# Receipt Matching

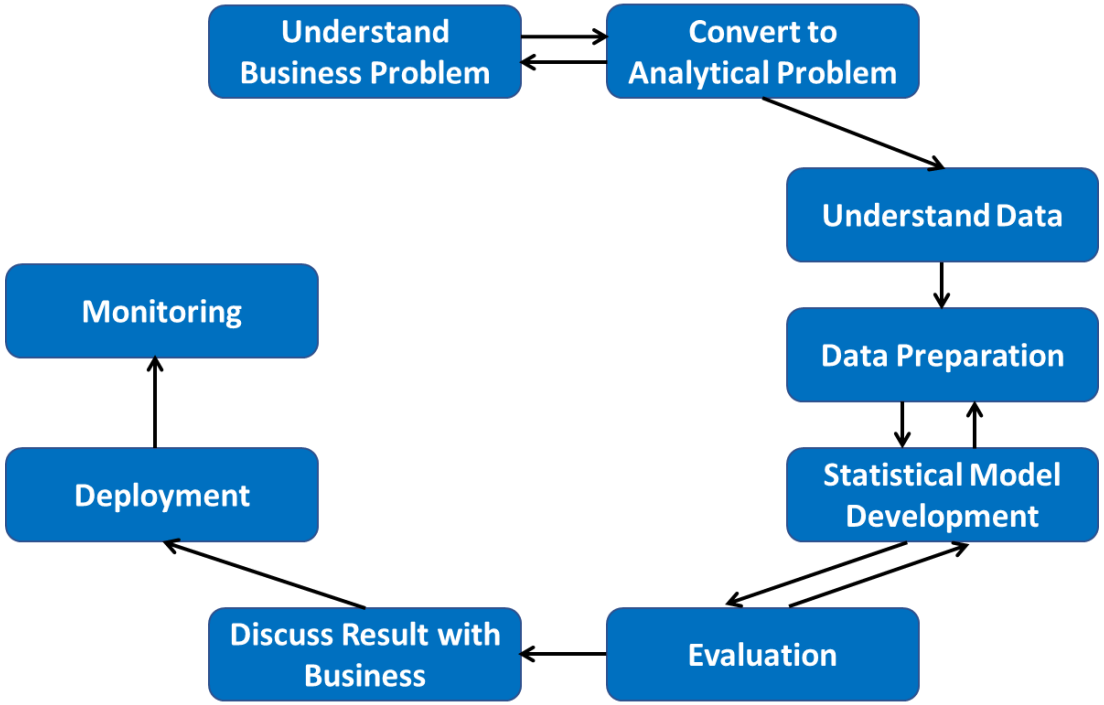
# Topics

- Business Problem
- Analytical Plan
- Workflow
- Exploratory Data Analysis
- Variable Insights
- Class Imbalance
- Model Development
- Model Performance
- Recommendation

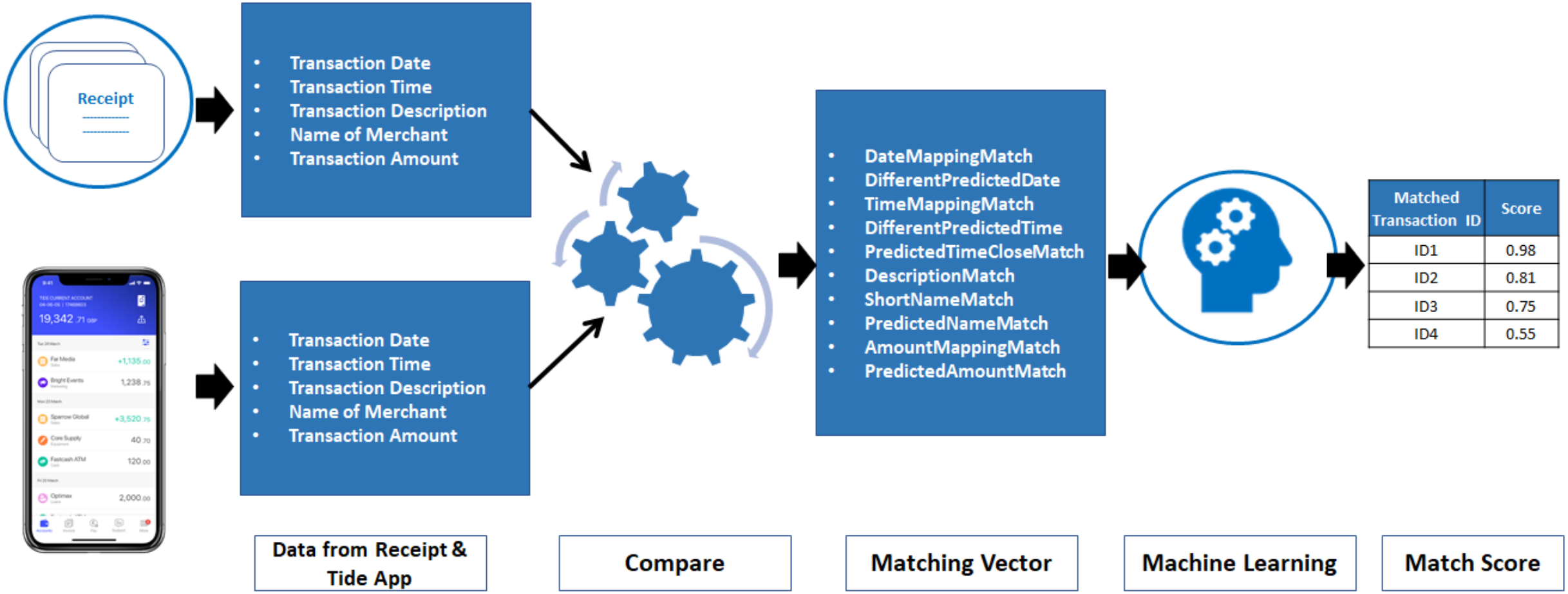
# Business Problem

Automatically match receipt images to the associated transaction within the Tide app using data extracted from receipt images and information in Tide transaction.

# Analytical Plan



# Workflow


Receipt
Transaction Date
Transaction Time
Transaction Description
Name of Merchant
Transaction Amount
Transaction Date
Transaction Time
Transaction Description
Name of Merchant
Transaction Amount
DateMappingMatch
DifferentPredictedDate
TimeMappingMatch
DifferentPredictedTime
PredictedTimeCloseMatch
DescriptionMatch
ShortNameMatch
PredictedNameMatch
AmountMappingMatch
PredictedAmountMatch
Matched Transaction ID
Score
ID1
0.98
ID2
0.81
ID3
0.75
ID4
0.55
Data from Receipt & Tide App
Compare
Matching Vector
Machine Learning
Match Score

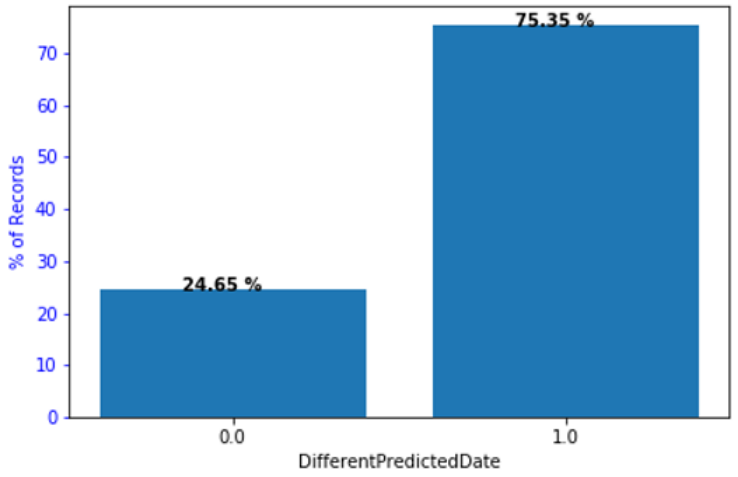
# Data Understanding

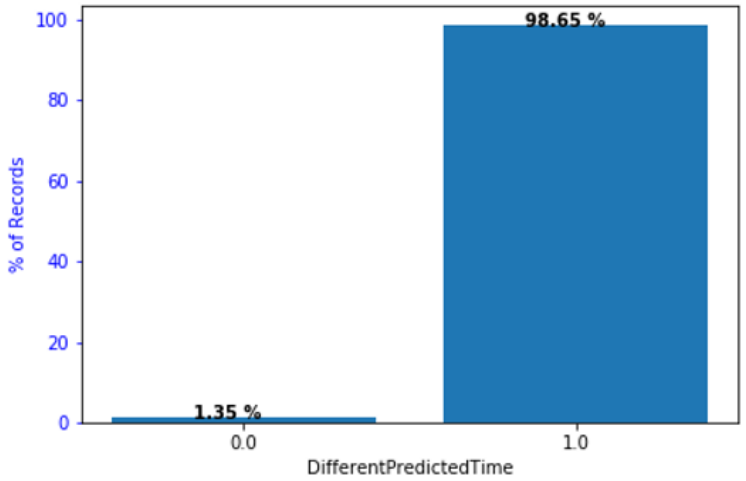
The data consists of a csv file with below columns and their descriptions.

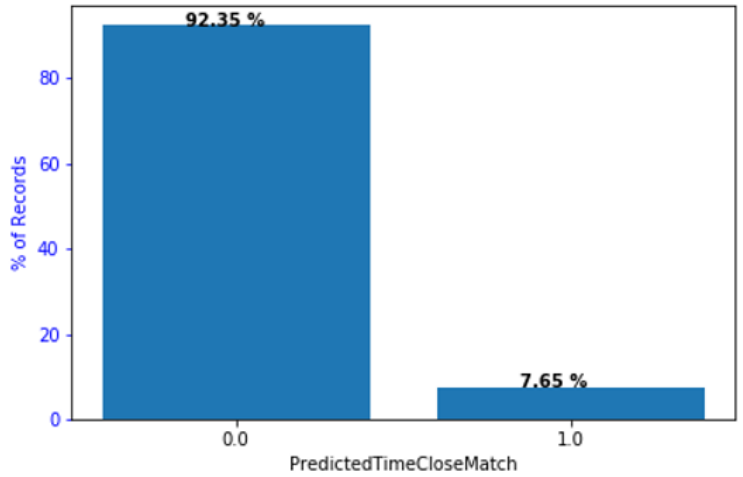
| Sl No. | Column Name | # Recocrds | # Missing Records | # Unique Values | Data Type | Description |
|---|---|---|---|---|---|---|
| 1 | receipt_id | 12,034 | 0 | 1,155 | Categorical | Unique identifier for a receipt image |
| 2 | company_id | 12,034 | 0 | 5 | Categorical | Tide customer identifier |
| 3 | matched_transaction_id | 12,034 | 0 | 1,155 | Categorical | Unique identifier for the transaction that we know is the correct match for the receipt_id |
| 4 | feature_transaction_id | 12,034 | 0 | 2,132 | Categorical | Unique identifier for the transaction combined with the receipt_id to produce the matching vector |
| 5 | DateMappingMatch | 12,034 | 0 | 11 | Numerical | Matching vector for the given receipt_id and feature_transaction_id |
| 6 | AmountMappingMatch | 12,034 | 0 | 5 | Numerical | |
| 7 | DescriptionMatch | 12,034 | 0 | 5 | Numerical | |
| 8 | DifferentPredictedTime | 12,034 | 0 | 2 | Binary | |
| 9 | TimeMappingMatch | 12,034 | 0 | 2 | Binary | |
| 10 | PredictedNameMatch | 12,034 | 0 | 5 | Numerical | |
| 11 | ShortNameMatch | 12,034 | 0 | 2 | Binary | |
| 12 | DifferentPredictedDate | 12,034 | 0 | 2 | Binary | |
| 13 | PredictedAmountMatch | 12,034 | 0 | 6 | Numerical | |
| 14 | PredictedTimeCloseMatch | 12,034 | 0 | 2 | Binary | |

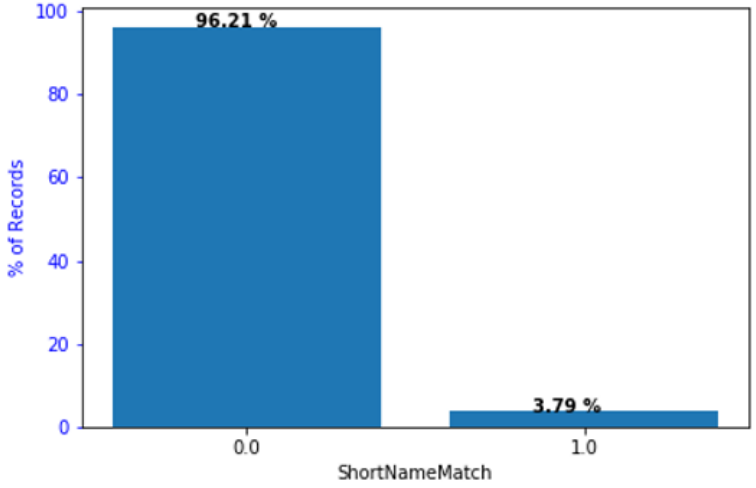
There are 10 Matching vector variables that will be used as input to calculate likelihood score of match between receipt and corresponding transaction in Tide. We will perform Exploratory Data Analysis on these variables to gain more insight about the data.

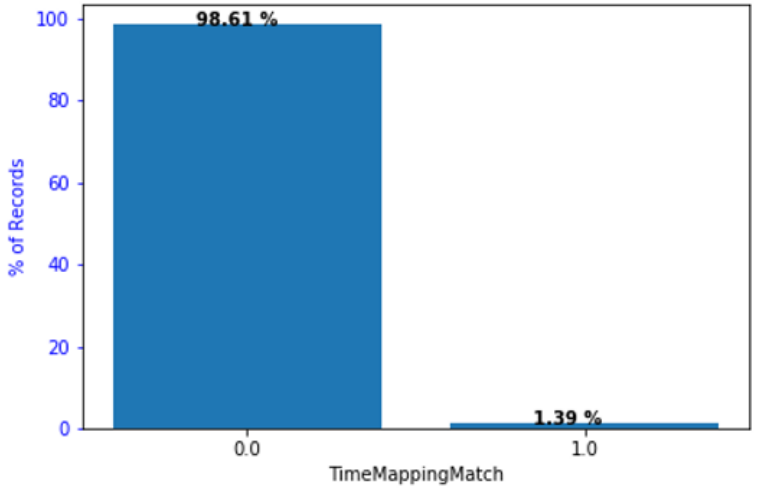
# Exploratory Data Analysis (Binary Variables)



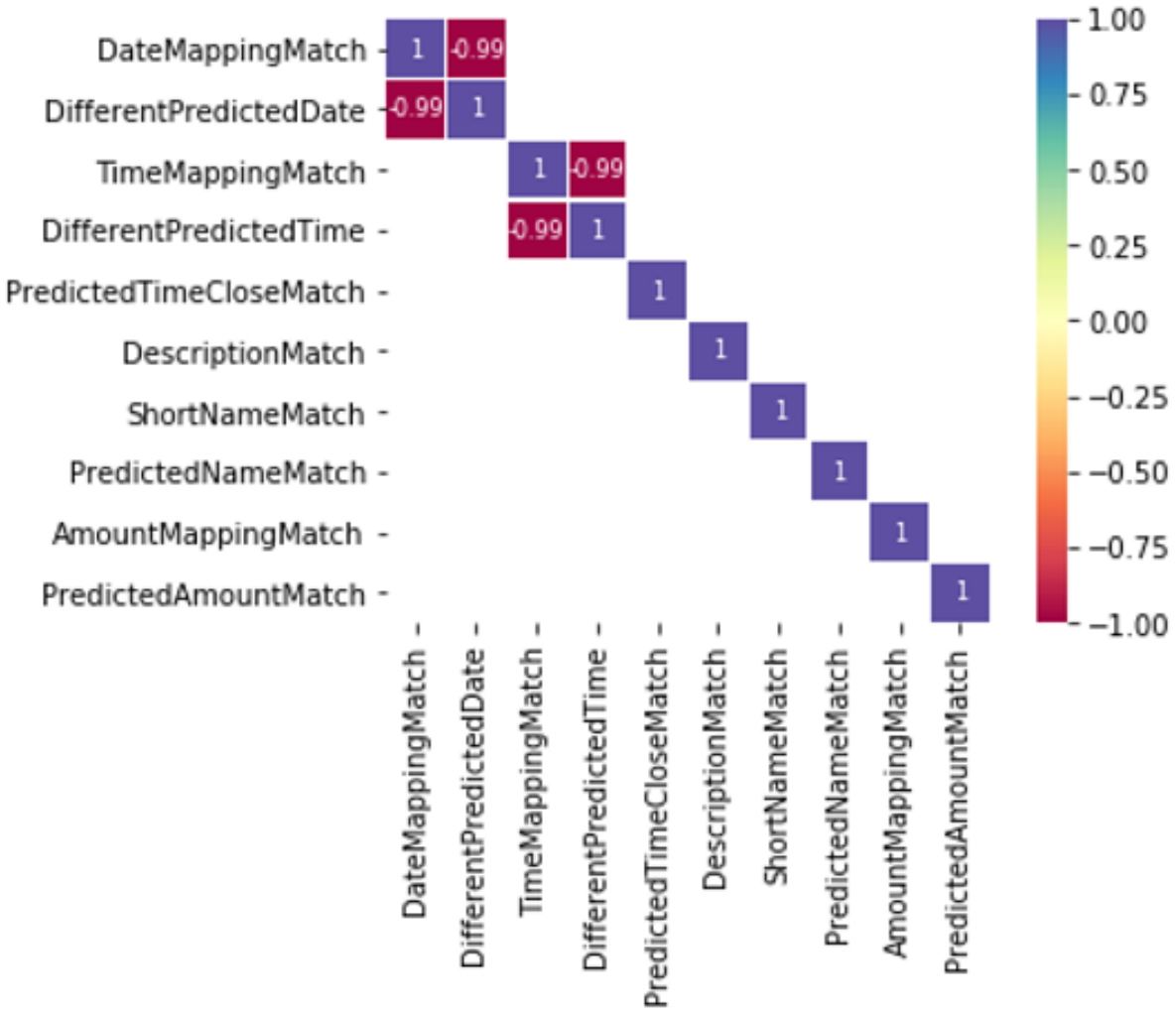

Apart from DifferentPredictedDate variable, all other variables are highly imbalance towards one value. We will examine its behavior in detail with the dependent variable.

# Exploratory Data Analysis (Numerical Variables)

| Variable | count | # missing | % missing | # unique value | # zero | % zero | mean | std | min | max | p1 | p5 | p10 | p25 | median | p75 | p90 | p95 | p99 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DateMappingMatch | 12,034 | 0 | 0.0% | 11 | 9,068 | 75.4% | 0.2179 | 0.3845 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.95 | 0.95 | 0.95 |
| AmountMappingMatch | 12,034 | 0 | 0.0% | 5 | 11,225 | 93.3% | 0.0317 | 0.1226 | 0 | 0.9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.4 | 0.7 |
| DescriptionMatch | 12,034 | 0 | 0.0% | 5 | 11,581 | 96.2% | 0.0215 | 0.1170 | 0 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 |
| PredictedNameMatch | 12,034 | 0 | 0.0% | 5 | 11,589 | 96.3% | 0.0242 | 0.1286 | 0 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 |
| PredictedAmountMatch | 12,034 | 0 | 0.0% | 6 | 11,989 | 99.6% | 0.0010 | 0.0201 | 0 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

All the 5 numerical variables are matched scores scaled between 0 to 1 and we have no missing values. From the above quantile distribution , we can see that variables are skewed towards right.

# Multicollinearity




From the correlation matrix it is evident that there is very high inverse correlation between:

- DateMappingMatch & DifferentPredictedDate
- TimeMappingMatch & DifferentPredictedTime

Depending on the type of algorithm that we will use for our solution, we may need to treat this by removing 1 variable from each pair which contains the same information.

# Modeling Base & Target

**Modeling Base**

The base on which the model is built is called Modeling base. Here Modeling base is historical data of customers where matching status of receipt with Tide transaction is available along with matching vectors.

**Target**

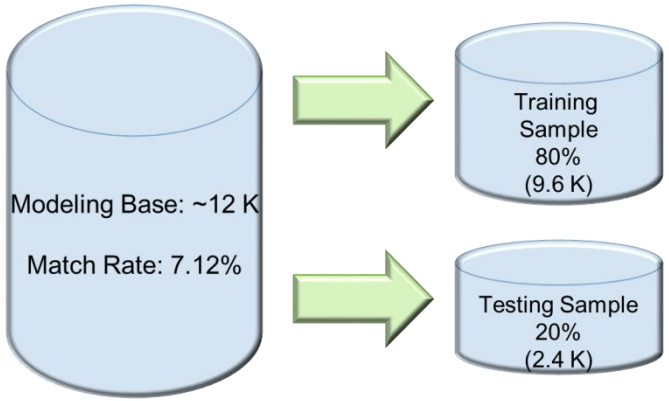
The phenomenon for which the model is being built is called Target. Here the Target is to predict whether receipt images matches to the associated transaction within the Tide app.

**Target Variable Definition**

Target=1, if matched_transaction_id = feature_transaction_id

0, otherwise

Based on this calculation our Target/Match Rate is **7.12 %**




Modeling base is divided into training and testing sample in the ratio of **80:20** to ensure that model is not over fitting on training data and works well with unseen data also.

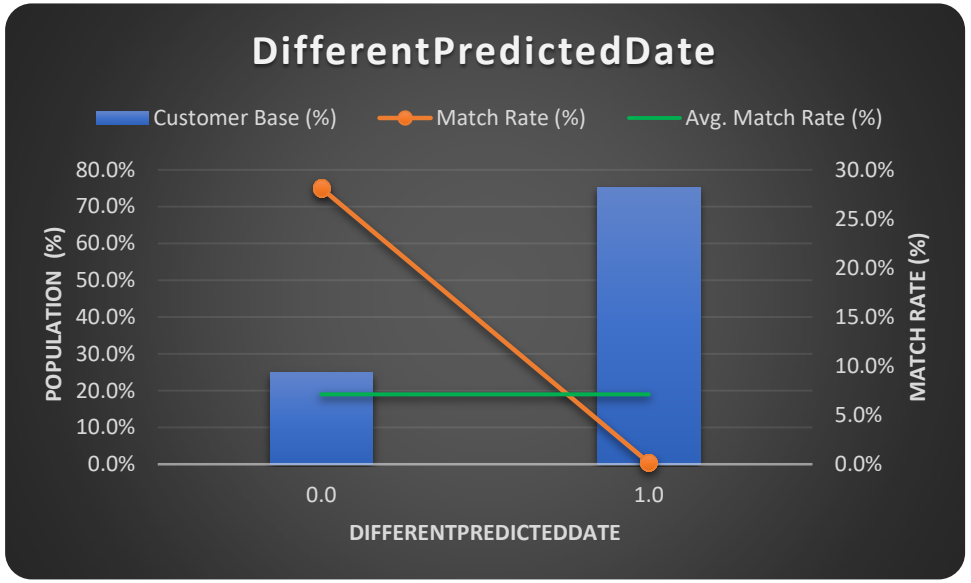
# Information Value

| Sl No. | Variable | Information value |
|---|---|---|
| 1 | DifferentPredictedDate | 4.71 |
| 2 | DateMappingMatch | 3.41 |
| 3 | TimeMappingMatch | 0.85 |
| 4 | DifferentPredictedTime | 0.84 |
| 5 | ShortNameMatch | 0.65 |
| 6 | DescriptionMatch | 0.63 |
| 7 | PredictedNameMatch | 0.56 |
| 8 | PredictedTimeCloseMatch | 0.44 |
| 9 | PredictedAmountMatch | 0.02 |
| 10 | AmountMappingMatch | 0.02 |

**Information Value (IV)** helps us to understand the predictive power of independent variables.
Interpretation of IV is given in the below table and we can see that 2 of our variables have unexpectedly high IV which is putting them in suspicious category. But after detailed analysis of data it is found that there is no issue with the data.

| IV | Information Value Interpretation |
|---|---|
| **<=0.02** | Very Weak Predictive Power |
| **0.02 - 0.1** | Weak Predictive Power |
| **0.1 - 0.3** | Strong Predictive Power |
| **0.3 - 0.5** | Very Strong Predictive Power |
| **>0.5** | Suspicious/Too good |

# Bivariate Analysis with Target

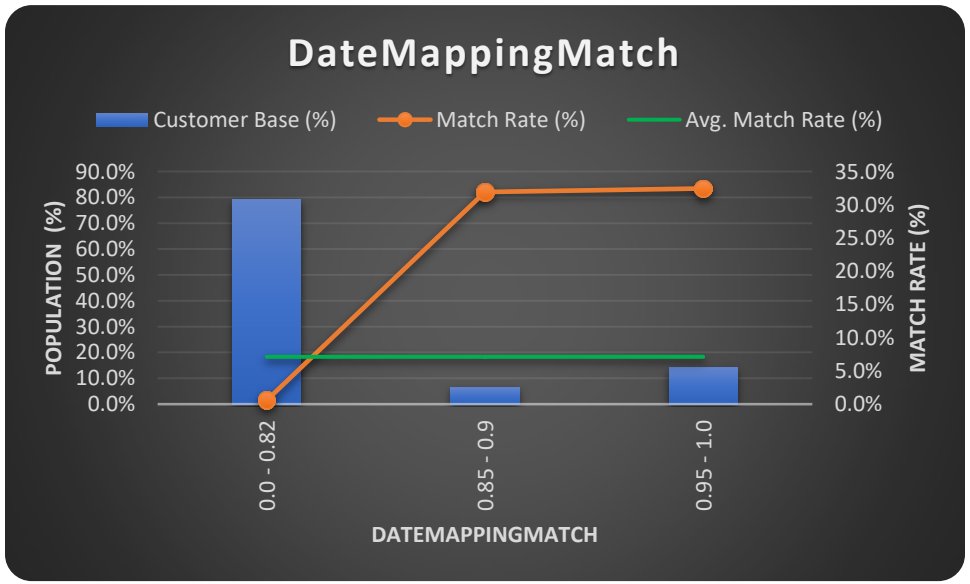



**Nomenclature of this bivariate chart:**

**X-axis:** Different segments of the independent variable

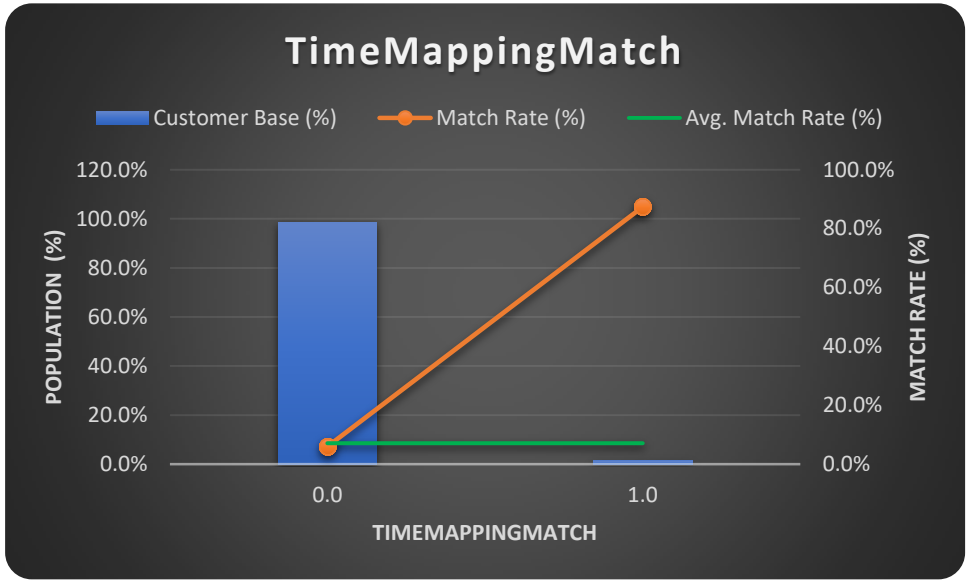
**Primary Y-axis:** Population in % for different segments of independent variable

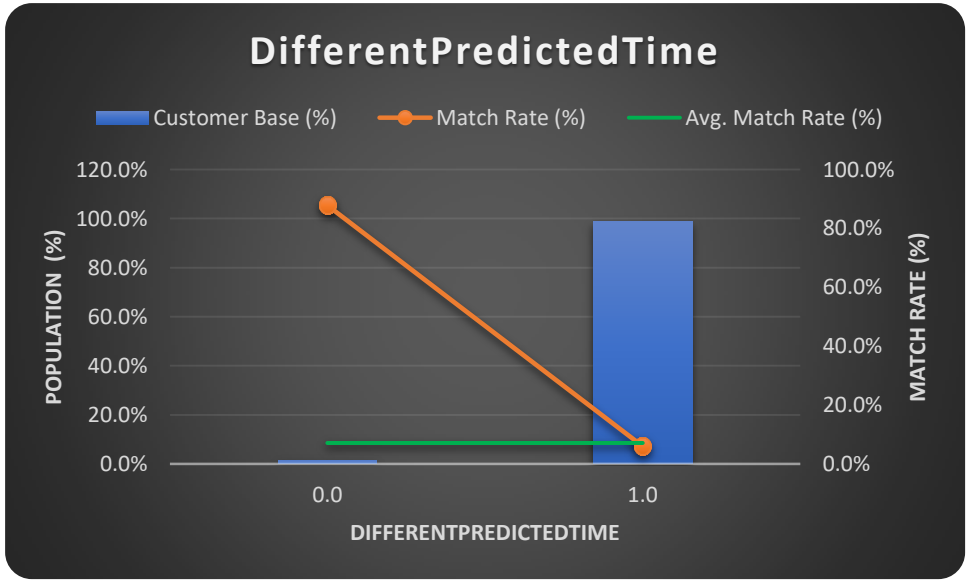
**Secondary Y-axis**: Response Rate in % of different segments of independent variable w.r.t Target variable.




~4X high Match rate in receipt-transaction pair where DateMappingMatch score is greater than 0.82.

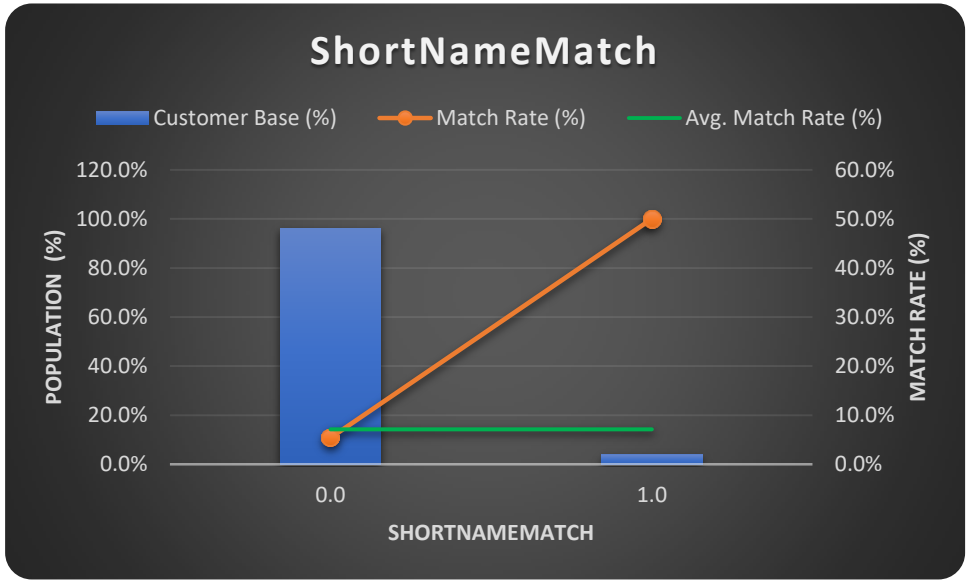
As we already know DifferentPredictedDate & DateMappingMatch have high inverse correlation, both the charts are indicating same pattern for match rate.



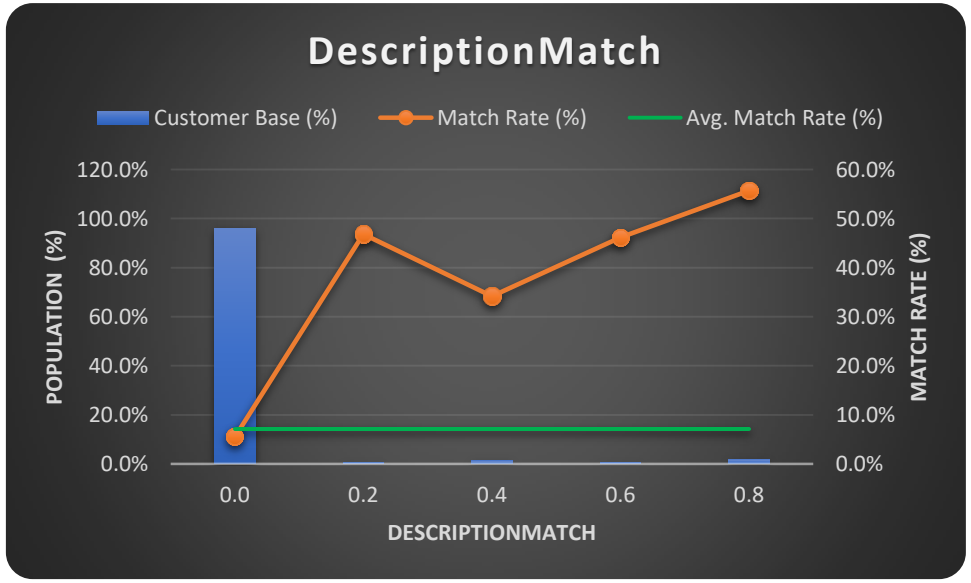




1.4% of receipt-transaction pair have TimeMappingMatch flag=1 and Match rate of this segment is very high ~80%.

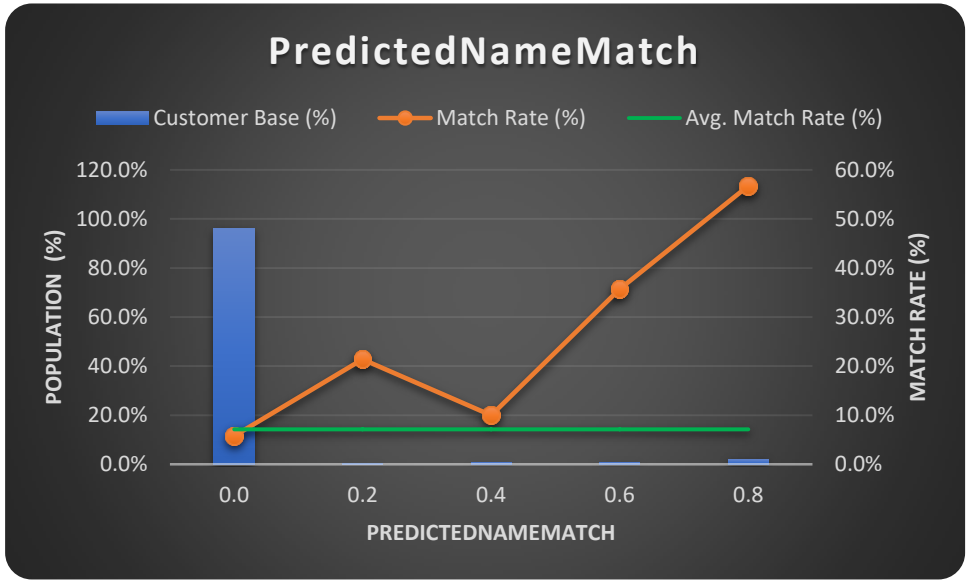
This indicates very high predictive power of this variable and as TimeMappingMatch is highly correlated with DifferentPredictedTime variable, it is also showing the same behavior.



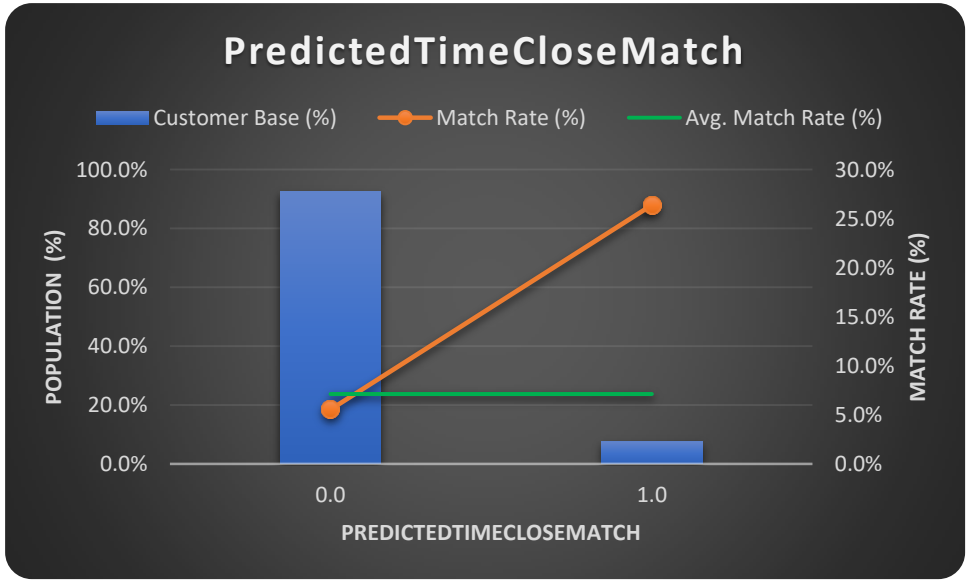

3.8 % of receipt-transaction pair have ShortNameMatch status as 1 and Match rate of this segment is high ~50%. This indicates high predictive power of this variable.




3.9 % of receipt-transaction pair have DescriptionMatch score >-0.2, Match rate is high and varies between 35% - 55%. This indicates high predictive power of this variable.




PredictedNameMatch is showing a linear behavior in match rate after score of 0.4 although base size is very small. Match rate is also high for PredictedNameMatch >0.4




PredictedTimeCloseMatch showing a decent lift in match rate ~3.7 X, where this flag is True.

# Class Imbalance

The challenge of working with imbalanced datasets is that most machine learning techniques will have poor performance on the minority class, although typically it is performance on the minority class that is most important.

In our case target variable has a distribution of  7.12 % for match cases and 92.88 % for not match cases.

Oversampling of the minority class is used by us to address class imbalance and our final training data has equal distribution of match and non-match cases.

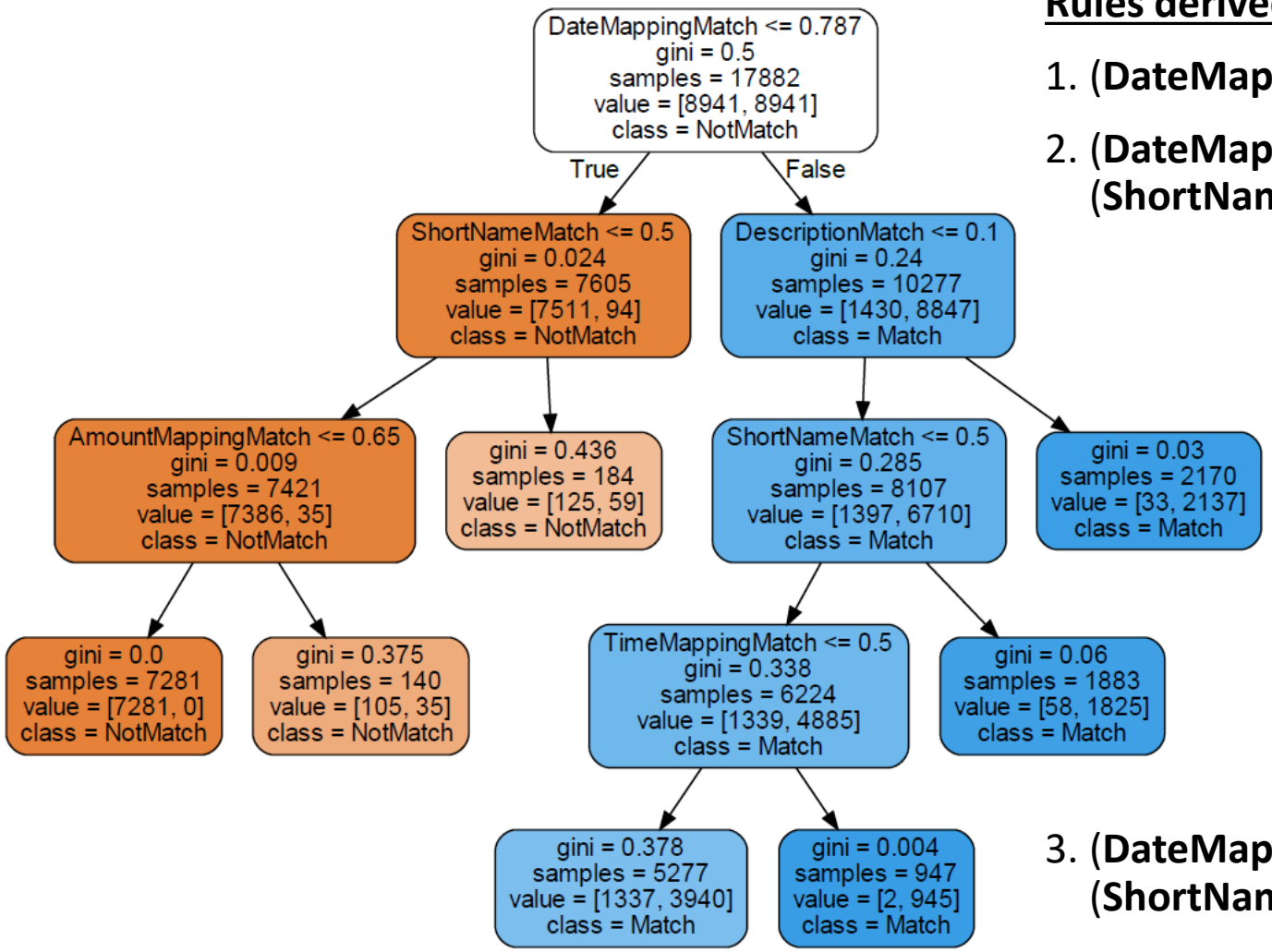
# Model Development

Below 2 techniques are used for model development.

**Decision Tree**

**Logistic Regression**

# Decision Tree




**Rules derived from Decision Tree:**

1. (**DateMappingMatch**>=0.8 ) **AND** (**DescriptionMatch**>0.1)
2. (**DateMappingMatch** >=0.8 ) **AND** (**DescriptionMatch**<=0.1) **AND** (**ShortNamematch**==1)
3. (**DateMappingMatch** >=0.8) **AND** (**DescriptionMatch** <= 0.1) **AND** (**ShortNamematch**==0) **AND** (**TimemappingMatch**==1)
4. (**DateMappingMatch** >=0.8) **AND** (**DescriptionMatch** <= 0.1) **AND** (**ShortNamematch**==0) **AND** (**TimemappingMatch**==0)

# Logistic Regression

Logistic Regression model summary **statsmodel** python library.

Logit Regression Results

| | | | |
|---|---|---|---|
| Dep. Variable: | target | No. Observations: | 9627 |
| Model: | Logit | Df Residuals: | 9620 |
| Method: | MLE | Df Model: | 6 |
| Date: | Wed, 02 Mar 2022 | Pseudo R-squ.: | 0.5692 |
| Time: | 20:48:14 | Log-Likelihood: | -1065.3 |
| converged: | True | LL-Null: | -2473.0 |
| Covariance Type: | nonrobust | LLR p-value: | 0.000 |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| const | -7.4170 | 0.316 | -23.467 | 0.000 | -8.037 | -6.798 |
| DateMappingMatch | 6.2652 | 0.339 | 18.505 | 0.000 | 5.602 | 6.929 |
| DescriptionMatch | 4.4843 | 0.345 | 12.983 | 0.000 | 3.807 | 5.161 |
| TimeMappingMatch | 3.7636 | 0.471 | 7.999 | 0.000 | 2.841 | 4.686 |
| ShortNameMatch | 1.9951 | 0.172 | 11.580 | 0.000 | 1.657 | 2.333 |
| PredictedNameMatch | 1.4951 | 0.273 | 5.477 | 0.000 | 0.960 | 2.030 |
| PredictedTimeCloseMatch | 0.5651 | 0.170 | 3.318 | 0.001 | 0.231 | 0.899 |

**From the model summary of logistic regression, we can see that below 6 variables are statistically significant in predicting transaction-receipt match in the below order of predicting power.**

1. **DateMappingMatch**
2. **DescriptionMatch**
3. **TimeMappingMatch**
4. **ShortNameMatch**
5. **PredictedNameMatch**
6. **PredictedTimeCloseMatch**

# Model Performance

Model performance of both Decision Tree & Logistic Regression for training and testing data is given below:

| Performance Measure | Decision Tree | | Logistic Regression | |
|---|---|---|---|---|
| | Train | Test | Train | Test |
| **AUC** | 0.959 | 0.953 | 0.962 | 0.963 |
| **True Positive Rate (Sensitivity)** | 0.987 | 0.977 | 0.988 | 0.988 |
| **False Positive Rate** | 0.160 | 0.163 | 0.163 | 0.167 |

- For both the models, testing data performance is inline with training data performance. Hence we can infer that both the **Models are not overfitting**.
- Performance of both the models are almost similar (Logistic Regression is slightly better)
- Decision Tree is easy to understand but Logistic Regression gives more granularity to final likelihood score. So for the given problem where multiple possible transaction-receipt matches has to be predicted, it is recommended to use Logistic regression Model.

# Recommendations to improve the outcome

- Possibility of improving the OCR output to extract data from receipt should be explored especially for **Description** and **ShortName** variables.

- Improving the logic to calculate transaction-receipt matching vector can also help to improve the matching output.