

LAYOFF PREDICTION

ANALYSIS AND LAYOFF FORECASTING IN THE

UNITED STATES

A PROJECT REPORT

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TABLE OF CONTENTS

CHAPTER NO	TITLE	PAGE NO
1	INTRODUCTION	6
2	OBJECTIVES	9
3	EXPLORATORY DATA ANALYSIS	17
4	DATA MODELLING	25
5	RESULTS AND FUTURE ENHANCEMENTS	43

LIST OF TABLES

TABLE NO	TITLE	PAGE NO
4.1	Errors obtained for Linear Regression	26
4.2	Errors obtained for Logistic Regression	27
4.3	Errors obtained for Polynomial Regression	28
4.4	Errors obtained for Decision Regression	30
4.5	Errors obtained for Lasso Regression	31
4.6	Errors obtained for Ridge Regression	32
4.7	Errors obtained for Support Vector Regression	34
4.8	P, D, Q Values for all states	38
4.9	Forecasted data for next 3 years	40
5.1	Error values for all the States	43

LIST OF FIGURES

FIGURE NO	TITLE	PAGE NO
3.1	Top 5 states affected by lay-offs	19
3.2	Top 5 cities affected by lay-offs	21
3.3	Month-wise analysis in the year 2017	22
3.4	Choropleth map of the United States	23
3.5	Pie chart	24
4.1	Plotting the data after building the Linear Regression model	25
4.2	Actual vs Predicted values using Linear Regression	26
4.3	Plotting the data after building the Logistic Regression model	27
4.4	Actual vs Predicted values using Logistic Regression.	27
4.5	Plotting the data after building the Polynomial Regression model	28
4.6	Plotting the data after building the Decision Regression model	29
4.7	Actual vs Predicted values using Decision Regression	30
4.8	Plotting the data after building the Lasso Regression model	30

4.9	Actual vs Predicted values using Lasso Regression	31
4.10	Plotting the data after building the Ridge Regression model	32
4.11	Actual vs Predicted values using Ridge Regression	32
4.12	Plotting the data after building the SVR model	33
4.13	Actual vs Predicted values using Support Vector Regression	34
4.14	Differencing	36
4.15	Partial Autocorrelation	36
4.16	Autocorrelation	37
4.17	Forecasted graph	39
4.18	Forecasted graph after training the model	39
4.19	Below is the Actual vs Predicted graphs for all the states	42

1. INTRODUCTION

Layoffs, also known as temporary or permanent termination of the employees by an organization or a company. In a layoff, positions are often eliminated or the number of employees in a certain department, division, or organization is decreased. According to the rules and regulations of the nation or area, it frequently leads in a sudden and involuntary loss of employment for the affected employees, who may be given advance warning or be fired instantly. Layoffs may have a big effect on the people affected, their families, and the larger society. It may result in financial difficulty, unemployment, and an urge to look for new jobs. Layoffs may be a difficult decision for an organization to attain financial stability or adapt to changing markets.

Layoffs occur due to various reasons such as lack of work, economic downturns, downsizing, cost-cutting measures, restructuring. A company might lay off workers as a strategy to save costs and change the size of its personnel to meet current demands when it faces financial difficulties, a drop in sales, or the need to restructure its workforce.

From this project prediction we could be able to analyze that, there is a significant increase in layoffs from 2020-2021 in The United States of America. The COVID-19 pandemic significantly affected the world economy in 2020 and 2021, resulting in many layoffs and unemployment. Due to the economic downturn

brought on by the pandemic throughout 2020 and 2021, several businesses experienced financial difficulties and had to impose layoffs and employee cutbacks. The Travel and Tourism, Hospitality and Restaurants, Retail, Entertainment and Events, Manufacturing, and Airline Industry were most impacted. The unemployment rate in the United States significantly increased, peaking at 14.8% in April 2020.

For this project, we gathered data from the government's "WARN Database" website. The database provided in this site is a real time data. This project identifies the following:

1. The different states and cities that are most vulnerable to layoffs.
2. Patterns that signal future layoffs.
3. Reasons for layoffs based on past trends.
4. Forecast the likelihood of layoffs in various geographic locations.

This project predicts the following:

1. The top 5 states in the US affected by layoffs
2. The top 5 cities hit by layoff in the US.
3. Month-wise analysis.

“Layoff Prediction” predicts the future layoffs and potentially offering a number of benefits to people and businesses.

1. **Preparedness**: People could prepare both financially and emotionally if they were aware of probable layoffs in advance. They may start saving for emergencies, updating their resumes, and quickly looking for work elsewhere.
2. **Job Search**: People may start their job search early if they were aware in advance of any probable layoffs, which would provide them an advantage in a crowded employment market. They may investigate several fields or businesses that are anticipated to offer improved employment opportunities, upgrade or retrain themselves properly, and make wise professional selections.
3. **Transition Planning**: Employees who could be laid off would have more time to prepare for their exit from the company. To increase their chances of finding new job, they may concentrate on networking, requesting references, and getting ready for interviews.
4. **Training and skill Development**: People may decide to invest in training and skill development that is in line with changing labor market trends if they have advanced information about future layoffs. This would make them more marketable and have a better chance of finding a new employment.
5. **Employee Support**: Organizations might better help workers who may be impacted by future layoffs if they had access to trustworthy forecasting technologies. To aid impacted employees in making a seamless transition to new positions or

sectors, this might involve providing career counseling, training opportunities, or support with job placement services.

In conclusion, layoff forecasting would benefit both people and companies in many ways. It would make it possible for people to organize their job search, be more prepared, and spend money on skill development. Organizations might provide support to affected workers and help with easier transitions.

2. OBJECTIVES

The major objectives and steps are listed below.

Step 1: Identify the key industries and sectors most vulnerable to layoffs.

There are a multitude of factors that can contribute to the occurrence of layoffs within an organization, ranging from economic downturns and technological advancements to changes in consumer demand. Not all industries and sectors are equally susceptible to layoffs, as their vulnerability depends on the specific factors that are most likely to impact them.

Among the key industries and sectors that exhibit a higher vulnerability to layoffs are:

1. **Manufacturing:**

This sector involves the production of goods on a large scale, and it is highly sensitive to changes in the economy. During economic recessions or

periods of decreased consumer spending, manufacturing companies often experience a decline in demand, which can lead to layoffs as they strive to reduce costs.

2. **Retail:**

The retail industry is heavily influenced by consumer spending patterns. When there is a decrease in consumer confidence or a shift in consumer preferences, retail businesses may face reduced sales and revenue, prompting them to lay off employees to maintain profitability.

2. **Construction:**

The construction sector is closely tied to the economy's overall health. During economic downturns, there is typically a decline in construction projects, which can result in layoffs within the industry. Additionally, changes in government spending on infrastructure projects can also impact employment levels in construction.

3. **Transportation and warehousing:**

This sector encompasses various modes of transportation and logistics services. When economic conditions worsen, transportation and warehousing services demand may diminish, leading to layoffs as businesses adjust to lower demand.

4. *Leisure and hospitality:*

The leisure and hospitality industry rely heavily on discretionary consumer spending. During economic downturns or periods of reduced consumer confidence, individuals may cut back on travel, dining out, and other leisure activities, which can result in layoffs within this sector.

5. *Education and health services:*

Although generally considered more resilient than other industries, the education and health services sector is not immune to layoffs. Changes in government funding, budget constraints, or shifts in healthcare policies can lead to downsizing or restructuring within organizations operating in this sector.

These industries are characterized by their cyclical nature, meaning they are more prone to fluctuations in the economy. Consequently, they are more likely to experience layoffs during economic downturns or significant shifts in consumer behavior.

Step 2: Identify patterns that may signal future layoffs.

To anticipate potential layoffs within an organization, it is crucial to identify certain patterns or indicators that may serve as red flags. By recognizing these signals, both employees and employers can take proactive measures to mitigate the impact of layoffs. Some of the patterns that may suggest future layoffs include:

1. **Decreased sales or revenue:**

A significant decline in sales or revenue can be an indication that a company is facing financial challenges. When a company's financial performance is consistently poor, it may resort to layoffs as a cost-cutting measure.

2. **Increased competition:**

Intensified competition within an industry can put pressure on businesses to streamline operations and reduce expenses. To remain competitive, companies may resort to layoffs to optimize their workforce and cut costs.

3. **Changes in technology:**

Technological advancements can revolutionize industries and render certain job roles obsolete. When companies adopt new technologies or automate processes, it may result in a reduced need for human labor, leading to layoffs.

4. **Changes in consumer demand:**

Shifting consumer preferences and behaviors can have a direct impact on businesses. If a company's products or services are no longer in high demand, it may be forced to downsize its workforce to align with the reduced demand.

5. **Financial difficulties:**

Struggling with financial difficulties, such as mounting debts, declining profitability, or cash flow challenges, can create a precarious situation for companies. To address financial constraints, companies may implement layoffs as part of broader restructuring efforts to stabilize their operations.

Recognizing these patterns can provide individuals and organizations with valuable insights into the potential risks of layoffs. Employees can be better prepared to navigate uncertain times and explore opportunities in alternative sectors, while employers can proactively assess their strategies and explore alternatives to layoffs.

Step 3: Identify the reasons for layoffs based on past trends.

Layoffs can occur for various reasons, each specific to the circumstances faced by individual companies or industries. By analyzing past trends and observing common themes, it is possible to identify some of the most prevalent reasons behind layoffs. The following factors are frequently associated with layoffs:

1. **Economic downturn:**

Economic recessions or downturns often trigger layoffs across multiple industries. When the overall economy falters, businesses face reduced demand, declining sales, and revenue contraction. To adapt to adverse economic conditions and maintain financial stability, companies may resort to layoffs to reduce costs.

2. **Technological advancements:**

The rapid pace of technological innovation can lead to disruptive changes within industries. As businesses adopt new technologies to improve efficiency and productivity, certain job functions may become redundant or automated. This can result in layoffs as companies restructure their workforce to align with the evolving technological landscape.

3. **Changes in consumer demand:**

Consumer preferences and behaviors are constantly evolving, influenced by factors such as emerging trends, new products, or services, and shifting societal norms. When a company's offerings no longer align with consumer demand, sales may decline, prompting the organization to downsize its workforce to adjust to the reduced demand.

4. **Financial difficulties:**

Companies facing financial difficulties, such as mounting debts, reduced profitability, or liquidity challenges, often resort to cost-cutting measures, which can include layoffs. By reducing labor costs, businesses aim to improve their financial position and regain stability.

5. **Mergers and acquisitions:**

When two companies merge or one acquires another, redundancies in job roles and functions may arise. To streamline operations and eliminate

duplicated positions, layoffs may be implemented as part of the integration process.

While these reasons may serve as general indicators, it is important to note that each layoff situation is unique, and the specific factors contributing to layoffs can vary across industries, companies, and economic conditions. Understanding the historical trends and causes of layoffs provides valuable context and can assist both employees and employers in navigating uncertain circumstances.

Step 4: Forecast the likelihood of layoffs in various geographic locations.

The likelihood of layoffs occurring can vary depending on the geographic location. Different regions possess unique economic dynamics and industry concentrations, which can influence the prevalence of layoffs. Several factors contribute to the likelihood of layoffs in a particular area:

1. **The local economy:**

The overall health of the local economy plays a significant role in determining the likelihood of layoffs. Regions with robust and diverse economies tend to be more resilient and exhibit lower layoff rates. Conversely, areas with weaker economies or heavy reliance on a single industry may experience higher layoff rates during economic downturns.

2. **The industry mix:**

The composition of industries within a specific region can affect layoff rates. Areas with a diverse range of industries are generally more insulated from layoffs since they are not solely dependent on a single sector. Conversely, regions heavily concentrated in industries that are vulnerable to economic fluctuations or disruptive changes may experience higher layoff rates.

3. **The presence of major employers:**

The presence of large-scale employers within a region can have a significant impact on layoff rates. Major employers often have more resources to weather economic downturns, making them less likely to resort to layoffs. Additionally, these employers may actively engage in workforce retention strategies during challenging times.

4. **The cost of living:**

Areas with a higher cost of living may experience higher layoff rates due to the increased pressure on businesses to control costs. When operating expenses are elevated, companies may resort to layoffs to manage their financial obligations.

By considering these factors, it is possible to gain insights into the likelihood of layoffs occurring in various geographic locations. This knowledge can help

individuals make informed decisions regarding their careers and enable them to take proactive steps to safeguard their employment prospects.

In conclusion, understanding the industries and sectors most vulnerable to layoffs, identifying patterns that may signal future layoffs, recognizing the reasons behind past layoffs, and forecasting the likelihood of layoffs in different geographic locations can empower individuals and organizations to make informed decisions and take proactive measures. By staying vigilant and adaptable, individuals can navigate employment uncertainties more effectively, while businesses can strive to minimize the negative impact of layoffs and ensure the well-being of their workforce.

3. EXPLORATORY DATA ANALYSIS

To predict the top 5 states based on layoffs, we performed the following steps:

1. Data Preparation:

We began by cleaning and pre-processing the data to ensure its quality and consistency. This involved handling missing values, removing duplicates, and formatting the relevant columns, such as the WARN received date and the number of workers laid off.

2. **Filtering by Year (Optional):**

If the user provided a specific year, we filtered the data to include only layoffs that occurred in that year. This step helps in focusing the analysis on a particular period. If no year was provided, the analysis was conducted across all the available years in the dataset.

3. **Grouping by State:**

Next, we grouped the data by state to calculate the total number of workers laid off in each state. This aggregation provides a clear picture of the states with the highest layoff counts.

4. **Sorting and Selecting Top 5 States:**

We sorted the states in descending order based on the total number of workers laid off. Then, we selected the top 5 states with the highest layoff counts for the specified year or the entire dataset.

5. **Visualization:**

To visualize the top 5 states affected by layoffs, we used various chart types, such as bar charts one of which is shown below. These visualizations provide a clear comparison between the states and their layoff counts, enabling users to identify the most vulnerable regions.

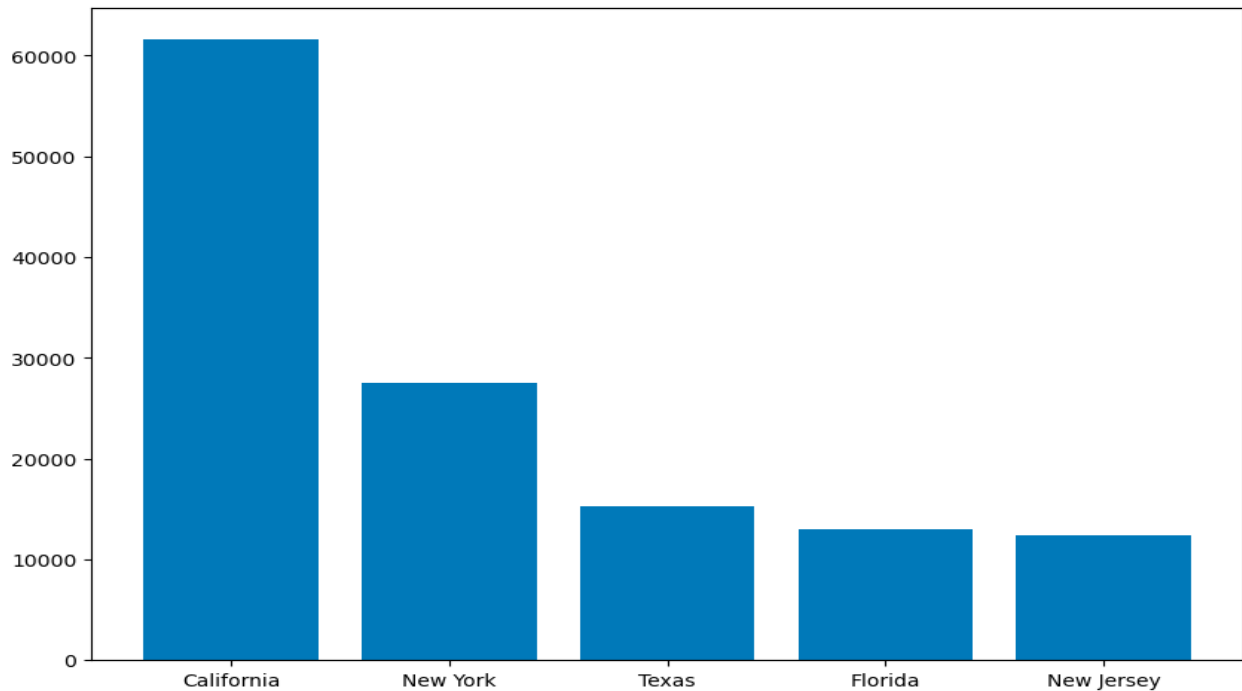


Figure 3.1 Top 5 states affected by lay-offs.

To predict the top 5 cities, we performed the following steps:

1. **Data Preparation:**

We performed data cleaning and pre-processing steps, including removing null values in the city column and filtering the data based on the provided state (mandatory) and year (optional).

2. **Filtering by State and Year:**

Using the provided state and year (if specified), we filtered the data to include layoffs from the desired state and year. If no year was provided, the analysis considered layoffs across all the available years in the dataset.

3. *Grouping by City:*

We grouped the filtered data by city to calculate the total number of workers laid off in each city. This is an important analysis because, sometimes the numbers might indicate that a state is highly prone to layoffs but some cities in that state might not be.

4. *Sorting and Selecting Top 5 Cities:*

The cities were sorted in descending order based on the total number of workers laid off. Then, we selected the top 5 cities with the highest layoff counts for the specified state and year (if provided).

5. *Visualization:*

To visualize the top 5 cities affected by layoffs, we used suitable charts such as bar charts one of which is shown below. These visualizations present a clear comparison of the cities, and their layoff counts, helping users to identify the cities most affected by layoffs within a specific state.

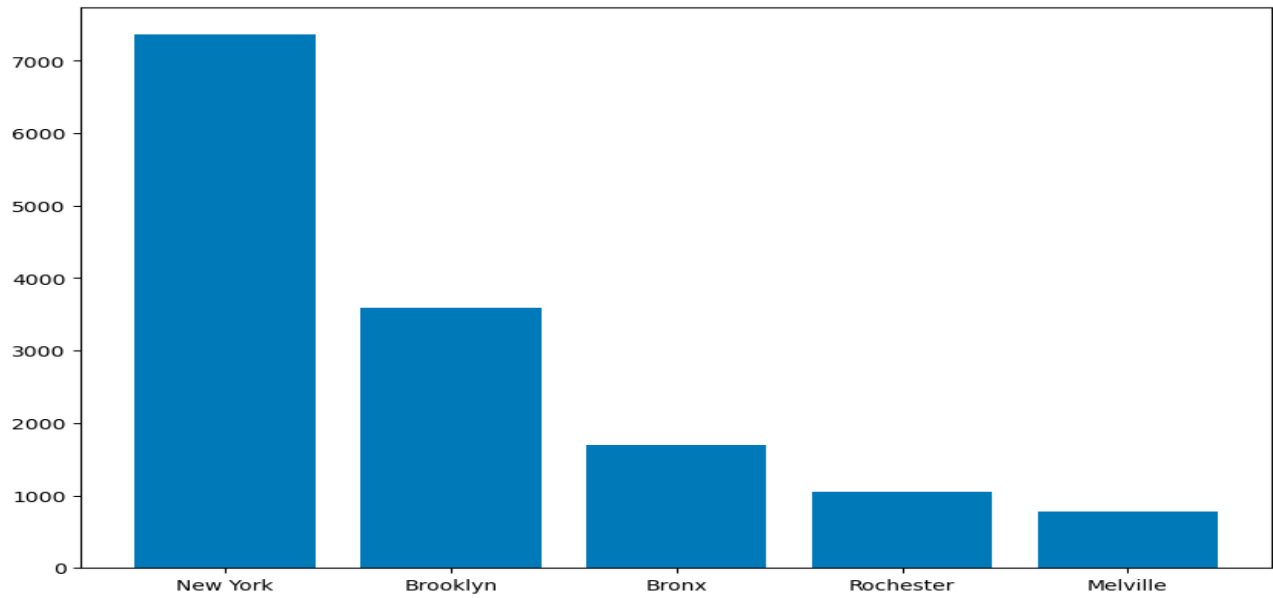


Figure 3.2 Top 5 cities affected by lay-offs.

Month-wise analysis:

The month-wise analysis of layoffs provides insights into the specific months or quarters of the year when employees are more likely to be laid off. This information can help individuals and organizations be cautious during those periods.

The steps involved in month-wise analysis are as follows:

1. Data Preparation:

We removed null values in the WARN received date column and performed data cleaning to ensure the data's integrity.

2. Splitting Date Values:

Using Python, we used the split function to separate the month, date, and year values from the WARN received date column. As a result, we were able to distinguish the monthly component for further analysis.

3. Grouping by month:

We grouped the data by month and calculated the total number of workers laid off in each month.

4. Filtering by Year (Optional):

If a specific year was provided, we filtered the data to include layoffs from that particular year. Otherwise, we included all the years available in the dataset for a cumulative analysis.

5. Visualization:

To visualize the month-wise layoffs, we used appropriate charts such as line charts or bar charts. These visualizations display the layoff trends across different months, providing valuable insights into the seasonal patterns of layoffs.

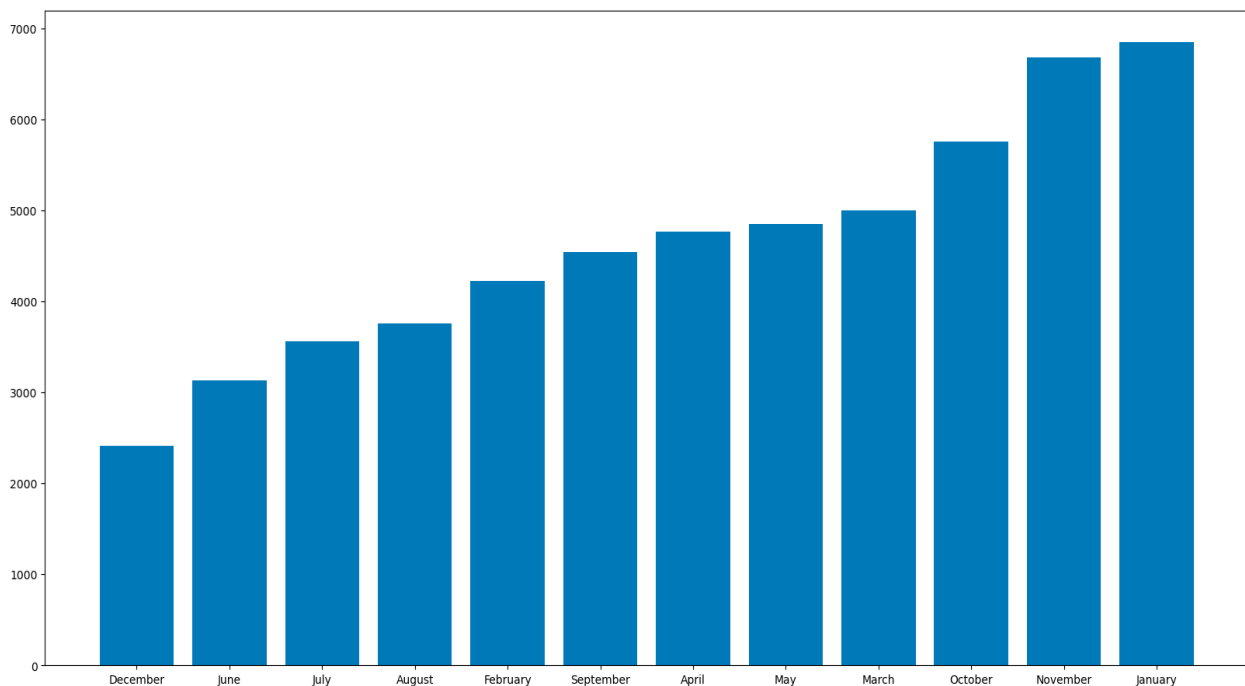


Figure 3.3 Month-wise analysis in the year 2017

Map:

The choropleth map of the United States visualizes the layoff counts in different states for a particular year. When users hover over a specific state on the map, the layoff count for that state is displayed. The map provides a geographical representation of layoffs, enabling users to identify regions with high layoff activity and understand the spatial distribution of workforce reductions. Some examples are shown below.

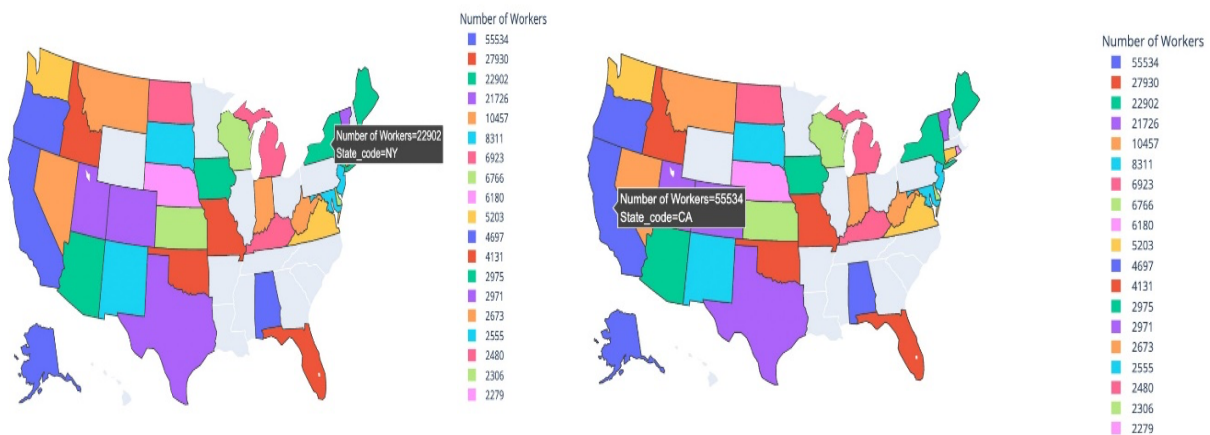


Figure 3.4 Choropleth map of the United States

Pie chart:

The pie chart represents the common reasons for layoffs in the past. It presents the distribution of layoffs based on different reasons, such as temporary layoffs, permanent layoffs, layoffs due to company closure, and other reasons. The pie chart helps stakeholders grasp the proportion of layoffs attributed to each reason and gain insights into the underlying causes behind workforce reductions.

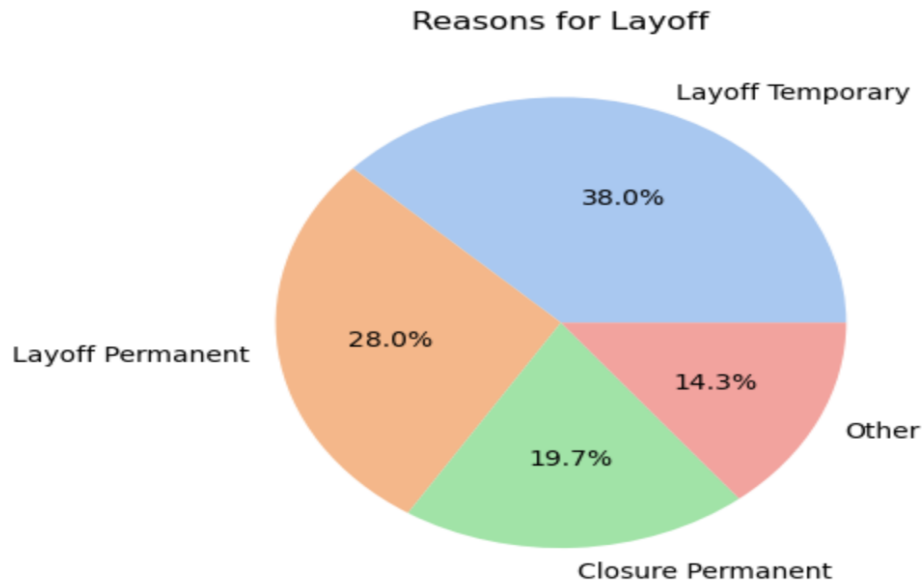


Figure 3.5 Pie chart

Features:

In the layoff prediction process, the top features selected were the WARN received date and the number of workers laid off. The WARN received date was chosen because time series models require date and time fields for accurate predictions. The number of workers laid off was included as it is a key indicator of the layoff severity and can help identify the region's most prone to layoffs.

By following these steps, the layoff prediction analysis provides valuable insights into the top states, top cities, month-wise patterns, and reasons behind layoffs. These insights enable users to make informed decisions, develop proactive strategies, and implement measures to mitigate the impact of layoffs on affected individuals.

4. DATA MODELLING

From the previously unseen dataset, all the machine learning models finds certain pattern or make decisions or predicts the output from the dataset. It performs those tasks by having it trained with large dataset. ML algorithms mostly finds patterns in the set of data that is been feed. Initially, for this dataset we started with Regression models. The following algorithms are built out for this dataset to predict the layoff.

1. Linear Regression

This is used to identify the relationship between the inputs which has been considered and predict the output based on the values of input variables.

[All these are for the state Texas]

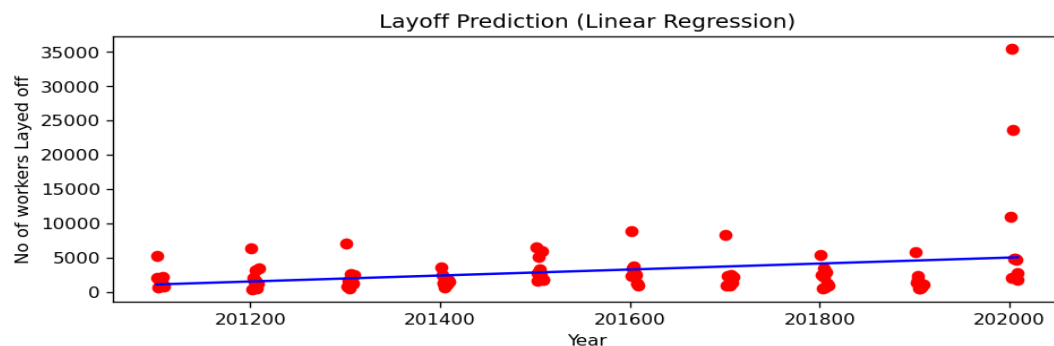


Figure 4.1 Plotting the data after building the Linear Regression model

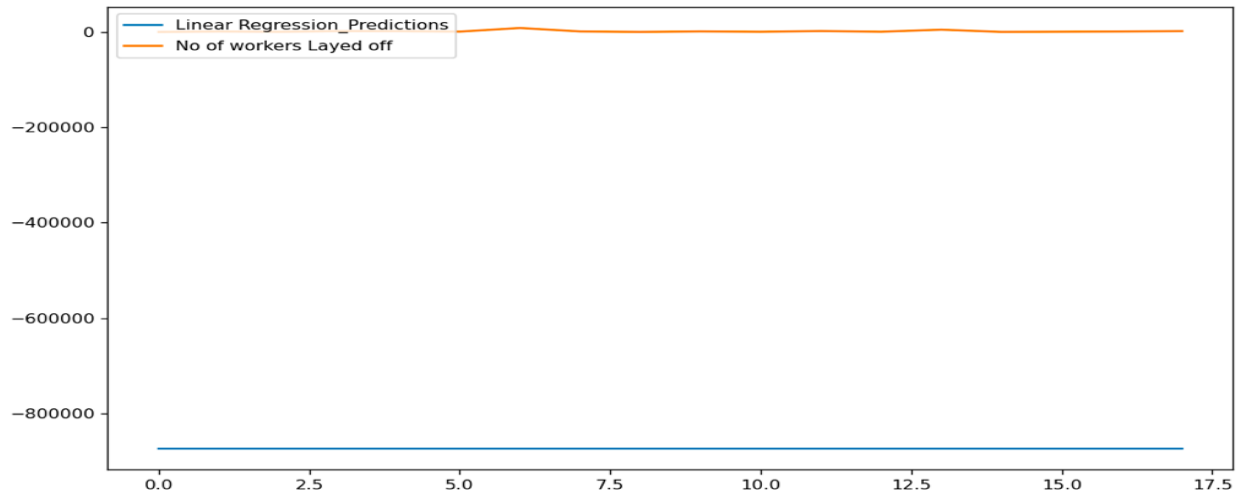


Figure 4.2 Actual vs Predicted values using Linear Regression

TABLE 4.1

Errors	Values Obtained
Mean Squared Error	4101415.72
Root Mean Squared Error	2025.19
Absolute Error	1425.05

2. Logistic Regression

It is used to determine if the given input belongs to a certain group or not.

[All these are for the state Texas]

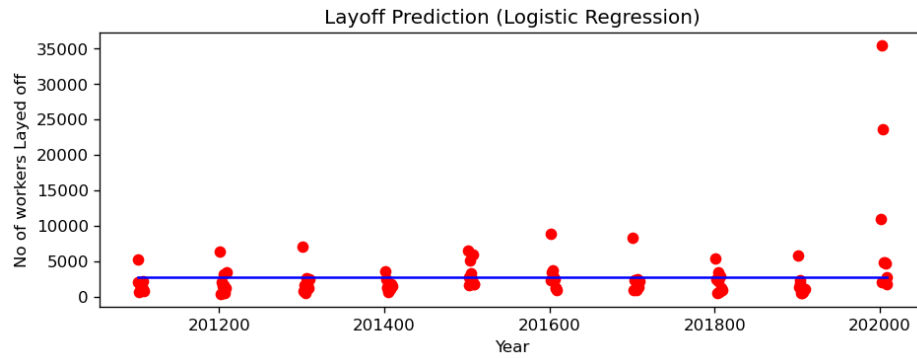


Figure 4.3 Plotting the data after building the Logistic Regression model.

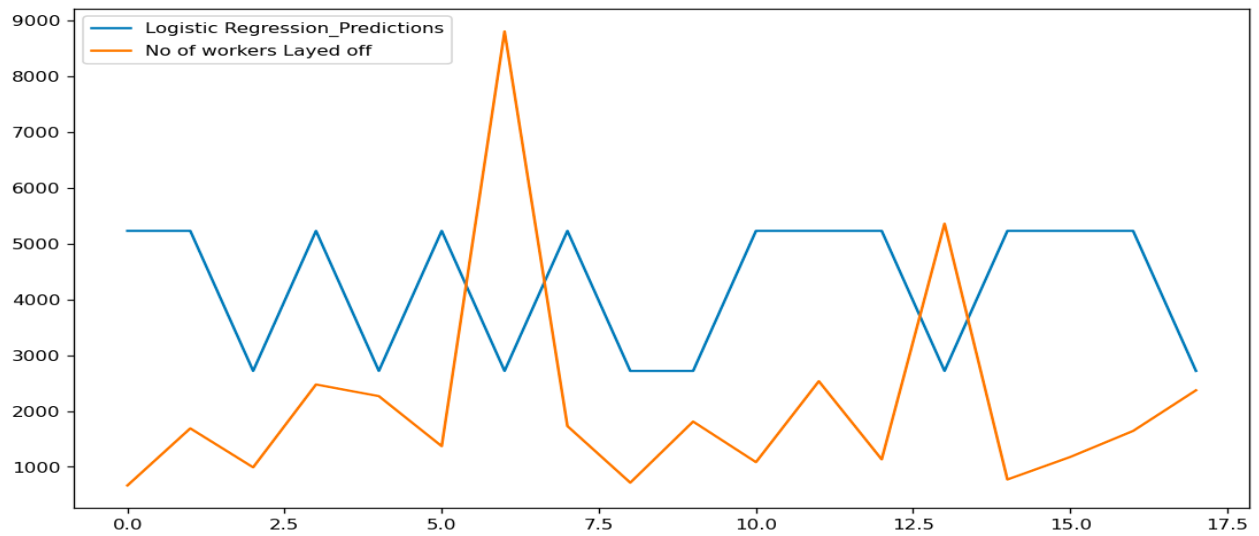


Figure 4.4 Actual vs Predicted values using Logistic Regression.

TABLE 4.2

Errors	Values Obtained
Mean Squared Error	4049505.55
Root Mean Squared Error	2012.33
Absolute Error	1544.88

3. Polynomial Regression

This is used to model the relationship between a dependent variable and one or more independent variable and is an extension of simple linear regression where polynomial terms come into picture.

[All these are for the state Texas]

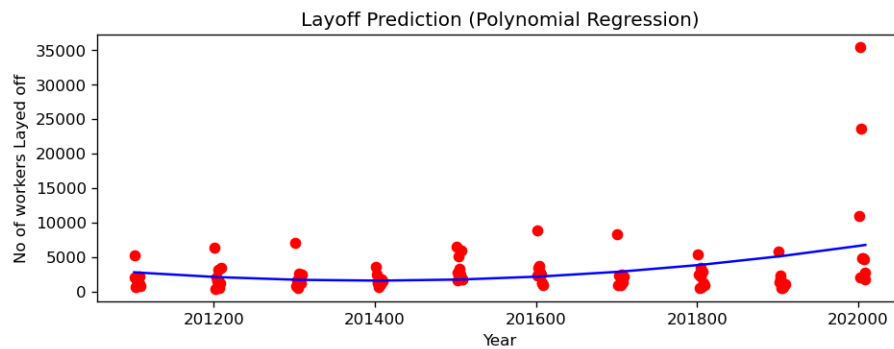


Figure 4.5 Plotting the data after building the Polynomial Regression model

TABLE 4.3

Errors	Values Obtained
Mean Squared Error	6053139.5
Root Mean Squared Error	2460.31
Absolute Error	1689.16

4. Decision Tree Regression

It is based on the decision tree model, where the data is recursively split into several regions where each node is a decision based on specific feature and each leaf node is the predicted value.

[All these are for the state Texas]

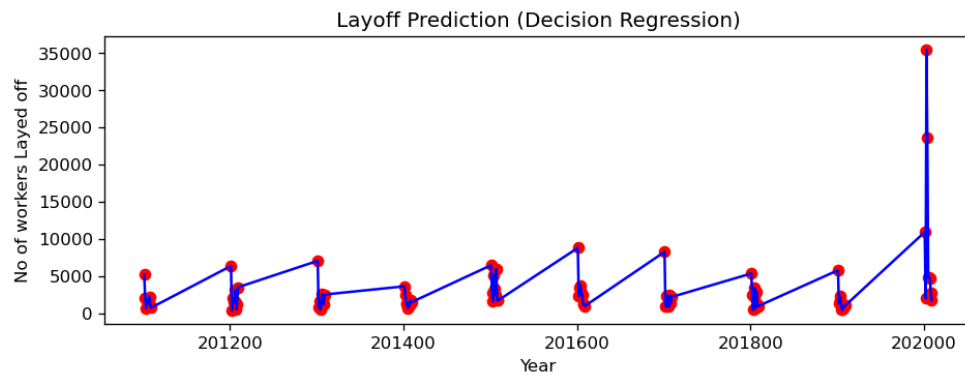


Figure 4.6 Plotting the data after building the Decision Regression model

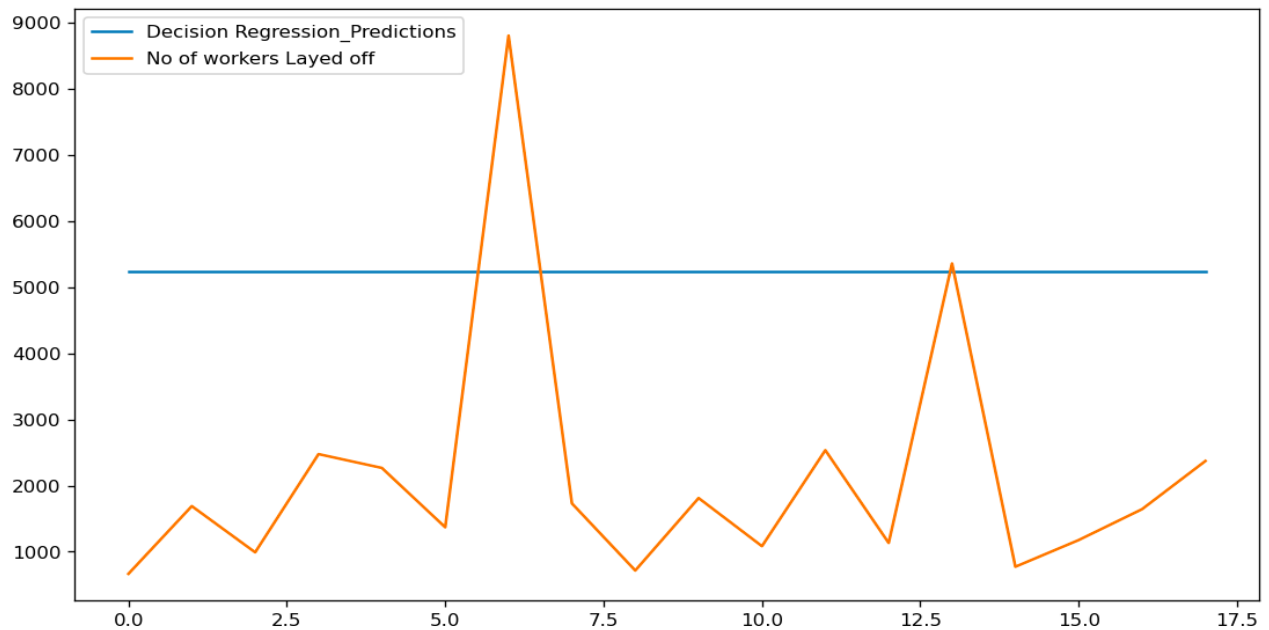


Figure 4.7 Actual vs Predicted values using Decision Regression

TABLE 4.4

Errors	Values Obtained
Mean Squared Error	0.0
Root Mean Squared Error	0.0
Absolute Error	0.0

5. Lasso Regression

Lasso stands for **Least Absolute Shrinkage and Selection Operator**. It is an L1 regularization or L1 penalization that implements regularization to improve the model performance.

[All these are for the state Texas]

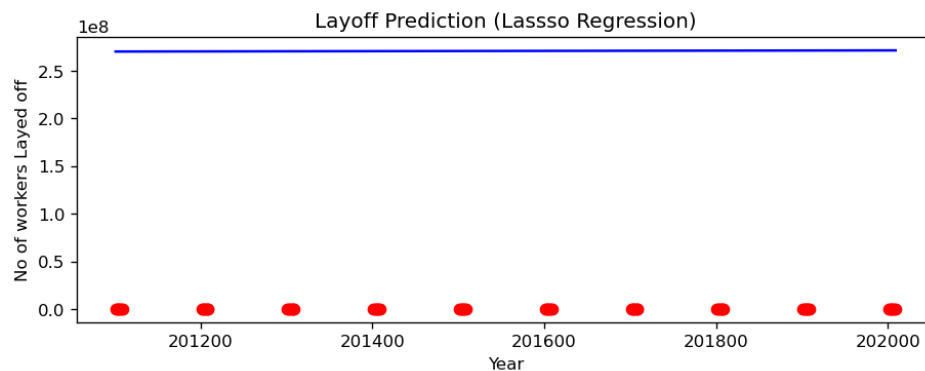


Figure 4.8 Plotting the data after building the Lasso Regression model

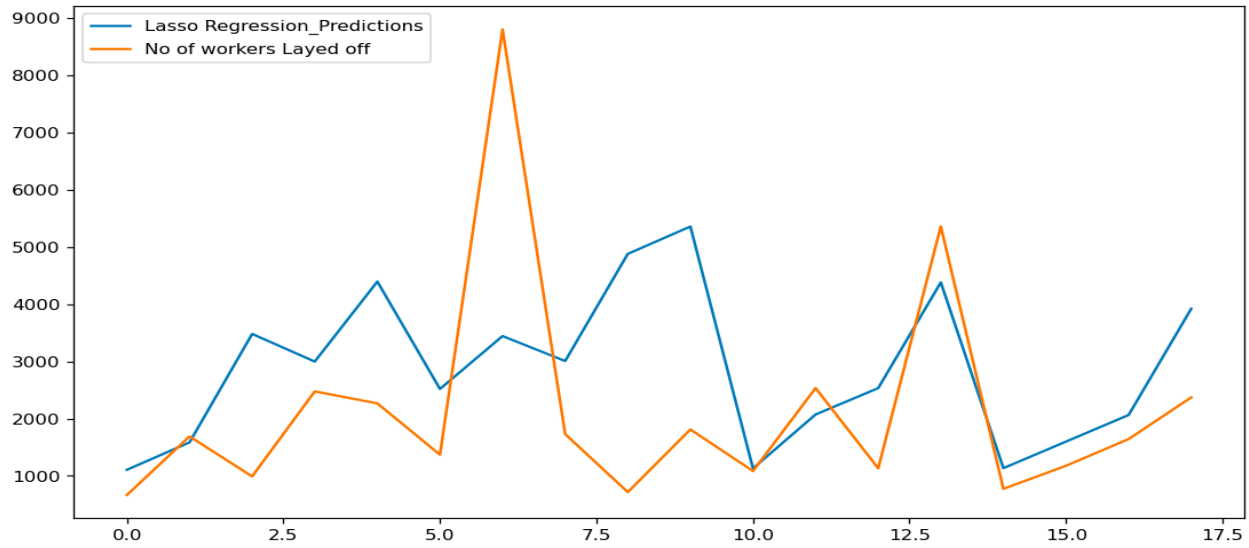


Figure 4.9 Actual vs Predicted values using Lasso Regression

TABLE 4.5

Errors	Values Obtained
Mean Squared Error	4383064.05
Root Mean Squared Error	2093.57
Absolute Error	1490.72

6. Ridge Regression

Ridge is also called L2 regularization or Tikhonov regularization that implements regularization to improve model performance and handles multicollinearity issues.

[All these are for the state Texas]

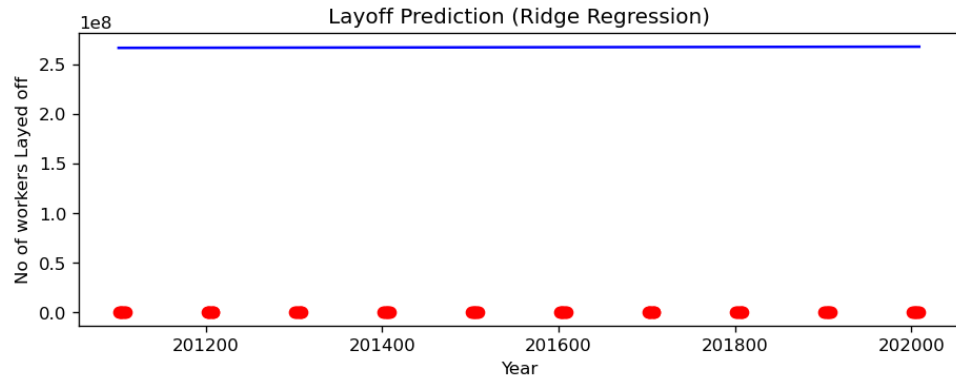


Figure 4.10 Plotting the data after building the Ridge Regression model

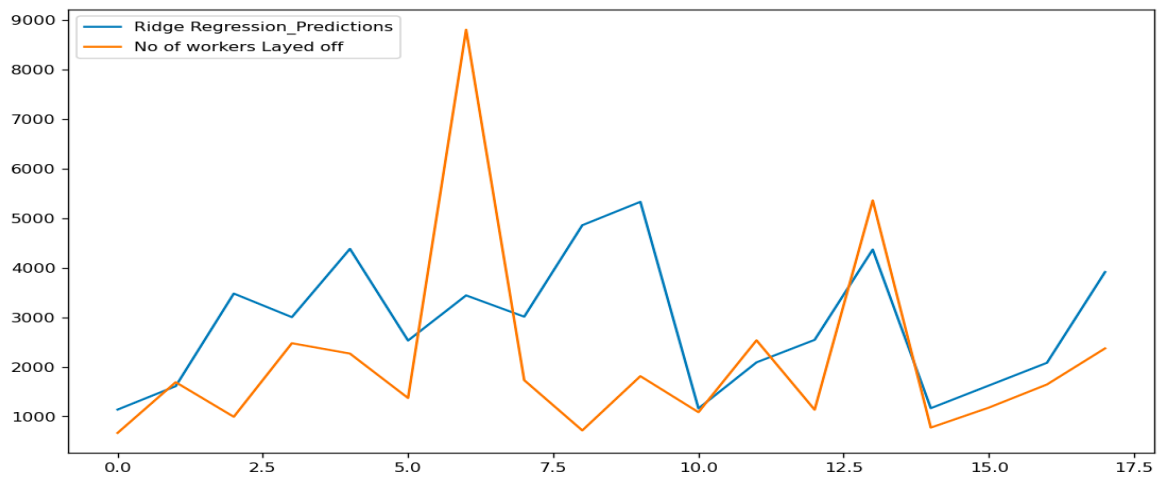


Figure 4.11 Actual vs Predicted values using Ridge Regression

TABLE 4.6

Errors	Values Obtained
Mean Squared Error	4383064.05
Root Mean Squared Error	2093.57
Absolute Error	1490.72

7. Support Vector Regression

It is an extension of Support Vector Machines for classification. It maximizes the margin between the specified threshold value and the predicted value. With the help of the kernel, it maps the input into a higher dimension and finds a hyperplane that fits the training data minimizing major deviations from the threshold.

[All these are for the state Texas]

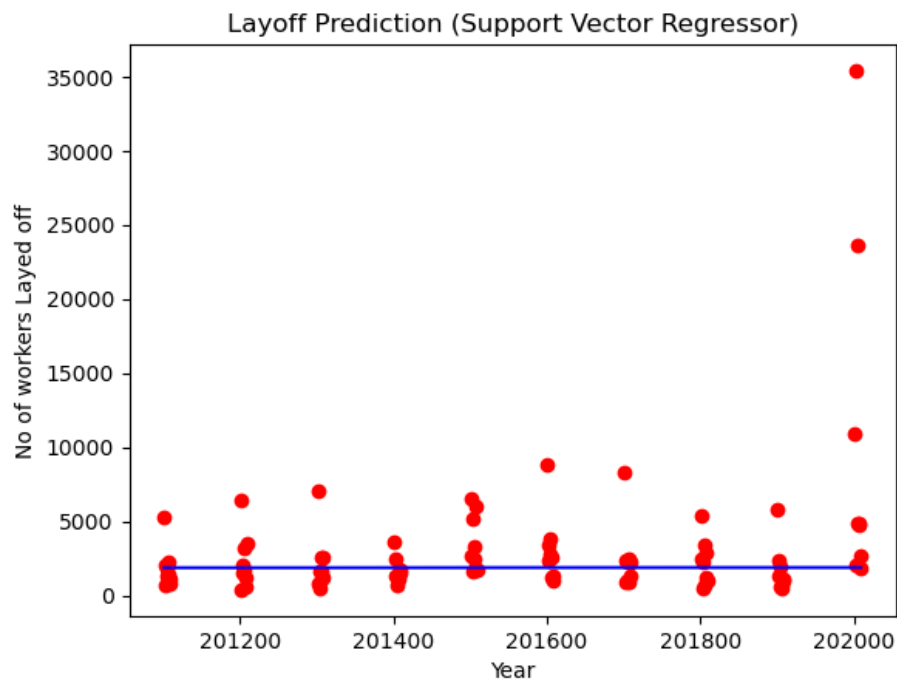


Figure 4.12 Plotting the data after building the SVR model.

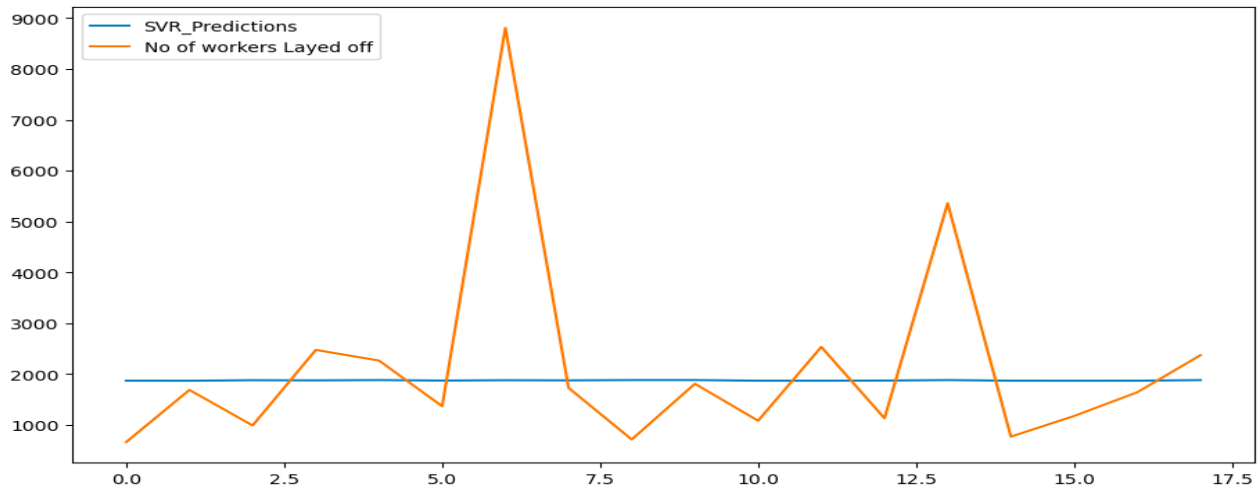


Figure 4.13 Actual vs Predicted values using Support Vector Regression

TABLE 4.7

Errors	Values Obtained
Mean Squared Error	3782606.0
Root Mean Squared Error	1944.89
Absolute Error	1125.66

Time Series Machine Learning

These are Machine learning models used to predict time bound events where one of the independent variables will be a continuous length of time (seconds, minutes, days, weeks, months, years etc.). One such time series machine learning model is *ARIMA*.

ARIMA

Auto Regressive Integrated Moving Average model is a model that uses time series data to either better understand the data set or to predict future trends. It gives the relation between one of the dependent variables relative to that of the changing variable.

Steps to build out ARIMA model:

1. Check if data is stationary or not.

In this dataset, the data was not stationary as the warn received date column was not continuous for some of the states, it was made stationary by differencing.

2. Determine order of differencing (denoted by d).

The number of times the differencing is performed is the order of differencing.

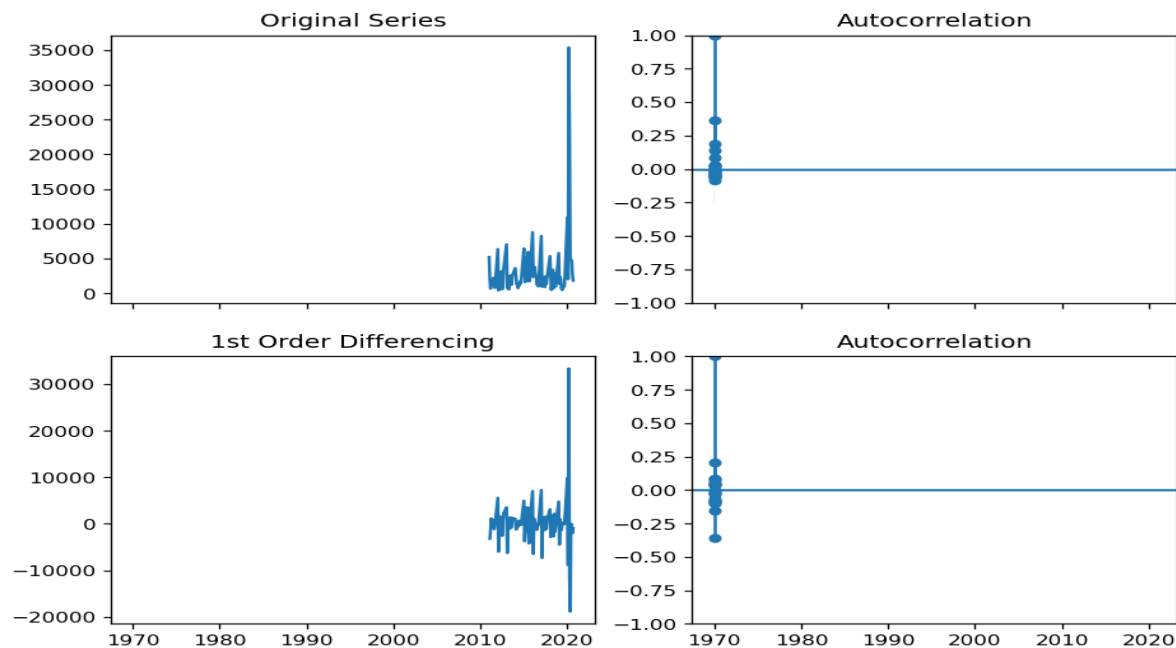


Figure 4.14 Differencing

3. Determine order of partial auto correlation (denoted by p)

Partial autocorrelation is the correlation between the series and its lag after excluding the contributions from the intermediate lags.

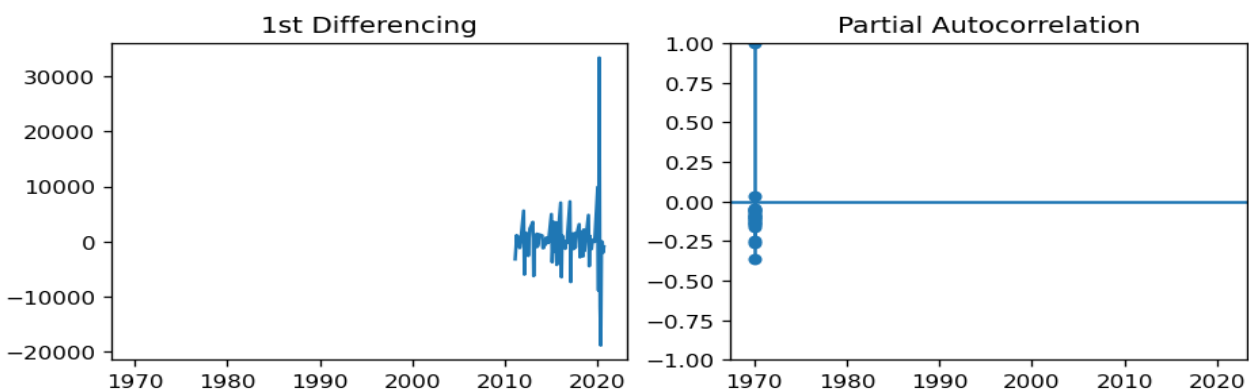


Figure 4.15 Partial Autocorrelation

4. Determine the order of auto correlation (order of moving average) (denoted by q).

Correlation between the observations at the current time spot and those at previous time spots.

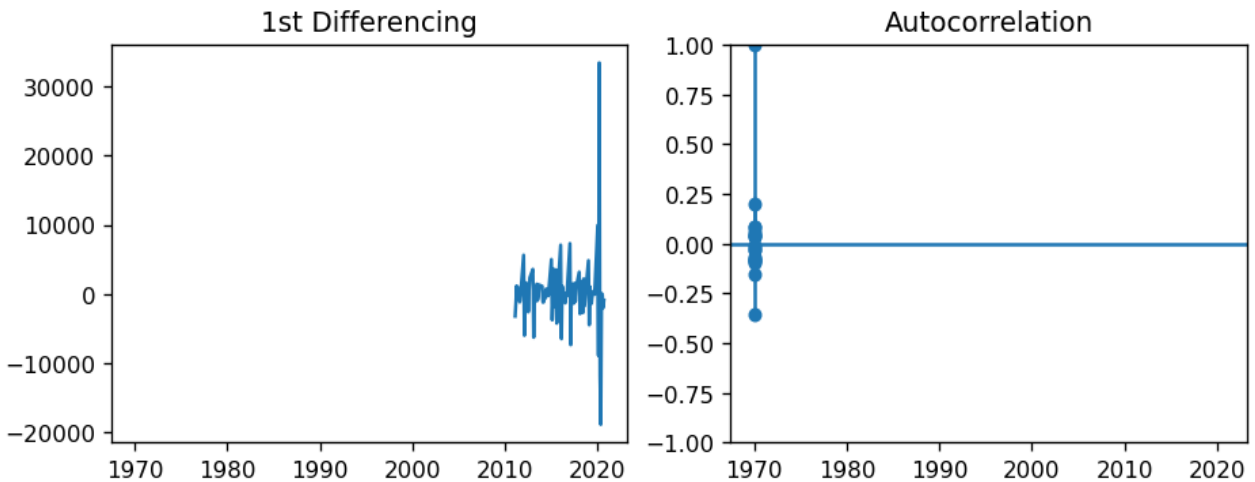


Figure 4.16 Autocorrelation

With the help of p , d , q values, the Arima model is build and the following one is the actual and the predicted value of the model.

Also, with the help of Auto-Arima which automatically provides the p , d , q values the model is been built out compared with the normal arima model, more than the normal model auto arima predicted the best fit p , d , q values so for almost all the states those values are taken from auto-arima model.

TABLE 4.8

States	P	D	Q		States	P	D	Q
Alabama	2	1	3		Minnesota	1	0	0
Alaska	5	1	0		Missouri	3	0	0
Arizona	1	0	4		Montana	1	0	0
California	2	0	1		Nebraska	2	0	0
Colorado	1	0	0		Nevada	0	0	3
Connecticut	1	0	0		New Jersey	1	0	1
Delaware	2	0	0		New Mexico	1	0	1
Florida	2	0	0		New York	5	0	0
Georgia	0	0	0		North Carolina	5	0	0
Illinois	1	0	0		North Dakota	2	0	0
Indiana	5	1	0		Ohio	1	0	0
Iowa	4	0	0		Oklahoma	1	0	2
Kansas	2	0	1		Oregon	1	0	1
Kentucky	5	1	0		Rhode Island	1	0	1
Louisiana	1	0	0		South Carolina	1	0	0
Maine	1	0	1		South Dakota	1	0	0
Maryland	1	0	1		Texas	1	0	4
Massachusetts	1	0	0		Utah	3	0	0
Michigan	3	0	0		Vermont	1	0	1
Louisiana	1	0	0		Virginia	1	0	1
Washington D. C	2	1	3		Washington	4	0	0
West Virginia	1	0	0		Wisconsin	1	0	3

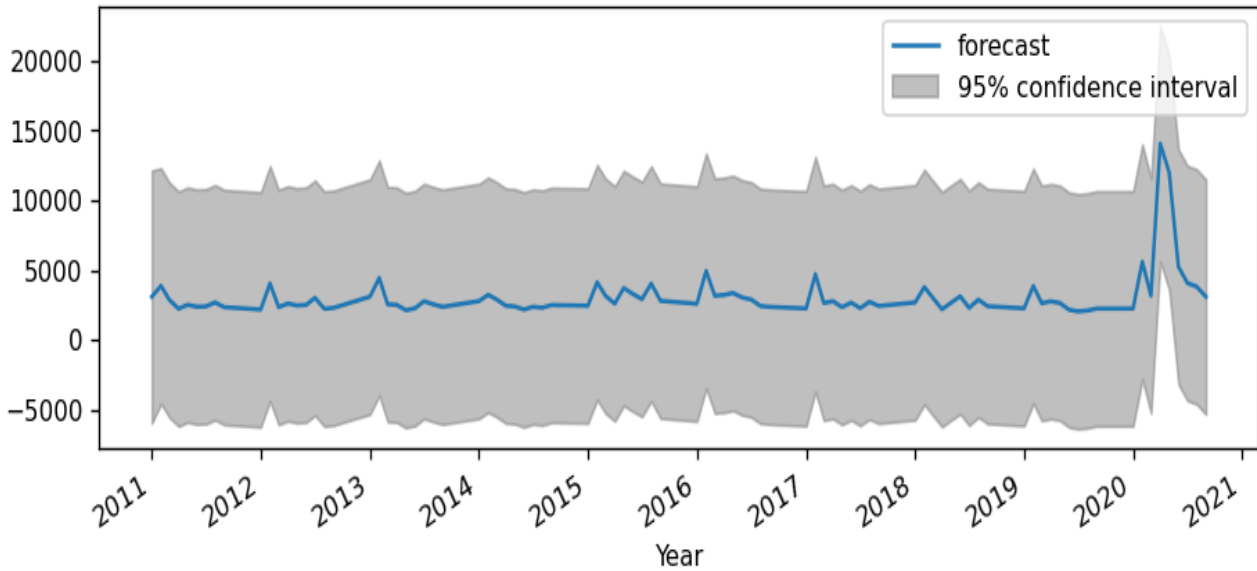


Figure 4.17 Forecasted graph.

The below is the forecasted manual once after the model has been trained.

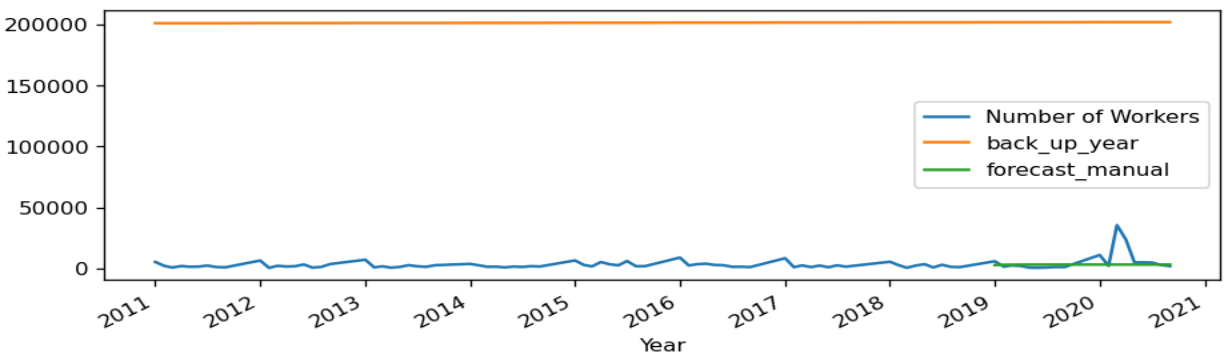


Figure 4.18 Forecasted graph after training the model.

The below table is the Forecasted data for next 3 years in all the states in the United States.

TABLE 4.9

<i>States</i>	<i>2023</i>	<i>2024</i>	<i>2025</i>		<i>States</i>	<i>2023</i>	<i>2024</i>	<i>2025</i>
Alabama	476.70	464.78	438.14		Missouri	3857.90	3741.03	2870.06
Alaska	301.96	374.32	783.73		Montana	103.38	105.28	105.43
Arizona	482.37	523.85	611.28		Nebraska	499.58	246.71	365.42
California	482626.18	675564.53	815679.16		New Mexico	302.42	293.37	299.76
Colorado	1946.44	1440.78	1159.34		New York	2315.83	2246.47	2739.28
Connecticut	831.49	612.45	499.43		North Carolina	5275.24	4379.64	1843.06
Delaware	378.37	398.35	397.87		North Dakota	407.0189	239.07	273.45
Florida	23440.70	22675.29	20662.77		Ohio	3118.17	4128.01	4592.57
Idaho	281.55	279.91	278.35		Oklahoma	371.68	386.95	340.86
Illinois	5373.95	6501.19	6816.81		Oregon	381.79	348.97	327.13
Indiana	623.41	345.01	845.89		Rhode Island	222.48	216.43	210.95

Iowa	310.16	416.20	451.73		South Carolina	1551.52	1831.01	1908.62
Kansas	442.15	454.87	463.41		South Dakota	136.49	137.27055 7	137.32
Kentucky	11196.67	1812.00	384.35		Texas	1717.24	1251.15	1409.32
Louisiana	1551.88	1841.39	1916.17		Utah	202.56	222.12	232.73
Maine	-0.83	165.79	212.05		Vermont	122.06	123.41	124.18
Maryland	504.86	410.41	437.21		Virginia	580.46	632.28	644.19
Massachusetts	1509.98	1757.01	1895.72		Washington	1260.25	646.78	432.23
Michigan	8294.03	7364.07	4010.16		Washington, D.C.	566.30	1216.45	5800.86
Minnesota	1280.80	1373.16	1400.97		West Virginia	2003.76	1180.19	810.21
New Jersey	1124.57	1140.56	1153.97		Wisconsin	7464.62	1756.92	2445.52
Nevada	-712.40	-1401.05	1966.74					

The actual vs predicted graphs for all the states in the United States is plotted and the model prediction is visually represented.



Figure 4.19 Below is the Actual vs Predicted graphs for all the states.

5. RESULTS AND FUTURE ENHANCEMENTS

The prediction of layoffs is done using different models like linear regression, logistic regression, polynomial regression, decision tree regression, lasso regression, ridge regression and support vector regression among them ARIMA model had better accuracy in mean square value. The ARIMA model was applied to the dataset and for generating p, d, and q values for each state in the United States. These values represent the performance and accuracy measures of the ARIMA models applied to the respective states. The MSE (Mean Squared Error) indicates the average difference between the predicted and actual values, the MAPE (Mean Absolute Percentage Error) represents the percentage difference, and the RMSE (Root Mean Squared Error) measures the square root of the average squared differences.

TABLE 5.1

State	p	d	q	MSE	MAPE	RMSE
Alabama	4	1	0	206.85	1.08E+00	305.86
Alaska	0	1	2	409.15	8.72E-01	494.50
Arizona	4	0	1	1427.11	6.62E-01	2839.16
California	3	0	0	38437.03	7.16E-01	71268.13
Colorado	1	0	1	1834.59	9.86E-01	2658.08
Connecticut	1	0	1	718.80	6.56E+16	1093.97
Delaware	1	0	1	373.72	7.90E-01	716.64
Florida	1	0	1	14092.26	7.73E-01	18076.27
Georgia	0	0	0	0	0.00E+00	0
Idaho	3	0	0	156.65	1.32E+00	363.92
Illinois	1	0	0	760.16	6.25E-01	788.43
Indiana	5	1	0	944.10	8.34E-01	2007.49
Iowa	4	0	0	267.39	6.43E-01	369.35
Kansas	2	0	1	480.69	2.60E+00	833.57
Kentucky	0	1	4	1522.74	9.55E+00	2448.53
Louisiana	1	0	0	872.61	7.88E-01	1055.02
Maine	3	0	0	281.89	4.33E+00	311.56

Maryland	1	0	1	1073.78	1.12E+00	1905.59
Massachusetts	1	0	0	877.41	9.82E-01	1055.96
Michigan	1	0	2	3700.03	1.02E+00	5720.24
Minnesota	1	0	0	357.68	3.63E-01	460.41
Missouri	1	0	1	1999.14	7.01E-01	3364.67
Montana	1	0	0	90.14	5.72E-01	101.11
Nebraska	1	0	1	285.64	2.61E+00	395.59
New Mexico	2	0	0	301.39	5.12E-01	480.52
New York	5	0	0	6733.90	4.98E-01	16781.14
North Carolina	0	0	4	1123.73	8.51E-01	1554.98
North Dakota	2	0	0	251.08	7.15E-01	328.74
Ohio	1	0	0	248.98	3.18E-01	305.02
Oklahoma	1	0	2	338.26	1.42E+00	601.23
Oregon	1	0	1	921.45	9.00E-01	1708.01
Rhode Island	1	0	1	266.15	1.92E+01	459.83
South Carolina	1	0	0	669.38	9.42E-01	691.44
South Dakota	1	0	1	85.48	3.56E+00	130.01
Texas	1	0	3	3320.72	8.06E-01	8350.94
Utah	2	0	0	332.24	7.40E-01	629.2736
Vermont	1	0	1	104.97	2.69E+00	164.13
Virginia	1	0	2	1112.58	9.95E-01	1885.08
Washington	4	0	0	1119.53	1.04E+00	2067.26
Washington, D.C.	1	0	2	1395.37	6.87E-01	2079.49
West Virginia	2	0	2	1439.86	3.05E+00	2019.84
Wisconsin	1	0	0	3184.17	9.58E-01	5372.39
New Jersey	4	0	0	2312.14	7.61E-01	5378.46
Nevada	1	0	2	9343.27	1.09E+01	9672.69

The essential parameters for the ARIMA model, representing the autoregressive, differencing, and moving average components, respectively. Once the ARIMA model is fitted with the appropriate p, d, and q values for each state, it can be used to predict layoffs for the next three years. The predicted layoffs can be interpreted at both the state level and aggregated levels. It provides insights into which states are likely to experience higher or lower layoff rates over the next three

years. Regular monitoring and refinement of the model are necessary to ensure its accuracy and to capture any shifts or changes in labor market dynamics that may affect the layoff predictions.

Future Enhancements and Conclusion:

- **Accurate and Timely Results:** By automating the process of data collection and manipulation, we can ensure more accurate results at any given instance of time. This eliminates the potential for human error and enables us to have up-to-date information on layoffs.
- **Coordination among Industries:** Automation requires the coordination of all industries to provide the most recent layoff data on a timely basis. This encourages collaboration and information sharing, leading to a comprehensive and reliable dataset for analysis.
- **Global-Scale Data Manipulation:** Moving to a global-scale cloud server allows us to manipulate data not only within the US but also on a global scale. This expansion enables us to gather data from various countries and regions, providing a more holistic view of layoffs worldwide.
- **Comparative Analysis of MNC Operations:** The global-scale data manipulation capability allows us to compare how multinational corporations (MNCs) operate globally. We can analyze layoff trends across different countries and assess whether layoffs are justified at an industry level rather than being influenced by demographic factors.
- **Identifying Sectors with High Layoff Rates:** By predicting industry-wise layoffs, we gain valuable insights into sectors experiencing the highest number of job losses. This information helps in understanding the dynamics

of the job market, identifying vulnerable sectors, and potentially taking proactive measures to mitigate layoffs or support affected workers.

- **Strategic Workforce Planning**: Accurate industry-wise layoff predictions enable organizations and policymakers to engage in strategic workforce planning. This includes anticipating labor market shifts, identifying skill gaps, and implementing measures such as reskilling or job placement programs to support workers in affected industries.
- **Data-Driven Decision Making**: Automating data collection and manipulation ensures a solid foundation for data-driven decision making. Organizations, government agencies, and policymakers can rely on accurate and timely layoff data to make informed choices regarding labor market interventions, economic policies, and resource allocation.
- **Continuous Monitoring and Early Warning Systems**: Automated data processes can be set up for continuous monitoring of layoff trends, allowing for the establishment of early warning systems. This proactive approach helps detect emerging layoff patterns or potential economic downturns, enabling timely interventions and mitigating the negative impact on employment.

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