

# **MARKETING CAMPAIGN ANALYSIS AND OPTIMIZATION**



# INTRODUCTION

- ❖ Effective marketing campaigns are crucial for businesses to reach the right customers and maximize return on investment.
- ❖ This project analyzes a real-world marketing dataset to uncover customer behavior patterns and predict campaign responses using machine learning.
- ❖ Key insights are visualized through an interactive Power BI dashboard to support data-driven marketing decisions.

# PROBLEM STATEMENT

Ineffective targeting in marketing campaigns leads to low response rates, highlighting the need for data-driven methods to accurately predict customer behavior and optimize campaign performance.



# DATASET OVERVIEW

- The dataset used for this project is the Marketing Campaign Dataset sourced from Kaggle, originally provided by a Portuguese retail company. It contains 2,240 records and 29 features.

## Key Feature Categories:

- ***Customer Demographics:***
  - ✓ Age: Derived from Year\_Birth
  - ✓ Education: customer's level of education
  - ✓ Marital\_Status: customer's marital status
  - ✓ Income: Annual household income
- ***Household Composition:***
  - ✓ Kidhome, Teenhome: Number of children/teenagers at home

- ***Customer Behavior:***
  - ✓ Recency: Days since last purchase
  - ✓ Customer\_Tenure\_Years: Years since the customer joined
  - ✓ Complain: Whether the customer has complained in the past
- ***Product Spendings:***
  - ✓ MntWines, MntMeatProducts, MntFruits, MntSweetProducts, MntFishProducts, MntGoldProds: Amount spent in each category
- ***Campaign Responses:***
  - ✓ AcceptedCmp1 to AcceptedCmp5: Response to individual campaigns
  - ✓ Response: Overall response to the last campaign

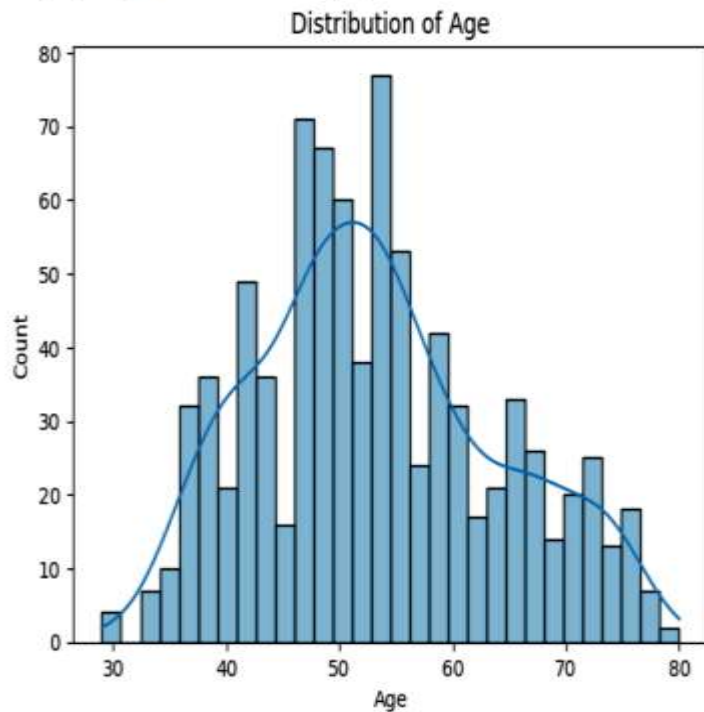
- ***Channel & Purchase Behavior:***
  - ✓ NumWebPurchases, NumCatalogPurchases, NumStorePurchases: Purchase channels
  - ✓ NumWebVisitsMonth: Website visits in last month
  - ✓ NumDealsPurchases: number of purchases made with discount
- ***Target Variable:***
  - ✓ Response: A binary variable (0 or 1) indicating whether the customer responded positively to the latest marketing campaign.

# EDA VISUALS

## DATA VISUALIZATION

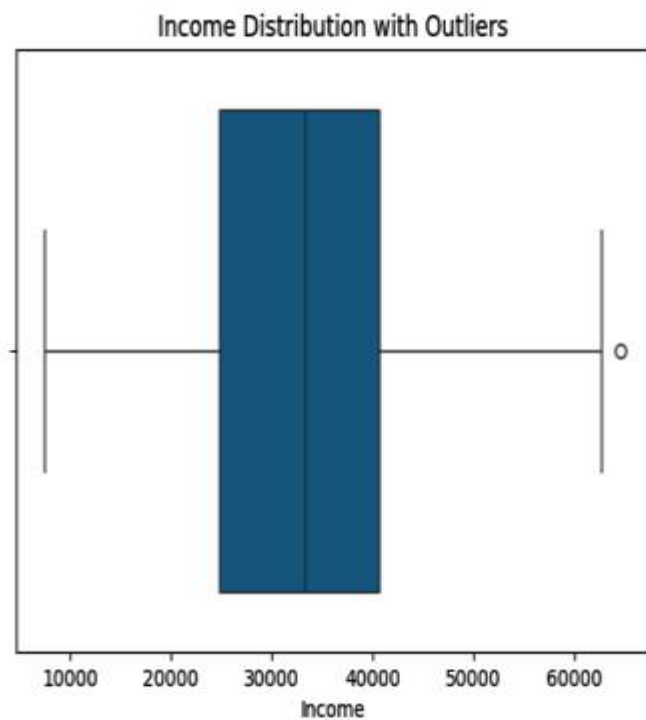
```
[39] # Histogram for Age  
sns.histplot(data['Age'], bins=30, kde=True)  
plt.title("Distribution of Age")
```

Text(0.5, 1.0, 'Distribution of Age')



```
✓ [40] # Boxplot for Income  
0s sns.boxplot(x=data['Income'])  
plt.title("Income Distribution with Outliers")
```

```
↔ Text(0.5, 1.0, 'Income Distribution with Outliers')
```



```
✓ [41] # Count of Education levels  
0s sns.countplot(x='Education', data=data)
```



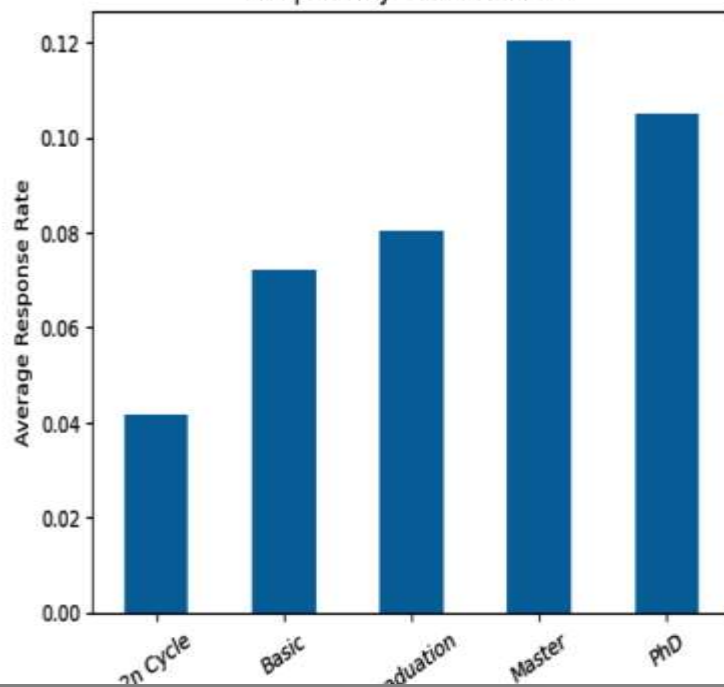
```
edu_map = {0: 'Basic', 1: '2n Cycle', 2: 'Graduation', 3: 'Master', 4: 'PhD'}

education_response = data.groupby(data['Education'].map(edu_map))['Response'].mean()

education_response.plot(kind='bar')
plt.title("Response by Education Level")
plt.xlabel("Education")
plt.ylabel("Average Response Rate")
plt.xticks(rotation=30)
plt.show()
```

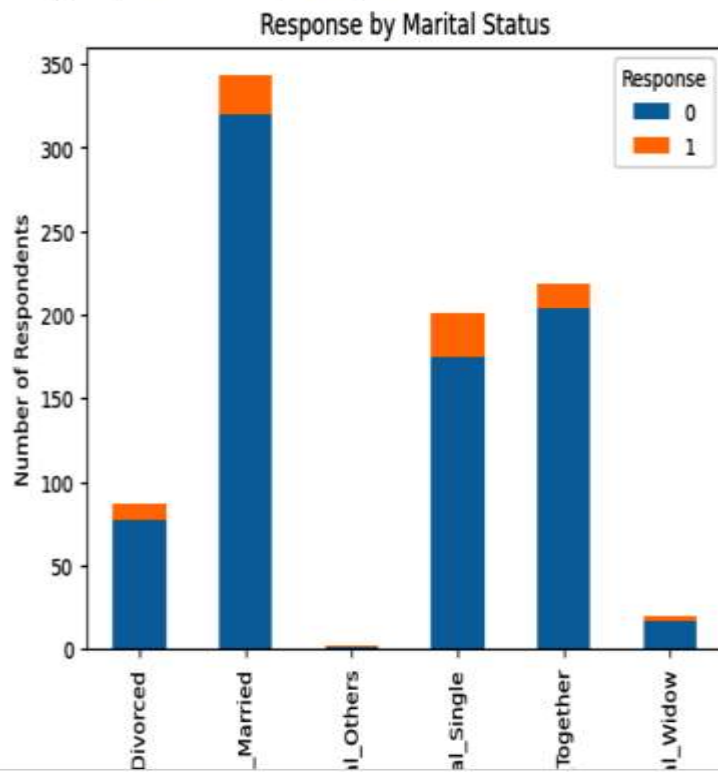
↕

Response by Education Level



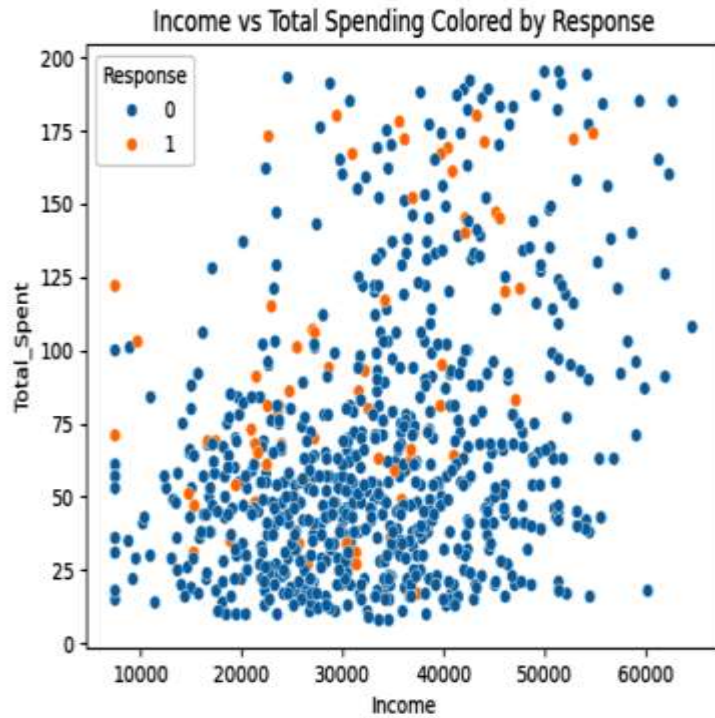
```
# Response rate by Marital Status
marital_cols = ['Marital_Divorced', 'Marital_Married', 'Marital_Others', 'Marital_Single', 'Marital_Together', 'Marital_Widow']
response_by_marital = data.groupby('Response')[marital_cols].sum().T
response_by_marital.plot(kind='bar', stacked=True)
plt.title("Response by Marital Status")
plt.ylabel("Number of Respondents")
```

```
Text(0, 0.5, 'Number of Respondents')
```



```
# Income vs. Total_Spent
sns.scatterplot(x='Income', y='Total_Spent', hue='Response', data=data)
plt.title("Income vs Total Spending Colored by Response")
```

```
Text(0.5, 1.0, 'Income vs Total Spending Colored by Response')
```



```
[48] accepted_cols = ['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5']
```

# MODELS USED AND RESULTS

## *Models Evaluated:*

### ➤ **Logistic Regression**

- ❑ Accuracy (CV=10): **91.39%**
- ❑ Accuracy (CV=50): **91.76%**
- ❑ Precision: **1.00**, Recall: **0.31**, F1 Score: **0.48**

### ➤ **Random Forest Classifier**

- ❑ Accuracy (CV=10, n=40): **91.85%**
- ❑ Accuracy (CV=50, n=5): **91.82%**
- ❑ Precision: **0.43**, Recall: **0.21**, F1 Score: **0.29**

### ➤ **Support Vector Classifier (SVC)**

- ❑ Accuracy (CV=50): **91.21%**
- ❑ Accuracy (CV=20): **91.16%**

➤ **K-Nearest Neighbors (KNN)**

❑ Accuracy (CV=10): **91.16%**

❑ Accuracy (CV=20): **91.16%**

➤ **Decision Tree Classifier**

❑ Accuracy (CV=50): **88.57%**

❑ Accuracy (CV=70): **87.88%**

➤ **Gaussian Naive Bayes**

❑ Accuracy (CV=20): **87.15%**

❑ Accuracy (CV=70): **87.06%**

➤ ***Summary:***

➤ **Best Accuracy: Random Forest (CV=10) with 91.85%**

➤ **Most Precise Prediction: Logistic Regression with Precision = 1.00**

➤ Although Random Forest achieved the highest accuracy, **Logistic Regression** showed better balance in predictive quality based on the F1 Score.

# POWER BI DASHBOARD



## MARKETING CAMPAIGN ANALYSIS AND OPTIMIZATION DASHBOARD



Education

All

Age group

All

Marital\_Status

All

Products Amount

All

Total customers

2216

Average Income

52247

Total Campaign Response Rate

15%

Average Age

56

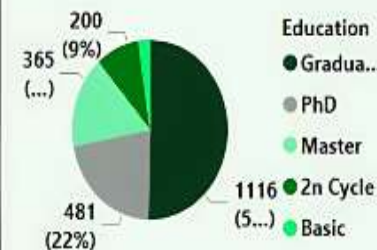
Total Complaints

21

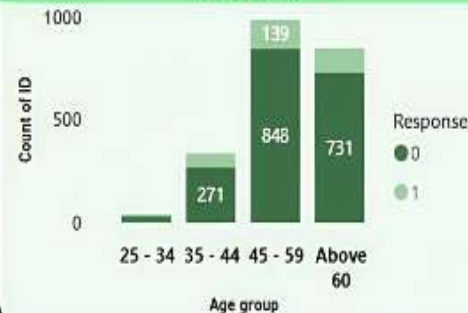
Response Rate (%) by Education



Customers by Education



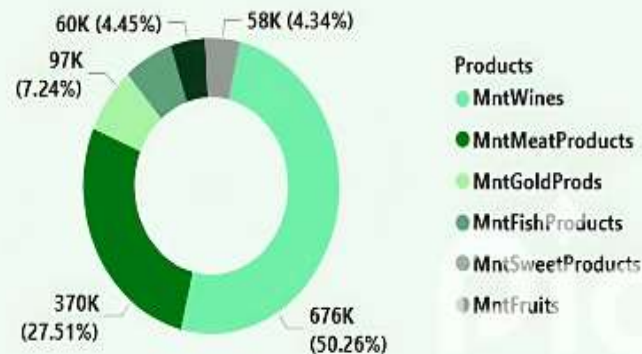
Count of customers by Age group and Response



Response Rate (%) by Marital\_Status



Spending on each product category



# CONCLUSION

This project combined machine learning and business intelligence to analyze and optimize marketing campaign performance using real-world customer data.

## *Key Findings:*

- **Education Impact:** Customers with high education showed the highest campaign response rates—**over 20%**, compared to **below 10%** for Basic education.
- **Channel Preference:** Most purchases were made through **store visits** and **web**, while **catalog purchases** had the lowest engagement—indicating a shift toward more modern retail channels.
- **Product Spending:** Customers spent most on **Wines (50.26%)**, followed by **Meat Products (27.5%)**, highlighting clear product preferences.



- **Customer Recency:** Customers who made recent purchases (lower recency values) were more likely to respond positively to new campaigns.
- **Family Composition:** Customers with 0 or 1 child at home responded more to campaigns than larger households, suggesting individual-focused targeting is more effective.
- **Demographics Summary:**
  - **Average Age:** 56 years
  - **Average Income:** \$52,247
  - **Total Customers:** 2,216
  - **Campaign Response Rate:** 15%
- **ML Insights:**
- Logistic Regression performed best in predicting campaign responses, with a Precision of 1.0, Recall of 0.31, and F1 Score of 0.48, ensuring minimal false positives in campaign targeting.



## ➤ Power BI Dashboard:

- The dashboard provided interactive filtering and visualization by **education, age, recency, spending behavior**, and more, enabling fast and informed decision-making.

## ➤ *Recommendations to Improve ROI:*

- Focus campaigns on high-response groups like highly educated customers and those with recent purchases.
- Personalize offers for high-spending segments (e.g., wine and meat buyers).
- Use modern channels (web and store) more than catalog-based outreach.
- Retrain ML models periodically with updated customer data to refine predictions.
- A/B test campaigns before full rollout to optimize messaging for each segment.

THANK YOU.....

