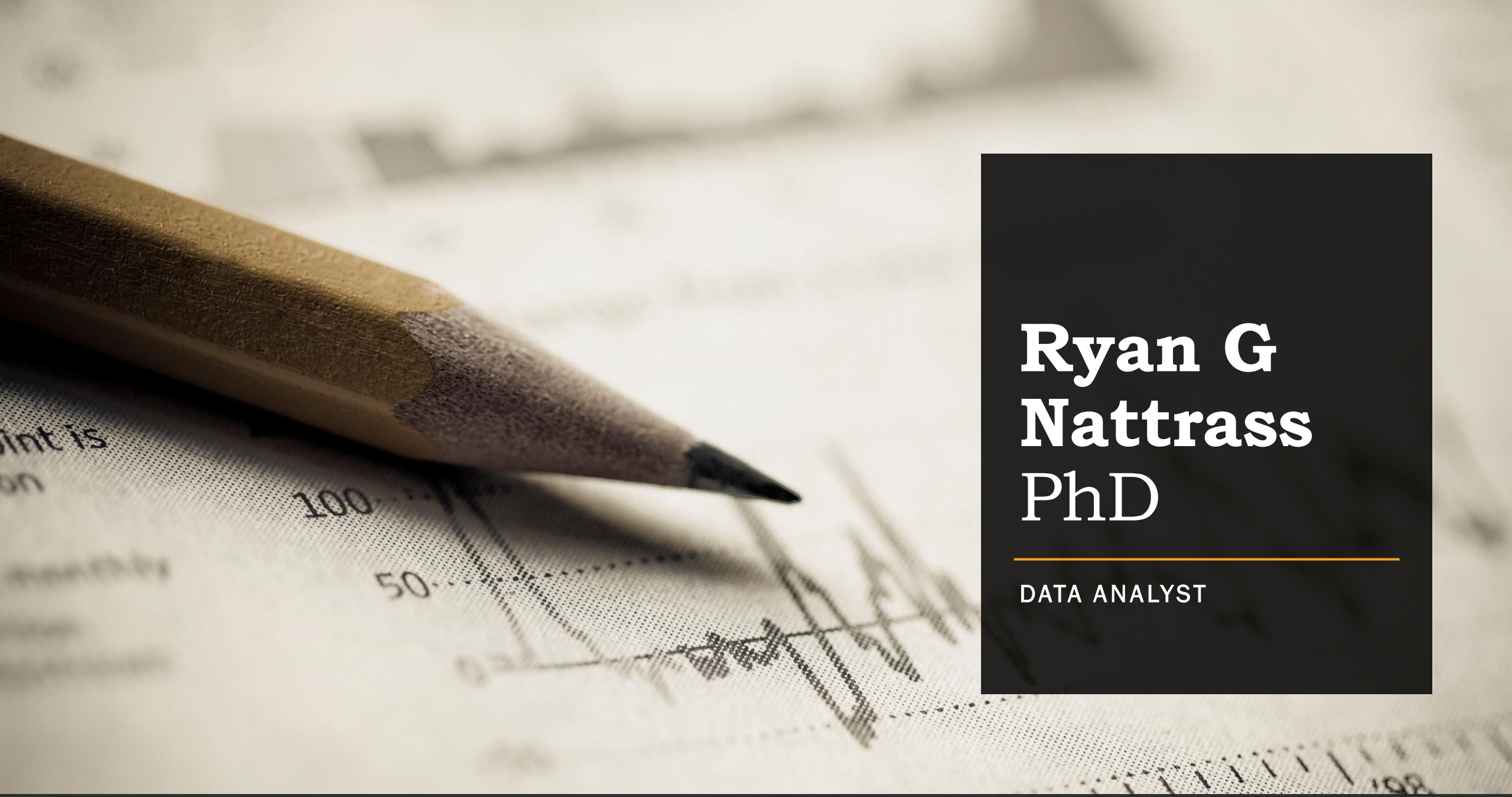


Ryan G Nattrass PhD

DATA ANALYST

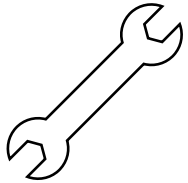
About Me

Education

- BSc Physiology
- Masters (Dist) in Research Techniques
- PhD in Immunology
- Data Analysis Certification

Professional Background – 6+ years

- Scientific Data Analysis
- Data communication and publication
- Scientific problem-solving



Tools and Skills

- Excel, Graphpad-Prism, SQL, Tableau, Python (pandas, numpy, matplot, visualizations)
- Data cleaning, statistical analysis, data communication, dashboarding

Portfolio Overview + GitHub

PROJECT	ANALYSING GLOBAL VIDEO-GAME SALES - 1	PREPARING FOR INFLUENZA SEASON IN THE U.S.A – 2	VIDEO-RENTAL COMPANY, BUSINESS-DATA ANALYSIS - 3	ONLINE GROCERY STORE, MARKETING STRATEGY - 4	ANALYSIS OF COVID-19 EFFECTS ON WORLD DEMOGRAPHICS - 5	DETERMINING OPTIMAL BIKE-DISTRIBUTION FOR A BIKE-RENTAL COMPANY IN NY - 6
GOALS MET	- Challenge assumptions that video-game sales in geographic regions are constant over time	- Determine different Influenza trends across the U.S.A to help medical staffing agencies more efficiently prepare	- Determine rental statistics - Geographic customer location and sales figures - Movie-genre sales analyses	- Wrangle, clean, organise & build database in Python with included customer profiles - Determine peak times, most popular products, customer loyalty, and impact on sales	- Source, clean, and merge data as well as ARIMA forecasting, clustering, and exploratory analysis, all in Python. - Determine if forecasted world demographics have returned to baseline levels in 2025	- Data sourcing, merging, cleaning, and addition of weather-aspect - Determine if weather impacts bike-rentals - Map bike station start-point, end-point and journeys on an interactive map - Determine stations that are accumulating bikes
OUTPUT	- PowerPoint presentation to stakeholders	- Interim Report - Video-presentation to stakeholders	- Cleaned & joined SQL database - Data dictionary - PPT presentation to stakeholders	- Cleaned, joined, and expanded Python database - Inform marketing of findings regarding data-informed recommendations	- Coding journey documented - Data Dictionary - Informed hypothesis rejection and Tableau presentation on findings	- Interactive Dashboard - Video Presentation to shareholders
TOOLS USED						

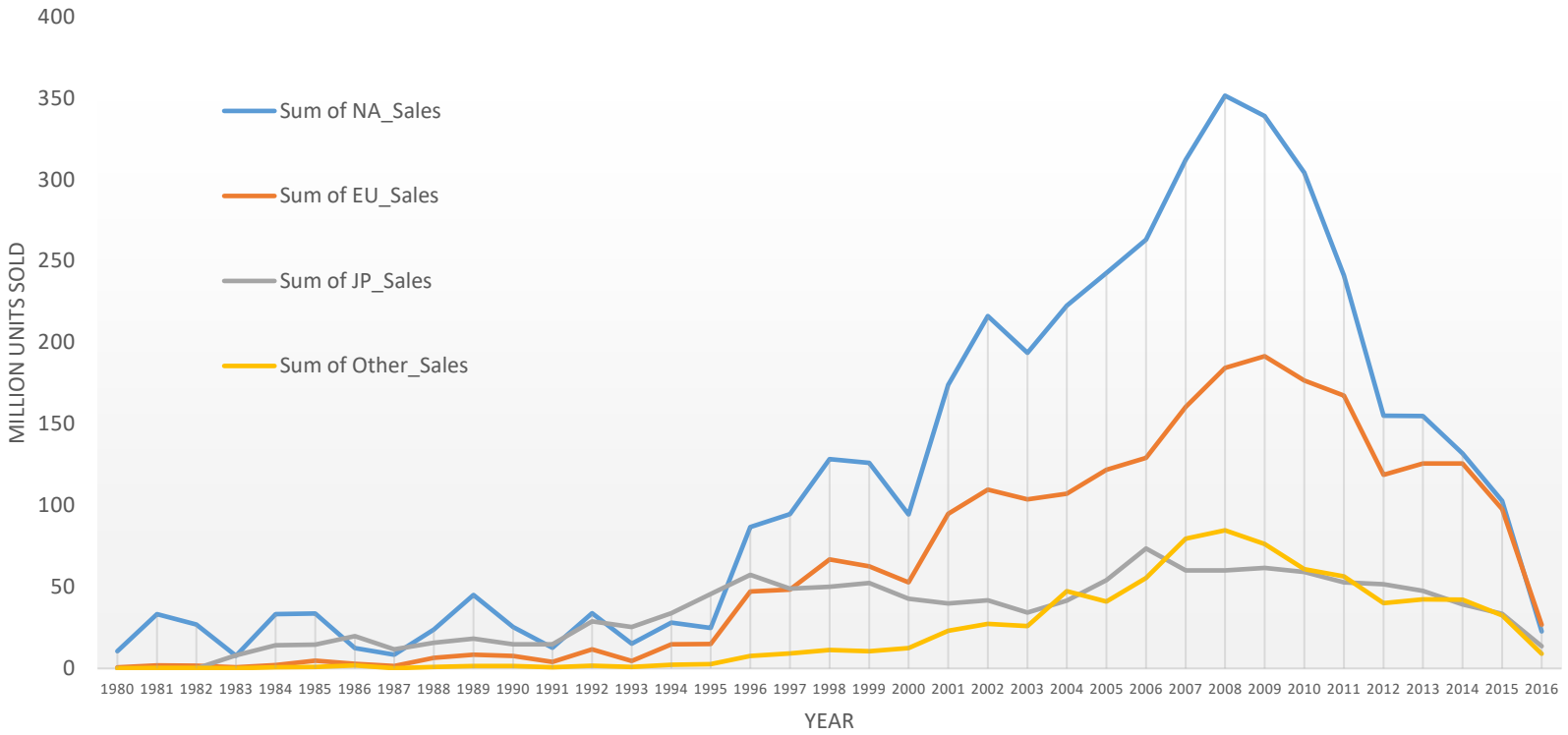
1 **GameCo** – Video-Game sales across Geographic Regions

Background: GameCo assumed sales across regions remained stable over time. Ahead of the 2017 marketing budget, they needed to confirm this assumption using historical data.

Objective: Analyse game sales from 1980–2016 and evaluate trends geographically to confirm or deny assumptions

Dataset: VGChartz (via Kaggle)

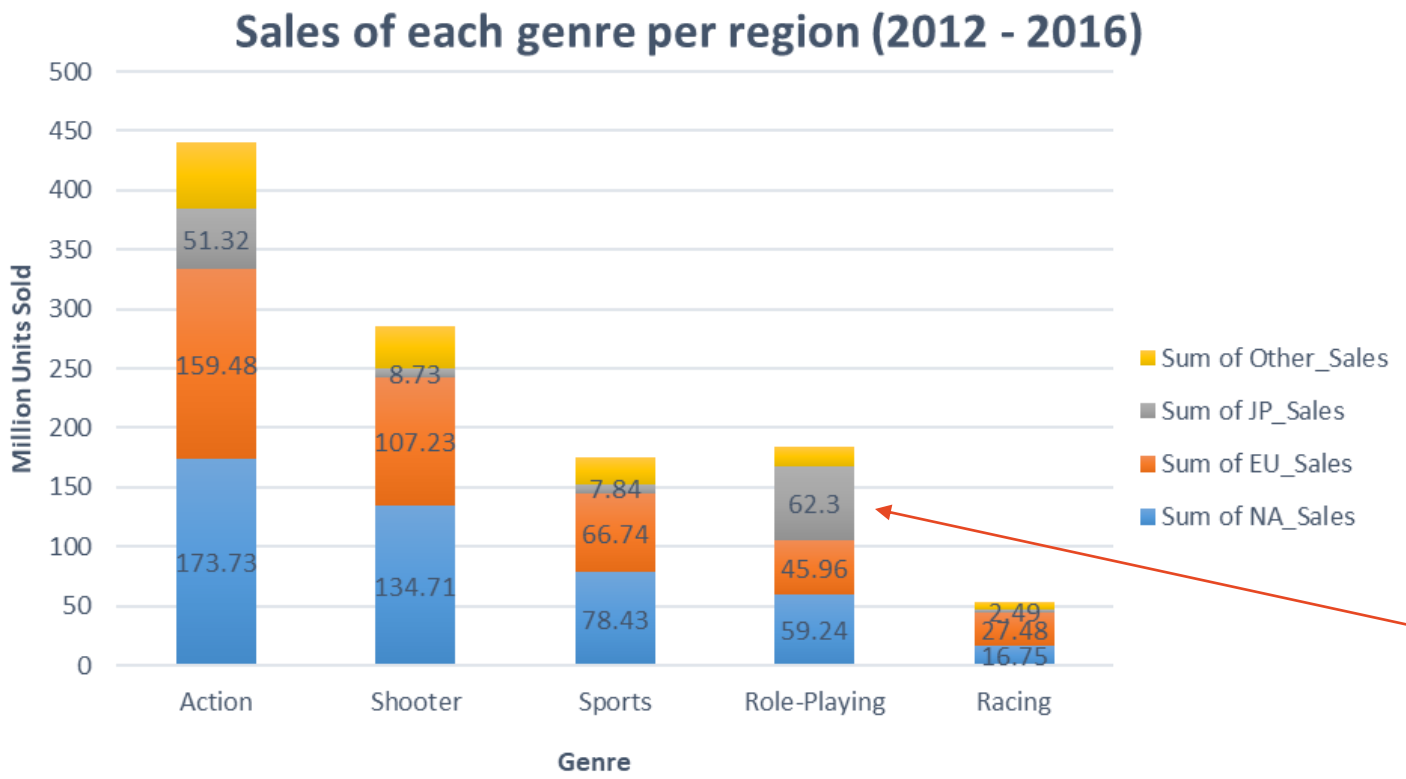
1 GameCo
Data Analyses and Insights



Geographic Observations:

- While historically, North America has been the largest market, the last 5 years have shown Europe to compete

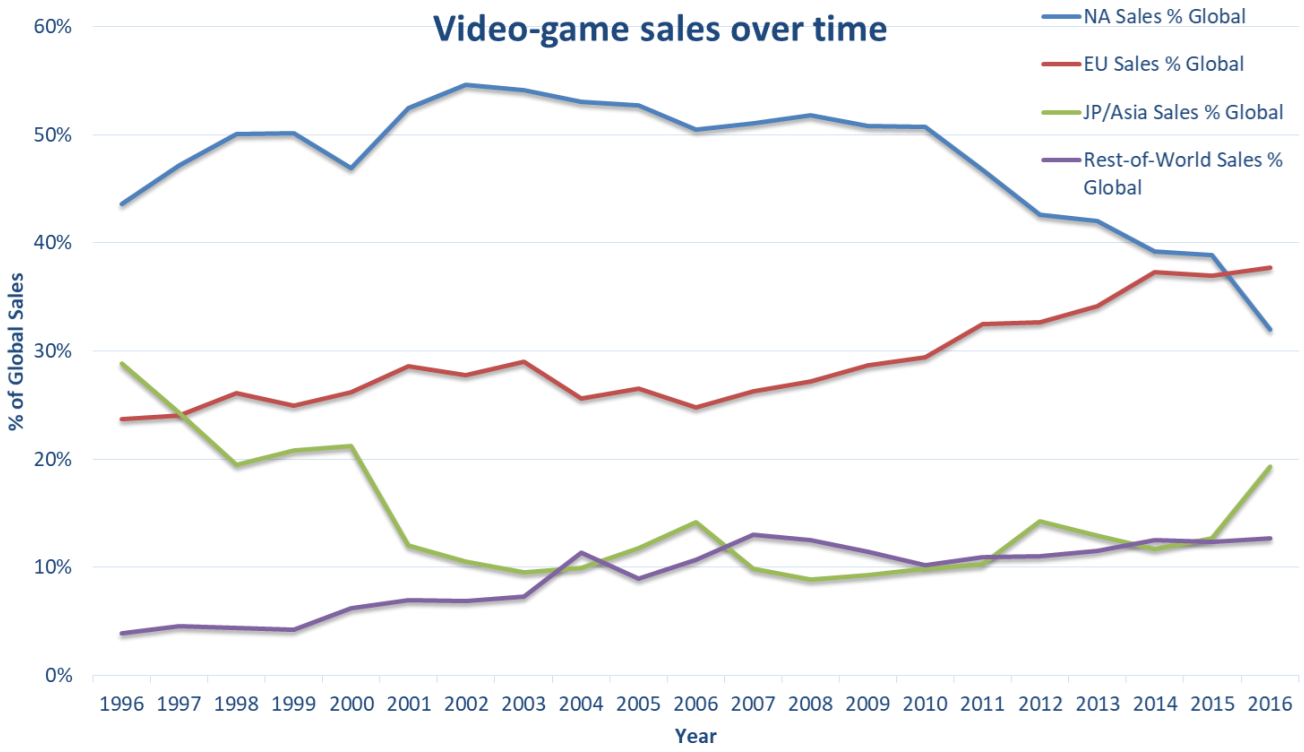
1 GameCo
Data Analyses and Insights



Genre-specific geographical observations from the last five years:

- The biggest selling genre of games in North America and Europe
  - Action
- The biggest selling genre in Japan
  - Role Playing Games

1 GameCo
Data-driven recommendations



- GameCo should reject their assumptions and adopt the new assumption that **sales across regions do NOT remain stable over time**
- Data suggests that the **EU may start to become the largest market globally, going forward.**
- GameCo should assume that different genres of games will sell differently across the globe.

2 Influenza Staffing Forecasting

Background: A U.S.-based temporary medical staffing agency needed help planning resource distribution ahead of flu season.

Objective:

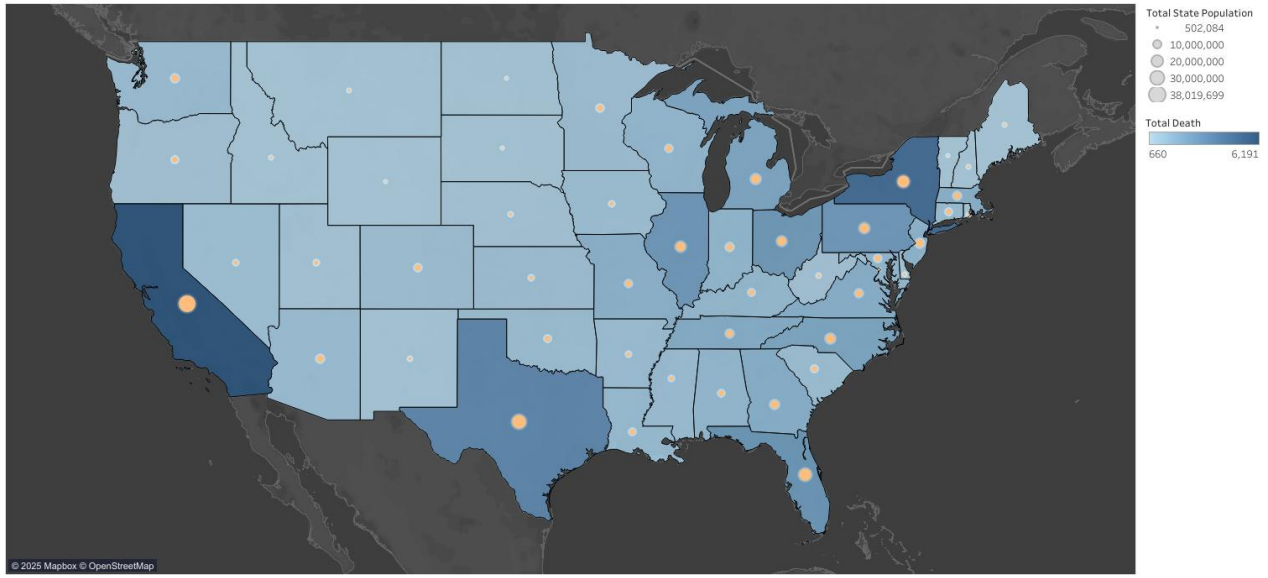
- Determine where, when, and how many staff to deploy based on historical influenza mortality trends.
- Forecast Seasonality
- Rank states on any potential vulnerable populations

Dataset:

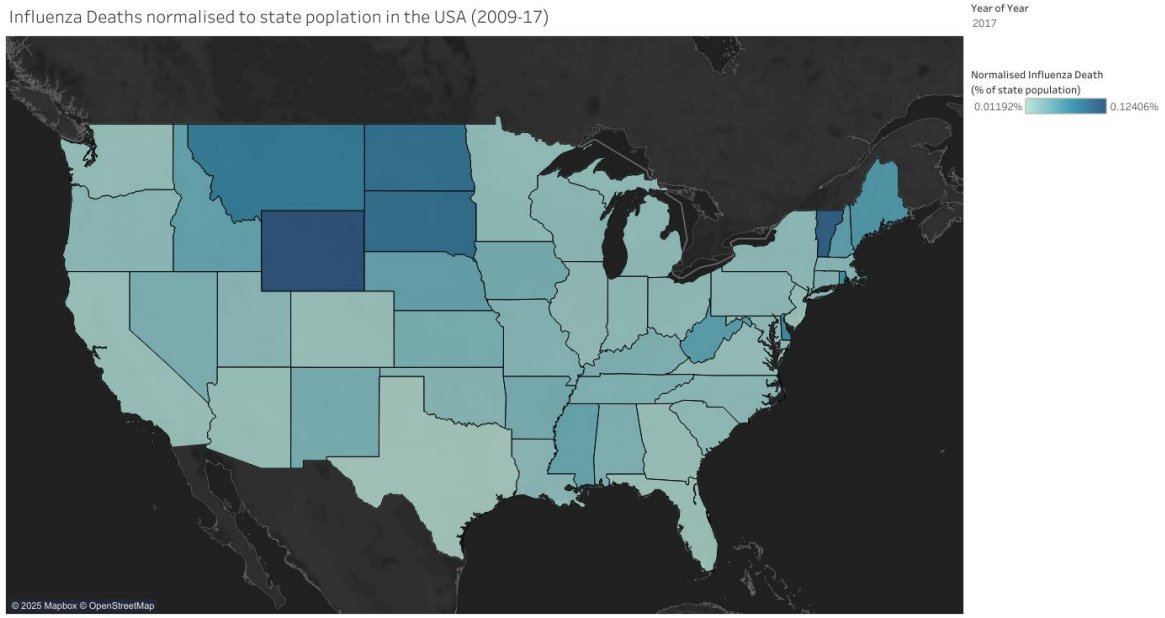
- Influenza death records from CDC (2009–2017)
- U.S. Census population data (by state and age)

2 Normalising Influenza deaths according to state population

Influenza Deaths and state populations in the USA (2009-17)



Influenza Deaths normalised to state poplation in the USA (2009-17)

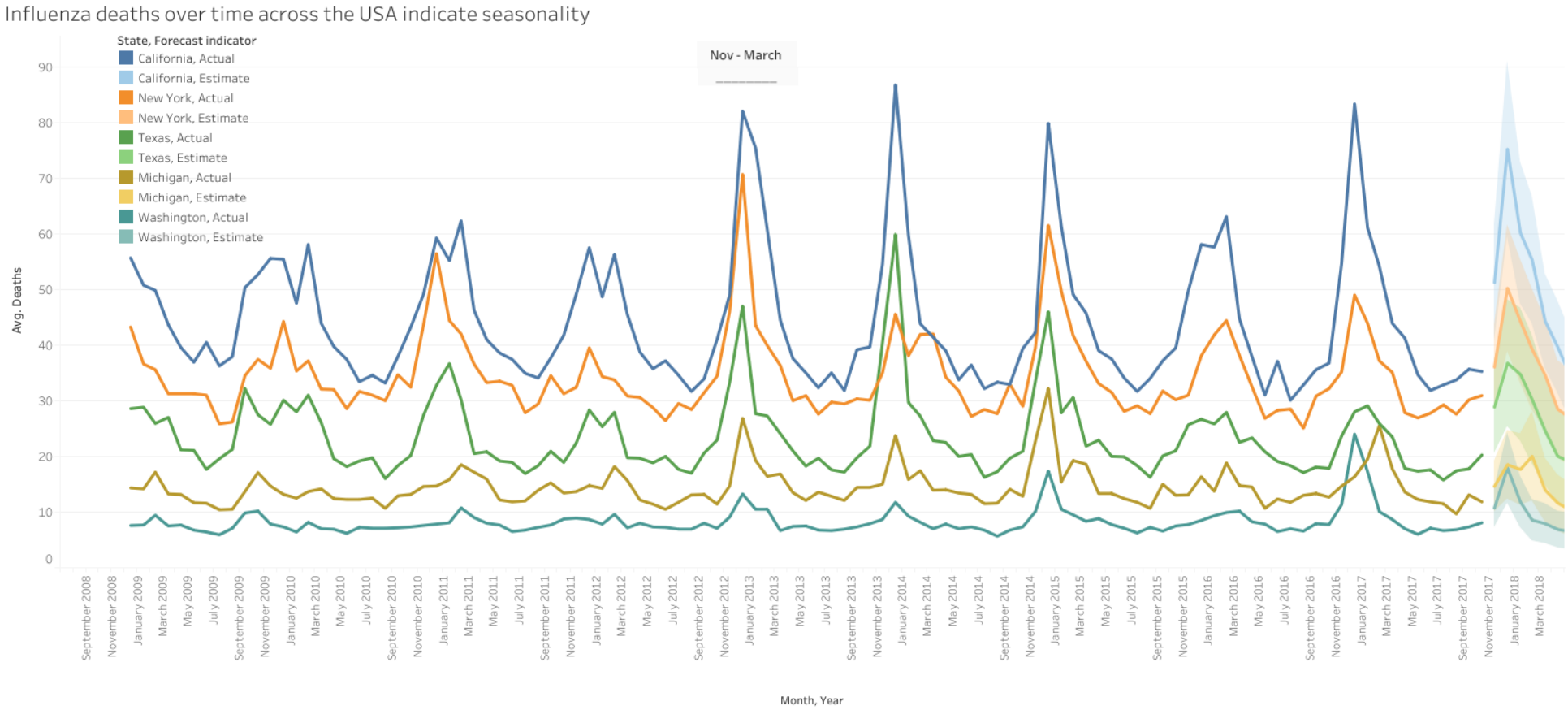


Without normalization the states with highest population have highest deaths

With normalization, states with highest relative influenza death can be distinguished

https://public.tableau.com/app/profile/ryan.nattrass/viz/E2_7Maps/NormDUALSh

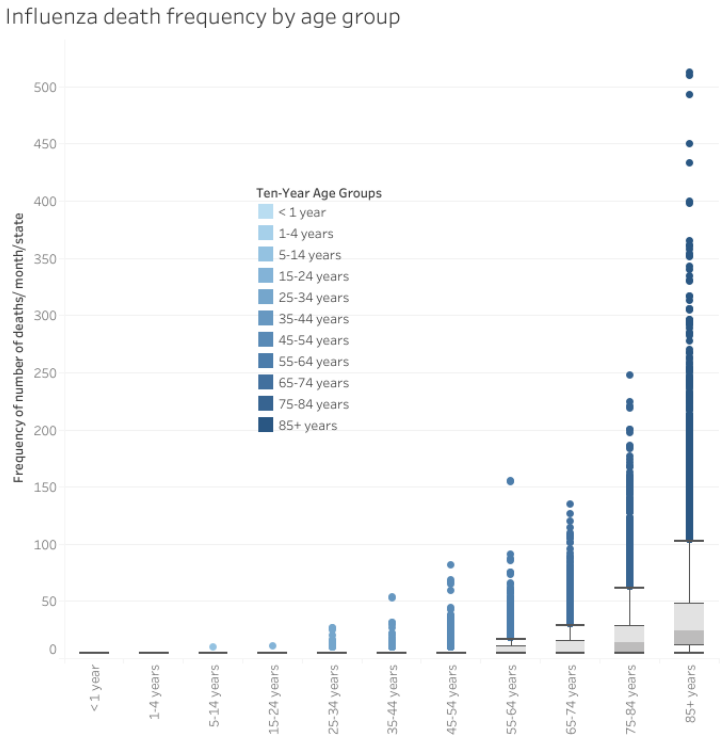
2 Forecasting indicates flu season is between November - March

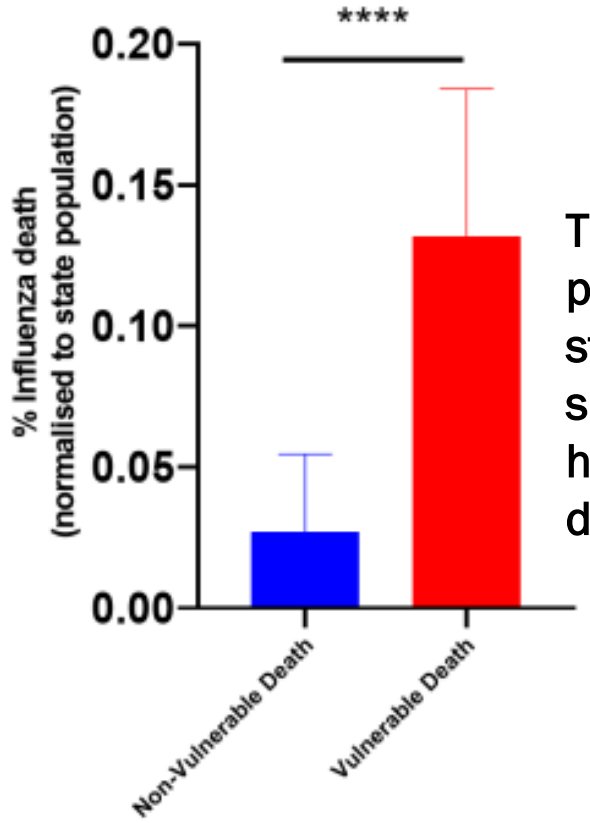


https://public.tableau.com/app/profile/ryan.nattrass/viz/DeathsForecastbyMonth/FinalSh

2 Age indicates influenza vulnerability

Vulnerable population deemed to be over 65 years-of-age





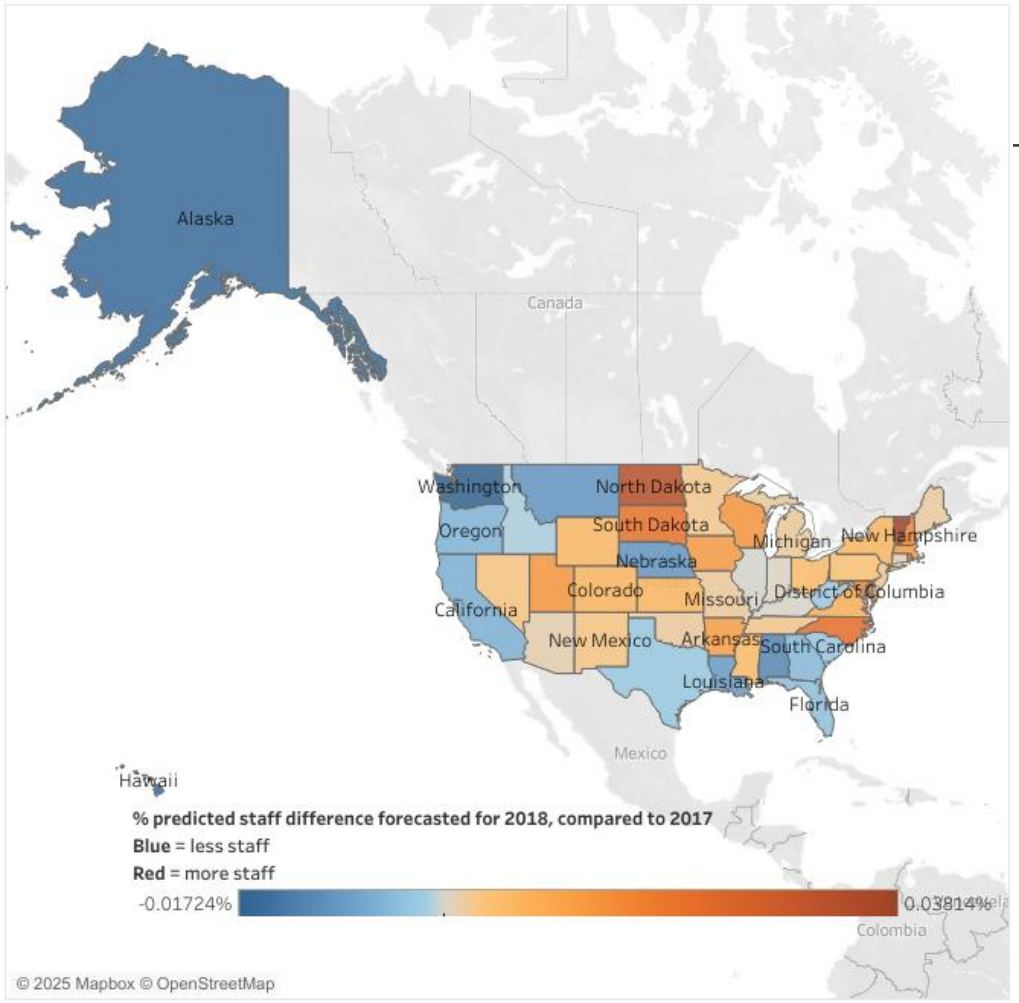
This vulnerable population has statistically significantly higher influenza death

https://public.tableau.com/app/profile/ryan.nattrass/viz/HistoBox/BoxSh

Staffing requirement forecasting

2

Predicted increase in vulnerable population death in 2018 compared to 2017



State	Difference in 2018 from 2017
Washington	-0.0172%
Alaska	-0.0154%
Hawaii	-0.0152%
Alabama	-0.0112%
Nebraska	-0.0094%
Montana	-0.0093%
Louisiana	-0.0084%
California	-0.0056%
Oregon	-0.0052%
Georgia	-0.0045%
Florida	-0.0034%
South Carolina	-0.0023%
Texas	-0.0022%
West Virginia	-0.0018%
Idaho	-0.0013%
Illinois	-0.0001%
Kentucky	0.0000%
Indiana	0.0003%
Connecticut	0.0010%
Arizona	0.0011%
District of Columbia	0.0017%
Maine	0.0017%
Oklahoma	0.0018%
Missouri	0.0018%
Michigan	0.0020%
New Jersey	0.0024%
Tennessee	0.0025%
Minnesota	0.0025%
New Mexico	0.0029%
Nevada	0.0029%
Pennsylvania	0.0036%
Ohio	0.0050%
Mississippi	0.0050%
Wyoming	0.0055%
New York	0.0057%

Blue - Reduce Medical staff
Grey - No suggested change
Orange - Increased medical staff
Red - Significantly increased medical staff

-0.01714% 0.04000%

State	Difference in 2018 from 2017
Colorado	0.0059%
Kansas	0.0060%
Virginia	0.0071%
Delaware	0.0072%
Arkansas	0.0104%
Massachusetts	0.0111%
Iowa	0.0113%
Utah	0.0122%
Wisconsin	0.0125%
Rhode Island	0.0151%
New Hampshire	0.0152%
Maryland	0.0153%
South Dakota	0.0197%
North Carolina	0.0204%
North Dakota	0.0325%
Vermont	0.0381%

Recommendations are that these changes are implemented before November 2018

https://public.tableau.com/app/profile/ryan.nattrass/viz/E2_9Storyboard_RGN_FINAL/DIffinVulnFULLTable

3

Rockbuster Stealth LLC SQL Analysis

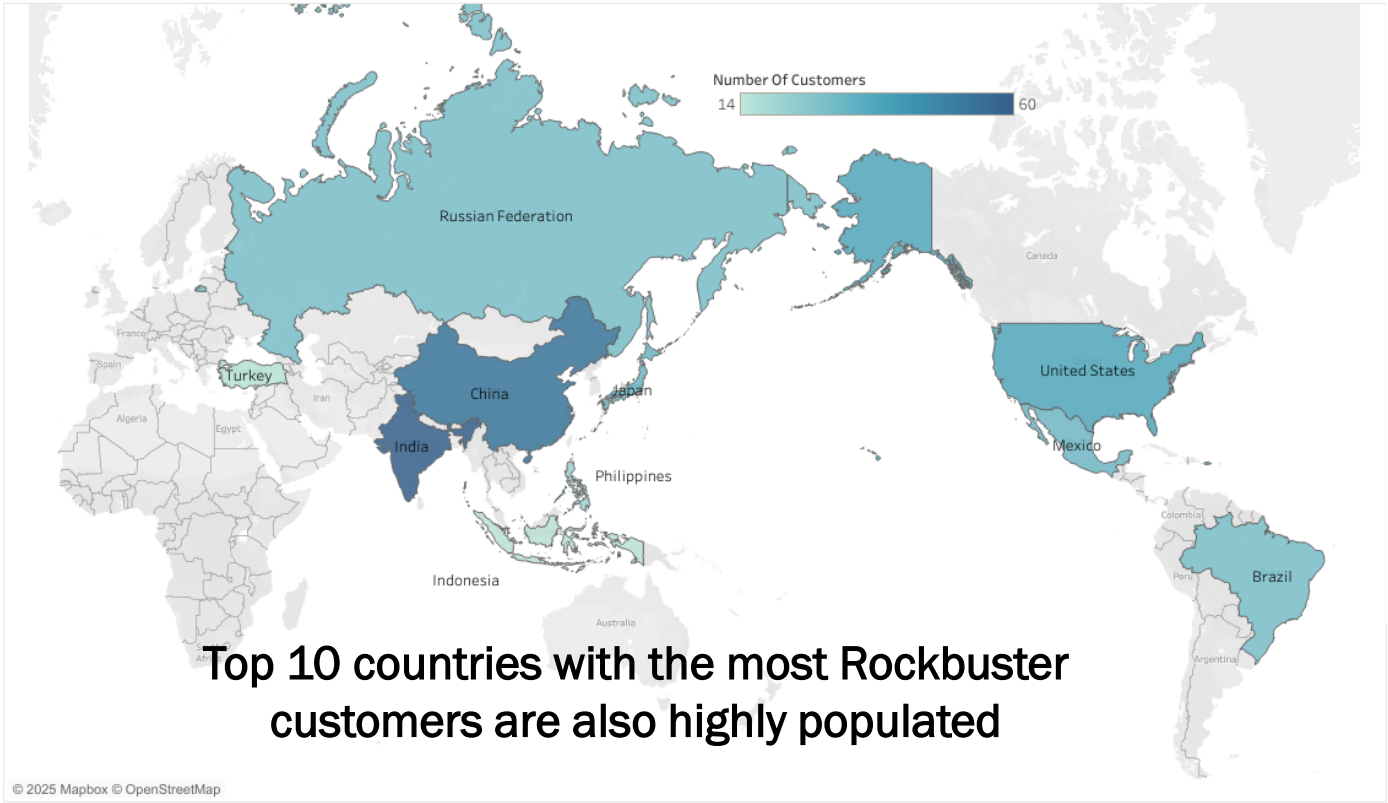
Background: Rockbuster Stealth LLC is a traditional DVD-rental company exploring digital streaming

Objective:

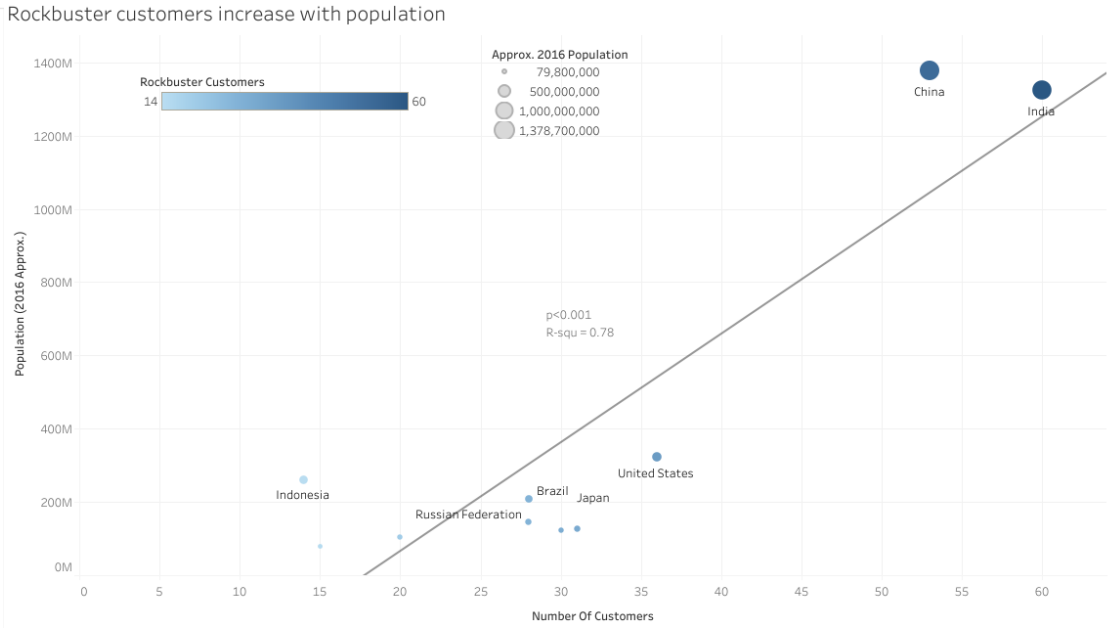
- Identify customer regions and trends
- Reveal most profitable rental movie-genres

Dataset: DVD Rental SQL Database

3 Which countries are Rockbuster customers based in?



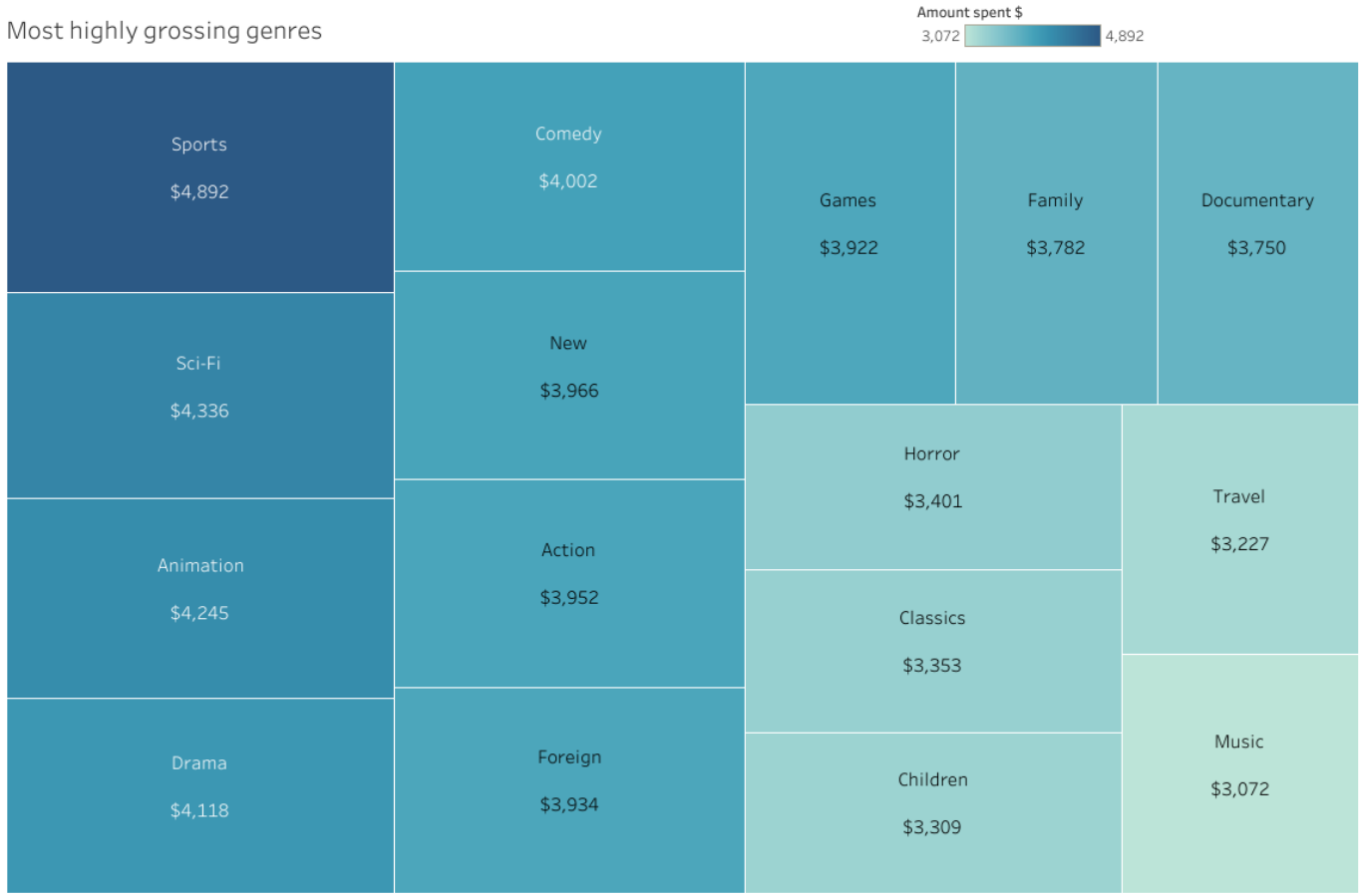
Top 10 countries with the most Rockbuster customers are also highly populated



As population increases, so does Rockbuster customers

https://public.tableau.com/app/profile/ryan.nattrass/viz/RGNE3_10/STORYboardRockbuster?publish=yes

3 Which genres generate the most revenue



- Highest grossing genres
  - Sports
  - Sci-fi
  - Animation
  - Drama

- Lowest grossing genres
  - Music
  - Travel
  - Children
  - Classics

https://public.tableau.com/app/profile/ryan.nattrass/viz/RGNE3_10-Genres/STORYboardRockbuster

3

Rockbuster
Data-driven recommendations

Customers increase with population:

- Recommendation would be to increase the availability of the product, as customers increase with populus

Sports, Sci-fi, Animation, and Drama are the most popular genres and generate the most revenue

- Recommendation would be to diversify further into these genres and away from those that are generating less revenue

4 Instacart
User Profiling and Analysis

Background: An online grocery store ‘Instacart’ would like understanding customer demographics and behavior in order to improve targeted advertising, and determine how different customers profiles impact customer behavior

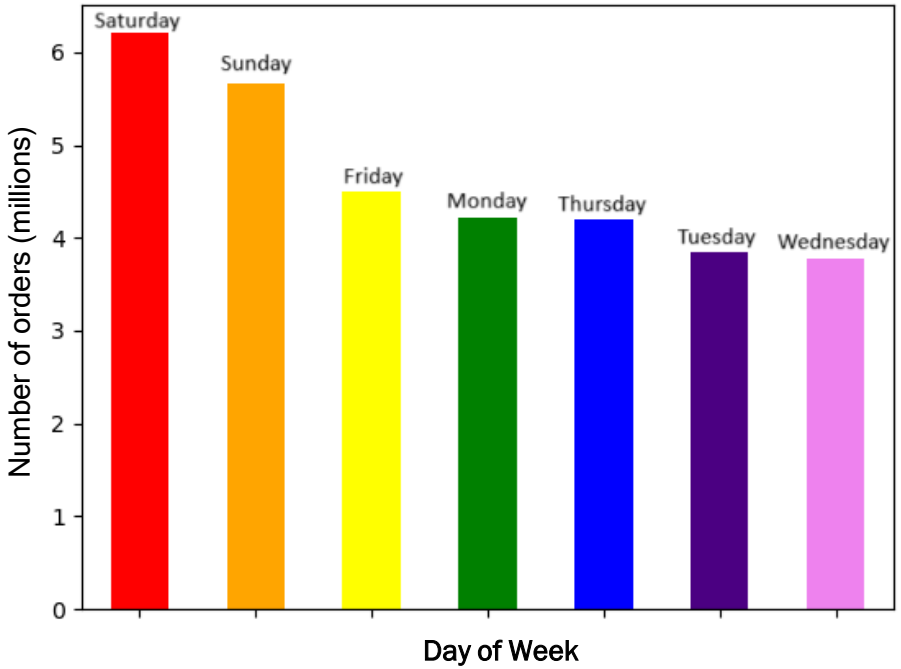
Objective:

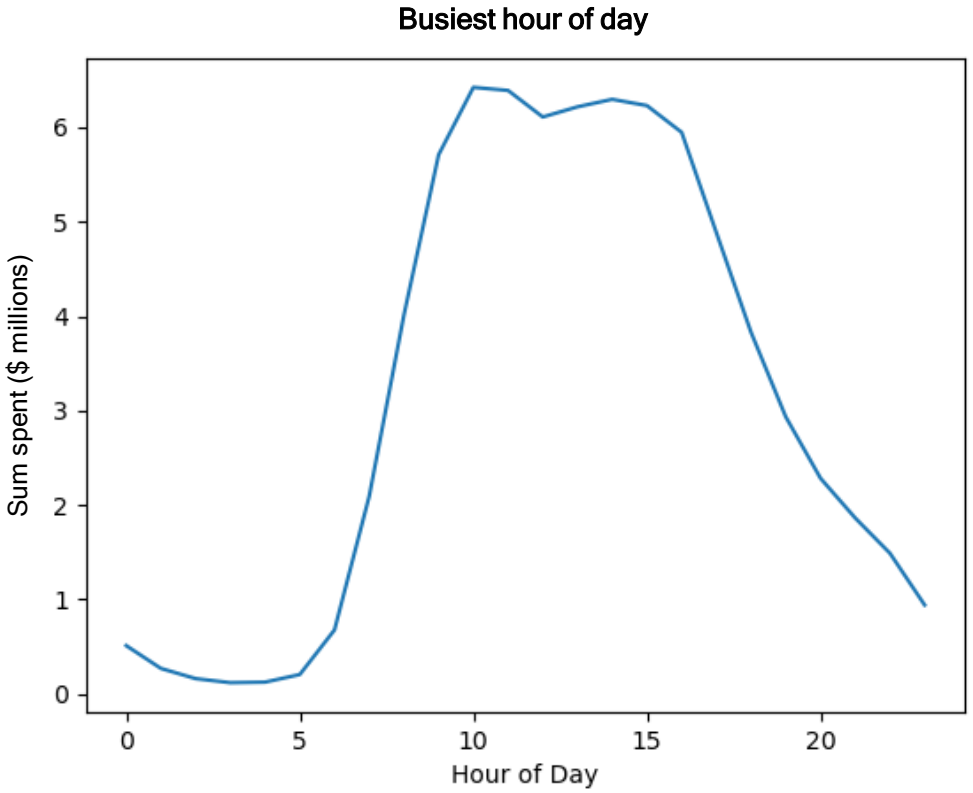
- Understand Instacart’s busiest periods for advertising purposes
- Determine and analyse customer loyalty levels to provide insights into marketing decisions
- Design customer profiles and analyse buying trends

Dataset: “The Instacart Online Grocery Shopping Dataset 2017”, Accessed from www.instacart.com/datasets/grocery-shopping-2017 via Kaggle

4 Instacart
Peak ordering times

The most orders for Instacart come during the weekend





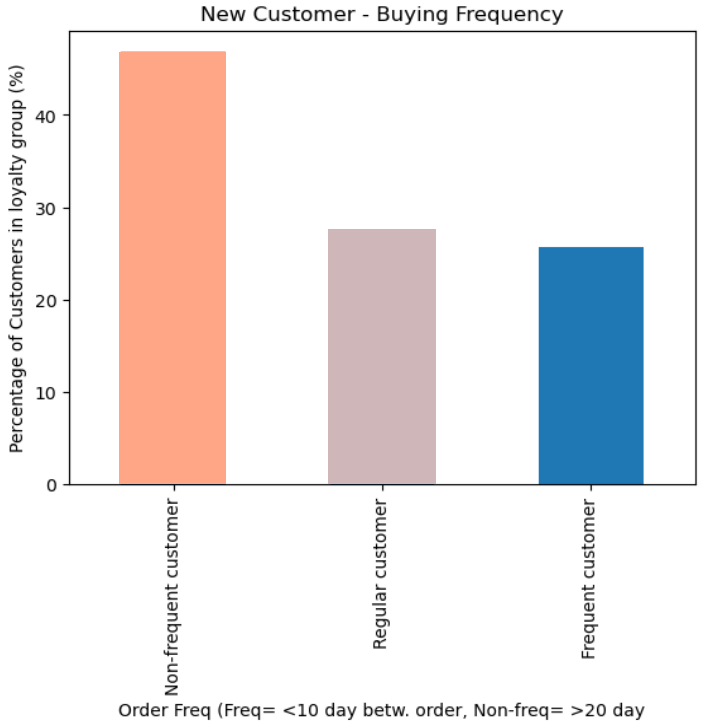
Peak-daily-orders are between 10am-4pm

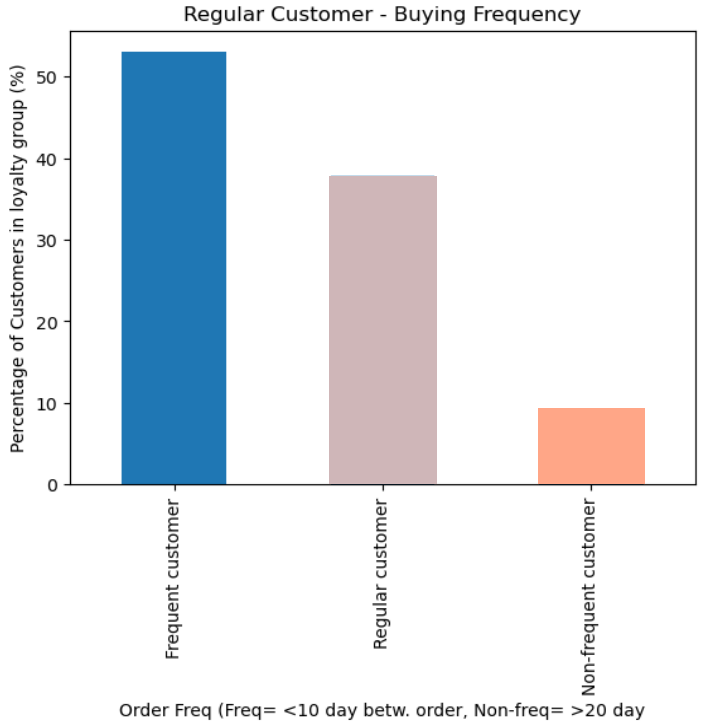
https://github.com/CarbonSnitch/Portfolio_Instacart_Python

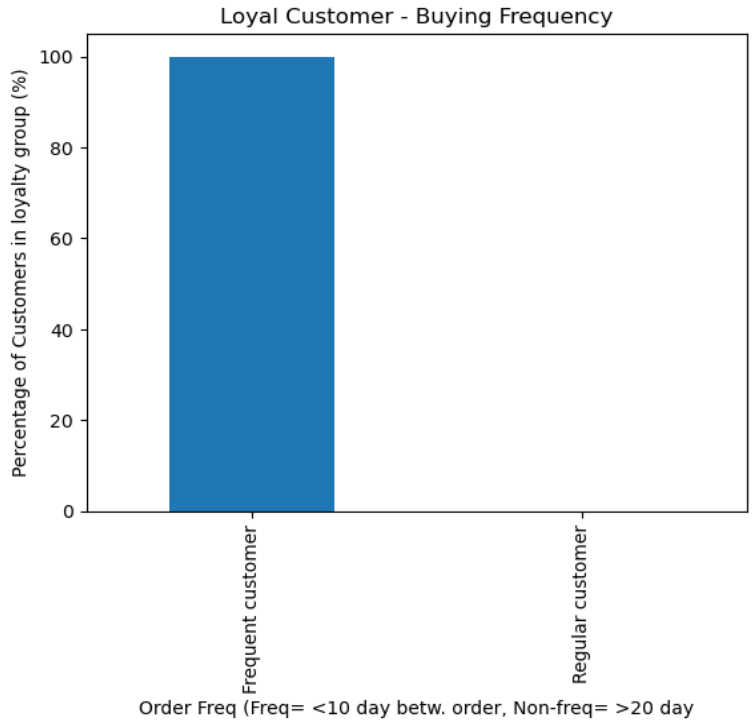
4 Customer-Loyalty and impact on orders

Less Loyal,
Less-frequent orders

More Loyal,
More-frequent orders

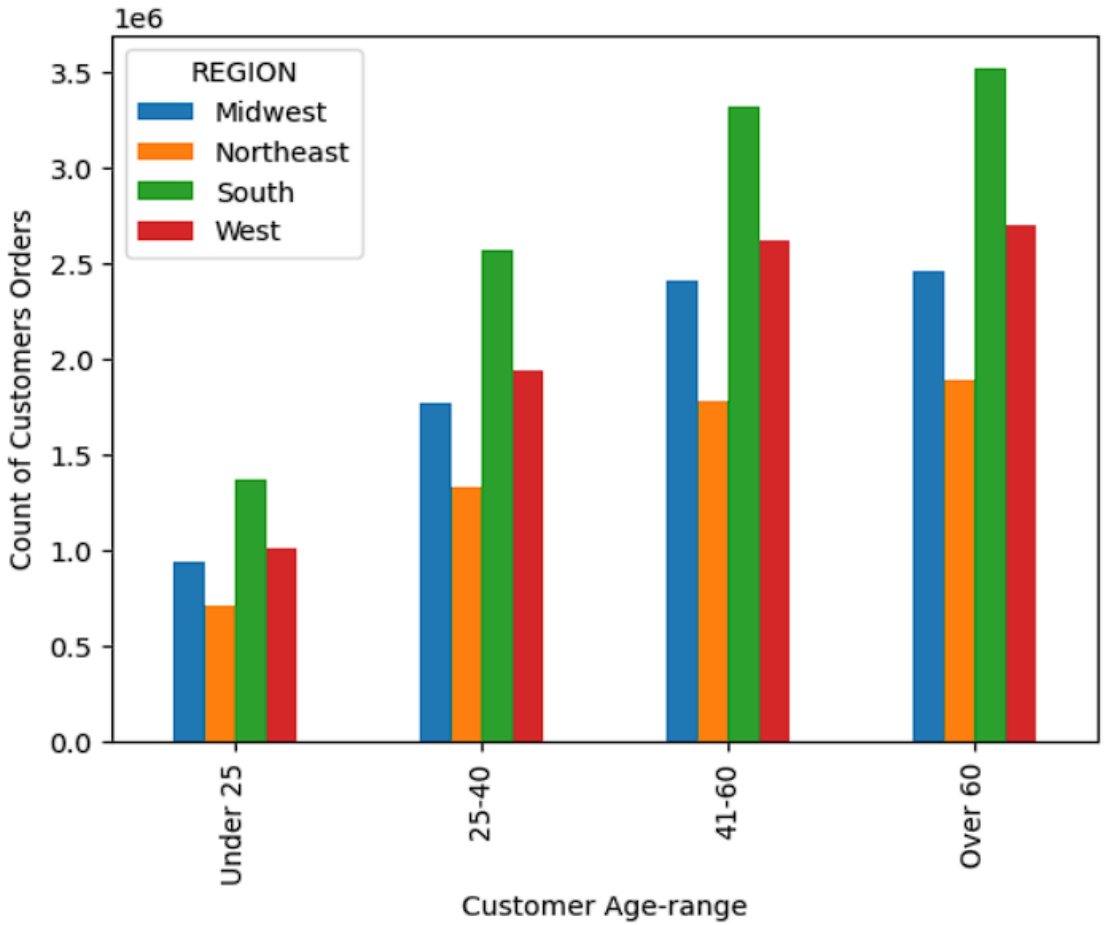






https://github.com/CarbonSnitch/Portfolio_Instacart_Python

4 Instacart
Biggest customer base

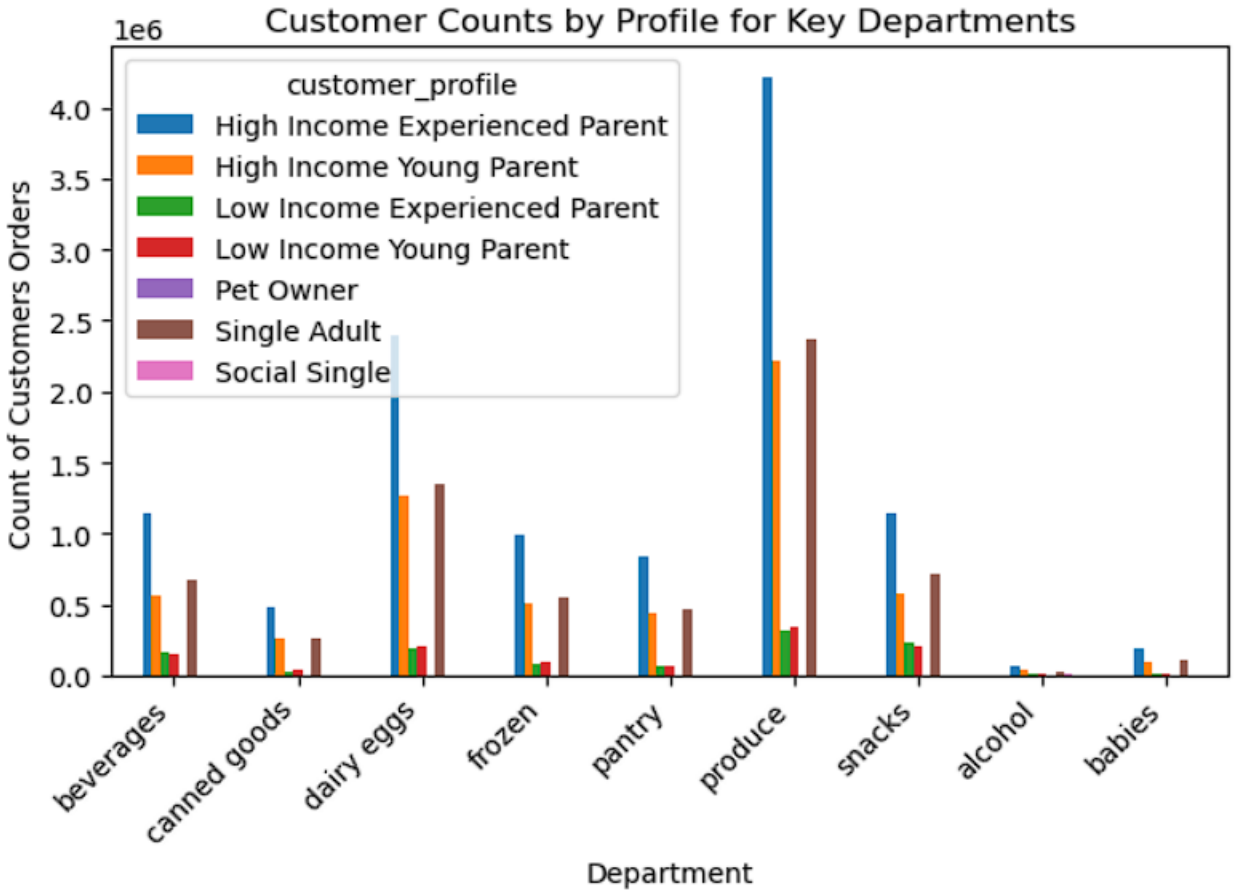


Instacart's biggest customer base:

- Is over the age of 40
- Resides in the south of the USA

https://github.com/CarbonSnitch/Portfolio_Instacart_Python

4 Customer Profiling & Most-popular department



The most customers that use Instacart are:

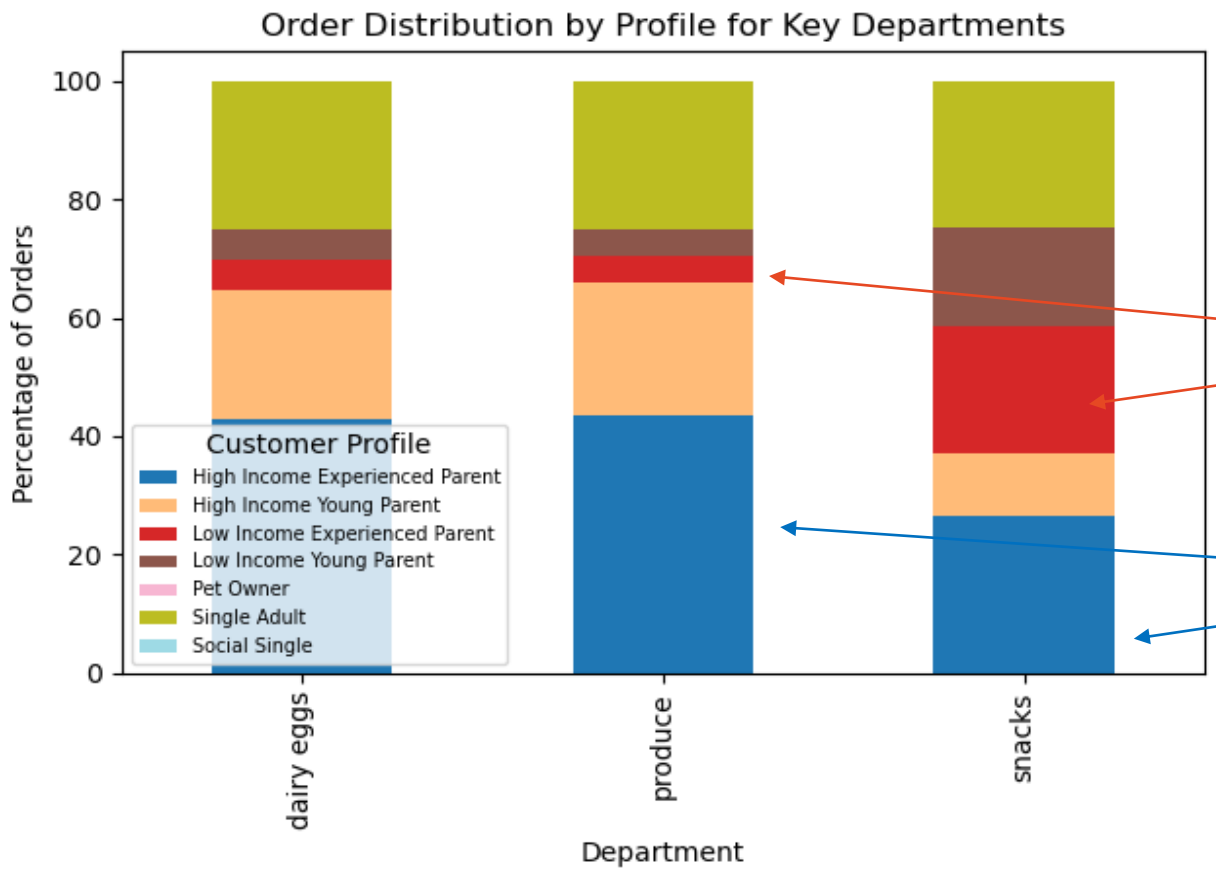
1. High-income parents >40
2. Single Adults
3. High-income parents < 40

The most orders come from the departments:

1. Produce
2. Dairy/ eggs
3. Snacks
4. Beverages

https://github.com/CarbonSnitch/Portfolio_Instacart_Python

4 Customer profiles and ordering habits



While produce is the most ordered-from department for most customer-profiles, **low-income families are much more likely to order from the snacks department than other customer-profiles**

https://github.com/CarbonSnitch/Portfolio_Instacart_Python

4 Instacart
Data-driven recommendations

- To maximise on the time most customers use Instacart the least, scheduled targeted-ads should run in the evenings of weekdays or before 10am on weekends.

- Data shows that the more orders a customer has completed with Instacart, the more likely they are to order again, therefore it may be beneficial to incentivize customers to make more orders

- With regards to targeted ads, the largest customer base Instacart has are parents older than 40 and have more than 50,000 annual income

- Produce is most-often ordered by everyone except low-income families who prefer to use Instacart to order snacks

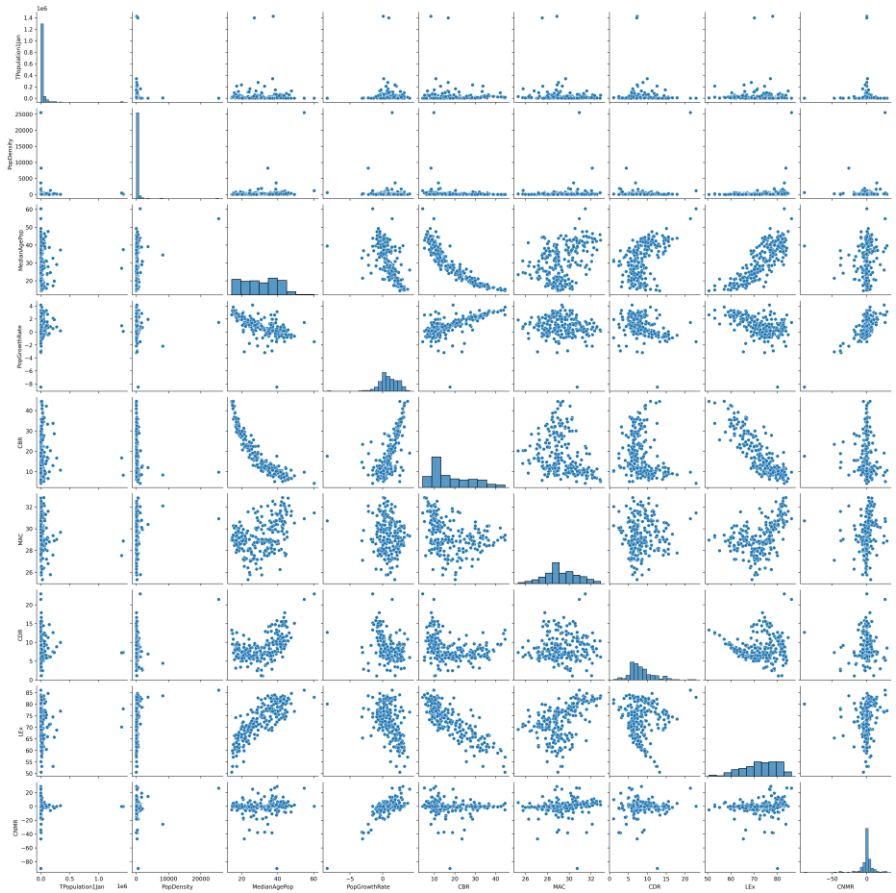
5 Has the world recovered from COVID-19 in 2025

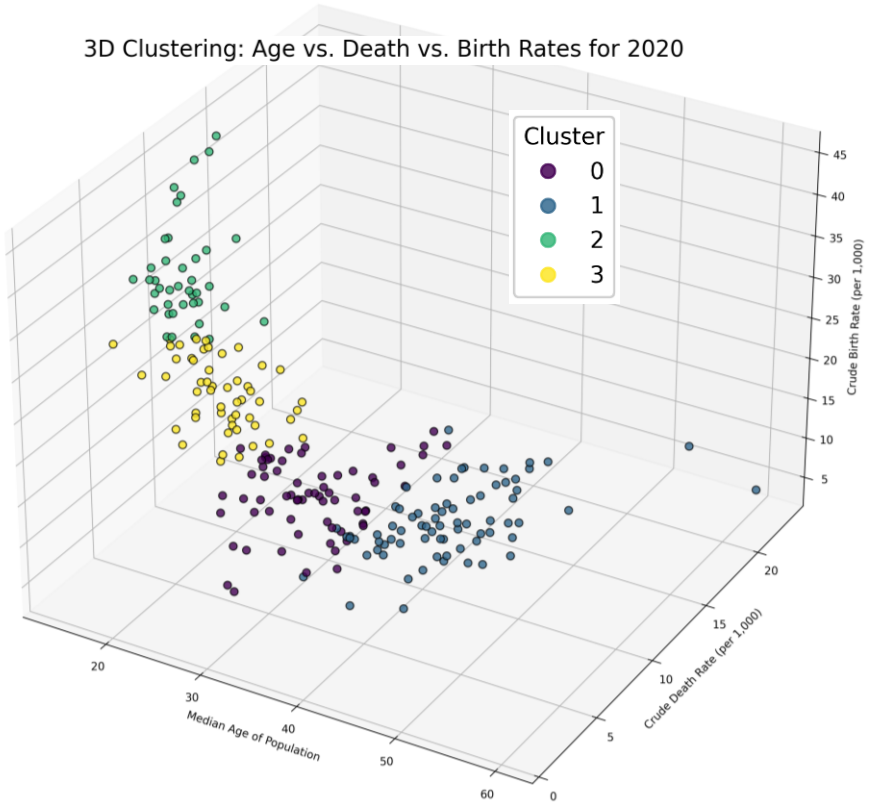
- **This Analyses seeks to answer the questions of:**
  - Did all countries respond the same way to the pandemic and if they differed, how? Why?
  - IF forecasted, does demographic data line up with current data, indicating that the pandemic has been recovered from?
  - Which countries fared the worst and should be most prepared for the future similar scenario?

Dataset: "United Nations, Department of Economic and Social Affairs, PopulationDivision(2024). World Population Prospects 2024, Online Edition." (https://population.un.org/wpp/downloads?folder=Standard%20Projections&group=CSV%20format)

5 COVID-19 Analyses
Finding Interesting Demographics

Python-tools enables quick analysis of multiple variables

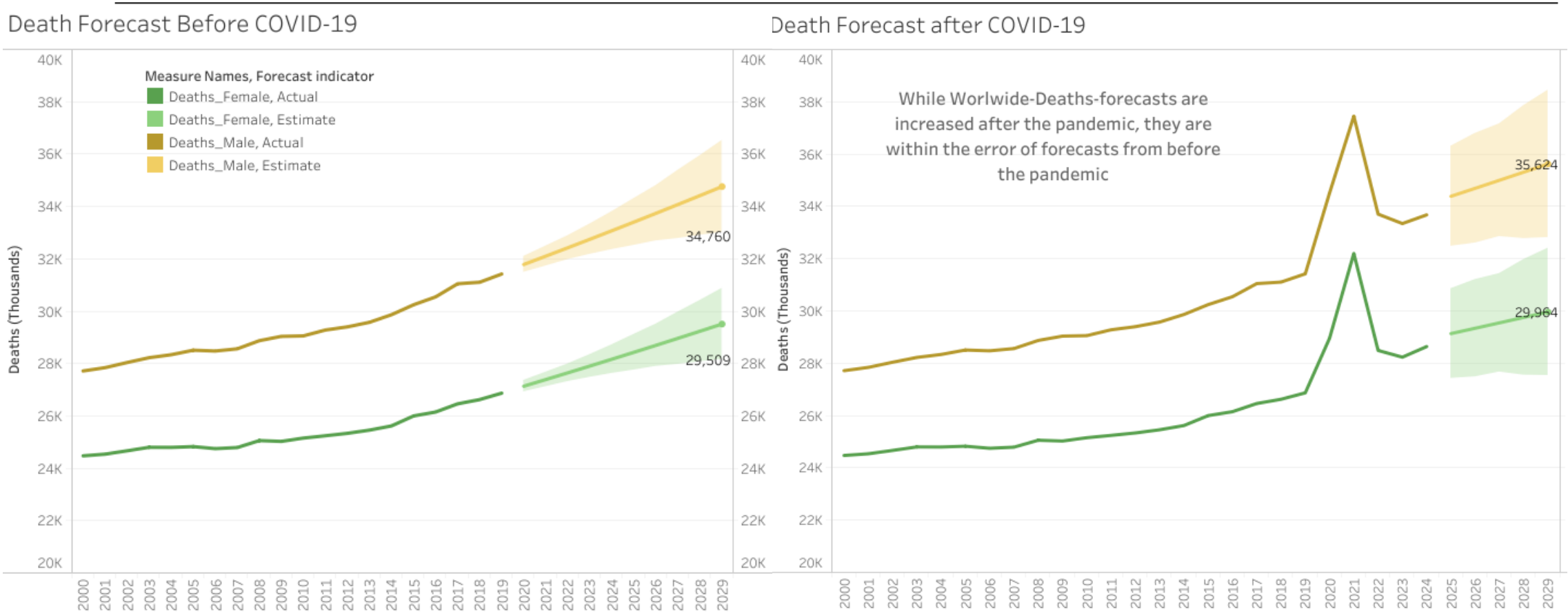




Most influential variables enable **Clustering** segmentation of countries for easier in-depth analysis

https://github.com/CarbonSnitch/RGN_UN_COVID_19_2025?tab=readme-ov-file

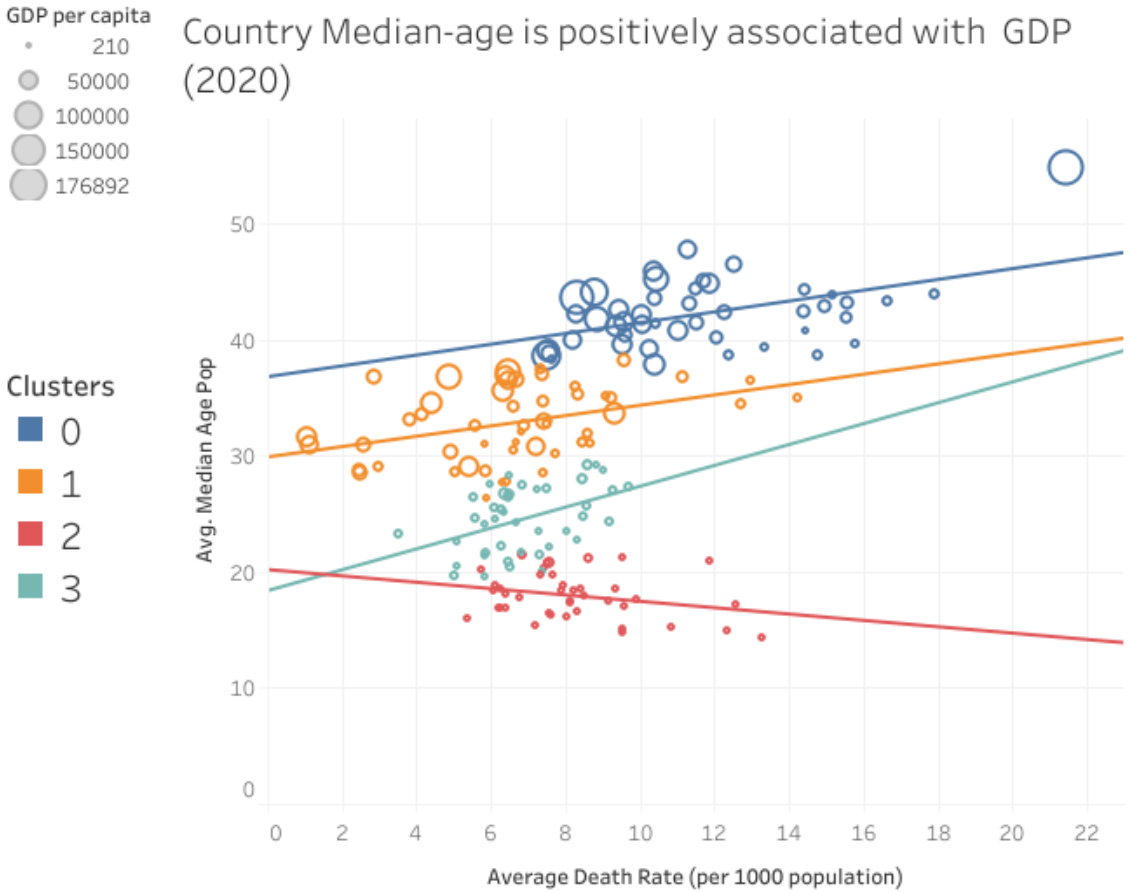
5 Death-rate has returned to normal in 2025

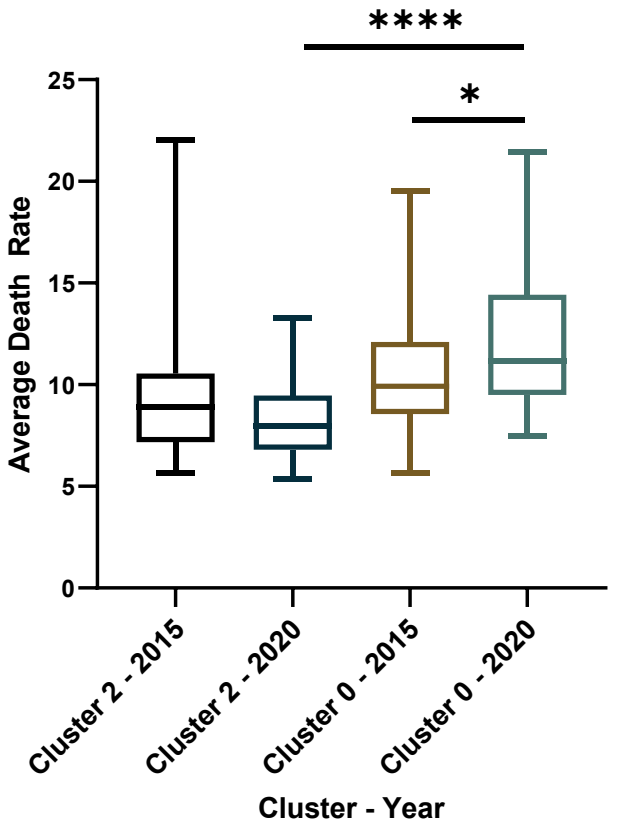


https://public.tableau.com/app/profile/ryan.nattrass/viz/Before_AfterCOVID_2015/COVID-19STORY?publish=yes

5 COVID-19 Analyses
Clustering

Clustering-analysis shows that the highest death-rate during COVID-19 pandemic is in High-GDP-per-capita, High-Median-Age Countries





Death-rate in cluster 0 in 2020 is statistically-significantly larger than the death-rate in cluster 2, the countries with the lowest GDP-per-capita

https://public.tableau.com/app/profile/ryan.nattrass/viz/Before_AfterCOVID_2015/COVID-19STORY?publish=yes

5 COVID-19 Demographic analysis Data-driven recommendations

- **All countries did NOT fare equally during COVID-19** with the countries with the highest GDP-per-capita having a larger death-rate during COVID-pandemic than the lowest GDP-per-capita countries

- It would appear that in 2025, the death-rate has returned to a level comparable to forecasts from pre-COVID. This would indicate that **the world has indeed recovered effectively from COVID-19 in 2025.**

6 Citibike - Analysis of optimal bike distribution

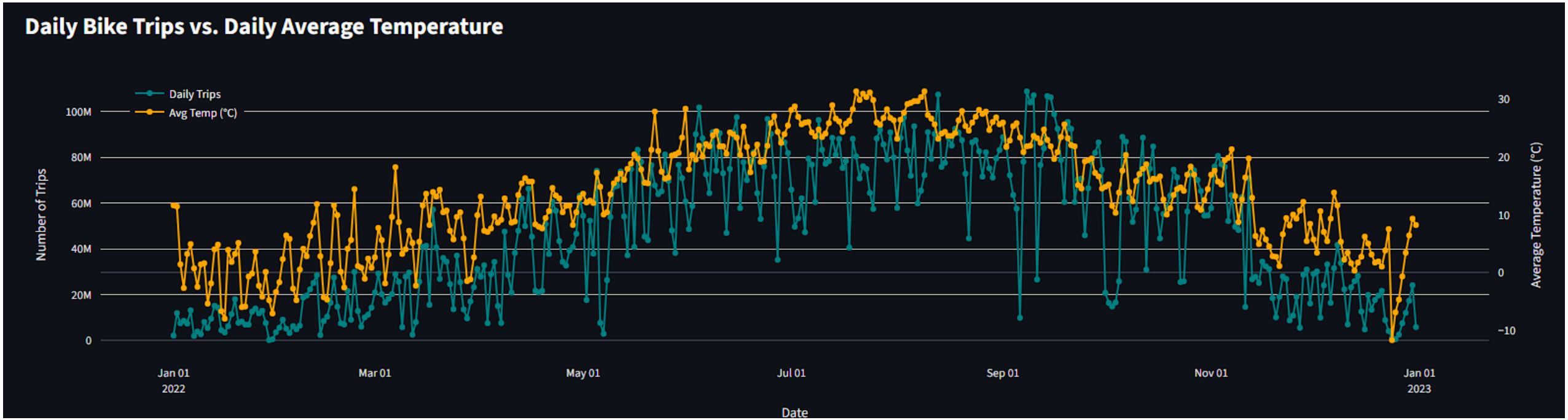
- **This Analyses seeks to answer the questions of:**
  - Is there a weather component linked to the number of bike-rentals?
  - Why are Citibike customers in NY complaining about a lack of bikes?
  - How could we better distribute bikes to optimise bike rental?

  Output should be an interactive dashboard

Dataset: Citibike tripdata for New York, 2022 - (https://s3.amazonaws.com/tripdata/index.html) and climate data from La Guardia Airport (https://www.ncei.noaa.gov/cdo-web/)

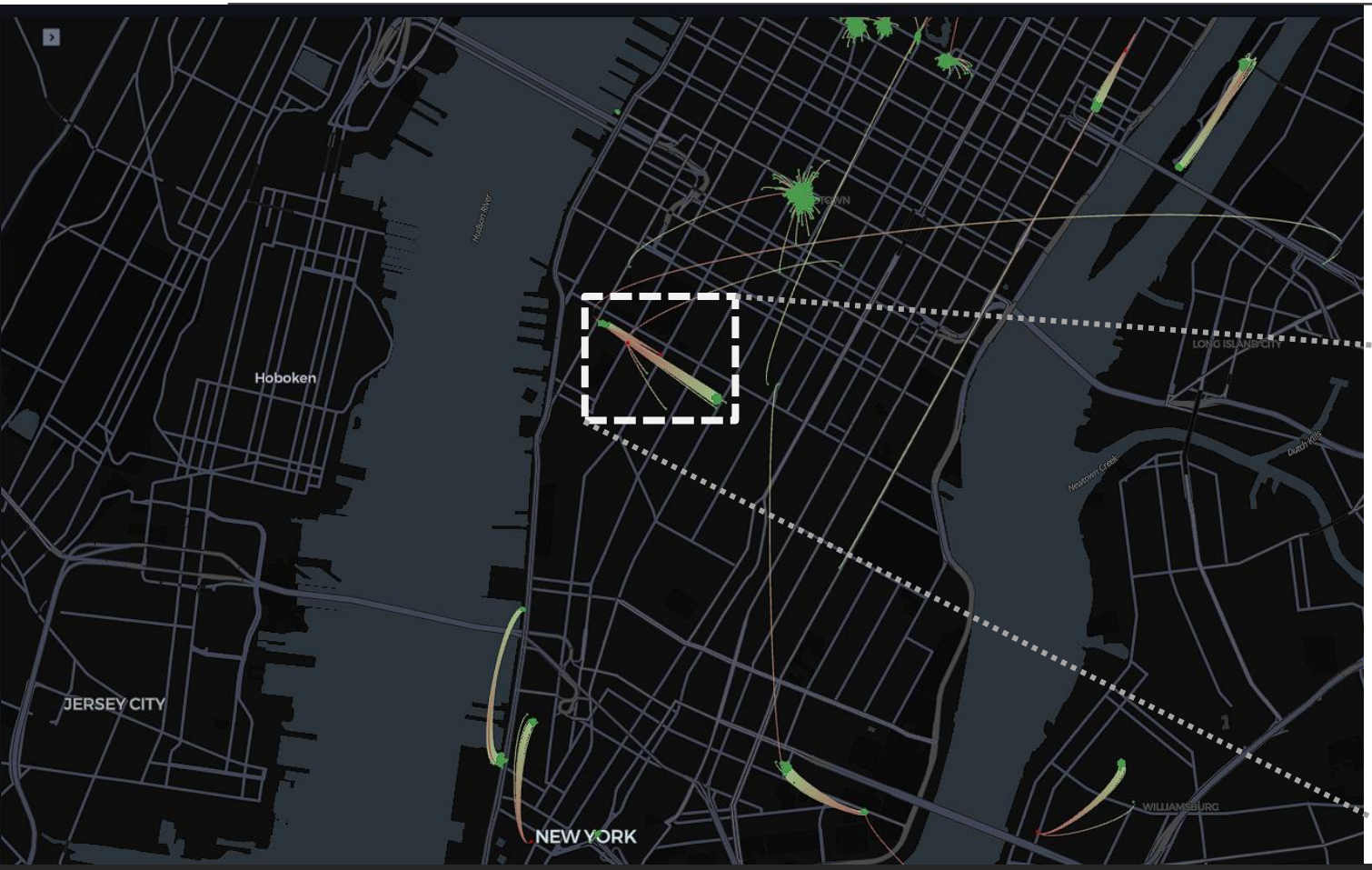
Full Dashboard Link

6 Citibike – Higher average temperature impact bike-rentals

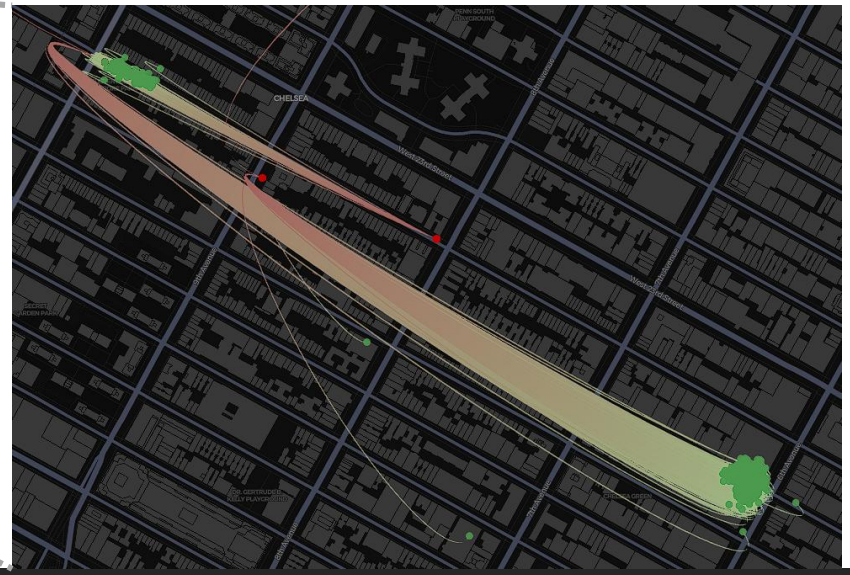


Full Dashboard Link

6 Citibike – Most popular stations and bike-trips

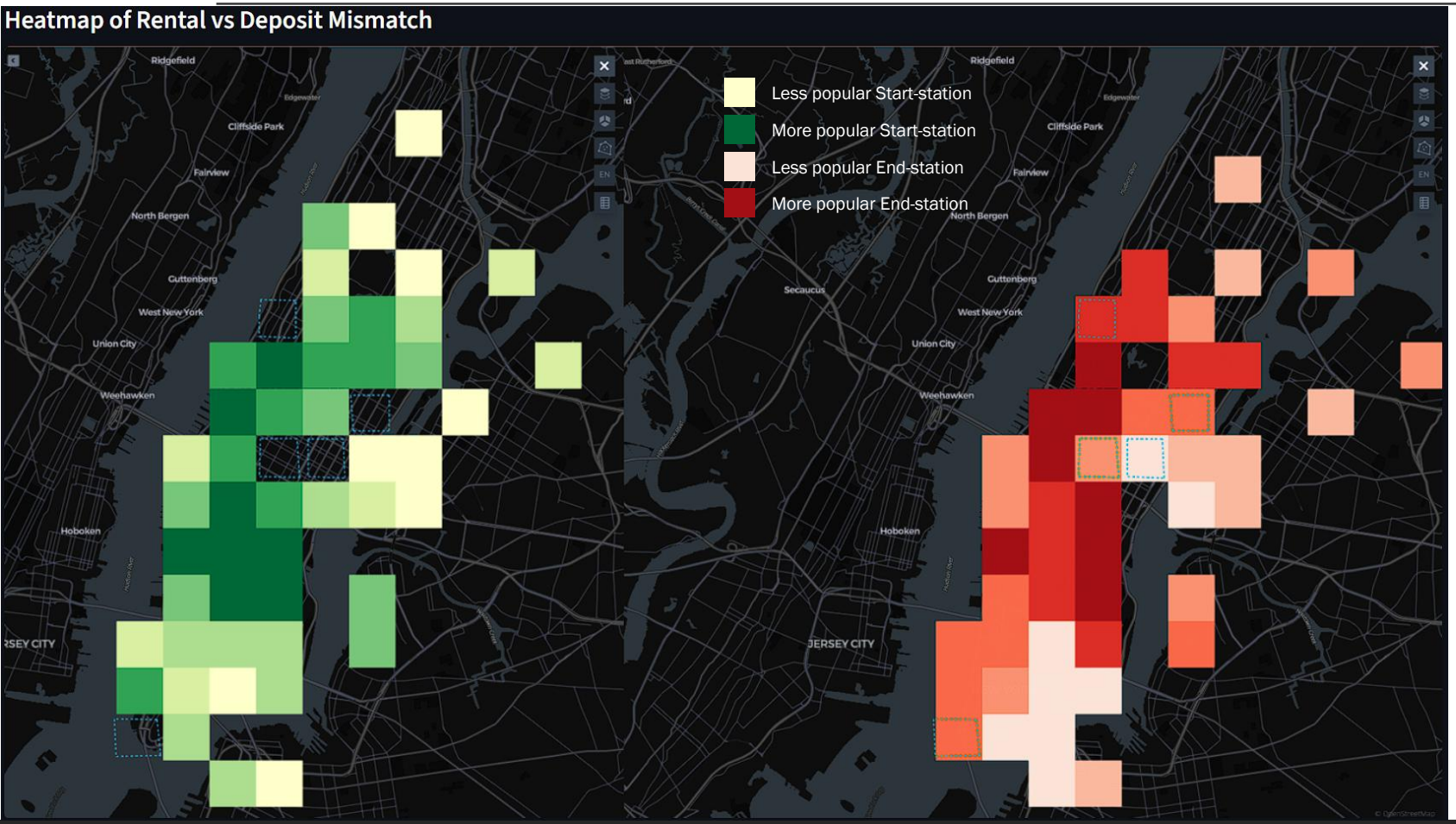


- The most popular stations are located South of Central Park
- Most popular stations in this area are:
  - 'W 21 & 6 Ave'
  - 'W St & Chambers St'
  - 'Broadway & W 58 St'.



[Full Dashboard Link]

6 Citibike – Determining areas of high bike build-up



- Heatmap shows areas where bikes are being rented-from and moved-to
- The Blue dotted squares show where bikes are being deposited-to, but not rented-from.
- This could lead to a bike build-up.

Full Dashboard Link

6 Citibike – Data-driven recommendations

- Be prepared for heavier bike-rental usage starting in May and going up until mid-November. If warmer temperatures are happening outside these months, then heavier bike-usage may also happen.

- Begin a re-distribution of bikes from build-up areas to the areas of highest bike-rental. Specifically, bikes should be moved from stations at:
  - **W 22 & 8 Ave**
  - **1 Ave & E 68 St**
  - **S 4 St & Wythe Ave**
  - **Pier 40 - Hudson River Park**

Full Dashboard Link