SENTIMENT ANALYSIS AND TOPIC MODELLING ON LAYOFFS IN THE TECH INDUSTRY

Social Media Research - Seminar
[INF-DSAM5A Advanced Business Analytics A]

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ABSTRACT

In this era of profound uncertainty, where the fabric of the future remains unpredictable, the realm of the tech industry has been significantly impacted, notably evident through the intricate interplay of layoffs. The same is the case with jobs, especially in the tech industry, which have resulted in uncertainty among the tech community. People use social media to give their take on these situations, and in this research, we use the opinions given on Reddit to characterize their sentiments and what they're talking about when it comes to layoffs. By using nearly 12,000 Reddit comments collected from different subreddits and feeding them into our model, we find that most people have a severely negative sentiment about layoffs. Then, we use our NLP model and identify the key topics of discussion, which also include some surprising reasons that people give for layoffs, including racial discrimination as a reason for layoffs.

Keywords

Reddit, layoffs, recession, BERT, LDA, sentiment analysis, topic modelling.

INTRODUCTION

Layoffs in the tech industry are being heard of with more frequency than ever before. Over the past few years, there have been various reasons for layoffs in tech. The tech industry is very volatile and keeps changing and evolving with time. So, some things work for some, and others, not so much. These hiccups have impacted individuals and companies in different ways depending on the reasons causing these sudden layoffs and budget cuts.

If we go back a bit to the recent worldwide events with COVID and political instability, there has been a rise in companies cutting their losses and laying off employees more than ever before. Even big-tech companies like Google and Microsoft have laid off thousands of employees at once worldwide. Such has been the dangerous repercussions of these past events.

Analyzing the sentiment surrounding these layoffs provides valuable insights into the emotions, concerns, and opinions expressed by individuals in online communities. By understanding the sentiment, researchers can gain a deeper understanding of the impact of layoffs and identify patterns or trends that could inform future strategies or policies.

That is what our aim was for the above-mentioned topic. This research aimed to conduct sentiment analysis on discussions related to layoffs in the tech industry, uncover valuable insights, and answer the question: How do individuals express their sentiment regarding layoffs in the tech industry, and what are their opinions about it? This is exactly what we aimed to achieve in our research.

In the following section, we explain how different approaches influence individual sentiments. Previous studies done on Reddit users have also been discussed, and how the sentiments of people change over time about controversial topics. How topics of interest change over time among people were also discussed.

Next comes the methodology, which comprises use of a pre-trained model to conduct sentiment analysis on the different comments collected from various subreddits on Reddit. Topic modeling is the next step of this research, which consists of the Latent Dirichlet Allocation (LDA) algorithm and how it works. At the end, we present our yearly results of the sentiment and the topics, which lead the way for limitations and future research areas to conclude.

THEORETICAL BACKGROUND

Recording sentiments from what people say and how they say online is an interesting domain. Researches have discussed the motivation behind the research, the methodology for identifying clusters and communities, and the application of sentiment analysis techniques in analyzing social media data (Chakraborty, 2020). The study contributes to understanding the dynamics of social networks and their influence on individual sentiments and interactions in online communities.

Various studies have been done on sentiment analysis over the past few years. Some have yielded expected results, while there have been some that have been very unpredictable when it came to results. Some researches have aimed to show the sentiment of Reddit users discussing vaccines at a time when there was great skepticism about vaccines and their side effects (Melton, 2021). The results showed that more than half the people had a positive sentiment about vaccines and their usage on them, and that trend remained static over a period.

We have seen not just the sentiment that individuals possess on social media about a particular topic but also the problems associated with the topic under discussion using topic modeling algorithms (Ernesto Lee, 2021). Topic modeling gives in-depth information rather than just the positivity and negativity of an opinion. It is also one of the best techniques to perform exploratory initial analysis on a corpus (Akira Murakami, 2017).

METHODOLOGY

The research consists of many sections. Our task is to identify the sentiment of people about layoffs in the tech industry on Reddit. Most of the past work was done on tweets, but this data comes from different subreddits. The first step is mainly about dealing with data collection and indicating some statistics about it.

After cleaning the data and making it fit to supply to the model, we perform the sentiment analysis and send the data further to perform topic modeling using Latent Dirichlet Allocation (LDA). After that, we perform further visual analysis to obtain valuable KPIs for the final visualization.

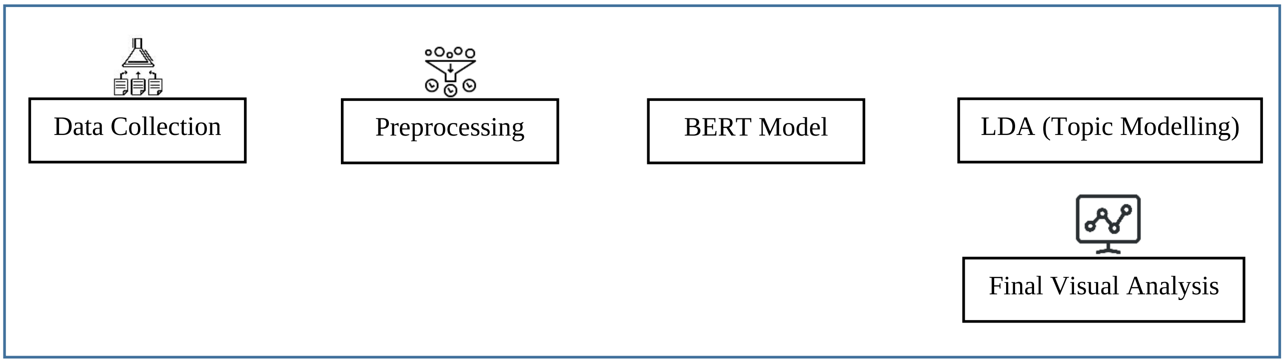

Figure 1. Methodology

Data Collection

There are many different stages of a data collection process depending on the kind of data we intend to collect. Our data collection was done from Reddit. There are different ways one can scrape data from reddit.

API

The first step to data collection from Reddit is having an API key to acquire access to data from different Reddit subreddits. That process usually requires an app creation on Reddit for developers. One needs to submit a username and password, and then an API is generated that allows data collection from different Reddit subreddits.

Python Script

The next step is to create a script in Python and use the API there. Reddit has a dedicated library “praw” for this exact task. Write down the details of the app created on Reddit including the unique username and password. Then, check if the API is connected. Once it’s connected, you’re good to go.

Subreddits

As the key focus was just on layoffs, many subreddits were part of the pool to have enough sample size. A total of **37** subreddits made the dataset of **11387** comments. The subreddits are as follows:

dataengineering	technology	tech
iiiiiiitttttttttttt	engineering	SoftwareEngineering
datascience	learnmachinelearning	MachineLearning
cscareerquestions	technews	networking
linuxadmin	remotework	AskReddit
jobs	careerguidance	ITCareerQuestions
personalfinance	Futurology	recruitinghell
deloitte	stocks	developersIndia
ProgrammerHumor	wallstreetbets	ExperiencedDevs
EYLayoffs2023	overemployed	science
programming	web_design	webdev
learnprogramming	apple	samsung
Android		

Table 1. Dictionary of Words

Other than the actual text comments, id, username, subreddit, title, and date were also scraped using the API. Timestamp was also scraped but it wasn’t relevant for the research so only dates were considered.

Time Period

The data that we collected were comments made by people on different subreddits, which means it is time-series data. The final dataset comprised of data from 2019 to May 2023 (Mazhar, Reddit Comments Layoffs Tech Data, 2023).

Keyword

The main keyword used for these subreddits was “layoff” for the most accurate final output relevant for the research.

Important Statistics

One key statistic is the distribution of data over the years. In the data from 2019 to 2023, although layoffs were a big part of discussion among the different tech communities, the difference between the first three years and the last two years is substantially high. That tells a lot about layoffs.

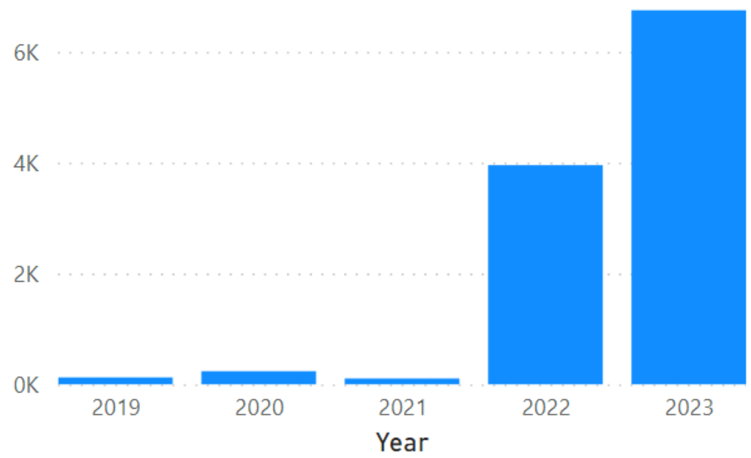

Figure 2. Data Statistics

Data Pre-Processing

Once we got the data setup, the next stage involved using Python to perform adequate data cleaning. This step is necessary to prepare the data in a way recommended to feed to the model for sentiment analysis. Now, to do this, one must have an idea about the type of text data fed from the comments and realize what characters or words might have a detrimental effect on our modeling at the end.

Removing Unwanted Characters

In our data, we found some characters that were repeatedly used by users that could have a negative impact going ahead in our research. People using “@” to tag usernames, and attaching gifs or images with hyperlinks are also not needed in the processed data. So, we used Python to filter these characters.

Removing lines and irrelevant spaces was also needed. In model inference, we found that in comments with multiple paragraphs, the model was crashing. So, a way had to be found to join these paragraphs to keep the model running.

Stop Words

Python provides a library that can be used to remove the stop words from the text. These words are not useful at all for the final data preparation, so it is best to remove them. The NLTK library has a “stopwords” package that was used to remove the stop words.

Upon further investigation, however, this step was not enough. Stop words vary for different niches and different kinds of texts. So, one must also go through and create a dictionary of stop words manually (Mazhar, Excluded Words Dictionary, 2023).

Sentiment Analysis

The next stage of the research was performing sentiment analysis by providing the text data as input to the model. VADER is a common algorithm used in NLP for sentiment analysis. It is a rule-based model for sentiment analysis of text data (Hutto, 2014). One can either train it from scratch or use a pre-trained one. In our research, various pre-trained models were tried, but the BERTWEET Base model from HugghingFace came out to be the best in terms of accuracy and efficiency, and the model had the best results at the end (Juan Manuel Pérez, 2021).

BERTweet is a model based on the training of the RoBERTa model, and it performs better than the RoBERTa model (Dat Quoc Nguyen, 2020). Its abbreviation is Bidirectional Encoder Representations from Transformers. It was originally trained on a corpus of 850m tweets, but it can also be used for the sentiment analysis of Reddit comments if we do adequate pre-processing.

In model configuration, the max sequence length is 128. So, any comment over 128 length was only considered for sentiment based on the first 128 sequence length. Then, we get logits and then use softmax to get the probability scores for **POS**, **NEG**, and **NEU**. At the end, we label the initial data with these sentiments for use in further analysis.

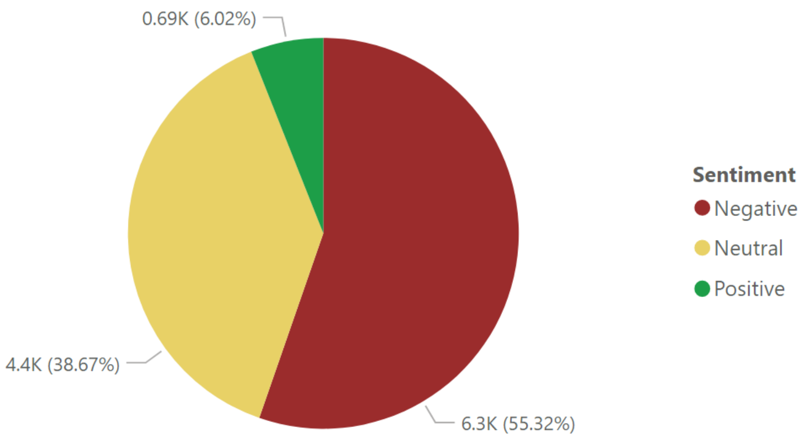

Figure 3. Sentiment Analysis

Topic Modeling

After sentiment analysis, the next stage is conducting topic modeling. Before we went for topic modeling, it was important to create another manual dictionary to further clamp down on irrelevant words that could make our final topics impure (Mazhar, Excluded Words Dictionary, 2023).

Once this is done, we took the pre-processed data and segmented it in 5 sections based on years from 2019 till 2023. Then, we performed topic modelling on each year's data, and received topics for each year.

For topic modelling, LDA and STM are two of the widely used approaches. Due to the limitations of STM to R and me using Python in our stack, we went with LDA. LDA is an acronym for Latent Dirichlet Allocation (David M. Blei, 2003). It generates a list of topics. We can choose the number of topics manually. However, the number of topics vary a lot depending on the size of the dataset provided.

It uses the Dirichlet distribution to select the most important and widely used words from the text. Dirichlet distribution is important for this because it supports the use of multiple random variables, and that comes in very handy when it comes to choosing multiple topics. From Musicology to Machine Learning (NLP), Latent Dirichlet has found its use everywhere.

To choose the ideal number of topics, we took a statistical approach by using semantic coherence or coherence scores and exclusivity. Coherence scores gave us the best results for 4 and 6 topics. So, we went with 6, and upon checking manually as well, 6 was the most accurate number of topics to display. Manual tests of other topic numbers were also done to come to an ideal number. Even after doing that, 4 and 6 were the best, which goes well with the statistical method of choosing the number of topics.

RESULTS

To investigate the opinions of people on layoffs in the tech industry, it is imperative to go through the sentiment and topic modelling results, and then analysing both. Some of the results were expected, but there were also some that were out of the ordinary. This is the purpose of conducting these researches as we can get something we least expected to.

Sentiment Analysis

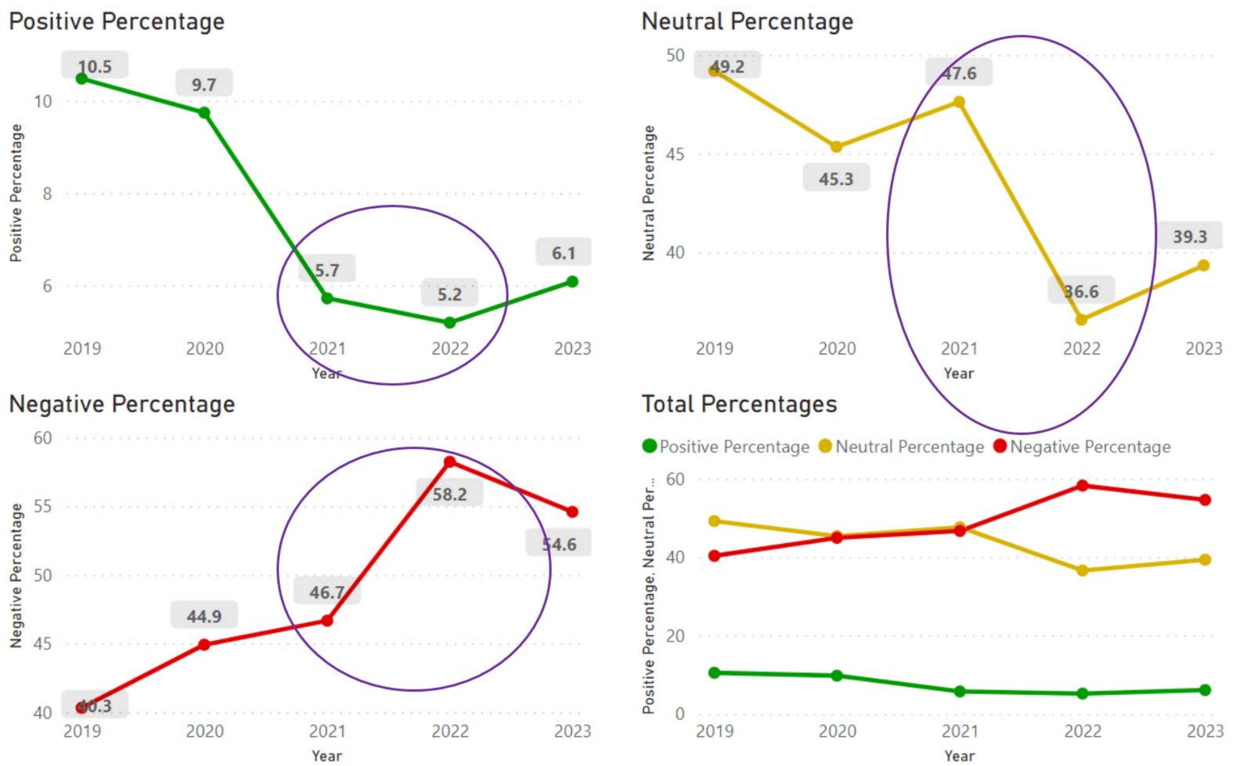

Figure 4. Sentiment Percentages

In sentiment analysis, around 6% of the sentiments were positive, which is expected. Around 39% of the opinions were neutral, with 55% negative sentiment as shown in **Figure 3**. We were surprised by the number of neutral percentages. But, in negative comments, harsh words were used.

Upon digging further, we came up with an interesting piece of information about these sentiments. As **Figure 4** shows, when we analyzed the year on percentages of the individual sentiments, it showed a higher percentage of positive and neutral sentiments. This shows that things in 2019 and 2020 were considerably better in the tech industry as people were less negative about layoffs.

In 2021, we can clearly see a nearly 50% decrease in positive sentiments and a spike in negative opinions. This indicates that something must've happened in terms of events that resulted in these negative spikes, and we got to the actual events as well, which are discussed further down the road.

The information below clearly indicates the occurring of specific events that contributed to the downfall in positive and neutral opinions, and a steep rise in negative sentiments. It also shows that despite being stressed and some people having mental health issues, they went to social media to express their views about layoffs and several pertinent issues about them (Shanthakumar, 2021). Most did so in a negative way, while very few did it in a positive way.

Topic Modelling

After the sentiment analysis completion, the next step is to see what people are talking about. Latent Dirichlet Allocation (LDA) makes it quite convenient to extract some key topics. The initial results might not exactly be what we'd want to see, but with more stop words and filters, we can reach a solid conclusion, which is what we did.

We created another dictionary of unnecessary words manually and made sure to filter them out before the final topic modeling processing. This additional filter increased the quality and relevance of the topics that LDA extracted. For selecting what exact topic number was good for our data, we chose to perform coherence measures and exclusivity as described before. The ideal topic numbers for this research were 4 and 6, and we went with 6.

For the topic modeling results, just like sentiments, the dataset was divided into five parts, with years from 2019 to 2023 constituting the given sub-datasets. There are various ways to visualize the top topics, but the best option for this turned out to be word cloud, which is easy to understand as compared to other options available.

Topics for 2019

Figure 5. Top Topics for 2019

When we discuss 2019, the above topics are what people usually discuss. The sample size for 2019 was considerably smaller than 2022, but we see many important things above. The main keywords for 2019 were future, IBM, skill, OpenAI, recession, and unemployment.

There was some news about recession, and people were discussing it, and same was the case with unemployment, which is understandable as layoffs and unemployment go hand in hand in most cases. Bloomberg posted their recession model predictions in 2019, which gave a 30% chance of recession, which prompted people to talk about their future, and that makes sense. From an employee perspective, the best way to deal with recession fears is to prepare in advance, and take necessary measures to combat it (Lovelock, 1997).

The other two key topics were IBM and OpenAI. In 2019, there was news about IBM laying off nearly 1,00,000 employees out of nowhere, which created panic in the community. When the big enterprises go through these rigorous procedures to cut costs, it has a ripple effect on the entire tech community. That's what prompted people to talk about IBM because when a big company does this, people will talk.

OpenAI is a big thing now, but it was launched in 2019 and no one knew much about them. What really made them come into the news was Microsoft’s investment of $1b in the company, which raised a few eyebrows. This big news was also a hot topic of discussion among the tech community.

Topics for 2020

Figure 6 Top Topics for 2020

The important topics for 2020 resonate a bit with the previous year’s topics, albeit with a few more additions. The keywords for the 2020 comments were engineer, full, software, IBM, unemployment, and Uber.

Software engineering jobs were discussed a lot in the IT community regarding layoffs, but most of them in a positive way. Software engineering talent is usually hard to find, so these jobs were called “recession-resistant”.

There were many more layoffs in other tech areas, and it is a fact that jobs that require a very high level of skill have a long and complicated hiring process. Companies usually take their time to decide the right candidate, and laying off several people and hiring someone again after some time is a hectic process.

A lot of technology startups also laid off employees due to COVID (Chebolu, 2021). As the aftereffects of COVID had started, IBM were in the headlines again, laying off around 10,000 full time workers in the Europe region. Uber was another company gravely affected by COVID. They had to lay off 14% of their entire worldwide workforce due to COVID. All these things can be considered as the reasons that triggered people in the tech communities to talk about layoffs in the tech industry in 2020.

However, if we talk about jobs in the IT industry, the forecast looks promising. Projections show a growth of 13.7% for computer related jobs in 2020-30, as compared to 7.7% overall average (Sara Hylton, 2022). Software developers, in fact, have a 22.2% increase in growth when it comes to jobs. So, as far as the IT industry is concerned, the future looks positive, even though the reddit IT community were sceptical about it in their opinions.

Topics for 2021

Figure 7 Top Topics for 2021

If there was any year that intrigued me the most due to its results, it was 2021 by far. The key areas of discussion in the communities were about covid, which isn't a surprise, but discrimination. Racial, black, and discrimination were the key words in this year.

When digging deep into what could be potential reasons for it, we came up with some very interesting facts. In the US, BAME workers reportedly faced more layoffs in the same roles as compared to white people. People raised many points on social media about potential discrimination in white collar jobs, and there was post-covid data showing that the rate of Black Americans facing layoffs was more than some other communities, including Hispanic Americans.

In another independent research, it was seen that immigrants also face more discrimination than the locals (Auer, 2022). The analysis done on data collected in Germany showed that migrants had a higher chance of losing their jobs than people who were natives. What's more interesting is that in industries that were hit harder than others, the chances of a migrant losing his/her job increases by three times more, which results in an increase in pressure on foreign workers in times of pandemics and other crisis.

Many other researches have been done on discrimination in organizations, and research shows that it is a factor in some places. The topics in 2021 point towards discrimination and race being a factor in companies deciding who to lay off and who not to.

Topics for 2022

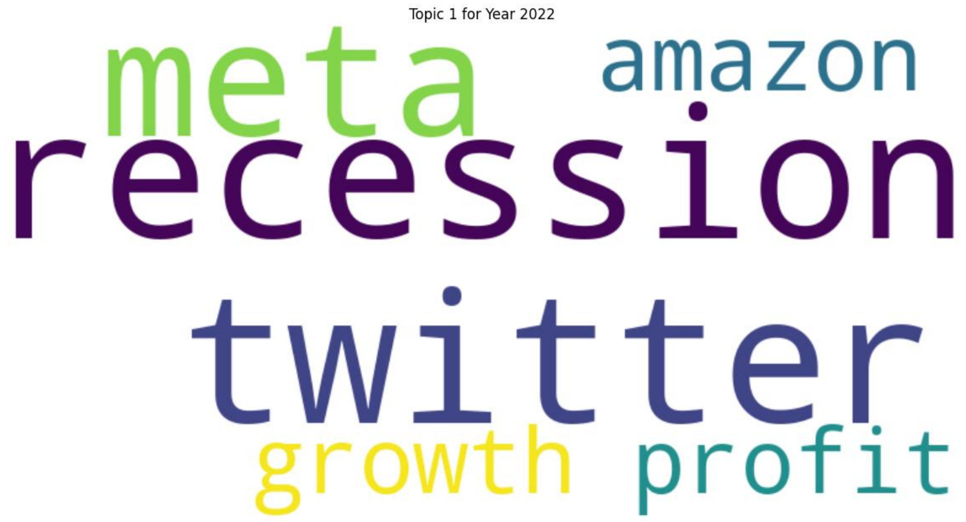

Figure 8 Top Topics for 2022

The year 2022 was the year when the effects of COVID-19 were being felt by businesses in full throttle. The start of a war in Europe raised even more eyebrows and increased uncertainty in global markets. The important topics for 2022 were meta, Amazon, recession, Twitter, growth, and profit. If we try to match these keywords with related news in the year, it becomes easy to understand why people were discussing these topics.

The year 2022 broke records in terms of profits for oil companies around the world with a big increase in their profits due to the Russian-Ukrainian war. An increase in demand plus a boycott of the Russian oil companies meant a decrease in supply while the demand remained the same. That prompted a big jump in oil prices resulting in huge profits made by the oil companies.

As for Meta, they laid off 13% of its entire workforce. Meta, being one of the biggest tech giants in Silicon Valley laying so many people off raised a lot of eyebrows in the Reddit tech community. Meanwhile, Twitter, on the other hand, laid off nearly 50% of its entire workforce, spreading even more panic in the community. The frequency of comments made by the public increased by many folds in 2022.

Amazon faced slowdowns in their sales in early and mid-2022. They too laid off 3% of their office working staff at the end of 2022. Most big tech giants laying off so many people at the same time was a definite cause of concern for the people linked to tech companies.

The recession probability was raised to 47.5%. Global growth also decreased significantly. As we’ve seen in the past, recession is always preceded by a decrease in global growth, and it has happened a lot in the past as well (Justin Damien Guénette, 2023). The same was expected to occur in 2022 and near future as well, leaving many users worried about their immediate and long-term future.

Topics for 2023

Figure 9 Top Topics for 2023

The data collected was till the end of May 2023. From January till May, Google, Apple, profit, investor, growth, and recession were the top topics that LDA found. We investigated the reasons for Reddit users discussing these topics.

The first thing found was global growth, which was forecasted to decline further in the second half of 2023. The recession probability for the US increased to 65%, and for the UK, it stood at a whopping 75%, while Germany entered a recession in early 2023. That sets a bad precedent for the employees working in the tech sector.

Google laid off 12,000 employees in early 2023, which caused plenty of distress in the Reddit tech user community. Apple was the only company among the big tech giants that resisted laying off employees to cut costs. They tried to find creative ways to combat losses, which was admired by the community. However, so much unpredictability doesn't help anyone.

World Bank did a study recently that the world would go towards a global recession in 2023, and that there was need for a unified approach to combat necessary supplies (Sarbunan, 2023). All these pointers are valid reasons for the community to panic, and till now, there hasn't been anything that could alleviate their fears about jobs.

DISCUSSION

Theoretical Discussion

The research's primary purpose is to investigate the sentiments and opinions of Reddit users, and what they talk about layoffs in the tech industry. The data collected from Reddit can be more, but the sample size of around 12k comments is enough to come up with interesting information.

If we talk about the sentiments, we can say Reddit users are mostly tilted toward the negative side and only partially toward the neutral area. Positive comments of 6.02% are a small number. However, given the topic name, it is bound to receive a lot of negative comments.

When we go one step deeper into the years when people made these sentiments, we see a lot of interesting information. How positive comments go down and the negative stuff suddenly spikes require attention and rings some bells. These negative comments could most likely be a panic response to news that people might have watched somewhere, and they come to social media to vent their anger or make their feelings known.

Studies have shown that unpredictability of the job market have led to panic in the masses regarding their future and job uncertainty (Godinic D, 2020). When someone watches news of other people being laid off, especially in their own field, it is highly likely that this will cause an increase in job uncertainty. That might be what prompts people to jump on social media to give their opinion on the situation.

An increase in sample size in 2022 and 2023 as compared to 2019, 2020, and 2021 suggests that there was more news or information about layoffs, which was prompted by an increase in firings by companies. These things cause users to panic, and they come to social media to make their feelings known.

Moreover, while going through the different yearly topics, we can see an increased frequency of companies' names. That also suggests layoff news about these companies being announced in those times and people coming to social media later to react to them. These things when combined also point towards an increase in layoffs. Now, the big spike in negative sentiments in 2022 and 2023 also becomes more understandable, and it correlates with our research findings.

Implications

This study investigates the sentiments and topics of interest of the people in the tech industry. Data mined from social media can be used for any sentiment or topic-modeling research. Layoffs are a topic that still requires further research.

This research enables an understanding of the masses on social media about layoffs in tech. A lot of people who comment on these subreddits are actual employees of different companies. So, if we combine this with negative sentiments, we can understand the changes in public behavior.

This study is a success, but it is not without its limitations. The data we have formulated contains nearly 12k Reddit comments. That number can be enough in some cases, but for extensive research, more data would be extremely useful. Other effective social media platforms other than Reddit could also be used, and more keywords can be tried with Reddit to increase the data obtained from the API.

Employee wellbeing is something that is also negatively affected by layoffs and layoff news, and this research certainly sheds some light on that. Moreover, companies that people haven't mentioned in high esteem in these times also affect the tech companies.

Analyzing social media for layoffs helps people in understanding what others are talking about. This research can also help policy and decision makers to form regulations for better support and safeguard mechanisms for the employees.

As the center point of this research is the data itself, concepts like topic modeling can help stakeholders gain valuable insights about layoffs and other things from social media. This text data comes to social media from people. So, these approaches can certainly help with regard to decision-making.

By analyzing the sentiments of people in Reddit comments, companies can gain more info about employee concerns, which enables them to tailor support initiatives during layoff periods. All things mentioned above illustrate the use of this research, and it is beneficial in both the short and long term.

LIMITATIONS AND FUTURE WORK

Many tech industry employees and users interested in the layoff topic use other social media like LinkedIn. So, it is likely that the overall sentiment or topics might vary outside the Reddit bubble depending on the data. Moreover, nearly half of the total traffic on Reddit comes from the US, which is many times more than any other country. So, the information we've learned might not apply as much to other countries as compared to the US.

Another important point is whether what we learn is dependent on cultures and languages. English is the general language accepted worldwide, but there are also countries that speak other languages. Chinese, Spanish, Portuguese, French, and Russian are also spoken widely around the world. This research does not cover opinions other than those in English.

Another thing we can do as part of our future research is compare different approaches. BERT and LDA are two of the widely used approaches. However, we can try to use multiple approaches and compare their results to see which one works best as part of our future research.

CONCLUSION

Layoffs have been a grave cause of concern for professionals in every domain of life, and the tech industry has been badly affected by it as well. In this research, we investigate the comments made by Reddit users on different tech subreddits and try to gauge the sentiments of people from them by using NLP techniques.

From a collection of 11387 comments from data collected from 2019 upto May 2023, we calculate the public sentiment about tech layoffs and how it varies over time by using BERTweet. We also identify the topics that people discussed from 2019 to 2023 by using Latent Dirichlet Allocation (LDA). To conclude, we visualize our results and do further analysis to gain useful insights. This research can be used by different stakeholders and policymakers to deal with employees regarding layoffs, and in a world whose economy is becoming more and more unstable, such measures will prove to be very useful.

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