A Survey of Temporal Data Visualization and Their Applications

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Abstract

Temporal data visualization has been the key to determining the relationship between dependent variables and time. Specifically how they vary over time. Recently, COVID-19 has become a global pandemic and has put the world on hold. Many countries have fighting to combat the virus and decrease the spread. In the midst of all this, scientists have been tracking the number of cases and deaths creating models to forecast predictions on how these numbers will change in the next few months. Temporal data visualization is heavily used today and its applications stretch far and wide but we will be concentrating on its use in combating COVID-19.

1 Introduction

Temporal data visualization has been a staple visualization technique for displaying the change of a continuous variable over time. One common example is visualizing stock prices over time and understanding its ebbs and flows. It helps us track trends over time and assess the performance of different variables.

2 NY Times COVID-19

There are a number of data sets available to visualize the statistics regarding COVID-19 however the NY Times was one of the first few that provided these statistics early on. With that in mind, we were able to extract and parse the number of cases and deaths in the United States. More specifically, we were able to examine the trends present in different states as well as the different counties. With this data set, it was a great opportunity to explore another avenue of temporal data visualization, that being forecasting/prediction models.

2.1 Tools Used

- R
- ARIMA(forecast)
- ggplot2
- calendarHeat

2.2 Data

Figure 1 displays the number of COVID-19 cases in Florida from March 1st to the 31st of 2020. A forecasting model based on the data is calculated

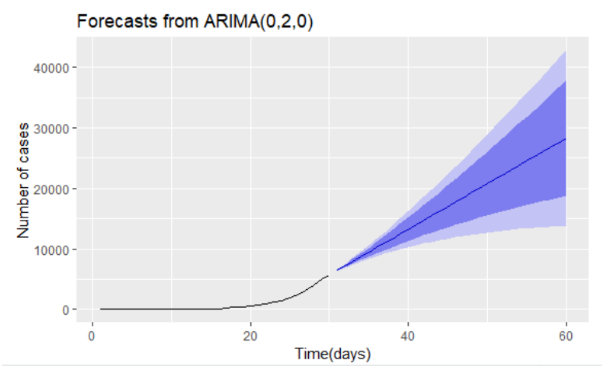

Figure 1: Given the trend in the data, the next 30 days are predicted according to the ARIMA model displaying a largely increasing trend in the number of COVID-19 cases

Figure 2 displays the number of COVID-19 deaths in Florida from March 1st to the 31st of 2020. A 30 day forecast is predicted.

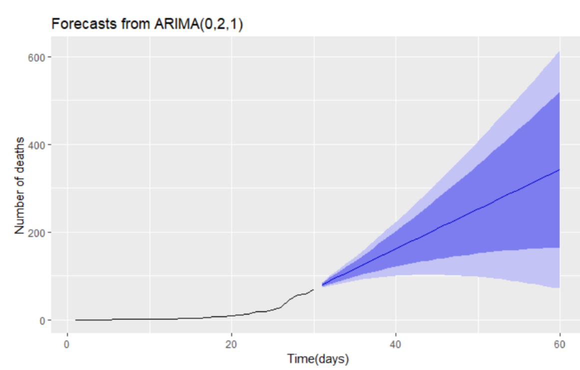

Figure 2: Given the trend in the data, the next 30 days are predicted according to the ARIMA model displaying a increasing trend in the number of COVID-19 deaths

Figure 3 displays the projection in the number of cases for Florida within the next 30 days

	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
31	6446	6348.258	6543.742	6296.517	6595.483
32	7198	6979.443	7416.557	6863.745	7532.255
33	7950	7584.284	8315.716	7390.685	8509.315
34	8702	8166.646	9237.354	7883.247	9520.753
35	9454	8729.127	10178.873	8345.403	10562.597
36	10206	9273.603	11138.397	8780.021	11631.979
37	10958	9801.504	12114.496	9189.291	12726.709
38	11710	10313.968	13106.032	9574.953	13845.047
39	12462	10811.929	14112.071	9938.434	14985.566
40	13214	11296.168	15131.832	10280.928	16147.072

1-10 of 30 rows Previous 1 2 3 Next

Figure 3: Utilizing the ARIMA model, a list of projections for the number of cases in Florida are determined. Lo 80 and Hi 80 refers to minimum projection and maximum projection with 80% confidence respectively. Lo 95 and Hi 95 refers to the minimum and maximum project with 95% confidence respectively.

Figure 4 displays the number of COVID-19 cases in Florida from March 1st to the 31st of 2020 in a heatmap.

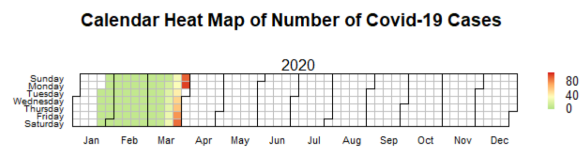

Figure 4: The outbreak of covid-19 cases has reach an all time high during the end of March and it doesn't seem to be stopping any time soon.

3 Temporal Data Visualization Techniques

This section describes some of the more innovative and modern temporal data visualization techniques created in the last few years that have been used to extract patterns and context from time dependent data i.e time series.

3.1 Popup Plots

Popup plots employs a 2.5D plot that allow users to view different aspects of the data through 3D rotation. There are three dimensions to a Popup plot: attributes, landmarks and time. Where time is our independent variable, and the rest are our dependent variables. Attributes concise of measurements such as temperature. Landmarks consist of fixed spatial locations. Different points in time are consider as timestamps. Different aspects of the data can be studied by changing the viewing direction which in turn will change the shape of the data[2]. Here is an illustration of this in action.

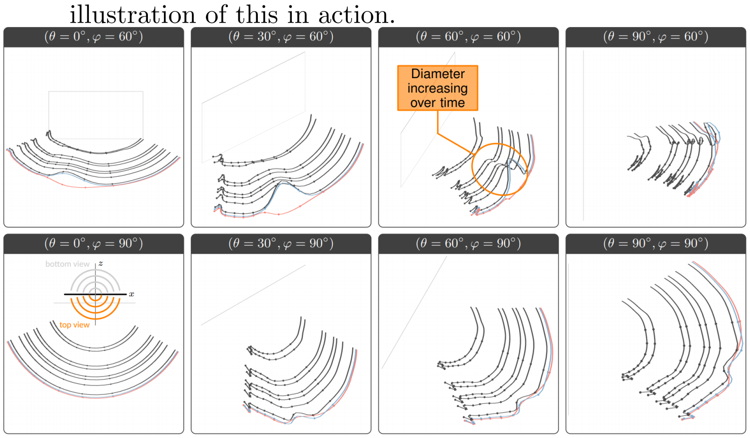

Fig. 7. Medical data set visualized with popup-plots (PPs). We present intrinsic views for the viewing angles $\theta, \varphi \in \{0°, 30°, 60°, 90°\}$ in a 4×4 matrix layout. Starting with $\theta = \varphi = 0°$ in the top-left corner, the columns represent θ, and the rows represent φ. Grid lines as well as labels have been omitted. In this use case the diameter of the aorta was measured at predefined locations. The drastic increase of the diameter (blue) before a surgery, and the intended decrease after the surgical intervention (orange) can be inspected ($\theta = 0°, \varphi = 0°$). Including time shows that the diameter already increased continuously before the surgery ($\theta = 60°, \varphi = 60°$). Generally, it is clearly visible that the patient underwent aortic surveillance, but with large time gaps between consecutive follow-up examinations ($\theta = 0°, \varphi = 90°$). The parameters λ and r have been empirically set to $\lambda = 0.08$ and $r = 320$ to render the images.

Figure 5: Shows the lines changing shape and direction as the user rotates plot(2019, p. 9)

References

[1] Smith, M., Yourish, K, & Allen J. (2020). *Coronavirus in the U.S.* NY Times. https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html

[2] Schmidt, J., Fleischmann, D., Preim, B., Brandle, N., & Mistelbauer, G. (2019). Popup-Plots: Warping Temporal Data Visualization. *IEEE Transactions on Visualization and Computer Graphics, 25* (7), 2443–2457. doi: 10.1109/tvcg.2018.2841385