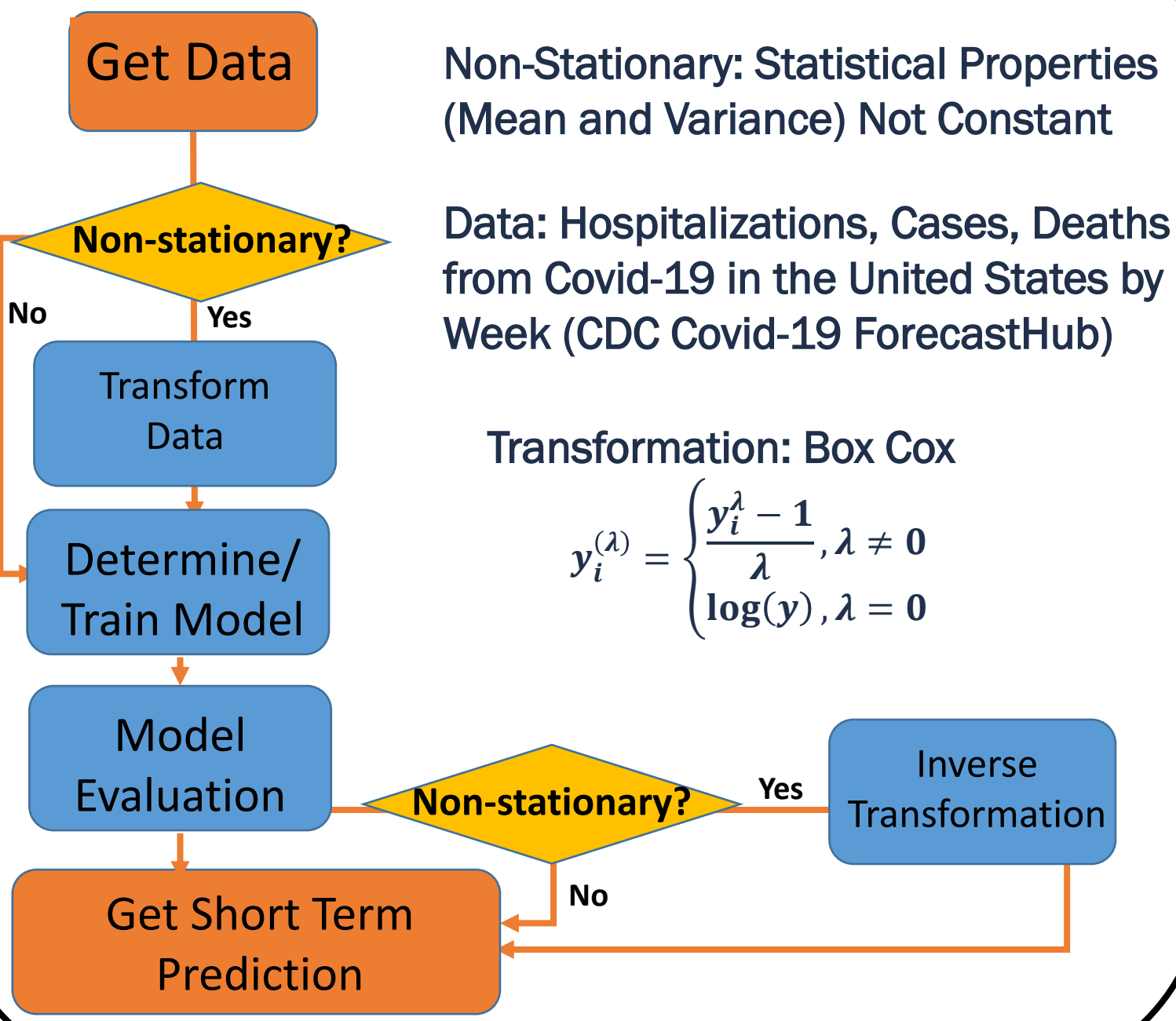


# Multiple Covid-19 Time Series Forecasting

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## Background and Process



## Seasonal Models

ETS: Separates Model into Trend and Seasonal Components and Uses Residuals as Error  
SARIMA: Same as ARIMA but Accounts for Seasonal Patterns  
Little to No Seasonal Component in Covid-19 Time Series  
Can Only Forecast Univariate Time Series

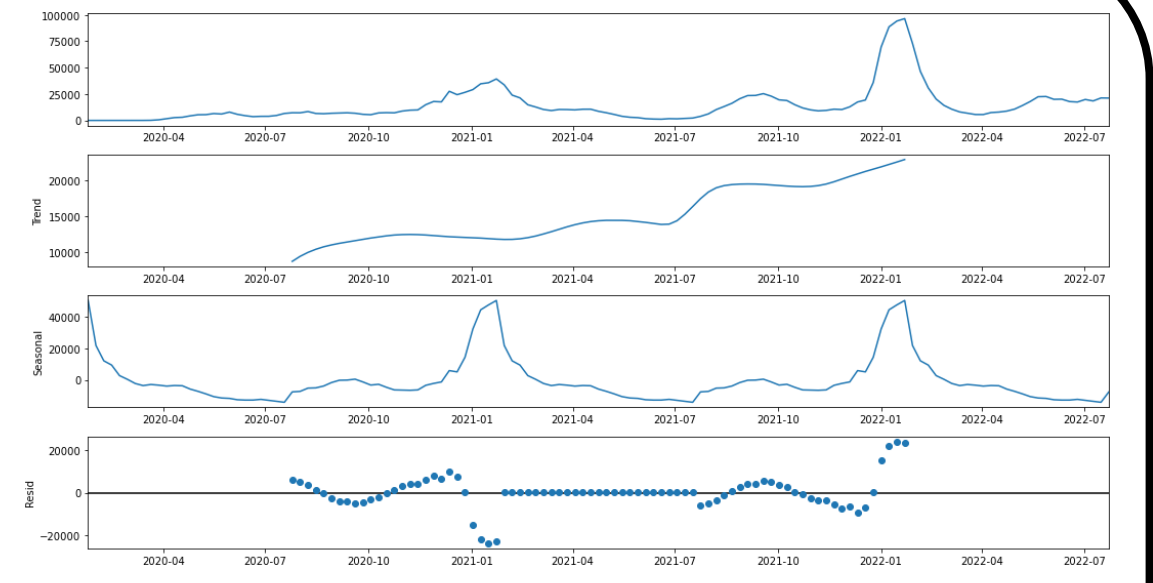
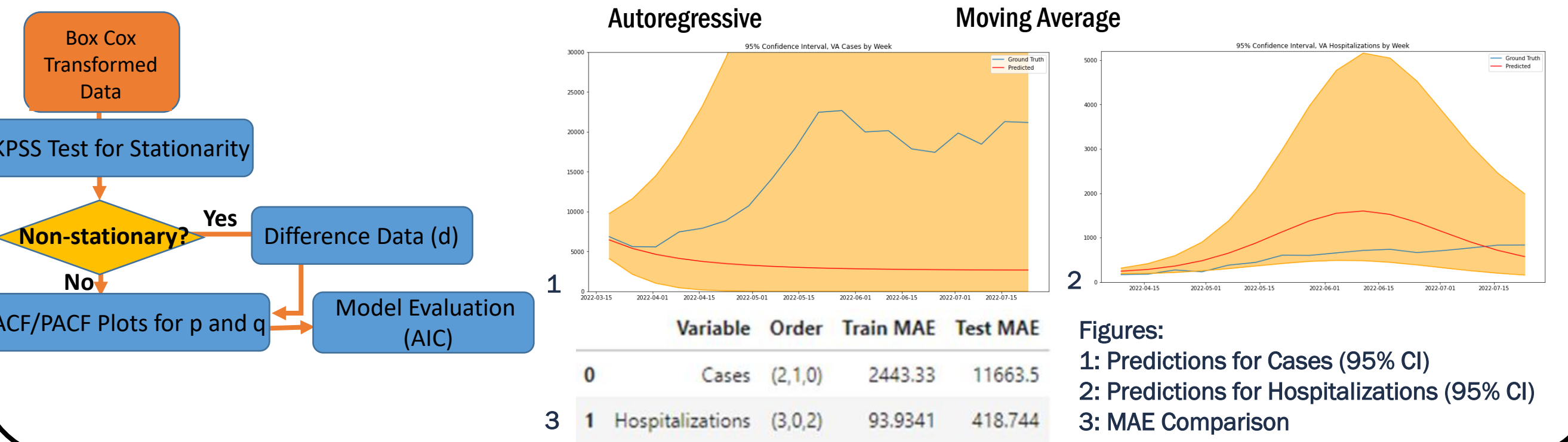


Figure: Covid-19 Cases (Virginia) Broken into Trend, Seasonal, and Error Components

## ARIMA(p,d,q) $y'_t = c + \phi_1 y'_{t-1} + \dots + \phi_p y'_{t-p} + \theta_{t-1} \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q} + \epsilon_t$



## Current Project

Forecasting Multiple Time Series Simultaneously for Covid-19

### Models Used:

- ETS - Error, Trend, Seasonality
- ARIMA - Autoregressive Integrated Moving Average
- SARIMA - Seasonal Autoregressive Integrated Moving Average
- VAR - Vector Autoregression
- LSTM - Long Short-Term Memory (Recurrent Neural Network)

Evaluating Using Probabilistic Forecast  
Using Intervals for Prediction Instead of Points

## Future Work

- Using Models to Forecast National and Other States' Covid-19 Cases
- Further Exploration of VAR Model for Modeling Three Time Series at Once (Deaths)
- LSTM Models with Covid-19 Deaths (Both Separate from and Joined with Cases and Hospitalizations)
- Determining Waves, Onsets, Peaks with Long Term Forecasts

## VAR(p)

Takes Multivariate Series and Captures Their Relationship Over Time

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix}$$

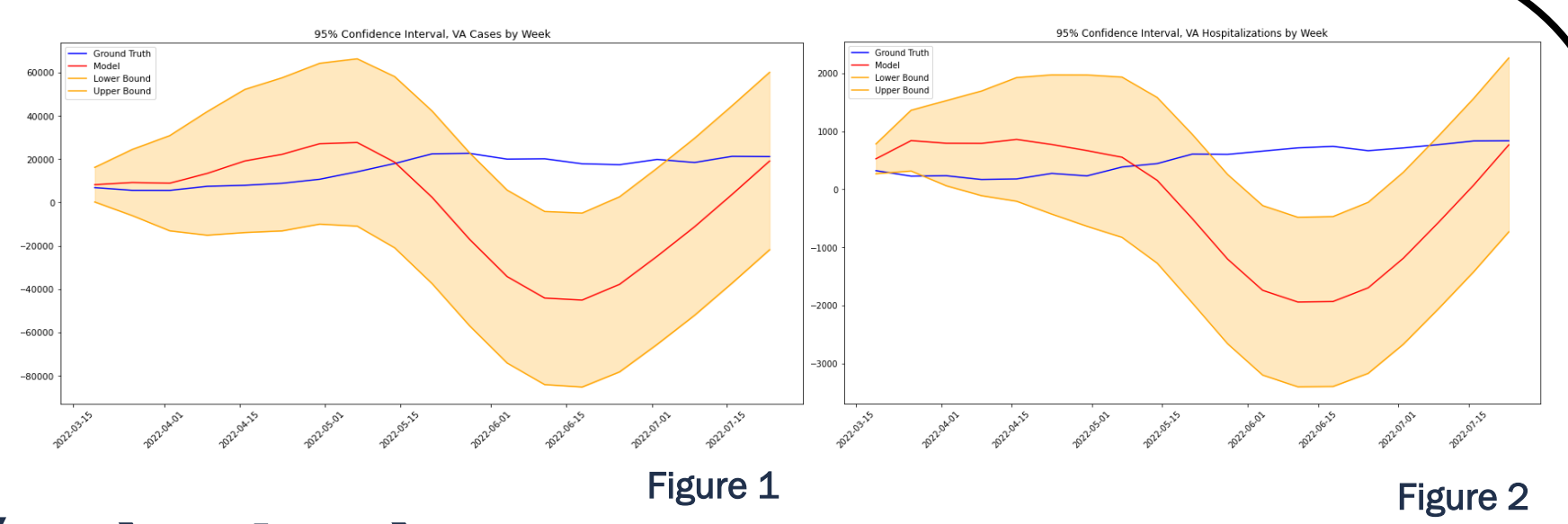
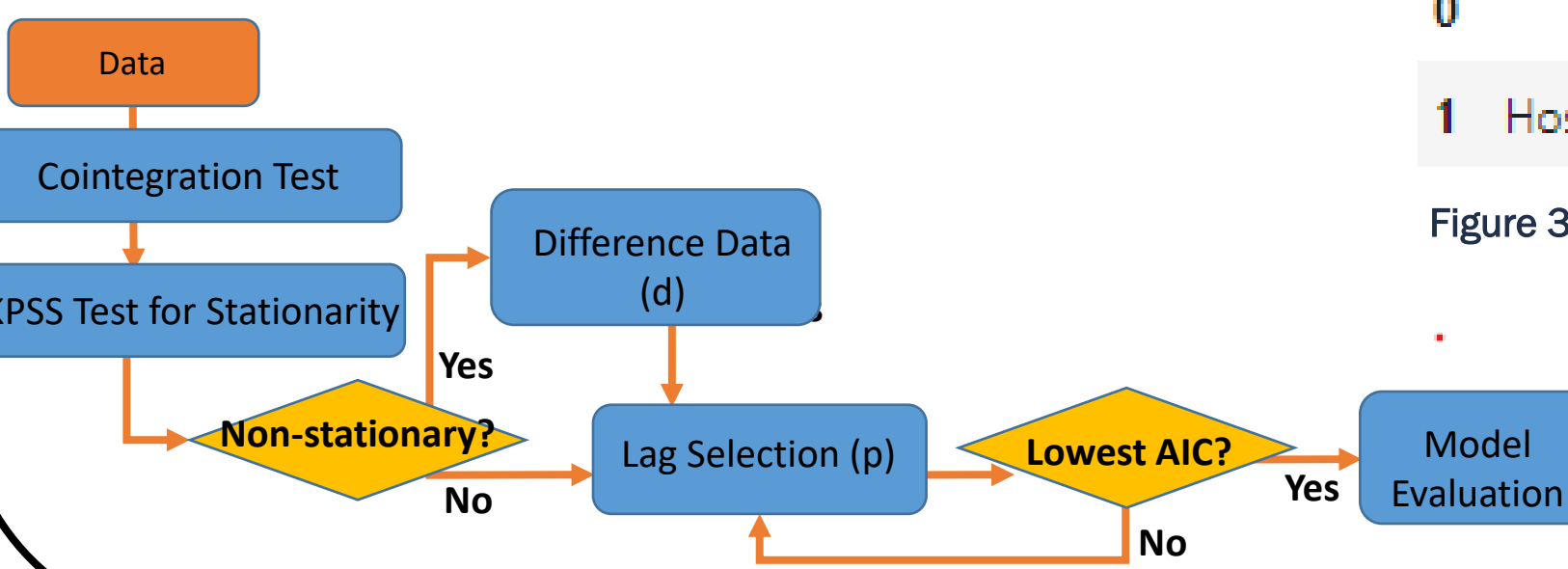


Figure 1

Figure 2

Variable	Train MAE	Test MAE
0 Cases	1956.02	2052.46
1 Hospitalizations	67.1032	70.4928

Figure 3

- Figures:  
1: Predictions for Cases with 95% CI  
2: Predictions for Hospitalizations with 95% CI  
3: MAE Comparisons

## LSTM

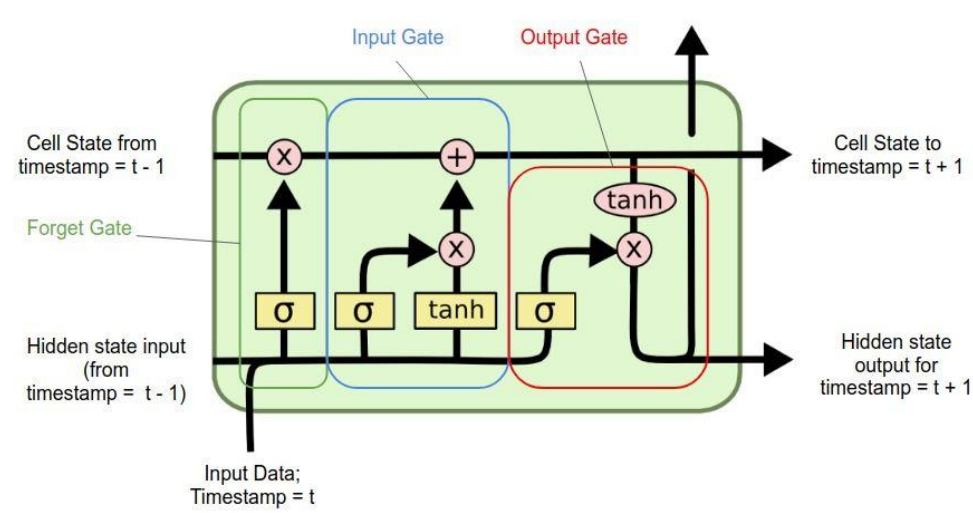


Figure 1: LSTM Model

### Sequential Model

Past Information Flows Through Memory Cell ("Cell State"  $t-1$ ) and "Remembers" Past Information

Current Data Input and Run Through Sigmoid (How Much Information to "Forget")

Data Outputs Through Hidden State And Cell State

Model	Variable	Train MAE	Test MAE
1 (Multivariate)	Cases	2449.86	1859.87
1	Hospitalizations	165.736	187.444
2 (Case Only)	Cases	2451.01	1916.83
3 (Hospitalization Only)	Hospitalizations	80.1825	65.0098

Figure 2: LSTM with Input  $[y_{t-1}, y_t]$

Model	Variable	Train MAE	Test MAE
1 (Multivariate)	Cases	2380.38	1802.63
1	Hospitalizations	132.89	165.176
2 (Case Only)	Cases	1944.93	2126.45
3 (Hospitalization Only)	Hospitalizations	49.3901	70.2071

Figure 3: LSTM with Input  $[y_{t-3}, y_{t-2}, y_{t-1}, y_t]$

Model	Variable	Train MAE	Test MAE
1 (Multivariate)	Cases	2294.07	1832.14
1	Hospitalizations	198.021	352.975
2 (Case Only)	Cases	1056.82	2773.04
3 (Hospitalization Only)	Hospitalizations	49.15	60.2068

Figure 4: LSTM with Input  $[y_{t-5}, y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t]$

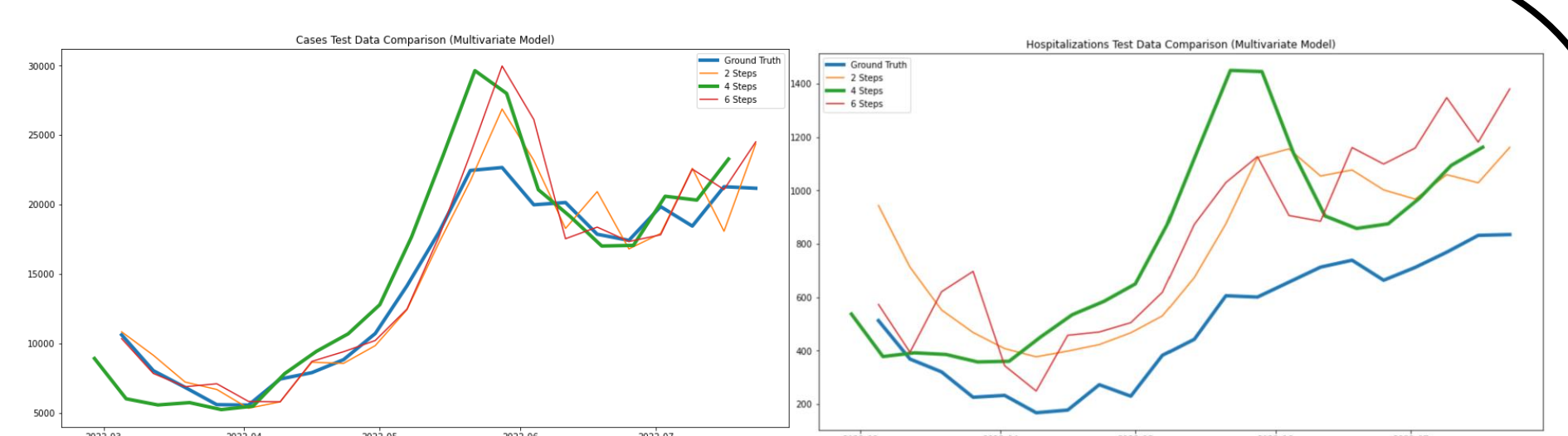


Figure 5

Figure 6



Figure 7

Figure 8

- Figures:  
5: Multivariate Models for Cases (Lowest Test MAE Bolded)  
6: Multivariate Models for Hospitalizations (Lowest Test MAE Bolded)  
7: Case Only Model (Lowest Test MAE Bolded)  
8: Hospitalization Only Model (Lowest Test MAE Bolded)