BCG_Model_V2

June 19, 2021

1 Churn prediction with XGboost (Work Flow)

1. Split dataset
   A. B. Training C. Validation
2. Modelling A. Xgboost
3. Model evaluation A. Accuracy, Precision, Recall B. ROC-AUC C. Stratified K-fold validation
4. Model finetuning A. Random search with cross validation
5. Understanding the model A. Feature importance B. Partial dependence plot (PDP) C. SHAP

[19]:
```
import datetime
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import pickle
import seaborn as sns
# import shap
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
import xgboost as xgb
```

[50]:
```
sns.set(color_codes = True)
```

2 Load Data

[20]:
```
train_data = pd.read_pickle('feature_engineered_train_data.pkl')
history_data = pd.read_pickle('feature_engineered_history_data.pkl')
```

[24]:
```
history_data
```

[24]:
```
                                 id  mean_year_price_p1_var  \
0  0002203ffbb812588b632b9e628cc38d                0.124338
1  0004351ebdd665e6ee664792efc4fd13                0.146426
2  0010bcc39e42b3c2131ed2ce55246e3c                0.181558
3  0010ee3855fdea87602a5b7aba8e42de                0.118757
4  00114d74e963e47177db89bc70108537                0.147926
```

```
…      …                                 …
16091  ffef185810e44254c3a4c6395e6b4d8a       0.138863
16092  fffac626da707b1b5ab11e8431a4d0a2       0.147137
16093  fffc0cacd305dd51f316424bbb08d1bd       0.153879
16094  fffe4f5646aa39c7f97f95ae2679ce64       0.123858
16095  ffff7fa066f1fb305ae285bb03bf325a       0.125360

       mean_year_price_p2_var  mean_year_price_p3_var  mean_year_price_p1_fix  \
0                    0.103794                0.073160               40.701732
1                    0.000000                0.000000               44.385450
2                    0.000000                0.000000               45.319710
3                    0.098292                0.069032               40.647427
4                    0.000000                0.000000               44.266930
…                        …                       …                       …
16091                0.115125                0.080780               40.896427
16092                0.000000                0.000000               44.311375
16093                0.129497                0.094842               41.160171
16094                0.103499                0.073735               40.606699
16095                0.104895                0.075635               40.647427

       mean_year_price_p2_fix  mean_year_price_p3_fix  mean_year_price_p1  \
0                   24.421038               16.280694           40.826071
1                    0.000000                0.000000           44.531877
2                    0.000000                0.000000           45.501268
3                   24.388455               16.258971           40.766185
4                    0.000000                0.000000           44.414856
…                        …                       …                   …
16091               24.637456               16.507972           41.035291
16092                0.000000                0.000000           44.458512
16093               24.895768               16.763569           41.314049
16094               24.364017               16.242678           40.730558
16095               24.388455               16.258971           40.772788

       mean_year_price_p2  mean_year_price_p3
0               24.524832           16.353854
1                0.000000            0.000000
2                0.000000            0.000000
3               24.486748           16.328003
4                0.000000            0.000000
…                   …                   …
16091           24.752581           16.588752
16092            0.000000            0.000000
16093           25.025265           16.858411
16094           24.467516           16.316414
16095           24.493350           16.334606

[16096 rows x 10 columns]
```

[23]:
```
train_data.isnull().sum()
```

[23]:
```
id                           0
cons_12m                     0
cons_gas_12m                 0
cons_last_month              0
date_activ                   0
date_end                     0
date_modif_prod              0
date_renewal                 0
forecast_cons_12m            0
forecast_cons_year          25
forecast_discount_energy     0
forecast_meter_rent_12m      0
forecast_price_energy_p1     0
forecast_price_energy_p2     0
forecast_price_pow_p1        0
has_gas                      0
imp_cons                     0
margin_gross_pow_ele         0
margin_net_pow_ele           0
nb_prod_act                  0
net_margin                   0
num_years_antig              0
pow_max                      0
churn                        0
tenure                       0
month_activ                  0
month_to_end                 0
month_modif_prod             0
month_renewal                0
channel_epu                  0
channel_ewp                  0
channel_fix                  0
channel_foo                  0
channel_lmk                  0
channel_nul                  0
channel_sdd                  0
channel_usi                  0
origin_ewx                   0
origin_kam                   0
origin_ldk                   0
origin_lxi                   0
origin_usa                   0
activity_apd                 0
activity_ckf                 0
activity_clu                 0
```

```
activity_cwo                0
activity_fmw                0
activity_kkk                0
activity_kwu                0
activity_sfi                0
activity_wxe                0
dtype: int64
```

[25]:
```python
train = train_data.merge(history_data, on = 'id')
```

[26]:
```python
train
```

[26]:
```
                                     id  cons_12m  cons_gas_12m  \
0      48ada52261e7cf58715202705a0451c9  5.490346      0.000000
1      24011ae4ebbe3035111d65fa7c15bc57  4.327104      4.739944
2      d29c2c54acc38ff3c0614d0a653813dd  3.668479      0.000000
3      764c75f661154dac3a6c254cd082ea7d  2.736397      0.000000
4      bba03439a292a1e166f80264c16191cb  3.200029      0.000000
…                                   …       …           …
16091  18463073fb097fc0ac5d3e040f356987  4.508812      4.680707
16092  d0a6f71671571ed83b2645d23af6de00  3.858778      0.000000
16093  10e6828ddd62cbcf687cb74928c4c2d2  3.265996      0.000000
16094  1cf20fd6206d7678d5bcafd28c53b4db  2.120574      0.000000
16095  563dde550fd624d7352f3de77c0cdfcd  3.941064      0.000000

       cons_last_month date_activ   date_end date_modif_prod date_renewal  \
0             4.001128 2012-11-07 2016-11-06      2012-11-07   2015-11-09
1             0.000000 2013-06-15 2016-06-15      2015-11-01   2015-06-23
2             0.000000 2009-08-21 2016-08-30      2009-08-21   2015-08-31
3             0.000000 2010-04-16 2016-04-16      2010-04-16   2015-04-17
4             0.000000 2010-03-30 2016-03-30      2010-03-30   2015-03-31
…                  …          …          …              …          …
16091         0.000000 2012-05-24 2016-05-08      2015-05-08   2014-05-26
16092         2.260071 2012-08-27 2016-08-27      2012-08-27   2015-08-28
16093         2.255273 2012-02-08 2016-02-07      2012-02-08   2015-02-09
16094         0.000000 2012-08-30 2016-08-30      2012-08-30   2015-08-31
16095         0.000000 2009-12-18 2016-12-17      2009-12-18   2015-12-21

       forecast_cons_12m  forecast_cons_year  …  activity_wxe  \
0               4.423595            4.001128  …             0
1               3.085953            0.000000  …             0
2               2.280920            0.000000  …             0
3               1.689841            0.000000  …             0
4               2.382089            0.000000  …             0
…                    …                  …   …            …
16091           3.667360            0.000000  …             0
16092           2.801191            2.260071  …             0
```

```
16093           2.281919          2.255273  …           0
16094           3.099541          0.000000  …           0
16095           2.882758          0.000000  …           0

       mean_year_price_p1_var  mean_year_price_p2_var  mean_year_price_p3_var  \
0                    0.103449                0.092115                0.067241
1                    0.122856                0.102137                0.072579
2                    0.149934                0.000000                0.000000
3                    0.170512                0.088421                0.000000
4                    0.151210                0.000000                0.000000
…                         …                      …                      …
16091                0.144124                0.000000                0.000000
16092                0.106799                0.095406                0.070817
16093                0.124338                0.103794                0.073160
16094                0.149934                0.000000                0.000000
16095                0.168662                0.087344                0.000000

       mean_year_price_p1_fix  mean_year_price_p2_fix  mean_year_price_p3_fix  \
0                   58.956502               36.356887                8.337051
1                   40.640023               24.384011               16.256008
2                   44.315416                0.000000                0.000000
3                   44.385450                0.000000                0.000000
4                   44.400265                0.000000                0.000000
…                         …                      …                      …
16091               44.370635                0.000000                0.000000
16092               59.015674               36.393379                8.345418
16093               40.701732               24.421038               16.280694
16094               44.315416                0.000000                0.000000
16095               44.266930                0.000000                0.000000

       mean_year_price_p1  mean_year_price_p2  mean_year_price_p3
0               59.059950           36.449002            8.404292
1               40.762879           24.486148           16.328586
2               44.465350            0.000000            0.000000
3               44.555962            0.088421            0.000000
4               44.551475            0.000000            0.000000
…                     …                   …                   …
16091           44.514760            0.000000            0.000000
16092           59.122473           36.488785            8.416235
16093           40.826071           24.524832           16.353854
16094           44.465350            0.000000            0.000000
16095           44.435592            0.087344            0.000000

[16096 rows x 60 columns]
```

[28]:

```
date_columns = ['date_activ','date_end','date_modif_prod','date_renewal']
train.drop(columns = date_columns, inplace=True)
```

```python
pd.DataFrame({'Df Columns': train.columns})
```

[28]:

	Df Columns
0	id
1	cons_12m
2	cons_gas_12m
3	cons_last_month
4	forecast_cons_12m
5	forecast_cons_year
6	forecast_discount_energy
7	forecast_meter_rent_12m
8	forecast_price_energy_p1
9	forecast_price_energy_p2
10	forecast_price_pow_p1
11	has_gas
12	imp_cons
13	margin_gross_pow_ele
14	margin_net_pow_ele
15	nb_prod_act
16	net_margin
17	num_years_antig
18	pow_max
19	churn
20	tenure
21	month_activ
22	month_to_end
23	month_modif_prod
24	month_renewal
25	channel_epu
26	channel_ewp
27	channel_fix
28	channel_foo
29	channel_lmk
30	channel_nul
31	channel_sdd
32	channel_usi
33	origin_ewx
34	origin_kam
35	origin_ldk
36	origin_lxi
37	origin_usa
38	activity_apd
39	activity_ckf
40	activity_clu
41	activity_cwo
42	activity_fmw
43	activity_kkk

```
44              activity_kwu
45              activity_sfi
46              activity_wxe
47     mean_year_price_p1_var
48     mean_year_price_p2_var
49     mean_year_price_p3_var
50     mean_year_price_p1_fix
51     mean_year_price_p2_fix
52     mean_year_price_p3_fix
53         mean_year_price_p1
54         mean_year_price_p2
55         mean_year_price_p3
```

3 Model

3.1 Splitting data

[29]:
```
y = train['churn']
X = train.drop(columns = ['id', 'churn'], axis = 1)
```

[30]:
```
X
```

[30]:
```
       cons_12m  cons_gas_12m  cons_last_month  forecast_cons_12m  \
0      5.490346      0.000000         4.001128           4.423595
1      4.327104      4.739944         0.000000           3.085953
2      3.668479      0.000000         0.000000           2.280920
3      2.736397      0.000000         0.000000           1.689841
4      3.200029      0.000000         0.000000           2.382089
…         …            …               …                  …
16091  4.508812      4.680707         0.000000           3.667360
16092  3.858778      0.000000         2.260071           2.801191
16093  3.265996      0.000000         2.255273           2.281919
16094  2.120574      0.000000         0.000000           3.099541
16095  3.941064      0.000000         0.000000           2.882758

       forecast_cons_year  forecast_discount_energy  forecast_meter_rent_12m  \
0                4.001128                       0.0                 2.556652
1                0.000000                       0.0                 0.444045
2                0.000000                       0.0                 1.237292
3                0.000000                       0.0                 1.599009
4                0.000000                       0.0                 1.318689
…                    …                        …                        …
16091            0.000000                       0.0                 1.291591
16092            2.260071                       0.0                 2.161458
16093            2.255273                       0.0                 2.115943
16094            0.000000                       0.0                 0.912753
```

```
16095            0.000000                      0.0                0.315970

       forecast_price_energy_p1  forecast_price_energy_p2  \
0                      0.095919                  0.088347
1                      0.114481                  0.098142
2                      0.145711                  0.000000
3                      0.165794                  0.087899
4                      0.146694                  0.000000
…                           …                        …
16091                  0.138305                  0.000000
16092                  0.100167                  0.091892
16093                  0.116900                  0.100015
16094                  0.145711                  0.000000
16095                  0.167086                  0.088454

       forecast_price_pow_p1  …  activity_wxe  mean_year_price_p1_var  \
0                  43.094358  …             0                0.103449
1                  40.606701  …             0                0.122856
2                  44.311378  …             0                0.149934
3                  44.311378  …             0                0.170512
4                  44.311378  …             0                0.151210
…                        …  …           …                     …
16091              44.311378  …             0                0.144124
16092              43.094358  …             0                0.106799
16093              40.606701  …             0                0.124338
16094              44.311378  …             0                0.149934
16095              45.311378  …             0                0.168662

       mean_year_price_p2_var  mean_year_price_p3_var  mean_year_price_p1_fix  \
0                    0.092115                0.067241               58.956502
1                    0.102137                0.072579               40.640023
2                    0.000000                0.000000               44.315416
3                    0.088421                0.000000               44.385450
4                    0.000000                0.000000               44.400265
…                       …                     …                      …
16091                0.000000                0.000000               44.370635
16092                0.095406                0.070817               59.015674
16093                0.103794                0.073160               40.701732
16094                0.000000                0.000000               44.315416
16095                0.087344                0.000000               44.266930

       mean_year_price_p2_fix  mean_year_price_p3_fix  mean_year_price_p1  \
0                   36.356887                8.337051           59.059950
1                   24.384011               16.256008           40.762879
2                    0.000000                0.000000           44.465350
3                    0.000000                0.000000           44.555962
4                    0.000000                0.000000           44.551475
```

```
…                    …                   …                  …
16091         0.000000            0.000000          44.514760
16092        36.393379            8.345418          59.122473
16093        24.421038           16.280694          40.826071
16094         0.000000            0.000000          44.465350
16095         0.000000            0.000000          44.435592

       mean_year_price_p2  mean_year_price_p3
0               36.449002            8.404292
1               24.486148           16.328586
2                0.000000            0.000000
3                0.088421            0.000000
4                0.000000            0.000000
…                     …                   …
16091            0.000000            0.000000
16092           36.488785            8.416235
16093           24.524832           16.353854
16094            0.000000            0.000000
16095            0.087344            0.000000

[16096 rows x 54 columns]
```

[32]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y ,test_size=0.25,␣
↪random_state=18)
```

3.2 Modeling

[33]:
```
model = xgb.XGBClassifier(learning_rate = 0.1, max_depth = 6, n_estimators =␣
↪500, n_jobs = -1)
result = model.fit(X_train, y_train)
```

```
/home/brian/miniconda3/lib/python3.8/site-packages/xgboost/sklearn.py:1146:
UserWarning: The use of label encoder in XGBClassifier is deprecated and will be
removed in a future release. To remove this warning, do the following: 1) Pass
option use_label_encoder=False when constructing XGBClassifier object; and 2)
Encode your labels (y) as integers starting with 0, i.e. 0, 1, 2, …,
[num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

```
[16:13:20] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
```

3.3 Model evaluation

Here using **Accuracy, Precision, Recall**:

```
Accuracy = Correct Observation / All Observation
Precision = The ratio of correctly predicted positive observations to the total predicted posi
Recall = The ratio of correctly predicted positive observations to the all observations in actu
```

[35]:
```python
def evaluate(model_, X_test_, y_test_):
    # Get model prediction
    prediction_test_ = model_.predict(X_test)

    # Print the evaluation metrics as Df
    results = pd.DataFrame({ "Accuracy" : [metrics.accuracy_score(y_test_,␣
 ↪prediction_test_)],
                           "Precision": [metrics.precision_score(y_test_,␣
 ↪prediction_test_)],
                           "Recall": [metrics.recall_score(y_test_,␣
 ↪prediction_test_)]
                           })

    return results
```

[37]:
```python
evaluate(model, X_test, y_test)
```

[37]:

	Accuracy	Precision	Recall
0	0.905815	0.7	0.151807

3.4 ROC-AUC

In a nutshell, it tells how much model is capable of distinguishing between classes.

model.predict_proba Usage

metrics.roc_curve Usage

[55]:
```python
def calculate_roc_auc(model_, X_test_,y_test_):
    # Get the model predictions
    # Note that we are using the prediction for the class 1 -> churn
    prediction_test_ = model_.predict_proba(X_test_)[:,1]

    # Compute ROC-AUC
    # Will return different "True Positive Rate", "False Positive Rate" given␣
 ↪different thresholds
    fpr, tpr, thresholds = metrics.roc_curve(y_test_, prediction_test_)

    score = pd.DataFrame({'ROC-AUC': [metrics.auc(fpr,tpr)]})

    return fpr,tpr,score,thresholds

def plot_roc_auc(fpr,tpr):
```

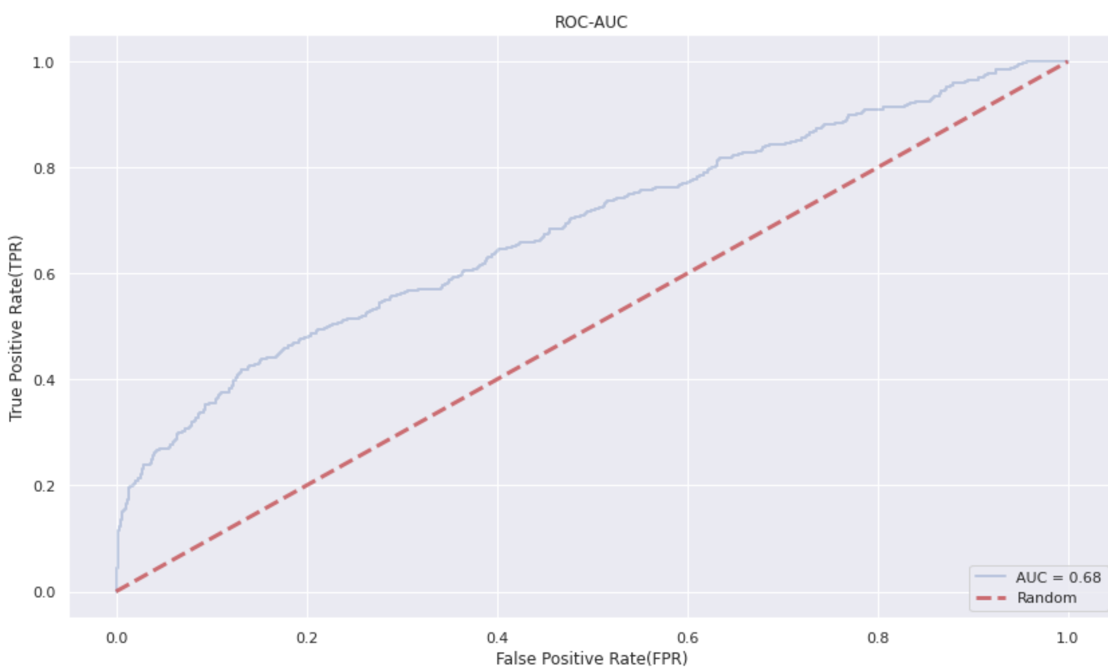
```
    f, ax = plt.subplots(figsize = (14,8))
    # Plot ROC
    roc_auc = metrics.auc(fpr, tpr)
    ax.plot(fpr, tpr, lw=2, alpha = 0.3, label = 'AUC = {:.2f}'.format(roc_auc))
    # Plot random  line
    plt.plot([0,1], [0,1], linestyle ='--', lw=3, color = 'r', label =␣
↪"Random", alpha = 0.8)

    ax.set_xlabel("False Positive Rate(FPR)")
    ax.set_ylabel("True Positive Rate(TPR)")
    ax.set_title("ROC-AUC")
    ax.legend(loc='lower right')
    plt.show()
```

[44]:
```
fpr, tpr, auc_score,thresholds = calculate_roc_auc(model, X_test, y_test)
```

[46]:
```
auc_score
```

[46]:
```
    ROC-AUC
0  0.683895
```

[56]:
```
plot_roc_auc(fpr, tpr)
```



3.5 Stratified K-fold validation

After first test,train split, we cannot assure that is the best way to split the data set
By using K-fold validation, we can know a better way to split data

[102]:
```
def plot_roc_curve(fprs, tprs):
    """
    Plot thge ROC from a list
    of
    """
    # Initilize useful lists + plot axes
    tprs_interp = []
    aucs = []
    mean_fpr = np.linspace(0,1,100)
    f,ax = plt.subplots(figsize=(18,10))

    #PLot ROC for each K-Fold + compute AUC socres
    for i, (fpr, tpr) in enumerate(zip(fprs, tprs)):
        tprs_interp.append(np.interp(mean_fpr, fpr, tpr))
        tprs_interp[-1][0]=0.0
        roc_auc = metrics.auc(fpr, tpr)
        aucs.append(roc_auc)
        ax.plot(fpr, tpr, lw=2, alpha=0.3,
                    label = "ROC fold {}: AUC {:.2f}".format(i, roc_auc))

    # Plot luck line
    plt.plot([0,1], [0,1], linestyle = '--', lw=3, color = 'r',label =␣
 ↪"Random", alpha=.8)

    # Plot the mean ROC
    mean_tpr = np.mean(tprs_interp, axis = 0)
    mean_tpr[-1] = 1.0
    mean_auc = metrics.auc(mean_fpr, mean_tpr)
    std_auc = np.std(aucs)
    ax.plot(mean_fpr, mean_tpr, color = 'b', label = "Mean ROC (AUC: {:.2f}␣
 ↪STD{:.2f})".format(mean_auc, std_auc),lw = 4, alpha=0.8)

    # set plot
    ax.set_xlabel('FPR')
    ax.set_ylabel('TPR')
    ax.set_title("ROC-AUC")
    ax.legend(loc = 'lower right')
    plt.show()
    return (f, ax)


def compute_roc_auc(model_, index):
    y_predict = model_.predict_proba(X.iloc[index])[:,1]
```

```
    fpr, tpr, thresholds = metrics.roc_curve(y.iloc[index], y_predict)
    auc_score = metrics.auc(fpr,tpr)
    return fpr, tpr,auc_score
```

[82]:

```
cv = StratifiedKFold(n_splits = 5, random_state=13, shuffle=True) # Perform␣
 ↪5-fold validation
# These three array is used to store fpr, tpr, score for different fold␣
 ↪validation
fprs, tprs, scores = [],[],[]
```

[95]:

```
model = xgb.XGBClassifier(learning_rate = 0.1, max_depth = 6, n_estimators =␣
 ↪500, n_jobs = -1, use_label_encoder=False)

for (train, test), i in zip(cv.split(X,y), range(5)):
    # Fit model by each fold of dataset
    # KEY, cv split  ,   index,    iloc assign
    model.fit(X.loc[train], y.loc[train])

    # After train the model, send train data to get the auc_score
    _, _, auc_score_train = compute_roc_auc(model, train)
    # Use test data to get auc_score
    fpr, tpr, auc_score = compute_roc_auc(model, test)
    scores.append((i, auc_score_train, auc_score))
    # append fpr, tpr, for this fold to final list
    fprs.append(fpr)
    tprs.append(tpr)
```

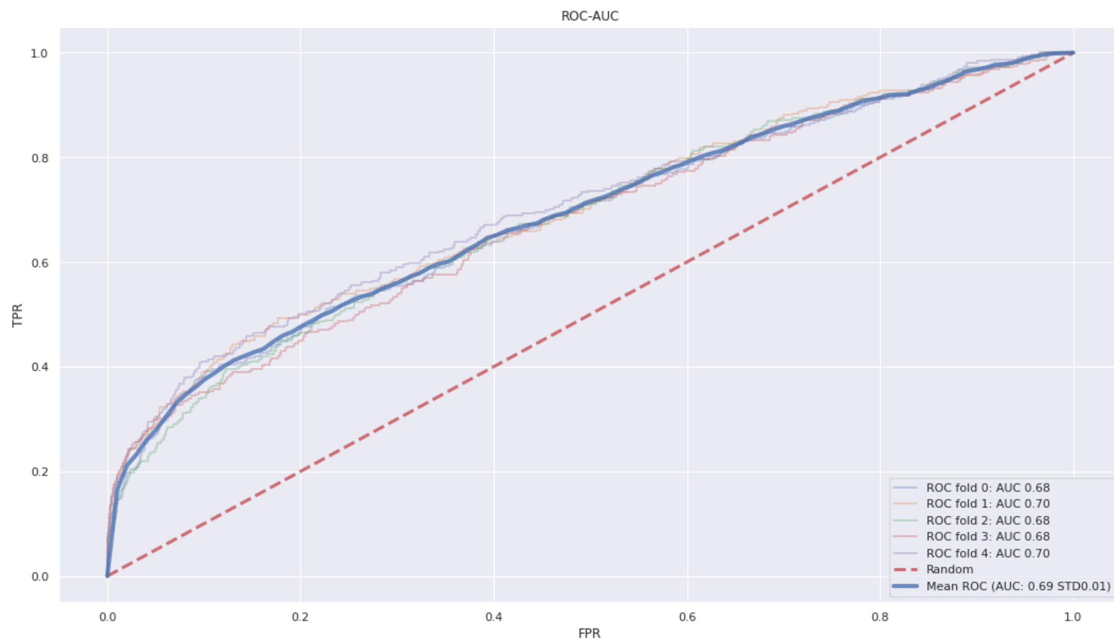
```
[17:40:11] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
[17:40:18] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
[17:40:26] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
[17:40:33] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
[17:40:40] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
```

```
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
```

[97]:
```
scores
```

[97]:
```
[(0, 0.9994150632364068, 0.6847022808046949),
 (1, 0.9994542276784592, 0.696179872446222),
 (2, 0.99931493042298, 0.6846297697546211),
 (3, 0.9995963622204225, 0.6784725975570209),
 (4, 0.9994781419502534, 0.7021186898713653)]
```

[103]:
```
plot_roc_curve(fprs,tprs)
```



[103]:
```
(<Figure size 1296x720 with 1 Axes>,
 <AxesSubplot:title={'center':'ROC-AUC'}, xlabel='FPR', ylabel='TPR'>)
```

3.6 Model finetuning

3.6.1 RandomizedSearchCV

[145]:
```
from sklearn.model_selection import RandomizedSearchCV
```

[151]:
```
# Create the random grid
params = { 'min_child_weight': [i for i in np.arange(1,15,1)],
           'gamma': [i for i in np.arange(0,6,0.5)],
           'subsample': [i for i in np.arange(0,1.1,0.1)],
           'colsample_bytree': [i for i in np.arange(0,1.1,0.1)],
```

```
            'max_depth': [i for i in np.arange(1,15,1)],
            'scale_pos_weight':[i for i in np.arange(1,15,1)],
            'learning_rate': [i for i in np.arange(0,0.15,0.01)],
            'n_estimators' : [i for i in np.arange(0,2000,100)]
          }
```

[162]:
```
# Create modeL
xg = xgb.XGBClassifier( nthread=1, use_label_encoder=False)
```

[163]:
```
# Random search of parameters, using 5
xg_random = RandomizedSearchCV(estimator = xg, param_distributions=params,␣
 ↪n_iter=1, scoring= "roc_auc",
                               n_jobs=4, cv=5, verbose=3, random_state=1001)
# Fit the random search model
xg_random.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 1 candidates, totalling 5 fits
[20:02:12] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
```

[163]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamma=None,
                                           gpu_id=None, importance_type='gain',
                                           interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None, max_depth=None,
                                           min_child_weight=None, missing=nan,
                                           monotone_constraints=None,
                                           n_estimators=100,…
                                        'min_child_weight': [1, 2, 3, 4, 5, 6,
                                                             7, 8, 9, 10, 11,
                                                             12, 13, 14],
                                        'n_estimators': [0, 100, 200, 300, 400,
                                                         500, 600, 700, 800,
                                                         900, 1000, 1100, 1200,
                                                         1300, 1400, 1500, 1600,
                                                         1700, 1800, 1900],
                                        'scale_pos_weight': [1, 2, 3, 4, 5, 6,
                                                             7, 8, 9, 10, 11,
                                                             12, 13, 14],
                                        'subsample': [0.0, 0.1, 0.2,
                                                      0.30000000000000004, 0.4,
```

```
                                                    0.5, 0.6000000000000001,
                                                    0.7000000000000001, 0.8,
                                                    0.9, 1.0]},
                          random_state=1001, scoring='roc_auc', verbose=3)
```

[203]:
```
xg_random.best_params_
best_random = xg_random.best_params_
# best_random

best_random = {'subsample': 0.8,
               'scale_pos_weight': 1,
               'n_estimators': 1100,
               'min_child_weight': 1,
               'max_depth': 12,
               'learning_rate': 0.01,
               'gamma': 4.0,
               'colsample_bytree': 0.60}
```

[204]:
```
# best_random['subsample']=0.8
best_random
```

[204]:
```
{'subsample': 0.8,
 'scale_pos_weight': 1,
 'n_estimators': 1100,
 'min_child_weight': 1,
 'max_depth': 12,
 'learning_rate': 0.01,
 'gamma': 4.0,
 'colsample_bytree': 0.6}
```

[175]:
```
# create a model with the parameters found
model_random = xgb.XGBClassifier(objective='binary:
 ↪logistic',use_label_encoder=False,
                                silent = True,
                                nthread = 1,
                                **best_random)
fprs, tprs, scores= [], [], []
```

[142]:
```
#  Using best_random params provided by BCG
for (train, test), i in zip(cv.split(X,y), range(5)):
    model_random.fit(X.iloc[train], y.iloc[train])
    _, _, auc_score_train = compute_roc_auc(model_random, train)
    fpr, tpr, auc_score = compute_roc_auc(model_random, test)
    scores.append((i,auc_score_train, auc_score))
    fprs.append(fpr)
    tprs.append(tpr)
```

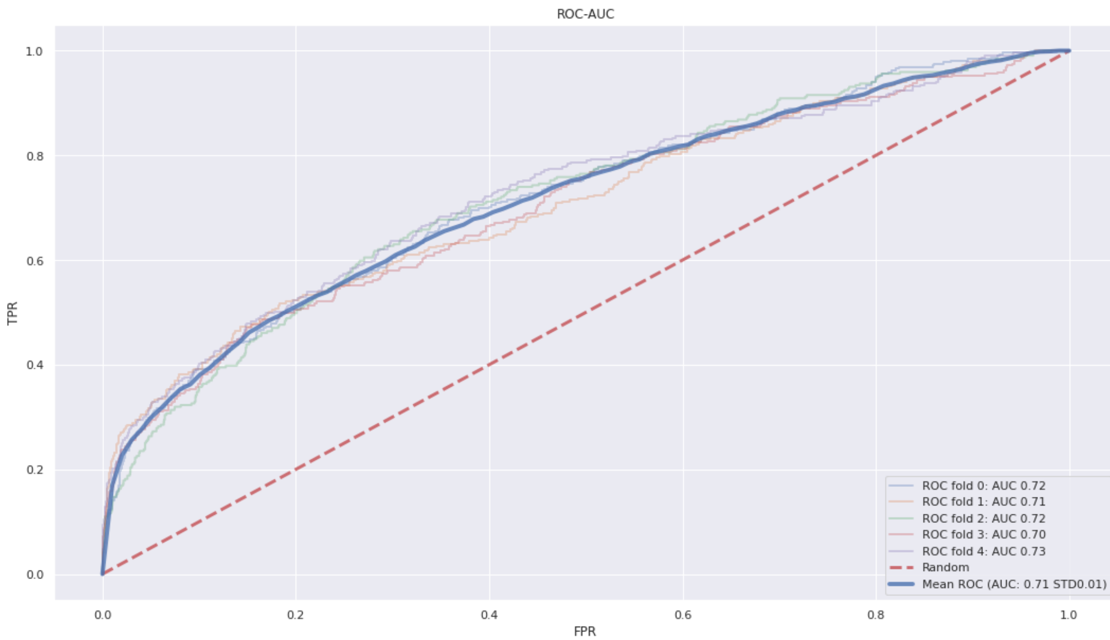
```
[19:21:10] WARNING: ../src/learner.cc:573:
Parameters: { "silent" } might not be used.

  This may not be accurate due to some parameters are only used in language
bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through
this
  verification. Please open an issue if you find above cases.


[19:21:10] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
[19:22:26] WARNING: ../src/learner.cc:573:
Parameters: { "silent" } might not be used.

  This may not be accurate due to some parameters are only used in language
bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through
this
  verification. Please open an issue if you find above cases.


[19:22:26] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
[19:23:42] WARNING: ../src/learner.cc:573:
Parameters: { "silent" } might not be used.

  This may not be accurate due to some parameters are only used in language
bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through
this
  verification. Please open an issue if you find above cases.


[19:23:42] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
[19:24:59] WARNING: ../src/learner.cc:573:
Parameters: { "silent" } might not be used.

  This may not be accurate due to some parameters are only used in language
bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through
```

```
this
  verification. Please open an issue if you find above cases.


[19:24:59] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
[19:26:13] WARNING: ../src/learner.cc:573:
Parameters: { "silent" } might not be used.

  This may not be accurate due to some parameters are only used in language
bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through
this
  verification. Please open an issue if you find above cases.


[19:26:13] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
```

[143]:
```
scores
```

[143]:
```
[(0, 0.9911554156307427, 0.7176824768023998),
 (1, 0.9907005908851766, 0.7080077829423845),
 (2, 0.9912302176955343, 0.7178483407199221),
 (3, 0.9911592179789928, 0.7040817208950383),
 (4, 0.9910743696022314, 0.7253248297481354)]
```

[144]:
```
plot_roc_curve(fprs, tprs)
```



[144]:
```
(<Figure size 1296x720 with 1 Axes>,
 <AxesSubplot:title={'center':'ROC-AUC'}, xlabel='FPR', ylabel='TPR'>)
```

3.6.2 Grid search with cross validation (Time consuming)

[179]:
```python
from sklearn.model_selection import GridSearchCV
```

[180]:
```python
params_grid = { 'min_child_weight': [i for i in np.arange(1,15,1)],
           'gamma': [i for i in np.arange(0,6,0.5)],
           'subsample': [i for i in np.arange(0,1.1,0.1)],
           'colsample_bytree': [i for i in np.arange(0,1.1,0.1)],
           'max_depth': [i for i in np.arange(1,15,1)],
           'scale_pos_weight':[i for i in np.arange(1,15,1)],
           'learning_rate': [i for i in np.arange(0,0.15,0.01)],
           'n_estimators' : [i for i in np.arange(0,2000,100)]
          }
```

[184]:
```python
xg = xgb.XGBClassifier(objective='binary:logistic', silent = False, nthread=1)
```

[185]:
```python
grid_search = GridSearchCV(estimator=xg, param_grid=params_grid, cv =5, n_jobs␣
↪=-1, verbose =2, scoring ='roc_auc')
```

[187]:
```python
grid_search.fit(X_train, y_train)
```

[ ]:
```python
best_grid = grid_search.best_params_best_grid
```

[ ]:
```
model_grid = xgb.XGBClassifier(objective='binary:logistic', silent=True,␣
↪nthread=1, **best_grid)fprs, tprs, scores = [], [], []
```

[ ]:
```
for (train, test), i in zip(cv.split(X, y), range(5)):
    model_grid.fit(X.iloc[train], y.iloc[train])
    _, _, auc_score_train = compute_roc_auc(model_grid, train)
    fpr, tpr, auc_score = compute_roc_auc(model_grid, test)
    scores.append((auc_score_train, auc_score))
    fprs.append(fpr)
    tprs.append(tpr)
```

[ ]:
```
plot_roc_curve(fprs, tprs)
plt.show()
```

4 Understanding the model

4.1 Feature importance

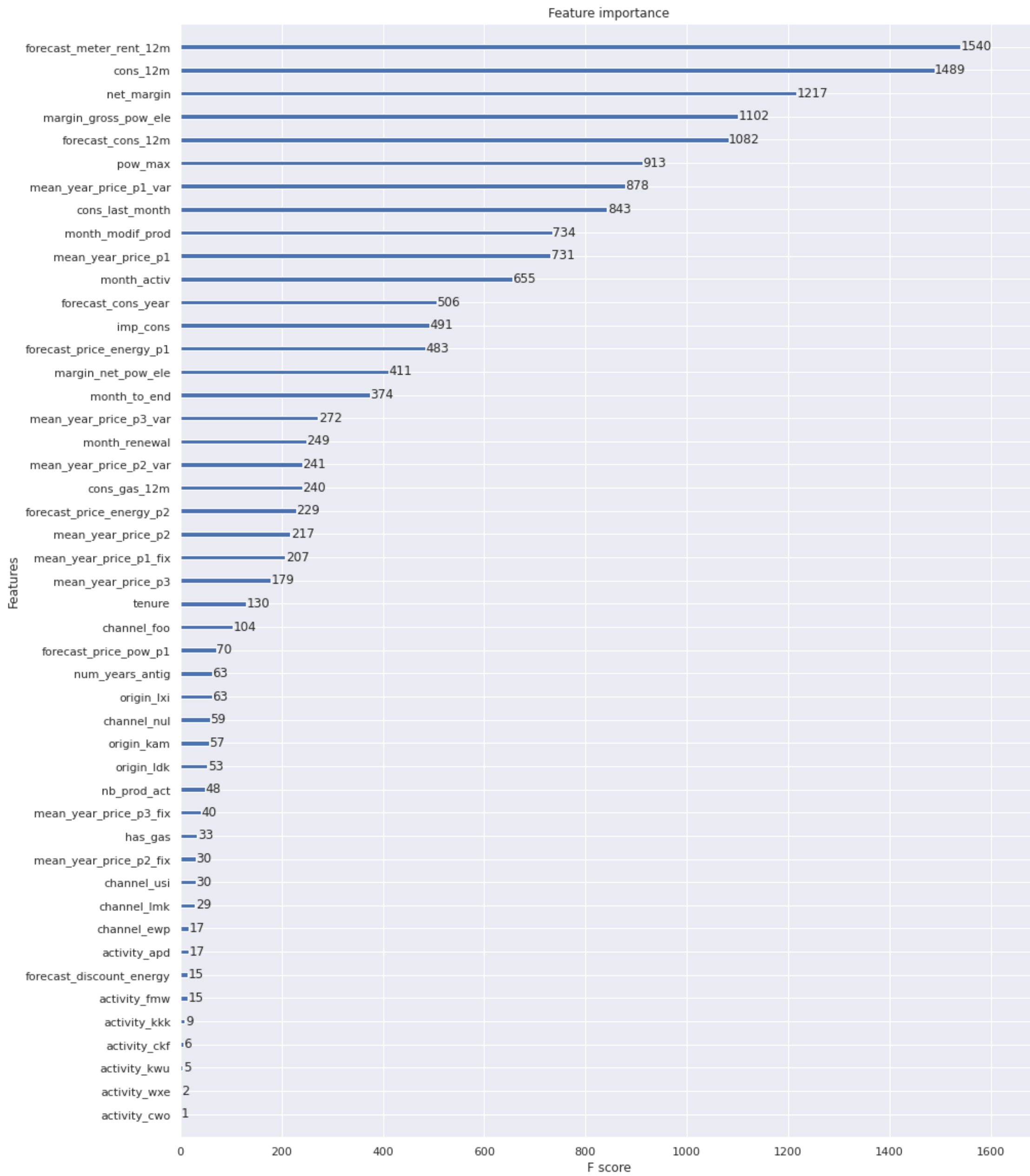
One simple way of boserving the feature importance is through counting the number of times each feature is split on across all boosting rounds (trees)in the model, and then visualizing the result as a bar graph, with the features ordered according to how many times they appear

[190]:
```
model_random
```

[190]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1.0, gamma=2.5, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.1, max_delta_step=0, max_depth=12,
              min_child_weight=10, missing=nan, monotone_constraints='()',
              n_estimators=300, n_jobs=1, nthread=1, num_parallel_tree=1,
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=6,
              silent=True, subsample=0.8, tree_method='exact',
              use_label_encoder=False, validate_parameters=1, verbosity=None)
```

[196]:
```
fig, ax = plt.subplots( figsize=(15,20) )
xgb.plot_importance(model_random, ax = ax)
```

[196]:
```
<AxesSubplot:title={'center':'Feature importance'}, xlabel='F score',
ylabel='Features'>
```



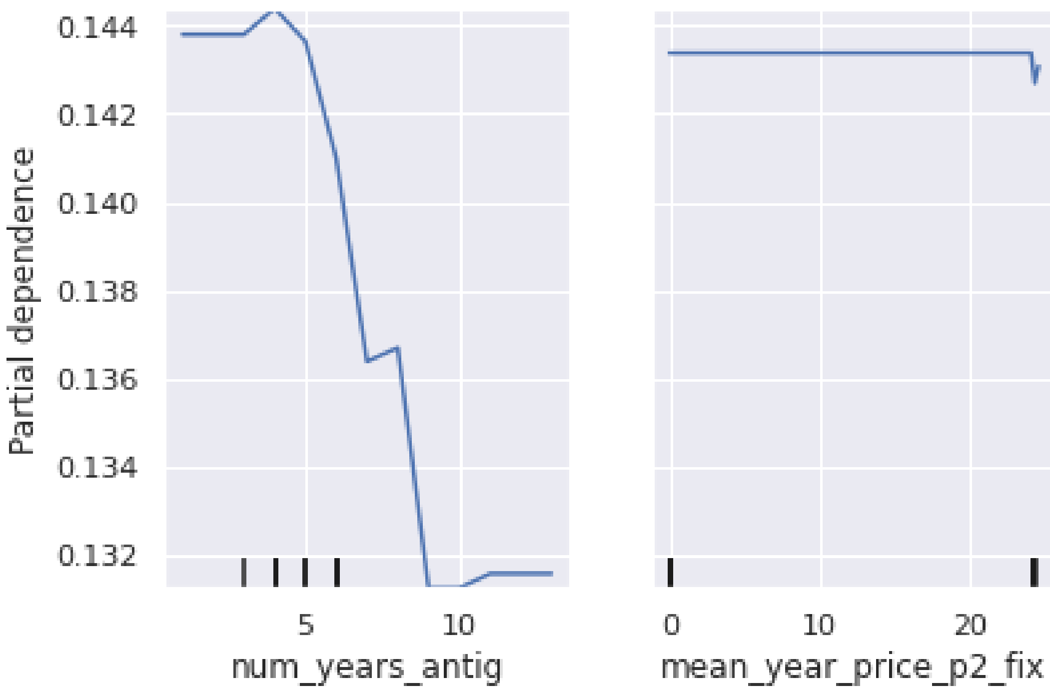
In the feature importance graph above we can see that **cons_12m and net_margin** are the features that appear the most in our model andwe could infere that these two features have a significant importnace in our model

[198]:
```
from sklearn.inspection import plot_partial_dependence
```

[207]:
```
fig = plt.figure(figsize=(15,15))
plot_partial_dependence(model_random, X_test.values, features=[16, 49],
                        feature_names=X_test.columns.tolist())
```

[207]: <sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay at 0x7f7718fc9280>

```
<Figure size 1080x1080 with 0 Axes>
```



5 Business Impact of discount

5.1 Workflow

Task is to calculate the forecast revenue of the set of customers:

```
1. When no discount is offered, and
2. When a discount is offered based on some probability cut-off to decide who should receive a
and therefore can decide the cut-off to maximise revenue.
```

[216]:
```python
predictions = pd.DataFrame(train_data)
```

[217]:
```python
predictions['predict_prob'] = model_random.predict_proba(X)[:,1]
```

5.1.1 Calculate a baseline revenue estimate (no intervention)

Calculate a **baseline estimate of the electricity revenue for every customer for the next twelve months based on the forecast consumption and forecastprice and actual churn outcome.** Call this **basecase_revenue**

For customers who end up churning, we should reduce our forecast revenue calculation by 91.9% to account for the customers churn some time between January 2016 and the start of March 2016. (Not knowing when they churn, a reasonable assumption for the lost revenue is the averageof 100%, corresponding to churn on 1 January 2016, and 83.9%, corresponding to churn at the end of February, or 59 days into a 365 day year).Call this new variable **basecase_revenue_after_churn** , ie basecase_revenue_after_churn = basecase_revenue*(1-0.919*churn)

[218]:
```
predictions['basecase_revenue'] = \
    (np.power(10, predictions['forecast_cons_12m']) +1 ) * predictions['forecast_price_energy_p1'] + predictions['forecast_meter_rent_12m']
predictions['basecase_revenue_after_churn'] = predictions['basecase_revenue'] * (1 - 0.919*predictions['churn'])
```

5.1.2 Calculate the estimated benefits and costs of intervention

Pick a cut-off probability so that:

```
* Customers with a higher churn probability than the cut-off get a discount, and
* Customers below the churn-probability get a discount
```

From this, calculate the revenue of the intervention scenario of this scenario assuming:

```
* All customers who are offered a discount accept it
* Customers who do receive a discount are are assumed not to churn in the next twelve months (
0.8*basecase_revenue , being  (1-discount_fraction)*basecase_revenue
* Customers who do not receive a discount are assumed to churn based on the observed dependent
```

Now, map out the revenue delta as a function of the cut-off probability in a graph **What cut-off probability approximately optimises the revenue outcome?**

Assume for these calculations that the customer does not consume more or less electricity because the price changes. (In practice, we would expectthat if the customer's cost goes down then their consumption might increase.)

We will see two counterbalancing effects at play:

```
* For true postives we will see revenue retention vs the no-discount scenario
* For false positives we will see reduced revenue from giving them a discount when they wouldn
```

(False negatives represent an opportunity cost but not an actual cost difference between the two scenarios.)

The optimal cut-off point will balance the benefits from true positives against the costs of false positives.

Our task is to approximately find the optimal cut-off point. We may need to make additional assumptions.
If we feel the assumptions above aren't justified and that others are better then we should modify our assumptions.

[236]:
```python
def get_rev_delta(pred: pd.DataFrame, cutoff = 0.5, discount = 0.2):
    pred['discount_revenue'] = pred['basecase_revenue_after_churn']

    # If predicted churn --> discount is given, customer will stay, but revenue␣
 ↪hsa to be 1-discount * revenue
    pred.loc[pred['predict_prob'] >=cutoff, 'discount_revenue'] =␣
 ↪pred['basecase_revenue'] * (1 - discount)

    # Save
    pred['revenue_delta'] = pred['discount_revenue'] -␣
 ↪pred['basecase_revenue_after_churn']

    return pred['revenue_delta'].sum()
```

[237]:
```python
# Generate a list of possible cutoffs and the corresponding overall revenue␣
 ↪deltas
rev_deltas = pd.Series({ cutoff: get_rev_delta(predictions, cutoff= cutoff) for␣
 ↪cutoff in np.arange(0, 1, 0.01)
            })
```

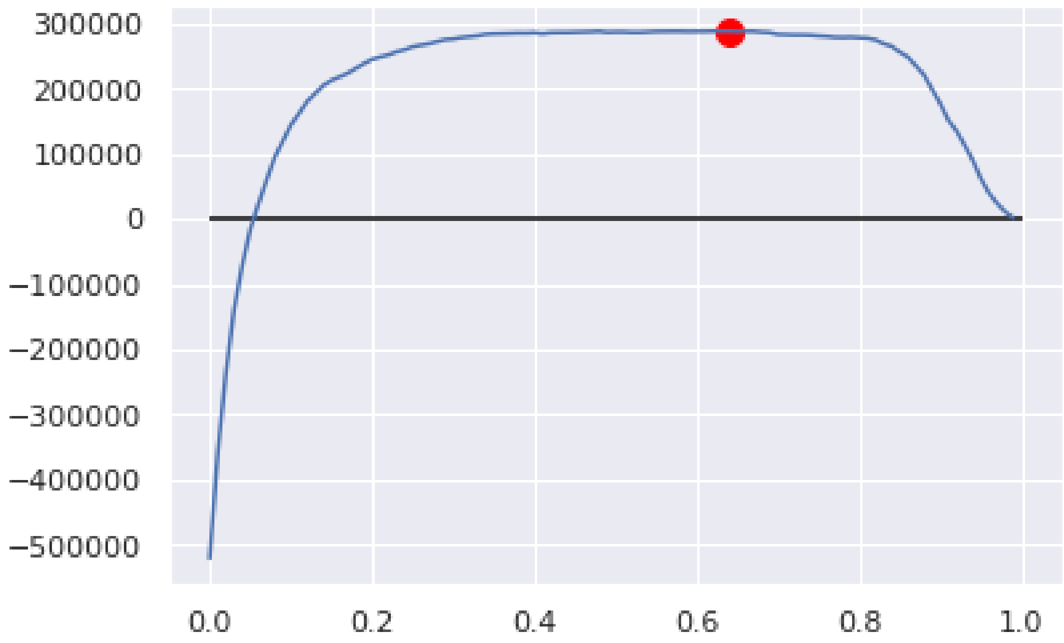
[239]:
```python
# predictions[predictions['predict_prob'] > 0.5]
rev_deltas.value_counts()
```

[239]:
```
281232.328869    1
282484.986240    1
286214.205028    1
284380.791139    1
286905.563591    1
                ..
192619.752634    1
287649.938142    1
284407.333607    1
248578.938632    1
285013.390047    1
Length: 100, dtype: int64
```

[246]:
```python
def plot_tradeoff(rev_deltas):
    rev_deltas.plot()

    # Mark optimal point
    max_pred = rev_deltas.idxmax()
    plt.scatter(max_pred, rev_deltas.loc[max_pred], s= 100, c='red')

    # Reference line for break-even
    plt.hlines(0,0,1, colors='black')
    plt.show()
```

```
print('Maximum benefit at cutoff {} with revenue delta of {:.2f}'.
↪format(max_pred, rev_deltas.loc[max_pred]))
```

[247]:
```
plot_tradeoff(rev_deltas)
```




```
Maximum benefit at cutoff 0.64 with revenue delta of 288264.93
```

5.2 How to select the discount?

In the strategy suggested by the SME division head we offer a 20% discount to all customer targeted. However, this might not be optimal either.

We assumed before that customers offered a discount will not churn. However, that may not be true in reality. The discount may not be large enoughto prevent churn.

In fact, we can predict the churn probability for each customer as a function of price, margin and other factors. Therefore, we can try to find a strategyfor each customer that optimises either their expected revenue or profit.

In order to go further, we'll need to try to:

```
1. Change the level of discount offered overall
2. Predict the response of customers to that discount (ie, the churn probability) based on how
3. Take care that we've applied the discount to all affected variables. To make this easier, we
4. Find the discount level that balances customer retention vs the cost of false positives.
```

In fact, this could be turned into a 2d optimisation problem:

```
Objective: maximise net revenue(including the benefits of true positives and the cost of false
Decision variables:
    Level of discount offered, and
    Fraction of people who are offered a discount
```

[ ]:

```

```