Mobility, Policy and COVID-19 Data in Prediction of Death Case Load

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Abstract

The COVID-19 pandemic has resulted in a significant loss of economic output and human life. A means by which to accurately forecast the spread of the disease in relation to government policy is of critical importance when determining how to minimize both the spread of disease and economic impact. The objectives of our study are to investigate the dependence of COVID-19-related deaths on the mobility habits of individuals and the government response data. We will investigate if there are differences in the effects of incorporating the mobility and government policy data for regions of varying population density. We will use the Apple mobility dataset in conjunction with The New York Times dataset for COVID-19 cases and deaths as well as government response data from Oxford University to train an LSTM model, evaluate its performance using the root mean squared error between the predicted number of deaths and the actual number of deaths, and compare it to an ARIMA model.

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1 Introduction

1.1 Response to Milestone Comments

1.1.1 Adding simple models for comparison We have added ARIMA model to get a comprehensive understanding of predictive capabilities and the feasibility of LSTM models for a short term prediction against the challenge of using a sparse data-set. As ARIMA models are known to work in such situations, this exercise gave us insight on the challenges to overcome when Recurrent Neural Networks are used for epidemic predictions.

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1.2 Aim

The COVID-19 pandemic has affected a large part of the globe in the past year. However, the impact that the disease had varied for different nations. Some nations or regions within the countries could handle the pandemic much more efficiently than others. Here efficiency of measures taken by the governments primarily indicates the impact on the lives of the people as well as the economy of the country while successfully stopping the infection spread [7]. Since many parts of the world are yet to procure vaccines and administer to their citizens, it becomes highly important to understand which policies are effective to curb the disease while causing minimum disruption to the daily lives of the citizens. To achieve this, a data-driven approach becomes of paramount importance, as governments across the globe plan to ease the restrictions. Decisions based on data can provide granular detail on the importance of restrictions that are the most responsible for stopping the spread of disease while easing up on restrictions that hardly have any effect on the spread but, on the other hand, are majorly accountable in the disruption of the economy.

We will attempt to determine the relative strength of the correlation between specific mobility data metrics (walking and driving), COVID-19-related policies, population density, and the rate of the spread of COVID-19. We will do this by training a long short-term memory (LSTM) model on COVID-19 cases, deaths, mobility and policy data, and make predictions 7 and 14 days out. The real-world implications of this information include the ability to infer the types of mobility restrictions that can mitigate the spread of the disease whilst also minimizing economic impact, as well as the relationship between population density and effectiveness of different policies.

1.3 Impact

The estimated global death toll from COVID-19 is about 15 million [14], while the estimated GDP loss globally escalates into trillions of dollars [4]. While imposing strict restrictions and stopping the mobility altogether seems to be the spontaneous and natural conclusion of any government to save its citizens, the efficacy of various restrictions however, remains debatable. The long term effects of some of the restrictions might turn out to be more harmful to the general public and the economy than their benefits in curbing the disease.

Hence, a data driven prediction of the effectiveness of policies will help governments to take calculated and accurate decisions on how much disruption is required, specially as the face of pandemic changes with the availability of vaccines and emergence of new variants.

In conclusion, the project aims to impact the efficient decision making to end the pandemic, primarily focusing on the correlation of mobility with the spread of the infection.

2 Problem Definition

To formally define the problem, we will attempt to minimize the root mean squared error between the predicted number of deaths and the actual number of deaths using an LSTM network trained on one of the following combinations of input features: cases, deaths, and mobility data; cases, deaths and policy data; and cases, deaths, mobility data, and policy data.

3 Related Work and Survey

The paper by Adhikari et al. [1] makes use of neural networks to learn meaningful representations of incidence curves in a continuous feature space and accurately predict future incidences. Their paper explores very interesting challenges. For instance, when there is a clear similarity between flu seasons of different years, traditional models such as ARIMA might not work. Several Neural Network models and Deep Learning models would fail when the data is relatively sparse. Their model, an end-to-end time-series embedding, clustering and forecasting approach named Epi-Deep is shown to outperform other non-trivial deep-learning approaches for epidemic forecasting. Further, a better model is suggested in [9] where the authors have modeled the forecasting task as a probabilistic generative process and proposed a functional neural process model, named EpiFNP. The model has proven to generate well calibrated and accurate epidemic predictions. Using this model, the probability density of the forecast value can be directly modeled.

Ensemble models have also been used for the forecasting of deaths attributable to COVID-19 [13]. Using mean absolute error (MAE) as the evaluation metric, the authors found that ensemble models performed well for short-term forecasts, while accuracy deteriorated as the time-span expanded up to a duration of four weeks. The high accuracy for short-term predictions indicates the viability of a combination of machine learning models for the prediction of COVID-19-related deaths, and supports the idea that the combination of a number of models can compensate for the shortcomings or inaccuracies of any singular model.

The paper by Lin et al. [8] forecasts the impact of non-pharmaceutical interventions (NPIs) — including school closures, public transport shutdowns, shop shutdowns — on the spread of the infection using regression models. They approached the problem by creating two models. First, a behavioral model predicts the change in behavior when NPI changes. Second, an infection model predicts the change in infections when behavior changes. The results of this study suggest that mobility data alone is sufficient to meaningfully forecast the COVID-19 infections 7-10 days ahead at every scale [8]. However, it concludes that mobility is not the biggest determinant of infection spread [8].

Rashed and Hirata, in their literature [12], have used deep learning architecture based on long short-term memory networks (LSTM). This model was used to predict the spread of COVID-19, incorporating meteorological data and public mobility estimates. The excellent performance of the model indicates potential for forecasting the spread of COVID-19, and is in line with the findings of the paper from Lin et al. [8].

There are a number of possible aims with real-time epidemic forecasting, including case counts, mobility, host susceptibility, environmental susceptibility, healthcare capacity, and population density, each of which has unique data needs [3]. Any combination of these can be used to help predict another (e.g. the use of mobility and host susceptibility data to predict case counts). While this review paper [3] does a good job providing an overview of the different types of forecasting, and highlights some common challenges (such as a lack of open-source data), much of the content is not pertinent to our proposed work.

Another common means of disease modeling is spatiotemporal modeling, which includes user modeling, place modeling, and trajectory modeling, all of which attempt to account for the different locations that a user is moving to, and how that affects the spread of a disease [14]. While spatiotemporal models do incorporate mobility data, the data required for spatiotemporal models is much more granular than the data that we are proposing to work with. Thus the use of a spatiotemporal model is likely not possible for us. The papers from Rashed and Hirata [12] and Lin et al. [8] are significantly more pertinent in this regard. However, if the standard models with aggregate mobility data do not perform well, we can incorporate spatiotemporal elements into our model.

Carteni et al. [2] investigated the relationship between mobility with the spread of the coronavirus in Italy. Multiple linear regression was employed to link the number of cases in the "active population" (14-80 year olds) to socioeconomic and environmental variables, as well as mobility habits. It was concluded that mobility habits best explained the number of infections. Additionally, the number of new COVID cases in one day was found to be directly related to the trips performed three weeks before. While this is in contrast with the findings of the paper from Lin et al. [8], it aligns with the findings of Rashed and Hirata [12], indicating the potential for mobility data in classifying models. This paper was able to perform well using just a linear regression model [2], achieving similar performance to the paper [12].

Liu et al. [10] combined COVID-19 case data with mobility data to estimate a modified susceptible-infected-recovered (SIR) model in the United States. The salient feature of this modified SIR model was the inclusion of an exponent on the number of infectious individuals, which allows the rate of growth of COVID-19 to be less than proportionate with the number of infectious individuals in order to incorporate social distancing into the model. Study showed that social distancing had a large impact on the spread of COVID-19, whereas the effects of humidity and temperature were insignificant. The findings regarding the effects of social distancing being significant are in line with and the findings regarding meteorological data being insignificant are in contrast with Rashed and Hirata [12].

Garcia et al. [5] showed that ML models were able to predict the cases and deaths of COVID-19 in Spain using only the endogenous variable, i.e the previous observations of the cases and deaths. An ensemble approach was used with a wide branch of models - statistical models like AR or ARIMA and artificial neural network models such as LSTM and GRU.

Overall, papers have found that meteorological data may or may not be significant, but mobility data is almost certainly significant. According to the literature review, papers have found success with different models - both deep learning models (i.e. LSTMs) and simple regression models perform well.

4 Proposed Methodology

4.1 Intuition

COVID-19 deaths are dependent on a number of factors and reasons that decide the face of the pandemic. It is important to take in account of these factors while forecasting the future of the pandemic. Since, the state of the art models are usually auto-regressive, and do not use other features for predictions, they would fail as soon as there is a change in these features. For instance, if the number of deaths are rising in a region, and the government imposes strict lockdown to curb the infection spread, the nature of the curve will change quickly. This change would be evident if the policy implementation is taken in account. Hence, using LSTM models make a lot of sense in such situation as the LSTM models are known to learn the importance of these features and use them to predict a target variable.

Two of the most important features that affect the pandemic are the public behavior (captured by the Mobility Data) and the policies that are implemented to reduce the spread of the infection (captured by the Policy Data). These two features contain a great amount of information that have a potential to predict the nature of the curve.

As it is well known that COVID-19 has an incubation period of approximately 14 days, we 'lag' the aforementioned features by either 7 or 14 days to predict the number of deaths on a given day. Intuitively, LSTMs should capture the relationship between these features to give an accurate forecast of the number of deaths for a reasonably short distance into the future.

Lastly, we trained our model using sequence length of 14, as we believe this to be the minimum amount of data needed for the LSTM model to sufficiently understand trends in the COVID-19-related death count.

4.2 Description

We propose using an LSTM to forecast the total number of infections and deaths from COVID-19 on a particular date using a combination of mobility data (walking and driving metrics), the current number of infections and the policy data. RMSE will be used as the loss function. Our model will output the number of deaths from COVID-19 on a future date, which will be 7 days and 14 days after. The loss metric will be the root mean squared error between the predicted values for the deaths and the true number of deaths.

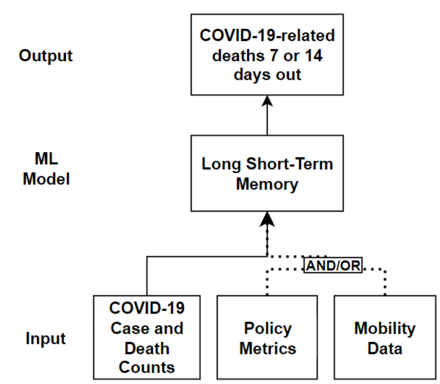

Figure 1. The LSTM system design. There will be three separate data sources, mobility, policy, and COVID-19 data, that will be combined into a single vector and input to the LSTM model. The output vector will be the number of COVID-19 related deaths for the date we are forecasting for.

4.3 Dataset Description

The New York Times (NYT) dataset with cumulative deaths for COVID-19 in the United States (at the state and county level) is available on a Github repository. The time-series data is compiled from state and local governments and starts from 21 January 2020, when the first case was reported in Washington state. The state-level data consists of 5 columns - date, state, FIPS (a geographic identifier), deaths. The county-level data consists of an additional column that specifies the name of the county.

Apple's mobility trend reports for COVID-19 are freely available on their website. The data is generated by counting the number of requests made to Apple Maps for directions in select regions. The volume of direction requests per country/region, sub-region or city on 13 January 2020 is used as

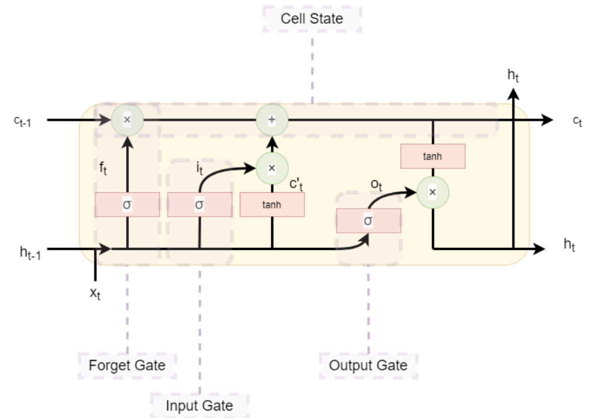

Figure 2. Image shows the different gates in an LSTM, and how the information flow occurs. Image Source: [11]

a baseline (value of 100) and the CSV files show a volume that is relative to this baseline for each subsequent day. The first six columns identify the country/region and the transportation type - one of driving and walking. Each subsequent column corresponds to a new day and holds a measure of the mobility with respect to the defined baseline.

Government response data from The Oxford Coronavirus Government Response Tracker (OxCGRT) [6] for different regions quantifies the level of government response in a region for different types of policies - containment and closure policies, economic policies, health system policies and vaccination policies. The policy indices are a measure of the degree to which the government has acted on the relevant indicators. The scales for each policy range from 0-2 to 0-5, but they will all be normalized on a per-policy basis to a 0-1 scale. The augmentation of these features will help the model predict more accurately.

All of the data will be in the form of CSV files and will amount to a total size of 100 megabytes.

5 Model Description

5.1 Data Collection

The data for this project was collected by accessing open-source Github repositories created by the curators of the COVID, mobility, and government policy data (The New York Times, Apple, and Oxford, respectively). The comma-separated value files were downloaded an capable of being used immediately. No web scraping or other data curation methodologies were necessary.

5.2 Mathematical Background

LSTMs are a special kind of recurrent neural networks which can learn long term dependencies. It solves the problem of vanishing gradient during back propagation, that usual RNNs suffer from. A pictorial representation of LSTM is shown in Figure 5. An LSTM uses several gates to regulate the flow of information. These gates primarily decide which information to keep and which to discard. The different gates can be informally named as:

- **Forget Gate:** Deciding what information needs to be thrown away
$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f)$$
- **Input Gate:** The historical information is passed along with the current input in a tanh function that maps the information from -1 to 1. The sigma function then prunes out the unimportant part from this output.
$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i)$$
$$c'_t = \tanh(W_c.[h_{t-1}, x_t] + b_c)$$
- **Cell State:** Cell State carries information from the earlier timestep all the way to the last timestep with modification at each timestep, deciding on what to discard and how much to update.
$$c_t = f_t \times c_{t-1} + i_t \times c'_t$$
- **Output Gate:** The output simply decides what information should the hidden state h_t should carry. The hidden state contains information of the previous inputs
$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \times \tanh(c_t)$$

6 Results

6.1 Overview

We attempt to elucidate whether mobility and policy data is a meaningful addition to the number of COVID-19 cases and deaths in forecasting the number of deaths.

By performing case studies on the different cities, based on the population density, we are able to better understand the relationship between population density, mobility, government policy, and the spread of the disease. Thus, we designed several LSTM models, each with inputs that include a combination of: COVID-19 cases and deaths data, mobility data and policy data. These different combinations have provided insight into the different effects that the mobility and policy data have on the predictions based on the population densities. The results were interesting as we found out that the same feature is enhancing the prediction capabilities of LSTM in one region while making it worse in another.

6.2 Experiments, Observations, and Findings.

We cropped the data-set for the date range of 15^{th} March 2020 to 2^{nd} July 2021. This was done to ensure that all the dates chosen are available as data points in all the data-sets under consideration. Our training data consisted of 90% data points from the above date-range and the remaining 10% was the test data.

6.2.1 Using the data: The data used is that of Deaths, Mobility and Government Policies. To feed the data through the LSTM model, the following steps were followed:

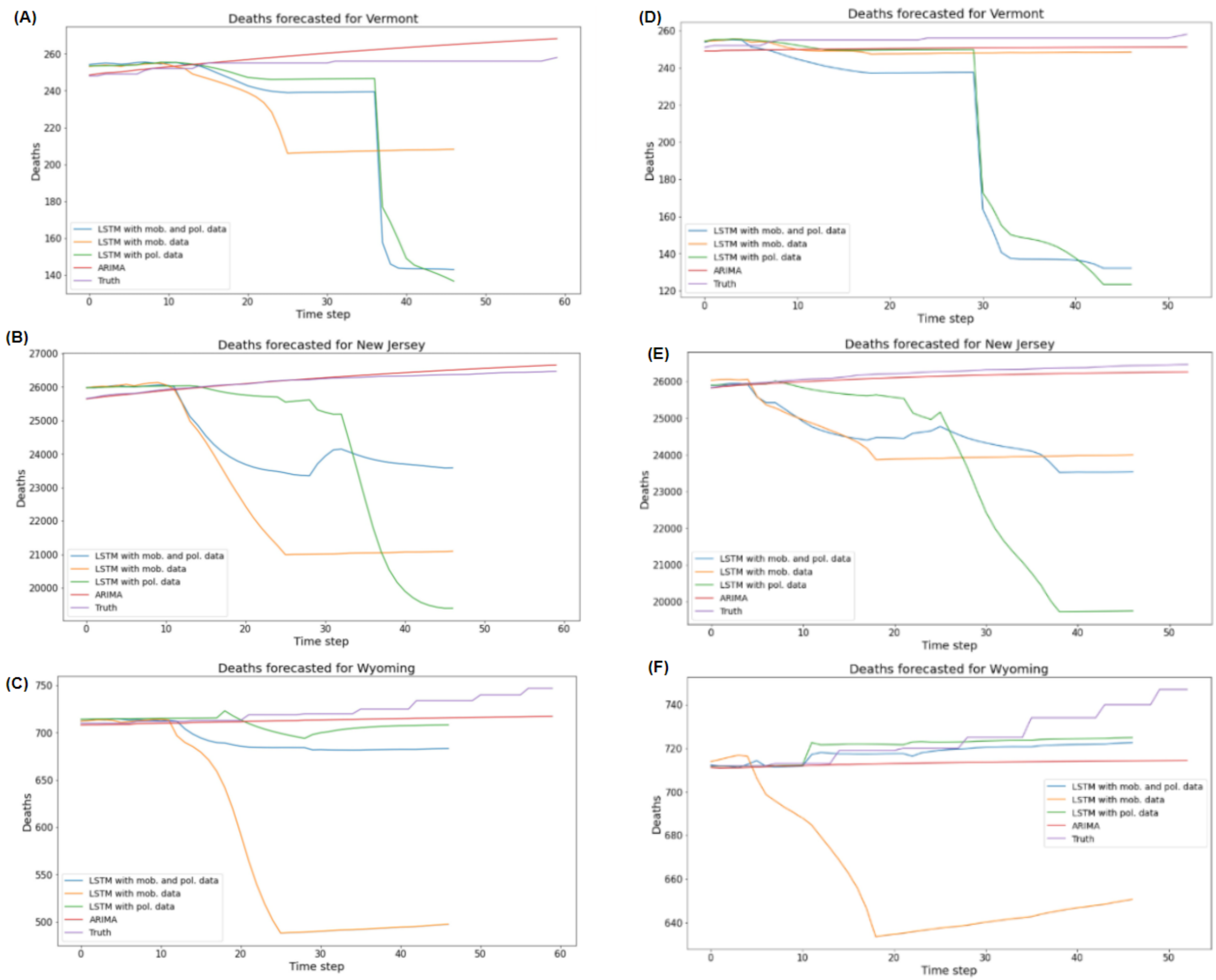

Figure 3. Plots showing the predictions of the models on the test data. Each plot consists of predictions from LSTMs with 3 combinations of features - with mobility and policy data, with only mobility data and with only policy data and from an ARIMA model. (A-C) Deaths forecasted with various models for different regions with a 7-day forecast lead. (D-F) Deaths forecasted with various models for different regions with a 14-day forecast lead.

1. Extracting the desired date-range and the region form the raw data files. Three different regions had three different data-frames.
2. Concatenating the columns of all the data frames to make a single data frame for each region, such that the indices are the dates and the columns are [`Cases`, `Deaths`, `Feature 1`, `..`. `Feature n`].
3. The next step was to normalize the data. Each feature was normalized according to its mean and standard deviation.
4. To make the data appropriate to be fed in the LSTM implementation, we used a PyTorch Dataloader function.
5. The feature shape, fed to the LSTM model is of the size: *(Batch Size)*×*(Sequence Length)*×*(Number of Features)*.
6. It was an important point to note that the shuffle attribute had to be set to `False`, since the data used is sequential unlike a normal machine learning algorithm.
7. A sequence length of 14 was used, which means that for a given date, features from 14 different dates would be used as a feature vector to predict the deaths on that

Region	Forecast Lead	Model RMSE			
		LSTM w/ Mobility and Policy Data	LSTM w/ Mobility Data	LSTM w/ Policy Data	ARIMA
New Jersey	7-Day Forecast Lead	1947.64	2040	3746	**127.89**
	14-Day Forecast Lead	2170.477	4053.862	3235.55	**92.256**
Wyoming	7-Day Forecast Lead	11.654	75.118	**9.86**	15.613
	14-Day Forecast Lead	40.576	178.833	23.213	**13.496**
Vermont	7-Day Forecast Lead	71.92	6.817	69.427	**4.845**
	14-Day Forecast Lead	52.377	34.77	49.752	**6.384**

Figure 4. Table presenting the RMSE for different models, forecast leads, and regions. The ARIMA model tends to significantly outperform the LSTM models.

given date. Now for the set sequence length, the forecast lead was set to 7 and 14. This means that to predict the value at t_k, we use the sequence $\{t_{k-7}, t_{k-8}, ..t_{k-20}\}$ when the forecast lead is set to 7 and $\{t_{k-14}, t_{k-8}, ..t_{k-27}\}$ when the forecast lead is set to 14.

8. Since we are setting a specific sequence length, we need to pad the data for observations which do not have the required length of past history. For this, we used the required number of latest observations from the training set to use as features for the test dataset.
9. Finally the data was passed through LSTM model for generating predictions.

The results of the predictions are shown in Figure 3 for 3 different states. These states were chosen based on varying population densities to attempt to see the difference in importance of mobility and policy data for these states. For each state, we have used different features for the LSTM model. To compare the predictions, we have further used ARIMA to predict the COVID-19-related deaths. The three LSTM models used: cases, deaths, and mobility data; cases, deaths and policy data; and cases, deaths, mobility data, and policy data; respectively.

To compare these predictions with the ARIMA model, we built an ARIMA (p, 1, 0) model where p is equal to the forecast lead. We use a differencing of order 1 to remove any mean-related non-stationarities in the data.

As seen from the graphs, ARIMA model is performing better than the LSTM model, even when we use the mobility and policy data as the input features. This means that due to highly aggregated data, the mobility and policy data is unable to provide any useful insight into the number of deaths due to COVID-19.

Running the LSTM model on different feature lengths also gave us an insight on the importance of the features while predicting COVID-19 cases and deaths. From the results in Figures 3 and 4, we see that incorporating the same feature, say mobility data gives excellent predictions in one region, for example, Vermont, but on the other hand, performed poorly in a different region, for example, New Jersey. In many cases, using a more traditional time-series model such as ARIMA gave better predictions, specially in the regions where the population density is on the higher side. Our results also suggest that the predictive power of the 7-day and 14-day forecast depends highly on the region under consideration as well as the features used.

7 Discussion and Conclusion

7.1 Discussion

Due to the difficulties in obtaining high performance form LSTM models with a irregular time series dataset, we attempted to increase the features input in LSTM to determine if the model becomes more reliable than the simpler models, such as an ARIMA model. However, we believe that in conjunction with the irregularity of the time series data, the additional input features served only as noise to the model, reducing the model's ability to generalize over the testing set.

We have also found the LSTM models with mobility data but no policy data to perform worse than the other models for most regions. This may indicate the size of the region over which we are attempting to forecast may be too large for a small number of mobility metrics to capture, thus only serving as noise to our model. The performance of the LSTM model with mobility data but no policy data may be improved if we were to forecast for a county or city.

7.2 Future Work

LSTMs are a work in progress. Although there have been a lot of work related to epidemic prediction using LSTM (Example: EpiDeep was used to predict flu data [1]), yet LSTM can't be naively applied to a relatively newer pandemic like COVID-19. The data available for Flu prediction is more than decade long. Comparatively COVID-19 data is just months long. Hence, a lot of work is required to make LSTM work to make predictions for epidemics that are relatively new. Some of the directions in which work can be done to further improve the model is listed below:

- A significant determinant in the performance of LSTM models is the regularity of the time series data. Literature has shown irregular time series data results in poor performance for LSTM models [15]. Improved methods for imputing missing values, input augmentation, and time decay factors can improve model performance [15].
- The recurrent neural networks can be improved further by incorporating attention mechanism/transformation models to improve the ability of the model to incorporate the relationship between past observations in the series.
- Increasing the granularity of the data may permit more accurate forecasting, as aggregating data for a large region may lead to a loss of region-specific relationships between the input features.
- When padding the data, repeatedly concatenating the last value of the data to complete the sequence length, may be leading to sub-optimal performance. A more sophisticated measure such as linear regression to extrapolate and pad the missing data to complete the sequence may improve performance.

7.3 Conclusion

In this project, we used LSTM models to predict the COVID-19 deaths for three different regions within the United States. The regions were selected based on the population density and the variation and extent of public policies implemented. We compared the results with the more traditional ARIMA time-series model. The results showed us that the effect of inclusion of the additional features, namely the mobility data and the policy data is not predictable. The impact of their inclusion is different for each region. Additionally, we discovered that traditional ARIMA models perform better than the LSTMs, especially in the regions where the population density is high.

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