Santander Customer Satisfaction

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Outline

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1. Introduction

Problem statement

Customer satisfaction is an important factor for businesses. Every business wants to know happy and unhappy customers to take action. We will predict Santander Bank customers' happiness. So they can take action before they leave the bank.

2. Dataset

This is a Kaggle project. This data set has **370 anonymous features** and **76020 rows**. Target feature is binary, happy or unhappy customers. The goal is to predict customers' satisfaction.

For TARGET feature, 0 represents happy and 1 represents unhappy customers.

The first thing I check is the percentage of happy and unhappy customers. 96/4 ratio means this dataset is **unbalanced**. I have to consider under and over sampling methods.

Secondly the missing values are checked. There are **no missing values** in the dataset.

3. Feature Selection

All features are anonymous so we have to use statistical techniques to see whether the features are important or not. The original number of features : **370**

- **Basic Methods Remove constant and quasi-constant features 370 - > 273**

  First I applied basic methods and removed constant and quasi-constant features. With the help of this method I reduced the number of features from 370 to 273.

- **Univariate Selection Methods 273 - > 30 - > 22**

  Secondly I applied univariate methods like ANOVA F-value and Fisher. By applying these two methods I choose the top 30 features. Then I looked at the common features of both methods. At the end 22 features are found in common.

- **Correlation Matrix Method 22 - > 11**

  I created a correlation matrix and found features with a correlation greater than 0.90. I drop those features and 11 features are left.

4. Exploratory Data Analysis

Selected features:

1. var15',
2. 'ind_var5',
3. 'ind_var8_0',
4. 'ind_var12_0',
5. 'ind_var13_0',
6. 'ind_var30',
7. 'num_var30_0',
8. 'num_var30',
9. 'num_var42',
10. 'saldo_var30',
11. 'var36'

Plots-1

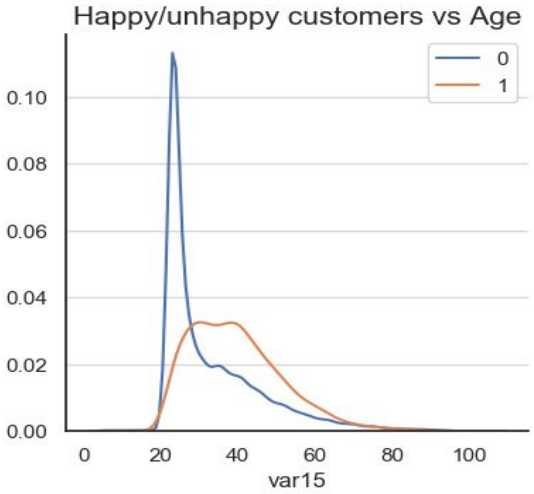


Fig 1: var15

has definitely resolving power. According to a Kaggle form post var15 is the age of the customers. Younger people are mostly happy customers.

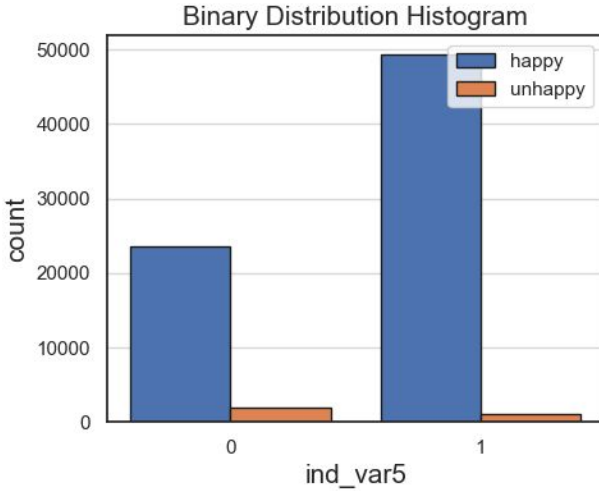


Fig 2: ind_var5

The customer dissatisfaction is 3.3 times more likely when ind_var5 is absent obtained from P(Target=1|ind_var5=0) / P(Target=1|ind_var5=1) = 7.7/2.1 = 3.7

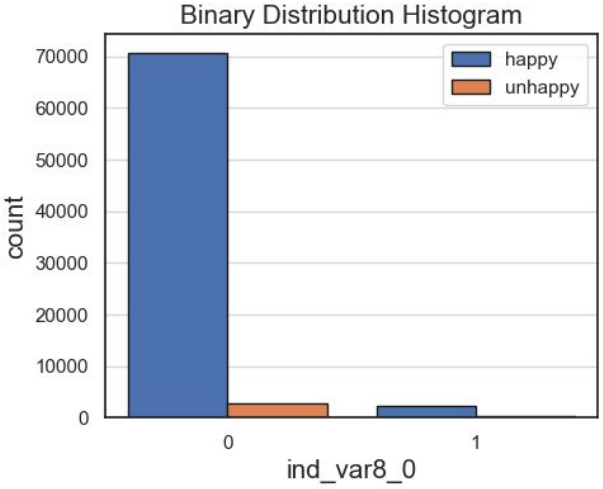
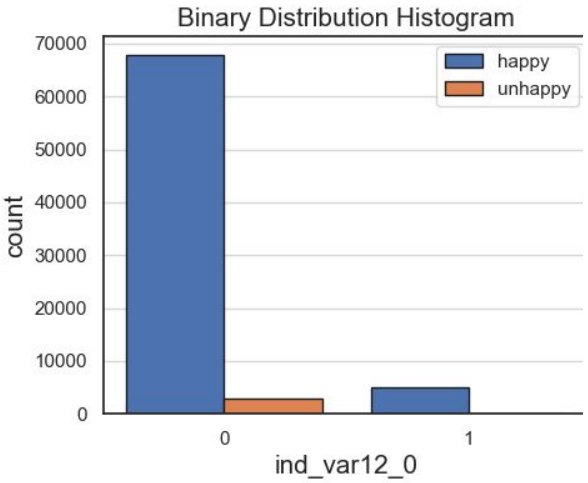
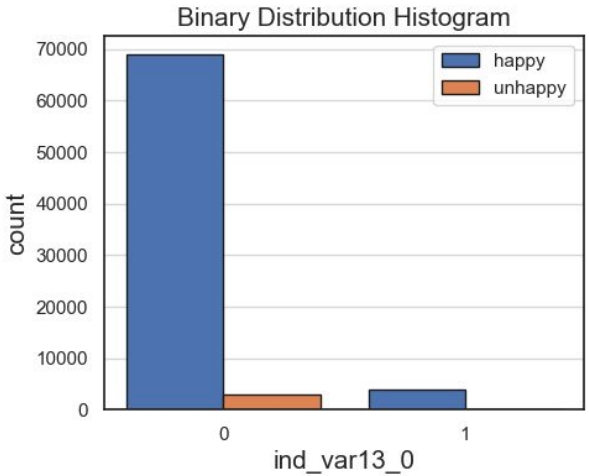


Fig 3: Ind_var8_0

The customer dissatisfaction is 0.4 times more likely when ind_var8_0 is absent (obtained from P(Target=1|ind_var8_0=0) / P(Target=1|ind_var8_0=1) = 0.4)

Plots-2





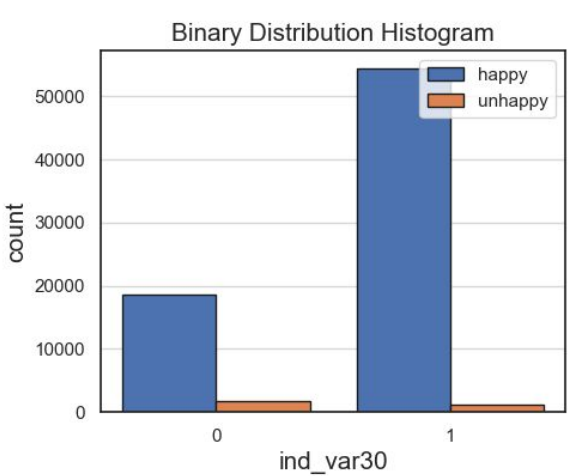


Fig 4: ind_var12_0

The customer dissatisfaction is 3.5 times more likely when ind_var12_0 is absent obtained from P(Target=1|ind_var12_0=0) / P(Target=1|ind_var12_0=1) = 3.5)

Fig 5: ind_var13_0

The customer dissatisfaction is 6.1 times more likely when ind_var13_0 is absent

Fig 6: ind_var30

The customer dissatisfaction is 4 times more likely when ind_var30 is absent

Plots-3

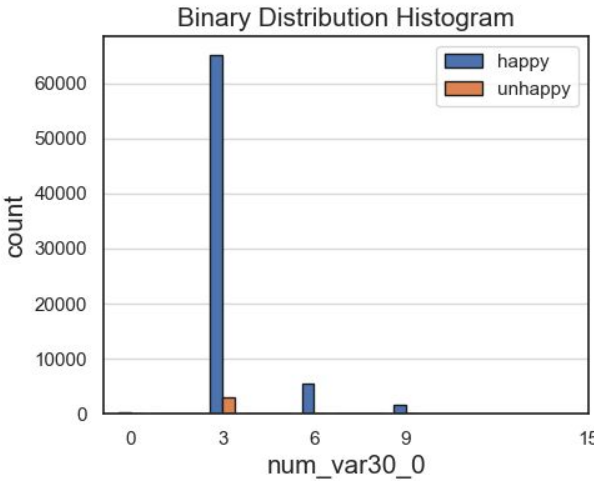


Fig 7: num_var30_0

The customer dissatisfaction is more likely when num_var30_0 is 3,6, or 9.

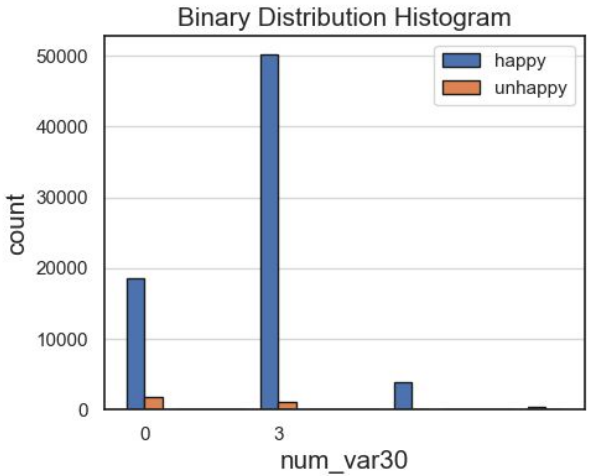


Fig 8: num_var30

The customer dissatisfaction is more likely when num_var30_0 is 0.

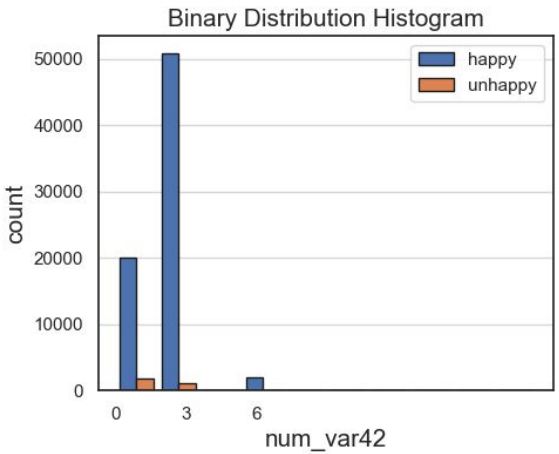
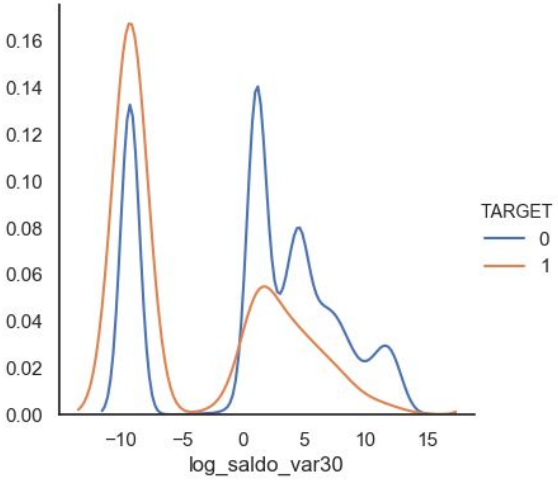


Fig 9: num_var42

The customer dissatisfaction is more likely when num_var42 is 0.

Plots-4



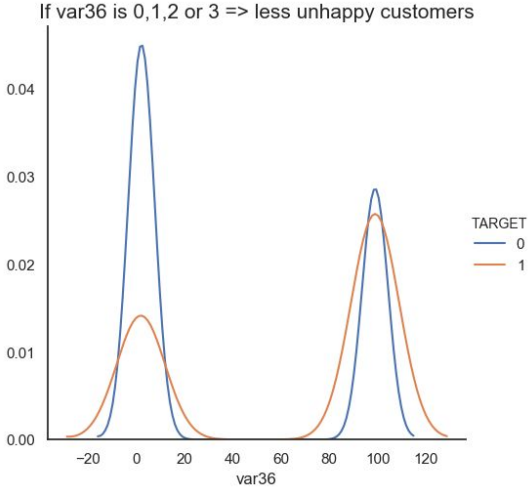


Fig 7: saldo_var30

Unsatisfied customers more likely log_saldo_var30<-5

Fig 8: var36

Unsatisfied customers are more likely with the value 99

5. Predictive Models

This is a binary classification problem. 5 predictive models are tested.

1. Logistic Regression
2. Support Vector Machine
3. Random Forest
4. K-nearest Neighbor Classifiers
5. Decision tree classifiers.

These models are tested on the Base Model, Smote model, and Random Under Sampling Model

5. Model Scores

Table 1: Weighted average f1-scores

Model Name	Base Model	Smote Model	Random Under Sampling Model(RUS)
LR	0.94	0.77	0.77
SVM	0.94	0.25	0.21
RF	0.94	0.86	0.83
kNN	0.94	0.89	0.87
DT	0.94	0.79	0.86

5. Model Scores

Table 2: Recall-1

Model Name	Base Model	Smote Model	Random Under Sampling Model(RUS)
LR	0	0.68	0.67
SVM	0	0.96	0.97
RF	0.2	0.59	0.71
kNN	0.04	0.23	0.32
DT	0.	0.78	0.69

5. Model Scores

Table 3: AUC

Model Name	Base Model	Smote Model	Random Under Sampling Model(RUS)
LR	0.74	0.76	0.76
SVM	0.60	0.60	0.71
RF	0.74	0.74	0.79
kNN	0.64	0.62	0.58
DT	0.82	0.79	0.81

5. Parameter Tuning DT

Table 4: AUC

Model Name	Weighted average F1	Recall 1	AUC
DT Base	0.94	0.03	0.60
DT Base with best parameters	0.94	0.03	0.81
DT SMOTE	0.86	0.58	0.69
DT SMOTE with best parameters	0.85	0.66	0.79
DT RUS	0.82	0.68	0.70
DT RUS with best parameters	0.85	0.71	0.85

6. Conclusion

- During parameter tuning, recall for 1 and AUC scores are always increased.
- AUC is always the same for untuned models(~0.69).
- Sampling models increased the recall 1 score.
- The best AUC score 0.85 is coming from tuned DT - RUS model and also this model gives the best recall -1 score, 0.71, over all.