In [61]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
import seaborn as sns
from sklearn import metrics
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.tree import export_graphviz
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import RidgeClassifier
import xgboost
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
from sklearn.metrics import average_precision_score
from sklearn.metrics import recall_score
from copy import deepcopy
from sklearn.metrics import roc_auc_score, precision_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
import scipy.stats as ss
```

In [62]:
```
#Load the balanced dataset
dir1 = 'subsample_data'
data = pd.read_csv(dir1,header=0)
```

```
/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshell.p
y:3020: DtypeWarning: Columns (33,35,56) have mixed types. Specify dtyp
e option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [63]:
```
#Load the imbalanced dataset(ratio 1:16) for test
dir2 = 'test.csv'
test = pd.read_csv(dir2,header=0)
```

```
/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshell.p
y:3020: DtypeWarning: Columns (13,14,26,43,46,62,63,64,65,66,67,68,69,7
0,71,74,75,77,80,81,82,174,179) have mixed types. Specify dtype option
on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [64]:
```
#Split the balanced datset into the targeted feature and predictive feat
ures
target = data['Target']
features = data.drop('Target', axis=1)

#Extract only numeric features from data
numerics = features._get_numeric_data()

#Extract categorical features and store the list of names of categorical
features
categoricals = features.select_dtypes(include='object')
```

Task 1: Identify Features

In [65]:
```
#Check the number of missing values of numeric features
num = numerics.isnull().sum()
num

#Check the number of missing values of categorical features
categ = categoricals.isnull().sum()
categ
```

Out[65]:
```
Unnamed: 0
0
Physician_License_State_code2                                       987
7
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_5          994
1
Recipient_State                                                       1
1
Recipient_Country
7
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1          179
5
Form_of_Payment_or_Transfer_of_Value
0
Associated_Drug_or_Biological_NDC_4                                989
8
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_4          984
9
Covered_or_Noncovered_Indicator_3                                  953
3
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_5           994
1
Physician_Specialty                                                480
2
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_4           984
9
Date_of_Payment
0
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_3           954
3
Recipient_City
7
Submitting_Applicable_Manufacturer_or_Applicable_GPO_Name
0
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_2          868
8
Related_Product_Indicator
0
Covered_or_Noncovered_Indicator_4                                  984
9
Product_Category_or_Therapeutic_Area_4                             985
1
Dispute_Status_for_Publication
0
Recipient_Primary_Business_Street_Address_Line1
7
Associated_Drug_or_Biological_NDC_3                                963
6
Recipient_Province                                                 999
7
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Country
0
Associated_Drug_or_Biological_NDC_2                                894
4
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_3          954
3
Delay_in_Publication_Indicator
```

```
0
Physician_License_State_code4                                  999
6
Recipient_Postal_Code                                          999
6
Physician_License_State_code5                                  999
8
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_1       183
2
Physician_First_Name                                           479
5
Change_Type
0
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_2       868
8
Payment_Publication_Date
0
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State  55
8
Physician_Name_Suffix                                          987
7
Recipient_Zip_Code                                               1
1
Physician_Primary_Type                                         479
5
Recipient_Primary_Business_Street_Address_Line2                685
8
Covered_or_Noncovered_Indicator_5                              994
1
Physician_License_State_code1                                  479
5
Physician_Last_Name                                            479
5
Covered_or_Noncovered_Indicator_2                              863
3
Product_Category_or_Therapeutic_Area_2                         869
1
Physician_Middle_Name                                          694
9
Product_Category_or_Therapeutic_Area_3                         954
5
Associated_Drug_or_Biological_NDC_5                            998
4
Associated_Drug_or_Biological_NDC_1                            388
3
Covered_Recipient_Type
0
Product_Category_or_Therapeutic_Area_5                         994
3
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Name
0
Physician_License_State_code3                                  997
2
Product_Category_or_Therapeutic_Area_1                         205
1
Covered_or_Noncovered_Indicator_1                               89
9
```

```
Teaching_Hospital_Name                                                    919
2
dtype: int64
```

In [66]:
```
#Check data info
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 67 columns):
Unnamed: 0                                                        100
00 non-null object
Unnamed: 1                                                        100
00 non-null int64
Physician_License_State_code2                                     123
non-null object
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_5         59
non-null object
Recipient_State                                                   998
9 non-null object
Recipient_Country                                                 999
3 non-null object
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1         820
5 non-null object
Form_of_Payment_or_Transfer_of_Value                              100
00 non-null object
Associated_Drug_or_Biological_NDC_4                               102
non-null object
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_4         151
non-null object
Covered_or_Noncovered_Indicator_3                                 467
non-null object
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_5          59
non-null object
Physician_Specialty                                               519
8 non-null object
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_4          151
non-null object
Date_of_Payment                                                   100
00 non-null object
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_3          457
non-null object
Recipient_City                                                    999
3 non-null object
Teaching_Hospital_CCN                                             808
non-null float64
Submitting_Applicable_Manufacturer_or_Applicable_GPO_Name         100
00 non-null object
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_2         131
2 non-null object
Total_Amount_of_Payment_USDollars                                 100
00 non-null float64
Related_Product_Indicator                                         100
00 non-null object
Covered_or_Noncovered_Indicator_4                                 151
non-null object
Product_Category_or_Therapeutic_Area_4                            149
non-null object
Dispute_Status_for_Publication                                    100
00 non-null object
Recipient_Primary_Business_Street_Address_Line1                   999
3 non-null object
Associated_Drug_or_Biological_NDC_3                               364
non-null object
```

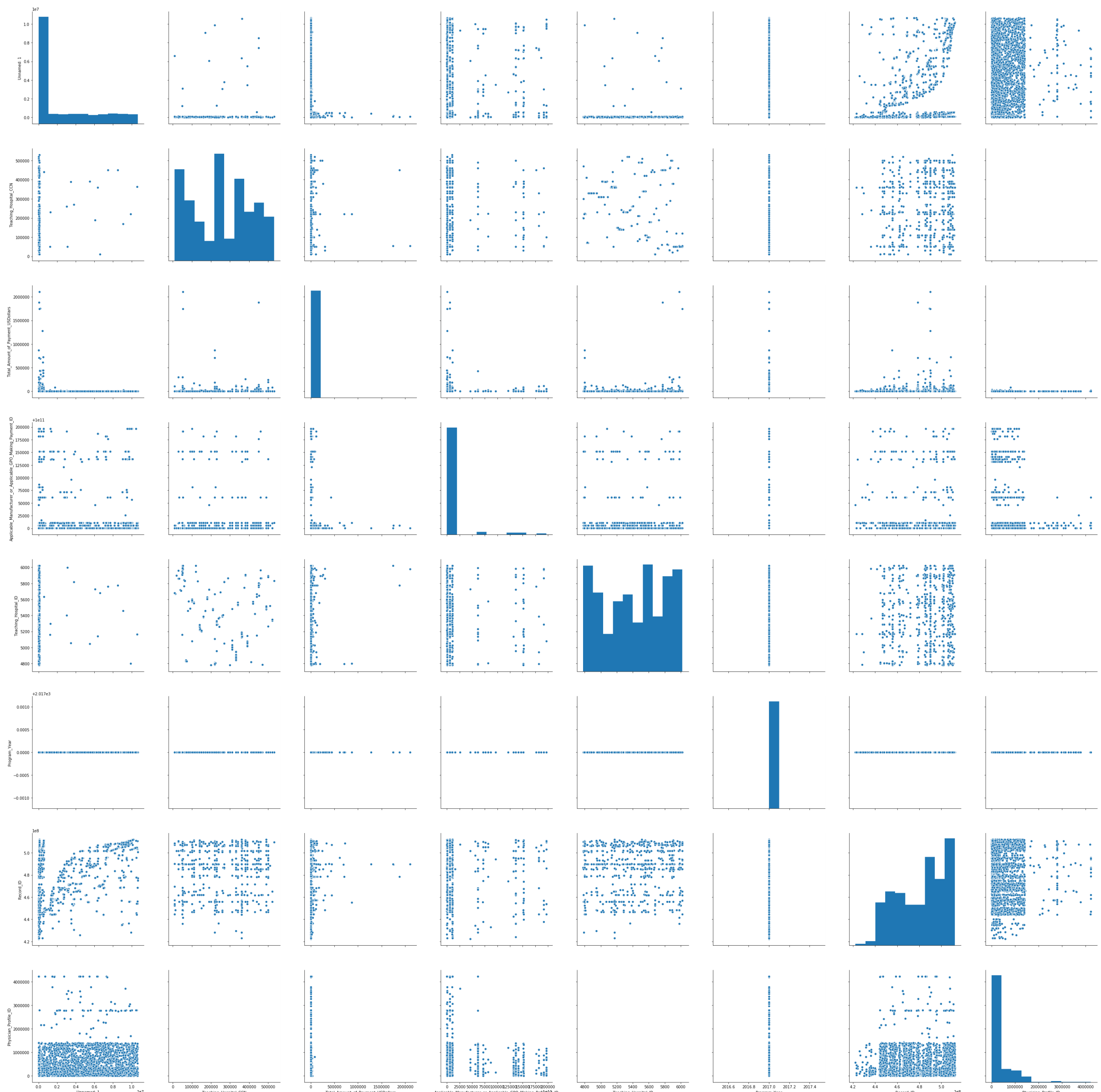
```
Recipient_Province                                                   3 n
on-null object
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_ID          100
00 non-null int64
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Country     100
00 non-null object
Associated_Drug_or_Biological_NDC_2                                  105
6 non-null object
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_3            457
non-null object
Delay_in_Publication_Indicator                                       100
00 non-null object
Physician_License_State_code4                                        4 n
on-null object
Recipient_Postal_Code                                                4 n
on-null object
Physician_License_State_code5                                        2 n
on-null object
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_1             816
8 non-null object
Physician_First_Name                                                 520
5 non-null object
Change_Type                                                          100
00 non-null object
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_2             131
2 non-null object
Payment_Publication_Date                                             100
00 non-null object
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State       944
2 non-null object
Physician_Name_Suffix                                                123
non-null object
Teaching_Hospital_ID                                                 808
non-null float64
Recipient_Zip_Code                                                   998
9 non-null object
Program_Year                                                         100
00 non-null int64
Physician_Primary_Type                                               520
5 non-null object
Recipient_Primary_Business_Street_Address_Line2                      314
2 non-null object
Covered_or_Noncovered_Indicator_5                                    59
non-null object
Physician_License_State_code1                                        520
5 non-null object
Physician_Last_Name                                                  520
5 non-null object
Record_ID                                                            100
00 non-null int64
Covered_or_Noncovered_Indicator_2                                    136
7 non-null object
Product_Category_or_Therapeutic_Area_2                               130
9 non-null object
Physician_Middle_Name                                                305
1 non-null object
Product_Category_or_Therapeutic_Area_3                               455
```

```
non-null object
Associated_Drug_or_Biological_NDC_5                                        16
non-null object
Associated_Drug_or_Biological_NDC_1                                        611
7 non-null object
Covered_Recipient_Type                                                     100
00 non-null object
Product_Category_or_Therapeutic_Area_5                                     57
non-null object
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Name              100
00 non-null object
Physician_License_State_code3                                              28
non-null object
Product_Category_or_Therapeutic_Area_1                                     794
9 non-null object
Physician_Profile_ID                                                       520
5 non-null float64
Covered_or_Noncovered_Indicator_1                                          910
1 non-null object
Teaching_Hospital_Name                                                     808
non-null object
Target                                                                     100
00 non-null int64
dtypes: float64(4), int64(5), object(58)
memory usage: 5.1+ MB
```

In [7]:
```
#Create a pairplot for numeric features to see how they are distributed
sns.pairplot(numerics,size=5)
```

```
/anaconda3/lib/python3.7/site-packages/seaborn/axisgrid.py:2065: UserWa
rning: The `size` parameter has been renamed to `height`; pleaes update
your code.
  warnings.warn(msg, UserWarning)
/anaconda3/lib/python3.7/site-packages/numpy/lib/histograms.py:754: Run
timeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
/anaconda3/lib/python3.7/site-packages/numpy/lib/histograms.py:755: Run
timeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```

Out[7]: <seaborn.axisgrid.PairGrid at 0x1a1f7628d0>



Preprocessing & Data Cleansing (For Balanced Data)

In [67]:
```
#Extract columns which have fewer than 5000 nulls
num_name = []
for i in range(len(num)):
    if(num[i-1] < 5000):
        num_name.append(num.index.tolist()[i-1])
    else:
        continue
num_name = ['Total_Amount_of_Payment_USDollars','Applicable_Manufacturer
_or_Applicable_GPO_Making_Payment_ID','Program_Year','Physician_Profile_
ID']

#Create the dataframe for numeric variables , create a new dataframe nam
ed num_name, and store each variable's name
temp = data[num_name]
num_temp = temp[['Total_Amount_of_Payment_USDollars']]
num_name = list(num_temp)
print('Numerical features with less than 50% nulls : ', num_name)
```

```
Numerical features with less than 50% nulls :  ['Total_Amount_of_Paymen
t_USDollars']
```

In [68]:
```
#Store the list of names of numeric features
numeric_features = list(numerics)

#Store the list of names of categorical features
categorical_features = list(categoricals)
```

In [69]:
```
#Extract columns which have fewer than 5000 nulls
categ_name = []
for i in range(len(categ)):
    if(categ[i-1] < 5000):
        categ_name.append(categ.index.tolist()[i-1])
    else:
        continue

#Create the dataframe for categorical variables, create a new dataframe
 named categ_name, and store each variable's name
categ_temp = data[categ_name]
categ_name = list(categ_temp)
print('Categorical features with less than 50% nulls : ', len(categ_name
), categ_name)
```

```
Categorical features with less than 50% nulls :  28 ['Unnamed: 0', 'Rec
ipient_State', 'Recipient_Country', 'Indicate_Drug_or_Biological_or_Dev
ice_or_Medical_Supply_1', 'Form_of_Payment_or_Transfer_of_Value', 'Phys
ician_Specialty', 'Date_of_Payment', 'Recipient_City', 'Submitting_Appl
icable_Manufacturer_or_Applicable_GPO_Name', 'Related_Product_Indicato
r', 'Dispute_Status_for_Publication', 'Recipient_Primary_Business_Stree
t_Address_Line1', 'Applicable_Manufacturer_or_Applicable_GPO_Making_Pay
ment_Country', 'Delay_in_Publication_Indicator', 'Name_of_Drug_or_Biolo
gical_or_Device_or_Medical_Supply_1', 'Physician_First_Name', 'Change_T
ype', 'Payment_Publication_Date', 'Applicable_Manufacturer_or_Applicabl
e_GPO_Making_Payment_State', 'Recipient_Zip_Code', 'Physician_Primary_T
ype', 'Physician_License_State_code1', 'Physician_Last_Name', 'Associat
ed_Drug_or_Biological_NDC_1', 'Covered_Recipient_Type', 'Applicable_Man
ufacturer_or_Applicable_GPO_Making_Payment_Name', 'Product_Category_or_
Therapeutic_Area_1', 'Covered_or_Noncovered_Indicator_1']
```

In [70]:
```
# Categories with high dimensional one hot vectors
remove_categories = []
for a in categ_name:
    if len(data[a].unique()) > 100:
        remove_categories.append(a)
print(remove_categories)
```

```
['Physician_Specialty', 'Date_of_Payment', 'Recipient_City', 'Submittin
g_Applicable_Manufacturer_or_Applicable_GPO_Name', 'Recipient_Primary_B
usiness_Street_Address_Line1', 'Name_of_Drug_or_Biological_or_Device_or
_Medical_Supply_1', 'Physician_First_Name', 'Recipient_Zip_Code', 'Phys
ician_Last_Name', 'Associated_Drug_or_Biological_NDC_1', 'Applicable_Ma
nufacturer_or_Applicable_GPO_Making_Payment_Name', 'Product_Category_or
_Therapeutic_Area_1']
```

In [71]:
```
# Analysis of correlation between target and each categorical feature
from copy import deepcopy
categ_name_copy1 = deepcopy(categ_name)
print(categ_name)
new = pd.concat([num_temp,categ_temp],axis=1)
print("Baseline Logistic Regression for :")
for c in categ_name_copy1:
    categ_name1 = [c]
    #Build a pipeline to handle the numeric features
    numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='median')),
                        ('scaler', StandardScaler())])

    #Build a pipeline to handle the categorical features
    categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(
strategy='constant', fill_value='missing')),
                                             ('onehot',OneHotEncoder(handl
e_unknown='ignore'))])

    #Build a column transformer to apply transformers above to the given
dataset
    preprocessor = ColumnTransformer(
        transformers=[
            ('num', numeric_transformer, num_name),
            ('cat', categorical_transformer, categ_name1)])

    #Create a pipeline which contains our model
    clf = Pipeline(steps=[('preprocessor', preprocessor),
                          ('classifier',LogisticRegression(solver='lbfg
s'))])

    #Split the dataset into the training set and test set
    X_train, X_test, y_train, y_test = train_test_split(new, target, str
atify=target, test_size=0.3)

    #Cross validation
    scores = cross_val_score(clf,X_train, y_train, cv=5)
    scores = sum(scores) / float(len(scores))
    print(c,scores)

categ_name = deepcopy(categ_name_copy1)
```

```
['Unnamed: 0', 'Recipient_State', 'Recipient_Country', 'Indicate_Drug_o
r_Biological_or_Device_or_Medical_Supply_1', 'Form_of_Payment_or_Transf
er_of_Value', 'Physician_Specialty', 'Date_of_Payment', 'Recipient_Cit
y', 'Submitting_Applicable_Manufacturer_or_Applicable_GPO_Name', 'Relat
ed_Product_Indicator', 'Dispute_Status_for_Publication', 'Recipient_Pri
mary_Business_Street_Address_Line1', 'Applicable_Manufacturer_or_Applic
able_GPO_Making_Payment_Country', 'Delay_in_Publication_Indicator', 'Na
me_of_Drug_or_Biological_or_Device_or_Medical_Supply_1', 'Physician_Fir
st_Name', 'Change_Type', 'Payment_Publication_Date', 'Applicable_Manufa
cturer_or_Applicable_GPO_Making_Payment_State', 'Recipient_Zip_Code',
'Physician_Primary_Type', 'Physician_License_State_code1', 'Physician_L
ast_Name', 'Associated_Drug_or_Biological_NDC_1', 'Covered_Recipient_Ty
pe', 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Name',
'Product_Category_or_Therapeutic_Area_1', 'Covered_or_Noncovered_Indica
tor_1']
Baseline Logistic Regression for :
Unnamed: 0 1.0
Recipient_State 0.6735714285714286
Recipient_Country 0.6981428571428572
Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1 0.73457142857
14285
Form_of_Payment_or_Transfer_of_Value 0.8372857142857143
Physician_Specialty 0.9754285714285714
Date_of_Payment 0.7051428571428572
Recipient_City 0.7428571428571429
Submitting_Applicable_Manufacturer_or_Applicable_GPO_Name 0.82585714285
71428
Related_Product_Indicator 0.6971428571428573
Dispute_Status_for_Publication 0.7037142857142857
Recipient_Primary_Business_Street_Address_Line1 0.7835714285714286
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Country 0.7181
428571428572
Delay_in_Publication_Indicator 0.6987142857142856
Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_1 0.857142857142
8571
Physician_First_Name 0.9768571428571429
Change_Type 0.7005714285714285
Payment_Publication_Date 0.6931428571428571
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State 0.745
Recipient_Zip_Code 0.7891428571428571
Physician_Primary_Type 0.9754285714285714
Physician_License_State_code1 0.9765714285714285
Physician_Last_Name 0.976
Associated_Drug_or_Biological_NDC_1 0.7908571428571428
Covered_Recipient_Type 0.9757142857142856
Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Name 0.8790000
000000001
Product_Category_or_Therapeutic_Area_1 0.8244285714285713
Covered_or_Noncovered_Indicator_1 0.7271428571428571
```

In [72]:

```python
#Concatenate num_temp and categ_temp
new = pd.concat([num_temp,categ_temp],axis=1)
```

In [73]:
```
#Remove meaningless features
irrelavant = ['Unnamed: 0','Physician_Specialty','Submitting_Applicable_
Manufacturer_or_Applicable_GPO_Name',
    'Name_of_Drug_or_Biological_or_Device_or_Medical_Supply_1','Physicia
n_First_Name','Physician_Primary_Type',
            'Physician_License_State_code1','Physician_Last_Name','Assoc
iated_Drug_or_Biological_NDC_1','Covered_Recipient_Type',
            'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Na
me', 'Product_Category_or_Therapeutic_Area_1']
rec_details = ['Recipient_City','Recipient_Primary_Business_Street_Addre
ss_Line1','Recipient_Zip_Code']
new_remove = ['Date_of_Payment','Payment_Publication_Date','Delay_in_Pub
lication_Indicator']
num_name = ['Total_Amount_of_Payment_USDollars']
categ_name_copy = deepcopy(categ_name)
remove_list = irrelavant + new_remove + rec_details
for a in remove_list:
    if a in categ_name_copy:
        categ_name_copy.remove(a)
(categ_name_copy)
```

Out[73]:
```
['Recipient_State',
 'Recipient_Country',
 'Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1',
 'Form_of_Payment_or_Transfer_of_Value',
 'Related_Product_Indicator',
 'Dispute_Status_for_Publication',
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Country',
 'Change_Type',
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State',
 'Covered_or_Noncovered_Indicator_1']
```

In [55]:
```
#Reference: https://towardsdatascience.com/the-search-for-categorical-co
rrelation-a1cf7f1888c9
#Create a function called cramer_v to compute a correlation between cate
gorical features
def cramers_v(x, y):

    confusion_matrix = pd.crosstab(x,y)
    chi2 = ss.chi2_contingency(confusion_matrix)[0]
    n = confusion_matrix.sum().sum()
    phi2 = chi2/n
    r,k = confusion_matrix.shape
    phi2corr = max(0, phi2-((k-1)*(r-1))/(n-1))
    rcorr = r-((r-1)**2)/(n-1)
    kcorr = k-((k-1)**2)/(n-1)
    return np.sqrt(phi2corr/min((kcorr-1),(rcorr-1)))
```

In [58]:
```
columns = categ_temp.columns
cell = np.zeros(shape=(len(columns),len(columns)))

for i in range(0,len(columns)):
    for j in range(0,len(columns)):
        if i == j:
            cell[i][j] = categ_temp[columns[i]][columns[j]] = 1.0

            j +=1

        else:
            cell[i][j] = cramers_v(categ_temp[columns[i]],categ_temp[col
umns[j]])

            j +=1
```

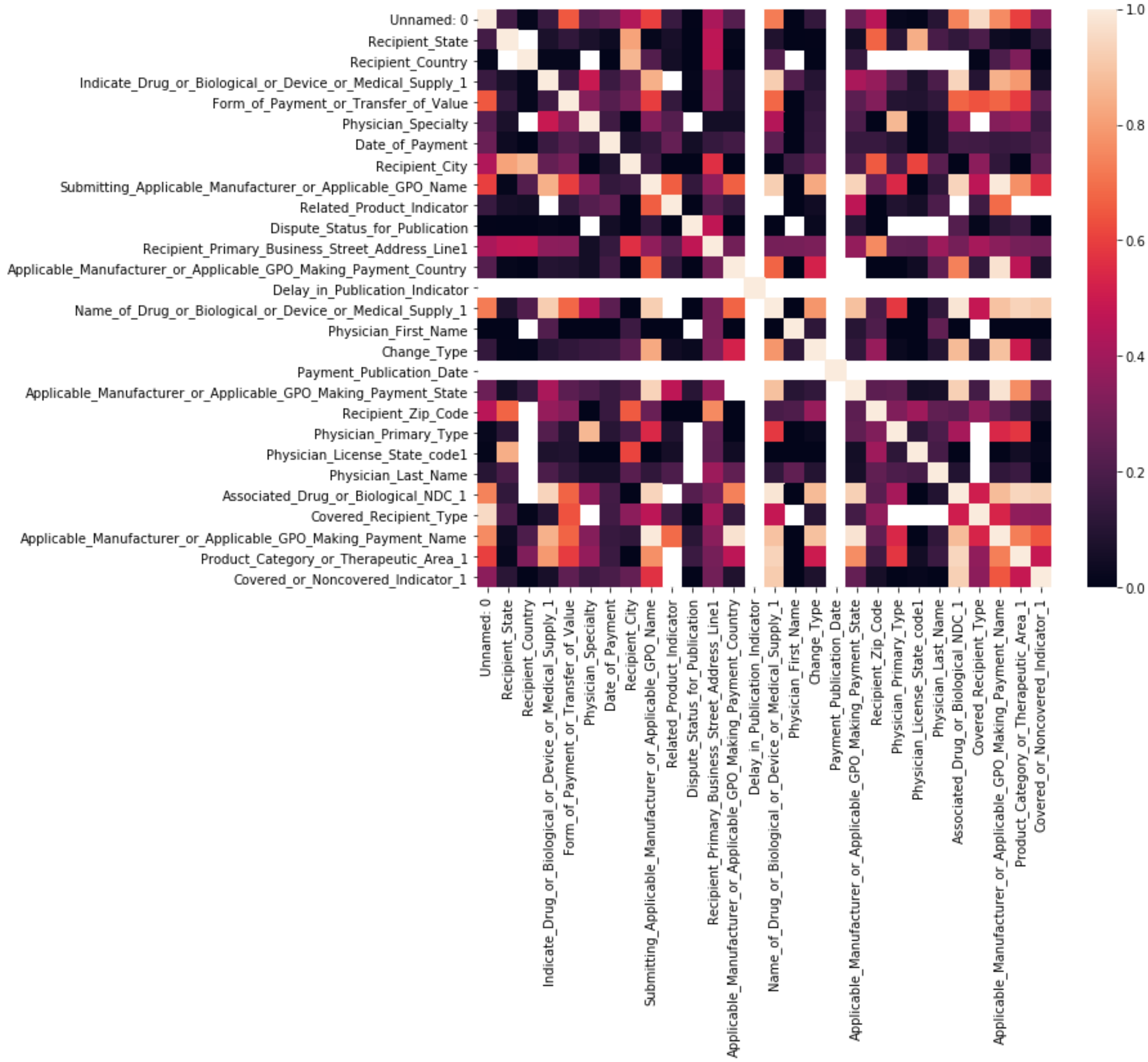
```
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:7: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  import sys
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:12: Runtim
eWarning: invalid value encountered in double_scalars
  if sys.path[0] == '':
/anaconda3/lib/python3.7/site-packages/pandas/core/series.py:915: Setti
ngWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  self.loc[key] = value
/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshell.p
y:3267: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  exec(code_obj, self.user_global_ns, self.user_ns)
```

In [82]:
```
#Calculate the correlation between each categorical feature by the crame
rs_v
new_df = pd.concat([categ_temp,target],axis=1)
columns = new_df.columns
cell = np.zeros(shape=(len(columns),len(columns)))

for i in range(0,len(columns)):
    for j in range(0,len(columns)):
        if i == j:
            cell[i][j] = new_df[columns[i]][columns[j]] = 1.0

            j +=1

        else:
            cell[i][j] = cramers_v(new_df[columns[i]],new_df[columns[j
]])

            j +=1
```

```
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:8: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy

/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:12: Runtim
eWarning: invalid value encountered in double_scalars
  if sys.path[0] == '':
```

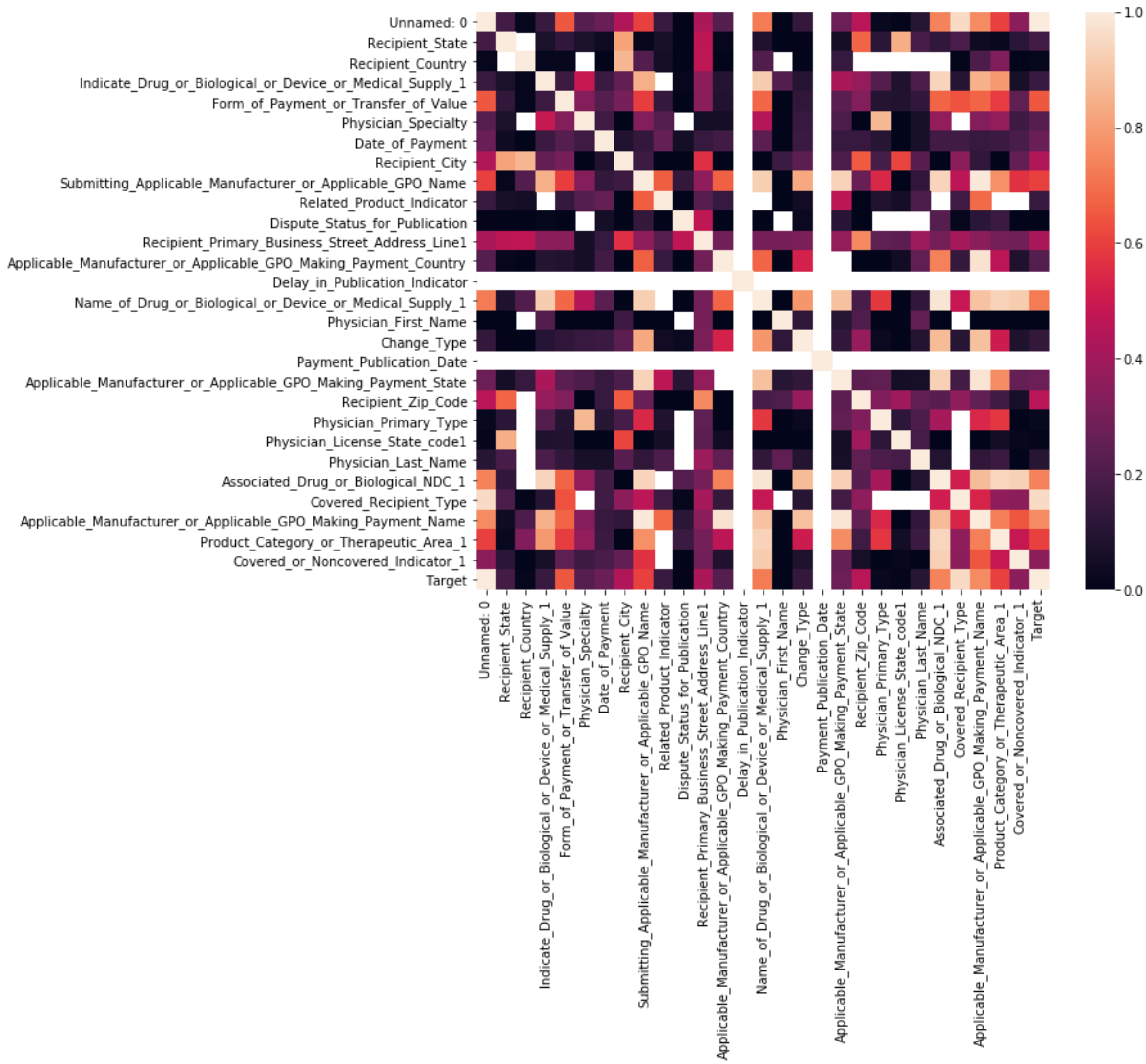
In [59]:
```
cell_df = pd.DataFrame(cell,index=columns, columns=columns)
size = (10, 8.27)
fig, ax = plt.subplots(figsize=size)
sns.heatmap(cell_df)
```

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x1a24eb9550>



In [83]:
```
#Visualize a correlation matrix by seaborn
cell_df = pd.DataFrame(cell,index=columns, columns=columns)
size = (10, 8.27)
fig, ax = plt.subplots(figsize=size)
sns.heatmap(cell_df)
```

Out[83]: <matplotlib.axes._subplots.AxesSubplot at 0x1a247e7a58>



We categorized the features as numeric and categorical features and removed features based on the following :

- As the first level of screening, we checked which features have more than 5000 rows (50% of the data) as NULL and retained the remaining.
  - Numerical features : we were left with just 1 feature (Total_Amount_of_Payment_USDollars)
  - Categorical features : we were left with 28 features (stored in the list categ_name)
- From the heat map for the categorical features, we can see that, features like Payment_Publication_Date and Delay_in Publication_Indicator are highly correlated to the other features and thus, we can exclude them
- Among the features left, we analyzed highly correlated features by training Logistic regression for each of the feature separately.
  - We then removed the ones that were highly correlated to the target.
  - The features are stored in the list irrelavant
- Among the remaining categorical features, we found that some of the features result in a very big one-hot encoded vector and they do not logically contribute to the model as well (eg: Recipient_Primary_Business_Street_Address_Line1, Date_of_Payment, Recipient_Zip_Code, Recipient_City), and we removed these features as well.

Finally, we ended up with 10 features. 'Recipient_State', 'Recipient_Country', 'Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1', 'Form_of_Payment_or_Transfer_of_Value', 'Related_Product_Indicator', 'Dispute_Status_for_Publication', 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Country', 'Change_Type', 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State', 'Covered_or_Noncovered_Indicator_1'

Similarly, for imbalanced data.

Preprocessing & Data Cleansing (For Imbalanced Data)

In [74]:
```
#Split the balanced datset into the targeted feature and predictive feat
ures
imb_target = test['Target']
imb_features = test.drop('Target', axis=1)

#Extract only numeric features from data
imb_numerics = imb_features._get_numeric_data()

#Extract categorical features and store the list of names of categorical
features
imb_categoricals = imb_features.select_dtypes(include='object')
```

In [75]:
```
#Check the number of missing values of numeric features
imb_num = imb_numerics.isnull().sum()

#Check the number of missing values of categorical features
imb_categ = imb_categoricals.isnull().sum()
```

In [76]:
```
#Extract columns which have fewer than 5000 nulls
imb_num_name = []
for i in range(len(imb_num)):
    if(imb_num[i-1] < 5000):
        imb_num_name.append(imb_num.index.tolist()[i-1])
    else:
        continue
imb_num_name = ['Total_Amount_of_Payment_USDollars','Applicable_Manufact
urer_or_Applicable_GPO_Making_Payment_ID','Program_Year','Physician_Prof
ile_ID']

#Create the dataframe for numeric variables , create a new dataframe nam
ed num_name, and store each variable's name
imb_temp = test[imb_num_name]
imb_num_temp = imb_temp[['Total_Amount_of_Payment_USDollars']]
imb_num_name = list(imb_num_temp)
```

In [77]:
```
#Store the list of names of numeric features
imb_numeric_features = list(imb_numerics)

#Store the list of names of categorical features
imb_categorical_features = list(imb_categoricals)
```

In [78]:
```
#Extract columns which have fewer than 5000 nulls
imb_categ_name = []
for i in range(len(imb_categ)):
    if(imb_categ[i-1] < 5000):
        imb_categ_name.append(imb_categ.index.tolist()[i-1])
    else:
        continue

#Create the dataframe for categorical variables, create a new dataframe
 named categ_name, and store each variable's name
imb_categ_temp = test[imb_categ_name]
imb_categ_name = list(imb_categ_temp)
```

In [79]:
```
#Concatenate num_temp and categ_temp
new_new = pd.concat([imb_num_temp,imb_categ_temp],axis=1)
```

Task 2: Baseline Model (Logistic Regression)

We used a logistic regression model for baseline as it is a linear model and is quite robust.

Preprocessing:

- For numerical features, we imputed the missing values using Median imputer and scaled the data for regression.
- For categorical features, we imputed the data and did a one-hot encoding to make it trainable in a logistic regression model

In [80]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                        ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                         ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', LogisticRegression(C=0.01))])

#Split the dataset into the training set and test set
X_train, X_test, y_train, y_test = train_test_split(new, target, stratif
y=target, test_size=0.3)


#Cross validation
scores = cross_val_score(clf,X_train, y_train, cv=10)
scores = sum(scores) / float(len(scores))
print("Baseline Model Cross Validation Score:")
print(scores)
```

```
Baseline Model Cross Validation Score:
0.8525714285714286
```

Task 3: Feature Engineering

In [ ]:
```
from sklearn.preprocessing import PolynomialFeatures
print(categ_name_copy)
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                        ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('polynomial_features',PolynomialFeatures(degree=3
)),
                      ('classifier', LogisticRegression(C=0.01))])

#Split the dataset into the training set and test set
X_train, X_test, y_train, y_test = train_test_split(new, target, stratif
y=target, test_size=0.3)


#Cross validation
scores = cross_val_score(clf,X_train, y_train, cv=10)
scores = sum(scores) / float(len(scores))
print("Score with polynomial features:")
print(scores)
```

```
['Recipient_State', 'Recipient_Country', 'Indicate_Drug_or_Biological_o
r_Device_or_Medical_Supply_1', 'Form_of_Payment_or_Transfer_of_Value',
'Related_Product_Indicator', 'Dispute_Status_for_Publication', 'Applica
ble_Manufacturer_or_Applicable_GPO_Making_Payment_Country', 'Change_Typ
e', 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State',
'Covered_or_Noncovered_Indicator_1']
```

With polynomial features, the model overfits. Since, the baseline logistic regression model works pretty well, combining features does not seem to be relevant for the given task.

Task 4: Any model

Logistic Regression with GridSearch

In [81]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                                      ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                          ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', LogisticRegression())])

#Split the dataset into the training set and test set
X_train, X_test, y_train, y_test = train_test_split(new, target, stratif
y=target, test_size=0.3)

param_grid = {'classifier__C': [0.01,0.1, 1, 10, 100]}

logistic_grid = GridSearchCV(clf, param_grid=param_grid, cv=5)
logistic_grid.fit(X_train, y_train)

print("best mean cross-validation score of Logistic Regression: {:.3f}".
format(logistic_grid.best_score_))
print("best parameters of Logistic Regression: {}".format(logistic_grid.
best_params_))
print("test-set score of Logistic Regression: {:.3f}".format(logistic_gr
id.score(X_test, y_test)))
print("")

logistic = LogisticRegression(C=logistic_grid.best_params_['classifier__
C'])
final_pipe = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', logistic)])
final_pipe.fit(X_train, y_train)
y_pred = final_pipe.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
print("ROC AUC score:" )
print(roc_auc_score(y_test, y_pred))
print("")
print("Precision Score:")
print(precision_score(y_test, y_pred))
print("")
```

```
print("Recall Score:")
print(recall_score(y_test, y_pred, average='weighted'))
```

```
best mean cross-validation score of Logistic Regression: 0.896
best parameters of Logistic Regression: {'classifier__C': 100}
test-set score of Logistic Regression: 0.895

Confusion Metrix:
[[1345  155]
 [ 159 1341]]

ROC AUC score:
0.8953333333333334

Precision Score:
0.8963903743315508

Recall Score:
0.8953333333333333
```

TRAIN THE BEST MODEL ON THE BALANCED TRAINING DATA SET WITH THE BEST PARAMS AGAIN AND TEST ON IMBALANCED DATASET

In [84]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                        ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                       ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', LogisticRegression(C=logistic_grid.
best_params_['classifier__C']))])

clf.fit(features,target)

#Test the modeld with the imbalanced dataset to check its performance
y_pred = clf.predict(new_new)
cm = confusion_matrix(imb_target, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
print("ROC AUC score:" )
print(roc_auc_score(imb_target, y_pred))
print("")
print("Precision Score:")
print(average_precision_score(imb_target, y_pred, average='weighted'))
print("")
print("Recall Score:")
print(recall_score(imb_target, y_pred, average='weighted'))
```

```
Confusion Metrix:
[[8323 1121]
 [  59  497]]

ROC AUC score:
0.8875925942854357

Precision Score:
0.28047403669153675

Recall Score:
0.882
```

Ridge Regression with GridSearch

In [85]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                        ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                       ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', RidgeClassifier())])

#Split the dataset into the training set and test set
X_train, X_test, y_train, y_test = train_test_split(new, target, stratif
y=target, test_size=0.3)

param_grid = {'classifier__alpha': [0.01,0.1, 1, 10, 100]}
ridge_grid = GridSearchCV(clf, param_grid=param_grid, cv=5)
ridge_grid.fit(X_train, y_train)

print("best mean cross-validation score of Ridge Regression: {:.3f}".for
mat(ridge_grid.best_score_))
print("best parameters of Ridge Regression: {}".format(ridge_grid.best_p
arams_))
print("test-set score of Ridge Regression: {:.3f}".format(ridge_grid.sco
re(X_test, y_test)))
print("")

ridge = RidgeClassifier(alpha=ridge_grid.best_params_['classifier__alph
a'])
final_pipe = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', ridge)])
final_pipe.fit(X_train, y_train)
y_pred = final_pipe.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
print("ROC AUC score:" )
print(roc_auc_score(y_test, y_pred))
print("")
print("Precision Score:")
print(precision_score(y_test, y_pred))
print("")
print("Recall Score:")
print(recall_score(y_test, y_pred, average='weighted'))
```

```
best mean cross-validation score of Ridge Regression: 0.875
best parameters of Ridge Regression: {'classifier__alpha': 0.01}
test-set score of Ridge Regression: 0.864

Confusion Metrix:
[[1301  199]
 [ 210 1290]]

ROC AUC score:
0.8636666666666666

Precision Score:
0.8663532572196104

Recall Score:
0.8636666666666667
```

TRAIN THE BEST MODEL ON THE BALANCED TRAINING DATA SET WITH THE BEST PARAMS AGAIN AND TEST ON IMBALANCED DATASET

In [86]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                        ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                       ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', RidgeClassifier(alpha=ridge_grid.be
st_params_['classifier__alpha']))])

clf.fit(features,target)

#Test the modeld with the imbalanced dataset to check its performance
y_pred = clf.predict(new_new)
cm = confusion_matrix(imb_target, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
print("ROC AUC score:" )
print(roc_auc_score(imb_target, y_pred))
print("")
print("Precision Score:")
print(average_precision_score(imb_target, y_pred, average='weighted'))
print("")
print("Recall Score:")
print(recall_score(imb_target, y_pred, average='weighted'))
```

```
Confusion Metrix:
[[8166 1278]
 [  65  491]]

ROC AUC score:
0.8738847549660399

Precision Score:
0.25160962174296736

Recall Score:
0.8657
```

Random Forest with GridSearch

In [89]:
```
#Split the dataset into the training set and the test set
X_train, X_test, y_train, y_test = train_test_split(features, target, st
ratify=target, test_size=0.3,shuffle=True)

#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='mean')),
                    ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                       ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to given dataset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

param_grid = {'classifier__max_depth' : range(1,10)}

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', RandomForestClassifier(warm_start=T
rue))])

grid = GridSearchCV(clf, param_grid,cv=10, scoring='roc_auc')
grid.fit(X_train, y_train)

print('Score', grid.best_score_)
print('Best params',grid.best_params_)


rfc = RandomForestClassifier(n_estimators=200,
                              max_depth=grid.best_params_['classifier__
max_depth'],random_state=0)
final_pipe = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', rfc)])
final_pipe.fit(X_train, y_train)
y_pred = final_pipe.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
print(roc_auc_score(y_test, y_pred))
print("")
print("Precision Score:")
print(precision_score(y_test, y_pred))
print("")
print("Recall Score:")
print(recall_score(y_test, y_pred, average='weighted'))
```

```
Score 0.9675881632653062
Best params {'classifier__max_depth': 9}
[[1374  126]
 [  77 1423]]
0.9323333333333333

Precision Score:
0.9186571981923822

Recall Score:
0.9323333333333333
```

TRAIN THE BEST MODEL ON THE BALANCED TRAINING DATA SET WITH THE BEST PARAMS AGAIN AND TEST ON IMBALANCED DATASET

In [91]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='mean')),
                    ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                        ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to given dataset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

param_grid = {'classifier__n_estimators': range(50, 300, 50),
             'classifier__max_depth' : range(1,10)}

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', RandomForestClassifier(n_estimators
=200,
                               max_depth=grid.best_params_['classifier__
max_depth'],random_state=0))])

clf.fit(features,target)

#Test the modeld with the imbalanced dataset to check its performance
y_pred = clf.predict(new_new)
cm = confusion_matrix(imb_target, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
print("ROC AUC score:" )
print(roc_auc_score(imb_target, y_pred))
print("")
print("Precision Score:")
print(average_precision_score(imb_target, y_pred, average='weighted'))
print("")
print("Recall Score:")
print(recall_score(imb_target, y_pred, average='weighted'))
```

```
Confusion Metrix:
[[8576  868]
 [  43  513]]

ROC AUC score:
0.9153758314822094

Precision Score:
0.34704115826817183

Recall Score:
0.9089
```

XGBoost with GridSearch

In [124]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                          ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                        ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', XGBClassifier())])

#Split the dataset into the training set and test set
X_train, X_test, y_train, y_test = train_test_split(new, target, stratif
y=target, test_size=0.3)

params = {
        'classifier__gamma': [0.5, 1, 1.5, 2, 5],
        'classifier__subsample': [0.6, 0.8, 1.0],
        'classifier__max_depth': [3, 4, 5]
        }
grid = GridSearchCV(clf, param_grid=params, cv=5)
grid.fit(X_train, y_train)

print("best mean cross-validation score of Ridge Regression: {:.3f}".for
mat(grid.best_score_))
print("best parameters of Ridge Regression: {}".format(grid.best_params_
))
print("test-set score of Ridge Regression: {:.3f}".format(grid.score(X_t
est, y_test)))
print("")

XGBoost = XGBClassifier(gamma=grid.best_params_['classifier__gamma'],
                        subsample=grid.best_params_['classifier__subsamp
le'],
                        max_depth=grid.best_params_['classifier__max_dep
th'])

final_pipe = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier',XGBoost)])
final_pipe.fit(X_train, y_train)
y_pred = final_pipe.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
```

```
print("ROC AUC score:" )
print(roc_auc_score(y_test, y_pred))
print("")
print("Precision Score:")
print(precision_score(y_test, y_pred))
print("")
print("Recall Score:")
print(recall_score(y_test, y_pred, average='weighted'))
```

```
best mean cross-validation score of Ridge Regression: 0.940
best parameters of Ridge Regression: {'classifier__gamma': 1.5, 'classi
fier__max_depth': 5, 'classifier__subsample': 1.0}
test-set score of Ridge Regression: 0.943

Confusion Metrix:
[[1397  103]
 [  69 1431]]

ROC AUC score:
0.9426666666666667

Precision Score:
0.9328552803129074

Recall Score:
0.9426666666666667
```

TRAIN THE BEST MODEL ON THE BALANCED TRAINING DATA SET WITH THE BEST PARAMS AGAIN AND TEST ON IMBALANCED DATASET

In [116]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                          ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                        ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', XGBClassifier())])

clf.fit(features,target)

#Test the modeld with the imbalanced dataset to check its performance
y_pred = clf.predict(new_new)
cm = confusion_matrix(imb_target, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
print("ROC AUC score:" )
print(roc_auc_score(imb_target, y_pred))
print("")
print("Precision Score:")
print(average_precision_score(imb_target, y_pred, average='weighted'))
print("")
print("Recall Score:")
print(recall_score(imb_target, y_pred, average='weighted'))
```

```
Confusion Metrix:
[[8656  788]
 [  20  536]]

ROC AUC score:
0.9402947781546046

Precision Score:
0.39227146862570367

Recall Score:
0.9192
```

The best model we found through the experiments is XGBoost. We will now try to understand feature importances for XGBoost

Removing a couple of least important features

In [117]:
```
from copy import deepcopy
least_imp = np.argsort(np.absolute(final_pipe.named_steps['classifier'].
feature_importances_))[-20:]
for i in range(20):
    least_imp[i]-=1

print(final_pipe.named_steps['preprocessor'].transformers_[1][1].named_s
teps.onehot.get_feature_names(categ_name_copy)[least_imp])
least_imp_features = ['Applicable_Manufacturer_or_Applicable_GPO_Making_
Payment_State',
                      'Indicate_Drug_or_Biological_or_Device_or_Medical_
Supply_1']

categ_name_copy_drop = deepcopy(categ_name_copy)
for l in least_imp_features:
    categ_name_copy_drop.remove(l)
```

```
['Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_NY'
 'Change_Type_NEW'
 'Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1_Drug'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_CT'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_MD'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Country_Irel
and'
 'Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1_Biological'
 'Change_Type_CHANGED'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_OR'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_NJ'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_TX'
 'Covered_or_Noncovered_Indicator_1_Covered'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_CA'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_DE'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_MA'
 'Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1_Device'
 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_Country_Unit
ed States'
 'Covered_or_Noncovered_Indicator_1_Non-Covered'
 'Form_of_Payment_or_Transfer_of_Value_Cash or cash equivalent'
 'Covered_or_Noncovered_Indicator_1_missing']
```

Training after remove a couple of least important features

In [118]:

```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                        ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                       ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy_drop)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', XGBClassifier())])

#Split the dataset into the training set and test set
X_train, X_test, y_train, y_test = train_test_split(new, target, stratif
y=target, test_size=0.3)

params = {
        'classifier__gamma': [0.5, 1, 1.5, 2, 5],
        'classifier__subsample': [0.6, 0.8, 1.0],
        'classifier__max_depth': [3, 4, 5]
        }
grid = GridSearchCV(clf, param_grid=params, cv=5)
grid.fit(X_train, y_train)

print("best mean cross-validation score of Ridge Regression: {:.3f}".for
mat(grid.best_score_))
print("best parameters of Ridge Regression: {}".format(grid.best_params_
))
print("test-set score of Ridge Regression: {:.3f}".format(grid.score(X_t
est, y_test)))
print("")

XGBoost = XGBClassifier(gamma=grid.best_params_['classifier__gamma'],
                        subsample=grid.best_params_['classifier__subsamp
le'],
                        max_depth=grid.best_params_['classifier__max_dep
th'])

final_pipe = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier',XGBoost)])
final_pipe.fit(X_train, y_train)
y_pred = final_pipe.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
```

```
print("ROC AUC score:" )
print(roc_auc_score(y_test, y_pred))
print("")
print("Precision Score:")
print(precision_score(y_test, y_pred))
print("")
print("Recall Score:")
print(recall_score(y_test, y_pred, average='weighted'))
```

```
best mean cross-validation score of Ridge Regression: 0.922
best parameters of Ridge Regression: {'classifier__gamma': 0.5, 'classi
fier__max_depth': 5, 'classifier__subsample': 0.8}
test-set score of Ridge Regression: 0.933

Confusion Metrix:
[[1357  143]
 [  57 1443]]

ROC AUC score:
0.9333333333333333

Precision Score:
0.9098360655737705

Recall Score:
0.9333333333333333
```

TRAINING ON BALANCED AND TESTING ON IMBALANCED

In [119]:
```
#Build a pipeline to handle the numeric features
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='median')),
                        ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                       ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to the given dat
aset
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, num_name),
        ('cat', categorical_transformer, categ_name_copy_drop)])

#Create a pipeline which contains our model
clf = Pipeline(steps=[('preprocessor', preprocessor),
                      ('classifier', XGBClassifier())])

clf.fit(features,target)

#Test the modeld with the imbalanced dataset to check its performance
y_pred = clf.predict(new_new)
cm = confusion_matrix(imb_target, y_pred)
print("Confusion Metrix:")
print(cm)
print("")
print("ROC AUC score:" )
print(roc_auc_score(imb_target, y_pred))
print("")
print("Precision Score:")
print(average_precision_score(imb_target, y_pred, average='weighted'))
print("")
print("Recall Score:")
print(recall_score(imb_target, y_pred, average='weighted'))
```

```
Confusion Metrix:
[[8395 1049]
 [  21  535]]

ROC AUC score:
0.925577200247426

Precision Score:
0.32709568526996585

Recall Score:
0.893
```

Task 5: Feature Selections

In [125]:
```
# Taking the most important features from the
most_imp = np.argsort(np.absolute(final_pipe.named_steps['classifier'].f
eature_importances_))[:5]

for i in range(5):
    most_imp[i]-=1

most_imp
```

Out[125]:
```
array([126,  66, 113,  64, 114])
```

In [126]:
```
final_pipe.named_steps['preprocessor'].transformers_[1][1].named_steps.o
nehot.get_feature_names(categ_name_copy)[most_imp]
```

Out[126]:
```
array(['Covered_or_Noncovered_Indicator_1_missing',
       'Related_Product_Indicator_Yes',
       'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_
PR',
       'Form_of_Payment_or_Transfer_of_Value_In-kind items and service
s',
       'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_
RI'],
      dtype=object)
```

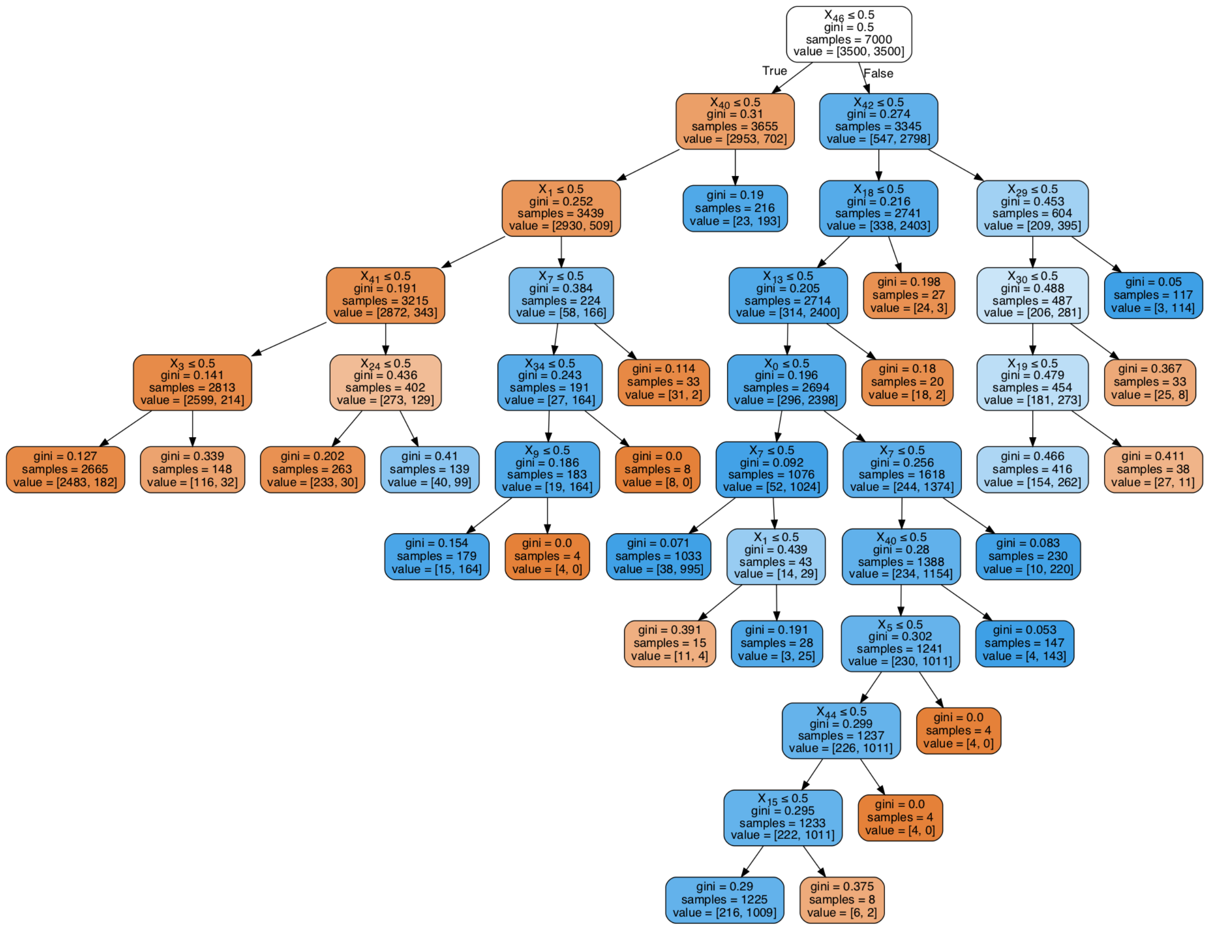
- Based on the XGBoost model, the top 5 important features are : 'Covered_or_Noncovered_Indicator_1_missing', 'Related_Product_Indicator_Yes', 'Form_of_Payment_or_Transfer_of_Value_In-kind items and services', 'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_State_TN', 'Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1_Medical Supply'.
- We will build a decision tree based on these 5 features and check the accuracy.
- We tried removing 2 unimportant features, but model based on XGBoost, performed worse. This is possibly because we already dropped the highly irrelevant features as part of preprocessing.

Task 6: An explainable model

In [112]:
```
#Package for visualizing the decision tree
!pip install pydotplus

# Training a decision tree

X_train, X_test, y_train, y_test = train_test_split(features, target, st
ratify=target, test_size=0.3,shuffle=True)

# TO be replaced by the best features of the xgboost model
cat_names = ['Covered_or_Noncovered_Indicator_1',
            'Related_Product_Indicator',
            'Applicable_Manufacturer_or_Applicable_GPO_Making_Payment_St
ate',
             'Indicate_Drug_or_Biological_or_Device_or_Medical_Supply_1'
,
             'Form_of_Payment_or_Transfer_of_Value'
            ]
numeric_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy
='mean')),
                    ('scaler', StandardScaler())])

#Build a pipeline to handle the categorical features
categorical_transformer = Pipeline(steps=[('imputer', SimpleImputer(stra
tegy='constant', fill_value='missing')),
                                       ('onehot',OneHotEncoder(handle_un
known='ignore'))])

#Build a column transformer to apply transformers above to given dataset
preprocessor = ColumnTransformer(
    transformers=[('cat', categorical_transformer, cat_names)])

X_train_processed = preprocessor.fit_transform(X_train[cat_names])
dtree=DecisionTreeClassifier(max_leaf_nodes=24)
dtree.fit(X_train_processed,y_train)

X_test_processed = preprocessor.transform(X_test[cat_names])
print('Decision Tree score',dtree.score(X_test_processed,y_test))

# Plotting the decision tree
from sklearn.externals.six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus
dot_data = StringIO()
export_graphviz(dtree, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```

```
Requirement already satisfied: pydotplus in /anaconda3/lib/python3.7/si
te-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in /anaconda3/lib/pytho
n3.7/site-packages (from pydotplus) (2.3.0)
Decision Tree score 0.8933333333333333
```

Out[112]:



We built a decision tree on the top 5 features according to XGBoost. This gives us a slightly better accuracy than the baseline model (at around 90%)

In [ ]: