Interpreting County Level COVID-19 Infection and Feature Sensitivity using Deep Learning Time Series Models

Md Khairul Islam, Di Zhu, Yingzheng Liu, Andrej Erkelens, Nick Daniello, Judy Fox

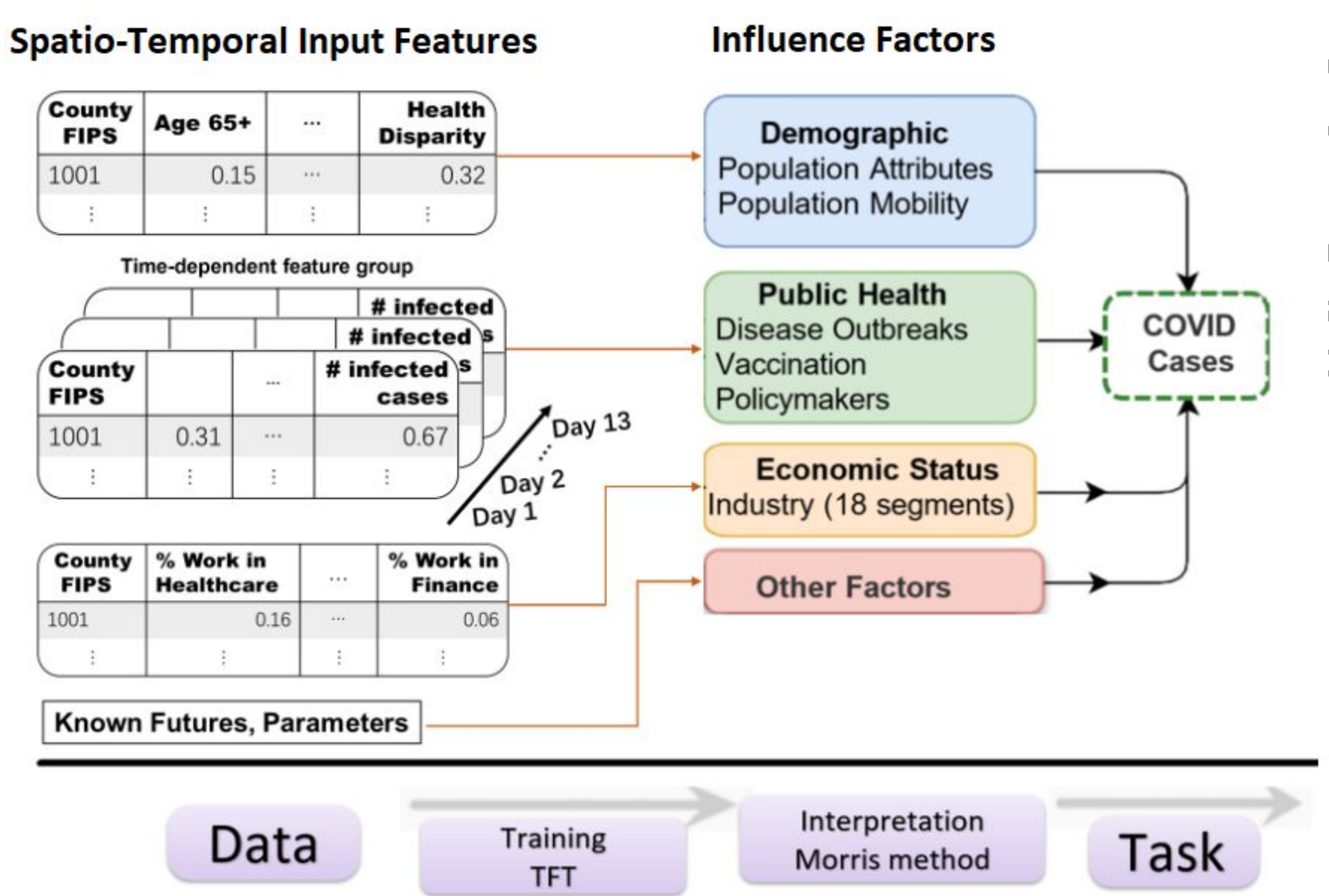
University of Virginia

Abstract

In this work we forecast and interpret the COVID-19 infections using the **Temporal Fusion Transformer** (TFT) [1] model. We collected data over 2.5 years for 3142 US counties, 2 target variables (cases and deaths), and a number of static and dynamic features. We analyze the temporal attention patterns learned by TFT. Then we perform sensitivity analysis with Morris Method [2] to see the model's sensitivity with respect to the input features. Interpreting the disease at a county level will allow administrators to make more precise decisions for the future.

Data Collection and Features

We collect county-level data from multiple sources like CDC, USA facts, NIH. Our workflow is below:

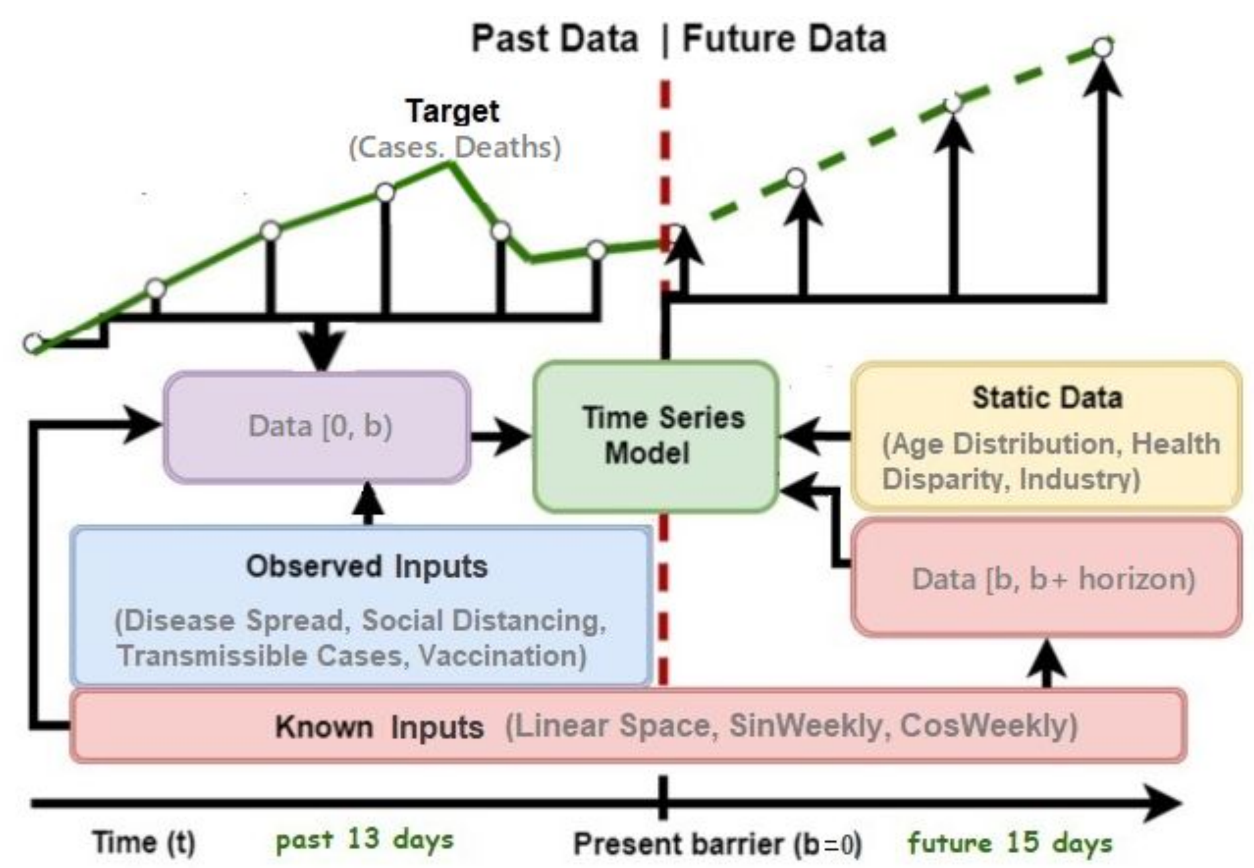


Following is the table for static and dynamic features:

Feature	Definition	Source
Age Distribution	% age 65 and over	CDC SVI
Health Disparities	Socioeconomics status and % uninsured	CDC SVI

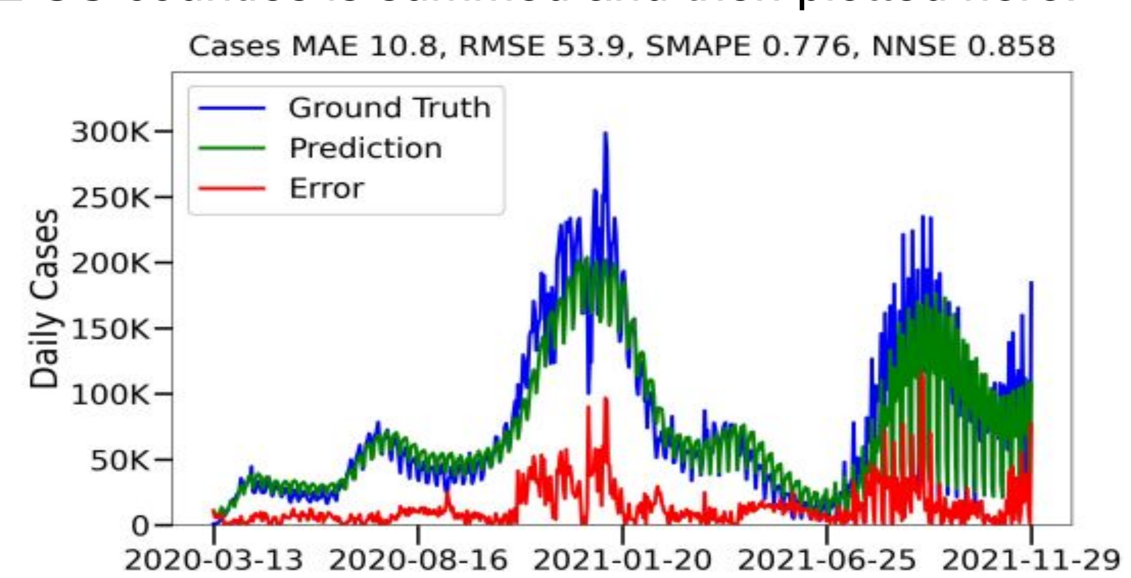
Feature	Definition	Source
Disease Spread	Fraction of total cases from the last 14 days	NIH
Transmissible Cases	Cases from the last 14 days divided by population	NIH
Vaccination	# of population with series completed	CDC
Social Distancing	based on mobility	Unacast. NIH PVI dashboard

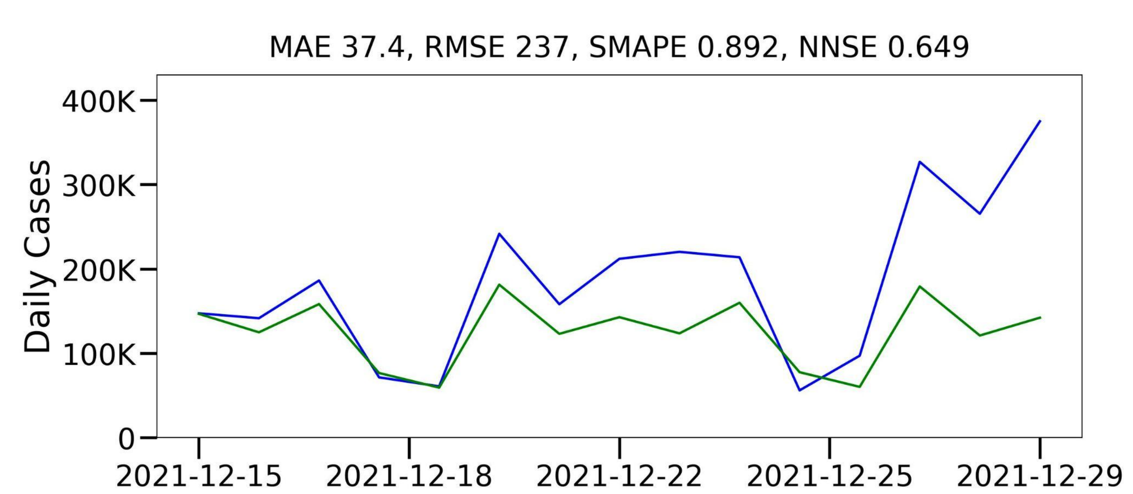
Model Workflow

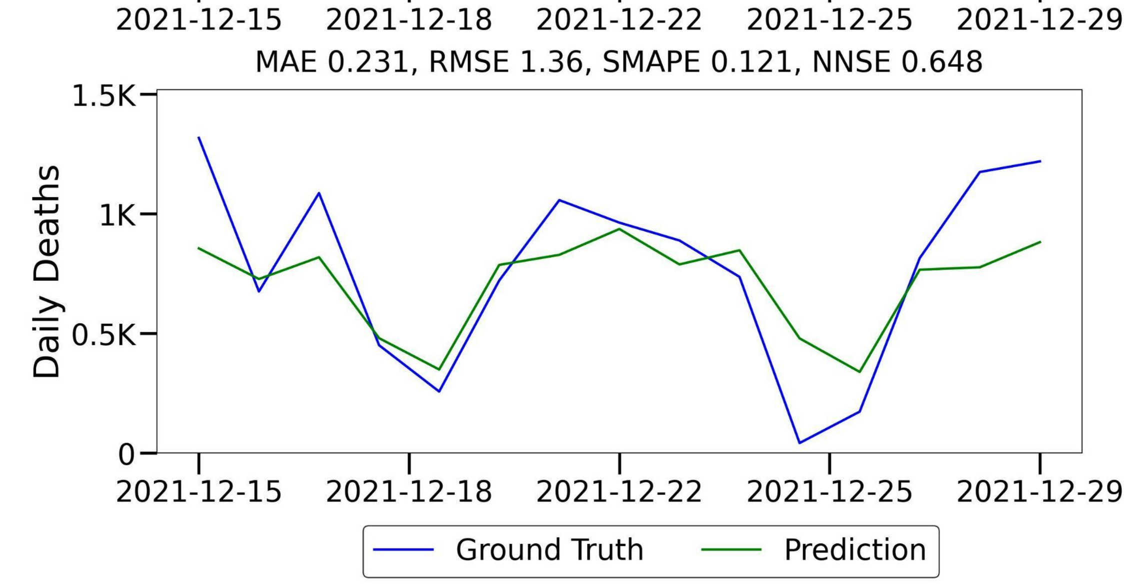


Result

We train our model from 02-29-2020 to 11-19-2021, validate from 11-30-2021 to 12-14-2021 and test from 12-15-2021 to 12-29-2021. Evaluation metrics are calculated at daily county level. Model hyper-parameters are tuned and the predictions from the best model on the 3142 US counties is summed and then plotted here:







Morris Method for Spatio-Temporal Data

Input: $\boldsymbol{X} = \{x_1, x_2, \ldots, x_k\}$, target feature $x_i \in \boldsymbol{X}$ with dimension $[C, T]$, model y, Δ

// $\boldsymbol{X}$ is a set of k input features, Δ is the change to x_i

$\boldsymbol{Y}_\Delta = y(x_1, x_2, \ldots, x_i + \Delta, \ldots, x_k)$

$\boldsymbol{Y} = y(\boldsymbol{X})$

while $t < T$ **do** /* Temporal */

// Loop through 640 Days

while $c < C$ **do** /* Spatial */

// Loop through 3142 US Counties

$G \leftarrow G + |\boldsymbol{Y}_\Delta[c][t] - \boldsymbol{Y}[c][t]|$ /*Total Change*/

$c \leftarrow c + 1$

$t \leftarrow t + 1$

$c \leftarrow 0$

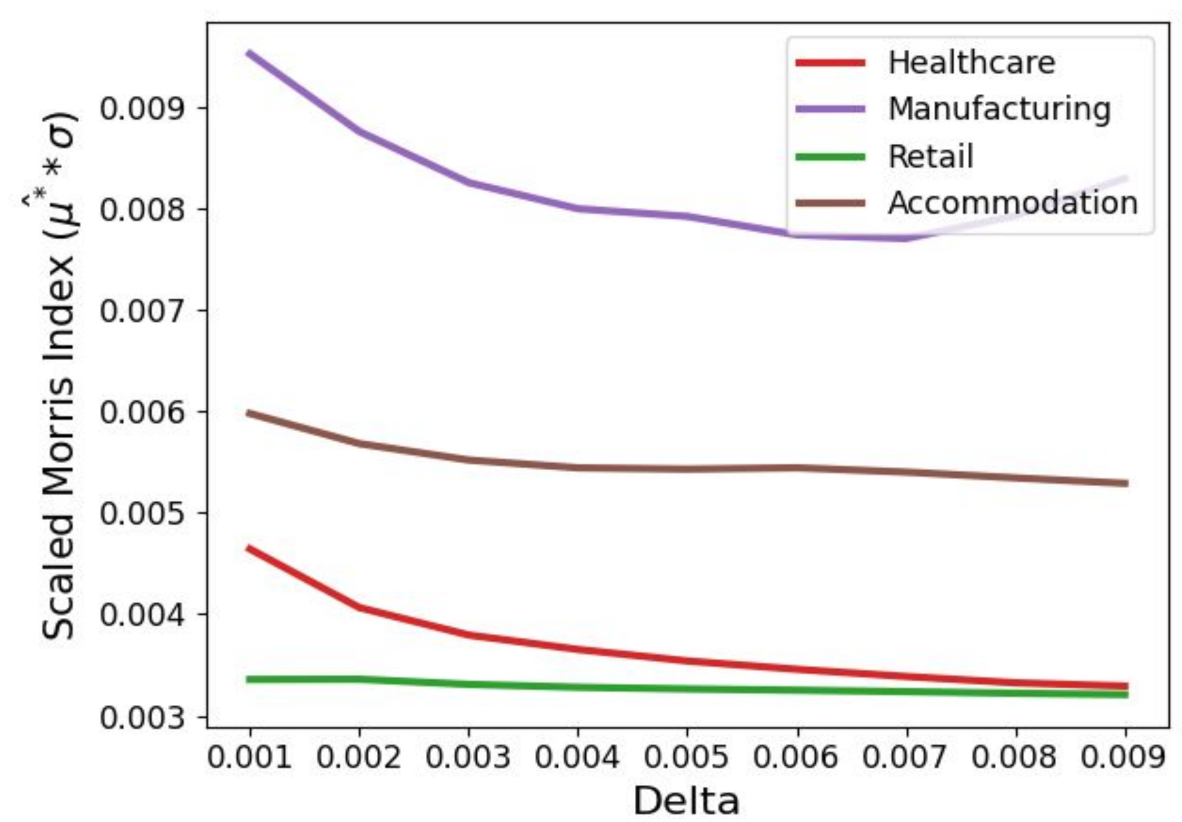
// Calculate normalized Morris Index $\hat{\mu^*}$

$\hat{\mu^*} = G/(C * T * \Delta)$

return $\hat{\mu^*}$

Population by Industry

We stratified the population by industry segments, based on 2017 North American Industry Classification System (NAICS).The population is divided into 18 groups, and we studied the top 4 largest industry segments:

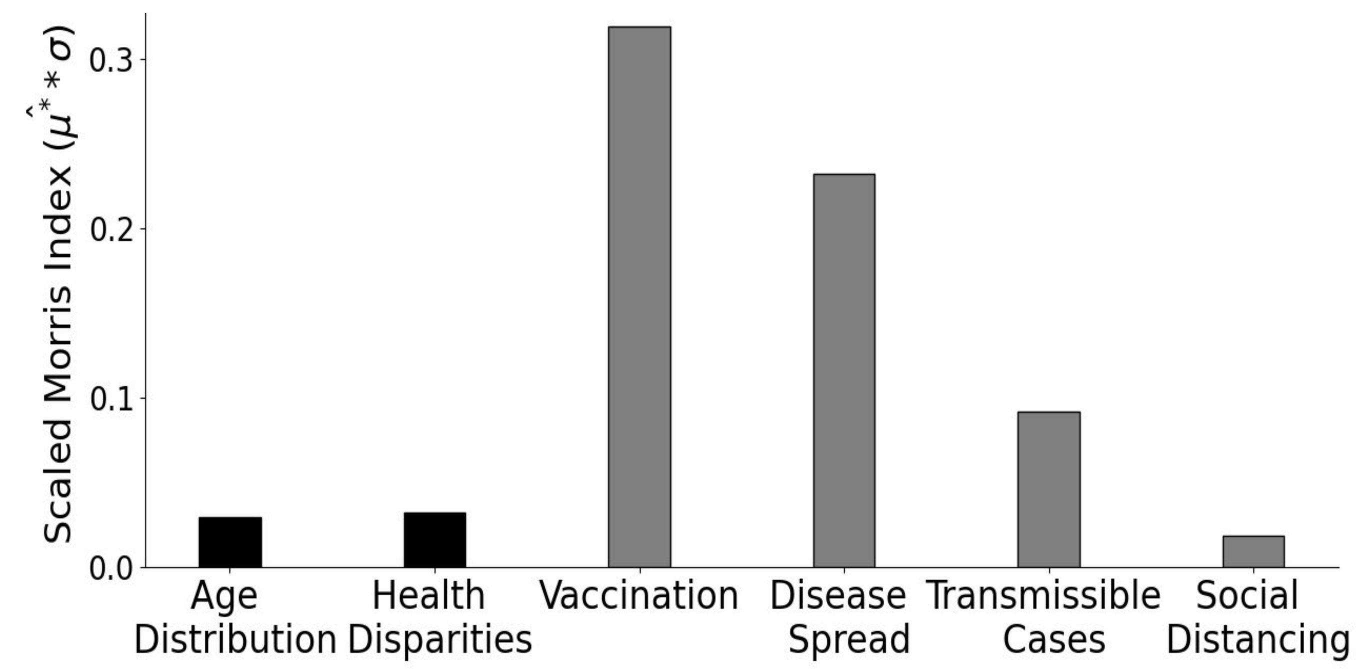


Conclusion and Future Works

TFT works significantly well for learning different trends and events even from very granular data. The feature sensitivity study enable us to look into stratifying the modeling based on population groups, and how that effects administering covid responses to vaccination and other important features. Comparison with other time-series models can be explored in future with more extensive feature set. Sensitivity interpretations could be used to improve predictive accuracy.

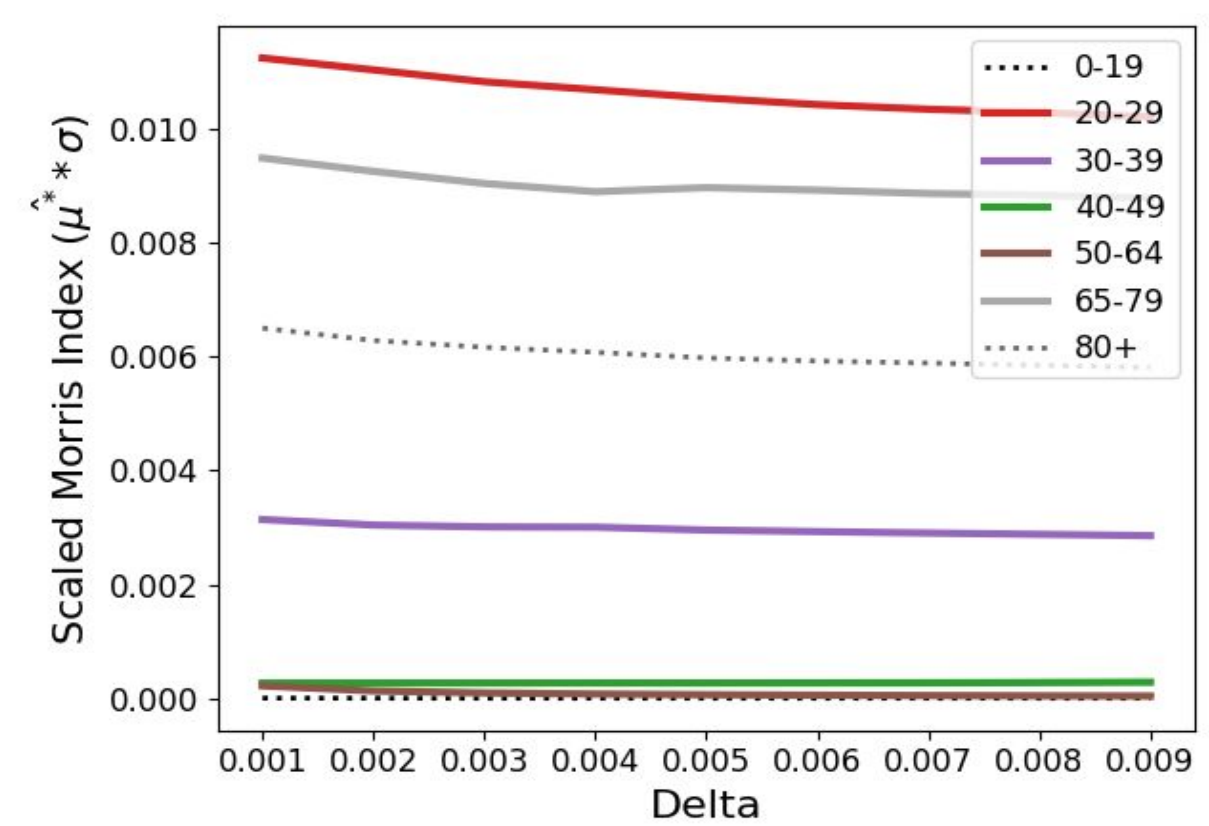
Sensitivity Analysis

We scale the Morris index by multiplying the Morris Index with the standard deviation of each feature. The sensitivity of observed features is shown below.



Population by Age

We divided the population into 7 age groups in accordance with CDC's recent evaluations, and studied the sensitivity of each age group:



Acknowledgement

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References

[1] Bryan Lim, Sercan O. Arik, Nicolas Loeff, and Tomas Pfister. Temporal fusion transformers for interpretable multi-horizon time series forecasting.

[2] M. D. Morris, "Factorial sampling plans for preliminary computational experiments,"

[3] The repository for this work is available at https://github.com/Data-ScienceHub/gpce-sensitivity

[4] The link to our paper: https://arxiv.org/abs/2210.03258