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A Selection of My Work for the Digital Marketing Executive Role

In this portfolio, you'll find examples of my work, demonstrating my skills in leveraging data science, marketing analytics, and visual storytelling to drive impactful marketing strategies and optimize decision-making. **Key highlights include:**

1. Maximising Sales through Optimal Marketing Budget Allocation at AXA:

Introduction:

As an Online Marketing Webmaster at AXA and worked with multiple marketing channels, including television advertising, online display ads, and social media campaigns. The primary objective was to determine the optimal allocation of the marketing budget across these channels to maximise sales and deliver personalised experiences to customers.

To achieve data-driven decision-making, advanced techniques like A/B Testing and Multivariate Testing (MVT) were employed to continuously refine marketing strategies. These experiments allowed comparisons of different variations of campaigns, landing pages, and content to identify the most effective approaches for the target audience.

Additionally, the power of Machine Learning was harnessed to unveil valuable customer insights. Customer segmentation analysis revealed five distinct customer clusters based on behaviours, preferences, and needs. This understanding facilitated crafting hyper-personalised marketing messages tailored to each cluster's unique characteristics.

The primary objectives for this project include:

- **Marketing Budget Optimisation**: Analysing historical marketing data to identify channels with the highest returns and determining the most effective allocation of the marketing budget.

- **A/B Testing and MVT**: Conducting controlled experiments to test various marketing variables and campaign strategies, revealing combinations that drive optimal engagement and conversion rates.

- **Machine Learning Customer Clustering**: Leveraging Machine Learning algorithms to segment the customer base into five distinct clusters, enabling the creation of targeted marketing campaigns based on preferences and behaviours.

- **Personalised Marketing Approach**: Crafting personalised marketing strategies that cater to each segment's needs, fostering deeper connections with customers.

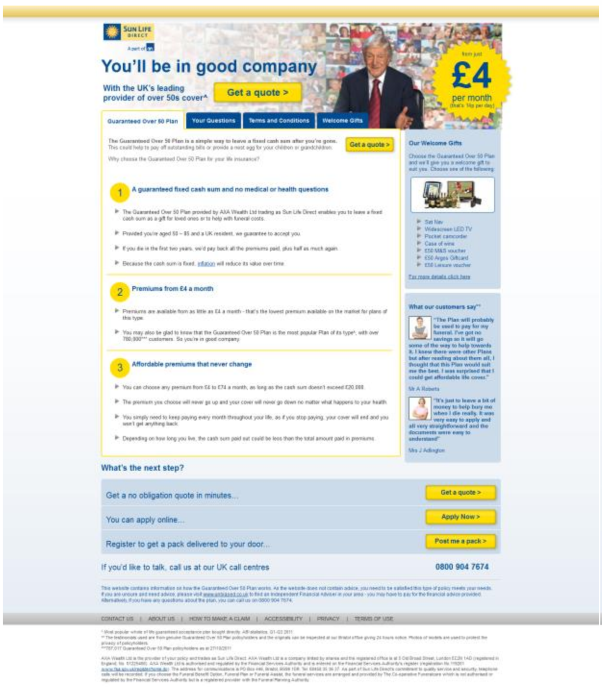
Through the integration of data-driven decision-making, innovative experimentation, and Machine Learning insights, the goal is to drive business growth, enhance customer experiences, and position AXA as a market leader in the insurance industry.

Throughout this journey, actionable insights will be showcased through visualisations, dashboards, or reports. Effective communication of results to stakeholders empowers AXA with the knowledge to make informed decisions and embark on a journey towards a more personalised and impactful marketing approach.

1A Examples of A/B Testing and Multivariate Testing (MVT) from when I worked at AXA.
The two examples below depict different versions of the same webpage, which were used to provide insight to drive future strategies and identify business opportunities and problems.

Achieved significant accomplishments during my tenure at AXA, including:

- Devised and implemented effective tracking metrics to monitor online customer behaviours.
- Built models to transform data points into actionable business insights.
- Utilised machine learning techniques to accelerate testing processes and enhance recommendation engines.
- Successfully contributed to a 30% increase in incremental revenue.



Key Points:

- A/B testing compares two versions (A and B) to determine which one performs better.
- The conversion rates for version A and version B were 0.1230 and 0.1360 respectively.
- The Z-score measures the deviation of the observed difference from the expected difference under the null hypothesis.
- The p-value represents the probability of observing a difference as extreme as the one observed, assuming no true difference between versions.
- The calculated Z-score of 0.8659 and p-value of 0.2681 indicated that the difference in conversion rates was not statistically significant.
- This means that the observed difference could be due to random chance, and it is not conclusive that one version performs better than the other.

1B Market Mixing Models project:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

# Load the dataset
data = pd.read_csv('marketing_data.csv')

# Select the features (independent variables) and target (dependent variable)
X = data[['television_spending', 'online_spending', 'social_media_spending']]
y = data['sales_revenue']

# Split the data into training and testing sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model's performance using R-squared (coefficient of determination)
r_squared = r2_score(y_test, y_pred)
print("R-squared:", r_squared)

# Print the coefficients of the model
coefficients = pd.DataFrame({'Feature': X.columns, 'Coefficient': model.coef_})
print(coefficients)

```

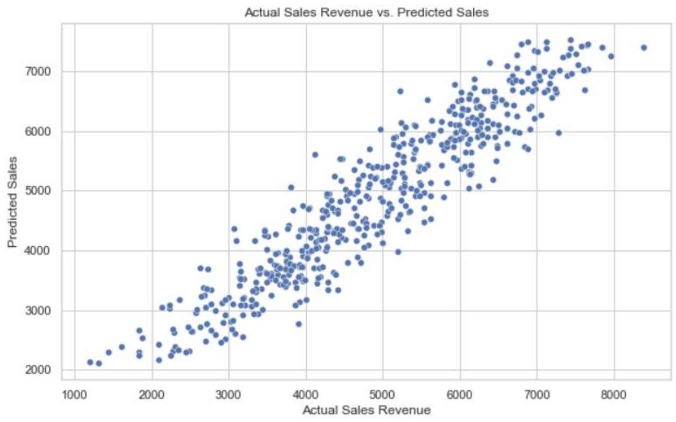
```
R-squared: 0.9007431826905605
                 Feature  Coefficient
0    television_spending     4.845151
1        online_spending     3.107265
2  social_media_spending     1.815924
```

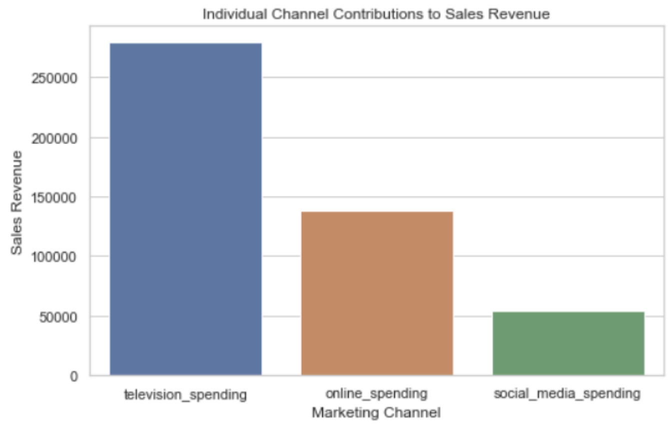
1. **R-squared (R^2)**:
   - R-squared is a statistical metric that measures how well the regression model fits the data. It indicates the proportion of the variance in the dependent variable (sales revenue) that can be explained by the independent variables (‘television_spending’, ‘online_spending’, and ‘social_media_spending’).
   - The R-squared value is approximately 0.901, suggesting that about 90.1% of the variability in sales revenue is explained by the independent variables in the model. A higher R-squared value indicates that the model's predictions are closer to the actual values.
2. **Coefficients**:
   - The coefficients represent the slope or effect of each independent variable on the dependent variable when holding other variables constant.
   - For example, an increase of one unit in 'television_spending' is associated with an expected increase of approximately 4.85 units in sales revenue.
   - Similarly, an increase of one unit in 'online_spending' is associated with an expected increase of around 3.11 units in sales revenue.
   - Additionally, an increase of one unit in 'social_media_spending' is associated with an expected increase of about 1.82 units in sales revenue.

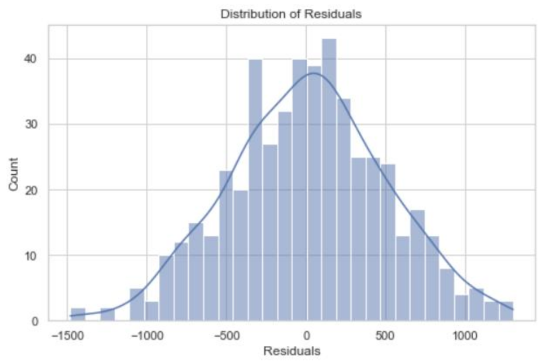
The coefficient values show the direction and magnitude of the relationships between the independent variables and the dependent variable. Positive coefficients indicate that an increase in the respective independent variable leads to an increase in the dependent variable (sales revenue), while negative coefficients suggest a decrease in the dependent variable with an increase in the independent variable.

In summary, the R-squared value of approximately 0.901 indicates a reasonably good fit of the model to the data, and the coefficients provide insight into the contributions of each marketing channel (television, online, and social media spending) to the sales revenue in the Market Mixing Model project.

An example of visualising the MMM analysis results. It creates scatter plots to compare actual sales revenue with predicted sales, a distribution plot to show the residuals' distribution, and a bar plot to visualise the individual contributions of each marketing channel to sales revenue.



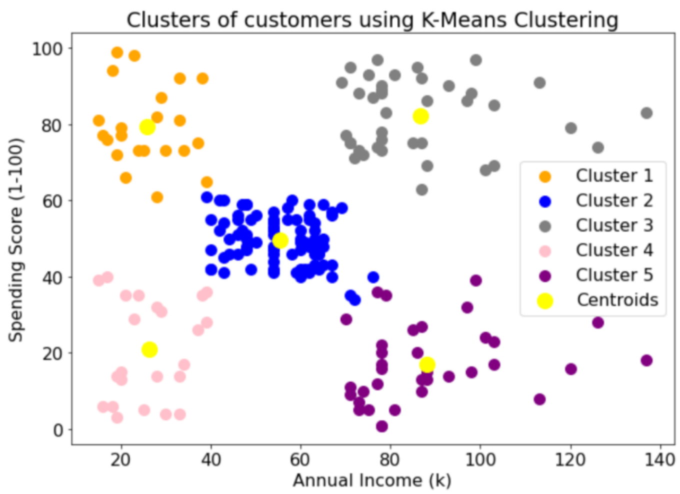




	sales_revenue	television_spending	online_spending \
count	500.000000	500.000000	500.000000
mean	4885.660073	558.358000	275.740000
std	1434.653693	263.241421	128.150214
min	1189.707963	101.000000	50.000000
25%	3824.813023	328.250000	170.500000
50%	4830.691333	567.500000	272.000000
75%	6056.205191	784.250000	390.250000
max	8382.015677	999.000000	499.000000

	social_media_spending
count	500.000000
mean	108.598000
std	52.234867
min	20.000000
25%	63.750000
50%	109.000000
75%	153.000000
max	199.000000

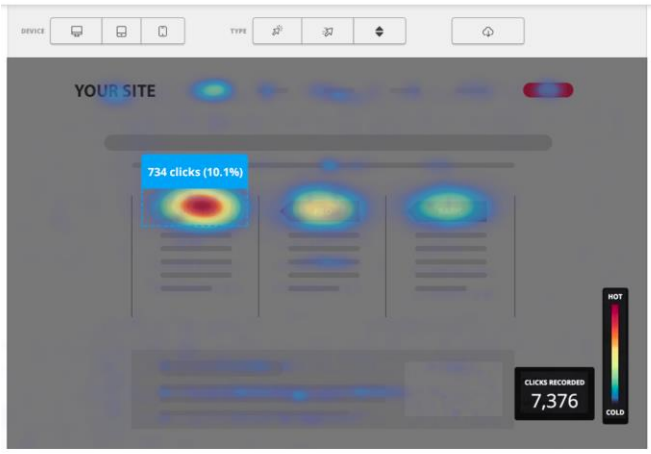
1C Leveraging Machine Learning for Customer Understanding and Personalised Marketing: Unveiling Five Distinct Customer Clusters



Just looking at the graph tells us about the five different types of customers

I. Cluster 1: Low income, High spenders
II. Cluster 2: Average income, Average expenditure
III. Cluster 3: High income, High spenders
IV. Cluster 4: Low income, Low Spenders
V. Cluster 5: High income, Low spenders

Machine learning is used to understand customers, drive personalisation, streamline processes and create convenient and memorable customer experiences.



Rather than relying on a marketer’s intuition to separate customers into groups for campaigns, data scientists can use clustering and classification algorithms to group customers into personas based on specific variations among them with similar needs and behaviours. These personas account for customer differences across multiple dimensions such as demographics, browsing behaviour, and affinity. Connecting these traits to patterns of purchasing behaviour allows data-savvy companies to roll out highly personalised marketing campaigns that are more effective at boosting sales than generalised campaigns.

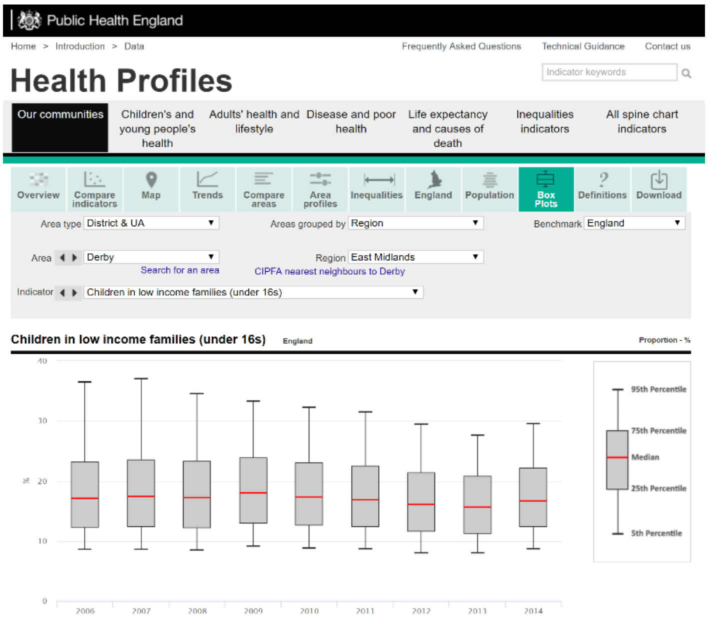
Achieved significant accomplishments during my tenure at AXA, including:

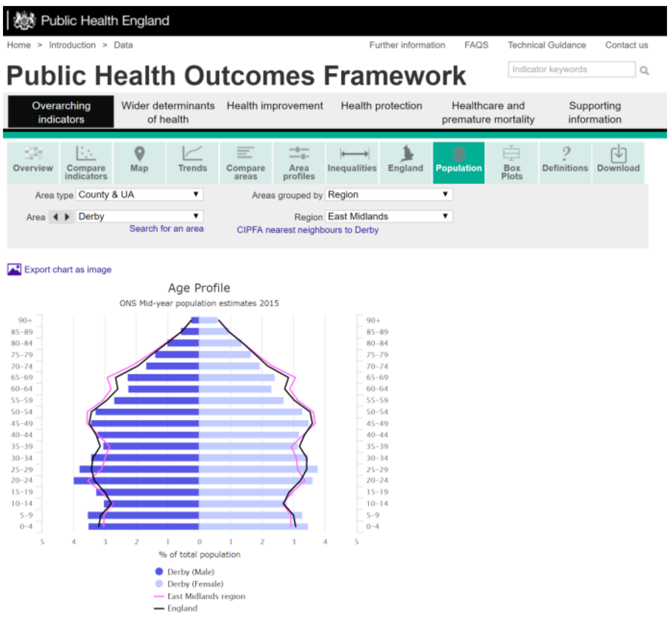
- Developed a customer segmentation strategy using machine learning techniques to identify five distinct customer clusters based on income and spending behaviour.
- Implemented clustering and classification algorithms to group customers into personas, allowing for personalised marketing campaigns based on specific customer needs and behaviours.
- Utilised multiple dimensions such as demographics, browsing behaviour, and affinity to create comprehensive customer personas.
- Connected customer traits to patterns of purchasing behaviour, resulting in highly personalised and effective marketing campaigns.
- Contributed to streamlining processes and enhancing customer experiences by leveraging machine learning insights.
- Shifted marketing strategies from intuition-based decisions to data-driven approaches, resulting in improved sales and customer engagement.
- Led efforts to understand customers through machine learning, driving personalisation and creating convenient and memorable customer experiences.

2. Data Visualization for Public Health England's Fingertips Website: (Government Agency):

This project involved creating insightful visualizations, such as boxplots and demographic bar charts, to present complex information on public health metrics. My work here enabled data-driven decision-making in a clear and accessible format for stakeholders.

On the left are boxplots depicting the percentage of children in low income families in the East Midlands between the years 2006 and 2014; on the right is a bar graph with negative stack depicting the proportion of males and females of different age groups in the East Midlands region.





- **Successfully contributed to data visualisation projects while working on the 'Fingertips' website for Public Health England (Government Agency), including:**

    - Created informative boxplots showcasing the percentage of children in low-income families in the East Midlands region from 2006 to 2014, effectively conveying the distribution and trends over time.
    - Developed a visually compelling bar graph with a negative stack to represent the proportion of males and females in different age groups within the East Midlands region, providing insights into demographic patterns and gender distribution.
    - Leveraged data visualisation techniques to present complex information in a clear and concise manner, facilitating understanding and communication of key findings to stakeholders.
    - Ensured visualisations adhered to best practices in data visualisation, employing appropriate design choices to enhance readability and interpretability.
    - Played a crucial role in making data-driven insights accessible and actionable, empowering decision-makers to utilise the visualisations to drive strategies and policies.
    - Collaborated with cross-functional teams to gather requirements, identify key metrics, and deliver impactful visualisations that supported evidence-based decision-making processes.

3: Executive Dashboards in Microsoft Power BI & Tableau

- The aim was to create Executive Dashboard, tracked and reported on business metrics & the KPIs
- This dashboard included key performance, top ten products, top performing cities and top performing cities, customer reviews and sales by Month.

Demonstrated expertise in data visualisation using Microsoft Power BI and Tableau, including:

- Created an Executive Dashboard to track and report on business metrics and key performance indicators (KPIs).
- Developed visually appealing and informative visualisations to provide actionable insights to stakeholders.
- Incorporated various data sources to create a comprehensive view of business performance, including top ten products, top-performing cities, customer reviews, and sales by month.
- Utilised interactive features and drill-down capabilities to enable users to explore data and gain deeper insights.
- Collaborated with cross-functional teams to gather requirements, design visually impactful dashboards, and deliver timely and relevant information to decision-makers.
- Ensured the Executive Dashboard adhered to best practices in data visualisation, including clear data storytelling, effective use of colours and layout, and user-friendly navigation.

Microsoft Power BI:

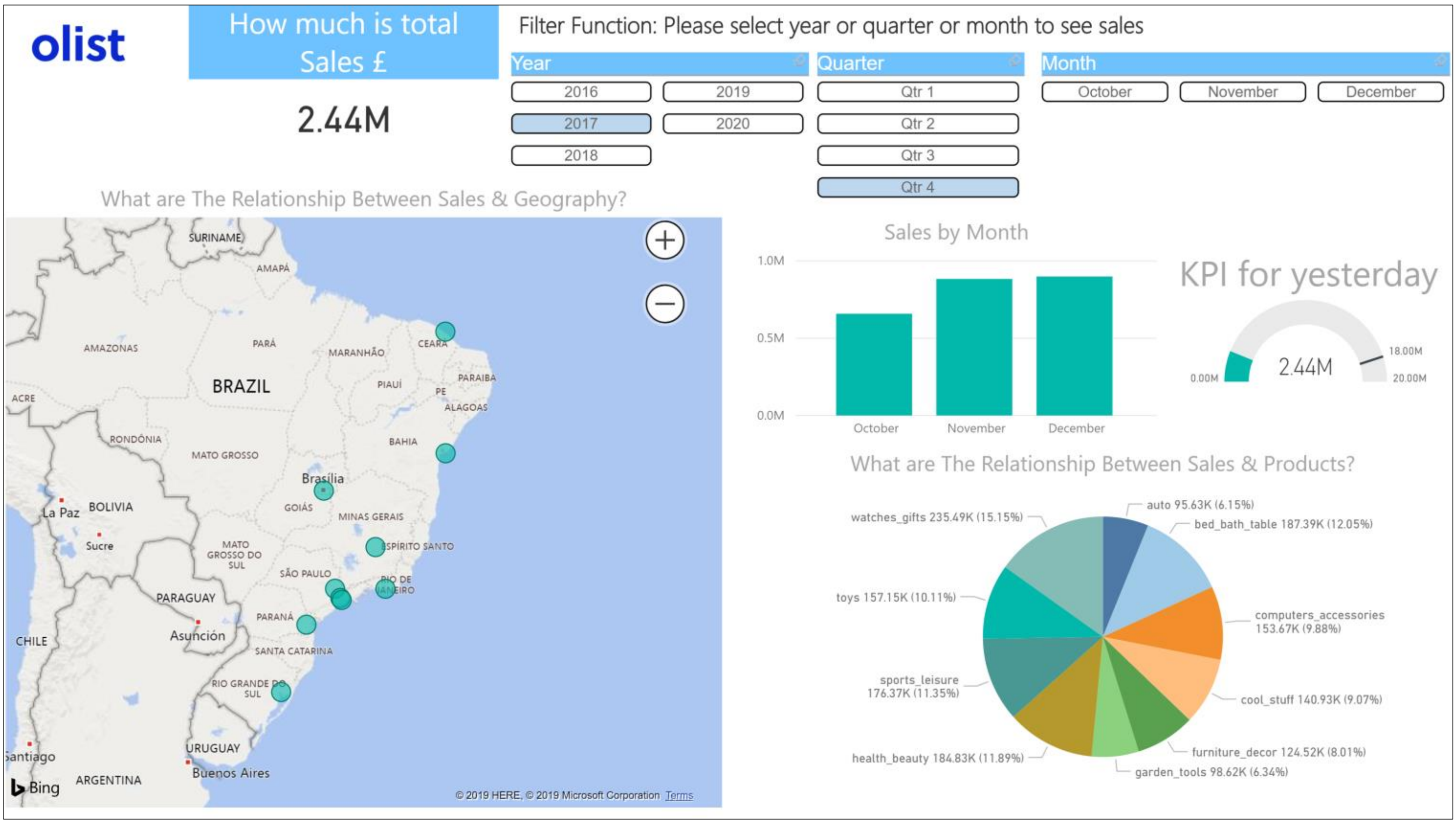
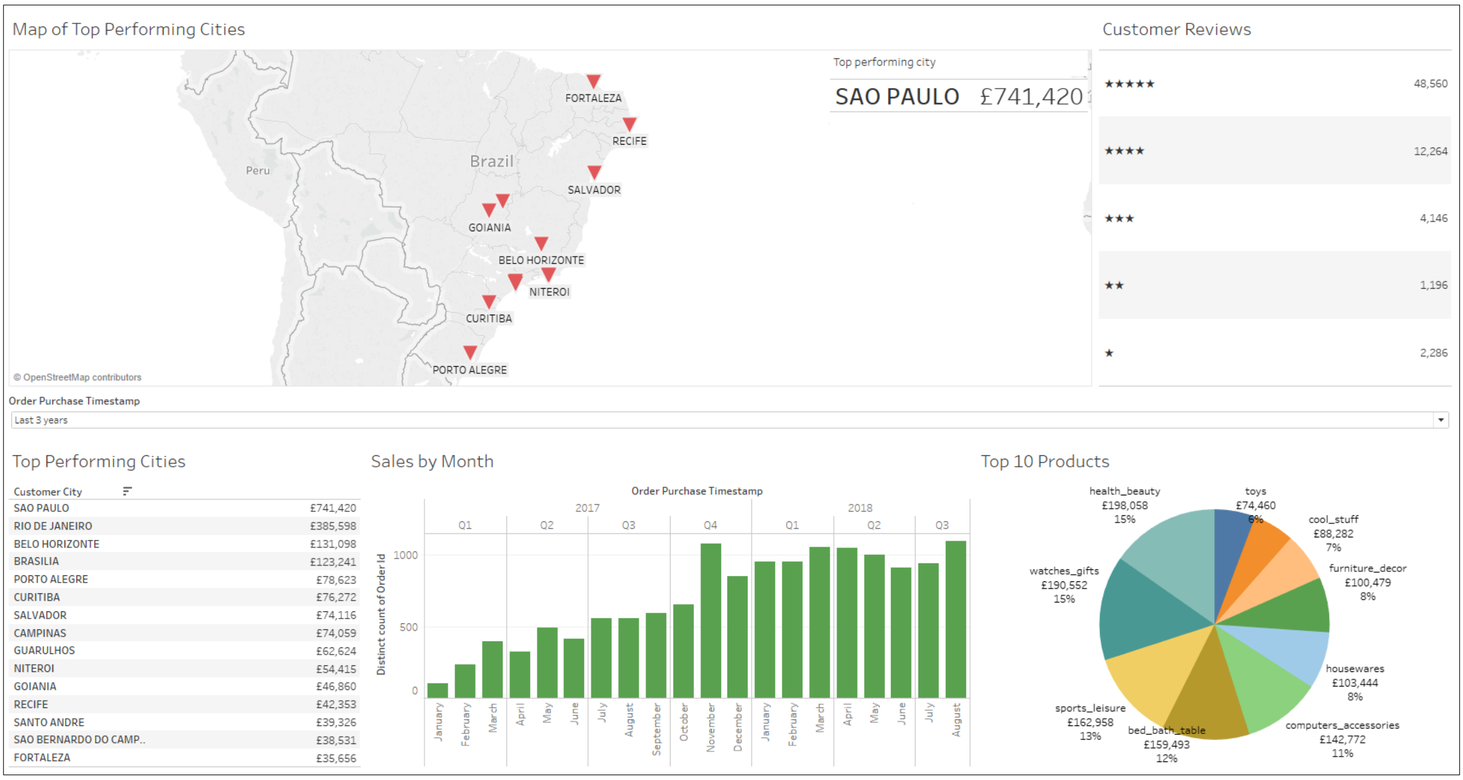
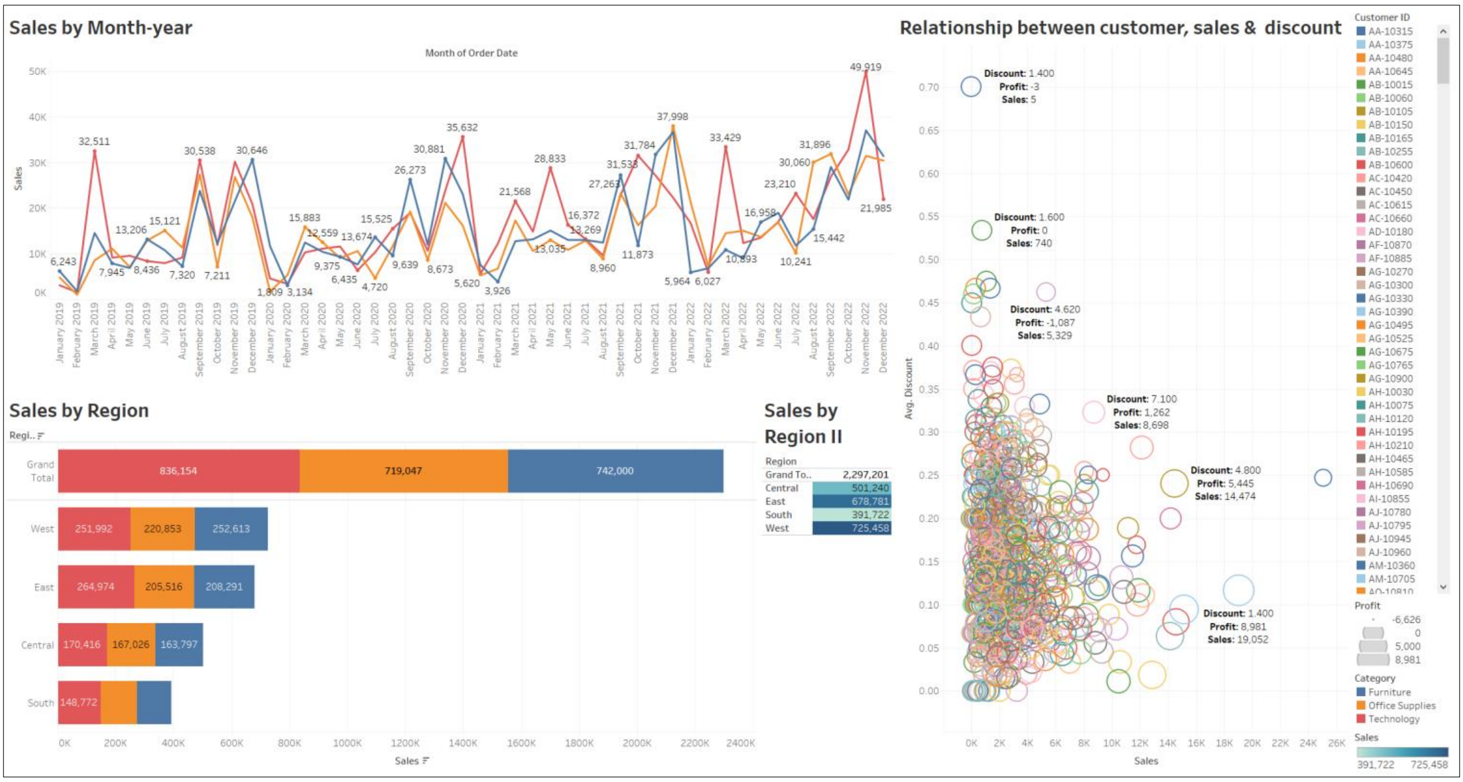


Tableau:



Map of Top Performing Cities
FORTALEZA
RECIFE
Brazil
Peru
SALVADOR
GOIANIA
BELO HORIZONTE
NITEROI
CURITIBA
PORTO ALEGRE
© OpenStreetMap contributors
Top performing city
SAO PAULO £741,420
Customer Reviews
★★★★★ 48,560
★★★★ 12,264
★★★ 4,146
★★ 1,196
★ 2,286
Order Purchase Timestamp
Last 3 years
Top Performing Cities
Customer City
SAO PAULO £741,420
RIO DE JANEIRO £385,598
BELO HORIZONTE £131,098
BRASILIA £123,241
PORTO ALEGRE £78,623
CURITIBA £76,272
SALVADOR £74,116
CAMPINAS £74,059
GUARULHOS £62,624
NITEROI £54,415
GOIANIA £46,860
RECIFE £42,353
SANTO ANDRE £39,326
SAO BERNARDO DO CAMP.. £38,531
FORTALEZA £35,656
Sales by Month
Order Purchase Timestamp
2017
2018
Q1
Q2
Q3
Q4
Distinct count of Order Id
1000
500
0
January
February
March
April
May
June
July
August
September
October
November
December
Top 10 Products
health_beauty £198,058 15%
toys £74,460 6%
cool_stuff £88,282 7%
furniture_decor £100,479 8%
watches_gifts £190,552 15%
housewares £103,444 8%
sports_leisure £162,958 13%
bed_bath_table £159,493 12%
computers_accessories £142,772 11%



Sales by Month-year
Month of Order Date
Sales
50K
40K
30K
20K
10K
0K
Relationship between customer, sales & discount
Avg. Discount
Sales
Customer ID
Profit
Category
Furniture
Office Supplies
Technology
Sales
391,722
725,458
Sales by Region
Regi..
Grand Total 836,154 719,047 742,000
West 251,992 220,853 252,613
East 264,974 205,516 208,291
Central 170,416 167,026 163,797
South 148,772
Sales
Sales by Region II
Region
Grand To.. 2,297,201
Central 501,240
East 678,781
South 391,722
West 725,458