Lab2 Part II

2.1 The data set description

[ ]:
```
#1.
import pandas as pd
bankrupt = pd.read_csv("D:/study/A3/ML_lab2/bankrupt.txt" , sep=",")
```

[23]:
```
#2.observations and variables
num_observations, num_variables = bankrupt.shape
print("Number of observations:", num_observations)
print("Number of variables:", num_variables)
```

```
Number of observations: 6819
Number of variables: 96
```

[24]:
```
#3.
bankrupt.describe()
```

[24]:
```
         Bankrupt?  ROA(C) before interest and depreciation before interest  \
count  6819.000000                                        6819.000000
mean      0.032263                                           0.505180
std       0.176710                                           0.060686
min       0.000000                                           0.000000
25%       0.000000                                           0.476527
50%       0.000000                                           0.502706
75%       0.000000                                           0.535563
max       1.000000                                           1.000000

       ROA(A) before interest and % after tax  \
count                             6819.000000
mean                                 0.558625
std                                  0.065620
min                                  0.000000
25%                                  0.535543
50%                                  0.559802
75%                                  0.589157
max                                  1.000000

       ROA(B) before interest and depreciation after tax  \
count                                        6819.000000
```

```
mean                                                0.553589
std                                                 0.061595
min                                                 0.000000
25%                                                 0.527277
50%                                                 0.552278
75%                                                 0.584105
max                                                 1.000000

        Operating Gross Margin   Realized Sales Gross Margin  \
count              6819.000000                   6819.000000
mean                  0.607948                      0.607929
std                   0.016934                      0.016916
min                   0.000000                      0.000000
25%                   0.600445                      0.600434
50%                   0.605997                      0.605976
75%                   0.613914                      0.613842
max                   1.000000                      1.000000

        Operating Profit Rate   Pre-tax net Interest Rate  \
count             6819.000000                 6819.000000
mean                 0.998755                    0.797190
std                  0.013010                    0.012869
min                  0.000000                    0.000000
25%                  0.998969                    0.797386
50%                  0.999022                    0.797464
75%                  0.999095                    0.797579
max                  1.000000                    1.000000

        After-tax net Interest Rate  \
count                   6819.000000
mean                       0.809084
std                        0.013601
min                        0.000000
25%                        0.809312
50%                        0.809375
75%                        0.809469
max                        1.000000

        Non-industry income and expenditure/revenue  …  \
count                                  6819.000000  …
mean                                      0.303623  …
std                                       0.011163  …
min                                       0.000000  …
25%                                       0.303466  …
50%                                       0.303525  …
75%                                       0.303585  …
max                                       1.000000  …
```

	Net Income to Total Assets	Total assets to GNP price \
count	6819.000000	6.819000e+03
mean	0.807760	1.862942e+07
std	0.040332	3.764501e+08
min	0.000000	0.000000e+00
25%	0.796750	9.036205e-04
50%	0.810619	2.085213e-03
75%	0.826455	5.269777e-03
max	1.000000	9.820000e+09

	No-credit Interval	Gross Profit to Sales \
count	6819.000000	6819.000000
mean	0.623915	0.607946
std	0.012290	0.016934
min	0.000000	0.000000
25%	0.623636	0.600443
50%	0.623879	0.605998
75%	0.624168	0.613913
max	1.000000	1.000000

	Net Income to Stockholder s Equity	Liability to Equity \
count	6819.000000	6819.000000
mean	0.840402	0.280365
std	0.014523	0.014463
min	0.000000	0.000000
25%	0.840115	0.276944
50%	0.841179	0.278778
75%	0.842357	0.281449
max	1.000000	1.000000

	Degree of Financial Leverage (DFL) \
count	6819.000000
mean	0.027541
std	0.015668
min	0.000000
25%	0.026791
50%	0.026808
75%	0.026913
max	1.000000

	Interest Coverage Ratio (Interest expense to EBIT)	Net Income Flag \
count	6819.000000	6819.0
mean	0.565358	1.0
std	0.013214	0.0
min	0.000000	1.0
25%	0.565158	1.0

```
50%                                                0.565252              1.0
75%                                                0.565725              1.0
max                                                1.000000              1.0

        Equity to Liability
count           6819.000000
mean               0.047578
std                0.050014
min                0.000000
25%                0.024477
50%                0.033798
75%                0.052838
max                1.000000

[8 rows x 96 columns]
```

[25]:
```
#4.Bankrupt number and percentage
target_variable = "Bankrupt?"
bankrupt_counts = bankrupt[target_variable].value_counts()
num_bankrupt = bankrupt_counts[1]
num_not_bankrupt = bankrupt_counts[0]

percentage_bankrupt = (num_bankrupt / num_observations) * 100
percentage_not_bankrupt = (num_not_bankrupt / num_observations) * 100

print("Number of companies that went bankrupt:", num_bankrupt)
print("Number of companies that did not go bankrupt:", num_not_bankrupt)
print("Percentage of companies that went bankrupt:", percentage_bankrupt, "%")
print("Percentage of companies that did not go bankrupt:",␣
↪percentage_not_bankrupt, "%")
```

```
Number of companies that went bankrupt: 220
Number of companies that did not go bankrupt: 6599
Percentage of companies that went bankrupt: 3.2262795131250916 %
Percentage of companies that did not go bankrupt: 96.77372048687491 %
```

[26]:
```
#5.
from sklearn.preprocessing import StandardScaler

# Import the data sets
x_train = pd.read_csv("D:/study/A3/ML_lab2/x_train.csv", index_col=0)
x_test = pd.read_csv("D:/study/A3/ML_lab2/x_test.csv", index_col=0)
y_train = pd.read_csv("D:/study/A3/ML_lab2/y_train.csv", index_col=0)
y_test = pd.read_csv("D:/study/A3/ML_lab2/y_test.csv", index_col=0)
```

[27]:
```
num_observations_train = x_train.shape[0]
num_observations_test = x_test.shape[0]
```

```
print("Number of observations in x_train:", num_observations_train)
print("Number of observations in x_test:", num_observations_test)
```

```
Number of observations in x_train: 5455
Number of observations in x_test: 1364
```

[28]:
```
class_distribution_train = y_train['Bankrupt'].value_counts()
class_distribution_test = y_test['Bankrupt'].value_counts()

print("Class distribution in y_train:")
print(class_distribution_train)

print("Class distribution in y_test:")
print(class_distribution_test)
```

```
Class distribution in y_train:
0    5281
1     174
Name: Bankrupt, dtype: int64
Class distribution in y_test:
0    1318
1      46
Name: Bankrupt, dtype: int64
```

[32]:
```
scaler = StandardScaler()

# Fit and transform the training data
x_train_standardized = scaler.fit_transform(x_train)

# Transform the test data using the same scaler
x_test_standardized = scaler.transform(x_test)

# Create new DataFrames with standardized data
x_train_standardized = pd.DataFrame(x_train_standardized, columns=x_train.
 ↪columns)
x_test_standardized = pd.DataFrame(x_test_standardized, columns=x_test.columns)

# Verify the lengths of the new DataFrames
assert x_train_standardized.shape == x_train.shape
assert x_test_standardized.shape == x_test.shape
```

2.2 Logistic regression

[40]:
```
import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn.metrics import confusion_matrix, classification_report
```

[36]:
```
#1.
# Merge x_train and y_train dataframes
bankrupt_train = pd.concat([x_train, y_train], axis=1)

# Define the formula for logistic regression
formula = 'Bankrupt ~ ROAC + ROAA + ROAB + TRA + TAGR + DR + WKTA + CTA + CLA +␣
↪CFOA + CLCA + NITA'

# Fit the logistic regression model
model = smf.glm(formula=formula, data=bankrupt_train, family=sm.families.
↪Binomial())
logreg = model.fit()
```

[37]:
```
print(logreg.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:               Bankrupt   No. Observations:                 5455
Model:                            GLM   Df Residuals:                     5443
Model Family:                Binomial   Df Model:                           11
Link Function:                  Logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -513.79
Date:                Thu, 12 Oct 2023   Deviance:                       1027.6
Time:                        15:36:22   Pearson chi2:                 4.44e+06
No. Iterations:                    10   Pseudo R-squ. (CS):            0.08988
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      6.0644      3.655      1.659      0.097      -1.099      13.228
ROAC         -11.3247      7.788     -1.454      0.146     -26.589       3.940
ROAA          -1.5478      6.154     -0.252      0.801     -13.609      10.513
ROAB          -3.5475      8.761     -0.405      0.686     -20.718      13.623
TRA           -1.7574      0.973     -1.807      0.071      -3.664       0.149
TAGR        3.738e-11   3.79e-11      0.985      0.324    -3.7e-11    1.12e-10
DR            20.5210      2.743      7.480      0.000      15.144      25.898
WKTA          -4.9171      2.429     -2.024      0.043      -9.678      -0.156
CTA           -6.7206      1.708     -3.934      0.000     -10.068      -3.373
CLA           -6.6835      2.378     -2.810      0.005     -11.345      -2.022
CFOA           2.7174      1.772      1.534      0.125      -0.755       6.190
CLCA           0.5781      2.178      0.265      0.791      -3.690       4.847
NITA          -1.3517      6.213     -0.218      0.828     -13.529      10.825
==============================================================================
```

[38]:
```
#2.
print(logreg.fittedvalues)
```

```
1524    0.018523
```

```
2819    0.011718
1957    0.003200
5020    0.000507
4443    0.010251
          …
4931    0.035072
3264    0.000354
1653    0.002176
2607    0.001122
2732    0.001647
Length: 5455, dtype: float64
```

[41]:
```python
# Convert these probabilities into classes labels
yhat_logreg_probs = logreg.fittedvalues
yhat = [1 if x > 0.5 else 0 for x in yhat_logreg_probs]

# Compute the confusion matrix and obtain a report of performance metrics
confusion = confusion_matrix(yhat, y_train)
report = classification_report(yhat, y_train, digits=3)

print("Confusion Matrix:")
print(confusion)
print("Classification Report:")
print(report)
```

```
Confusion Matrix:
[[5266  143]
 [  15   31]]
Classification Report:
              precision    recall  f1-score   support

           0      0.997     0.974     0.985      5409
           1      0.178     0.674     0.282        46

    accuracy                          0.971      5455
   macro avg      0.588     0.824     0.634      5455
weighted avg      0.990     0.971     0.979      5455
```

The model has high accuracy, precision, and recall for the majority class (non-bankrupt), but its performance for the minority class (bankrupt) is relatively lower. It correctly identifies most non-bankrupt cases but has difficulty correctly classifying bankrupt cases. The F1-Score for the bankrupt class is notably lower, indicating a trade-off between precision and recall.

[42]:
```python
#3.
# Convert probabilities into classes labels and compute confusion matrix  for␣
↪test set
yhat_test_logreg_probs = logreg.predict(x_test)
```

```
yhat_test = [1 if x > 0.5 else 0 for x in yhat_test_logreg_probs]

confusion_test = confusion_matrix(yhat_test, y_test)
report_test = classification_report(yhat_test, y_test, digits=3)

print("Confusion Matrix (Test Set):")
print(confusion_test)
print("Classification Report (Test Set):")
print(report_test)
```

```
Confusion Matrix (Test Set):
[[1306   39]
 [  12    7]]
Classification Report (Test Set):
              precision    recall  f1-score   support

           0      0.991     0.971     0.981      1345
           1      0.152     0.368     0.215        19

    accuracy                          0.963      1364
   macro avg      0.572     0.670     0.598      1364
weighted avg      0.979     0.963     0.970      1364
```

Considering these results of test set, it is clear that overall accuracy (96.3%) can be misleading in this imbalanced dataset. The model achieves high accuracy primarily because it correctly classifies the majority class (non-bankrupt) but performs poorly on the minority class (bankrupt). The low precision and recall for the bankrupt class, as well as the low F1-Score, indicate that the model's performance in identifying bankrupt companies is not satisfactory.

In an imbalanced dataset, it's more appropriate to focus on precision, recall, and the F1-Score, especially for the minority class, as these metrics provide a better assessment of the model's effectiveness in correctly identifying the positive class (bankrupt). Additionally, considering other techniques such as changing the decision threshold, or using different algorithms might be necessary to improve the model's performance in imbalanced scenarios.

2.3 K-Nearest Neighbors

[71]:
```
#1.
from sklearn.neighbors import KNeighborsClassifier
import numpy as np
from sklearn.metrics import balanced_accuracy_score
```

[72]:
```
# Initialize
best_k = 1
best_balanced_accuracy = 0
# Calculate the balanced accuracy and choose the best k ranging from 1 to 20
for k in range(1, 21):
    # Create a KNN classifier with the current K value
```

```
    knn = KNeighborsClassifier(n_neighbors=k)

    # Fit the model on the training data
    knn.fit(x_train, np.ravel(y_train))

    # Make predictions on the test data
    yhat_knn = knn.predict(x_test)

    # Calculate balanced accuracy
    balanced_acc = balanced_accuracy_score(y_test, yhat_knn)

    # Check if this K value results in higher balanced accuracy
    if balanced_acc > best_balanced_accuracy:
        best_k = k
        best_balanced_accuracy = balanced_acc

print("Best K value:", best_k)
print("Best Balanced Accuracy:", best_balanced_accuracy)
```

```
Best K value: 1
Best Balanced Accuracy: 0.5534571485122386
```

[73]:
```
# Fit a KNN model with the best K and make predictions
n_neighbors = 1
knn = KNeighborsClassifier(n_neighbors=n_neighbors)
knn.fit(x_train, np.ravel(y_train))
yhat_knn = knn.predict(x_test)

# Calculate performance metrics
confusion_best_knn = confusion_matrix(y_test, yhat_knn)
report_best_knn = classification_report(y_test, yhat_knn, digits=3)

print("Confusion Matrix (Best KNN Model):")
print(confusion_best_knn)
print("Classification Report (Best KNN Model):")
print(report_best_knn)
```

```
Confusion Matrix (Best KNN Model):
[[1287   31]
 [  40    6]]
Classification Report (Best KNN Model):
              precision    recall  f1-score   support

           0      0.970     0.976     0.973      1318
           1      0.162     0.130     0.145        46

    accuracy                          0.948      1364
   macro avg      0.566     0.553     0.559      1364
```

```
weighted avg      0.943     0.948     0.945      1364
```

The best KNN model demonstrates reasonably high overall accuracy, but it faces challenges in correctly classifying the minority class (bankrupt). The model's performance for the bankrupt class is not satisfactory, and further improvements may be necessary, such as adjusting the classification threshold, exploring different algorithms like the previous.

2.4 Discriminant Analysis

1.Interpret the Prior Probabilities and Group Means:

Prior Probabilities (0 and 1): These represent the probabilities of belonging to each class. In binary classification, 0 is the prior probability of being in class 0 (non-bankrupt), and 1 is the prior probability of being in class 1 (bankrupt). These values are based on the proportions of each class in the training data. They give us an idea of the class distribution.

Group Means: The group means represent the mean values of each predictor variable (features) for each class. In the order they were given, they provide insights into how the predictor variables differ between the two classes. They help identify which predictors have significant differences between the classes.

[74]:
```python
#2.Calculate the Confusion Matrix and Classification Report for the LDA Model
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

lda = LinearDiscriminantAnalysis()
model_lda = lda.fit(x_train, np.ravel(y_train))
yhat_lda = model_lda.predict(x_test)
print("Prior probabilities:")
print(model_lda.priors_)
print("Group Means:")
print(model_lda.means_)

# Confusion Matrix
confusion_lda = confusion_matrix(y_test, yhat_lda)
print("Confusion Matrix (LDA Model):")
print(confusion_lda)

# Classification Report
report_lda = classification_report(y_test, yhat_lda, digits=3)
print("Classification Report (LDA Model):")
print(report_lda)
```

```
Prior probabilities:
[0.96810266 0.03189734]
Group Means:
[[5.07499371e-01 5.61487295e-01 5.56092411e-01 1.17719099e-01
  5.55001102e+09 1.11500340e-01 8.15420501e-01 1.25669967e-01
  8.96077591e-02 5.93879112e-01 3.06814657e-02 8.09838677e-01]
 [4.21282047e-01 4.58457712e-01 4.65005880e-01 3.33512513e-02
  4.96788333e+09 1.85968720e-01 7.49489244e-01 4.96204862e-02
```

```
 1.39421993e-01 5.58209193e-01 6.24193244e-02 7.39513902e-01]]
Confusion Matrix (LDA Model):
[[1299   19]
 [  31   15]]
Classification Report (LDA Model):
              precision    recall  f1-score   support

           0      0.977     0.986     0.981      1318
           1      0.441     0.326     0.375        46

    accuracy                          0.963      1364
   macro avg      0.709     0.656     0.678      1364
weighted avg      0.959     0.963     0.961      1364
```

Specificity (True Negative Rate): 0.986 This indicates that the LDA model correctly identifies 98.6% of the non-bankrupt cases, which is a high specificity.

Sensitivity (Recall): 0.326 The model correctly identifies only 32.6% of the bankrupt cases. This is a low sensitivity, suggesting that the model struggles to identify bankrupt cases.

Precision: For class 0 (Non-Bankrupt): 0.977 High precision indicates that 97.7% of the instances classified as non-bankrupt are indeed non-bankrupt. For class 1 (Bankrupt): 0.441 The precision for bankrupt cases is lower, indicating that 44.1% of the instances classified as bankrupt are truly bankrupt.

F1-Score: For class 0 (Non-Bankrupt): 0.981 The F1-Score for non-bankrupt cases is high, indicating a good balance between precision and recall.

For class 1 (Bankrupt): 0.375 The F1-Score for bankrupt cases is lower, suggesting that the model's performance in identifying bankrupt cases is not strong. Accuracy: 0.963

The overall accuracy of the LDA model is high (96.3%).

Macro-Averaged F1-Score: 0.678 The macro-average F1-Score takes the average of the F1-Scores for each class. It is relatively high at 0.678, indicating a good overall balance.

Weighted-Averaged F1-Score: 0.961 The weighted-average F1-Score accounts for class imbalances and is high at 0.961. This suggests that the model performs well overall but may struggle with the minority class (bankrupt).

In summary, like the previous, the overall accuracy is high, but it has low sensitivity to classify correctly the minority class (bankrupt).

[75]:
```python
#3.Calculate the confusion matrix and then classification report on the test␣
↪set for the QDA classifier
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis

qda = QuadraticDiscriminantAnalysis()
model_qda = qda.fit(x_train, np.ravel(y_train))
yhat_qda = model_qda.predict(x_test)
```

```python
# Confusion Matrix for QDA
confusion_qda = confusion_matrix(y_test, yhat_qda)
print("Confusion Matrix (QDA Model):")
print(confusion_qda)

# Classification Report for QDA
report_qda = classification_report(y_test, yhat_qda, digits=3)
print("Classification Report (QDA Model):")
print(report_qda)
```

```
Confusion Matrix (QDA Model):
[[1280   38]
 [  30   16]]
Classification Report (QDA Model):
              precision    recall  f1-score   support

           0      0.977     0.971     0.974      1318
           1      0.296     0.348     0.320        46

    accuracy                          0.950      1364
   macro avg      0.637     0.659     0.647      1364
weighted avg      0.954     0.950     0.952      1364
```

Performance is alomost same as LDA

2.5 ROC (Receiver operating characteristic) curve

[79]:
```python
#1.Interpret the outputs of the roc_curve() function
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
# LDA Model
lda_scores = lda.predict_proba(x_test)[:, 1]
fpr_lda, tpr_lda, thresholds_lda = roc_curve(y_test, lda_scores)
auc_lda = auc(fpr_lda, tpr_lda)
```

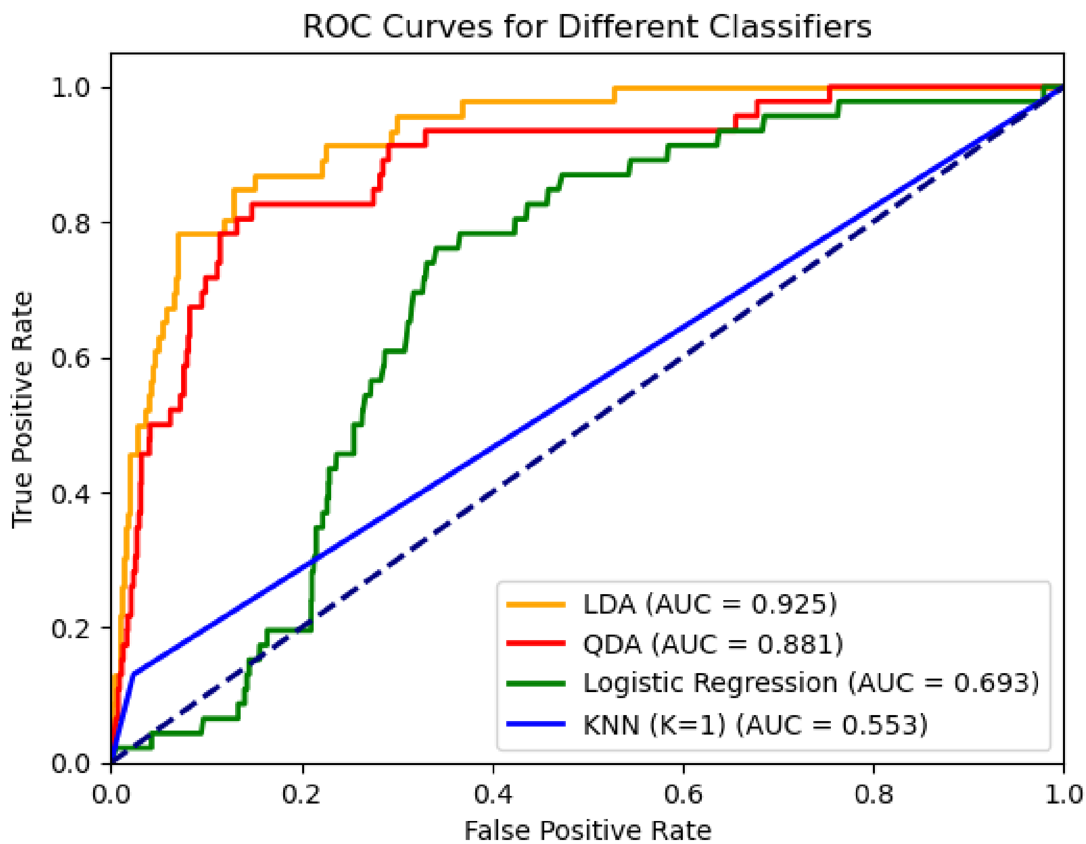
fpr represents the false positive rate at different threshold values. tpr represents the true positive rate (or recall) at different threshold values. The thresholds array contains the threshold values at which these rates are calculated. The ROC curve is essentially a plot of fpr on the x-axis and tpr on the y-axis. It shows how the true positive rate and false positive rate change with different threshold values.

[93]:
```python
# Calculate the auc for 4 models
# QDA Model
from sklearn.linear_model import LogisticRegression
qda_scores = qda.predict_proba(x_test)[:, 1]
fpr_qda, tpr_qda, thresholds_qda = roc_curve(y_test, qda_scores)
auc_qda = auc(fpr_qda, tpr_qda)
```

```
# Logistic Regression Model
model = LogisticRegression()
logreg = model.fit(x_train, np.ravel(y_train))
logreg_scores = logreg.predict_proba(x_test)[:, 1]
fpr_logreg, tpr_logreg, thresholds_logreg = roc_curve(y_test, logreg_scores)
auc_logreg = auc(fpr_logreg, tpr_logreg)

# KNN Model with Chosen K
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(x_train, np.ravel(y_train))
knn_scores = knn.predict_proba(x_test)[:, 1]
fpr_knn, tpr_knn, thresholds_knn = roc_curve(y_test, knn_scores)
auc_knn = auc(fpr_knn, tpr_knn)

# Plot ROC Curves
plt.figure()
plt.plot(fpr_lda, tpr_lda, color='orange', lw=2, label='LDA (AUC = {:.3f})'.
  ↪format(auc_lda))
plt.plot(fpr_qda, tpr_qda, color='red', lw=2, label='QDA (AUC = {:.3f})'.
  ↪format(auc_qda))
plt.plot(fpr_logreg, tpr_logreg, color='green', lw=2, label='Logistic␣
  ↪Regression (AUC = {:.3f})'.format(auc_logreg))
plt.plot(fpr_knn, tpr_knn, color='blue', lw=2, label='KNN (K={}) (AUC = {:.
  ↪3f})'.format(best_k, auc_knn))
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Different Classifiers')
plt.legend(loc="lower right")
plt.show()
```



3. LDA (AUC = 0.925): The ROC curve for LDA shows a good balance between true positives and false positives. We can choose a threshold that maximizes true positives without significantly increasing false positives.

QDA (AUC = 0.881): QDA also shows a reasonable balance. Similar to LDA, we can choose a threshold that provides a good compromise between true positives and false positives.

Logistic Regression (AUC = 0.693): Logistic regression appears to have a lower AUC compared to LDA and QDA. The ROC curve suggests that adjusting the threshold can improve its performance on the minority class. We may need to choose a lower threshold to increase sensitivity.

KNN (K=1) (AUC = 0.553): KNN with K=1 has the lowest AUC and is not well-suited for this imbalanced dataset. We would need to adjust the threshold significantly, but it may not be effective in improving model performance.

[92]:
```
##Find Optimal Threshold
# For LDA
j_stat_lda = tpr_lda - fpr_lda
optimal_threshold_lda = thresholds_lda[np.argmax(j_stat_lda)]
sensitivity_lda = tpr_lda[np.argmax(j_stat_lda)]
specificity_lda = 1 - fpr_lda[np.argmax(j_stat_lda)]
```

```python
# For QDA
j_stat_qda = tpr_qda - fpr_qda
optimal_threshold_qda = thresholds_qda[np.argmax(j_stat_qda)]
sensitivity_qda = tpr_qda[np.argmax(j_stat_qda)]
specificity_qda = 1 - fpr_qda[np.argmax(j_stat_qda)]

# For Logistic Regression
j_stat_logreg = tpr_logreg - fpr_logreg
optimal_threshold_logreg = thresholds_logreg[np.argmax(j_stat_logreg)]
sensitivity_logreg = tpr_logreg[np.argmax(j_stat_logreg)]
specificity_logreg = 1 - fpr_logreg[np.argmax(j_stat_logreg)]

# For KNN (K=1)
j_stat_knn = tpr_knn - fpr_knn
optimal_threshold_knn = thresholds_knn[np.argmax(j_stat_knn)]
sensitivity_knn = tpr_knn[np.argmax(j_stat_knn)]
specificity_knn = 1 - fpr_knn[np.argmax(j_stat_knn)]

# Print the optimal thresholds and corresponding sensitivity and specificity␣
↪for each model
print(f"LDA: Optimal Threshold = {optimal_threshold_lda}, Sensitivity =␣
↪{sensitivity_lda:.3f}, Specificity = {specificity_lda:.3f}")
print(f"QDA: Optimal Threshold = {optimal_threshold_qda}, Sensitivity =␣
↪{sensitivity_qda:.3f}, Specificity = {specificity_qda:.3f}")
print(f"Logistic Regression: Optimal Threshold = {optimal_threshold_logreg},␣
↪Sensitivity = {sensitivity_logreg:.3f}, Specificity = {specificity_logreg:.
↪3f}")
print(f"KNN (K=1): Optimal Threshold = {optimal_threshold_knn}, Sensitivity =␣
↪{sensitivity_knn:.3f}, Specificity = {specificity_knn:.3f}")
```

```
LDA: Optimal Threshold = 0.013827884679596955, Sensitivity = 0.848, Specificity
= 0.871
QDA: Optimal Threshold = 0.00462082624977362, Sensitivity = 0.826, Specificity =
0.852
Logistic Regression: Optimal Threshold = 0.04056792064928132, Sensitivity =
0.761, Specificity = 0.659
KNN (K=1): Optimal Threshold = 1.0, Sensitivity = 0.130, Specificity = 0.976
```

Advantages and Disadvantages of Dealing with Imbalanced Data:

Advantages:

You can tune your model to focus on the class of interest (e.g., bankrupt companies) by adjusting the classification threshold. Threshold tuning can lead to a better trade-off between the two classes, improving model performance.

Disadvantages:

Imbalanced datasets can result in models that are overly biased toward the majority class. Tuning the threshold may lead to a decrease in overall accuracy, which might not be suitable for all use cases. The choice of the threshold is subjective and context-dependent, making it important to consider the specific goals of your analysis.

[ ]:

```

```