SUSAN WANG

Data Analytics Portfolio

PROJECTS

SPOTIFY ANALYSIS	*Exploratory Analysis*
ROCKBUSTER	*Query-based Analysis*
GAMECO	*Descriptive analysis*
CDC INFLUENZA	*Statistical analysis*
INSTACART	*Exploratory Analysis*
PIG E BANK	*Predictive Analysis*

Spotify Music Analysis

Advanced Analytics and Dashboard Design

Overview

Context:

Spotify is one of the most popular music streaming apps today. There is ample data collected on artists and songs on its platform. An exploration of the top hits over two decades aims to discover trends and patterns of the most popular songs.

Key Questions:

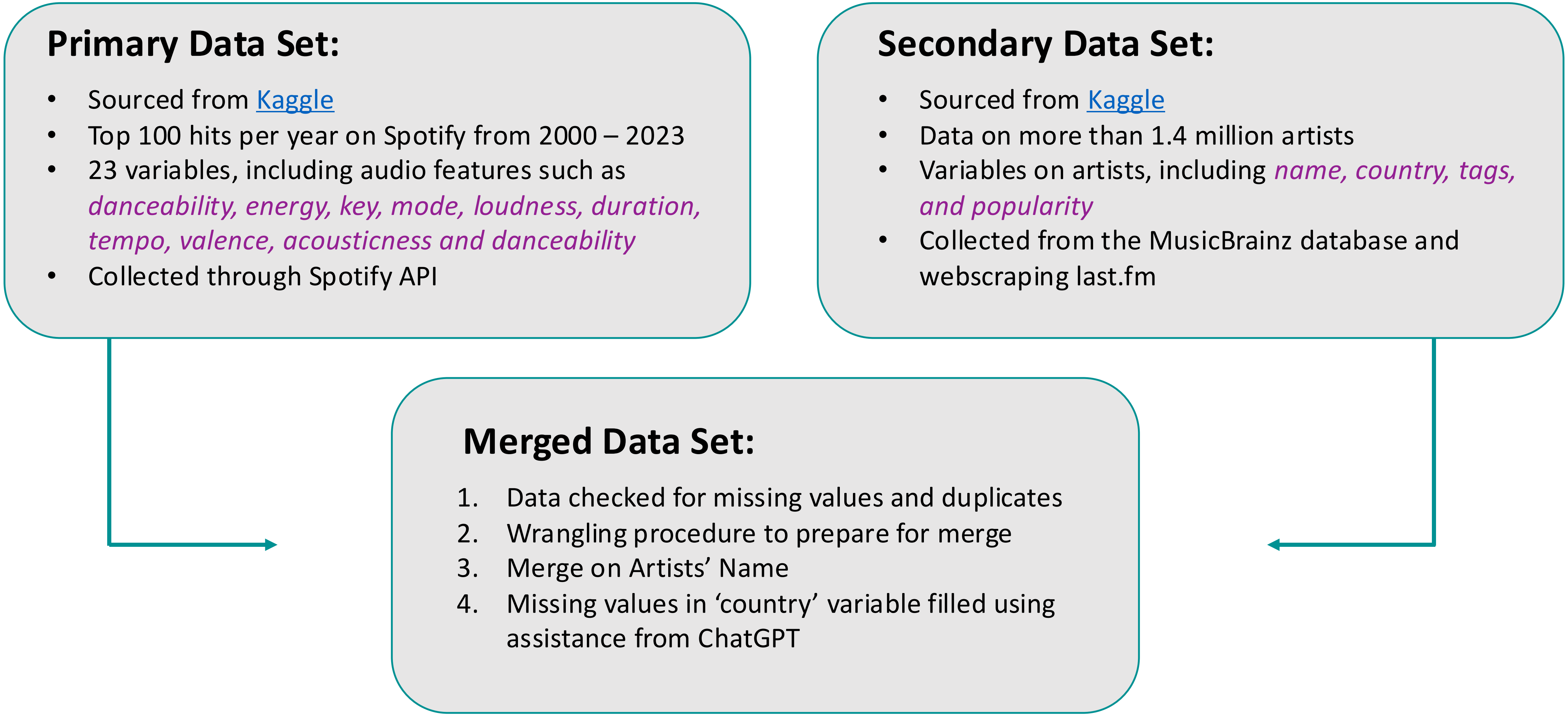
- Where do most popular songs come from?
- Which audio features define a top hit?
- How has the music changed over the years?
- Can we predict how popular music sounds in the future?

Data:	Spotify Top Hit Playlist 2000 – 2023, Music Artists Popularity Data Set
Skills:	Data cleaning and wrangling, Exploratory analysis, Machine learning models, Dashboard creation
Tools:	Python, Tableau

Process:

- Preparing the data – cleaning and wrangling
- Exploratory visual analysis – finding correlations
- Regression analysis – testing a hypothesis
- Time series analysis – testing for stationarity
- Geospatial analysis – visual insights through mapping

Sourcing and Preparing Data



Primary Data Set:

- Sourced from Kaggle
- Top 100 hits per year on Spotify from 2000 – 2023
- 23 variables, including audio features such as *danceability, energy, key, mode, loudness, duration, tempo, valence, acousticness and danceability*
- Collected through Spotify API

Secondary Data Set:

- Sourced from Kaggle
- Data on more than 1.4 million artists
- Variables on artists, including *name, country, tags, and popularity*
- Collected from the MusicBrainz database and webscraping last.fm

Merged Data Set:

1. Data checked for missing values and duplicates
2. Wrangling procedure to prepare for merge
3. Merge on Artists’ Name
4. Missing values in ‘country’ variable filled using assistance from ChatGPT

Exploratory Visual Analysis

1

Relevant variables were placed in a **correlation matrix heatmap** with the following results:

- Strong positive correlation (0.69) between energy and loudness
- Strong negative correlation (-0.55) between acousticness and energy

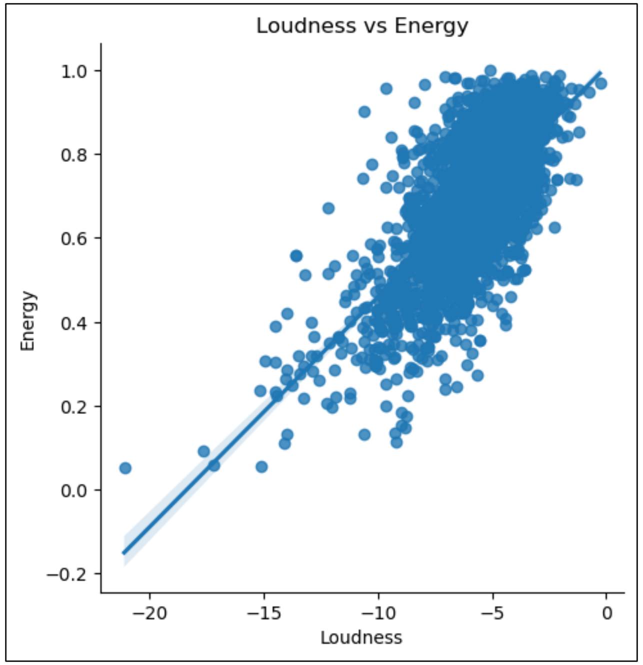
2

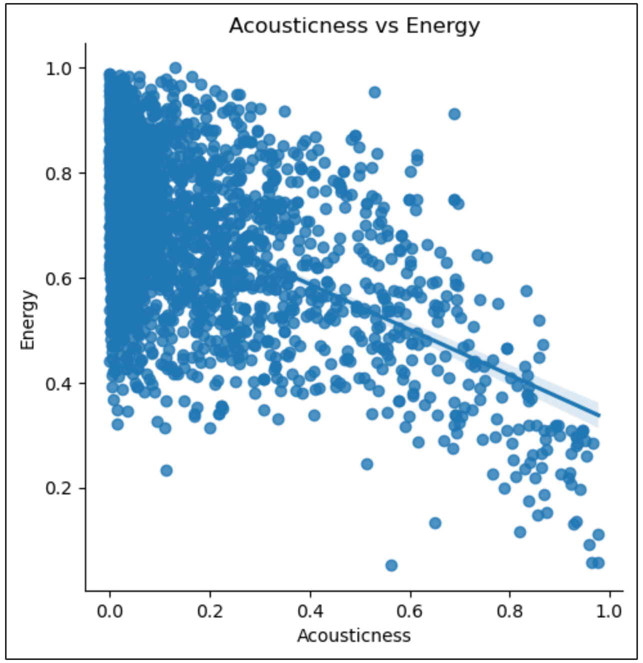
The correlations were visualized through scatterplots. The relationship between energy and acousticness was chosen for further exploration.

3

Hypothesis:

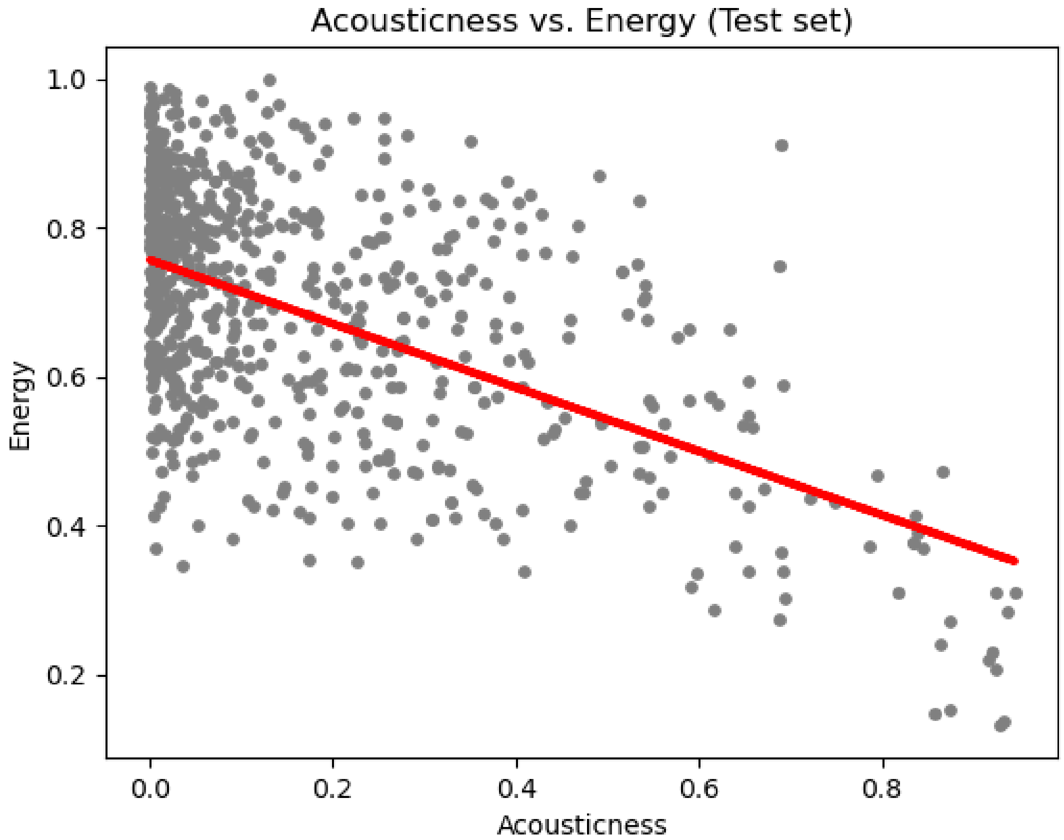
The more acoustic a song is, the less energy (or calmer) it feels.





Linear Regression

Regression analysis performed in Python on following hypothesis:
The more acoustic a song is, the less energy (or calmer) it feels.



Model performance statistics on test set:

Slope: -0.42
MSE: -0.019
R2 Score: 0.309

- The negative slope confirms the negative correlation between acousticness and energy.
- The low MSE shows that the model's predictions are close to the actual values.
- The low R2 score indicates that this model **cannot** explain almost 70% of the variances in the data: the model is a **poor fit**.

Interpretation of results:

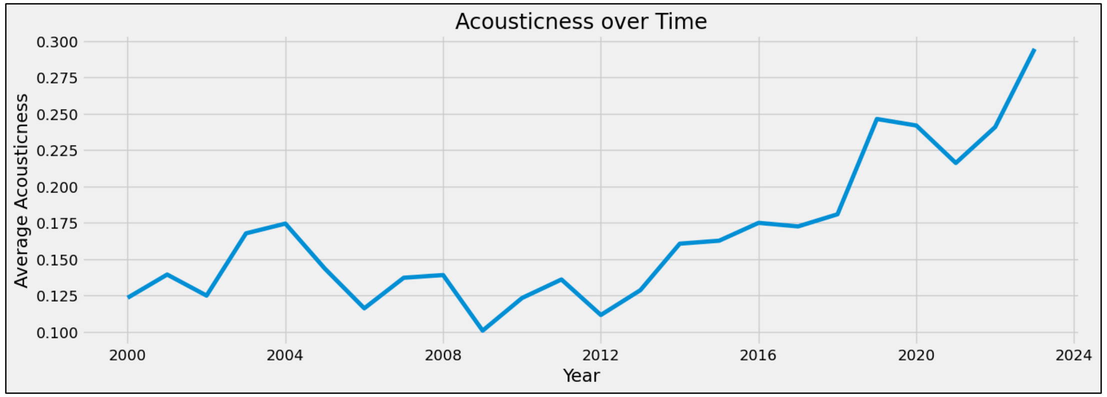
Acousticness alone does not explain energy level of a song. For the complexity of this case, a more advanced multiple linear regression model may prove a better fit.

Time Series Analysis

Acousticness over time:

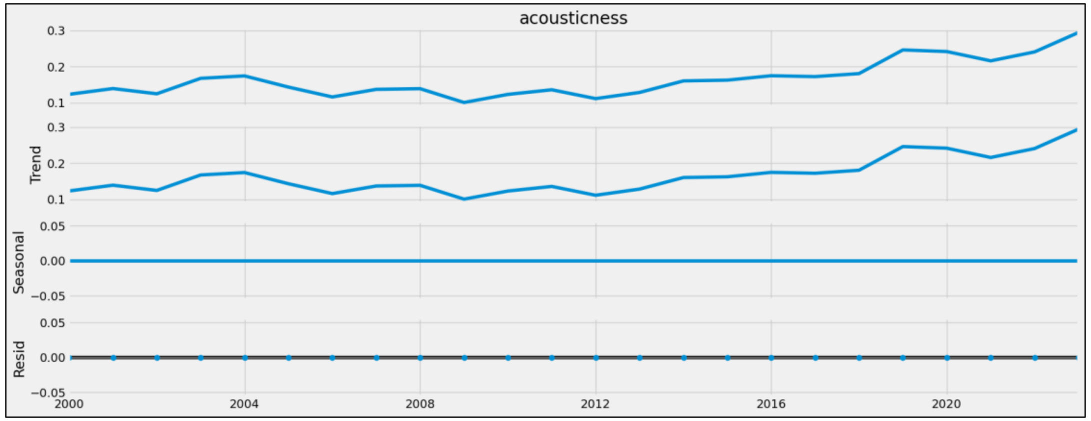
The introduction of electronics to music came only in about the last half century and is a relatively young genre in the long history of music.

Has the use of electronics continued to gain prominence since the beginning of this millenium?

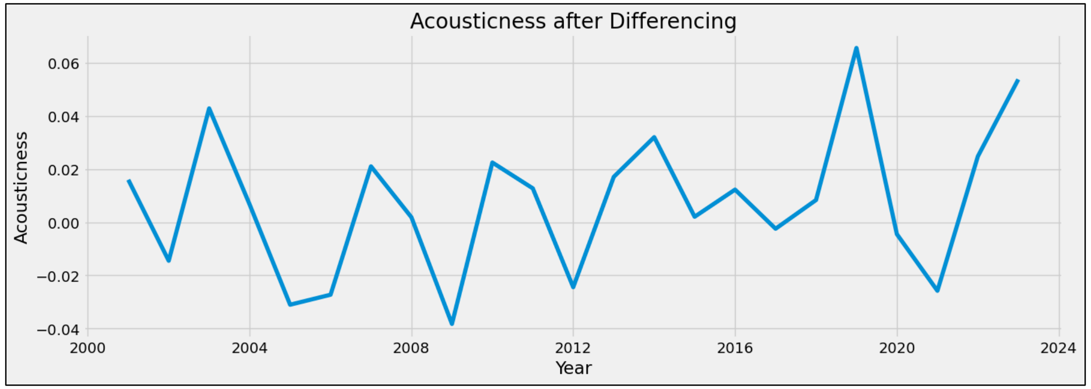


Surprisingly, average acousticness of the top hits since 2000 show a **rise in the last decade**. It seems that the electronic age may have peaked in the early 2000's and acoustic instrumentation is now making a comeback.

Stationarizing the time series:



The decomposition of the time series show a slight upwards trend, with no seasonality nor residuals.



Even after differencing, this time series could not be stationarized.

Conclusion: This time series is not suitable for forecasting.

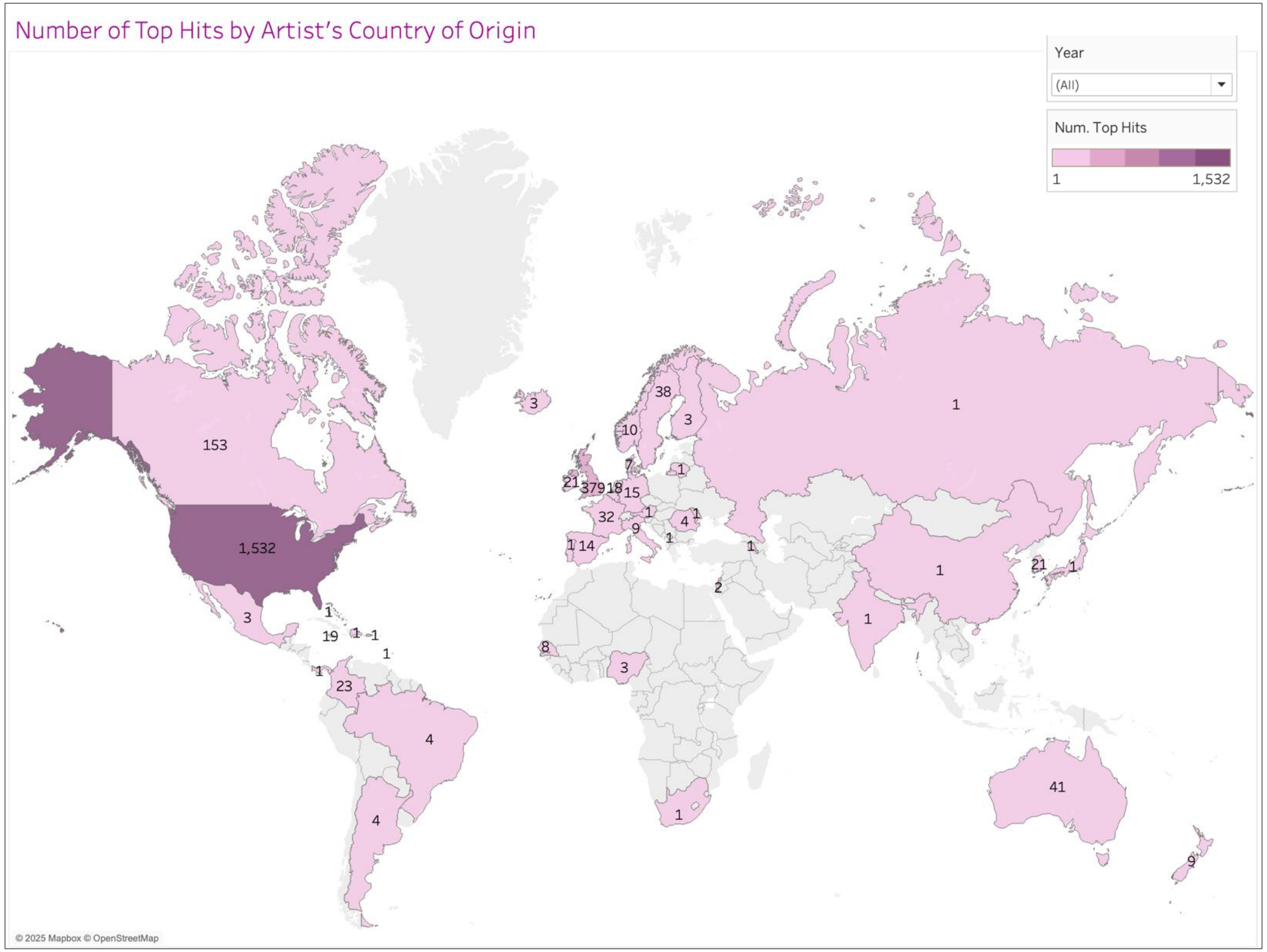
Geospatial Analysis

Where do the top hits come from?

Key takeaways from the geospatial analysis:

- The **USA** is home to the highest number of top hit artists.
- **English-speaking countries** (USA, UK, Canada and Australia) dominate in total number of hits over the last two decades.
- **South Korea** starts to gain significant numbers of top hits after 2019 and currently produces the highest number of popular artists in Asia.

Please click here to visit the interactive version of this map on Tableau.


Number of Top Hits by Artist's Country of Origin

Conclusions

Key Insights:

- American artists continue to top the charts in popular music.
- The last two decades have been a flourishing time for electronic (non-acoustic) music that are high in energy.
- Acoustic instrumentation has gradually returned over the last few years.
- The data doesn’t allow for forecasting, therefore we cannot predict how popular music will evolve in the future.

Project assessment:

The accuracy and reliability of the data on audio features are highly dependent on the specifications of Spotify's algorithms.
Ultimately, the data proved unsuitable for various models, such as linear regression, cluster analysis and time series forecasting.
Although these limitations created challenges in producing the insights to popular music I was hoping for, it reminded me that music is an art, and numbers cannot always capture the essence of art.

Next steps for further analysis:

- Perform an advanced multiple linear regression model on multiple audio features.
- Observe and compare audio features of top hits by various artist's nationalities.

The Tableau Storyboard and GitHub Repository are available to view:

Rockbuster Analysis Project

Launch Strategy for an Online Movie Rental Service

Overview

Context:

Rockbuster Stealth LLC* is a movie rental company looking to launch an online video rental service in order to stay competitive with online streaming services such as Amazon Prime and Netflix.

Objectives:

The Rockbuster management would like to have a better understanding of their customer base. They have business questions and expect data-driven answers to use for their launch strategy.

Role:

Data analyst for Rockbuster's business intelligence department, tasked to help with the launch strategy for the new online video service.

Data:	Rockbuster data set*
Skills:	data modeling, data cleaning and summarizing, database querying, data visualizations, reporting
Tools:	PostgreSQL, Excel, and Tableau

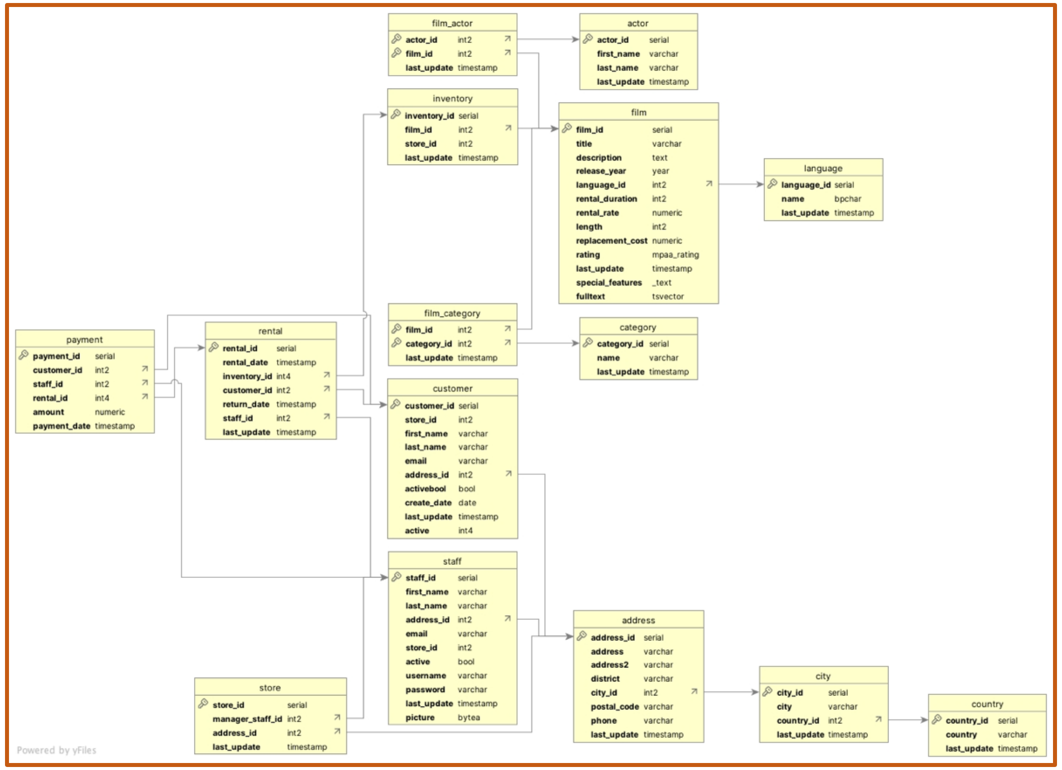
Process:

- Understanding the data structure
- Exploring and preparing the data
- Answer business questions through queries
- Report findings and offer recommendations

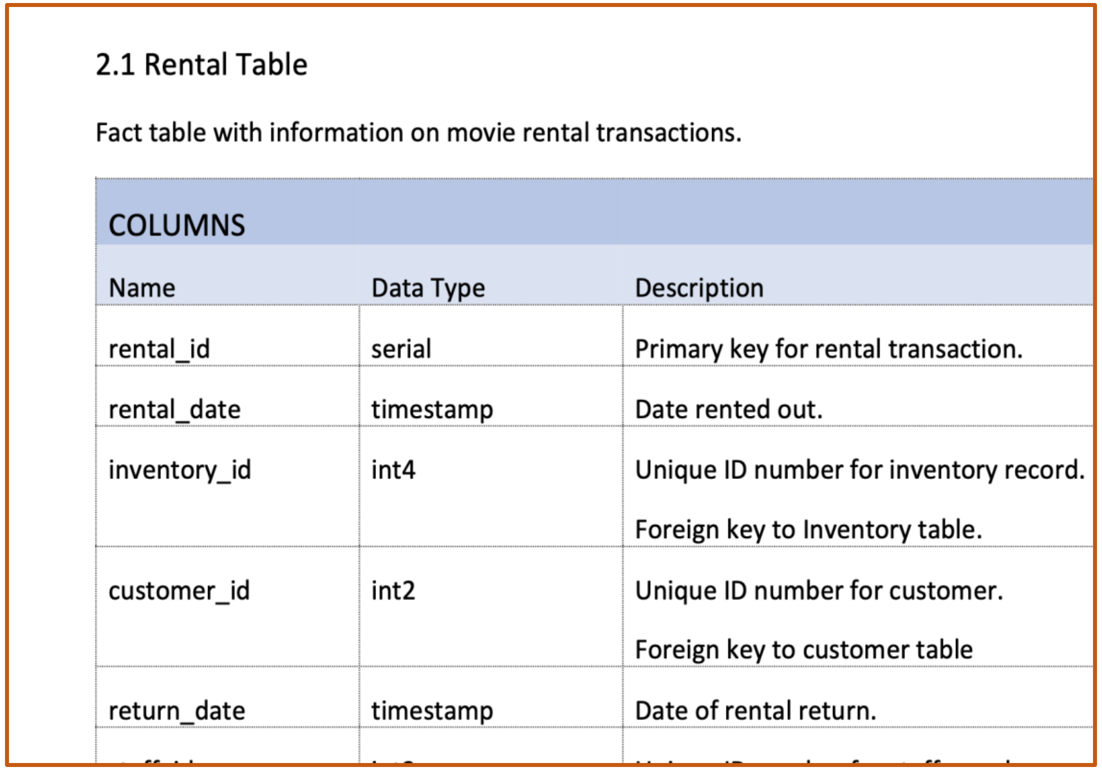
**This project and data set were created as part of the CareerFoundry data analytics course.*

Understanding the Data

The Entity Relationship Diagram of the Rockbuster database shows the relationships between the various tables and how they are linked.
Creating a data dictionary helps to clarify the complex relationships and define the data within each table.
The data dictionary serves as a reference document for the data analyst when accessing and querying the database.



Entity Relationship Diagram, extracted using DbVisualizer



2.1 Rental Table

Fact table with information on movie rental transactions.

COLUMNS

Name	Data Type	Description
rental_id	serial	Primary key for rental transaction.
rental_date	timestamp	Date rented out.
inventory_id	int4	Unique ID number for inventory record. Foreign key to Inventory table.
customer_id	int2	Unique ID number for customer. Foreign key to customer table
return_date	timestamp	Date of rental return.

Example from the data dictionary created for this project.

Exploring the Data

1 Data Cleaning: the data was checked for duplicates, missing values or inconsistencies.

2 Exploration: summary statistics were made on various tables:

Stores
Customers
Rentals
Payments
Inventory
Films

Statistics on customer data:	
Number of customers:	599
Most customers registered at store in:	Lethbridge, Canada
Number of active customers:	584
All customers’ accts created:	2006-02-14

Statistics on film data:	
Number of films:	1000
Average rental duration:	5 days
Average rental rate:	$ 2.98
Most frequent film rating:	PG-13
All films released in the year:	2006
All films in language:	English

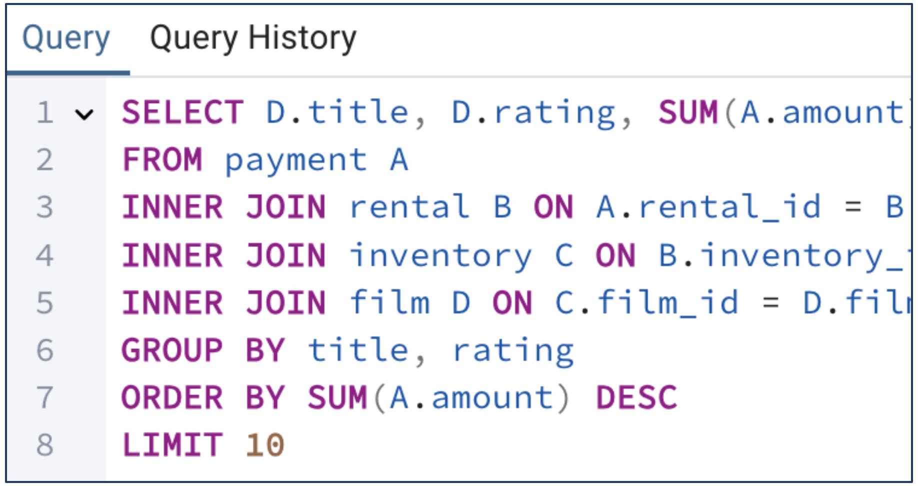
Answering Business Questions

More complex queries use filtering, joining tables, or nesting subqueries to answer some of the management's key questions.

Who are our most valued paying customers?

First Name	Country	Total Rev
Eleanor	Runion	$ 211.55
Karl	United States	$ 208.58
Marion	Brazil	$ 194.61
Rhonda	Netherlands	$ 191.62
Clara	Belarus	$ 189.60

Which movies bring in the most revenue?



```sql
SELECT D.title, D.rating, SUM(A.amount
FROM payment A
INNER JOIN rental B ON A.rental_id = B
INNER JOIN inventory C ON B.inventory_
INNER JOIN film D ON C.film_id = D.fil
GROUP BY title, rating
ORDER BY SUM(A.amount) DESC
LIMIT 10
```

Snapshot of the SQL query input

Movie Title	Rating	Total Rev
Telegraph Voyage	PG	$ 215.75
Zorro Ark	NC-17	$ 199.72
Wife Turn	NC-17	$ 198.73
Innocent Usual	PG-13	$ 191.74
Hustler Party	NC-17	$ 190.78

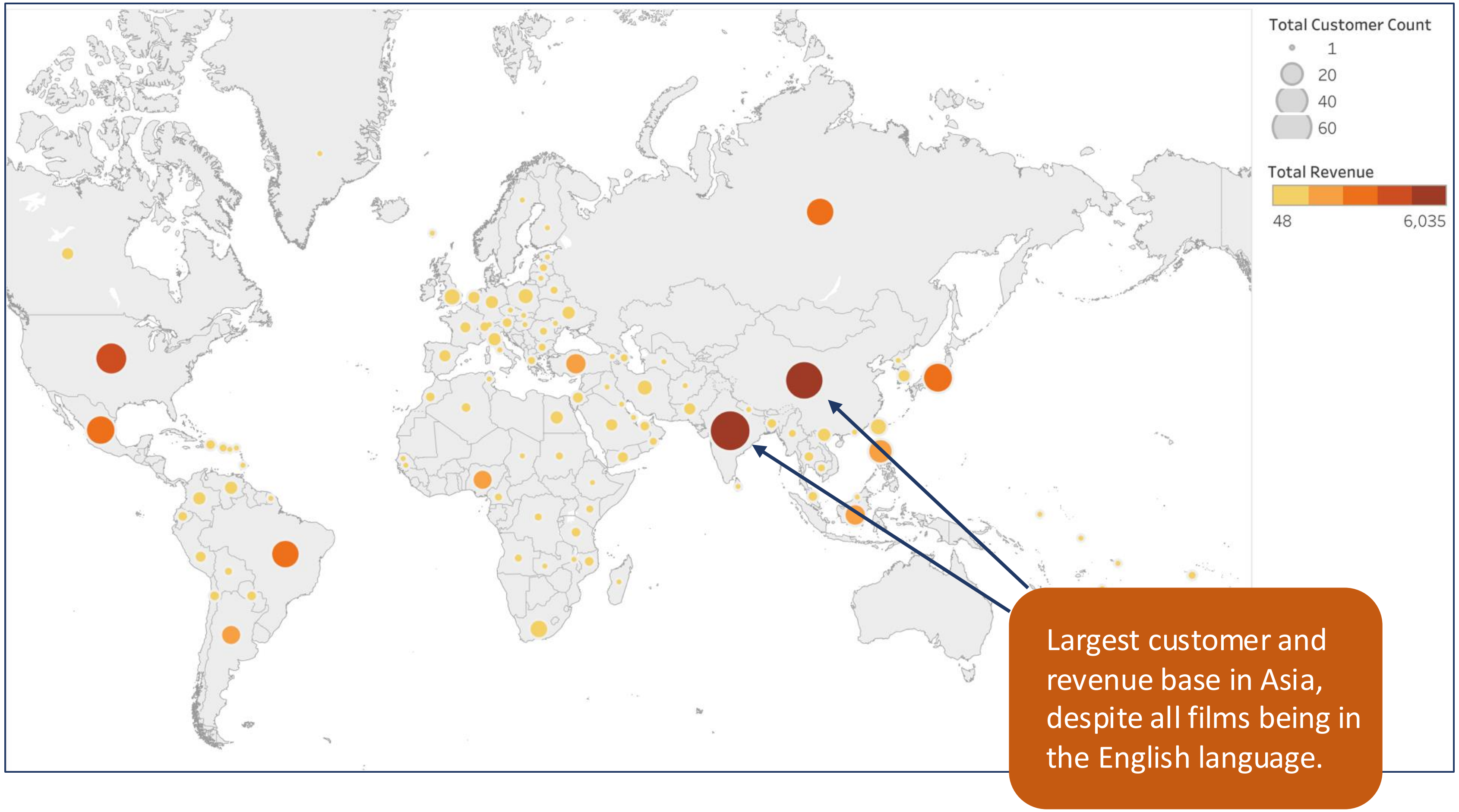
Please get in touch if you are interested in viewing the Excel Workbook with all SQL queries and results.

Data Visualization

Which countries have the most customers?
Which countries bring the most revenue?

Visualizing the result of a query can illuminate a pattern that may otherwise go unnoticed!

Number of Customers and Total Revenue by Country



Largest customer and revenue base in Asia, despite all films being in the English language.

Click to view the interactive map on Tableau.

Conclusions

Recommendations for Launch:

Following my exploratory analysis, these are some recommendations I would make to the Rockbuster launch team:

- Invest more advertising for the new platform in countries with the highest number of customers (India, China, US).
- Feature top revenue films on the front page of the online site.
- Expand and update the Rockbuster inventory to include films in more languages and release years.
- Retain valued customers when transitioning to the online platform by offering top payers a reward or discount.

Project assessment:

Through this project, I learned about the **challenges** in accessing data from a relational database. It is very important to understand the structure of the database, as it can be quite complex.

The various business questions gave me an opportunity to refine my SQL programming skills, especially in the task of **joining tables** and performing **subqueries**.

The frame of the project allowed me to answer the business questions presented, but I would have liked to further **explore** follow-up questions such as:

- *Which films are most popular in the top countries?*
- *Are there film ratings that produce more revenue?*

The final project presentation and GitHub Repository are available to view:

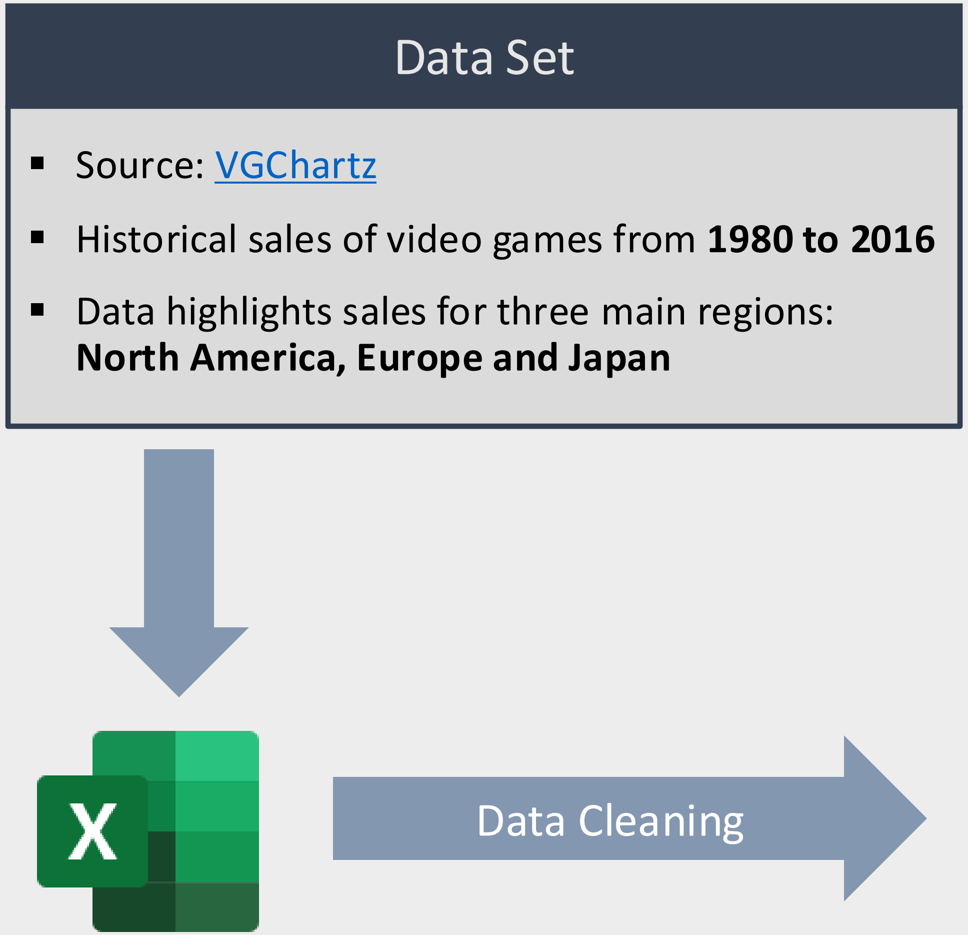
GAMECO

Analyzing video game sales by geographical region

Case Study

GameCo is a new video game company, whose executive board assumes that video game sales across various geographical regions have remained the same over time.

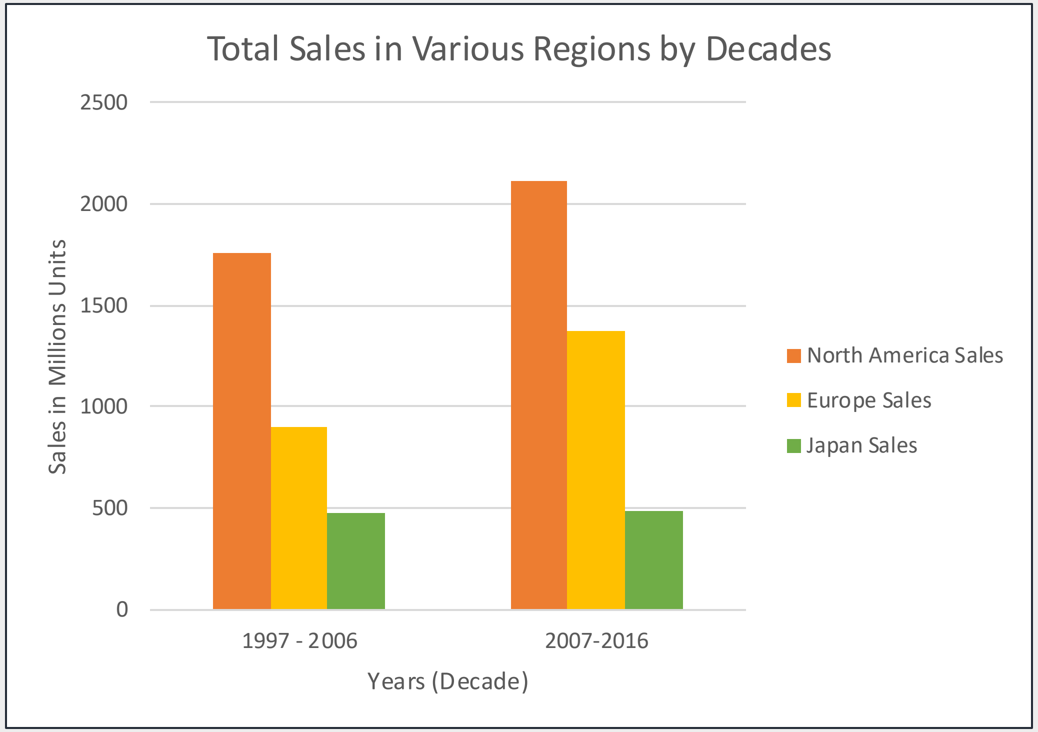
This analysis aims to provide a better understanding of the market and inform the board on effective distribution of the marketing budget.



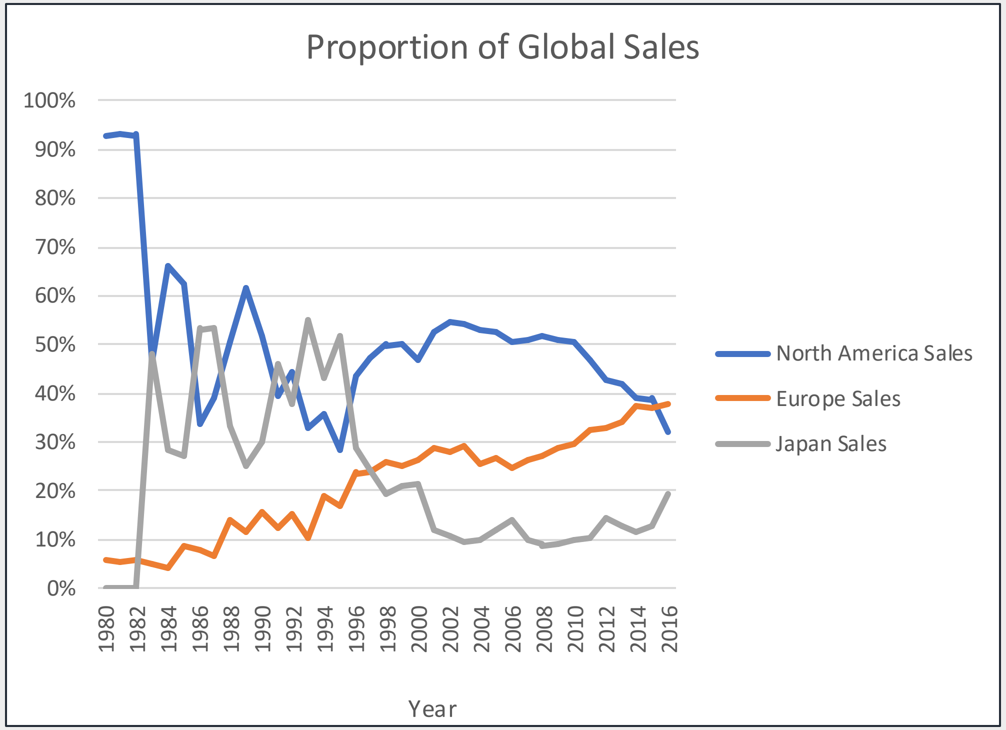
Data Set

- Source: VGChartz
- Historical sales of video games from **1980 to 2016**
- Data highlights sales for three main regions: **North America, Europe and Japan**

Descriptive Analysis



When the data is grouped and summarized by **total sales** in the various regions, it seems that the distribution among the top three regions have stayed the same over the decades.



But if the data is summarized by the **proportion** of sales by region over the years, a different story emerges. The most recent trend shows European sales have surpassed North American sales.

Results and Recommendations

Analysis on the historical data shows a **change** in global distribution of the video games market.

Europe sales surpassed North America sales in 2016, and Japan sales are on the rise.

Following the recent trend, GameCo would profit from a larger investment in the rising European market.

← Link to Project Presentation

CDC INFLUENZA

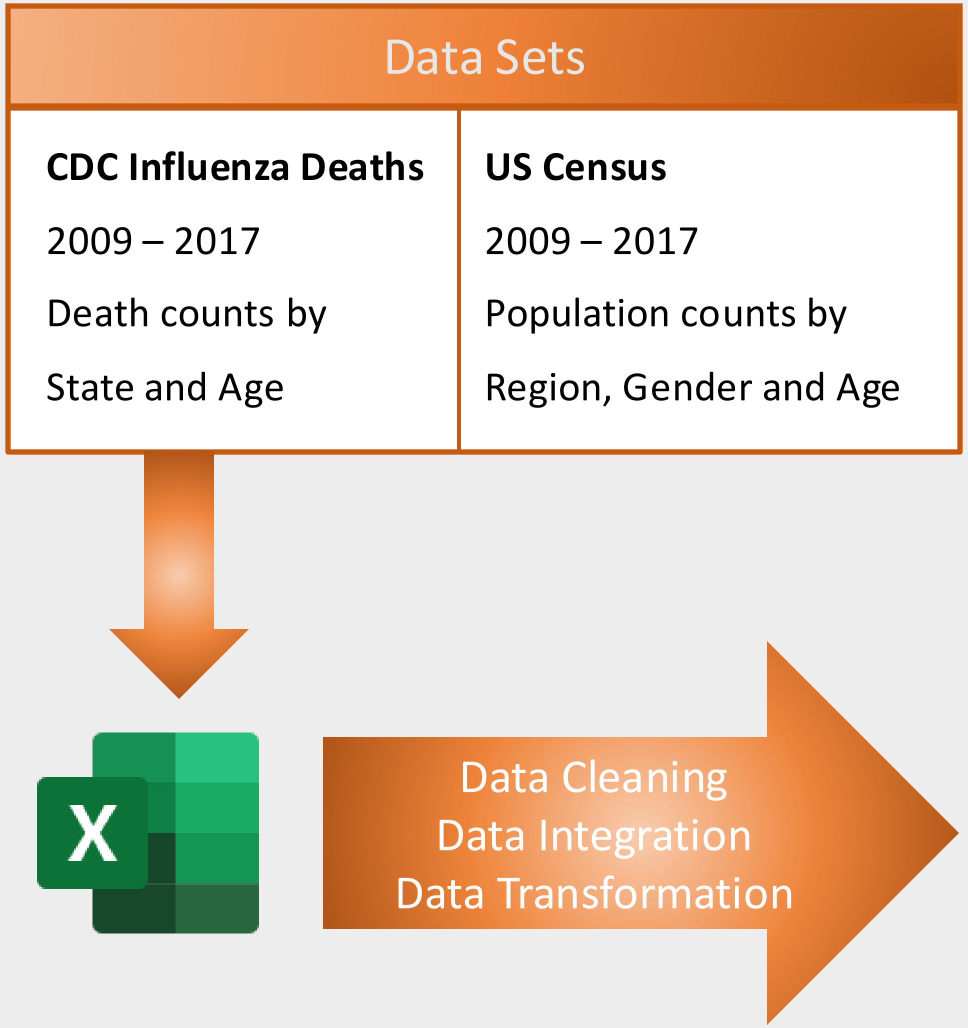
Preparing for the Influenza Season in the U.S.

Case Study

The United States has an influenza season where more people suffer from the flu, particularly those in **vulnerable** populations.

The medical staffing agency provides temporary workers to hospitals and clinics to adequately treat patients during these times.

This analysis examines trends in influenza to advise the medical staffing agency on how to plan for the influenza season and optimize staff distribution across the country.



Data Sets	
CDC Influenza Deaths 2009 – 2017 Death counts by State and Age	**US Census** 2009 – 2017 Population counts by Region, Gender and Age

Data Cleaning
Data Integration
Data Transformation

Statistical Analysis

1

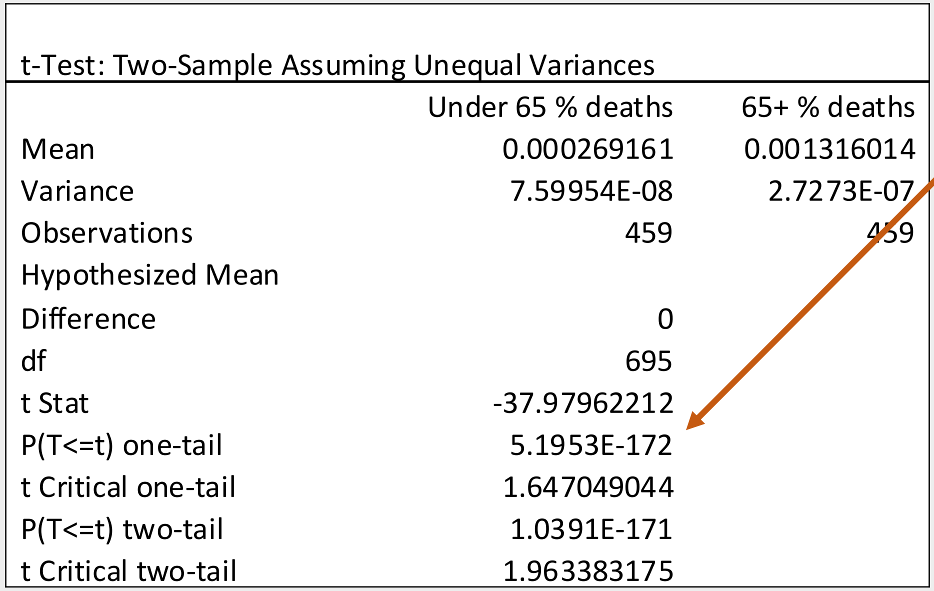
Research hypothesis:
If a state has a higher number of senior citizens over 65, then it will also have a higher proportion of severe cases or deaths from influenza.

Null hypothesis:
The flu mortality rate for people 65 years and older is the same or less than the flu mortality rate for the population under 65.

Alternative hypothesis:
The flu mortality rate for people 65 and older is higher than the flu mortality rate for people under 65.

2

Statistical Hypothesis Testing:
Conduct a one-tailed two-sample t-test on the null hypothesis.



t-Test: Two-Sample Assuming Unequal Variances

	Under 65 % deaths	65+ % deaths
Mean	0.000269161	0.001316014
Variance	7.59954E-08	2.7273E-07
Observations	459	459
Hypothesized Mean Difference	0	
df	695	
t Stat	-37.97962212	
P(T<=t) one-tail	5.1953E-172	
t Critical one-tail	1.647049044	
P(T<=t) two-tail	1.0391E-171	
t Critical two-tail	1.963383175	

Because the observed p-value is 5.1953E-172, which is significantly smaller than the alpha of 0.05, we can **reject the null hypothesis.**

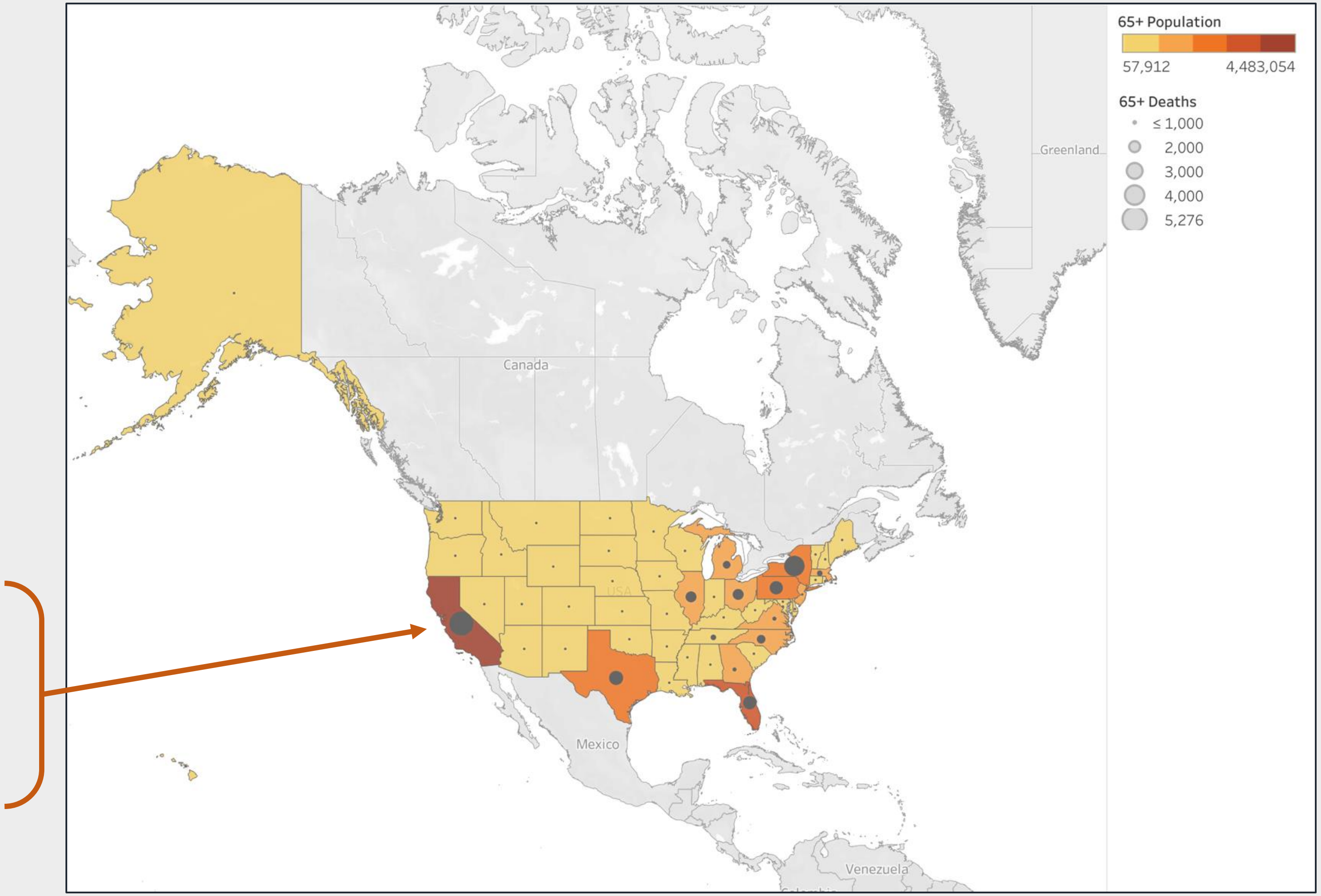
The staffing agency could optimize the distribution of their medical staff by focusing on areas with a higher proportion of citizens aged 65 and older.

Spatial Analysis

Building on the results of the hypothesis testing, the next step is to determine **which states** have a higher proportion of vulnerable elderly population.

This Tableau map shows the states with the highest population of citizens 65 years and above, as well as the states with the highest mortality rates in that age group.

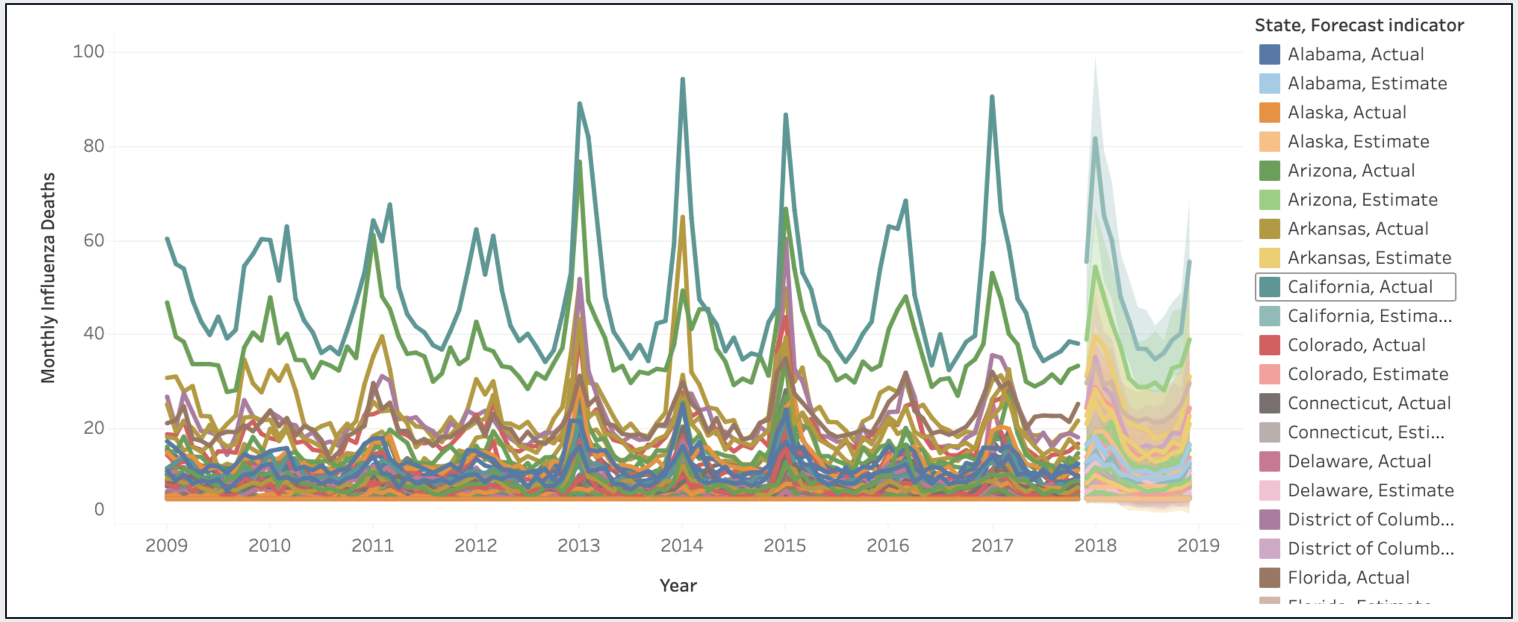
It is clear to see on this visualization that **California** leads in both highest population and highest mortality rate for seniors over the age of 65.



Results and Recommendations

This temporal forecast shows a clear seasonal trend in influenza cases every year. The flu season starts in the winter, peaking in January, and ends in spring.

With the combination of the results of the previous spatial analysis and this temporal chart, the medical agency can forecast the coming influenza season and distribute staff to the states with most need, at the time of most need.



On Tableau Public for this project, there is an **interactive tree map** that shows each state, its influenza statistics and its respective seasonal forecast chart.

On Vimeo, there is a video available on the presentation of this project.

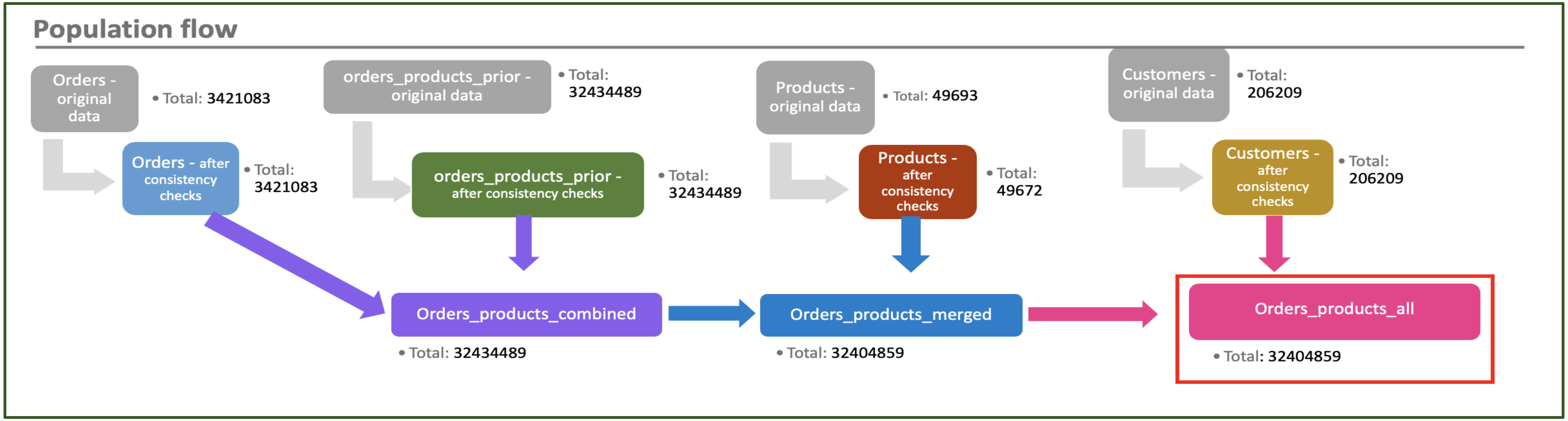
INSTACART

Marketing Strategy for an Online Grocery Store

Case Study

The Instacart stakeholders are interested in the variety of customers in their database. They are considering a targeted marketing strategy and would like to know more about sales patterns as well as their customers' purchasing behaviors. The large size of the data set requires the use of the powerful Python pandas library.

The Instacart data sets from Kaggle must go through **wrangling** and **consistency checks** before being **merged** into one useful data set for the purpose of this analysis. This population flow chart shows the transformation of the data sets through the various stages of consistency checks and merges.



Population flow

Orders - original data
- Total: 3421083

Orders - after consistency checks
- Total: 3421083

orders_products_prior - original data
- Total: 32434489

orders_products_prior - after consistency checks
- Total: 32434489

Products - original data
- Total: 49693

Products - after consistency checks
- Total: 49672

Customers - original data
- Total: 206209

Customers - after consistency checks
- Total: 206209

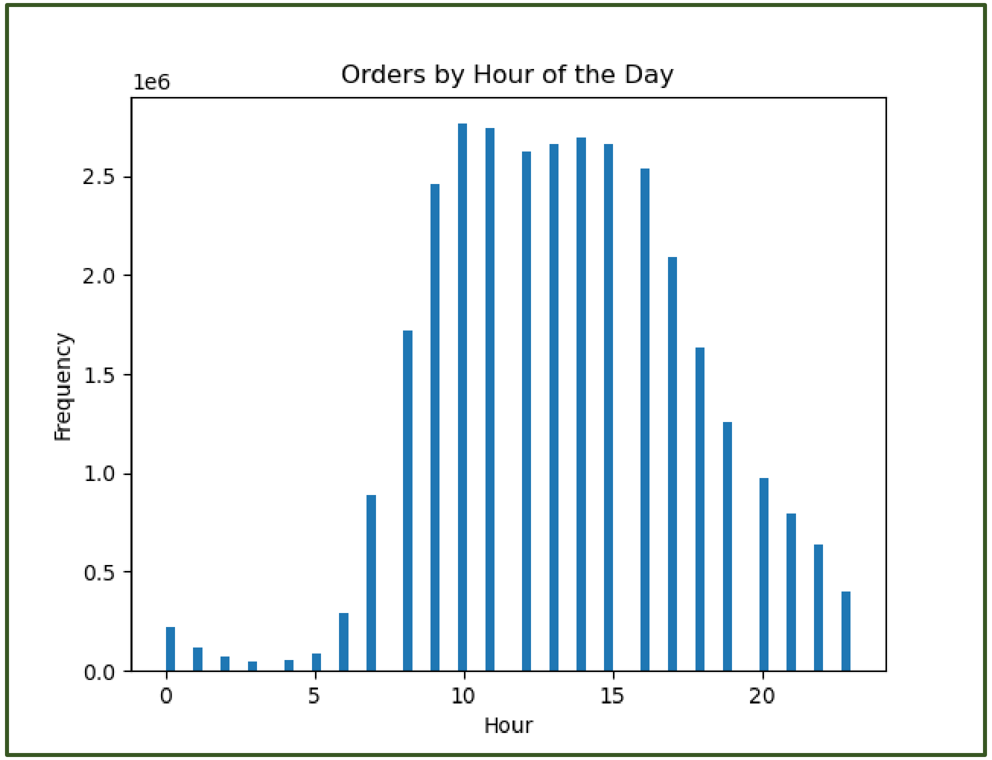
Orders_products_combined
- Total: 32434489

Orders_products_merged
- Total: 32404859

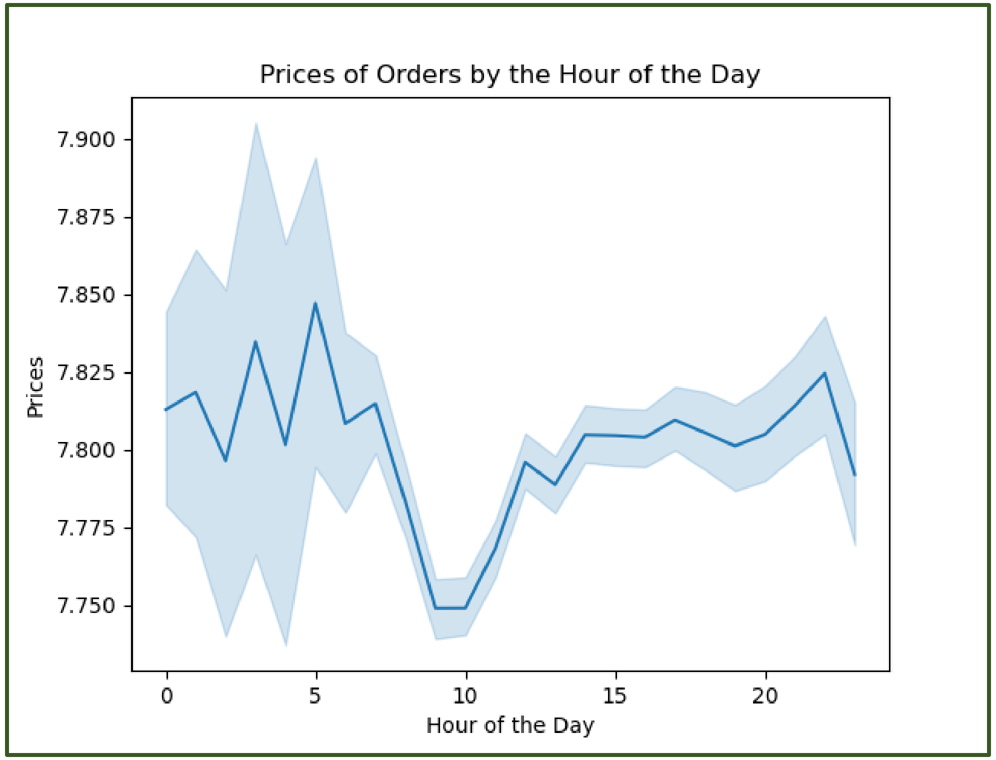
Orders_products_all
- Total: 32404859

Exploratory Analysis I

Customer Purchasing Behavior by Time of Day



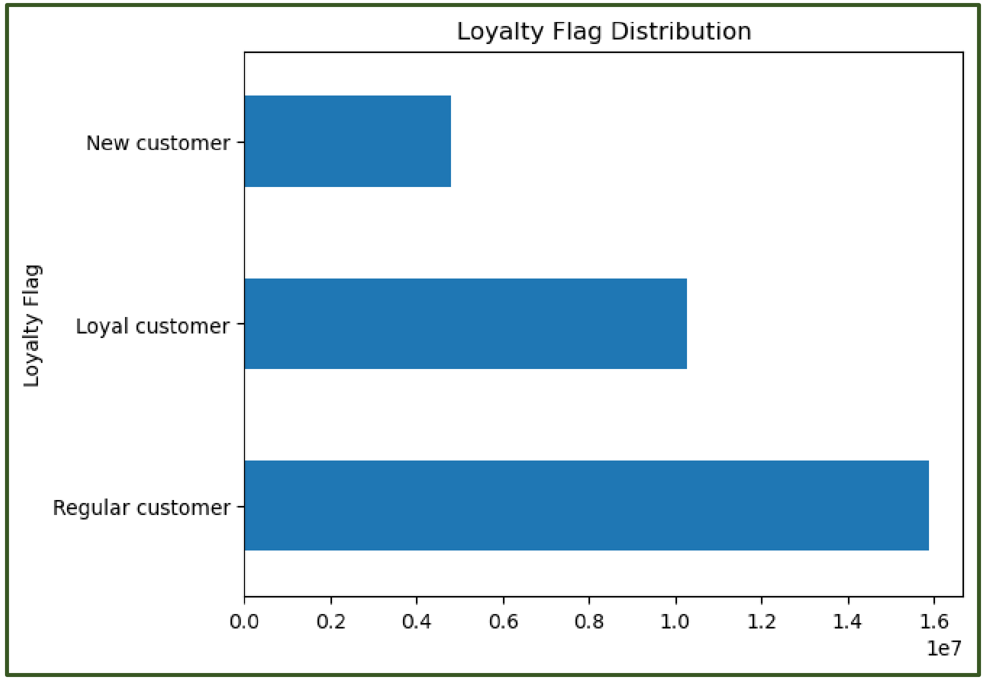
Viewing the data by the frequency of orders per hour shows the midday hours have the highest volume of orders.



However, an analysis of the average prices of orders show customers are purchasing lower priced items during those midday orders.

Exploratory Analysis II

Customer Ordering Habits and Demographics



A loyalty flag was created based on the number of orders each customer made. Loyal customers made over 40 orders while new customers made under 10 orders. Regular customers fall into the middle.

It is concerning to see that the smallest group are the new customers: if we want to increase the customer base, there should be efforts to increase as well as keep the new customers.

In order to further analyze customer ordering habits by demographics, customer profile tags were created on classifications of age and number of dependents.

There seems to be little difference in the average prices each group is paying.

Customer Profile	Mean Num Orders	Mean Prices
Older family	34.20	7.79
Single adult	**34.94**	7.79
Single youth	34.21	7.78
Young family	34.60	7.79

Additionally, we can see the breakdown of these customer types by regions in the US:

Customer Profile	Midwest	Northeast	South	West
Older family	48.12%	**48.42%**	47.55%	48.12%
Single adult	16.20%	15.83%	15.84%	**16.21%**
Single youth	8.90%	8.96%	**9.20%**	8.78%
Young family	26.78%	26.79%	**27.41%**	26.90%

Results and Recommendations

The marketing team can schedule ads in the early morning and times when they are less orders. They can choose to advertise pricier products, as customers seem more willing to pay for more during these off-hours.

The distribution of loyalty flags show that the smallest group of customers are new customers. Marketing may want to focus on attracting more customers as well as retaining the current ones in order to continue to expand the customer base.

Single adults over 40 order most frequently and also pay for pricier items.
Stores in various regions can target ads toward customer profile groups that are most prominent in their area.

Link to GitHub Repository with full Analysis and Jupyter Notebooks →

PIG E BANK

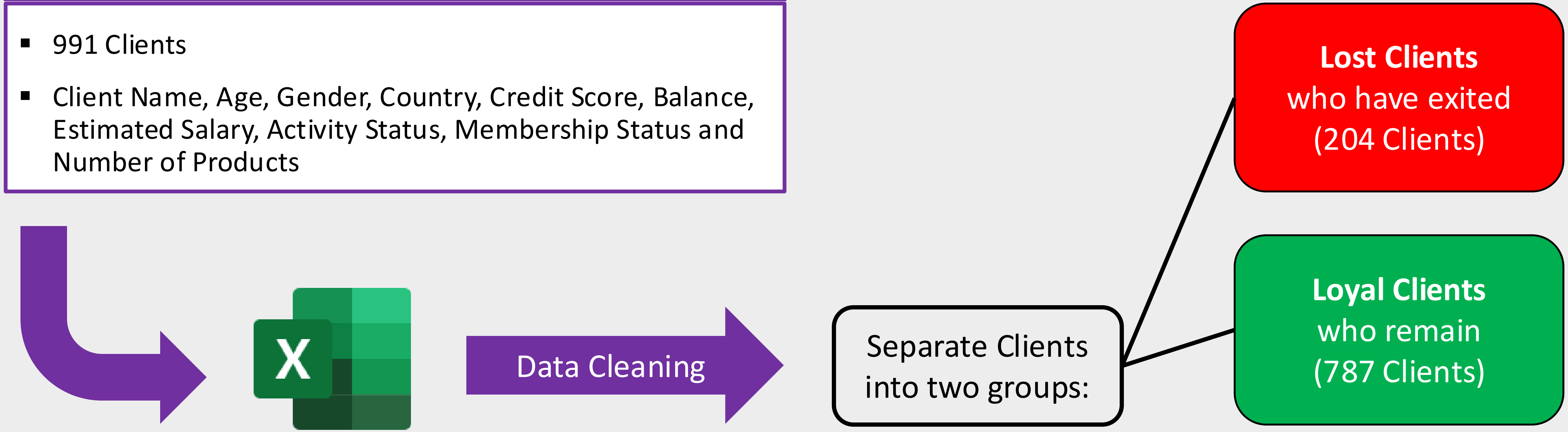
Analyzing Client Retention at a Global Bank

Case Study

To increase customer retention, the sales team at Pig E Bank wants to identify the leading indicators that a customer will leave the bank.

Client Data Set

- 991 Clients
- Client Name, Age, Gender, Country, Credit Score, Balance, Estimated Salary, Activity Status, Membership Status and Number of Products



Data Cleaning

Separate Clients into two groups:

Lost Clients who have exited (204 Clients)

Loyal Clients who remain (787 Clients)

Statistical Analysis

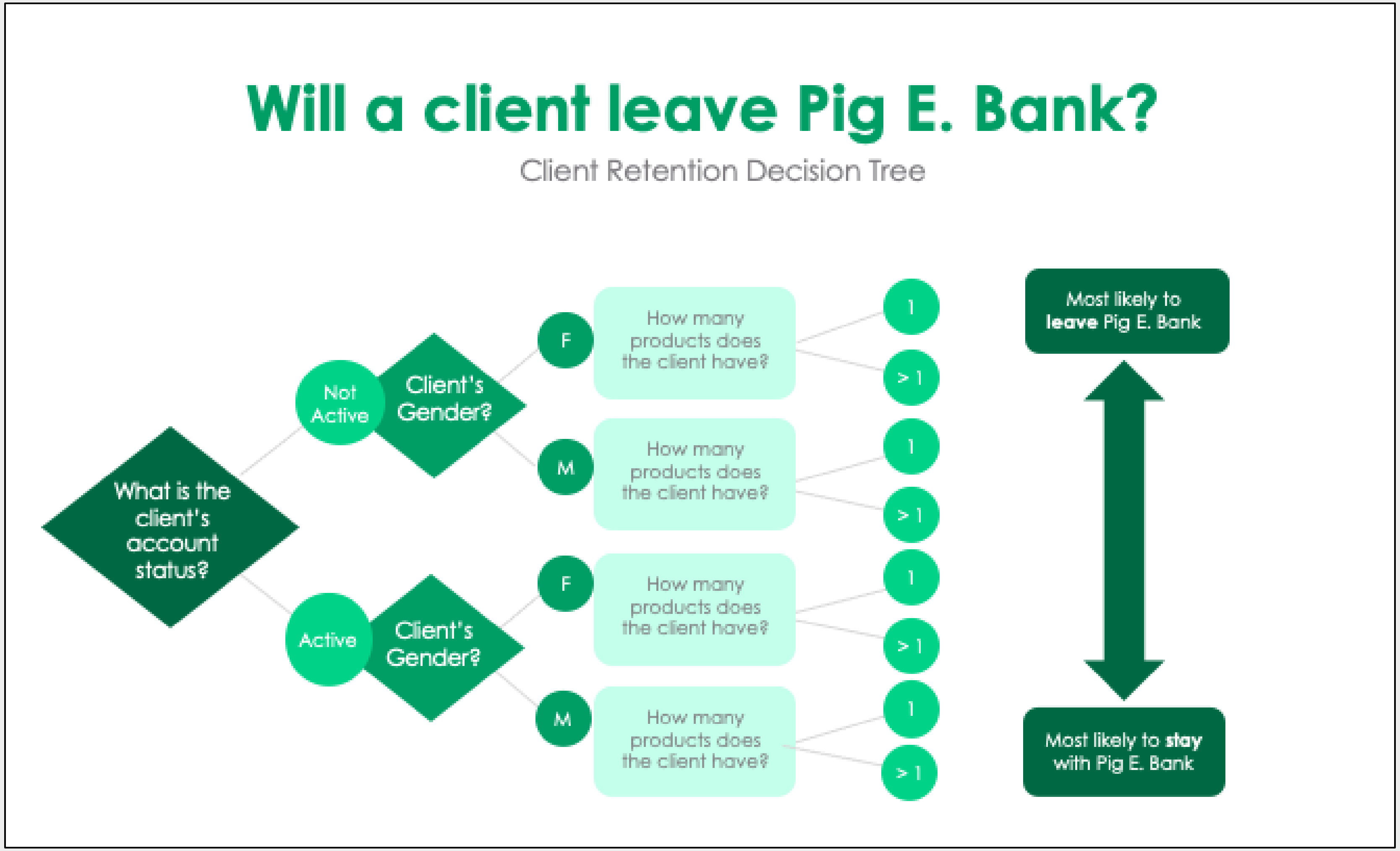
After examining the distribution of each group by different variables, comparisons of these statistics show that the following variables may be the leading factors that contribute to client loss.

If a client is **inactive**, they are twice as likely to leave. **Female** clients also have a higher churn rate. The chart also shows that clients who leave also tend to have **less products** on their account.

GROUP	GENDER	ACTIVE STATUS	NUM PRODUCTS
LOST Clients	Female 59.31 % Male 40.69 %	Active 29.90 % Inactive 70.10 %	1 69.61 % 2 15.69 % 3 13.73 % 4 00.98 %
LOYAL Clients	Female 43.46 % Male 56.54 %	Active 43.84 % Inactive 56.16 %	1 46.76 % 2 52.60 % 3 00.64 % 4 00.00 %

Predictive Analysis

We can implement a decision tree with the factors that were found in the statistical analysis that seem to influence client loss the most.



Will a client leave Pig E. Bank?

Client Retention Decision Tree

What is the client's account status?
Not Active
Active
Client's Gender?
Client's Gender?
F
M
F
M
How many products does the client have?
How many products does the client have?
How many products does the client have?
How many products does the client have?
1
> 1
1
> 1
1
> 1
1
> 1
Most likely to leave Pig E. Bank
Most likely to stay with Pig E. Bank

Next Steps

This project is in its modeling phase.
A decision tree has been created based on statistical analysis.

This model must now go through a testing and evaluation phase, in order to assess whether it meets the business goal of predicting client loss.

If successful, the model may then be implemented in the deployment phase and would be further monitored on its effectiveness.

CONTACT

If you have questions, or are interested in working with me, please get in touch!