Company_Bankruptcy

July 17, 2023

1 Company Bankruptcy Prediction

Bankruptcy data from the Taiwan Economic Journal for the years 1999–2009

1.1 Goal

how many firms are bankrupt, and how many are not.

2 Attribute Information

Updated column names and description to make the data easier to understand (Y = Output feature, X = Input features)

Y - Bankrupt?: Class label

X1 - ROA(C) before interest and depreciation before interest: Return On Total Assets(C)

X2 - ROA(A) before interest and % after tax: Return On Total Assets(A)

X3 - ROA(B) before interest and depreciation after tax: Return On Total Assets(B)

X4 - Operating Gross Margin: Gross Profit/Net Sales

X5 - Realized Sales Gross Margin: Realized Gross Profit/Net Sales

X6 - Operating Profit Rate: Operating Income/Net Sales

X7 - Pre-tax net Interest Rate: Pre-Tax Income/Net Sales

X8 - After-tax net Interest Rate: Net Income/Net Sales

X9 - Non-industry income and expenditure/revenue: Net Non-operating Income Ratio

X10 - Continuous interest rate (after tax): Net Income-Exclude Disposal Gain or Loss/Net Sales

X11 - Operating Expense Rate: Operating Expenses/Net Sales

X12 - Research and development expense rate: (Research and Development Expenses)/Net Sales

X13 - Cash flow rate: Cash Flow from Operating/Current Liabilities

X14 - Interest-bearing debt interest rate: Interest-bearing Debt/Equity

X15 - Tax rate (A): Effective Tax Rate

X16 - Net Value Per Share (B): Book Value Per Share(B)

X17 - Net Value Per Share (A): Book Value Per Share(A)

X18 - Net Value Per Share (C): Book Value Per Share(C)

X19 - Persistent EPS in the Last Four Seasons: EPS-Net Income

X20 - Cash Flow Per Share

X21 - Revenue Per Share (Yuan ¥): Sales Per Share

X22 - Operating Profit Per Share (Yuan ¥): Operating Income Per Share

X23 - Per Share Net profit before tax (Yuan ¥): Pretax Income Per Share

X24 - Realized Sales Gross Profit Growth Rate

X25 - Operating Profit Growth Rate: Operating Income Growth

X26 - After-tax Net Profit Growth Rate: Net Income Growth

X27 - Regular Net Profit Growth Rate: Continuing Operating Income after Tax Growth

X28 - Continuous Net Profit Growth Rate: Net Income-Excluding Disposal Gain or Loss Growth

X29 - Total Asset Growth Rate: Total Asset Growth

X30 - Net Value Growth Rate: Total Equity Growth

X31 - Total Asset Return Growth Rate Ratio: Return on Total Asset Growth

X32 - Cash Reinvestment %: Cash Reinvestment Ratio

X33 - Current Ratio

X34 - Quick Ratio: Acid Test

X35 - Interest Expense Ratio: Interest Expenses/Total Revenue

X36 - Total debt/Total net worth: Total Liability/Equity Ratio

X37 - Debt ratio %: Liability/Total Assets

X38 - Net worth/Assets: Equity/Total Assets

X39 - Long-term fund suitability ratio (A): (Long-term Liability+Equity)/Fixed Assets

X40 - Borrowing dependency: Cost of Interest-bearing Debt

X41 - Contingent liabilities/Net worth: Contingent Liability/Equity

X42 - Operating profit/Paid-in capital: Operating Income/Capital

X43 - Net profit before tax/Paid-in capital: Pretax Income/Capital

X44 - Inventory and accounts receivable/Net value: (Inventory+Accounts Receivables)/Equity

```
X45 - Total Asset Turnover
X46 - Accounts Receivable Turnover
X47 - Average Collection Days: Days Receivable Outstanding
X48 - Inventory Turnover Rate (times)
X49 - Fixed Assets Turnover Frequency
X50 - Net Worth Turnover Rate (times): Equity Turnover
```

X51 - Revenue per person: Sales Per Employee
X52 - Operating profit per person: Operation Income Per Employee
X53 - Allocation rate per person: Fixed Assets Per Employee
X54 - Working Capital to Total Assets
X55 - Quick Assets/Total Assets
X56 - Current Assets/Total Assets
X57 - Cash/Total Assets
X58 - Quick Assets/Current Liability
X59 - Cash/Current Liability
X60 - Current Liability to Assets
X61 - Operating Funds to Liability
X62 - Inventory/Working Capital
X63 - Inventory/Current Liability
X64 - Current Liabilities/Liability
X65 - Working Capital/Equity
X66 - Current Liabilities/Equity
X67 - Long-term Liability to Current Assets
X68 - Retained Earnings to Total Assets
X69 - Total income/Total expense
X70 - Total expense/Assets
X71 - Current Asset Turnover Rate: Current Assets to Sales
X72 - Quick Asset Turnover Rate: Quick Assets to Sales
X73 - Working capitcal Turnover Rate: Working Capital to Sales
X74 - Cash Turnover Rate: Cash to Sales
X75 - Cash Flow to Sales
X76 - Fixed Assets to Assets
X77 - Current Liability to Liability
X78 - Current Liability to Equity
X79 - Equity to Long-term Liability
X80 - Cash Flow to Total Assets
X81 - Cash Flow to Liability
X82 - CFO to Assets
X83 - Cash Flow to Equity
X84 - Current Liability to Current Assets
X85 - Liability-Assets Flag: 1 if Total Liability exceeds Total Assets, 0 otherwise
X86 - Net Income to Total Assets
X87 - Total assets to GNP price
X88 - No-credit Interval
X89 - Gross Profit to Sales
X90 - Net Income to Stockholder's Equity
X91 - Liability to Equity
X92 - Degree of Financial Leverage (DFL)
X93 - Interest Coverage Ratio (Interest expense to EBIT)
X94 - Net Income Flag: 1 if Net Income is Negative for the last two years, 0 otherwise
X95 - Equity to Liability

```
[89]: # Import libraries here
      import matplotlib.pyplot as plt
      import pandas as pd
      import seaborn as sns

      import ipywidgets as widgets
      from ipywidgets import interact

      from imblearn.over_sampling import RandomOverSampler
      from imblearn.under_sampling import RandomUnderSampler

      from sklearn.impute import SimpleImputer
      from sklearn.metrics import (
          ConfusionMatrixDisplay,
          classification_report,
          confusion_matrix,
      )
      from sklearn.model_selection import GridSearchCV,␣
       ↪cross_val_score,train_test_split
      from sklearn.pipeline import make_pipeline
      from sklearn.tree import DecisionTreeClassifier
      from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier
```

```
[3]: df=pd.read_csv('data/data.csv')
     df.head()
```

```
[3]:    Bankrupt?   ROA(C) before interest and depreciation before interest  \
     0          1                                                 0.370594
     1          1                                                 0.464291
     2          1                                                 0.426071
     3          1                                                 0.399844
     4          1                                                 0.465022

         ROA(A) before interest and % after tax  \
     0                                 0.424389
     1                                 0.538214
     2                                 0.499019
     3                                 0.451265
     4                                 0.538432

         ROA(B) before interest and depreciation after tax  \
     0                                            0.405750
     1                                            0.516730
     2                                            0.472295
     3                                            0.457733
     4                                            0.522298
```

```
   Operating Gross Margin   Realized Sales Gross Margin  \
0                0.601457                     0.601457
1                0.610235                     0.610235
2                0.601450                     0.601364
3                0.583541                     0.583541
4                0.598783                     0.598783

   Operating Profit Rate   Pre-tax net Interest Rate  \
0               0.998969                    0.796887
1               0.998946                    0.797380
2               0.998857                    0.796403
3               0.998700                    0.796967
4               0.998973                    0.797366

   After-tax net Interest Rate   Non-industry income and expenditure/revenue  \
0                     0.808809                                     0.302646
1                     0.809301                                     0.303556
2                     0.808388                                     0.302035
3                     0.808966                                     0.303350
4                     0.809304                                     0.303475

  …   Net Income to Total Assets   Total assets to GNP price  \
0 …                     0.716845                    0.009219
1 …                     0.795297                    0.008323
2 …                     0.774670                    0.040003
3 …                     0.739555                    0.003252
4 …                     0.795016                    0.003878

   No-credit Interval   Gross Profit to Sales  \
0            0.622879                0.601453
1            0.623652                0.610237
2            0.623841                0.601449
3            0.622929                0.583538
4            0.623521                0.598782

   Net Income to Stockholder's Equity   Liability to Equity  \
0                            0.827890              0.290202
1                            0.839969              0.283846
2                            0.836774              0.290189
3                            0.834697              0.281721
4                            0.839973              0.278514

   Degree of Financial Leverage (DFL)  \
0                            0.026601
1                            0.264577
2                            0.026555
3                            0.026697
```

```
4                              0.024752

    Interest Coverage Ratio (Interest expense to EBIT)   Net Income Flag  \
0                                            0.564050                1
1                                            0.570175                1
2                                            0.563706                1
3                                            0.564663                1
4                                            0.575617                1

    Equity to Liability
0             0.016469
1             0.020794
2             0.016474
3             0.023982
4             0.035490

[5 rows x 96 columns]
```

3 Explore

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6819 entries, 0 to 6818
Data columns (total 96 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   Bankrupt?                                                 6819 non-null
int64
 1    ROA(C) before interest and depreciation before interest  6819 non-null
float64
 2    ROA(A) before interest and % after tax                   6819 non-null
float64
 3    ROA(B) before interest and depreciation after tax        6819 non-null
float64
 4    Operating Gross Margin                                   6819 non-null
float64
 5    Realized Sales Gross Margin                              6819 non-null
float64
 6    Operating Profit Rate                                    6819 non-null
float64
 7    Pre-tax net Interest Rate                                6819 non-null
float64
 8    After-tax net Interest Rate                              6819 non-null
float64
```

```
 9    Non-industry income and expenditure/revenue             6819 non-null
float64
 10   Continuous interest rate (after tax)                    6819 non-null
float64
 11   Operating Expense Rate                                  6819 non-null
float64
 12   Research and development expense rate                   6819 non-null
float64
 13   Cash flow rate                                          6819 non-null
float64
 14   Interest-bearing debt interest rate                     6819 non-null
float64
 15   Tax rate (A)                                            6819 non-null
float64
 16   Net Value Per Share (B)                                 6819 non-null
float64
 17   Net Value Per Share (A)                                 6819 non-null
float64
 18   Net Value Per Share (C)                                 6819 non-null
float64
 19   Persistent EPS in the Last Four Seasons                 6819 non-null
float64
 20   Cash Flow Per Share                                     6819 non-null
float64
 21   Revenue Per Share (Yuan ¥)                              6819 non-null
float64
 22   Operating Profit Per Share (Yuan ¥)                     6819 non-null
float64
 23   Per Share Net profit before tax (Yuan ¥)                6819 non-null
float64
 24   Realized Sales Gross Profit Growth Rate                 6819 non-null
float64
 25   Operating Profit Growth Rate                            6819 non-null
float64
 26   After-tax Net Profit Growth Rate                        6819 non-null
float64
 27   Regular Net Profit Growth Rate                          6819 non-null
float64
 28   Continuous Net Profit Growth Rate                       6819 non-null
float64
 29   Total Asset Growth Rate                                 6819 non-null
float64
 30   Net Value Growth Rate                                   6819 non-null
float64
 31   Total Asset Return Growth Rate Ratio                    6819 non-null
float64
 32   Cash Reinvestment %                                     6819 non-null
float64
```

```
 33   Current Ratio                                          6819 non-null
float64
 34   Quick Ratio                                            6819 non-null
float64
 35   Interest Expense Ratio                                 6819 non-null
float64
 36   Total debt/Total net worth                             6819 non-null
float64
 37   Debt ratio %                                           6819 non-null
float64
 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 Assets/Total Assets                              6819 non-null
float64
 56   Current Assets/Total Assets                            6819 non-null
float64
```

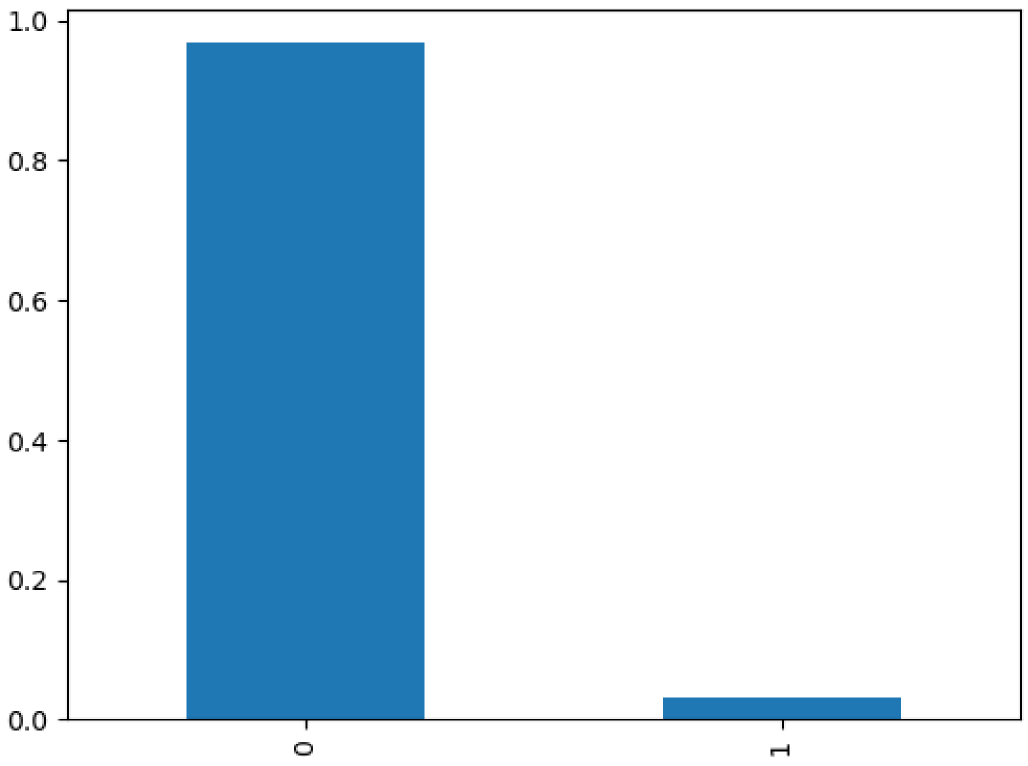
```
 57   Cash/Total Assets                              6819 non-null
float64
 58   Quick Assets/Current Liability                 6819 non-null
float64
 59   Cash/Current Liability                         6819 non-null
float64
 60   Current Liability to Assets                    6819 non-null
float64
 61   Operating Funds to Liability                   6819 non-null
float64
 62   Inventory/Working Capital                      6819 non-null
float64
 63   Inventory/Current Liability                    6819 non-null
float64
 64   Current Liabilities/Liability                  6819 non-null
float64
 65   Working Capital/Equity                         6819 non-null
float64
 66   Current Liabilities/Equity                     6819 non-null
float64
 67   Long-term Liability to Current Assets          6819 non-null
float64
 68   Retained Earnings to Total Assets              6819 non-null
float64
 69   Total income/Total expense                     6819 non-null
float64
 70   Total expense/Assets                           6819 non-null
float64
 71   Current Asset Turnover Rate                    6819 non-null
float64
 72   Quick Asset Turnover Rate                      6819 non-null
float64
 73   Working capitcal Turnover Rate                 6819 non-null
float64
 74   Cash Turnover Rate                             6819 non-null
float64
 75   Cash Flow to Sales                             6819 non-null
float64
 76   Fixed Assets to Assets                         6819 non-null
float64
 77   Current Liability to Liability                 6819 non-null
float64
 78   Current Liability to Equity                    6819 non-null
float64
 79   Equity to Long-term Liability                  6819 non-null
float64
 80   Cash Flow to Total Assets                      6819 non-null
float64
```

```
 81   Cash Flow to Liability                                 6819 non-null
float64
 82   CFO to Assets                                          6819 non-null
float64
 83   Cash Flow to Equity                                    6819 non-null
float64
 84   Current Liability to Current Assets                    6819 non-null
float64
 85   Liability-Assets Flag                                  6819 non-null
int64
 86   Net Income to Total Assets                             6819 non-null
float64
 87   Total assets to GNP price                              6819 non-null
float64
 88   No-credit Interval                                     6819 non-null
float64
 89   Gross Profit to Sales                                  6819 non-null
float64
 90   Net Income to Stockholder's Equity                     6819 non-null
float64
 91   Liability to Equity                                    6819 non-null
float64
 92   Degree of Financial Leverage (DFL)                     6819 non-null
float64
 93   Interest Coverage Ratio (Interest expense to EBIT)     6819 non-null
float64
 94   Net Income Flag                                        6819 non-null
int64
 95   Equity to Liability                                    6819 non-null
float64
dtypes: float64(93), int64(3)
memory usage: 5.0 MB
```

That's solid information. We know all our features are numerical and that we have no missing data. But,it's a good idea to do some visualizations to see if there are any interesting trends or ideas we should keep in mind while we work. First, let's take a look at how many firms are bankrupt, and how many are not.

[5]:
```
df['Bankrupt?'].value_counts(normalize=True).plot(kind='bar')
```

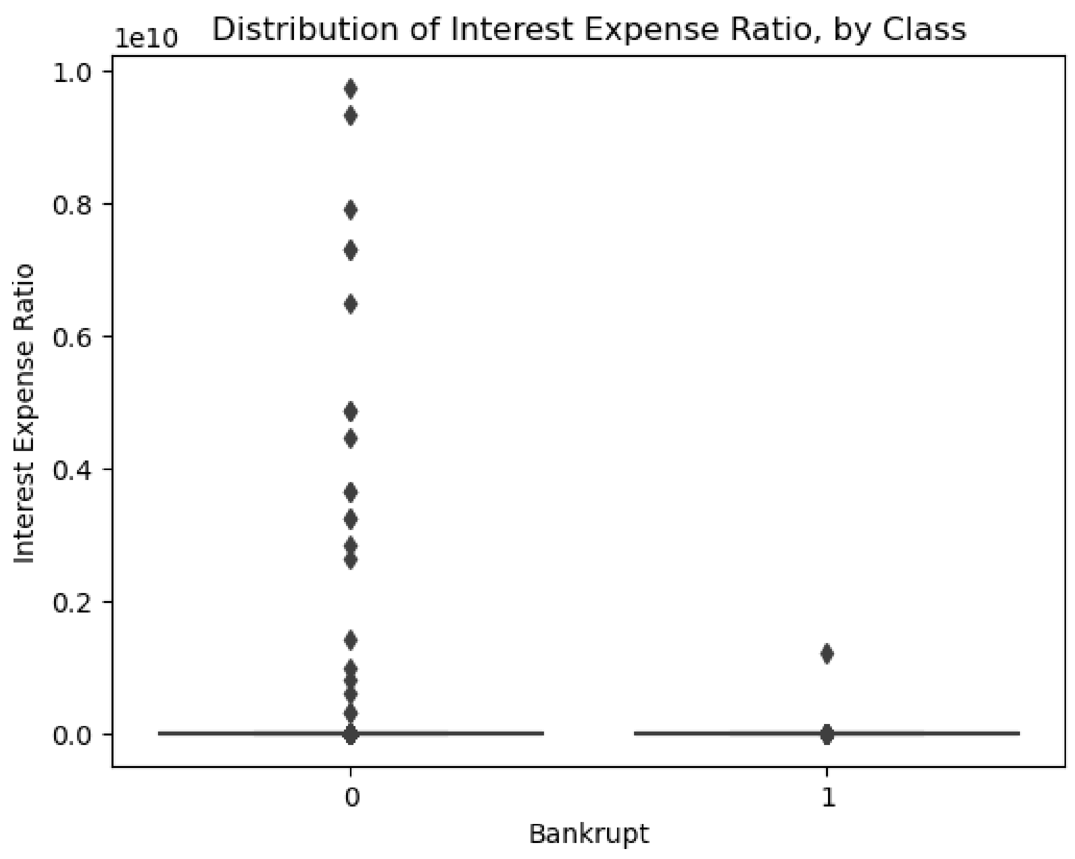
[5]:
```
<AxesSubplot:>
```



That's good news for Japan's economy! Since it looks like most of the companies in our dataset are doing all right for themselves, let's drill down a little farther. However, it also shows us that we have an **imbalanced** dataset, where our majority class is far bigger than our minority class.

there were 64 features of each company, each of which had some kind of numerical value. It might be useful to understand where the values for one of these features cluster, so let's make a boxplot to see how the values in `"Interest Expense Ratio"` are distributed.

[6]:
```
# Create boxplot
sns.boxplot(y=' Accounts Receivable Turnover',x='Bankrupt?',data=df)
plt.xlabel("Bankrupt")
plt.ylabel("Interest Expense Ratio")
plt.title("Distribution of Interest Expense Ratio, by Class");
```



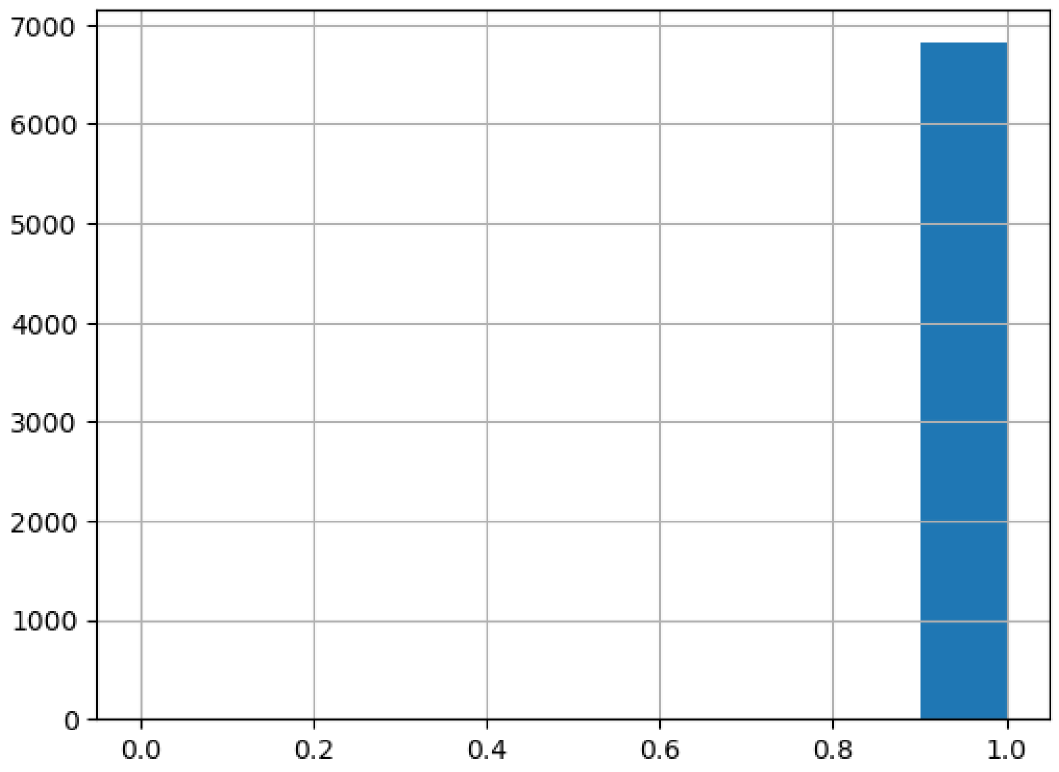
Why does this look so funny? Remember that boxplots exist to help us see the quartiles in a dataset, and this one doesn't really do that. Let's check the distribution of `"Interest Expense Ratio"`to see if we can figure out what's going on here.

```
[7]: # Summary statistics for ` Operating Profit Rate`
     df[' Operating Profit Rate'].describe().apply('{0:,.0f}'.format)
```

```
[7]: count    6,819
     mean         1
     std          0
     min          0
     25%          1
     50%          1
     75%          1
     max          1
     Name:  Operating Profit Rate, dtype: object
```

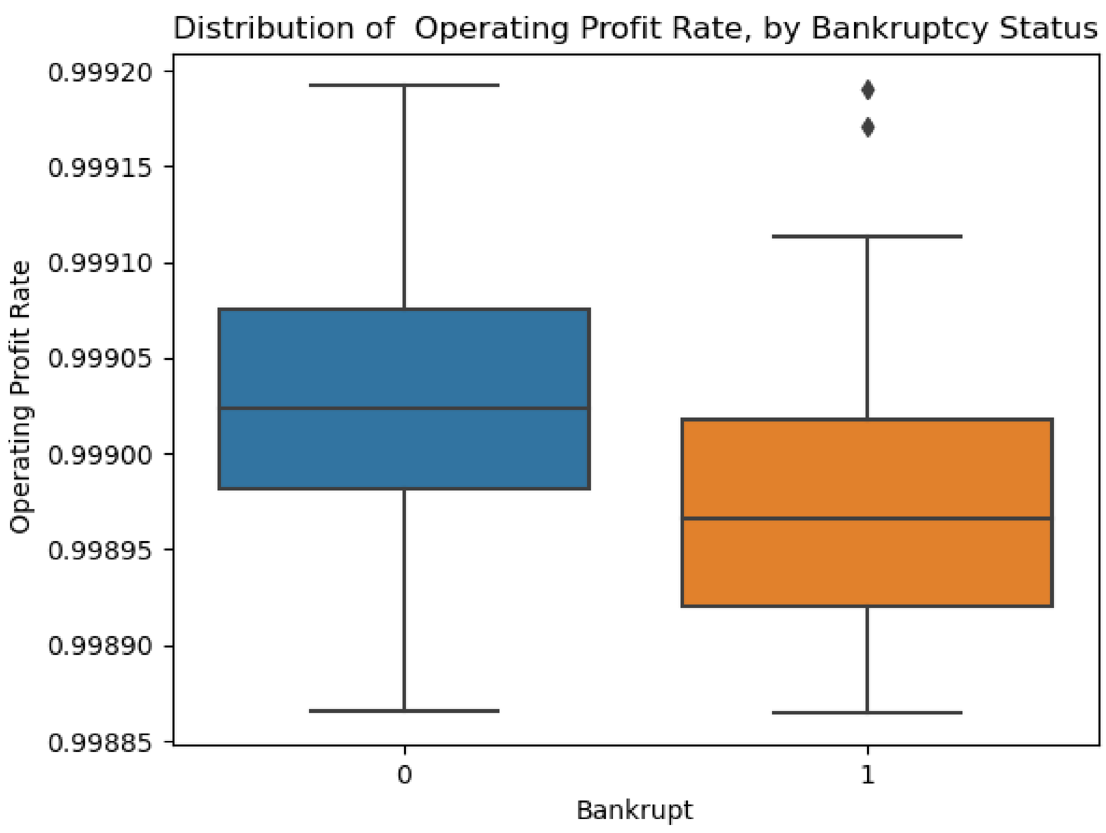
```
[8]: df[' Operating Profit Rate'].hist()
```

```
[8]: <AxesSubplot:>
```



Aha! We saw it in the numbers and now we see it in the histogram. The data is very skewed. So, in order to create a helpful boxplot, we need to trim the data.

```
[9]: # Create clipped boxplot
q1,q9=df[' Operating Profit Rate'].quantile([0.1,0.9])
mask=df[' Operating Profit Rate'].between(q1,q9)
sns.boxplot(x='Bankrupt?',y=' Operating Profit Rate',data=df[mask])
plt.xlabel("Bankrupt")
plt.ylabel(" Operating Profit Rate")
plt.title("Distribution of  Operating Profit Rate, by Bankruptcy Status");
```

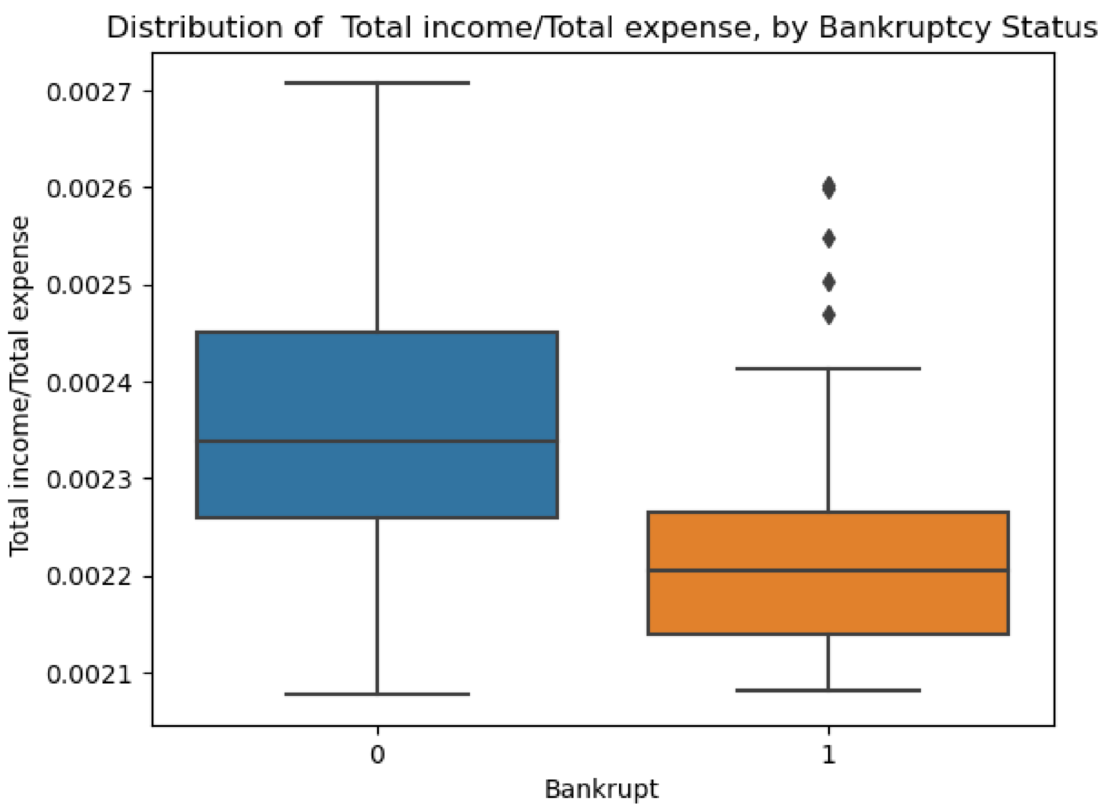


That makes a lot more sense. Let's take a look at some of the other features in the dataset to see what else is out there.

[10]:
```
df[' Total income/Total expense'].describe().apply('{0:,.0f}'.format)
```

[10]:
```
count    6,819
mean         0
std          0
min          0
25%          0
50%          0
75%          0
max          1
Name:  Total income/Total expense, dtype: object
```

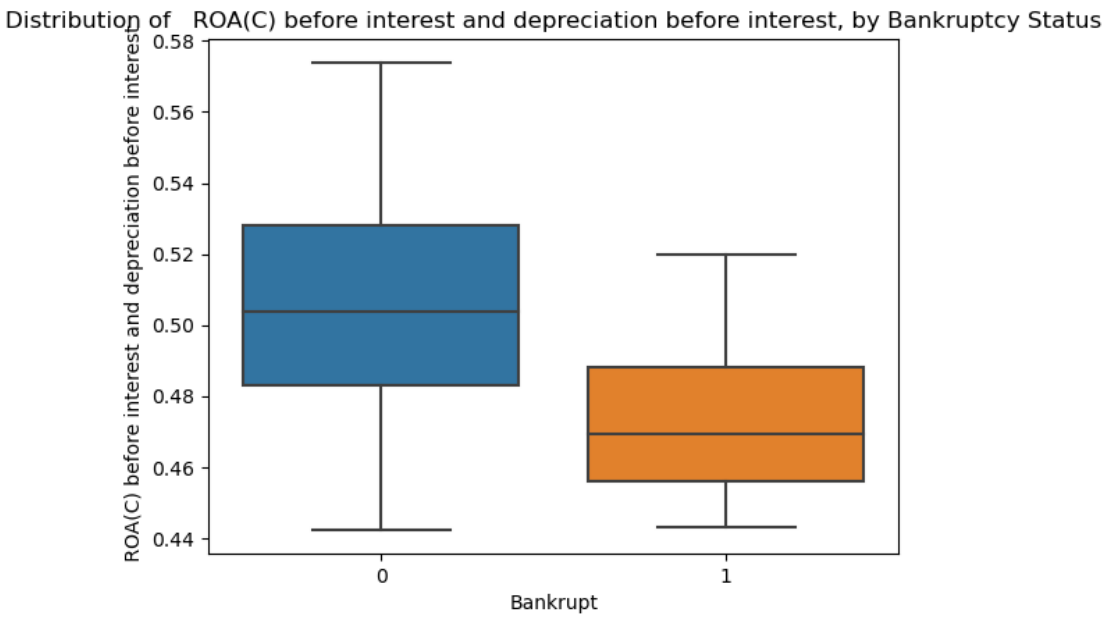
[11]:
```
q1,q9=df[' Total income/Total expense'].quantile([0.1,0.9])
mask=df[' Total income/Total expense'].between(q1,q9)
sns.boxplot(x='Bankrupt?',y=' Total income/Total expense',data=df[mask])
plt.xlabel("Bankrupt")
plt.ylabel(" Total income/Total expense")
plt.title("Distribution of  Total income/Total expense, by Bankruptcy Status");
```



```
[12]: df[' ROA(C) before interest and depreciation before interest'].describe().
       ↪apply('{0:,.0f}'.format)
```

```
[12]: count    6,819
      mean         1
      std          0
      min          0
      25%          0
      50%          1
      75%          1
      max          1
      Name:  ROA(C) before interest and depreciation before interest, dtype: object
```

```
[13]: q1,q9=df[' ROA(C) before interest and depreciation before interest'].
       ↪quantile([0.1,0.9])
      mask=df[' ROA(C) before interest and depreciation before interest'].
       ↪between(q1,q9)
      sns.boxplot(x='Bankrupt?',y=' ROA(C) before interest and depreciation before␣
       ↪interest',data=df[mask])
      plt.xlabel("Bankrupt")
      plt.ylabel(" ROA(C) before interest and depreciation before interest")
      plt.title("Distribution of   ROA(C) before interest and depreciation before␣
       ↪interest, by Bankruptcy Status");
```

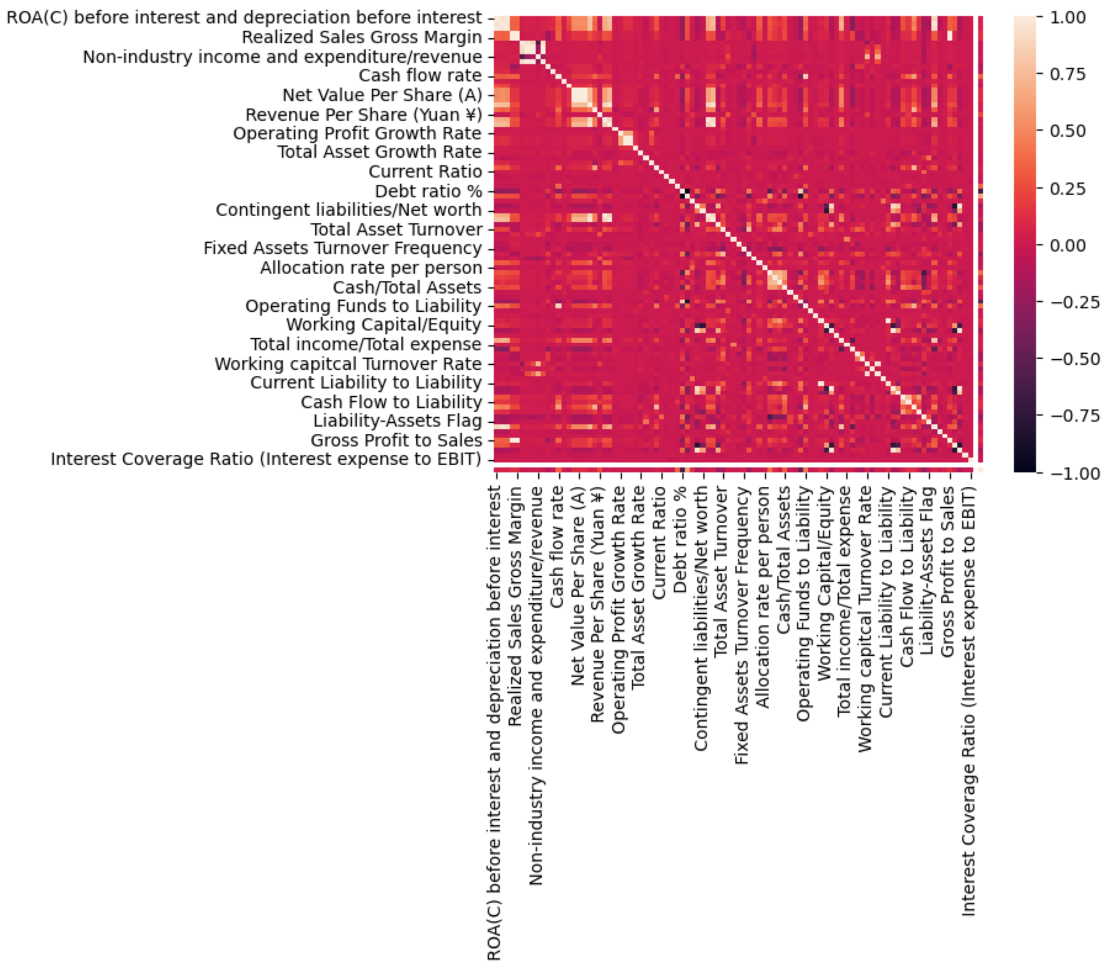


Looking at other features, we can see that they're skewed, too. This will be important to keep in mind when we decide what type of model we want to use.

Another important consideration for model selection is whether there are any issues with multicollinearity in our model. Let's check.

```
[14]: corr=df.drop(columns='Bankrupt?').corr()
      sns.heatmap(corr)
```

```
[14]: <AxesSubplot:>
```



So what did we learn from this EDA? First, our data is imbalanced. This is something we need to address in our data preparation. Second,our features haven't missing but if there are values that we'll need to impute. And since the features are highly skewed, the best imputation strategy is likely median, not mean. Finally, we have autocorrelation issues, which means that we should steer clear of linear models, and try a tree-based model instead.

4 Split

[15]:
```
target = "Bankrupt?"
X = df.drop(columns=target)
y = df[target]

print("X shape:", X.shape)
print("y shape:", y.shape)
```

```
X shape: (6819, 95)
y shape: (6819,)
```

[16]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.
 ↪2,random_state=42)

print("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)
print("X_test shape:", X_test.shape)
print("y_test shape:", y_test.shape)
```

```
X_train shape: (5455, 95)
y_train shape: (5455,)
X_test shape: (1364, 95)
y_test shape: (1364,)
```

5 Resample

Now that we've split our data into training and validation sets, we can address the class imbalance we saw during our EDA. One strategy is to resample the training data. There are many to do this, so let's start with under-sampling.

[17]:
```
under_sampler =RandomUnderSampler(random_state=42)
X_train_under, y_train_under = under_sampler.fit_resample(X_train,y_train)
print(X_train_under.shape)
X_train_under.head()
```

```
(338, 95)
```

[17]:
```
       ROA(C) before interest and depreciation before interest  \
5782                                            0.547409
5200                                            0.575196
3786                                            0.490567
1338                                            0.543899
4804                                            0.608980

       ROA(A) before interest and % after tax  \
5782                                 0.597580
5200                                 0.622928
3786                                 0.552933
1338                                 0.598779
4804                                 0.658689

       ROA(B) before interest and depreciation after tax  \
5782                                            0.583757
5200                                            0.609187
3786                                            0.539483
1338                                            0.593180
4804                                            0.655174

       Operating Gross Margin   Realized Sales Gross Margin  \
5782                0.604707                      0.604707
5200                0.606142                      0.606142
3786                0.629665                      0.629520
1338                0.602740                      0.602754
4804                0.612491                      0.613183

       Operating Profit Rate   Pre-tax net Interest Rate  \
5782               0.999089                    0.797593
5200               0.999085                    0.797859
3786               0.999108                    0.797607
1338               0.999041                    0.797495
4804               0.999193                    0.798374

       After-tax net Interest Rate  \
5782                     0.809456
5200                     0.809654
3786                     0.809484
1338                     0.809399
4804                     0.810111

       Non-industry income and expenditure/revenue  \
5782                                     0.303629
5200                                     0.304102
3786                                     0.303613
1338                                     0.303559
4804                                     0.304774

       Continuous interest rate (after tax)  …   Net Income to Total Assets  \
5782                              0.781726  …                     0.831586
5200                              0.781934  …                     0.845096
3786                              0.781755  …                     0.810341
1338                              0.781664  …                     0.828565
4804                              0.782440  …                     0.867959

       Total assets to GNP price   No-credit Interval   Gross Profit to Sales  \
5782                    0.001479             0.624287                0.604706
5200                    0.001891             0.624553                0.606139
3786                    0.001115             0.624214                0.629664
1338                    0.001621             0.623379                0.602735
4804                    0.010567             0.621156                0.612491

       Net Income to Stockholder's Equity   Liability to Equity  \
5782                             0.842928              0.279743
5200                             0.843117              0.277089
3786                             0.840741              0.275084
1338                             0.843240              0.282201
4804                             0.843773              0.275537
```

```
      Degree of Financial Leverage (DFL)  \
5782                            0.026801
5200                            0.026791
3786                            0.026791
1338                            0.026865
4804                            0.026791

      Interest Coverage Ratio (Interest expense to EBIT)   Net Income Flag  \
5782                                           0.565205                 1
5200                                           0.565159                 1
3786                                           0.565158                 1
1338                                           0.565489                 1
4804                                           0.565158                 1

      Equity to Liability
5782             0.029354
5200             0.050445
3786             0.250781
1338             0.023104
4804             0.123342

[5 rows x 95 columns]
```

And then we'll over-sample.

[18]:
```
over_sampler = RandomOverSampler(random_state=42)
X_train_over, y_train_over = over_sampler.fit_resample(X_train,y_train)
print(X_train_over.shape)
X_train_over.head()
```

```
(10572, 95)
```

[18]:
```
    ROA(C) before interest and depreciation before interest  \
0                                            0.498513
1                                            0.506606
2                                            0.508799
3                                            0.499976
4                                            0.477892

    ROA(A) before interest and % after tax  \
0                                 0.542848
1                                 0.562309
2                                 0.561001
3                                 0.562527
4                                 0.547700

    ROA(B) before interest and depreciation after tax  \
0                                          0.544622
1                                          0.558863
2                                          0.554687
3                                          0.546764
4                                          0.529150

   Operating Gross Margin   Realized Sales Gross Margin  \
0                0.599194                      0.599036
1                0.609334                      0.609334
2                0.614242                      0.614055
3                0.597825                      0.597825
4                0.600362                      0.600362

   Operating Profit Rate   Pre-tax net Interest Rate  \
0               0.998986                   0.797412
1               0.999027                   0.797450
2               0.999094                   0.797533
3               0.999004                   0.797411
4               0.998975                   0.797412

   After-tax net Interest Rate   Non-industry income and expenditure/revenue  \
0                     0.809330                                      0.303528
1                     0.809375                                      0.303508
2                     0.809424                                      0.303514
3                     0.809329                                      0.303490
4                     0.809333                                      0.303551

   Continuous interest rate (after tax)  …   Net Income to Total Assets  \
0                              0.781593  …                     0.801313
1                              0.781637  …                     0.810914
2                              0.781692  …                     0.809740
3                              0.781590  …                     0.810082
4                              0.781584  …                     0.804638

   Total assets to GNP price   No-credit Interval   Gross Profit to Sales  \
0                   0.005821             0.623649                0.599196
1                   0.000481             0.623932                0.609332
2                   0.001397             0.623714                0.614241
3                   0.000998             0.623986                0.597824
4                   0.002826             0.623845                0.600363

   Net Income to Stockholder's Equity   Liability to Equity  \
0                            0.840580              0.282564
1                            0.841339              0.280570
2                            0.840969              0.277772
3                            0.841885              0.286871
4                            0.840885              0.282073
```

```
    Degree of Financial Leverage (DFL)  \
0                             0.027239
1                             0.026843
2                             0.026864
3                             0.026951
4                             0.026959

    Interest Coverage Ratio (Interest expense to EBIT)   Net Income Flag  \
0                                            0.566658                 1
1                                            0.565395                 1
2                                            0.565484                 1
3                                            0.565820                 1
4                                            0.565848                 1

    Equity to Liability
0              0.022512
1              0.026670
2              0.041556
3              0.018173
4              0.023328

[5 rows x 95 columns]
```

6 Build Model

6.1 base line

[19]:
```python
acc_baseline = y_train.value_counts(normalize=True).max()
print("Baseline Accuracy:", round(acc_baseline, 4))
```

```
Baseline Accuracy: 0.969
```

Note here that, because our classes are imbalanced, the baseline accuracy is very high. We should keep this in mind because, even if our trained model gets a high validation accuracy score, that doesn't mean it's actually *good.*

6.2 Iterate

6.3 1- Decision Tree model

[20]:
```python
# Fit on `X_train`, `y_train`
model_reg =␣
 ↪make_pipeline(SimpleImputer(strategy='median'),DecisionTreeClassifier(random_state=42))
model_reg.fit(X_train, y_train)

# Fit on `X_train_under`, `y_train_under`
```

```
model_under =␣
 ↪make_pipeline(SimpleImputer(strategy='median'),DecisionTreeClassifier(random_state=42))
model_under.fit(X_train_under, y_train_under)

# Fit on `X_train_over`, `y_train_over`
model_over =␣
 ↪make_pipeline(SimpleImputer(strategy='median'),DecisionTreeClassifier(random_state=42))
model_over.fit(X_train_over, y_train_over)
```

[20]:
```
Pipeline(steps=[('simpleimputer', SimpleImputer(strategy='median')),
                ('decisiontreeclassifier',
                 DecisionTreeClassifier(random_state=42))])
```

6.4 Evaluate

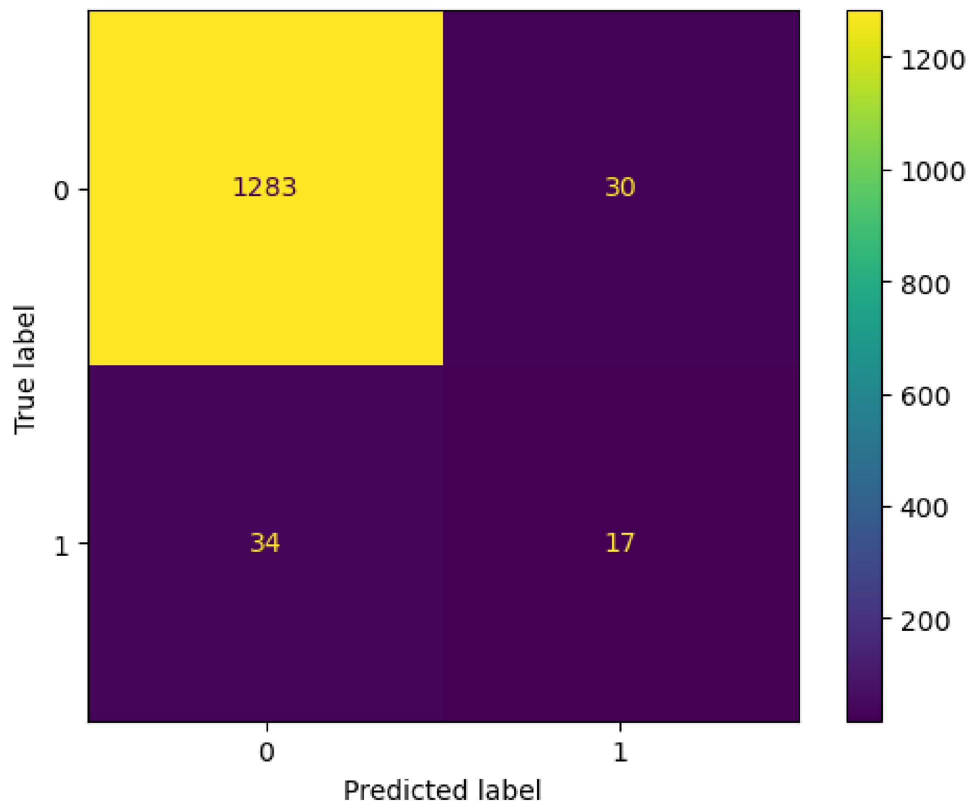
[21]:
```
for m in [model_reg, model_under, model_over]:
    acc_train = m.score(X_train,y_train)
    acc_test = m.score(X_test,y_test)

    print("Training Accuracy:", round(acc_train, 4))
    print("Test Accuracy:", round(acc_test, 4))
```

```
Training Accuracy: 1.0
Test Accuracy: 0.9531
Training Accuracy: 0.813
Test Accuracy: 0.8057
Training Accuracy: 1.0
Test Accuracy: 0.9604
```

“good” accuracy scores don’t tell us much about the model’s performance when dealing with imbalanced data. So instead of looking at what the model got right or wrong

[22]:
```
# Plot confusion matrix
ConfusionMatrixDisplay.from_estimator(model_reg,X_test,y_test)
```

[22]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x19f73b43220>
```



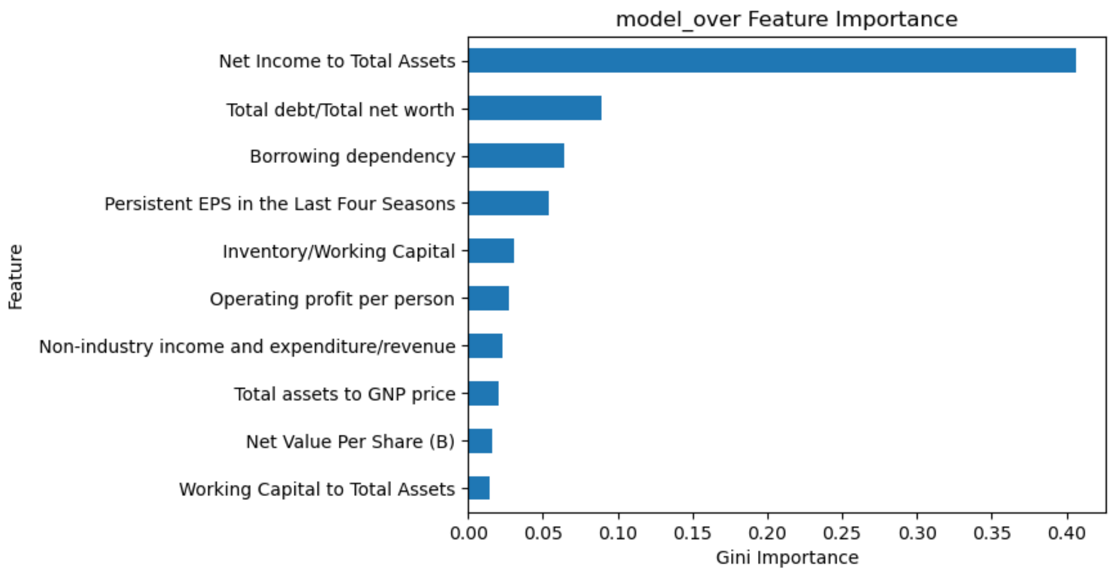
[23]:
```
#Determine the depth of the decision tree in model_over
depth = model_over.named_steps['decisiontreeclassifier'].get_depth()
print(depth)
```

```
53
```

6.5 Communicate

Now that we have a reasonable model, let's graph the importance of each feature.

[24]:
```
# Get importances
importances = model_over.named_steps['decisiontreeclassifier'].
 ↪feature_importances_

# Put importances into a Series
feat_imp = pd.Series(importances,index=X_train_over.columns).sort_values()

# Plot series
feat_imp.tail(10).plot(kind='barh')
plt.xlabel("Gini Importance")
plt.ylabel("Feature")
plt.title("model_over Feature Importance");
```



confusion matrix does not give us the best result so we need another model to get more ***TP*** ***,TN*** results

6.6 2- Random Forest Classifier

[26]:
```
clf = make_pipeline(SimpleImputer(),RandomForestClassifier(random_state=42))
print(clf)
```

```
Pipeline(steps=[('simpleimputer', SimpleImputer()),
                ('randomforestclassifier',
                 RandomForestClassifier(random_state=42))])
```

[27]:
```
cv_acc_scores = cross_val_score(clf,X_train_over,y_train_over,cv=5,n_jobs=-1)
print(cv_acc_scores)
```

```
[0.99338061 0.99432624 0.99432356 0.99668874 0.99432356]
```

[28]:
```
params ={'simpleimputer__strategy':['mean','median'],
        'randomforestclassifier__max_depth':range(10,50,10),
        'randomforestclassifier__n_estimators':range(25,100,25)}
```

[29]:
```
model = GridSearchCV(clf,param_grid=params,cv=5,n_jobs=-1,verbose=1)
model.fit(X_train_over,y_train_over)
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
```

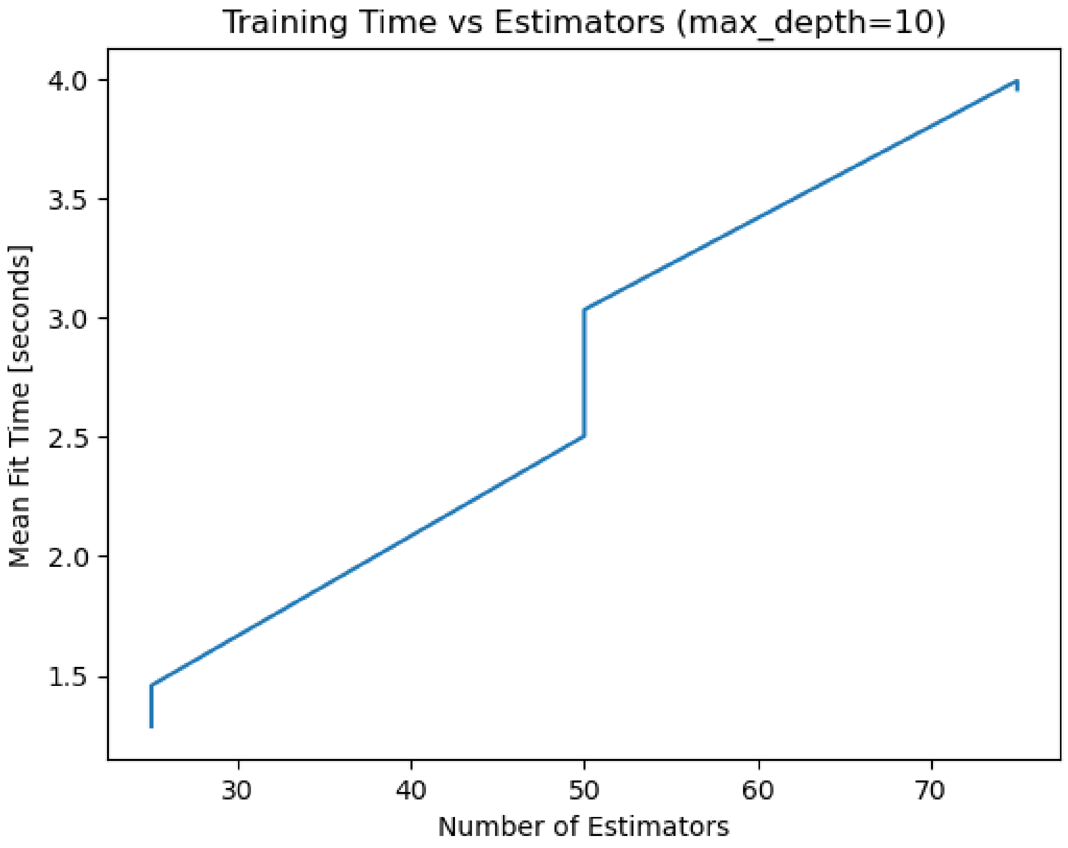
[29]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('simpleimputer', SimpleImputer()),
                                       ('randomforestclassifier',
RandomForestClassifier(random_state=42))]),
             n_jobs=-1,
             param_grid={'randomforestclassifier__max_depth': range(10, 50, 10),
                         'randomforestclassifier__n_estimators': range(25, 100,
25),
                         'simpleimputer__strategy': ['mean', 'median']},
             verbose=1)
```

[32]:
```
cv_results = pd.DataFrame(model.cv_results_)
cv_results.head(5)
```

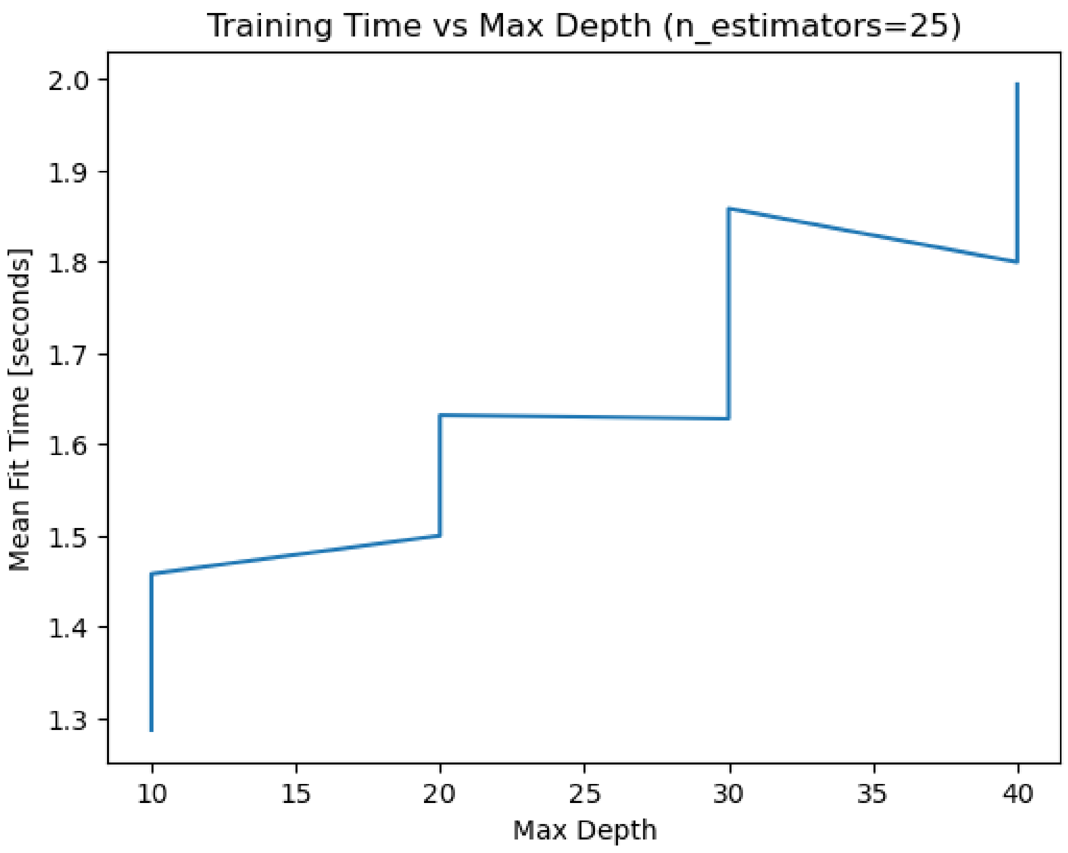
[32]:
```
   mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
0       1.287459      0.049826         0.034180        0.003967
1       1.458360      0.024056         0.035780        0.005841
2       2.503959      0.076076         0.069960        0.025022
3       3.033654      0.096780         0.054369        0.011032
4       3.993904      0.078464         0.079954        0.013805

  param_randomforestclassifier__max_depth  \
0                                      10
1                                      10
2                                      10
3                                      10
4                                      10

  param_randomforestclassifier__n_estimators param_simpleimputer__strategy  \
0                                         25                          mean
1                                         25                        median
2                                         50                          mean
3                                         50                        median
4                                         75                          mean

                                              params  split0_test_score  \
0  {'randomforestclassifier__max_depth': 10, 'ran…           0.979196
1  {'randomforestclassifier__max_depth': 10, 'ran…           0.979196
2  {'randomforestclassifier__max_depth': 10, 'ran…           0.979669
3  {'randomforestclassifier__max_depth': 10, 'ran…           0.979669
4  {'randomforestclassifier__max_depth': 10, 'ran…           0.979196

   split1_test_score  split2_test_score  split3_test_score  split4_test_score  \
0           0.977778           0.980132           0.978713           0.979659
1           0.977778           0.980132           0.978713           0.979659
2           0.979196           0.980132           0.979186           0.979186
3           0.979196           0.980132           0.979186           0.979186
4           0.980142           0.977294           0.979659           0.978713

   mean_test_score  std_test_score  rank_test_score
0         0.979096        0.000811               21
```

```
1          0.979096        0.000811                21
2          0.979474        0.000378                19
3          0.979474        0.000378                19
4          0.979001        0.000977                23
```

[36]:
```
# Create mask
mask = cv_results['param_randomforestclassifier__max_depth']==10
# Plot fit time vs n_estimators
plt.
 ↪plot(cv_results[mask]['param_randomforestclassifier__n_estimators'],cv_results[mask]['mean_
# Label axes
plt.xlabel("Number of Estimators")
plt.ylabel("Mean Fit Time [seconds]")
plt.title("Training Time vs Estimators (max_depth=10)");
```



[38]:
```
# Create mask
mask = cv_results['param_randomforestclassifier__n_estimators']==25
# Plot fit time vs max_depth
plt.
 ↪plot(cv_results[mask]['param_randomforestclassifier__max_depth'],cv_results[mask]['mean_fit
# Label axes
plt.xlabel("Max Depth")
plt.ylabel("Mean Fit Time [seconds]")
plt.title("Training Time vs Max Depth (n_estimators=25)");
```



There's a general upwards trend, but we see a lot of up-and-down here. That's because for each max depth, grid search tries two different imputation strategies: mean and median. Median is a lot faster to calculate, so that speeds up training time.

Finally, let's look at the hyperparameters that led to the best performance.

[39]:
```
# Extract best hyperparameters
model.best_params_
```

[39]:
```
{'randomforestclassifier__max_depth': 40,
 'randomforestclassifier__n_estimators': 50,
 'simpleimputer__strategy': 'mean'}
```

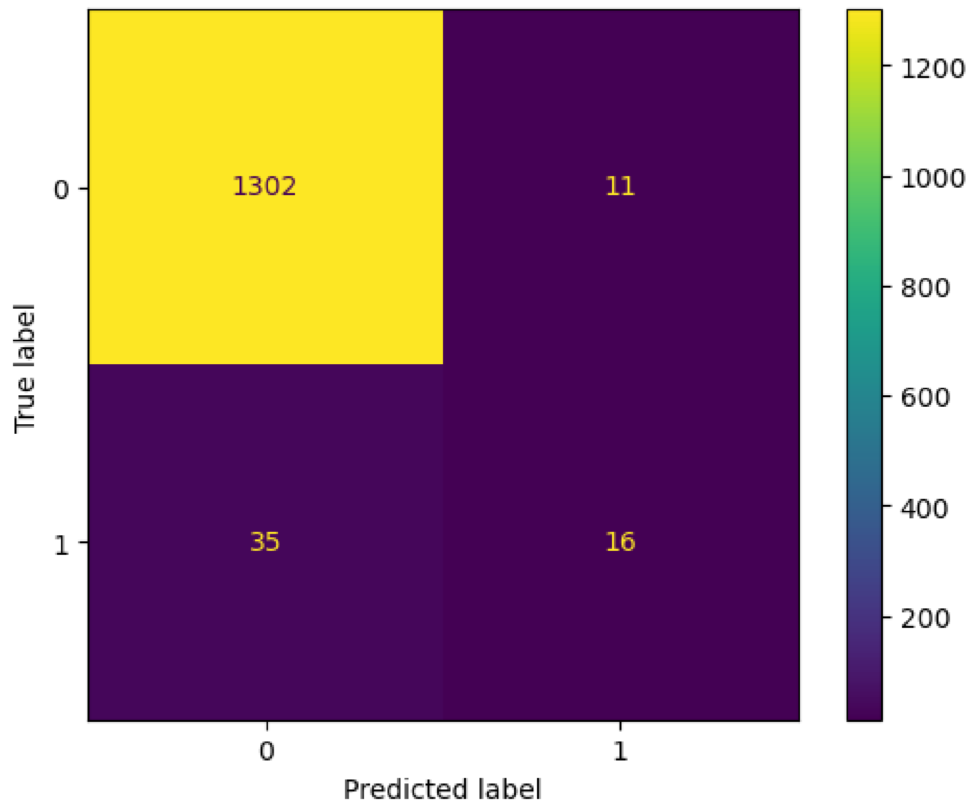
6.7 Evaluate

[40]:
```
acc_train = model.score(X_train,y_train)
acc_test = model.score(X_test,y_test)

print("Training Accuracy:", round(acc_train, 4))
print("Test Accuracy:", round(acc_test, 4))
```

```
Training Accuracy: 1.0
Test Accuracy: 0.9663
```

[41]:
```
# Plot confusion matrix
ConfusionMatrixDisplay.from_estimator(model,X_test,y_test)
```

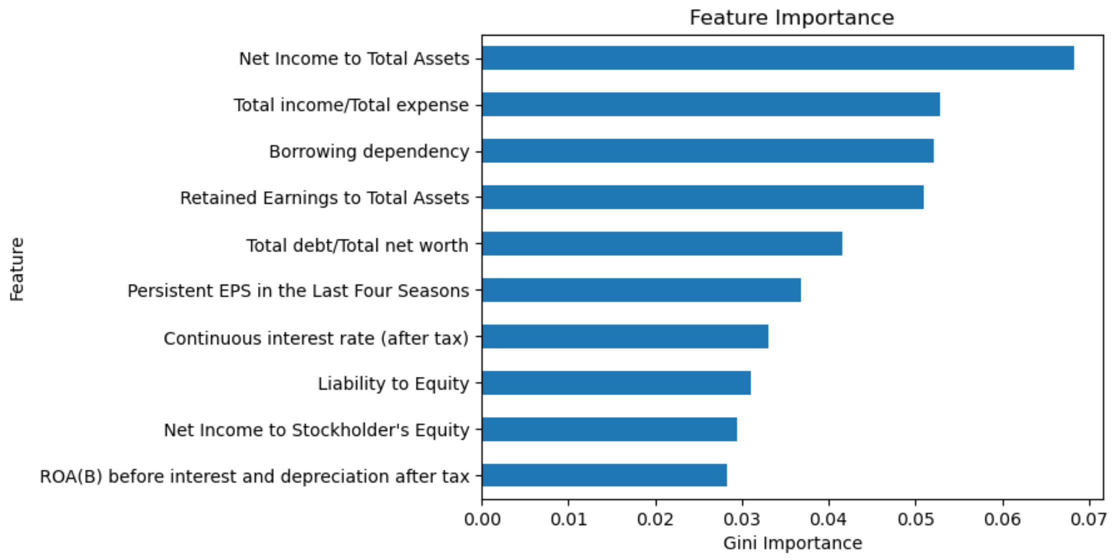
[41]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x19f7395e910>
```



6.8 Communicate

[43]:
```
# Get feature names from training data
features = X_train_over.columns
# Extract importances from model
```

```
importances = model.best_estimator_.named_steps['randomforestclassifier'].
↪feature_importances_
# Create a series with feature names and importances
feat_imp = pd.Series(importances,index=features).sort_values()
# Plot 10 most important features
feat_imp.tail(10).plot(kind='barh')
plt.xlabel("Gini Importance")
plt.ylabel("Feature")
plt.title("Feature Importance");
```



[45]:
```
# save the model
import pickle
with open( "Random_Forest_model.pkl",'wb') as f :
    pickle.dump(model,f)
```

[65]:
```
X_test.to_csv("data/X_test.csv",index=False)
```

[66]:
```
def make_predictions(data_filepath, model_filepath):
    # Wrangle JSON file
    X_test = pd.read_csv(data_filepath)
    # Load model
    with open(model_filepath,'rb') as file:
        model=pickle.load(file)
    # Generate predictions
    y_test_pred = model.predict(X_test)
    # Put predictions into Series with name "bankrupt", and same index as X_test
    y_test_pred = pd.Series(y_test_pred,index=X_test.index,name='bankrupt')
    return y_test_pred
```

[67]:
```
y_test_pred = make_predictions(
    data_filepath="data/X_test.csv",
    model_filepath="Random_Forest_model.pkl",
)

print("predictions shape:", y_test_pred.shape)
y_test_pred.head()
```

```
predictions shape: (1364,)
```

[67]:
```
0    0
1    0
2    0
3    1
4    0
Name: bankrupt, dtype: int64
```

6.9 3- Gradient Boosting Classifier

[71]:
```
clf = make_pipeline(SimpleImputer(),GradientBoostingClassifier())
print(clf)
```

```
Pipeline(steps=[('simpleimputer', SimpleImputer()),
                ('gradientboostingclassifier', GradientBoostingClassifier())])
```

[72]:
```
params = {'simpleimputer__strategy':['mean','median']
         ,'gradientboostingclassifier__max_depth':range(2,5)
         ,'gradientboostingclassifier__n_estimators':range(20,31,5)}
params
```

[72]:
```
{'simpleimputer__strategy': ['mean', 'median'],
 'gradientboostingclassifier__max_depth': range(2, 5),
 'gradientboostingclassifier__n_estimators': range(20, 31, 5)}
```

Note that we're trying much smaller numbers of n_estimators. This is because GradientBoostingClassifier is slower to train than the RandomForestClassifier. You can try increasing the number of estimators to see if model performance improves, but keep in mind that you could be waiting a long time!

[73]:
```
model = GridSearchCV(clf,param_grid=params,cv=5,n_jobs=-1,verbose=1)
```

[74]:
```
# Fit model to over-sampled training data
model.fit(X_train_over,y_train_over)
```

```
Fitting 5 folds for each of 18 candidates, totalling 90 fits
```

[74]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('simpleimputer', SimpleImputer()),
                                       ('gradientboostingclassifier',
                                            GradientBoostingClassifier())]),
             n_jobs=-1,
             param_grid={'gradientboostingclassifier__max_depth': range(2, 5),
                         'gradientboostingclassifier__n_estimators': range(20,
31, 5),
                         'simpleimputer__strategy': ['mean', 'median']},
             verbose=1)
```

[75]:
```
results = pd.DataFrame(model.cv_results_)
results.sort_values("rank_test_score").head(10)
```

[75]:
```
    mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
16      10.763213      0.056432         0.019989        0.005997
17      11.110814      0.148439         0.015791        0.002039
15       9.220324      0.104813         0.016591        0.002243
14       9.269073      0.249547         0.015791        0.000399
13       8.057969      0.085673         0.020789        0.007164
12       8.097546      0.107288         0.016591        0.002330
10       9.478034      0.150210         0.018589        0.002153
11       9.734389      0.149561         0.017191        0.001165
9        8.219004      0.069603         0.016591        0.001019
8        8.365986      0.155735         0.021588        0.008208

   param_gradientboostingclassifier__max_depth  \
16                                           4
17                                           4
15                                           4
14                                           4
13                                           4
12                                           4
10                                           3
11                                           3
9                                            3
8                                            3

   param_gradientboostingclassifier__n_estimators  \
16                                              30
17                                              30
15                                              25
14                                              25
13                                              20
12                                              20
10                                              30
11                                              30
9                                               25
8                                               25
```

```
   param_simpleimputer__strategy  \
16                          mean   
17                        median   
15                        median   
14                          mean   
13                        median   
12                          mean   
10                          mean   
11                        median   
9                         median   
8                           mean   

                                               params  split0_test_score  \
16  {'gradientboostingclassifier__max_depth': 4, '…           0.963121   
17  {'gradientboostingclassifier__max_depth': 4, '…           0.962648   
15  {'gradientboostingclassifier__max_depth': 4, '…           0.961229   
14  {'gradientboostingclassifier__max_depth': 4, '…           0.961229   
13  {'gradientboostingclassifier__max_depth': 4, '…           0.957447   
12  {'gradientboostingclassifier__max_depth': 4, '…           0.957447   
10  {'gradientboostingclassifier__max_depth': 3, '…           0.945154   
11  {'gradientboostingclassifier__max_depth': 3, '…           0.945154   
9   {'gradientboostingclassifier__max_depth': 3, '…           0.939007   
8   {'gradientboostingclassifier__max_depth': 3, '…           0.939007   

    split1_test_score  split2_test_score  split3_test_score  \
16           0.964066           0.964522           0.966887   
17           0.964066           0.964522           0.966414   
15           0.962175           0.962157           0.964995   
14           0.962175           0.962157           0.964995   
13           0.960284           0.957900           0.960738   
12           0.960284           0.957900           0.960738   
10           0.948936           0.950804           0.947020   
11           0.948936           0.950804           0.946547   
9            0.942317           0.932829           0.942763   
8            0.942317           0.932829           0.942763   

    split4_test_score  mean_test_score  std_test_score  rank_test_score  
16           0.971618         0.966043        0.003051                1  
17           0.972091         0.965948        0.003299                2  
15           0.970199         0.964151        0.003277                3  
14           0.969726         0.964056        0.003104                4  
13           0.966887         0.960651        0.003373                5  
12           0.966887         0.960651        0.003373                5  
10           0.945601         0.947503        0.002113                7  
11           0.945601         0.947408        0.002143                8  
9            0.942763         0.939936        0.003822                9  
8            0.942763         0.939936        0.003822                9  
```

```
[76]: # Extract best hyperparameters
      model.best_params_
```

```
[76]: {'gradientboostingclassifier__max_depth': 4,
       'gradientboostingclassifier__n_estimators': 30,
       'simpleimputer__strategy': 'mean'}
```

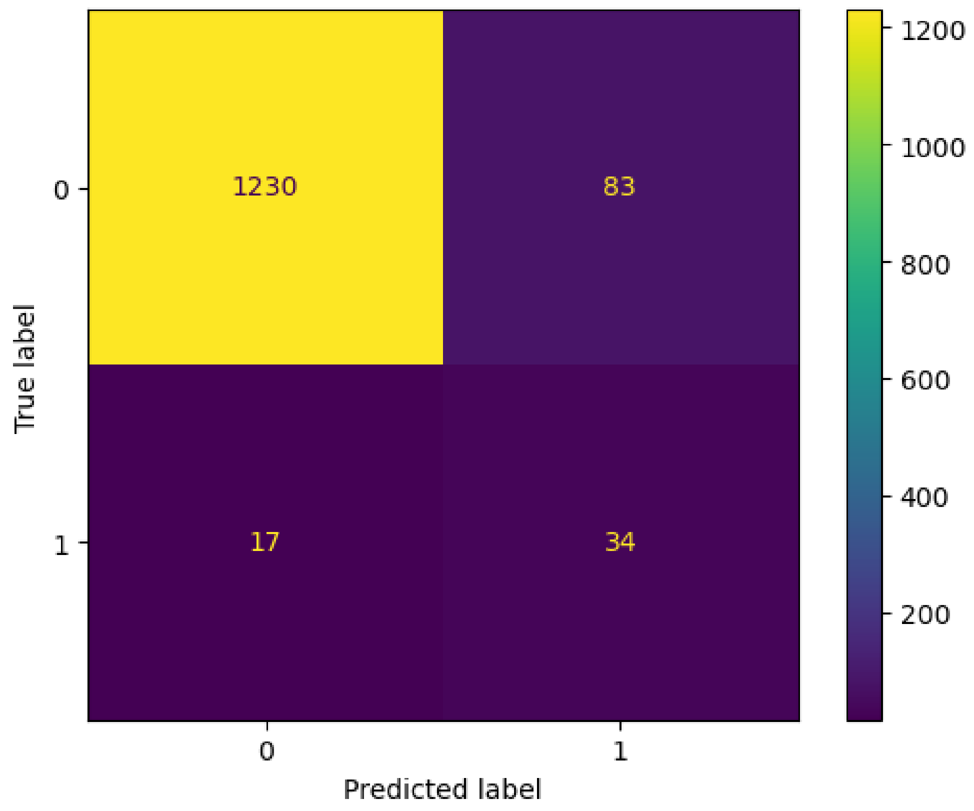
6.10 Evaluate

```
[77]: acc_train = model.score(X_train,y_train)
      acc_test = model.score(X_test,y_test)

      print("Training Accuracy:", round(acc_train, 4))
      print("Validation Accuracy:", round(acc_test, 4))
```

```
Training Accuracy: 0.9487
Validation Accuracy: 0.9267
```

```
[78]: # Plot confusion matrix
      ConfusionMatrixDisplay.from_estimator(model,X_test,y_test)
```

```
[78]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x19f7b4e8880>
```



This matrix is a great reminder of how imbalanced our data is, and of why accuracy isn't always the best metric for judging whether or not a model is giving us what we want. After all, if 95% of the companies in our dataset didn't go bankrupt, all the model has to do is always predict {"bankrupt": 0}, and it'll be right 95% of the time. The accuracy score will be amazing, but it won't tell us what we really need to know.

Instead, we can evaluate our model using two new metrics: precision and recall. The precision score is important when we want our model to only predict that a company will go bankrupt if its very confident in its prediction. The recall score is important if we want to make sure to identify all the companies that will go bankrupt, even if that means being incorrect sometimes.

[81]:
```
# Print classification report
print(classification_report(y_test,model.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.99      0.94      0.96      1313
           1       0.29      0.67      0.40        51

    accuracy                           0.93      1364
   macro avg       0.64      0.80      0.68      1364
weighted avg       0.96      0.93      0.94      1364
```

suupose a manager give me a task that that every time i predict tp i will get a profit for my company = 100_000_000 for each tp

and

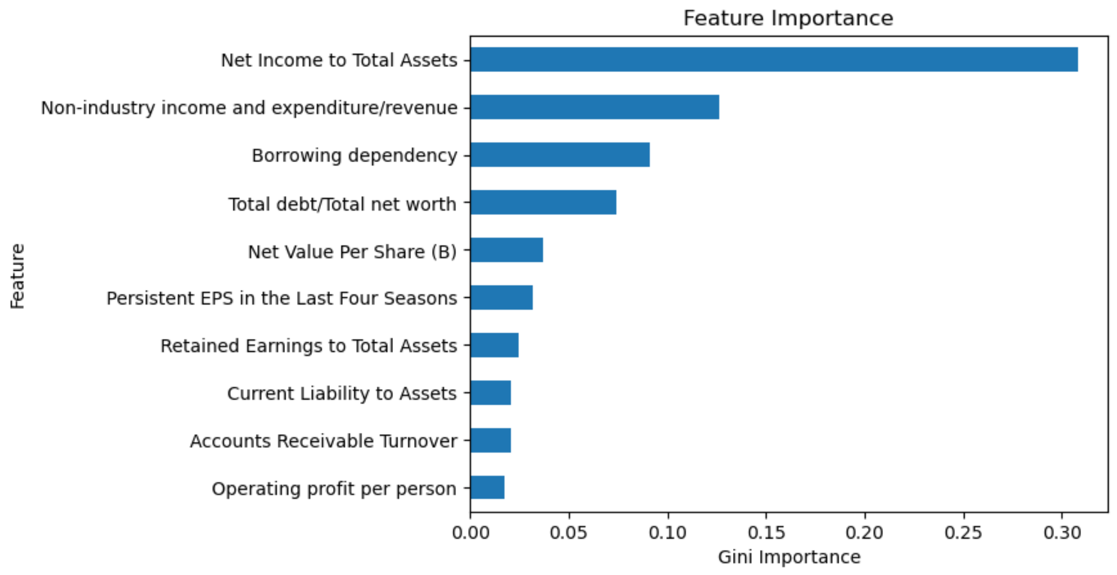
every time i predict fp i will make a lose for my company = 2500_000_000 for each fp

[93]:
```
def make_cnf_matrix(threshold):
    y_pred_prob=model.predict_proba(X_test)[:,-1]
    y_pred=y_pred_prob>threshold
    con=confusion_matrix(y_test,y_pred)
    tn,fp,fn,tp=con.ravel()
    print(f'profit: ${tp*100_000_000}')
    print(f'losses: ${fp*250_000_000}')
    ConfusionMatrixDisplay.from_predictions(y_test,y_pred,colorbar=False)



thresh_widget = widgets.FloatSlider(min=0,max=1,step=0.05,value=0.5)

interact(make_cnf_matrix, threshold=thresh_widget);
```

```
interactive(children=(FloatSlider(value=0.5, description='threshold', max=1.0,␣
 ↪step=0.05), Output()), _dom_cla…
```

6.11 Communicate

[94]:
```
# Get feature names from training data
features = X_train_over.columns
# Extract importances from model
importances = model.best_estimator_.named_steps['gradientboostingclassifier'].
 ↪feature_importances_
# Create a series with feature names and importances
feat_imp = pd.Series(importances,index=features).sort_values()
# Plot 10 most important features
feat_imp.tail(10).plot(kind='barh')
plt.xlabel("Gini Importance")
plt.ylabel("Feature")
plt.title("Feature Importance");
```



[95]:
```
# save the model
import pickle
with open( "Gradient_boosting_model.pkl",'wb') as f :
    pickle.dump(model,f)
```

[96]:
```
def make_predictions(data_filepath, model_filepath):
    # Wrangle JSON file
    X_test = pd.read_csv(data_filepath)
    # Load model
    with open(model_filepath,'rb') as file:
        model=pickle.load(file)
    # Generate predictions
    y_test_pred = model.predict(X_test)
    # Put predictions into Series with name "bankrupt", and same index as X_test
    y_test_pred = pd.Series(y_test_pred,index=X_test.index,name='bankrupt')
    return y_test_pred
```

[97]:
```
y_test_pred = make_predictions(
    data_filepath="data/X_test.csv",
    model_filepath="Gradient_boosting_model.pkl",
)

print("predictions shape:", y_test_pred.shape)
y_test_pred.head()
```

```
predictions shape: (1364,)
```

[97]:
```
0    0
1    0
2    0
3    1
4    0
Name: bankrupt, dtype: int64
```

[ ]:
```

```