Modelling the Pandemic

Sociodemographic predictors of COVID-19 impact in Chicago neighborhoods

by

Bored Grads Yacht Club

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Group repository: https://github.com/uic-cs418/cs418-spring22-bored-grad-yacht-club

Our motivation for this project

- The COVID-19 pandemic has been a historic, life-changing and terribly unfortunate event in our lives.
- As data science students, we were very interested in the widely available data for this pandemic.
- The main question we landed on through our initial research was:
    - **Is there a way to link COVID-19 impact to socio-demographic data?**
- With our project, we hope to answer this question!

Some definitions

- How do we define sociodemographic data?
  - Physical factors like age, gender, ethnicity etc.
  - Social factors like income, level of education, time spent on public transit etc.
- How do we define COVID-19 impact?
  - Number of COVID-19 cases.
  - Number of COVID-19 deaths.

Where we started off

- We focused on COVID-19 data for the city of Chicago.
- We found an existing COVID-19 risk metric called the CCVI index:
  - This model ranks Chicago neighborhoods on sociodemographic data.
  - Assigns a COVID risk score for each neighborhood based on the rankings.
- A potential flaw with this model is that the score relies on neighborhood rankings.
- For example, 2 neighborhoods could be one rank apart in terms of income, but have vastly different average income compared to the next ranked neighborhood.
- Our model aims to improve upon this index.

Our COVID-19 model

- With our model, we aim to achieve:
  - Quantifiability of COVID-19 impact
    - The model should be able to predict the number of COVID-19 cases/deaths based on socio-demographic data.
  - Accuracy and uniformity
    - The predictions should be based on exact variable values, not rankings.
- Why is this important?
  - Distributing healthcare resources more equitably.
  - Targeting vaccinations.
  - Designing policy to help areas most in need.

Gathering data

- Gathered COVID-19 data and socio-demographic data for Chicago.
- COVID-19 data was collected from the Chicago Data portal:
  - Included COVID-19 case/death data along with the victim’s ZIP code.
- Socio-demographic data was collected from the CensusReporter website:
  - Scraped ZIP code-based data to match granularity of COVID-19 data.

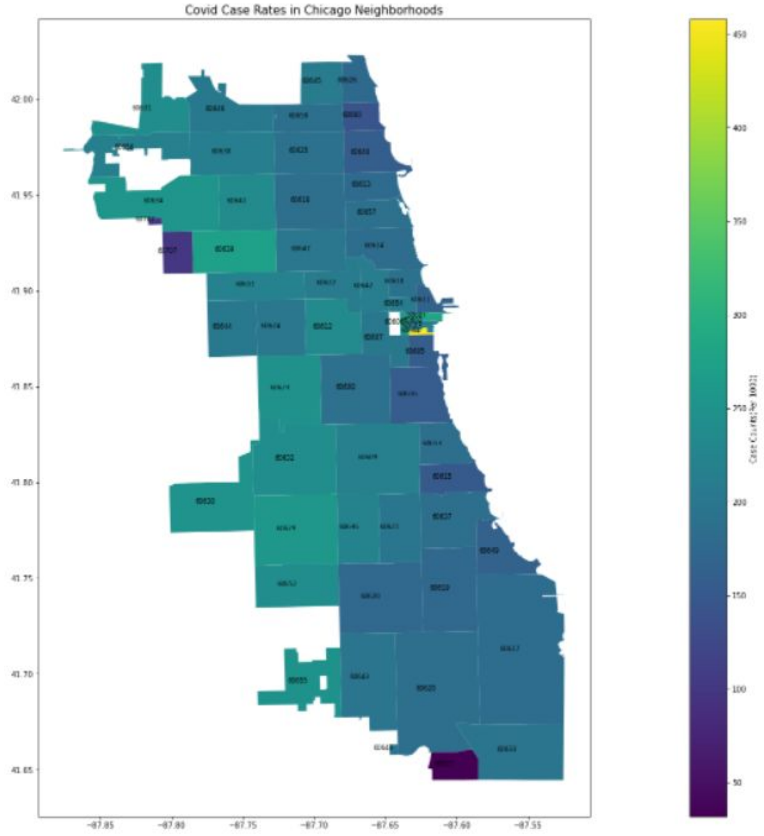
Cleaning data

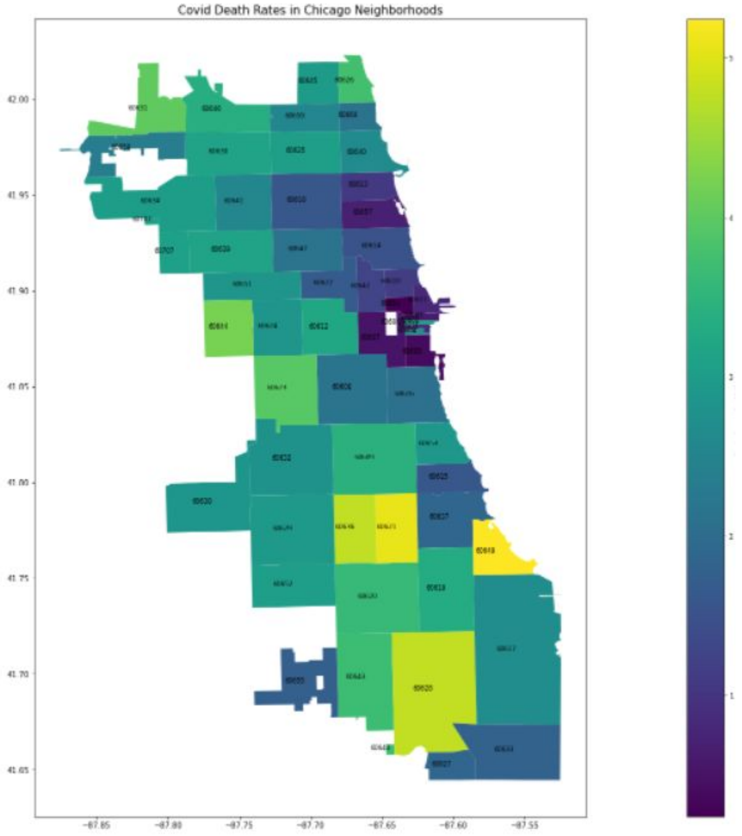
- Cleaned COVID-19 data for Chicago:
  - Removed instances of death where manner of death was accident or suicide.
  - Removed ZIP codes outside of Chicago.
  - Removed unneeded columns.
  - Aggregated cases and deaths per ZIP code.
- Cleaned socio-demographic data for Chicago:
  - Removed unneeded columns
- Merged the datasets:
  - Each line represents a ZIP code with its COVID-19 and socio-demographic data.
- Normalized Covid deaths and cases by each ZIP code's population:
  - Cases/deaths per 1000.

EDA and Visualizations

- For our EDA, we looked at the correlations between different socio-demographic factors and COVID-19 data.
- We created some visualizations to better understand these relationships.

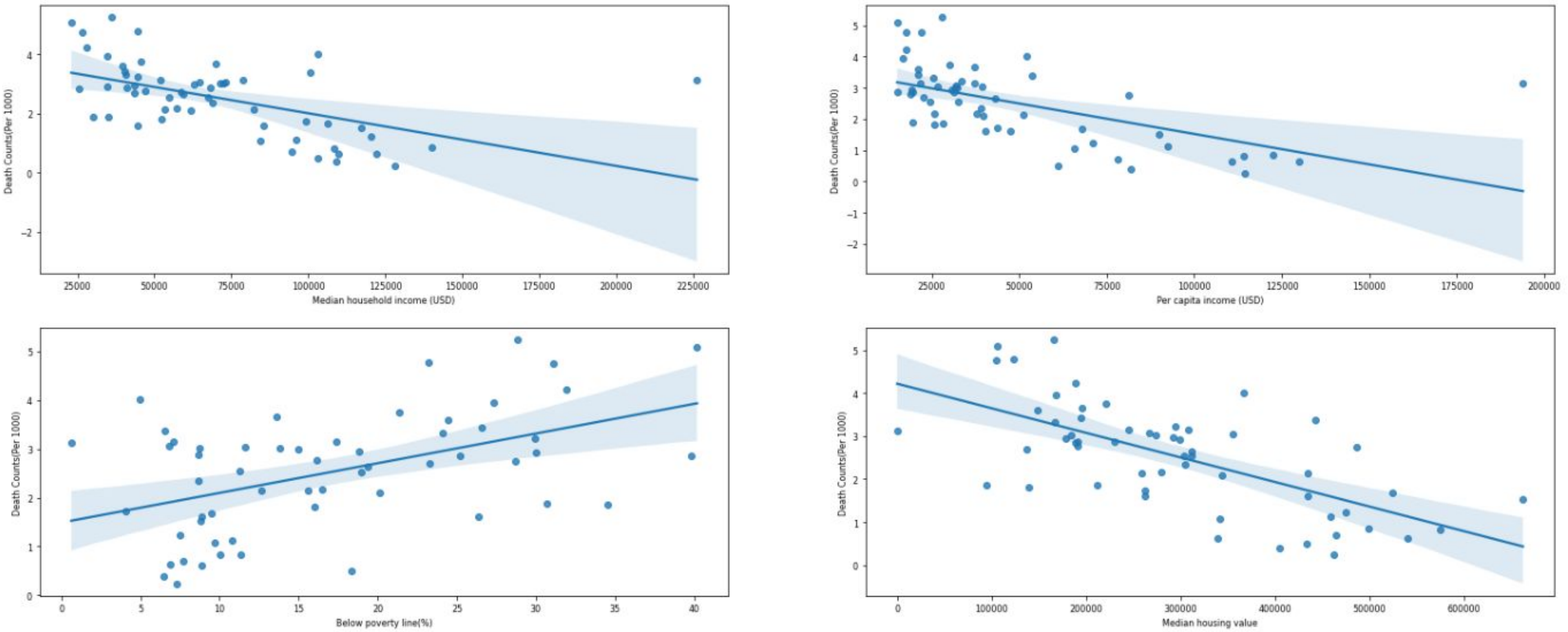
EDA and Visualizations





EDA and Visualizations

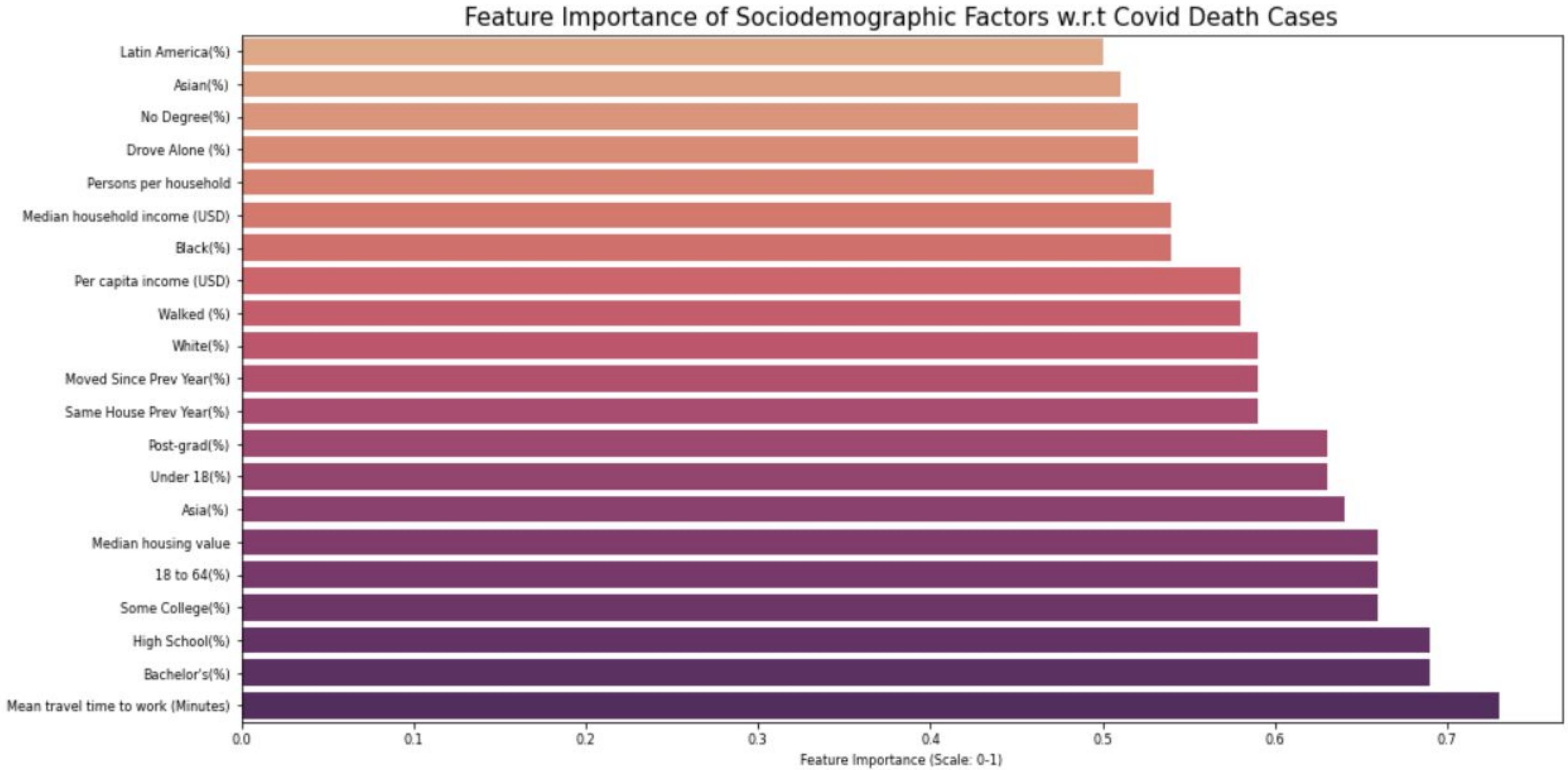
Correlation of Sociodemographic factors with Covid Death Cases



Selecting socio-demographic factors

- We wanted to see which features were most important to predicting COVID-19 cases/deaths.
- The importance (on a 0-1 scale) indicates a correlation between that socio-demographic factor and COVID-19 (1 being the highest correlation).
- We selected features with an importance of above 0.5.

Selecting socio-demographic factors



Random forest regression model

- Baseline model: deaths/1000 equal to median for all ZIP codes.
- Average absolute baseline error = 1.03 deaths per 1000.
- Data split into 70% training data, 30% testing data.
- Socio-demographic factors with correlation coefficients >0.5 were selected.
- Optimizing hyperparameters for RFR:
    - Randomized search strategy across a grid of possible hyperparameter values.
    - Repeated K-fold cross validation, 5 repeats of 2 splits for each randomly-selected combination.
- Average absolute model error = 0.62 deaths per 1000.

Principal Component Analysis

- PCA to visualize the distribution of COVID-19-related death rates across factors.
- Only training data from RFR model was used for this analysis.
- We found a pattern between socio-demographic factors and COVID-19 deaths.
- Substantial amount of noise present in the data.

XGBoost Model

- 70% training data, 30% testing data
- Socio-demographic factors with correlation coefficients >0.5 were selected.
- Average absolute baseline error = 0.96 deaths per 1000.
- Average absolute model error = 0.63 deaths per 1000.

Key takeaways

- 21 of the 48 socio-demographic factors from census data showed strong correlation to COVID-19 impact.
- Some of the most important indicators for COVID-19 impact were:
    - Travel time to work
    - Education level
    - Age
- Principal Component Analysis showed pattern between COVID-19 deaths and socio-demographic factors.
- Our RFR model predicted COVID-19 death rate with an error rate of 0.62 deaths/1000.
- Our XGBoost model predicted COVID-19 death rate with an model error rate of 0.63 deaths/1000.

Improving the model

- Our current model only incorporates 60 ZIP codes.
- We are currently in the process of incorporating more ZIP code based data into our model.
- This new data is from different cities and states in America.
- More data points will allow us to train a more accurate model and reduce our model error rate.