SentimentIntensityAnalyzer()
```

```
In [ ]: sia.polarity_scores('I am so happy!')
```

```
In [ ]: sia.polarity_scores('This is the worst thing ever.')
```

```
In [ ]: sia.polarity_scores(example)
```

```
In [ ]:
```

Run the polarity score on the entire dataset

```
In [ ]: res = {}
        for i, row in tqdm(df.iterrows(), total=len(df)):
            text = row['Text']
            myid = row['Id']
            res[myid] = sia.polarity_scores(text)
```

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

Sentiment score and metadata

```
In [ ]: vaders.head()
```

Plot VADER results

```
In [ ]: ax = sns.barplot(data=vaders, x='Score', y='compound')
        ax.set_title('Compund Score by Amazon Star Review')
        plt.show()
```

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

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.

```
In [ ]: from transformers import AutoTokenizer
        from transformers import AutoModelForSequenceClassification
        from scipy.special import softmax
```

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

```
In [ ]: # results on example
        print(example)
        sia.polarity_scores(example)
```

Run for Roberta Model

```
In [ ]: 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)
```

```
In [ ]: 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
```

```
In [ ]: 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}')
```

```
In [ ]: 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

```
In [ ]: results_df.columns
```

Combine and compare

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

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.

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

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

nevative sentiment 5-Star view

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

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

The Transformers Pipeline

- Quick & easy way to run sentiment predictions

```
In [ ]: from transformers import AutoTokenizer, AutoModelForSequenceClassification,

        tokenizer = AutoTokenizer.from_pretrained("distilbert-base-uncased-finetuned

        sent_pipeline = pipeline("sentiment-analysis")

        model = AutoModelForSequenceClassification.from_pretrained("distilbert-base-
```

```
In [ ]: sent_pipeline('I hate Rathinam College!')
```

```
In [ ]: sent_pipeline('Keep it up!')
```

```
In [ ]: sent_pipeline('Bad product!')
In [ ]: def predict_sentiment(customer_reviews_cleaned):
            result = pipeline(customer_reviews_cleaned)[0]
            label = result['label']
            score = result['score']
            if label == 'LABEL_0':
                sentiment = 'negative'
            elif label == 'LABEL_1':
                sentiment = 'positive'
            else:
                sentiment = 'neutral'
            return sentiment, score
```

Exploratory Data Analysis

```
In [ ]: df.describe()
```

```
In [ ]: df.info()
```

Based on the information above:

- we have no null values to worry about, so no missing values
- we have two type of columns, either int64 or object, in other word strings.
- we will focus on the score, summary and text column so we can drop the rest

```
In [ ]: all_cols = df.columns
        keep_cols = ['Score', 'Summary', 'Text']
        df.drop([c for c in all_cols if c not in keep_cols], axis=1, inplace=True)
        df.head()
```

Score Distribution Before Aggregation

```
In [ ]: plt.figure(figsize=(8,6))
        plt.title('Score distribution')
        sns.histplot(df['Score'], discrete=True);
```

Creating a new column ‘sentiment’ based on ‘Score’

```
In [ ]: def sentiments(df):
            return 'Positive' if (df['Score'] > 3) else 'Negative'
        df['sentiment'] = df.apply(sentiments, axis=1)
        df.head()
```

```
In [ ]: df.drop(['Score'], axis=1, inplace=True)
```

Plot Score after Aggregation

In [ ]:
```
plt.figure(figsize=(6,6))
plt.title('Sentiment distribution')
sns.histplot(df['sentiment']);
```

- We can see that the data is highly imbalanced toward positive reviews so we need to be careful when splitting the dataset into training and testing datasets.

Combine columns Summary with Text into full_text

In [ ]:
```
df['full_text'] = df['Summary'] + '. ' + df['Text']
df.head()
```

In [ ]:
```
df.drop(['Summary', 'Text'], axis=1, inplace=True)
```

Clean the text

- Data cleaning involves deleting special letters, digits, irrelevant symbols, and stop words. It is also necessary to translate the terms to their root form for easier interpretation.

In [ ]:
```
def replace_contractions(s):
    #dictionary consisting of the contraction and the actual value
    Apos_dict={"'s":" is","n't":" not","'m":" am","'ll":" will",
               "'d":" would","'ve":" have","'re":" are"}

    #replace the contractions
    for key,value in Apos_dict.items():
        if key in s:
            s=s.replace(key,value)
    return s
```

In [ ]:
```
def remove_punctuation(s, punct_list):
    for punc in punct_list:
        if punc in s:
            s = s.replace(punc, ' ')
    return s.strip()
```

In [ ]:
```
def truncate_large_review(s, seq_length):
    ''' Return a truncated s to the input seq_length.
    '''
    review_len = len(s)

    if review_len > seq_length:
        return s[0:seq_length]
    return s
```

In [ ]:
```
def cleaning(df):
    # make text lowercase
    df['full_text'] = df['full_text'].apply(lambda s: str(s).lower())
    print('To lowercase is done')

    # replace contractions
    df['full_text'] = df['full_text'].apply(lambda s: replace_contractions(s
    print('Contractions replacement is done')

    # remove html tags
    df['full_text'] = df['full_text'].apply(lambda s: re.compile(r'<[^>]+>')
    print('HTML tags removal is done')

    # remove punctuation
    regular_punct = list(string.punctuation)
    df['full_text'] = df['full_text'].apply(lambda s: remove_punctuation(s,
    print('Punctuation removal is done')

    # split attached words
    df['full_text'] = df['full_text'].apply(lambda s: " ".join([x for x in r
    print('Splitting attached words is done')

    # Replacing the digits/numbers
    df['full_text'] = df['full_text'].apply(lambda s: re.sub(r'\d+', '', s))
    print('Numbers replacement is done')

    # truncate large review
    df['full_text'] = df['full_text'].apply(lambda s: truncate_large_review(
    print('Truncation of large reviews is done')

    return df

df = cleaning(df)
```

In [ ]:
```
common_words=''
for i in df.full_text:
    i = str(i)
    tokens = i.split()
    common_words += " ".join(tokens)+" "
wordcloud = wordcloud.WordCloud().generate(common_words)
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```

In [ ]:
```
df.head()
```

Deductions From Data Exploration

- we can see in the word cloud that most reviews are positive since one of the biggest word is love, and we see words like good, great, delicious, etc.
- We can also see that the dataset is related to food since we see words like taste, coffee, eat, etc.

Querrying Structured Data using NLTK

In [ ]:
```
tqa = pipeline(task="table-question-answering",
               model="google/tapas-base-finetuned-wtq")
```

In [ ]:
```
table = pd.read_csv('Data.csv')
table = table.astype(str)
```

```
In [ ]: table
```

```
In [ ]: query = "what is the name of the restaurant with highest negative review?"
        print(tqa(table=table, query=query)["answer"])
```

```
In [ ]: query = ["Span of vishnu tea shop?"]

        print(tqa(table=table, query=query)["answer"])
```

The End

9.5 SCREENSHOTS

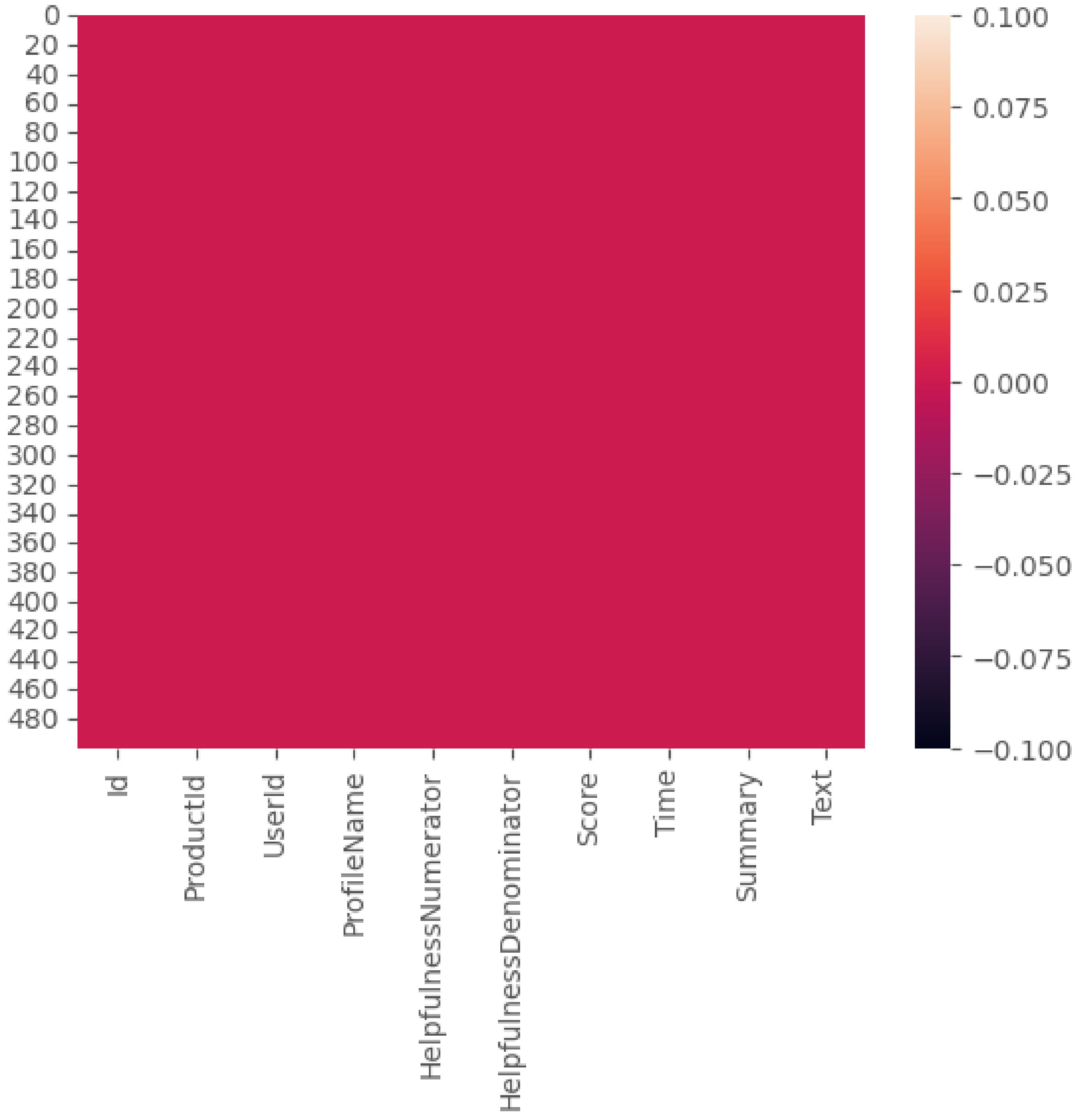


Figure 4.0 Heatmap of Null Values

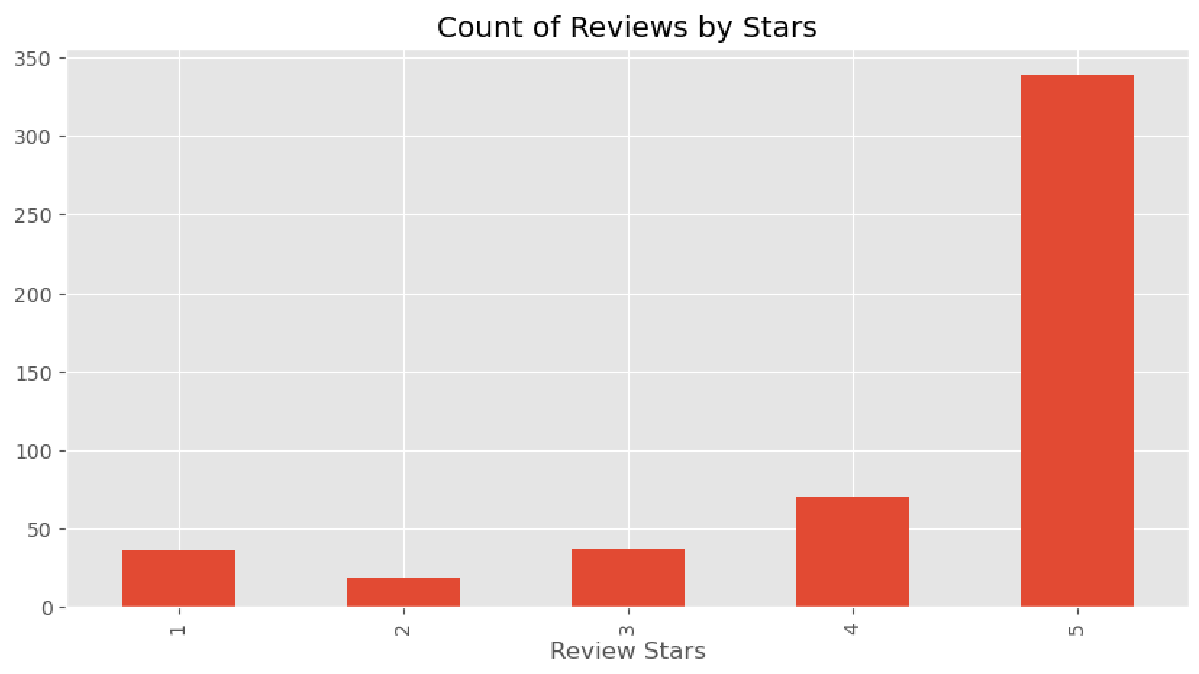


Figure 4.1 Count of Reviews Stars

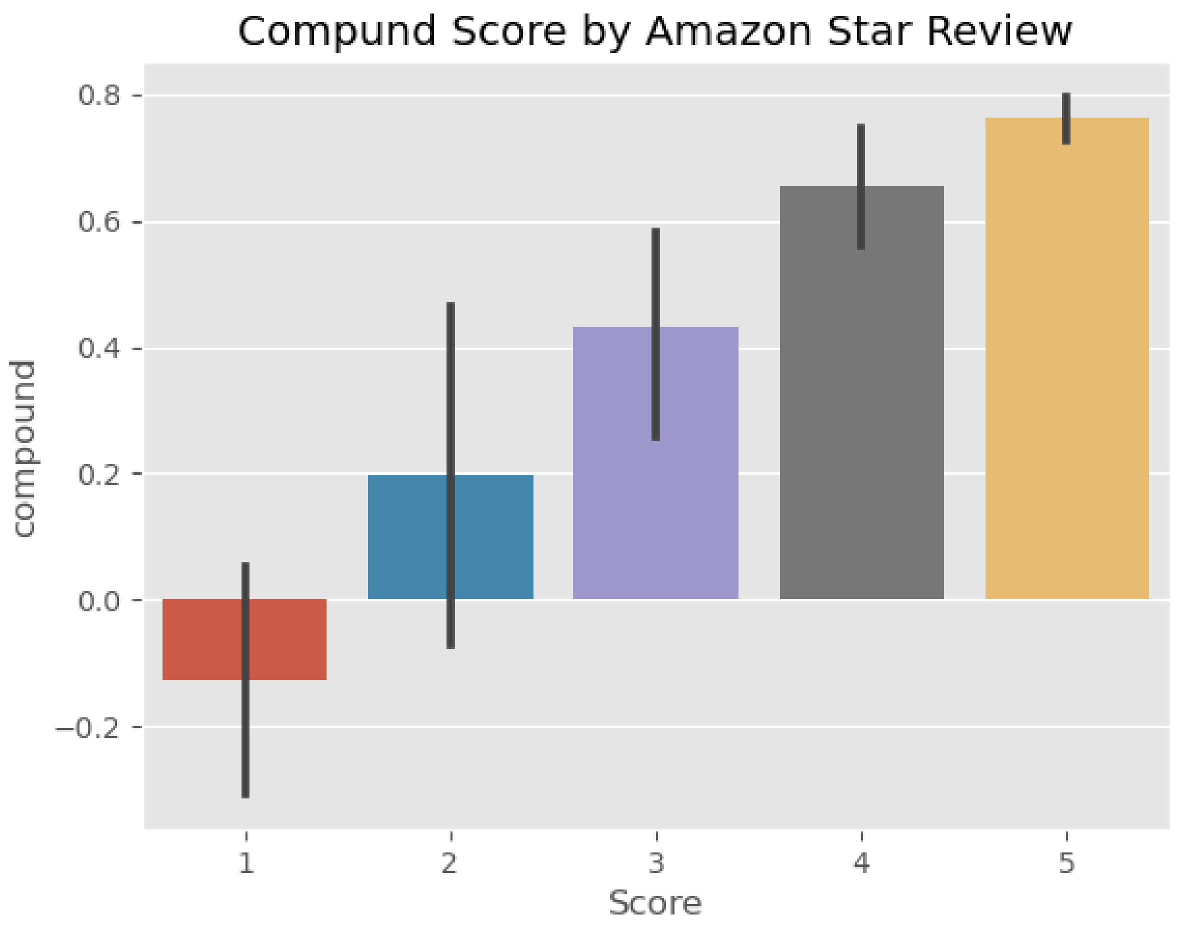


Figure 4.2 Compound Score by Amazon Star Review

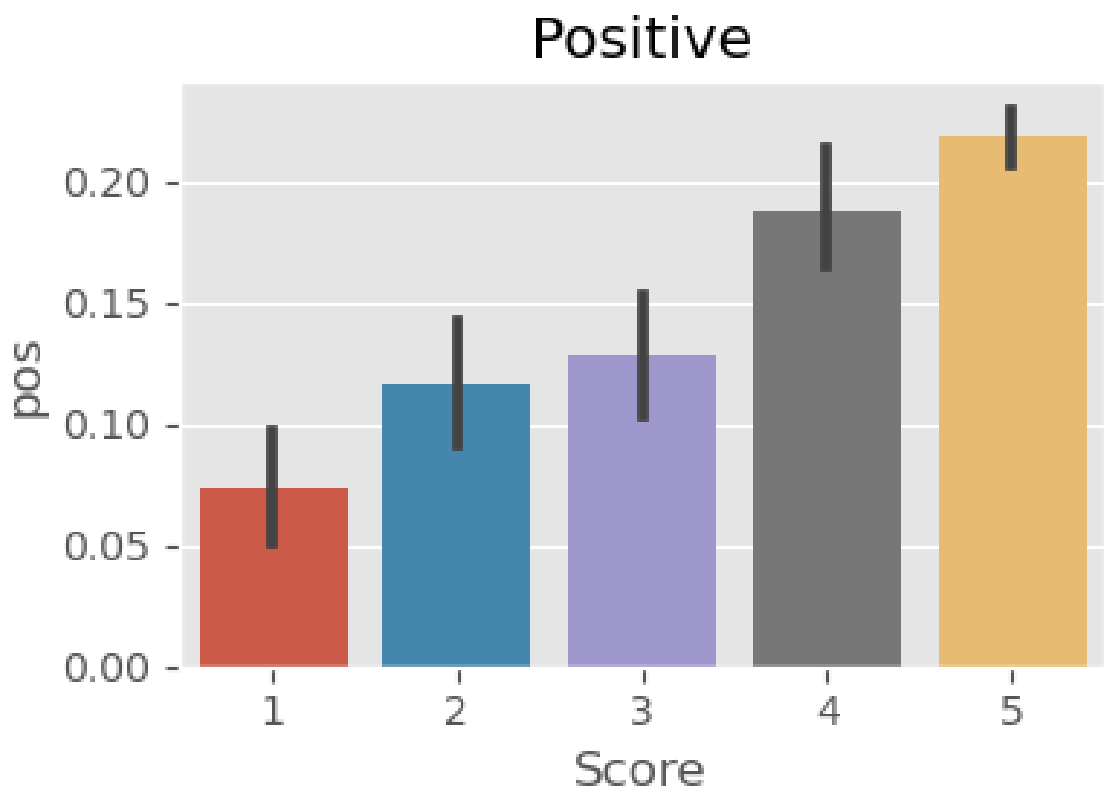


Figure 4.3 VADER Positive Sentiment Results

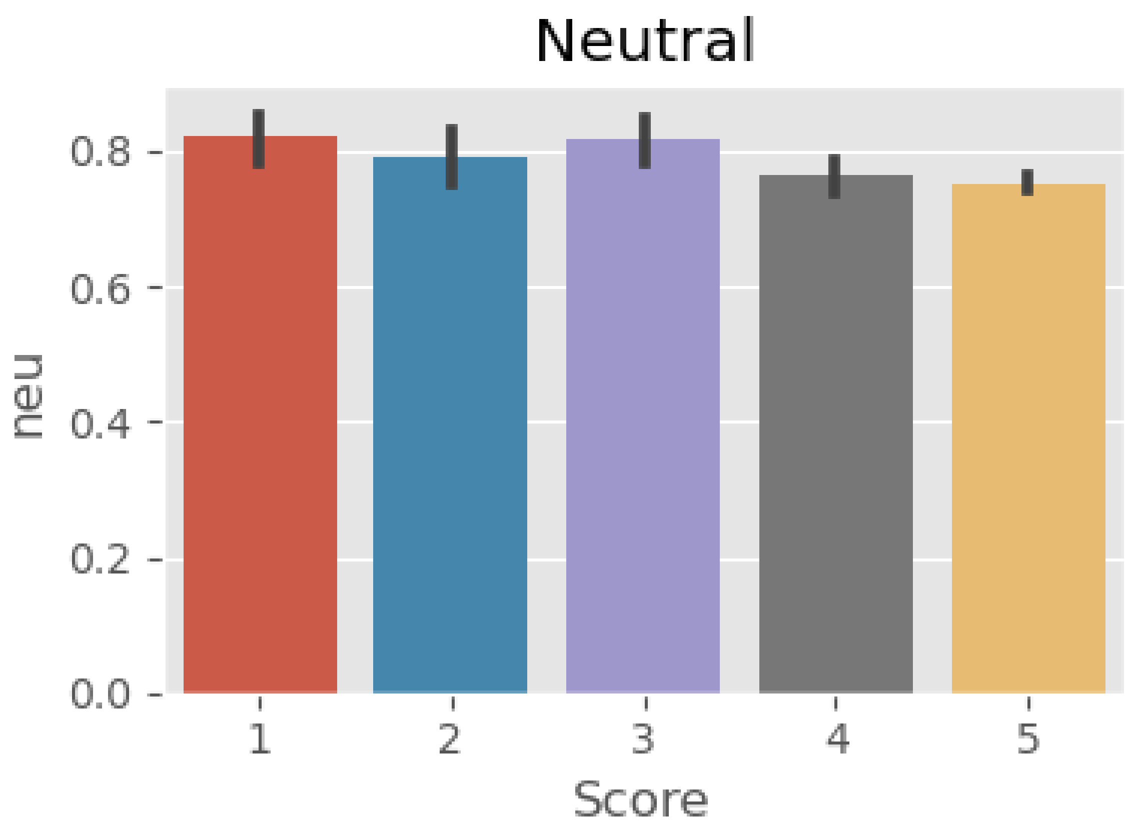


Figure 4.4 VADER Neutral Sentiment Results

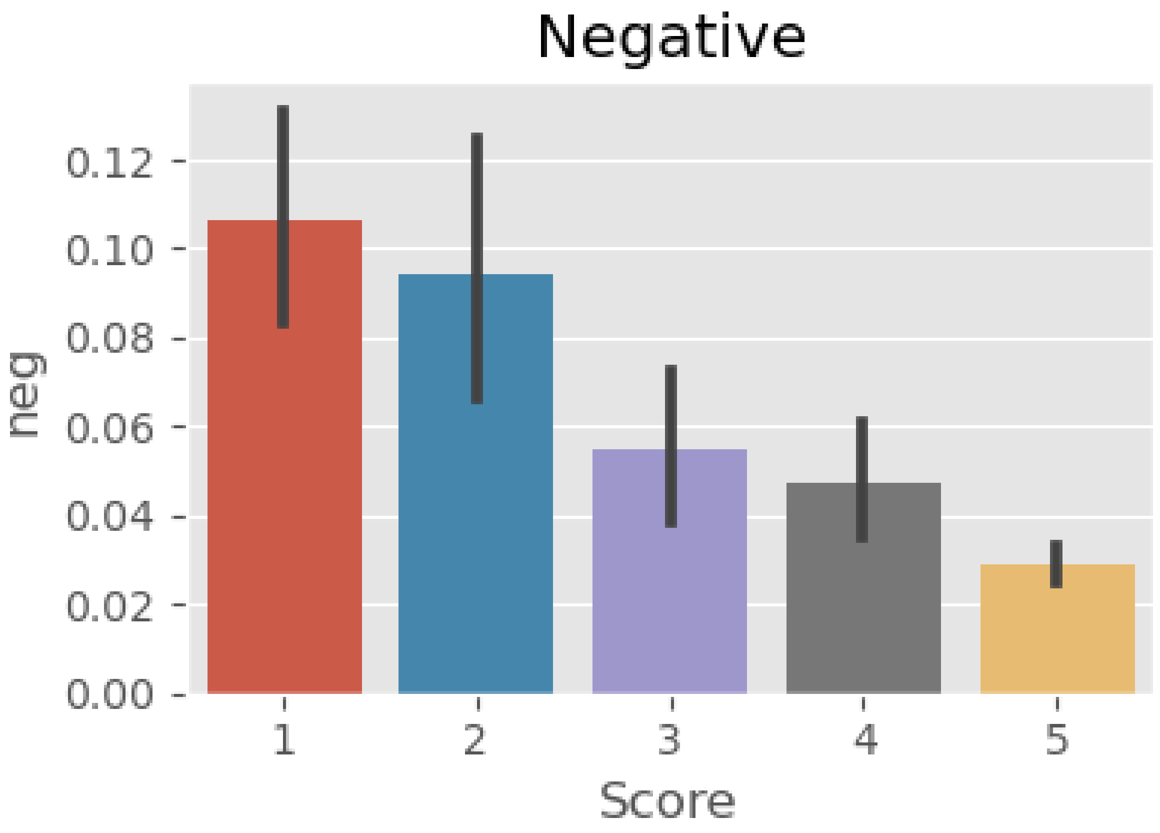


Figure 4.5 VADER Negative Sentiment Results

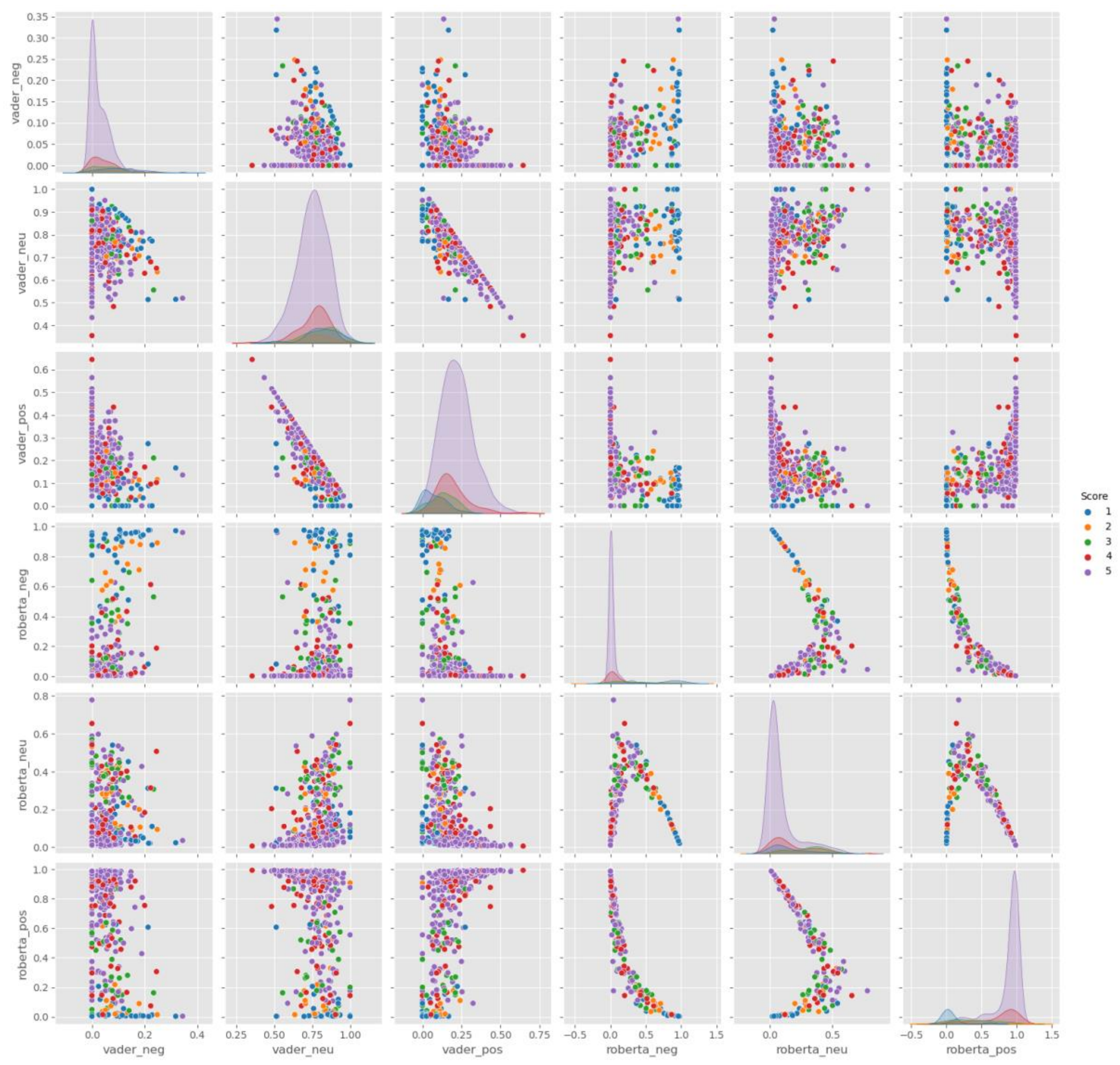


Figure 4.6 Combining & Comparing Scores Between VADER and RoBERTa

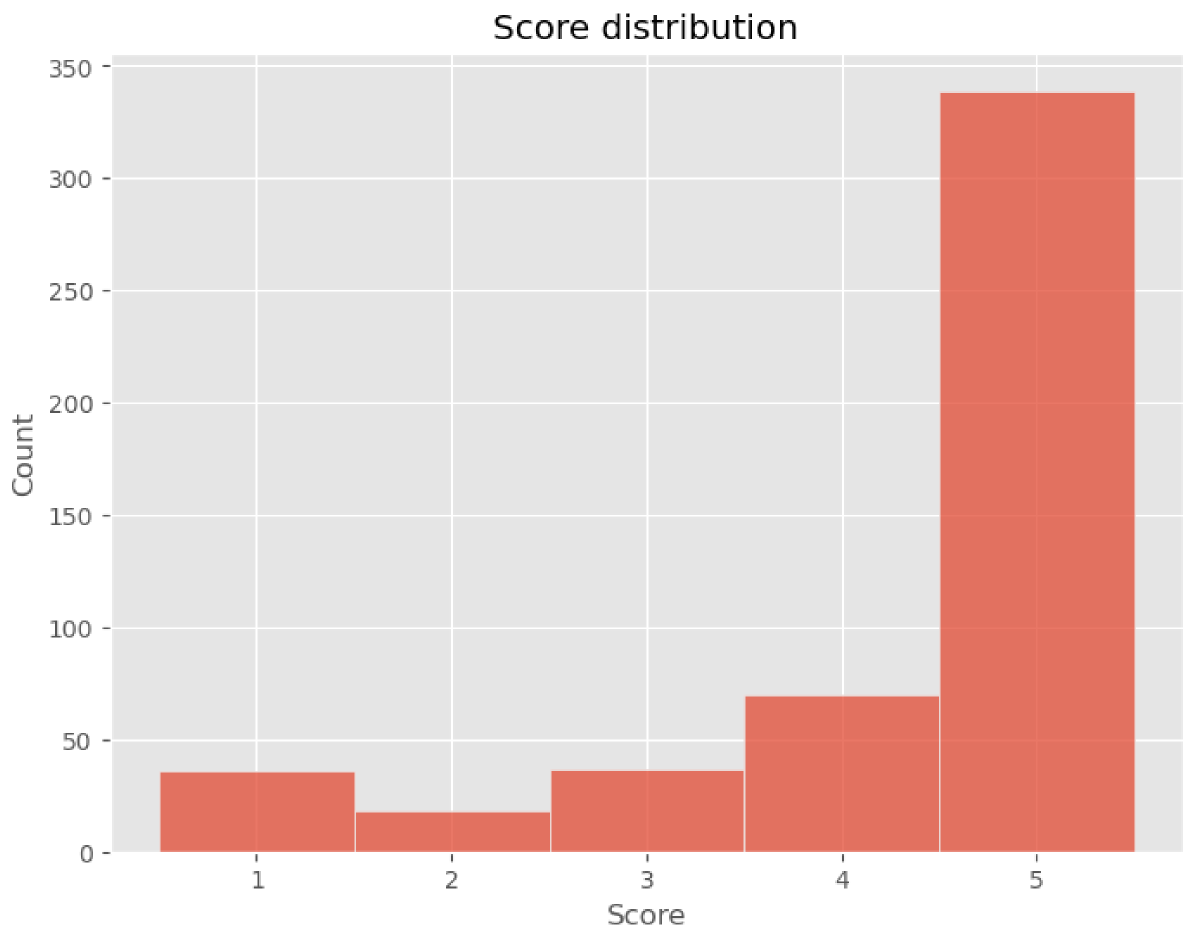


Figure 4.7 Score Distribution Before Aggregation

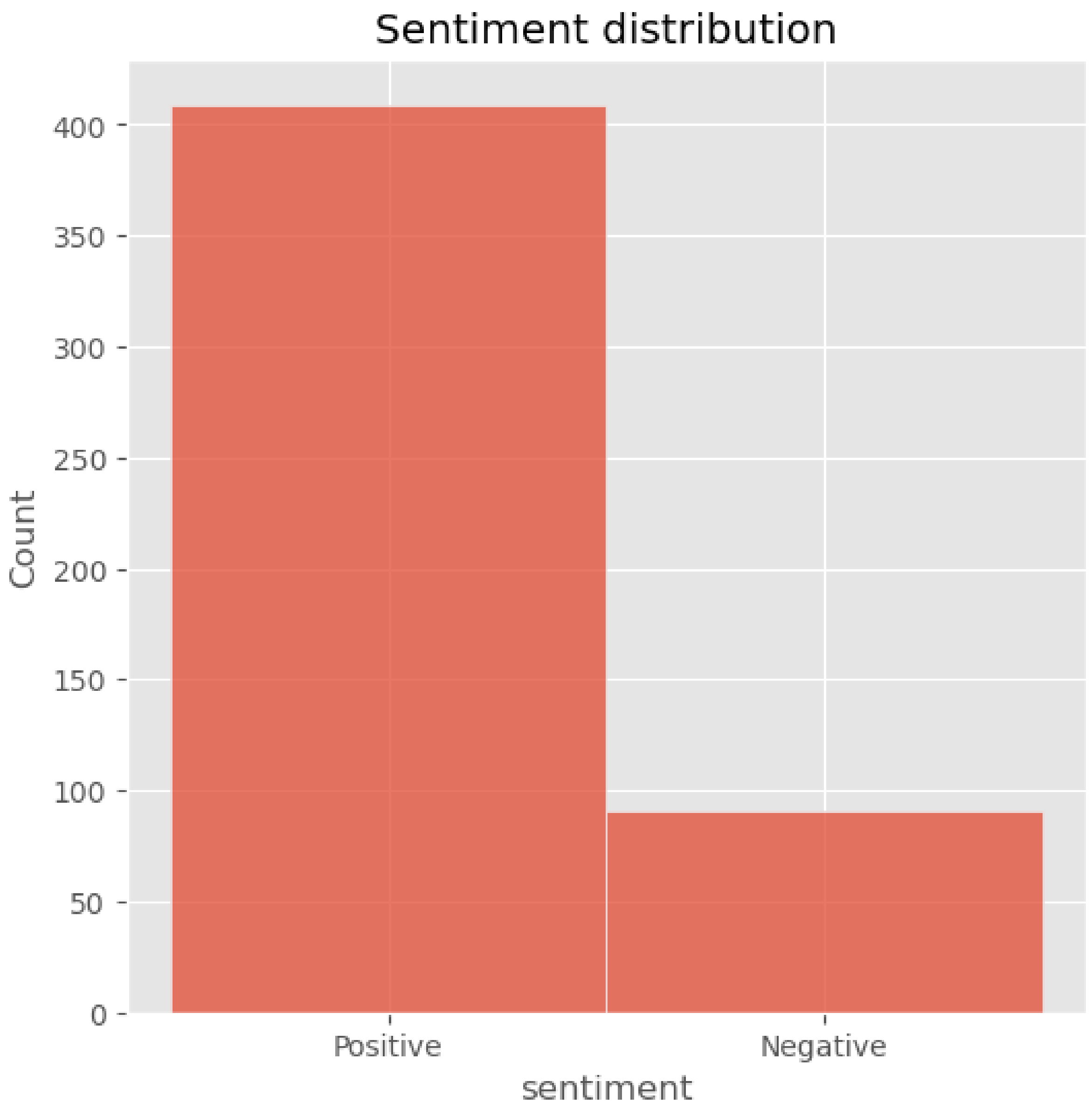


Figure 4.8 Sentiment Distribution After Aggregation

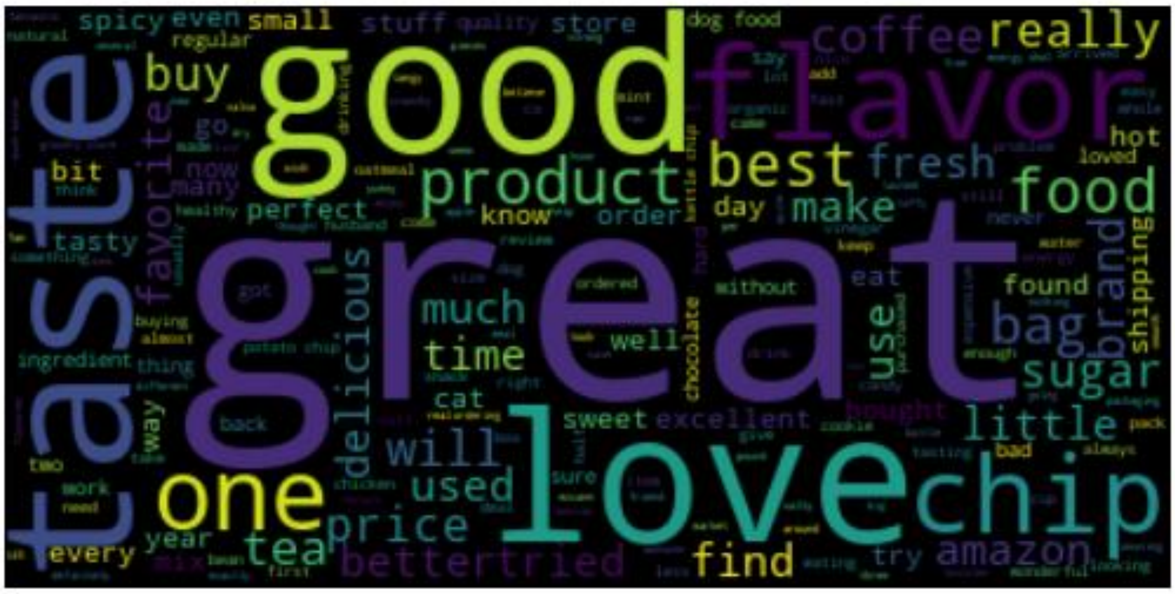
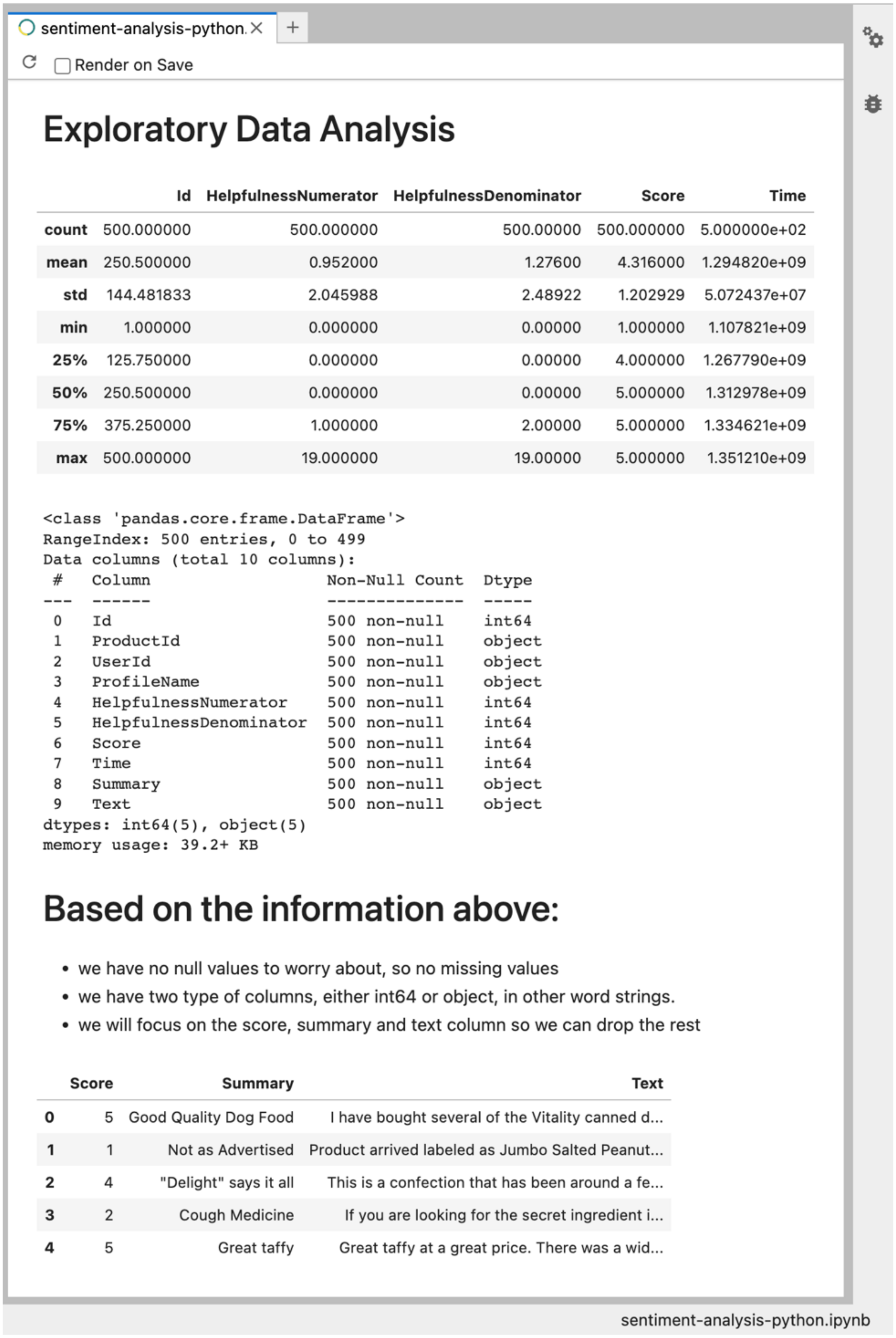


Figure 4.9 Word Cloud Visualization



Exploratory Data Analysis

	Id	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
count	500.000000	500.000000	500.00000	500.000000	5.000000e+02
mean	250.500000	0.952000	1.27600	4.316000	1.294820e+09
std	144.481833	2.045988	2.48922	1.202929	5.072437e+07
min	1.000000	0.000000	0.00000	1.000000	1.107821e+09
25%	125.750000	0.000000	0.00000	4.000000	1.267790e+09
50%	250.500000	0.000000	0.00000	5.000000	1.312978e+09
75%	375.250000	1.000000	2.00000	5.000000	1.334621e+09
max	500.000000	19.000000	19.00000	5.000000	1.351210e+09

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 10 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Id                      500 non-null    int64
 1   ProductId               500 non-null    object
 2   UserId                  500 non-null    object
 3   ProfileName             500 non-null    object
 4   HelpfulnessNumerator    500 non-null    int64
 5   HelpfulnessDenominator  500 non-null    int64
 6   Score                   500 non-null    int64
 7   Time                    500 non-null    int64
 8   Summary                 500 non-null    object
 9   Text                    500 non-null    object
dtypes: int64(5), object(5)
memory usage: 39.2+ KB
```

Based on the information above:

- we have no null values to worry about, so no missing values
- we have two type of columns, either int64 or object, in other word strings.
- we will focus on the score, summary and text column so we can drop the rest

	Score	Summary	Text
0	5	Good Quality Dog Food	I have bought several of the Vitality canned d...
1	1	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...
2	4	"Delight" says it all	This is a confection that has been around a fe...
3	2	Cough Medicine	If you are looking for the secret ingredient i...
4	5	Great taffy	Great taffy at a great price. There was a wid...

Figure 5.0 Voilà Web App Visualization