# The Relationship Between Unemployment and Automation

**New Mexico Supercomputing Challenge Final Report**

**Team: 4**
**Cottonwood Classical and Del Norte High School**

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# Executive Summary:

New advances in technology, such as robots and computers, have been created to expand the workforce and make the hard labor in jobs easier. However, does this hurt the employment of people? We decided to analyze this relationship because we are interested in knowing whether or not automation has the potential to take away jobs, or create new ones. Economic crises, such as the Great Depression and the Recession, made us interested in this project because we wanted to see if the influx in technology can impact unemployment and if it can be prevented. We know that automation is not a prime factor in unemployment and that there are multiple factors and events that also increase and decrease unemployment. We wanted to discover if there could be a relationship between unemployment and automation, and what variables impact this. Examples of these variables are unemployment, industrial robot orders, productivity rate, hours worked, and sales. This year we decided to primarily focus on the manufacturing industry. This is because we found out that this industry is one of the industries that has negatively impacted employment compared to other industries. We have been in contact with librarians and mentors in order to guide us to where we research and find the most accurate data. We are using python to visualize how different data affects unemployment and automation. We have created multiple graphs to see if there is some sort of trend between unemployment and automation or its other variables. We were able to create a line of best fit that allowed us to predict and visualize the relationship between unemployment in the manufacturing industry and industrial robot orders. This scatter graph has helped us figure out if there is a relationship between automation and unemployment.

# Problem:

New technological innovations have the potential to create an increase in unemployment rates. With the rapidly growing technological advancements in the workplace, the use of humans for jobs like architecture, health, composition, and more, are becoming less necessary. Technology has changed the usual skill set of humans needed for certain jobs. Automation makes it more difficult for workers who didn't go to college or finish high school that may not have the skills necessary to operate a computer. These technological advances are also more likely to be used because they are able to create goods for a lesser amount of money compared to jobs taken by humans. For example, ATM machines came out in 1980 and shifted the jobs available to bank tellers(12). This is a good thing for big corporations who would rather incorporate more automation and less human labor costs, but on the other hand, can hurt the employment of people. We want to see which one is more beneficial to the world as a whole. These huge corporations and business managers believe these innovations will actually increase the diversity of jobs, while people who are looking for jobs may think it is limiting the number of jobs left for humans. In manufacturing companies, jobs are easily given to robots and 82% of people in the United States said that within the next 30 years much of the work done by humans will probably be done by computers(13). Jobs are changing rapidly and this can affect workers' lifestyles and possibly the economy, whether negative or positive. The advancements in technology in the workplace could affect unemployment rates in the future and this is important for employees to know so that they can get more experience in operating technology and stay ahead of the job market.

# Objectives:

The focus of our project this year was to compare and understand the relationship between automation and unemployment. The original questions that we wondered about were whether or not automation has a direct effect on unemployment rates rising, how to understand the relationship they have, and whether automation has a positive or negative effect on the economy and quality of life. Because these questions were focused on broad employment information and therefore difficult to answer, we narrowed our project down to the specific industry of manufacturing. We chose manufacturing because automation has a big impact on the necessity for hard labor that workers may have in that industry. Once we decided to narrow our project down we collected data on robot orders, employment rates, and productivity rates in manufacturing. Productivity rates are relevant to our project because it is important to grasp whether or not robots have a beneficial effect by making industry more productive. Next, we used that data to create a graph in python to help others understand the relationship that automation and unemployment have. By comparing robot orders, productivity, and employment people are able to comprehend the effects one may have on the other. Then we wanted to model our findings into a graph using python. This helped us get an idea of how these different variables can correlate with another. Lastly, we wanted to research about the different types of predictions that could be used in order to see the impact of automation on unemployment.

# Research:

Unemployment in the United States can be affected by a lot of factors; automation being one of those. To begin our research we looked into unemployment rates from 1950-2020 in the United States and we saw that they fluctuated greatly over the years. For example, only 4% of the population was unemployed in 2000 but by 2010, 9.6% of the population was; most likely due to the recession in 2008(6). Because this data varied so much, we had to figure out which variables may affect unemployment rates. Some of those were automation, global competition, lack of education opportunities, and demographics. We chose to focus on the effects of automation alone in order to see if there is a relationship between automation and unemployment rates. We discovered that things like productivity rates, quality of life, and jobs affected by automation would be important to our project. We found that automation makes it harder for people to find and keep jobs, especially as “About two-thirds of workers in the U.S. don't have a college degree” (8). This could mean that people need more access to education in order to sustain a society where so much of the job market calls for experience with technology. We found that the effect of automation varies as jobs in healthcare and financial services benefit while people working in manufacturing and agriculture may suffer. Then we chose to narrow down our project specifically to manufacturing so that there would not be a surplus of data. Lastly, we wanted to see if there was a way to predict what variables can help predict the future of unemployment rates in manufacturing. We ultimately decided to incorporate the line of best fit in order to do this.

Figure 1:

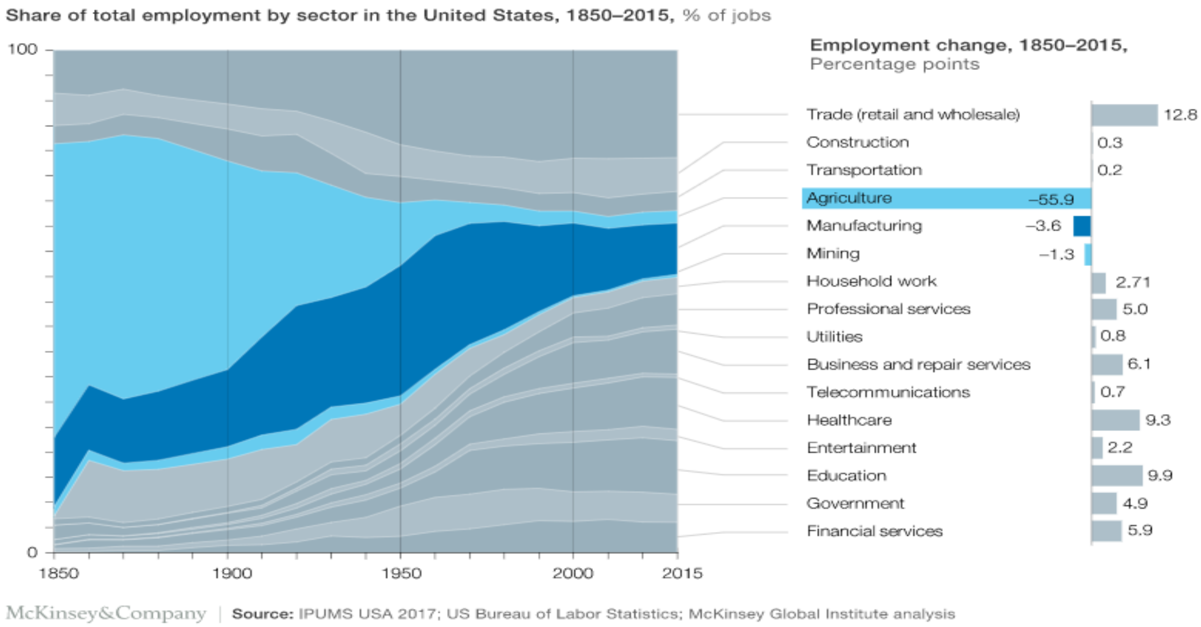



Figure 1 shows the percent change in employment specific to certain industries. Manufacturing and mining see negative effects while education and healthcare see positive ones. This graphic helped us narrow down our project because we wanted to focus on an industry that had a lot of automation used and potential negative effects. (*9*)

It was difficult for us to find a way to represent automation because there was not a lot of direct numerical data as there was for unemployment. We had to research types of robots and technological inventions that contribute to automation rates over the years. We decided to use industrial robot orders to represent automation in the workplace. We also wanted to know the impact of automation in manufacturing companies. According to Reuters.com, (5), North American companies have increased spending on industrial robots. In 2019, there was a 7 percent increase in industrial robot orders in the first two quarters, compared to 2018. However, as more businesses are shifting to industrial robots for labor tasks, the average price of these robots is going down. This causes the market of robots to be more accessible for companies.

Figure 2:

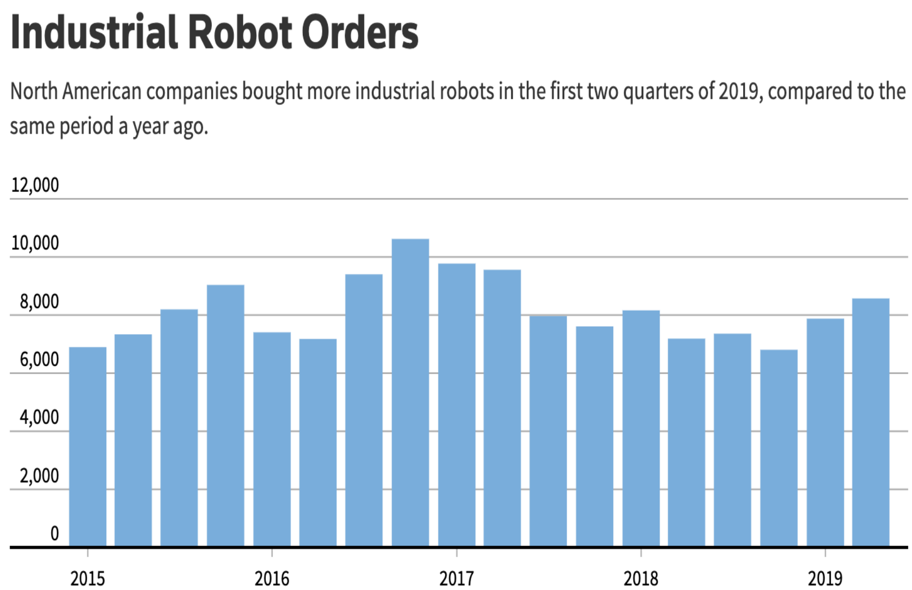
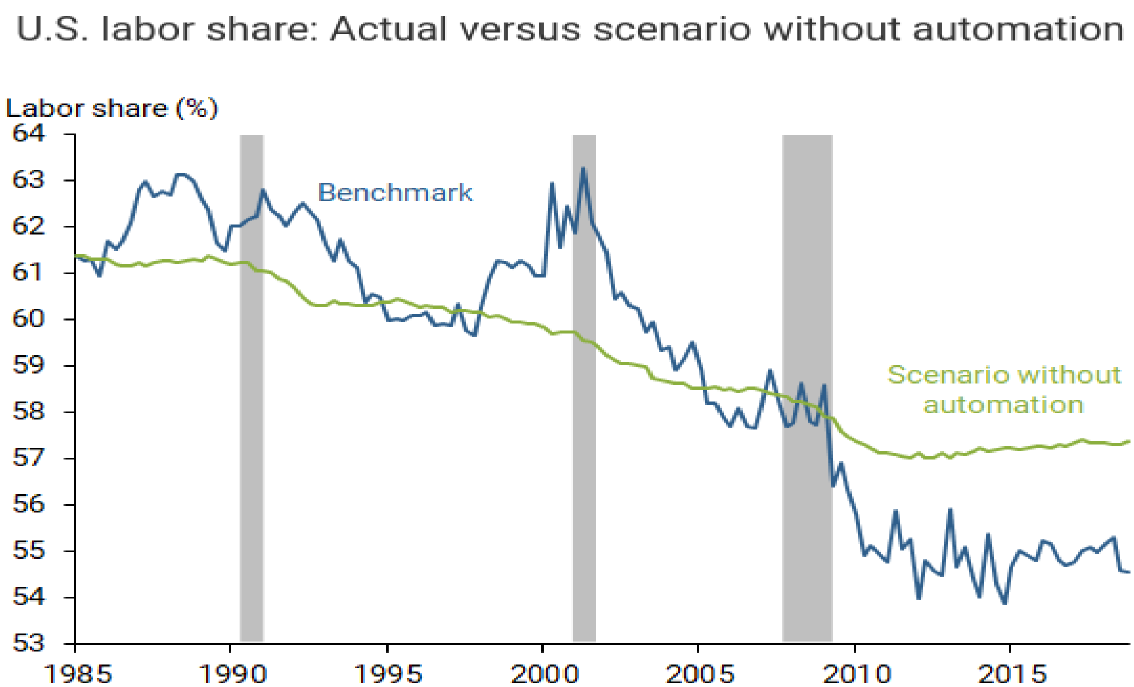



Figure 2 shows the amount of industrial robots that were ordered in the thousands. We used this in our comparisons to unemployment rates (5).

We wanted to also look at how manufacturing companies are performing in terms of sales. This is important because we want to see how well these companies are selling and if the volume of robots has sold more products in recent years. According to the United States Census Bureau, manufacturing monthly sales have been steadily growing since 1992. By the end of 2020, the number of sales was 503,716 in December. This was nearly triple the number of sales in December of 1992, which was about 155,614 (10). This data shows that monthly sales of the manufacturing industry have been steadily growing.

Once we decided to narrow down our project to manufacturing we found new data on employment in that industry from the Bureau of Labor Statistics and we compared that to productivity rates. We decided to look into productivity rates as a form of representing the effects of automation because it is a way to measure whether or not the use of automation has a beneficial or negative effect on companies. Even if unemployment rates rise, productivity rates still have the possibility to remain high with the use of automation. This could mean that the quality of life and the economy is better off with more robots in the workplace. In the year 2015, productivity rates went down by 0.3% and 12,275 people were employed in manufacturing(7). Comparatively, 6,500 industrial robot orders were made in that year(5). This shows us that in 2015 there could be a correlation between fewer people being employed, productivity going down, and more robot orders being made.

Figure 3:




In figure 3 it shows that the national income for the U.S has decreased by 7 percentage points over the past few decades. The decline started in the early 2000s but had increased greatly during the great recession. It is clear that without automation labor shares could have not gone down as much. This means that automation can have a negative effect on labor shares. (11)

Figure 4:

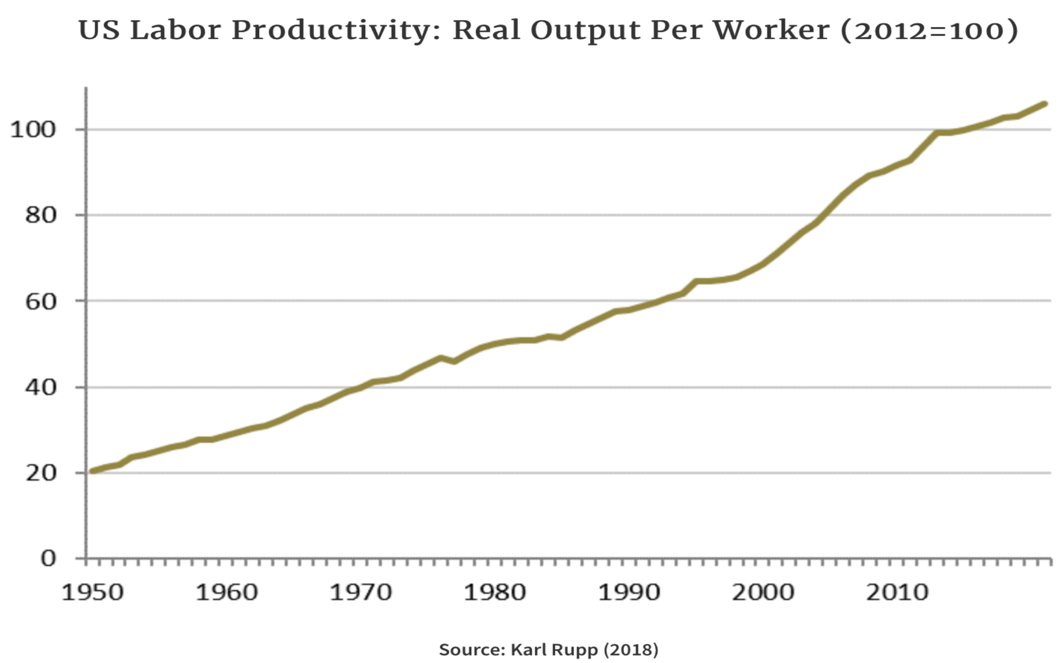



Figure 4 shows labor productivity in the United States. Productivity rates have gone up from 1950-2010 which could be due to automation. (12)

We also looked into ways to make predictions as a way to determine the effects that automation would have on unemployment if there is a relationship between the two. We considered linear and logistic regression, however, those were difficult to use because the data that we found is very scattered, and would be hard to find an accurate line of best fit. We also looked into machine learning to use algorithms in our code to make predictions. Some methods that we found were forecasting and time analysis. Although machine learning would be the ideal way to make predictions, we decided not to use it because we simply do not have enough accumulative data going into years past since this is our first year doing this project. We decided to use the line of best fit with a simple y=mx+b formula to make predictions that only consider unemployment rates and the number of robots in manufacturing.

# Methods:

**Start:**

At the beginning of the year, we wanted to find a correlation between unemployment and automation, and if there was a way to predict how this can impact the future of jobs. We wanted to learn more about how different unemployment is between the past, present, and what it could look like in the future. We began by looking at the entire workforce as a whole, before narrowing it down to one industry, manufacturing. There were many variables that impacted unemployment and automation. These variables were productivity, hours worked, and the employment of the manufacturing industry from 1994-2020.

**After Evaluations:**

After evaluations, we clarified our goal of the project, organized our graphs in the code, and made our code into a matrix instead of being multiple lists. At the beginning of the year, we did not have a specific goal as to what we wanted to achieve. However, after evaluations, we decided to make our goal to see if there is a relationship between unemployment and automation, as well as how it impacts the future of workers and businesses. We also organized our graphs in the code more by adding titles, legends, and markers to clarify what our graphs are about. After evaluations, we wanted to make our code into a matrix that would be easier to navigate as opposed to multiple lists of data.

**Python and Pycharm:**

Our program visualizes and shows the different data that impact unemployment and automation. We are using Python and the Python libraries in order to plot our data using graphs and lists. This year we used the python library to implement a graph into our code. We used Matplot libraries in order to create a visualization of the different variables of unemployment and automation. As well as NumPy to create plotting data and line of best fit. In our code, we were trying to visualize how different aspects of automation and the workforce correspond to one another. These variables consisted of productivity growth in the workforce as a whole and productivity growth in manufacturing specifically, unemployment in the United States, employment in the manufacturing industry, labor productivity, industrial robots, and hours worked in the manufacturing industry and their output. We compared these different variables to one another to see how they correlate, as well as the same variable but in different years. We also made multiple lists that show and store our data for each variable, however, we later changed this to become a matrix in order to create multiple lists in one file. We added multiple functions and for loops in order to make our code read our data text files and create loops to add more information for each year. Our model shows different graphs and functions that contribute to how unemployment and automation increase or decrease. Lastly, we created a plotting graph using the unemployment rates from the manufacturing industry file and industrial robot orders file, to create a prediction according to the NumPy package by making a line of best fit.

Figure 5:

```
import matplotlib.pyplot as plt
```

```
import numpy
```

Figure 5 shows how we inserted the plotting library in order to make graphs in our code, and how we inserted the NumPy library in order to get a line of best fit for our predictions.

Figure 6:

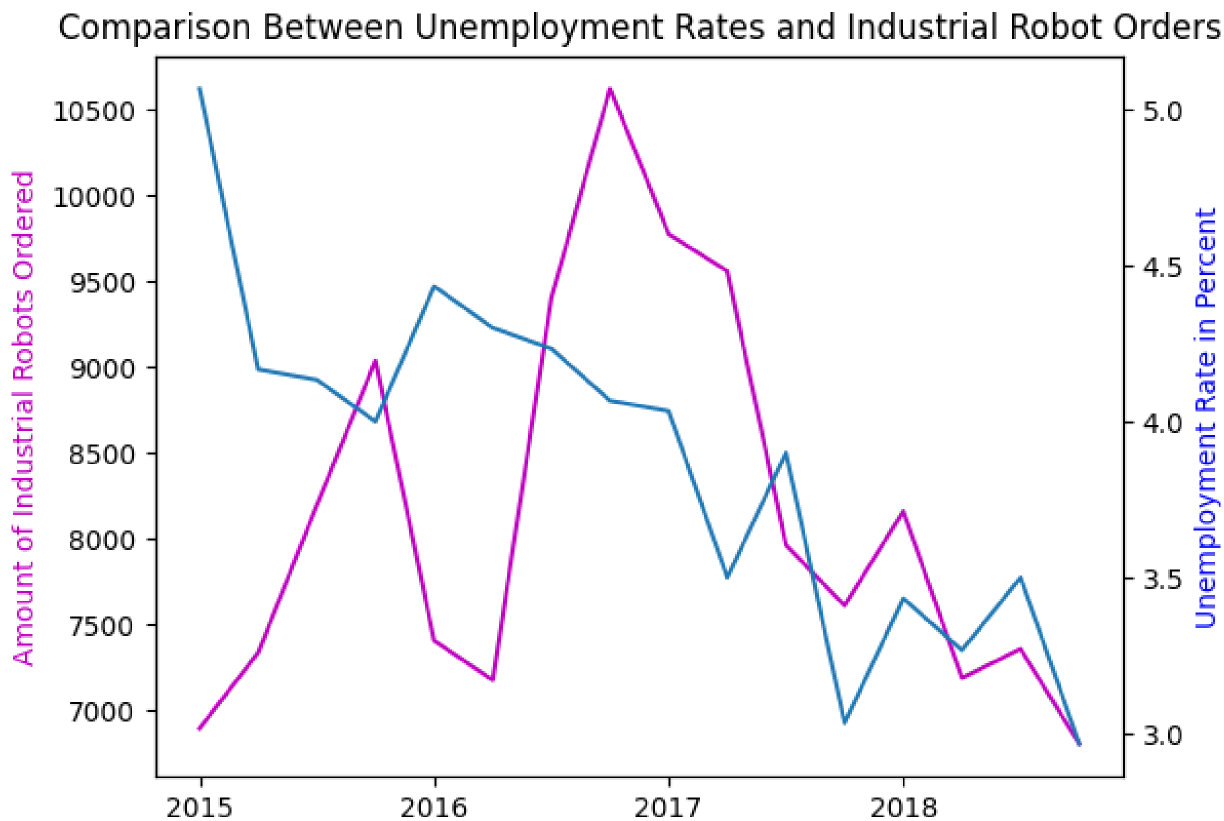



Figure 6 shows how we compared employment in manufacturing industries from 1994-2003. There are two y-axes present in this graph. The one on the right shows the number of industrial robots ordered as a quantity in thousands. The one on the left shows the Unemployment rate at the same time in percentages. The colors of the axes correspond to the lines on the graph. The x-axis shows the years.

Figure 7:

```
2015, 6500
['2015', ' 6500', '']
2016, 7500
['2016', ' 7500', '']
2017, 9800
['2017', ' 9800', '']
2018, 8100
['2018', ' 8100', '']
2019, 7900['2019', ' 7900']
```

Figure 7 shows how we made and stored a list for industrial robot orders.

Figure 8:

```
def months_quarters(unemployment_months):
    # function changes the format of the data of each year into four quarters
    # which consists of the first three months, second three months, and fourth three months of a year
    store_years_quarterly = []
    for year in unemployment_months:
        quarter_1 = (year[0]+year[1]+year[2])/3
        quarter_2 = (year[3]+year[4]+year[5])/3
        quarter_3 = (year[6] + year[7] + year[8]) / 3
        quarter_4 = (year[9] + year[10] + year[11]) / 3
        store_years_quarterly.append(quarter_1)
        store_years_quarterly.append(quarter_2)
        store_years_quarterly.append(quarter_3)
        store_years_quarterly.append(quarter_4)
    return store_years_quarterly
```

Figure 8 shows how we made the data from a month to month format to a quarterly format. This function found the average of every three months and turned them into quarters. This helped us keep data in the same units to get a relatively accurate result.

Figure 9:

```python
def store_input(file_name):

    # Create a new file object
    input_file_object = open(file_name, "r")

    # Create empty matrix
    input_matrix = []

    # Loop over the lines in the input file
    # Each line will be one row of the matrix
    for line in input_file_object:

        # Create empty row
        row = []

        # Look for the comma in each line and split the string
        # This will return an array of strings
        split_result = line.split(',')

        # Get the integer value of the strings and
        # add it to the row
        for value in split_result:
            row.append(float(value))

        # Append the row
        input_matrix.append(row)

    return input_matrix
```

Figure 9 shows the function we used to read input values from a file and store them in a matrix. It also returns an array of strings. It allows us to store and read the data in our text files in order to create a graph and compare data.

Figure 10:

```
plt.scatter(industrial_robot, store_years_quarterly)
plt.title("Industrial robot orders and unemployment rate")
plt.xlabel("industrial robot orders")
plt.ylabel("unemployment rate percentage")
robotandunemployment = numpy.poly1d(numpy.polyfit(industrial_robot, store_years_quarterly, 1))
plt.plot(industrial_robot, robotandunemployment(industrial_robot))
plt.scatter(7876, 3.03, color = 'g')
plt.scatter(8572, 2.7, color = 'g')
plt.scatter(7876, robotandunemployment(7876), color = 'm')
plt.scatter(8572, robotandunemployment(8572), color = 'm')
plt.show()
```

Figure 10 shows how we incorporated the NumPy package in order to create a line of best fit as well as create points that are predicted using the robotandunemployment variable.

# Tables and Graphs:

Figure 11:

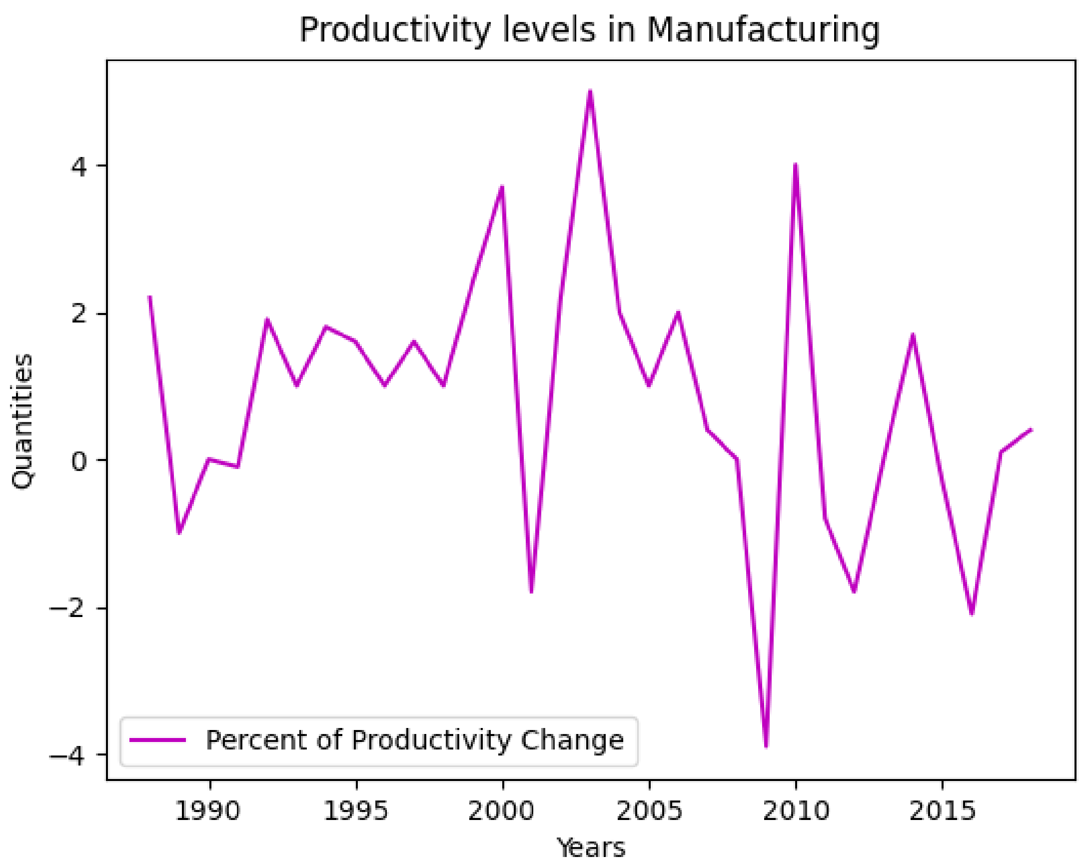



Figure 11 is a graph from our code that shows Productivity levels in Manufacturing. The pink line represents the percent of productivity change and it mostly stayed the same from 1990-2015. (7)

Figure 12:

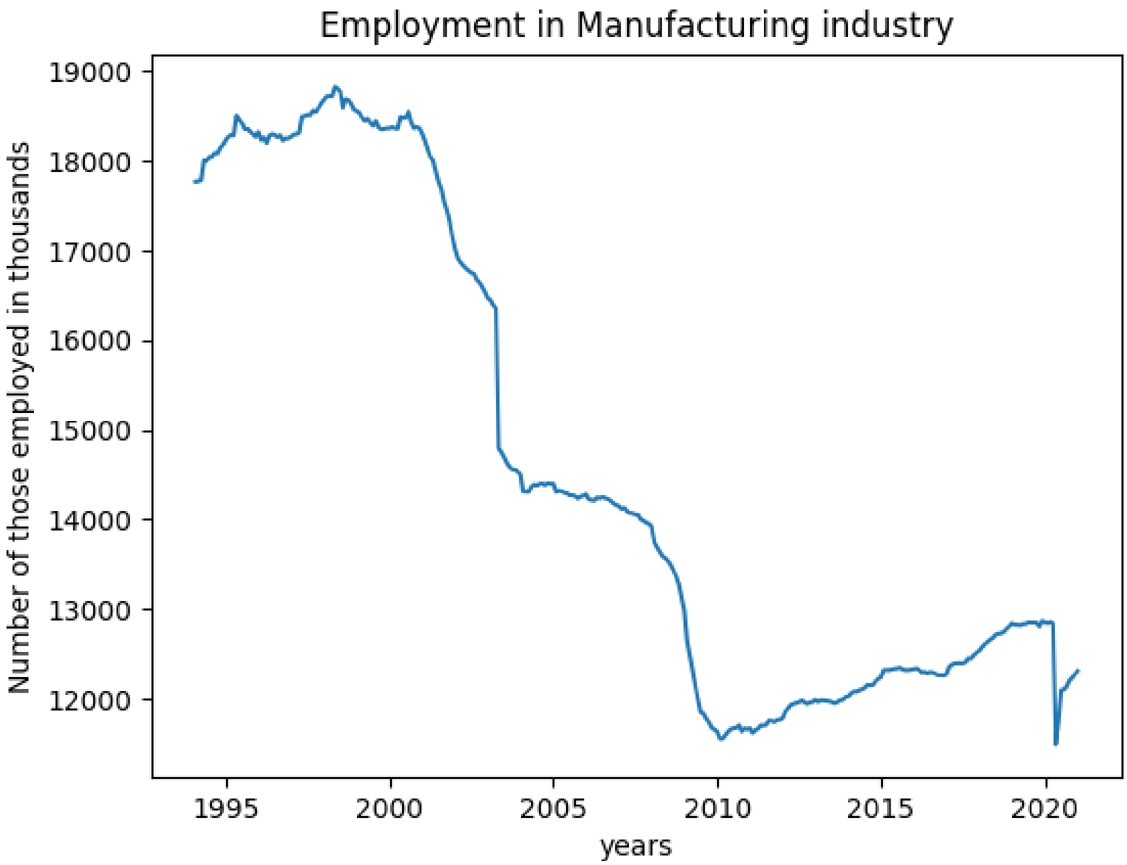



Figure 12 is a graph from our code that shows the number of people employed in manufacturing from 1995-2020. (7)

Figure 13:

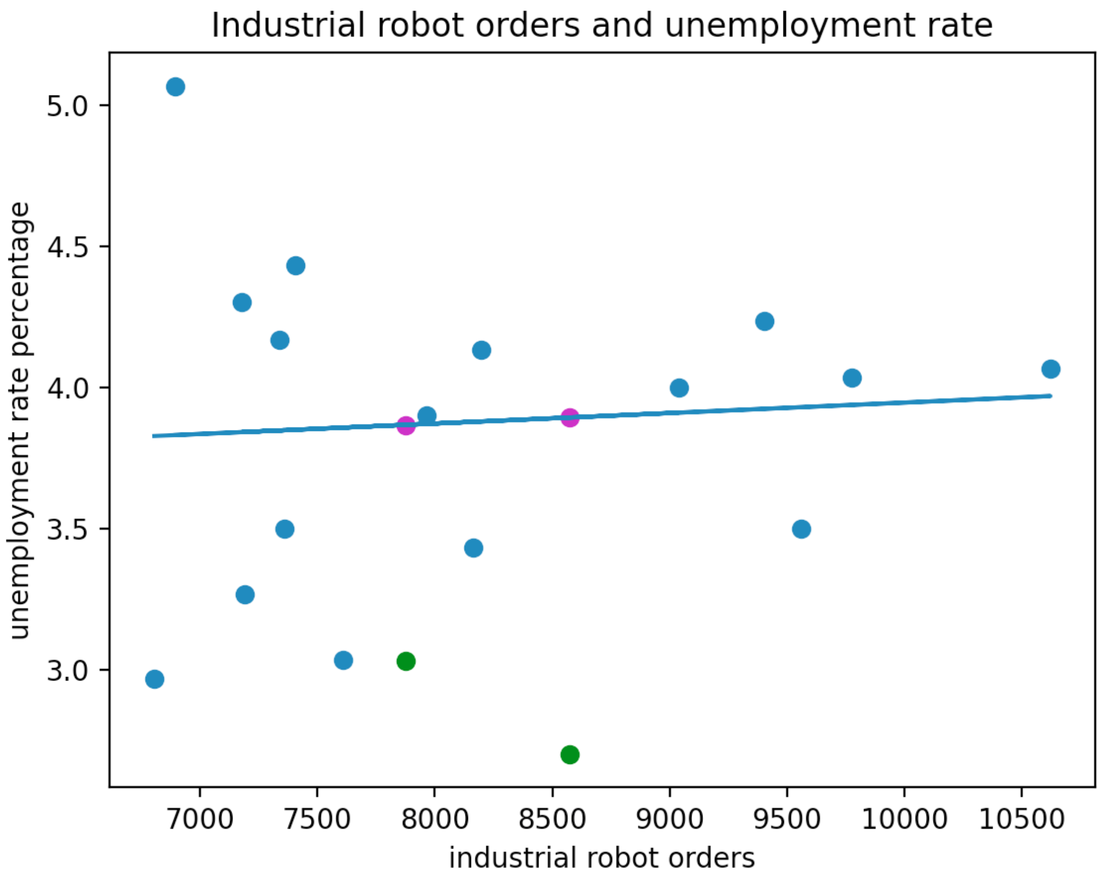



Figure 13 is the scatter plot that we used to compare industrial robot orders and the unemployment percentage in manufacturing. The line across the middle is a line of best fit used to predict where unemployment rates will be as more industrial robot orders are made. The pink dots represent the predicted unemployment rate while the green dots represent the actual unemployment rate in 2019. As shown, they do not match up because the data is very scattered and does not follow a certain shape.

# Results:

In our results, we found out that automation and unemployment have multiple variables that can impact the workforce. We created multiple graphs in our program to visualize different scenarios. These scenarios consisted of more than two lines on one graph to show multiple variables in the same year and a line of best fit to create predictions. We also want to take into account that automation is not the only variable that impacts unemployment. For example, we know that unemployment went down in 2008 due to the recession and in 2020 due to the Coronavirus. These events have impacted unemployment rates negatively. In our final graph, seen in figure 13, we use a scatter graph to predict how industrial robot orders can have a factor in how unemployment rates can increase and decrease. Each dot stands for a quarter of a year. We used the data on the number of industrial robot orders and their corresponding unemployment rate of that year in the manufacturing industry to predict how industrial robot orders can contribute to unemployment rates. The pink plots stand for the prediction and the green plots stand for the actual data. We used these plots to check the validity of our graph by comparing our prediction based on the line of best fit, to the actual data. We noticed that there was a common range in the plots between 7000 robot orders and 8500 robot orders. The unemployment rate in these areas stays mainly between 3 percent and 4.5 percent. However, there are also few outliers that are shown such as a plot when there were less than 7000 robot orders, but the unemployment was above 5 percent. As well as a plot with less than 7000 robot orders but an unemployment rate that is about 3 percent. This could mean that the graph does not follow any sort of pattern.

# Conclusion:

There is a relationship between unemployment and automation, however, we are still not clear as to whether that is a primarily negative or positive one. As shown in figure 13, there are several outliers that show that unemployment rates do not always directly correlate to industrial robot orders. In addition, the graph does not follow any sort of pattern as we see that the line of best fit did not accurately predict the unemployment rates for the year 2019. However, we do have to keep in mind that this graph only takes into consideration unemployment rates and the number of industrial robot orders over the course of 3 years. Throughout this year we have discovered that there are many other factors that are also relevant to our project; some of those being productivity rates, total sales, hours worked, the economy, quality of life, and even the level of education a worker has. With this in mind, we have also found that while unemployment may cause unemployment rates to rise for people who did not get a college degree, it could help other people who are more advanced in technology get a job. In addition, we have learned that the quality of life may be better when automation is used in the workplace because workers do not have to do as much hard labor. As seen in figures 11 and 12 productivity rates had a negative percent change between 2000-2005 and at the same time employment rates went down from 18,000 people to around 14,000. This could mean that companies are less productive as more people are unemployed, which would be a bad sign for there being more robots used in the workplace. While unemployment and automation do have a very present relationship, it varies greatly in all of the different variables that go hand in hand with each other.

Going forward, we would like to continue this project next year to further investigate the relationship unemployment and automation have over a longer period of time. We would also like to try to solve the negative effects that automation does have on unemployment. We plan to make more accurate predictions about what will happen in the future if technology continues to advance rapidly in order to better understand the effects of automation on people’s everyday lives.

# Significant Achievements:

This year, the most significant achievements that our team had were learning how to use a python library, understanding functions, becoming more comfortable with python and GitHub, and communicating on an online-only platform. This is only our second year using python so we still had a lot to learn about it. We became more familiar with how to use pycharm and commit/push changes to the Github repository so that we could both work on the code, especially as we have not been able to work together in person this year. The python library that we used was called matplotlib and we used it to show graphs of the different variables and how they relate to one another by adding more than one line in the graph. We were previously unfamiliar with that library but it has helped us greatly this year. We also learned how to use functions in our code and understand what they do. Another thing that we had to work on this year was communicating and getting everything done online. We both have very busy schedules with other extracurriculars so we had to be organized and have set times every week that both of us could meet with each other and with our mentors.

**Ayvree Urrea:**

The most significant achievement that I had this year was getting better at using Python. More specifically I learned how to create functions and what they are used for, learned about loops, and a new python graphing library. Since this is only my second year using python I still had much to learn. Throughout the year I think that I have become better at writing code independently and this came from doing extra coding courses and working with our mentor, Flora Coleman. I have also learned how to apply the project that I am doing to Python to create a representational model; in our case, we used a graph to show a comparison between different aspects of automation and unemployment. Along with becoming better at coding, I also applied for an Aspirations in Technology Award at NCWIT and got the Regional Affiliate Award.

**Kiara Onomoto:**

The most significant achievement that I had this year was mainly expanding my knowledge in coding on Python. As this is my second year learning Python, I feel more confident in writing and explaining our program and how it works. This year I have been able to communicate and write code more confidently and independently compared to earlier years. This has made me understand how to create a code in Python and communicate how it works to others. In addition to learning more about coding, I have also had the opportunity as a woman in STEM to apply for an Aspirations in Technology award at NCWIT and achieve the honorable mention award. These achievements have expanded my knowledge in computing and motivate me to work harder.

# Acknowledgements:

Flora Coleman, Sandia National Laboratories

Jonathan Wheeler, Data Curation Librarian at University of New Mexico

Todd Quinn, Economic and Business Librarian at University of New Mexico

Karen Glennon, Retired Teacher

Patty Meyer, Retired teacher

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(3)Todd Quinn, Economics and Business Librarian at UNM

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