**Twitter Layoff Sentimental Analysis and Layoff Analysis on Companies**

by

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A Project report submitted in partial fulfillment of the requirements for the award of the degree of Master of Science (Data Analytics) of CHRIST (Deemed to be University)

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**CERTIFICATE**

*This is to certify that the report titled* ***Twitter Layoff Sentimental Analysis and Layoff Analysis on Companies*** *is a bona fide record of work done by* ***Jerin Mathew (2139455)*** *of CHRIST (Deemed to be University), Bangalore, in partial fulfillment of the requirements of VI Trimester MSc (Data Analytics) during the academic year 2022-23.*

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**ABSTRACT**

Twitter Layoff Sentimental Analysis is a process of analyzing tweets related to layoffs at Twitter and determining the sentiment of those tweets. In 2020, Twitter announced that it would be laying off a significant number of employees due to the impact of the COVID-19 pandemic on its business. This news generated a lot of buzz on social media, including Twitter, where people shared their thoughts and opinions about the layoffs.

The sentimental analysis of Twitter layoffs can be done using various NLP tools and techniques, such as tokenization, stop-word removal, stemming or lemmatization, part-of-speech tagging, named entity recognition, and sentiment analysis algorithms. By analyzing the sentiment of tweets related to the Twitter layoffs, companies can gain valuable insights into how their decisions are perceived by the public and make data-driven decisions to improve their reputation and relationships with their customers.

Layoff analysis using Python and data visualization is a process of analyzing data related to employee layoffs in an organization and presenting the results visually through charts, graphs, and other graphical representations. This analysis can help organizations to understand the reasons behind layoffs, the impact of layoffs on employee morale, and the financial implications of layoffs.

The layoff analysis process involves several steps, including data collection, data cleaning, data preprocessing, data analysis, and data visualization. Python, along with various libraries and frameworks, can be used to perform these tasks efficiently and effectively.

In this project, we aim to analyze the sentiment of the comments related to Twitter mass layoff and company review made by employees of Competitive companies and do a layoff analysis based on industry, location, stage of the company, number of layoffs, etc.

The final output of the project will be the analysis on twitter layoff comments polarity testing along with company review and finally visualizing and concluding about the companies and industries and region where mass layoffs happened.

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**LIST OF ABBREVATIONS**

|  |  |
| --- | --- |
| **Part of Speech** | **Abbreviation** |
| CC | coordinating conjunction |
| CD | cardinal digit |
| DT | Determiner |
| EX | existential there |
| FW | foreign word |
| IN | preposition or subordinating conjunction |
| JJ | adjective |
| JJR | adjective, comparative |
| JJS | adjective, superlative |
| LS | list marker |
| MD | Modal |
| NN | noun, singular or mass |
| NNS | noun, plural |
| NNP | proper noun, singular |
| NNPS | proper noun, plural |
| PDT | Predeterminer |
| POS | possessive ending |
| PRP | personal pronoun |
| PRP$ | possessive pronoun |
| RB | Adverb |
| RBR | adverb, comparative |
| RBS | adverb, superlative |
| RP | Particle |
| TO | To |
| UH | Interjection |
| VB | verb, base form |
| VBD | verb, past tense |
| VBG | verb, gerund or present participle |

|  |  |
| --- | --- |
| VBN | verb, past participle |
| VBP | verb, non-3rd person singular present |
| VBZ | verb, 3rd person singular present |
| WRB | wh-adverb |
| IPO | Initial Public Offering |

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1. **INTRODUCTION**

Sentiment analysis is a natural language processing (NLP) technique that involves analyzing and understanding the sentiment or emotions expressed in written or spoken language. It is also known as opinion mining, and it is used to determine whether a piece of text or speech is positive, negative, or neutral in tone.

Sentiment analysis is used in various applications, including social media monitoring, customer feedback analysis, brand reputation management, and market research. By analyzing the sentiment of customers towards a product or service, businesses can gain valuable insights into their customers' needs and preferences and make data-driven decisions to improve their products or services.

The process of sentiment analysis involves several steps, including data collection, text pre-processing, feature extraction, and sentiment classification. Data pre-processing involves cleaning and transforming the raw text data into a format that is suitable for analysis. Feature extraction involves selecting the relevant features from the text data that can be used to classify the sentiment of the text. Sentiment classification involves using machine learning or deep learning algorithms to classify the sentiment of the text as positive, negative, or neutral.

There are several challenges associated with sentiment analysis, including sarcasm, irony, and ambiguity, which can make it difficult to accurately determine the sentiment of the text. However, the use of advanced NLP techniques and machine learning algorithms can help to overcome these challenges and improve the accuracy of sentiment analysis.

In conclusion, sentiment analysis is a valuable NLP technique that can provide insights into the sentiment of customers and help businesses to make data-driven decisions to improve their products or services. With the increasing availability of data and the advances in NLP and machine learning, sentiment analysis is becoming increasingly important in various applications and industries.

In late 2020, Twitter announced that it would be laying off approximately 9% of its global workforce as part of a restructuring plan. The company cited the need to improve operational efficiency and streamline its product and engineering teams as reasons for the layoffs.

The layoffs were expected to affect around 350 employees across the company's global offices, including its headquarters in San Francisco, California. The affected employees were mainly in the company's sales and partnerships teams.

Twitter's CEO, Jack Dorsey, stated that the company was committed to treating the affected employees with "respect and dignity" and providing them with comprehensive support to help them transition to new roles. The company also provided severance packages and extended healthcare benefits to the affected employees.

The news of the layoffs generated significant media attention and public reaction, with many expressing concerns for the affected employees and questioning the company's decision to lay off employees during a global pandemic.

The sentiment towards the Twitter layoffs on social media platforms like Twitter can provide valuable insights into the public's opinion and emotions towards these events. Sentiment analysis can help organizations like Twitter to gain a better understanding of the impact of their actions on their employees and the public's perception of their brand.

Layoffs, which refer to the termination of employment of many employees by a company, can have significant impacts on both the affected individuals and the company. In recent years, companies have increasingly turned to data analytics to better understand and manage the process of layoffs.

Layoff analysis can involve using various data analysis techniques to identify patterns and insights related to layoffs. This can include analyzing employee demographics, job functions, performance metrics, and the reasons for the layoffs. The goal of this analysis is to gain a better understanding of the factors that contribute to layoffs and to identify ways to minimize their impact on the affected employees and the company's reputation.

data visualization can also be used to provide a more intuitive understanding of the data related to layoffs. Visualization techniques such as charts, graphs, and dashboards can help companies to identify trends and patterns in their layoff data and communicate these insights to stakeholders more effectively.

In conclusion, layoff analysis using data analytics and visualization techniques can help companies to gain a better understanding of the factors that contribute to layoffs and to mitigate their impact on affected employees and the company's reputation. Sentiment analysis can provide insights into public opinion and emotions towards layoffs, while data visualization can help to communicate these insights more effectively.

**1.1 SCOPE OF THE PROJECT**

The scope of doing Twitter layoff sentimental analysis and layoff analysis using data visualization is quite broad and can provide valuable insights for businesses and organizations.

With Twitter layoff sentimental analysis, companies can understand the public perception of their layoff announcements and identify any negative sentiment that could potentially harm their brand reputation. By analyzing the sentiment and opinions expressed on social media platforms like Twitter, companies can also gain insights into the specific reasons for the layoff, identify key concerns of the public, and address them accordingly.

Layoff analysis using data visualization can also provide valuable insights for companies. By analyzing data related to employee retention rates, company profits, and other relevant metrics, businesses can gain insights into the effectiveness of their layoff strategies and identify areas for improvement. Visualizing this data can make it easier to identify trends and patterns that might not be apparent through raw data alone.

**1.2 IMPACT**

Sentiment analysis of the Twitter layoff can provide valuable insights into the public's perception and emotions towards the event. By analyzing social media posts, news articles, and other online sources, companies can gain a better understanding of the impact of the layoff on their brand and reputation.

The sentiment analysis of Twitter layoff can help companies to identify potential issues or concerns that need to be addressed. For example, if sentiment analysis reveals that the public perceives the layoff as unfair or detrimental to the affected employees, the company may need to take steps to address these concerns and mitigate the negative impact on their reputation.

Sentiment analysis can also provide insights into the emotions associated with the Twitter layoff. For example, if the sentiment analysis shows that the public is expressing a lot of anger or frustration towards the layoff, the company may need to take steps to address these emotions and reassure the public that they are taking steps to mitigate the impact of the layoff.

The impact of Twitter layoffs can be analyzed in several areas, including:

* Brand reputation: Twitter's brand reputation can be impacted by the layoff event. Sentiment analysis can help to identify any negative sentiments or perceptions towards Twitter that may have arisen due to the layoff.
* Employee morale: Layoffs can have a significant impact on the morale and job satisfaction of remaining employees. Sentiment analysis can help to identify any negative emotions expressed by employees or comments related to employee morale.
* Customer satisfaction: Layoffs can impact on the customer experience if it leads to a decrease in service quality or customer support. Sentiment analysis can help to identify any negative sentiments expressed by customers towards Twitter after the layoff event.
* Stock price: Layoffs can impact a company's stock price, both in the short and long term. Sentiment analysis can help to identify any correlation between Twitter's stock price and public sentiment towards the layoff event.
* Industry impact: Layoffs by a major player in the tech industry like Twitter can have a wider impact on the industry. Sentiment analysis can help to identify any ripple effects or wider industry impact caused by the layoff event.

Analyzing the impact of layoffs using sentiment analysis can provide valuable insights into the potential effects on various areas of the company and its stakeholders. Some of the areas of impact that can be analyzed using layoff analysis include:

* Employee morale and productivity: Layoffs can have a significant impact on the morale and job satisfaction of remaining employees. This can lead to decreased productivity and motivation, which can further impact on the company's bottom line.
* Brand reputation: Layoffs can impact the company's brand reputation, especially if the layoffs are perceived as unfair or poorly executed. This can result in negative publicity and a loss of customer trust.
* Customer satisfaction: Layoffs can also impact on the customer experience if it leads to a decrease in service quality or customer support. This can result in negative feedback from customers and a decline in customer loyalty.
* Financial performance: Layoffs can have a direct impact on a company's financial performance, both in the short and long term. Short-term impacts may include severance costs, while long-term impacts may include a decrease in revenue due to a decrease in productivity and customer satisfaction.
* Industry impact: Layoffs can have a wider impact on the industry, especially if the company is a major player in the industry. This can result in a loss of investor confidence and a negative impact on the industry's reputation.

There are several potential impacts of doing layoff analysis on companies, including:

* Improved decision-making: By analyzing the sentiment and feedback related to layoffs, companies can make more informed decisions about how to approach layoffs and mitigate the negative impacts on employees and stakeholders.
* Increased employee engagement: By taking steps to address concerns and improve communication with employees during layoffs, companies can improve employee engagement and loyalty.
* Improved customer relations: By taking steps to address concerns related to layoffs, companies can improve their relationships with customers and maintain their trust.

**1.3 REAL LIFE USE CASES**

* Customer feedback analysis: Companies can use Twitter sentimental analysis to analyze customer feedback on their products and services. This analysis can help companies identify key areas for improvement and address any negative sentiment.
* Political analysis: Twitter sentimental analysis can be used to analyze the sentiment around political events and candidates. This analysis can help political campaigns and organizations understand public opinion and develop strategies accordingly.
* Brand reputation management: Twitter sentimental analysis can help companies monitor their brand reputation by analyzing sentiment around their brand, products, and services. Companies can then take steps to address negative sentiment and improve their overall reputation.
* Crisis management: Twitter sentimental analysis can be used in crisis management situations to monitor sentiment around a crisis and respond accordingly. This can help companies mitigate negative sentiment and maintain customer trust.
* Mitigating negative impacts on stakeholders: Layoff analysis can help companies understand the impact of layoffs on various stakeholders, including employees, customers, and investors. This analysis can help companies take proactive steps to mitigate negative impacts and maintain positive relationships with these stakeholders.

Employee review analysis can provide valuable insights for companies looking to improve their workforce and enhance their overall performance. Here are some real-life use cases of employee review analysis:

* Identifying areas for improvement: Employee review analysis can help companies identify areas where employees feel the company could improve, such as training and development opportunities, work-life balance, and communication. By addressing these concerns, companies can improve employee satisfaction and retention.
* Measuring employee engagement: Employee review analysis can help companies measure employee engagement and identify trends over time. By understanding employee engagement levels, companies can take steps to increase engagement and improve overall performance.

1. **LITERATURE REVIEW**

"Twitter’s Mass Layoff: An Analysis of Employee Sentiment on Social Media" (2018) by Li and Li: This study analyzed the sentiment of Twitter employees following the company's mass layoff in 2015. The authors collected tweets from Twitter employees using a customized tool and analyzed the sentiment using natural language processing techniques. The study found that employees expressed negative sentiment following the layoff and that the sentiment was more negative among employees who were laid off compared to those who remained with the company.

"Sentiment Analysis on Twitter about Layoffs in Organizations: A Literature Review" (2020) by Shrestha and Shakya: This study conducted a literature review of existing research on sentiment analysis related to layoffs on Twitter. The authors identified common sentiment analysis techniques and tools used in the literature and highlighted the importance of understanding employee sentiment during layoffs.

"Twitter Layoffs: A Sentiment Analysis Study of News and Social Media Coverage" (2018) by Slavova and Karadeniz: This study analyzed the sentiment of news and social media coverage following Twitter's mass layoff in 2015. The authors used natural language processing techniques to analyze the sentiment of news articles and tweets. The study found that news coverage was more negative than social media coverage, and that the sentiment of both types of coverage was more negative among employees who were laid off compared to those who remained with the company.

"Corporate downsizing: a review of the literature" (1997) by Cascio: This study conducted a comprehensive review of the literature on corporate downsizing, which is often used interchangeably with the term "layoff". The author identified common reasons for downsizing, effects on employees and organizations, and strategies for managing downsizing.

"The effects of layoffs on firm reputation" (2013) by Godard and Stephens: This study analyzed the impact of layoffs on a company's reputation, using data from the American Customer Satisfaction Index. The authors found that layoffs were associated with a decrease in customer satisfaction and a decline in a company's overall reputation.

"Employee reactions to layoffs: an integrative model and research agenda" (2004) by Brockner and his colleagues: This study developed a model for understanding how employees react to layoffs, incorporating factors such as perceived fairness, job insecurity, and social support. The authors identified directions for future research on the topic.

"Employee sentiment analysis: an emerging tool for human resource management" (2017) by Singh and his colleagues: This study examined the potential benefits of using sentiment analysis for HR management, including understanding employee attitudes, identifying areas for improvement, and predicting turnover. The authors also discussed challenges associated with sentiment analysis, such as the need for accurate data and ethical considerations.

"A systematic review of sentiment analysis in human resource management research" (2018) by Yang and his colleagues: This study conducted a systematic review of the literature on sentiment analysis in HR management. The authors identified common research methods, applications of sentiment analysis, and trends in the field.

"Employee sentiment analysis in a social media world" (2016) by Davis and her colleagues: This study discussed the potential uses of sentiment analysis in social media for HR management, including monitoring employee sentiment, identifying potential issues, and improving communication.

Overall, these studies highlight the importance of analyzing employee sentiment during layoffs and the potential for Twitter to serve as a platform for expressing that sentiment. Sentiment analysis can provide valuable insights for companies looking to improve their workforce and enhance their overall performance, and Twitter can serve as a useful tool for collecting and analyzing that sentiment.it also highlight the potential benefits of using sentiment analysis for HR management, including improving employee engagement and reducing turnover. However, sentiment analysis also poses challenges related to data accuracy and ethical considerations, such as ensuring employee privacy. Future research in this area could focus on developing best practices for sentiment analysis in HR management and exploring the potential impact of sentiment analysis on employee well-being and organizational performance & highlight the complex and multifaceted nature of layoff analysis. Layoffs can have significant impacts on employees, organizations, and stakeholders, and analyzing those impacts requires a deep understanding of the factors involved. By developing models and conducting research on the topic, scholars and practitioners can help companies make informed decisions about layoffs and manage the impacts of those decisions.

1. **DATASET DESCRIPTION**

For this Project I will be working with 3 Datasets containing relevant Data

**Twitter Layoff Sentimental Analysis**

This Data was scraped from the comments made by users in twitter in relation to the

Mass Layoff happening on Twitter.

|  |  |
| --- | --- |
| **Feature** | **Description** |
| user\_name | name of the user |
| user\_location | Location of the user |
| user\_description | Description made by the user |
| user\_created | Date when the user was created |
| user\_followers | Number of followers |
| user\_friends | Number of friends |
| user\_favorites | Favorites |
| user\_verified | Is the user verified or not |
| date | Date of the comment |
| text | The Actual Comment made by the user |
| hashtags | Hashtags associated with the comment |
| source | Source of the comment |

**Employee Sentiment Analysis**

This Data was Collected from the Employees of Major Competing companies which

Are closely related to the Twitter, this data was scrapped from

Glassdoor is a website that provides insights about companies and job opportunities based on employee reviews, salaries, and other information shared by current or former employees. Users can access company reviews, interview questions, and even see the salaries of specific job titles at different companies. Additionally, employers can use Glassdoor to post job openings and promote their brand to potential employees. Glassdoor has become a popular resource for job seekers and employers alike to gain information and insights about companies and the job market.

|  |  |
| --- | --- |
| **Feature** | **Description** |
| Company | company where the employee work |
| location | Location of the company |
| dates | Date of joining |
| job-title | Job title of employee |
| summary | Summary of the company |
| pros | Pros of the company |
| cons | Cons of the company |
| advice-to-mgmt. | Comment made to management |
| overall-ratings | Overall rating |
| work-balance-star | Work balance star rating |
| culture-values-stars | Culture value star rating |
| career-opportunities-stars | Career opportunity star rating |
| comp-benefit-stars | Company benefit star rating |
| senior-management-stars | Senior management star rating |
| Helpful-count | Helpful count of the employee |
| link | Link to the comment |

**Layoff Analysis**

This dataset was scraped from Layoffs.fyi with the hope to enable Kaggle community to look into analysing recent mass layoffs and discover useful insights and patterns.

Original dataset can be tracked at <https://layoffs.fyi/>

|  |  |
| --- | --- |
| **Feature** | **Description** |
| Company | Company which made the layoff |
| Location | Location of layoff |
| Industry | Industry of company |
| Laid\_Off\_Count | Number of layoffs |
| Percentage | Percentage of layoff |
| Source | Source from the where the data was taken |
| Funds\_Raised | Funds raised due to the layoff |
| Stage | Stage of the company |
| Country | Country of the layoffs |

1. **METHODOLOGY**

**4.1 Twitter Sentimental Analysis**

**NLTK** stands for Natural Language Toolkit. It is a leading platform for building Python programs to work with human language data. It provides a wide range of tools and resources for tasks such as tokenization, stemming, tagging, parsing, and semantic reasoning. NLTK is free, open-source software and is widely used by researchers, industry professionals, and educators in the field of natural language processing.

**TextBlob** is a popular Python library for natural language processing, which includes a built-in sentiment analysis tool. TextBlob uses a pre-trained sentiment classifier that is trained on a movie review dataset to classify the polarity of a text as positive, negative, or neutral.

TextBlob sentiment analysis returns two values: polarity and subjectivity. The polarity value ranges from -1 to 1, where -1 indicates a highly negative sentiment, 0 indicates a neutral sentiment, and +1 indicates a highly positive sentiment. The subjectivity value ranges from 0 to 1, where 0 indicates an objective statement and 1 indicates a highly subjective statement.

TextBlob also provides the option to customize the sentiment analysis by training a new classifier on a specific dataset. This can improve the accuracy of the sentiment analysis for a particular domain or language.

TextBlob is often used for sentiment analysis in social media monitoring, customer feedback analysis, and product review analysis. Its simplicity and ease of use make it a popular choice for beginners and small-scale sentiment analysis projects.

Graphical user interface, application

Description automatically generated

*Fig 4.1.1 Importing Libraries and loading the data.*

**4.1.1 Data Preprocessing**

Preprocessing is an essential step in natural language processing (NLP) that involves cleaning, normalizing, and transforming raw text data into a format that is suitable for analysis. Here are some common preprocessing steps in NLP:

* **Tokenization:** This is the process of breaking a text document into individual words or tokens. This is typically done by splitting the text on whitespace or punctuation characters.

Graphical user interface, text, application, email

Description automatically generated

*Fig 4.1.2 Tokenizing the text.*

* **Case normalization:** This involves converting all text to lowercase or uppercase, depending on the specific use case. This can help reduce the number of unique words and make it easier to compare and analyze text.



*Fig 4.1.3 Case Normalization of the text*

* **Stop word removal:** Stop words are common words that do not carry much meaning, such as "the", "and", and "a". Removing stop words can help reduce the size of the vocabulary and improve the efficiency of downstream processing.

Graphical user interface, text, application, email

Description automatically generated

*Fig 4.1.4 Applying stop word removal.*

* **Stemming and lemmatization:** Stemming and lemmatization are techniques for reducing words to their base or root form. This can help reduce the number of unique words and improve the accuracy of text analysis.

Graphical user interface, text, application, email

Description automatically generated

Graphical user interface, text, application

Description automatically generated

*Fig 4.1.5 Stemming and Lemmatization*

* **Removing special characters and numerical values:** This involves removing special characters, such as punctuation marks and symbols, as well as numerical values from the text. This can help remove noise and improve the accuracy of text analysis.

Graphical user interface, text, application, email

Description automatically generated

*Fig 4.1.6 Removing Special and numerical values.*

* **Part-of-speech tagging:** This involves identifying the part of speech of each word in the text, such as noun, verb, adjective, or adverb. This can be useful for tasks such as sentiment analysis or named entity recognition.

Graphical user interface, text, application, email

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Calendar

Description automatically generated

*Fig 4.1.7 Applying POS-tagging on the text.*

**4.1.2 Polarity and Subjectivity**

Polarity checking in NLP refers to the process of determining the sentiment polarity of a text or document, which can be positive, negative, or neutral. It is a common task in sentiment analysis and involves analyzing the words, phrases, and context of the text to determine the overall sentiment expressed.

There are various approaches to polarity checking in NLP, including rule-based methods, lexicon-based methods, and machine learning-based methods. Rule-based methods use handcrafted rules to identify sentiment-bearing words and phrases and assign a sentiment score based on their context. Lexicon-based methods use sentiment lexicons or dictionaries to assign a sentiment score to each word in the text, and then combine them to determine the overall sentiment. Machine learning-based methods use supervised or unsupervised algorithms to learn from labeled or unlabeled data and predict the sentiment polarity of new texts.

Subjectivity in NLP refers to the degree of personal opinion, feeling, or emotion expressed in a text or document. It is a common task in sentiment analysis and involves analyzing the language and context of the text to determine whether it expresses a subjective or objective viewpoint.

Subjectivity analysis is typically based on a set of pre-defined rules, or a machine learning model trained on labeled data. The rules or model can be used to identify subjective language patterns, such as the use of opinion words, personal pronouns, and emotional expressions. The output of subjectivity analysis can be a binary classification (subjective or objective) or a continuous score reflecting the degree of subjectivity.

Graphical user interface, text, application

Description automatically generated

*Fig 4.1.8 Code for Applying Polarity and Subjectivity*

Graphical user interface, table

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*Fig 4.1.9 Getting the scores in two separate columns in the dataset.*

**4.1.3 Finalizing the Sentiment**

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A picture containing table

Description automatically generated

*Fig 4.1.10 Final output of the scores on Sentiments*

*Fig 4.1.11 Pie chart showing percentage distribution of Comments.*

*Fig 4.1.12 Bar chart showing count of sentiments.*

**4.2 Employee Sentiment Analysis**

**VADER** (Valence Aware Dictionary and Sentiment Reasoner) is a popular rule-based sentiment analysis tool that uses a lexicon of words and their associated sentiment scores to calculate the polarity of a text. The polarity scoring scale in VADER ranges from -1 to +1, with -1 indicating a highly negative sentiment, 0 indicating a neutral sentiment, and +1 indicating a highly positive sentiment.

VADER also provides scores for three different types of sentiment: positive, negative, and neutral. These scores represent the proportion of the text that is classified as each type of sentiment. For example, a text with a positive score of 0.8, a negative score of 0.1, and a neutral score of 0.1 would be classified as highly positive.

In addition to the polarity scores, VADER also provides a compound score, which represents an overall score for the sentiment of the text. The compound score is a normalized, weighted composite score of the positive, negative, and neutral scores, and it ranges from -1 to +1. A compound score of 0 indicates a neutral sentiment, while scores above 0 indicate positive sentiment and scores below 0 indicate negative sentiment.

Polarity score refers to the sentiment expressed in a text as either positive, negative, or neutral. It is measured on a scale ranging from -1 to 1, where -1 indicates a highly negative sentiment, 0 indicates a neutral sentiment, and +1 indicates a highly positive sentiment.

Subjectivity score refers to the degree of personal opinion, emotion, or judgment expressed in a text. It is measured on a scale ranging from 0 to 1, where 0 indicates an objective statement and 1 indicates a highly subjective statement that is based on opinion or emotion.

Both polarity and subjectivity scores are important measures in sentiment analysis as they help in understanding the tone, attitude, and emotional content of a text. They are widely used in various applications such as social media monitoring, customer feedback analysis, and product review analysis.

**4.2.1 Data Preprocessing:**

* Tokenization: This is the process of breaking a text document into individual words or tokens. This is typically done by splitting the text on whitespace or punctuation characters.
* Case normalization: This involves converting all text to lowercase or uppercase, depending on the specific use case. This can help reduce the number of unique words and make it easier to compare and analyze text.
* Stop word removal: Stop words are common words that do not carry much meaning, such as "the", "and", and "a". Removing stop words can help reduce the size of the vocabulary and improve the efficiency of downstream processing.
* Stemming and lemmatization: Stemming and lemmatization are techniques for reducing words to their base or root form. This can help reduce the number of unique words and improve the accuracy of text analysis.
* Removing special characters and numerical values: This involves removing special characters, such as punctuation marks and symbols, as well as numerical values from the text. This can help remove noise and improve the accuracy of text analysis.
* Spell correction: This involves correcting common spelling mistakes or typos in the text. This can help improve the accuracy of downstream processing and analysis.
* Part-of-speech tagging: This involves identifying the part of speech of each word in the text, such as noun, verb, adjective, or adverb. This can be useful for tasks such as sentiment analysis or named entity recognition.

Graphical user interface, text, application, email

Description automatically generated

*Fig 4.2.1 Importing necessary libraries.*

A picture containing diagram

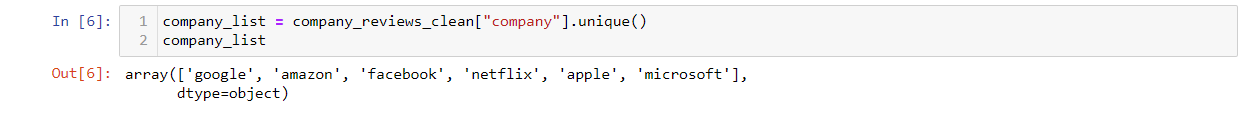
Description automatically generated

*Fig 4.2.2 Data Head showing first 5 rows.*

**4.2.2 Filtering the data to just display one company at a time.**

A screenshot of a computer

Description automatically generated with medium confidence



*Fig 4.2.3 filtering for viewing one company at a time.*

**4.2.3 Variables for holding Each sentiment for each sentence.**

1. **Google**

Text

Description automatically generated

*Fig 4.2.4 Calculating the Google review score.*

1. **Amazon**

Text

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*Fig 4.2.5 Calculating the Amazon review score.*

1. **Meta**

Text

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*Fig 4.2.6 Calculating the Meta review score.*

1. **Netflix**

Text

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*Fig 4.2.7 Calculating the Netflix review score.*

1. **Apple**

Graphical user interface, text

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*Fig 4.2.8 Calculating the Apple review score.*

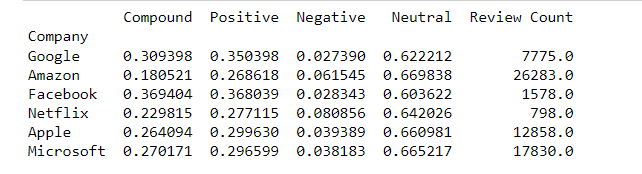
1. **Microsoft**

Graphical user interface, text, application

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*Fig 4.2.9 Calculating the Microsoft review score.*

**4.2.4 Finalizing the score for Reviews**



*Fig 4.2.10 Summarized review score of all companies*

*Fig 4.2.11 line chart showing review count of each company.*

*Fig 4.2.12 bar chart showing compound count on each company.*

*Fig 4.2.13 pie chart on percentage distribution of positive comments on company*

*Fig 4.2.14**pie chart on percentage distribution of positive comments on company*

*Fig 4.2.15**13 pie chart on percentage distribution of Neutral comments on company*

**4.3 Layoff Analysis**

**4.3.1 Matplotlib and Seaborn**

Matplotlib is a data visualization library in Python that is used to create static, interactive, and animated visualizations in Python programming language. It provides various plotting options and allows you to create high-quality visualizations such as line charts, scatter plots, histograms, bar charts, and more.

Matplotlib is open-source and can be installed using pip or conda. It has a user-friendly interface that makes it easy to create a variety of visualizations using just a few lines of code. Matplotlib can also be used with other Python libraries such as NumPy, Pandas, and Scikit-learn to create advanced visualizations.

Some of the key features of Matplotlib include support for multiple operating systems, customization of visualizations, support for different types of data, and the ability to create animations and interactive visualizations.

Overall, Matplotlib is a powerful and versatile data visualization library in Python that is widely used in data science and machine learning applications.

Seaborn is a data visualization library built on top of matplotlib in Python. It provides a high-level interface for creating informative and attractive statistical graphics. Seaborn can be used to create a variety of visualizations, including scatter plots, line plots, bar charts, histograms, heatmaps, and more.

One of the main advantages of Seaborn is its ability to easily create complex statistical visualizations with just a few lines of code. Seaborn also comes with a variety of color palettes and themes that can be customized to match the needs of a particular analysis or project.

Another advantage of Seaborn is its integration with Pandas, a popular data manipulation library in Python. This makes it easy to create visualizations directly from a Pandas DataFrame, without having to do any data manipulation.

Overall, Seaborn is a powerful data visualization library that can help users to quickly and easily create informative and attractive visualizations to explore their data.

**4.3.2 Data Wrangling**

Data wrangling, also known as data cleaning, is the process of transforming raw data into a form that is suitable for analysis. It involves identifying and handling missing or incorrect data, converting data types, renaming columns, merging data sets, and creating new variables.

The process of data wrangling begins with data collection, where data is acquired from various sources such as databases, spreadsheets, or online platforms. Once the data is collected, it is then cleaned and transformed to ensure that it is accurate, consistent, and complete.

Data wrangling is an important step in the data analysis process because it helps to ensure that the data is reliable and accurate. Without proper data wrangling, the analysis of the data may be skewed or incorrect, leading to inaccurate insights and decisions.

Graphical user interface, text, application

Description automatically generated

*Fig 4.3.1 Data Wrangling on the data*

**4.3.3 Exploratory Data Analysis**

Exploratory Data Analysis (EDA) is a crucial step in data analysis that involves the process of analyzing and understanding the data to derive insights and identify patterns.

The goal of EDA is to discover patterns and relationships in the data and communicate these insights to stakeholders. Python provides various libraries such as Pandas, NumPy, and Matplotlib that allow for the visualization of data and making it easier to analyze.

EDA involves several steps including cleaning and preprocessing the data, visualizing the data, and summarizing the findings. The process of cleaning and preprocessing involves identifying and handling missing values, dealing with outliers, and ensuring consistency in data. Visualization techniques include scatter plots, histograms, bar charts, and heat maps, among others. The summary findings include descriptive statistics, correlation matrices, and other insights derived from the visualization.

Overall, EDA is a critical step in data analysis that helps to ensure the accuracy and reliability of the findings. It also helps to communicate the insights and patterns to stakeholders effectively.

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*Fig 4.3.2 defining the shape and columns of the data*

Table

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*Fig 4.3.3 Data information*

Table

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*Fig 4.3.4 finding the data type and describing the data.*

Graphical user interface, application, Word

Description automatically generated

*Fig 4.3.5 finding the null and unique values of company*

Graphical user interface, text, application

Description automatically generated

*Fig 4.3.6 finding the unique values for stage and country column.*

Graphical user interface

Description automatically generated

*Fig 4.3.7 query for percentage == 1.00*

**4.3.4 Cleaning the Data**

### Issues

1. Drop Unwanted Columns
2. Change Columns Names to Small Letters
3. Change Date column data type to datetime.
4. Extract (year-month-day) From Date Column to Create New Columns
5. Filling Missing values with zeros
6. Change Laid\_Off\_Count column data type to integer.

Graphical user interface, application

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*Fig 4.3.8 Dropping unwanted columns.*

Graphical user interface, text, application

Description automatically generated

Graphical user interface, application

Description automatically generated

*Fig 4.3.9 changing date column format and splitting it into year, month & day*

Graphical user interface, application

Description automatically generatedGraphical user interface, text, application

Description automatically generated

*Fig 4.3.10 checking for null values and change data type of column to integer*

**4.3.5 Data Visualization**

Data visualization is an essential aspect of any data analysis task, including layoff analysis. By visualizing the data, we can easily identify trends, patterns, and insights that might be missed through numerical analysis. In the case of layoff analysis, data visualization can help identify the departments, locations, or positions that were most affected by the layoff, among other things.

To visualize the layoff data, we can use a variety of data visualization tools available in Python, such as Matplotlib, Seaborn, Plotly, and more. With these tools, we can create various types of visualizations, such as bar charts, line charts, pie charts, histograms, and scatterplots.

**A picture containing shoji, crossword puzzle, clipart

Description automatically generated**

*Fig 4.3.11 Basic EDA Visualization*

Graphical user interface, application

Description automatically generated

**Chart

Description automatically generated with medium confidence**

*Fig 4.3.12 bar chart showing layoffs for each year.*

Graphical user interface, text, application

Description automatically generated

**Shape, rectangle

Description automatically generated**

*Fig 4.3.13 bar chart showing layoffs for each country.*

Graphical user interface, text, application

Description automatically generated

*Fig 4.3.14 proportion of United states and India layoffs to Total Layoffs*

Graphical user interface

Description automatically generated with medium confidence

*Fig 4.3.15 number of layoffs by industry*

Graphical user interface, text, application

Description automatically generated

*Fig 4.3.16 checking the companies where industry is not defined*

**Chart, histogram

Description automatically generated**

*Fig 4.3.17 Bar chart showing the number of layoffs by industry.*

Graphical user interface, text

Description automatically generated with medium confidence

*Fig 4.3.18 average layoff count on each industry*

**Chart, bar chart

Description automatically generated**

*Fig 4.3.19 bar chart showing average layoff on industries.*

Graphical user interface, text, application, email

Description automatically generated

**A picture containing histogram

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*Fig 4.3.20 Data and chart on Layoff by Stage*

Graphical user interface, text, application

Description automatically generated

*Fig 4.3.21 proportion of layoff in IPO and Seed Stage to Total Layoff*

Table

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*Fig 4.3.22 layoff table for each month in each year*

**Chart, line chart

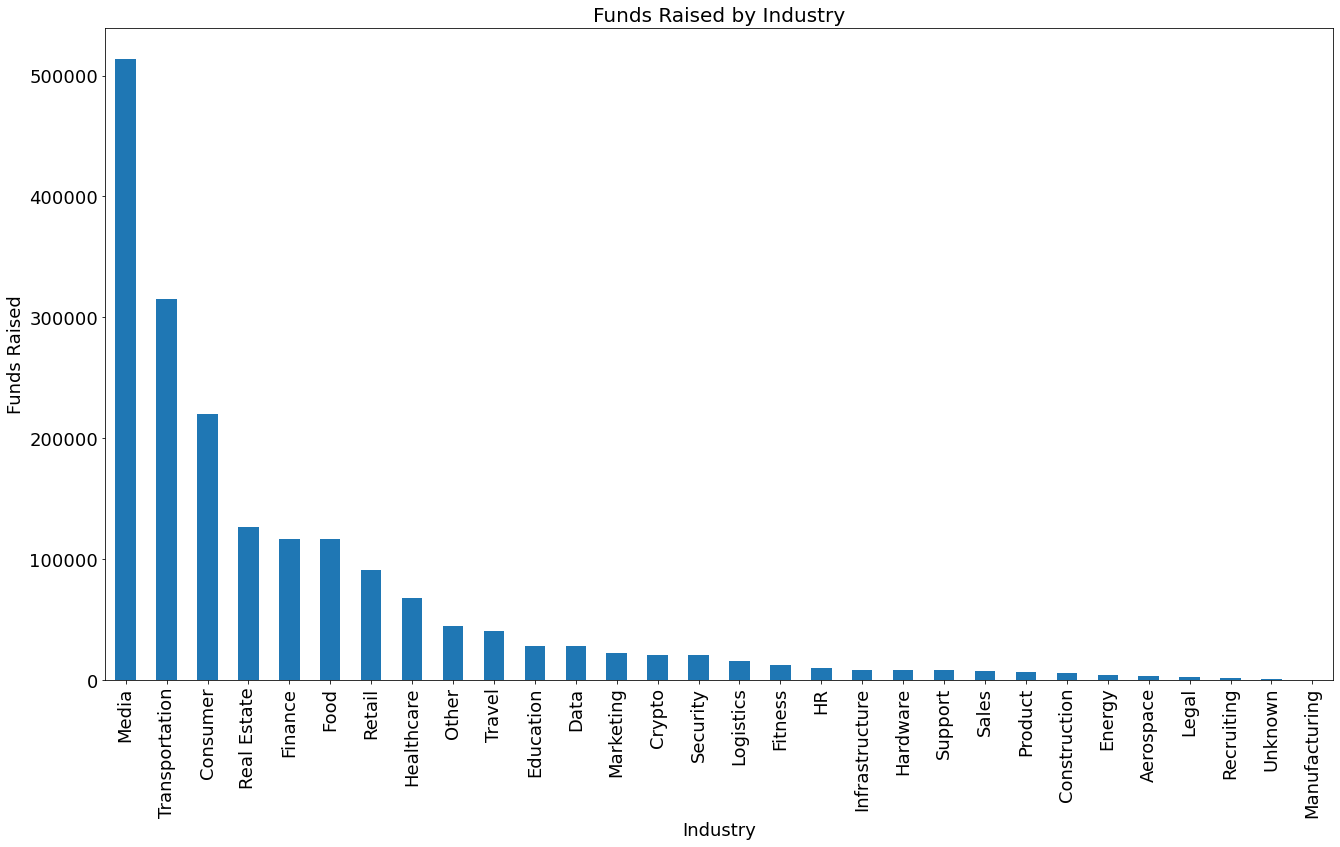
Description automatically generated**

*Fig 4.3.23 line Chart for Layoffs in each month over the years*

Graphical user interface, application

Description automatically generated

*Fig 4.3.24 Count on funds raised by industry.*

****

*Fig 4.3.25 Bar chart on funds raised by industry.*

**Shape

Description automatically generated with medium confidence**

*Fig 4.3.26 bar chart on funds raised in accordance with company stage.*

Graphical user interface, text, application

Description automatically generated

**A picture containing histogram

Description automatically generated**

*Fig 4.3.27 Count and bar chart on funds raised by company.*

Table

Description automatically generated with medium confidence

*Fig 4.3.28 Top 10 largest layoff dates*

Graphical user interface, text, application, email

Description automatically generated

**Chart, bar chart

Description automatically generated**

*Fig 4.3.29 Bar chart showing the top 10 Layoffs by company.*

Graphical user interface

Description automatically generated

*Fig 4.3.30 Filtering dataframe on the number of companies that went bankrupt*

Background pattern

Description automatically generated with medium confidence

*Fig 4.3.31 The total count and count over the years on companies that went bankrupt*

**Chart

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*Fig 4.3.32 bar chart on companies gone bankrupt over the years.*

**Histogram

Description automatically generated**

*Fig 4.3.33 Bar chart on bankrupt companies by country*

**Chart

Description automatically generated**

*Fig 4.3.34 Bar chart on bankrupt companies by stage*

**Chart, bar chart

Description automatically generated**

*Fig 4.3.35 Bar chart on bankrupt companies by Industry*

Graphical user interface, text, application, email

Description automatically generated

*Fig 4.3.36 Creating dataframe with only US companies.*

**Histogram

Description automatically generated**

*Fig 4.3.37 Bar chart on US location with number of layoffs*

1. **RESULTS AND INTERPRETATION**

Based on the given result, we can see that the majority of the sentiments expressed on Twitter about the Twitter layoff were neutral (6436 out of 11937 total tweets). There were also a significant number of negative tweets (1804) and positive tweets (3697). This suggests that while there were some positive sentiments expressed about the layoff, a large number of Twitter users had negative reactions to the news.

Using Vader Sentiment Analysis, the following insights were found Amazon has the highest number of reviews, including highest scores for positive comments and comparatively low negative scores. Microsoft and Apple have almost the same positive and negative scores making them almost same. Google has the least positive score and least negative scores.

This is a fun exercise on Vader Sentiment Analysis and conclusions on which company is best to work cannot be made due to limitations such as number of reviews available (i.e, not all companies have the same number of reviews and hence any conclusions could be biased), certain comments are in non-English languages, and a detailed analysis would be required on how the scores were calculated.

The Analysis on the employee review of competing companies’ data table in the figure shows the results of sentimental analysis performed on the reviews of six companies - Google, Amazon, Facebook, Netflix, Apple, and Microsoft. The table lists the compound, positive, negative, and neutral scores for each company, as well as the count of reviews analyzed.

The compound score ranges from -1 to +1 and represents an overall sentiment score for the text. A score closer to +1 indicates a positive sentiment, while a score closer to -1 indicates a negative sentiment. In this table, all companies have positive compound scores ranging from 0.180 to 0.369, indicating an overall positive sentiment towards these companies in the reviews analyzed.

Among the six companies (Google, Amazon, Facebook, Netflix, Apple, Microsoft), Facebook has the highest compound score of 0.369404, indicating a generally positive sentiment in the tweets related to Facebook's layoffs. Amazon has the second highest compound score of 0.180521, indicating a somewhat positive sentiment but less positive than Facebook.

Among the six companies, Microsoft has the highest number of reviews with 17830 tweets related to layoffs, followed by Apple with 12858 tweets and Amazon with 26283 tweets.

The review count may affect the sentiment scores. For instance, the sentiment score for Facebook is higher than Amazon's even though Amazon has a much higher review count. This could be because the sentiment scores are calculated based on the text in the tweets, and not simply on the number of tweets.

The negative sentiment score is higher than the positive sentiment score for all the companies, except for Facebook. This indicates that most of the tweets related to layoffs for these companies have a negative sentiment.

And on the Layoff Analysis we can see that

**In 2020, almost 81k employees were laid off. In 2021, the situation has become better with 15k laid off but unfortunately in 2022, the situation got worse than in 2020 with over 147k laid off.**

**we can see that the United States has the most layoff by far with (65.9%) of the total layoffs, followed by India with (12.7%).**

**The United States and India, having (78.6%) of all the layoffs, which leaves only (21.4%) shared by the other countries.**

**If we look at the numbers of layoffs in every industry, we will find that Transportation followed by consumer, retail, and finance have layoffs between 20k to 30k.**

**Food followed by real estate, travel, healthcare and education have layoffs between 10k to 20k.**

**Legal has the least layoffs followed by aerospace, product and energy.**

**If we look at the average percentage of layoffs in every industry, we can see that Aerospace has the most average percentage of layoffs (37.7%), followed by Product (25.5%).**

**Sales has the least layoff percentage (5.5%).**

**If we looked from the employee side, Transportation followed by consumer, retail, and finance were the most affected industries by covid-19. Legal followed by aerospace, product, and energy were the least affected industries by covid-19.**

**But if we looked from the industries owner's side, Aerospace followed by Product, were the most affected industries by covid-19. And Sales was the least affected industry by covid-19.**

**IPO stage companies have the most layoffs with (39.8%).**

**Seed stage companies have the least layoffs with (0.6%)**

**In 2020, starting from March when the covid-19 hit the world, the most layoff month was Abril with (26710) layoff, followed by May then started to decrease, until in December layoffs starts to increase again.**

**In 2021, the layoffs were the least between the years 2020,2021,2022. January has the most layoffs (6013), followed by June and November.**

**In 2022, November has the worst layoff, not only in that year but in all the 3 years with (51300) layoffs.**

**The Media industry has the most funds raised, followed by Transportation and Consumer.**

**The legal industry has the least funds raised.**

**The IPO stage companies have by far, the most funds raised, and the Seed stage has the least funds raised.**

**Netflix has the largest funds raised with (487600), followed by Uber with (123500).**

**From the largest 10 layoffs happened, we can see they are all companies in the United States except the third place is in the Netherlands.**

**Also, we can see that almost all of the companies are in the IPO stage except the third place in the Acquired stage and the seventh-place unknown stage.**

**Five of the ten companies are in SF Bay Area in the United States.**

**Four of the ten happened in November 2022.**

**Meta is the most layoff company with a layoff count of (11000) which represent (13%) of the company employees. Followed by Amazon with a layoff count of (10000) which represent (3%) of the company employees.**

**Twitter is the fifth most layoff company with a layoff count of (3700), but it represents (50%) of the company employees.**

**Some companies have more than layoffs happened, so now I will show the total layoff by companies.**

**Meta still the most layoff company with (11000), followed by Amazon with (10000).**

**But now we can see that Uber is in third place with (7585), which has more than layoffs dates.**

**Followed by Booking-com with (4601), Cisco with (4100), etc.**

**Bankrupt Companies Insights**

**We have 100 companies that had been bankrupt over 3 years. In 2020 (36) companies, in 2021 (8) companies, and in 2022 (56) companies.**

**We cannot see how many employees had been laid off because (60) of (100) companies, the data about laid off counts were null values filled with zero.**

**In the United States, over 3 years, (65) companies had been bankrupt, followed by India (7) companies.**

**Most of these companies' stages are unknown. The seed stage is the most known bankrupt stage with (21) companies, followed by Series B (19).**

**The most bankrupt companies are in the Retail industry (12), followed by the Food industry (11), and the Finance industry (10).**

**We know that the largest layoffs were in the United States, so I want to separate it and show the top 10 location that has the largest layoffs.**

**SF Bay Area by far has the largest layoffs with (80267), followed by New York City with (22043) layoffs, and Seattle with (16051) layoffs.**

1. **CONCLUSION**

We can infer that the overall sentiment towards the topic is mostly neutral, followed by positive and negative sentiments. However, without knowing the context and the topic of the sentiment analysis, it is difficult to draw any specific conclusions or take any actionable insights. It appears that there were more neutral tweets than positive or negative tweets. The number of neutral tweets (6436) is higher than both positive (3697) and negative (1804) tweets. This suggests that people might have been more objective and less emotional while tweeting about the layoffs on Twitter.

The results of sentiment analysis on employee reviews for six major tech companies: Google, Amazon, Facebook, Netflix, Apple, and Microsoft. The sentiment analysis was based on three categories: negative, neutral, and positive, and a compound score, which provides an overall measure of the sentiment.

The analysis reveals that Facebook has the highest positive sentiment score of 0.37, followed by Google with 0.31, Apple with 0.26, Microsoft with 0.27, Netflix with 0.23, and Amazon with 0.18. However, Amazon has the highest review count of 26,283, while Facebook has the lowest review count of 1,578.

The neutral sentiment scores are high for all companies, indicating that employees tend to express their opinions in a neutral tone. However, Facebook has the lowest neutral sentiment score of 0.60, indicating that their employees are more likely to express strong opinions in their reviews.

In conclusion, the sentiment analysis provides valuable insights into the overall employee satisfaction levels for these companies. While the positive sentiment scores are relatively high for all companies, the analysis also highlights areas where companies can focus on improving employee satisfaction, particularly for Amazon and Netflix, which have lower positive sentiment scores compared to other companies.

The conclusion on layoff Analysis was the COVID-19 pandemic had a significant impact on the job market, with a substantial number of layoffs across various industries and regions.

The United States and India were the most affected countries, with the transportation, consumer, retail, and finance industries being hit the hardest. Aerospace and product industries had the most significant average percentage of layoffs, while sales were the least affected industry.

IPO stage companies had the most layoffs and the most funds raised, while seed stage companies had the least layoffs and the least funds raised. Netflix and Uber were among the companies that raised the most funds.

Meta, Amazon, and Uber were the companies with the most layoffs, and most of the bankrupt companies were in the retail, food, and finance industries. The largest layoffs occurred in the SF Bay Area, followed by New York City and Seattle.

Overall, the data shows that the COVID-19 pandemic had a severe impact on the job market, and some industries and regions were hit harder than others. However, some companies managed to raise significant funds despite the challenging circumstances.

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