Time Series Sensitivity Analysis of Population Age Groups in Multi-Horizon COVID-19 Infection Forecasting

Md Khairul Islam [1], Tyler Valentine [2], Royal Wang [2], Levi Davis [2], Zhengguang Wang [1], Timothy Joowon Sue [1], Ayush Karmacharya [1], Matt Manner [2], Luke Neil Benham [1], Judy Fox [1, 2]

[1] Computer Science Department, University of Virginia, USA.
[2] School of Data Science, University of Virginia, USA.
Email: {mi3se, xje4cy, rjw8ng, ljd3frf, zw4re, und2yw, psb7wm, xkv3na, lnb6grp, cwk9mp}@virginia.edu

Abstract

Sensitivity analysis is a popular feature selection approach employed to identify the important input features. This work proposes a novel approach that involves the perturbation of input features using the Morris method in the time-series transformer model. Each input feature is perturbed one at a time and the response of the model is examined to determine the feature's rank. Its efficacy in determining important features for real-world datasets is demonstrated with the COVID-19 forecasting model and this work quantifies the impact of population age groups. We calculated the sensitivity of our trained model to the age group features using the Morris Method and then ranked them based on sensitivity scores. We evaluated this rank with the case reports from the CDC. The results show that our method can predict infections and interpret the more impacted age groups. These results can inform public health policies in preventive with targeted vaccination strategies, to better control future pandemics.

Introduction

AI transparency has received considerable attention and has practical applications such as medicine, policy making, and science. Explaining these models is important to understand the influencing factors, which is essential for developing targeted public health policies and interventions. Interpretable forecasting for COVID-19 mostly used white-box methods (Zhou et al. 2022) or found difficulties evaluating interpretation due to the lack of ground truth (Ramchandani, Fan, and Mostafavi 2020).

We propose a black-box method to interpret the sensitivity of different age groups to COVID-19 disease transmission because it is a critical factor in COVID-19 transmission (Bae et al. 2021). We collected over 2.5 years of daily COVID-19 data at US county-level data, including age groups, vaccination percent, and past infections, then trained the Temporal Fusion Transformer (TFT) (Lim et al. 2021) model on the dataset. TFT was chosen because of its state-of-the-art performance in heterogeneous datasets using special architectures for static, observed, and known-future features. We adapted the widely used Morris method (Morris 1991) for the static feature in our dataset. This provides a simple approach to rank input factors. We collected the weekly infection rate of these age groups from the Centers for Disease Control and Prevention (CDC), shown in Figure 1. This is used to evaluate the interpretation results.

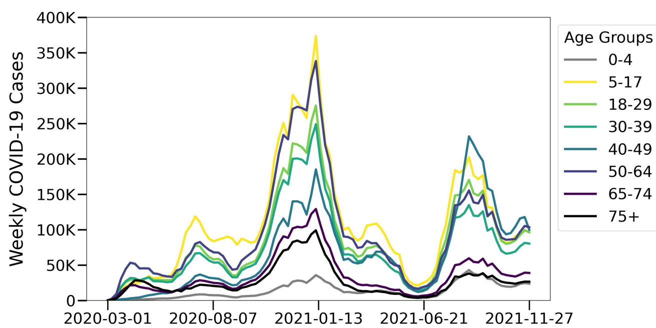

Figure 1: Ground truth: weekly COVID-19 case numbers for each of the eight age subgroups over the study period.

Related Work

Numerous past works have explored various sensitivity analysis methods. Utans et al. (1995) introduced a sensitivity analysis technique that determined a saliency measure for each feature variable, which is the resulting training error after its removal from the model. Gasca, Sánchez, and Alonso (2006) measured the relative importance of each input feature and sought to measure redundant features by finding whether any pair of features reached some benchmark value of correlation.Naik and Kiran (2021) took a complex-step perturbation approach (CSPA) to perform sensitivity analysis and determine the relevant features. Ramchandani, Fan, and Mostafavi (2020) explained the feature interactions in the growth classification of cases by randomizing feature values and ranking them based on performance drop.

Experiments

Methodology

We design a multivariate forecasting model $f(\mathbf{X})$ which each time t uses the last 13 days of data to predict the COVID-19 cases at the daily US county level for the next 15 days. Given a model $f(\mathbf{X})$, Morris Method (Morris 1991) approximates the sensitivity of an input feature x_i using

Equation 1. We then multiply $\mu_i(X)$ with the standard deviation of that feature to consider the temporal nature, this score is referred to as the *Scaled Morris Index* in Figure 2.

$$\mu_i(X) = [f(x_1, \cdots, x_i + \Delta, \cdots, x_k) - f(\mathbf{X})]/\Delta \quad (1)$$

Input Data and Features

We collected COVID-19 data for 3,148 US counties at a daily level from 03/01/2020 to 12/27/2021. The last 15 days and the 15 days prior to that were used for test and validation respectively. We use the percentage of the population in different age groups as a static feature. The eight age groups are listed in Table 1. The dynamic features are the percentage of fully vaccinated people and past COVID-19 cases. The age groups are defined following the age group cases reported by the CDC so that we can evaluate our predicted sensitivity ranking with the actual infection rate.

Feature Sensitivity Analysis

A separate TFT model was trained for each age group with the two dynamic features, for a total of eight models. This separation ensures the identification of a specific subgroup's contribution without the interference of others. Following the methodology in Section , the calculated Morris indices for each delta value are shown below (Fig. 2). We rank the age groups at each delta by their sensitivity scores (rank 1 has the highest sensitivity) and take the average over those different delta values to get the final sensitivity rank for evaluation (Table 1).

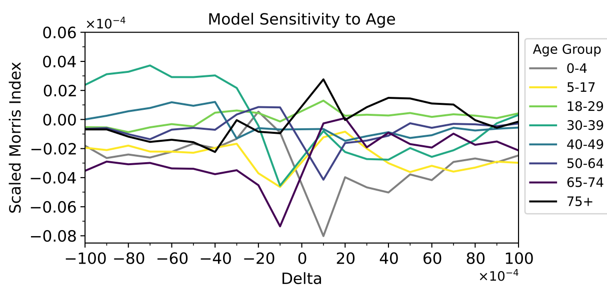

Figure 2: Morris sensitivity scores calculated at intervals of 0.001, excluding zero.

We define the infection rate by, the total infection cases per population for each age group over our study period. Then ranked the group with the most infection rate to 1, and the lowest one to 8. This ranking is also shown in Table 1. Our results indicate that the Morris ranking closely matches the ground truth ranking, deviating at most by 1.5. This verifies our model's ability to accurately identify the vulnerable age group just from the overall COVID-19 cases.

Conclusion and Future Work

A novel sensitivity analysis-based feature ranking method is proposed in this work using a time-series deep learning forecasting model (TFT). Its efficacy on real-world datasets is demonstrated in time-series forecasting and interpretation. We successfully used the Morris method in explaining the sensitivity mapping of COVID-19 infections to population age groups. In the future, we want to extend this to more sensitivity analysis and compare it with other sample-based local interpretation methods to predict the age group sensitivity at any time point.

Table 1: Ranking of the actual and predicted sensitivity of each age group along with the difference.

Age Group (by years)	Infection Rate(%)	Rank		Diff.
		Infection	Morris	
0 - 4	6.4	8	8	0
5 - 17	11.2	6	7	1
18 - 29	18.9	1	1	0
30 - 39	17.2	2	3.5	1.5
40 - 49	16.5	3	2	1
50 - 64	13.8	4	5	1
65 - 74	10.2	7	6	1
75+	11.5	5	3.5	1.5

Acknowledgment

This work is supported by NSF grant CCF-1918626 Expeditions: Collaborative Research: Global Pervasive Computational Epidemiology.

References

Bae, S.; Kim, S. R.; Kim, M.-N.; Shim, W. J.; and Park, S.-M. 2021. Impact of cardiovascular disease and risk factors on fatal outcomes in patients with COVID-19 according to age: a systematic review and meta-analysis. *Heart*, 107(5): 373–380.

Gasca, E.; Sánchez, J.; and Alonso, R. 2006. Eliminating redundancy and irrelevance using a new MLP-based feature selection method. *Pattern Recognition*, 8(2): 313–315. Part Special Issue: Complexity Reduction.

Lim, B.; Arık, S. Ö.; Loeff, N.; and Pfister, T. 2021. Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, 37(4): 1748–1764.

Morris, M. 1991. Factorial sampling plans for preliminary computational experiments. *Technometrics*, 33(2): 161–174.

Naik, D.; and Kiran, R. 2021. A novel sensitivity-based method for feature selection. *Journal of Big Data*, 39(1): 128–144.

Ramchandani, A.; Fan, C.; and Mostafavi, A. 2020. Deepcovidnet: An interpretable deep learning model for predictive surveillance of covid-19 using heterogeneous features and their interactions. *Ieee Access*, 8: 159915–159930.

Utans, J.; Moody, J.; Rehfuss, S.; and Siegelmann, H. 1995. Input variable selection for neural networks: application to predicting the U.S. business cycle. In *Proceedings of 1995 Conference on Computational Intelligence for Financial Engineering (CIFEr)*, 118–122.

Zhou, B.; Yang, G.; Shi, Z.; and Ma, S. 2022. Interpretable Temporal Attention Network for COVID-19 forecasting. *Applied Soft Computing*, 120: 108691.