1 Predicting Bankruptcies in Taiwan

In [1]:
```
#importing relevant libraries
import pandas as pd
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.utils import resample
from imblearn.over_sampling import SMOTE

from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier

from sklearn import tree
import xgboost as xgb
from numpy import loadtxt
from xgboost import XGBClassifier
from xgboost import plot_tree
```

executed in 1.43s, finished 23:37:34 2021-02-22

In [2]:
```
pd.set_option('display.max_rows', 75)
```

executed in 15ms, finished 23:37:35 2021-02-22

In [3]:
```
def find_best_k_recall(X_train, y_train, X_test, y_test, min_k=1, max_k=25):
    best_k = 0
    best_score = 0.0
    for k in range(min_k, max_k+1, 2):
        knn = KNeighborsClassifier(n_neighbors=k)
        knn.fit(X_train, y_train)
        preds = knn.predict(X_test)
        recall = recall_score(y_test, preds)
        if recall > best_score:
            best_k = k
            best_score = recall

    print("Best Value for k: {}".format(best_k))
    print("Recall-Score: {}".format(best_score))
```

executed in 12ms, finished 23:37:35 2021-02-22

In [4]:
```
def find_best_k(X_train, y_train, X_test, y_test, min_k=1, max_k=25):
    best_k = 0
    best_score = 0.0
    for k in range(min_k, max_k+1, 2):
        knn = KNeighborsClassifier(n_neighbors=k)
        knn.fit(X_train, y_train)
        preds = knn.predict(X_test)
        f1 = f1_score(y_test, preds)
        if f1 > best_score:
            best_k = k
            best_score = f1

    print("Best Value for k: {}".format(best_k))
    print("F1-Score: {}".format(best_score))
```

executed in 15ms, finished 23:37:35 2021-02-22

In [5]:
```
#bringing in file as pandas dataframe
df = pd.read_csv('data/taiwan_bankruptcy_data.csv')
df.head()
```

executed in 105ms, finished 23:37:35 2021-02-22

Out[5]:

	Bankrupt?	ROA(C) before interest and depreciation before interest	ROA(A) before interest and % after tax	ROA(B) before interest and depreciation after tax	operating gross margin	realized sales gross margin	operating profit rate	tax Pre-net interest rate	after-tax net interest rate	non-industry income and expenditure/revenue
0	1	0.370594	0.424389	0.405750	0.601457	0.601457	0.998969	0.796887	0.808809	0.302
1	1	0.464291	0.538214	0.516730	0.610235	0.610235	0.998946	0.797380	0.809301	0.303
2	1	0.426071	0.499019	0.472295	0.601450	0.601364	0.998857	0.796403	0.808388	0.302
3	1	0.399844	0.451265	0.457733	0.583541	0.583541	0.998700	0.796967	0.808966	0.303
4	1	0.465022	0.538432	0.522298	0.598783	0.598783	0.998973	0.797366	0.809304	0.303

5 rows × 96 columns

1.0.1 Pre-Processing data

In [6]:
```
f = np.array(df.isna().sum())
f
```
executed in 11ms, finished 23:37:35 2021-02-22

Out[6]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)
```

In [7]:
```
#checking info on entire dataframe
df.info()
```
executed in 28ms, finished 23:37:35 2021-02-22

```
 38   net worth/assets                                  6819 non-null   float64
 39   long-term fund suitability ratio (A)              6819 non-null   float64
 40   borrowing dependency                              6819 non-null   float64
 41   contingent liabilities/net worth                  6819 non-null   float64
 42   Operating profit/paid-in capital                  6819 non-null   float64
 43   net profit before tax/paid-in capital             6819 non-null   float64
 44   inventory and accounts receivable/net value       6819 non-null   float64
 45   total asset turnover                              6819 non-null   float64
 46   accounts receivable turnover                      6819 non-null   float64
 47   average collection days                           6819 non-null   float64
 48   inventory turnover rate (times)                   6819 non-null   float64
 49   fixed assets Turnover frequency                   6819 non-null   float64
 50   net worth turnover rate (times)                   6819 non-null   float64
 51   revenue per person                                6819 non-null   float64
 52   operating profit per person                       6819 non-null   float64
 53   allocation rate per person                        6819 non-null   float64
 54   working capital to total assets                   6819 non-null   float64
 55  Quick asset/Total asset                            6819 non-null   float64
 56  current assets/total assets                        6819 non-null   float64
 57  cash / total assets                                6819 non-null   float64
```

Looking through the info method I see all my datatype are float or int so no need for extra cleaning there. Also no nan values for any variables so clean there as well

Columns I predict will be significant predictors:

- interest expense ratio
- interest-bearing debt interest rate
- total debt/total net worth
- long-term liability to current assets
- cash flow to liability
- current liabilities to current assets
- Degree of financial leverage (DFL)

In [8]:
```
#checking for unique values
for col in df.columns:
    print(col)
    print(df[col].value_counts(normalize = True, ascending=False).head(5))
    print("------------------------------------------------------------")
```

executed in 186ms, finished 23:37:36 2021-02-22

```
0.689702    0.000440
Name:  regular net profit growth rate, dtype: float64
------------------------------------------------------------
 continuous net profit growth rate
0.217580    0.000587
0.217631    0.000440
0.217612    0.000440
0.217581    0.000440
0.217576    0.000440
Name:  continuous net profit growth rate, dtype: float64
------------------------------------------------------------
 total asset growth rate
6.370000e+09    0.004106
6.400000e+09    0.004106
6.890000e+09    0.003960
6.300000e+09    0.003960
6.440000e+09    0.003960
Name:  total asset growth rate, dtype: float64
------------------------------------------------------------
 net value growth rate
```

In [9]:
```
## contingent liabilities of
```

executed in 14ms, finished 23:37:37 2021-02-22

In [10]:
```
#checking predictors for multicollinearity

test = df.corr().abs().stack().reset_index().sort_values(0,ascending=False)
test['pairs'] = list(zip(test.level_0,test.level_1))
test.set_index(['pairs'], inplace=True)
test.drop(columns=['level_1','level_0'], inplace=True)
test.columns = ['cc']
test.drop_duplicates(inplace=True)
test.sort_values('cc',ascending=False, inplace=True)
multicollinear_predictors = test[test.cc >.75]
multicollinear_predictors.reset_index(inplace=True)
```

executed in 147ms, finished 23:37:37 2021-02-22

In [11]:
```
multicollinear_predictors['column_1'] = multicollinear_predictors.pairs.map(lambda x : x[0])
multicollinear_predictors['column_2'] = multicollinear_predictors.pairs.map(lambda x : x[1])
```

executed in 10ms, finished 23:37:37 2021-02-22

```
<ipython-input-11-a30768636eb9>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  multicollinear_predictors['column_1'] = multicollinear_predictors.pairs.map(lambda x : x[0])
<ipython-input-11-a30768636eb9>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  multicollinear_predictors['column_2'] = multicollinear_predictors.pairs.map(lambda x : x[1])
```

In [12]:
```
1 multicollinear_predictors
```
executed in 39ms, finished 23:37:37 2021-02-22

Out[12]:

	pairs	cc	column_1	column_2
0	(net worth/assets, debt ratio %)	1.000000	net worth/assets	debt ratio %
1	(regular net profit growth rate, regular net...	1.000000	regular net profit growth rate	regular net profit growth rate
2	(Gross profit to Sales, operating gross margin)	1.000000	Gross profit to Sales	operating gross margin
3	(Net Value Per Share (C), Net Value Per Shar...	0.999837	Net Value Per Share (C)	Net Value Per Share (A)
4	(operating gross margin, realized sales gros...	0.999518	operating gross margin	realized sales gross margin
5	(realized sales gross margin, Gross profit to...	0.999518	realized sales gross margin	Gross profit to Sales
6	(Net Value Per Share (A), per Net Share Valu...	0.999342	Net Value Per Share (A)	per Net Share Value (B)
7	(per Net Share Value (B), Net Value Per Shar...	0.999179	per Net Share Value (B)	Net Value Per Share (C)
8	(Operating profit/paid-in capital, Operating...	0.998696	Operating profit/paid-in capital	Operating Profit Per Share (Yuan)
9	(regular net profit growth rate, after-tax n...	0.996186	regular net profit growth rate	after-tax net profit growth rate
10	(continuous interest rate (after tax), tax P...	0.993617	continuous interest rate (after tax)	tax Pre-net interest rate
11	(ROA(C) before interest and depreciation befo...	0.986849	ROA(C) before interest and depreciation befor...	ROA(B) before interest and depreciation after...
12	(after-tax net interest rate, tax Pre-net in...	0.986379	after-tax net interest rate	tax Pre-net interest rate
13	(continuous interest rate (after tax), after...	0.984452	continuous interest rate (after tax)	after-tax net interest rate
14	(current liability/equity, liability to equity)	0.963908	current liability/equity	liability to equity
15	(Per Share Net profit before tax (yuan), net...	0.962723	Per Share Net profit before tax (yuan)	net profit before tax/paid-in capital
16	(ROA(A) before interest and % after tax, net ...	0.961552	ROA(A) before interest and % after tax	net income to total assets
17	(net profit before tax/paid-in capital, Pers...	0.959461	net profit before tax/paid-in capital	Persistent EPS in the Last Four Seasons
18	(liability to equity, borrowing dependency)	0.955857	liability to equity	borrowing dependency
19	(ROA(B) before interest and depreciation afte...	0.955741	ROA(B) before interest and depreciation after...	ROA(A) before interest and % after tax

	pairs	cc	column_1	column_2
20	(Per Share Net profit before tax (yuan), Per...	0.955591	Per Share Net profit before tax (yuan)	Persistent EPS in the Last Four Seasons
21	(Cash flow to Sales, working capitcal turnov...	0.948194	Cash flow to Sales	working capitcal turnover rate
22	(ROA(C) before interest and depreciation befo...	0.940124	ROA(C) before interest and depreciation befor...	ROA(A) before interest and % after tax
23	(tax Pre-net interest rate, operating profit...	0.916448	tax Pre-net interest rate	operating profit rate
24	(operating profit rate, continuous interest ...	0.915544	operating profit rate	continuous interest rate (after tax)
25	(ROA(B) before interest and depreciation afte...	0.912040	ROA(B) before interest and depreciation after...	net income to total assets
26	(borrowing dependency, current liability/equity)	0.892772	borrowing dependency	current liability/equity
27	(net income to total assets, ROA(C) before in...	0.887670	net income to total assets	ROA(C) before interest and depreciation befor...
28	(Operating profit/paid-in capital, net profi...	0.887370	Operating profit/paid-in capital	net profit before tax/paid-in capital
29	(net profit before tax/paid-in capital, Oper...	0.886157	net profit before tax/paid-in capital	Operating Profit Per Share (Yuan)
30	(operating funds to liability, cash flow rate)	0.880562	operating funds to liability	cash flow rate
31	(Operating Profit Per Share (Yuan), Persiste...	0.876769	Operating Profit Per Share (Yuan)	Persistent EPS in the Last Four Seasons
32	(Operating profit/paid-in capital, Persisten...	0.873641	Operating profit/paid-in capital	Persistent EPS in the Last Four Seasons
33	(after-tax net interest rate, operating prof...	0.862191	after-tax net interest rate	operating profit rate
34	(Per Share Net profit before tax (yuan), Ope...	0.861813	Per Share Net profit before tax (yuan)	Operating Profit Per Share (Yuan)
35	(Operating profit/paid-in capital, Per Share...	0.858310	Operating profit/paid-in capital	Per Share Net profit before tax (yuan)
36	(current liability to assets, net worth/assets)	0.842583	current liability to assets	net worth/assets
37	(debt ratio %, current liability to assets)	0.842583	debt ratio %	current liability to assets
38	(equity to long-term liability, borrowing dep...	0.806889	equity to long-term liability	borrowing dependency
39	(borrowing dependency, Net income to stockhol...	0.806478	borrowing dependency	Net income to stockholder's Equity
40	(Retained Earnings/Total assets, net income to...	0.794189	Retained Earnings/Total assets	net income to total assets
41	(liability to equity, Net income to stockholde...	0.791836	liability to equity	Net income to stockholder's Equity

	pairs	cc	column_1	column_2
42	(equity to long-term liability, liability to e...	0.778135	equity to long-term liability	liability to equity
43	(Persistent EPS in the Last Four Seasons, RO...	0.775006	Persistent EPS in the Last Four Seasons	ROA(C) before interest and depreciation befor...
44	(working capital/equity, contingent liabiliti...	0.767778	working capital/equity	contingent liabilities/net worth
45	(Persistent EPS in the Last Four Seasons, RO...	0.764828	Persistent EPS in the Last Four Seasons	ROA(A) before interest and % after tax
46	(Persistent EPS in the Last Four Seasons, RO...	0.764597	Persistent EPS in the Last Four Seasons	ROA(B) before interest and depreciation after...
47	(net profit before tax/paid-in capital, ROA(...	0.758234	net profit before tax/paid-in capital	ROA(A) before interest and % after tax
48	(total asset turnover, net worth turnover ra...	0.757414	total asset turnover	net worth turnover rate (times)
49	(Persistent EPS in the Last Four Seasons, pe...	0.755568	Persistent EPS in the Last Four Seasons	per Net Share Value (B)
50	(current assets/total assets, Quick asset/Tota...	0.755453	current assets/total assets	Quick asset/Total asset
51	(Net Value Per Share (A), Persistent EPS in ...	0.755409	Net Value Per Share (A)	Persistent EPS in the Last Four Seasons
52	(Persistent EPS in the Last Four Seasons, Ne...	0.755217	Persistent EPS in the Last Four Seasons	Net Value Per Share (C)
53	(ROA(C) before interest and depreciation befo...	0.753339	ROA(C) before interest and depreciation befor...	net profit before tax/paid-in capital
54	(ROA(A) before interest and % after tax, Per...	0.752578	ROA(A) before interest and % after tax	Per Share Net profit before tax (yuan)
55	(ROA(C) before interest and depreciation befo...	0.750564	ROA(C) before interest and depreciation befor...	Per Share Net profit before tax (yuan)

In [13]:
```
1 df.columns
```
executed in 9ms, finished 23:37:38 2021-02-22

Out[13]:
```
Index(['Bankrupt?', ' ROA(C) before interest and depreciation before interest',
       ' ROA(A) before interest and % after tax',
       ' ROA(B) before interest and depreciation after tax',
       ' operating gross margin', ' realized sales gross margin',
       ' operating profit rate', ' tax Pre-net interest rate',
       ' after-tax net interest rate',
       ' non-industry income and expenditure/revenue',
       ' continuous interest rate (after tax)', ' operating expense rate',
       ' research and development expense rate', ' cash flow rate',
       ' interest-bearing debt interest rate', ' tax rate (A)',
       ' per Net Share Value (B)', ' Net Value Per Share (A)',
       ' Net Value Per Share (C)', ' Persistent EPS in the Last Four Seasons',
       ' Cash Flow Per Share', ' Revenue Per Share (Yuan)',
       ' Operating Profit Per Share (Yuan)',
       ' Per Share Net profit before tax (yuan)',
       ' realized sales gross profit growth rate',
       ' operating profit growth rate', ' after-tax net profit growth rate',
       ' regular net profit growth rate', ' continuous net profit growth rate',
       ' total asset growth rate', ' net value growth rate',
       ' total asset return growth rate Ratio', ' cash reinvestment %',
       ' current ratio', ' quick ratio', ' interest expense ratio',
       ' total debt/total net worth', ' debt ratio %', ' net worth/assets',
       ' long-term fund suitability ratio (A)', ' borrowing dependency',
       ' contingent liabilities/net worth',
       ' Operating profit/paid-in capital',
       ' net profit before tax/paid-in capital',
       ' inventory and accounts receivable/net value', ' total asset turnover',
       ' accounts receivable turnover', ' average collection days',
       ' inventory turnover rate (times)', ' fixed assets Turnover frequency',
       ' net worth turnover rate (times)', ' revenue per person',
       ' operating profit per person', ' allocation rate per person',
       ' working capital to total assets', 'Quick asset/Total asset',
       'current assets/total assets', 'cash / total assets',
       'Quick asset /current liabilities', 'cash / current liability',
       'current liability to assets', 'operating funds to liability',
       'Inventory/working capital', 'Inventory/current liability',
       'current liability / liability', 'working capital/equity',
       'current liability/equity', 'long-term liability to current assets',
       'Retained Earnings/Total assets', 'total income / total expense',
       'total expense /assets', ' current asset turnover rate',
```

```
       ' quick asset turnover rate', ' working capitcal turnover rate',
       ' cash turnover rate', ' Cash flow to Sales', ' fix assets to assets',
       ' current liability to liability', 'current liability to equity',
       'equity to long-term liability', 'Cash flow to total assets',
       'cash flow to liability', 'CFO to ASSETS', 'cash flow to equity',
       'current liabilities to current assets',
       'one if total liabilities exceeds total assets zero otherwise',
       'net income to total assets', 'total assets to GNP price',
       'No-credit interval', 'Gross profit to Sales',
       'Net income to stockholder's Equity', 'liability to equity',
       'Degree of financial leverage (DFL)',
       'Interest coverage ratio( Interest expense to EBIT )',
       'one if net income was negative for the last two year zero otherwise',
       'equity to liability'],
      dtype='object')
```

In [14]:

```
#Unsurprisingly, there are many columns that are correlated above .75 as my features
# are different line items on a financial statement
# below are chosen columns I think that models will still have accurate results without while
# still dealing with multicollinearity

columns_to_drop = [' net worth/assets','Gross profit to Sales',' Net Value Per Share (A)',' per Net Share V
                   ' realized sales gross margin',' Operating profit/paid-in capital',' regular net profit g
                   ' continuous interest rate (after tax)',' ROA(A) before interest and % after tax',' ROA(B
                   ' tax Pre-net interest rate',' net profit before tax/paid-in capital',
                   ' borrowing dependency',' Per Share Net profit before tax (yuan)',
                   'liability to equity',' Cash flow to Sales','operating funds to liability',' Operating Pr
                   ' after-tax net interest rate','one if net income was negative for the last two year zero
```

executed in 16ms, finished 23:37:38 2021-02-22

In [15]:

```
pre_pro = df.drop(columns=columns_to_drop,axis=1)
```

executed in 14ms, finished 23:37:38 2021-02-22

In [16]:

```
# seperating out my target and predictors into X and y and training and test groups
X = pre_pro.drop(columns='Bankrupt?',axis=1)
y = pre_pro['Bankrupt?']
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=.25,random_state=42)

```

executed in 10ms, finished 23:37:38 2021-02-22

In [17]:
```
#checking for class imbalance which we clearly have with our data
#this will need to be accounted for by resmapling in some way
y.value_counts(normalize=True), y.value_counts()
```
executed in 14ms, finished 23:37:39 2021-02-22

Out[17]:
```
(0    0.967737
 1    0.032263
 Name: Bankrupt?, dtype: float64,
 0    6599
 1     220
 Name: Bankrupt?, dtype: int64)
```

In [18]:
```
#making function to generate a panda df with relevant scores
def model_scores(y_true,y_pred,model_name):

    results = ({'Model':model_name,
                    'precision_score': precision_score(y_true,y_pred),
                    'recall_score': recall_score(y_true,y_pred),
                     'accuracy_score': accuracy_score(y_true,y_pred),
                     'f1_score':f1_score(y_true,y_pred)
                    })
    model_results = pd.DataFrame(data=results,index=[0])
    return model_results
```
executed in 14ms, finished 23:37:39 2021-02-22

In [19]:
```
#defining sigmoid function to scale my data from 0-1
def sigmoid(x):
    x = np.array(x)
    return 1/(1 + np.e**(-1*x))
```
executed in 12ms, finished 23:37:39 2021-02-22

In [20]:
```
#Using smote on my training data
#this will allow me to resample my training data and fit my model based on the resampled training data
# After doing so, when i predict based on my unchanged X_test values my class imbalance issues should not b

smote = SMOTE()
X_train_smote, y_train_smote = smote.fit_sample(X_train, y_train)
X_train_smote_sig = X_train_smote.apply(sigmoid)
X_test_sig = X_test.apply(sigmoid)
```
executed in 81ms, finished 23:37:40 2021-02-22

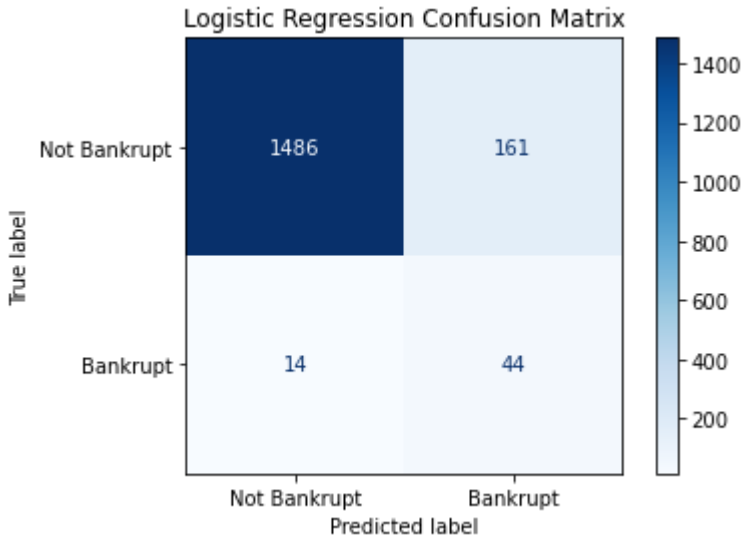
1.1 Models

1.1.1 Logistic Regression Model

In [21]:
```
logreg = LogisticRegression(C=1e12,fit_intercept=True,solver='liblinear')
log_model = logreg.fit(X_train_smote_sig, y_train_smote)
y_hat_log = logreg.predict(X_test_sig)
y_score_log = log_model.decision_function(X_test_sig)
fpr,tpr,thresholds = roc_curve(y_test,y_score_log)

print('AUC: {}'.format(auc(fpr, tpr)))
cf = confusion_matrix(y_test,y_hat_log)

plot_confusion_matrix(log_model,X_test_sig,y_test,cmap=plt.cm.Blues,
                      display_labels=["Not Bankrupt", "Bankrupt"],
                       values_format=".5g")
plt.title("Logistic Regression Confusion Matrix")

print(confusion_matrix(y_test, y_hat_log))
print(classification_report(y_test, y_hat_log))
```

executed in 6.49s, finished 23:37:47 2021-02-22

```
AUC: 0.9113539769277474
[[1486  161]
 [  14   44]]
              precision    recall  f1-score   support

           0       0.99      0.90      0.94      1647
           1       0.21      0.76      0.33        58

    accuracy                           0.90      1705
   macro avg       0.60      0.83      0.64      1705
weighted avg       0.96      0.90      0.92      1705


C:\Users\sergi\anaconda3\envs\learn-env\lib\site-packages\sklearn\svm\_base.py:976: ConvergenceWarning: Liblin
ear failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
```



In [22]:
```
log_scores = model_scores(y_test,y_hat_log,'Logistic Regression')
log_scores
```

executed in 13ms, finished 23:37:47 2021-02-22

Out[22]:

	Model	precision_score	recall_score	accuracy_score	f1_score
0	Logistic Regression	0.214634	0.758621	0.897361	0.334601

1.1.2 Decision Tree Model

In [23]:
```
dtree = DecisionTreeClassifier(max_depth=12,min_samples_leaf=2,min_samples_split=9)
```

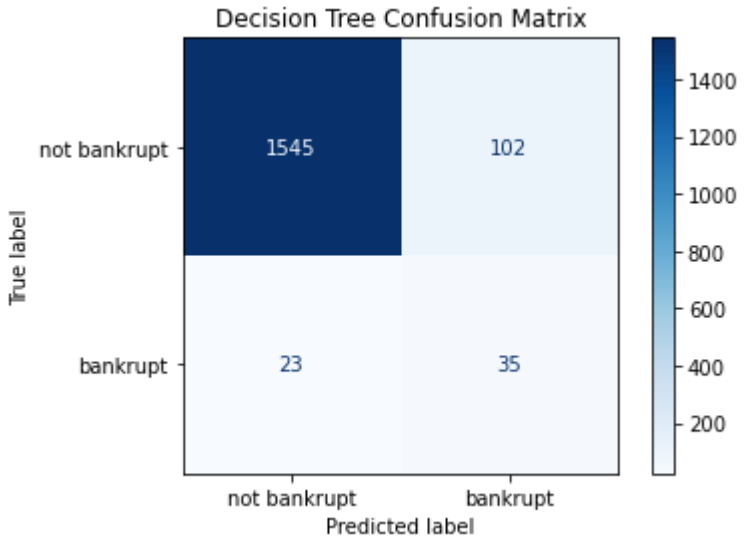
executed in 13ms, finished 23:37:48 2021-02-22

In [24]:

```
dtree.fit(X_train_smote_sig,y_train_smote)

y_pred_tree = dtree.predict(X_test_sig)

fpr, tpr, thresholds = roc_curve(y_test, y_pred_tree)

print('AUC: {}'.format(auc(fpr, tpr)))
cf = confusion_matrix(y_test,y_pred_tree)

plot_confusion_matrix(dtree,X_test_sig,y_test,cmap=plt.cm.Blues,
                      display_labels=["not bankrupt", "bankrupt"],
                       values_format=".5g")
plt.title("Decision Tree Confusion Matrix")

print(confusion_matrix(y_test, y_pred_tree))
print(classification_report(y_test, y_pred_tree))
```

executed in 758ms, finished 23:37:49 2021-02-22

```
AUC: 0.7707587463099053
[[1545  102]
 [  23   35]]
              precision    recall  f1-score   support

           0       0.99      0.94      0.96      1647
           1       0.26      0.60      0.36        58

    accuracy                           0.93      1705
   macro avg       0.62      0.77      0.66      1705
weighted avg       0.96      0.93      0.94      1705
```



In [25]:
```
dtree_scores = model_scores(y_test,y_pred_tree,"Decision Tree")
dtree_scores
```

executed in 15ms, finished 23:37:49 2021-02-22

Out[25]:

	Model	precision_score	recall_score	accuracy_score	f1_score
0	Decision Tree	0.255474	0.603448	0.926686	0.358974

1.1.3 Random Forest Model

In [26]:
```
forest = RandomForestClassifier(criterion='entropy',max_depth=5,min_samples_leaf=2,min_samples_split=5)
```

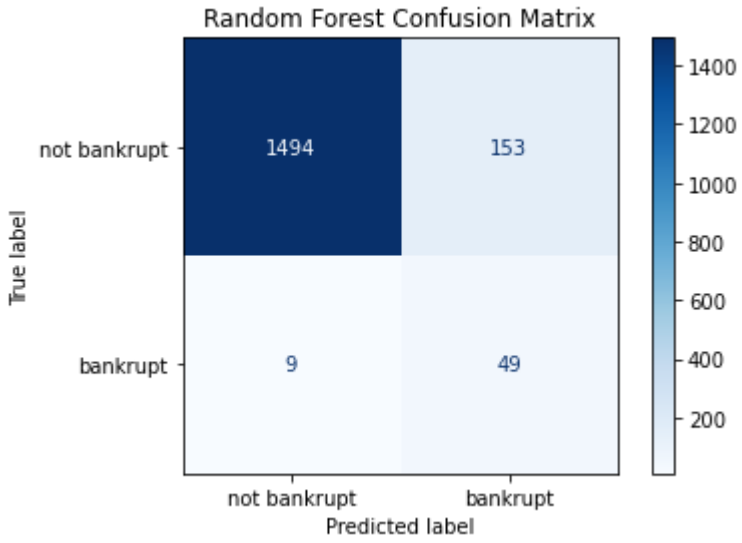
executed in 14ms, finished 23:37:49 2021-02-22

In [27]:

```
forest.fit(X_train_smote_sig,y_train_smote)

forest.predict(X_test_sig)

y_pred_forest = forest.predict(X_test_sig)

plot_confusion_matrix(forest,X_test_sig,y_test,cmap=plt.cm.Blues,
                      display_labels=["not bankrupt", "bankrupt"],
                       values_format=".5g")

plt.title("Random Forest Confusion Matrix")

print(confusion_matrix(y_test, y_pred_forest))
print(classification_report(y_test, y_pred_forest))
```

executed in 2.95s, finished 23:37:53 2021-02-22

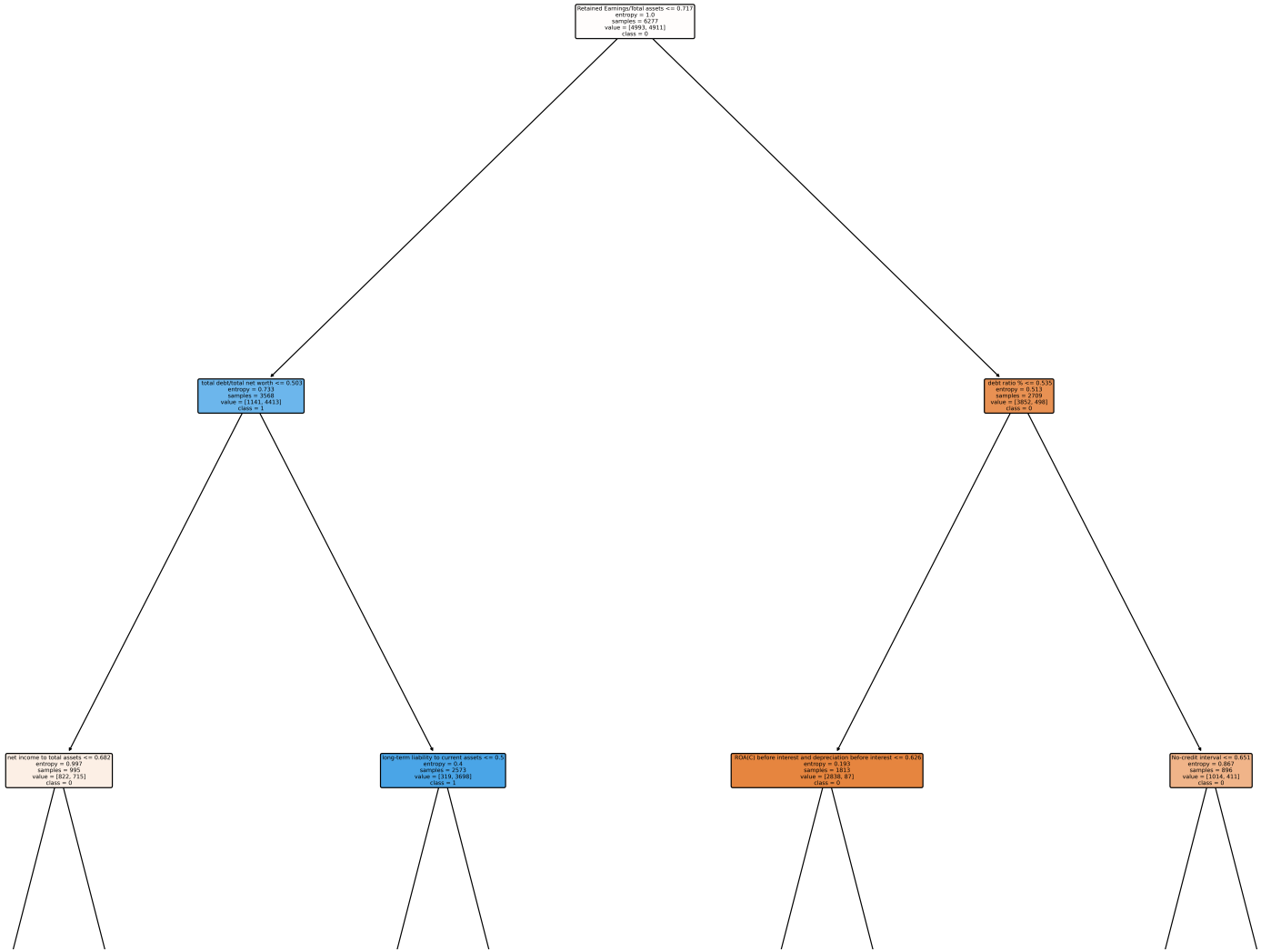
```
[[1494  153]
 [   9   49]]
              precision    recall  f1-score   support

           0       0.99      0.91      0.95      1647
           1       0.24      0.84      0.38        58

    accuracy                           0.90      1705
   macro avg       0.62      0.88      0.66      1705
weighted avg       0.97      0.90      0.93      1705
```

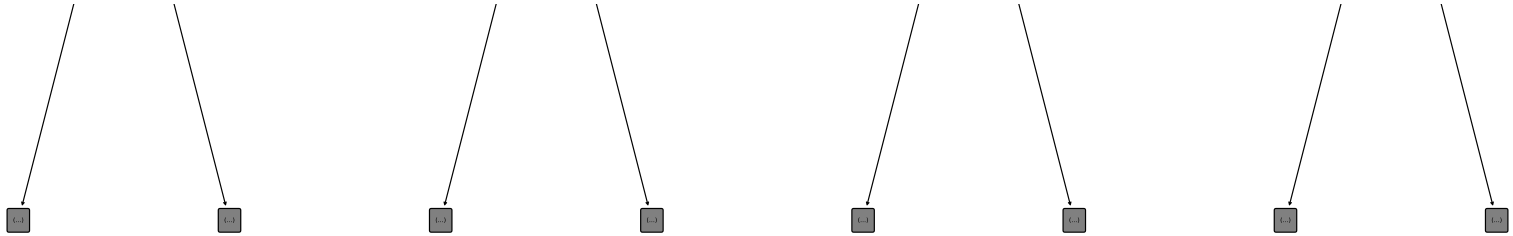


After running our Random forest model through gridsearchcv to optimize our hyperparameters we were able to improve our model all around from our prior decision tree. For our 1 value of our bankruptcy class 'target variable', we improved recall by .05 to .62 and precision from .26 to .38. F1 score and accuracy were also improved as well

In [28]:
```
#getting a tree from our random forest
rf_tree_1 = forest.estimators_[0]
plt.figure(figsize=(25,25), dpi=1000)
_ = tree.plot_tree(forest.estimators_[0], feature_names=X.columns, filled=True,
                   class_names = np.unique(y).astype('str'), rounded=True,max_depth=2)
```

executed in 16.0s, finished 23:38:09 2021-02-22





In [29]:
```
rf_scores = model_scores(y_test,y_pred_forest,"Random Forest")
rf_scores
```

executed in 15ms, finished 23:38:09 2021-02-22

Out[29]:

	Model	precision_score	recall_score	accuracy_score	f1_score
0	Random Forest	0.242574	0.844828	0.904985	0.376923

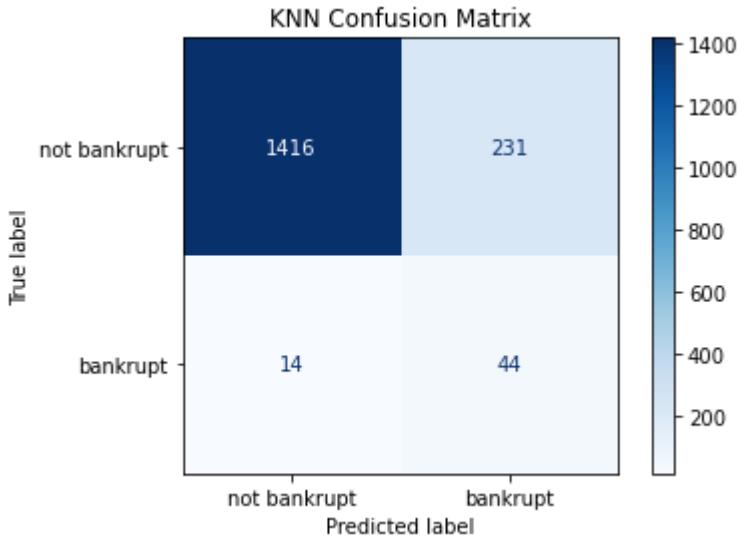
1.1.4 K-nearest Neighbors Model

In [30]:

```
knn = KNeighborsClassifier(n_neighbors=13,p=1)
knn.fit(X_train_smote_sig,y_train_smote)
y_pred_knn = knn.predict(X_test_sig)

fpr, tpr, thresholds = roc_curve(y_test, y_pred_knn)

print('AUC: {}'.format(auc(fpr, tpr)))
cf = confusion_matrix(y_test,y_pred_knn)

plot_confusion_matrix(knn,X_test_sig,y_test,cmap=plt.cm.Blues,
                      display_labels=["not bankrupt", "bankrupt"],
                       values_format=".5g")
plt.title("KNN Confusion Matrix")

print(confusion_matrix(y_test, y_pred_knn))
print(classification_report(y_test, y_pred_knn))

```

executed in 1.87s, finished 23:38:12 2021-02-22

```
AUC: 0.8091828402738521
[[1416  231]
 [  14   44]]
              precision    recall  f1-score   support

           0       0.99      0.86      0.92      1647
           1       0.16      0.76      0.26        58

    accuracy                           0.86      1705
   macro avg       0.58      0.81      0.59      1705
weighted avg       0.96      0.86      0.90      1705
```



In [31]:
```
knn_scores = model_scores(y_test,y_pred_knn,'KNN')
knn_scores
```

executed in 15ms, finished 23:38:12 2021-02-22

Out[31]:

	Model	precision_score	recall_score	accuracy_score	f1_score
0	KNN	0.16	0.758621	0.856305	0.264264

1.1.5 Gradient Boosted Model

In [32]:
```
grad_clf = GradientBoostingClassifier(learning_rate=.2,max_depth=1,
                                      min_samples_leaf=7,min_samples_split=1.0,n_estimators=100)
```

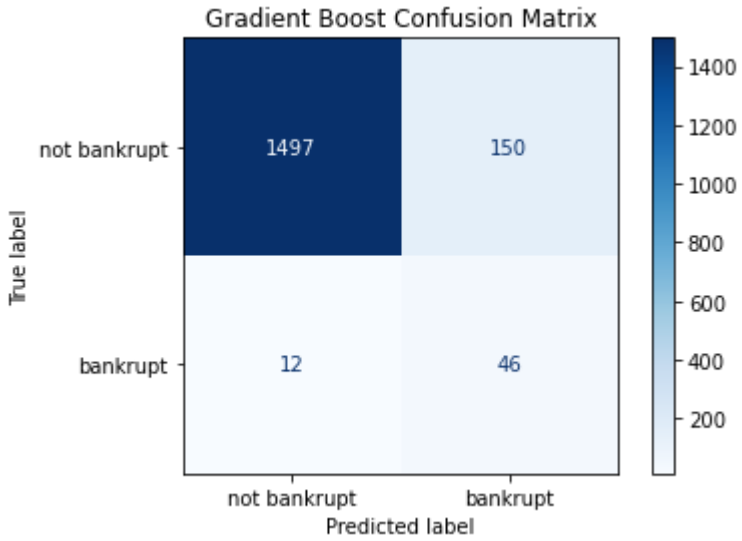
executed in 15ms, finished 23:38:12 2021-02-22

In [33]:

```
grad_clf.fit(X_train_smote_sig,y_train_smote)

y_pred_grad = grad_clf.predict(X_test_sig)

fpr, tpr, thresholds = roc_curve(y_test, y_pred_grad)

print('AUC: {}'.format(auc(fpr, tpr)))
cf = confusion_matrix(y_test,y_pred_grad)

plot_confusion_matrix(grad_clf,X_test_sig,y_test,cmap=plt.cm.Blues,
                      display_labels=["not bankrupt", "bankrupt"],
                       values_format=".5g")
plt.title("Gradient Boost Confusion Matrix")

print(confusion_matrix(y_test, y_pred_grad))
print(classification_report(y_test, y_pred_grad))
```

executed in 5.32s, finished 23:38:18 2021-02-22

```
AUC: 0.8510143835186234
[[1497  150]
 [  12   46]]
              precision    recall  f1-score   support

           0       0.99      0.91      0.95      1647
           1       0.23      0.79      0.36        58

    accuracy                           0.90      1705
   macro avg       0.61      0.85      0.66      1705
weighted avg       0.97      0.90      0.93      1705
```



In [34]:
```
grad_scores = model_scores(y_test,y_pred_grad,"Gradient Boost")
grad_scores
```

executed in 15ms, finished 23:38:18 2021-02-22

Out[34]:

	Model	precision_score	recall_score	accuracy_score	f1_score
0	Gradient Boost	0.234694	0.793103	0.904985	0.362205

1.1.6 Adaboost Model

In [35]:
```
ada_clf = AdaBoostClassifier(base_estimator=forest)
```

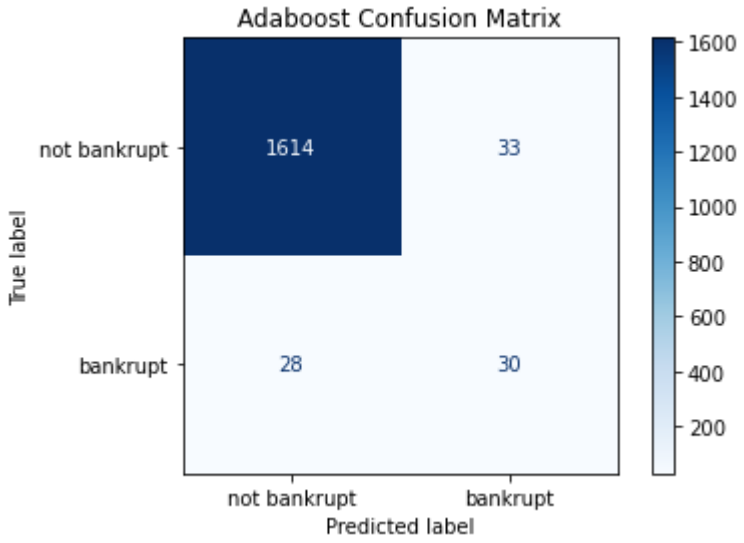
executed in 15ms, finished 23:38:19 2021-02-22

In [36]:

```
ada_clf.fit(X_train_smote_sig,y_train_smote)
y_pred_ada = ada_clf.predict(X_test_sig)

fpr, tpr, thresholds = roc_curve(y_test, y_pred_ada)

print('AUC: {}'.format(auc(fpr, tpr)))
cf = confusion_matrix(y_test,y_pred_ada)

plot_confusion_matrix(ada_clf,X_test_sig,y_test,cmap=plt.cm.Blues,
                      display_labels=["not bankrupt", "bankrupt"],
                       values_format=".5g")
plt.title("Adaboost Confusion Matrix")

print(confusion_matrix(y_test, y_pred_ada))
print(classification_report(y_test, y_pred_ada))

```

executed in 1m 17.6s, finished 23:39:37 2021-02-22

```
AUC: 0.7486024747189246
[[1614   33]
 [  28   30]]
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1647
           1       0.48      0.52      0.50        58

    accuracy                           0.96      1705
   macro avg       0.73      0.75      0.74      1705
weighted avg       0.97      0.96      0.96      1705
```



In [37]:
```
ada_scores = model_scores(y_test,y_pred_ada,"Adaboost")
ada_scores
```

executed in 28ms, finished 23:39:37 2021-02-22

Out[37]:

	Model	precision_score	recall_score	accuracy_score	f1_score
0	Adaboost	0.47619	0.517241	0.964223	0.495868

1.1.7 XGBoost

In [38]:
```
XG = XGBClassifier(objective='binary:logistic',learning_rate=.05,max_depth=1,min_child_weight=1.5,
                   n_estimators=300,subsample=.75,tree_method='approx',gamma=1.5)
```

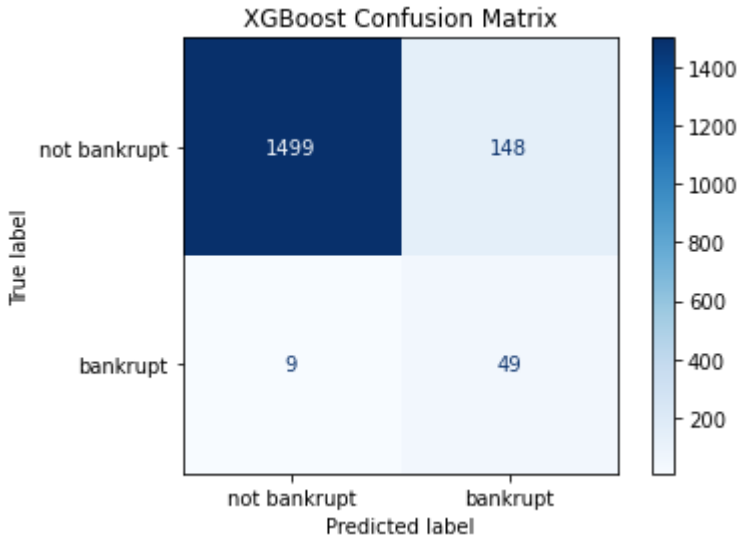
executed in 11ms, finished 23:39:37 2021-02-22

In [39]:

```
XG.fit(X_train_smote_sig,y_train_smote)
y_pred_XG = XG.predict(X_test_sig)


fpr, tpr, thresholds = roc_curve(y_test, y_pred_XG)

print('AUC: {}'.format(auc(fpr, tpr)))
cf = confusion_matrix(y_test,y_pred_XG)

plot_confusion_matrix(XG,X_test_sig,y_test,cmap=plt.cm.Blues,
                      display_labels=["not bankrupt", "bankrupt"],
                       values_format=".5g")
plt.title("XGBoost Confusion Matrix")

print(confusion_matrix(y_test, y_pred_XG))
print(classification_report(y_test, y_pred_XG))

```

executed in 1.60s, finished 23:39:39 2021-02-22

```
AUC: 0.8774836170257312
[[1499  148]
 [   9   49]]
              precision    recall  f1-score   support

           0       0.99      0.91      0.95      1647
           1       0.25      0.84      0.38        58

    accuracy                           0.91      1705
   macro avg       0.62      0.88      0.67      1705
weighted avg       0.97      0.91      0.93      1705
```



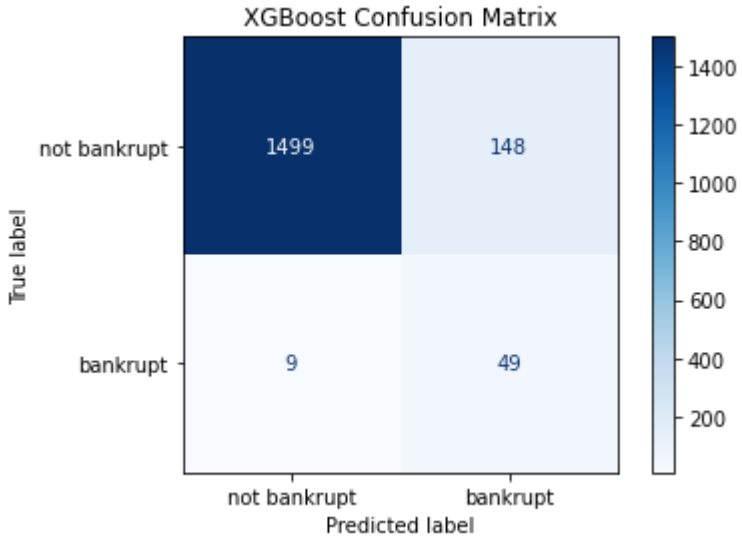
In [40]:
```
1 print(classification_report(y_test, y_pred_XG))
```

executed in 14ms, finished 23:39:40 2021-02-22

```
              precision    recall  f1-score   support

           0       0.99      0.91      0.95      1647
           1       0.25      0.84      0.38        58

    accuracy                           0.91      1705
   macro avg       0.62      0.88      0.67      1705
weighted avg       0.97      0.91      0.93      1705
```

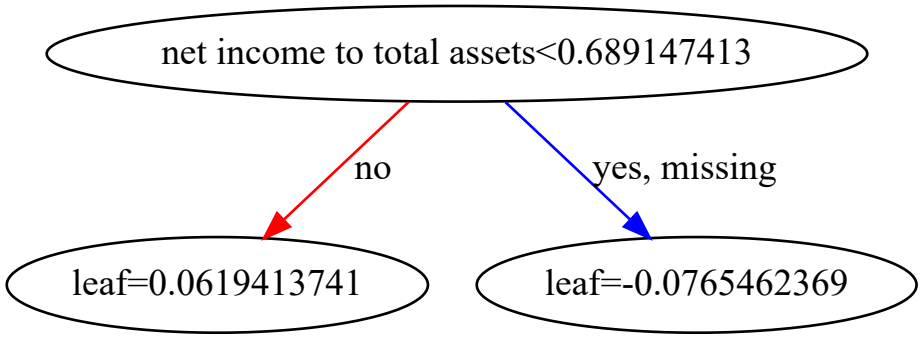
In [41]:
```
plot_confusion_matrix(XG,X_test_sig,y_test,cmap=plt.cm.Blues,
                      display_labels=["not bankrupt", "bankrupt"],
                       values_format=".5g")
plt.title("XGBoost Confusion Matrix")

plt.savefig('images/XGBoost_cm1.png')
```

executed in 267ms, finished 23:39:40 2021-02-22



In [42]:
```
1 xgb.to_graphviz(XG, rankdir='UT')
2
```
executed in 108ms, finished 23:39:41 2021-02-22

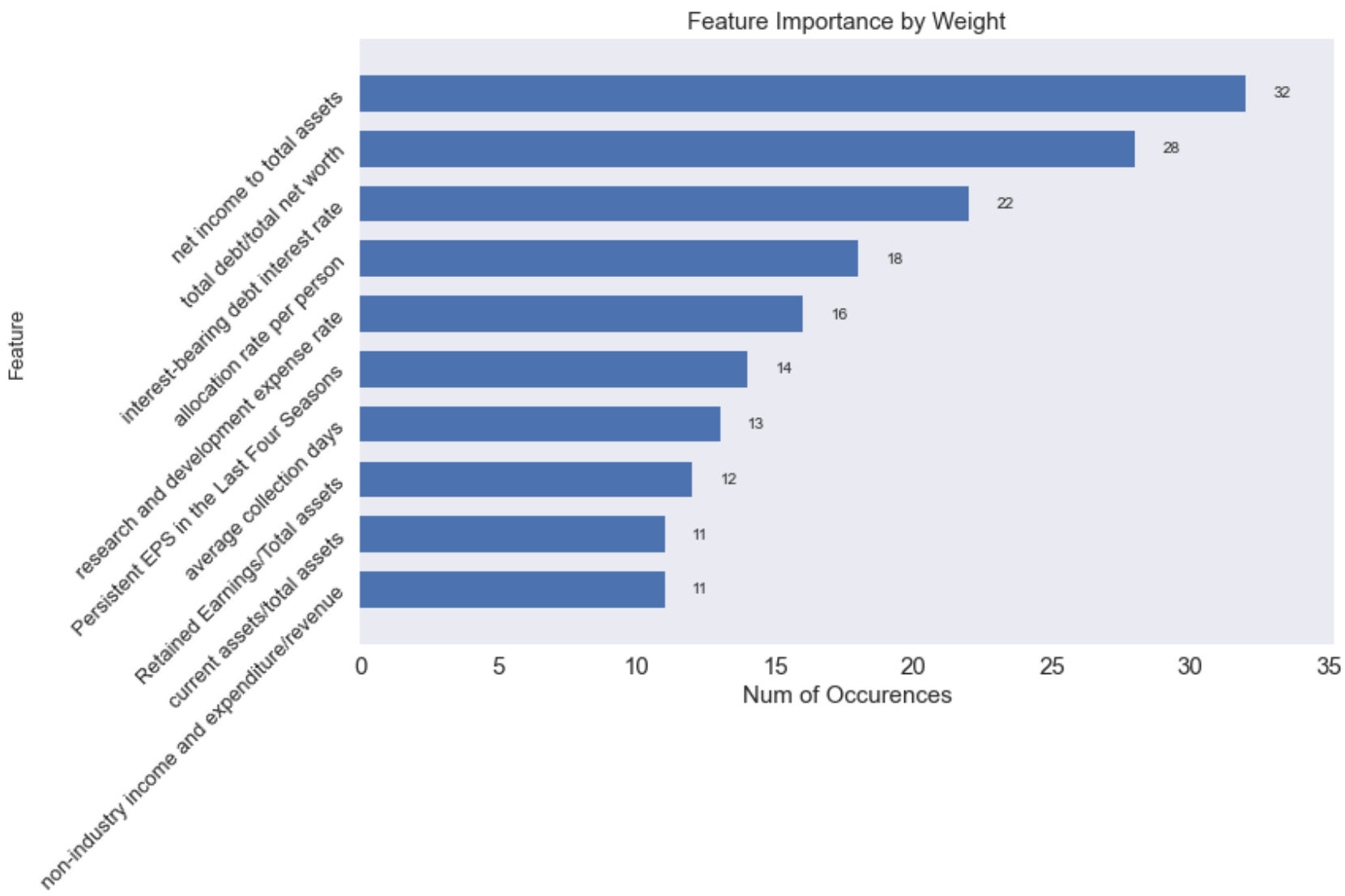
Out[42]:



In [50]:

```
fig, ax = plt.subplots(figsize=(12,8))
xgb.plot_importance(XG,max_num_features=10 ,importance_type='weight',ax=ax,height=.65,grid=False)
plt.yticks(fontsize=13, rotation=45)
plt.xticks(fontsize=15)
plt.xlabel('Num of Occurences',size=15)
plt.ylabel('Feature',size=13)
plt.title('Feature Importance by Weight',size=15)
plt.tight_layout()

plt.savefig('images/xgboost_weight.png')
```

executed in 371ms, finished 23:52:14 2021-02-22


Feature Importance by Weight
Feature
net income to total assets
total debt/total net worth
interest-bearing debt interest rate
allocation rate per person
research and development expense rate
Persistent EPS in the Last Four Seasons
average collection days
Retained Earnings/Total assets
current assets/total assets
non-industry income and expenditure/revenue
32
28
22
18
16
14
13
12
11
11
0
5
10
15
20
25
30
35
Num of Occurences

In [44]:
```
XG_scores= model_scores(y_test,y_pred_XG,"XGBoost")
XG_scores
```
executed in 15ms, finished 23:39:42 2021-02-22

Out[44]:

	Model	precision_score	recall_score	accuracy_score	f1_score
0	XGBoost	0.248731	0.844828	0.907918	0.384314

In [45]:
```
final_results = pd.DataFrame(data=None,index=[0])
```
executed in 14ms, finished 23:39:42 2021-02-22

In [46]:
```
final_results = pd.concat([log_scores,dtree_scores,rf_scores,knn_scores,grad_scores,ada_scores,XG_scores])
```
executed in 15ms, finished 23:39:43 2021-02-22

In [47]:
```
final_results = final_results.set_index('Model')
```
executed in 15ms, finished 23:39:43 2021-02-22

In [48]:
```
final_results
```
executed in 15ms, finished 23:39:44 2021-02-22

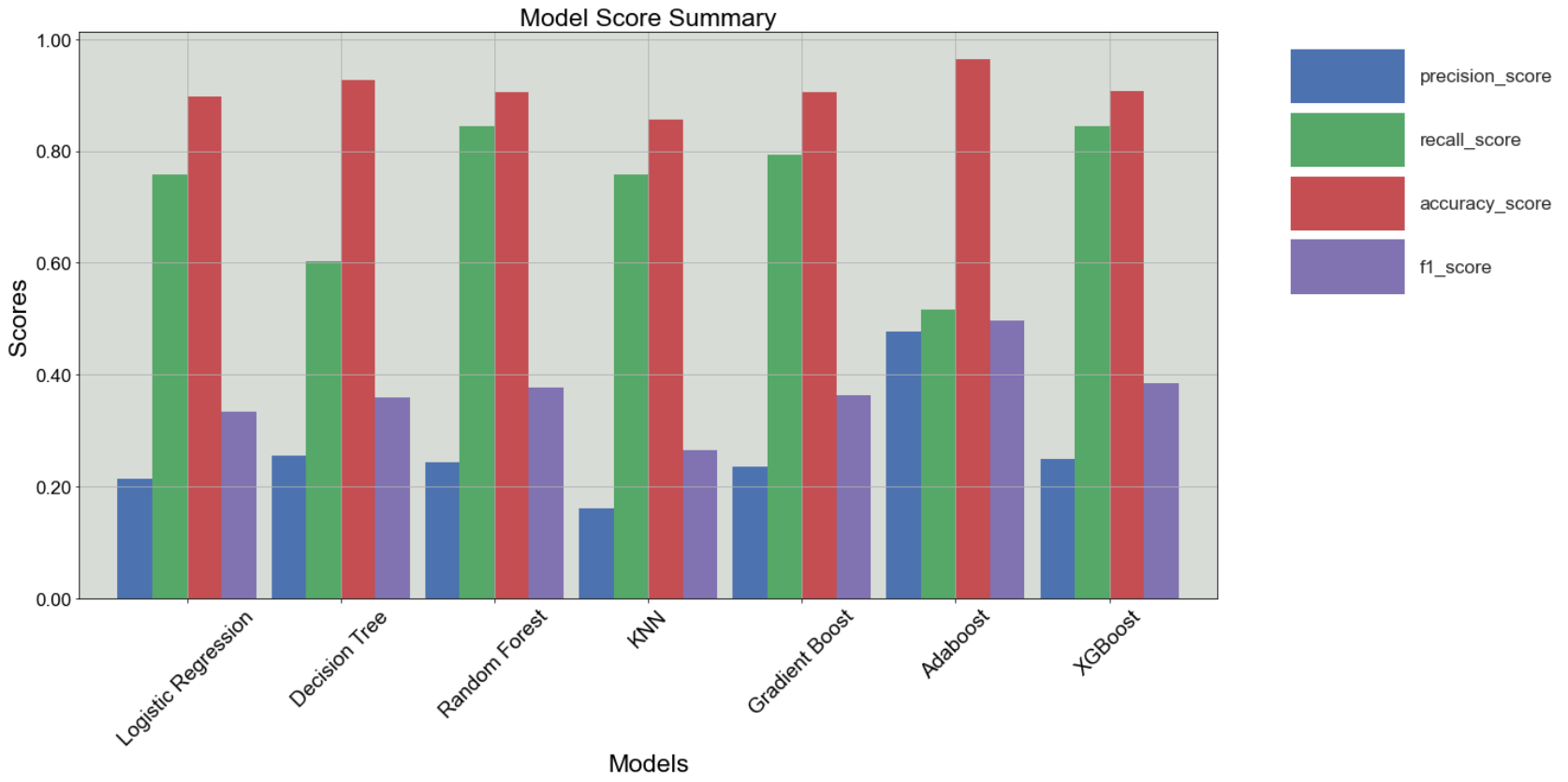
Out[48]:

Model	precision_score	recall_score	accuracy_score	f1_score
Random Forest	0.242574	0.844828	0.904985	0.376923
XGBoost	0.248731	0.844828	0.907918	0.384314
Gradient Boost	0.234694	0.793103	0.904985	0.362205
Logistic Regression	0.214634	0.758621	0.897361	0.334601
KNN	0.160000	0.758621	0.856305	0.264264
Decision Tree	0.255474	0.603448	0.926686	0.358974
Adaboost	0.476190	0.517241	0.964223	0.495868

In [49]:

```
from matplotlib.ticker import FormatStrFormatter

fig, ax = plt.subplots()

plt.style.use('seaborn')
ax.yaxis.set_major_formatter(FormatStrFormatter('%.2f'))
ax.set_facecolor('#d8dcd6')
final_results.plot(kind='bar',figsize=(20,10), ax=ax,width=.9)
plt.xticks(rotation=45)
plt.legend(loc='upper left', bbox_to_anchor=( 1.05,1),
          ncol=1, fancybox=True, shadow=True,handlelength=6, handleheight=4,fontsize="xx-large")
plt.title("Model Score Summary",size=23)
plt.ylabel('Scores',size=23)
plt.xlabel('Models',size=23)
plt.xticks(size = 19)
plt.yticks(size=17)
plt.tight_layout()
plt.savefig('images/model_summary_scores')
```

executed in 432ms, finished 23:39:44 2021-02-22


Model Score Summary
Scores
1.00
0.80
0.60
0.40
0.20
0.00
Logistic Regression
Decision Tree
Random Forest
KNN
Gradient Boost
Adaboost
XGBoost
Models
precision_score
recall_score
accuracy_score
f1_score

In [ ]:
```
1
```

In [ ]:
```
1
```