01_predictive_modelling_1

October 12, 2021

1 Wells Fargo Challenge

- https://www.mindsumo.com/contests/campus-analytics-challenge-2021

1.0.1 To Complete a Submission:

Build a classification model for predicting elder fraud in the digital payments space as described in Rule 4, which:

- Handles missing variables
- Maximizes the F1 score
- Uses the given data set
- Includes suitable encoding schemes
- Has the least set of feature variables

1.0.2 Resources

- https://github.com/pdglenn/WellsFargoAnalyticsChallenge

[1]:
```
import pandas as pd
import numpy as np
import pylab as plt
import seaborn as sns

data_dir = "./dataset/"

# following few lines are to supress the pandas warnings
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=UserWarning)

pd.options.mode.chained_assignment = None
pd.options.display.max_columns = 20
np.set_printoptions(suppress=True)

data_dir = "./dataset/"
image_dir = "./images/"
```

1.1 Loading the data

Note `pd.read_excel` gave me an errow while reading the `xlsx` file so had to install `openpyxl` using `pip3 install openpyxl` and give `engine=openpyxl` as an extra arguement.

[2]:
```
#!pip3 install openpyxl
```

[3]:
```
# load the file
df_orig = pd.read_excel(data_dir+"trainset.xlsx", engine='openpyxl')
df_orig.head(2)
```

[3]:
```
   TRAN_AMT  ACCT_PRE_TRAN_AVAIL_BAL  CUST_AGE  OPEN_ACCT_CT  WF_dvc_age  \
0      5.38                 23619.91        47             4        2777
1     65.19                     0.00        45             5        2721

         PWD_UPDT_TS                 CARR_NAME   RGN_NAME STATE_PRVNC_TXT  \
0  1/16/2018 11:3:58  cox communications inc.  southwest          nevada
1                NaN    charter communications  southwest      california

  ALERT_TRGR_CD  … CUST_STATE      PH_NUM_UPDT_TS CUST_SINCE_DT  \
0          MOBL  …         NV  2/24/2021 15:55:10    1993-01-06
1          MOBL  …         CA                 NaN    1971-01-07

              TRAN_TS    TRAN_DT ACTN_CD ACTN_INTNL_TXT TRAN_TYPE_CD  \
0    5/3/2021 18:3:58   5/3/2021  SCHPMT     P2P_COMMIT          P2P
1  1/13/2021 19:19:37  1/13/2021  SCHPMT     P2P_COMMIT          P2P

     ACTVY_DT FRAUD_NONFRAUD
0   5/3/2021      Non-Fraud
1  1/13/2021      Non-Fraud

[2 rows x 24 columns]
```

[4]:
```
print ("Original data shape:", df_orig.shape)
```

```
Original data shape: (14000, 24)
```

[5]:
```
#information of the dataset
df_orig.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14000 entries, 0 to 13999
Data columns (total 24 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   TRAN_AMT                 14000 non-null  float64
 1   ACCT_PRE_TRAN_AVAIL_BAL  14000 non-null  float64
 2   CUST_AGE                 14000 non-null  int64
```

```
 3   OPEN_ACCT_CT            14000 non-null  int64
 4   WF_dvc_age              14000 non-null  int64
 5   PWD_UPDT_TS             10875 non-null  object
 6   CARR_NAME               11291 non-null  object
 7   RGN_NAME                11291 non-null  object
 8   STATE_PRVNC_TXT         11291 non-null  object
 9   ALERT_TRGR_CD           14000 non-null  object
 10  DVC_TYPE_TXT            12239 non-null  object
 11  AUTHC_PRIM_TYPE_CD      14000 non-null  object
 12  AUTHC_SCNDRY_STAT_TXT   13926 non-null  object
 13  CUST_ZIP                14000 non-null  int64
 14  CUST_STATE              13964 non-null  object
 15  PH_NUM_UPDT_TS          6939 non-null   object
 16  CUST_SINCE_DT           14000 non-null  datetime64[ns]
 17  TRAN_TS                 14000 non-null  object
 18  TRAN_DT                 14000 non-null  object
 19  ACTN_CD                 14000 non-null  object
 20  ACTN_INTNL_TXT          14000 non-null  object
 21  TRAN_TYPE_CD            14000 non-null  object
 22  ACTVY_DT                14000 non-null  object
 23  FRAUD_NONFRAUD          14000 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(4), object(17)
memory usage: 2.6+ MB
```

[6]:
```
# check the target classes
df_orig["FRAUD_NONFRAUD"].unique()
```

[6]:
```
array(['Non-Fraud', 'Fraud'], dtype=object)
```

1.2 Train test split

Before doing any data visualization let's set some test data aside and use them to score the model later on.

[7]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# stratify the target column so that the distribution look similar in the train␣
↪and test data
df_train0, df_test0 = train_test_split(df_orig,
                               test_size = .2,
                               random_state = 8848,
                               shuffle = True,
                               stratify = df_orig["FRAUD_NONFRAUD"])
```

[8]:
```
df = df_train0.copy()
```

[9]:
```
df.head(2)
```

[9]:
```
      TRAN_AMT  ACCT_PRE_TRAN_AVAIL_BAL  CUST_AGE  OPEN_ACCT_CT  WF_dvc_age  \
2413    487.93                  3714.91        43             5        1037
1003      4.84                     0.00        53             5         305

             PWD_UPDT_TS CARR_NAME RGN_NAME STATE_PRVNC_TXT ALERT_TRGR_CD  \
2413                 NaN       NaN      NaN             NaN          MOBL
1003  4/12/2017 15:54:53       NaN      NaN             NaN          MOBL

      … CUST_STATE     PH_NUM_UPDT_TS CUST_SINCE_DT            TRAN_TS  \
2413  …         CO  5/0/2020 12:33:41    1988-01-11    4/13/2021 5:2:29
1003  …         TX                NaN    1987-04-05  4/29/2021 22:54:53

        TRAN_DT ACTN_CD ACTN_INTNL_TXT TRAN_TYPE_CD   ACTVY_DT FRAUD_NONFRAUD
2413  4/13/2021  SCHPMT     P2P_COMMIT          P2P  4/13/2021          Fraud
1003  4/29/2021  SCHPMT     P2P_COMMIT          P2P  4/29/2021      Non-Fraud

[2 rows x 24 columns]
```

[10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11200 entries, 2413 to 114
Data columns (total 24 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   TRAN_AMT                 11200 non-null  float64
 1   ACCT_PRE_TRAN_AVAIL_BAL  11200 non-null  float64
 2   CUST_AGE                 11200 non-null  int64
 3   OPEN_ACCT_CT             11200 non-null  int64
 4   WF_dvc_age               11200 non-null  int64
 5   PWD_UPDT_TS              8684 non-null   object
 6   CARR_NAME                9022 non-null   object
 7   RGN_NAME                 9022 non-null   object
 8   STATE_PRVNC_TXT          9022 non-null   object
 9   ALERT_TRGR_CD            11200 non-null  object
 10  DVC_TYPE_TXT             9805 non-null   object
 11  AUTHC_PRIM_TYPE_CD       11200 non-null  object
 12  AUTHC_SCNDRY_STAT_TXT    11140 non-null  object
 13  CUST_ZIP                 11200 non-null  int64
 14  CUST_STATE               11172 non-null  object
 15  PH_NUM_UPDT_TS           5579 non-null   object
 16  CUST_SINCE_DT            11200 non-null  datetime64[ns]
 17  TRAN_TS                  11200 non-null  object
 18  TRAN_DT                  11200 non-null  object
 19  ACTN_CD                  11200 non-null  object
 20  ACTN_INTNL_TXT           11200 non-null  object
 21  TRAN_TYPE_CD             11200 non-null  object
```

```
 22  ACTVY_DT                 11200 non-null  object
 23  FRAUD_NONFRAUD           11200 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(4), object(17)
memory usage: 2.1+ MB
```

[11]:
```python
df.shape
```

[11]:
```
(11200, 24)
```

[12]:
```python
# find numerical and categorical columns
nume_cols = list(df.select_dtypes(include="number").columns)
cate_cols = list(df.select_dtypes(exclude="number").columns)
cate_cols.remove('FRAUD_NONFRAUD')
```

[13]:
```python
print ("Numeric Columns:\n", nume_cols)
print ("")
print ("Categorical Columns:\n", cate_cols)
```

```
Numeric Columns:
 ['TRAN_AMT', 'ACCT_PRE_TRAN_AVAIL_BAL', 'CUST_AGE', 'OPEN_ACCT_CT',
'WF_dvc_age', 'CUST_ZIP']

Categorical Columns:
 ['PWD_UPDT_TS', 'CARR_NAME', 'RGN_NAME', 'STATE_PRVNC_TXT', 'ALERT_TRGR_CD',
'DVC_TYPE_TXT', 'AUTHC_PRIM_TYPE_CD', 'AUTHC_SCNDRY_STAT_TXT', 'CUST_STATE',
'PH_NUM_UPDT_TS', 'CUST_SINCE_DT', 'TRAN_TS', 'TRAN_DT', 'ACTN_CD',
'ACTN_INTNL_TXT', 'TRAN_TYPE_CD', 'ACTVY_DT']
```

[14]:
```python
df[nume_cols].head(2)
```

[14]:
```
      TRAN_AMT  ACCT_PRE_TRAN_AVAIL_BAL  CUST_AGE  OPEN_ACCT_CT  WF_dvc_age  \
2413    487.93                  3714.91        43             5        1037
1003      4.84                     0.00        53             5         305

      CUST_ZIP
2413     80234
1003     75232
```

[15]:
```python
nume_cols.remove('CUST_ZIP')
cate_cols.append('CUST_ZIP')
```

[16]:
```python
print ("Numeric Columns:\n", nume_cols)
print ("")
print ("Categorical Columns:\n", cate_cols)
```

```
Numeric Columns:
 ['TRAN_AMT', 'ACCT_PRE_TRAN_AVAIL_BAL', 'CUST_AGE', 'OPEN_ACCT_CT',
'WF_dvc_age']
```

```
Categorical Columns:
 ['PWD_UPDT_TS', 'CARR_NAME', 'RGN_NAME', 'STATE_PRVNC_TXT', 'ALERT_TRGR_CD',
'DVC_TYPE_TXT', 'AUTHC_PRIM_TYPE_CD', 'AUTHC_SCNDRY_STAT_TXT', 'CUST_STATE',
'PH_NUM_UPDT_TS', 'CUST_SINCE_DT', 'TRAN_TS', 'TRAN_DT', 'ACTN_CD',
'ACTN_INTNL_TXT', 'TRAN_TYPE_CD', 'ACTVY_DT', 'CUST_ZIP']
```

[17]:
```
df[nume_cols].head(5)
```

[17]:

	TRAN_AMT	ACCT_PRE_TRAN_AVAIL_BAL	CUST_AGE	OPEN_ACCT_CT	WF_dvc_age
2413	487.93	3714.91	43	5	1037
1003	4.84	0.00	53	5	305
8660	494.94	2525.50	70	9	583
6349	0.01	0.00	70	6	467
1860	488.36	4344.55	38	4	0

[18]:
```
impute_vals={}

for col in df.columns:
    if col in nume_cols:
        impute_vals[col] = df[col].median()
    elif col in cate_cols:
        impute_vals[col] = df[col].mode()[0]

impute_vals
```

[18]:
```
{'TRAN_AMT': 162.07,
 'ACCT_PRE_TRAN_AVAIL_BAL': 2396.1549999999997,
 'CUST_AGE': 59.0,
 'OPEN_ACCT_CT': 5.0,
 'WF_dvc_age': 366.5,
 'PWD_UPDT_TS': '5/18/2020 4:7:20',
 'CARR_NAME': 'cox communications inc.',
 'RGN_NAME': 'southwest',
 'STATE_PRVNC_TXT': 'california',
 'ALERT_TRGR_CD': 'MOBL',
 'DVC_TYPE_TXT': 'MOBILE',
 'AUTHC_PRIM_TYPE_CD': 'UN_PWD',
 'AUTHC_SCNDRY_STAT_TXT': 'ALLOW',
 'CUST_ZIP': 77459,
 'CUST_STATE': 'CA',
 'PH_NUM_UPDT_TS': '7/8/2019 6:45:37',
 'CUST_SINCE_DT': Timestamp('1997-08-01 00:00:00'),
 'TRAN_TS': '2/3/2021 9:0:51',
 'TRAN_DT': '2/28/2021',
 'ACTN_CD': 'SCHPMT',
 'ACTN_INTNL_TXT': 'P2P_COMMIT',
```

```
 'TRAN_TYPE_CD': 'P2P',
 'ACTVY_DT': '2/28/2021'}
```

[19]:
```
cols_to_drop = ['PH_NUM_UPDT_TS', 'PWD_UPDT_TS', 'CARR_NAME', 'RGN_NAME',␣
 ↪'STATE_PRVNC_TXT']
nume_cols    = [c for c in nume_cols if c not in cols_to_drop]
cate_cols    = [c for c in cate_cols if c not in cols_to_drop]
```

[20]:
```
def impute_data(df, impute_dict=impute_vals):
    """
    this function takes in a dataframe and list of columns which have missing␣
 ↪values
    then imputes those columns using the precomputed values.
    """
    for col in list(impute_dict.keys()):
        df[col] = df[col].fillna(impute_dict[col])
    return df
```

[21]:
```
# impute the columns : cols_to_impute
df=impute_data(df)
```

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

[22]:
```
TRAN_AMT                   0
ACCT_PRE_TRAN_AVAIL_BAL    0
CUST_AGE                   0
OPEN_ACCT_CT               0
WF_dvc_age                 0
PWD_UPDT_TS                0
CARR_NAME                  0
RGN_NAME                   0
STATE_PRVNC_TXT            0
ALERT_TRGR_CD              0
DVC_TYPE_TXT               0
AUTHC_PRIM_TYPE_CD         0
AUTHC_SCNDRY_STAT_TXT      0
CUST_ZIP                   0
CUST_STATE                 0
PH_NUM_UPDT_TS             0
CUST_SINCE_DT              0
TRAN_TS                    0
TRAN_DT                    0
ACTN_CD                    0
ACTN_INTNL_TXT             0
TRAN_TYPE_CD               0
ACTVY_DT                   0
FRAUD_NONFRAUD             0
```

```
dtype: int64
```

[23]:
```
df[nume_cols].head(2)
```

[23]:

	TRAN_AMT	ACCT_PRE_TRAN_AVAIL_BAL	CUST_AGE	OPEN_ACCT_CT	WF_dvc_age
2413	487.93	3714.91	43	5	1037
1003	4.84	0.00	53	5	305

1.3 Feature Transformation

- Convert the categorical featurs into small number of categories when possible

[24]:
```
def wrangle_column_data(df):
    #CUST_STATE
    # keep only CO, TX, MN, AZ and convert rest into OTHER
    df["CUST_STATE"] = df["CUST_STATE"].apply(lambda x: x if x in ["CO", "TX",␣
 ↪"MN", "AZ"] else "OTHER")
    #OPEN_ACCT_CT
    #keep only the [2,9] and convert others to 10
    df["OPEN_ACCT_CT"] = df["OPEN_ACCT_CT"].apply(lambda x: x if x in␣
 ↪range(1,13) else 13)
    return df
```

[25]:
```
df=wrangle_column_data(df)
```

[26]:
```
nume_cols
```

[26]:
```
['TRAN_AMT',
 'ACCT_PRE_TRAN_AVAIL_BAL',
 'CUST_AGE',
 'OPEN_ACCT_CT',
 'WF_dvc_age']
```

[27]:
```
cate_cols_to_keep = ['ALERT_TRGR_CD', "CUST_STATE"]
```

[28]:
```
df[cate_cols_to_keep].head()
```

[28]:

	ALERT_TRGR_CD	CUST_STATE
2413	MOBL	CO
1003	MOBL	TX
8660	MOBL	TX
6349	ONLN	MN
1860	MOBL	AZ

1.4 Build a model with only Numerical features

[29]:
```
# map Fraud to 1 and Non-Fraud to 0 in the dataframe for both train and test␣
↪data
df["FRAUD_NONFRAUD"] = df["FRAUD_NONFRAUD"].map({"Fraud":1, "Non-Fraud":0})
```

[30]:
```
X_train1, y_train1 = df[nume_cols], df["FRAUD_NONFRAUD"]
```

[31]:
```
# prepare test data
df_test = df_test0.copy()
print ("missing values in test data:\n", df_test[nume_cols].isnull().sum() )
df_test["FRAUD_NONFRAUD"] = df_test["FRAUD_NONFRAUD"].map({"Fraud":
↪1,"Non-Fraud":0})
X_test1,  y_test1  = df_test[nume_cols], df_test["FRAUD_NONFRAUD"]
```

```
missing values in test data:
 TRAN_AMT                    0
ACCT_PRE_TRAN_AVAIL_BAL    0
CUST_AGE                   0
OPEN_ACCT_CT               0
WF_dvc_age                 0
dtype: int64
```

[32]:
```
X_train1.shape, y_train1.shape, X_test1.shape, y_test1.shape
```

[32]:
```
((11200, 5), (11200,), (2800, 5), (2800,))
```

1.4.1 Base Model: Logistic Regression, Random Forest, XGBoost

[33]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, f1_score, precision_score,␣
↪recall_score
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score, plot_roc_curve
```

[34]:
```
class Model_training:
    def __init__(self, model, X_train, y_train, X_test, y_test, savename="Fig"):
        self.model = model
        self.X_train = X_train
        self.y_train = y_train
        self.X_test  = X_test
        self.y_test  = y_test
        self.savename = savename
```

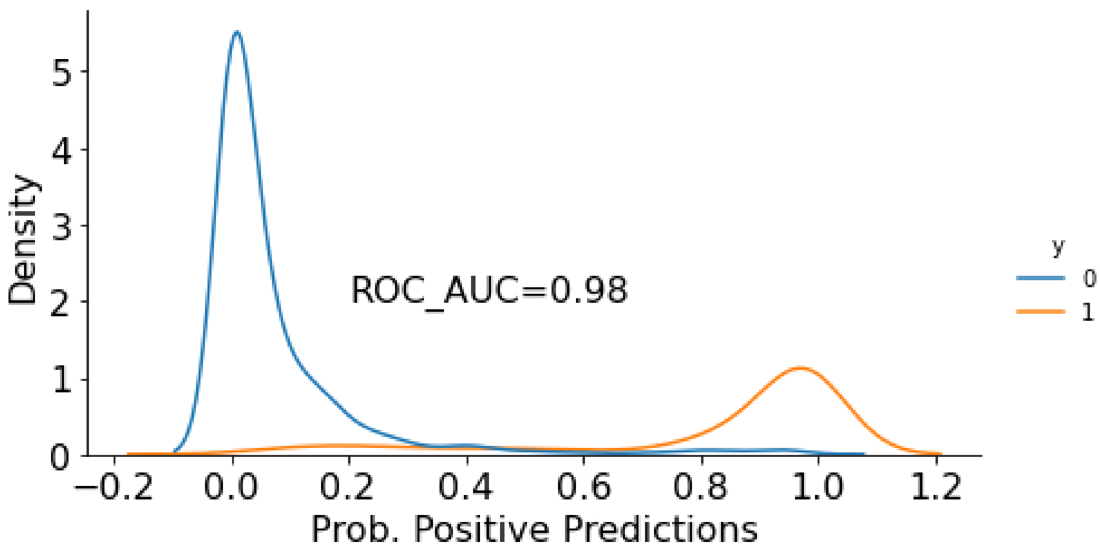
```
        self.model.fit(self.X_train, self.y_train)

    def print_metrics(self):
        round_to_pct = lambda x: np.round(100*x, 2)
        y_pred = self.model.predict(self.X_test)
        ac = round_to_pct(accuracy_score(self.y_test, y_pred))
        f1 = round_to_pct(f1_score(self.y_test, y_pred))
        pr = round_to_pct(precision_score(self.y_test, y_pred))
        re = round_to_pct(recall_score(self.y_test, y_pred))
        print (f"Accuracy = {ac}% F1 Score= {f1}% \nPrecision={pr}% Recall=␣
↪{re}%")
        print (classification_report(self.y_test, y_pred))
        return (self.model, (ac, f1, pr, re))

    def displot(self):
        pr=self.model.predict_proba(self.X_test)
        roc_auc = np.round(roc_auc_score(self.y_test,
                                         self.model.predict_proba(self.X_test)[:
↪, 1]), 2)

        pr_df = pd.DataFrame({'pred_0':pr[:,0],
                              'pred_1':pr[:,1],
                              'y': self.y_test})

        ax=sns.displot(data=pr_df,
                       x='pred_1',
                       hue='y',
                       alpha=0.8,
                       kind="kde",
                       height = 3.5,
                       aspect=1.8);

        plt.xlabel("Prob. Positive Predictions", fontsize=16)
        plt.text(0.2, 2, "ROC_AUC="+str(roc_auc), fontsize=16)
        plt.ylabel("Density", fontsize=16)

        plt.yticks(fontsize=16);
        plt.xticks(fontsize=16);
        figname = "images/displot_"+self.savename+"_nb1.png"
        plt.savefig(figname, dpi=300, bbox_inches='tight')

    def feature_importance(self):

        df_imp = pd.DataFrame({"Feature":self.X_train.columns,
                               "Feature Importance":self.model.
↪feature_importances_})
```

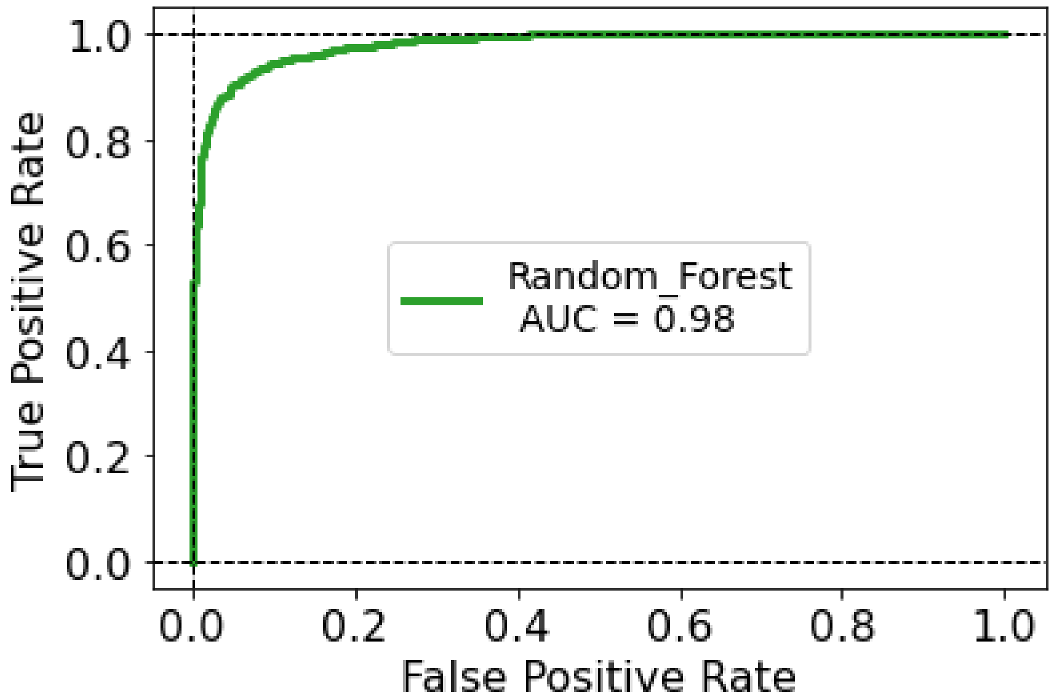
```
        df_imp = df_imp.sort_values(by=['Feature Importance'],
                                    axis=0,
                                    ascending=True)

        df_imp.plot(kind='barh',
                    x='Feature',
                    y='Feature Importance',
                    color="C2", figsize=(8,5));

        plt.grid(axis='x')
        plt.yticks(fontsize=16);
        plt.ylabel('');
        plt.xticks(fontsize=16);
        plt.legend(loc='best',fontsize=16);

        figname = "images/feat_imp_"+self.savename+"_nb1.png"
        plt.savefig(figname, dpi=300, bbox_inches='tight')

    def plot_roc_curve(self):
        roc_auc = np.round(roc_auc_score(self.y_test,
                                         self.model.predict_proba(self.X_test)[:
 ↪, 1]), 2)
        label_name = self.savename +"\n AUC = "+str(roc_auc)

        plot_roc_curve(self.model, self.X_test, self.y_test,
                       lw=3., color='C2', label=label_name)
        plt.xlabel("False Positive Rate", fontsize=16)
        plt.ylabel("True Positive Rate", fontsize=16)
        plt.xticks(fontsize=16);
        plt.yticks(fontsize=16);
        plt.legend(loc="center", fontsize=14);
        plt.axvline(x=0, color='k', ls='--', lw=1)
        plt.axhline(y=0, color='k', ls='--', lw=1)
        plt.axhline(y=1, color='k', ls='--', lw=1)

        figname = "images/roc_curve_"+self.savename+"_nb1.png"
        plt.savefig(figname, dpi=300, bbox_inches='tight')
```

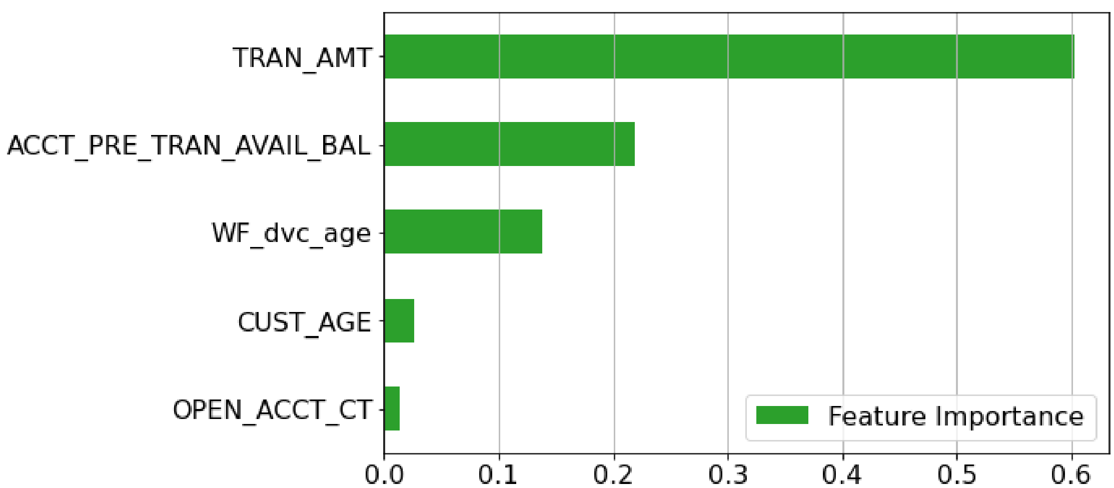
[35]:
```
model_rf = RandomForestClassifier(max_depth=10,
                                  random_state=8848)

mod = Model_training(model_rf,
                     X_train1, y_train1,
                     X_test1, y_test1,
                     "Random_Forest")
mod_tr, _= mod.print_metrics()
mod.displot()
```

```
mod.plot_roc_curve()
mod.feature_importance()
```

```
Accuracy = 93.64% F1 Score= 88.81%
Precision=93.26% Recall= 84.75%
              precision    recall  f1-score   support

           0       0.94      0.97      0.96      1967
           1       0.93      0.85      0.89       833

    accuracy                           0.94      2800
   macro avg       0.94      0.91      0.92      2800
weighted avg       0.94      0.94      0.94      2800
```





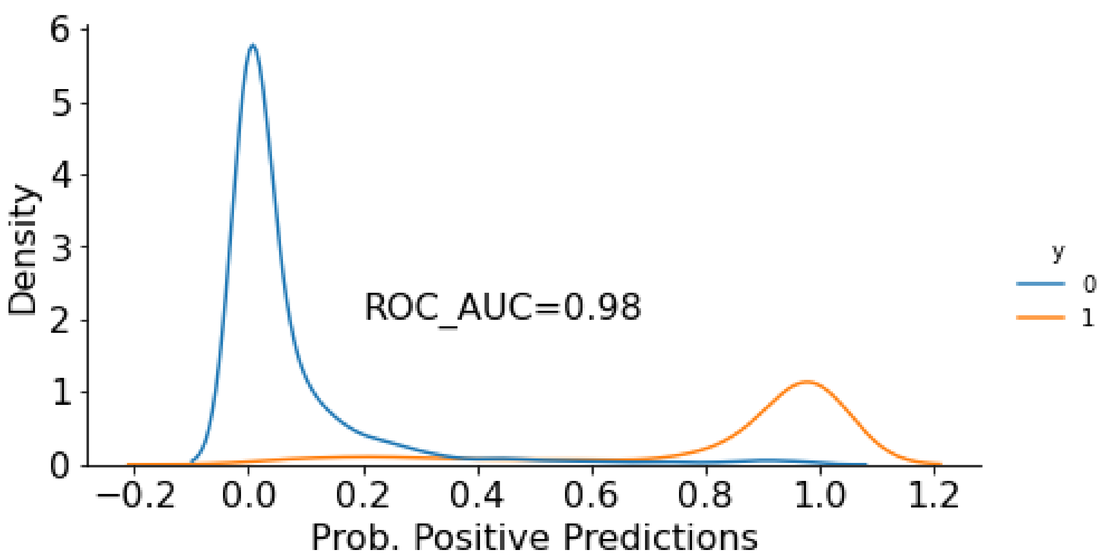


For a base model: F1 score ~ 88% is a great result.

[36]:
```
model_rf_gs = GridSearchCV(RandomForestClassifier(),
                           param_grid={'max_depth':[8, 9, 10, 11, 12, 14]},
                           scoring ='f1',
                           verbose=1)
```

```python
mod2 = Model_training(model_rf_gs,
                      X_train1, y_train1, X_test1, y_test1,
                      "random_forest_grid_search")
mod_tr, _= mod2.print_metrics()
mod2.displot()
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  30 out of  30 | elapsed:   32.0s finished

Accuracy = 93.57% F1 Score= 88.78%
Precision=92.35% Recall= 85.47%
              precision    recall  f1-score   support

           0       0.94      0.97      0.95      1967
           1       0.92      0.85      0.89       833

    accuracy                           0.94      2800
   macro avg       0.93      0.91      0.92      2800
weighted avg       0.94      0.94      0.93      2800
```



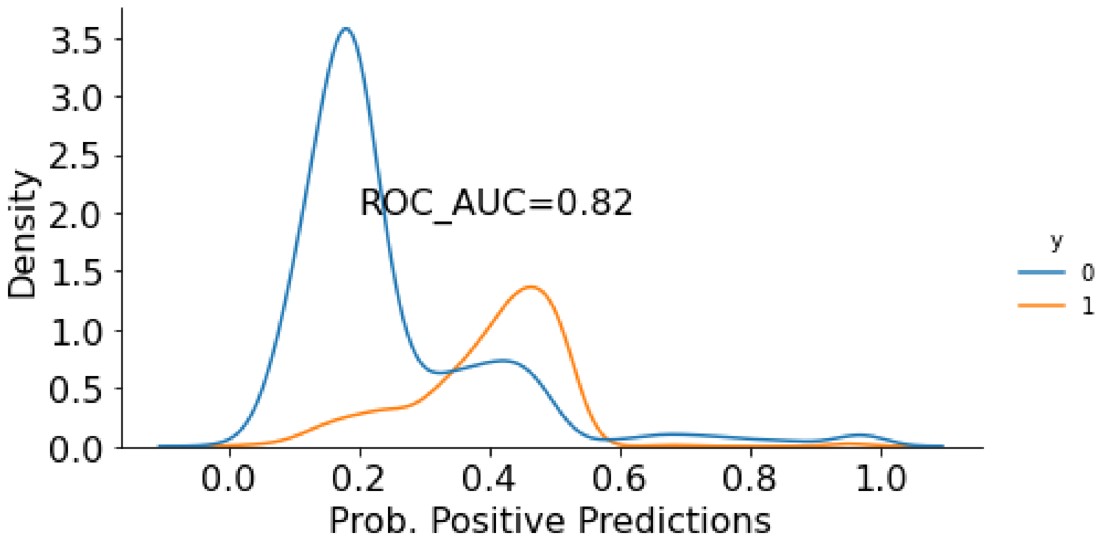
[37]:
```python
mod_tr.best_params_
```

[37]: `{'max_depth': 14}`

[38]:
```python
model_lr = LogisticRegression(max_iter=5000)
```

```
mod3 = Model_training(model_lr, X_train1, y_train1, X_test1, y_test1,␣
 ↪"logistic_regression")
mod_tr, _= mod3.print_metrics()
mod3.displot()
```

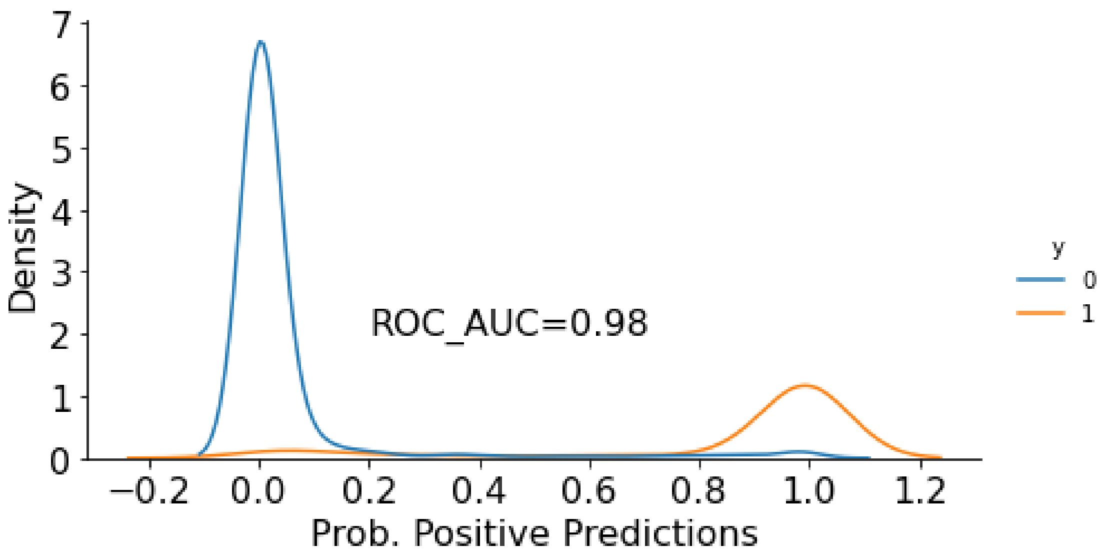
```
Accuracy = 70.86% F1 Score= 23.02%
Precision=53.74% Recall= 14.65%
              precision    recall  f1-score   support

           0       0.72      0.95      0.82      1967
           1       0.54      0.15      0.23       833

    accuracy                           0.71      2800
   macro avg       0.63      0.55      0.53      2800
weighted avg       0.67      0.71      0.64      2800
```

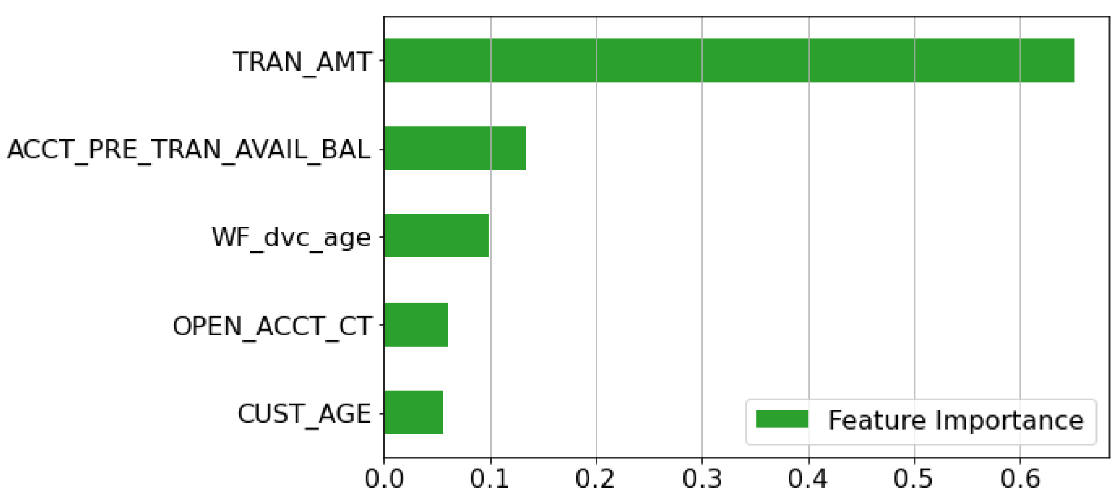


[39]:
```
xgb = XGBClassifier(verbosity=1,
                    use_label_encoder=False,
                    max_depth=10,
                    eval_metric = "logloss")

mod4 = Model_training(xgb, X_train1, y_train1, X_test1, y_test1, "xgb")
mod_tr, _= mod4.print_metrics()
mod4.displot()
mod4.feature_importance()
```

```
Accuracy = 93.14% F1 Score= 88.13%
Precision=90.83% Recall= 85.59%
```

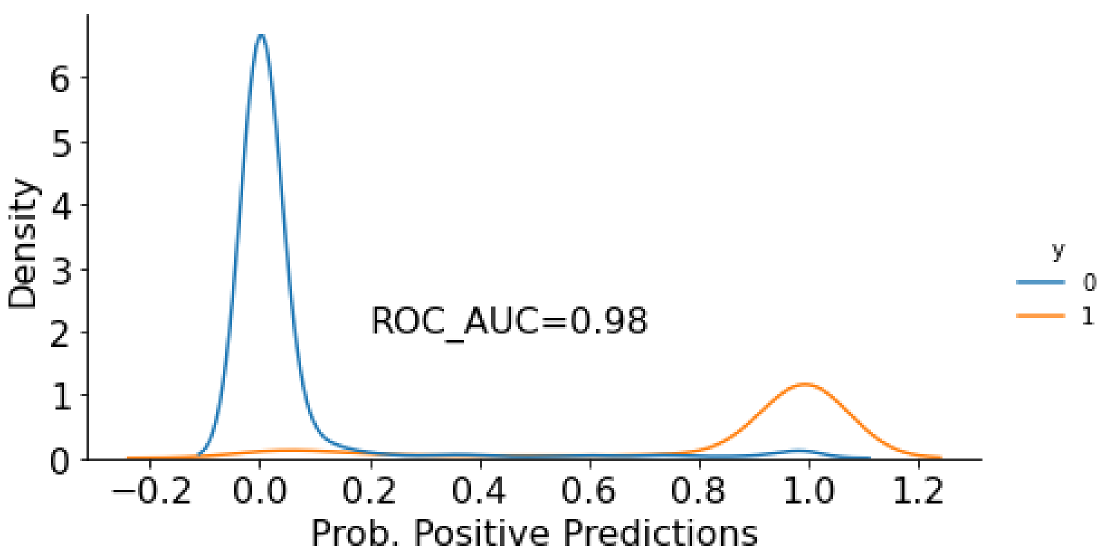
	precision	recall	f1-score	support
0	0.94	0.96	0.95	1967
1	0.91	0.86	0.88	833
accuracy			0.93	2800
macro avg	0.92	0.91	0.92	2800
weighted avg	0.93	0.93	0.93	2800





[40]:
```
xgb_gs = GridSearchCV(XGBClassifier(),
                      param_grid={'max_depth':[8, 9, 10, 11, 12, 14],
                                  'eval_metric' :["logloss"],
                                  'reg_alpha':[0.1, 0.5]},
                      scoring = 'f1',
                      verbose = 0 )

mod5 = Model_training(xgb_gs, X_train1, y_train1, X_test1, y_test1,␣
 ↪"xgb_grid_search")
mod_tr, _= mod5.print_metrics()
mod5.displot()
```

```
Accuracy = 92.93% F1 Score= 87.78%
Precision=90.34% Recall= 85.35%
              precision    recall  f1-score   support

           0       0.94      0.96      0.95      1967
           1       0.90      0.85      0.88       833

    accuracy                           0.93      2800
   macro avg       0.92      0.91      0.91      2800
weighted avg       0.93      0.93      0.93      2800
```



[41]:
```
mod_tr.best_params_
```

[41]: {'eval_metric': 'logloss', 'max_depth': 11, 'reg_alpha': 0.1}

[ ]:

```

```

[ ]:

```

```

[ ]:

```

```

[ ]:

```

```

1.5 Deep learning models

[42]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import Dense, Dropout, Flatten
from tensorflow.keras.layers import Conv1D, MaxPooling1D, GlobalMaxPool1D,␣
 ↪BatchNormalization
from tensorflow.keras import backend as K
```

[43]:

```
# this piece of code copied from
#https://neptune.ai/blog/implementing-the-macro-f1-score-in-keras
def custom_f1(y_true, y_pred):
    def recall_m(y_true, y_pred):
        TP = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
        Positives = K.sum(K.round(K.clip(y_true, 0, 1)))

        recall = TP / (Positives+K.epsilon())
        return recall

    def precision_m(y_true, y_pred):
        TP = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
        Pred_Positives = K.sum(K.round(K.clip(y_pred, 0, 1)))

        precision = TP / (Pred_Positives+K.epsilon())
        return precision

    precision, recall = precision_m(y_true, y_pred), recall_m(y_true, y_pred)

    return 2*((precision*recall)/(precision+recall+K.epsilon()))
```

[44]:

```
def make_model_dense(X_train, y_train):
    model = Sequential()
    model.add(Dense(1, input_shape=(X_train.shape[1],), activation='relu'))
    model.add(Dropout(0.25))
    model.add(Dense(1, activation='relu'))
    opt = Adam(learning_rate=0.001)
    model.compile(loss='binary_crossentropy',
                  optimizer=opt,
```

```
                    metrics=custom_f1)
    return model
```

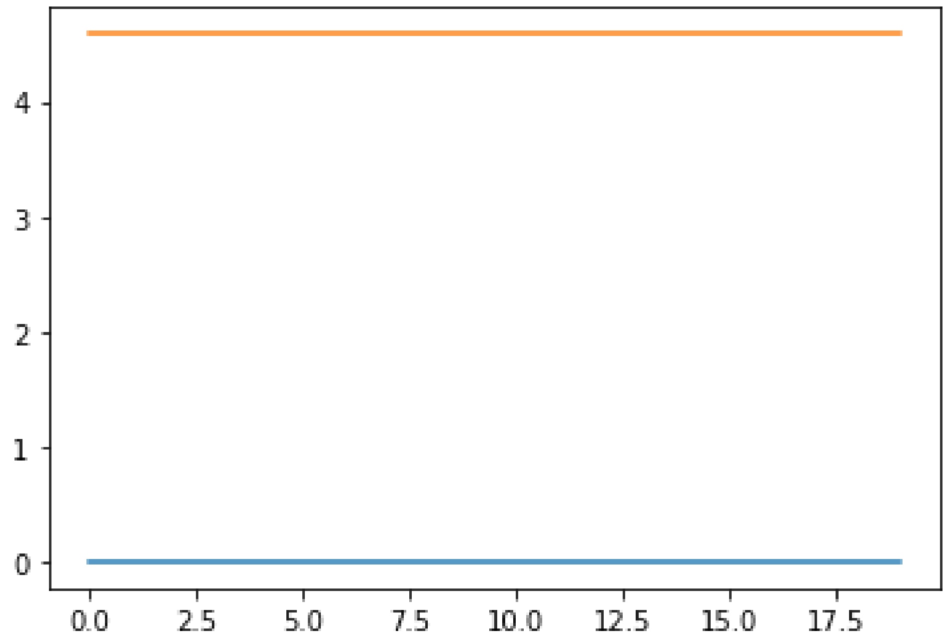
[45]:
```
model_dnn = make_model_dense(X_train1, y_train1)
model_dnn.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 1)                 6
_________________________________________________________________
dropout (Dropout)            (None, 1)                 0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 2
=================================================================
Total params: 8
Trainable params: 8
Non-trainable params: 0
_________________________________________________________________
```

[46]:
```
history_dnn = model_dnn.fit(X_train1, y_train1,
                            validation_data=(X_test1, y_test1),
                            epochs=20,
                            batch_size=32,
                            verbose=0)
```

[47]:
```
plt.plot(history_dnn.history['val_custom_f1'])
plt.plot(history_dnn.history['val_loss'])
```

[47]:
```
[<matplotlib.lines.Line2D at 0x158570490>]
```



1.6 Modeling including categorical features

[48]:
```
import category_encoders as ce
```

[49]:
```
df2 = df_train0.copy()
df2["FRAUD_NONFRAUD"] =  df2["FRAUD_NONFRAUD"].map({"Fraud":1, "Non-Fraud":0})
df2 = impute_data(df2)
df2 = wrangle_column_data(df2)
```

[50]:
```
encoder = ce.OneHotEncoder()
df2_tr_cat = encoder.fit_transform(df[cate_cols_to_keep])
df2_tr_join = pd.concat( [df2[nume_cols], df2_tr_cat], axis=1)
X_train2 = df2_tr_join.values
y_train2 = df2["FRAUD_NONFRAUD"].values
```

[51]:
```
# test data

df2_te = df_test0.copy()
df2_te["FRAUD_NONFRAUD"] = df2_te["FRAUD_NONFRAUD"].map({"Fraud":1, "Non-Fraud":
↪0})
df2_te = impute_data(df2_te)
df2_te = wrangle_column_data(df2_te)
```

[52]:
```
df2_te_cat = encoder.transform(df2_te[cate_cols_to_keep])
df2_te_join = pd.concat( [df2_te[nume_cols], df2_te_cat], axis=1)
```

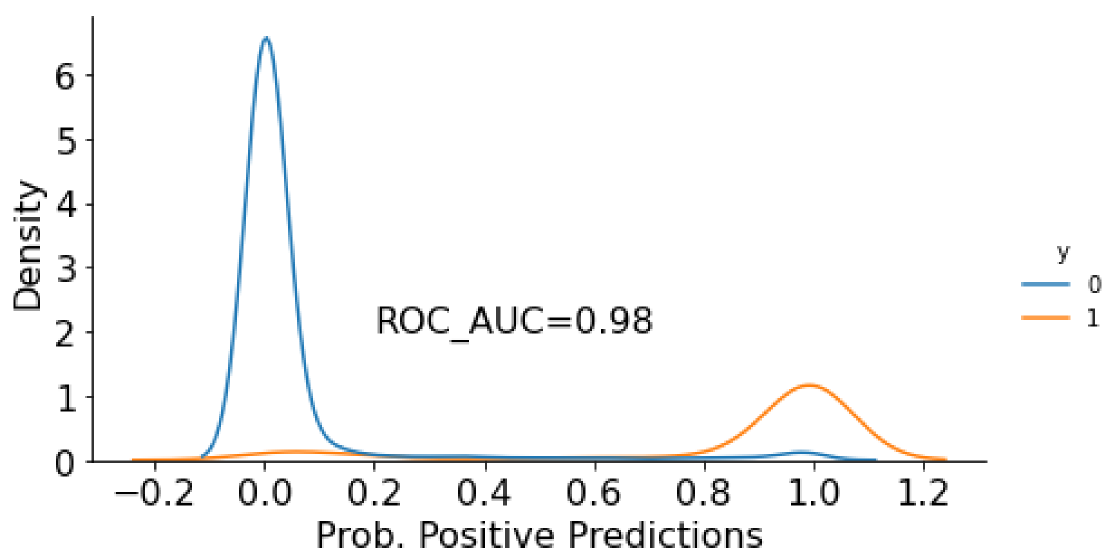
```
X_test2 = df2_te_join.values
y_test2 = df2_te["FRAUD_NONFRAUD"].values
```

[53]:
```
X_train2.shape, y_train2.shape, X_test2.shape, y_test2.shape
```

[53]: ((11200, 12), (11200,), (2800, 12), (2800,))

[54]:
```
xgb = XGBClassifier(verbosity=1,
                    max_depth=10,
                    eval_metric = "logloss")

mod6 = Model_training(xgb, X_train2, y_train2, X_test2, y_test2)
mod_trained, _ = mod5.print_metrics()
mod6.displot()
```

```
Accuracy = 92.93% F1 Score= 87.78%
Precision=90.34% Recall= 85.35%
              precision    recall  f1-score   support

           0       0.94      0.96      0.95      1967
           1       0.90      0.85      0.88       833

    accuracy                           0.93      2800
   macro avg       0.92      0.91      0.91      2800
weighted avg       0.93      0.93      0.93      2800
```

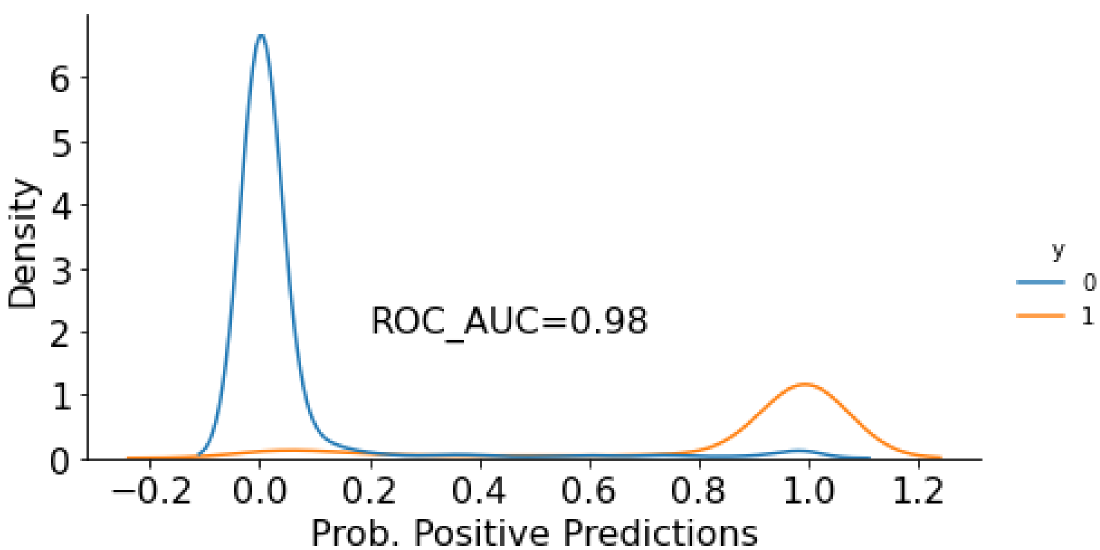


[ ]:

[55]:
```
from sklearn.svm import SVC
```

[56]:
```
svm = SVC(gamma='auto')
mod = Model_training(xgb_gs, X_train1, y_train1, X_test1, y_test1)
mod_tr, _= mod.print_metrics()
mod.displot()
```

```
Accuracy = 92.93% F1 Score= 87.78%
Precision=90.34% Recall= 85.35%
              precision    recall  f1-score   support

           0       0.94      0.96      0.95      1967
           1       0.90      0.85      0.88       833

    accuracy                           0.93      2800
   macro avg       0.92      0.91      0.91      2800
weighted avg       0.93      0.93      0.93      2800
```



[57]:
```
def train_svm_gs():
    svm_gs = GridSearchCV(SVC(),
                          param_grid={'C':[0.1, 0.5, 1.0],
                                      'kernel':['poly', 'rbf'],
                                      'gamma': ['scale', 'auto']},
                          scoring = 'f1',
                          verbose = 1 )

    mod = Model_training(svm_gs, X_train1, y_train1, X_test1, y_test1)
```

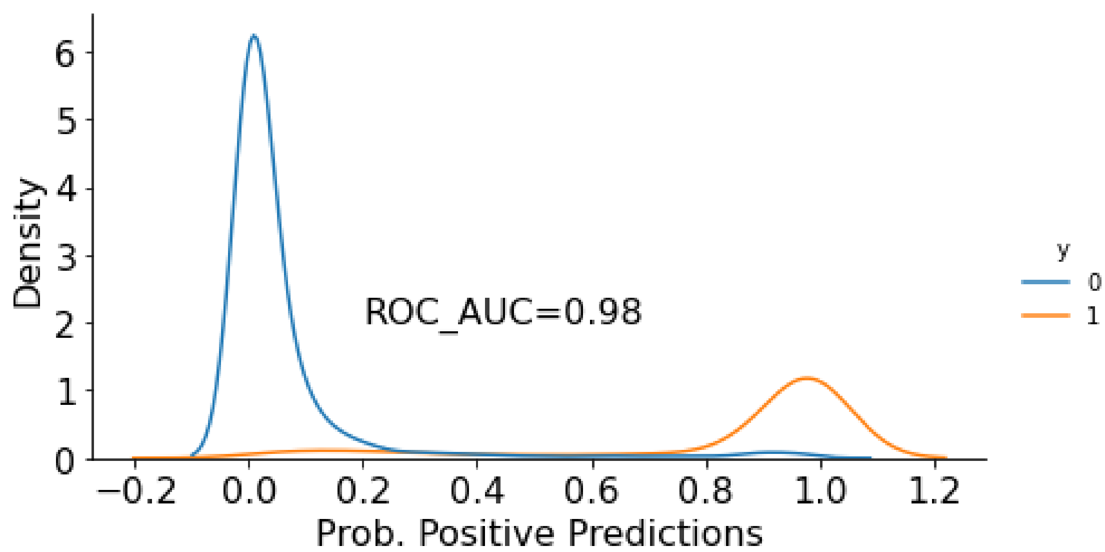
```
    mod_tr, _= mod.print_metrics()
    mod.displot()

#this takes a little long time so think before running
#train_svm_gs()
```

1.7 Voting Classifier

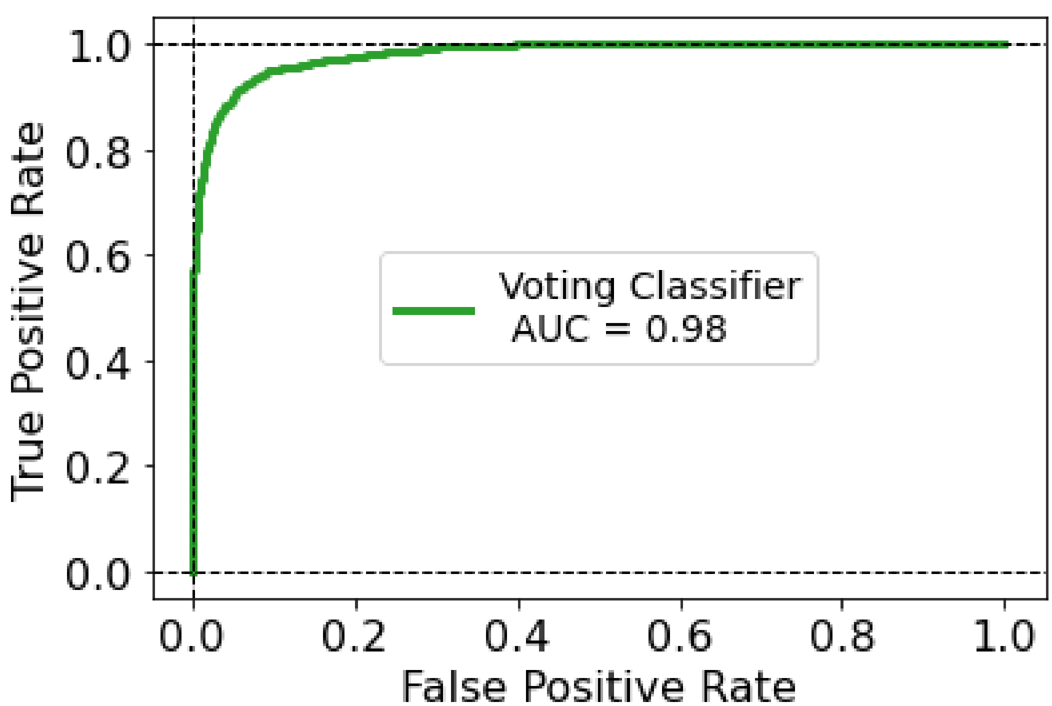
[58]:
```
clf1 = LogisticRegression(multi_class='multinomial', random_state=1)
clf2 = RandomForestClassifier(max_depth=10,
                              random_state=8848)

clf3 = XGBClassifier(verbosity=1,
                    max_depth=13,
                    eval_metric = "logloss")

clf_voting = VotingClassifier(
    estimators=[('rf', clf2), ('xgb', clf3)],
    voting='soft')
```

[59]:
```
mod8 = Model_training(clf_voting, X_train1, y_train1, X_test1, y_test1, "Voting␣
 ↪Classifier")
mod_tr, _= mod8.print_metrics()
mod8.displot()
mod8.plot_roc_curve()
#mod8.feature_importance()
```

```
Accuracy = 93.46% F1 Score= 88.58%
Precision=92.21% Recall= 85.23%
              precision    recall  f1-score   support

           0       0.94      0.97      0.95      1967
           1       0.92      0.85      0.89       833

    accuracy                           0.93      2800
   macro avg       0.93      0.91      0.92      2800
weighted avg       0.93      0.93      0.93      2800
```



Density
ROC_AUC=0.98
Prob. Positive Predictions
y
0
1



True Positive Rate
False Positive Rate
Voting Classifier
AUC = 0.98

[ ]:

[ ]: