ADS-505 Technical Presentation

Team 1:

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Technical Problem Statement

- Rising rates environment necessitate an enhanced review process for business lending loan applicants. Current staffing limitations require an automated solution
- Current business process of credit review is a manual Excel worksheet with data points input by a junior level credit analyst
- There is an increase in demand to use AI/ML techniques to aid in credit risk management and the bank wishes to incorporate AI/ML into their business processes
- Business Credit department has requested an AI/ML solution to help aid in identifying high risk business loan applicants that reduce workload, manual review process, and to aid in credit risk management

Current state: All manual review

Goal: Automation, selected review only

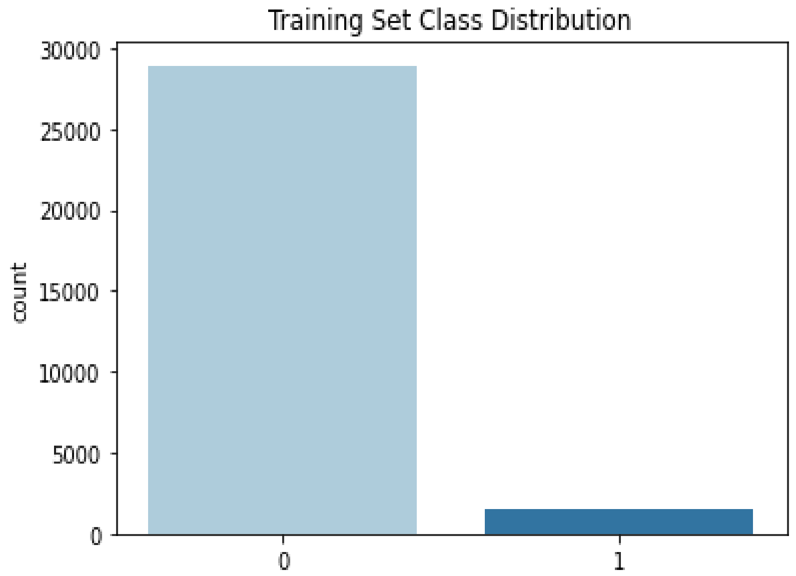
Exploratory Data Analysis (EDA)

- Our data was downloaded from UCI Machine Learning Repository
- Total data : **43,405** instances with **65** features (such as: net_prof_to_tot_assets_ratio, tot_liab_to_tot_assets_ratio, work_cap_to_tot_assets_ratio, etc.)
- Binary class for target feature
- Data is extreme imbalance:

    Still-operating companies: 95.2%

    Bankrupted companies: 4.8%

Figure 1. *Full Data Set Class Distribution*



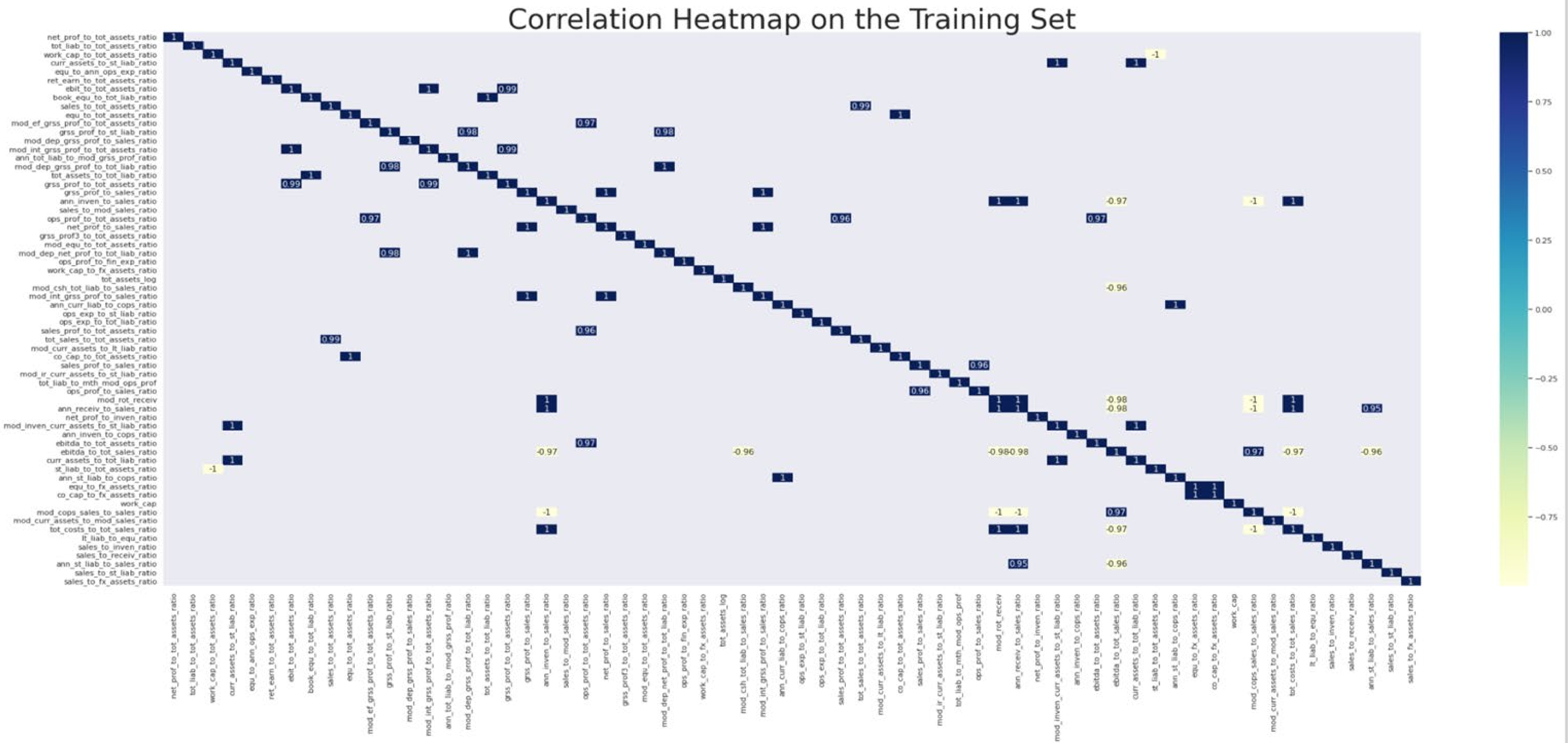
EDA cont’d

- A training set of **30,383** instances and **65** features were used for exploring the data

- 209 row of duplicates was found and dropped from the training set

EDA cont'd

Figure 2. *Observe Features with High Correlation (| r | > 0.95)*



EDA cont'd

- Features with $r > 0.95$ were dropped

- Number of features reduced from 65 to 42

EDA cont’d

Table 1. *Summary Statistics for the First Three Columns*

	net_prof_to_tot_assets_ratio	tot_liab_to_tot_assets_ratio	work_cap_to_tot_assets_ratio
count	30168.000000	30168.000000	30168.000000
mean	0.027545	0.571545	0.127836
std	3.218895	5.291554	4.639301
min	-463.890000	-430.870000	-479.730000
25%	0.003039	0.271487	0.020666
50%	0.048891	0.472075	0.195640
75%	0.128395	0.689253	0.400930
max	87.459000	480.730000	22.769000

Many features has either very small minimum or large maximum compared to the means which cause highly skewed data.

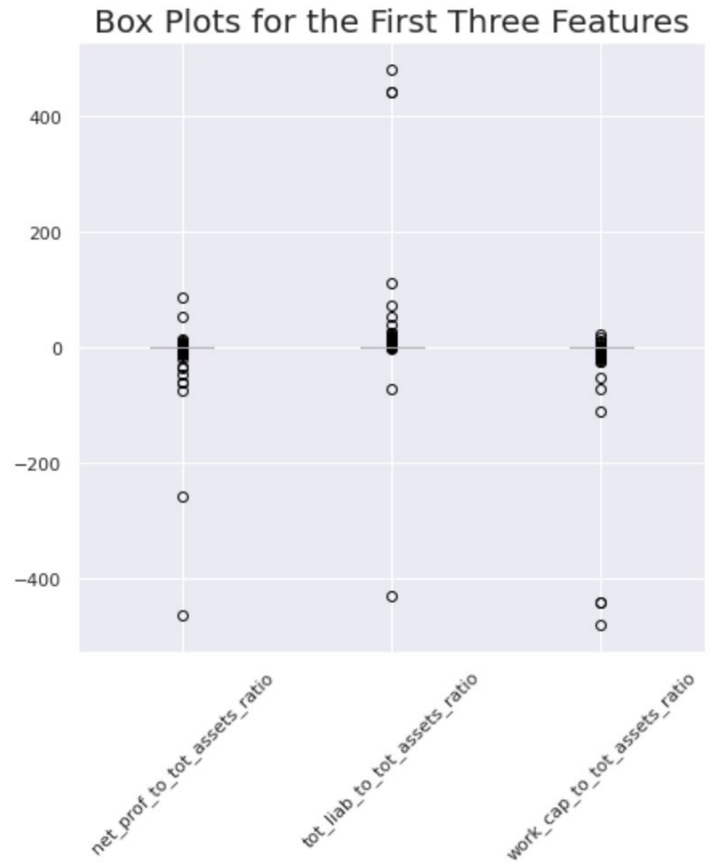
EDA cont'd

Table 2. *A Sample Showing Outlier Positions in the First Three Columns*

	net_prof_to_tot_assets_ratio	tot_liab_to_tot_assets_ratio	work_cap_to_tot_assets_ratio
2397	NaN	NaN	NaN
2398	0.52753	NaN	NaN
2399	-1.94800	25.005	NaN
2400	NaN	NaN	NaN
2401	NaN	NaN	NaN
...	...	...	...

- There are large numbers of rows with outliers (26,504 out of 30,174 rows total) in the training set.
- All outliers are kept and proceeded with processing

Figure 3. *Observing Outliers Using Boxplots for the First Three Columns*



Data Wrangling & Preprocessing

- Multiple weka format (.arff) files
  - Import*, combine, rename columns
  - Factorize binary, nominal target to 0/1
- Create 70/30 train/test random stratified split
- Check for features with near zero variance
- Check for features with null values
  - Remove any above 15% of *N*

Figure 4. *Code Sample: Load .arff file and Convert to Pandas Dataframe*

```
raw_arff01 = arff.loadarff(folder_path + '/1year.arff')
df01a = pd.DataFrame(raw_arff01[0])
```

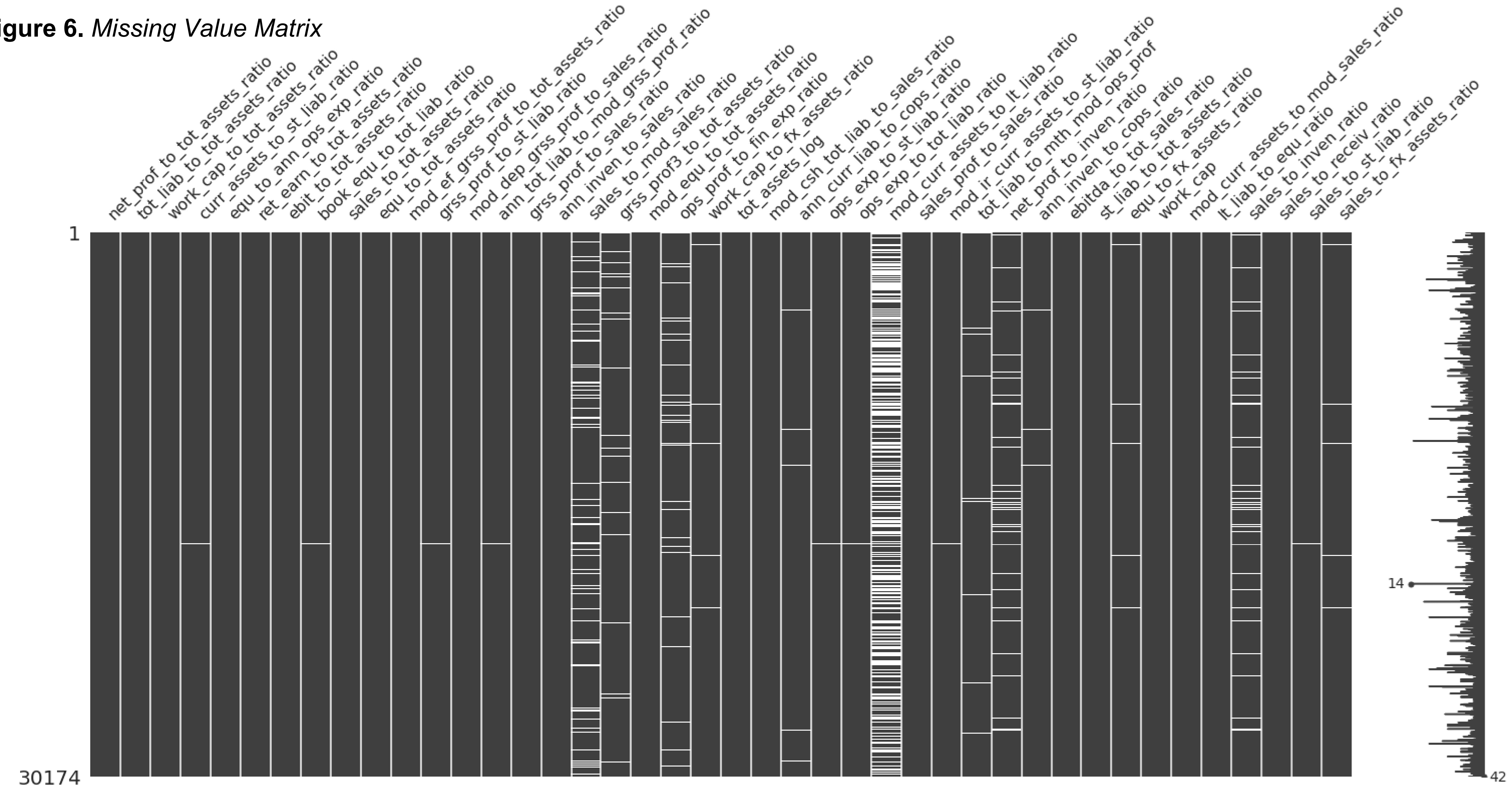
Figure 5. *Code Sample: Train/Test Split*

```
# Create train & test sets for X & Y (NOTE: stratification by y)
train_x01_df01, test_x01_df01, \
train_y01_df01, test_y01_df01 = train_test_split(x01_df01,
                                                 y01_df01,
                                                 test_size=.3,
                                                 random_state=1699,
                                                 stratify=y01_df01)

# Convert y df's to vector arrays
train_y01_vc01 = train_y01_df01.to_numpy()
test_y01_vc01 = test_y01_df01.to_numpy()
```

* Zięba et al., 2016

Missing Value Matrix

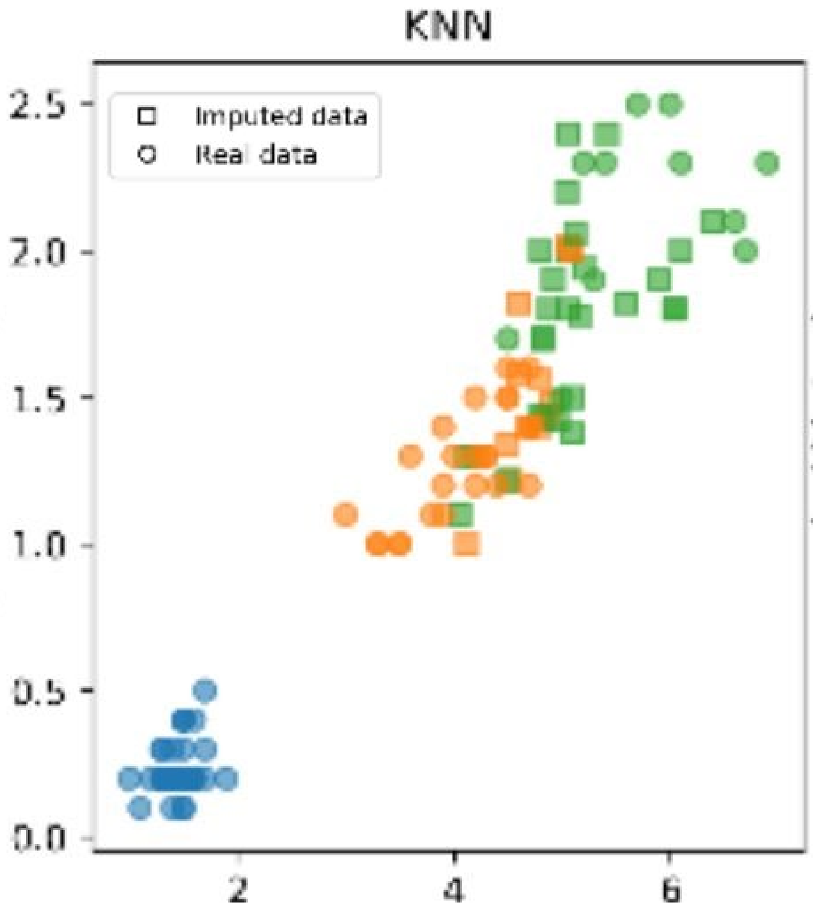
Figure 6. *Missing Value Matrix*



Data Wrangling & Preprocessing (cont'd)

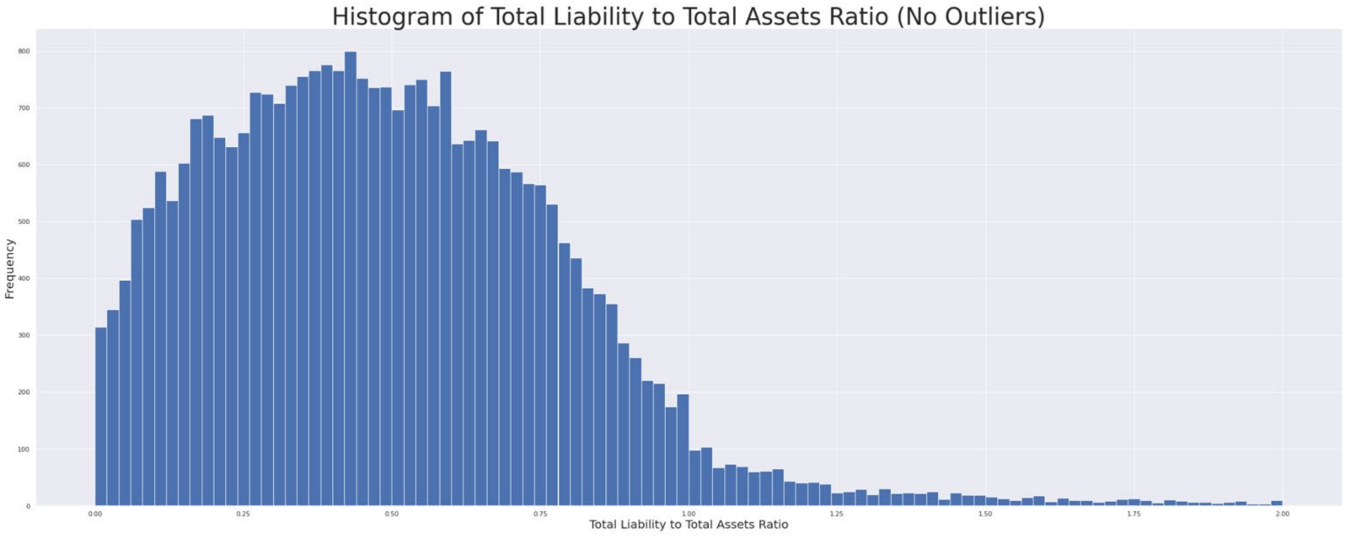
- Fill in missing values using KNN Imputer
- Scale all feature values
- Address skew

Figure 7. *Example of Imputation*



From "Gunden Geri Kalanlar - 17," by A. Baryirli, 2020 (see References).

Figure 8. *Illustration of Right Skew*



Address Class Imbalance

- Positive class is ~4.8% of training *n*
- Apply class rebalancing techniques: SMOTE, Random Oversampling

Figure 9. *Training Data Set Class Distribution*

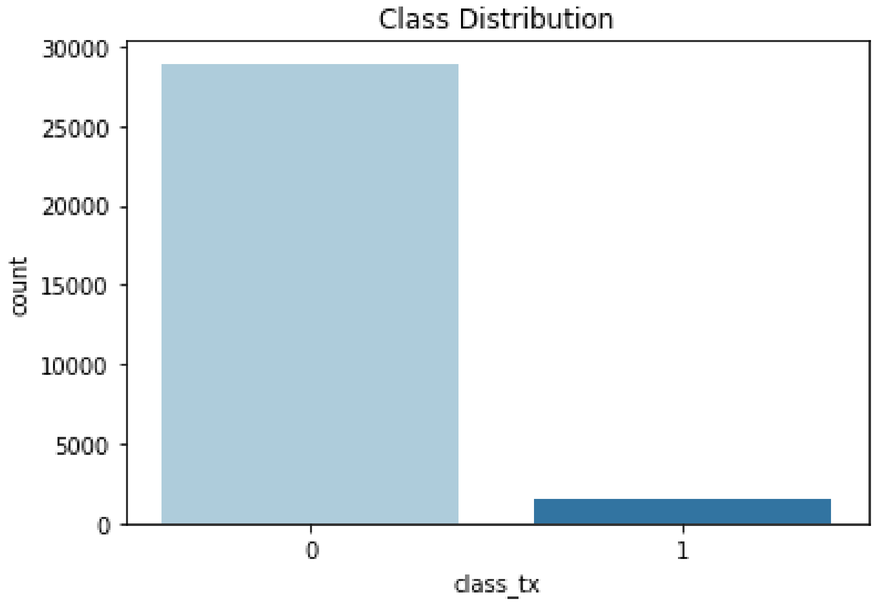
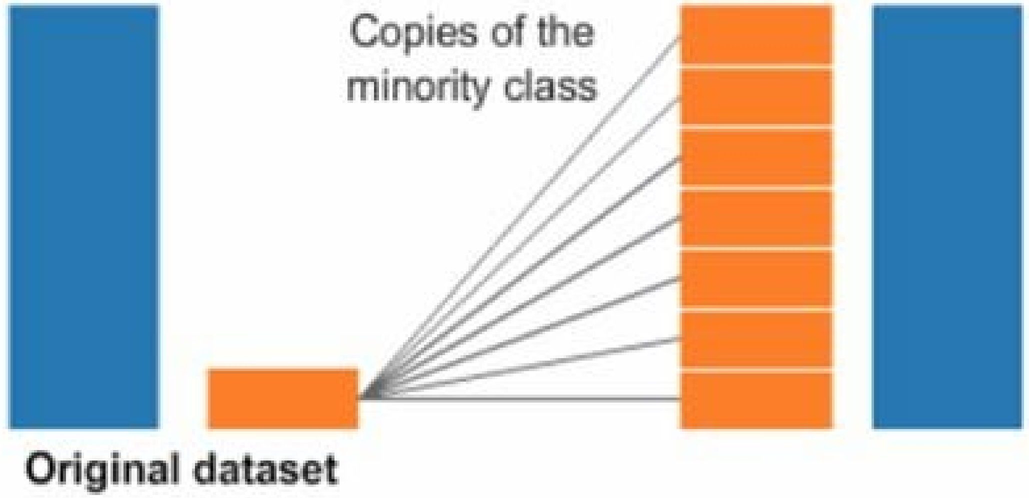


Figure 10. *Example of Oversampling Process*



From "cfa-level-2-oversampling-and-undersampling," by Analyst Prep, 2021 (see References).

Models & Strategies

- Binary classification
- Baseline
  - KNN, LDA
- Robust to outliers
  - Single tree
- Ensemble
  - Random Forests, Gradient Boost, XGBoost
- Complex relationships
  - Neural Network

Models & Strategies (cont'd)

- Use multiple data frames to accommodate needs for different model algorithms
- Hyperparameter tuning
  - Grid searches
- Pickling
  - Saves trained model for ease of deploying
  - Prevents Python from regularly running computationally expensive training

Model Evaluation

- Evaluation metrics assisted in choosing optional model
- There is a business need to select a sufficient number of True Positives, while accounting for not including a large number of False Positives
- Accuracy was the least important metric. Instead, a balance between Precision & Recall was needed
- *F_1* Score proved to be the most useful metric

Table 3. *Model Performance Summary*

Comparsion between model evaluation measures using test set

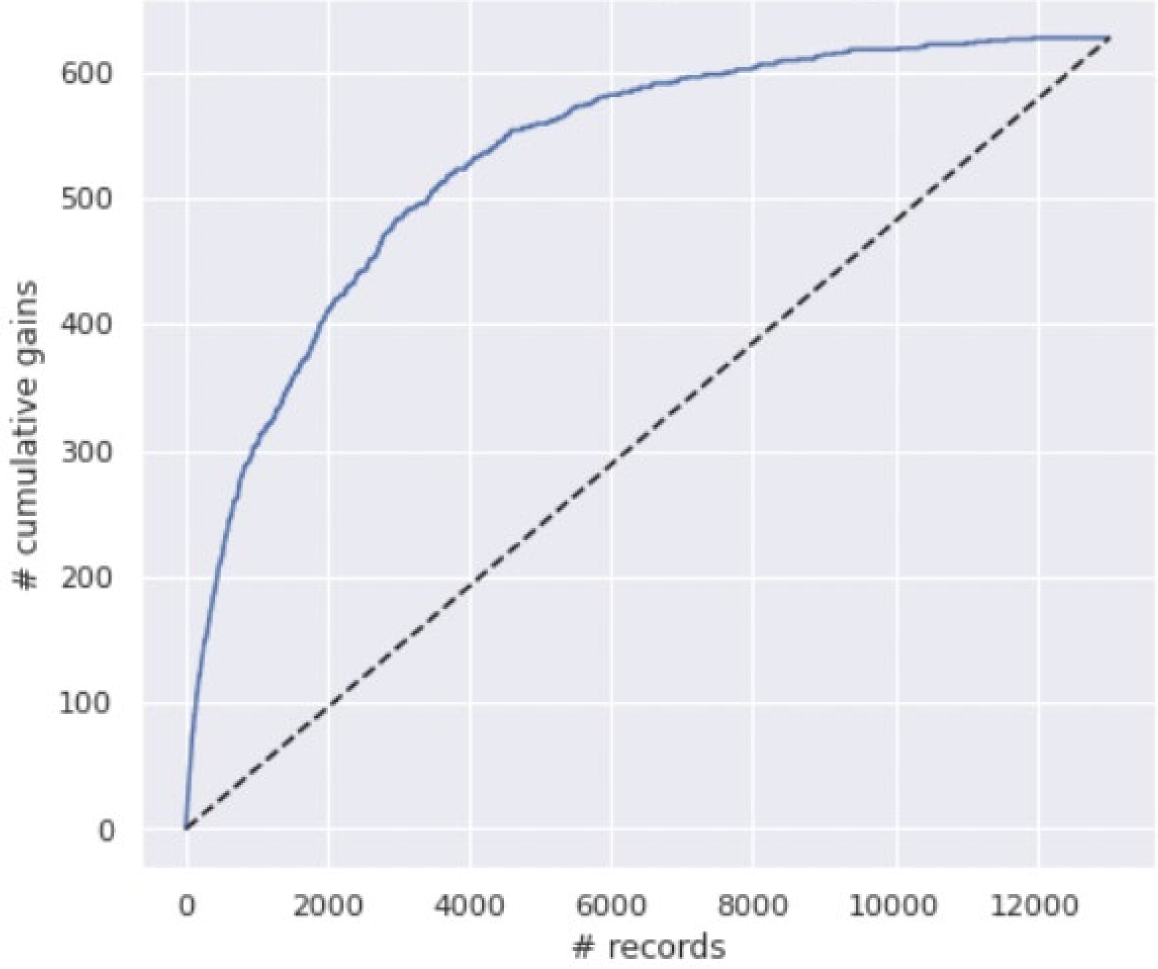
	Accuracy	Precision	Recall	F1_score
boost_1	0.920135	0.298537	0.488038	0.37046
boost_2	0.876363	0.206567	0.551834	0.300608
boost_3	0.822685	0.171997	0.703349	0.276402
boost_4	0.299493	0.0605277	0.933014	0.113681
xgboost_1	0.818691	0.172088	0.725678	0.278202
xgboost_2	0.230303	0.0580433	0.984051	0.109621
NN_tune	0.590002	0.0818246	0.735247	0.147261
dec_tree	0.952235	0.524752	0.0845295	0.145604
rand_for	0.950008	0.360465	0.0494418	0.0869565
knn_1	0.951467	0.142857	0.0015949	0.00315457
knn_2	0.865612	0.124916	0.298246	0.176083
knn_3	0.951928	0.571429	0.00637959	0.0126183
knn_4	0.937106	0.0384615	0.0127592	0.0191617
lda_1	0.951697	0.333333	0.00318979	0.00631912
lda_2	0.581938	0.0642301	0.566188	0.115372
lda_3	0.950315	0.261905	0.0175439	0.0328849
lda_4	0.863308	0.0976971	0.223285	0.135922

Results & Final Model Selection

- The Gradient Boosting Classifier produced the the largest cumulative gains of pos predictions when viewing the data in a Gains Chart

- By binning the predicted probabilities of the Gradient Boosting model, the credit team will be provided with credit risk tiers for each loan that have a corresponding review requirement

Figure 11. Gains chart for GradientBoostingClassifier(n_estimators=500)



Discussion

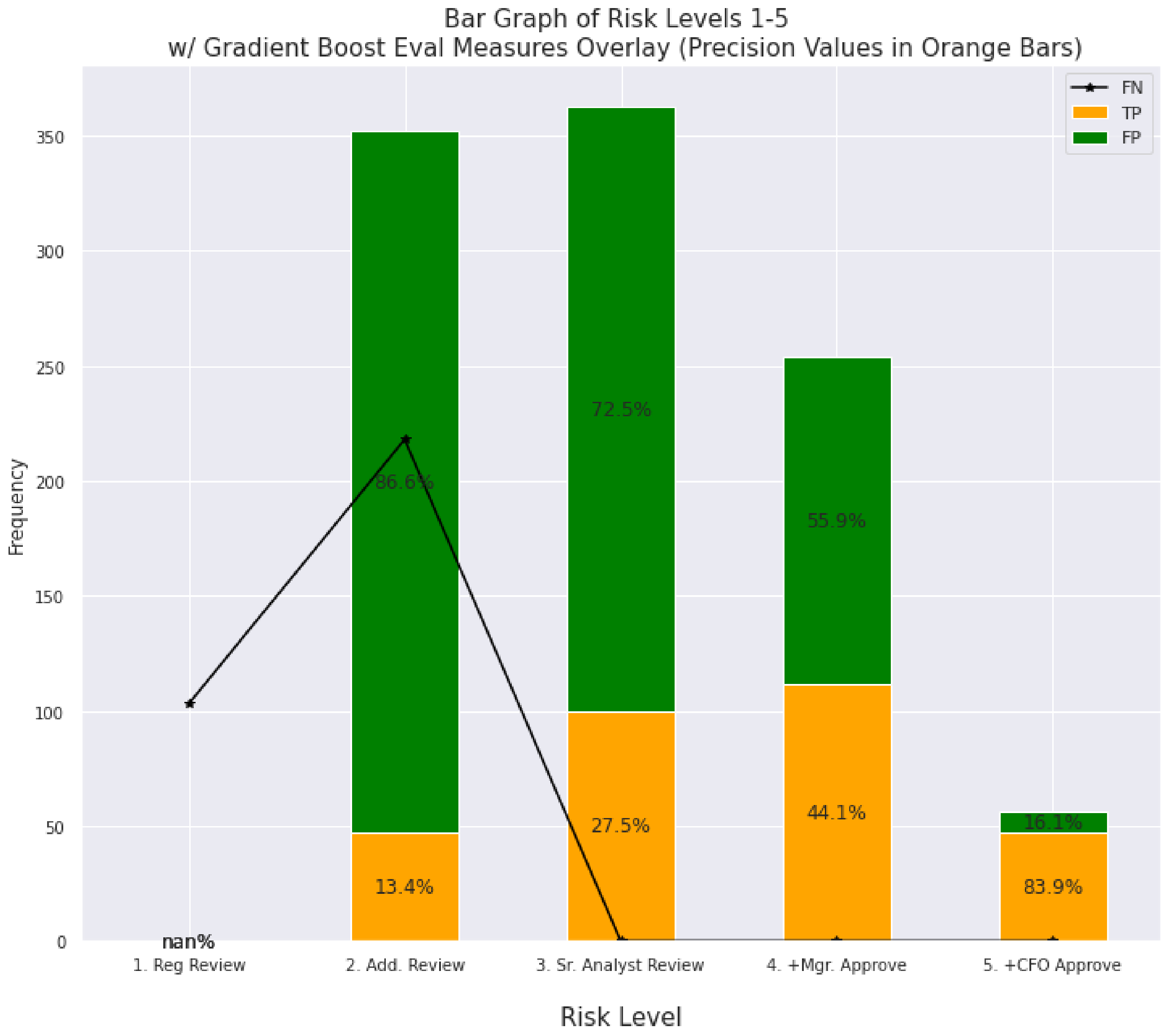
Table 4. *Risk Level Tiers*

Credit Risk Tier	Recommended Review Requirement	Predicted Probabilities	Notes
High Risk	Senior Analyst Review + CFO Sign-off	[.90, 1]	“High Risk” tier applicants have an 84% chance of bankruptcy from the test data. Due to high risk, executive level approval is needed to approve a loan in this tier
Moderate Risk 1	Senior Analyst Review + Management Sign-off	[.75, .90)	Moderate Risk 1 tier applicants have a 44% chance of bankruptcy from the test data. Due to the elevated risk, senior management approval is needed to approve a loan in this tier
Moderate Risk 2	Senior Analyst Review	[.60, .75)	Moderate Risk 2 tier applicants have a 28% chance of bankruptcy from the test data. Due to the elevated risk, senior management approval is needed to approve a loan in this tier
Low Risk 1	Additional Review	[.16, .60)	Low Risk 1 tier applicants have a low likelihood of bankruptcy. These applicants are recommended to have a second review by a peer analyst for accuracy
Low Risk 2	Basic Review	[0, .16)	Low Risk 2 tier applicants have the least likelihood of bankruptcy from the test data set. Recommend no change to current business process

Conclusion

- As risk levels increase:
  - ⇧ Precision / confidence in IDing TPs
  - ⇩ Review pool
- Probability thresh. for level 2 decreased to capture more FNs in additional review pool
- Result:
  - Minimized review time/cost increase (incl. less reviews for Sr. Analysts)
  - More at-risk companies receive elevated review

Figure 12.



ADS-505_Team1_Final_Project_v2

October 17, 2022

505-01-FA22

Team 1

Final Project

Github Repository:

https://github.com/amcarr-ds/ads505_business_proj.git

Bankruptcy Data Set (Zięba et al., 2016b):

https://archive.ics.uci.edu/ml/datasets/Polish+companies+bankruptcy+data

[1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[2]:
```
%pip install dmba
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting dmba
  Downloading dmba-0.1.0-py3-none-any.whl (11.8 MB)
     |                 | 11.8 MB 25.4 MB/s
Installing collected packages: dmba
Successfully installed dmba-0.1.0
```

Feature name conversion map

Original Feature Name	Changed	New Feature Name
X1 net profit / total assets	-->	net_prof_to_tot_asset

Original Feature Name	Changed	New Feature Name
		s_ratio
X2 total liabilities / total assets	-->	tot_liab_to_tot_assets_ratio
X3 working capital / total assets	-->	work_cap_to_tot_assets_ratio
X4 current assets / short-term liabilities	-->	curr_assets_to_st_liab_ratio
X5 [(cash + short-term securities + receivables - short-term liabilities) / (operating expenses - depreciation)] * 365	-->	equ_to_ann_ops_exp_ratio
X6 retained earnings / total assets	-->	ret_earn_to_tot_assets_ratio
X7 EBIT / total assets	-->	ebit_to_tot_assets_ratio
X8 book value of equity / total liabilities	-->	book_equ_to_tot_liab_ratio
X9 sales / total assets	-->	sales_to_tot_assets_ratio
X10 equity / total assets	-->	equ_to_tot_assets_ratio
X11 (gross profit + extraordinary items + financial expenses) / total assets	-->	mod_ef_grss_prof_to_tot_assets_ratio
X12 gross profit / short-term liabilities	-->	grss_prof_to_st_liab_ratio
X13 (gross profit + depreciation) / sales	-->	mod_dep_grss_prof_to_sales_ratio
X14 (gross profit + interest) / total assets	-->	mod_int_grss_prof_to_tot_assets_ratio
X15 (total liabilities * 365) / (gross profit + depreciation)	-->	ann_tot_liab_to_mod_grss_prof_ratio
X16 (gross profit + depreciation) / total liabilities	-->	mod_dep_grss_prof_to_tot_liab_ratio
X17 total assets / total liabilities	-->	tot_assets_to_tot_liab_ratio
X18 gross profit / total assets	-->	grss_prof_to_tot_assets_ratio
X19 gross profit / sales	-->	grss_prof_to_sales_ratio
X20 (inventory * 365) / sales	-->	ann_inven_to_sales_ratio
X21 sales (n) / sales (n-1)	-->	sales_to_mod_sales_ratio
X22 profit on operating activities / total assets	-->	ops_prof_to_tot_assets_ratio
X23 net profit / sales	-->	net_prof_to_sales_ratio

Original Feature Name	Changed	New Feature Name
X24 gross profit (in 3 years) / total assets	-->	grss_prof3_to_tot_ass ets_ratio
X25 (equity - share capital) / total assets	-->	mod_equ_to_tot_assets _ratio
X26 (net profit + depreciation) / total liabilities	-->	mod_dep_net_prof_to_t ot_liab_ratio
X27 profit on operating activities / financial expenses	-->	ops_prof_to_fin_exp_r atio
X28 working capital / fixed assets	-->	work_cap_to_fx_assets _ratio
X29 logarithm of total assets	-->	tot_assets_log
X30 (total liabilities - cash) / sales	-->	mod_csh_tot_liab_to_s ales_ratio
X31 (gross profit + interest) / sales	-->	mod_int_grss_prof_to_ sales_ratio
X32 (current liabilities * 365) / cost of products sold	-->	ann_curr_liab_to_cops _ratio
X33 operating expenses / short-term liabilities	-->	ops_exp_to_st_liab_ra tio
X34 operating expenses / total liabilities	-->	ops_exp_to_tot_liab_r atio
X35 profit on sales / total assets	-->	sales_prof_to_tot_ass ets_ratio
X36 total sales / total assets	-->	tot_sales_to_tot_asse ts_ratio
X37 (current assets - inventories) / long-term liabilities	-->	mod_curr_assets_to_lt _liab_ratio
X38 constant capital / total assets	-->	co_cap_to_tot_assets_ ratio
X39 profit on sales / sales	-->	sales_prof_to_sales_r atio
X40 (current assets - inventory - receivables) / short-term l iabilities	-->	mod_ir_curr_assets_to _st_liab_ratio
X41 total liabilities / ((profit on operating activities + de preciation) * (12/365))	-->	tot_liab_to_mth_mod_o ps_prof
X42 profit on operating activities / sales	-->	ops_prof_to_sales_rat io
X43 rotation receivables + inventory turnover in days	-->	mod_rot_receiv
X44 (receivables * 365) / sales	-->	ann_receiv_to_sales_r atio
X45 net profit / inventory	-->	net_prof_to_inven_rat io
X46 (current assets - inventory) / short-term liabilities	-->	mod_inven_curr_assets _to_st_liab_ratio
X47 (inventory * 365) / cost of products sold	-->	ann_inven_to_cops_rat io

Original Feature Name	Changed	New Feature Name
X48 EBITDA (profit on operating activities - depreciation) / total assets	-->	ebitda_to_tot_assets_ratio
X49 EBITDA (profit on operating activities - depreciation) / sales	-->	ebitda_to_tot_sales_ratio
X50 current assets / total liabilities	-->	curr_assets_to_tot_liab_ratio
X51 short-term liabilities / total assets	-->	st_liab_to_tot_assets_ratio
X52 (short-term liabilities * 365) / cost of products sold)	-->	ann_st_liab_to_cops_ratio
X53 equity / fixed assets	-->	equ_to_fx_assets_ratio
X54 constant capital / fixed assets	-->	co_cap_to_fx_assets_ratio
X55 working capital	-->	work_cap
X56 (sales - cost of products sold) / sales	-->	mod_cops_sales_to_sales_ratio
X57 (current assets - inventory - short-term liabilities) / (sales - gross profit - depreciation)	-->	mod_curr_assets_to_mod_sales_ratio
X58 total costs /total sales	-->	tot_costs_to_tot_sales_ratio
X59 long-term liabilities / equity	-->	lt_liab_to_equ_ratio
X60 sales / inventory	-->	sales_to_inven_ratio
X61 sales / receivables	-->	sales_to_receiv_ratio
X62 (short-term liabilities *365) / sales	-->	ann_st_liab_to_sales_ratio
X63 sales / short-term liabilities	-->	sales_to_st_liab_ratio
X64 sales / fixed assets	-->	sales_to_fx_assets_ratio
class	-->	Class

Import libraries

[3]:
```
import pandas as pd
import numpy as np
import datetime as dt
import matplotlib.pylab as plt
from matplotlib import figure
import seaborn as sns
import missingno as msno
import os
import joblib
import textwrap
from textwrap import wrap
```

```
from tabulate import tabulate
from imblearn.over_sampling import RandomOverSampler
from imblearn.over_sampling import SMOTE
from scipy.io import arff
from sklearn import metrics
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis, \
LinearDiscriminantAnalysis
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.feature_selection import VarianceThreshold
from sklearn.impute import KNNImputer
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV, \
LinearRegression
from sklearn.metrics import confusion_matrix, accuracy_score, \
plot_confusion_matrix, classification_report
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, r2_score, recall_score, \
precision_score, f1_score
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncoder, \
OrdinalEncoder, LabelEncoder, PowerTransformer
from sklearn.neighbors import NearestNeighbors, KNeighborsClassifier, \
KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier
import statsmodels.api as sm
import statsmodels.tools.tools as stattools
from xgboost import XGBClassifier
from geopy.distance import great_circle
import dmba
from dmba import classificationSummary, regressionSummary, gainsChart, \
liftChart, backward_elimination, stepwise_selection, plotDecisionTree
from dmba.metric import AIC_score, adjusted_r2_score
import warnings

warnings.filterwarnings('ignore')
%matplotlib inline
```

```
no display found. Using non-interactive Agg backend
```

1. Data preprocessing (Phase 1)

Load data and display characteristics

[4]:
```
directory_path = os.getcwd()
print("My current directory is: " + directory_path)
folder_name = os.path.basename(directory_path)
print("My directory name is: " + folder_name)
```

```python
parent = os.path.dirname(directory_path)
print("Parent directory", parent)
```

```
My current directory is: /content
My directory name is: content
Parent directory /
```

[5]:
```python
folder_path = r'/content/drive/MyDrive/ADS505_Team1_Final_Project/Working Files'
folder_path_mods = r'/content/drive/MyDrive/ADS505_Team1_Final_Project/Working␣
↪Files/models'

raw_arff01 = arff.loadarff(folder_path + '/1year.arff')
df01a = pd.DataFrame(raw_arff01[0])
#display(df01a.shape) # Display dimensions
#display(df01a.describe()) # Display simple descriptive stats
#display(df01a.head()) # Display first 5 rows
#display(df01a.info())

raw_arff02 = arff.loadarff(folder_path + '/2year.arff')
df01b = pd.DataFrame(raw_arff02[0])
#display(df01b.shape) # Display dimensions
#display(df01b.describe()) # Display simple descriptive stats
#display(df01b.head()) # Display first 5 rows
#display(df01b.info())

raw_arff03 = arff.loadarff(folder_path + '/3year.arff')
df01c = pd.DataFrame(raw_arff03[0])
#display(df01c.shape) # Display dimensions
#display(df01c.describe()) # Display simple descriptive stats
#display(df01c.head()) # Display first 5 rows
#display(df01c.info())

raw_arff04 = arff.loadarff(folder_path + '/4year.arff')
df01d = pd.DataFrame(raw_arff04[0])
#display(df01d.shape) # Display dimensions
#display(df01d.describe()) # Display simple descriptive stats
#display(df01d.head()) # Display first 5 rows
#display(df01d.info())

raw_arff05 = arff.loadarff(folder_path + '/5year.arff')
df01e = pd.DataFrame(raw_arff05[0])
#display(df01e.shape) # Display dimensions
#display(df01e.describe()) # Display simple descriptive stats
#display(df01e.head()) # Display first 5 rows
#display(df01e.info())
```

Preprocessing phase 1 explanation 1.1
Import five separate weka formatted (.arff) files downloaded from the UCI Machine Learning Repository. Convert each to a pandas dataframe (df).

Merge multiple raw dataframes

[6]:
```
#comment out the first or second df01 to return the full list or just the --
#--first list
df01 = pd.concat([df01a, df01b, df01c, df01d, df01e],
                 axis=0)
#df01 = df01a
```

Preprocessing phase 1 explanation 1.2
Use pandas .concat() function to combine the five separate df's into one.

Define feature space

[7]:
```
xy01_lst01 = ['net_prof_to_tot_assets_ratio',
              'tot_liab_to_tot_assets_ratio',
              'work_cap_to_tot_assets_ratio',
              'curr_assets_to_st_liab_ratio',
              'equ_to_ann_ops_exp_ratio',
              'ret_earn_to_tot_assets_ratio',
              'ebit_to_tot_assets_ratio',
              'book_equ_to_tot_liab_ratio',
              'sales_to_tot_assets_ratio',
              'equ_to_tot_assets_ratio',
              'mod_ef_grss_prof_to_tot_assets_ratio',
              'grss_prof_to_st_liab_ratio',
              'mod_dep_grss_prof_to_sales_ratio',
              'mod_int_grss_prof_to_tot_assets_ratio',
              'ann_tot_liab_to_mod_grss_prof_ratio',
              'mod_dep_grss_prof_to_tot_liab_ratio',
              'tot_assets_to_tot_liab_ratio',
              'grss_prof_to_tot_assets_ratio',
              'grss_prof_to_sales_ratio',
              'ann_inven_to_sales_ratio',
              'sales_to_mod_sales_ratio',
              'ops_prof_to_tot_assets_ratio',
              'net_prof_to_sales_ratio',
              'grss_prof3_to_tot_assets_ratio',
              'mod_equ_to_tot_assets_ratio',
              'mod_dep_net_prof_to_tot_liab_ratio',
              'ops_prof_to_fin_exp_ratio',
```

```
                'work_cap_to_fx_assets_ratio',
                'tot_assets_log',
                'mod_csh_tot_liab_to_sales_ratio',
                'mod_int_grss_prof_to_sales_ratio',
                'ann_curr_liab_to_cops_ratio',
                'ops_exp_to_st_liab_ratio',
                'ops_exp_to_tot_liab_ratio',
                'sales_prof_to_tot_assets_ratio',
                'tot_sales_to_tot_assets_ratio',
                'mod_curr_assets_to_lt_liab_ratio',
                'co_cap_to_tot_assets_ratio',
                'sales_prof_to_sales_ratio',
                'mod_ir_curr_assets_to_st_liab_ratio',
                'tot_liab_to_mth_mod_ops_prof',
                'ops_prof_to_sales_ratio',
                'mod_rot_receiv',
                'ann_receiv_to_sales_ratio',
                'net_prof_to_inven_ratio',
                'mod_inven_curr_assets_to_st_liab_ratio',
                'ann_inven_to_cops_ratio',
                'ebitda_to_tot_assets_ratio',
                'ebitda_to_tot_sales_ratio',
                'curr_assets_to_tot_liab_ratio',
                'st_liab_to_tot_assets_ratio',
                'ann_st_liab_to_cops_ratio',
                'equ_to_fx_assets_ratio',
                'co_cap_to_fx_assets_ratio',
                'work_cap',
                'mod_cops_sales_to_sales_ratio',
                'mod_curr_assets_to_mod_sales_ratio',
                'tot_costs_to_tot_sales_ratio',
                'lt_liab_to_equ_ratio',
                'sales_to_inven_ratio',
                'sales_to_receiv_ratio',
                'ann_st_liab_to_sales_ratio',
                'sales_to_st_liab_ratio',
                'sales_to_fx_assets_ratio',
                'Class']
```

Label Encode target feature values

[8]:
```
# Change df columns names
df01.columns = xy01_lst01

# Convert (factorize) nominal target var to binary (0/1)
df01_ohe_fit = LabelEncoder().fit(df01['Class'])
```

```
df01['class_tx'] = df01_ohe_fit.transform(df01['Class'])

print(f'{df01.head(3)}\n{df01.shape}')
display(df01.info())
```

```
   net_prof_to_tot_assets_ratio  tot_liab_to_tot_assets_ratio  \
0                       0.20055                       0.37951
1                       0.20912                       0.49988
2                       0.24866                       0.69592

   work_cap_to_tot_assets_ratio  curr_assets_to_st_liab_ratio  \
0                       0.39641                        2.0472
1                       0.47225                        1.9447
2                       0.26713                        1.5548

   equ_to_ann_ops_exp_ratio  ret_earn_to_tot_assets_ratio  \
0                   32.3510                       0.38825
1                   14.7860                       0.00000
2                   -1.1523                       0.00000

   ebit_to_tot_assets_ratio  book_equ_to_tot_liab_ratio  \
0                   0.24976                     1.33050
1                   0.25834                     0.99601
2                   0.30906                     0.43695

   sales_to_tot_assets_ratio  equ_to_tot_assets_ratio  …  \
0                     1.1389                  0.50494  …
1                     1.6996                  0.49788  …
2                     1.3090                  0.30408  …

   mod_curr_assets_to_mod_sales_ratio  tot_costs_to_tot_sales_ratio  \
0                             0.39718                       0.87804
1                             0.42002                       0.85300
2                             0.81774                       0.76599

   lt_liab_to_equ_ratio  sales_to_inven_ratio  sales_to_receiv_ratio  \
0              0.001924                8.4160                 5.1372
1              0.000000                4.1486                 3.2732
2              0.694840                4.9909                 3.9510

   ann_st_liab_to_sales_ratio  sales_to_st_liab_ratio  \
0                      82.658                  4.4158
1                     107.350                  3.4000
2                     134.270                  2.7185

   sales_to_fx_assets_ratio  Class  class_tx
0                    7.4277   b'0'         0
```

```
1                   60.9870   b'0'         0
2                    5.2078   b'0'         0

[3 rows x 66 columns]
(43405, 66)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 43405 entries, 0 to 5909
Data columns (total 66 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   net_prof_to_tot_assets_ratio            43397 non-null  float64
 1   tot_liab_to_tot_assets_ratio            43397 non-null  float64
 2   work_cap_to_tot_assets_ratio            43397 non-null  float64
 3   curr_assets_to_st_liab_ratio            43271 non-null  float64
 4   equ_to_ann_ops_exp_ratio                43316 non-null  float64
 5   ret_earn_to_tot_assets_ratio            43397 non-null  float64
 6   ebit_to_tot_assets_ratio                43397 non-null  float64
 7   book_equ_to_tot_liab_ratio              43311 non-null  float64
 8   sales_to_tot_assets_ratio               43396 non-null  float64
 9   equ_to_tot_assets_ratio                 43397 non-null  float64
 10  mod_ef_grss_prof_to_tot_assets_ratio    43361 non-null  float64
 11  grss_prof_to_st_liab_ratio              43271 non-null  float64
 12  mod_dep_grss_prof_to_sales_ratio        43278 non-null  float64
 13  mod_int_grss_prof_to_tot_assets_ratio   43397 non-null  float64
 14  ann_tot_liab_to_mod_grss_prof_ratio     43369 non-null  float64
 15  mod_dep_grss_prof_to_tot_liab_ratio     43310 non-null  float64
 16  tot_assets_to_tot_liab_ratio            43311 non-null  float64
 17  grss_prof_to_tot_assets_ratio           43397 non-null  float64
 18  grss_prof_to_sales_ratio                43277 non-null  float64
 19  ann_inven_to_sales_ratio                43278 non-null  float64
 20  sales_to_mod_sales_ratio                37551 non-null  float64
 21  ops_prof_to_tot_assets_ratio            43397 non-null  float64
 22  net_prof_to_sales_ratio                 43278 non-null  float64
 23  grss_prof3_to_tot_assets_ratio          42483 non-null  float64
 24  mod_equ_to_tot_assets_ratio             43397 non-null  float64
 25  mod_dep_net_prof_to_tot_liab_ratio      43310 non-null  float64
 26  ops_prof_to_fin_exp_ratio               40641 non-null  float64
 27  work_cap_to_fx_assets_ratio             42593 non-null  float64
 28  tot_assets_log                          43397 non-null  float64
 29  mod_csh_tot_liab_to_sales_ratio         43278 non-null  float64
 30  mod_int_grss_prof_to_sales_ratio        43278 non-null  float64
 31  ann_curr_liab_to_cops_ratio             43037 non-null  float64
 32  ops_exp_to_st_liab_ratio                43271 non-null  float64
 33  ops_exp_to_tot_liab_ratio               43311 non-null  float64
 34  sales_prof_to_tot_assets_ratio          43397 non-null  float64
 35  tot_sales_to_tot_assets_ratio           43397 non-null  float64
 36  mod_curr_assets_to_lt_liab_ratio        24421 non-null  float64
 37  co_cap_to_tot_assets_ratio              43397 non-null  float64
```

```
 38   sales_prof_to_sales_ratio                43278 non-null   float64
 39   mod_ir_curr_assets_to_st_liab_ratio      43271 non-null   float64
 40   tot_liab_to_mth_mod_ops_prof             42651 non-null   float64
 41   ops_prof_to_sales_ratio                  43278 non-null   float64
 42   mod_rot_receiv                           43278 non-null   float64
 43   ann_receiv_to_sales_ratio                43278 non-null   float64
 44   net_prof_to_inven_ratio                  41258 non-null   float64
 45   mod_inven_curr_assets_to_st_liab_ratio   43270 non-null   float64
 46   ann_inven_to_cops_ratio                  43108 non-null   float64
 47   ebitda_to_tot_assets_ratio               43396 non-null   float64
 48   ebitda_to_tot_sales_ratio                43278 non-null   float64
 49   curr_assets_to_tot_liab_ratio            43311 non-null   float64
 50   st_liab_to_tot_assets_ratio              43397 non-null   float64
 51   ann_st_liab_to_cops_ratio                43104 non-null   float64
 52   equ_to_fx_assets_ratio                   42593 non-null   float64
 53   co_cap_to_fx_assets_ratio                42593 non-null   float64
 54   work_cap                                 43404 non-null   float64
 55   mod_cops_sales_to_sales_ratio            43278 non-null   float64
 56   mod_curr_assets_to_mod_sales_ratio       43398 non-null   float64
 57   tot_costs_to_tot_sales_ratio             43321 non-null   float64
 58   lt_liab_to_equ_ratio                     43398 non-null   float64
 59   sales_to_inven_ratio                     41253 non-null   float64
 60   sales_to_receiv_ratio                    43303 non-null   float64
 61   ann_st_liab_to_sales_ratio               43278 non-null   float64
 62   sales_to_st_liab_ratio                   43271 non-null   float64
 63   sales_to_fx_assets_ratio                 42593 non-null   float64
 64   Class                                    43405 non-null   object
 65   class_tx                                 43405 non-null   int64
dtypes: float64(64), int64(1), object(1)
memory usage: 22.2+ MB
```

```
None
```

Preprocessing phase 1 explanation 1.3
The default column names from the downloaded weka files were not descriptive. Using the feature name map provided on the UCI Machine Learning Repositiry as reference, column names were converted. Additionally, the nominal values of the target (dependent) variable were converted to binary (0/1) for ease of use during processing and machine learning (ML) modeling.

[9]:
```python
#create dataframe of key values to incorporate into final model metrics
key_ratio = df01[['tot_liab_to_tot_assets_ratio',
                  'curr_assets_to_tot_liab_ratio',
                  'work_cap_to_tot_assets_ratio']]

display(key_ratio.head())
print(key_ratio.shape)
```

```
   tot_liab_to_tot_assets_ratio  curr_assets_to_tot_liab_ratio  \
0                       0.37951                          2.0420
1                       0.49988                          1.9447
2                       0.69592                          1.0758
3                       0.30734                          2.4928
4                       0.61323                          1.2959

   work_cap_to_tot_assets_ratio
0                       0.39641
1                       0.47225
2                       0.26713
3                       0.45879
4                       0.22960


(43405, 3)
```

[10]:
```
print(df01.shape)
df01.head()
```

```
(43405, 66)
```

[10]:
```
   net_prof_to_tot_assets_ratio  tot_liab_to_tot_assets_ratio  \
0                      0.200550                       0.37951
1                      0.209120                       0.49988
2                      0.248660                       0.69592
3                      0.081483                       0.30734
4                      0.187320                       0.61323

   work_cap_to_tot_assets_ratio  curr_assets_to_st_liab_ratio  \
0                       0.39641                        2.0472
1                       0.47225                        1.9447
2                       0.26713                        1.5548
3                       0.45879                        2.4928
4                       0.22960                        1.4063

   equ_to_ann_ops_exp_ratio  ret_earn_to_tot_assets_ratio  \
0                   32.3510                       0.38825
1                   14.7860                       0.00000
2                   -1.1523                       0.00000
3                   51.9520                       0.14988
4                   -7.3128                       0.18732

   ebit_to_tot_assets_ratio  book_equ_to_tot_liab_ratio  \
0                  0.249760                     1.33050
1                  0.258340                     0.99601
2                  0.309060                     0.43695
3                  0.092704                     1.86610
```

```
4                  0.187320                     0.63070

   sales_to_tot_assets_ratio  equ_to_tot_assets_ratio  …  \
0                     1.1389                  0.50494  …
1                     1.6996                  0.49788  …
2                     1.3090                  0.30408  …
3                     1.0571                  0.57353  …
4                     1.1559                  0.38677  …

   mod_curr_assets_to_mod_sales_ratio  tot_costs_to_tot_sales_ratio  \
0                             0.39718                       0.87804
1                             0.42002                       0.85300
2                             0.81774                       0.76599
3                             0.14207                       0.94598
4                             0.48431                       0.86515

   lt_liab_to_equ_ratio  sales_to_inven_ratio  sales_to_receiv_ratio  \
0              0.001924                8.4160                 5.1372
1              0.000000                4.1486                 3.2732
2              0.694840                4.9909                 3.9510
3              0.000000                4.5746                 3.6147
4              0.124440                6.3985                 4.3158

   ann_st_liab_to_sales_ratio  sales_to_st_liab_ratio  \
0                      82.658                  4.4158
1                     107.350                  3.4000
2                     134.270                  2.7185
3                      86.435                  4.2228
4                     127.210                  2.8692

   sales_to_fx_assets_ratio  Class  class_tx
0                    7.4277   b'0'         0
1                   60.9870   b'0'         0
2                    5.2078   b'0'         0
3                    5.5497   b'0'         0
4                    7.8980   b'0'         0

[5 rows x 66 columns]
```

Display overall class percentages

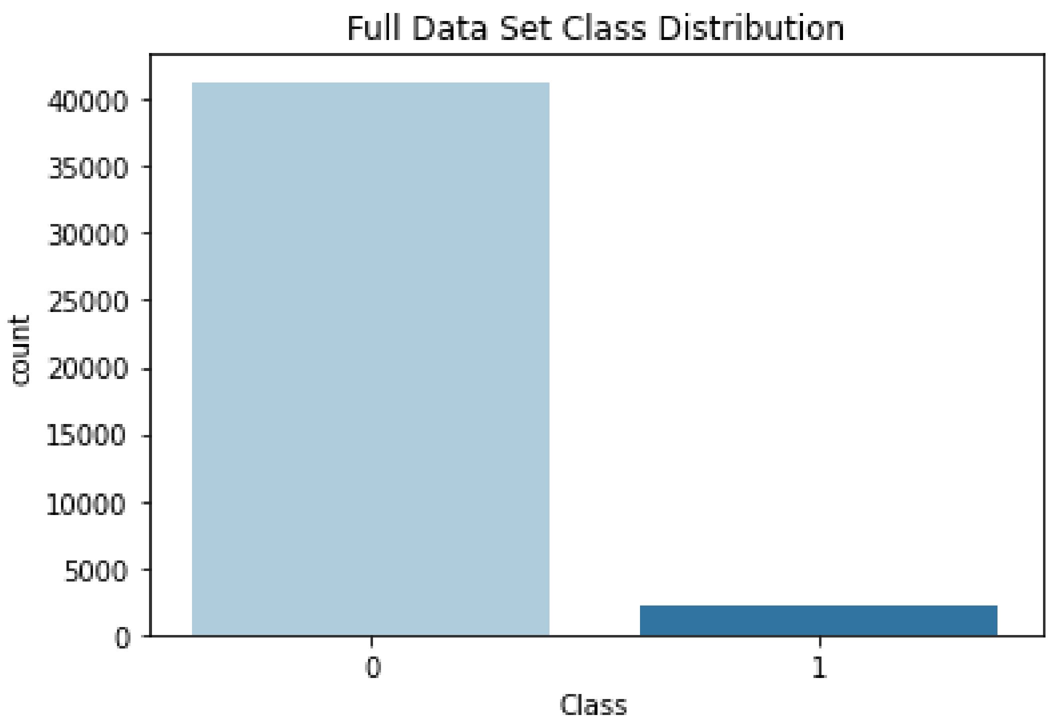
[11]:
```
# Calc proportions by class
df01_y01_cnt = pd.value_counts(df01['class_tx'])
df01_y01_cnt_df01 = pd.DataFrame(df01_y01_cnt)
df01_y01_cnt_df01['class_percent'] = round((df01_y01_cnt_df01['class_tx'] /
                                  np.sum(df01_y01_cnt_df01['class_tx']))*100, 1)
```

```
print(f'Full data set count and percent per class:\n{df01_y01_cnt_df01}')
```

```
Full data set count and percent per class:
   class_tx  class_percent
0     41314           95.2
1      2091            4.8
```

[12]:
```
# Plot class distribution
sns.countplot(x=df01['class_tx'], palette="Paired")
plt.title("Full Data Set Class Distribution")
plt.xlabel("Class")
```

[12]:
```
Text(0.5, 0, 'Class')
```



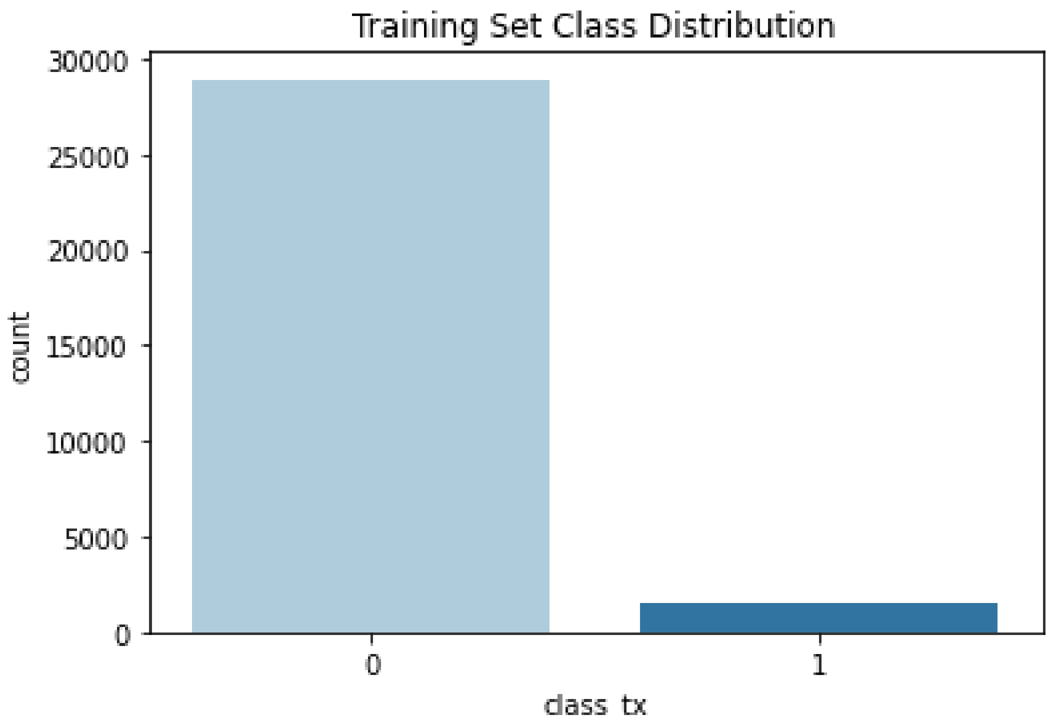
Preprocessing phase 1 explanation 1.4
Create a table and bar plot to display the count and relative proportion of each class in the full data set. The class of interest (1), which corresponds with those companies labeled as "bankrupt", represent 4.8% of the overall sample (n = 2,091).

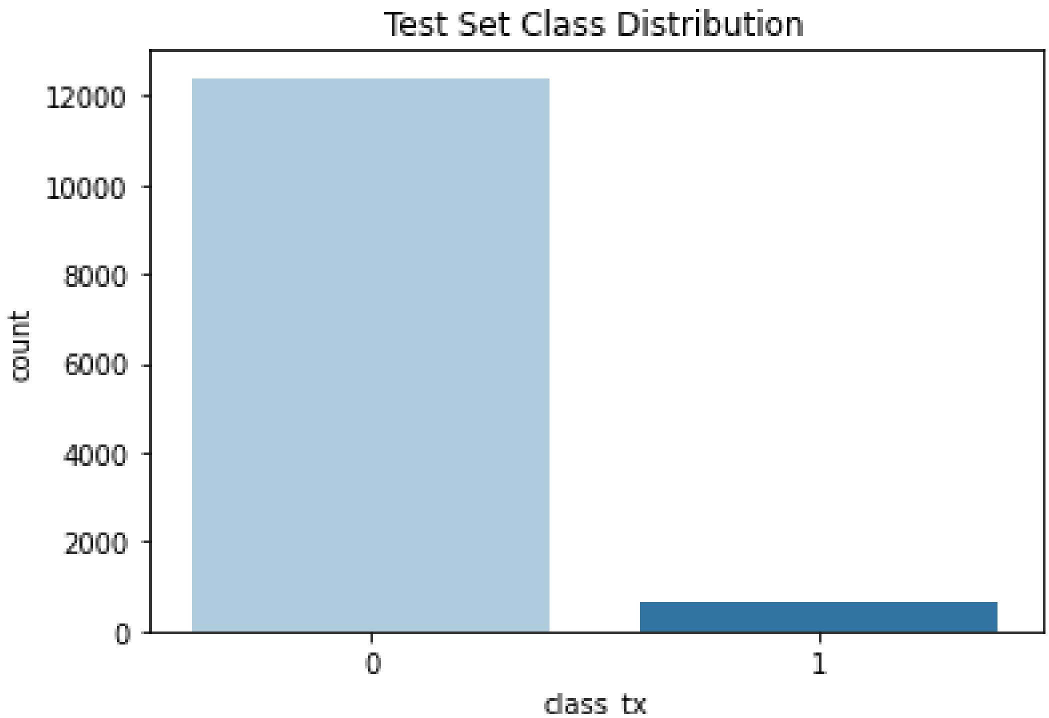
Create train/test split

[13]:
```
# Copy full df to begin preprocessing
df02 = df01.copy()
#print(df02.columns)

df02_x01_drp_lst01 = ['Class',
                      'class_tx']

# Create X & Y matrices
x01_df01 = df02.drop(df02_x01_drp_lst01, axis=1)
y01_df01 = df02['class_tx']

# Create train & test sets for X & Y (NOTE: stratification by y)
train_x01_df01, test_x01_df01, \
train_y01_df01, test_y01_df01 = train_test_split(x01_df01,
                                                 y01_df01,
                                                 test_size=.3,
                                                 random_state=1699,
                                                 stratify=y01_df01)

# Convert y df's to vector arrays
train_y01_vc01 = train_y01_df01.to_numpy()
test_y01_vc01 = test_y01_df01.to_numpy()

# Display train & test set df's
print(f'\nTraining X matrix dimensions = {train_x01_df01.shape}')
print(f'Test X matrix dimensions = {test_x01_df01.shape}')

print(f'\nTraining y matrix dimensions = {train_y01_df01.shape}')
print(f'Test y matrix dimensions = {test_y01_df01.shape}')

# Plot class distribution
df02a = pd.concat([train_x01_df01, train_y01_df01], axis=1)
df02b = pd.concat([test_x01_df01, test_y01_df01], axis=1)

sns.countplot(x=df02a['class_tx'], palette="Paired")
plt.title("Training Set Class Distribution")
plt.show()
#print('\n')
# Plot class distribution
sns.countplot(x=df02b['class_tx'], palette="Paired")
plt.title("Test Set Class Distribution")
plt.show()
```

```
Training X matrix dimensions = (30383, 64)
```

```
Test X matrix dimensions = (13022, 64)

Training y matrix dimensions = (30383,)
Test y matrix dimensions = (13022,)
```





Preprocessing phase 1 explanation 1.5
Setup X and Y matrices, then perform a 70/30 training/test split. Fitting of all transformations and model algorithms will be done on the training, which will then be used to transform the test sets as applicable. *Note:* The splitting was based on a random stratification to perserve the proportion of class 1 relative to the overall sample.

Check for and remove features with near zero variance

[14]:
```
# Remove near-zero variance (NZV) features
train_x01_df01_nzv_fit = VarianceThreshold().fit(train_x01_df01)
train_x02_tx_vc01 = train_x01_df01_nzv_fit.transform(train_x01_df01)

train_x02_tx_df01 = pd.DataFrame(train_x02_tx_vc01,
                        columns=train_x01_df01_nzv_fit.get_feature_names_out())
test_x02_tx_df01 = test_x01_df01[train_x01_df01_nzv_fit.get_feature_names_out()]

print(f'Training X NZV transformed matrix dimensions = \
                                                    {train_x02_tx_df01.shape}')
print(f'Test X NZV transformed matrix dimensions = {test_x02_tx_df01.shape}')

print(f'\n{train_x01_df01.shape[1] - train_x02_tx_df01.shape[1]} \
```

```
                                    near zero variance features were eliminated')
```

```
Training X NZV transformed matrix dimensions =
(30383, 64)
Test X NZV transformed matrix dimensions = (13022, 64)

0                                    near zero variance features were eliminated
```

Preprocessing phase 1 explanation 1.6
Check for any features that have near-zero variance (NZV) values in attempts to reduce dimensionality and complexity. In this case, none of the features had NZV.

2. Exploratory data analysis (EDA)

Display preprocessed df's ready for EDA

[15]:
```
'''NOTE: Numbers in variable names refer to the version/copy and:
"df"=dataframe, "vc"=vector; see feature map in section 3 for full df list'''
# Full (pre-split) X & Y data sets to use for EDA
print(f'{x01_df01.shape}')
print(f'{y01_df01.shape}')

# Alternatively, train X & Y data sets to use for EDA
print(f'\n{train_x02_tx_df01.shape}')
print(f'{train_y01_vc01.shape}')
```

```
(43405, 64)
(43405,)

(30383, 64)
(30383,)
```

EDA explanation 2.1
Using Splitted data

Check for duplicates and drop them

[16]:
```
#Check for duplicates
duplicate = train_x02_tx_df01[train_x02_tx_df01.duplicated()]
duplicate.shape
```

[16]: (209, 64)

EDA explanation 2.2
There would be very small chance that companies had the same exact financial data through out 64 features, so they could be due to some input errors. Therefore, we drop them.

[17]:
```
#Drop the duplicates in predictors dataframe
train_x02_tx_df01_eda1 = train_x02_tx_df01.drop_duplicates(inplace=False)

#Drop the duplicates in response dataframe
train_y01_vc01_eda1 = pd.DataFrame(train_y01_vc01).drop(duplicate.index, axis=0)
train_y01_vc01_eda1 = train_y01_vc01_eda1.to_numpy(). \
                                            reshape((len(train_y01_vc01_eda1),))
print(train_x02_tx_df01_eda1.shape)
print(train_y01_vc01_eda1.shape)
```

```
(30174, 64)
(30174,)
```

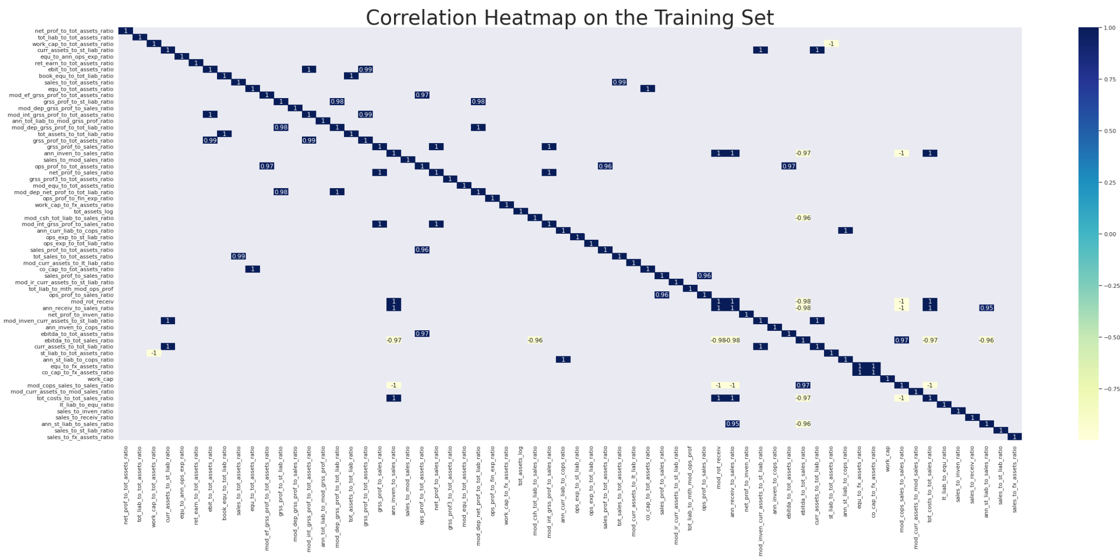
Review feature correlations

[18]:
```
#Create correaltion matrix
corr_matrix = train_x02_tx_df01_eda1.corr()
```

[19]:
```
#Correlation heatmap
sns.set(rc = {'figure.figsize': (40,15)})
sns.heatmap(corr_matrix, cmap="YlGnBu", annot=True)
plt.title('Correlation Heatmap on the Training Set', fontsize=40)
plt.show()
```

Output hidden; open in https://colab.research.google.com to view.

[20]:
```
# Correlation heatmap for only those vals greater than |.95|
#print(pd.MultiIndex.from_frame(corr_matrix))
corr_matrix2 = corr_matrix[abs(corr_matrix) > .95]
#print(corr_matrix2)
sns.set(rc = {'figure.figsize': (40,15)})
sns.heatmap(corr_matrix2, cmap="YlGnBu", annot=True)
plt.title('Correlation Heatmap on the Training Set', fontsize=40)
plt.show()
```



EDA explanation 2.3
A lot of high correlated feature could be seen on the correlation heatmap.

Drop features with high correlation ($r > .95$)

[21]:
```
#Select columns with high correlation using upper half triangle of the matrix
upper_tri = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).\
                                                                  astype(bool))
to_drop = [column for column in upper_tri.columns if
                                                  any(upper_tri[column] > 0.95)]
to_drop
```

[21]:
```
['mod_int_grss_prof_to_tot_assets_ratio',
 'mod_dep_grss_prof_to_tot_liab_ratio',
 'tot_assets_to_tot_liab_ratio',
 'grss_prof_to_tot_assets_ratio',
 'ops_prof_to_tot_assets_ratio',
 'net_prof_to_sales_ratio',
 'mod_dep_net_prof_to_tot_liab_ratio',
 'mod_int_grss_prof_to_sales_ratio',
 'sales_prof_to_tot_assets_ratio',
 'tot_sales_to_tot_assets_ratio',
 'co_cap_to_tot_assets_ratio',
 'ops_prof_to_sales_ratio',
 'mod_rot_receiv',
 'ann_receiv_to_sales_ratio',
 'mod_inven_curr_assets_to_st_liab_ratio',
```

```
 'ebitda_to_tot_assets_ratio',
 'curr_assets_to_tot_liab_ratio',
 'ann_st_liab_to_cops_ratio',
 'co_cap_to_fx_assets_ratio',
 'mod_cops_sales_to_sales_ratio',
 'tot_costs_to_tot_sales_ratio',
 'ann_st_liab_to_sales_ratio']
```

[22]:
```
#Drop high correlation features in train set
train_x02_tx_df01_eda1.drop(to_drop,
                            axis=1,
                            inplace=True)
#Drop high correlation features in test set
test_x02_tx_df01_eda1 = test_x02_tx_df01_eda1.copy()
test_x02_tx_df01_eda1.drop(to_drop,
                           axis=1,
                           inplace=True)
print(train_x02_tx_df01_eda1.shape)
print(test_x02_tx_df01_eda1.shape)
```

```
(30174, 42)
(13022, 42)
```

EDA explanation 2.4
The number of features has reduced from 64 to 42.

[23]:
```
#Pair scatter plots for the first 11 features
g = sns.PairGrid(train_x02_tx_df01_eda1.iloc[:, 0:11],
                 diag_sharey=False,
                 corner=True)
g.map_lower(sns.scatterplot)
g.map_diag(sns.kdeplot)
```

[23]: `<seaborn.axisgrid.PairGrid at 0x7f318ed03d10>`

Summary Statistics and outliers

[24]:
```
#Summary statistics
train_x02_tx_df01_eda1.describe()
```

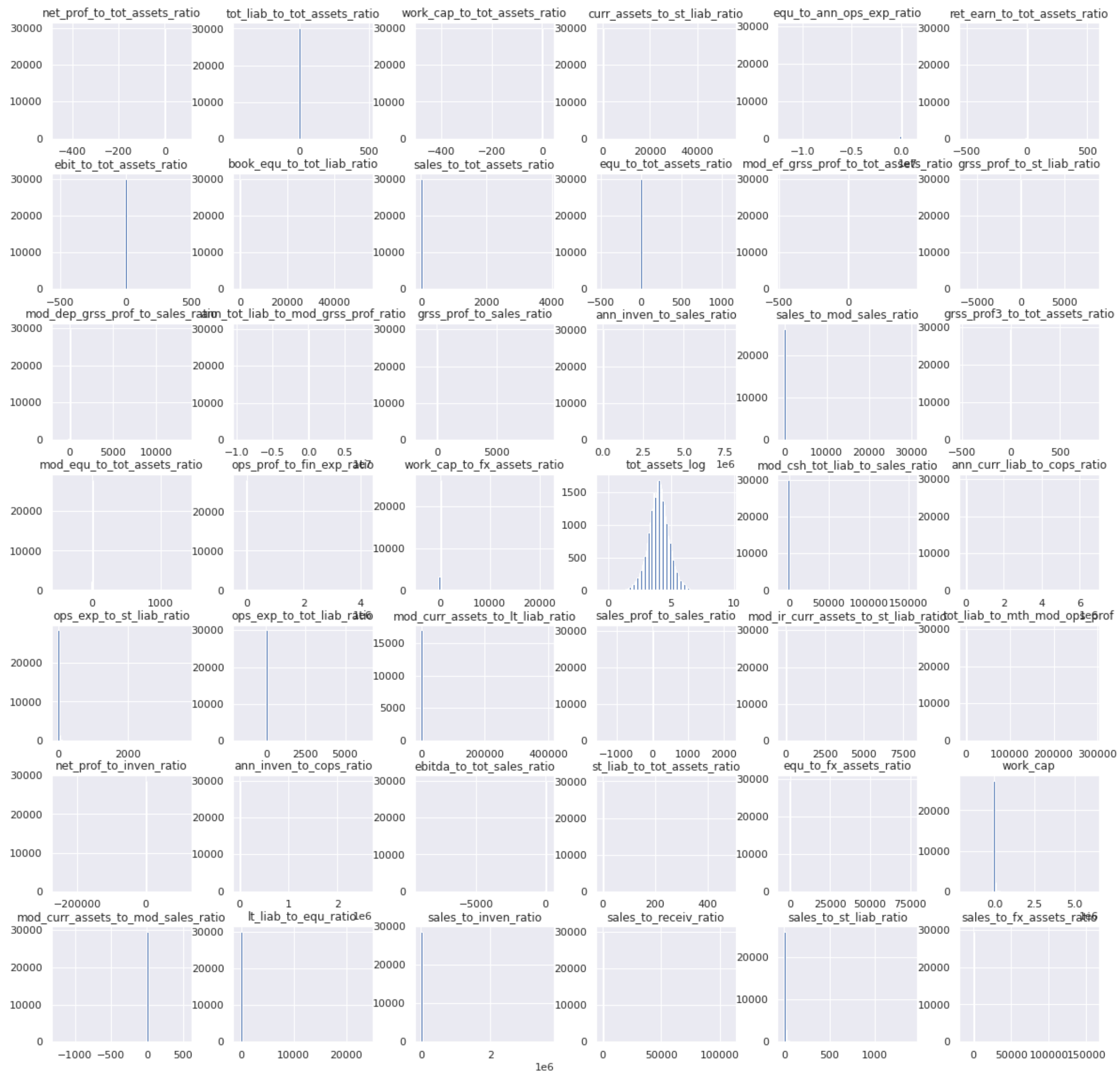
[24]:
```
         net_prof_to_tot_assets_ratio  tot_liab_to_tot_assets_ratio  \
count                    30168.000000                  30168.000000
mean                         0.027545                      0.571545
std                          3.218895                      5.291554
min                       -463.890000                   -430.870000
25%                          0.003039                      0.271487
50%                          0.048891                      0.472075
```

```
75%                       0.128395                        0.689253
max                      87.459000                      480.730000

       work_cap_to_tot_assets_ratio  curr_assets_to_st_liab_ratio  \
count                  30168.000000                  30080.000000
mean                       0.127836                      6.050144
std                        4.639301                    313.180715
min                     -479.730000                     -0.403110
25%                        0.020666                      1.048500
50%                        0.195640                      1.567900
75%                        0.400930                      2.752975
max                       22.769000                  53433.000000

       equ_to_ann_ops_exp_ratio  ret_earn_to_tot_assets_ratio  \
count              3.011400e+04                  30168.000000
mean              -4.955621e+02                     -0.034775
std                7.262682e+04                      6.945786
min               -1.190300e+07                   -508.120000
25%               -4.944275e+01                      0.000000
50%               -1.290000e+00                      0.000000
75%                5.022875e+01                      0.088102
max                1.034100e+06                    543.250000

       ebit_to_tot_assets_ratio  book_equ_to_tot_liab_ratio  \
count              30168.000000                30108.000000
mean                   0.077446                   12.457331
std                    5.582060                  535.455617
min                 -517.480000                 -141.410000
25%                    0.005166                    0.427053
50%                    0.059015                    1.068400
75%                    0.149572                    2.585400
max                  453.770000                53432.000000

       sales_to_tot_assets_ratio  equ_to_tot_assets_ratio  …  \
count               30165.000000             30168.000000  …
mean                    2.429359                 0.662647  …
std                    42.829654                14.798294  …
min                    -3.496000              -479.730000  …
25%                     1.017700                 0.293598  …
50%                     1.190100                 0.505170  …
75%                     2.065400                 0.707205  …
max                  3876.100000              1099.500000  …

       ebitda_to_tot_sales_ratio  st_liab_to_tot_assets_ratio  \
count               30077.000000                 30168.000000
mean                   -0.576657                     0.469322
std                    53.543411                     4.638281
```

```
min                -9001.000000                        -0.186610
25%                   -0.027767                         0.191670
50%                    0.010592                         0.341900
75%                    0.061366                         0.534920
max                  178.890000                       480.730000

       equ_to_fx_assets_ratio      work_cap  \
count            29620.000000  3.017400e+04
mean                16.599028  7.681001e+03
std                619.954901  7.454397e+04
min              -3828.900000 -1.805200e+06
25%                  0.682408  2.641750e+01
50%                  1.200600  1.071600e+03
75%                  2.225525  4.918575e+03
max              75450.000000  6.123700e+06

       mod_curr_assets_to_mod_sales_ratio  lt_liab_to_equ_ratio  \
count                        30169.000000          30169.000000
mean                            -0.041043              1.445195
std                             12.431378            139.344425
min                          -1236.300000           -327.970000
25%                              0.013769              0.000000
50%                              0.119320              0.006486
75%                              0.282470              0.235250
max                            527.220000          23853.000000

       sales_to_inven_ratio  sales_to_receiv_ratio  sales_to_st_liab_ratio  \
count          2.865400e+04           30104.000000            30080.000000
mean           3.717762e+02              18.086122                8.439761
std            2.571343e+04             656.380446               23.615707
min           -1.244000e+01              -0.092493               -1.543200
25%            5.523875e+00               4.507725                3.086250
50%            9.766400e+00               6.639300                5.056350
75%            2.017150e+01              10.373000                8.552200
max            3.660200e+06          108000.000000             1396.600000

       sales_to_fx_assets_ratio
count              29620.000000
mean                  57.698125
std                 1509.051143
min               -10677.000000
25%                    2.164000
50%                    4.300550
75%                    9.845500
max               158180.000000

[8 rows x 42 columns]
```

EDA explanation 2.5
Data seem skewed in most columns. Most columns have large range with either max values are very large or min values very small compared the means indicating outliers.

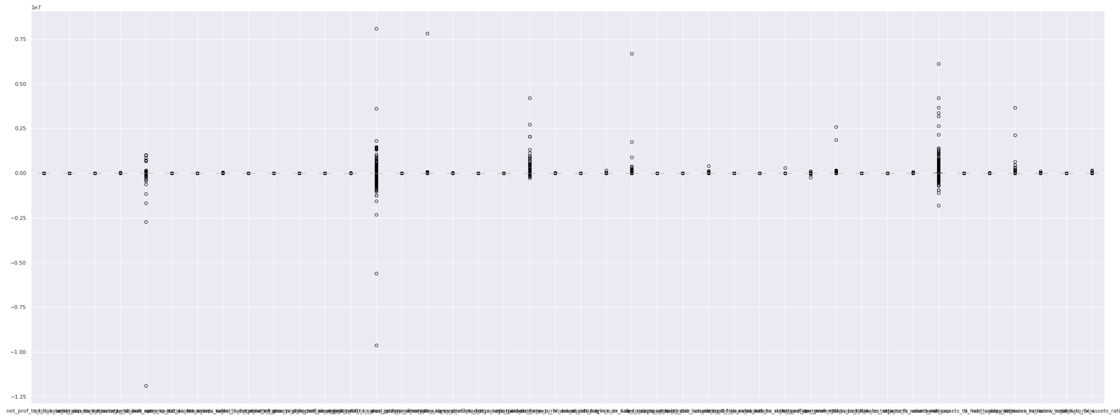
[25]:
```
#Visualize the distribution of data in each coulumn of the train set
train_x02_tx_df01_eda1.hist(bins=100, figsize=(20, 20));
```



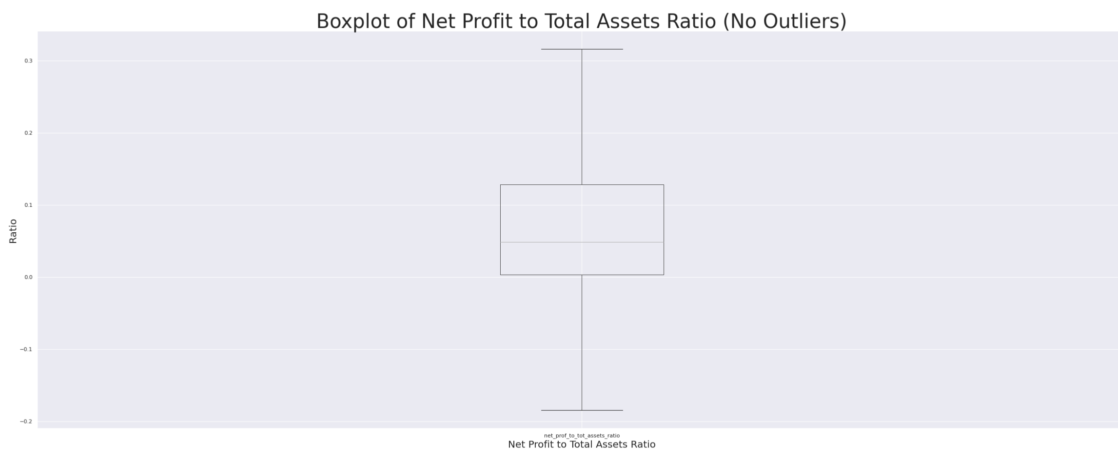
EDA explanation 2.6
Due to large range and skew data, most of the features are concentrate near the means which only showed as vertical lines in the distribution charts

[26]:
```
#Show boxplots for data distribution of each column on the training set
train_x02_tx_df01_eda1.boxplot()
```

[26]: <matplotlib.axes._subplots.AxesSubplot at 0x7f318d3c21d0>

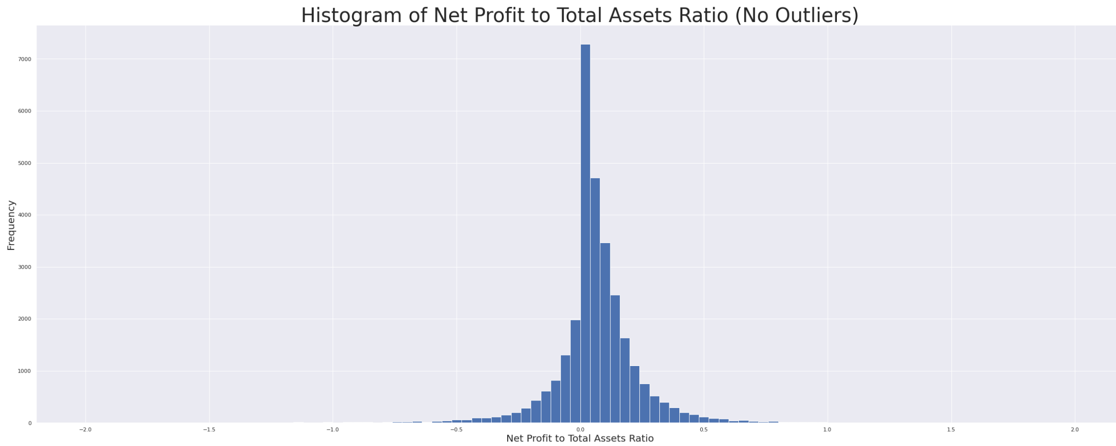


[27]:
```
#Boxplot of data on a single column within the lower and upper limits
train_x02_tx_df01_eda1[['net_prof_to_tot_assets_ratio']].boxplot(
                                                              showfliers=False)
plt.xlabel('Net Profit to Total Assets Ratio', fontsize=20)
plt.ylabel('Ratio', fontsize=20)
plt.title('Boxplot of Net Profit to Total Assets Ratio (No Outliers)',
          fontsize=40)
plt.show()
```



[28]:
```
#Histogram of data on a single column within the lower and upper limits
plt.hist(train_x02_tx_df01_eda1['net_prof_to_tot_assets_ratio'],
         range=[-2, 2],
         bins=100);
plt.xlabel('Net Profit to Total Assets Ratio',
           fontsize=20)
plt.ylabel('Frequency',
           fontsize=20)
```

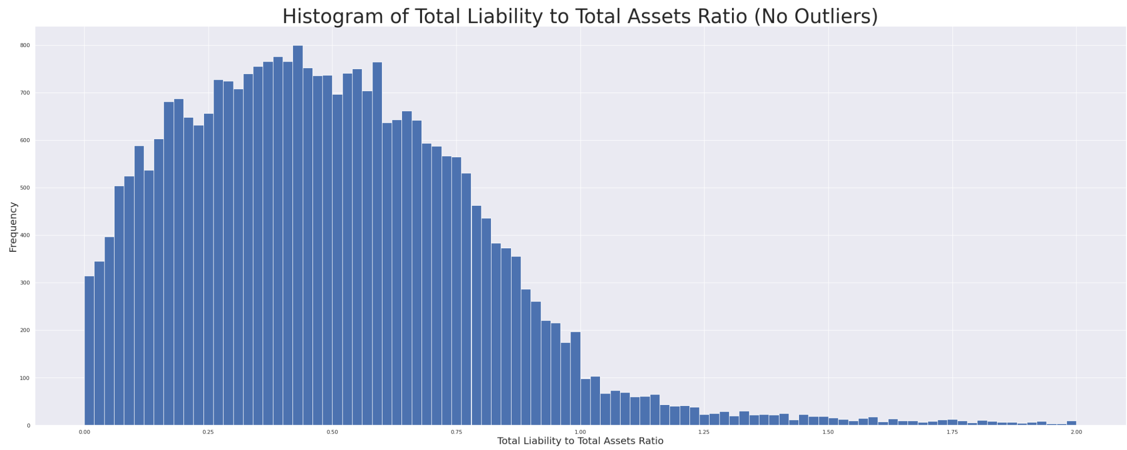
```python
plt.title('Histogram of Net Profit to Total Assets Ratio (No Outliers)',
          fontsize=40)
plt.show()
```



[29]:
```python
#Boxplot of data on a single column within the lower and upper limits
train_x02_tx_df01_eda1[['tot_liab_to_tot_assets_ratio']].
 ↪boxplot(showfliers=True)
plt.xlabel('Total Liability to Total Assets Ratio', fontsize=20)
plt.ylabel('Ratio', fontsize=20)
plt.title('Boxplot of Total Liability to Total Assets Ratio', fontsize=40)
plt.show()
```

[30]:
```python
#Histogram of data on a single column within the lower and upper limits
plt.hist(train_x02_tx_df01_eda1['tot_liab_to_tot_assets_ratio'],
         range=[0, 2],
         bins=100);
```

```
plt.xlabel('Total Liability to Total Assets Ratio',
           fontsize=20)
plt.ylabel('Frequency',
           fontsize=20)
plt.title('Histogram of Total Liability to Total Assets Ratio (No Outliers)',
          fontsize=40)
plt.show()
```



Identify and review outliers

[31]:
```
#Detect outliers using IQR
cols = train_x02_tx_df01_eda1.columns
Q1 = train_x02_tx_df01_eda1[cols].quantile(0.25)
Q3 = train_x02_tx_df01_eda1[cols].quantile(0.75)
IQR = Q3 - Q1
#Checking row having outliers
outliers = train_x02_tx_df01_eda1[((train_x02_tx_df01_eda1[cols] <
                                    (Q1 - 1.5 * IQR)) |
                                   (train_x02_tx_df01_eda1[cols] >
                                    (Q3 + 1.5 * IQR))).any(axis=1)]
#remove ouliers
#train_x02_tx_df01_eda2 = train_x02_tx_df01_eda1[~(
    #(train_x02_tx_df01_eda1[cols] < (Q1 - 1.5 * IQR)) |
    #(train_x02_tx_df01_eda1[cols] > (Q3 + 1.5 * IQR))).any(axis=1)]
print(outliers.shape)
outliers.head()
```

```
(26504, 42)
```

[31]:
```
   net_prof_to_tot_assets_ratio  tot_liab_to_tot_assets_ratio  \
0                     -0.023908                       0.67869
1                      0.280690                       0.42708
2                      0.124390                       0.39996
3                      0.030410                       0.52344
4                     -0.101190                       0.42663

   work_cap_to_tot_assets_ratio  curr_assets_to_st_liab_ratio  \
0                      0.013342                       1.02670
1                      0.250370                       2.06470
2                      0.404580                       2.41050
3                     -0.102460                       0.66978
4                      0.482710                       2.13440

   equ_to_ann_ops_exp_ratio  ret_earn_to_tot_assets_ratio  \
0                 -120.3700                      -0.45312
1                    8.2409                       0.83446
2                   23.6530                       0.62886
3                 -109.7400                       0.24133
4                   33.6220                       0.19492

   ebit_to_tot_assets_ratio  book_equ_to_tot_liab_ratio  \
0                 -0.033635                     0.47342
1                  0.280690                     1.34150
2                  0.154240                     1.05860
3                  0.041528                     0.85918
4                 -0.111890                     1.28550

   sales_to_tot_assets_ratio  equ_to_tot_assets_ratio  …  \
0                    0.44747                  0.32131  …
1                    1.03990                  0.57292  …
2                    1.21330                  0.42338  …
3                    1.09860                  0.44973  …
4                    0.92958                  0.54844  …

   ebitda_to_tot_sales_ratio  st_liab_to_tot_assets_ratio  \
0                  -0.200620                      0.50016
1                   0.025332                      0.23516
2                   0.158220                      0.28683
3                  -0.022984                      0.31027
4                  -0.174620                      0.42552

   equ_to_fx_assets_ratio  work_cap  mod_curr_assets_to_mod_sales_ratio  \
0                 0.66045    1571.0                           -0.074410
1                 1.11360    2265.0                            0.489920
2                 1.37200   39811.0                            0.293800
3                 0.56771   -1591.1                            0.067618
```

```
4                5.97640    2770.4                          -0.184510

   lt_liab_to_equ_ratio  sales_to_inven_ratio  sales_to_receiv_ratio  \
0               0.50712                2.7735                 1.9724
1               0.33498              113.0700                22.0970
2               0.26721                2.4551                 2.6089
3               0.47400               12.8230                 5.5998
4               0.00203                2.2529                 1.9561

   sales_to_st_liab_ratio  sales_to_fx_assets_ratio
0                 0.89464                   0.91978
1                34.10700                  15.59000
2                 2.98890                   2.77800
3                 2.34880                   0.91992
4                 2.09290                   9.70480

[5 rows x 42 columns]
```

[32]:
```
#Number of outliers in each columns
((train_x02_tx_df01_eda1[cols] < (Q1 - 1.5 * IQR)) |
          (train_x02_tx_df01_eda1[cols] > (Q3 + 1.5 * IQR))).sum().sort_values(
                                                                  ascending=False)
```

[32]:
```
ret_earn_to_tot_assets_ratio            7829
ops_prof_to_fin_exp_ratio               5806
ann_tot_liab_to_mod_grss_prof_ratio     5158
work_cap                                5130
tot_liab_to_mth_mod_ops_prof            4856
net_prof_to_inven_ratio                 4831
lt_liab_to_equ_ratio                    4760
equ_to_ann_ops_exp_ratio                4275
work_cap_to_fx_assets_ratio             4151
equ_to_fx_assets_ratio                  4029
grss_prof_to_st_liab_ratio              3966
sales_to_fx_assets_ratio                3884
ebitda_to_tot_sales_ratio               3816
mod_curr_assets_to_mod_sales_ratio      3803
mod_ir_curr_assets_to_st_liab_ratio     3661
grss_prof_to_sales_ratio                3626
sales_to_inven_ratio                    3418
sales_prof_to_sales_ratio               3330
net_prof_to_tot_assets_ratio            3263
book_equ_to_tot_liab_ratio              3254
curr_assets_to_st_liab_ratio            3150
mod_dep_grss_prof_to_sales_ratio        2977
ebit_to_tot_assets_ratio                2925
sales_to_receiv_ratio                   2743
```

```
mod_ef_grss_prof_to_tot_assets_ratio    2688
mod_curr_assets_to_lt_liab_ratio        2634
mod_csh_tot_liab_to_sales_ratio         2596
sales_to_st_liab_ratio                  2366
ops_exp_to_st_liab_ratio                2284
grss_prof3_to_tot_assets_ratio          2247
ops_exp_to_tot_liab_ratio               2230
ann_curr_liab_to_cops_ratio             2218
sales_to_tot_assets_ratio               2071
ann_inven_to_cops_ratio                 1842
sales_to_mod_sales_ratio                1840
ann_inven_to_sales_ratio                1715
mod_equ_to_tot_assets_ratio             1042
st_liab_to_tot_assets_ratio              838
work_cap_to_tot_assets_ratio             824
equ_to_tot_assets_ratio                  789
tot_liab_to_tot_assets_ratio             751
tot_assets_log                           582
dtype: int64
```

EDA explanation 2.7
There are not a lot of outliers overlapping in the columns, resulting in high number of rows containing outliers (26,504 rows).

[33]:
```
outlier_row = train_x02_tx_df01_eda1.loc[train_x02_tx_df01_eda1
                              ['net_prof_to_tot_assets_ratio'] == 87.459000, :]
outlier_row
```

[33]:
```
       net_prof_to_tot_assets_ratio  tot_liab_to_tot_assets_ratio  \
28504                        87.459                       -430.87

       work_cap_to_tot_assets_ratio  curr_assets_to_st_liab_ratio  \
28504                        -6.459                       0.44818

       equ_to_ann_ops_exp_ratio  ret_earn_to_tot_assets_ratio  \
28504                    8.0767                        543.25

       ebit_to_tot_assets_ratio  book_equ_to_tot_liab_ratio  \
28504                   -517.48                    -0.78876

       sales_to_tot_assets_ratio  equ_to_tot_assets_ratio  …  \
28504                     65.607                   339.85  …

       ebitda_to_tot_sales_ratio  st_liab_to_tot_assets_ratio  \
28504                   -0.31584                       11.705

       equ_to_fx_assets_ratio  work_cap  mod_curr_assets_to_mod_sales_ratio  \
```

```
28504                     1.0    -394.0                            0.25734

       lt_liab_to_equ_ratio  sales_to_inven_ratio  sales_to_receiv_ratio  \
28504               0.37639               0.59018                 285.86

       sales_to_st_liab_ratio  sales_to_fx_assets_ratio
28504                   5.605                   0.19304

[1 rows x 42 columns]
```

[34]:
```
#A look at overlap outliers (those show values) among features. NaN values--
#-- are not outliers
outliers = train_x02_tx_df01_eda1[((train_x02_tx_df01_eda1 <
                                    (Q1 - 1.5 * IQR)) |
                                   (train_x02_tx_df01_eda1 >
                                    (Q3 + 1.5 * IQR)))]
outliers.head()
```

[34]:
```
   net_prof_to_tot_assets_ratio  tot_liab_to_tot_assets_ratio  \
0                           NaN                           NaN
1                           NaN                           NaN
2                           NaN                           NaN
3                           NaN                           NaN
4                           NaN                           NaN

   work_cap_to_tot_assets_ratio  curr_assets_to_st_liab_ratio  \
0                           NaN                           NaN
1                           NaN                           NaN
2                           NaN                           NaN
3                           NaN                           NaN
4                           NaN                           NaN

   equ_to_ann_ops_exp_ratio  ret_earn_to_tot_assets_ratio  \
0                       NaN                      -0.45312
1                       NaN                       0.83446
2                       NaN                       0.62886
3                       NaN                       0.24133
4                       NaN                           NaN

   ebit_to_tot_assets_ratio  book_equ_to_tot_liab_ratio  \
0                       NaN                         NaN
1                       NaN                         NaN
2                       NaN                         NaN
3                       NaN                         NaN
4                       NaN                         NaN

   sales_to_tot_assets_ratio  equ_to_tot_assets_ratio  …  \
```

```
0                        NaN                        NaN  …
1                        NaN                        NaN  …
2                        NaN                        NaN  …
3                        NaN                        NaN  …
4                        NaN                        NaN  …

   ebitda_to_tot_sales_ratio  st_liab_to_tot_assets_ratio  \
0                   -0.20062                          NaN
1                        NaN                          NaN
2                        NaN                          NaN
3                        NaN                          NaN
4                   -0.17462                          NaN

   equ_to_fx_assets_ratio  work_cap  mod_curr_assets_to_mod_sales_ratio  \
0                     NaN       NaN                                 NaN
1                     NaN       NaN                                 NaN
2                     NaN   39811.0                                 NaN
3                     NaN       NaN                                 NaN
4                  5.9764       NaN                                 NaN

   lt_liab_to_equ_ratio  sales_to_inven_ratio  sales_to_receiv_ratio  \
0                   NaN                   NaN                    NaN
1                   NaN                113.07                 22.097
2                   NaN                   NaN                    NaN
3                   NaN                   NaN                    NaN
4                   NaN                   NaN                    NaN

   sales_to_st_liab_ratio  sales_to_fx_assets_ratio
0                     NaN                       NaN
1                  34.107                       NaN
2                     NaN                       NaN
3                     NaN                       NaN
4                     NaN                       NaN

[5 rows x 42 columns]
```

Display final df's from EDA

[35]:
```python
# Train set
print(train_x02_tx_df01_eda1.shape)
print(train_y01_vc01_eda1.shape)

# Test set
print(test_x02_tx_df01_eda1.shape)
print(test_y01_vc01.shape)
```

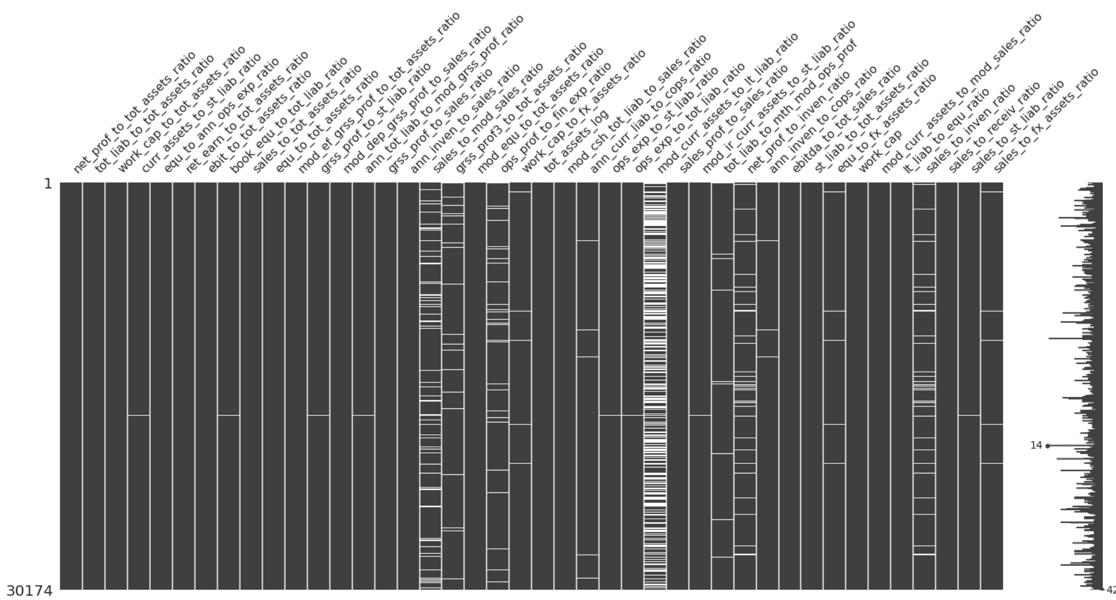
```
(30174, 42)
(30174,)
(13022, 42)
(13022,)
```

3. Additional preprocessing (Phase 2, post-EDA)

Check for Missing data

[36]:
```python
# Visualize missing values in each column
msno.matrix(train_x02_tx_df01_eda1)
```

[36]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f318ed33bd0>
```



Display all training instances with null values

[37]:
```python
null_val_df01 = train_x02_tx_df01_eda1.loc[train_x02_tx_df01_eda1.isnull().any(
                                                                    axis=1)]
print(f'{null_val_df01.head()}\n{null_val_df01.shape}')
```

```
   net_prof_to_tot_assets_ratio  tot_liab_to_tot_assets_ratio  \
5                     -0.002297                      0.881090
6                      0.004913                      0.498890
7                      0.031102                      0.390130
8                      0.000029                      0.000426
9                      0.438780                      0.410180
```

```
   work_cap_to_tot_assets_ratio  curr_assets_to_st_liab_ratio  \
5                      -0.20510                       0.73775
6                       0.40923                       1.82030
7                       0.24344                       1.62400
8                       0.40601                    3171.70000
9                       0.39582                       2.02840

   equ_to_ann_ops_exp_ratio  ret_earn_to_tot_assets_ratio  \
5                  -121.130                     -0.079250
6                 -1766.600                      0.000000
7                102170.000                      0.000000
8                 10876.000                      0.000000
9                    24.713                      0.013508

   ebit_to_tot_assets_ratio  book_equ_to_tot_liab_ratio  \
5                 -0.002297                     0.13495
6                  0.007097                     1.00450
7                  0.042698                     1.56330
8                  0.000036                  2345.40000
9                  0.541930                     1.43800

   sales_to_tot_assets_ratio  equ_to_tot_assets_ratio  …  \
5                   0.907900                  0.11891  …
6                  10.992000                  0.50111  …
7                   2.156100                  0.60987  …
8                   0.016226                  0.99957  …
9                   4.006800                  0.58982  …

   ebitda_to_tot_sales_ratio  st_liab_to_tot_assets_ratio  \
5                  -0.036820                     0.782090
6                  -0.005276                     0.498890
7                   0.002425                     0.390130
8                  -0.166140                     0.000128
9                   0.127670                     0.384890

   equ_to_fx_assets_ratio  work_cap  mod_curr_assets_to_mod_sales_ratio  \
5                 0.28109   -461.88                           -0.019319
6                 5.45390    240.97                            0.009804
7                 1.66440   1344.10                            0.050998
8                 1.68320    415.37                            0.000029
9                 2.68960   2769.80                            0.743920

   lt_liab_to_equ_ratio  sales_to_inven_ratio  sales_to_receiv_ratio  \
5                   0.0                7.7281               4.493100
6                   0.0               34.4990             112.330000
7                   0.0               23.8530               4.010300
8                   0.0                   NaN               0.082615
```

```
9                    0.0               24.9440             14.738000

   sales_to_st_liab_ratio  sales_to_fx_assets_ratio
5                  1.1609                  2.146300
6                 22.0330                119.630000
7                  5.5266                  5.884000
8                126.7200                  0.027323
9                 10.4100                 18.271000

[5 rows x 42 columns]
(16226, 42)
```

Remove features with high count of missing values

[38]:
```python
# Remove any features for which the number of null vals exceed a threshold--
#-- (15% of total N)
train_x02_tx_df01_eda1_null_summ01 = pd.DataFrame(
                      train_x02_tx_df01_eda1.isnull().sum(), columns=['count'])

train_x02_tx_df01_eda1_null_summ02 = train_x02_tx_df01_eda1_null_summ01.loc[
              (train_x02_tx_df01_eda1_null_summ01['count'] != 0)].sort_values(
                                                      'count', ascending=False)
train_x02_tx_df01_eda1_null_summ03 = \
                               train_x02_tx_df01_eda1_null_summ02.reset_index()
print(train_x02_tx_df01_eda1_null_summ03)

train_x02_tx_df01_eda1_null_summ04 = train_x02_tx_df01_eda1_null_summ03.loc[
                              train_x02_tx_df01_eda1_null_summ03['count'] > (
                                             len(train_x02_tx_df01_eda1)*.15)]
print('\n', train_x02_tx_df01_eda1_null_summ04)

train_x02_tx_df01_eda1_null_summ04_remove_lst01 = list(
                                  train_x02_tx_df01_eda1_null_summ04['index'])
print('\n', train_x02_tx_df01_eda1_null_summ04_remove_lst01)

train_x03_tx_df01 = train_x02_tx_df01_eda1.drop(
                       train_x02_tx_df01_eda1_null_summ04_remove_lst01, axis=1)
test_x03_tx_df01 = test_x02_tx_df01_eda1.drop(
                      train_x02_tx_df01_eda1_null_summ04_remove_lst01, axis=1)

print(f'\n{train_x03_tx_df01.shape}')
print(f'\n{test_x03_tx_df01.shape}')
```

```
                             index  count
0       mod_curr_assets_to_lt_liab_ratio  13155
1              sales_to_mod_sales_ratio   4093
2             ops_prof_to_fin_exp_ratio   1902
```

```
3                  sales_to_inven_ratio   1520
4               net_prof_to_inven_ratio   1516
5        grss_prof3_to_tot_assets_ratio    641
6           work_cap_to_fx_assets_ratio    554
7                equ_to_fx_assets_ratio    554
8              sales_to_fx_assets_ratio    554
9          tot_liab_to_mth_mod_ops_prof    541
10          ann_curr_liab_to_cops_ratio    259
11               ann_inven_to_cops_ratio    209
12             grss_prof_to_sales_ratio     98
13     mod_dep_grss_prof_to_sales_ratio     97
14             ann_inven_to_sales_ratio     97
15            sales_prof_to_sales_ratio     97
16            ebitda_to_tot_sales_ratio     97
17      mod_csh_tot_liab_to_sales_ratio     97
18             ops_exp_to_st_liab_ratio     94
19           grss_prof_to_st_liab_ratio     94
20   mod_ir_curr_assets_to_st_liab_ratio    94
21               sales_to_st_liab_ratio     94
22          curr_assets_to_st_liab_ratio    94
23                sales_to_receiv_ratio     70
24            ops_exp_to_tot_liab_ratio     66
25           book_equ_to_tot_liab_ratio     66
26             equ_to_ann_ops_exp_ratio     60
27  mod_ef_grss_prof_to_tot_assets_ratio    31
28   ann_tot_liab_to_mod_grss_prof_ratio    23
29            sales_to_tot_assets_ratio      9
30          st_liab_to_tot_assets_ratio      6
31         work_cap_to_tot_assets_ratio      6
32              equ_to_tot_assets_ratio      6
33         ret_earn_to_tot_assets_ratio      6
34                       tot_assets_log      6
35         tot_liab_to_tot_assets_ratio      6
36             ebit_to_tot_assets_ratio      6
37          mod_equ_to_tot_assets_ratio      6
38         net_prof_to_tot_assets_ratio      6
39    mod_curr_assets_to_mod_sales_ratio     5
40                 lt_liab_to_equ_ratio      5

                              index  count
0  mod_curr_assets_to_lt_liab_ratio  13155

 ['mod_curr_assets_to_lt_liab_ratio']

(30174, 41)

(13022, 41)
```

Preprocessing phase 2 explanation 3.1
Determine number of null values for each feature and eliminate all of those above a specificed threshold (> 15% of N) based on the assumption that the imputation of values for those features above the threshold will introduce more bias than is off-set by any information those features' values will add to prediction.

Impute missing values

[39]:
```
# Implement KNN Imputer for remaining missing vals
train_x03_tx_df01_kni_fit = KNNImputer().fit(train_x03_tx_df01)
train_x03_tx_vc02 = train_x03_tx_df01_kni_fit.transform(train_x03_tx_df01)
test_x03_tx_vc02 = train_x03_tx_df01_kni_fit.transform(test_x03_tx_df01)

train_x03_tx_df02 = pd.DataFrame(train_x03_tx_vc02,
                                  columns=train_x03_tx_df01.columns)
test_x03_tx_df02 = pd.DataFrame(test_x03_tx_vc02,
                                 columns=train_x03_tx_df01.columns)

train_x03_tx_df02_null_summ01 = pd.DataFrame(train_x03_tx_df02.isnull().sum(),
                                              columns=['count'])

display(train_x03_tx_df02_null_summ01.loc[
                                (train_x03_tx_df02_null_summ01['count'] != 0)])
```

```
Empty DataFrame
Columns: [count]
Index: []
```

Preprocessing phase 2 explanation 3.2
Imputation is the process of deriving an unknown value and can be done using either simple methods (e.g., mean value imputation) or more sophisticated methods (e.g., KNN imputation). In this instance, KNN imputation has been used, which uses distances calculated between each instance to fill in values calculated from a record's closest neighbor(s) on the basis that close records would most likely have similar values for the unknown features, were they actually known.

Scale X values in two ways

[40]:
```
# Z-score normalization
train_x03_tx_df02_sts_fit = StandardScaler().fit(train_x03_tx_df02)
train_x03_tx_vc03 = train_x03_tx_df02_sts_fit.transform(train_x03_tx_df02)
test_x03_tx_vc03 = train_x03_tx_df02_sts_fit.transform(test_x03_tx_df02)

train_x03_tx_df03 = pd.DataFrame(train_x03_tx_vc03,
```

```
                                 columns=train_x03_tx_df01.columns)
test_x03_tx_df03 = pd.DataFrame(test_x03_tx_vc03,
                                columns=train_x03_tx_df01.columns)

print(f'{train_x03_tx_df03.shape}')
print(f'{test_x03_tx_df03.shape}')

'''___________________________________________________________________________'''
# Min-max scaling
train_x03_tx_df02_mms_fit = MinMaxScaler().fit(train_x03_tx_df02)
train_x03_tx_vc04 = train_x03_tx_df02_mms_fit.transform(train_x03_tx_df02)
test_x03_tx_vc04 = train_x03_tx_df02_mms_fit.transform(test_x03_tx_df02)

train_x03_tx_df04 = pd.DataFrame(train_x03_tx_vc04,
                                 columns=train_x03_tx_df01.columns)
test_x03_tx_df04 = pd.DataFrame(test_x03_tx_vc04,
                                columns=train_x03_tx_df01.columns)

print(f'\n{train_x03_tx_df04.shape}')
print(f'{test_x03_tx_df04.shape}')
```

```
(30174, 41)
(13022, 41)

(30174, 41)
(13022, 41)
```

Preprocessing phase 2 explanation 3.3
Perform two separate scaling procedures based on different ML algorithms working better with specifically formatted data values. *Z*-score scaling converts values by deducting the mean from each value, then dividing by the standard deviation (s.d.); therefore the mean is 0 and s.d. is 1. Min-max scaling converts all values to the range of 0-1.

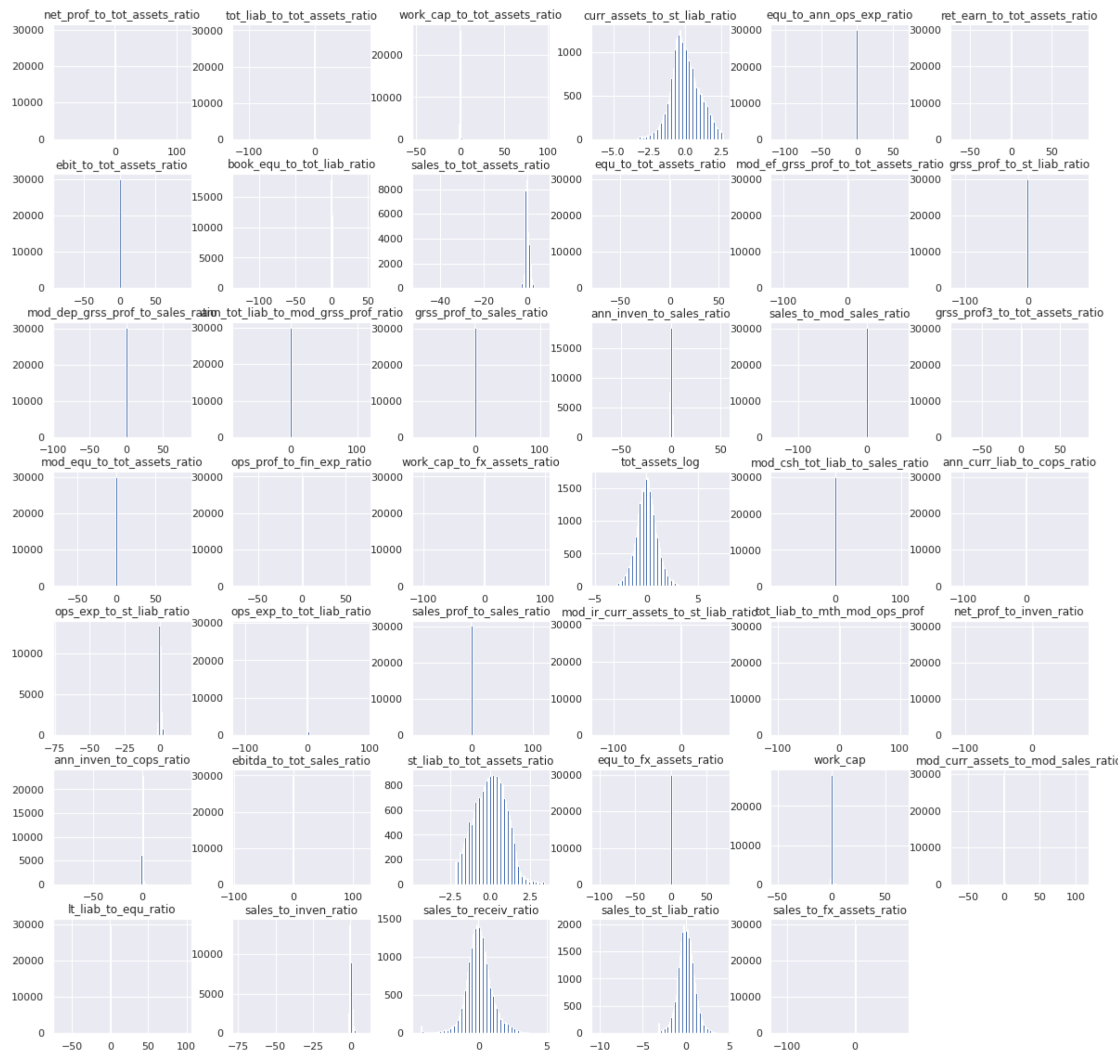
Check for and mitigate skew

[41]:
```
# Use transformer to adjust for skew (includes standardization)
train_x03_tx_df02_skw = train_x03_tx_df02.skew(axis=0,
                                               skipna=True)
train_skewed = train_x03_tx_df02_skw[train_x03_tx_df02_skw > abs(0)]
print(train_x03_tx_df02.shape)
print(f'{train_x03_tx_df02_skw.sort_values(ascending=False)}\n␣
 ↪{train_x03_tx_df02_skw.shape}')

'''Use scikit-learn power transformer function (with Yeo-Johnson
transformation) to adjust skewed features closer to normal dist'''
```

```python
train_x03_tx_df02_sts_fit = PowerTransformer().fit(train_x03_tx_df02)
train_x03_tx_vc05 = train_x03_tx_df02_sts_fit.transform(train_x03_tx_df02)
test_x03_tx_vc05 = train_x03_tx_df02_sts_fit.transform(test_x03_tx_df02)

train_x03_tx_df05 = pd.DataFrame(train_x03_tx_vc05,
                                 columns=train_x03_tx_df01.columns)
test_x03_tx_df05 = pd.DataFrame(test_x03_tx_vc05,
                                columns=train_x03_tx_df01.columns)

# Plot histograms of features after adjusting for skew
train_x03_tx_df05.hist(bins=100, figsize=(20, 20));
```

```
(30174, 41)
ann_inven_to_sales_ratio                173.618471
tot_liab_to_mth_mod_ops_prof            173.503404
lt_liab_to_equ_ratio                    166.605052
curr_assets_to_st_liab_ratio            165.925827
mod_csh_tot_liab_to_sales_ratio         144.750764
sales_to_receiv_ratio                   144.486530
grss_prof_to_sales_ratio                141.418514
mod_ir_curr_assets_to_st_liab_ratio     123.277591
sales_to_inven_ratio                    116.078226
ann_inven_to_cops_ratio                 110.896006
ann_curr_liab_to_cops_ratio             109.457278
work_cap_to_fx_assets_ratio             108.450848
mod_dep_grss_prof_to_sales_ratio        100.585481
st_liab_to_tot_assets_ratio              94.504982
sales_to_mod_sales_ratio                 93.283983
ops_exp_to_tot_liab_ratio                85.733190
sales_to_tot_assets_ratio                79.158760
equ_to_fx_assets_ratio                   78.890728
book_equ_to_tot_liab_ratio               77.826100
sales_to_fx_assets_ratio                 74.367281
ops_prof_to_fin_exp_ratio                69.657099
mod_equ_to_tot_assets_ratio              66.537423
ops_exp_to_st_liab_ratio                 58.298981
equ_to_tot_assets_ratio                  50.759688
grss_prof_to_st_liab_ratio               47.636332
tot_liab_to_tot_assets_ratio             45.568106
grss_prof3_to_tot_assets_ratio           40.189841
sales_prof_to_sales_ratio                38.516237
work_cap                                 37.498898
sales_to_st_liab_ratio                   27.146702
mod_ef_grss_prof_to_tot_assets_ratio     10.281816
tot_assets_log                           -0.087284
ret_earn_to_tot_assets_ratio            -11.986268
ann_tot_liab_to_mod_grss_prof_ratio     -20.326293
```

```
ebit_to_tot_assets_ratio                  -22.046908
mod_curr_assets_to_mod_sales_ratio        -59.768462
net_prof_to_inven_ratio                   -63.811352
work_cap_to_tot_assets_ratio              -94.181161
net_prof_to_tot_assets_ratio             -116.301826
equ_to_ann_ops_exp_ratio                 -148.317936
ebitda_to_tot_sales_ratio                -159.208088
dtype: float64
 (41,)
```



Preprocessing phase 2 explanation 3.4
As previously noted in the EDA section, the values for the vast majority of features is highly skewed; this is most likely do to a large amount of similarly ranged values with several very large outliers. Using the Yeo-Johnson transformation method, some

of the features were able to be adjusted to have more normal distributions, as seen in the set of histograms.

Apply rebalancing technique (using SMOTE) for scaled data

[42]:
```
# Apply SMOTE to address class imbalance on training set only (Geeks for Geeks,␣
↪2022)
smote_txr = SMOTE(random_state=1699)
train_x03_tx_df03a, \
train_y01_vc01_eda1a = smote_txr.fit_resample(train_x03_tx_df03,
                                              train_y01_vc01_eda1)

print(f'{train_x03_tx_df03.shape}')
print(f'{train_x03_tx_df03a.shape}')
print(f'{train_y01_vc01_eda1a.shape}')

'''____________________________________________________________________________'''
train_x03_tx_df04a, \
train_y01_vc01_eda1b = smote_txr.fit_resample(train_x03_tx_df04,
                                              train_y01_vc01_eda1)

print(f'\n{train_x03_tx_df04.shape}')
print(f'{train_x03_tx_df04a.shape}')
print(f'{train_y01_vc01_eda1b.shape}')

'''____________________________________________________________________________'''
train_x03_tx_df05a, \
train_y01_vc01_eda1c = smote_txr.fit_resample(train_x03_tx_df05,
                                              train_y01_vc01_eda1)

print(f'\n{train_x03_tx_df05.shape}')
print(f'{train_x03_tx_df05a.shape}')
print(f'{train_y01_vc01_eda1c.shape}')
```

```
(30174, 41)
(57424, 41)
(57424,)

(30174, 41)
(57424, 41)
(57424,)

(30174, 41)
(57424, 41)
(57424,)
```

Apply rebalancing technique (using SMOTE) for unscaled data

[43]:
```
# fit and apply the transform
X_over2, \
y_over2 = smote_txr.fit_resample(train_x03_tx_df02,
                                 train_y01_vc01_eda1)
```

Apply rebalancing technique (using random oversampling) for unscaled data

[44]:
```
# define oversampling strategy
oversample = RandomOverSampler(sampling_strategy='minority')

# fit and apply the transform
X_over, \
y_over = oversample.fit_resample(train_x03_tx_df02,
                                 train_y01_vc01_eda1)
```

Preprocessing phase 2 explanation 3.5
As there is a relatively significant imbalance in classes for the data set, additional df's were created using: 1) Synthetic Minority Oversampling Technique (SMOTE), which works by creating synthetic data points based on those in the minority class (Korstanje, 2021); and 2) Random over sampling.

4. Modeling

Data Frame Map

Feature Set (X)	Data Frame Name	Comments
1	x01__df01	full X data set, no transformations
2a	train__x01__df01	train X, no transformations
2b	test__x01__df01	test X, no transformations
3a	train__x02__tx__df01	train X, near zero variance features (if any) removed
3b	test__x02__tx__df01	test X, near zero variance features (if any) removed
3c	train__x02__tx__df01__eda1	train X, #3a + drop duplicates + drop highly correlated
3d	test__x02__tx__df01__eda1	train X, #3b + drop highly correlated
4a	train__x03__tx__df01	train X, #3c + remove features w/ null count > N*.15
4b	test__x03__tx__df01	test X, #3d + remove features w/ null count > N*.15
5a	train__x03__tx__df02	train X, #4a + missing values imputed

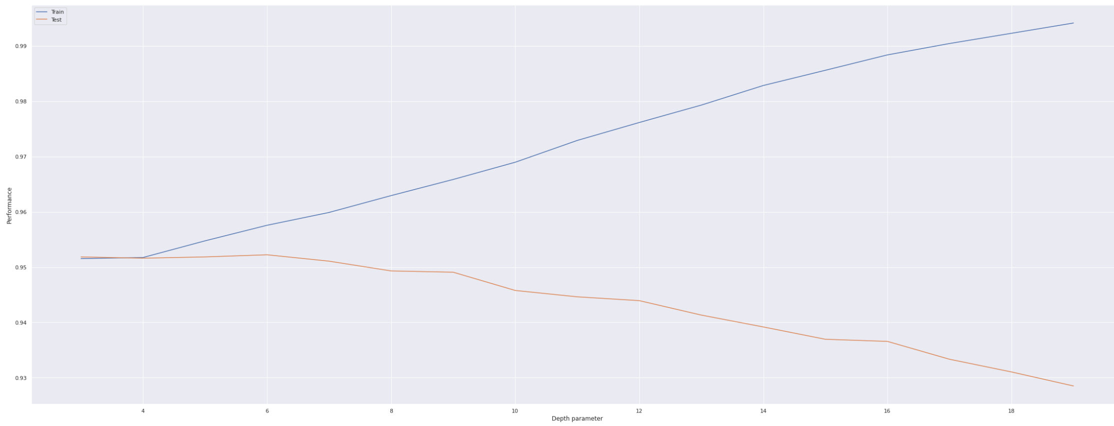
Feature Set (X)	Data Frame Name	Comments
5b	test_x03_tx_df02	test X, #4b + missing values imputed
6a	train_x03_tx_df03	train X, #5a + z-score scaling
6b	test_x03_tx_df03	test X, #5b + z-score scaling
6c	train_x03_tx_df03a	train X, #6a + SMOTE rebalancing
7a	train_x03_tx_df04	train X, #5a + min-max scaling
7b	test_x03_tx_df04	test X, #5b + min-max scaling
7c	train_x03_tx_df04a	train X, #7a + SMOTE rebalancing
8a	train_x03_tx_df05	train X, #5a + skew transformation
8b	test_x03_tx_df05	test X, #5b + skew transformation
8c	train_x03_tx_df05a	train X, #8a + SMOTE rebalancing

Feature Set (Y)	Data Frame Name	Comments
9	y01_df01	full Y data set, no transformations
10a	train_y01_vc01	train Y, no transformations
10b	train_y01_vc01_eda1	train Y, #10a + drop duplicates
10c	test_y01_vc01	test Y, no transformations
10d	train_y01_vc01_eda1a	train Y, #6a/#10b + SMOTE rebalancing
10e	train_y01_vc01_eda1b	train Y, #7a/#10b + SMOTE rebalancing
10f	train_y01_vc01_eda1c	train Y, #8a/#10b + SMOTE rebalancing

Decision Tree Classifier

[45]:
```
#list to store the output of for loops
train_errors = list()
test_errors = list()
accuracy = list()

#for loop for tree depths between 3 and 20
for x in range(3,20):
  clf = DecisionTreeClassifier(max_depth=x, random_state=1)
  clf = clf.fit(train_x03_tx_df03, train_y01_vc01_eda1)
  y_pred = clf.predict(test_x03_tx_df03)
  train_errors.append(clf.score(train_x03_tx_df03, train_y01_vc01_eda1))
  test_errors.append(clf.score(test_x03_tx_df03, test_y01_vc01))
  accuracy.append(accuracy_score(test_y01_vc01, y_pred))

# Plot of test and training errors
plt.plot(range(3,20),train_errors, label='Train')
plt.plot(range(3,20),test_errors, label='Test')
plt.legend(loc='upper left')
plt.xlabel('Depth parameter')
plt.ylabel('Performance')
```

[45]: Text(0, 0.5, 'Performance')

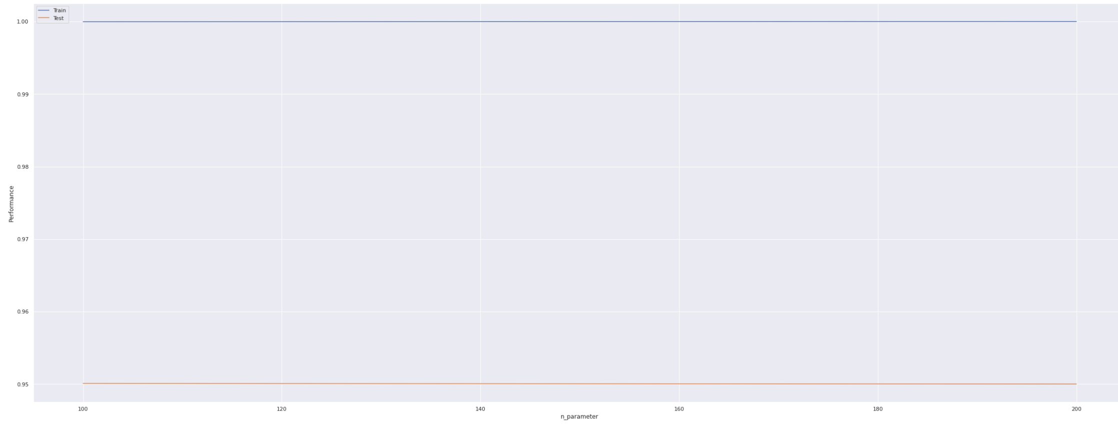


Random Forests

[46]:
```
#list to store the output of for loops
train_errors = list()
test_errors = list()
accuracy = list()

#for loop for n_estimators between 100 and 1000
for x in range(100,300,100):
  rf = RandomForestClassifier(n_estimators=x, random_state=1)
  rf = rf.fit(train_x03_tx_df03, train_y01_vc01_eda1)
  y_pred = rf.predict(test_x03_tx_df03)
  train_errors.append(rf.score(train_x03_tx_df03, train_y01_vc01_eda1))
  test_errors.append(rf.score(test_x03_tx_df03, test_y01_vc01))
  accuracy.append(accuracy_score(test_y01_vc01, y_pred))
```

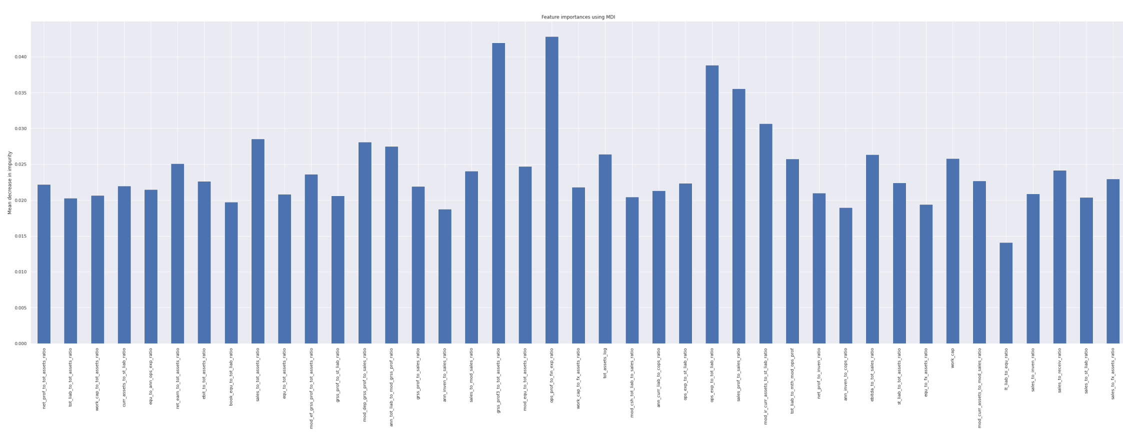
[47]:
```
# Plot of test and training errors
plt.plot(range(100,300,100), train_errors, label='Train')
plt.plot(range(100,300,100), test_errors, label='Test')
plt.legend(loc='upper left')
plt.xlabel('n_parameter')
plt.ylabel('Performance')
```

[47]: Text(0, 0.5, 'Performance')



```
[48]: #develop the final rf model based on the best n_estimators
rf_final = RandomForestClassifier(n_estimators=200, random_state=1)
rf_final = rf_final.fit(train_x03_tx_df03, train_y01_vc01_eda1)
```

```
[49]: #create the feature names from the training data
feature_names = train_x03_tx_df03.columns

#variable importance variables from the rf model
importances = rf_final.feature_importances_
forest_importances = pd.Series(importances, index=feature_names)

#plot the feature importance of RF
fig, ax = plt.subplots()
forest_importances.plot.bar(ax=ax)
ax.set_title("Feature importances using MDI")
ax.set_ylabel("Mean decrease in impurity")
fig.tight_layout()
```



Define custom function to apply scikit-learn classification grid tuning

[50]:
```
# Define function to create scikit-learn classification model standard output
class_names = ['going_concern', 'bankrupt']
def skl_class_model(train_x=None,
                    train_y=None,
                    val_x=None,
                    val_y=None,
                    skl_model=None,
                    grid=None,
                    cv=5):
  '''takes a scikit-learn classifier, train X/Y, val XY, and grid as input;
  displays class eval metrics for training & val; returns the best fit model'''
  start_time = dt.datetime.today()
  print('++++++++++++++++++++++++++++++++++++++++++++++++')
  if grid == None:
      model_fit = skl_model.fit(train_x, train_y)
  else:
      model_gridcv_fit = GridSearchCV(skl_model,
                                      grid,
                                      cv=cv).fit(train_x, train_y)
      model_fit = model_gridcv_fit.best_estimator_
      print(f'Best CV grid parameters for {skl_model}: {model_gridcv_fit.
↪best_params_}')
  print('Training set')
  classificationSummary(train_y,
                        model_fit.predict(train_x))
  print(f'\nAdditional Eval Measures for {skl_model}:')
  print(f'Recall = {recall_score(train_y, model_fit.predict(train_x))}')
  print(f'Precision = {precision_score(train_y, model_fit.predict(train_x))}')
  print(f'F1 = {f1_score(train_y, model_fit.predict(train_x))}')

  print('\n_________________________________________________')
  print('Val/Test set')
  classificationSummary(val_y,
                        model_fit.predict(val_x))
  print(f'\nAdditional Eval Measures for {skl_model}:')
  print(f'Recall = {recall_score(val_y, model_fit.predict(val_x))}')
  print(f'Precision = {precision_score(val_y, model_fit.predict(val_x))}')
  print(f'F1 = {f1_score(val_y, model_fit.predict(val_x))}')

  end_time = dt.datetime.today()
  time_elapsed = end_time - start_time
  print(f'\nStart Time = {start_time}')
  print(f'End Time = {end_time}')
  print(f'Script Time = {time_elapsed}')
  return model_fit
```

Custom modeling function explanation
Create a custom function to standardize scikit-learn classification process. It was deployed for the KNN, LDA, the boosting methods, and NN modeling.

Gradient Boosting

GBT model 1 (dataset with SMOTE)

[51]:
```
# #Build GBT model with tuning on number of trees
# boost_1 = GradientBoostingClassifier()
# boost_grid ={'n_estimators':[100,200,500]}
# boost_fit = skl_class_model(train_x=X_over2,
#                                    train_y=y_over2,
#                                    val_x= test_x03_tx_df02,
#                                    val_y=test_y01_vc01,
#                                    skl_model=boost_1,
#                                    grid=boost_grid)
# #Pickle fitted model
# joblib.dump(boost_fit, folder_path_mods + '/boost_1')
```

GBT model 2 (dataset with SMOTE)

[52]:
```
# #Build GBT model with 200 trees
# boost_2 = GradientBoostingClassifier(n_estimators=200)
# #boost_grid ={}
# boost_fit = skl_class_model(train_x=X_over2,
#                                    train_y=y_over2,
#                                    val_x= test_x03_tx_df02,
#                                    val_y=test_y01_vc01,
#                                    skl_model=boost_2,
#                                    grid=None)
# #Pickle fitted model
# joblib.dump(boost_fit, folder_path_mods + '/boost_2')
```

GBT model 3 (dataset with RandomSampling)

[53]:
```
# #Build GBT model with 200 trees
# boost_3 = GradientBoostingClassifier(n_estimators=200)
# #boost_grid ={}
# boost_fit = skl_class_model(train_x=X_over,
#                                    train_y=y_over,
#                                    val_x= test_x03_tx_df02,
#                                    val_y=test_y01_vc01,
#                                    skl_model=boost_3,
#                                    grid=None)
# #Pickle fitted model
# joblib.dump(boost_fit, folder_path_mods + '/boost_3')
```

GBT model 4 (bundle 4: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced, removed skew)

```
[54]: # boost_4 = GradientBoostingClassifier(n_estimators=200)
# #boost_grid = None
# boost_fit = skl_class_model(train_x=train_x03_tx_df05a,
#                                    train_y=train_y01_vc01_eda1c,
#                                    val_x=test_x03_tx_df03,
#                                    val_y=test_y01_vc01,
#                                    skl_model=boost_4,
#                                    grid=None)
# #Pickle fitted model
# joblib.dump(boost_fit, folder_path_mods + '/boost_4')
```

XGBoosting

XGBoost 1 (dataset with RandomSampling)

```
[55]: # #Build GBT model with 200 trees
# XGB = XGBClassifier(n_estimators=200)
# SGB_fit = skl_class_model(train_x= X_over,
#                                    train_y=y_over,
#                                    val_x= test_x03_tx_df02,
#                                    val_y=test_y01_vc01,
#                                    skl_model=XGB,
#                                    grid=None)
# #Pickle fitted model
# joblib.dump(SGB_fit, folder_path_mods + '/xgboost_1')
```

XGBoost 2 (bundle 4: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced, removed skew)

```
[56]: # xgboost_2 = GradientBoostingClassifier(n_estimators=200)
# #boost_grid = None
# boost_fit_2 = skl_class_model(train_x=train_x03_tx_df05a,
#                                    train_y=train_y01_vc01_eda1c,
#                                    val_x=test_x03_tx_df03,
#                                    val_y=test_y01_vc01,
#                                    skl_model=xgboost_2,
#                                    grid=None)
# #Pickle fitted model
# joblib.dump(boost_fit_2, folder_path_mods + '/xgboost_2')
```

Neural Network (NN)

Neural Network model (dataset with RandomOversampling)

[57]:
```
#Build neural Network with tuning parameters
#NN = MLPClassifier(max_iter=100)
#grid = {
#    'hidden_layer_sizes': [(20,20,20),(20,)],
#    'activation': ['identity', 'logistic', 'tanh', 'relu'],
#    'solver': ['sgd', 'adam'],
#    'alpha': [0.0001, 0.05],
#    'learning_rate': ['constant','adaptive'],
#}
#NN_tune = GridSearchCV(NN, grid, n_jobs=-1, cv=2)
#NN_tune.fit(X_over, y_over)
```

[58]:
```
# #Build Neural Network model
# NN =MLPClassifier(max_iter=100)
# NN_grid = {'hidden_layer_sizes': [(20,20,20),(20,)],
#             'activation': ['identity', 'logistic', 'tanh', 'relu'],
#             'solver': ['sgd', 'adam'],
#             'alpha': [0.0001, 0.05],
#             'learning_rate': ['constant','adaptive']}
# NN_fit= skl_class_model(train_x= X_over,
#                          train_y=y_over,
#                          val_x= test_x03_tx_df02,
#                          val_y=test_y01_vc01,
#                          skl_model=NN,
#                          grid=NN_grid,
#                          cv=2)
# #Pickle fitted model
# joblib.dump(NN_fit, folder_path_mods + '/NN_tune')
```

K-nearest neighbors (KNN)

[59]:
```
'''
These algorithms were run using the custom function defined above to return
a fit model; however, as the models took several hours to train, the fitted
model has been pickled and the code has been commented out to avoid
repeated need to absorb computation resources. Evaluation measure
outputs for each model are included in the appropriate section below.
'''


# # Run k-nearest neighbors (KNN) algorithm
# # Sets Bundle 1: Cleaned, eliminated features, z-score scaled, no rebalancing
# knn_mod_v1 = KNeighborsClassifier()

# knn_mod_v1_grd = {'n_neighbors': range(1, 30, 2),
#                    'weights': ['uniform', 'distance'],
#                    'p': [1, 2]}
```

```
# knn_mod_v1_fit = skl_class_model(train_x=train_x03_tx_df03,
#                                  train_y=train_y01_vc01_eda1,
#                                  val_x=test_x03_tx_df03,
#                                  val_y=test_y01_vc01,
#                                  skl_model=knn_mod_v1,
#                                  grid=knn_mod_v1_grd,
#                                  cv=5)

# #print(knn_mod_v1_fit.kneighbors_graph())

# # Sets Bundle 2: Cleaned, eliminated features, z-score scaled, SMOTE␣
 ↪rebalanced
# knn_mod_v2_fit = skl_class_model(train_x=train_x03_tx_df03a,
#                                  train_y=train_y01_vc01_eda1a,
#                                  val_x=test_x03_tx_df03,
#                                  val_y=test_y01_vc01,
#                                  skl_model=knn_mod_v1,
#                                  grid=knn_mod_v1_grd,
#                                  cv=5)

# # Sets Bundle 3: Cleaned, eliminated features, z-score scaled, no rebalancing,
# #-- removed skew
# knn_mod_v3_fit = skl_class_model(train_x=train_x03_tx_df05,
#                                  train_y=train_y01_vc01_eda1,
#                                  val_x=test_x03_tx_df05,
#                                  val_y=test_y01_vc01,
#                                  skl_model=knn_mod_v1,
#                                  grid=knn_mod_v1_grd,
#                                  cv=5)

# # Sets Bundle 4: Cleaned, eliminated features, z-score scaled, SMOTE␣
 ↪rebalanced,
# #-- removed skew
# knn_mod_v4_fit = skl_class_model(train_x=train_x03_tx_df05a,
#                                  train_y=train_y01_vc01_eda1c,
#                                  val_x=test_x03_tx_df03,
#                                  val_y=test_y01_vc01,
#                                  skl_model=knn_mod_v1,
#                                  grid=knn_mod_v1_grd,
#                                  cv=5)
```

[59]: '\nThese algorithms were run using the custom function defined above to return\na fit model; however, as the models took several hours to train, the fitted\nmodel has been pickled and the code has been commented out to avoid\nrepeated need to absorb computation resources. Evaluation measure\noutputs for each model are included in the appropriate section

```
below.\n'
```

KNN modeling explanation
Deploy four different KNN classifiers, using different df's to determine which is best in turns of maximizing efficiency and performance.
The data sets have the following characteristics:
*** Data Sets Bundle 1: Cleaned, eliminated features, *z*-score scaled, no rebalancing**
*** Data Sets Bundle 2: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced**
*** Data Sets Bundle 3: Cleaned, eliminated features, z-score scaled, no rebalancing, removed skew**
*** Data Sets Bundle 4: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced, removed skew**

KNN is generally suspetible to noise in the data, which given the relative size and prevalance of the outliers is very likely to be present in this data. As such, KNN is being used more as comparative model.

Linear Discriminant Analysis (LDA)

[60]:
```
'''
These algorithms were run using the custom function defined above to return
a fit model; however, as the models took several hours to train, the fitted
model has been pickled and the code has been commented out to avoid
repeated need to absorb computation resources. Evaluation measure
outputs for each model are included in the appropriate section below.
'''

# # Run linear discriminant analysis (LDA) algorithm
# lda_mod_v1 = LinearDiscriminantAnalysis()

# lda_mod_v1_grd = {'solver': ['svd', 'lsqr', 'eigen'],
#                   'shrinkage': [.001, .01, .05, .1, .5, 1, 'auto', None],
#                   'store_covariance': [True, False]}

# # Sets Bundle 1: Cleaned, eliminated features, z-score scaled, no rebalancing
# lda_mod_v1_fit = skl_class_model(train_x=train_x03_tx_df03,
#                                  train_y=train_y01_vc01_eda1,
#                                  val_x=test_x03_tx_df03,
#                                  val_y=test_y01_vc01,
#                                  skl_model=lda_mod_v1,
#                                  grid=lda_mod_v1_grd,
#                                  cv=5)
```

```
# # Sets Bundle 2: Cleaned, eliminated features, z-score scaled, SMOTE␣
↪rebalanced
# lda_mod_v2_fit = skl_class_model(train_x=train_x03_tx_df03a,
#                                  train_y=train_y01_vc01_eda1a,
#                                  val_x=test_x03_tx_df03,
#                                  val_y=test_y01_vc01,
#                                  skl_model=lda_mod_v1,
#                                  grid=lda_mod_v1_grd,
#                                  cv=5)

# # Sets Bundle 3: Cleaned, eliminated features, z-score scaled, no␣
↪rebalancing,
# #--removed skew
# lda_mod_v3_fit = skl_class_model(train_x=train_x03_tx_df05,
#                                  train_y=train_y01_vc01_eda1,
#                                  val_x=test_x03_tx_df05,
#                                  val_y=test_y01_vc01,
#                                  skl_model=lda_mod_v1,
#                                  grid=lda_mod_v1_grd,
#                                  cv=5)

# # Sets Bundle 4: Cleaned, eliminated features, z-score scaled, SMOTE␣
↪rebalanced,
# #-- removed skew
# lda_mod_v4_fit = skl_class_model(train_x=train_x03_tx_df05a,
#                                  train_y=train_y01_vc01_eda1c,
#                                  val_x=test_x03_tx_df03,
#                                  val_y=test_y01_vc01,
#                                  skl_model=lda_mod_v1,
#                                  grid=lda_mod_v1_grd,
#                                  cv=5)
```

[60]:
```
'\nThese algorithms were run using the custom function defined above to
return\na fit model; however, as the models took several hours to train, the
fitted\nmodel has been pickled and the code has been commented out to
avoid\nrepeated need to absorb computation resources. Evaluation
measure\noutputs for each model are included in the appropriate section
below.\n'
```

LDA modeling explanation
Deploy four different LDA classifiers, using different df's to determine which is best in turns of maximizing efficiency and performance.
The data sets have the following characteristics:
- Data Sets Bundle 1: Cleaned, eliminated features, z-score scaled, no rebalancing
- Data Sets Bundle 2: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced

- Data Sets Bundle 3: Cleaned, eliminated features, z-score scaled, no rebalancing, removed skew
- Data Sets Bundle 4: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced, removed skew LDA is generally suspetible to outliers which appear to be inherent in this data. As such, LDA is being used more as comparative model.

5. Model evaluation

File paths to NNet, XGBoost and GBT

[61]:
```
##For these use test set: test_y01_vc01test_x03_tx_df02, test_y01_vc01
boost_1 = joblib.load(folder_path_mods + '/boost_1')
#boost_2=joblib.load(folder_path_mods + '/boost_2.pickle')
boost_3 = joblib.load(folder_path_mods + '/boost_3')
#xgboost_1=joblib.load(folder_path_mods + '/xgboost_1.pickle')
NN_tune = joblib.load(folder_path_mods + '/NN_tune')

#For these use test set: test_x03_tx_df03, test_y01_vc01
xgboost_2 = joblib.load(folder_path_mods + '/xgboost_2')
boost_4 = joblib.load(folder_path_mods + '/boost_4')
```

File paths to KNN and LDA output

[62]:
```
# Load best estimator grid parameters and final model fit to training data set

# KNN
# Sets Bundle 1: Cleaned, eliminated features, z-score scaled, no rebalancing
knn_mod_v1_path = r'/
 ↪KNeighborsClassifier^n_neighbors-13_p-1^2022-10-07_00-25-33-358581.pickle'
knn_mod_v1_fit = joblib.load(folder_path + r'/models' + knn_mod_v1_path)
knn_mod_v1_fit_grd = joblib.load(folder_path + r'/grids' + knn_mod_v1_path)
print(knn_mod_v1_fit_grd)
print(knn_mod_v1_fit)

# Sets Bundle 2: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced
knn_mod_v2_path = r'/
 ↪KNeighborsClassifier^n_neighbors-1_p-1^2022-10-07_00-52-41-032112.pickle'
knn_mod_v2_fit = joblib.load(folder_path + r'/models' + knn_mod_v2_path)
knn_mod_v2_fit_grd = joblib.load(folder_path + r'/grids' + knn_mod_v2_path)
print('\n', knn_mod_v2_fit_grd)
print(knn_mod_v2_fit)

# Sets Bundle 3: Cleaned, eliminated features, z-score scaled, no rebalancing,
#--removed skew
knn_mod_v3_path = r'/
 ↪KNeighborsClassifier^n_neighbors-21^2022-10-07_02-35-01-540637.pickle'
knn_mod_v3_fit = joblib.load(folder_path + r'/models' + knn_mod_v3_path)
```

```
knn_mod_v3_fit_grd = joblib.load(folder_path + r'/grids' + knn_mod_v3_path)
print('\n', knn_mod_v3_fit_grd)
print(knn_mod_v3_fit)

# Sets Bundle 4: Cleaned, eliminated features, z-score scaled, SMOTE␣
 ↪rebalanced,
#--removed skew
knn_mod_v4_path = r'/
 ↪KNeighborsClassifier^n_neighbors-1^2022-10-07_03-01-04-140264.pickle'
knn_mod_v4_fit = joblib.load(folder_path + r'/models' + knn_mod_v4_path)
knn_mod_v4_fit_grd = joblib.load(folder_path + r'/grids' + knn_mod_v4_path)
print('\n', knn_mod_v4_fit_grd)
print(knn_mod_v4_fit)

# LDA
# Sets Bundle 1: Cleaned, eliminated features, z-score scaled, no rebalancing
lda_mod_v1_path = r'/LinearDiscriminantAnalysis^shrinkage-0.
 ↪5_solver-lsqr_store_covariance-True^2022-10-07_11-08-29-174541.pickle'
lda_mod_v1_fit = joblib.load(folder_path + r'/models' + lda_mod_v1_path)
lda_mod_v1_fit_grd = joblib.load(folder_path + r'/grids' + lda_mod_v1_path)
print(lda_mod_v1_fit_grd)
print(lda_mod_v1_fit)

# Sets Bundle 2: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced
lda_mod_v2_path = r'/
 ↪LinearDiscriminantAnalysis^store_covariance-True^2022-10-07_11-08-46-890084.
 ↪pickle'
lda_mod_v2_fit = joblib.load(folder_path + r'/models' + lda_mod_v2_path)
lda_mod_v2_fit_grd = joblib.load(folder_path + r'/grids' + lda_mod_v2_path)
print('\n', lda_mod_v2_fit_grd)
print(lda_mod_v2_fit)

# Sets Bundle 3: Cleaned, eliminated features, z-score scaled, no rebalancing,
#--removed skew
lda_mod_v3_path = r'/LinearDiscriminantAnalysis^shrinkage-0.
 ↪1_solver-lsqr_store_covariance-True^2022-10-07_11-09-21-893014.pickle'
lda_mod_v3_fit = joblib.load(folder_path + r'/models' + lda_mod_v3_path)
lda_mod_v3_fit_grd = joblib.load(folder_path + r'/grids' + lda_mod_v3_path)
print('\n', lda_mod_v3_fit_grd)
print(lda_mod_v3_fit)

# Sets Bundle 4: Cleaned, eliminated features, z-score scaled, SMOTE rebalanced,
#-- removed skew
lda_mod_v4_path = r'/
 ↪LinearDiscriminantAnalysis^store_covariance-True^2022-10-07_11-09-40-471260.
 ↪pickle'
```

```python
lda_mod_v4_fit = joblib.load(folder_path + r'/models' + lda_mod_v4_path)
lda_mod_v4_fit_grd = joblib.load(folder_path + r'/grids' + lda_mod_v4_path)
print('\n', lda_mod_v4_fit_grd)
print(lda_mod_v4_fit)
```

```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': range(1, 30, 2), 'p': [1, 2],
                         'weights': ['uniform', 'distance']})
KNeighborsClassifier(n_neighbors=13, p=1)

 GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': range(1, 30, 2), 'p': [1, 2],
                         'weights': ['uniform', 'distance']})
KNeighborsClassifier(n_neighbors=1, p=1)

 GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': range(1, 30, 2), 'p': [1, 2],
                         'weights': ['uniform', 'distance']})
KNeighborsClassifier(n_neighbors=21)

 GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': range(1, 30, 2), 'p': [1, 2],
                         'weights': ['uniform', 'distance']})
KNeighborsClassifier(n_neighbors=1)
GridSearchCV(cv=5, estimator=LinearDiscriminantAnalysis(),
             param_grid={'shrinkage': [0.001, 0.01, 0.05, 0.1, 0.5, 1, 'auto',
                                       None],
                         'solver': ['svd', 'lsqr', 'eigen'],
                         'store_covariance': [True, False]})
LinearDiscriminantAnalysis(shrinkage=0.5, solver='lsqr', store_covariance=True)

 GridSearchCV(cv=5, estimator=LinearDiscriminantAnalysis(),
             param_grid={'shrinkage': [0.001, 0.01, 0.05, 0.1, 0.5, 1, 'auto',
                                       None],
                         'solver': ['svd', 'lsqr', 'eigen'],
                         'store_covariance': [True, False]})
LinearDiscriminantAnalysis(store_covariance=True)

 GridSearchCV(cv=5, estimator=LinearDiscriminantAnalysis(),
             param_grid={'shrinkage': [0.001, 0.01, 0.05, 0.1, 0.5, 1, 'auto',
                                       None],
                         'solver': ['svd', 'lsqr', 'eigen'],
                         'store_covariance': [True, False]})
LinearDiscriminantAnalysis(shrinkage=0.1, solver='lsqr', store_covariance=True)

 GridSearchCV(cv=5, estimator=LinearDiscriminantAnalysis(),
             param_grid={'shrinkage': [0.001, 0.01, 0.05, 0.1, 0.5, 1, 'auto',
```

```
                                                None],
                                  'solver': ['svd', 'lsqr', 'eigen'],
                                  'store_covariance': [True, False]})
LinearDiscriminantAnalysis(store_covariance=True)
```

Final models and training/testing output

Decision Tree Classifer Model

[63]:
```
#develop the final decision tree classifier from
clf_final = DecisionTreeClassifier(max_depth=6,
                                   random_state=1)
clf_final.fit(train_x03_tx_df03, train_y01_vc01_eda1)
```

[63]:
```
DecisionTreeClassifier(max_depth=6, random_state=1)
```

[64]:
```
#predictions for the training data and test data
clf_train_pred = clf_final.predict(train_x03_tx_df03)
clf_test_pred = clf_final.predict(test_x03_tx_df03)

#return the predicted probabilites into a single variable for training and test
clf_train_prob = clf_final.predict_proba(train_x03_tx_df03)
clf_test_prob = clf_final.predict_proba(test_x03_tx_df03)
```

[65]:
```
#confusion matrix for decision tree training
print("Confusion Matrix for Decision Tree Training")
classificationSummary(train_y01_vc01_eda1,
                      clf_final.predict(train_x03_tx_df03),
                      class_names=class_names)
```

```
Confusion Matrix for Decision Tree Training
Confusion Matrix (Accuracy 0.9576)

              Prediction
       Actual going_concern      bankrupt
going_concern         28654            58
     bankrupt          1222           240
```

[66]:
```
#classifiation report for decision tree training
print("Classification Report for Decision Tree Training")
print(classification_report(train_y01_vc01_eda1,
                            clf_train_pred,
                            target_names=class_names))
```

```
Classification Report for Decision Tree Training
               precision    recall  f1-score   support

going_concern       0.96      1.00      0.98     28712
```

```
     bankrupt       0.81      0.16      0.27      1462

     accuracy                           0.96     30174
    macro avg       0.88      0.58      0.63     30174
 weighted avg       0.95      0.96      0.94     30174
```

[67]:
```
#confusion matrix for decision tree test
print("Confusion Matrix for Decision Tree Test")
classificationSummary(test_y01_vc01,
                      clf_final.predict(test_x03_tx_df03),
                      class_names=class_names)
```

```
Confusion Matrix for Decision Tree Test
Confusion Matrix (Accuracy 0.9522)

              Prediction
       Actual going_concern      bankrupt
going_concern         12347            48
     bankrupt           574            53
```

[68]:
```
#classifiation report for decision tree
print("Classification Report for Decision Tree Test")
print(classification_report(test_y01_vc01,
                            clf_test_pred,
                            target_names=class_names))
```

```
Classification Report for Decision Tree Test
               precision    recall  f1-score   support

going_concern       0.96      1.00      0.98     12395
     bankrupt       0.52      0.08      0.15       627

     accuracy                           0.95     13022
    macro avg       0.74      0.54      0.56     13022
 weighted avg       0.93      0.95      0.94     13022
```

[69]:
```
#Model performance on the test set
classificationSummary(test_y01_vc01,
                      clf_final.predict(test_x03_tx_df03),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {clf_final}:')
print(f'Recall = {recall_score(test_y01_vc01, clf_final.
 ↪predict(test_x03_tx_df03))}')
print(f'Precision = {precision_score(test_y01_vc01, clf_final.
 ↪predict(test_x03_tx_df03))}')
```

```
print(f'F1 = {f1_score(test_y01_vc01, clf_final.predict(test_x03_tx_df03))}')
```

```
Confusion Matrix (Accuracy 0.9522)

              Prediction
       Actual going_concern      bankrupt
going_concern         12347            48
     bankrupt           574            53

Additional Eval Measures for DecisionTreeClassifier(max_depth=6,
random_state=1):
Recall = 0.08452950558213716
Precision = 0.5247524752475248
F1 = 0.14560439560439561
```

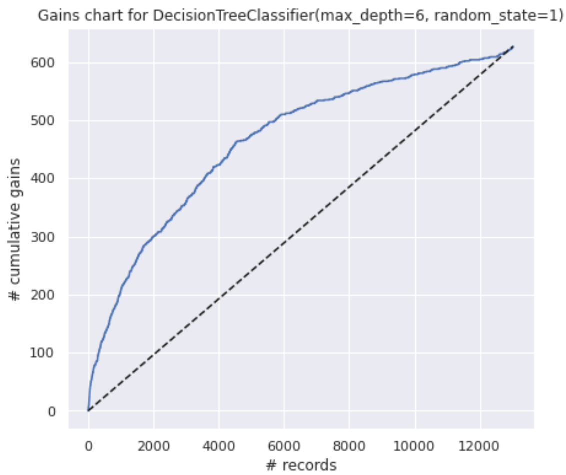
[70]:
```
#create the results dataframe for the full predictor set probability values
test_clf_results = pd.DataFrame({'actual': test_y01_vc01,
                                 'p(0)': [p[0] for p in clf_test_prob],
                                 'p(1)': [p[1] for p in clf_test_prob],
                                 'predicted': clf_test_pred})
test_clf_results = test_clf_results.sort_values(by=['p(1)'],
                                                ascending=False)
test_clf_results.head()
```

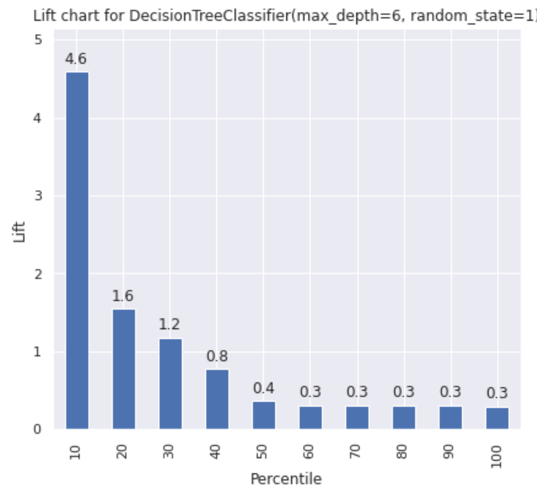
[70]:

	actual	p(0)	p(1)	predicted
6865	0	0.0	1.0	1
273	1	0.0	1.0	1
11038	0	0.0	1.0	1
12710	0	0.0	1.0	1
6314	0	0.0	1.0	1

Lift and Gains charts

[71]:
```
#develop the lift and gain charts for the decision tree classifier
clf_df = test_clf_results.sort_values(by=['p(1)'],
                                      ascending=False)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,6))
gainsChart(clf_df.actual, ax=axes[0])
liftChart(clf_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title(f'Gains chart for {clf_final}')
axes[1].set_title(f'Lift chart for {clf_final}')
plt.show()
```





Random Forests Model

[72]:
```
#develop the final rf model based on the best n_estimators
rf_final = RandomForestClassifier(n_estimators=200,
                                  random_state=1)
rf_final = rf_final.fit(train_x03_tx_df03, train_y01_vc01_eda1)
```

[73]:
```
#create the feature names from the training data
feature_names = train_x03_tx_df03.columns
```

[74]:
```
#predictions for the training data and test data
rf_train_pred = rf_final.predict(train_x03_tx_df03)
rf_test_pred = rf_final.predict(test_x03_tx_df03)

#return the predicted probabilites into a single variable for training and test
rf_train_prob = rf_final.predict_proba(train_x03_tx_df03)
rf_test_prob = rf_final.predict_proba(test_x03_tx_df03)
```

[75]:
```
#confusion matrix for random forest training
print("Confusion Matrix for Random Forest Training")
classificationSummary(train_y01_vc01_eda1,
                      rf_final.predict(train_x03_tx_df03),
                      class_names=class_names)
```

```
Confusion Matrix for Random Forest Training
Confusion Matrix (Accuracy 1.0000)

              Prediction
       Actual going_concern      bankrupt
going_concern         28712             0
```

```
     bankrupt             0          1462
```

[76]:
```python
#classifiation report for random forest training
print("Classification Report for Random Forest Training")
print(classification_report(train_y01_vc01_eda1,
                            rf_train_pred,
                            target_names=class_names))
```

```
Classification Report for Random Forest Training
               precision    recall  f1-score   support

going_concern       1.00      1.00      1.00     28712
     bankrupt       1.00      1.00      1.00      1462

     accuracy                           1.00     30174
    macro avg       1.00      1.00      1.00     30174
 weighted avg       1.00      1.00      1.00     30174
```

[77]:
```python
#confusion matrix for random forest test
print("Confusion Matrix for Random Forest Test")
classificationSummary(test_y01_vc01,
                      rf_final.predict(test_x03_tx_df03),
                      class_names=class_names)
```

```
Confusion Matrix for Random Forest Test
Confusion Matrix (Accuracy 0.9500)

              Prediction
       Actual going_concern      bankrupt
going_concern         12340            55
     bankrupt           596            31
```

[78]:
```python
#classifiation report for random forest
print("Classification Report for Random Forest Test")
print(classification_report(test_y01_vc01,
                            rf_test_pred,
                            target_names=class_names))
```

```
Classification Report for Random Forest Test
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.97     12395
     bankrupt       0.36      0.05      0.09       627

     accuracy                           0.95     13022
    macro avg       0.66      0.52      0.53     13022
 weighted avg       0.93      0.95      0.93     13022
```

[79]:
```
#Model performance on the test set
classificationSummary(test_y01_vc01,
                      rf_final.predict(test_x03_tx_df03),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {rf_final}:')
print(f'Recall = {recall_score(test_y01_vc01, rf_final.
 ↪predict(test_x03_tx_df03))}')
print(f'Precision = {precision_score(test_y01_vc01, rf_final.
 ↪predict(test_x03_tx_df03))}')
print(f'F1 = {f1_score(test_y01_vc01, rf_final.predict(test_x03_tx_df03))}')
```

```
Confusion Matrix (Accuracy 0.9500)

              Prediction
       Actual going_concern      bankrupt
going_concern         12340            55
     bankrupt           596            31

Additional Eval Measures for RandomForestClassifier(n_estimators=200,
random_state=1):
Recall = 0.049441786283891544
Precision = 0.36046511627906974
F1 = 0.08695652173913043
```

[80]:
```
#create the results dataframe for the full predictor set probability values
test_rf_results = pd.DataFrame({'actual': test_y01_vc01,
                                'p(0)': [p[0] for p in rf_test_prob],
                                'p(1)': [p[1] for p in rf_test_prob],
                                'predicted': rf_test_pred})
test_rf_results = test_clf_results.sort_values(by=['p(1)'],ascending=False)
test_rf_results.head()
```

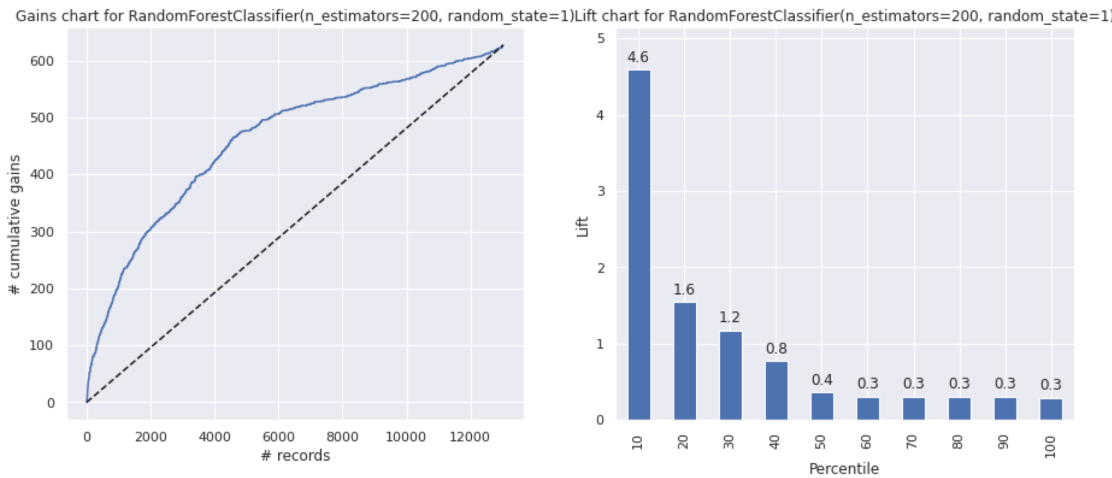
[80]:

	actual	p(0)	p(1)	predicted
6865	0	0.0	1.0	1
7044	1	0.0	1.0	1
12377	1	0.0	1.0	1
3705	1	0.0	1.0	1
7534	1	0.0	1.0	1

Lift and Gains charts

[81]:
```
#develop the lift and gain charts for the decision tree classifier
rf_df = test_rf_results.sort_values(by=['p(1)'],
                                    ascending=False)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,6))
```

```
gainsChart(rf_df.actual, ax=axes[0])
liftChart(rf_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title(f'Gains chart for {rf_final}')
axes[1].set_title(f'Lift chart for {rf_final}')
plt.show()
```



Gradient Boosted Trees (GBT) Models

GBT Model 1

[82]:
```
#Load pickled model
boost_1 = joblib.load(folder_path_mods + '/boost_1')
print(boost_1)

#Model performance on the test set
classificationSummary(test_y01_vc01,
                      boost_1.predict(test_x03_tx_df02),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {boost_1}:')
print(f'Recall = {recall_score(test_y01_vc01, boost_1.
↪predict(test_x03_tx_df02))}')
print(f'Precision = {precision_score(test_y01_vc01, boost_1.
↪predict(test_x03_tx_df02))}')
print(f'F1 = {f1_score(test_y01_vc01, boost_1.predict(test_x03_tx_df02))}')
```

```
GradientBoostingClassifier(n_estimators=500)
Confusion Matrix (Accuracy 0.9201)

              Prediction
       Actual going_concern      bankrupt
```

```
going_concern          11676           719
     bankrupt            321           306

Additional Eval Measures for GradientBoostingClassifier(n_estimators=500):
Recall = 0.4880382775119617
Precision = 0.29853658536585365
F1 = 0.3704600484261501
```

[83]:
```
#predictions for the training data and test data
gbt_train_pred = boost_1.predict(train_x03_tx_df02)
gbt_test_pred = boost_1.predict(test_x03_tx_df02)

#return the predicted probabilites into a single variable for training and test
gbt_train_prob = boost_1.predict_proba(train_x03_tx_df02)
gbt_test_prob = boost_1.predict_proba(test_x03_tx_df02)
```

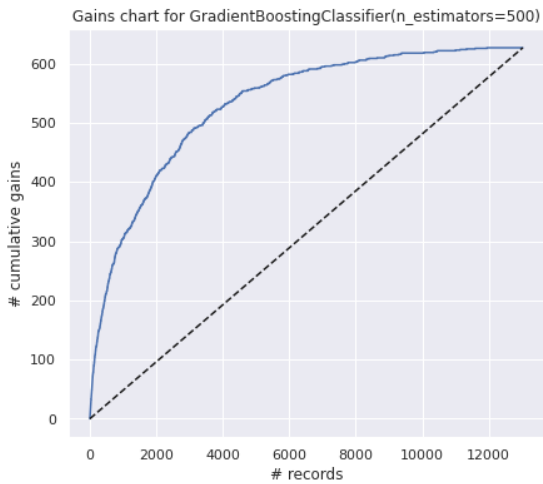
[84]:
```
#create the results dataframe for the full predictor set probability values
test_gbt_results = pd.DataFrame({'actual': test_y01_vc01,
                                 'p(0)': [p[0] for p in gbt_test_prob],
                                 'p(1)': [p[1] for p in gbt_test_prob],
                                 'predicted': gbt_test_pred})

test_gbt_results = test_gbt_results.sort_values(by=['p(1)'],
                                                ascending=False)
test_gbt_results.head()
```

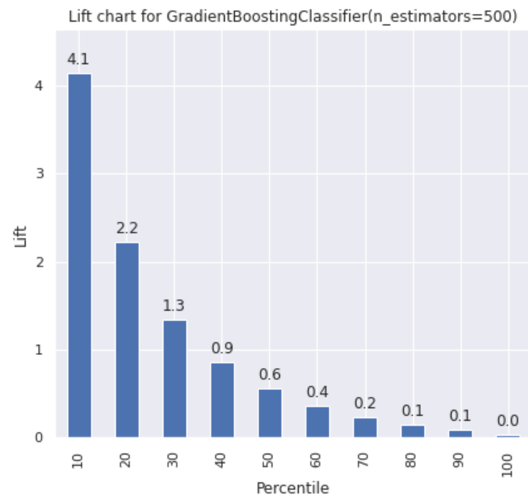
[84]:

	actual	p(0)	p(1)	predicted
6739	1	0.004984	0.995016	1
9096	1	0.012047	0.987953	1
366	1	0.019239	0.980761	1
2907	1	0.019930	0.980070	1
2548	1	0.021847	0.978153	1

Lift and Gains charts

[85]:
```
#develop the lift and gain charts for the decision tree classifier
gbt_df = test_gbt_results.sort_values(by=['p(1)'],
                                      ascending=False)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,6))
gainsChart(gbt_df.actual, ax=axes[0])
liftChart(gbt_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title(f'Gains chart for {boost_1}')
axes[1].set_title(f'Lift chart for {boost_1}')
plt.show()
```





[86]:

```
# Examine evaluation measure impact based on setting ROI cutoff
gbt_df['cum_gains'] = gbt_df['actual'].cumsum()
#gbt_df = gbt_df.loc[gbt_df['actual'] == 1]

variable = 150
print(gbt_df[gbt_df['cum_gains'] == variable])

gbt_df02 = gbt_df.loc[gbt_df['cum_gains'] <= variable]
gbt_df02a = gbt_df.copy()
print(gbt_df02.shape)
print(gbt_df02a.shape)

#Model performance on the test set
classificationSummary(gbt_df02['actual'],
                      gbt_df02['predicted'],
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {boost_1}:')
print(f'Recall = {recall_score(gbt_df02.actual, gbt_df02.predicted)}')
print(f'Precision = {precision_score(gbt_df02.actual, gbt_df02.predicted)}')
print(f'F1 = {f1_score(gbt_df02.actual, gbt_df02.predicted)}')
```

```
      actual      p(0)      p(1)  predicted  cum_gains
1894       1  0.232175  0.767825          1        150
3657       0  0.232388  0.767612          1        150
7555       0  0.233120  0.766880          1        150
(276, 5)
(13022, 5)
Confusion Matrix (Accuracy 0.5435)

              Prediction
```

```
       Actual going_concern      bankrupt
going_concern               0           126
     bankrupt               0           150

Additional Eval Measures for GradientBoostingClassifier(n_estimators=500):
Recall = 1.0
Precision = 0.5434782608695652
F1 = 0.704225352112676
```

GBT Model 2

[87]:
```
#Load pickled model
boost_2 = joblib.load(folder_path_mods + '/boost_2.pickle')
print(boost_2)

#Model performamce on the test set
classificationSummary(test_y01_vc01,
                      boost_2.predict(test_x03_tx_df02),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {boost_2}:')
print(f'Recall = {recall_score(test_y01_vc01, boost_2.
 ↪predict(test_x03_tx_df02))}')
print(f'Precision = {precision_score(test_y01_vc01, boost_2.
 ↪predict(test_x03_tx_df02))}')
print(f'F1 = {f1_score(test_y01_vc01, boost_2.predict(test_x03_tx_df02))}')
```

```
GradientBoostingClassifier(n_estimators=200)
Confusion Matrix (Accuracy 0.8764)

              Prediction
       Actual going_concern      bankrupt
going_concern           11066          1329
     bankrupt             281           346

Additional Eval Measures for GradientBoostingClassifier(n_estimators=200):
Recall = 0.5518341307814992
Precision = 0.20656716417910448
F1 = 0.3006081668114683
```

GBT Model 3

[88]:
```
#Load pickled model
boost_3 = joblib.load(folder_path_mods + '/boost_3')
print(boost_3)

#Model performamce on the test set
classificationSummary(test_y01_vc01,
                      boost_3.predict(test_x03_tx_df02),
```

```
                          class_names=class_names)
print(f'\nAdditional Eval Measures for {boost_3}:')
print(f'Recall = {recall_score(test_y01_vc01, boost_3.
 ↪predict(test_x03_tx_df02))}')
print(f'Precision = {precision_score(test_y01_vc01, boost_3.
 ↪predict(test_x03_tx_df02))}')
print(f'F1 = {f1_score(test_y01_vc01, boost_3.predict(test_x03_tx_df02))}')
```

```
GradientBoostingClassifier(n_estimators=200)
Confusion Matrix (Accuracy 0.8227)

              Prediction
       Actual going_concern      bankrupt
going_concern         10272          2123
     bankrupt           186           441

Additional Eval Measures for GradientBoostingClassifier(n_estimators=200):
Recall = 0.7033492822966507
Precision = 0.17199687987519502
F1 = 0.27640238169852716
```

GBT Model 4

[89]:
```
#Load pickled model
boost_4 = joblib.load(folder_path_mods + '/boost_4')
print(boost_4)

#Model performamce on the test set
classificationSummary(test_y01_vc01,
                          boost_4.predict(test_x03_tx_df03),
                          class_names=class_names)
print(f'\nAdditional Eval Measures for {boost_4}:')
print(f'Recall = {recall_score(test_y01_vc01, boost_4.
 ↪predict(test_x03_tx_df03))}')
print(f'Precision = {precision_score(test_y01_vc01, boost_4.
 ↪predict(test_x03_tx_df03))}')
print(f'F1 = {f1_score(test_y01_vc01, boost_4.predict(test_x03_tx_df03))}')
```

```
GradientBoostingClassifier(n_estimators=200)
Confusion Matrix (Accuracy 0.2995)

              Prediction
       Actual going_concern      bankrupt
going_concern          3315          9080
     bankrupt            42           585

Additional Eval Measures for GradientBoostingClassifier(n_estimators=200):
```

```
Recall = 0.9330143540669856
Precision = 0.060527677185721676
F1 = 0.1136805285658764
```

XGBoost Models

XGBoost Model 1

[90]:
```
#Load pickled model
xgboost_1 = joblib.load(folder_path_mods + '/xgboost_1.pickle')
print(xgboost_1)

#Model performamce on the test set
classificationSummary(test_y01_vc01,
                      xgboost_1.predict(test_x03_tx_df02),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {xgboost_1}:')
print(f'Recall = {recall_score(test_y01_vc01, xgboost_1.
 ↪predict(test_x03_tx_df02))}')
print(f'Precision = {precision_score(test_y01_vc01, xgboost_1.
 ↪predict(test_x03_tx_df02))}')
print(f'F1 = {f1_score(test_y01_vc01, xgboost_1.predict(test_x03_tx_df02))}')
```

```
XGBClassifier(missing=nan, n_estimators=200)
Confusion Matrix (Accuracy 0.8187)

              Prediction
       Actual going_concern      bankrupt
going_concern         10206          2189
     bankrupt           172           455

Additional Eval Measures for XGBClassifier(missing=nan, n_estimators=200):
Recall = 0.7256778309409888
Precision = 0.1720877458396369
F1 = 0.2782023845918679
```

[91]:
```
#predictions for the training data and test data
xgb_train_pred = xgboost_1.predict(train_x03_tx_df02)
xgb_test_pred = xgboost_1.predict(test_x03_tx_df02)

#return the predicted probabilites into a single variable for training and test
xgb_train_prob = xgboost_1.predict_proba(train_x03_tx_df02)
xgb_test_prob = xgboost_1.predict_proba(test_x03_tx_df02)
```

[92]:
```
#create the results dataframe for the full predictor set probability values
test_xgb_results = pd.DataFrame({'actual': test_y01_vc01,
                                 'p(0)': [p[0] for p in xgb_test_prob],
```

```
                                     'p(1)': [p[1] for p in xgb_test_prob],
                                     'predicted': xgb_test_pred})

test_xgb_results = test_xgb_results.sort_values(by=['p(1)'],ascending=False)

test_xgb_results.head()
```

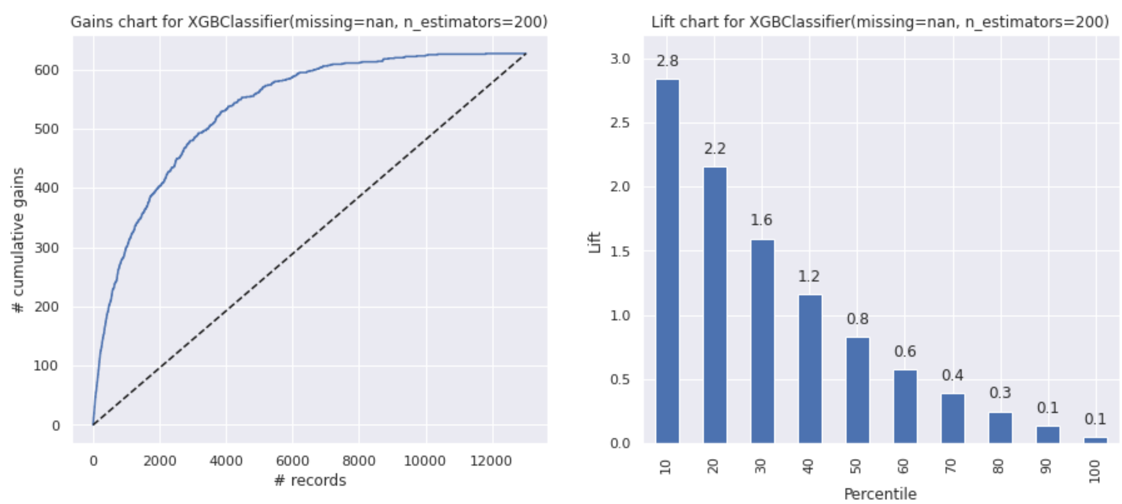
[92]:

	actual	p(0)	p(1)	predicted
1811	1	0.026374	0.973626	1
11267	0	0.033347	0.966653	1
10998	1	0.033360	0.966640	1
7095	0	0.036633	0.963367	1
3113	1	0.037111	0.962889	1

Lift and Gains charts

[93]:

```
#develop the lift and gain charts
xgb_df = test_xgb_results.sort_values(by=['p(1)'],
                                      ascending=False)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,6))
gainsChart(xgb_df.actual, ax=axes[0])
liftChart(xgb_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title(f'Gains chart for {xgboost_1}')
axes[1].set_title(f'Lift chart for {xgboost_1}')
plt.show()
```



XGBoost Model 2

```
[94]: #Load pickled model
xgboost_2 = joblib.load(folder_path_mods + '/xgboost_2')
print(xgboost_2)

#Model performamce on the test set
classificationSummary(test_y01_vc01,
                      xgboost_2.predict(test_x03_tx_df03),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {xgboost_2}:')
print(f'Recall = {recall_score(test_y01_vc01, xgboost_2.
 ↪predict(test_x03_tx_df03))}')
print(f'Precision = {precision_score(test_y01_vc01, xgboost_2.
 ↪predict(test_x03_tx_df03))}')
print(f'F1 = {f1_score(test_y01_vc01, xgboost_2.predict(test_x03_tx_df03))}')
```

```
XGBClassifier(missing=nan, n_estimators=200)
Confusion Matrix (Accuracy 0.2303)

              Prediction
       Actual going_concern      bankrupt
going_concern          2382         10013
     bankrupt            10           617

Additional Eval Measures for XGBClassifier(missing=nan, n_estimators=200):
Recall = 0.9840510366826156
Precision = 0.058043273753527753
F1 = 0.10962068046548816
```

Neural Network Model

```
[95]: #Load pickled model
NN_tune = joblib.load(folder_path_mods + '/NN_tune')
print(NN_tune)

#Model performamce on the test set
classificationSummary(test_y01_vc01,
                      NN_tune.predict(test_x03_tx_df02),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {NN_tune}:')
print(f'Recall = {recall_score(test_y01_vc01, NN_tune.
 ↪predict(test_x03_tx_df02))}')
print(f'Precision = {precision_score(test_y01_vc01, NN_tune.
 ↪predict(test_x03_tx_df02))}')
print(f'F1 = {f1_score(test_y01_vc01, NN_tune.predict(test_x03_tx_df02))}')
```

```
GridSearchCV(cv=2, estimator=MLPClassifier(max_iter=100), n_jobs=-1,
             param_grid={'activation': ['identity', 'logistic', 'tanh', 'relu'],
                         'alpha': [0.0001, 0.05],
```

```
                        'hidden_layer_sizes': [(20, 20, 20), (20,)],
                        'learning_rate': ['constant', 'adaptive'],
                        'solver': ['sgd', 'adam']})
Confusion Matrix (Accuracy 0.5900)

              Prediction
       Actual going_concern      bankrupt
going_concern          7222          5173
     bankrupt           166           461

Additional Eval Measures for GridSearchCV(cv=2,
estimator=MLPClassifier(max_iter=100), n_jobs=-1,
             param_grid={'activation': ['identity', 'logistic', 'tanh', 'relu'],
                         'alpha': [0.0001, 0.05],
                         'hidden_layer_sizes': [(20, 20, 20), (20,)],
                         'learning_rate': ['constant', 'adaptive'],
                         'solver': ['sgd', 'adam']}):
Recall = 0.7352472089314195
Precision = 0.08182463613773518
F1 = 0.147260820955119
```

[96]:
```python
#predictions for the training data and test data
nn_train_pred = NN_tune.predict(train_x03_tx_df02)
nn_test_pred = NN_tune.predict(test_x03_tx_df02)

#return the predicted probabilites into a single variable for training and test
nn_train_prob = NN_tune.predict_proba(train_x03_tx_df02)
nn_test_prob = NN_tune.predict_proba(test_x03_tx_df02)
```

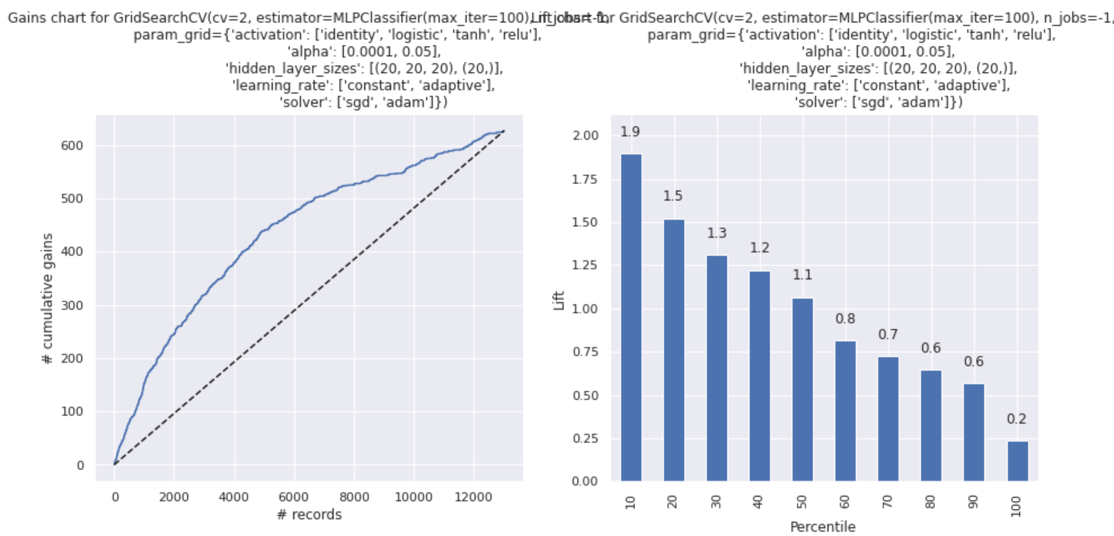
[97]:
```python
#create the results dataframe for the full predictor set probability values
test_nn_results = pd.DataFrame({'actual': test_y01_vc01,
                                'p(0)': [p[0] for p in nn_test_prob],
                                'p(1)': [p[1] for p in nn_test_prob],
                                'predicted': nn_test_pred})

test_nn_results = test_nn_results.sort_values(by=['p(1)'],
                                              ascending=False)

test_nn_results.head()
```

[97]:

	actual	p(0)	p(1)	predicted
1629	0	0.035471	0.964529	1
10651	0	0.045020	0.954980	1
6969	0	0.045575	0.954425	1
5584	1	0.045575	0.954425	1
11632	0	0.052656	0.947344	1

Lift and Gains charts

[98]:
```
#develop the lift and gain charts
nn_df = test_nn_results.sort_values(by=['p(1)'],
                                    ascending=False)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,6))
gainsChart(nn_df.actual, ax=axes[0])
liftChart(nn_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title(f'Gains chart for {NN_tune}')
axes[1].set_title(f'Lift chart for {NN_tune}')
plt.show()
```



K-nearest neighbors (KNN) Models

[99]:
```
#reassign knn pick filepath varialbes to knn_final models
knn_final_1 = knn_mod_v1_fit
knn_final_2 = knn_mod_v2_fit
knn_final_3 = knn_mod_v3_fit
knn_final_4 = knn_mod_v4_fit
```

KNN Model 1

[100]:
```
#predictions for the training data and test data
knn_train_pred = knn_final_1.predict(train_x03_tx_df03)
knn_test_pred = knn_final_1.predict(test_x03_tx_df03)

#return the predicted probabilites into a single variable for training and test
knn_train_prob = knn_final_1.predict_proba(train_x03_tx_df03)
knn_test_prob = knn_final_1.predict_proba(test_x03_tx_df03)
```

[101]:
```
#confusion matrix for KNN_1training
print("Confusion Matrix for KNN_1 Training")
classificationSummary(train_y01_vc01_eda1,
                      knn_train_pred,
                      class_names=class_names)
```

```
Confusion Matrix for KNN_1 Training
Confusion Matrix (Accuracy 0.9518)

              Prediction
       Actual going_concern      bankrupt
going_concern         28700            12
     bankrupt          1442            20
```

[102]:
```
#classifiation report for KNN_1 training
print("Classification Report for KNN_1 Training")
print(classification_report(train_y01_vc01_eda1,
                            knn_train_pred,
                            target_names=class_names))
```

```
Classification Report for KNN_1 Training
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.98     28712
     bankrupt       0.62      0.01      0.03      1462

     accuracy                           0.95     30174
    macro avg       0.79      0.51      0.50     30174
 weighted avg       0.94      0.95      0.93     30174
```

[103]:
```
#confusion matrix for KNN_1 test
print("Confusion Matrix for KNN_1 Test")
classificationSummary(test_y01_vc01,
                      knn_test_pred,
                      class_names=class_names)
```

```
Confusion Matrix for KNN_1 Test
Confusion Matrix (Accuracy 0.9515)

              Prediction
       Actual going_concern      bankrupt
going_concern         12389             6
     bankrupt           626             1
```

[104]:
```
#classifiation report for KNN_1 test
print("Classification Report for KNN_1 Test")
print(classification_report(test_y01_vc01,
```

```
                            knn_test_pred,
                            target_names=class_names))
```

```
Classification Report for KNN_1 Test
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.98     12395
     bankrupt       0.14      0.00      0.00       627

     accuracy                           0.95     13022
    macro avg       0.55      0.50      0.49     13022
 weighted avg       0.91      0.95      0.93     13022
```

KNN Model 2

[105]:
```
#predictions for the training data and test data
knn_train_pred2 = knn_final_2.predict(train_x03_tx_df03a)
knn_test_pred2 = knn_final_2.predict(test_x03_tx_df03)

#return the predicted probabilites into a single variable for training and test
knn_train_prob2 = knn_final_2.predict_proba(train_x03_tx_df03a)
knn_test_prob2 = knn_final_2.predict_proba(test_x03_tx_df03)
```

[106]:
```
#confusion matrix for KNN_2 training
print("Confusion Matrix for KNN_2 Training")
classificationSummary(train_y01_vc01_eda1a,
                      knn_train_pred2,
                      class_names=class_names)
```

```
Confusion Matrix for KNN_2 Training
Confusion Matrix (Accuracy 1.0000)

              Prediction
       Actual going_concern      bankrupt
going_concern         28712             0
     bankrupt             0         28712
```

[107]:
```
#classifiation report for KNN_2 training
print("Classification Report for KNN_2 Training")
print(classification_report(train_y01_vc01_eda1a,
                            knn_train_pred2,
                            target_names=class_names))
```

```
Classification Report for KNN_2 Training
               precision    recall  f1-score   support

going_concern       1.00      1.00      1.00     28712
```

```
     bankrupt       1.00      1.00      1.00     28712

     accuracy                           1.00     57424
    macro avg       1.00      1.00      1.00     57424
 weighted avg       1.00      1.00      1.00     57424
```

[108]:
```
#confusion matrix for KNN_2 test
print("Confusion Matrix for KNN_2 Test")
classificationSummary(test_y01_vc01,
                      knn_test_pred2,
                      class_names=class_names)
```

```
Confusion Matrix for KNN_2 Test
Confusion Matrix (Accuracy 0.8656)

              Prediction
       Actual going_concern      bankrupt
going_concern         11085          1310
     bankrupt           440           187
```

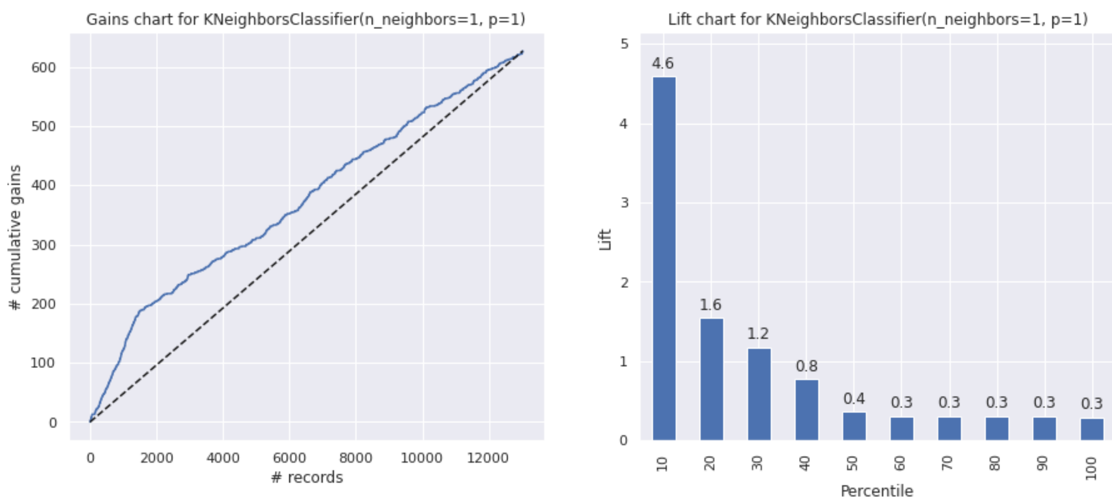
[109]:
```
#classifiation report for KNN_2 test
print("Classification Report for KNN_2 Test")
print(classification_report(test_y01_vc01,
                            knn_test_pred2,
                            target_names=class_names))
```

```
Classification Report for KNN_2 Test
               precision    recall  f1-score   support

going_concern       0.96      0.89      0.93     12395
     bankrupt       0.12      0.30      0.18       627

     accuracy                           0.87     13022
    macro avg       0.54      0.60      0.55     13022
 weighted avg       0.92      0.87      0.89     13022
```

[110]:
```
#create the results dataframe for the full predictor set probability values
test_knn2_results = pd.DataFrame({'actual': test_y01_vc01,
                                  'p(0)': [p[0] for p in knn_test_prob2],
                                  'p(1)': [p[1] for p in knn_test_prob2],
                                  'predicted': knn_test_pred2})
test_knn2_results = test_knn2_results.sort_values(by=['p(1)'],ascending=False)
#test_knn3_results.head()
```

Lift and Gains charts

[111]:
```
#develop the lift and gain charts for the decision tree classifier
knn_df_2 = test_knn2_results.sort_values(by=['p(1)'],
                                        ascending=False)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,6))
gainsChart(knn_df_2.actual, ax=axes[0])
liftChart(rf_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title(f'Gains chart for {knn_final_2}')
axes[1].set_title(f'Lift chart for {knn_final_2}')
plt.show()
```



KNN Model 3

[112]:
```
#predictions for the training data and test data
knn_train_pred3 = knn_final_3.predict(train_x03_tx_df05)
knn_test_pred3 = knn_final_3.predict(test_x03_tx_df05)

#return the predicted probabilites into a single variable for training and test
knn_train_prob3 = knn_final_3.predict_proba(train_x03_tx_df05)
knn_test_prob3 = knn_final_3.predict_proba(test_x03_tx_df05)
```

[113]:
```
#confusion matrix for KNN_3 training
print("Confusion Matrix for KNN_3 Training")
classificationSummary(train_y01_vc01_eda1,
                      knn_train_pred3,
                      class_names=class_names)
```

```
Confusion Matrix for KNN_3 Training
Confusion Matrix (Accuracy 0.9518)
```

```
              Prediction
       Actual going_concern      bankrupt
going_concern         28706             6
     bankrupt          1449            13
```

[114]:
```python
#classifiation report for KNN_3 training
print("Classification Report for KNN_3 Training")
print(classification_report(train_y01_vc01_eda1,
                            knn_train_pred3,
                            target_names=class_names))
```

```
Classification Report for KNN_3 Training
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.98     28712
     bankrupt       0.68      0.01      0.02      1462

     accuracy                           0.95     30174
    macro avg       0.82      0.50      0.50     30174
 weighted avg       0.94      0.95      0.93     30174
```

[115]:
```python
#confusion matrix for KNN_3 test
print("Confusion Matrix for KNN_3 Test")
classificationSummary(test_y01_vc01,
                      knn_test_pred3,
                      class_names=class_names)
```

```
Confusion Matrix for KNN_3 Test
Confusion Matrix (Accuracy 0.9519)

              Prediction
       Actual going_concern      bankrupt
going_concern         12392             3
     bankrupt           623             4
```

[116]:
```python
#classifiation report for KNN_3 test
print("Classification Report for KNN_3 Test")
print(classification_report(test_y01_vc01,
                            knn_test_pred3,
                            target_names=class_names))
```

```
Classification Report for KNN_3 Test
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.98     12395
     bankrupt       0.57      0.01      0.01       627
```

```
    accuracy                           0.95     13022
   macro avg       0.76      0.50      0.49     13022
weighted avg       0.93      0.95      0.93     13022
```

KNN Model 4

[117]:
```
#predictions for the training data and test data
knn_train_pred4 = knn_final_4.predict(train_x03_tx_df05a)
knn_test_pred4 = knn_final_4.predict(test_x03_tx_df03)

#return the predicted probabilites into a single variable for training and test
knn_train_prob4 = knn_final_4.predict_proba(train_x03_tx_df05a)
knn_test_prob4 = knn_final_4.predict_proba(test_x03_tx_df03)
```

[118]:
```
#confusion matrix for KNN_4 training
print("Confusion Matrix for KNN_4 Training")
classificationSummary(train_y01_vc01_eda1c,
                      knn_train_pred4,
                      class_names=class_names)
```

```
Confusion Matrix for KNN_4 Training
Confusion Matrix (Accuracy 1.0000)

              Prediction
       Actual going_concern      bankrupt
going_concern         28712             0
     bankrupt             0         28712
```

[119]:
```
#classifiation report for KNN_4 training
print("Classification Report for KNN_4 Training")
print(classification_report(train_y01_vc01_eda1c,
                            knn_train_pred4,
                            target_names=class_names))
```

```
Classification Report for KNN_4 Training
               precision    recall  f1-score   support

going_concern       1.00      1.00      1.00     28712
     bankrupt       1.00      1.00      1.00     28712

     accuracy                           1.00     57424
    macro avg       1.00      1.00      1.00     57424
 weighted avg       1.00      1.00      1.00     57424
```

[120]:
```
#confusion matrix for KNN_4 test
print("Confusion Matrix for KNN_4 Test")
```

```
classificationSummary(test_y01_vc01,
                      knn_test_pred4,
                      class_names=class_names)
```

```
Confusion Matrix for KNN_4 Test
Confusion Matrix (Accuracy 0.9371)

              Prediction
       Actual going_concern      bankrupt
going_concern         12195           200
     bankrupt           619             8
```

[121]:
```
#classifiation report for KNN_4 test
print("Classification Report for KNN_4 Test")
print(classification_report(test_y01_vc01,
                            knn_test_pred4,
                            target_names=class_names))
```

```
Classification Report for KNN_4 Test
               precision    recall  f1-score   support

going_concern       0.95      0.98      0.97     12395
     bankrupt       0.04      0.01      0.02       627

     accuracy                           0.94     13022
    macro avg       0.50      0.50      0.49     13022
 weighted avg       0.91      0.94      0.92     13022
```

Linear Discriminant Analysis (LDA) Models

[122]:
```
lda_final_1 = lda_mod_v1_fit
lda_final_2 = lda_mod_v2_fit
lda_final_3 = lda_mod_v3_fit
lda_final_4 = lda_mod_v4_fit
```

LDA Model 1

[123]:
```
#predictions for the training data and test data
lda_train_pred1 = lda_final_1.predict(train_x03_tx_df03)
lda_test_pred1 = lda_final_1.predict(test_x03_tx_df03)

#return the predicted probabilites into a single variable for training and test
lda_train_prob1 = lda_final_1.predict_proba(train_x03_tx_df03)
lda_test_prob1 = lda_final_1.predict_proba(test_x03_tx_df03)
```

[124]:
```
#confusion matrix for LDA_1training
print("Confusion Matrix for LDA_1 Training")
classificationSummary(train_y01_vc01_eda1,
                      lda_final_1.predict(train_x03_tx_df03),
                      class_names=class_names)
```

```
Confusion Matrix for LDA_1 Training
Confusion Matrix (Accuracy 0.9513)

              Prediction
       Actual going_concern      bankrupt
going_concern         28699            13
     bankrupt          1455             7
```

[125]:
```
#classifiation report for LDA_1 training
print("Classification Report for LDA_1 Training")
print(classification_report(train_y01_vc01_eda1,
                            lda_train_pred1,
                            target_names=class_names))
```

```
Classification Report for LDA_1 Training
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.98     28712
     bankrupt       0.35      0.00      0.01      1462

     accuracy                           0.95     30174
    macro avg       0.65      0.50      0.49     30174
 weighted avg       0.92      0.95      0.93     30174
```

[126]:
```
#confusion matrix for LDA_1 test
print("Confusion Matrix for LDA_1 Test")
classificationSummary(test_y01_vc01,
                      lda_final_1.predict(test_x03_tx_df03),
                      class_names=class_names)
```

```
Confusion Matrix for LDA_1 Test
Confusion Matrix (Accuracy 0.9517)

              Prediction
       Actual going_concern      bankrupt
going_concern         12391             4
     bankrupt           625             2
```

[127]:
```
#classifiation report for LDA_1 test
print("Classification Report for LDA_1 Test")
print(classification_report(test_y01_vc01,
```

```
                             lda_test_pred1,
                             target_names=class_names))
```

```
Classification Report for LDA_1 Test
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.98     12395
     bankrupt       0.33      0.00      0.01       627

     accuracy                           0.95     13022
    macro avg       0.64      0.50      0.49     13022
 weighted avg       0.92      0.95      0.93     13022
```

[128]:
```
#Model performance on the test set
classificationSummary(test_y01_vc01,
                      lda_final_1.predict(test_x03_tx_df03),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {lda_final_1}:')
print(f'Recall = {recall_score(test_y01_vc01, lda_final_1.
 ↪predict(test_x03_tx_df03))}')
print(f'Precision = {precision_score(test_y01_vc01, lda_final_1.
 ↪predict(test_x03_tx_df03))}')
print(f'F1 = {f1_score(test_y01_vc01, lda_final_1.predict(test_x03_tx_df03))}')
```

```
Confusion Matrix (Accuracy 0.9517)

              Prediction
       Actual going_concern      bankrupt
going_concern         12391             4
     bankrupt           625             2

Additional Eval Measures for LinearDiscriminantAnalysis(shrinkage=0.5,
solver='lsqr', store_covariance=True):
Recall = 0.003189792663476874
Precision = 0.3333333333333333
F1 = 0.006319115323854660
```

LDA Model 2

[129]:
```
#predictions for the training data and test data
lda_train_pred2 = lda_final_2.predict(train_x03_tx_df03a)
lda_test_pred2 = lda_final_2.predict(test_x03_tx_df03)

#return the predicted probabilites into a single variable for training and test
lda_train_prob2 = lda_final_2.predict_proba(train_x03_tx_df03a)
lda_test_prob2 = lda_final_2.predict_proba(test_x03_tx_df03)
```

[130]:
```
#confusion matrix for LDA_2 training
print("Confusion Matrix for LDA_2 Training")
classificationSummary(train_y01_vc01_eda1a,
                      lda_final_2.predict(train_x03_tx_df03a),
                      class_names=class_names)
```

```
Confusion Matrix for LDA_2 Training
Confusion Matrix (Accuracy 0.5703)

              Prediction
       Actual going_concern      bankrupt
going_concern         16581         12131
     bankrupt         12544         16168
```

[131]:
```
#classifiation report for LDA_2 training
print("Classification Report for LDA_2 Training")
print(classification_report(train_y01_vc01_eda1a,
                            lda_train_pred2,
                            target_names=class_names))
```

```
Classification Report for LDA_2 Training
               precision    recall  f1-score   support

going_concern       0.57      0.58      0.57     28712
     bankrupt       0.57      0.56      0.57     28712

     accuracy                           0.57     57424
    macro avg       0.57      0.57      0.57     57424
 weighted avg       0.57      0.57      0.57     57424
```

[132]:
```
#confusion matrix for LDA_2 test
print("Confusion Matrix for LDA_2 Test")
classificationSummary(test_y01_vc01,
                      lda_final_2.predict(test_x03_tx_df03),
                      class_names=class_names)
```

```
Confusion Matrix for LDA_2 Test
Confusion Matrix (Accuracy 0.5819)

              Prediction
       Actual going_concern      bankrupt
going_concern          7223          5172
     bankrupt           272           355
```

[133]:
```
#classifiation report for LDA_2 test
print("Classification Report for LDA_2 Test")
print(classification_report(test_y01_vc01,
```

```
                              lda_test_pred2,
                              target_names=class_names))
```

```
Classification Report for LDA_2 Test
               precision    recall  f1-score   support

going_concern       0.96      0.58      0.73     12395
     bankrupt       0.06      0.57      0.12       627

     accuracy                           0.58     13022
    macro avg       0.51      0.57      0.42     13022
 weighted avg       0.92      0.58      0.70     13022
```

[134]:
```
#Model performance on the test set
classificationSummary(test_y01_vc01,
                      lda_final_2.predict(test_x03_tx_df03),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {lda_final_2}:')
print(f'Recall = {recall_score(test_y01_vc01, lda_final_2.
 ↪predict(test_x03_tx_df03))}')
print(f'Precision = {precision_score(test_y01_vc01, lda_final_2.
 ↪predict(test_x03_tx_df03))}')
print(f'F1 = {f1_score(test_y01_vc01, lda_final_2.predict(test_x03_tx_df03))}')
```

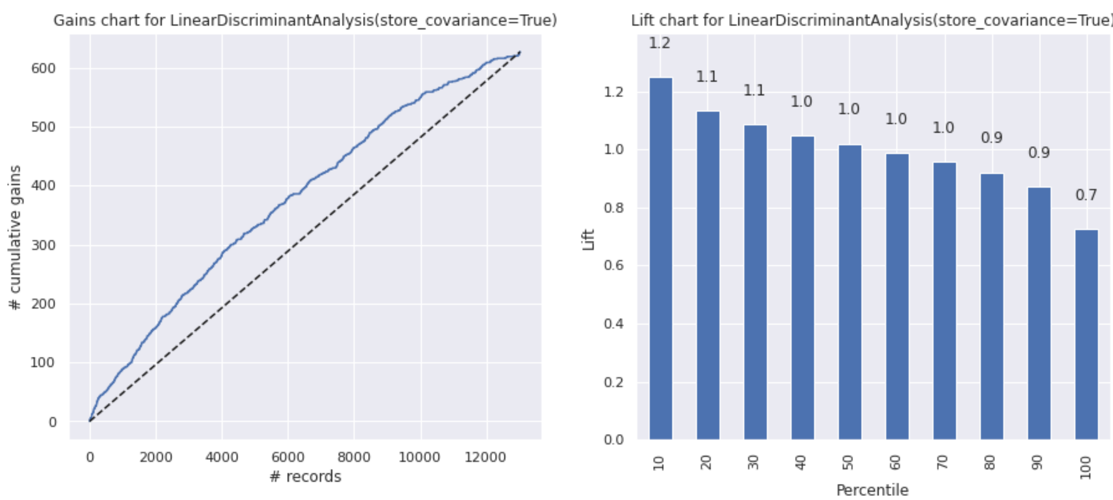
```
Confusion Matrix (Accuracy 0.5819)

              Prediction
       Actual going_concern      bankrupt
going_concern          7223          5172
     bankrupt           272           355

Additional Eval Measures for LinearDiscriminantAnalysis(store_covariance=True):
Recall = 0.5661881977671451
Precision = 0.06423014293468428
F1 = 0.11537211569710756
```

[135]:
```
#create the results dataframe for the full predictor set probability values
test_lda2_results = pd.DataFrame({'actual': test_y01_vc01,
                                  'p(0)': [p[0] for p in lda_test_prob2],
                                  'p(1)': [p[1] for p in lda_test_prob2],
                                  'predicted': lda_test_pred2})

test_lda2_results = test_lda2_results.sort_values(by=['p(1)'],
                                                  ascending=False)
test_lda2_results.head()
```

[135]:
```
      actual          p(0)      p(1)  predicted
8158       1  4.440892e-16  1.000000          1
2134       0  3.344583e-03  0.996655          1
1252       0  1.534000e-02  0.984660          1
711        0  2.123494e-02  0.978765          1
194        0  6.474752e-02  0.935252          1
```

Lift and Gains charts

[136]:
```python
#develop the lift and gain charts for the decision tree classifier
lda2_df = test_lda2_results.sort_values(by=['p(1)'],
                                        ascending=False)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,6))
gainsChart(lda2_df.actual, ax=axes[0])
liftChart(lda2_df['p(1)'], title=False, ax=axes[1])
axes[0].set_title(f'Gains chart for {lda_final_2}')
axes[1].set_title(f'Lift chart for {lda_final_2}')
plt.show()
```



LDA Model 3

[137]:
```python
#predictions for the training data and test data
lda_train_pred3 = lda_final_3.predict(train_x03_tx_df05)
lda_test_pred3 = lda_final_3.predict(test_x03_tx_df05)

#return the predicted probabilites into a single variable for training and test
lda_train_prob3 = lda_final_3.predict_proba(train_x03_tx_df05)
lda_test_prob3 = lda_final_3.predict_proba(test_x03_tx_df05)
```

[138]:
```
#confusion matrix for LDA_3 training
print("Confusion Matrix for LDA_3 Training")
classificationSummary(train_y01_vc01_eda1,
                      lda_final_3.predict(train_x03_tx_df05),
                      class_names=class_names)
```

```
Confusion Matrix for LDA_3 Training
Confusion Matrix (Accuracy 0.9503)

              Prediction
       Actual going_concern      bankrupt
going_concern         28650            62
     bankrupt          1439            23
```

[139]:
```
#classifiation report for LDA_3 training
print("Classification Report for LDA_3 Training")
print(classification_report(train_y01_vc01_eda1,
                            lda_train_pred3,
                            target_names=class_names))
```

```
Classification Report for LDA_3 Training
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.97     28712
     bankrupt       0.27      0.02      0.03      1462

     accuracy                           0.95     30174
    macro avg       0.61      0.51      0.50     30174
 weighted avg       0.92      0.95      0.93     30174
```

[140]:
```
#confusion matrix for LDA_3 test
print("Confusion Matrix for LDA_3 Test")
classificationSummary(test_y01_vc01,
                      lda_final_3.predict(test_x03_tx_df05),
                      class_names=class_names)
```

```
Confusion Matrix for LDA_3 Test
Confusion Matrix (Accuracy 0.9503)

              Prediction
       Actual going_concern      bankrupt
going_concern         12364            31
     bankrupt           616            11
```

[141]:
```
#classifiation report for LDA_3 test
print("Classification Report for LDA_3 Test")
print(classification_report(test_y01_vc01,
```

```
                                    lda_test_pred3,
                                    target_names=class_names))
```

```
Classification Report for LDA_3 Test
               precision    recall  f1-score   support

going_concern       0.95      1.00      0.97     12395
     bankrupt       0.26      0.02      0.03       627

     accuracy                           0.95     13022
    macro avg       0.61      0.51      0.50     13022
 weighted avg       0.92      0.95      0.93     13022
```

[142]:
```
#Model performance on the test set
classificationSummary(test_y01_vc01,
                      lda_final_3.predict(test_x03_tx_df05),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {lda_final_3}:')
print(f'Recall = {recall_score(test_y01_vc01, lda_final_3.
 ↪predict(test_x03_tx_df05))}')
print(f'Precision = {precision_score(test_y01_vc01, lda_final_3.
 ↪predict(test_x03_tx_df05))}')
print(f'F1 = {f1_score(test_y01_vc01, lda_final_3.predict(test_x03_tx_df05))}')
```

```
Confusion Matrix (Accuracy 0.9503)

              Prediction
       Actual going_concern      bankrupt
going_concern         12364            31
     bankrupt           616            11

Additional Eval Measures for LinearDiscriminantAnalysis(shrinkage=0.1,
solver='lsqr', store_covariance=True):
Recall = 0.017543859649122806
Precision = 0.2619047619047619
F1 = 0.032884902840059786
```

LDA Model 4

[143]:
```
#predictions for the training data and test data
lda_train_pred4 = lda_final_4.predict(train_x03_tx_df05a)
lda_test_pred4 = lda_final_4.predict(test_x03_tx_df03)

#return the predicted probabilites into a single variable for training and test
lda_train_prob4 = lda_final_4.predict_proba(train_x03_tx_df05a)
lda_test_prob4 = lda_final_4.predict_proba(test_x03_tx_df03)
```

[144]:
```
#confusion matrix for LDA_4 training
print("Confusion Matrix for LDA_4 Training")
classificationSummary(train_y01_vc01_eda1c,
                      lda_final_4.predict(train_x03_tx_df05a),
                      class_names=class_names)
```

```
Confusion Matrix for LDA_4 Training
Confusion Matrix (Accuracy 0.6715)

              Prediction
       Actual going_concern      bankrupt
going_concern         19346          9366
     bankrupt          9499         19213
```

[145]:
```
#classifiation report for LDA_4 training
print("Classification Report for LDA_4 Training")
print(classification_report(train_y01_vc01_eda1c,
                            lda_train_pred4,
                            target_names=class_names))
```

```
Classification Report for LDA_4 Training
               precision    recall  f1-score   support

going_concern       0.67      0.67      0.67     28712
     bankrupt       0.67      0.67      0.67     28712

     accuracy                           0.67     57424
    macro avg       0.67      0.67      0.67     57424
 weighted avg       0.67      0.67      0.67     57424
```

[146]:
```
#confusion matrix for LDA_4 test
print("Confusion Matrix for LDA_4 Test")
classificationSummary(test_y01_vc01,
                      lda_final_4.predict(test_x03_tx_df03),
                      class_names=class_names)
```

```
Confusion Matrix for LDA_4 Test
Confusion Matrix (Accuracy 0.8633)

              Prediction
       Actual going_concern      bankrupt
going_concern         11102          1293
     bankrupt           487           140
```

[147]:
```
#classifiation report for LDA_4 test
print("Classification Report for LDA_4 Test")
print(classification_report(test_y01_vc01,
```

```
                                lda_test_pred4,
                                target_names=class_names))
```

```
Classification Report for LDA_4 Test
               precision    recall  f1-score   support

going_concern       0.96      0.90      0.93     12395
     bankrupt       0.10      0.22      0.14       627

     accuracy                           0.86     13022
    macro avg       0.53      0.56      0.53     13022
 weighted avg       0.92      0.86      0.89     13022
```

[148]:
```
#Model performance on the test set
classificationSummary(test_y01_vc01,
                      lda_final_4.predict(test_x03_tx_df03),
                      class_names=class_names)
print(f'\nAdditional Eval Measures for {lda_final_4}:')
print(f'Recall = {recall_score(test_y01_vc01, lda_final_4.
 ↪predict(test_x03_tx_df03))}')
print(f'Precision = {precision_score(test_y01_vc01, lda_final_4.
 ↪predict(test_x03_tx_df03))}')
print(f'F1 = {f1_score(test_y01_vc01, lda_final_4.predict(test_x03_tx_df03))}')
```

```
Confusion Matrix (Accuracy 0.8633)

              Prediction
       Actual going_concern      bankrupt
going_concern         11102          1293
     bankrupt           487           140

Additional Eval Measures for LinearDiscriminantAnalysis(store_covariance=True):
Recall = 0.22328548644338117
Precision = 0.09769713886950454
F1 = 0.13592233009708737
```

Final Evaluations

Results table

[149]:
```
#Create table of accuracy comparision between models
comp = [['boost_1',
         accuracy_score(test_y01_vc01, boost_1.predict(test_x03_tx_df02)),
         precision_score(test_y01_vc01, boost_1.predict(test_x03_tx_df02)),
         recall_score(test_y01_vc01, boost_1.predict(test_x03_tx_df02)),
         f1_score(test_y01_vc01, boost_1.predict(test_x03_tx_df02))
```

```
        ],
       ['boost_2',
        accuracy_score(test_y01_vc01, boost_2.predict(test_x03_tx_df02)),
        precision_score(test_y01_vc01, boost_2.predict(test_x03_tx_df02)),
        recall_score(test_y01_vc01, boost_2.predict(test_x03_tx_df02)),
        f1_score(test_y01_vc01, boost_2.predict(test_x03_tx_df02))
        ],
       ['boost_3',
        accuracy_score(test_y01_vc01, boost_3.predict(test_x03_tx_df02)),
        precision_score(test_y01_vc01, boost_3.predict(test_x03_tx_df02)),
        recall_score(test_y01_vc01, boost_3.predict(test_x03_tx_df02)),
        f1_score(test_y01_vc01, boost_3.predict(test_x03_tx_df02))
        ],
       ['boost_4',
        accuracy_score(test_y01_vc01, boost_4.predict(test_x03_tx_df03)),
        precision_score(test_y01_vc01, boost_4.predict(test_x03_tx_df03)),
        recall_score(test_y01_vc01, boost_4.predict(test_x03_tx_df03)),
        f1_score(test_y01_vc01, boost_4.predict(test_x03_tx_df03))
        ],
       ['xgboost_1',
        accuracy_score(test_y01_vc01, xgboost_1.predict(test_x03_tx_df02)),
        precision_score(test_y01_vc01, xgboost_1.predict(test_x03_tx_df02)),
        recall_score(test_y01_vc01, xgboost_1.predict(test_x03_tx_df02)),
        f1_score(test_y01_vc01, xgboost_1.predict(test_x03_tx_df02))
        ],
       ['xgboost_2',
        accuracy_score(test_y01_vc01, xgboost_2.predict(test_x03_tx_df03)),
        precision_score(test_y01_vc01, xgboost_2.predict(test_x03_tx_df03)),
        recall_score(test_y01_vc01, xgboost_2.predict(test_x03_tx_df03)),
        f1_score(test_y01_vc01, xgboost_2.predict(test_x03_tx_df03))
        ],
       ['NN_tune',
        accuracy_score(test_y01_vc01, NN_tune.predict(test_x03_tx_df02)),
        precision_score(test_y01_vc01, NN_tune.predict(test_x03_tx_df02)),
        recall_score(test_y01_vc01, NN_tune.predict(test_x03_tx_df02)),
        f1_score(test_y01_vc01, NN_tune.predict(test_x03_tx_df02))
        ],
       ['dec_tree',
        accuracy_score(test_y01_vc01, clf_final.predict(test_x03_tx_df03)),
        precision_score(test_y01_vc01, clf_final.predict(test_x03_tx_df03)),
        recall_score(test_y01_vc01, clf_final.predict(test_x03_tx_df03)),
        f1_score(test_y01_vc01, clf_final.predict(test_x03_tx_df03))
        ],
       ['rand_for',
        accuracy_score(test_y01_vc01, rf_final.predict(test_x03_tx_df03)),
        precision_score(test_y01_vc01, rf_final.predict(test_x03_tx_df03)),
        recall_score(test_y01_vc01, rf_final.predict(test_x03_tx_df03)),
```

```
         f1_score(test_y01_vc01, rf_final.predict(test_x03_tx_df03))
         ],
        ['knn_1',
         accuracy_score(test_y01_vc01, knn_final_1.predict(test_x03_tx_df03)),
         precision_score(test_y01_vc01, knn_final_1.predict(test_x03_tx_df03)),
         recall_score(test_y01_vc01, knn_final_1.predict(test_x03_tx_df03)),
         f1_score(test_y01_vc01, knn_final_1.predict(test_x03_tx_df03))
         ],
        ['knn_2',
         accuracy_score(test_y01_vc01, knn_final_2.predict(test_x03_tx_df03)),
         precision_score(test_y01_vc01, knn_final_2.predict(test_x03_tx_df03)),
         recall_score(test_y01_vc01, knn_final_2.predict(test_x03_tx_df03)),
         f1_score(test_y01_vc01, knn_final_2.predict(test_x03_tx_df03))
         ],
        ['knn_3',
         accuracy_score(test_y01_vc01, knn_final_3.predict(test_x03_tx_df05)),
         precision_score(test_y01_vc01, knn_final_3.predict(test_x03_tx_df05)),
         recall_score(test_y01_vc01, knn_final_3.predict(test_x03_tx_df05)),
         f1_score(test_y01_vc01, knn_final_3.predict(test_x03_tx_df05))
         ],
        ['knn_4',
         accuracy_score(test_y01_vc01, knn_final_4.predict(test_x03_tx_df03)),
         precision_score(test_y01_vc01, knn_final_4.predict(test_x03_tx_df03)),
         recall_score(test_y01_vc01, knn_final_4.predict(test_x03_tx_df03)),
         f1_score(test_y01_vc01, knn_final_4.predict(test_x03_tx_df03))
         ],
        ['lda_1',
         accuracy_score(test_y01_vc01, lda_final_1.predict(test_x03_tx_df03)),
         precision_score(test_y01_vc01, lda_final_1.predict(test_x03_tx_df03)),
         recall_score(test_y01_vc01, lda_final_1.predict(test_x03_tx_df03)),
         f1_score(test_y01_vc01, lda_final_1.predict(test_x03_tx_df03))
         ],
        ['lda_2',
         accuracy_score(test_y01_vc01, lda_final_2.predict(test_x03_tx_df03)),
         precision_score(test_y01_vc01, lda_final_2.predict(test_x03_tx_df03)),
         recall_score(test_y01_vc01, lda_final_2.predict(test_x03_tx_df03)),
         f1_score(test_y01_vc01, lda_final_2.predict(test_x03_tx_df03))
         ],
        ['lda_3',
         accuracy_score(test_y01_vc01, lda_final_3.predict(test_x03_tx_df05)),
         precision_score(test_y01_vc01, lda_final_3.predict(test_x03_tx_df05)),
         recall_score(test_y01_vc01, lda_final_3.predict(test_x03_tx_df05)),
         f1_score(test_y01_vc01, lda_final_3.predict(test_x03_tx_df05))
         ],
        ['lda_4',
         accuracy_score(test_y01_vc01, lda_final_4.predict(test_x03_tx_df03)),
         precision_score(test_y01_vc01, lda_final_4.predict(test_x03_tx_df03)),
```

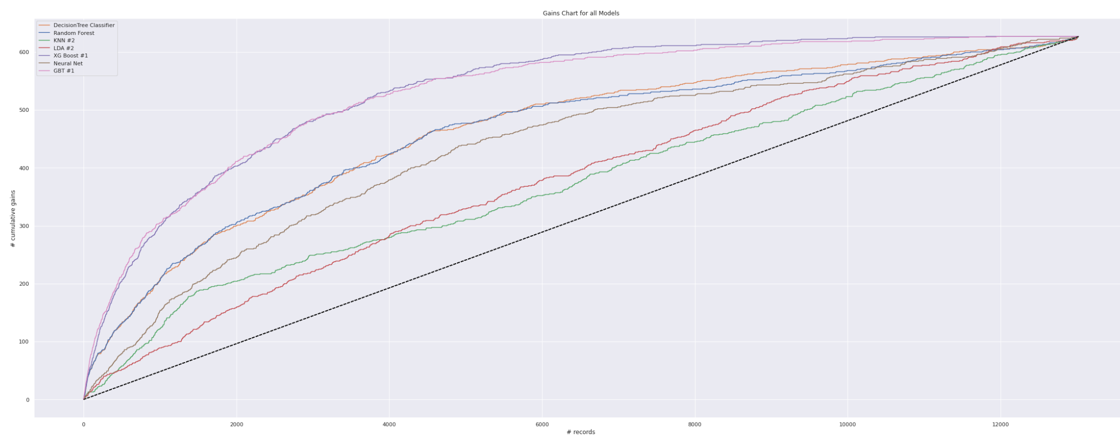
```
        recall_score(test_y01_vc01, lda_final_4.predict(test_x03_tx_df03)),
        f1_score(test_y01_vc01, lda_final_4.predict(test_x03_tx_df03))]
       ]

col_names= ['Accuracy', 'Precision', 'Recall', 'F1_score']
print ('Comparsion between model evaluation measures using test set')
print(tabulate(comp, headers= col_names, tablefmt="fancy_grid"))
```

```
Comparsion between model evaluation measures using test set
```

	Accuracy	Precision	Recall	F1_score
boost_1	0.920135	0.298537	0.488038	0.37046
boost_2	0.876363	0.206567	0.551834	0.300608
boost_3	0.822685	0.171997	0.703349	0.276402
boost_4	0.299493	0.0605277	0.933014	0.113681
xgboost_1	0.818691	0.172088	0.725678	0.278202
xgboost_2	0.230303	0.0580433	0.984051	0.109621
NN_tune	0.590002	0.0818246	0.735247	0.147261
dec_tree	0.952235	0.524752	0.0845295	0.145604
rand_for	0.950008	0.360465	0.0494418	0.0869565
knn_1	0.951467	0.142857	0.0015949	0.00315457
knn_2	0.865612	0.124916	0.298246	0.176083
knn_3	0.951928	0.571429	0.00637959	0.0126183
knn_4	0.937106	0.0384615	0.0127592	0.0191617
lda_1	0.951697	0.333333	0.00318979	0.00631912
lda_2	0.581938	0.0642301	0.566188	0.115372
lda_3	0.950315	0.261905	0.0175439	0.0328849
lda_4	0.863308	0.0976971	0.223285	0.135922

Consolidate Lift and Gains charts

[150]:
```python
#develop the gains charts for each of the final models (for multiple models,--
#--the best performing model was chosen)
ax = gainsChart(clf_df.actual, color='C1', label='DecisionTree Classifier')
ax = gainsChart(rf_df.actual, color='C0', label='Random Forest', ax=ax)
ax = gainsChart(knn_df_2.actual, color='C2',label='KNN #2', ax=ax)
ax = gainsChart(lda2_df.actual, color='C3', label='LDA #2', ax=ax)
ax = gainsChart(xgb_df.actual, color='C4', label='XG Boost #1', ax=ax)
ax = gainsChart(nn_df.actual, color='C5', label='Neural Net', ax=ax)
ax = gainsChart(gbt_df.actual, color='C6', label='GBT #1', ax=ax)

plt.title("Gains Chart for all Models")
ax.legend()
plt.show()
```



6. Recommendation and Conclusion

Final Model

Based on peformance measures, including recall, precision, and their harmonic mean (F_1-score), as well as results seen on the combined Gains Chart, gradient boost model 1 (GBT M_1) was chosen as the final model.
GBT M_1 did not have either the highest accuracy (92.0%), precision (29.9%), or recall (48.8%); however, because both precision and recall were relatively mid-range, the GBT M_1 F_1 (37.0%) was the highest by a significant margin--two of the three closest where also boosted tree algortithms, GBT M_2 (30.1%), XGBoost M_1 (27.8%), and GBT M_3 (27.6%).
Accordingly GBT M_1 is used below as the basis for developing a business-oriented risk-level prediction structure.

[151]:
```python
#gbt_df = xgb_df
display(gbt_df.head())
```

```python
print(gbt_df.shape)
```

```
      actual      p(0)      p(1)  predicted  cum_gains
6739       1  0.004984  0.995016          1          1
9096       1  0.012047  0.987953          1          2
366        1  0.019239  0.980761          1          3
2907       1  0.019930  0.980070          1          4
2548       1  0.021847  0.978153          1          5
```

```
(13022, 5)
```

Establish risk levels based on prediction probability ranges

[152]:
```python
risk_level_1 = '1. Low Risk: Basic Review'
risk_level_2 = '2. Low Risk: Additional Review'
risk_level_3 = '3. Moderate Risk: Senior analyst review'
risk_level_4 = '4. Moderate Risk: Senior analyst review + management signoff'
risk_level_5 = '5. High Risk: Senior analyst review + CFO signoff'

#create logic to assess risk to each prediction
gbt_df['risk_level'] = np.where(gbt_df['p(1)'] >= .90, risk_level_5,
                       np.where(gbt_df['p(1)'] >= .75, risk_level_4,
                       np.where(gbt_df['p(1)'] >= .60, risk_level_3,
                       np.where(gbt_df['p(1)'] >= .16, risk_level_2,
                                                       risk_level_1))))
display(gbt_df.head())
print(gbt_df.shape)
```

```
      actual      p(0)      p(1)  predicted  cum_gains  \
6739       1  0.004984  0.995016          1          1
9096       1  0.012047  0.987953          1          2
366        1  0.019239  0.980761          1          3
2907       1  0.019930  0.980070          1          4
2548       1  0.021847  0.978153          1          5

                                             risk_level
6739  5. High Risk: Senior analyst review + CFO signoff
9096  5. High Risk: Senior analyst review + CFO signoff
366   5. High Risk: Senior analyst review + CFO signoff
2907  5. High Risk: Senior analyst review + CFO signoff
2548  5. High Risk: Senior analyst review + CFO signoff
```

```
(13022, 6)
```

[153]:
```python
risk_level_cnt = gbt_df.groupby(['risk_level'], sort=False).count()
risk_level_cnt.iloc[:,3]
```

[153]:

```
risk_level
5. High Risk: Senior analyst review + CFO signoff                 56
4. Moderate Risk: Senior analyst review + management signoff     254
3. Moderate Risk: Senior analyst review                          363
2. Low Risk: Additional Review                                  3264
1. Low Risk: Basic Review                                       9085
Name: predicted, dtype: int64
```

[154]:

```
gbt_df['risk_probabilities'] = np.where(gbt_df['risk_level'] ==
                                         risk_level_5, '.90 - 1.00',
                              np.where(gbt_df['risk_level'] ==
                                         risk_level_4, '.75 - .899',
                              np.where(gbt_df['risk_level'] ==
                                         risk_level_3, '.60 - .749',
                              np.where(gbt_df['risk_level'] ==
                                 risk_level_2, '.16 - .599', '0.00 - 0.159'))))
#gbt_df = gbt_df.join(key_ratio)
display(gbt_df.head())
print(gbt_df.shape)
```

```
      actual      p(0)      p(1)  predicted  cum_gains  \
6739       1  0.004984  0.995016          1          1
9096       1  0.012047  0.987953          1          2
366        1  0.019239  0.980761          1          3
2907       1  0.019930  0.980070          1          4
2548       1  0.021847  0.978153          1          5

                                             risk_level risk_probabilities
6739  5. High Risk: Senior analyst review + CFO signoff         .90 - 1.00
9096  5. High Risk: Senior analyst review + CFO signoff         .90 - 1.00
366   5. High Risk: Senior analyst review + CFO signoff         .90 - 1.00
2907  5. High Risk: Senior analyst review + CFO signoff         .90 - 1.00
2548  5. High Risk: Senior analyst review + CFO signoff         .90 - 1.00


(13022, 7)
```

[155]:

```
gbt_df03 = gbt_df.join(key_ratio)
#gbt_df03 = gbt_df03.sort_values(by = ['p(1)'], ascending = False)
#gbt_df03 = test_gbt_results.sort_values(by=['p(1)'],
#                                        ascending=False)
display(gbt_df03.head())
print(gbt_df03.shape)
```

```
   actual      p(0)      p(1)  predicted  cum_gains  \
0       0  0.989545  0.010455          0        625
0       0  0.989545  0.010455          0        625
0       0  0.989545  0.010455          0        625
```

```
0       0  0.989545  0.010455          0        625
0       0  0.989545  0.010455          0        625

                  risk_level risk_probabilities  tot_liab_to_tot_assets_ratio  \
0  1. Low Risk: Basic Review       0.00 - 0.159                       0.37951
0  1. Low Risk: Basic Review       0.00 - 0.159                       0.46500
0  1. Low Risk: Basic Review       0.00 - 0.159                       0.41299
0  1. Low Risk: Basic Review       0.00 - 0.159                       0.46240
0  1. Low Risk: Basic Review       0.00 - 0.159                       0.55472

   curr_assets_to_tot_liab_ratio  work_cap_to_tot_assets_ratio
0                         2.0420                       0.39641
0                         1.5167                       0.24038
0                         1.3480                       0.14371
0                         1.1669                       0.07773
0                         1.0193                       0.01134
```

```
(45924, 10)
```

[156]:
```python
gbt_df03 = gbt_df03.sort_values(by = ['p(1)'], ascending = False)
display(gbt_df03.head())
print(gbt_df03.shape)
```

```
      actual      p(0)      p(1)  predicted  cum_gains  \
6739       1  0.004984  0.995016          1          1
6739       1  0.004984  0.995016          1          1
6739       1  0.004984  0.995016          1          1
6739       1  0.004984  0.995016          1          1
9096       1  0.012047  0.987953          1          2

                                           risk_level risk_probabilities  \
6739  5. High Risk: Senior analyst review + CFO signoff        .90 - 1.00
6739  5. High Risk: Senior analyst review + CFO signoff        .90 - 1.00
6739  5. High Risk: Senior analyst review + CFO signoff        .90 - 1.00
6739  5. High Risk: Senior analyst review + CFO signoff        .90 - 1.00
9096  5. High Risk: Senior analyst review + CFO signoff        .90 - 1.00

      tot_liab_to_tot_assets_ratio  curr_assets_to_tot_liab_ratio  \
6739                       0.75314                        0.76494
6739                       0.57898                        0.76051
6739                       0.17752                        3.03290
6739                       0.81499                        0.36020
9096                       0.16195                        3.73300

      work_cap_to_tot_assets_ratio
6739                     -0.015497
6739                     -0.095395
```

```
6739                       0.436620
6739                      -0.163050
9096                       0.450280

(45924, 10)
```

[157]:
```
tot_liab_to_assets = gbt_df03.groupby('risk_level')[
                                     'tot_liab_to_tot_assets_ratio'].median()
tot_liab_to_assets
```

[157]:
```
risk_level
1. Low Risk: Basic Review                                    0.471240
2. Low Risk: Additional Review                               0.472275
3. Moderate Risk: Senior analyst review                      0.480830
4. Moderate Risk: Senior analyst review + management signoff    0.469690
5. High Risk: Senior analyst review + CFO signoff            0.507420
Name: tot_liab_to_tot_assets_ratio, dtype: float64
```

[158]:
```
curr_assets_total_lia = gbt_df03.groupby('risk_level')[
                                     'work_cap_to_tot_assets_ratio'].median()
curr_assets_total_lia
```

[158]:
```
risk_level
1. Low Risk: Basic Review                                    0.198105
2. Low Risk: Additional Review                               0.194210
3. Moderate Risk: Senior analyst review                      0.188220
4. Moderate Risk: Senior analyst review + management signoff    0.195055
5. High Risk: Senior analyst review + CFO signoff            0.201740
Name: work_cap_to_tot_assets_ratio, dtype: float64
```

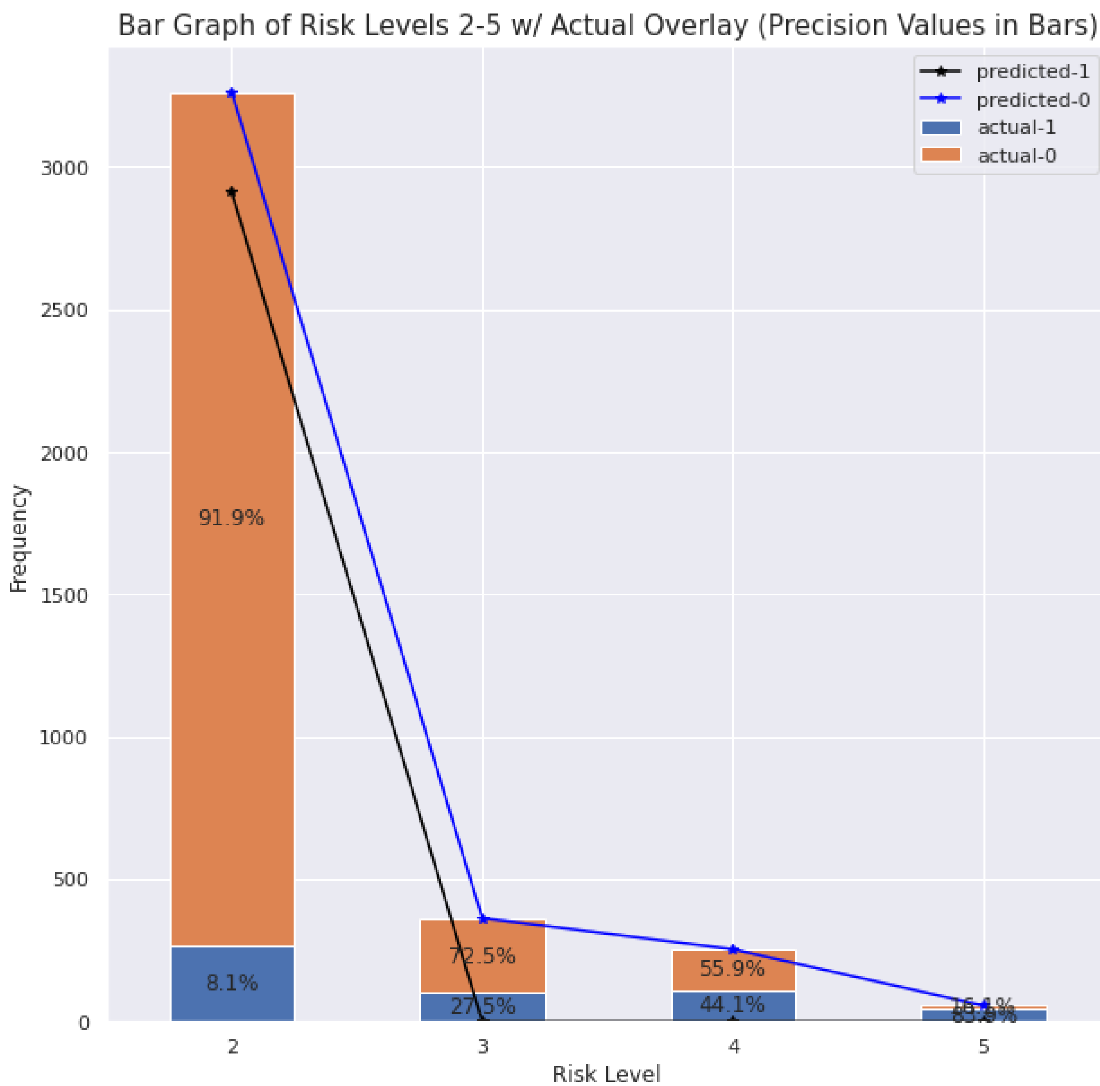
Graph Risk Levels 2-5 by Actual

[159]:
```
# Create cross-tab report & plot as bar graph
gbt_bar_df = gbt_df.sort_values(by='risk_level',
                                ascending=True)
print(gbt_bar_df.shape)
gbt_bar_ct = pd.crosstab(gbt_bar_df['risk_level'],
                         gbt_bar_df['actual'])
gbt_bar_ct = gbt_bar_ct.drop(risk_level_1)
gbt_bar_ct = gbt_bar_ct[[1, 0]]
gbt_bar_ct02 = gbt_bar_ct.div(gbt_bar_ct.sum(1),
                              axis=0)
gbt_bar_ct03 = pd.crosstab(gbt_bar_df['risk_level'],
                           gbt_bar_df['predicted'])
gbt_bar_ct03 = gbt_bar_ct03.drop(risk_level_1)
#gbt_bar_ct03 = gbt_bar_ct03[[1, 0]]
print(gbt_bar_ct)
```

```
print(gbt_bar_ct03)

ax10 = gbt_bar_ct.plot(kind='bar',
                       stacked=True,
                       figsize=(10, 10))
gbt_bar_ct03.plot(kind='line',
                  stacked=True,
                  ax=ax10,
                  marker='*',
                  color=['black', 'blue'])

# Label stacked bars
height_lst01 = []
for b in ax10.patches:
  height_lst01.append(b.get_height())

bar_len = int(len(height_lst01) / 2)
height_lst01a = height_lst01[:bar_len]
height_lst01b = height_lst01[bar_len:]
counter = 0

# Label individual bars (Kumar, 2021)
for b in ax10.patches:
    bar_h = b.get_height()
    bar_w = b.get_width()
    bar_x = b.get_x()
    bar_y = b.get_y()
    label_text = str(round((bar_h / (height_lst01a[counter] \
                                     + height_lst01b[counter]))*100, 1)) + '%'
    label_x = bar_x + bar_w / 2
    label_y = bar_y + bar_h / 2
    ax10.text(label_x,
            label_y,
            label_text,
            ha='center',
            va='center')

    counter += 1
    if counter >= bar_len:
      counter = 0

plt.title(
    'Bar Graph of Risk Levels 2-5 w/ Actual Overlay (Precision Values in Bars)',
     fontsize=15)
ax10.set_xticklabels(['2', '3', '4', '5'])
plt.xlabel('Risk Level')
plt.ylabel('Frequency')
```

```
plt.legend(['predicted-1', 'predicted-0', 'actual-1', 'actual-0'])
plt.show()
```

```
(13022, 7)
actual                                                   1     0
risk_level
2. Low Risk: Additional Review                          265  2999
3. Moderate Risk: Senior analyst review                 100   263
4. Moderate Risk: Senior analyst review + manag…    112   142
5. High Risk: Senior analyst review + CFO signoff      47     9
predicted                                                0     1
risk_level
2. Low Risk: Additional Review                         2912   352
3. Moderate Risk: Senior analyst review                   0   363
4. Moderate Risk: Senior analyst review + manag…      0   254
5. High Risk: Senior analyst review + CFO signoff         0    56
```

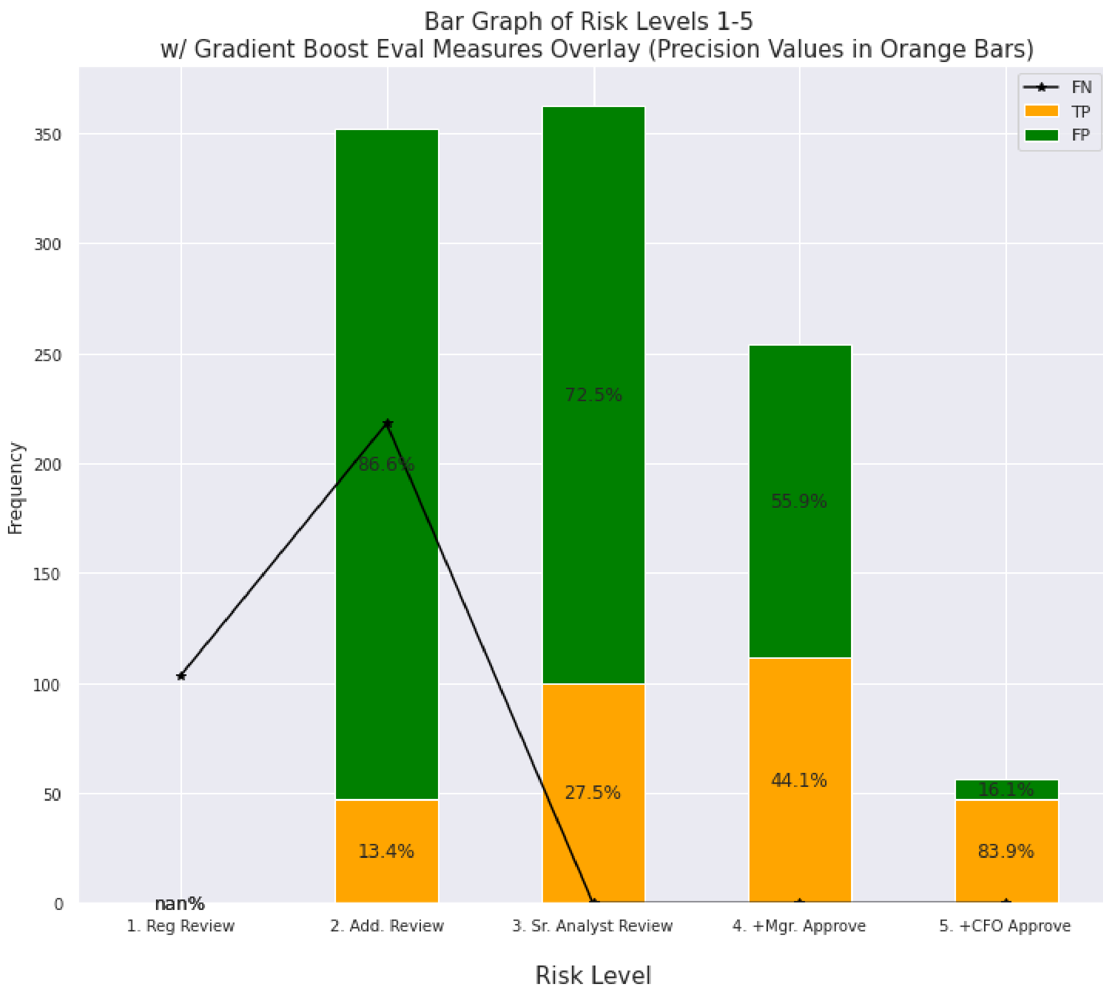


Graph Risk Levels 1-5 by Confusion Matrix

[160]:
```
gbt_bar_df02 = gbt_bar_df.copy()
gbt_bar_df02['tp'] = 0
gbt_bar_df02['fp'] = 0
gbt_bar_df02['tn'] = 0
gbt_bar_df02['fn'] = 0

gbt_bar_df02.loc[(gbt_bar_df02.actual == 1) & (gbt_bar_df02.predicted == 1),
                                                                     'tp'] = 1
gbt_bar_df02.loc[(gbt_bar_df02.actual == 0) & (gbt_bar_df02.predicted == 1),
                                                                     'fp'] = 1
gbt_bar_df02.loc[(gbt_bar_df02.actual == 0) & (gbt_bar_df02.predicted == 0),
                                                                      'tn'] = 1
gbt_bar_df02.loc[(gbt_bar_df02.actual == 1) & (gbt_bar_df02.predicted == 0),
                                                                      'fn'] = 1
#display(gbt_bar_df02.head())
print(gbt_bar_df02.shape)
gbt_bar_df02_gb = gbt_bar_df02.groupby(['risk_level'],
                                       sort=False)['tp', 'fp', 'tn', 'fn'].sum()
print(gbt_bar_df02_gb)

ax20 = gbt_bar_df02_gb[['tp', 'fp']].plot(kind='bar',
                                          stacked=True,
                                          figsize=(12, 10),
                                          color=['orange', 'green'])
gbt_bar_df02_gb['fn'].plot(kind='line',
                           stacked=True,
                           ax=ax20,
                           marker='*',
                           color='black')

# Label stacked bars
height_lst01 = []
for b in ax20.patches:
  height_lst01.append(b.get_height())

bar_len = int(len(height_lst01) / 2)
height_lst01a = height_lst01[:bar_len]
height_lst01b = height_lst01[bar_len:]
counter = 0

# Label individual bars (Kumar, 2021)
for b in ax20.patches:
```

```
    bar_h = b.get_height()
    bar_w = b.get_width()
    bar_x = b.get_x()
    bar_y = b.get_y()
    label_text = str(round((bar_h / (height_lst01a[counter] \
                                    + height_lst01b[counter]))*100, 1)) + '%'
    label_x = bar_x + bar_w / 2
    label_y = bar_y + bar_h / 2
    ax20.text(label_x,
              label_y,
              label_text,
              ha='center',
              va='center')

    counter += 1
    if counter >= bar_len:
      counter = 0

# plt.title(
#     'Normalized Bar Graph of Risk Levels 1-5 \n w/ Gradient Boost Eval␣
↪Measures Overlay',
#                                                   fontsize=20,  x=0.5, y=1.0)
plt.title(
    'Bar Graph of Risk Levels 1-5 \n w/ Gradient Boost Eval Measures Overlay␣
↪(Precision Values in Orange Bars)',
                                                   fontsize=15, x=0.5, y=1.0)
ax20.set_xticklabels(['1. Reg Review', '2. Add. Review', '3. Sr. Analyst␣
↪Review',
                                         '4. +Mgr. Approve', '5. +CFO Approve'])
#plt.xlabel('Risk Level')
ax20.tick_params(axis='both', which='major', labelsize=10)
plt.xlabel('Risk Level',labelpad=20, fontsize=15)
plt.ylabel('Frequency')
plt.legend(['FN', 'TP', 'FP'])
plt.show()
```

```
(13022, 11)
                                                     tp   fp    tn   fn
risk_level
1. Low Risk: Basic Review                             0    0  8982  103
2. Low Risk: Additional Review                       47  305  2694  218
3. Moderate Risk: Senior analyst review             100  263     0    0
4. Moderate Risk: Senior analyst review + manag…  112  142     0    0
5. High Risk: Senior analyst review + CFO signoff    47    9     0    0
```



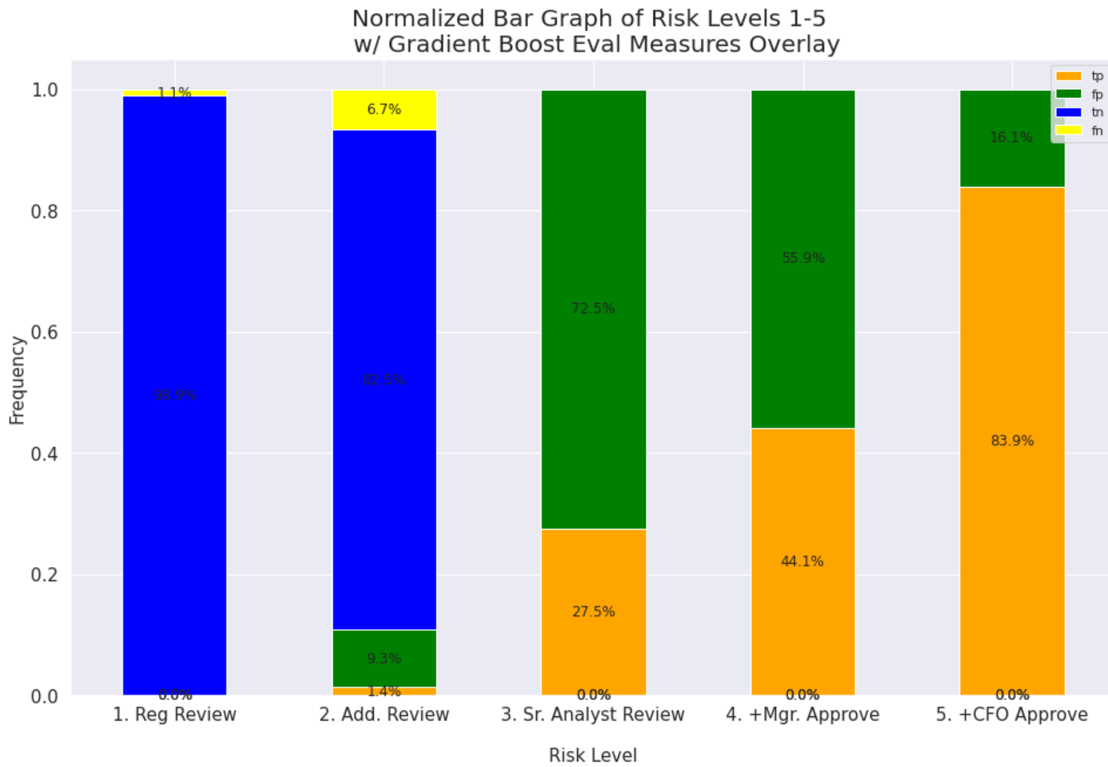
Graph Risk Levels 1-5 by Normalized Confusion Matrix

[161]:
```
plt.tick_params(axis='x', labelrotation=30)
```

[162]:
```
gbt_bar_df02_gb02 = gbt_bar_df02_gb.copy()
gbt_bar_df02_gb03 = gbt_bar_df02_gb02.div(gbt_bar_df02_gb02.sum(1), axis=0)
print(gbt_bar_df02_gb02)
#print(gbt_bar_df02_gb03)

ax30 = gbt_bar_df02_gb03[['tp',
                          'fp',
                          'tn',
                          'fn']].plot(kind='bar',
                                      stacked=True,
                                      figsize=(16, 10),
                                      color=['orange',
                                             'green',
                                             'blue',
                                             'yellow'])
#gbt_bar_df02_gb03['fn'].plot(kind='line',
#                             stacked=True,
#                             ax=ax30,
#                             marker='*',
#                             color='black')

# Label stacked bars
height_lst01 = []
for b in ax30.patches:
  height_lst01.append(b.get_height())

bar_len = int(len(height_lst01) / 2)
height_lst01a = height_lst01[:bar_len]
height_lst01b = height_lst01[bar_len:]
counter = 0

# Label individual bars (Kumar, 2021)
for b in ax30.patches:
    bar_h = b.get_height()
    bar_w = b.get_width()
    bar_x = b.get_x()
    bar_y = b.get_y()
#    label_text = str(round((bar_h / (height_lst01a[counter] \
#                                     + height_lst01b[counter]))*100, 1)) + '%'
    label_text = str(round(bar_h*100,1)) + '%'
    label_x = bar_x + bar_w / 2
    label_y = bar_y + bar_h / 2
    ax30.text(label_x,
              label_y,
              label_text,
```

```
                ha='center',
                va='center')

     counter += 1
     if counter >= bar_len:
       counter = 0
plt.title(
    'Normalized Bar Graph of Risk Levels 1-5 \n w/ Gradient Boost Eval Measures␣
 ↪Overlay',
                                                fontsize=20, x=0.5, y=1.0)
ax30.set_xticklabels(['1. Reg Review', '2. Add. Review', '3. Sr. Analyst␣
 ↪Review',
                      '4. +Mgr. Approve', '5. +CFO Approve'])
plt.tick_params(axis='x', labelrotation=0)
ax30.tick_params(axis='both', which='major', labelsize=15)
plt.xlabel('Risk Level',labelpad=20, fontsize=15)
plt.ylabel('Frequency', fontsize=15)
#plt.legend(['FN', 'TP', 'FP'])
plt.show()
```

```
                                                      tp   fp    tn   fn
risk_level
1. Low Risk: Basic Review                              0    0  8982  103
2. Low Risk: Additional Review                        47  305  2694  218
3. Moderate Risk: Senior analyst review              100  263     0    0
4. Moderate Risk: Senior analyst review + manag…   112  142     0    0
5. High Risk: Senior analyst review + CFO signoff     47    9     0    0
```




```
[ ]: # Convert Colab to PDF (Stack Overflow, n.d.)
#''''
!apt-get install texlive texlive-xetex texlive-latex-extra pandoc
!pip install pypandoc
!jupyter nbconvert --to PDF '/content/drive/MyDrive/ADS505_Team1_Final_Project/
↪Working Files/ADS-505_Team1_Final_Project_v2.ipynb'
#'''
```

```
Reading package lists… Done
Building dependency tree
Reading state information… Done
pandoc is already the newest version (1.19.2.4~dfsg-1build4).
pandoc set to manually installed.
The following package was automatically installed and is no longer required:
  libnvidia-common-460
Use 'apt autoremove' to remove it.
The following additional packages will be installed:
  fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono fonts-texgyre
  javascript-common libcupsfilters1 libcupsimage2 libgs9 libgs9-common
  libijs-0.35 libjbig2dec0 libjs-jquery libkpathsea6 libpotrace0 libptexenc1
  libruby2.5 libsynctex1 libtexlua52 libtexluajit2 libzzip-0-13 lmodern
  poppler-data preview-latex-style rake ruby ruby-did-you-mean ruby-minitest
  ruby-net-telnet ruby-power-assert ruby-test-unit ruby2.5
```

```
Preparing to unpack …/06-fonts-texgyre_20160520-1_all.deb …
Unpacking fonts-texgyre (20160520-1) …
Selecting previously unselected package javascript-common.
Preparing to unpack …/07-javascript-common_11_all.deb …
Unpacking javascript-common (11) …
Selecting previously unselected package libcupsfilters1:amd64.
Preparing to unpack …/08-libcupsfilters1_1.20.2-0ubuntu3.1_amd64.deb …
Unpacking libcupsfilters1:amd64 (1.20.2-0ubuntu3.1) …
```

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