An Unsupervised Machine Learning Approach to Assess the ZIP Code Level Impact of COVID-19 in NYC

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Abstract

New York City has been recognized as the world’s epicenter of the novel Coronavirus pandemic. To identify the key inherent factors that are highly correlated to the Increase Rate of COVID-19 new cases in NYC, we propose an unsupervised machine learning framework. Based on the assumption that ZIP code areas with similar demographic, socioeconomic, and mobility patterns are likely to experience similar outbreaks, we select the most relevant features to perform a clustering that can best reflect the spread, and map them down to 9 interpretable categories. We believe that our findings can guide policy makers to promptly anticipate and prevent the spread of the virus by taking the right measures.

1. Introduction

The World Health Organization has declared the novel Coronavirus as a global pandemic (Organization et al., 2020). NYC is one of the hardest-hit cities worldwide. Lockdown and social distancing have brought urban life to a halt. Based on the current information provided by (Dowd et al., 2020; Garg, 2020; Kraemer et al., 2020), demographic and health characteristics as well as mobility factors can contribute to an increased risk of getting the virus. Therefore, an early identification of the risk-prone areas based on these features is essential. In addition to understanding the link between these characteristics and COVID-19 cases, this kind of studies can be very useful. In fact, NYC can serve as a starting point to model and understand the spread of the pandemic. The obtained findings can be extrapolated to other regions with similar patterns.

The goal of this paper is to determine patterns of ZIP code-level increase in number of new COVID-19 cases in megacities like NYC by combining clustering and feature selection techniques.

2. Motivations

Several solutions have been introduced in order to leverage the existing machine learning tools and tackle many aspects of the COVID-19 crisis (Bullock et al., 2020). Only few of them remain reliable enough to show operational impact (Bullock et al., 2020).

In NYC, most of the existing studies were either limited to a small number of patients (Vaid et al., 2020), (Richardson et al., 2020), or studying the importance of just a few factors for the outbreak (Hooper et al., 2020), (Yadaw et al., 2020).

NYC is one of the most diverse, populous, and population dense cities in the United States. Nowadays, most of the city’s operations are based on data-driven governance and automated procedures. Unlike many other cities, NYC has succeeded over the last few years in making an immense quantity of its data more publicly available and actionable (Howard, 2014). This offers a great opportunity for the data-driven fight against the Coronavirus pandemic. For instance, performing feature selection in this context can be very useful. In fact, NYC can serve as a starting point to model and understand the spread of the pandemic. The obtained findings can be extrapolated to other regions with similar patterns.

Taking these factors into consideration, we propose an unsupervised machine learning approach that, starting from a large set of features that are aggregated from different NYC datasets, aims to identify the key factors that can best model the spread of the virus at the ZIP code level.

This research would also serve as a framework for future studies and accelerate both the geo-modeling and the forecasting of the pandemic’s immanent risk.
3. Dataset and Proposed Approach

3.1. Dataset

Based on previous studies on factors that contribute to an increased infection risk (Dowd et al., 2020; Garg, 2020; Kraemer et al., 2020), we quantify relevant variables from the following datasets:

The US census data for NYC between the year 2013-2018 at the ZIP code level which consists of 177 ZIP codes and 236 features. Some of the features in the Census data include: Basic population characteristics, household composition, household size, etc. This dataset was retrieved from BigQuery\(^1\). The COVID dataset\(^2\) was collected from April 4\(^{th}\), 2020 till May 19\(^{th}\), 2020. This dataset consists of the total number of positive cases per ZIP code for each day. The NYC subway dataset from 2013-2018 was retrieved from BigQuery\(^3\). We calculated and included features for the total number of stations and average ridership per ZIP code. The Citibike dataset\(^4\) from 2013-present includes the start station and the end station along with their respective latitude and longitudes. We calculated and included features for total number of trips to and from each ZIP code for the month of March, 2020. The above-mentioned datasets are merged based on the ZIP code. It is worth noting that another feature called population density is also added. The population density is calculated by dividing the total populations by the land area.

3.2. Proposed Approach

Based on the assumption that regions with similar social and demographic behaviors are more likely to exhibit similar COVID-19 outcomes, we propose to investigate how the daily increase rate of new COVID-19 cases varies across ZIP codes in NYC.

We define our target as the Average Daily Increase Rate (IR) of new COVID-19 cases. For each given ZIP code, IR is calculated as follows:

\[
IR = \frac{\sum_d NewCases(d+1) - NewCases(d)}{N_D}
\]  

where \(d \in Day_1, \ldots, Day_{N_D} - 1\) and \(N_D\) is the total number of recorded days.

IR reflects the degree of acceleration of the spread of COVID-19 cases. We use it to select the most relevant features for our clustering as well as to assign the cluster IDs. Basing our study on this target can help us assess the risk of an outbreak in a given geo-unit.

The main goal of this study is to find the optimal clusters’ partition that better reflects the Increase Rate trends. The proposed unsupervised machine learning pipeline is depicted in Figure 1. After collecting and pre-processing the data as discussed in section 3.1, we perform feature selection using Lasso technique (Fonti & Belitser, 2017) which, by taking into account the target variable, sets the weights of irrelevant features to zero based on \(L_1\) regularization. We also perform RReliefF (Robnik-Šikonja & Kononenko, 1997) which estimates the strong dependencies between features and removes redundancy. The final set of features is then obtained using the union of the two selected subsets.

The optimal selected subset of features is then used for clustering. Afterwards, features within this subset are grouped into different categories (Age, Mobility, Race, etc) which will be embedded into a 1D dimension using t-SNE (Maaten & Hinton, 2008) to better interpret the clusters behaviors. For the reported results, we used k-means clustering (MacQueen et al., 1967). The number of clusters \(k\) was selected based on the Elbow method (Kodinariya & Makwana, 2013).

4. Results and Key Findings

4.1. Results

After performing feature selection and combining the two subsets selected by Lasso and RReliefF, we were able to reduce the original 245 input features to just 150. Next, we...
run k-means clustering using $k = 6$. The cluster IDs are assigned to the different ZIP codes such that they reflect the ranking of the average IR across each cluster’s ZIP codes. That is, we assign the highest cluster ID to the cluster that has the highest average IR. Figure 3 shows the distribution of the Increase Rate within each cluster. Figure 4 depicts how the number of positive cases has changed over time for the obtained six clusters. This plot validates our clustering results in terms of separation and compactness. In fact, the similarity of the Increase Rate between ZIP codes within the same cluster is maintained over time. Moreover, even though the overall behavior is the same across the different clusters, the IR distributions are mostly disjoint.

Figure 2 illustrates the geo-visualization of our clustering results. The map is color-coded based on the cluster IDs assigned to each of the studied NYC ZIP codes. It also reflects the geographical proximity of ZIP codes belonging to the same clusters. Bronx, Staten Island, East Brooklyn and most of Queens belong to clusters 4 and 5 which exhibit the highest IR whereas Lower Manhattan and West Brooklyn belong to Clusters 0-3 which are characterized by a slower spread. Even though our results were obtained based on an unsupervised approach, they still yield a high agreement with the statistics provided by the NYC Health Department which verifies the effectiveness of our feature selection.

Table 1. Factors assigned to the sub-categories of the selected feature subsets

| Category       | Sub-Category                                                                 |
|----------------|-------------------------------------------------------------------------------|
| Mobility       | dwellings, no cars, more than two cars, commuters by bus, commute < 15 minutes, commute > 15 minutes, worked at home, station count, number of inbound trips, number of outbound trips, average number riders |
| Race           | white population, black population, asian population, hispanic population, other race |
| Education      | associates degree, bachelors degree, high school diploma, college < 1 year, masters degree |
| Age and Gender | male population, female population, median age, female < 50 years old, male > 50 years old, male < 50 years old |
| Family         | single, married, divorced, widowed, parents with young children, single parent with children |
| Income         | median income, income < 100k, income > 100k, income per capita |
| Occupation     | employed population, unemployed population, public administration, retail trade, transportation, natural resources construction, armed forces, education health social, manufacturing |
| Household      | households, housing units, occupied housing units, vacant housing units |
| General Demographics | population density |

Figure 3. Boxplots for the COVID-19 Increase Rates as grouped by cluster ID

Figure 4. Distribution of new positive cases per cluster, overtime.

5https://www1.nyc.gov/site/doh/covid/covid-19-data-boroughs.page
4.2. Key Findings

We classify the selected subset of features into 9 categories, which we will be referring to as “factors”, as summarized in Table 1. In order to assess the behavior of these factors inside the different clusters, we then define 9 levels. Each factor level is computed using t-SNE 1D-embedding of all the features within the corresponding category.

This approach aims to improve the interpretability of our findings. For instance, Figure 5 displays the distribution of factor levels within the 6 obtained clusters. We notice that our factors succeed, to a large extent, in discriminating between the different clusters.

4.3. Discussion

Figure 5 represents the gist of our study. Keeping in mind that these embeddings do not reflect the actual weights nor the behavior of the original features, we can only use them as key indicators of which factor needs to be addressed more in order to mitigate the spread in a given geo-unit. For instance, Clusters 4 and 5 (Bronx, some areas in Queens, East Brooklyn and Staten Island) are characterized by a relatively high level of Mobility, Education and Occupation. These zones have a high variability of both the Race and Income factors. These areas also exhibit the highest daily increase of new COVID-19 cases (Figure 3). These trends are almost reversed for areas from Clusters 0-2. Policy makers can refer to this embedding to gauge and eventually predict the behavior of newly affected areas. This framework can be further improved to serve as a risk assessment tool for COVID-19 outbreak. In the appendix we provide the geo-distribution of each of the embedded feature factors across the studied NYC ZIP codes. Readers can refer to those plots for more insights.

Although our approach has shown promising results, it still has some limitations that need to be considered. First, our study is missing one month worth of records. The reason is that NYC Department of Health and Mental Hygiene started releasing COVID-19 statistics at a ZIP code level only from April 1st, 2020 (Goldstein & McKinley, 2020). Moreover, the availability of tests in NYC was disparate and as tests became more widely accessible, the number of positive COVID-19 cases in these areas also increased.

5. Conclusions and Future Work

We propose a model that combines Feature Selection and clustering techniques. Our model successfully maps similarities between ZIP codes based on mobility, socioeconomic, and demographic features with the COVID-19 daily Increase Rate trends.

Further work will investigate the link between IR at the ZIP
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code level and the availability of tests, PPE kits, and hospitals. Our future work will also focus on improving the model by applying other clustering techniques and by investigating more temporal patterns of the outbreak. Furthermore, our selected subset of features can be used to build a predictive model. A GUI can be designed to interactively visualize the weighted contribution of each of the input features to the embedded factors. This framework can further be extended to other regions to identify risk-prone ZIP codes.

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https://covid19challenge.mit.edu/datathon/
Appendix

Figure 6. Geo-distribution of the Race factor level between the different NYC ZIP codes

Figure 7. Geo-distribution of the Income factor level between the different NYC ZIP codes

Figure 8. Geo-distribution of the Mobility factor level between the different NYC ZIP codes

Figure 9. Geo-distribution of the Family factor level between the different NYC ZIP codes
Figure 10. Geo-distribution of the **Age and Gender** factor level between the different NYC ZIP codes

Figure 11. Geo-distribution of the **General Demographics** factor level between the different NYC ZIP codes

Figure 12. Geo-distribution of the **Household** factor level between the different NYC ZIP codes

Figure 13. Geo-distribution of the **Education** factor level between the different NYC ZIP codes
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Figure 14. Geo-distribution of the Occupation factor level between the different NYC ZIP codes