

# Campaign Response Model

To train and test the campaign response model by using last 2 years data and comparing 2 model methods ; Logistic Regression and XGBoost

## Data Preparation

- RFM model will be used to predict campaign response. Recency is calculated and create data set with RFM variables

```
campaign_date = dt.datetime(2015,3,17)
df_transactions['recent']= campaign_date - df_transactions['trans_date']
df_transactions['recent'].astype('timedelta64[D]')
df_transactions['recent']=df_transactions['recent'] / np.timedelta64(1, 'D')
df_transactions.head()
```

	customer_id	trans_date	tran_amount	recent
0	CS5295	2013-02-11	35	764.0
1	CS4768	2015-03-15	39	2.0
2	CS2122	2013-02-26	52	749.0
3	CS1217	2011-11-16	99	1217.0
4	CS1850	2013-11-20	78	482.0

```
df_transactions = df_transactions[df_transactions['trans_date'] >= dt.datetime(2013,3,17)]
df_rfm = df_transactions.groupby('customer_id').agg({'recent': lambda x:x.min(), # Recency
                                                    'customer_id': lambda x: len(x), # Frequency
                                                    'tran_amount': lambda x: x.sum()}) # Monetary Value

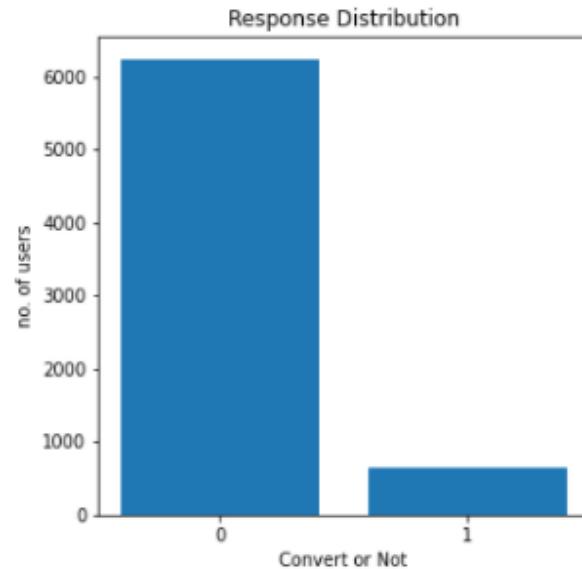
df_rfm.rename(columns={'recent': 'recency',
                      'customer_id': 'frequency',
                      'tran_amount': 'monetary_value'}, inplace=True)
```

```
df_rfm = df_rfm.reset_index()
df_rfm.head()
```

	customer_id	recency	frequency	monetary_value
0	CS1112	62.0	6	358
1	CS1113	36.0	11	775
2	CS1114	33.0	11	804
3	CS1115	12.0	11	831
4	CS1116	204.0	5	333

# Calculating response rate

- Found out that data is imbalanced

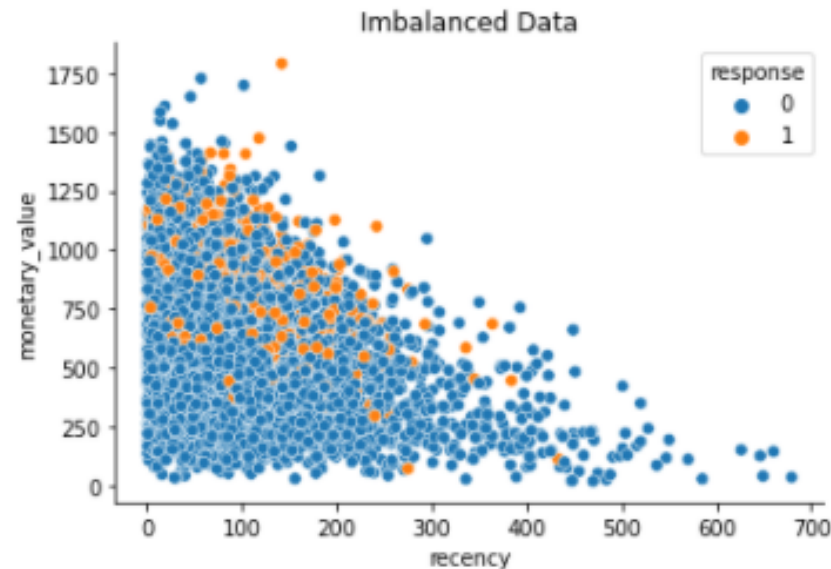


## Creating train and test dataset

- Splitting data frame into X and y, using scatterplot to see the spread of data by recency, monetary value, and response

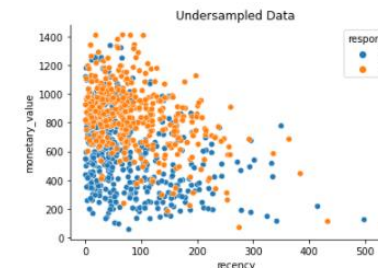
```
sns.scatterplot(data=df_modeling, x='recency', y='monetary_value', hue='response')  
sns.despine()  
plt.title("Imbalanced Data")
```

```
Text(0.5, 1.0, 'Imbalanced Data')
```



# Fixing imbalanced with Undersampling

- Using the fixed data to training 2 models methods : Logistic Regression and XGBoost.

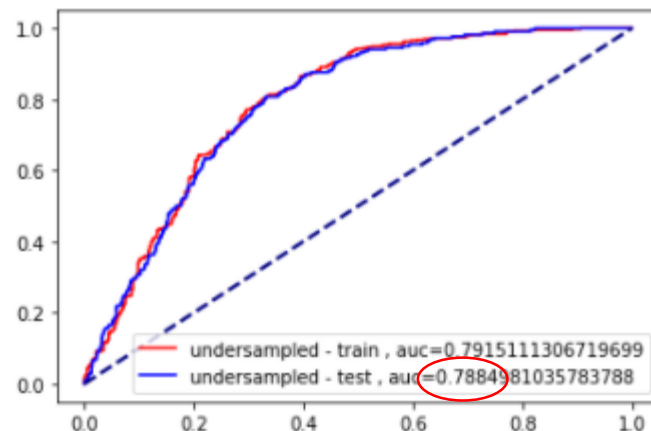


logistic regression model - undersampled  
training set

	precision	recall	f1-score	support
0	0.76	0.69	0.72	429
1	0.71	0.78	0.75	429
accuracy			0.73	858
macro avg	0.74	0.73	0.73	858
weighted avg	0.74	0.73	0.73	858

test set

	precision	recall	f1-score	support
0	0.96	0.68	0.80	1848
1	0.22	0.78	0.35	218
accuracy			0.69	2066
macro avg	0.59	0.73	0.57	2066
weighted avg	0.89	0.69	0.75	2066



Logistic Regression

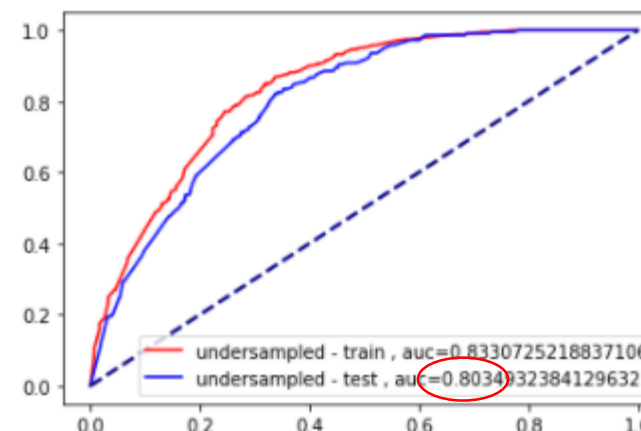
Stopping. Best iteration:  
[16] validation\_0-auc:0.803493

training set

	precision	recall	f1-score	support
0	0.82	0.68	0.74	429
1	0.73	0.85	0.78	429
accuracy			0.76	858
macro avg	0.77	0.76	0.76	858
weighted avg	0.77	0.76	0.76	858

test set

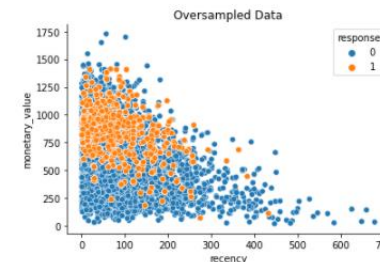
	precision	recall	f1-score	support
0	0.97	0.65	0.78	1848
1	0.22	0.83	0.35	218
accuracy			0.67	2066
macro avg	0.59	0.74	0.56	2066
weighted avg	0.89	0.67	0.73	2066



XGBoost

# Fixing imbalanced with Oversampling

- Using the fixed data to training 2 models methods : Logistic Regression and XGBoost.

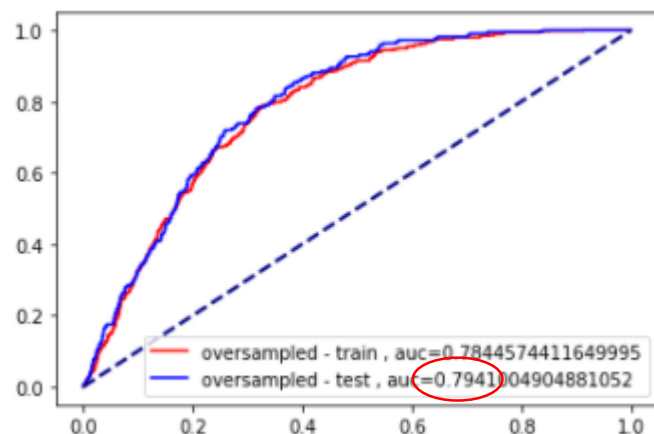


logistic regression model - oversampled  
training set

	precision	recall	f1-score	support
0	0.73	0.70	0.71	4389
1	0.71	0.74	0.72	4389
accuracy			0.72	8778
macro avg	0.72	0.72	0.72	8778
weighted avg	0.72	0.72	0.72	8778

test set

	precision	recall	f1-score	support
0	0.96	0.69	0.80	1848
1	0.23	0.77	0.35	218
accuracy			0.70	2066
macro avg	0.59	0.73	0.58	2066
weighted avg	0.88	0.70	0.76	2066



Logistic Regression

Stopping. Best iteration:

[3] validation\_0-auc:0.800103

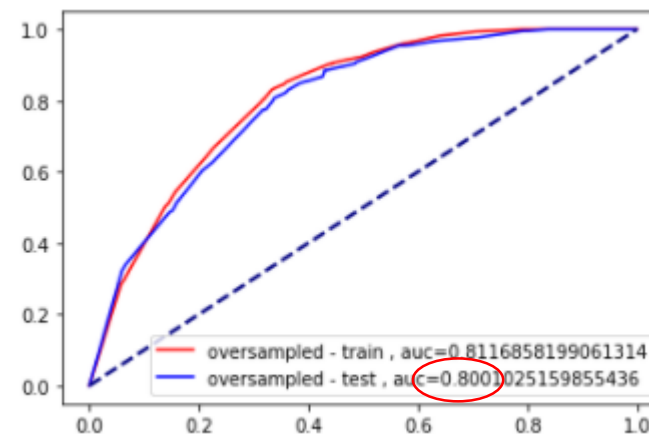
training set

	precision	recall	f1-score	support
0	0.80	0.66	0.72	4389
1	0.71	0.83	0.77	4389
accuracy			0.75	8778
macro avg	0.76	0.75	0.75	8778
weighted avg	0.76	0.75	0.75	8778

test set

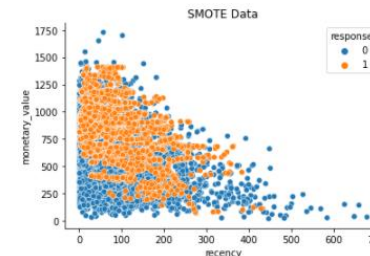
	precision	recall	f1-score	support
0	0.97	0.66	0.79	1848
1	0.22	0.81	0.35	218
accuracy			0.68	2066
macro avg	0.59	0.73	0.57	2066
weighted avg	0.89	0.68	0.74	2066

XGBoost



# Fixing imbalanced with SMOTE

- Using the fixed data to training 2 models methods : Logistic Regression and XGBoost.

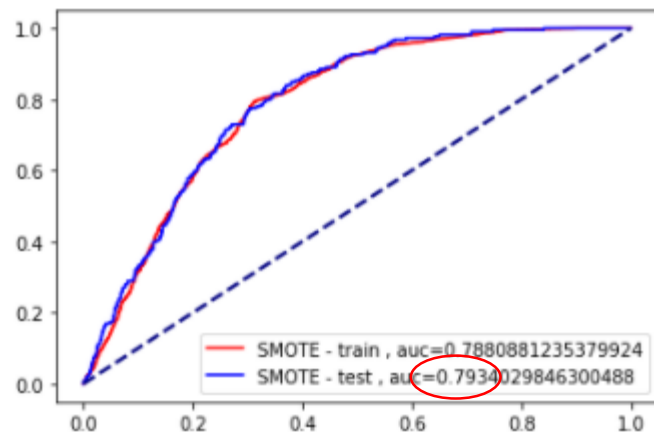


logistic regression model - SMOTE  
training set

	precision	recall	f1-score	support
0	0.75	0.70	0.72	4389
1	0.72	0.77	0.74	4389
accuracy			0.73	8778
macro avg	0.73	0.73	0.73	8778
weighted avg	0.73	0.73	0.73	8778

test set

	precision	recall	f1-score	support
0	0.96	0.70	0.81	1848
1	0.23	0.78	0.36	218
accuracy			0.70	2066
macro avg	0.60	0.74	0.58	2066
weighted avg	0.89	0.70	0.76	2066



Logistic Regression

Stopping. Best iteration:  
[28] validation\_0-auc:0.803673

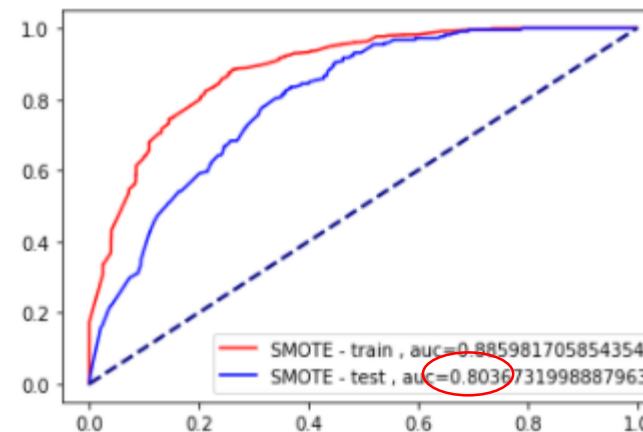
training set

	precision	recall	f1-score	support
0	0.86	0.74	0.80	4389
1	0.77	0.87	0.82	4389
accuracy			0.81	8778
macro avg	0.82	0.81	0.81	8778
weighted avg	0.82	0.81	0.81	8778

test set

	precision	recall	f1-score	support
0	0.95	0.74	0.83	1848
1	0.24	0.68	0.35	218
accuracy			0.73	2066
macro avg	0.59	0.71	0.59	2066
weighted avg	0.88	0.73	0.78	2066

XGBoost



# Conclusion

The highest accuracy test set and highest AUC are **XGBoost** model with **SMOTE** data

## Logistic Regression

Modeling from last 2 years data	Undersampling	Oversampling	SMOTE
Test Set Accuracy	0.69	0.70	0.70
Test Set AUC	0.788	0.794	0.793

## XGBoost

Modeling from last 2 years data	Undersampling	Oversampling	SMOTE
Test Set Accuracy	0.67	0.68	0.73
Test Set AUC	0.803	0.800	0.803