Importing libraries and datasets

In [5]:

```
import numpy as np
import pandas as pd
import datetime as dt

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler
from imblearn.over_sampling import SMOTE

from sklearn.linear_model import LogisticRegression
import xgboost as xgb

from sklearn.metrics import precision_score, recall_score, f1_score, auc, roc_auc_score, accuracy_scor
from xgboost import plot_importance
```

In [6]:

```
df_response = pd.read_csv('Retail_Data_Response.csv')
df_transactions = pd.read_csv('Retail_Data_Transactions.csv', parse_dates=['trans_date'])
```

In [7]:

```
df_response.head()
```

Out[7]:

	customer_id	response
0	CS1112	0
1	CS1113	0
2	CS1114	1
3	CS1115	1
4	CS1116	1

In [8]:

```
df_transactions.head()
```

Out[8]:

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

In [9]:

```
print(df_transactions['trans_date'].min())
print(df_transactions['trans_date'].max())
```

```
2011-05-16 00:00:00
2015-03-16 00:00:00
```

Data Preparation

In [10]:

```
## since the last date of the data is 16 March 2015, the campaign date is assumed to be 17 March 2015
## RFM model will be used to predict campaign response. Recency is calculated

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()
```

Out[10]:

	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

In [11]:

```
## create data set with RFM variables

df_rfm = df_transactions.groupby('customer_id').agg({'recent': lambda x:x.min(),                 # Rec
                                                   '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)
```

In [12]:

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

Out[12]:

	customer_id	recency	frequency	monetary_value
0	CS1112	62.0	15	1012
1	CS1113	36.0	20	1490
2	CS1114	33.0	19	1432
3	CS1115	12.0	22	1659
4	CS1116	204.0	13	857

In [13]:

```
## create data set with CLV variables

df_clv = df_transactions.groupby('customer_id').agg({'recent': lambda x:x.min(),                 # Rece
                                                   'customer_id': lambda x: len(x),              # Frequency
                                                   'tran_amount': lambda x: x.sum(),             # Monetary Value
                                                   'trans_date': lambda x: (x.max() - x.min()).days})       # AOU

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

```
df_clv['ticket_size'] = df_clv['monetary_value'] / df_clv['frequency']
```

In [14]:

```
df_clv = df_clv.reset_index()
df_clv.head()
```

Out[14]:

	customer_id	recency	frequency	monetary_value	AOU	ticket_size
0	CS1112	62.0	15	1012	1309	67.466667
1	CS1113	36.0	20	1490	1354	74.500000
2	CS1114	33.0	19	1432	1309	75.368421
3	CS1115	12.0	22	1659	1303	75.409091
4	CS1116	204.0	13	857	1155	65.923077

Calculating response rate

In [15]:

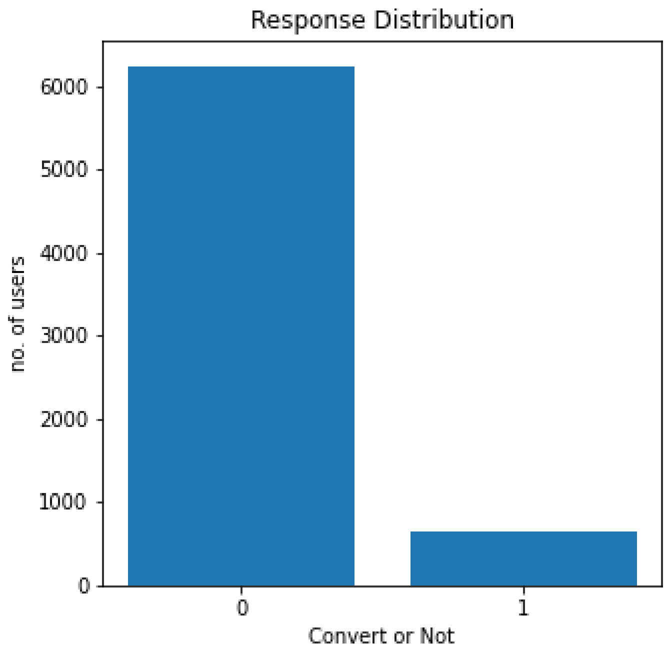
```
response_rate = df_response.groupby('response').agg({'customer_id': lambda x: len(x)}).reset_index()
response_rate.head()
```

Out[15]:

	response	customer_id
0	0	6237
1	1	647

In [16]:

```
plt.figure(figsize=(5,5))
x=range(2)
plt.bar(x,response_rate['customer_id'])
plt.xticks(response_rate.index)
plt.title('Response Distribution')
plt.xlabel('Convert or Not')
plt.ylabel('no. of users')
plt.show()

## data is imbalanced
```



In [17]:

```
## merging two data sets - RFM

df_modeling_rfm = pd.merge(df_response,df_rfm)
df_modeling_rfm.head()
```

Out[17]:

	customer_id	response	recency	frequency	monetary_value
0	CS1112	0	62.0	15	1012
1	CS1113	0	36.0	20	1490
2	CS1114	1	33.0	19	1432
3	CS1115	1	12.0	22	1659
4	CS1116	1	204.0	13	857

In [18]:

```
## merging two data sets - CLV

df_modeling_clv = pd.merge(df_response,df_clv)
df_modeling_clv.head()
```

Out[18]:

	customer_id	response	recency	frequency	monetary_value	AOU	ticket_size
0	CS1112	0	62.0	15	1012	1309	67.466667
1	CS1113	0	36.0	20	1490	1354	74.500000
2	CS1114	1	33.0	19	1432	1309	75.368421
3	CS1115	1	12.0	22	1659	1303	75.409091
4	CS1116	1	204.0	13	857	1155	65.923077

Creating train and test dataset

In [19]:

```
## spliting dataframe into X and y

X_rfm = df_modeling_rfm.drop(columns=['response','customer_id'])
```

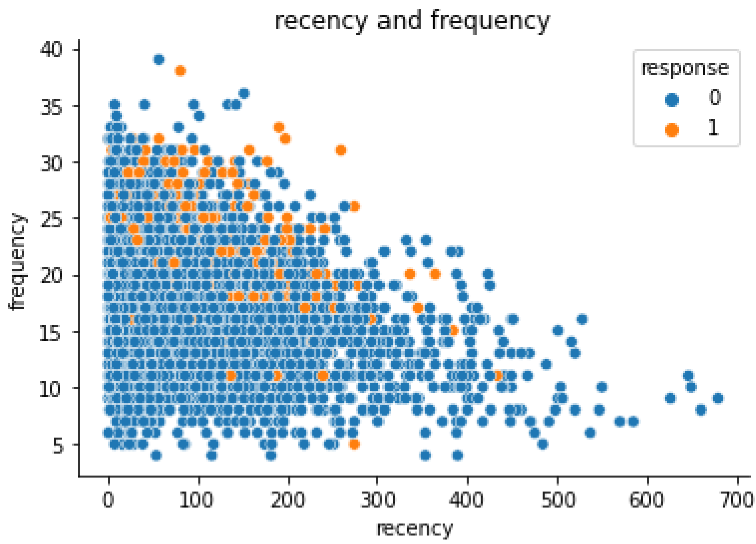
```
y_rfm = df_modeling_rfm['response']

X_clv = df_modeling_clv.drop(columns=['response','customer_id'])
y_clv = df_modeling_clv['response']
```

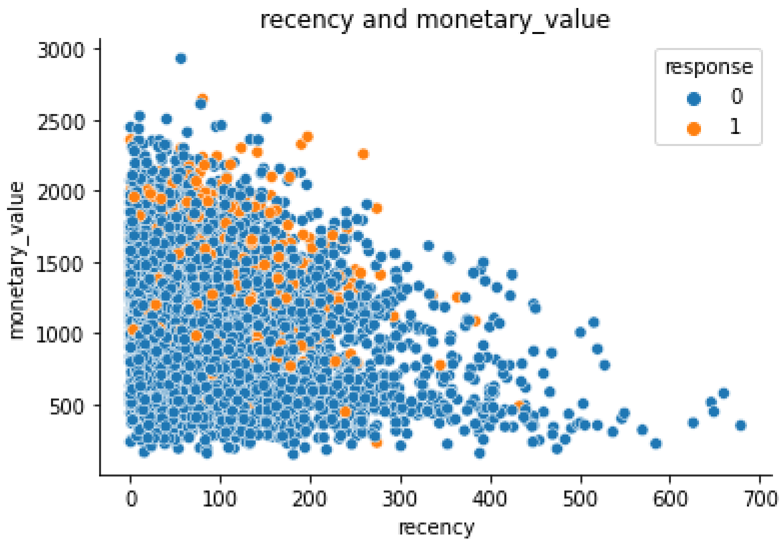
In [20]:

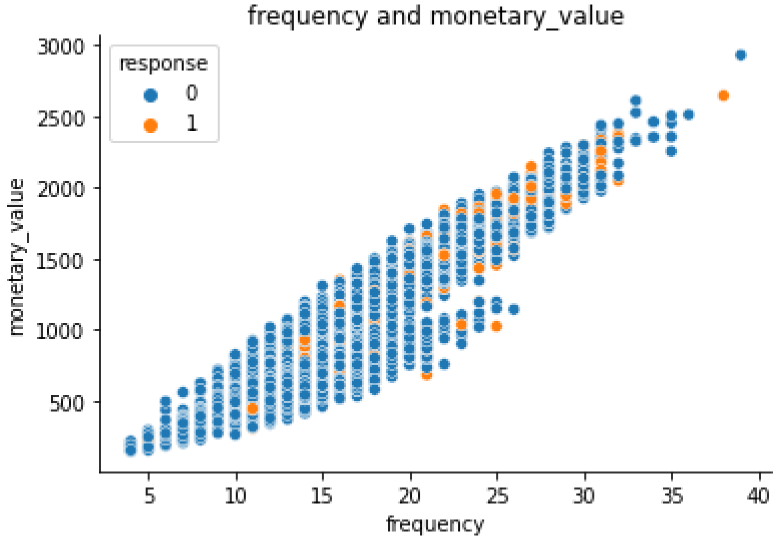
```
## creating train and test dataset

X_train_rfm, X_test_rfm, y_train_rfm, y_test_rfm = train_test_split(X_rfm, y_rfm, test_size=0.3, randon
X_train_clv, X_test_clv, y_train_clv, y_test_clv = train_test_split(X_clv, y_clv, test_size=0.3, random_sta
```

In [21]:

```
for i, col_i in enumerate(df_modeling_rfm[['recency', 'frequency', 'monetary_value']].columns):
  for j, col_j in enumerate(df_modeling_rfm[['recency', 'frequency', 'monetary_value']].columns):
    if i < j :
      plt.title(col_i + ' and ' + col_j)
      sns.scatterplot(data=df_modeling_rfm, x=col_i, y=col_j, hue='response')
      sns.despine()
      plt.show()
```

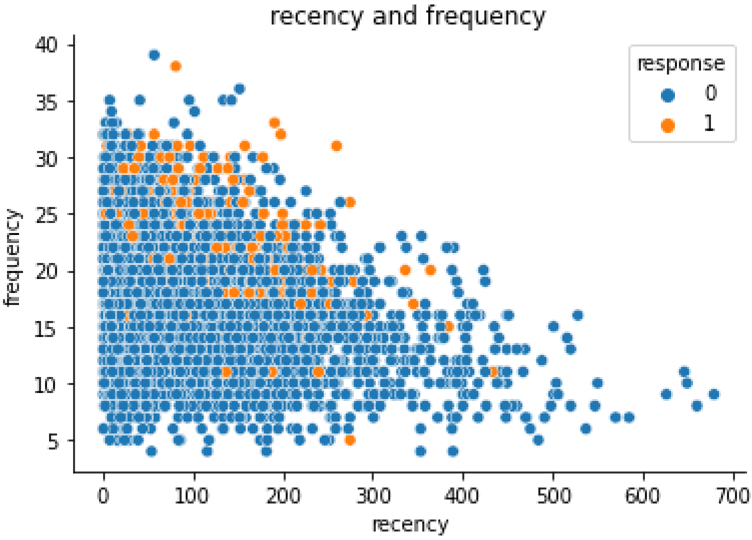


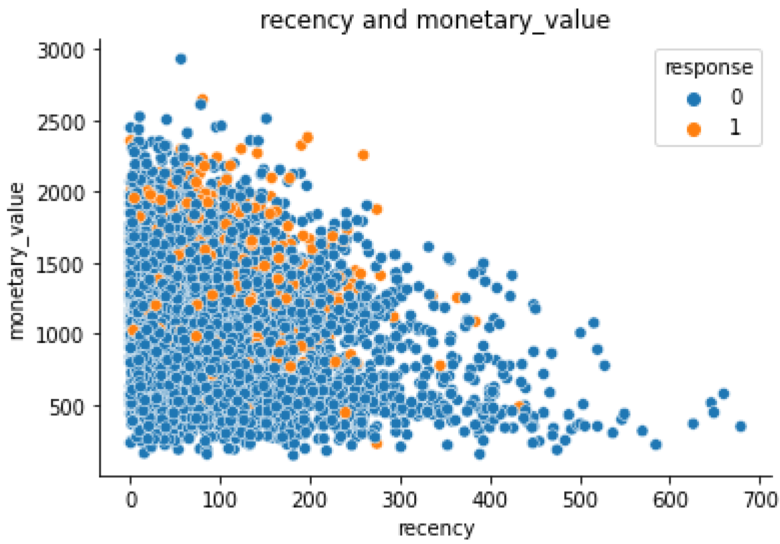


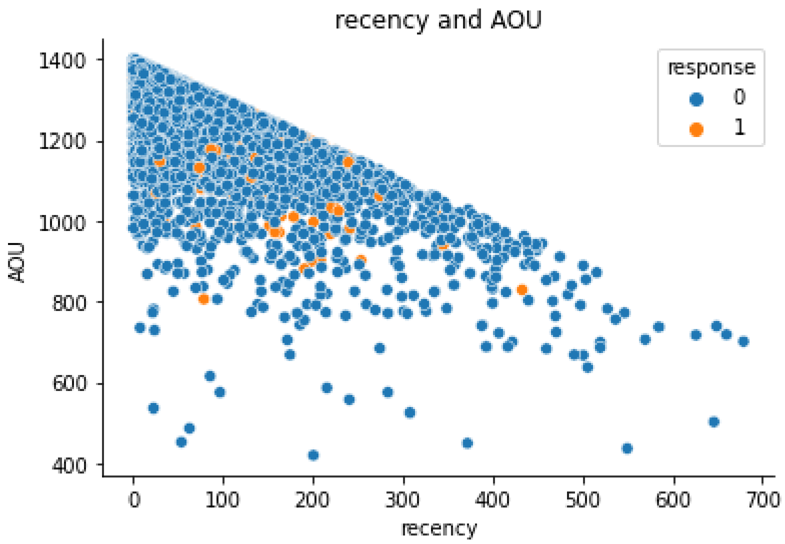


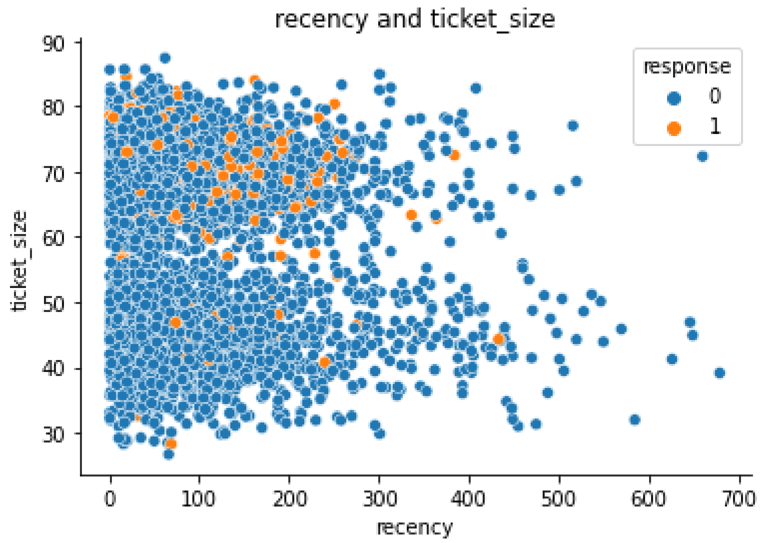
In [22]:

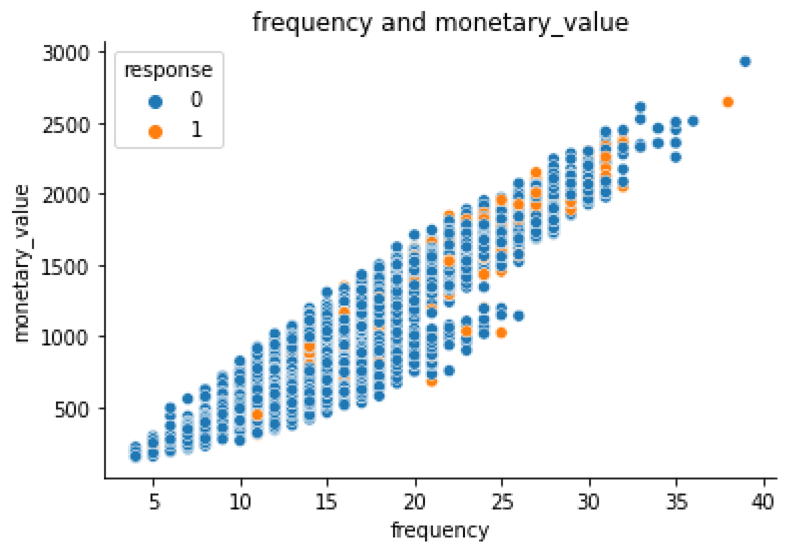
```
for i, col_i in enumerate(df_modeling_clv[['recency', 'frequency', 'monetary_value', 'AOU', 'ticket_size']].
  for j, col_j in enumerate(df_modeling_clv[['recency', 'frequency', 'monetary_value', 'AOU', 'ticket_size']]
    if i < j :
      plt.title(col_i + ' and ' + col_j)
      sns.scatterplot(data=df_modeling_clv, x=col_i, y=col_j, hue='response')
      sns.despine()
      plt.show()
```

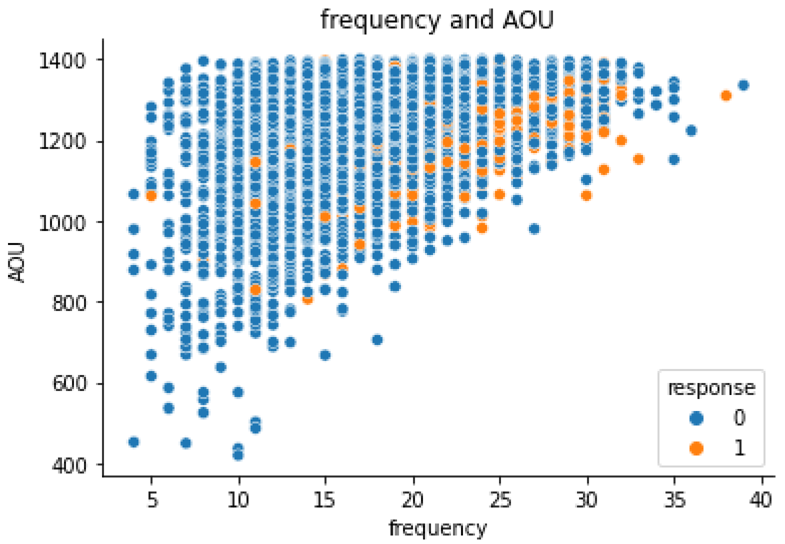


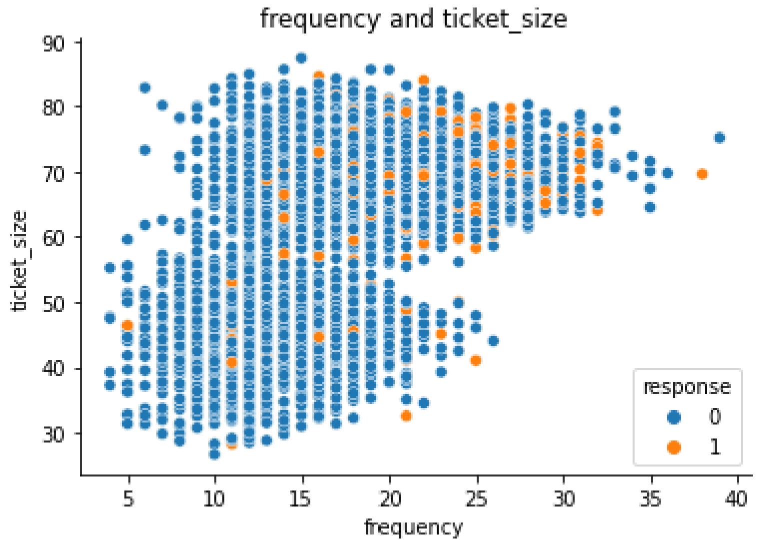


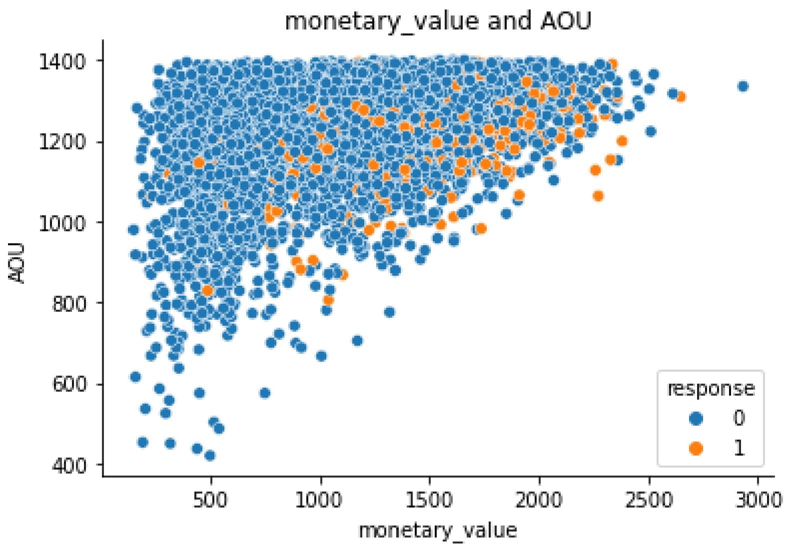

recency and AOU
response
0
1
AOU
1400
1200
1000
800
600
400
0
100
200
300
400
500
600
700
recency

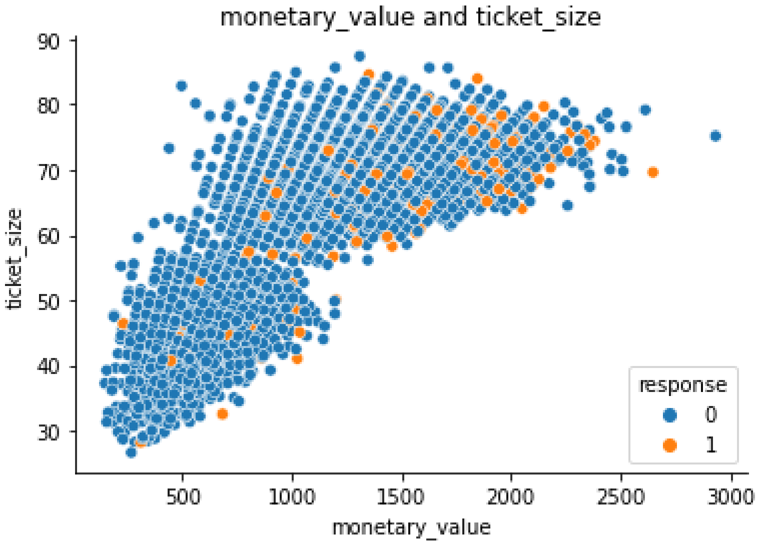

recency and ticket_size
response
0
1
ticket_size
90
80
70
60
50
40
30
0
100
200
300
400
500
600
700
recency

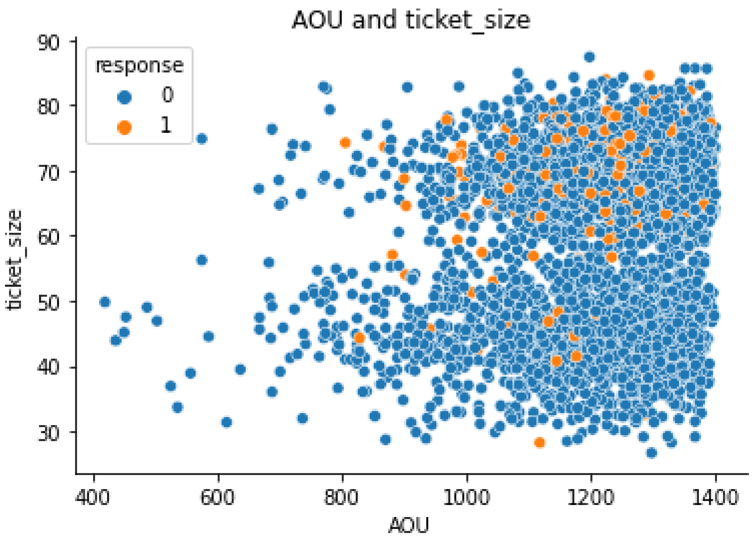

frequency and monetary_value
response
0
1
monetary_value
3000
2500
2000
1500
1000
500
5
10
15
20
25
30
35
40
frequency


frequency and AOU
AOU
frequency
response
0
1
400
600
800
1000
1200
1400
5
10
15
20
25
30
35
40


frequency and ticket_size
ticket_size
frequency
response
0
1
30
40
50
60
70
80
90
5
10
15
20
25
30
35
40


monetary_value and AOU
AOU
monetary_value
response
0
1
400
600
800
1000
1200
1400
500
1000
1500
2000
2500
3000





Fixing imbalanced with SMOTE

In [23]:

```
sm = SMOTE(random_state=0)

sm.fit(X_train_rfm, y_train_rfm)
X_SMOTE_rfm, y_SMOTE_rfm = sm.fit_sample(X_train_rfm, y_train_rfm)

sm.fit(X_train_clv, y_train_clv)
X_SMOTE_clv, y_SMOTE_clv = sm.fit_sample(X_train_clv, y_train_clv)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function safe_ind
exing is deprecated; safe_indexing is deprecated in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function safe_ind
exing is deprecated; safe_indexing is deprecated in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

Logistic Regression

In [24]:

```
print('logistic regression model - SMOTE RFM')
logreg = LogisticRegression(solver='liblinear', class_weight='balanced')
predicted_y = []
expected_y = []

logreg_model_SMOTE_rfm = logreg.fit(X_SMOTE_rfm, y_SMOTE_rfm)
```

```
predictions = logreg_model_SMOTE_rfm.predict(X_SMOTE_rfm)
predicted_y.extend(predictions)
expected_y.extend(y_SMOTE_rfm)
report_train = classification_report(expected_y, predicted_y)
print('training set')
print(report_train)

predicted_y = []
expected_y = []
predictions = logreg_model_SMOTE_rfm.predict(X_test_rfm)
predicted_y.extend(predictions)
expected_y.extend(y_test_clv)
report_test = classification_report(expected_y, predicted_y)
print('test set')
print(report_test)
```

```
logistic regression model - SMOTE RFM
training set
              precision    recall  f1-score   support

           0       0.68      0.62      0.65      4389
           1       0.65      0.71      0.68      4389

    accuracy                           0.67      8778
   macro avg       0.67      0.67      0.67      8778
weighted avg       0.67      0.67      0.67      8778

test set
              precision    recall  f1-score   support

           0       0.95      0.63      0.75      1848
           1       0.18      0.71      0.29       218

    accuracy                           0.64      2066
   macro avg       0.57      0.67      0.52      2066
weighted avg       0.87      0.64      0.71      2066
```

In [25]:

```
print('logistic regression model - SMOTE CLV')
logreg = LogisticRegression(solver='liblinear', class_weight='balanced')
predicted_y = []
expected_y = []

logreg_model_SMOTE_clv = logreg.fit(X_SMOTE_clv, y_SMOTE_clv)
predictions = logreg_model_SMOTE_clv.predict(X_SMOTE_clv)
predicted_y.extend(predictions)
expected_y.extend(y_SMOTE_clv)
report_train = classification_report(expected_y, predicted_y)
print('training set')
print(report_train)

predicted_y = []
expected_y = []
predictions = logreg_model_SMOTE_clv.predict(X_test_clv)
predicted_y.extend(predictions)
expected_y.extend(y_test_clv)
report_test = classification_report(expected_y, predicted_y)
print('test set')
print(report_test)
```

```
logistic regression model - SMOTE CLV
training set
              precision    recall  f1-score   support
```

```
           0       0.68      0.62      0.65      4389
           1       0.65      0.71      0.68      4389

    accuracy                           0.67      8778
   macro avg       0.67      0.67      0.67      8778
weighted avg       0.67      0.67      0.67      8778

test set
              precision    recall  f1-score   support

           0       0.95      0.62      0.75      1848
           1       0.18      0.72      0.29       218

    accuracy                           0.63      2066
   macro avg       0.57      0.67      0.52      2066
weighted avg       0.87      0.63      0.70      2066
```

XGBoost

In [26]:

```
print('XGBoost model - SMOTE RFM')

xgb_model = xgb.XGBClassifier(objective='binary:logistic', eval_metric='auc',
 learning_rate =0.01,
 n_estimators=100,
 max_depth=2,
 gamma=0.0,
 colsample_bytree=0.6)

predicted_y = []
expected_y = []

xgb_model_SMOTE_rfm = xgb_model.fit(X_SMOTE_rfm, y_SMOTE_rfm, early_stopping_rounds=5, eval
predictions =  xgb_model_SMOTE_rfm.predict(X_SMOTE_rfm)
predicted_y.extend(predictions)
expected_y.extend(y_SMOTE_rfm)
report_train = classification_report(expected_y, predicted_y)
print('training set')
print(report_train)

predicted_y = []
expected_y = []
predictions = xgb_model_SMOTE_rfm.predict(X_test_rfm.to_numpy())
predicted_y.extend(predictions)
expected_y.extend(y_test_rfm)
report_test = classification_report(expected_y, predicted_y)
print('test set')
print(report_test)
```

```
XGBoost model - SMOTE RFM
[0]	validation_0-auc:0.567615
Will train until validation_0-auc hasn't improved in 5 rounds.
[1]	validation_0-auc:0.713189
[2]	validation_0-auc:0.709773
[3]	validation_0-auc:0.69828
[4]	validation_0-auc:0.711449
[5]	validation_0-auc:0.713189
[6]	validation_0-auc:0.708296
Stopping. Best iteration:
[1]	validation_0-auc:0.713189

training set
```

```
              precision    recall  f1-score   support

           0       0.75      0.57      0.65      4389
           1       0.65      0.81      0.72      4389

    accuracy                           0.69      8778
   macro avg       0.70      0.69      0.69      8778
weighted avg       0.70      0.69      0.69      8778

test set
              precision    recall  f1-score   support

           0       0.96      0.57      0.71      1848
           1       0.18      0.79      0.29       218

    accuracy                           0.59      2066
   macro avg       0.57      0.68      0.50      2066
weighted avg       0.88      0.59      0.67      2066
```

In [27]:

```
print('XGBoost model - SMOTE CLV')

xgb_model = xgb.XGBClassifier(objective='binary:logistic', eval_metric='auc',
 learning_rate =0.01,
 n_estimators=100,
 max_depth=2,
 gamma=0.0,
 colsample_bytree=0.6)

predicted_y = []
expected_y = []

xgb_model_SMOTE_clv = xgb_model.fit(X_SMOTE_clv, y_SMOTE_clv, early_stopping_rounds=5, eval_s
predictions =  xgb_model_SMOTE_clv.predict(X_SMOTE_clv)
predicted_y.extend(predictions)
expected_y.extend(y_SMOTE_clv)
report_train = classification_report(expected_y, predicted_y)
print('training set')
print(report_train)

predicted_y = []
expected_y = []
predictions = xgb_model_SMOTE_clv.predict(X_test_clv.to_numpy())
predicted_y.extend(predictions)
expected_y.extend(y_test_clv)
report_test = classification_report(expected_y, predicted_y)
print('test set')
print(report_test)
```

```
XGBoost model - SMOTE CLV
[0]	validation_0-auc:0.68482
Will train until validation_0-auc hasn't improved in 5 rounds.
[1]	validation_0-auc:0.717808
[2]	validation_0-auc:0.724408
[3]	validation_0-auc:0.725875
[4]	validation_0-auc:0.723803
[5]	validation_0-auc:0.726727
[6]	validation_0-auc:0.72539
[7]	validation_0-auc:0.724427
[8]	validation_0-auc:0.723888
[9]	validation_0-auc:0.724839
[10]	validation_0-auc:0.724921
Stopping. Best iteration:
[5]	validation_0-auc:0.726727
```

```
training set
              precision    recall  f1-score   support

           0       0.77      0.55      0.64      4389
           1       0.65      0.84      0.73      4389

    accuracy                           0.70      8778
   macro avg       0.71      0.70      0.69      8778
weighted avg       0.71      0.70      0.69      8778

test set
              precision    recall  f1-score   support

           0       0.96      0.55      0.70      1848
           1       0.17      0.80      0.28       218

    accuracy                           0.58      2066
   macro avg       0.57      0.67      0.49      2066
weighted avg       0.88      0.58      0.66      2066
```

In [28]:

```python
## building pipeline for hyperparameter tuning

from sklearn.pipeline import Pipeline
from sklearn.feature_selection import SelectKBest, chi2

# Create a pipeline
pipe = Pipeline([
  ('fs', SelectKBest()),
  ('clf', xgb.XGBClassifier(objective='binary:logistic', scale_pos_weight=9))
])
```

In [43]:

```python
## hyper parameter tuning - grid search

from sklearn.model_selection import KFold, GridSearchCV
from sklearn.metrics import accuracy_score, make_scorer
# Define our search space for grid search
search_space = [
  {
    'clf__n_estimators': [100,500,5],
    'clf__learning_rate': [0.01,1.0,0.01],
    'clf__max_depth': range(2, 8),
    'clf__colsample_bytree': [i/10.0 for i in range(4, 7)],
    'clf__gamma': [i/10.0 for i in range(3)],
    'fs__score_func': [chi2],
    'fs__k': [2],
  }
]
# Define cross validation
kfold = KFold(n_splits=10, random_state=None)
# AUC and F1 as score
scoring = {'AUC':'roc_auc','F1 score': 'f1_micro'}
# Define grid search
grid = GridSearchCV(
  pipe,
  param_grid=search_space,
  cv=kfold,
  scoring=scoring,
  refit='AUC',
  verbose=1,
  n_jobs=-1
```

```
)

# Fit grid search
xgb_model_clv_GS = grid.fit(X_train_clv, y_train_clv)
```

```
Fitting 10 folds for each of 486 candidates, totalling 4860 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  85 tasks      | elapsed:   14.0s
[Parallel(n_jobs=-1)]: Done 258 tasks      | elapsed:   49.0s
[Parallel(n_jobs=-1)]: Done 508 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 858 tasks      | elapsed:  2.8min
[Parallel(n_jobs=-1)]: Done 1308 tasks      | elapsed:  4.2min
[Parallel(n_jobs=-1)]: Done 1858 tasks      | elapsed:  6.0min
[Parallel(n_jobs=-1)]: Done 2508 tasks      | elapsed:  8.1min
[Parallel(n_jobs=-1)]: Done 3258 tasks      | elapsed: 10.5min
[Parallel(n_jobs=-1)]: Done 4108 tasks      | elapsed: 13.2min
[Parallel(n_jobs=-1)]: Done 4860 out of 4860 | elapsed: 15.6min finished
```

In [44]:

```
predicted_y = []
expected_y = []
predictions = xgb_model_clv_GS.predict(X_test_clv)
print('Best AUC Score: {}'.format(xgb_model_clv_GS.best_score_))
print(confusion_matrix(y_test_clv,predictions))


predicted_y.extend(predictions)
expected_y.extend(y_test_clv)
report_test = classification_report(expected_y, predicted_y)
print('test set')
print(report_test)
```

```
Best AUC Score: 0.7097654735186156
[[1089  759]
 [  51  167]]
test set
              precision    recall  f1-score   support

           0       0.96      0.59      0.73      1848
           1       0.18      0.77      0.29       218

    accuracy                           0.61      2066
   macro avg       0.57      0.68      0.51      2066
weighted avg       0.87      0.61      0.68      2066
```

In [31]:

```
print(xgb_model_clv_GS.best_params_)
```

```
{'clf__colsample_bytree': 0.4, 'clf__gamma': 0.0, 'clf__learning_rate': 0.01, 'clf__max_depth': 2, 'clf__n_estimators': 100, 'fs__k': 2, 'fs__score_func': <function chi2 at 0x7f140be053b0>}
```