Ang Wei Jie

Data Analyst

Portfolio

Projects

01

GameCo

Sales Analysis of Gaming Company

02

Influenza Season

Influenza Death Analysis of United States

03

Rockbuster

Video & Customers Analysis of Video Rental Company

04

Instacart

Consumer Behavior Analysis Of Online Grocery Store

05

Pig E. Bank

Client Loss Analysis Of Bank

06

League of Legends

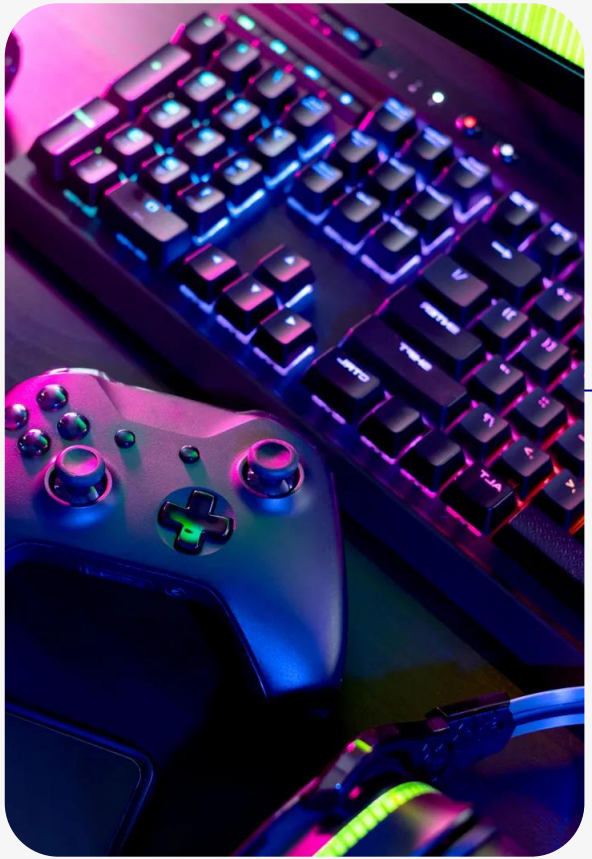
Exploratory Analysis Of Competitive Gameplay

Projects

07

ClimateWins

Machine Learning Model Prediction
Of Weather Conditions & Climate Change



01

GameCo

Sales Analysis
of Gaming Company

GameCo

Sales Analysis of Gaming Company

Background

GameCo, a new video game company, which wants to use data to inform the development of new games and how it might fare in the market so as to re-allocate their marketing budget.

Objective

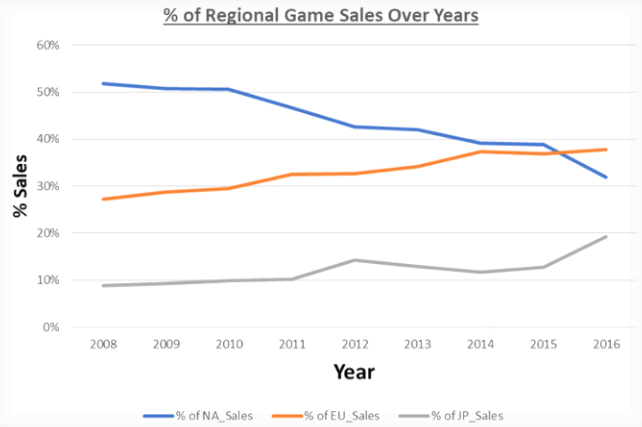
To conduct a descriptive analysis of the video game regional sales dataset to understand the market trend and give recommendation for marketing budget re-allocation.

Skills

- Data cleaning
- Data grouping
- Data summarizing
- Pivot tables
- Descriptive analysis
- Visualizatiton Charts

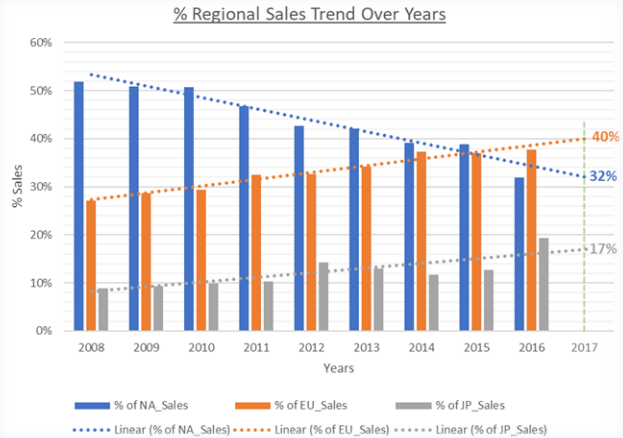
Tools Used:

Analysis



- Grouped sales data into 3 main regions (NA, EU, JP) and analyze their market share contributions from year 2008 to 2016.
- EU sales have been slowly rising and have taken over the top market share for % sales contribution as of year 2016.

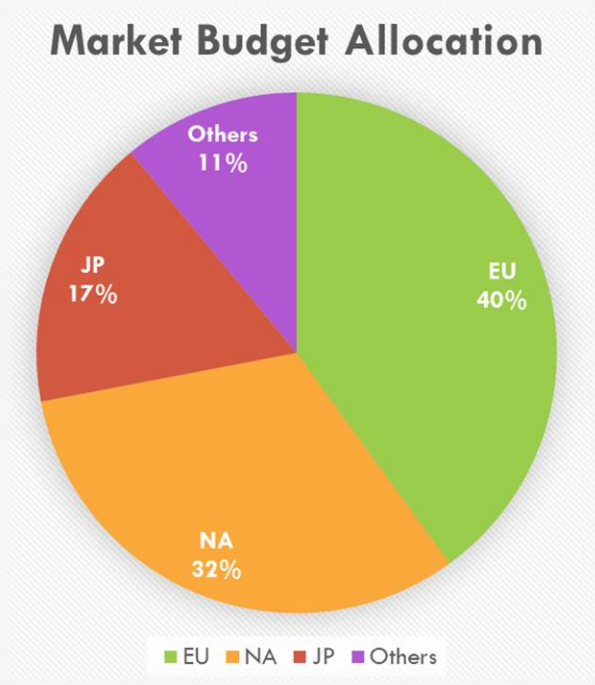
- Conducted trend analysis and forecast using the regional sales data to show the potential % sales contribution of the market share for the different region in the upcoming year of 2017.
- Identified that EU will be GameCo top market leader in terms of regional sales in the future following the sales data trend.



Recommendations

- To re-allocate the market budget for year 2017 based on the changing sales trend from the sales data from 2008 to 2016.

- The recommended reallocation of budget should be as follows:
  - EU – 40%
  - NA – 32 %
  - JP – 17%
  - Others – 11%



02

Influenza Season

Influenza Death Analysis of United States

Influenza Season

Influenza Death Analysis of United States

Background

The medical staffing agency wants to use data to prepare their additional staffing support plans to hospitals and clinics to adequately treat Influenza patients during the Influenza season.

Objective

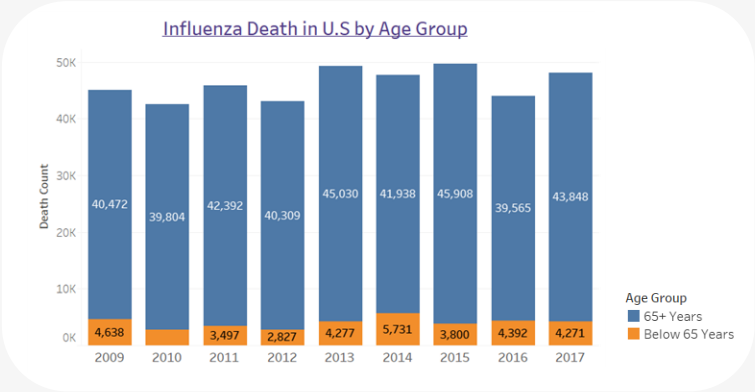
To analyze historical data and identify trends in the Influenza outbreak in United States and recommend a staffing plan for the upcoming influenza season.

Skills

- Data cleaning
- Data transformation
- Data integration
- Hypothesis testing
- Tableau Visualizatitons

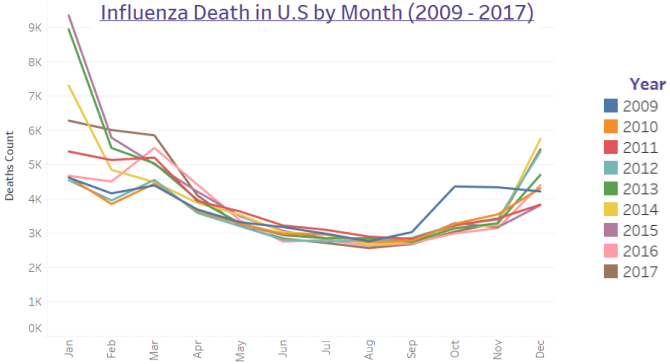
Tools Used:

Analysis



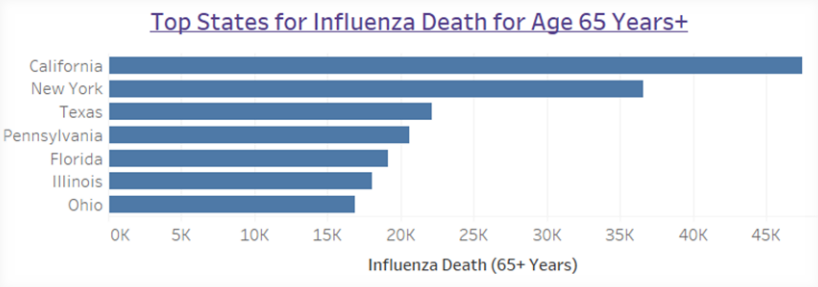
- Research hypothesis states that states with **higher percentage of vulnerable population (adults over 65 years)** will have **higher death count** due to Influenza.
- Vulnerable population contribute to majority (90%~ of U.S population) of the Influenza death in U.S each year.

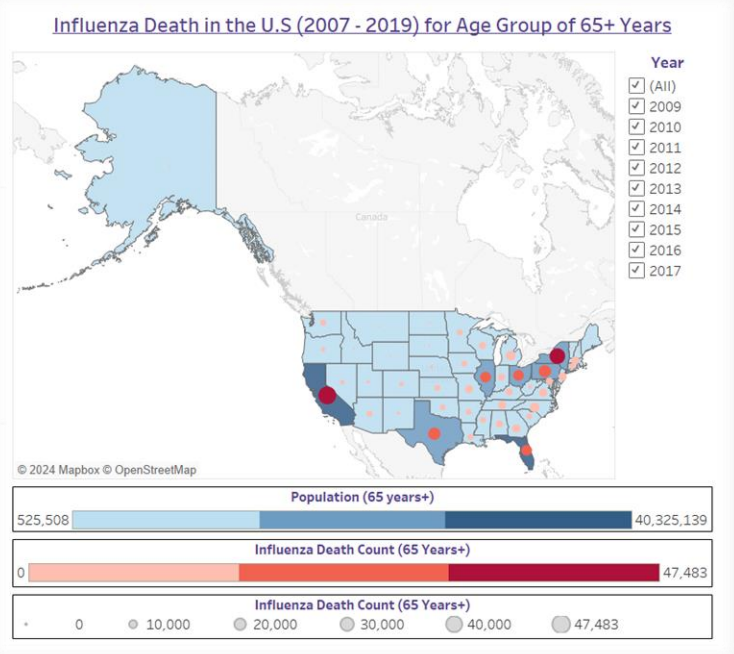
- Plotted a temporal line chart using Influenza death by months to check for seasonality of Influenza.
- Data suggests that Influenza **starts from November** and **ends at March**.
- **Peak period** of Influenza is on **January**.



Analysis

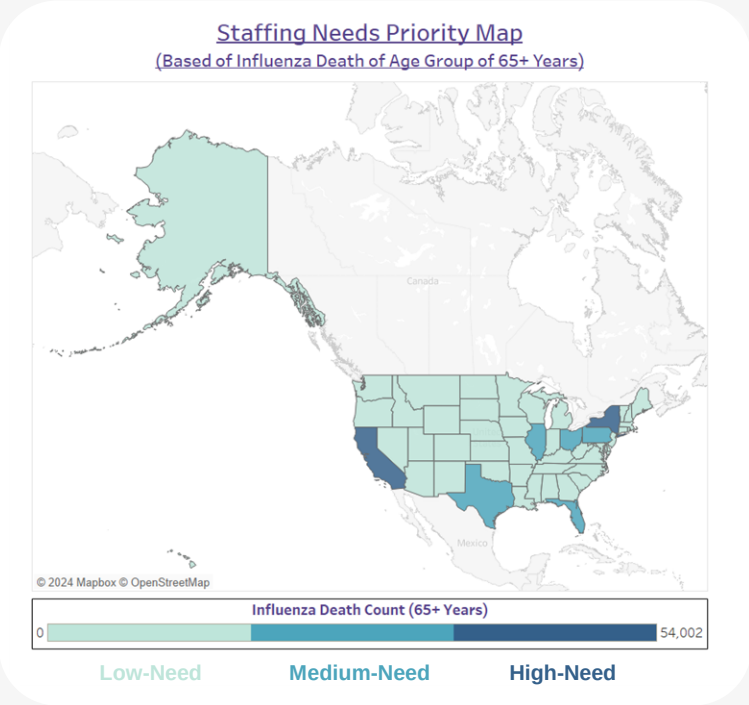
- Plotted a choropleth map to see the relationship between population of vulnerable population in each states and their respective Influenza death count.
- The top 7 states with the **highest vulnerable population (age 65 years and above)** is also the top 7 states which contributed to the **highest death count** of U.S over the years (2007-2019).





Recommendations

- Using the historical Influenza death count of each states, the states have been classified into 3 categories.
(**High-Need**, **Medium-Need**, Low-Need)
- First priority for allocation of additional staffing support are **California & New York**.
- Second priority for allocation of additional staffing support are **Texas, Florida, Illinois, Ohio & Pennsylvania.**
- Additional medical staffing should be scheduled to sent over to the various statie in the **beginning of November**.



03

Rockbuster

Video & Customers Analysis of Video Rental Company

Rockbuster

Video & Customers Analysis of Video Rental Company

Background

Rockbuster Stealth LLC is a movie rental company that is trying to analyze the data of their current video and customers to provide strategic insights to aid their launch of an online video rental service in order to stay competitive.

Objective

To conduct an SQL data analysis on their current database to provide the management with insights on their current customer base and to give recommendation for their buisness plan.

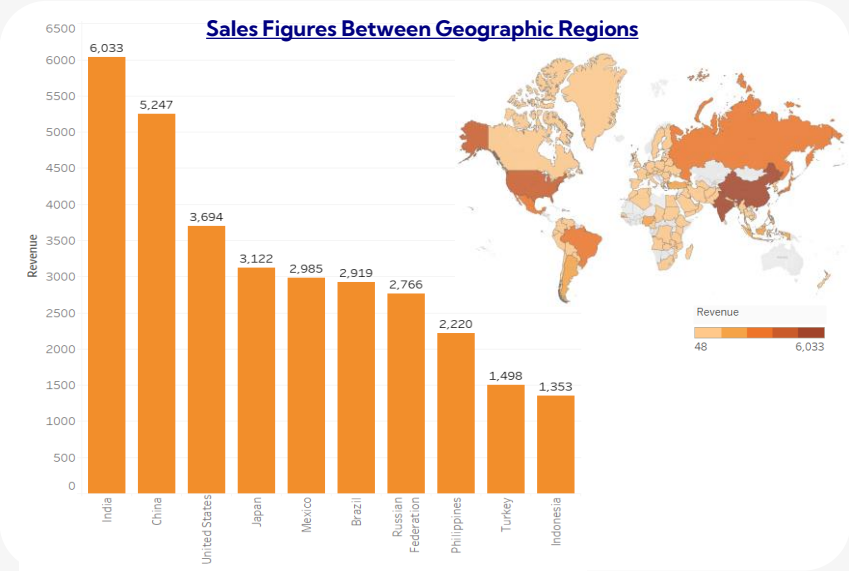
Skills

- Data cleaning
- SQL
- Database manipulation
- CTE, subqueries, joins
- Visualizatiton Charts

Tools Used:

Analysis

Query Rockbuster database using CTE, joins and subqueries to group and gather the data required and plot the necessary chart.



- From the top 10 countries, it can be seen that most of Rockbuster revenue comes from rental in Asia countries (India, China, Japan, Philippines, Indonesia).

Rockbuster Database Analysis

Total Films
- 1000

Total Customer
- 599

Rental Duration Stats:
- 3 days (Min)
- 7 days (Max)
- 5 days(Mean)

Top Performing Movie Genre
- Sports

Lowest Performing Movie Genre
- Thriller

Most Rented Movie Language
- English

- Top 10 countries contributed to 53% of Rockbuster customer based.

Recommendations

1. Inventory Update

- Update Rockbuster current inventory to bring in more movies from top movies genre such as Sports.
- Phase out Thriller genre movies as they are the genre which generated the least revenue, to cut the cost incurred from the Thriller genre movie license

2. Marketing Strategy

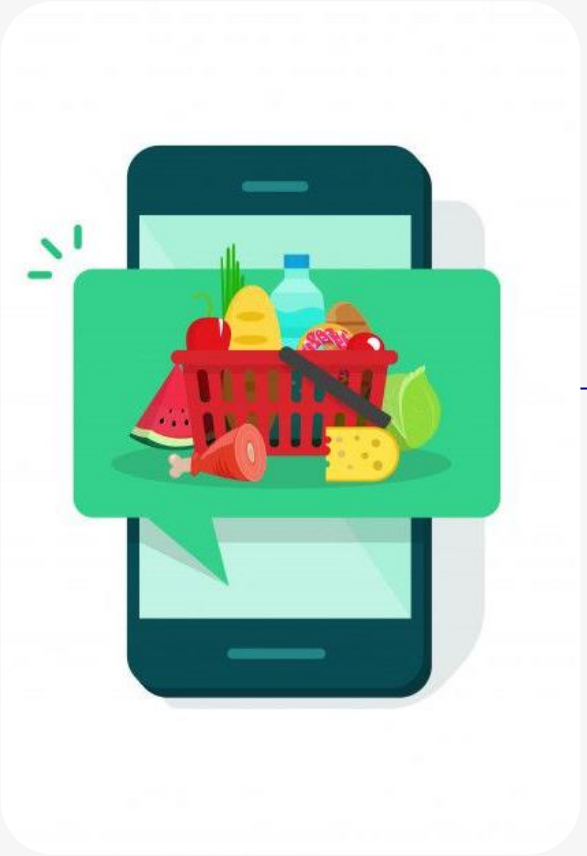
- Formula marketing strategies that target the top 10 countries based on customer counts and revenue.

3. Expand Content Language

- Bring in movie content with different language specifically Asia language, as it was shown that majority of Rockbuster customers are based in Asia countries.

4. Movie Rental Strategy

- Given that the minimum rental duration is 3 days, we can use a dynamic rental rate charges which starts of at a minimum of 3 days and increases per day.



04

Instacart

Consumer Behavior Analysis Of Online Grocery Store

Instacart

Consumer Behavior Analysis Of Online Grocery Store

Background

Instacart, an online grocery store, wants to use data to uncover more information about their sales patterns and to derive insights and suggest strategies for better segmentation.

Objective

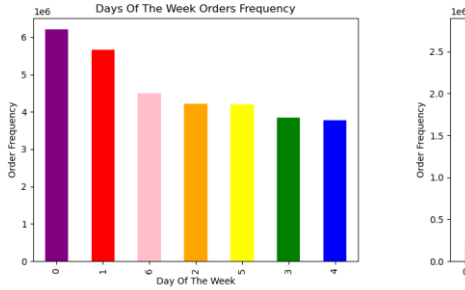
To conduct an analysis on Instacart customer's dataset to extract insights on customers behaviors and sales pattern and to give recommendations on how to improve their marketing and segmentation strategies.

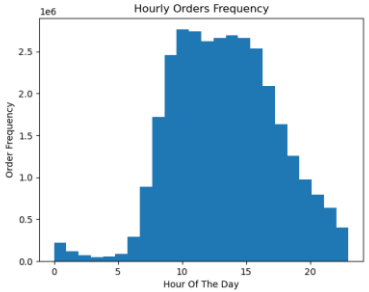
Skills

- Python
- Data wrangling
- Data merging
- Grouping data
- Aggregating data
- Visualizations

Tools Used:

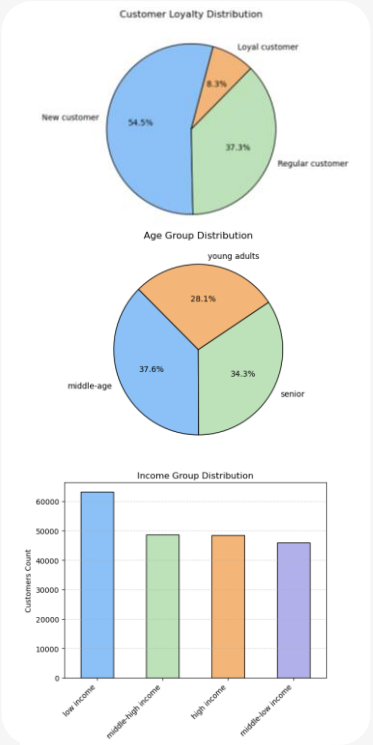

Analysis





0 – Sunday 1 – Monday 2 – Tuesday 3 – Wednesday
4 – Thursday 5 – Friday 6 - Saturday

- Grouped sales data by days and hour to determine which is the busiest days of the week and busiest hour of the day in order to let Instacart know when to schedule ads to promote their products.
- Busiest day were Sunday (0) and Monday (1).
- Busiest hours of the day is 10am to 11am.



- Group customers using various variable to check on the distribution of customer profile of Instacart.
  - Brand Loyalty
  - Age Group
  - Income Group
- Regular customer make up less distribution of the customer base, each of these regular customer purchase multiple times from Instacart which contribute to more orders from them.
- Middle-age group (age 36 to 60) contributes to majority of the customer base.
- Majority of the customer consists of people with low income (<= $67,000).

Recommendations

1. Targeted Marketing

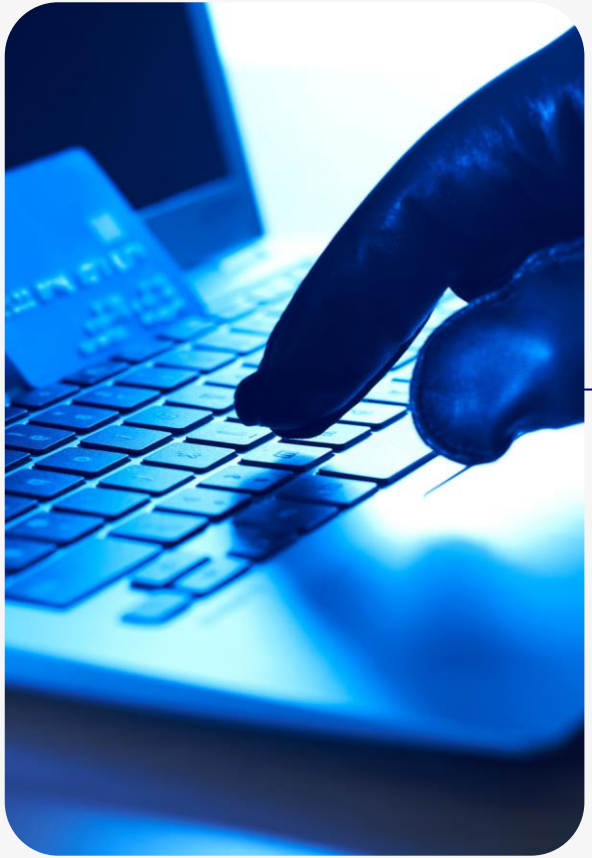
- Have promotions or targeted marketing advertisement on Sunday and Monday between 10am to 11am for new products as that is the period where Instacart is the busiest, this could increase sales for those items that Instacart want to promote.

2. Loyalty Program

- Have a loyalty program to improve the new customer conversion into regular customer which will be willing to order more frequently from Instacart.

3. Expand Product Inventory

- Look into products in the produce section that low income customer tend to buy and have sales or promotion for those items, as this may increase the sales for produce section from low income group customer (as they contribute the most in customer count).
- Instacart can also look to bring in products which attracter middle-age, low income customer with family members to improve their sales as they contribute to majority of the customer based situation.



05

Pig E. Bank

Client Loss Analysis Of Bank

Pig E. Bank

Client Loss Analysis Of Bank

Background

Pig E, Bank, a global bank, which wants to use data to provide analytical support to identify the leading indicators that a customer will leave the bank and to increase customer retention

Objective

To identify the top risk factors that contribute to client loss and model them in a decision tree and to give recommendations on client retention.

Skills

- Big data
- Data mining
- Predictive analysis
- Time series analysis and forecasting
- Github

Tools Used:

Analysis

Contributing Factors of Client Loss

Female (58.91 %)

Age 40-49 (41.58 %)

Owns 1 Product (69.31 %)

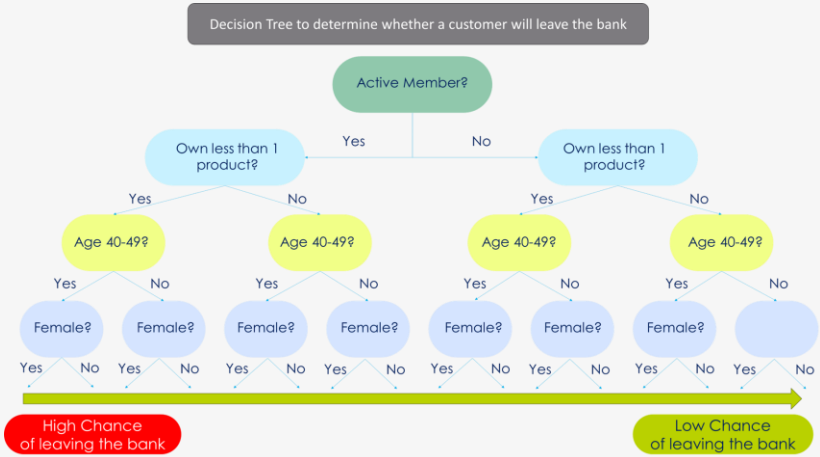
Inactive Member (69.80 %)

% are based off the client that left the bank.

- Majority of exited customers is female (58.91 %) while the majority of customer who are still with the bank is male (43.37 %).
- Majority of exited customers is are within age of 40-49 (41.58 %) while the majority of customer who are still with the bank is within 30-39 (48.98 %).
- Majority of exited customers owns 1 product with the bank (69.31 %) while the majority of customers who are still with the bank own 2 products with the bank (52.55 %).
- Majority of exited customers are not an active member (69.80 %) while the majority of customers who are still with the bank are an active member (56.38 %).

Predictive Analysis

- Plotted a decision tree to determine the probability of customers leaving the bank.
- Decision node at the top of the decision tree is deemed to have the greatest impact.



Recommendations

1. Increase Engagement

- Increase customer engagement and communications to improve usage rate of the inactive customers.

2. Products Packaging

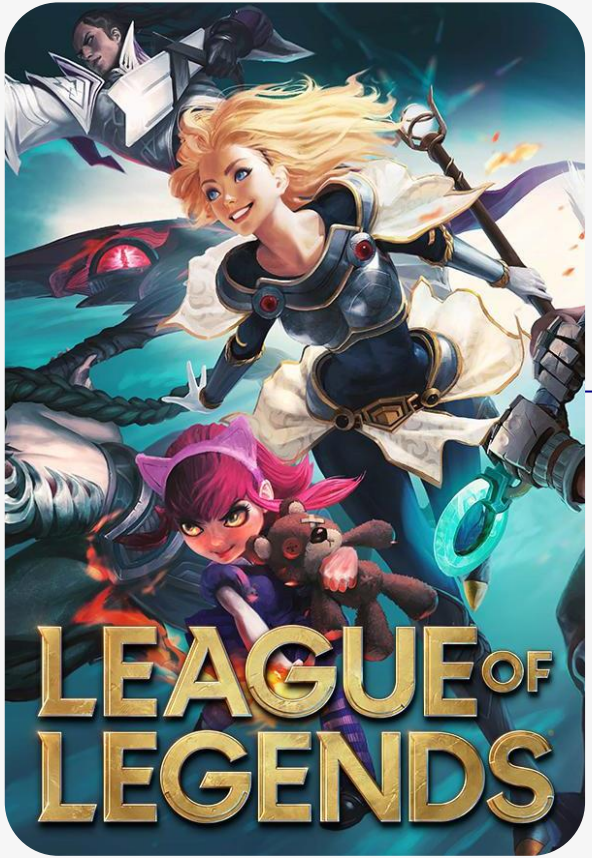
- Package different products that compliments each other together to improve the adoption of the number of products own by customers.

3. Female-Centric Products

- Provide more female-centric products to target the female clients to address the female attrition rates.

4. Age Group Strategies

- Investigate and develop products suited to customers between age 40 to 49 to address their needs to improve loyalty with the bank.



06

League of Legends

Exploratory Analysis
Of Competitive Gameplay

League of Legends

Exploratory Analysis of Competitive Gameplay

Background

The balancing team want to use the data on popular competitive champion pick and bans to improve the overall game play in competitive game and to allow for more variations in champions select.

Objective

To conduct an exploratory analysis on competitive league of legends dataset to extract insights on highest pick/ban champion and their respective performance.

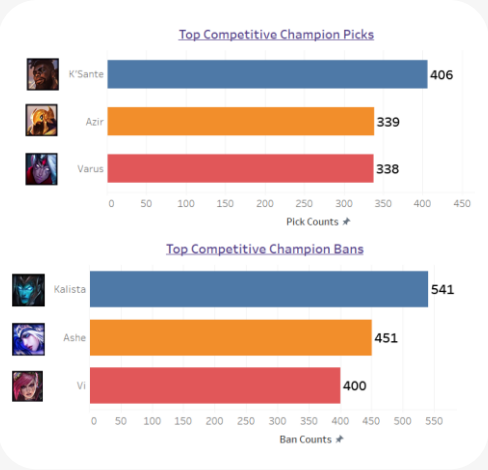
Skills

- Sourcing Open Data
- Data Cleaning
- Descriptive Analysis
- Linear Regression
- K-Means Clustering Analysis
- Tableau Visualization

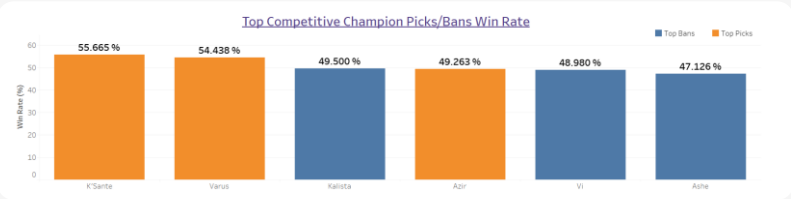
Tools Used:

Analysis

Competitive Pick & Bans Statistics

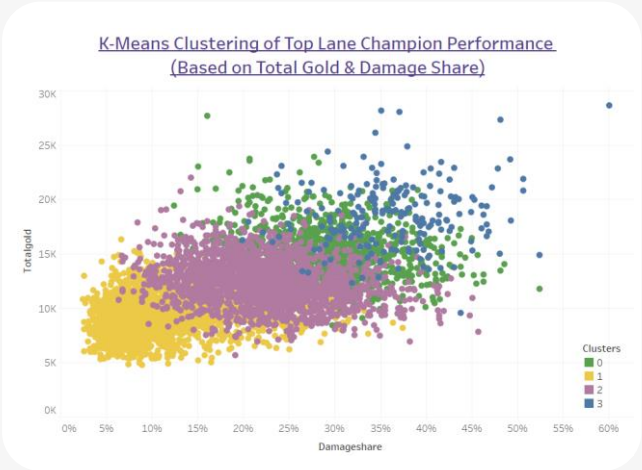


K'Sante was identified as the top picks with a count of **406 games picked** in competitive gameplay and have a higher than average **win rate of 55%.**



K-Means Clustering

- K-means clustering is performed on the top lane competitive players dataset to categorized the performance of champions to benchmark against K'Sante.
- The clusters is based off total gold earned and damage share contribution.



Cluster is based of Performance:

- Blue: Highest
- Green: High
- Purple: Moderate
- Yellow: Low

Results & Recommendations

1. Insights

- From the analysis we can see that even though K'Sante have a higher than average win rate of 55%, in terms of champion performance, it did not fair as well as I thought it would be, as in terms of damage share contribution and total gold earned, it falls within the moderate and low performing clusters.
- Therefore, I can conclude that K'Sante is not over-tuned based on these current champion statistics data set and his higher win rate might be due to other reasons.

2. Limitations

- There weren't enough data points to give a more in-depth analysis.
- Data contained a limited number of variables which we can conduct the analysis on.

3. Recommendation

- Gather data from not only competitive gaming scenes, but also from top ranks of online players statistics.
- Analyze the different builds of the champions to identify if the champions is overpowered or specific items in game is over-tuned which caused the champion to be stronger than expected.

07

ClimateWins

Machine Learning Model Prediction Of Weather Conditions & Climate Change

ClimateWins

ML Model Prediction of Weather Conditions & Climate Changes

Background

ClimateWins, a European nonprofit organization, is interested in using machine learning to help predict the consequences of climate change around Europe and, potentially, the world.

Objective

To investigate the various machine learning models available for the prediction of weather conditions using temperature data and identify the best machine learning model for the most accurate predictions.

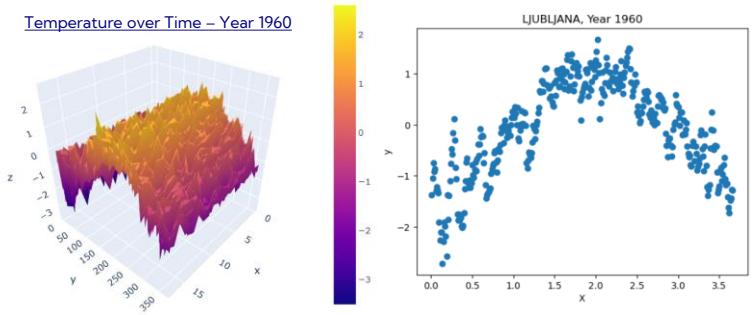
Skills

- Data cleaning
- Optimization
- Gradient Descent
- Machine learning Modeling
- K-Nearest Neighbor
- Decision Tree
- Artificial Neural Network
- Random Forest
- Convolutional Neural Network

Tools Used:

Analysis

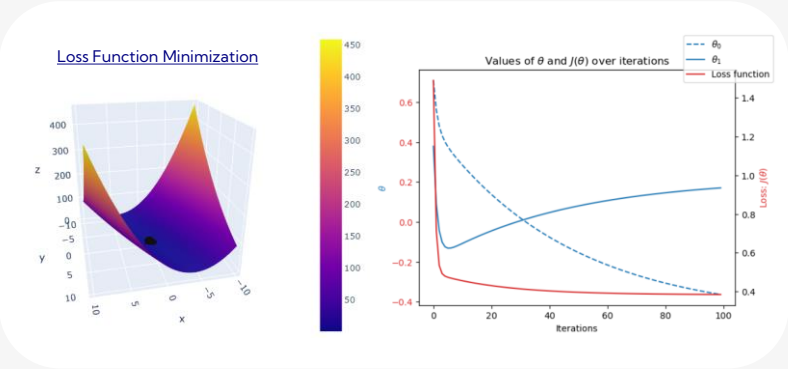
3D Visualization of Temperature Data



- Plotted data into a 3D visualization to view the temperature between the various weather stations throughout the year to get a general overview of the temperature data variation of the different weather stations.
- Extracted data from different weather stations of interests from specific years to further investigate the data points.

Gradient Descent

- Applied gradient descent to find the local minimum of the temperature data set.
- Optimize model performance towards finding the optimal solutions by minimizing loss function which assess the deviation between predicted and actual weather data.



Analysis

Supervised Machine Learning Model Accuracy Comparison

K-Nearest Neighbours (KNN)

Weather Station	Accurate Prediction (Unpleasant Weather)	Accurate Prediction (Pleasant Weather)	False Positive	False Negative	Overall Accuracy	Unpleasant Weather Accuracy	Pleasant Weather Accuracy
Basel	3917	961	421	439	85%	90%	69%
Belgrade	3252	1544	524	418	84%	86%	79%
Budapest	3424	1462	476	376	85%	88%	80%
Debilt	4320	723	317	378	88%	93%	66%
Dusseldorf	4164	810	343	421	87%	92%	66%
Heathrow	4138	744	432	424	85%	91%	64%
Kassel	4563	614	252	309	90%	95%	67%
Ljubljana	3740	1180	455	363	86%	89%	76%
Maastricht	4253	824	309	352	88%	93%	70%
Madrid	2750	2261	418	309	87%	87%	88%
Munchenb	4237	792	309	400	88%	93%	66%
Oslo	4637	512	242	347	90%	95%	60%
Sonnblick	5738	0	0	0	100%	100%	N/A
Stockholm	4483	607	283	365	89%	94%	62%
Valentia	5404	74	58	202	95%	99%	27%
				Average	**88%**	**92%**	**67%**

- **Training Accuracy Score**: 0.5562
- **Testing Accuracy Score:** 0.4465
- **Overall Prediction Accuracy:** 88%

Parameter	
K Value	3

Decision Tree

Weather Station	Accurate Prediction (Unpleasant Weather)	Accurate Prediction (Pleasant Weather)	False Positive	False Negative	Overall Accuracy	Unpleasant Weather Accuracy	Pleasant Weather Accuracy
Basel	3871	943	467	457	84%	89%	67%
Belgrade	3183	1407	593	555	80%	84%	72%
Budapest	3394	1336	506	502	82%	87%	73%
Debilt	4289	749	348	352	88%	92%	68%
Dusseldorf	4106	832	401	399	86%	91%	68%
Heathrow	4092	759	478	409	85%	90%	65%
Kassel	4475	603	340	320	88%	93%	65%
Ljubljana	3679	1103	516	440	83%	88%	71%
Maastricht	4164	804	398	372	87%	91%	68%
Madrid	2828	2155	340	415	87%	89%	84%
Munchenb	4177	805	369	387	87%	92%	68%
Oslo	4542	549	337	310	89%	93%	64%
Sonnblick	5738	0	0	0	100%	100%	N/A
Stockholm	4422	601	344	371	88%	93%	62%
Valentia	5303	103	159	173	94%	97%	37%
				Average	**87%**	**91%**	**67%**

- **Training Accuracy Score**: 0.4617
- **Testing Accuracy Score:** 0.4726
- **Overall Prediction Accuracy:** 87%

Artificial Neural Network (ANN)

Weather Station	Accurate Prediction (Unpleasant Weather)	Accurate Prediction (Pleasant Weather)	False Positive	False Negative	Overall Accuracy	Unpleasant Weather Accuracy	Pleasant Weather Accuracy
Basel	4061	1051	277	349	89%	94%	75%
Belgrade	3363	1682	413	280	88%	89%	86%
Budapest	3568	1528	332	310	89%	91%	83%
Debilt	4418	803	219	298	91%	95%	73%
Dusseldorf	4177	935	330	296	89%	93%	76%
Heathrow	4272	872	298	296	90%	93%	75%
Kassel	4617	703	198	220	93%	96%	76%
Ljubljana	3790	1309	405	234	89%	90%	85%
Maastricht	4281	908	281	268	90%	94%	77%
Madrid	2882	2334	286	236	91%	91%	91%
Munchenb	4286	894	260	298	90%	94%	75%
Oslo	4725	566	154	293	92%	97%	66%
Sonnblick	5738	0	0	0	100%	100%	N/A
Stockholm	4463	822	303	150	92%	94%	85%
Valentia	5367	170	95	106	96%	98%	62%
				Average	**91%**	**94%**	**77%**

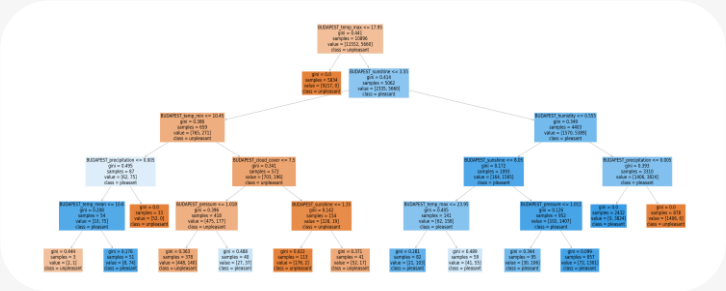
- **Training Accuracy Score**: 0.6325
- **Testing Accuracy Score:** 0.5019
- **Overall Prediction Accuracy:** 91%

Parameter	
Hidden Layer	100,200,20
Max Iterations	5000
Tolerance	0.0001

Analysis

Unsupervised Machine Learning Model Accuracy Comparison

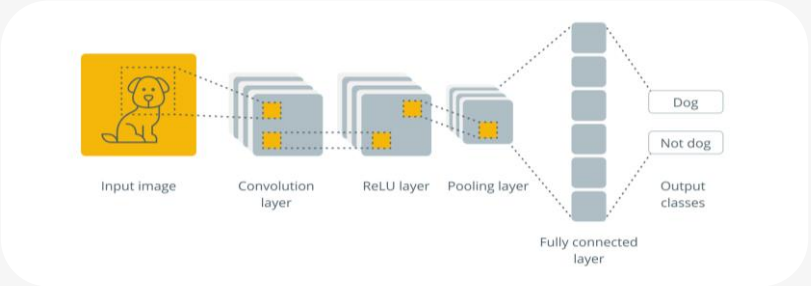
Random Forest



- **Overall Prediction Accuracy:** 97.81%

Parameter	
N_estimator	100
Max_feature	15
Min_samples_leaf	3
Min_samples_split	3
Criterion	Gini

Convolutional Neural Network (CNN)



- **Overall Prediction Accuracy:** 96.60%

Parameter	
Epoch	35
Batch Size	284
Optimizer	Adadelta
Hidden Layers	76
Kernal	3
Activation	Softplus

Parameter	
Learning Rate	0.8516
Layer 1	2
Layer 2	2
Normalization	0.6817
Dropout	0.8208
Dropout Rate	0.3063

Insights & Recommendations

1. Insights

- **Random Forest model** have the high prediction accuracy for prediction of weather conditions based on temperature data.
  - ✓ Highest overall accuracy of **97.81% correct prediction** across the different models.
- **Overfitting** of model **for Sonnblick weather station.**
  - ✓ All weather data points from this station are unpleasant weather conditions
  - ✓ Lead to model to **predict unpleasant weather condition 100% of the time**.
- **Lower prediction accuracy of pleasant weather** prediction may be due to the **lower amount of data for pleasant weather days.**
- **Maximum temperature** and **precipitation** was identified as the **top 2 factors** for **prediction of pleasant and unpleasant weather.**

2. Recommendations

- To use the **Random forest model** to build a model to **predict future weather conditions based on past historical weather data.**
  - Weather data to consider should be **maximum temperature** of the region and **precipitations** for the regions.
  - **Breakdown the data** to the **4 various seasons of the year** and use those data separately for better prediction due to less drastic fluctuations for each of the different seasons weather variables.
- To **gather more pleasant weather data points** for specific weather station to enhance the prediction accuracy for pleasant weather day. The recommended stations are:
  - ✓ Sonnblick
  - ✓ Oslo
  - ✓ Valentia

Thanks!

Ang Wei Jie


weiji3x@gmail.com


linkedin.com/in/angweijie94

github.com/weiji3x