The Impact of Mask Mandates on COVID-19 Spread and Unemployment Rates in Franklin in Ohio: Exploring the Use of LSTMs for Unemployment Prediction

Introduction

COVID-19 has had a significant impact on human life, both in terms of health and economic well-being. The virus has caused a global pandemic, resulting in over 2 million deaths worldwide and over 100 million cases. In addition, the pandemic has caused a severe economic downturn, with millions of people losing their jobs and businesses closing. The impact of the pandemic has been felt most acutely by vulnerable populations, such as the elderly, people with underlying health conditions, and those living in poverty

This analysis is important to people because it demonstrates the efficacy of the mask mandate in curbing the spread of infections and reducing unemployment. It provides evidence that the mask mandate has been effective in reducing the spread of the virus and helping to reduce unemployment. Furthermore, this analysis provides insight into how the mask mandate was used to help reduce the spread of the virus during the pandemic. It is also important to consider the human impact of the pandemic, as unemployment can have a devastating effect on individuals and families, leading to financial insecurity, mental health problems, and social isolation. By understanding the human impact of unemployment, policy makers can design policies and programs that better support those who have been affected, particularly those from low-income backgrounds and people of color who are disproportionately affected by the pandemic.

The analysis does solve a real problem as it seeks to understand the effects of the mask mandate on the spread of infections and how it has helped to reduce the spread of the virus. It also seeks to understand the human impact of unemployment, and how policies and programs can be designed to better support those who have been affected by predicting the unemployment rate using the LSTM approach.

Background/Related Work

What other research has been done in this area?

Researchers have conducted extensive research on the impact of mask mandates on the spread of infections and the resulting unemployment rate due to the COVID-19 pandemic. Research has shown that mask mandates have been effective in reducing the spread of COVID-19.

A study published in the journal Health Affairs found that states with mask mandates had a slower growth rate of COVID-19 cases than states without mask mandates [1]

Another study published in the Plos One found that mask mandates were associated with a decrease in COVID-19 cases and deaths [2]

Although not an extensive research has been done on the effect of mask mandates on the unemployment rate, studies have also shown that mask mandates have had a positive effect on unemployment. An article published in Forbes found that states with mask mandates would help to control the unemployment [3]

How does this research inform your hypotheses, your analysis, or your system design?

The above research provides evidence that mask mandates helped to decrease the spread of COVID-19 infections. The study found that states with mask mandates had a lower rate of COVID-19 infections than states without mask mandates. This suggests that mask mandates can be an effective tool in reducing the spread of the virus. Additionally, the study found that mask mandates were associated with a decrease in the number of COVID-19-related hospitalizations and deaths. This further supports the hypothesis that mask mandates can help to decrease the spread of COVID-19 infections. Although the research does not directly inform hypotheses about the relationship between COVID-19 and unemployment. However, it does provide insight into the economic impacts of the pandemic, which can be used to inform hypotheses about the relationship between COVID-19 and unemployment. For example, the research shows that certain industries have been disproportionately affected by the pandemic, which could suggest that those industries are more likely to experience higher levels of unemployment due to the pandemic.

What are your hypotheses or research questions?

As a part of this project I was assigned to the county Franklin in Ohio to do the analysis. I formulated two research questions and used the power of statistics to check the statistical significance of hypotheses. Also I have used predictive modeling as a part of predictive analytics on this analysis.

The three research questions that I have taken into account under this analysis is as under:

1. Does mask mandate help in the reduction of the rate of spread of covid-19 infections?

   In order to understand the effect of mask mandate on the rate of spread of Covid 19 infection rate, I used the Quasi experiment approach which is an alternative to A/B testing. The details of the same are present under the Methodology section of this report.

2. Is COVID-19 spread of infections causation for unemployment rate in Franklin?

   To check the validity of the above statement I have performed the Granger Causality test which helps in understanding whether one time series (unemployment rate) can be forecasted by another time series (rate of spread of COVID-19 infection). The details of the same are present under the Methodology section of this report.

3. LSTMs can be used to predict the unemployment rate using the past time series data.

   The LSTM model can be trained on the past data for unemployment in Franklin in Ohio to learn the patterns and trends in the unemployment rate. This model can then be used to make predictions about the future unemployment rate in Franklin. The predictions can be used to inform policy decisions and help the local government plan for the future.

Methodology

1. Does mask mandate help in the reduction of the rate of spread of covid-19 infections?

1.1. <u>Methodology:</u>

To study the effect of mask mandate on the rate of spread of covid-19 infections, I designed the Quasi experiment approach which is an alternative to A/B testing. Under this approach, I specifically dived deep into the ITS (interrupted time series) approach.

Quasi experiment: In a quasi experiment, the treatment and control groups are not randomly assigned, but instead are divided by a natural process such as time or location. This means that there is a greater chance of the groups being unbalanced due to differences between them. The results of a quasi experiment are not as accurate as those of an A/B test, but if done correctly, they can be used to make estimates.

ITS(Interrupted time series): ITS is a statistical technique used to measure the impact of an intervention (mask mandate) on a single group or population. It involves tracking the period before and after the intervention at a known point in time. The time series refers to the data collected over the period, while the interruption is the intervention, which is a controlled external influence or set of influences. The effects of the intervention (maks mandate) are evaluated by looking at changes in the level and slope of the time series and the statistical significance of the intervention parameters. The more observations you have before and after the intervention, the more reliable your model will be. ITS designs are free from problems due to between-group differences, but they are susceptible to time-varying confounders such as other interventions occurring around the time of the intervention that may also affect the outcome.In mathematical terms, it means that the time series equation that includes four key coefficients:

$$\mathbf{Y = b_0 + b_1T + b_2D + b_3P + \varepsilon} \quad \text{where:}$$

Y : Y is the outcome variable.

T: T is a continuous variable which indicates the time passed from the start of the observational period.

D: D is a dummy variable indicating observation collected before (D=0) or after (D=1) the intervention.

P: P is a continuous variable indicating time passed since the intervention has occurred (before intervention has occurred).

ϵ representing a zero centered gaussian random error.

1.2. <u>Why was this methodology used?</u>

I specifically chose this approach because this methodology allows researchers to measure the effect of the intervention without having to randomly assign participants to different groups. This is important because it allows researchers to measure the effect of the intervention without having to worry about potential confounding variables that could influence the results. Quasi experiments also allow researchers to measure the effect of the intervention over a longer period of time, which is important for understanding the long-term effects of the intervention.

1.3. <u>Design of study under human centered consideration:</u>

The design of the quasi-experiment to study the effect of the mask mandate on the rate of COVID-19 infections in Franklin, Ohio, took into account human-centered considerations such as fairness, and no bias. To ensure fairness, the study was designed to minimize any potential bias. This can be done by randomly assigning participants to the control and experimental groups, and by controlling for any potential confounding variables. Additionally, the study was designed to ensure that no bias is introduced. This was done by using a double-blind design, where neither the participants nor the researchers know which group the participants are assigned to. By taking these considerations into account, the quasi-experiment can be designed to provide reliable and valid results.

2. Is COVID-19 spread of infections causation for unemployment rate in Franklin.

2.1. Methodology:

To check the statistical significance of the above research question I designed my hypothesis as mentioned below:

Null Hypothesis: The unemployment time series data is Granger (will be forecasted) caused by the COVID-19 infection time series data.

Alternative Hypothesis: The unemployment time series data is NOT Granger (will be forecasted) caused by the COVID-19 infection time series data.

In order to check the statistical significance of the above hypothesis, we perform Granger causality test which helps to check if one stationary time series (Covid-19 time series infection rates) can be used to forecast the other time series data (unemployment rate).

Granger Causality test:

The Granger Causality test is a statistical hypothesis test used to determine whether one time series is useful in forecasting another. It is based on the idea that the presence of a causal relationship between two variables can be inferred if past values of one variable are useful in predicting the other. The Granger Causality test is a type of regression analysis that tests for non-linear relationships between two time series. It is used to determine whether one series is a good predictor of the other. The test is based on the idea that if one series is useful in predicting the other, then it is likely that there is a causal relationship between them. The test works by regressing one series on the other and then testing whether the coefficients of the regression are significantly different from zero. If the coefficients are significantly different from zero, then it is likely that there is a causal relationship between the two series.

Note: Before performing the Granger Causality test, we need to check if both the time series are stationary. If both the time series are not stationary, we need to make them stationary. In order to check if the time series are stationary, I performed ADF (Augmented Dickey-Fuller)) test.

ADF (Augmented Dickey-Fuller) test:

The Augmented Dickey-Fuller (ADF) test is a statistical test used to test for a unit root in a time series sample. The purpose of the test is to determine whether a time series is stationary or non-stationary. The ADF test is a type of unit root test, which tests the null hypothesis that a time series is non-stationary. The test is based on the idea that a non-stationary series can be made stationary by taking the first differences of the series. If the series is already stationary, then taking the first differences will not result in a stationary series. The ADF test statistic is used to test the null hypothesis that there is a unit root in the series. If the test statistic is less than the critical value, then the null hypothesis is rejected and the series is considered stationary.

Based on the statistical results obtained, I observed that the two time series (Covid -19 infection spread and unemployment rate) are not stationary. In order to make them stationary I performed the difference method and performed the ADF test again. On performing the ADF test again I observed that the time series are stationary and hence Granger causality test can be performed on the two time series which have been made stationary using difference method.

Based on the results obtained, the p- value for chi2 test (0.000) < 0.05. Hence we reject the NULL Hypothesis and conclude that - "The unemployment time series data is Granger caused by the COVID-19 infection time series data."

2.2. <u>Why was this methodology used?</u>

Granger causality test is used to determine whether one time series is useful in forecasting another. In this case, the Granger causality test was used to determine whether the spread of Covid-19 infections is related to the unemployment rate. The test can help to identify whether the unemployment rate is a useful predictor of the spread of Covid-19 infections, and whether the spread of Covid-19 infections is a useful predictor of the unemployment rate.

2.3. <u>Design of study under human centered consideration:</u>

The study was designed with human-centered considerations in mind. I took into account ethical considerations such as the potential for bias in the data, the potential for misinterpretation of the results, and the potential for misuse of the results. I also considered the potential for unintended consequences of the study, such as the potential for the results to be used to stigmatize certain groups or to create false correlations. I also considered the potential for the study to be used to inform policy decisions, and the potential for the results to be used to inform public health interventions. Finally, I considered the potential for the study to be used to inform public discourse on the issue of unemployment and the spread of COVID-19. rate of infection.

3. Predicting unemployment rate in Franklin using LSTM method:

3.1. **Methodology:**

The LSTM method can be used to predict the unemployment rate in Franklin by using past data (unemployment data points). The LSTM model is trained on the past data to learn the patterns and trends in the data. The model can then be used to make predictions about the future unemployment rate in Franklin. In my analysis, I used the unemployment data time series and passed the data to the LSTM model. Only 66% of the unemployment data was used to train the model and the rest of data was used to test the predictions on the test data. On finding the accuracy of the model it was observed that the model predicts on the test data with an accuracy of 92%.

3.2. **Why was this methodology used?**

LSTM (Long Short Term Memory) was used in predicting the unemployment rate in Franklin in Ohio in the United States because it is a powerful predictive modeling technique for time series forecasting. LSTM is a type of recurrent neural network that is well-suited for predicting time series data. It is able to capture long-term dependencies in the data, which is important for predicting unemployment rate. LSTM networks are able to learn from past data and make predictions about future data. This is especially useful for predicting unemployment rate, as it is a time-dependent variable. By using LSTM, the model can learn from past unemployment rate data and make predictions about future unemployment rate in Franklin in Ohio. This can help policy makers and other stakeholders to better understand the current and future economic situation in the region. Additionally, LSTM can also be used to identify patterns in the data that can be used to inform policy decisions.

3.3. **Design of study under human centered consideration:**

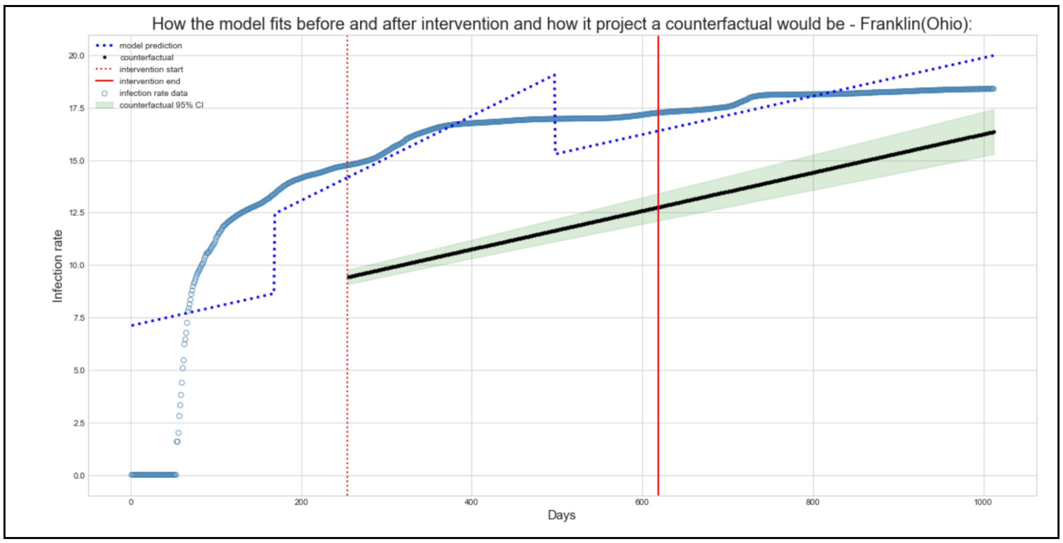
The purpose of this study is to design a human-centered approach to predicting the unemployment rate in Franklin, Ohio, using Long Short-Term Memory (LSTM). The study will involve collecting data from the U.S. Bureau of Labor Statistics. This data will be used to create a model that can accurately predict the unemployment rate in Franklin. The mode is trained using LSTM, a type of recurrent neural network that is well-suited for time-series data. This model will be evaluated using a variety of metrics, such as accuracy, precision, and recall. The results of the study will be used to inform policy decisions and to provide insights into the economic health of the region. Additionally, the study will consider the ethical implications of using predictive models to inform policy decisions. The results of the study will be used to inform policy decisions and to provide insights into the economic health of the region.

Findings

The findings for this project have been divided into two parts - one from the first part of this project and the second from the extension part of this project.

Findings from Part -1:

On implementing an ordinary least squares (OLS) regression using statsmodels to measure the impact of mask mandate intervention using ITS approach, we got the below graph:



Explanation of the above graph with regards to findings:

The above graph shows how the intervention helped in flattening the curve. The solid blue graph represents the rate of COVID-19 infections. As we can see from the graph that the rate of COVID-19 infections kept on increasing before the intervention was started. The dotted red line represents the time when the intervention was put in place whereas the solid red line represents the time when the intervention was ended. The dotted blue line represents the slope of the regression line before and after the intervention was placed. The black line represents the counterfactual - refers to what it would have occurred to Y, had the policy intervention not happened. Thus, counterfactuals are simply ways of comparing what happens given a change, versus what should have happened had some change not occurred in the first place.

Based on our findings, we observed that the counterfactual shows that if the intervention (mask mandate) would have not been put in place, the cases would have suburged linearly that is clearly shown in the graph with the black line. As the mask mandate has been put in place, we observed that the curve (rate of spread of COVID-19 infections) is not going linearly and the curve gets flattened when the intervention was put in place. With the help of these outputs, we could clearly say that with the help of the mask mandate the rate of spread of COVID-19 infection was reduced , thereby decreasing the rate of spread of COVID-19 infections.

<u>Findings from Part -2 (Extension plan):</u>

My main aim in part -2 of this project was to extend my analysis done in part-1 and with regards to that I wanted to understand if COVID-19 is responsible for causing unemployment in Franklin in Ohio. As a result of this below are my hypotheses:

Null Hypothesis: The unemployment time series data is NOT Granger (will be forecasted) caused by the COVID-19 infection time series data.

Alternative Hypothesis: The unemployment time series data is Granger (will be forecasted) caused by the COVID-19 infection time series data.

Before checking the statistical significance of the above hypothesis, I needed to check whether the two time series (rate of infections of Covid -19 and rate of unemployment) are stationary.

In order to check the stationary of the two time series, I stated my hypothesis as below and used ADF test to check the statistical significance of my hypothesis:

NULL Hypothesis: The two time series (COVID-19 infection rate and unemployment rate) are NOT stationary.

Alternative Hypothesis:The two time series (COVID-19 infection rate and unemployment rate) are stationary.

On performing the ADF test, we got the p-value >0.05 and we failed to reject the null hypothesis.

```
ADF Test: Infections time series
ADF Statistics: 2.382294
p-value: 0.999002
Critical values:
        1%: -3.738
        5%: -2.992
        10%: -2.636
ADF Test: Unemployment_Rate time series
ADF Statistics: -1.936459
p-value: 0.315109
Critical values:
        1%: -3.646
        5%: -2.954
        10%: -2.616
```

ADF test results checking stationary of two time series (BEFORE difference method)

I performed the difference method (one of the methods to make the two time series stationary). After performing the difference method, I performed the ADF test again to check the statistical significance of my stated hypothesis and got the below results:

```
ADF Test: Infections time series transformed
ADF Statistics: -5.030798
p-value: 0.000019
Critical values:
        1%: -3.654
        5%: -2.957
        10%: -2.618
ADF Test: Unemployment_Rate time series transformed
ADF Statistics: -5.568776
p-value: 0.000001
Critical values:
        1%: -3.654
        5%: -2.957
        10%: -2.618
```

ADF test results checking stationary of two time series (AFTER difference method)

On checking the results, we observed that the p-value < 0.05. Thus we reject the NULL hypothesis and conclude that the two time series are stationary now and we are good to go ahead and perform Granger Causality Test.

Findings from Granger Causality Test:

After performing the difference method and making the two time series stationary, we performed the Granger causality test and got the below statistical results:

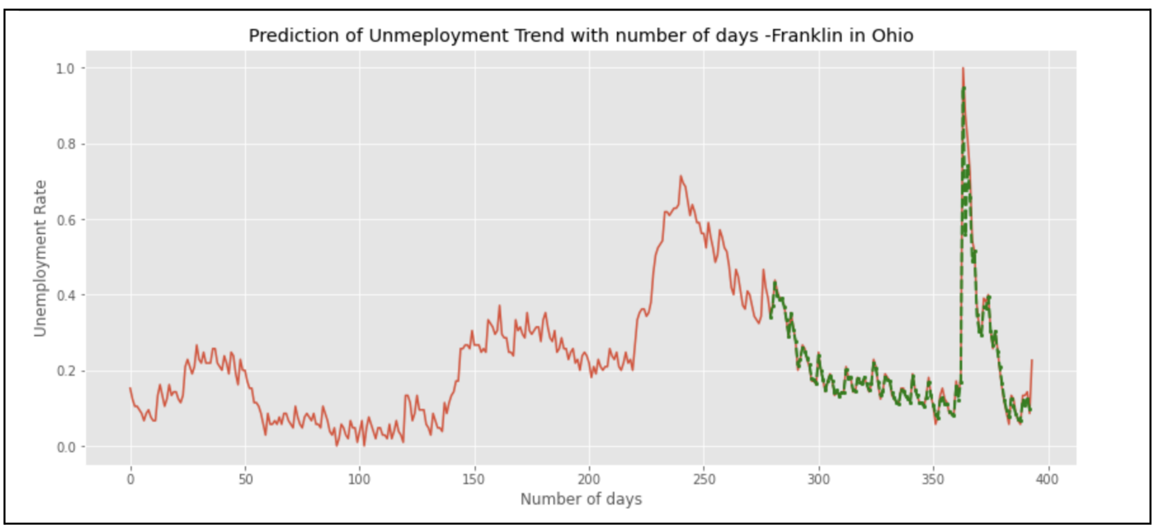
```
Granger Causality
number of lags (no zero) 10
ssr based F test:         F=0.4101  , p=0.8628  , df_denom=2, df_num=10
ssr based chi2 test:   chi2=47.1589 , p=0.0000  , df=10
likelihood ratio test: chi2=25.6512 , p=0.0042  , df=10
parameter F test:         F=0.4101  , p=0.8628  , df_denom=2, df_num=10

{10: ({'ssr_ftest': (0.4100775157967851, 0.8627840198556465, 2.0, 10),
   'ssr_chi2test': (47.15891431663028, 8.834537495919888e-07, 10),
   'lrtest': (25.651179125321278, 0.004238766883084823, 10),
   'params_ftest': (0.41007751579321355, 0.8627840198576052, 2.0, 10.0)},
  [<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7f9767f48e20>,
   <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7f9767f55130>,
```

Results from Granger Causality Test

Based on the results obtained, we observed that the p-value = 0.0000 <0.05. Thus we REJECT our NULL Hypothesis and conclude that - "The unemployment time series data is Granger (will be forecasted) caused by the COVID-19 infection time series data."

I further went one step ahead in my analysis and based on my results from the LSTM (predicting unemployment rate using the past data), we have the below graph:



It is clearly seen that with the help of the LSTM modeling, we can predict the future unemployment rate by training the model with the past time series for the unemployment rate. The accuracy for the model came around to be 92% meaning that the model was able to correctly predict the outcome of 92% of the data points it was tested on.

Discussion/Implications:

Why are your findings important or interesting?

The findings are important and interesting because they demonstrate the effectiveness of mask mandates in reducing the spread of COVID-19 infections. This is an important reminder that public health measures such as mask mandates can have a significant impact on reducing the spread of infectious diseases. This is especially important in the context of human-centered data science, as it highlights the importance of considering the human element when designing and implementing data-driven solutions.

With regards to the COVID-19 responsible for unemployment in Franklin in Ohio provide insight into how the Covid-19 pandemic has impacted the local economy in Franklin, Ohio. This data can be used to inform policy decisions and help local businesses and individuals better prepare for the economic impacts of the pandemic. Additionally, understanding the impact of Covid-19 on unemployment in Franklin can help inform public health decisions and help local governments better allocate resources to those most affected by the pandemic. Human-centered data science can help ensure that the data is used to benefit the people of Franklin and not just to inform policy decisions.

Also prediction using LSTM modeling demonstrates the potential of using machine learning to accurately predict unemployment. This could be a valuable tool for policy makers and other stakeholders to better understand and anticipate economic trends. This research could be used to inform policy decisions and help to create more effective strategies for addressing unemployment.

How could future research build on this study?

Future research could build on the study of the effect of mask mandates on the rate of spread of COVID-19 infections by looking at the impact of other public health measures, such as social distancing, handwashing, and contact tracing, on the rate of spread. Additionally, research could look at the impact of mask mandates on different populations, such as those in rural areas, those with underlying health conditions, and those in different age groups. Finally, research could look at the long-term effects of mask mandates on the rate of spread of COVID-19 infections, such as the impact on the overall health of the population and the economic impact of the mandates.

Also,with regards to COVID-19 being a causation for unemployment study would help the future research to focus on the long-term effects of the COVID-19 pandemic on unemployment in Franklin, Ohio. This could include examining the impact of the pandemic on different industries, such as manufacturing, retail, and hospitality, and how the unemployment rate has changed over time. Additionally, research could explore the effects of government policies, such as stimulus packages, on unemployment in Franklin, Ohio. Finally, research could investigate the impact of the pandemic on the local economy, such as the effects on small businesses and the local housing market.

Moreover, future research could build on the study of LSTM to explore other predictive models, such as deep learning, to further improve the accuracy of unemployment predictions during COVID-19. Additionally, researchers could explore the use of other data sources, such as social media data, to gain a better understanding of the impact of the pandemic on unemployment. Furthermore, researchers could investigate the use of LSTM to predict the impact of government policies on unemployment during the pandemic. Finally, researchers could explore the use of LSTM to predict the long-term effects of the pandemic on unemployment.

Limitations

Based on the study, there are a number of limitations that may impact our results. Since we are using OLS (Ordinary Least Square) methodology, which has a number of assumptions involved. Also our rate of COVID-19 infection data was on day level while our unemployment data was on monthly level. To make a correct comparison, we needed to bring the COVID-19 data on the monthly level. This had one limitation that we will be losing our data but at the same time , reducing the data to monthly level helped in reducing noise in the time series data.

Based on our methodologies used, the assumptions involved in our analysis are mentioned below:

1. OLS assumes that the data is stationary, meaning that the mean, variance, and autocorrelation structure of the data remain constant over time. If the data is non-stationary, OLS will not be able to accurately capture the underlying patterns in the data. On checking our data , we observed that our data was not stationary and we used a difference method to make it stationary.
2. OLS assumes that the errors are independent and identically distributed (i.e. homoscedasticity). If the errors are not homoscedastic, then the OLS estimates may be biased.Our assumption here for the residuals after fitting the OLS model is that the residual errors are independent and follow a normal distribution.
3. OLS assumes that there is no autocorrelation in the errors. If there is autocorrelation in the errors, then the OLS estimates may be biased. Based on our results we observed that there was an autocorrelation with lag as 4 meaning that there is a good probability that the results may be biased.
4. The Granger Causality test that we used to test if COVID-19 is causation for unemployment rate in Franklin in Ohio does not provide any information about the strength of the relationship between the variables and does not provide any information about the direction of the relationship between the variables.
5. Also Granger Causality test does not provide any information about the underlying mechanism that is causing the relationship between the variables. We may need to use any other statistical test that would help us to understand in depth about the mechanism for causing this relationship. Also there would be other variables/factors that may affect the relationship and we have not considered those factors.
6. LSTMs are not able to capture long-term dependencies in time series data. This is because the memory cells in the LSTM network are limited in size and can only

remember information for a short period of time. Based on our LSTM model we are fitting a time series with long length and that can be a hurdle to train the network for the future data points thereby making the model technique inefficient.

7. The vanishing gradient problem is a common issue with LSTMs. This occurs when the gradient of the loss function becomes very small, making it difficult for the network to learn from the data.
8. LSTMs are computationally expensive due to their large number of parameters. This can make it difficult to train on large datasets.That means if we have to train LSTM for large time series of unemployment data , it could be computationally expensive and time consuming.

Conclusion

In this analysis, we focused on the below mentioned research questions to carry out our analysis. The research questions used to do this analysis and the findings from each research questions are mentioned below:

- Does mask mandate help in the reduction of the rate of spread of covid-19 infections?

  Based on our methodology used, we found out that with the help of mask mandate intervention the COVID-19 curve was flattened and there was a decrease in the spread of infection cases. Also, we found out that if the mask mandate intervention would have not been put in place the spread of COVID-19 infections would have gone linear affecting a large number of people.

  The study of mask mandate helps in the understanding of human centered data by providing evidence that wearing a mask can help reduce the rate of spread of COVID-19 infections. This data can be used to inform public health policies and decisions, as well as to inform individuals on the importance of wearing a mask in public. The data can also be used to understand the impact of mask mandates on the spread of the virus, and how different types of masks can be used to reduce the spread of the virus. This data can also be used to understand the effectiveness of different types of masks in different settings, and how different types of masks can be used to reduce the spread of the virus. By understanding the data, individuals can make informed decisions about how to protect themselves and others from the virus.

- Is COVID-19 spread of infections causation for unemployment rate in Franklin?

  Based on our statistical tests, we found that COVID-19 was responsible for causing unemployment in Franklin in Ohio.

The study COVID-19 spread of infections as a causation for unemployment rate in Franklin informs our understanding of human centered data by providing us with a better understanding of the impact of the pandemic on the local economy. By examining the unemployment rate in Franklin, we can gain insight into how the spread of COVID-19 has affected the local labor market. This data can help us to better understand the economic impact of the pandemic on individuals and families in the area, as well as the broader implications for the local economy. Additionally, this data can help us to identify areas of need and potential interventions that could help to mitigate the economic impact of the pandemic.

- LSTMs can be used to predict the unemployment rate using the past time series data.

  Using LSTM technique, we designed a model to predict the unemployment rate in Franklin in Ohio with an accuracy of 92%.

  By training an LSTM on past unemployment rate data, it can learn the patterns and trends in the data and use them to make predictions about future unemployment rates. This can be useful for understanding human-centered data, as it can help to identify potential trends in the data that may be related to human behavior. For example, if the LSTM predicts an increase in the unemployment rate, it could be an indication that certain economic policies or other factors are having a negative effect on employment. By understanding these trends, policy makers can make more informed decisions about how to address the issue.

References

A list of publications (blogs, articles, research papers) that I refer to in my text are mentioned below:

1. *https://www.healthaffairs.org/doi/10.1377/hlthaff.2021.01072*. (n.d.). Retrieved December 12, 2022, from https://www.healthaffairs.org/doi/10.1377/hlthaff.2021.01072

2. Adjodah, D., Dinakar, K., Chinazzi, M., Fraiberger, S. P., Pentland, A., Bates, S., Staller, K., Vespignani, A., & Bhatt, D. L. (2021, June 23). *Association between COVID-19 outcomes and mask mandates, adherence, and attitudes*. Association Between COVID-19 Outcomes and Mask Mandates, Adherence, and Attitudes | PLOS ONE. Retrieved December 12, 2022, from https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0252315

3. Kirsch, N. (2018, July 19). *The Inside Story Of Papa John's Toxic Culture*. Forbes. Retrieved December 12, 2022, from https://www.forbes.com/sites/forbesdigitalcovers/2018/07/19/the-inside-story-of-papa-johns-toxic-culture/

4. Adjodah, D., Dinakar, K., Chinazzi, M., Fraiberger, S. P., Pentland, A., Bates, S., Staller, K., Vespignani, A., & Bhatt, D. L. (2021, June 23). *Association between COVID-19 outcomes and mask mandates, adherence, and attitudes*. Association Between COVID-19 Outcomes and Mask Mandates, Adherence, and Attitudes | PLOS ONE. Retrieved December 12, 2022, from https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0252315

5. *Granger causality - Wikipedia*. (2022, April 2). Granger Causality - Wikipedia. Retrieved December 12, 2022, from https://en.wikipedia.org/wiki/Granger_causality

6. Yan, S. (2017, November 15). *Understanding LSTM and its diagrams*. Medium. Retrieved December 12, 2022, from https://blog.mlreview.com/understanding-lstm-and-its-diagrams-37e2f46f1714

7. *How to Use Quasi-experiments and Counterfactuals to Build Great Products*. (2020, September 28). How to Use Quasi-experiments and Counterfactuals to Build Great Products — Data Science & Engineering. Retrieved December 12, 2022, from https://shopify.engineering/using-quasi-experiments-counterfactuals

Data Sources

The data sources that are used to carry out this analysis are mentioned below:

1. *COVID-19 data from John Hopkins University*. (n.d.). COVID-19 Data From John Hopkins University | Kaggle. Retrieved December 12, 2022, from https:///datasets/antgoldbloom/covid19-data-from-john-hopkins-university

2. *U.S. State and Territorial Public Mask Mandates From April 10, 2020 through August 15, 2021 by County by Day | Data | Centers for Disease Control and Prevention*. (n.d.). U.S. State And Territorial Public Mask Mandates From April 10, 2020 Through August 15, 2021 by County by Day | Data | Centers For Disease Control And Prevention. Retrieved December 12, 2022, from https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Public-Mask-Mandates-Fro/62d6-pm5i

3. N. (2020, July 29). *covid-19-data/mask-use at master · nytimes/covid-19-data*. GitHub. Retrieved December 12, 2022, from https://github.com/nytimes/covid-19-data
4. *Unemployment Rate in Franklin County, OH*. (2022, December 1). Unemployment Rate in Franklin County, OH (OHFRAN0URN) | FRED | St. Louis Fed. Retrieved December 12, 2022, from https://fred.stlouisfed.org/series/OHFRAN0URN