Determine customer purchasing on demographic features through Bagging and Random Forest

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0.1 Data

The dataset came from the edX course-Microsoft: DAT275x Principles of Machine Learning. In 1998, the Adventure Works Cycles company collected a large volume of data about their existing customers, including demographic features and information about purchases they have made. We are particularly interested in analyzing customer data to determine any apparent relationships between demographic features known about the customers and the likelihood of a customer purchasing a bike.

0.2 Algorithm

I will perform a widely used ensemble method known as **bootstrap aggregating** or simply **bagging**. Bagging follows a simple procedure: 1. N learners (machine learning models) are defined. 2. N subsamples of the training data are created by **Bernoulli sampling with replacement**. 3. The N learners are trained on the subsamples of the training data. 4. The ensemble is scored by averaging, or taking a majority vote, of the predictions from the N learners.

Classification models are most typically used with bagging methods. The most common such algorithm is know as the **random forest**. The random forest method is highly scalable and generally produces good results, even for complex problems. By using random forest method, we are able to predict whether a customer will purchase the bike based on demographic features.

0.3 Application

STEP 1 Import packages and datasets

```
In [158]: from sklearn.ensemble import RandomForestClassifier
          from sklearn import preprocessing
          #from statsmodels.api import datasets
          from sklearn import datasets ## Get dataset from sklearn
          import sklearn.model_selection as ms
          import sklearn.metrics as sklm
          import matplotlib.pyplot as plt
          import seaborn as sns
          import pandas as pd
```

```
import numpy as np
import numpy.random as nr

%matplotlib inline

spenddata = pd.read_csv('/Users/lesliesmac/Desktop/AW_AveMonthSpend.csv')
demodata = pd.read_csv('/Users/lesliesmac/Desktop/AdvWorksCusts.csv')
bikedata = pd.read_csv('/Users/lesliesmac/Desktop/AW_BikeBuyer.csv')
```

```
In [45]: merge1 = pd.merge(spenddata, demodata, on='CustomerID')
         now = pd.Timestamp(pd.datetime.now())
         #create age variable from DOB as 'new_age'
         merge1['BirthDate'] = pd.to_datetime(merge1['BirthDate'])
         now = pd.datetime.now()
         merge1['age'] = (now - merge1['BirthDate'])/365
         merge1['age'].head()
         merge1['new_age']=merge1['age'].dt.days
```

STEP 2 Create master dataset - merge2

```
In [162]: merge2 = pd.merge(bikedata, merge1, on='CustomerID')
          print(merge2.dtypes)
          print('Shape of data:' +str(merge2.shape))
```

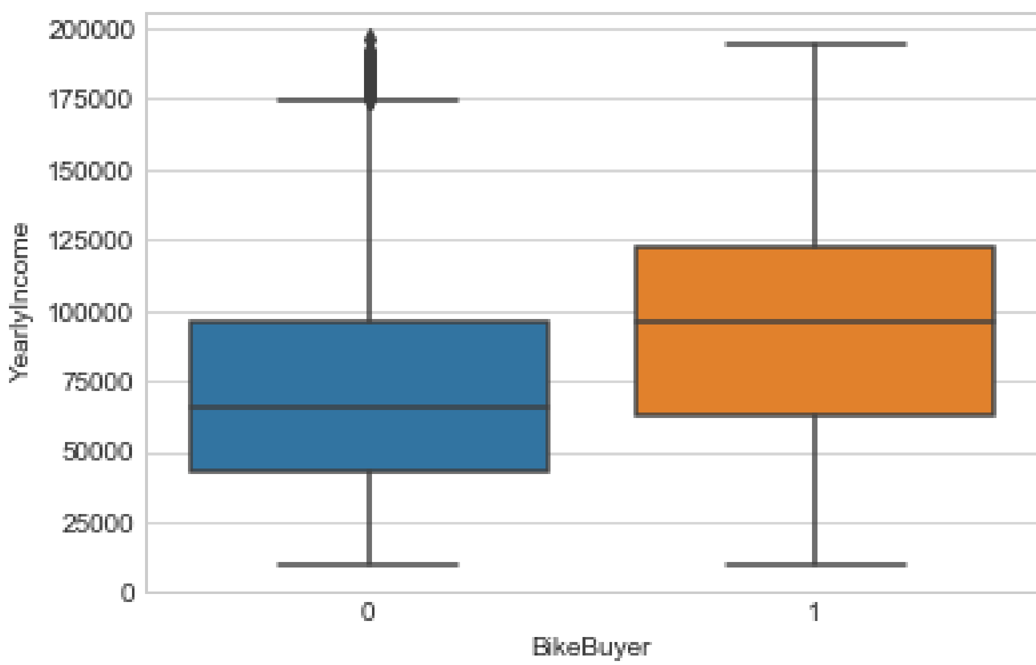
```
CustomerID                       int64
BikeBuyer                        int64
AveMonthSpend                    int64
Title                           object
FirstName                       object
MiddleName                      object
LastName                        object
Suffix                          object
AddressLine1                    object
AddressLine2                    object
City                            object
StateProvinceName               object
CountryRegionName               object
PostalCode                      object
PhoneNumber                     object
BirthDate               datetime64[ns]
Education                       object
Occupation                      object
Gender                          object
MaritalStatus                   object
HomeOwnerFlag                    int64
NumberCarsOwned                  int64
NumberChildrenAtHome             int64
TotalChildren                    int64
YearlyIncome                     int64
```

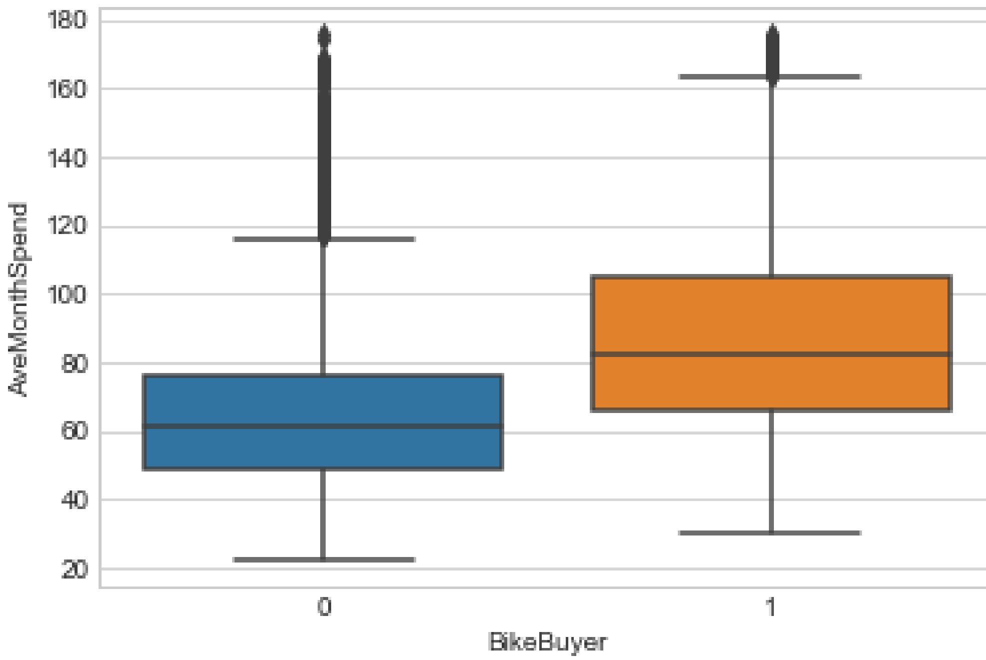
```
age                        timedelta64[ns]
new_age                              int64
agecate                             object
dtype: object
Shape of data:(17209, 28)
```

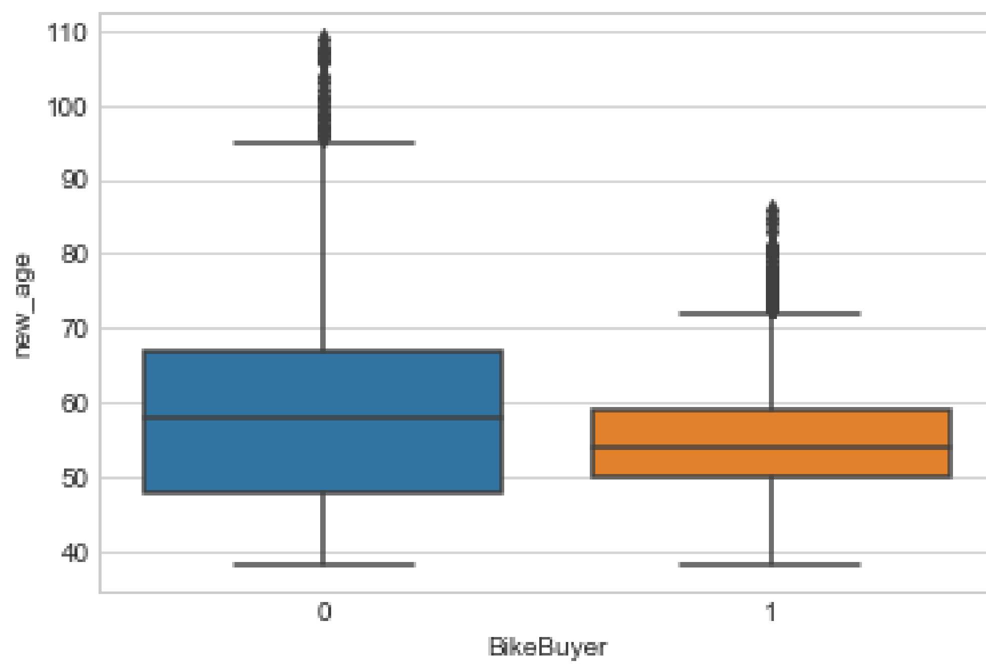
STEP 3 Plot numerical features.

```
In [167]: def plot_box(merge2, cols, col_x = 'BikeBuyer'):
              for col in cols:
                  sns.set_style("whitegrid")
                  sns.boxplot(x=col_x, y=col, data=merge2)
                  plt.xlabel(col_x) # Set text for the x axis
                  plt.ylabel(col)# Set text for y axis
                  plt.show()

          num_cols = ['YearlyIncome','AveMonthSpend','new_age']
          plot_box(merge2, num_cols, col_x = 'BikeBuyer')
```







Transfer categorical variables into dummy variables.

```
In [220]: df_2 = pd.get_dummies(merge2,drop_first=True)
```

```
Features = np.array(df_2[['YearlyIncome','Gender_M','MaritalStatus_S','new_age','AveM
Labels = np.array(df_2[['BikeBuyer']])
```

STEP 4 Bagging

```
In [221]: ## Randomly sample cases to create independent training and test data
          nr.seed(190)
          indx = range(Features.shape[0])
          indx = ms.train_test_split(indx, test_size = 10000)
          X_train = Features[indx[0],:]
          y_train = np.ravel(Labels[indx[0]])#return 1D array
          X_test = Features[indx[1],:]
          y_test = np.ravel(Labels[indx[1]])
```

STEP 5 Transform features into a Z-score scale

```
In [222]: scale = preprocessing.StandardScaler()
          scale.fit(X_train)
          X_train = scale.transform(X_train)

/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:475: DataConversionWarning:
  warnings.warn(msg, DataConversionWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:475: DataConversionWarning:
  warnings.warn(msg, DataConversionWarning)
```

STEP 6 Define and fit a random forest model. The code in the cell below defines random forest model with 5 trees using the `RandomForestClassifer` function from the Scikit Learn ensemble package, and then fits the model.

```
In [223]: nr.seed(444)
          rf_clf = RandomForestClassifier(n_estimators=5)
          rf_clf.fit(X_train, y_train)

Out[223]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=5, n_jobs=1,
                      oob_score=False, random_state=None, verbose=0,
                      warm_start=False)
```

STEP 7 Next, the code in the cell below performs the following processing to score the test data subset: 1. The test features are scaled using the scaler computed for the training features. 2. The `predict` method is used to compute the scores from the scaled features.

```
In [224]: X_test = scale.transform(X_test)
          scores = rf_clf.predict(X_test)
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:475: DataConversionWarning:
  warnings.warn(msg, DataConversionWarning)
```

STEP 8 Evaluate the model results.

Two label categories: Bike Buyer and NotBuy. Find the Accuracy, Precision and Recall for the model.

```
In [225]: def print_metrics_3(labels, scores):

              conf = sklm.confusion_matrix(labels, scores)
              print('                     Confusion matrix')
              print('                  Score Buy    Score NotBuy')
              print('Actual Buy      %6d' % conf[0,0] + '            %5d' % conf[0,1] )
              print('Actual NotBuy   %6d' % conf[1,0] + '            %5d' % conf[1,1] )
              ## Now compute and display the accuracy and metrics
              print('')
              print('Accuracy        %0.2f' % sklm.accuracy_score(labels, scores))
              metrics = sklm.precision_recall_fscore_support(labels, scores)

              print(' ')
              print('                  Buy          NotBuy  ')
              print('Num case      %0.2f' % metrics[3][0] + '         %0.2f' % metrics[3][1]  )
              print('Precision       %0.2f' % metrics[0][0] + '          %0.2f' % metrics[0][1
              print('Recall          %0.2f' % metrics[1][0] + '          %0.2f' % metrics[1][1
              print('F1              %0.2f' % metrics[2][0] + '          %0.2f' % metrics[2][1

          print_metrics_3(y_test, scores)
```

```
                     Confusion matrix
                 Score Buy    Score NotBuy
Actual Buy       5623          1115
Actual NotBuy    1282          1980

Accuracy        0.76

                 Buy           NotBuy
Num case      6738.00        3262.00
Precision       0.81           0.64
Recall          0.83           0.61
F1              0.82           0.62
```

0.4 Summary

The Machine learning model achieved 76% of accuracy in predicting customer purchasing. By looking at the Buyer cases vs NotBuy cases, we find a much higher accuracy in Buyer cases - since we are using more Buyer cases in training, the model assigned more weight in predicting Buyer cases. To adjust this, we need to include weight so that we can underweight the Buyer cases and overweight the NotBuy case to achieve better performance.