Optimizing retail marketing costs by classifying customers into unique segments using machine learning

By Vibodh Jadhav and Sneha Chandorkar

Every retail company runs marketing campaigns to provide exposure to their products. Significant amount of capital is spent in running these campaigns. In this project, we aim to reduce this capital to the minimum by predicting which customer is most likely to respond to the campaigns.

In this case, the company runs 5 consecutive campaigns. We look at the response to the campaigns. We take our focus off from the type of customers who don’t respond to all the campaigns consistently which reduces the spending on marketing. The ML algorithm decides this ‘type’ of customer from the training dataset.

Approach: Classification. We use binary feature of Campaign response as the target feature/variable(dependent variable) and select the most important features using EDA(Exploratory Data Analysis)

Features	Details
ID	Customer's unique identifier
Year_Birth	Customer's birth year
Education	Customer's education level
Marital_Status	Customer's marital status
Income	Customer's yearly household income
Kidhome	Number of children in customer's household
Teenhome	Number of teenagers in customer's household
Dt_Customer	Date of customer's enrollment with the company

Features	Details
MntFruits	Amount spent on fruits in last 2 years
MntMeatProducts	Amount spent on meat in last 2 years
MntFishProducts	Amount spent on fish in last 2 years
MntSweetProducts	Amount spent on sweets in last 2 years
MntGoldProds	Amount spent on gold in last 2 years
NumDealsPurchases	Number of purchases made with a discount
Recency	Number of days since customer's last purchase
Complain	1 if the customer complained in the last 2 years, 0 otherwise
MntWines	Amount spent on wine in last 2 years

Data Preprocessing

Data Cleaning is the first step of Preprocessing. Without good data, the model will not give good results.
We get rid of-

- Missing values (we impute them with mean, here only Income feature has missing values)
- Outliers (we treat outliers by using the IQR method)

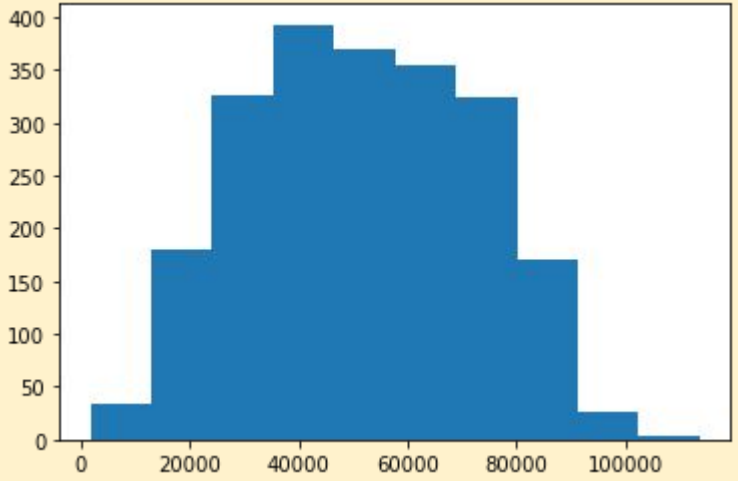
Feature Selection

Feature selection is one of the most important steps of the workflow. It significantly boosts the predictive power of the ML algorithms.
We do a three fold analysis for selecting the features-

- Univariate analysis by Visualization
- Bivariate analysis by Visualization
- Bivariate analysis using hypothesis testing(Z test)

Univariate analysis

We do univariate analysis to see whether is feature is normally distributed or not.
Let us look at the graphs-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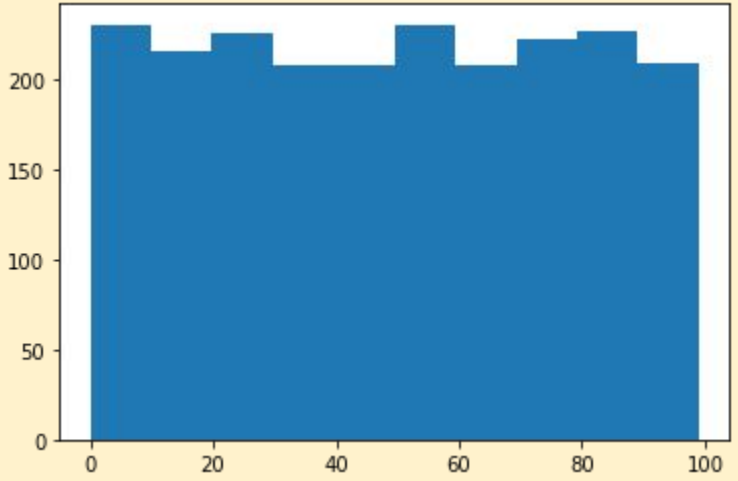
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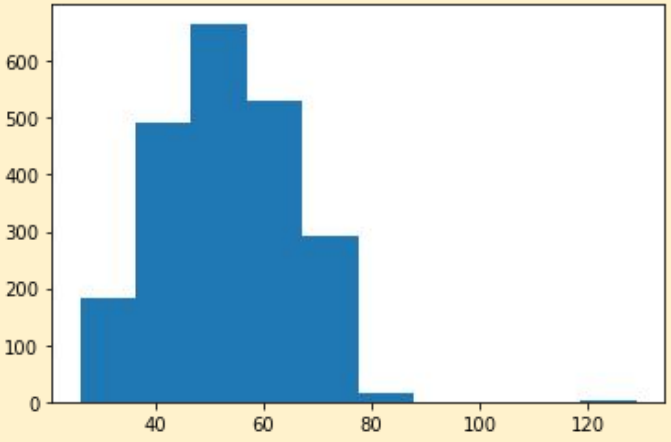
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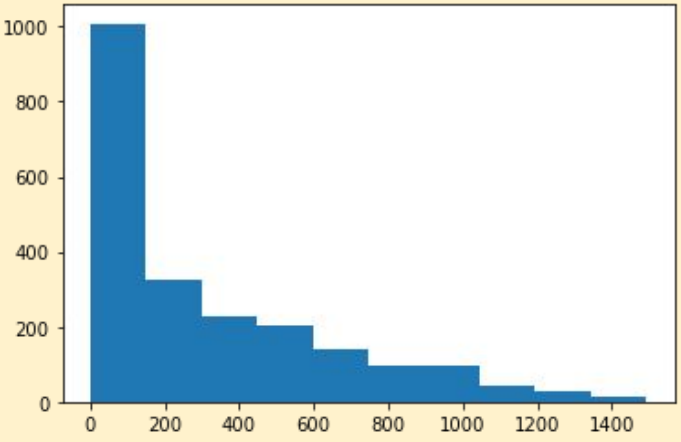
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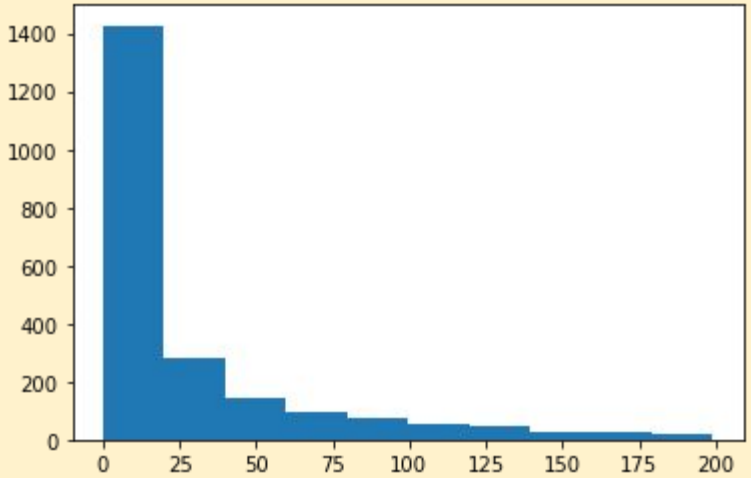
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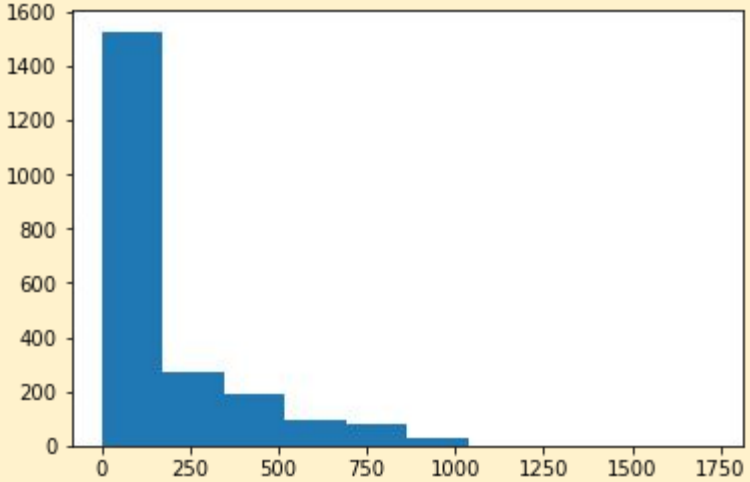
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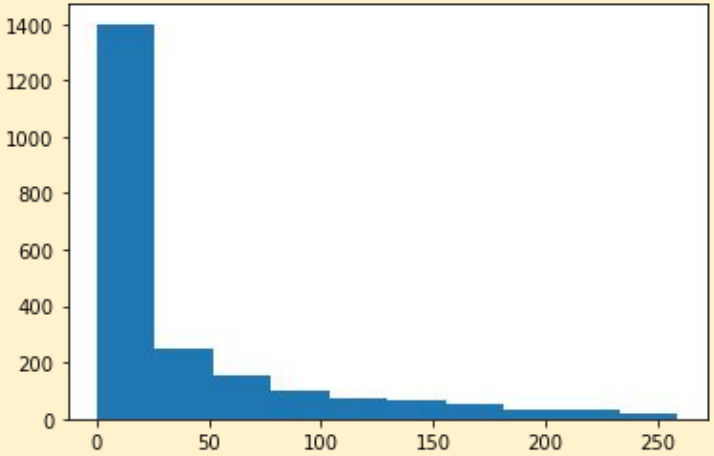
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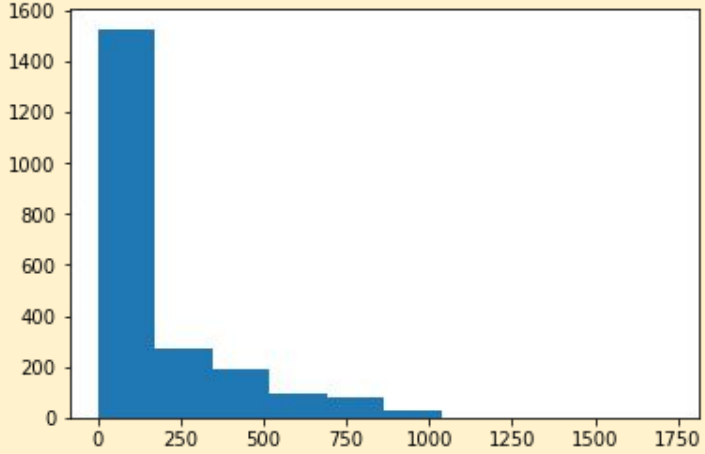
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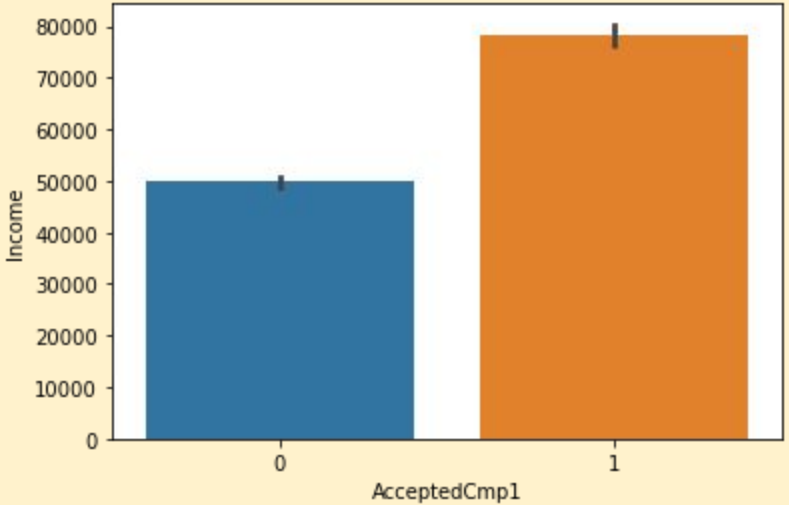
Bivariate analysis using Visualization

Bivariate analysis is used to understand the relationship between the binary target variable of Campaign response and the all the other features. This helps in feature selection. Let us look at the graphs-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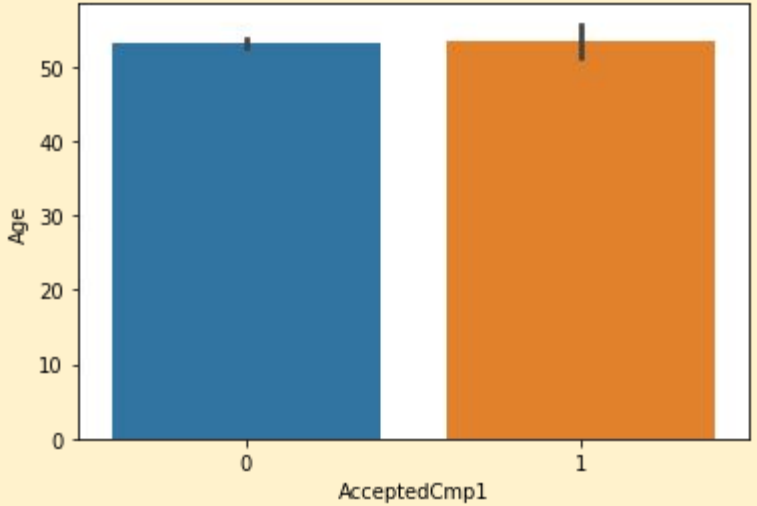
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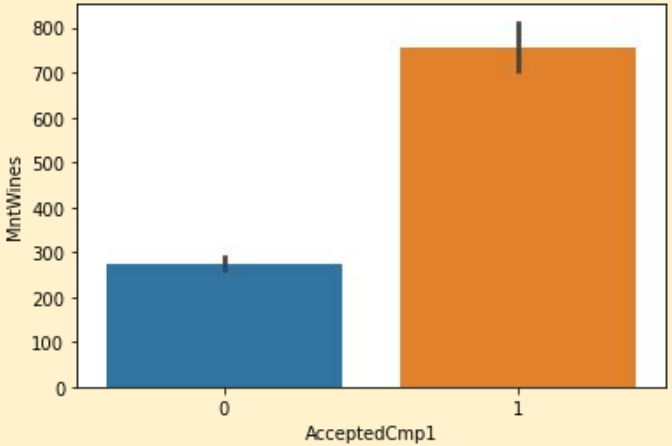
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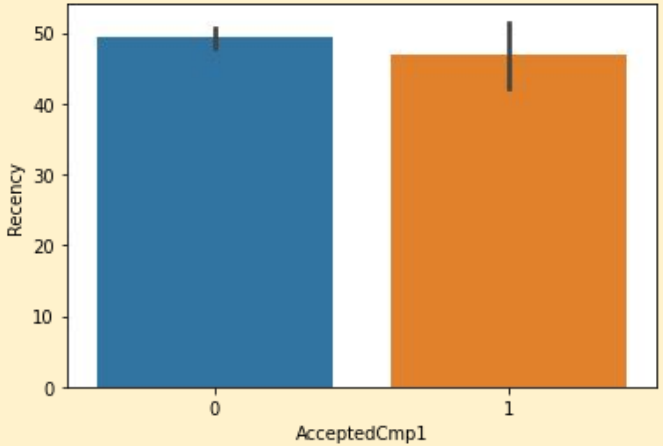
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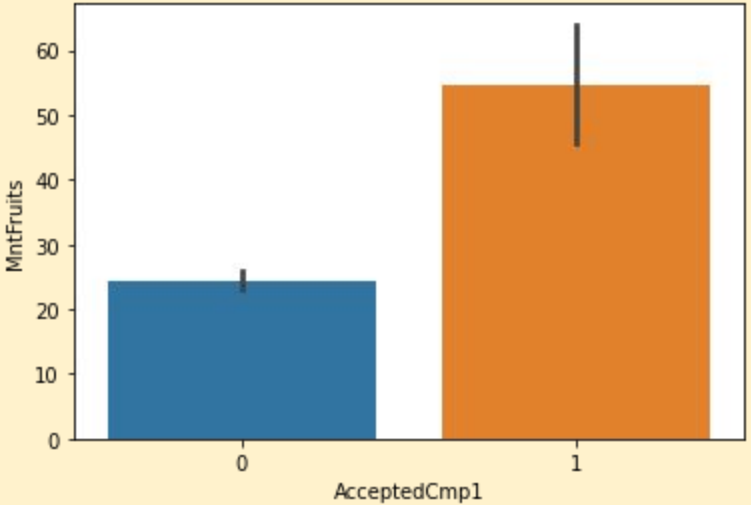
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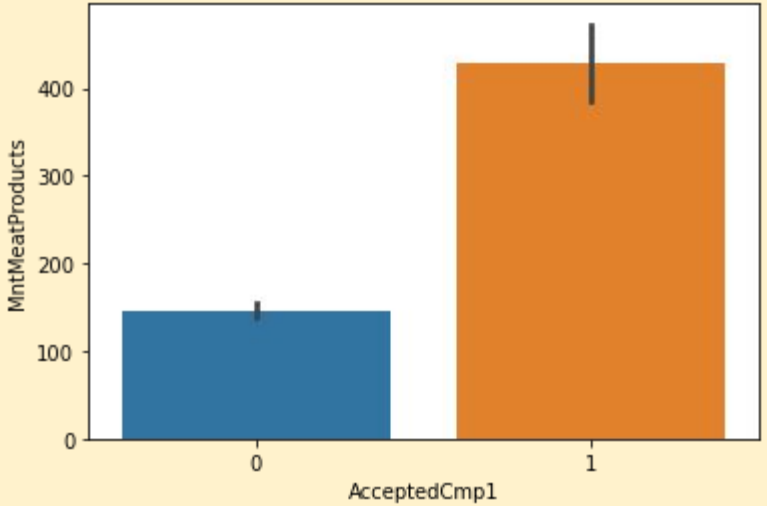
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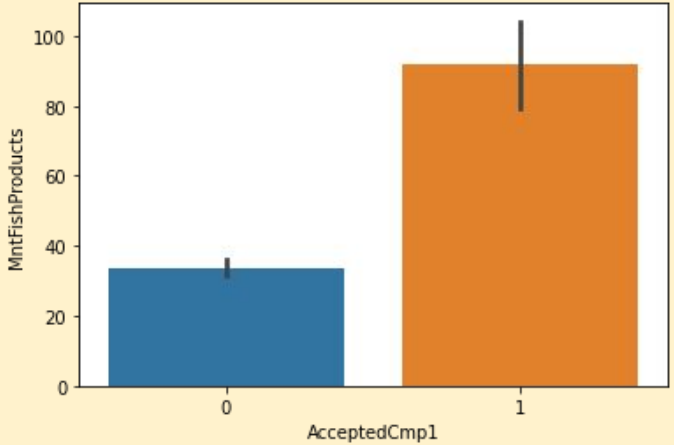
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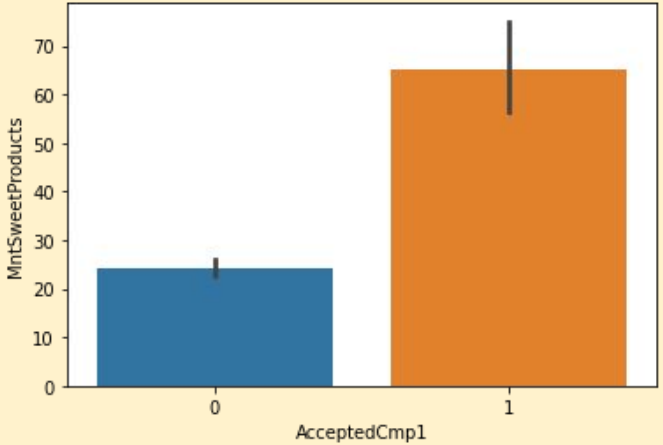
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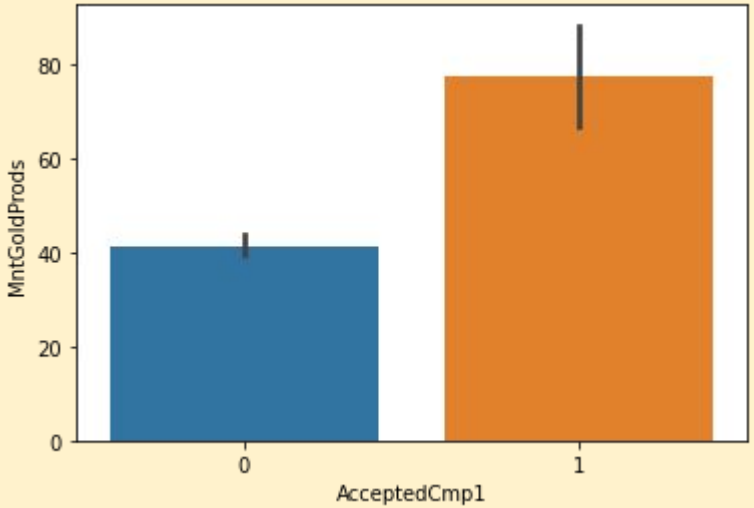
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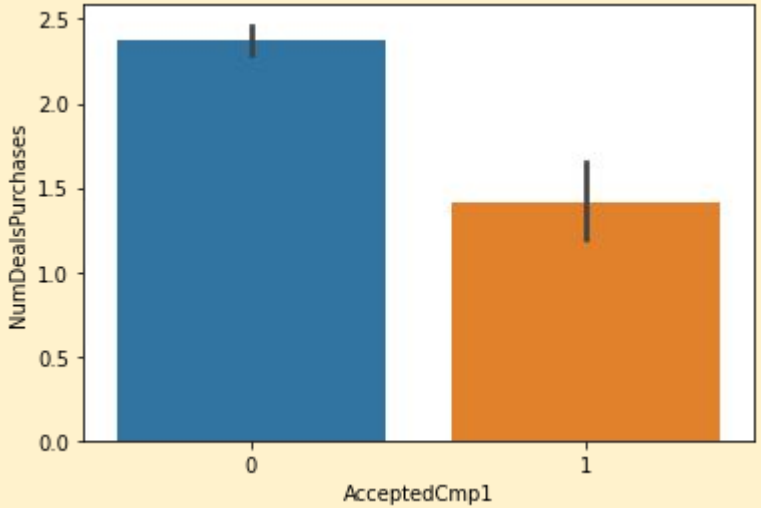
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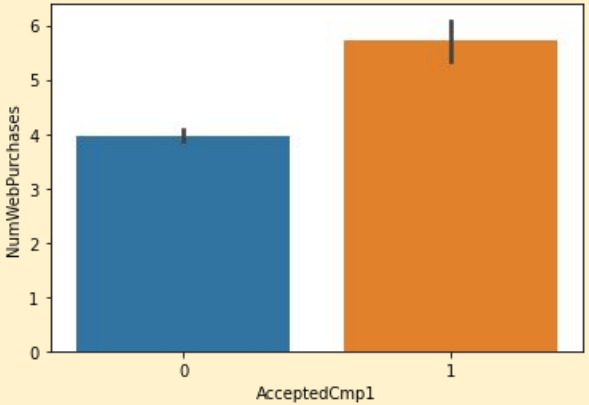
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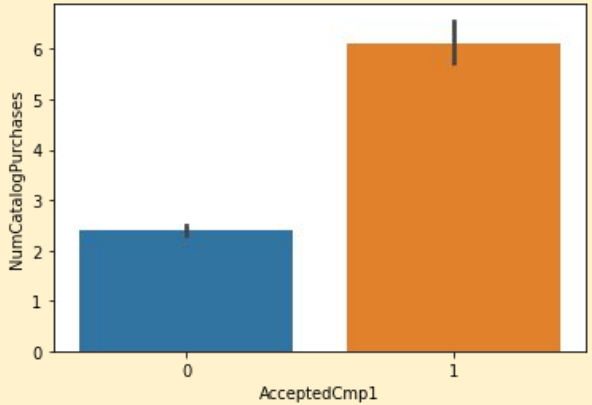
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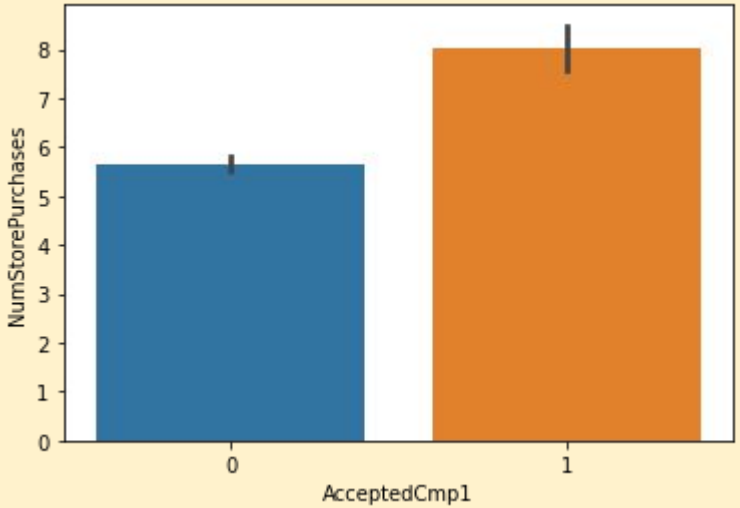
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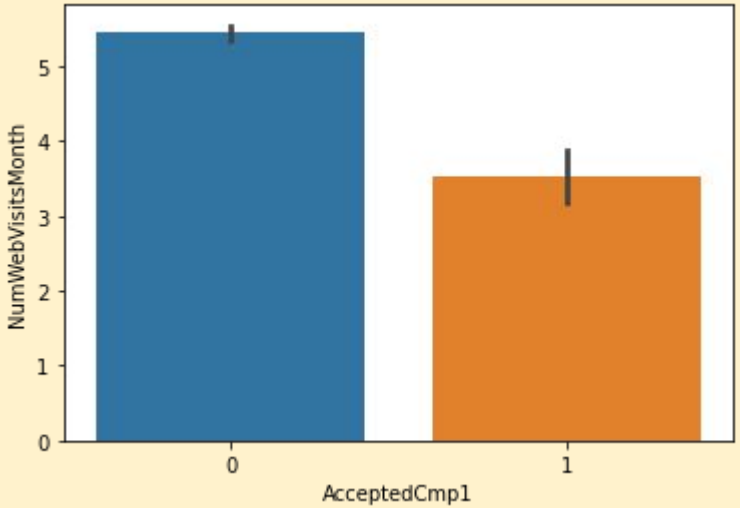
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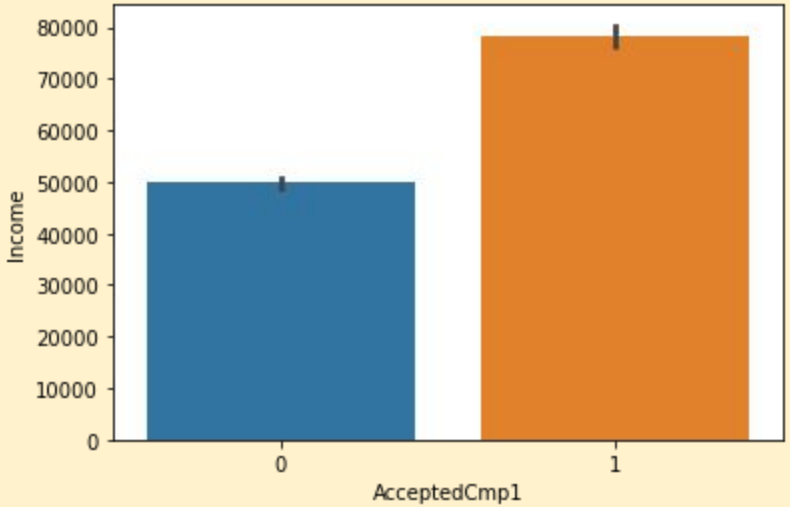
Bivariate analysis using hypothesis testing

Visualization is not enough! Sometimes the relationship between two variables is influenced by another hidden variable(s). To confirm the relationship, we use statistical hypothesis testing with the Z test.

Here, the null hypothesis is- The difference of average between the two groups(for eg- income group who responded to the campaign and income group who didn’t respond to the campaign) is zero.

The alternate hypothesis is- The difference is significant.

For 95% significance, we will choose the features whose z score>1.96 OR z-score<-1.96(implying p-value<0.05). Even after choosing from them, we will reduce the number of features for the model(s) to improve their predictive power.



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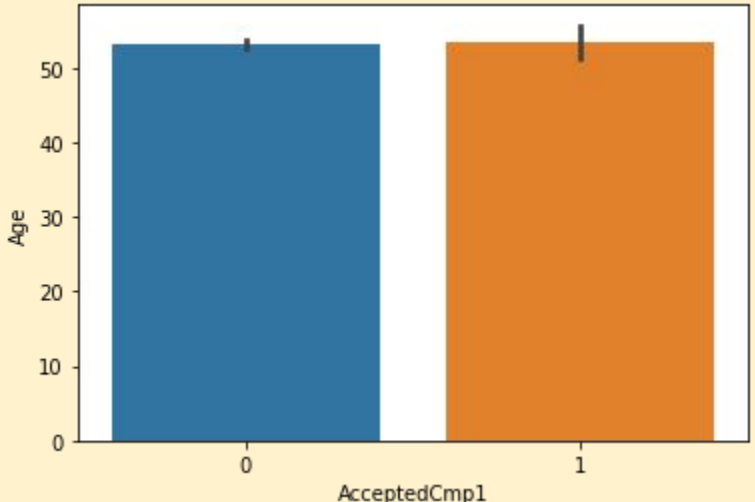

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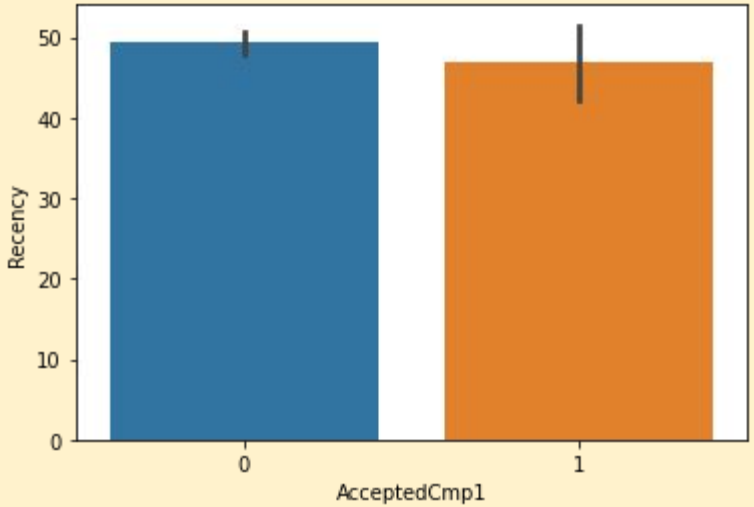

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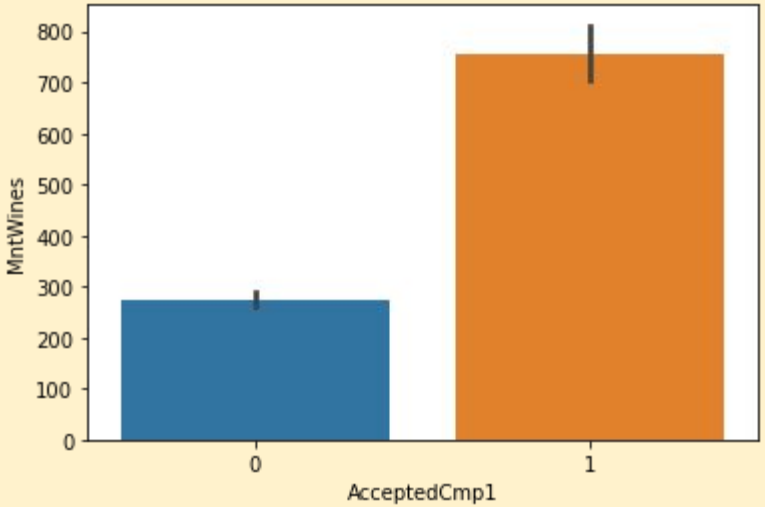

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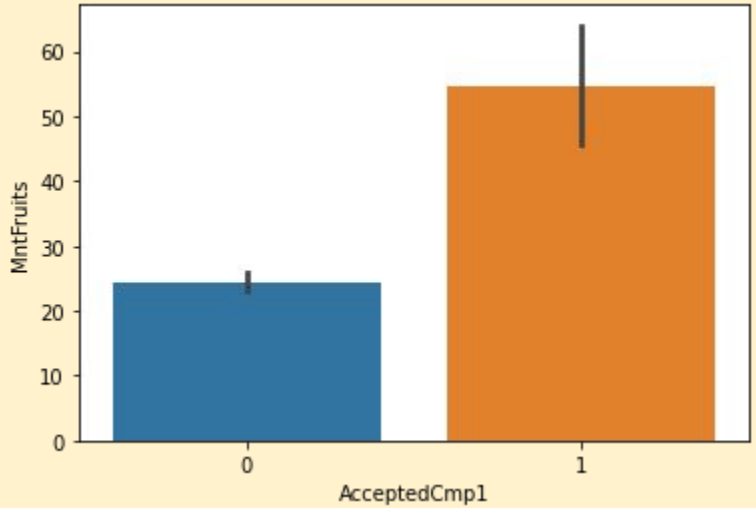

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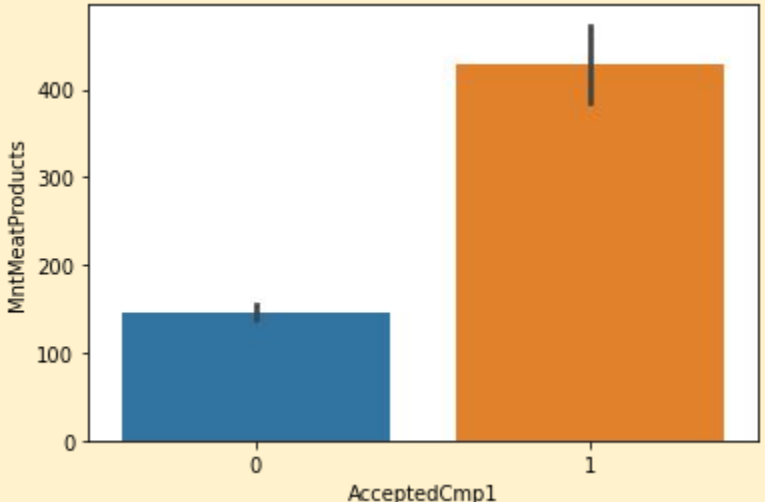

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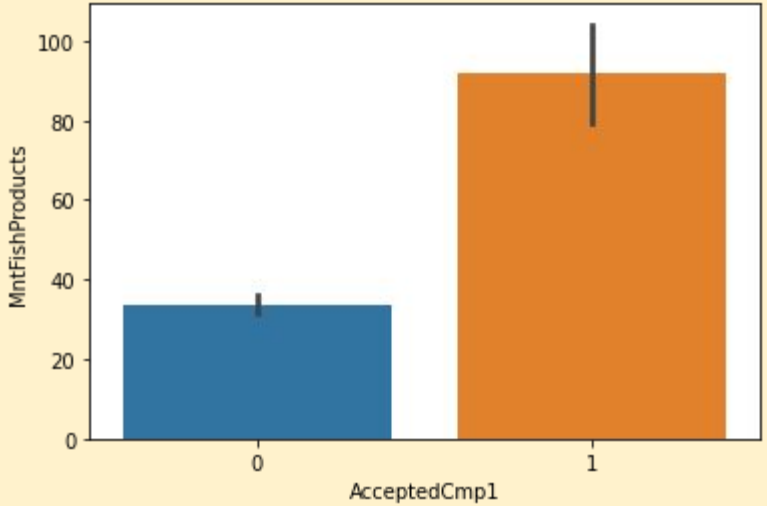

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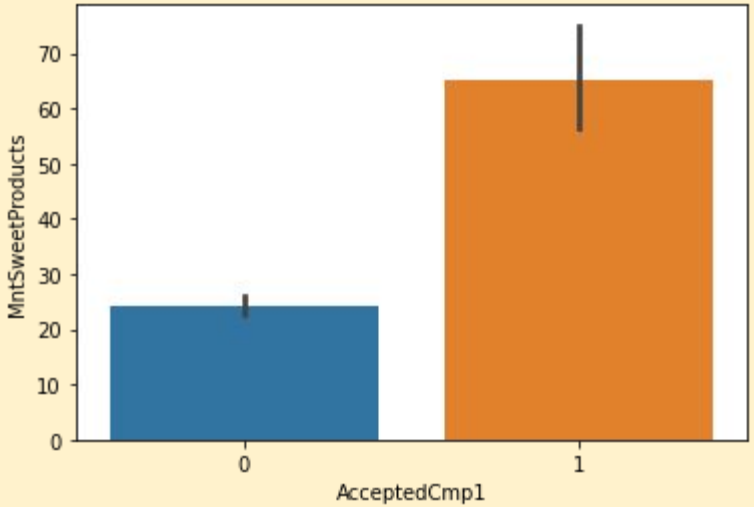

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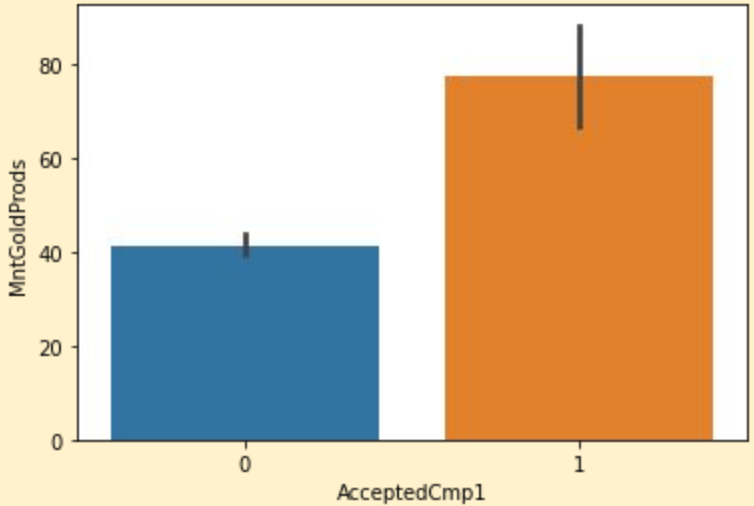

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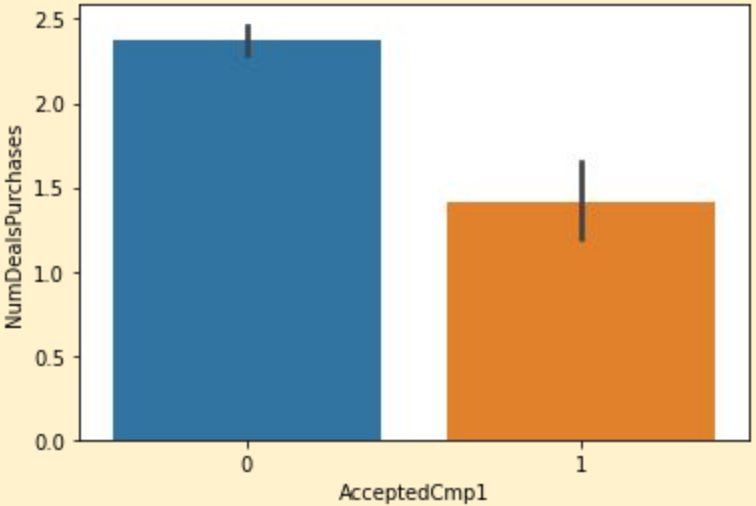

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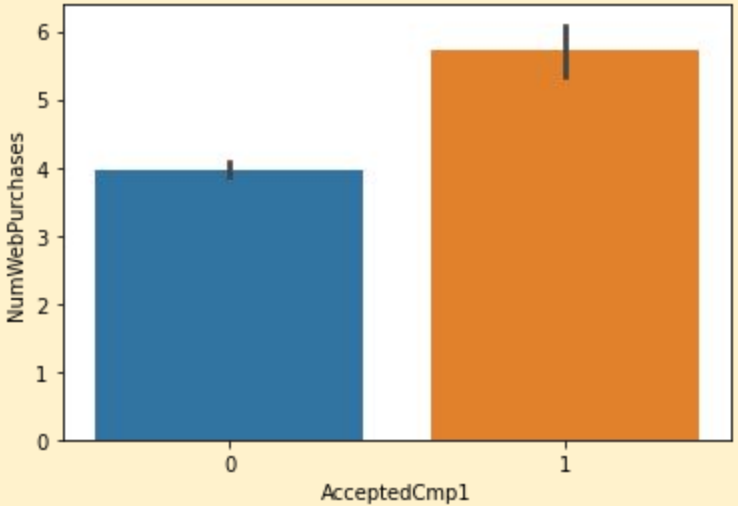

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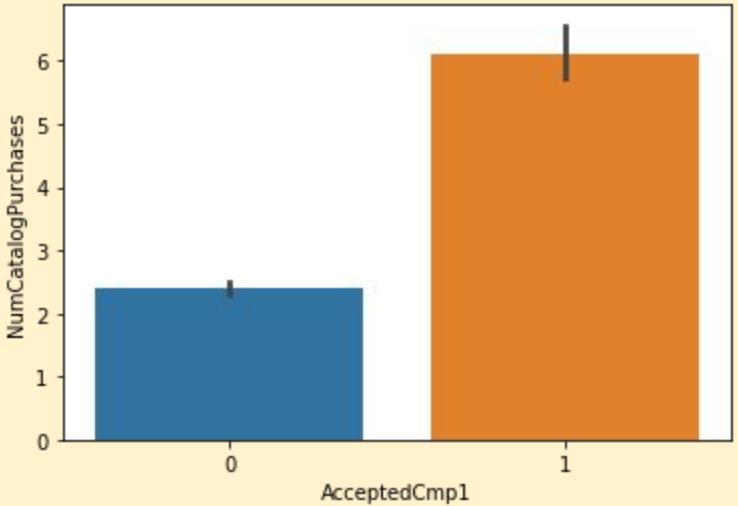

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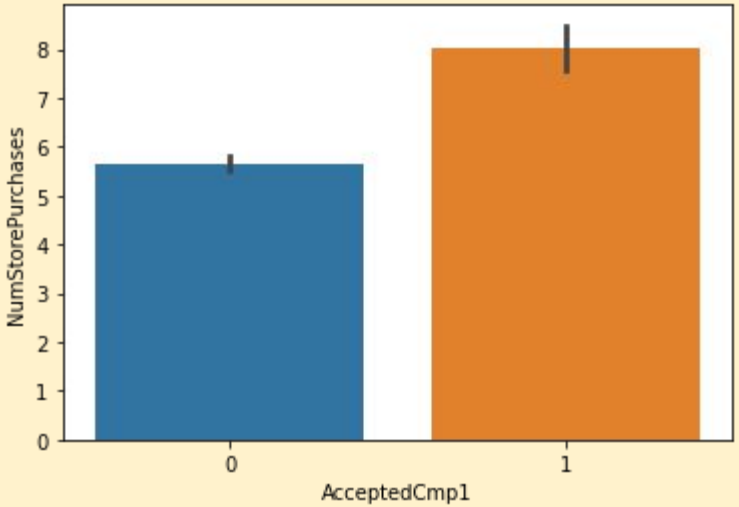

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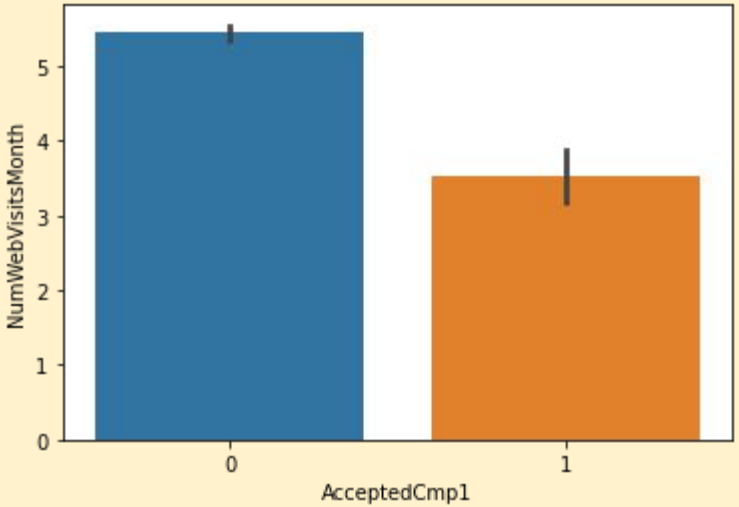

Z score
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Scaling

We scale the continuous features so that the model doesn’t get biased towards the features that have values larger in scale. For eg- Income and MntWines(Amount spent on Wine by the customer in the last 2 years)

Encoding of categorical variables

We use label encoding to encode the two important categorical variables in this dataset-

- Education
- Marital_Status

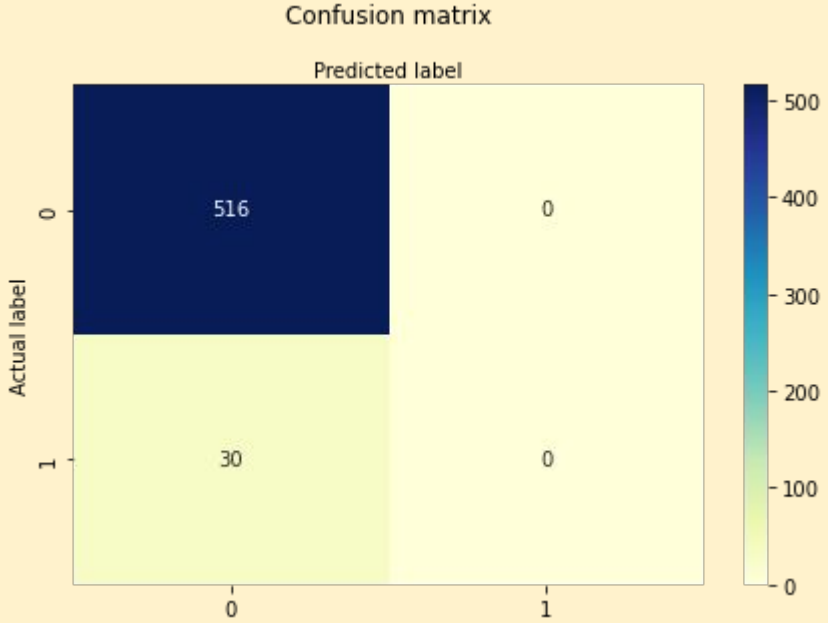
Model fitting

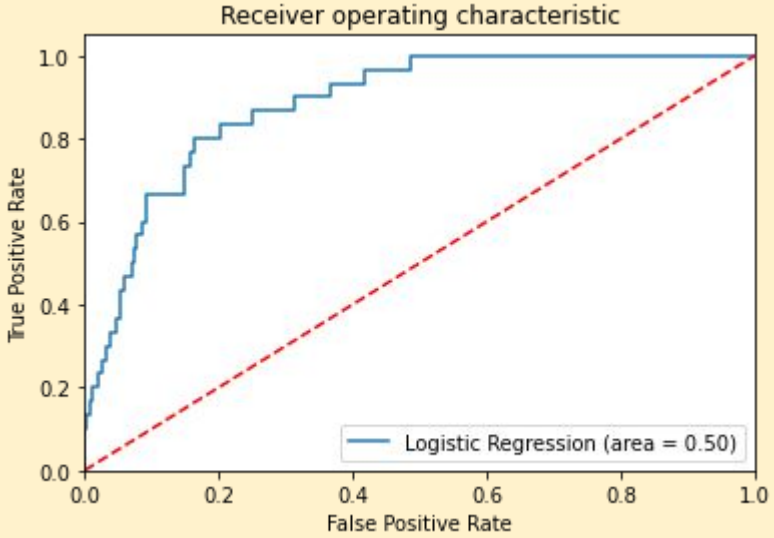
We split the training and test dataset in the ratio 75:25.
We use the following Machine learning algorithms for classification-

- Logistic Regression
- Decision Tree
- KNN
- SVM

Model Evaluation

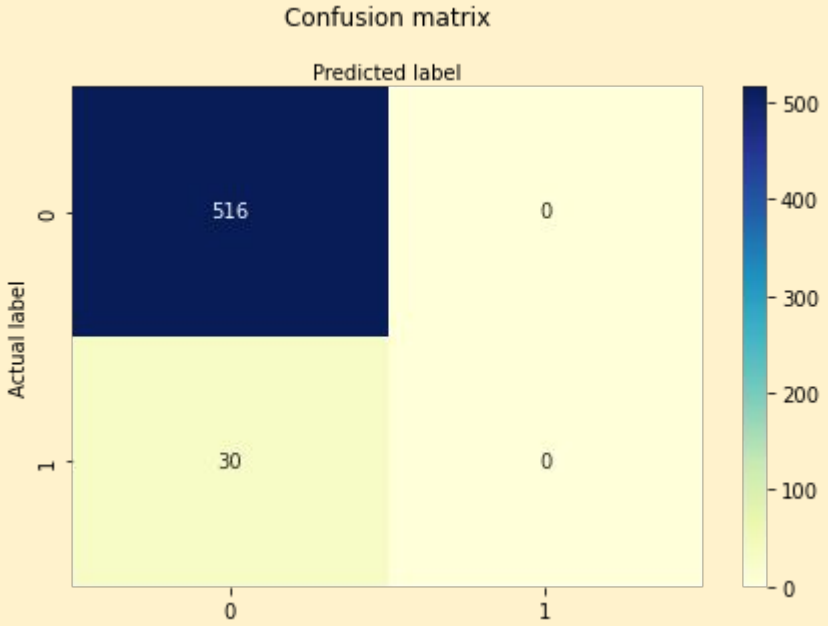
Logistic Regression





Model evaluation

Decision Tree



Evaluation metric

Here, we use accuracy as a metric to decide which model is giving us the best results-

Model	Accuracy
Logistic Regression	0.945054945054945
Decision Tree	0.9194139194139194
KNN	0.9432234432234432
SVM	0.945054945054945

We can see that SVM and Logistic Regression are giving the best results so they will be our preferred models for the predicting the campaign responses for the remaining 4 campaigns using the same methods.

Thank you!