credit_card_prediction

May 30, 2021

0.1 Credit Card Lead Prediction

This notebook will be describing machine learning and data science concepts by exploring the problem of credit card lead **classification**.

Classification involves deciding whether a sample is part of one class or another (single-class classification)

Since we already have a dataset, we'll approach the problem with the following machine learning modelling framework.

0.2 1.Problem Defination

Happy Customer Bank is a mid-sized private bank that deals in all kinds of banking products, like Savings accounts, Current accounts, investment products, credit products, among other offerings. The bank also cross-sells products to its existing customers and to do so they use different kinds of communication like tele-calling, e-mails, recommendations on net banking, mobile banking, etc. In this case, the Happy Customer Bank wants to cross sell its credit cards to its existing customers. The bank has identified a set of customers that are eligible for taking these credit cards.

Now, the bank is looking to identify customers that could show higher intent towards a recommended credit card, given:

1.Customer details (gender, age, region etc.)

2.Details of his/her relationship with the bank (Channel_Code,Vintage, 'Avg_Asset_Value etc.)

0.3 2.Data

The datasets are downloaded from the given problem statement

0.4 3.Evaluation

The evaluation metric is something you might define at the start of a project.The evaluation metric for this competition is roc_auc_score.

0.5 4.Preparing the tools

At the start of any project, it's custom to see the required libraries imported in a big chunk. 1. Pandas for data analysis. 2. NumPy for numerical operations. 3. Matplotlib/seaborn for plotting or data visualization. 4. Scikit-Learn for machine learning modelling and evaluation.

[1]:
```
# Regular EDA and plotting libraries
import numpy as np # np is short for numpy
import pandas as pd # pandas is so commonly used, it's shortened to pd
import matplotlib.pyplot as plt
import seaborn as sns # seaborn gets shortened to sns

# We want our plots to appear in the notebook
%matplotlib inline

## Models
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC

## Model evaluators
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import plot_roc_curve
```

0.6 Load Data

Our data is in csv file

[2]:
```
df = pd.read_csv("train_data.csv") # 'DataFrame' shortened to 'df'
df.shape # (rows, columns)
```

[2]:
```
(245725, 11)
```

0.7 Data Exploration (exploratory data analysis or EDA)

[3]:
```
# Let's check the top 5 rows of our dataframe
df.head()
```

[3]:

	ID	Gender	Age	Region_Code	Occupation	Channel_Code	Vintage	\
0	NNVBBKZB	Female	73	RG268	Other	X3	43	
1	IDD62UNG	Female	30	RG277	Salaried	X1	32	

```
2  HD3DSEMC  Female   56       RG268  Self_Employed          X3       26
3  BF3NC7KV    Male   34       RG270       Salaried          X1       19
4  TEASRWXV  Female   30       RG282       Salaried          X1       33

  Credit_Product  Avg_Account_Balance Is_Active  Is_Lead
0             No              1045696        No        0
1             No               581988        No        0
2             No              1484315       Yes        0
3             No               470454        No        0
4             No               886787        No        0
```

[4]:
```
# And the top 10
df.head(10)
```

[4]:
```
         ID  Gender  Age Region_Code     Occupation Channel_Code  Vintage  \
0  NNVBBKZB  Female   73       RG268          Other           X3       43
1  IDD62UNG  Female   30       RG277       Salaried           X1       32
2  HD3DSEMC  Female   56       RG268  Self_Employed           X3       26
3  BF3NC7KV    Male   34       RG270       Salaried           X1       19
4  TEASRWXV  Female   30       RG282       Salaried           X1       33
5  ACUTYTWS    Male   56       RG261  Self_Employed           X1       32
6  ETQCZFEJ    Male   62       RG282          Other           X3       20
7  JJNJUQMQ  Female   48       RG265  Self_Employed           X3       13
8  ZMQFYKCB  Female   40       RG283  Self_Employed           X2       38
9  NVKTFBA2  Female   55       RG268  Self_Employed           X2       49

  Credit_Product  Avg_Account_Balance Is_Active  Is_Lead
0             No              1045696        No        0
1             No               581988        No        0
2             No              1484315       Yes        0
3             No               470454        No        0
4             No               886787        No        0
5             No               544163       Yes        0
6            NaN              1056750       Yes        1
7             No               444724       Yes        0
8             No              1274284        No        0
9            Yes              2014239        No        0
```

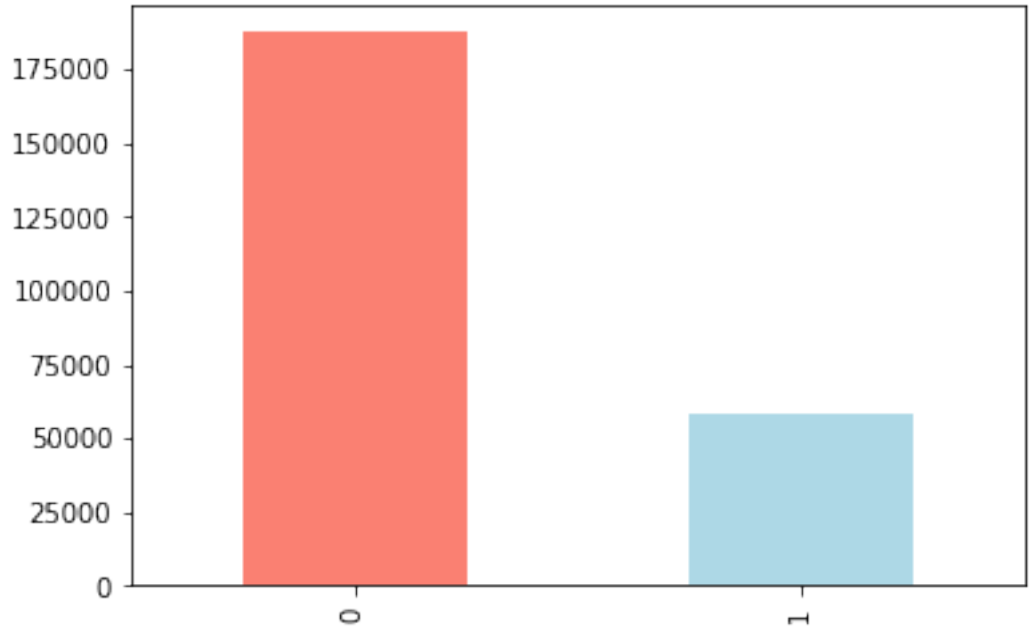
[5]:
```
# Let's see how many positive (1) and negative (0) samples we have in our␣
↪dataframe
df.Is_Lead.value_counts()
```

[5]:
```
0    187437
1     58288
Name: Is_Lead, dtype: int64
```

[6]:
```
# Normalized value counts
df.Is_Lead.value_counts(normalize=True)
```

[6]:
```
0    0.762792
1    0.237208
Name: Is_Lead, dtype: float64
```

[7]:
```
# Plot the value counts with a bar graph
df.Is_Lead.value_counts().plot(kind="bar", color=["salmon", "lightblue"]);
```



[8]:
```
df.info() #df.info() shows a quick insight to the number of missing values you␣
↪have and what type of data your working with.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 245725 entries, 0 to 245724
Data columns (total 11 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   ID                   245725 non-null  object
 1   Gender               245725 non-null  object
 2   Age                  245725 non-null  int64
 3   Region_Code          245725 non-null  object
 4   Occupation           245725 non-null  object
 5   Channel_Code         245725 non-null  object
 6   Vintage              245725 non-null  int64
 7   Credit_Product       216400 non-null  object
```

```
 8   Avg_Account_Balance  245725 non-null  int64
 9   Is_Active            245725 non-null  object
 10  Is_Lead              245725 non-null  int64
dtypes: int64(4), object(7)
memory usage: 20.6+ MB
```

[9]:
```
df.isnull().sum() #Checking For null values
```

[9]:
```
ID                         0
Gender                     0
Age                        0
Region_Code                0
Occupation                 0
Channel_Code               0
Vintage                    0
Credit_Product         29325
Avg_Account_Balance        0
Is_Active                  0
Is_Lead                    0
dtype: int64
```

Here we can find Credit_product has 29325 null values

[10]:
```
df.Gender.value_counts() #Checking no of males and females
```

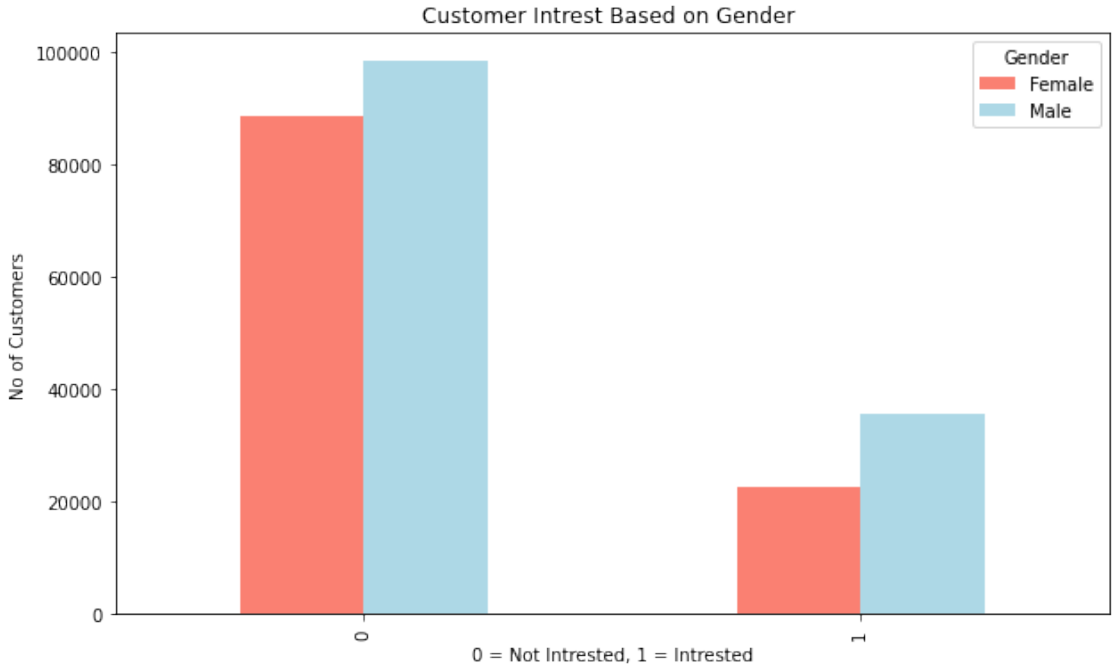
[10]:
```
Male      134197
Female    111528
Name: Gender, dtype: int64
```

[11]:
```
pd.crosstab(df.Is_Lead, df.Gender)
```

[11]:
```
Gender   Female   Male
Is_Lead
0         88823  98614
1         22705  35583
```

[12]:
```
# Create a plot
pd.crosstab(df.Is_Lead, df.Gender).plot(kind="bar",
                                        figsize=(10,6),
                                        color=["salmon", "lightblue"]);
# Add some attributes to it
plt.title("Customer Intrest Based on Gender ")
plt.xlabel("0 = Not Intrested, 1 = Intrested")
plt.ylabel("No of Customers")
```

[12]:
```
Text(0, 0.5, 'No of Customers')
```



[13]:
```
df.Region_Code.value_counts()
```

[13]:
```
RG268    35934
RG283    29416
RG254    26840
RG284    19320
RG277    12826
RG280    12775
RG269     7863
RG270     7720
RG261     7633
RG257     6101
RG251     5950
RG282     5829
RG274     5286
RG272     5252
RG281     5093
RG273     4497
RG252     4286
RG279     3976
RG263     3687
RG275     3245
RG260     3110
RG256     2847
RG264     2793
```

```
RG276     2764
RG259     2586
RG250     2496
RG255     2018
RG258     1951
RG253     1858
RG278     1822
RG262     1788
RG266     1578
RG265     1546
RG271     1542
RG267     1497
Name: Region_Code, dtype: int64
```

[14]:
```
pd.crosstab(df.Is_Lead, df.Region_Code)
```

[14]:
```
Region_Code  RG250  RG251  RG252  RG253  RG254  RG255  RG256  RG257  RG258  \
Is_Lead
0             2103   4569   3694   1377  21127   1549   2446   4931   1521
1              393   1381    592    481   5713    469    401   1170    430

Region_Code  RG259  …  RG275  RG276  RG277  RG278  RG279  RG280  RG281  \
Is_Lead             …
0             2085  …   2702   1996   9851   1422   3079   9766   3979
1              501  …    543    768   2975    400    897   3009   1114

Region_Code  RG282  RG283  RG284
Is_Lead
0             4709  20531  13504
1             1120   8885   5816

[2 rows x 35 columns]
```

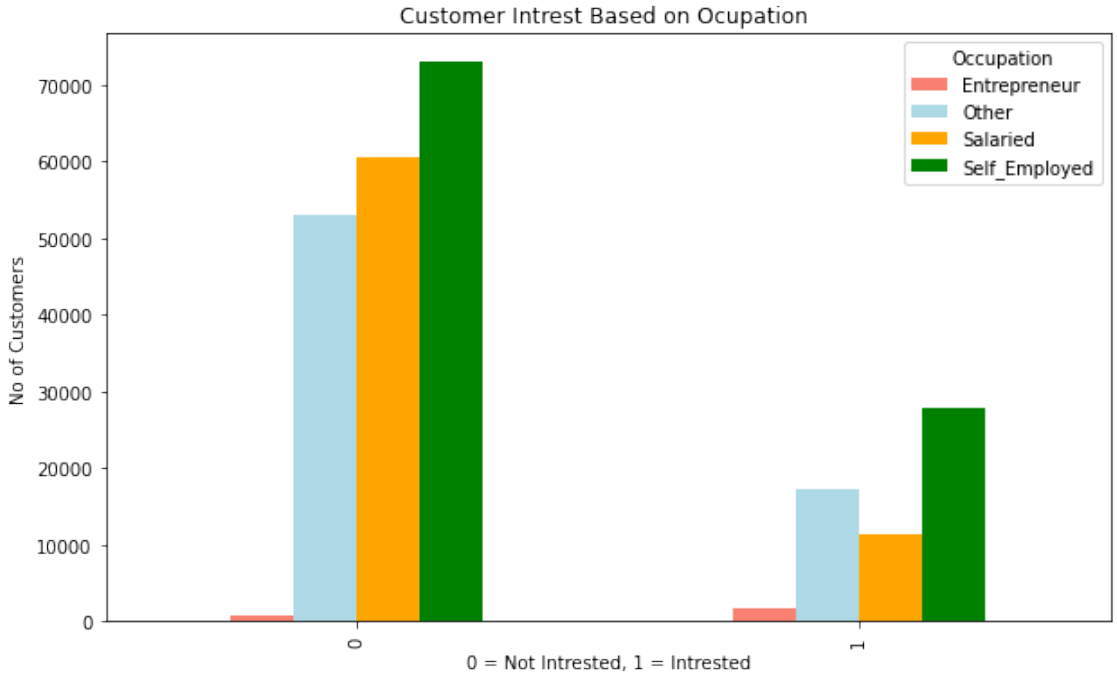
[15]:
```
df.Occupation.value_counts()
```

[15]:
```
Self_Employed    100886
Salaried          71999
Other             70173
Entrepreneur       2667
Name: Occupation, dtype: int64
```

[16]:
```
# Create a plot
pd.crosstab(df.Is_Lead, df.Occupation).plot(kind="bar",
                                    figsize=(10,6),
                                    color=["salmon",␣
 ↪"lightblue","orange","green"]);
# Add some attributes to it
```

```
plt.title("Customer Intrest Based on Ocupation ")
plt.xlabel("0 = Not Intrested, 1 = Intrested")
plt.ylabel("No of Customers")
```

[16]: Text(0, 0.5, 'No of Customers')

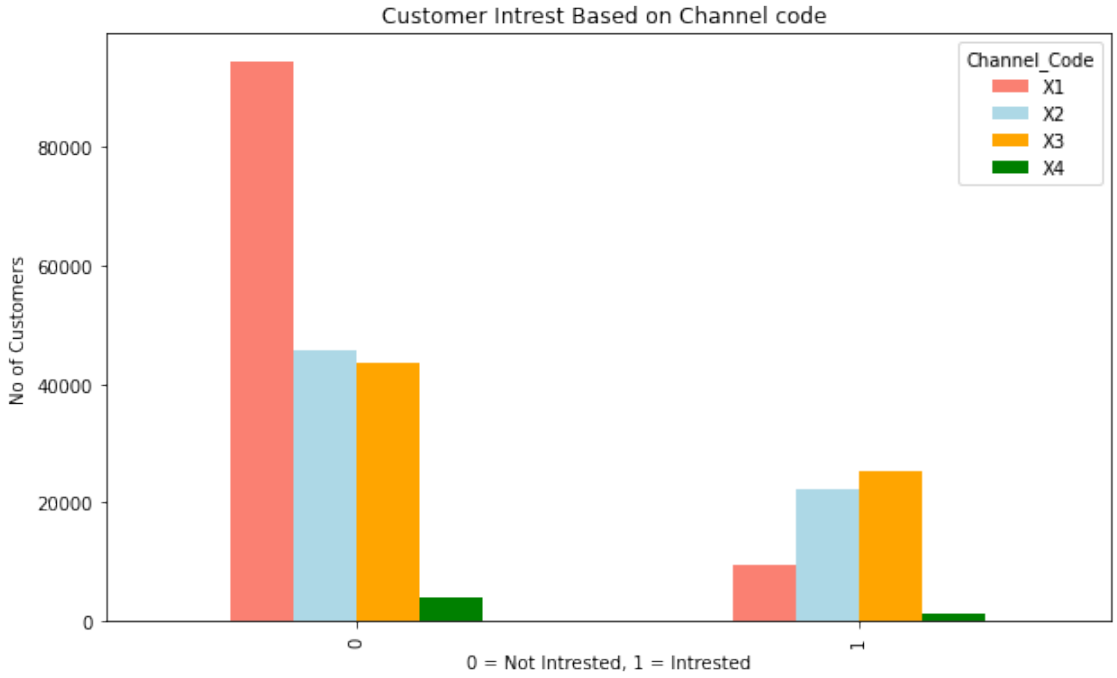


[17]:
```
df.Channel_Code.value_counts()
```

[17]:
```
X1    103718
X3     68712
X2     67726
X4      5569
Name: Channel_Code, dtype: int64
```

[18]:
```
# Create a plot
pd.crosstab(df.Is_Lead, df.Channel_Code).plot(kind="bar",
                                    figsize=(10,6),
                                    color=["salmon",␣
 ↪"lightblue","orange","green"]);
# Add some attributes to it
plt.title("Customer Intrest Based on Channel code ")
plt.xlabel("0 = Not Intrested, 1 = Intrested")
plt.ylabel("No of Customers")
```

[18]: Text(0, 0.5, 'No of Customers')



[19]:
```
df.Vintage.value_counts()
```

[19]:
```
13     12338
21     12277
14     12267
15     12242
19     12212
       …
128      501
129      499
135       19
133       18
134       14
Name: Vintage, Length: 66, dtype: int64
```

[20]:
```
pd.crosstab(df.Is_Lead, df.Vintage)
```

[20]:
```
Vintage   7    8    9     13     14     15     19     20     21     25   … \
Is_Lead                                                                  …
0       501  484  490  10499  10463  10501  10370  10316  10502  9249  …
1       147  135  148   1839   1804   1741   1842   1716   1775  1582  …

Vintage  117  121  122  123  127  128  129  133  134  135
Is_Lead
0        925  670  674  658  329  313  336   15    8   15
```

```
1        507  337  301  354  199  188  163    3    6    4

[2 rows x 66 columns]
```

[21]:
```
df.Credit_Product.value_counts()
```

[21]:
```
No     144357
Yes     72043
Name: Credit_Product, dtype: int64
```

[22]:
```
df.Credit_Product.isnull().sum()
```

[22]:
```
29325
```

[23]:
```
pd.crosstab(df.Is_Lead, df.Is_Active)
```

[23]:
```
Is_Active      No    Yes
Is_Lead
0          119007  68430
1           31283  27005
```

0.8 Splitting the Data into X & y

[24]:
```
# Everything except target variable
X=df.drop(["Is_Lead","ID"],axis=1)

# Target variable
y=df["Is_Lead"]
```

[25]:
```
X.head()
```

[25]:
```
   Gender  Age Region_Code     Occupation Channel_Code  Vintage  \
0  Female   73       RG268          Other           X3       43
1  Female   30       RG277       Salaried           X1       32
2  Female   56       RG268  Self_Employed           X3       26
3    Male   34       RG270       Salaried           X1       19
4  Female   30       RG282       Salaried           X1       33

  Credit_Product  Avg_Account_Balance Is_Active
0             No              1045696        No
1             No               581988        No
2             No              1484315       Yes
3             No               470454        No
4             No               886787        No
```

[26]:
```
X.Credit_Product.isna().sum()
```

[26]:
```
29325
```

[27]:
```
X["Credit_Product"].fillna("missing",inplace=True)
```

[28]:
```
X.Credit_Product.isna().sum()
```

[28]:
```
0
```

[29]:
```
X.head()
```

[29]:

	Gender	Age	Region_Code	Occupation	Channel_Code	Vintage	Credit_Product	Avg_Account_Balance	Is_Active
0	Female	73	RG268	Other	X3	43	No	1045696	No
1	Female	30	RG277	Salaried	X1	32	No	581988	No
2	Female	56	RG268	Self_Employed	X3	26	No	1484315	Yes
3	Male	34	RG270	Salaried	X1	19	No	470454	No
4	Female	30	RG282	Salaried	X1	33	No	886787	No

[30]:
```
#Turning the Catogeries into numbers

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

categorical_features = ["Gender", "Region_Code" ,"Occupation" ,"Channel_Code",␣
 ↪"Credit_Product", "Is_Active"]
one_hot=OneHotEncoder()

transformer=ColumnTransformer([("one_hot",
                                one_hot,categorical_features)],␣
 ↪remainder="passthrough")
transformed_X = transformer.fit_transform(X)
transformed_X.todense()
```

[30]:
```
matrix([[1.000000e+00, 0.000000e+00, 0.000000e+00, …, 7.300000e+01,
         4.300000e+01, 1.045696e+06],
        [1.000000e+00, 0.000000e+00, 0.000000e+00, …, 3.000000e+01,
         3.200000e+01, 5.819880e+05],
        [1.000000e+00, 0.000000e+00, 0.000000e+00, …, 5.600000e+01,
         2.600000e+01, 1.484315e+06],
        …,
        [1.000000e+00, 0.000000e+00, 0.000000e+00, …, 2.600000e+01,
```

```
        1.300000e+01, 6.706590e+05],
       [1.000000e+00, 0.000000e+00, 0.000000e+00, …, 2.800000e+01,
        3.100000e+01, 4.075040e+05],
       [0.000000e+00, 1.000000e+00, 0.000000e+00, …, 2.900000e+01,
        2.100000e+01, 1.129276e+06]])
```

[31]:
```
pd.DataFrame(transformed_X.todense())
```

[31]:

	0	1	2	3	4	5	6	7	8	9	…	43	44	45	\
0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	1.0	0.0	1.0	
1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	0.0	0.0	1.0	
2	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	1.0	0.0	1.0	
3	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	0.0	0.0	1.0	
4	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	0.0	0.0	1.0	
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	
245720	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	1.0	0.0	0.0	
245721	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	0.0	0.0	1.0	
245722	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	0.0	0.0	1.0	
245723	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	0.0	0.0	1.0	
245724	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	…	0.0	0.0	1.0	

	46	47	48	49	50	51	52
0	0.0	0.0	1.0	0.0	73.0	43.0	1045696.0
1	0.0	0.0	1.0	0.0	30.0	32.0	581988.0
2	0.0	0.0	0.0	1.0	56.0	26.0	1484315.0
3	0.0	0.0	1.0	0.0	34.0	19.0	470454.0
4	0.0	0.0	1.0	0.0	30.0	33.0	886787.0
…	…	…	…	…	…	…	…
245720	0.0	1.0	1.0	0.0	51.0	109.0	1925586.0
245721	0.0	0.0	0.0	1.0	27.0	15.0	862952.0
245722	0.0	0.0	1.0	0.0	26.0	13.0	670659.0
245723	0.0	0.0	1.0	0.0	28.0	31.0	407504.0
245724	0.0	0.0	1.0	0.0	29.0	21.0	1129276.0

[245725 rows x 53 columns]

[32]:
```
X_new=pd.get_dummies(X[["Gender","Age","Region_Code" ,"Occupation"␣
↪,"Channel_Code","Vintage","Credit_Product","Avg_Account_Balance",␣
↪"Is_Active"]])
X_new
```

[32]:

	Age	Vintage	Avg_Account_Balance	Gender_Female	Gender_Male	\
0	73	43	1045696	1	0	
1	30	32	581988	1	0	
2	56	26	1484315	1	0	
3	34	19	470454	0	1	
4	30	33	886787	1	0	

```
…      …       …                    …              …            …
245720   51      109              1925586              0            1
245721   27       15               862952              0            1
245722   26       13               670659              1            0
245723   28       31               407504              1            0
245724   29       21              1129276              0            1

        Region_Code_RG250  Region_Code_RG251  Region_Code_RG252  \
0                       0                  0                  0
1                       0                  0                  0
2                       0                  0                  0
3                       0                  0                  0
4                       0                  0                  0
…                     …                  …                  …
245720                  0                  0                  0
245721                  0                  0                  0
245722                  0                  0                  0
245723                  0                  0                  0
245724                  0                  0                  0

        Region_Code_RG253  Region_Code_RG254  …  Occupation_Self_Employed  \
0                       0                  0  …                         0
1                       0                  0  …                         0
2                       0                  0  …                         1
3                       0                  0  …                         0
4                       0                  0  …                         0
…                     …                  …  …                       …
245720                  0                  0  …                         1
245721                  0                  0  …                         0
245722                  0                  0  …                         0
245723                  0                  0  …                         0
245724                  0                  0  …                         0

        Channel_Code_X1  Channel_Code_X2  Channel_Code_X3  Channel_Code_X4  \
0                     0                0                1                0
1                     1                0                0                0
2                     0                0                1                0
3                     1                0                0                0
4                     1                0                0                0
…                   …                …                …              …
245720                0                0                1                0
245721                1                0                0                0
245722                1                0                0                0
245723                1                0                0                0
245724                1                0                0                0

        Credit_Product_No  Credit_Product_Yes  Credit_Product_missing  \
```

```
0                      1                    0                      0
1                      1                    0                      0
2                      1                    0                      0
3                      1                    0                      0
4                      1                    0                      0
…                    …                    …                      …
245720                 0                    0                      1
245721                 1                    0                      0
245722                 1                    0                      0
245723                 1                    0                      0
245724                 1                    0                      0

        Is_Active_No  Is_Active_Yes
0                  1              0
1                  1              0
2                  0              1
3                  1              0
4                  1              0
…                …              …
245720             1              0
245721             0              1
245722             1              0
245723             1              0
245724             1              0

[245725 rows x 53 columns]
```

0.9 Training and test split

we are using training set to train your model and test set to test it.

The test set must remain separate from your training set.

To split our data into a training and test set, we can use Scikit-Learn's train_test_split() and feed it our independent and dependent variables (X & y).

[33]:
```
# Random seed for reproducibility
np.random.seed(42)

# Split into train & test set
X_train, X_test, y_train, y_test = train_test_split(X_new, # independent␣
 ↪variables
                                                    y, # dependent variable
                                                    test_size = 0.3) #␣
 ↪percentage of data to use for test set
```

0.10 Model choices

Now we've got our data prepared, we can start to fit models. We'll be using the following and comparing their results.

1. Logistic Regression - LogisticRegression()
2. K-Nearest Neighbors - KNeighboursClassifier()
3. RandomForest - RandomForestClassifier()

Why these? If we look at the Scikit-Learn algorithm cheat sheet, we can see we're working on a classification problem and these are the algorithms it suggests (plus a few more).

[34]:
```
# Put models in a dictionary
models = {"KNN": KNeighborsClassifier(),
          "Logistic Regression": LogisticRegression(),
          "Random Forest": RandomForestClassifier()}

# Create function to fit and score models
def fit_and_score(models, X_train, X_test, y_train, y_test):
    """
    Fits and evaluates given machine learning models.
    models : a dict of different Scikit-Learn machine learning models
    X_train : training data
    X_test : testing data
    y_train : labels assosciated with training data
    y_test : labels assosciated with test data
    """
    # Random seed for reproducible results
    np.random.seed(42)
    # Make a list to keep model scores
    model_scores = {}
    # Loop through models
    for name, model in models.items():
        # Fit the model to the data
        model.fit(X_train, y_train)
        # Evaluate the model and append its score to model_scores
        model_scores[name] = model.score(X_test, y_test)
    return model_scores
```

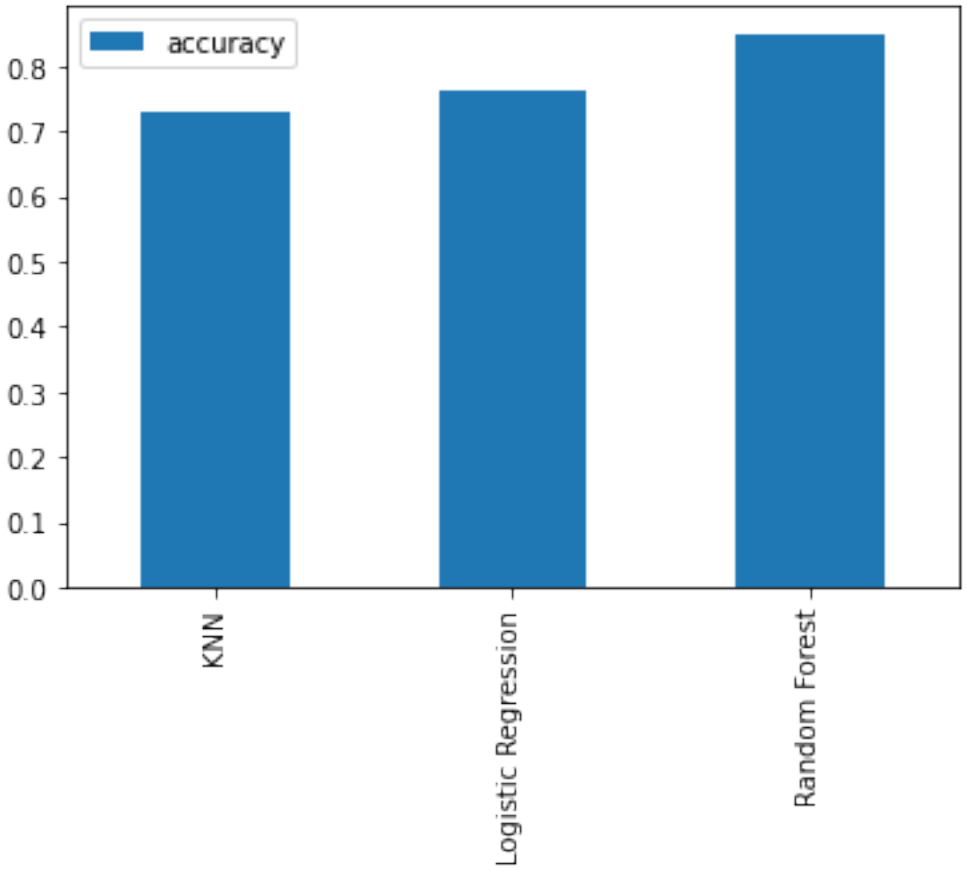
[35]:
```
model_scores = fit_and_score(models=models,
                             X_train=X_train,
                             X_test=X_test,
                             y_train=y_train,
                             y_test=y_test)
model_scores
```

[35]:
```
{'KNN': 0.7291299275617895,
 'Logistic Regression': 0.7631785995279308,
```

```
 'Random Forest': 0.8501044521012507}
```

1 Model Comparision

[36]:
```
model_compare = pd.DataFrame(model_scores, index=['accuracy'])
model_compare.T.plot.bar(); #comparision between 3 models
```



[37]:
```
# Create a list of train scores
train_scores = []

# Create a list of test scores
test_scores = []

# Create a list of different values for n_neighbors
neighbors = range(1, 21) # 1 to 20

# Setup algorithm
```

```
knn = KNeighborsClassifier()

# Loop through different neighbors values
for i in neighbors:
    knn.set_params(n_neighbors = i) # set neighbors value

    # Fit the algorithm
    knn.fit(X_train, y_train)

    # Update the training scores
    train_scores.append(knn.score(X_train, y_train))

    # Update the test scores
    test_scores.append(knn.score(X_test, y_test))
```

2 Hyperparameter Tuning and Corss validation

Tune KNeighborsClassifier (K-Nearest Neighbors or KNN) by hand

There's one main hyperparameter we can tune for the K-Nearest Neighbors (KNN) algorithm, and that is number of neighbours. The default is 5 (n_neigbors=5).

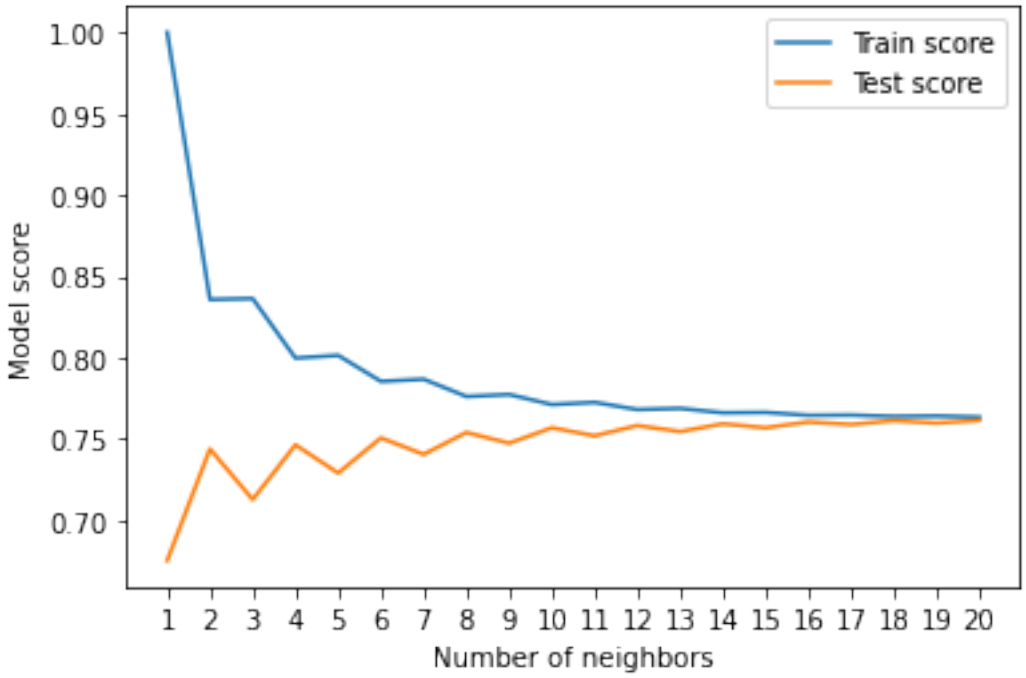
[38]:
```
train_scores
```

[38]:
```
[0.9999941862831164,
 0.8358206352067067,
 0.8363787520275338,
 0.7998046591127105,
 0.8014615684245409,
 0.7854738469945991,
 0.7868168155947142,
 0.776183527414582,
 0.777392780526374,
 0.7712302406297418,
 0.772573209229857,
 0.7681547843983094,
 0.7688582441412268,
 0.7661606795072293,
 0.7663932281825739,
 0.7646200445330713,
 0.7647770148889289,
 0.763945653374572,
 0.7642072706343347,
 0.7635154383251844]
```

[39]:
```
plt.plot(neighbors, train_scores, label="Train score")
plt.plot(neighbors, test_scores, label="Test score")
plt.xticks(np.arange(1, 21, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")
plt.legend()

print(f"Maximum KNN score on the test data: {max(test_scores)*100:.2f}%")
```

```
Maximum KNN score on the test data: 76.16%
```



Looking at the graph, n_neighbors = 20 seems best.

The KNN's model performance got near what LogisticRegression but far from the RandomForest-Classifier did.

Because of this, we'll discard KNN and focus on the other two.

We've tuned KNN by hand but let's see how we can LogisticsRegression and RandomForestClassifier using RandomizedSearchCV.

Instead of us having to manually try different hyperparameters by hand, RandomizedSearchCV tries a number of different combinations, evaluates them and saves the best.

3 Tuning models with with RandomizedSearchCV

Reading the Scikit-Learn documentation for LogisticRegression, we find there's a number of different hyperparameters we can tune.

The same for RandomForestClassifier.

Let's create a hyperparameter grid (a dictionary of different hyperparameters) for each and then test them out.

[40]:
```
# Different LogisticRegression hyperparameters
log_reg_grid = {"C": np.logspace(-4, 4, 20),
                "solver": ["liblinear"]}

# Different RandomForestClassifier hyperparameters
rf_grid = {"max_depth": [None, 3, 5, 10],
           "min_samples_split": np.arange(2, 20, 2),
           "min_samples_leaf": np.arange(1, 20, 2)}
```

Now let's use RandomizedSearchCV to try and tune our LogisticRegression model.

We'll pass it the different hyperparameters from log_reg_grid as well as set n_iter = 20. This means, RandomizedSearchCV will try 20 different combinations of hyperparameters from log_reg_grid and save the best ones.

[41]:
```
# Setup random seed
np.random.seed(42)

# Setup random hyperparameter search for LogisticRegression
rs_log_reg = RandomizedSearchCV(LogisticRegression(),
                                param_distributions=log_reg_grid,
                                cv=5,
                                n_iter=20,
                                verbose=True)

# Fit random hyperparameter search model
rs_log_reg.fit(X_train, y_train);
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:   36.9s finished
```

[42]:
```
rs_log_reg.best_params_
```

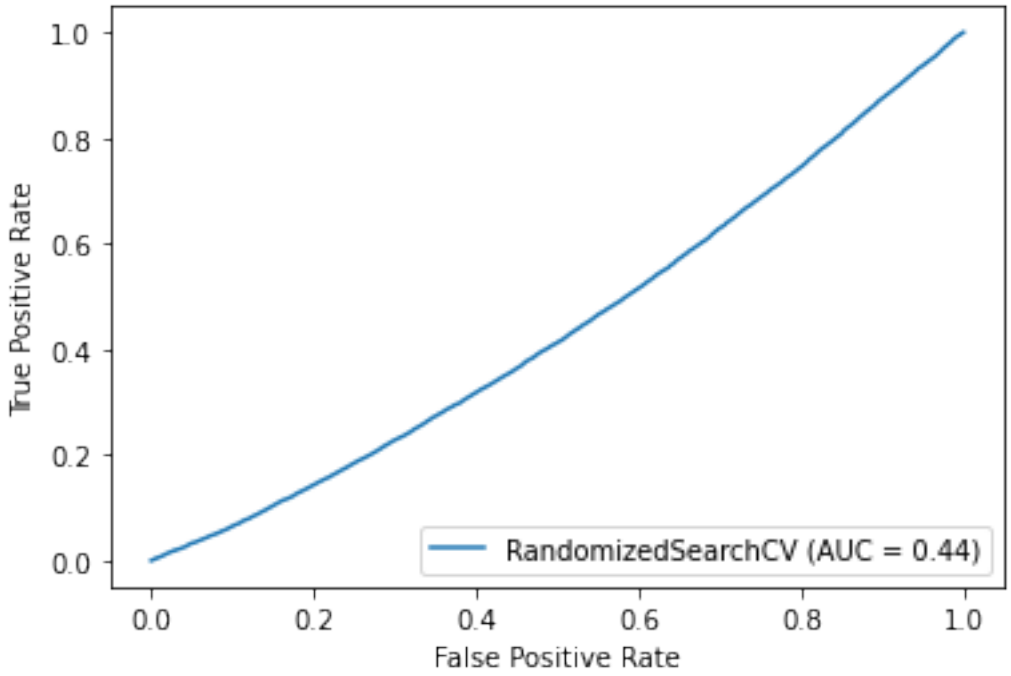
[42]:
```
{'solver': 'liblinear', 'C': 0.0001}
```

[43]:
```
rs_log_reg.score(X_test, y_test)
```

[43]:
```
0.7631785995279308
```

[44]:
```
# Import ROC curve function from metrics module
from sklearn.metrics import plot_roc_curve

# Plot ROC curve and calculate AUC metric
plot_roc_curve(rs_log_reg, X_test, y_test);
```



Now we've tuned LogisticRegression using RandomizedSearchCV, we'll do the same for RandomForestClassifier.

[45]:
```
#setup Random seed
rf_grid2= {"n_estimators": np.arange(10,100,50),
      "max_depth": [None,3,5,10],
      "min_samples_split": np.arange(2,20,2),
      "min_samples_leaf" : np.arange(1,20,2)
}

# Setup random seed
np.random.seed(42)

# Setup random hyperparameter search for RandomForestClassifier
rs_rf = RandomizedSearchCV(RandomForestClassifier(),
                           param_distributions=rf_grid2,
                           cv=5,
                           n_iter=20,
                           verbose=True)
```

```
# Fit random hyperparameter search model
rs_rf.fit(X_train, y_train);
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  6.6min finished
```

[46]:
```
rs_rf.best_params_
```

[46]:
```
{'n_estimators': 60,
 'min_samples_split': 2,
 'min_samples_leaf': 17,
 'max_depth': None}
```

[47]:
```
rs_rf.score(X_test,y_test)
```

[47]:
```
0.8592067066388128
```

Tuning the hyperparameters for each model saw a slight performance boost in both the RandomForestClassifier and LogisticRegression.

So comparing all models we can justify Random Forest Classifier as better model to approach. Lets fit the model using best params

[48]:
```
from sklearn.model_selection import cross_val_score #fitting the model using␣
 ↪best parms
clf = RandomForestClassifier(n_estimators= 60,
                             min_samples_split=2,
                             min_samples_leaf=17,
                             max_depth= None)
```

[49]:
```
clf.fit(X_train,y_train)
```

[49]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=17, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=60,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

[50]:
```
clf.score(X_test,y_test)
```

[50]:
```
0.8596950541251798
```

[51]:
```
# Cross-validated accuracy score
cv_acc = cross_val_score(clf,
                         X_new,
                         y,
                         cv=5, # 5-fold cross-validation
                         scoring="accuracy") # accuracy as scoring
cv_acc
```

[51]:
```
array([0.85976193, 0.85988402, 0.85951775, 0.85961949, 0.86169498])
```

[52]:
```
cv_acc=np.mean(cv_acc)
cv_acc
```

[52]:
```
0.8600956353647371
```

ROC Curve and AUC Scores What's a ROC curve?

It's a way of understanding how your model is performing by comparing the true positive rate to the false positive rate.

Scikit-Learn implements a function plot_roc_curve which can help us create a ROC curve as well as calculate the area under the curve (AUC) metric.

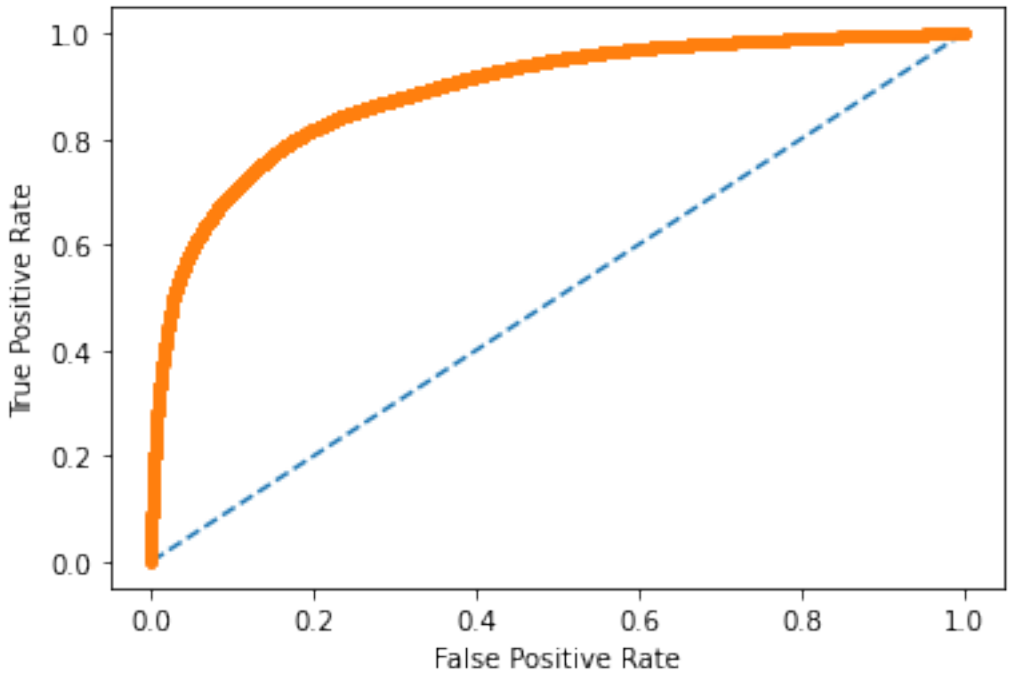
Reading the documentation on the plot_roc_curve function we can see it takes (estimator, X, y) as inputs. Where estiamator is a fitted machine learning model and X and y are the data you'd like to test it on.

[53]:
```
#Preparing ROC Curve (Receiver Operating Characteristics Curve)
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

# predict probabilities
probs = clf.predict_proba(X_new)
# keep probabilities for the positive outcome only
probs = probs[:, 1]
# calculate AUC
auc = roc_auc_score(y, probs)
print('AUC: %.3f' % auc)
# calculate roc curve
fpr, tpr, thresholds = roc_curve(y, probs)
print("True Positive Rate - {}, False Positive Rate - {} Thresholds - {}".
 ↪format(tpr,fpr,thresholds))
# plot no skill
plt.plot([0, 1], [0, 1], linestyle='--')
# plot the roc curve for the model
plt.plot(fpr, tpr, marker='.')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
```

```
AUC: 0.891
True Positive Rate - [0.0000000e+00 1.7156190e-05 1.3724952e-04 …
1.0000000e+00 1.0000000e+00
 1.0000000e+00], False Positive Rate - [0.         0.         0.         …
0.9998933  0.99990397 1.        ] Thresholds - [1.98697774 0.98697774 0.98445372
… 0.00606426 0.00604988 0.00395012]
```

[53]:
```
Text(0, 0.5, 'True Positive Rate')
```



[56]:
```
y_preds = clf.predict(X_test)
y_preds
```

[56]:
```
array([0, 0, 0, …, 0, 0, 0])
```

Confusion matrix A confusion matrix is a visual way to show where your model made the right predictions and where it made the wrong predictions (or in other words, got confused).

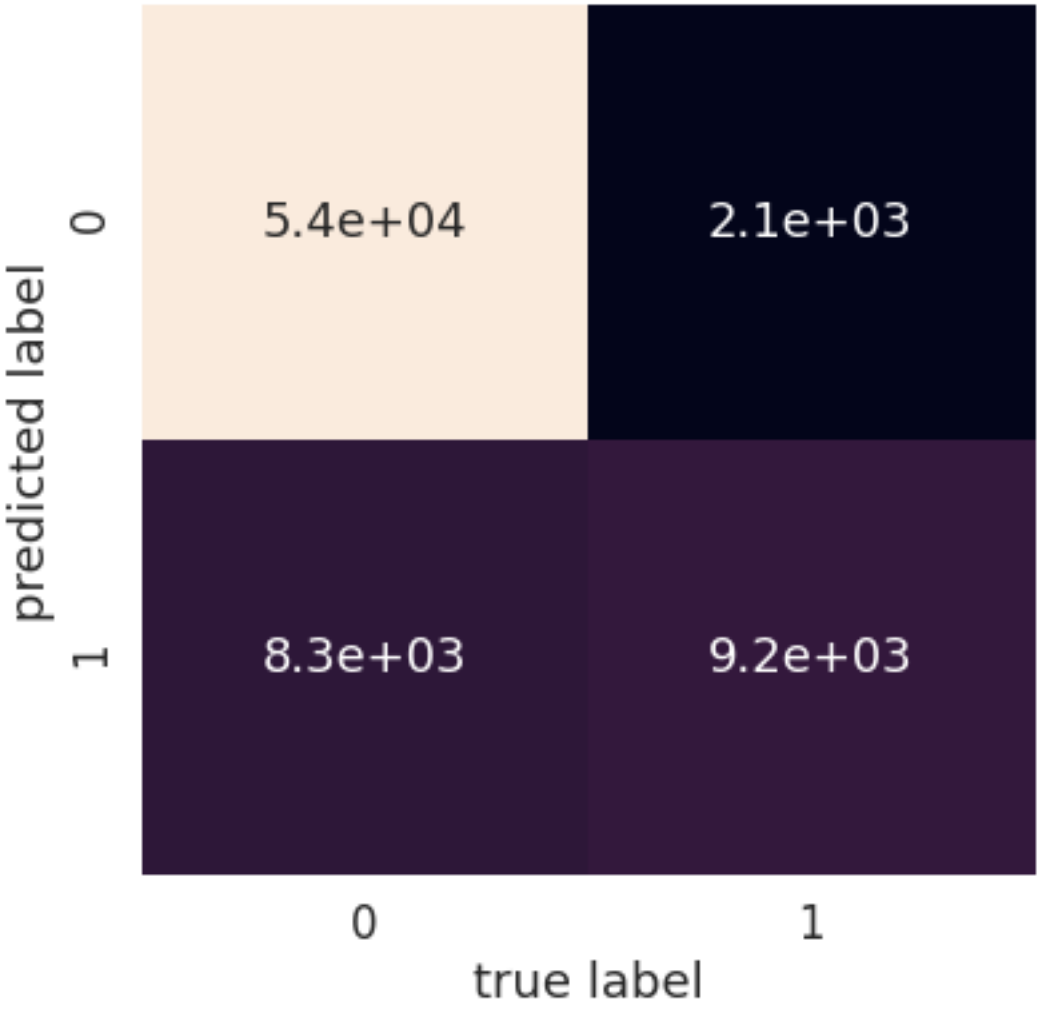
Scikit-Learn allows us to create a confusion matrix using confusion_matrix() and passing it the true labels and predicted labels.

[58]:
```
# Import Seaborn
import seaborn as sns
sns.set(font_scale=1.5) # Increase font size

def plot_conf_mat(y_test, y_preds):
    """
```

```
    Plots a confusion matrix using Seaborn's heatmap().
    """
    fig, ax = plt.subplots(figsize=(6, 6))
    ax = sns.heatmap(confusion_matrix(y_test,y_preds),
                     annot=True, # Annotate the boxes
                     cbar=False)
    plt.xlabel("true label")
    plt.ylabel("predicted label")

plot_conf_mat(y_test, y_preds)
```



3.1 Classification report

We can make a classification report using classification_report() and passing it the true labels as well as our models predicted labels.

A classification report will also give us information of the precision and recall of our model for each class.

[59]:
```
# Show classification report
print(classification_report(y_test, y_preds))
```

```
              precision    recall  f1-score   support

           0       0.87      0.96      0.91     56260
           1       0.82      0.53      0.64     17458

    accuracy                           0.86     73718
   macro avg       0.84      0.74      0.78     73718
weighted avg       0.86      0.86      0.85     73718
```

3.2 Feature importance

Feature importance is another way of asking, "which features contributing most to the outcomes of the model?"

[60]:
```
clf.feature_importances_
```

[60]:
```
array([6.23842833e-02, 9.69156923e-02, 1.99905405e-02, 1.94952044e-03,
       2.60420778e-03, 1.60000044e-04, 4.35412558e-04, 2.29336905e-04,
       1.58770407e-04, 1.09046759e-03, 1.06313298e-04, 1.32975097e-04,
       3.18072525e-04, 1.05209649e-04, 1.41152355e-04, 1.45171311e-04,
       4.13480244e-04, 1.20096781e-04, 3.02932282e-04, 1.53992750e-04,
       6.59192704e-05, 6.40743132e-05, 8.15713184e-05, 2.13200287e-03,
       5.03432249e-04, 3.04281933e-04, 8.07794125e-05, 3.30312826e-04,
       2.71505908e-04, 2.54619241e-04, 1.81879631e-04, 1.85522640e-04,
       7.72597711e-04, 9.76323881e-05, 2.27269477e-04, 6.39799918e-04,
       3.12519138e-04, 2.75688041e-04, 1.93465326e-03, 1.09440403e-03,
       4.90690697e-03, 8.22354732e-03, 3.04644849e-02, 7.05833779e-03,
       5.35566465e-02, 1.32875368e-02, 1.81271547e-02, 9.23194857e-04,
       2.30110993e-01, 6.95904966e-02, 3.45884240e-01, 1.03926480e-02,
       9.80571887e-03])
```

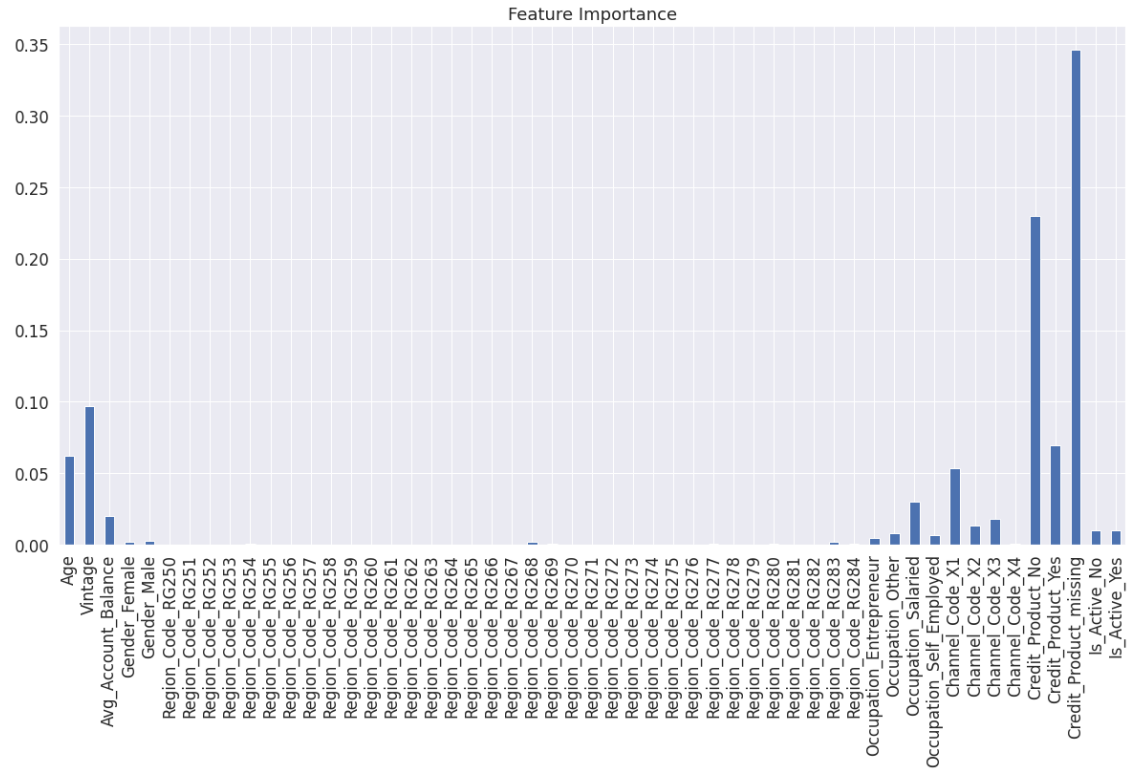
[68]:
```
features_dict = dict(zip(X_train.columns, list(clf.feature_importances_)))
features_dict
```

[68]:
```
{'Age': 0.06238428333804352,
 'Vintage': 0.09691569228297822,
```

```
'Avg_Account_Balance': 0.019990540519454297,
'Gender_Female': 0.0019495204432708566,
'Gender_Male': 0.0026042077826079484,
'Region_Code_RG250': 0.00016000004424896312,
'Region_Code_RG251': 0.0004354125579584707 5,
'Region_Code_RG252': 0.00022933690500046206,
'Region_Code_RG253': 0.00015877040672977958,
'Region_Code_RG254': 0.001090467593217863,
'Region_Code_RG255': 0.00010631329828161421,
'Region_Code_RG256': 0.00013297509652038635,
'Region_Code_RG257': 0.0003180725252329219,
'Region_Code_RG258': 0.0001052096491762464,
'Region_Code_RG259': 0.0001411523549286317,
'Region_Code_RG260': 0.00014517131090513154,
'Region_Code_RG261': 0.0004134802440265878 7,
'Region_Code_RG262': 0.00012009678070155737,
'Region_Code_RG263': 0.00030293228166830316,
'Region_Code_RG264': 0.00015399275031335193,
'Region_Code_RG265': 6.591927039676055e-05,
'Region_Code_RG266': 6.407431321947954e-05,
'Region_Code_RG267': 8.157131836074468e-05,
'Region_Code_RG268': 0.0021320028684282235,
'Region_Code_RG269': 0.0005034322493484745,
'Region_Code_RG270': 0.00030428193348051955,
'Region_Code_RG271': 8.07794125025594e-05,
'Region_Code_RG272': 0.00033031282570518427,
'Region_Code_RG273': 0.000271505908279267,
'Region_Code_RG274': 0.00025461924080288017,
'Region_Code_RG275': 0.00018187963131147803,
'Region_Code_RG276': 0.0001855226403521368,
'Region_Code_RG277': 0.0007725977108259159,
'Region_Code_RG278': 9.763238807064385e-05,
'Region_Code_RG279': 0.0002272694773511899,
'Region_Code_RG280': 0.0006397999180540622,
'Region_Code_RG281': 0.0003125191377506675,
'Region_Code_RG282': 0.00027568804089120737,
'Region_Code_RG283': 0.0019346532587655382,
'Region_Code_RG284': 0.001094404032051394,
'Occupation_Entrepreneur': 0.004906906970298178,
'Occupation_Other': 0.008223547316535077,
'Occupation_Salaried': 0.030464484890113556,
'Occupation_Self_Employed': 0.007058337785676835,
'Channel_Code_X1': 0.05355664652180969,
'Channel_Code_X2': 0.013287536774712332,
'Channel_Code_X3': 0.018127154683771282,
'Channel_Code_X4': 0.0009231948567090174,
'Credit_Product_No': 0.23011099274125538,
```

```
 'Credit_Product_Yes': 0.06959049655658173,
 'Credit_Product_missing': 0.34588424032709536,
 'Is_Active_No': 0.01039264796387301,
 'Is_Active_Yes': 0.009805718870355251}
```

[78]:
```
features_df = pd.DataFrame(features_dict, index=[0])
features_df.T.plot.bar(title="Feature Importance", legend=False,figsize=(20,␣
↪10));
```



[ ]:
```

```

As we have done with modelling the data lets predict it with our test set

[79]:
```
#Preprocessing data

def preprocess_data(XX):


    XX["Credit_Product"].fillna("missing",inplace=True)

    from sklearn.preprocessing import OneHotEncoder
    from sklearn.compose import ColumnTransformer
```

```
    categorical_features = ["Gender", "Region_Code" ,"Occupation"␣
↪,"Channel_Code", "Credit_Product", "Is_Active"]
    one_hot=OneHotEncoder()

    transformer=ColumnTransformer([("one_hot",
                                    one_hot,categorical_features)],␣
↪remainder="passthrough")
    transformed_X = transformer.fit_transform(XX)
    transformed_X.todense()

    pd.DataFrame(transformed_X.todense())

    X_new=pd.get_dummies(XX[["Gender","Age","Region_Code" ,"Occupation"␣
↪,"Channel_Code","Vintage","Credit_Product","Avg_Account_Balance",␣
↪"Is_Active"]])
    X_new

    return X_new
```

[80]:
```
df_test = pd.read_csv("test_data.csv") # 'DataFrame' shortened to 'df'
df_test.shape # (rows, columns)
```

[80]:
```
(105312, 10)
```

[81]:
```
df_test.isnull().sum() #check for null values
```

[81]:
```
ID                         0
Gender                     0
Age                        0
Region_Code                0
Occupation                 0
Channel_Code               0
Vintage                    0
Credit_Product         12522
Avg_Account_Balance        0
Is_Active                  0
dtype: int64
```

[ ]:
```
df_test.head()
```

[95]:
```
df_test1=df_test.drop("ID",axis=1)
df_test1 #Dropping the test data column
```

[95]:
```
        Gender  Age Region_Code Occupation Channel_Code  Vintage  \
0         Male   29       RG254      Other           X1       25
1         Male   43       RG268      Other           X2       49
2         Male   31       RG270   Salaried           X1       14
3         Male   29       RG272      Other           X1       33
4       Female   29       RG270      Other           X1       19
…         …  …         …         …          …      …
105307    Male   52       RG268   Salaried           X2       86
105308    Male   55       RG277      Other           X2       86
105309    Male   35       RG254   Salaried           X4       15
105310    Male   53       RG254      Other           X3       93
105311    Male   27       RG256   Salaried           X1       21

       Credit_Product  Avg_Account_Balance Is_Active
0                 Yes               742366        No
1                 NaN               925537        No
2                  No               215949        No
3                  No               868070        No
4                  No               657087        No
…                 …                 …       …
105307            Yes              4242558       Yes
105308            Yes              1159153        No
105309             No              1703727        No
105310             No               737178       Yes
105311             No               591565        No

[105312 rows x 9 columns]
```

[96]:
```
#Preprocessing Data

df_test_processed=preprocess_data(df_test1)
df_test_processed #Preprocessing the data
```

[96]:
```
        Age  Vintage  Avg_Account_Balance  Gender_Female  Gender_Male  \
0        29       25               742366              0            1
1        43       49               925537              0            1
2        31       14               215949              0            1
3        29       33               868070              0            1
4        29       19               657087              1            0
…     …       …                 …             …          …
105307   52       86              4242558              0            1
105308   55       86              1159153              0            1
105309   35       15              1703727              0            1
105310   53       93               737178              0            1
105311   27       21               591565              0            1

        Region_Code_RG250  Region_Code_RG251  Region_Code_RG252  \
```

```
0                      0                  0                  0
1                      0                  0                  0
2                      0                  0                  0
3                      0                  0                  0
4                      0                  0                  0
…                    …                  …                  …
105307                 0                  0                  0
105308                 0                  0                  0
105309                 0                  0                  0
105310                 0                  0                  0
105311                 0                  0                  0

        Region_Code_RG253  Region_Code_RG254  …  Occupation_Self_Employed  \
0                       0                  1  …                         0
1                       0                  0  …                         0
2                       0                  0  …                         0
3                       0                  0  …                         0
4                       0                  0  …                         0
…                     …                  …  …                       …
105307                  0                  0  …                         0
105308                  0                  0  …                         0
105309                  0                  1  …                         0
105310                  0                  1  …                         0
105311                  0                  0  …                         0

        Channel_Code_X1  Channel_Code_X2  Channel_Code_X3  Channel_Code_X4  \
0                     1                 0                0                0
1                     0                 1                0                0
2                     1                 0                0                0
3                     1                 0                0                0
4                     1                 0                0                0
…                   …                 …                …              …
105307                0                 1                0                0
105308                0                 1                0                0
105309                0                 0                0                1
105310                0                 0                1                0
105311                1                 0                0                0

        Credit_Product_No  Credit_Product_Yes  Credit_Product_missing  \
0                       0                   1                       0
1                       0                   0                       1
2                       1                   0                       0
3                       1                   0                       0
4                       1                   0                       0
…                     …                   …                     …
105307                  0                   1                       0
105308                  0                   1                       0
```

```
105309                  1                   0                       0
105310                  1                   0                       0
105311                  1                   0                       0

        Is_Active_No  Is_Active_Yes
0                  1              0
1                  1              0
2                  1              0
3                  1              0
4                  1              0
…                  …              …
105307             0              1
105308             1              0
105309             1              0
105310             0              1
105311             1              0

[105312 rows x 53 columns]
```

[97]:
```
X_train.head()
```

[97]:
```
        Age  Vintage  Avg_Account_Balance  Gender_Female  Gender_Male  \
138403   30       20              1726840              1            0
117015   55       37               303187              1            0
322      33       13               886813              1            0
64910    48       92              1227416              1            0
39919    31       19               717553              1            0

        Region_Code_RG250  Region_Code_RG251  Region_Code_RG252  \
138403                  0                  0                  0
117015                  0                  0                  0
322                     0                  0                  0
64910                   0                  0                  0
39919                   0                  0                  0

        Region_Code_RG253  Region_Code_RG254  …  Occupation_Self_Employed  \
138403                  0                  0  …                         0
117015                  0                  0  …                         1
322                     0                  0  …                         0
64910                   0                  0  …                         1
39919                   0                  0  …                         0

        Channel_Code_X1  Channel_Code_X2  Channel_Code_X3  Channel_Code_X4  \
138403                0                0                1                0
117015                1                0                0                0
322                   1                0                0                0
64910                 0                0                1                0
```

```
39919                 1                0                0                0

        Credit_Product_No  Credit_Product_Yes  Credit_Product_missing  \
138403                  1                   0                       0
117015                  1                   0                       0
322                     1                   0                       0
64910                   0                   1                       0
39919                   1                   0                       0

        Is_Active_No  Is_Active_Yes
138403             1              0
117015             1              0
322                1              0
64910              0              1
39919              1              0

[5 rows x 53 columns]
```

[98]:
```
df_test_processed.head()
```

[98]:
```
    Age  Vintage  Avg_Account_Balance  Gender_Female  Gender_Male  \
0    29       25               742366              0            1
1    43       49               925537              0            1
2    31       14               215949              0            1
3    29       33               868070              0            1
4    29       19               657087              1            0

   Region_Code_RG250  Region_Code_RG251  Region_Code_RG252  Region_Code_RG253  \
0                  0                  0                  0                  0
1                  0                  0                  0                  0
2                  0                  0                  0                  0
3                  0                  0                  0                  0
4                  0                  0                  0                  0

   Region_Code_RG254  …  Occupation_Self_Employed  Channel_Code_X1  \
0                  1  …                         0                1
1                  0  …                         0                0
2                  0  …                         0                1
3                  0  …                         0                1
4                  0  …                         0                1

   Channel_Code_X2  Channel_Code_X3  Channel_Code_X4  Credit_Product_No  \
0                0                0                0                  0
1                1                0                0                  0
2                0                0                0                  1
3                0                0                0                  1
4                0                0                0                  1
```

```
   Credit_Product_Yes  Credit_Product_missing  Is_Active_No  Is_Active_Yes
0                   1                       0             1              0
1                   0                       1             1              0
2                   0                       0             1              0
3                   0                       0             1              0
4                   0                       0             1              0

[5 rows x 53 columns]
```

[99]:
```
X_train.columns
```

[99]:
```
Index(['Age', 'Vintage', 'Avg_Account_Balance', 'Gender_Female', 'Gender_Male',
       'Region_Code_RG250', 'Region_Code_RG251', 'Region_Code_RG252',
       'Region_Code_RG253', 'Region_Code_RG254', 'Region_Code_RG255',
       'Region_Code_RG256', 'Region_Code_RG257', 'Region_Code_RG258',
       'Region_Code_RG259', 'Region_Code_RG260', 'Region_Code_RG261',
       'Region_Code_RG262', 'Region_Code_RG263', 'Region_Code_RG264',
       'Region_Code_RG265', 'Region_Code_RG266', 'Region_Code_RG267',
       'Region_Code_RG268', 'Region_Code_RG269', 'Region_Code_RG270',
       'Region_Code_RG271', 'Region_Code_RG272', 'Region_Code_RG273',
       'Region_Code_RG274', 'Region_Code_RG275', 'Region_Code_RG276',
       'Region_Code_RG277', 'Region_Code_RG278', 'Region_Code_RG279',
       'Region_Code_RG280', 'Region_Code_RG281', 'Region_Code_RG282',
       'Region_Code_RG283', 'Region_Code_RG284', 'Occupation_Entrepreneur',
       'Occupation_Other', 'Occupation_Salaried', 'Occupation_Self_Employed',
       'Channel_Code_X1', 'Channel_Code_X2', 'Channel_Code_X3',
       'Channel_Code_X4', 'Credit_Product_No', 'Credit_Product_Yes',
       'Credit_Product_missing', 'Is_Active_No', 'Is_Active_Yes'],
      dtype='object')
```

[100]:
```
df_test_processed.columns
```

[100]:
```
Index(['Age', 'Vintage', 'Avg_Account_Balance', 'Gender_Female', 'Gender_Male',
       'Region_Code_RG250', 'Region_Code_RG251', 'Region_Code_RG252',
       'Region_Code_RG253', 'Region_Code_RG254', 'Region_Code_RG255',
       'Region_Code_RG256', 'Region_Code_RG257', 'Region_Code_RG258',
       'Region_Code_RG259', 'Region_Code_RG260', 'Region_Code_RG261',
       'Region_Code_RG262', 'Region_Code_RG263', 'Region_Code_RG264',
       'Region_Code_RG265', 'Region_Code_RG266', 'Region_Code_RG267',
       'Region_Code_RG268', 'Region_Code_RG269', 'Region_Code_RG270',
       'Region_Code_RG271', 'Region_Code_RG272', 'Region_Code_RG273',
       'Region_Code_RG274', 'Region_Code_RG275', 'Region_Code_RG276',
       'Region_Code_RG277', 'Region_Code_RG278', 'Region_Code_RG279',
       'Region_Code_RG280', 'Region_Code_RG281', 'Region_Code_RG282',
       'Region_Code_RG283', 'Region_Code_RG284', 'Occupation_Entrepreneur',
       'Occupation_Other', 'Occupation_Salaried', 'Occupation_Self_Employed',
```

```
       'Channel_Code_X1', 'Channel_Code_X2', 'Channel_Code_X3',
       'Channel_Code_X4', 'Credit_Product_No', 'Credit_Product_Yes',
       'Credit_Product_missing', 'Is_Active_No', 'Is_Active_Yes'],
      dtype='object')
```

[101]:
```
test_preds = rs_rf.predict(df_test_processed)
test_preds #test set prediction
```

[101]:
```
array([0, 1, 0, …, 0, 0, 0])
```

[102]:
```
test_preds.shape
```

[102]:
```
(105312,)
```

[103]:
```
df_test.shape
```

[103]:
```
(105312, 10)
```

[105]:
```
df_preds=pd.DataFrame()  # making a data frame
df_preds["ID"]=df_test["ID"]
df_preds["Is_Lead"]=test_preds
df_preds
```

[105]:
```
              ID  Is_Lead
0       VBENBARO        0
1       CCMEWNKY        1
2       VK3KGA9M        0
3       TT8RPZVC        0
4       SHQZEYTZ        0
…          …      …
105307  DBENJOYI        1
105308  CWQ72DWS        1
105309  HDESC8GU        0
105310  2PW4SFCA        0
105311  F2NOYPPZ        0

[105312 rows x 2 columns]
```

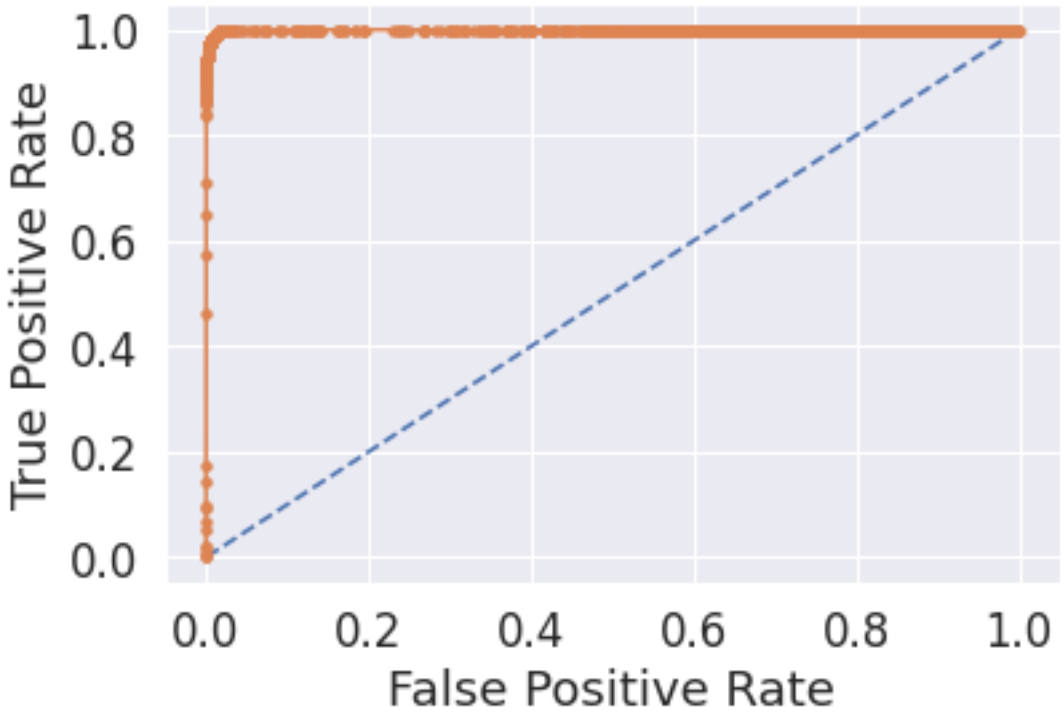
[106]:
```
#Preparing ROC Curve (Receiver Operating Characteristics Curve)
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

# predict probabilities
probs = clf.predict_proba(df_test_processed)
# keep probabilities for the positive outcome only
probs = probs[:, 1]
# calculate AUC
```

```
auc = roc_auc_score(test_preds, probs)
print('AUC: %.3f' % auc)
# calculate roc curve
fpr, tpr, thresholds = roc_curve(test_preds, probs)
print("True Positive Rate - {}, False Positive Rate - {} Thresholds - {}".
 ↪format(tpr,fpr,thresholds))
# plot no skill
plt.plot([0, 1], [0, 1], linestyle='--')
# plot the roc curve for the model
plt.plot(fpr, tpr, marker='.')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
```

```
AUC: 1.000
True Positive Rate - [0.00000000e+00 6.23596907e-05 3.36742330e-03 …
1.00000000e+00
 1.00000000e+00 1.00000000e+00], False Positive Rate - [0.         0.         0.
… 0.99896949 0.99899189 1.        ] Thresholds - [1.98735397 0.98735397
0.9774819  … 0.00840795 0.00839879 0.00453696]
```

[106]: `Text(0, 0.5, 'True Positive Rate')`



[107]:
```
#Exporting Prediction Data
df_preds.to_csv("test_predictions.csv",index=False)
```

[ ]:
```

```