United States COVID-19 Hospital Resource Forecasting

Problem

During times of crisis, hospitals, policy makers, and the public need crucial information about how expected need of resources align with existing resources, so that cities and states can best prepare. We will produce forecasts which show hospital bed use, need for intensive care beds, and invasive ventilator use due to COVID-19, based on projected deaths for all 50 U.S. states. These projections are produced by models and data from IHME (Institute for Health Metrics and Evaluation) based on observed death rates from COVID-19, and include uncertainty intervals.

Hypothesis

NULL Hypothesis (H_0): Input time series is stationary
Alternate Hypothesis (H_1): Input time series is non-stationary
The confidence level will be at 95%.

After this is verified by different statistical tests, we will check the forecasts by comparing them with the data given by IHME and see how closely they correlate.

Proposed Approach

IHME's database has three columns for each dimension. One representing the mean of the dimension in different locations distributed by date, second having lower uncertainty bound, and third having upper uncertainty bound corresponding to each dimension.
In this database, we are targeting three dimensions:

- All beds - Number of beds needed by day
    - Mean
    - Lower uncertainty bound
    - Upper uncertainty bound
- ICU beds - Number of intensive care unit beds needed by day
    - Mean
    - Lower uncertainty bound
    - Upper uncertainty bound
- Invasive Ventilators - Number of invasive ventilators needed by day
    - Mean
    - Lower uncertainty bound
    - Upper uncertainty bound

All these columns are distributed by location and date. Clearly, each of these columns form a time-series with time being represented by date column and value being represented by each of the above mentioned columns.

The proposed idea is to use time-series forecasting using ARIMA and SARIMAX in order to see how many COVID beds, ICU beds, and invasive ventilators will be needed in the coming year and how far the predicted upper and lower forecast values go from the given upper and lower uncertainty bounds in the dataset.

Also, I will be predicting the mean values of each of these dimensions for the upcoming three months, which will then help us and authorities prepare for additional amenities that should be available in times of need.

Evaluation (Testing for Accuracy)

For accuracy testing, we will implement the following:

- Comparing the observed data points and forecasts, as well as calculating the Mean Squared Error and Root Mean Squared Error. The less they are, the better the model.
- Running model diagnosis and observing the Q-Q plots and observing how much closer the points are to the theoretical quantiles, histogram of forecasts and residuals and seeing if they're having normal distribution.
- Checking the Akaike Information Criterion (AIC) value. After running grid search, the parameters which have lowest AIC value corresponding to them will be used for model building.
- After executing the above, I can then obtain quarterly, biannual, or annual forecasts and compare the already acquired data from the source for upcoming months and compare the same with the forecasts derived from the model.

Data Wrangling

What kind of cleaning steps were performed?

- First, checking that the data was distributed on the basis of states inside the US. I wanted to see the figures of the US as a country, so I removed this column and grouped the data by date.
    - For mean, I aggregated the mean columns by grouping them by date and taking the mean of the mean columns.
    - For the upper uncertainty bound, I grouped by date and aggregated it as sum.

    - For the lower uncertainty bound, I grouped by date and aggregated the column as sum.
- The next step is to look for any missing values now.
    - Firstly, I checked the distribution of each of these columns and saw what shape each of them were taking.
    - If the distribution was normal, I did missing value imputation by mean. That is, I replaced the missing values with the mean of the other values of the same column.
    - If the distribution was skewed, I replaced them by median.
- Then, I looked for any outliers.
    - I did box-plot analysis of each of the columns and saw if the columns were having values which were lying outside of the whiskers.
    - If yes, I took out the quantiles corresponding to each of these columns and replaced the outliers with the most optimum quantile values - generally, it's 96 percentile value in case of outliers above upper whisker and 4 percentile value in case of those below lower whisker.
    - I also used z-scores to handle them. I replaced all values having z-scores above +3 or below -3 with +3 and -3 respectively.

How did you deal with missing values and outliers, if any?

- Firstly, I checked the distribution of each of these columns and saw what shape each of them were taking.
- If the distribution was normal, I did missing value imputation by mean. That is, I replaced the missing values with the mean of the other values of the same column.
- If the distribution was skewed, I replaced them by median.
- Also, I used Imputation Using Multivariate Imputation by Chained Equation (MICE) and then saw which of the three methods were giving me better results and chose that method.

Were there outliers, and how did you handle them?

- I did the box-plot analysis of each of the columns and saw if the columns were having values which were lying outside of the whiskers.
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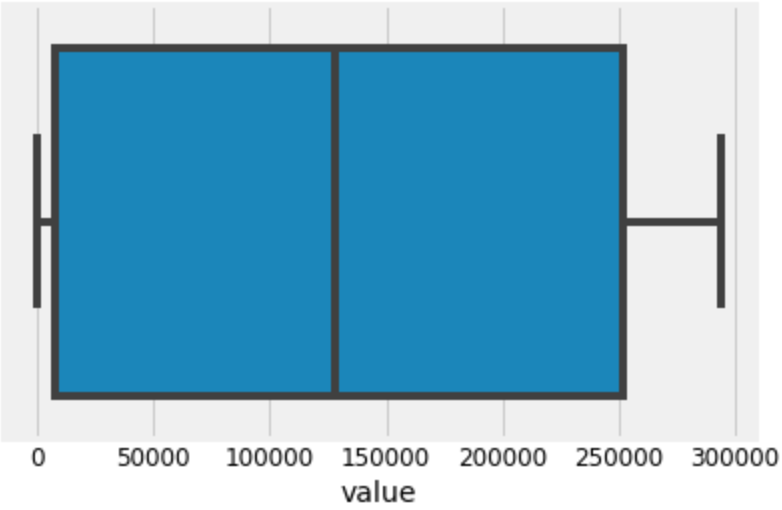


- I also used z-scores to handle them. I replaced all values having z-scores above +3 or below -3 with +3 and -3 respectively.
    - After executing z-score, every value has z-score less than +3 or greater than -3. Thus, no outliers are present in the data.

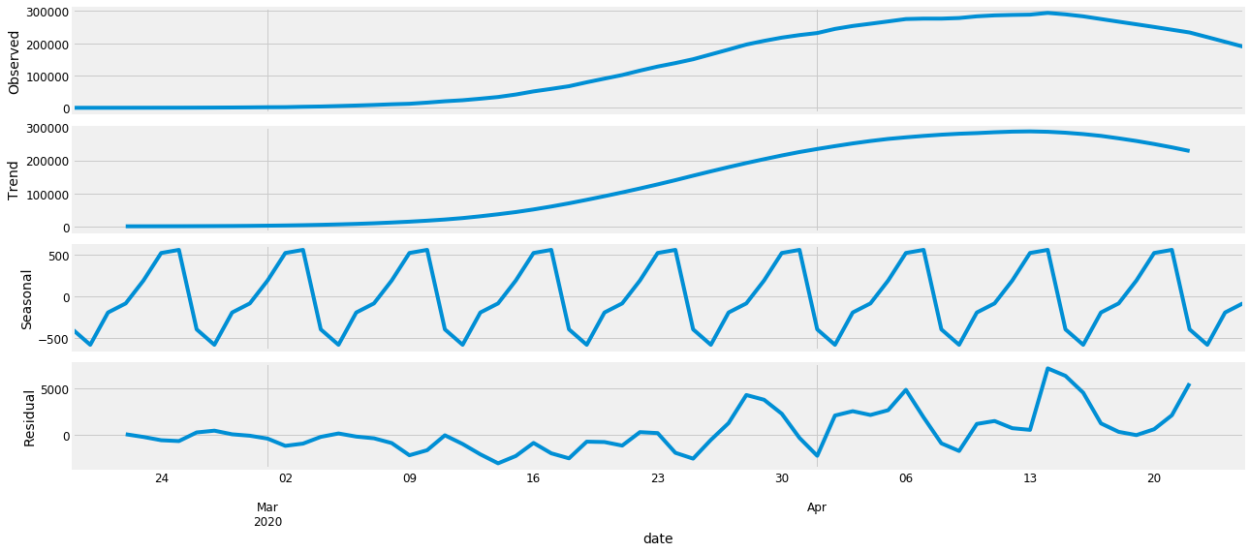
Statistical Data Analysis

Extracting Time-Series from Dataframe

We first need to extract the dataframe of all three dimensions (All Beds, ICU Beds, Invasive Ventilators) and convert them into a time-series. When extracted, plotting to begin visualization of said data showed that the time-series stays close to 0 need of resources till the end of February 2020, and begins increasing after that. It keeps on increasing till mid April where it reaches the highest point and then begins decreasing.

Decomposing the Time-Series

Now that we've visualized the data, we need to be able to identify and filter through its characteristics. We will use the decomposition model, which will narrow the time-series to the following four components: Observed, Trend, Seasonal, and Residual.

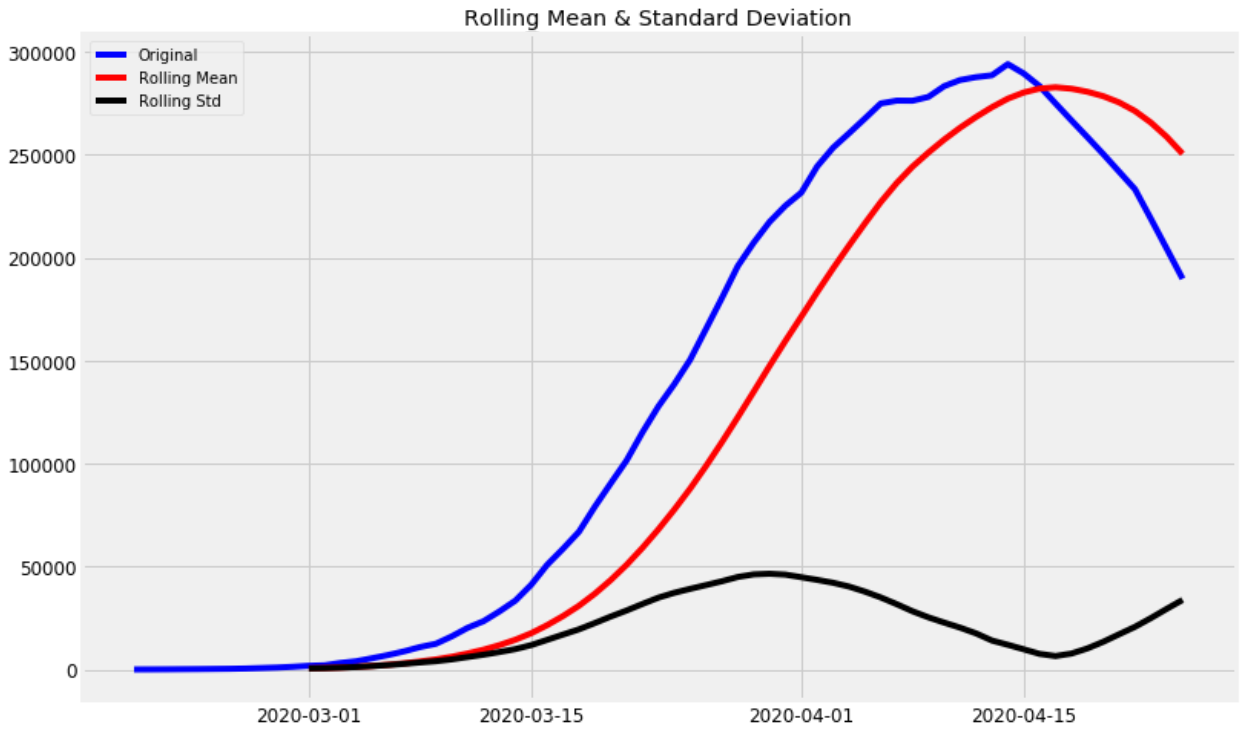


By implementing decomposition model, we can see that besides trend, there is a high amount of seasonality within the data.

Checking Stationarity

In a time series, we know that observations are time dependent. It turns out that a lot of nice results that hold for independent random variables hold for stationary random variables. So by making the data stationary, we can actually apply regression techniques to this time dependent variable.

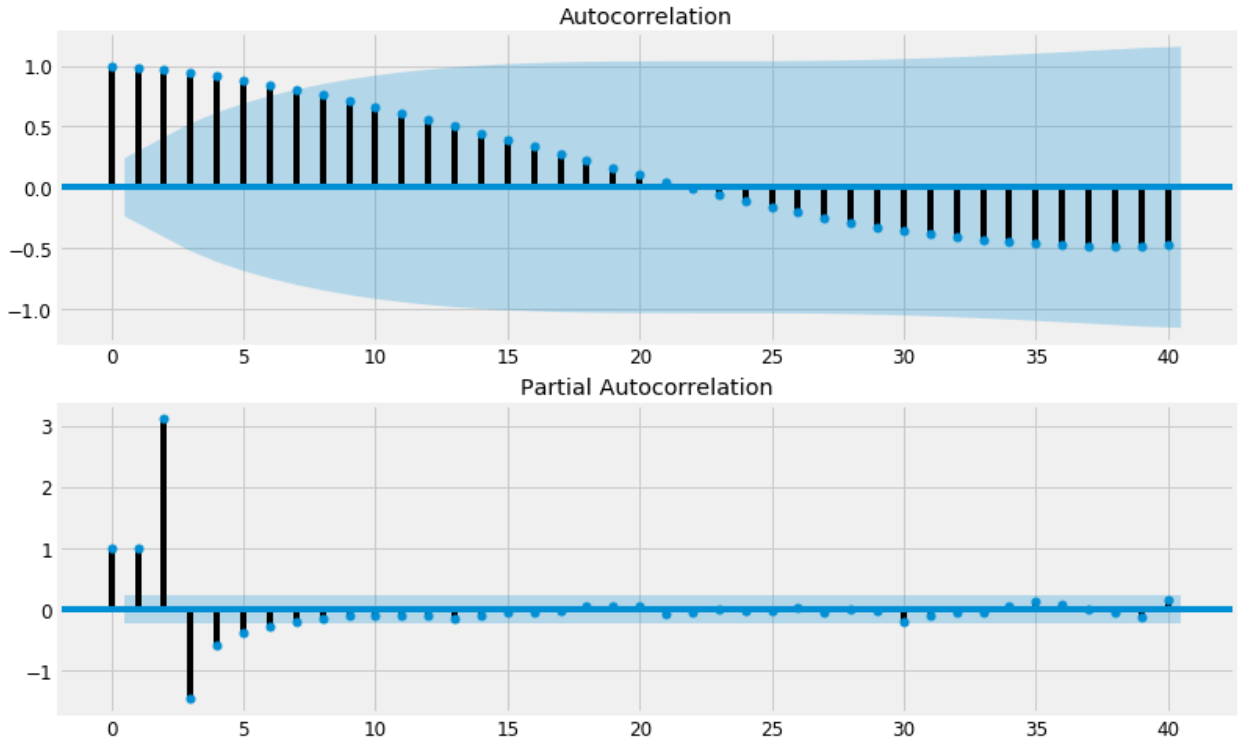
- The next step is to check if the series was stationary or not. A series is said to be stationary if over time, it satisfies following three conditions:
    - Constant mean
    - Constant variance
    - An autocovariance that doesn't depend upon time.
- To check for stationarity, I used two procedures:
    - Plotting rolling statistics
    - Dickey-fuller test
- For plotting rolling averages, I used both simple moving averages and exponential weighted moving averages and saw which of them gave me constant mean and variance and better Dickey-Fuller statistics figure and subtracted the resultant series from the original series to obtain stationary series.
- I also checked for trend and seasonality components and if they're present, I removed them from the original series to get a stationary series since both of them make a series non-stationary.



After determining/plotting the rolling statistic, plotting the standard deviation, and performing the Dickey-Fuller test, we can see that this time-series is stationary with p value of 0.00, confirming the time-series as stationary.

Plotting ACF and PACF

I used acf and pacf functions to find the autocorrelation and partial autocorrelation plots to obtain q(acf lag) and p(pacf lag) values by looking at the lags where each of these charts cross the upper interval for the first time.



Since seasonality is also present in the data as can be seen from above graphs, after 15 days, we're seeing some sine wave like pattern, let's consider SARIMA.

Acknowledgements

1. IHME: COVID-19 Projections. (2020). Retrieved May 3, 2020, from https://covid19.healthdata.org/united-states-of-america
2. Hyndman, R. J., & Athanasopoulos, G. (2018, May 6). Forecasting: Principles and Practice. Retrieved May 10, 2020, from https://otexts.com/fpp2/arima.html
3. Perktold, J., Skipper, S., & Taylor, J. (2019). SARIMAX: Introduction¶. Retrieved May 10, 2020, from https://www.statsmodels.org/dev/examples/notebooks/generated/statespace_sarimax_stata.html