sy3420_HW3

November 9, 2022

Homework 3: How much should you pay for this fraud-detection model?

Copyright (c) 2022 RM Stein

This version: 9-30-2022

[233]:
```
from datetime import datetime, date
import copy as cp
import pandas as pd
import numpy  as np
import matplotlib.pyplot as plt
import scipy.stats as stats

from IPython.core.magic import register_cell_magic
from IPython.display import HTML, display

import statsmodels.formula.api as sm


from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn import tree
from sklearn.metrics import roc_curve, auc, roc_auc_score, RocCurveDisplay,␣
↪confusion_matrix



# DATA_PATH = "./data/"
DATA_FN    = "cc_transactions.csv"
TODAY = date.today()
```

In this home work, you will get some experience working assessing the financial value of models that you build.

1 Business context

We have been asked by the CSO (Chief Security Officer), Xufeng, at MasterVista, a credit card company, to develop a fraud detection model to spot credit card transactions that may be suspicious. MasterVista is concerned that some fraud-detection systems are not practical as they either cost too much to run or are difficult to explain to senior management and regulators.

Therefore, in addition to developing two models for predicting the probability that a prospective transaction is fraudulent, you will need to determine the value of each model, so that Xufeng can determine whether which model to recommend to the the Senior Management team.

2 Helper functions

[234]:
```
def calc_age(birthday):
    #birthday = datetime.strptime(bdate, "%Y/%m/%d").date()
    today = date.today()
    return today.year - birthday.year - ((today.month, today.day) < (birthday.
 ↪month, birthday.day))
```

3 The data

The data can be found in the file `cc_tranactions.csv`.

The dataset contains individual credit card transactions over a the period 01-01-2019 - 12-31-2021. The transactions only represent a small subset of all users that we have sampled to keep the size of the dataset manageable. The data dictionary is given below.

The data set contains 1,997,859 observations of 26 variables per transaction.

(Note that for purposes of this home work, the data are synthetic, but based on a real data set. We do this to avoid privacy issues. Also note that we are making some simplifying assumptions about the costs and benefits of transactions, etc.)

3.1 Data Dictionary

| **variable** | **Description** | | :– | -:- | | `ssn` | Social Security number | `cc_num` | Credit card number | `first` | First name | `last` | Last name | `gender` | Gender | `street` | Street address | `city` | City of residence | `state` | State of residence | `zip` | Postal code of residence | `lat` | Latitude of residence | `long` | Longitude of residence | `city_pop` | Population of city of residence | `job` | Job title | `dob` | Date of birth | `acct_num` | User acct number | `profile` | Demographic cluster | `trans_num` | Transaction number | `trans_date` | Transaction date | `trans_time` | Transaction time | `unix_time` | UNIX time of transaction | `category` | Type of product | `amt` | Transaction amt | `is_fraud` | Dummy indicating fraud (1) or no-fraud (0) | `merchant` | Name of merchant executing transaction | `merch_lat` | Latitude of merchant location | `merch_long` | Longitude of merchant location

3.2 Selected data summaries

3.2.1 `is_fraud`

label	count
0	1,990,508
1	7,351

3.2.2 `profile`

label	count
adults_2550_female_rural	19738
adults_2550_female_urban	573037
adults_2550_male_rural	21969
adults_2550_male_urban	497764
adults_50up_female_rural	8756
adults_50up_female_urban	299042
adults_50up_male_rural	20862
adults_50up_male_urban	303322
young_adults_female_rural	7686

young_adults_female_urban 119580 young_adults_male_rural | 6577 young_adults_male_urban | 119526

3.2.3 `category`

Label	count
entertainment	145896
food_dining	150670
gas_transport	170316
grocery_net	86063
grocery_pos	187250
health_fitness	124189
home	186835
kids_pets	174024
misc_net	90653
misc_pos	131483
personal_care	141152
shopping_net	146755
shopping_pos	198182
travel	64391

3.3 Load the data

[235]:
```
data = pd.read_csv(DATA_FN)
```

4 Model building

4.1 Preprocessing

4.1.1 For each record, calculate the age of the customer based on `dob` and the day of the week of the transaction.

[237]:
```
dob = pd.to_datetime(data["dob"])
```

[238]:
```
trans_date =pd.to_datetime(data['trans_date'])
age_in_years = (trans_date - dob)/365
```

[239]:
```
data["age"] = age_in_years.dt.days
```

4.1.2 Perform any other preprocessing you think appropriate

(Be sure to note whether you are "peeking" at the test data (see below) in those cases, you may need to split the data *before* doing some preprocessing steps.)

[240]:
```
data["sex"] = data["gender"].apply(lambda x: 1 if x == 'M' else 0)
```

[241]:
```
data['dow'] = pd.to_datetime(data['trans_date']).dt.dayofweek
```

4.1.3 Split the data into training and test samples.

The test sample should include records with index 1,500,000 through end of the data.

[242]:
```
train = data[:1500000]
test = data[1500000:]
```

4.2 The current (incumbent) model

MasterVista has a model that was developed by an analyst at the bank. The model is a linear one with the following form:

$$y = logit(log(age) + log(city_pop) + dow$$

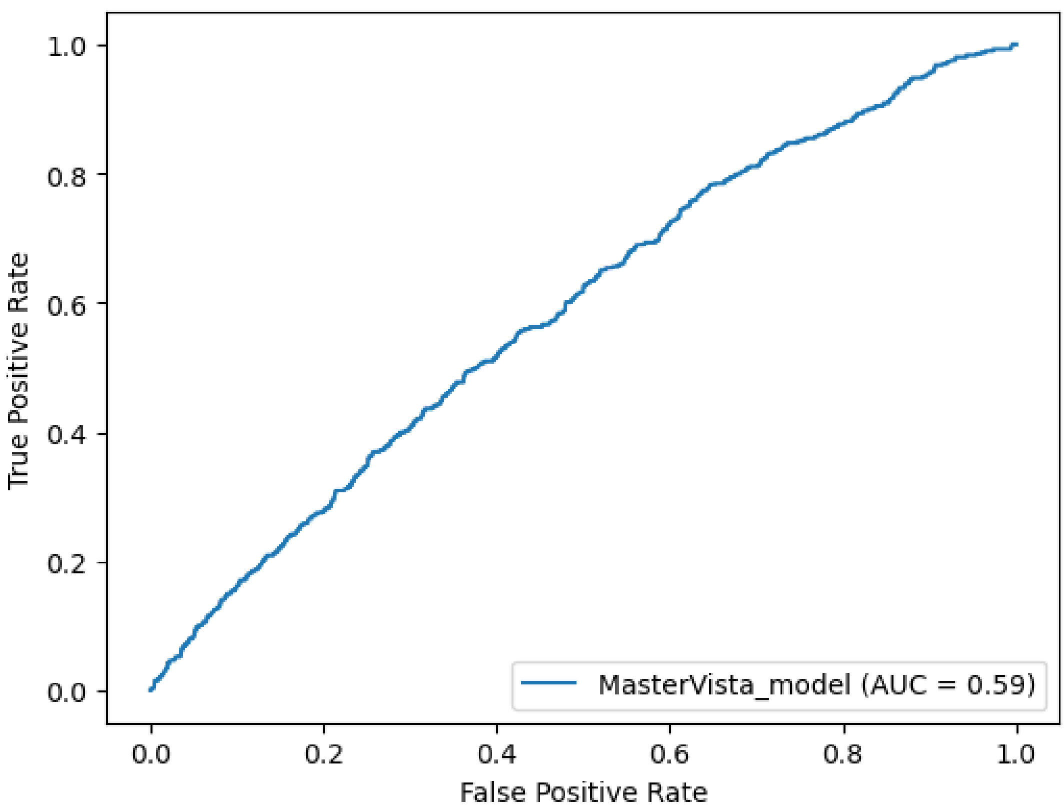
4.2.1 Estimate the MasterVista model on your training data. Use the test data to plot the ROC and calculate the ROC AUC

[244]:
```
MasterVista_model = sm.logit(formula = 'is_fraud ~ np.log(age) + np.
 ↪log(city_pop) + dow', data = train).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.022918
         Iterations 10
```

[230]:
```
dependent = test['is_fraud']
```

[250]:
```
y = MasterVista_model.predict(test)
fpr, tpr, thresholds = metrics.roc_curve(dependent, y)
roc_auc_scores1 = roc_auc_score(dependent, y_score=y)
display = RocCurveDisplay(fpr=fpr, tpr=tpr, roc_auc=roc_auc,␣
 ↪estimator_name='MasterVista_model')
display.plot()
plt.show()
print(roc_auc_scores1)
```



```
0.5882120095722705
```

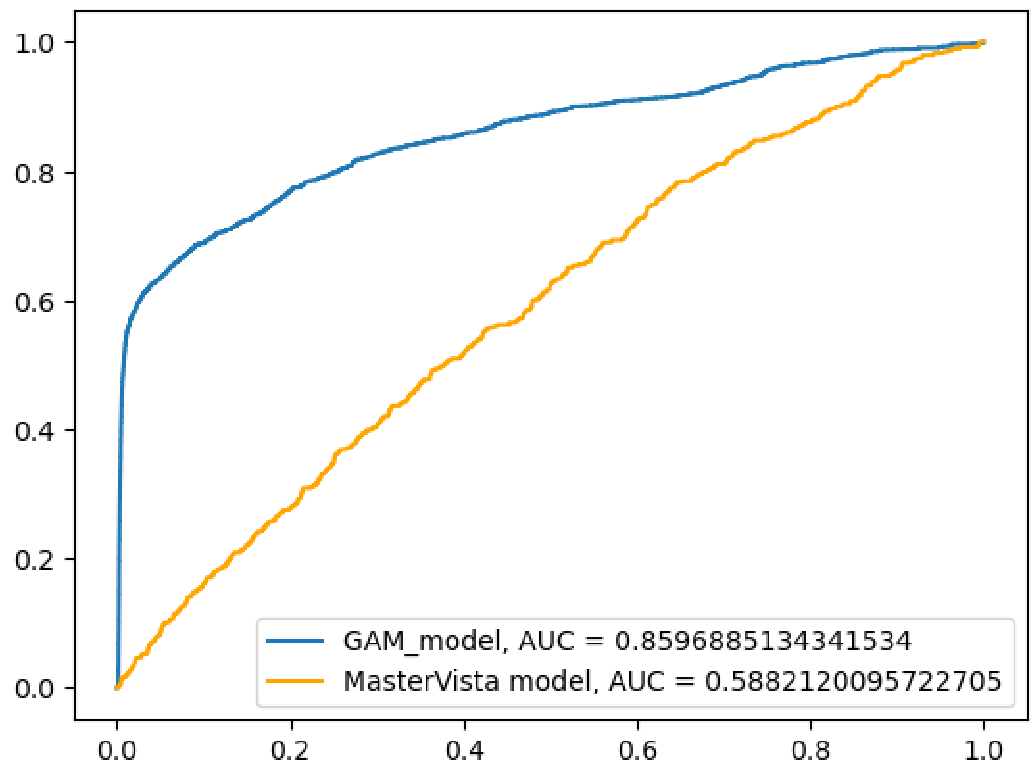
4.2.2 Build your own GAM (with logit link function) to predict `is_fraud`. Can you do better than MasterVista?

Only use the training data to build the model. Use the test data to plot the ROC and calculate the ROC AUC.

[252]:
```
GAM_model = sm.logit(formula = 'is_fraud ~ np.log(age) + np.log(city_pop) + dow␣
 ↪+ amt + sex', data = train).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.021523
         Iterations 10
```

[305]:
```
GAM_model_predict = GAM_model.predict(test)
fpr2, tpr2, thresholds2 = metrics.roc_curve(dependent, GAM_model_predict)
roc_auc_scores2 = roc_auc_score(y_true=dependent, y_score=GAM_model_predict)
plt.plot(fpr2, tpr2, label=f'GAM_model, AUC = {roc_auc_scores2}')
plt.plot(fpr, tpr, label=f'MasterVista model, AUC = {roc_auc_scores1}', color =␣
 ↪'orange')
plt.legend()
plt.show()
print(roc_auc_scores2)
```



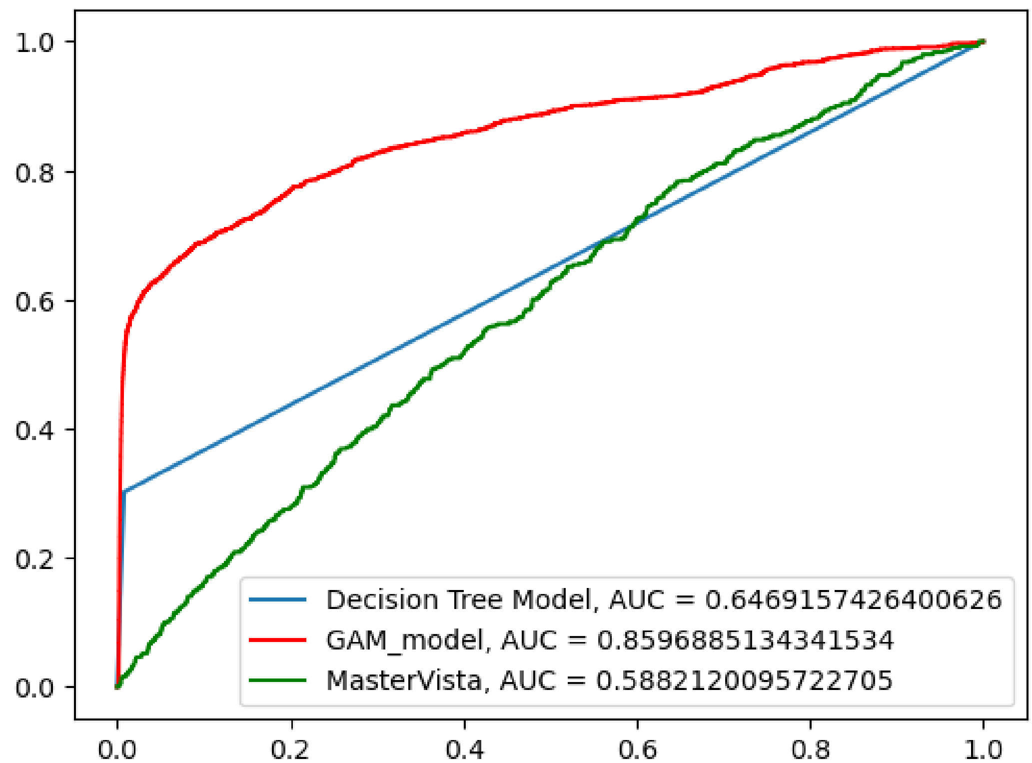
```
0.8596885134341534
```

4.3 Now build a tree model to predict `is_fraud`. Can you beat your GAM?

Only use the training data to build the model. Use the test data to plot the ROC and calculate the ROC AUC.

[290]:
```python
list_variables = ['age', 'city_pop', 'dow', 'amt', 'sex']

tree = DecisionTreeClassifier()
tree.fit(train[list_variables], train['is_fraud'])
y_vars = test[list_variables]
```

[318]:
```python
tree_y = tree.predict(y_vars)
fpr3, tpr3, thresholds3 = roc_curve(dependent, tree_y)
roc_auc_scores3 = roc_auc_score(y_true=dependent, y_score=tree_y)

plt.plot(fpr3, tpr3, label=f'Decision Tree Model, AUC = {roc_auc_scores3}')
plt.plot(fpr2, tpr2, label=f'GAM_model, AUC = {roc_auc_scores2}', color = 'red')
plt.plot(fpr, tpr, label=f'MasterVista, AUC = {roc_auc_scores1}', color =␣
 ↪'green')
plt.legend()
plt.show()
print(roc_auc_scores3)
```




```
0.6469157426400626
```

5 Finding good cutoffs

5.1 MasterVista's fraud costs

MasterVista makes money in its credit card business through two primary sources: - Merchant fees that are paid by the vendor to MasterVista to use the banking system - Late fees that are paid by customers on outstanding balances

If there is a suspected fraudulent transaction, MasterVista incurs costs in one of two ways: - In the event that there is a fraudulent transaction that is not prevented, MasterVista must reimburse the seller for the cost of the (fraudulently) purchased item - In the event that a suspicious transaction is investigated, there is a cost associated with the investigation.

If a transaction is flagged it is verified manually. If a flagged transaction is not authorized by the cardholder, it does not go through. Otherwise, if it is flagged, but found to be valid, it is processed after the verification.

The table, below, outlines these costs, in percentage terms for an average transaction. (In this section, we will make the simplifying assumption that the mean values purchases, etc. are sufficient for our analysis. In practice, we would likely do this dynamically.)

variable	value	Description
Mean late fee profit pct (per trans)	2.3%	*Average percentage of approved purchase financed over more than one billing cycle*
Mean loss pct on fraud	150%	*Mean loss of purchase amount lost if transaction is fraudulent*
Mean merchant fee profit pct	2%	*Mean fee paid by merchant for approved tranactions, as a percentage of transaction amount*
Mean cost of verification	6%	*Mean cost of investigating a potentially fruadulent transaction before approving*

5.1.1 Write down the cost-benefit matrix for MasterVista's operations

The cost of a false positive is the cost of verification minus the late fee minus the merchant fee. The true negative is minus the cost of verification because verification costs money, and the benefit of true positive is the late fee+merchant fee. The cost of false negative is 1.5 times larger than transaction price

	positive	negative
Yes	-0.06	0.017
No	1.5	0.042

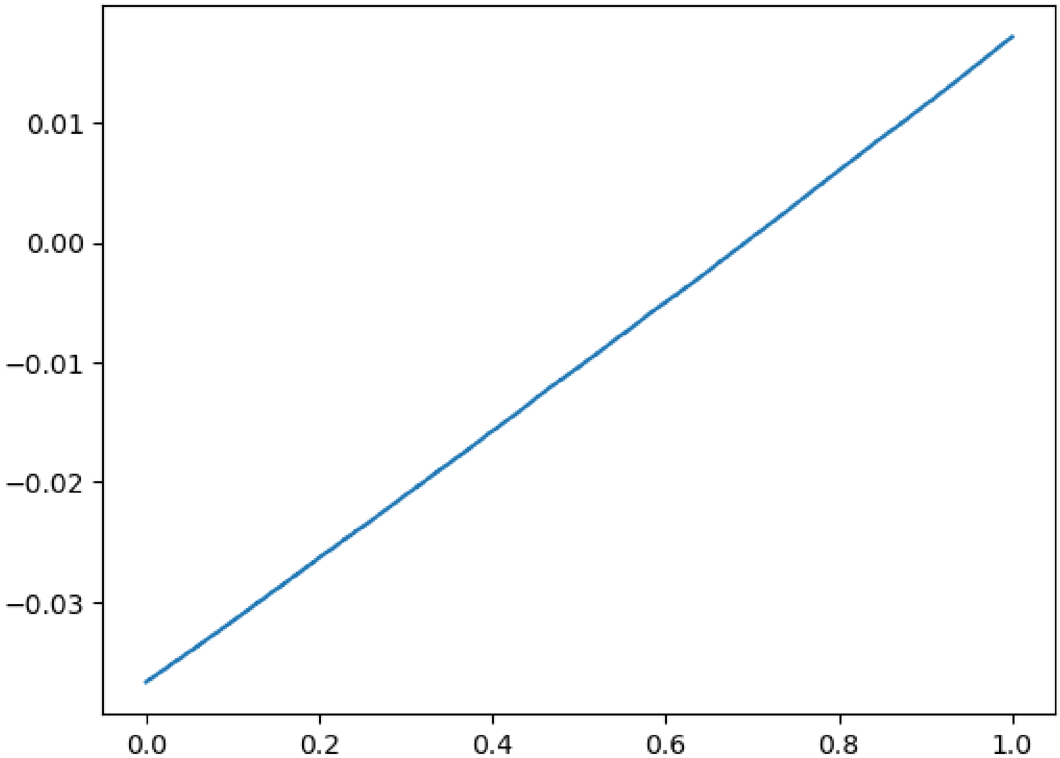
5.2 Find 'optimal' cutoff for MasterVista's model; plot the cost curve

[273]:
```
#we'll use training dataset for this
yes_positive = -0.06
no_positive = 1.5
yes_negative = 0.017
no_negative = 0.042

prob_of_fraud = np.sum(train['is_fraud'])/len(train['is_fraud'])
prob_of_no_fraud = 1 - prob_of_fraud
print("Probability of Fraud",{prob_of_fraud})
```

```
Probability of Fraud {0.0034613333333333333}
```

[276]:
```
cost = []
for i in range(len(fpr)):
    falsep = fpr[i]
    truep = tpr[i]
    falsen = 1-tp
```

```
    truen = 1-fp
    cost.append(-yes_positive*tp*prob_of_fraud -␣
 ↪no_negative*tn*prob_of_no_fraud + no_positive*fn*prob_of_fraud +␣
 ↪yes_negative*fp*prob_of_no_fraud)


plt.plot(fpr, cost)
plt.show()
```



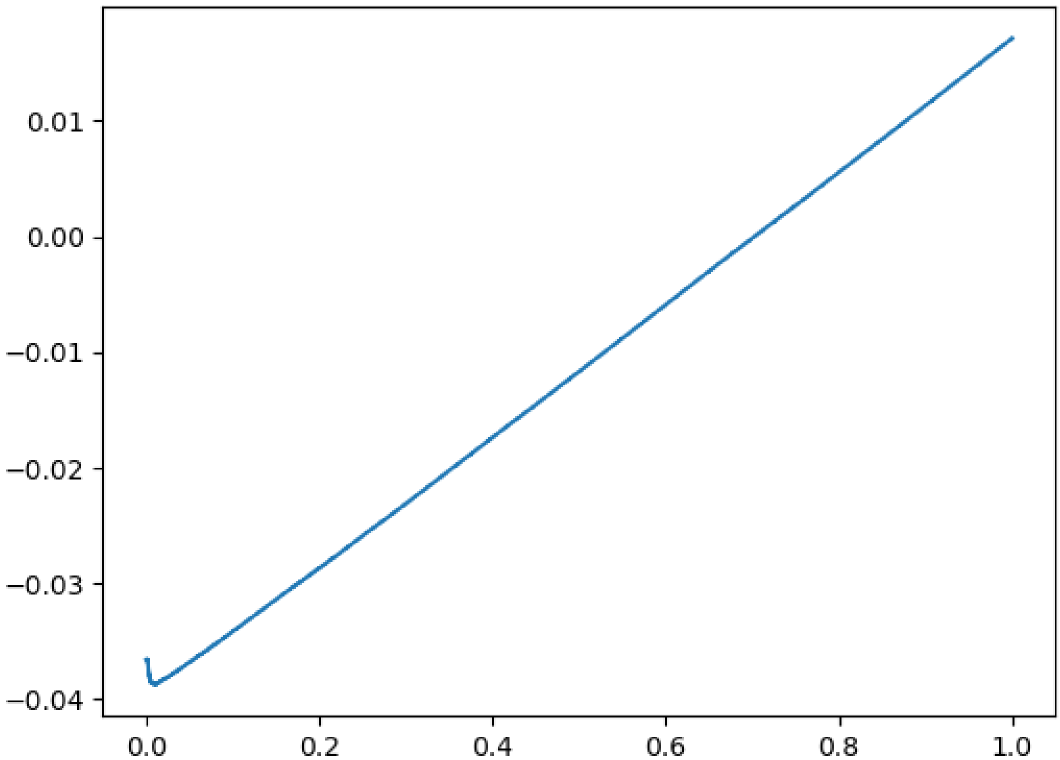
[261]:
```
#cutoff
print("optimal cutoff for MasterVista is", fpr[np.argmin(cost)])
```

```
optimal cutoff for MasterVista is 0.0
```

5.3 Find 'optimal' cutoff for your GLM

[278]:
```
cost2 = []
for i in range(len(fpr2)):
    falsep = fpr2[i]
    treup = tpr2[i]
    falsen = 1-tp
```

```
    truen = 1-fp
    cost2.append(-yes_positive*truep*prob_of_fraud -␣
 ↪no_negative*truen*prob_of_no_fraud + no_positive*falsen*prob_of_fraud +␣
 ↪yes_negative*falsep*prob_of_no_fraud)

plt.plot(fpr2, cost2)
plt.show()
```



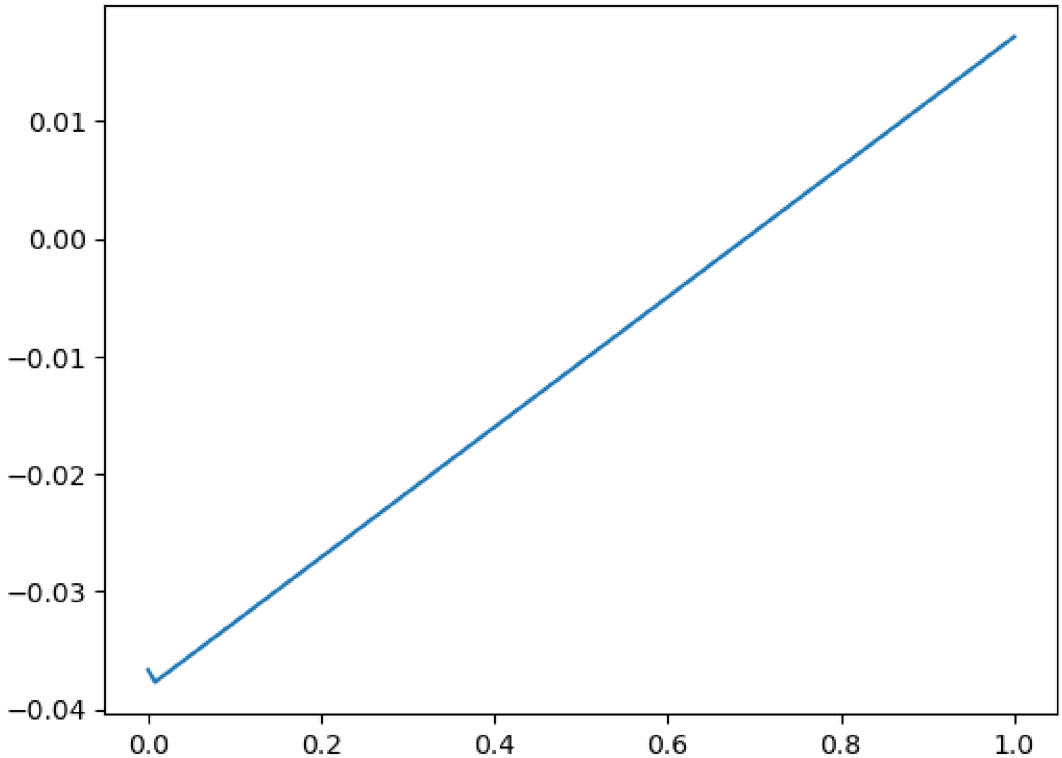
[279]:
```
print("optimal cutoff for MasterVista is", fpr2[np.argmin(cost2)])
```

```
optimal cutoff for MasterVista is 0.009554165826104499
```

5.4 Find 'optimal' cutoff for your tree model

[307]:
```
cost3 = []
for i in range(len(fpr3)):
    falsep = fpr3[i]
    truep = tpr3[i]
    falsen = 1-tp
    truen = 1-fp
```

```
    cost3.append(-yes_positive*truep*prob_of_fraud -␣
↪no_negative*truen*prob_of_no_fraud + no_positive*falsen*prob_of_fraud +␣
↪yes_negative*falsep*prob_of_no_fraud)

plt.plot(fpr3, cost3)
plt.show()
```



[309]:
```
print("optimal cutoff for MasterVista is", fpr3[np.argmin(cost3)])
```

```
optimal cutoff for MasterVista is 0.008160177526729876
```

6 Estimating economic value of models

6.1 Estimate cost of fraud with no model at optimal cutoff (per dollar loaned)

[298]:
```
-yes_positive*tp*real_fraud - no_negative*tn*real_no_fraud +␣
↪no_positive*fn*real_fraud + yes_negative*fp*real_no_fraud
```

[298]: 0.01786

6.2 Estimate cost of fraud with MasterVista's original model at it's optimal cutoff (per dollar loaned)

[299]:
```
arg_min = np.argmin(cost)
cost[arg_min]
```

[299]: -0.038760414621592965

6.3 Estimate cost of fraud with your GLM at it's optimal cutoff (per dollar loaned)

[301]:
```
arg_min2 = np.argmin(cost2)
cost2[arg_min2]
```

[301]: -0.038760414621592965

6.4 Estimate cost of fraud with with your tree model at it's optimal cutoff (per dollar loaned)

[300]:
```
arg_min3 = np.argmin(cost3)
cost3[arg_min3]
```

[300]: -0.03765496705234982

7 Summarize costs of each approach

7.1 Create a table that shows (a) the AUC of each model; (b) the optimal cutoff value for each model; and (c) the expected cost per transaction of if each model is used at its optimal cutoff.

Model	AUC	Optimal cutoff (k)	Cost per $1 loaned
MV original	0.588212	0	-0.0387604
my GLM	0.859688	0.0095541	-0.0387604
my tree	0.646915	0.0082126	-0.0376549

7.2 Which model would you recommend that the bank use to minimize its lending costs?

Although GLM model is stronger than tree model, I would recommend tree model because it would save the most money.

7.3 If the bank processes 300,000 transactions per day, with an average value of 25 dollars each, how much money would using the new model save the bank versus the current MasterVista model in the first 30 days of deploying the model?

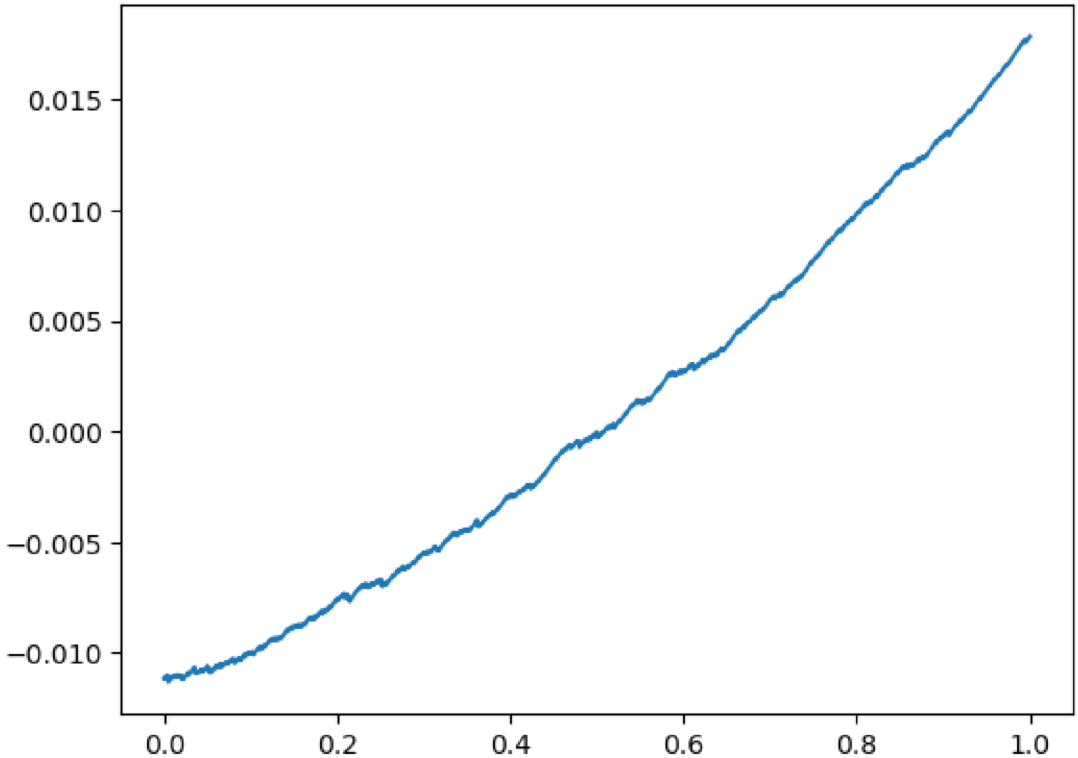
[316]:
```
dollar = 25
days = 30
num_trans = 30000

#we'll use tree model as new model
(cost[arg_min] - cost3[arg_min3])*dollar*days*num_trans
```

[316]: 24127.90988252155

8 Ooops!

8.1 Imagine that you now learn that the true rate of fraudulent transactions is 2%. Recalculate the optimal cutoff for the MasterVista model.

[195]:
```
real_fraud = 0.02
real_no_fraud = 1 - real_fraud

cost4 = []
for i in range(len(fpr)):
    falsep = fpr[i]
    truep = tpr[i]
    falsen = 1-tp
    truen = 1-fp
    cost4.append(-yes_positive*truep*real_fraud -␣
 ↪no_negative*truen*real_no_fraud + no_positive*falsen*real_fraud +␣
 ↪yes_negative*falsep*real_no_fraud)


plt.plot(fpr, cost4)
plt.show()
```



[317]:
```
fpr[np.argmin(cost4)]
print("optimal cutoff for true MasterVista is", fpr[np.argmin(cost4)])
```

optimal cutoff for true MasterVista is 0.004890054468428485