Development of a Data Pipeline for Sentiment and Similarity Analysis in Stack Overflow's Programming Language Discussions
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***Abstract*—This capstone project presents a data pipeline development for sentiment and similarity analysis of programming language discussions in the StackOverflow environment during the month of April 2024. By employing advanced language model technologies, the study systematically classifies emotional content and recognizes similarities across user interactions. Selenium and StackExchange Data Explorer were used to achieve an automated, up-to-date data collection, with the data processing executed in Python and stored within Google Cloud's BigQuery. EmoRoBERTa was employed to specify the principal emotional tones and precise sentiments associated with distinct programming issues. The sentiment analysis showed that 30% of user interactions contained various emotions, including anger, disappointment, and others. Simultaneously, the Sentence-BERT model and cosine similarity assessments were used to take out similar or almost identical posts to prevent the possible issue of accidental duplicate questions. The model was able to detect identical posts across the StackOverflow programming languages discussions with a similarity score of above 95%. The project improves the understanding of the community dynamic on the StackOverflow website with the help of studies of different algorithms and methods while revealing the potential of applying sophisticated natural language processing techniques to complex, real-world datasets.**

I. INTRODUCTION

StackOverflow, being the biggest open-source platform for programmers to share views, has changed the way that information is shared within the programming community to a great extent. This two-way platform makes it easy to share ideas and solutions at lightning speed and ultimately evolve the software development industry. The benefits that come from these forums can hardly be denied, but they are not left untouched by the problems that could jeopardize any other online community, and the main one is obviously the issue of toxic interaction among their members.

In recent years, people have found the community very toxic, which can lead to its users asking their questions in other communities, therefore harming StackOverflow as a business. Initially, everyone could ask anything; however, with the rise of users, StackOverflow presented a new regulation tactic, which is the rating system [9]. This rating system introduced a very unequal distribution among users, where more than 18 million users had a reputation under 200. Moreover, this low ranking does not allow users to have some privileges in the community. Therefore, users with very low rankings will mostly get answers full of sarcastic advice on how to be a proper member of the "elite" in the community or simply get harmful statements about their question (i.e., it is irrelevant or "stupid") [9].

Besides this bad treatment, another problem is the duplicate questions. After surfing the web, developers turn to StackOverflow to find a solution to their problem. Nevertheless, if they ask a similar question, it can be flagged as a duplicate and get deleted; this is referred to as "accidental duplicates" [11].

Studies show that harmful behaviors and hostile exchanges may hinder the spirit of cooperation and mutual support that StackOverflow wants to create. These negative interactions are not only detrimental to effective communication but also pose a threat to the sense of belonging and knowledge sharing as the users tend to avoid engagement. This might lead to a decrease in community interactions. However, StackOverflow is one of many cases. There is a general commonality of online hate among various digital platforms.

The main objective of the research is to overcome the problems by employing a data pipeline to analyze the sentiments and themes of general programming language discussions on Stack Overflow. This paper proposes to perform sentiment and similarity analysis in order to discover existing negative patterns and indicate signs that may be helpful in preventing asking questions and avoiding the "accidental duplicates" problem.

Moreover, innovative methodologies in transformers and computational linguistics are explored to evaluate and understand the sentiments in the programming-related discussions systematically. This research project aims to contribute to the general field of online community management by providing valuable insights that can help in managing a more positive interaction space. By emphasizing these needs that should be improved, the aim is to help StackOverflow, as well as other platforms, enhance their community atmosphere and prevent users from getting their questions deleted, thus providing a healthy and productive space for everyone.

II. Tools and Methods

In the development of the analytical framework, a combination of tools and methods was used to enable efficient data retrieval, analysis, and storage. The data retrieval was done using **SQL scripts** executed through **Python** and **Bash files**, and it was facilitated by **VisualStudioCode** as the main development environment. This automation of data retrieval provided coding and debugging processes.

The data was automatically downloaded from the **StackExchange** website. To do so, **Selenium**, which is a tool for automating web browsers, was incorporated to dynamically generate SQL queries, which adapted to weekly data requirements. After retrieval, the data was stored in a CSV format and managed using **Google APIs**, which allowed the automated download of these files to Google Drive, ensuring data was safe and readily obtainable.

After getting the data, the structure of the database was thoroughly designed using **DBDiagram.io** to visualize and plan the schema. The visualized database was implemented in **Google Cloud's BigQuery** platform. The latter provided strong architecture to handle the insertion and management of large datasets. **PowerBI** was used to show the overall statistics about the data and users and make the report more visually pleasing. **Matplotlib** and **Seaborn** data visualization Python packages were also used to visualize the analysis. To demonstrate the Pipeline Flow **draw.io** was used.

The environment of **Google Collab** was used to do both the sentiment and similarity analysis. **VADER** model (for Valence Aware Dictionary for sEntiment Reasoning) from the **NLTK** library, which is "a lexicon and rule-based feeling analysis instrument," was used in researching the nuances of sentiment in the obtained StackOverflow data [12]. **RoBERTa**: A Robustly Optimized BERT Pretraining Approach and **EmoRoBERTa** were integrated from **HuggingFace's transformers library** for the categorization of emotions more delicately and accurately [10] [14].

Sentence-BERT (SBERT) model, which analyzes words in a text by taking into account contexts from left to right and left to right, was used to perform similarity analysis on the data [13].

III. Data

A. Pipeline Flow

Implementing a data pipeline instead of depending on periodic data downloads ensures up-to-date and accurate data retrieval on a weekly basis, which is critical for dynamic and up-to-date analysis, a condition not satisfied by the quarterly updates of the Stack Exchange data dumps.

The first phase is the composition of the database with its appropriate dimensional fact tables initialized in BigQuery designed in dbdiagram.io 1. To perform this action, Python scripts were created that are run with the help of a bash file and specific authentication of Google APIs in the local terminal. There is also the creation of a folder in Google Drive with two subfolders, `raw_data` and `view_data`, for storing the fetched data later. This whole process is performed only once.

Fig. 1: Database Design

The next step is the running of one bash file in the local terminal, which initiates the automatic execution of four distinct bash files, each with its own usage and purpose.

1) The first bash file aids in the creation of the queries, logging into the website with the StackOverflow account, downloading the weekly data for the first query, moving the data from downloads to the current directory, creating a subfolder in the Google Drive with the given name of the week, uploading the already created CSV in the folder from the local environment to Google Drive, while deleting from it from the first location. After, the two CSV files are taken from the newly created folder, forming tables in the BigQuery based on the CSV, and the data is then inserted into the tables accordingly.
2) The second bash file does the same process for the second query, except for the folder creation in Google Drive.
3) The third bash file merges the two distinct tables into one, with an additional column that represents the upload time, as well as updates all the dimensional and fact tables.
4) The fourth bash file creates `view_post` and `view_table` data based on the specified week and saves them independently in the Google Drive `view_tables` folder.

The pipeline will consistently update and organize data within the designated folders.

B. Data Description

The fetched CSV files both contain different purposes. The first one downloads the posts in the given week range with their corresponding comments. The second CSV file focuses on the comments that were written in the same time span but whose posts were documented prior to that period. All of these posts and comments are downloaded if they include the following tags with the most common programming languages: Python, Java, Javascript, PHP, SQL, Postgres, Rand, Ruby, C++, C#, HTML, CSS, and R.

As of right now, the `view_table` folder contains eight files, divided equally between two datasets, `view_comments`, and `view_posts`, which collectively have approximately 100,000 rows. These datasets are organized into four sets each, corresponding to the weekly data segments of April 2024: April 1-7, April 8-14, April 15-21, and April 22-28.

IV. Literature Review

Lately, natural language processing and machine learning have provided novel opportunities for the exploration of textual data across various media. With the massive amount of data now flooding social media and technical forums like Stack Overflow, more and more attention has been focusing on the use of complex analytical methods to analyze these huge text corpora.

The development of text similarity measures over the years has tremendously enhanced how textual data is processed and understood in different fields, including academia and industry. Similarity analysis (which Sarkar calls Text Analytics with Python) pertains to both lexical and semantic dimensions, where it evaluates the proximity of the text entities to each other either through direct syntactic similarity or deeper, contextual relations [15] [17]. Lexical similarity is usually achieved by simple methods like Bag of Words, while semantic similarity addresses the meaning and contexts in text and is often based on more complex computing methods.

The SBERT, the Sentence BERT, was born in NLP a couple of years ago and has become a milestone in the domain of text similarity analysis [17]. SBERT, according to the writing of Sen and Efimov, extends BERT (Bidirectional Encoder Representations from Transformers) by combining the Siamese network architecture to ease the generation of embeddings for the sentences and, therefore, overcome the limitations of BERT in sentence embeddings [13] [18]. This development specifically gives a chance for effective sentence similarity measurement, which is crucial for tasks such as semantic search, text clustering, and more dynamic interaction systems like chatbots or recommendation systems. SBERT enhances similarity calculations by embedding phrases such that semantically close sentences are closer in vector space. They do that by using cosine similarity to measure these relationships.

By enhancing the precision and efficiency of generating sentence embeddings, SBERT supports more nuanced and scalable applications, enabling rapid comparisons across large text corpora [7] [8]. This capability is particularly valuable in fields requiring quick and accurate semantic analysis, such as content recommendation systems or automated customer support, where understanding and matching user queries to relevant answers is critical. Thus, the developments in sentence embedding technologies, spearheaded by innovations like SBERT, represent a crucial evolution in the analytics of text similarity, paving the way for more intelligent and responsive systems in information retrieval and natural language processing [17].

One of the key research studies by Ling and Larsén was centered around the sentiment in the Stack Overflow discussions [19]. The Senti4SD was then used to evaluate the sentiment based on different types of documents and coding languages, classifying them as either positive, negative, or neutral. Their results contained really high connections between sentiment trends, the type of document, and the programming language in use. This type of exploration would be useful in tracking the sentiment atmosphere as a whole and thus could be used as a basis for assessing the tone and state of health of the interactions on these technical forums.

The next phase of the study was led by Novielli, Calefato, and Lanubile from the University of Bari, and they did practical research to find out the emotions in Stack Overflow's question-and-answer environment [20]. They aimed to achieve this by scrutinizing the emotional lexicon of questions to be able to comprehend how emotions influence the interactions and engagement of users on the platform. This research contributes to a more in-depth understanding of the psychological aspects of the voting process, which in turn shows the reasons behind the user preferences and the choice of questions.

While working on the same project, Guzman, Azócar, and Li turned to sentiment analysis in GitHub, with attention to committing comments in open-source projects [21]. The author's approach involved lexical sentiment analysis that was used to uncover the emotions that might be embedded in commit messages and to offer a perspective on the expressive range and sentiment distribution across different projects. This research is the way to find the patterns of emotional communication among people who collaborate on software development, and it helps in gaining a deeper understanding of the culture and dynamics in open-source communities.

V. Pre-Processing

Before the analysis of the datasets was to be performed, data manipulation and planning were completed. The `view_comment` was initially made in a way that a new observation was created for each tag of the post. Since only the tags that contained any name of the above-mentioned programming languages were needed for the analysis, every other tag's irrelevant observation was filtered.

To address potential issues of data redundancy and computational inefficiency, observations differing only by tags were merged. This approach stopped posts from being compared to themselves and significantly lowered the time demanded to calculate sentiments for each entry.

After processing the columns that contain the texts, code segments were removed, and all uppercase letters were converted to lowercase. Special characters were also eliminated. Using the NLTK library, standard stopwords were removed, and additional stopwords specific to programming terminology were identified and excluded to refine the text further for analysis.

Three types of tokenization were used:

- **Sentence tokenization:** Dividing the text into individual sentences.
- **Word tokenization:** Splitting sentences into separate words.
- **Lemmatization:** Converting words to their base forms.

Based on these tokenized versions, new columns were introduced to the database.

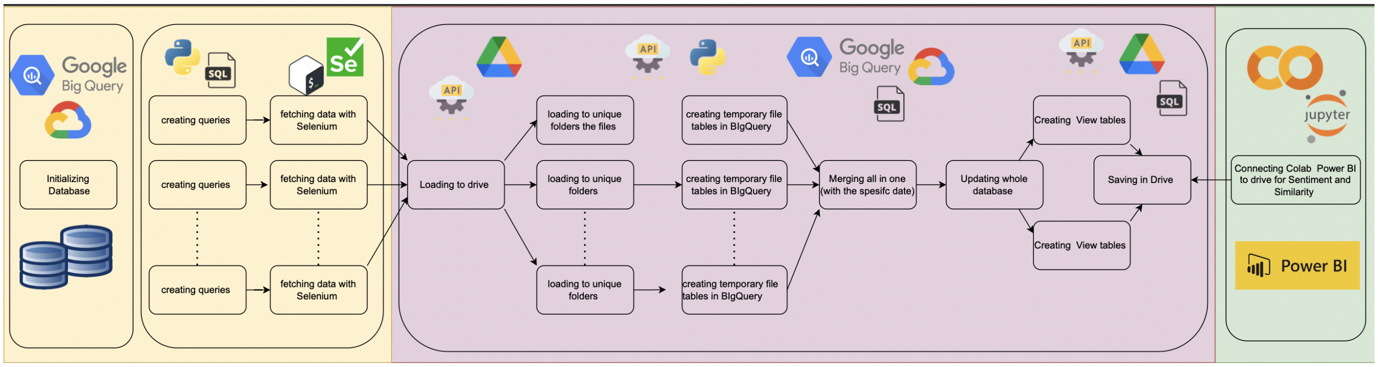


Fig. 2: The Flow of The Pipeline

VI. Similarity Analysis

A. Overview

The main objective of this similarity analysis is to help users identify nearly identical previously posted queries to their question, enabling them to receive instant answers and avoid future possible deletions while also assisting moderators in identifying duplicates for removal. For the similarity analysis, the four post datasets were preferred to gauge the degree of similarity among discussions, seeking to specify and reduce the creation of redundant threads on Stack Overflow. The use of SBERT allows the cleaned body texts from the dataset into embeddings that catch the nuanced comparisons of the textual content.

1) Cosine Similarity: Cosine Similarity provides the measure of the cosine of the angle between two terms when they are represented as non-zero positive vectors in an inner product space, assuming that the terms are vectorized [15]. Term vectors that are closely aligned will have similarity scores close to 1 (cos 0°), suggesting that the vectors lie in nearly exact directions with a tiny angle between them. Contrarily, term vectors with a similarity score around 0 (cos 90°) define terms that are mainly unrelated, showing an almost perpendicular orientation to each other. Term vectors with a similarity score near -1 (cos 180°) are opposing in direction [15]. 3 depicts this concept more clearly, where 'u' and 'v' express term vectors in the vector space model.

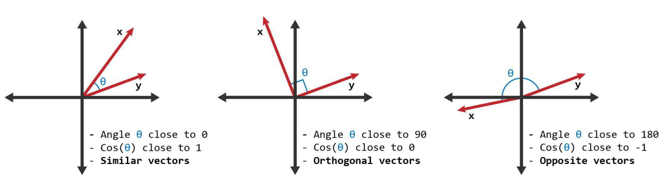


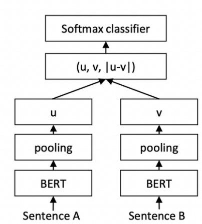
Fig. 3: Cosine similarity representations for term vectors [16]

Mathematically, the dot product can be represented as $u \cdot v = \|u\|\|v\| \cos(\theta)$ where θ is the angle between u and v, while u denotes the L2 norm for vector u and v is the L2 norm for vector v. Therefore, the formula for the Cosine Similarity can be derived as

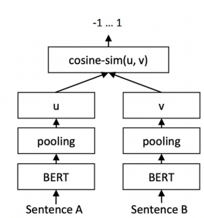
$$cs(u, v) = \cos(\theta) = \frac{u \cdot v}{\|u\|\|v\|} = \frac{\sum_{i=1}^{n} u_i v_i}{\sqrt{\sum_{i=1}^{n} u_i^2}\sqrt{\sum_{i=1}^{n} v_i^2}}$$

where cs(u, v) is the actual score between the two parties. In this case, the ranges of scores were modified from -1 to +1 to from 0 to 1 because frequency vectors cannot be negative; thus, the angle cannot exceed 90°.

2) SBERT: SBERT is a framework for computing sentence embeddings employing the BERT model, "an open source machine learning framework for natural language processing (NLP),"which may be used for a variety of downstream applications yet is computationally fast primarily for the usage of Siamese Networks, a kind of network design wherein two or more identical subnetworks are combined to create and compare feature vectors for each input [13] [8].



(a) "SBERT architecture with classification objective function, e.g., for fine-tuning on SNLI dataset. The two BERT networks have tied weights." [17]



(b) SBERT architecture at inference, for example, to compute similarity scores. This architecture is also used with the regression objective function. [17]

The model aggregates the output of BERT using a mean pooling strategy, typically generating embeddings of 768 dimensions for the 'bert-base' configuration. SBERT is specifically fine-tuned to identify sentence similarities by training on a variety of the SNLI and Multi-Genre NLI datasets, which together offer around one million annotated sentence pairs across various genres of text, both spoken and written. The workout configuration consists of a linear warm-up over 10% of the training data, an Adam optimizer, a batch size of 16, and a learning rate of 2e-5. Sentence similarity is effectively captured by this technique, as proven by its better performance on several benchmarks, such as the Argument Facet Similarity (AFS) corpus, the STS benchmark (STSb), and a Wikipedia dataset from Dor et al.

B. Similarity Results

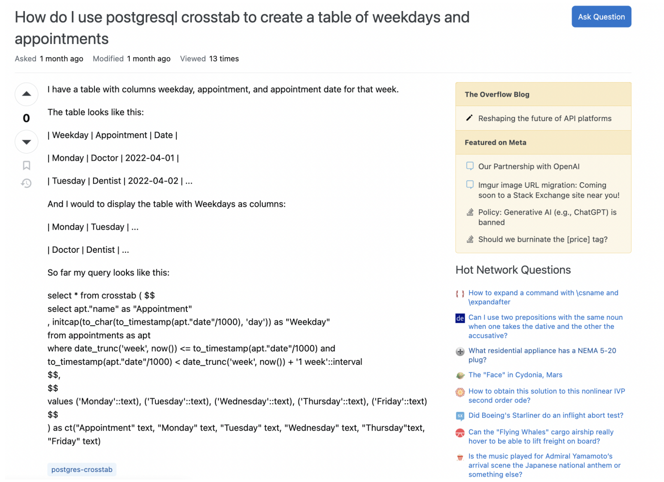
The results were broken down across the data for April and showed a real consistency of similar and duplicate posts, even in a short timespan. The primary outcome of the analysis was the successful labeling of nearly identical posts tagged as similar, with a similarity score exceeding 0.9.

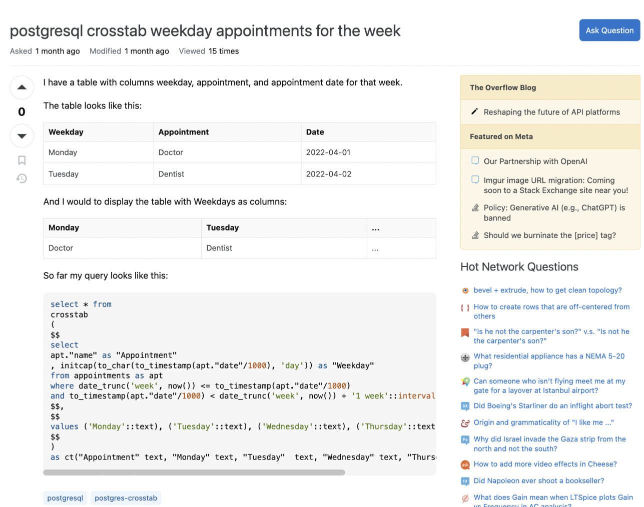
A pattern became apparent: identical questions were asked across multiple posts, even though they were made by different people. This might happen if someone makes a new account and reposts the question in the hopes of receiving more replies after their first post goes unanswered. This issue got as severe as a person posting the same questions up to three or four times.

Many posts with very parallel contexts were posted, and each got a different reply, which can lead to misunderstanding of the topic to third parties or the people who asked the questions in the first place.

1) Examples:

- The following posts contain identical texts and content. However, they are formatted differently and have different post titles. This can be an experiment of the user in an attempt to get more attention to the question. However, in both cases, the questions still remained unanswered despite being seen multiple times. These posts were identified with an accuracy of **0.9978** similarity score,





- Questions with titles *”Connecting tips between dendrograms in side-by-side subplots* and *”Connecting dendrograms in matplotlib”* were asking about the same topic. However, they used different wording, thus creating irrelevant data that can be harmful to the StackOverflow environment, as a lot of people get irritated because of this and start toxic conversations. These two posts were found similar, with a score of **0.8180**.

These findings illustrate that the efficiency of detection techniques for similarity that were applied manifests themselves in the identification of the content that is duplicated or almost duplicated. This is very important as it helps get rid of repetitive posts in platforms like Stack Overflow, which in turn makes user experience more efficient and content navigation a seamless process. By connecting related discussions, the community can avoid re-answering questions and, much to the point, generate new answers. The effect is a setup for more efficient knowledge transfer.

VII. Sentiment Analysis

A. Overview

For the sentiment analysis, the StackOverflow data was examined for both posts and comments throughout April 2024, covering approximately four weeks of activity. The analysis was done with the help of EmoRoBERTa to categorize the sentiments into these categories:

- **Neutral**
- **Positive Emotions**: Admiration, Gratitude, Approval, Optimism, Joy, and others.
- **Negative Emotions**: Confusion, Disapproval, Remorse, Sadness, Anger, Disgust, Annoyance, and others.

The overall sentiment scores are displayed as percentages to provide a more precise understanding of the distribution of emotions expressed within the posts during the weeks.

The main focus of the analysis was on identifying patterns in negative sentiments and exploring which programming languages and contexts attracted more negative emotional responses. The sentiment analysis function leverages the Hugging Face Transformers library and NLTK for effective text processing. It initializes a sentiment analysis pipeline and tokenizer using the EmoRoBERTa model. To guarantee robustness, the *safe_sentiment* function is designed to analyze sentiment while accounting for diverse edge cases, such as handling non-string inputs and managing large text segments by token truncation. In addition, the *add_sentiments_to_dataframe* function involves this sentiment analysis in batches, enabling scalable processing of a DataFrame without overloading memory resources. This batch-based approach enhances efficiency, allowing sentiment analysis of large datasets with clear progress indicators and a final report on total processing time. Together, these components demonstrate a reliable strategy for integrating sentiment analysis into DataFrame workflows.

B. Emotion Study

The assessment and classification of emotional expressions in textual data have become a focal point of modern research, mainly due to the increasing sophistication identified in human emotional states [2]. Traditional sentiment taxonomies such as those proposed by Ekman, which suggest six basic emotions [3], and Plutchik, who presents four bipolar emotion pairs [4], set the foundational frameworks. Conversely, Ortony and colleagues expand upon these models by documenting twenty-two separate emotions, incorporating complicated emotional states such as relief and admiration into the analysis [5].

In further work, Demszky et al. presents the GoEmotions dataset, which contains an even more extended range of twenty-eight emotions, declaring the necessity for a more subtle ”semantic space” of emotion recognition to better understand modern psychological insights [6]. This wide collection of emotions highlights the evolving understanding of emotional complexity that is more aligned with the nature of human experiences [2].

Language model-based systems, particularly Large Language Models (LLMs), have demonstrated bright qualifications in determining these diverse emotional ”signals” embedded within texts [2]. The comprehensive training on various and expansive datasets improves their ability to distinguish slight emotional nuances, thereby delivering a more accurate understanding of the sentiments shared in written communication [7].

This growing technology not only emphasizes the refined analytical ability of existing models but also highlights the constant need for tools that can adjust to and recollect the difficulties in human emotional expression.

C. Sentiment Results

While the initial goal was to identify common expressions of anger, the analysis found that Stack Overflow’s continuing efforts to improve community engagement and problem-solving help tend to reduce overt negative attitudes, resulting in fewer instances of rage than anticipated. The analysis showed that an extensive amount of the sentiments were neutral, totaling for approximately *70%* of the interactions on the website. The predominance is rooted in the platform’s format, which is a question-answer forum where some people tend not to express their emotions. Nevertheless, the remaining *30%* revealed that there were a lot of mixed emotions, which provided a lot of insights into the community interactions.

The emotional diversity beyond the interactions that were neutral included both negative and positive segments. Positive emotions mainly consist of admiration, gratitude, approval, joy, and optimism. Nevertheless, the negative emotions were much more evident than the opposite ones. They were more varied and pronounced, including confusion, sadness, anger, disgust, annoyance, disapproval, and remorse. They provided a bigger understanding that these challenges and frustrations were a reality for some developers.

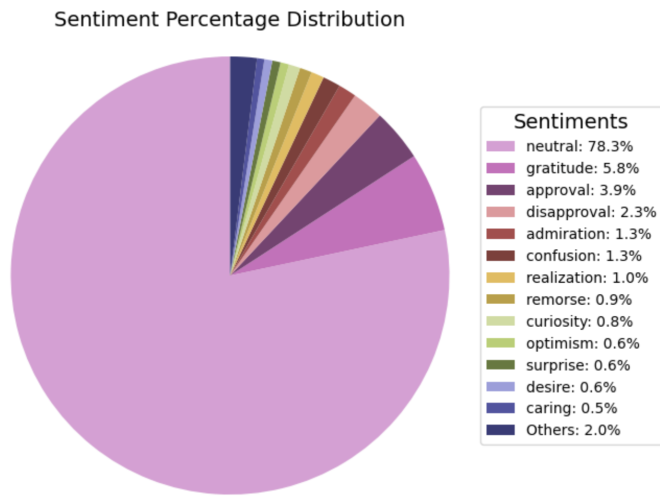


Fig. 5: The Distributions of Emotions in The Dataset

1) Negative Sentiments by Programming Language: The analysis mainly focused on the negative emotions to identify the specific programming languages that prompted stronger unfavorable comments. Each week of data brought forward a pattern of recurring negative sentiments associated with specific programming languages I II:

- **CSS**: Consistently displayed sentiments of sadness and remorse.
- **JavaScript**: Repeatedly associated with anger, possibly due to its complex and dynamic nature which can lead to challenging debugging experiences.
- **PHP**: Annoyance was dominant, likely originating from its diverse old and new coding techniques and inconsistencies in function naming and manners.
- **SQL**: Disgust appeared often, conceivably due to complex queries executing poorly or vague feedback from database systems.

TABLE I: Results of Negative Emotions from April 8 to 14

Post Tag	Sentiment	Percentage
C#	Anger	0.881057
Ruby	Annoyance	5.555556
Ruby	Disgust	5.555556
C#	Fear	2.643172
CSS	Remorse	6.250000
C#	Sadness	1.101322

TABLE II: Results of Negative Emotions from April 14 to 21

Post Tag	Sentiment	Percentage
JavaScript	Anger	0.534759
Ruby	Annoyance	4.347826
C++	Disgust	1.882845
C++	Fear	2.928870
CSS	Remorse	6.164384
HTML	Sadness	1.415094

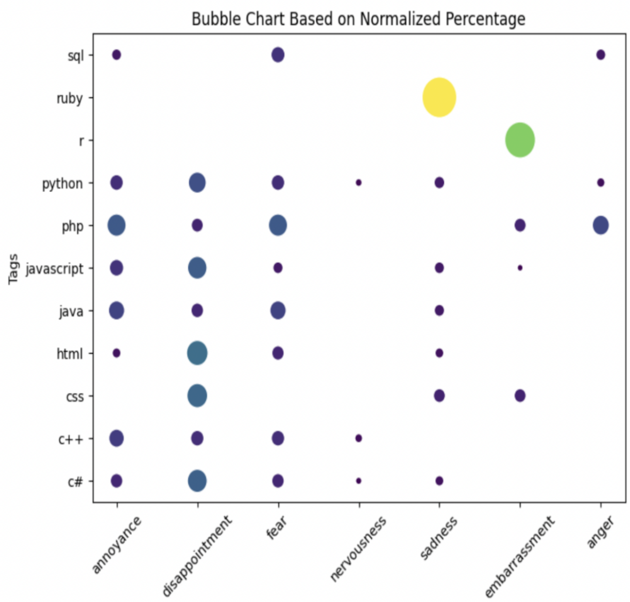


Fig. 6: Bubble Chart Based on April 1 to 7 Comment Data

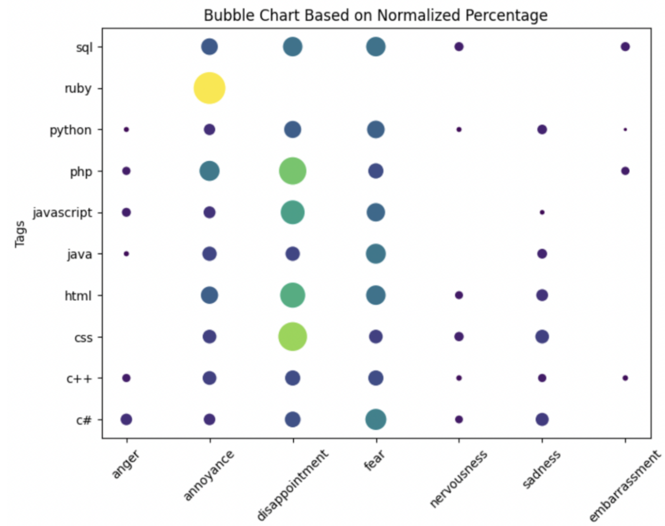


Fig. 7: Bubble Chart Based on April 15 to 21 Comment Data

2) Examples:

- For **anger**, comments like *"Your test_input function is completely nonsensical junk..."* and *"This sucks so much. I just don't get how people can bear so many config files in the project root."* reflect users' frustration and insensitive language.
- For **disapproval**, statements like *"To be honest: this code doesn't make any sense. You might want to take a step back in the tutorial."* highlight the disappointment and criticism within the community.
- For **annoyance**, remarks like *"Why do you create a nested multipart message when you only have one piece of content anyway? The new API shields you from that kind of nonsense."* show the arrogance in the person's tone.
- For **sadness**, there are comments that included heartbroken ideas like the following, *"There is sadly no general answer to the question.Specific answer for the utopia doesn't exist a or an algorithm which can be applied by anyone to anywhere."* and *"my bad.... same error."*
- For **disgust**, several declarations like the following one were made *"It looks ugly... that is subjective. What is the real problem?"* that demonstrated the true feelings of the writer.

3) Possible Explanations for The Negativity:

- **JavaScript's** flexibility and dynamic nature often lead to difficult codebases and bugs that can be hard to trace. This sophistication can provoke anger when developers encounter errors that are challenging to understand or resolve.
- **JavaScript** can conduct differently across various browsers, directing to anger when code works in one environment but fails in another.
- **PHP** has grown over decades, resulting in a mix of old and new coding practices. Developers may convey annoyance when dealing with legacy code or inconsistencies in function naming and behavior.
- **PHP** is known for allowing multiple ways to achieve the same task, leading to coding style inconsistency and annoyance among developers who desire standardization.
- **SQL** queries can become rigid and complicated to optimize. Developers may feel disgusted when a seemingly simple query performs poorly due to underlying database issues or poor indexing.
- **SQL** databases occasionally supply limited or unclear error feedback, causing disgust when developers stumble to comprehend why a query or operation failed.

4) Possible Solutions: This sentiment analys of provided some insights that can be utilized for creating a more genuine atmosphere of StackOverflow platform. The moderators need to devise a more tailored intervention to foster an environment that encourages learning rather than shaming it. The development of advanced moderation tools could enable the automatic flagging of posts that display extreme negative sentiments, thus helping to prevent further escalations. Furthermore, collaborating with experts to create genuine answers and tutorials could help users get more relieved from debugging challenges.

Moreover, the detected programming languages that are prone to anger and irritation could have separate sessions with specialists in the languages to lessen user confusion and potential outbursts. Beyond technical solutions, encouraging mental health awareness and cultural sensitivity within the community could manage underlying challenges. These strategies, reported by detailed sentiment analysis, promise not only to omit negative experiences but also to promote the overall quality of interactions on Stack Overflow, making it a more welcoming space for developers worldwide.

VIII. Insights from PowerBI dashboard

The data goes from BigQuery directly to PowerBI, where a dashboard with two pages is created.

The first page includes an overview of the data. The primary observations are:

- There are a total of approximately 100,000 rows divided into comments and posts with a ratio of 70% and 30%, respectively.
- On a daily basis, the dataset comprises approximately 1,500 posts and 3,500 comments.
- The most frequent programming languages that were given questions about were Python, Java, and C#.
- The highest rating score for the posts was observed in January 2024, followed by a notable decline thereafter.

The second page of the dashboard primarily focuses on users and their reputations. The main insights include:

- The dataset contains a total of 29,000 users, with an average reputation of 1,500. The spectrum of reputation scores ranges from a minimum of 1 to a maximum of 744,000.
- The users from the USA, Europe, and India were the ones to post and comment the most during the time period of April 2024.

IX. Discussion

A. Pipeline

The very first challenge that was encountered during the realization of the project was the continuous evolvement of the data, thus changing the preprocessing steps. However, once the pipeline was established, the preprocessing steps were finalized, allowing for the smoother flow of the analysis.

Another major problem was the data fetching with Selenium, as the pipeline was mainly perceived as a robot and was not able to pass human verifications. Thus, the infinite loop was created to repeat the process until the pipeline could move further in the flow.

One of the significant issues that tried to prevent the project from realization was the transfer of data into the BigQuery platform. The uploading of the data into the former platform was only possible with environments such as the local directory and Google Cloud. The solution included the creation of temporary folders where the Google Drive files were downloaded and inserted with the help of queries and table schemas.

After the insertion of the data into the BigQuery platform, another crisis arose. The initially created design of the database was not possible due to the lack of an auto-incrementation function, thus disabling the automatic creation of surrogate keys. This restriction demanded an innovative workaround to preserve the integrity of the structure of the database. A solution using the ”time” argument was applied to track the insertion order of the rows. By looking at the most recently inserted row based on the ”time” argument, the pipeline was configured to provide a unique index for each entry. The surrogate keys were created because the method constantly scanned the highest existing index and incremented each subsequent row.

Moreover, the creation of the queries in the BigQuery platform was disabled until a payment was made. This led to the inability to update and merge the data or create *view_tables* in the platform. Therefore, to overcome this obstacle, switching to the paid version was inevitable.

B. Similarity Analysis

The starting point of the Similarity Analysis was deciding on the model that was going to be used to handle an extensive 33,000-row dataset. In the beginning, the method of cosine similarity using TF-IDF vectors, traditional BERT, and FAISS methods was used to face the problem. However, all of these methods failed to handle the issue for different reasons. For example, BERT required about 50 million inference computations to discover the most similar pairs among the 10,000 sentences, which would take approximately 65 hours for each analysis.

After thorough research, an SBERT model was employed as the primary method for the analysis, along with cosine similarity. With this method, the computational load was significantly reduced by creating embeddings that prevented the semantic meanings better than BERT and also made the execution of weekly data that consisted of approximately 8000 rows possible in just 20-30 minutes.

The other models were mainly focused on surface-level word implementation and did not pay attention to the meaning and contexts of the posts. However, SBERT solved the problem with context-aware embeddings that captured deeper semantic relationships between texts. The mixture of SBERT and cosine similarity was able to detect similar posts with very high accuracy and identical posts with an accuracy of or higher than 0.95 similarity scores.

C. Sentiment Analysis

The main issue of the Sentiment Analysis was the fact that EmoRoBERTa was limited in the number of tokens it could take, the maximum being 512. The first approach was the division of the text into sentences, running the model for each sentence of the text, and combining the results into one list that was stored in a column. This was not cost-efficient, and the final emotion of the whole comment was not clear.

The second option was not performing the sentiment analysis on the tokens that were bigger than 512, but a significant amount of data would be lost. The third and adopted option was storing all the comments' data and doing save truncate, which keeps only the first 512 tokens of the comment body.

X. Conclusion and Future Work

This capstone project was successful in establishing a comprehensive data pipeline for sentiment and similarity analysis on StackOverflow, giving insights into the way that users interact within the selected programming language discussions. The NLP models, such as SBERT and EmoRoBERTa, enabled the identification of duplicate posts and the analysis of nuanced emotional undertones hidden across those conversations. The research highlights the potential of NLP models to improve community management and user experience on online platforms.

Subsequently, future research can further broaden the existing models by integrating real-time analysis tools for the immediate detection and cleansing of both duplicated content and toxic interactions as they happen on social media. Moreover, integrating a more extensive emotional analysis that is specific to each programming language can give better insights into the roots of the toxic behaviors. Therefore, by continuing to get up-to-date data from the pipeline and incorporating more dynamic models, this capstone project can broaden its impact and foster a healthier and more engaged community on StackOverflow and beyond.

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