# Giga Innovation Challenge: Mobility Analysis Report

### 1. Introduction

This report analyzes the impact of social distancing policies on mobility patterns in a specific city. The analysis utilizes aggregated mobility data for a 7-day period, provided in CSV files.

# 2. Data Acquisition and Processing

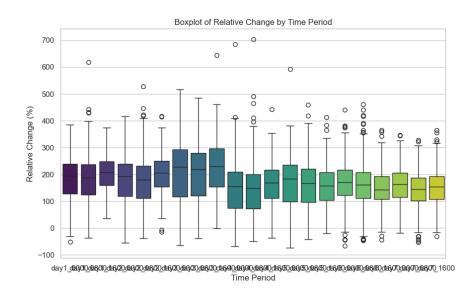
• **Data Source:** CSV files containing mobility data for each hour of the 7-day period. Each file represents a specific time period (e.g., day1 0000.csv).

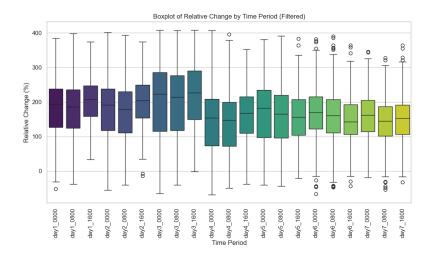
#### • Data Columns:

- o Baseline: People Moving (pre-pandemic mobility levels)
- Crisis: People Moving (post-pandemic mobility levels)
- o x0, y0 (origin coordinates)
- o x1, y1 (destination coordinates)
- index\_0, index\_1 (internal IDs)

### Processing Steps:

- o Merged all CSV files into a single Pandas DataFrame.
- Calculated the relative change in mobility for each record: (Crisis Baseline) / Baseline \* 100.
- Handled potential zero mobility values by assigning -100% change (assuming 100% reduction).
- Removed outliers in the relative change data (optional).



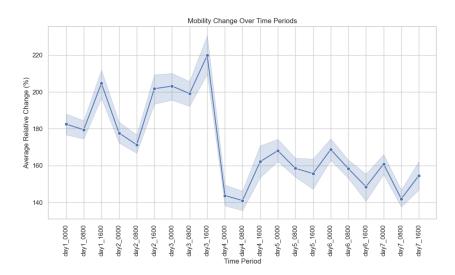


# 3. Exploratory Data Analysis

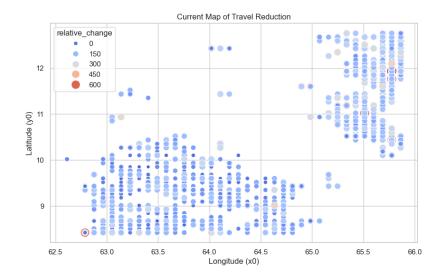
### • Data Visualization

Several visualizations were created to explore the mobility data and identify trends:

**Time Series Plot:** This plot shows the average relative change in mobility over the specified time periods. It reveals significant fluctuations, such as a peak in mobility during day1\_0000, followed by a steep decline at day4\_0800. This trend might indicate events that either encouraged or restricted mobility during these specific periods.

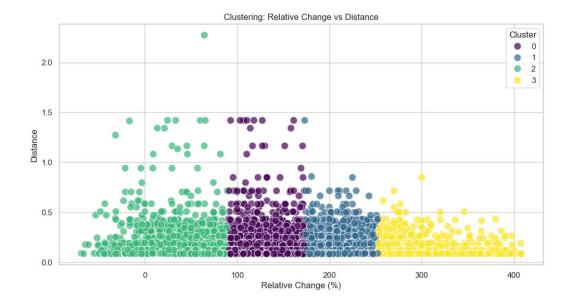


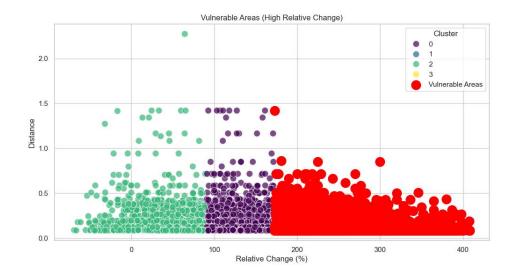
**Scatter Plot:** A scatter plot was used to visualize the relationship between mobility changes and geographical coordinates (latitude/longitude). The data points were colored by the relative change, allowing us to identify regions with the highest or lowest mobility shifts.



# • Clustering Analysis:

Using K-means clustering, the data was segmented into different clusters based on relative change and distance metrics. This clustering approach helped identify vulnerable areas where mobility changes were most significant, which could be critical for decision-making during a crisis.





#### **Interactive Visualizations**

To enhance the interactivity of the analysis, Plotly was used to create interactive scatter plots and time trend visualizations. These plots allowed users to explore the data dynamically and better understand the mobility changes across time and different regions.

• **Interactive Time Trends:** A line chart was created to show relative change trends over time, grouped by clusters. This interactive plot helps to visually track how different regions reacted to the crisis over time.

### 5. Conclusion

The analysis provided valuable insights into mobility changes during a crisis, offering a clear picture of how people moved relative to baseline conditions. Key findings include:

- Mobility significantly fluctuated at specific times, particularly during the day1\_0000 and day4 0800 periods.
- Certain clusters exhibited more drastic changes in mobility, potentially indicating higher vulnerability or other external factors influencing behavior.
- Interactive visualizations offer a deeper understanding of mobility patterns and can help inform crisis management strategies.