

analysis

February 18, 2024

0.0.1 Load modules libraries

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
```

0.0.2 Load the data

```
[ ]: xls = pd.ExcelFile('Data.xlsx')

data = {}
for sheet_name in xls.sheet_names:
    data[sheet_name] = pd.read_excel(xls, sheet_name)

# Perform analysis for each sheet
for sheet_name, df in data.items():
    print("Sheet Name:", sheet_name)
    print("Shape:", df.shape)

# Step 3: Descriptive and summary statistics
summary_stats = df.head()
print(summary_stats)
```

Sheet Name: Convertible bond Data

Shape: (207, 24)

	Bond	ISIN	Company	ISIN	Ticker	Issuer	\
0	US88160RAG65	69568X	TSLA			Tesla	
1	US021369AA17	9211QT	ALTR			Altair Eng	
2	US049164BJ49	29301P	RANPTA			Atlas Air WW	
3	US92336XAA72	9307U8	SSWPTA			Arriver Holdco	
4	US92886TAJ16	902179	VG			Vonage Holdings	

	Amount Issued (USD)/	Proceeds	Issue Price	Number of Issues	Coupon	\
0	1840000000		100.0	18400000.0	2.000	
1	2300000000		100.0	23000000.0	0.250	
2	2890000000		100.0	28900000.0	1.875	
3	2070000000		100.0	20700000.0	4.000	

4	345000000	100.0	3450000.0	1.750
---	-----------	-------	-----------	-------

	Maturity	No of years until final maturity	...	Country of Issue	\
0	2024-05-15	5.022810	...	United States	
1	2024-06-01	4.976277	...	United States	
2	2024-06-01	7.025325	...	United States	
3	2024-06-01	5.011861	...	United States	
4	2024-06-01	4.965328	...	United States	

	Issuer Type	Instrument Type	Bond Grade		Coupon Type	\
0	Corporate	Bond	NaN	Plain Vanilla	Fixed Coupon	
1	Corporate	Bond	NaN	Plain Vanilla	Fixed Coupon	
2	Corporate	Bond	NaN	Plain Vanilla	Fixed Coupon	
3	Corporate	Bond	NaN	Plain Vanilla	Fixed Coupon	
4	Corporate	Bond	NaN	Plain Vanilla	Fixed Coupon	

	Convertible	Bond Type	Country of Incorporation	\
0	Convertible	into Listed Securities	United States	
1	Convertible	into Listed Securities	United States	
2	Convertible	into Listed Securities	United States	
3	Convertible	into Listed Securities	United States	
4	Convertible	into Listed Securities	United States	

	TRBC Sector	Use of Proceeds	\
0	Electric (Alternative) Vehicles	General Purpose	
1	IT Services & Consulting (NEC)	NaN	
2	Air Freight	NaN	
3	Auto, Truck & Motorcycle Parts (NEC)	NaN	
4	Wireless Telecoms Service Providers	NaN	

	Placement Type/ Private Placement
0	0
1	0
2	0
3	0
4	0

[5 rows x 24 columns]

Sheet Name: Firm Data

Shape: (196, 14)

	Issue Year	Company ISIN	Placement Type	Issuer Name	Issue Size	\
0	2020.0	134966	1.0	VEECO INSTRUMENTS	125000000.0	
1	2019.0	151828	1.0	INSIGHT ENTERPRISES	350000000.0	
2	2014.0	152632	1.0	SUNEDISON INC	910000000.0	
3	2016.0	152632	1.0	SUNEDISON INC	225000000.0	
4	2019.0	152849	1.0	HARMONIC INC.	115500000.0	

	Log (Issue Size)	Total Assets Prior to Issue (USD)	\
--	------------------	-----------------------------------	---

0	8.096910	816539
1	8.544068	2767980
2	8.959041	6680500
3	8.352183	11499800
4	8.062582	510835

	Market Capitalization Prior to Issue (USD)	Log (Total Assets) \
0	719482	5.911977
1	1445892	6.442163
2	3481740	6.824809
3	5308671	7.060690
4	410909	5.708281

	Log (Market Cap)	Market to Book Prior to Issue (USD) \
0	5.857020	1.82
1	6.160136	1.54
2	6.541796	13.17
3	6.724986	16.28
4	5.613746	2.06

	FCF Per Share Prior to Issue (USD)	Altman Z Score	Debt ratio
0	-0.032	0.513836	0.367488
1	6.028	2.570023	0.072197
2	-3.144	0.302060	0.594387
3	-9.522	0.214342	0.626046
4	0.264	0.742330	0.263621

Sheet Name: Private Firm data

Shape: (158, 14)

	Issue Year	Company ISIN	Placement Type	Issuer Name	Issue Size \
0	2020.0	134966	1.0	VEECO INSTRUMENTS	125000000.0
1	2019.0	151828	1.0	INSIGHT ENTERPRISES	350000000.0
2	2014.0	152632	1.0	SUNEDISON INC	910000000.0
3	2016.0	152632	1.0	SUNEDISON INC	225000000.0
4	2019.0	152849	1.0	HARMONIC INC.	115500000.0

	Log (Issue Size)	Total Assets Prior to Issue (USD) \
0	8.096910	816539
1	8.544068	2767980
2	8.959041	6680500
3	8.352183	11499800
4	8.062582	510835

	Market Capitalization Prior to Issue (USD)	Log (Total Assets) \
0	719482	5.911977
1	1445892	6.442163
2	3481740	6.824809
3	5308671	7.060690
4	410909	5.708281

	Log (Market Cap)	Market to Book Prior to Issue (USD)	\
0	5.857020		1.82
1	6.160136		1.54
2	6.541796		13.17
3	6.724986		16.28
4	5.613746		2.06

	FCF Per Share Prior to Issue (USD)	Altman Z Score	Debt ratio
0	-0.032	0.513836	0.367488
1	6.028	2.570023	0.072197
2	-3.144	0.302060	0.594387
3	-9.522	0.214342	0.626046
4	0.264	0.742330	0.263621

Sheet Name: Public Firm data

Shape: (39, 14)

	Issue Year	Company ISIN	Placement Type	Issuer Name	Issue Size	\
0	2020.0	131745	0.0	PENN ENTERTAIN	330495000.0	
1	2020.0	134966	0.0	VEECO INSTRUMENTS	132500000.0	
2	2017.0	271153	0.0	BIOMARIN PHARMA	495000000.0	
3	2020.0	277428	0.0	NEOGENOMICS INC	201250000.0	
4	2020.0	286085	0.0	INSEEGO CORP	100000000.0	

	Log (Issue Size)	Total Assets Prior to Issue (USD)	\
0	8.519165	14194500.0	
1	8.122216	816539.0	
2	8.694605	3576904.0	
3	8.303736	709506.0	
4	8.000000	161373.0	

	Market Capitalization Prior to Issue (USD)	Log (Total Assets)	\
0	2963893	7.152120	
1	719482	5.911977	
2	14302126	6.553507	
3	3064851	5.850956	
4	600870	5.207831	

	Log (Market Cap)	Market to Book Prior to Issue (USD)	\
0	6.471863		1.56
1	5.857020		1.82
2	7.155401		5.10
3	6.486409		5.48
4	5.778781		-16.06

	FCF Per Share Prior to Issue (USD)	Altman Z Score	Debt ratio
0	4.899	0.375867	0.475797
1	-0.032	0.513836	0.367488
2	-1.301	0.407779	0.191014

3	0.345	0.670587	0.148639
4	-1.187	1.320851	1.213394

Sheet Name: Convertible bond - Public

Shape: (40, 24)

	Bond	ISIN	Company	ISIN	Ticker	Issuer	\
0	US88160RAG65	69568X	TSLA			Tesla	
1	US021369AA17	9211QT	ALTR			Altair Eng	
2	US049164BJ49	29301P	RANPTA			Atlas Air WW	
3	US92336XAA72	9307U8	SSWPTA			Arriver Holdco	
4	US92886TAJ16	902179	VG			Vonage Holdings	

	Amount Issued (USD)/	Proceeds	Issue Price	Number of Issues	Coupon	\
0	1.840000e+09		100.0	18400000.0	2.000	
1	2.300000e+08		100.0	2300000.0	0.250	
2	2.890000e+08		100.0	2890000.0	1.875	
3	2.070000e+08		100.0	2070000.0	4.000	
4	3.450000e+08		100.0	3450000.0	1.750	

	Maturity	No of years until final	maturity	...	Country of Issue	\
0	2024-05-15		5.022810	...	United States	
1	2024-06-01		4.976277	...	United States	
2	2024-06-01		7.025325	...	United States	
3	2024-06-01		5.011861	...	United States	
4	2024-06-01		4.965328	...	United States	

	Issuer Type	Instrument	Type	Bond	Grade	Coupon Type	\
0	Corporate		Bond	NaN	Plain Vanilla	Fixed Coupon	
1	Corporate		Bond	NaN	Plain Vanilla	Fixed Coupon	
2	Corporate		Bond	NaN	Plain Vanilla	Fixed Coupon	
3	Corporate		Bond	NaN	Plain Vanilla	Fixed Coupon	
4	Corporate		Bond	NaN	Plain Vanilla	Fixed Coupon	

	Convertible Bond Type	Country of	Incorporation	\
0	Convertible into Listed Securities		United States	
1	Convertible into Listed Securities		United States	
2	Convertible into Listed Securities		United States	
3	Convertible into Listed Securities		United States	
4	Convertible into Listed Securities		United States	

	TRBC Sector	Use of Proceeds	\
0	Electric (Alternative) Vehicles	General Purpose	
1	IT Services & Consulting (NEC)	NaN	
2	Air Freight	NaN	
3	Auto, Truck & Motorcycle Parts (NEC)	NaN	
4	Wireless Telecoms Service Providers	NaN	

	Placement Type/ Private Placement
0	0.0

1	0.0
2	0.0
3	0.0
4	0.0

[5 rows x 24 columns]

Sheet Name: Convertible bond private

Shape: (169, 24)

	Bond ISIN	Company ISIN	Ticker	Issuer \
0	US72941BAA44	9301L2	PLURS	Pluralsight
1	US925550AA34	357344	VIAVX	Viavi Solutions
2	US25470MAC38	51486H	DISH	DISH Network
3	US03823UAA07	89716W	AAOI	AOI
4	US401617AC92	883119	GES	Guess?

	Amount Issued (USD)/ Proceeds	Issue Price	Number of Issues	Coupon \
0	6.335000e+08	100.0	6335000.0	0.375
1	4.600000e+08	100.0	4600000.0	1.000
2	1.000000e+09	100.0	10000000.0	2.375
3	8.050000e+07	100.0	805000.0	5.000
4	3.000000e+08	100.0	3000000.0	2.000

	Maturity	No of years until final maturity	...	Country of Issue \
0	2024-03-01	4.973540	...	United States
1	2024-03-01	6.995209	...	United States
2	2024-03-15	6.995209	...	United States
3	2024-03-15	5.028285	...	United States
4	2024-04-15	4.970803	...	United States

	Issuer Type	Instrument Type	Bond Grade	Coupon Type \
0	Corporate	Bond	NaN	Plain Vanilla Fixed Coupon
1	Corporate	Bond	NaN	Plain Vanilla Fixed Coupon
2	Corporate	Bond	High Yield	Plain Vanilla Fixed Coupon
3	Corporate	Bond	NaN	Plain Vanilla Fixed Coupon
4	Corporate	Bond	NaN	Plain Vanilla Fixed Coupon

	Convertible Bond Type	Country of Incorporation \
0	Convertible into Listed Securities	United States
1	Convertible into Listed Securities	United States
2	Convertible into Listed Securities	United States
3	Convertible into Listed Securities	United States
4	Convertible into Listed Securities	United States

	TRBC Sector Use of Proceeds \
0	IT Services & Consulting (NEC) NaN
1	Communications & Networking (NEC) NaN
2	Cable Service Providers NaN
3	Electronic Components NaN

4 Apparel & Accessories Retailers (NEC) NaN

Placement Type/ Private Placement

0	1.0
1	1.0
2	1.0
3	1.0
4	1.0

[5 rows x 24 columns]

Sheet Name: Regression

Shape: (195, 19)

	Issue Year	Company ISIN	Placement Type	Issuer Name	Industry \
0	2020	134966	1	VEECO INSTRUMENTS	NaN
1	2019	151828	1	INSIGHT ENTERPRISES	NaN
2	2014	152632	1	SUNEDISON INC	NaN
3	2016	152632	1	SUNEDISON INC	NaN
4	2019	152849	1	HARMONIC INC.	NaN

	Proceeds (USD)	Issue Size	Ln (Issue Size)	Log (Proceeds)	Ln (Proceeds) \
0	125000000	153.085156	5.030994	8.096910	18.643824
1	350000000	126.446000	4.839815	8.544068	19.673444
2	910000000	136.217349	4.914252	8.959041	20.628955
3	225000000	19.565558	2.973771	8.352183	19.231611
4	115500000	226.100404	5.420979	8.062582	18.564781

	Ln (Total Assets)	Total Assets Prior to Issue (USD) \
0	13.612830	816539
1	14.833628	2767980
2	15.714703	6680500
3	16.257840	11499800
4	13.143802	510835

	Market Capitalization Prior to Issue (USD)	Log (Total Assets) \
0	719482	5.911977
1	1445892	6.442163
2	3481740	6.824809
3	5308671	7.060690
4	410909	5.708281

	Log (Market Cap)	Market to Book Prior to Issue (USD) \
0	5.857020	1.82
1	6.160136	1.54
2	6.541796	13.17
3	6.724986	16.28
4	5.613746	2.06

FCF Per Share Prior to Issue (USD) Altman Z Score Debt ratio

0	-0.032	0.513836	0.367488
1	6.028	2.570023	0.072197
2	-3.144	0.302060	0.594387
3	-9.522	0.214342	0.626046
4	0.264	0.742330	0.263621

```
[ ]: # Descriptive statistics for total assets, issue size, Altman's Z score, and
      ↪market-to-book ratio
variables_of_interest = ["Total Assets Prior to Issue (USD)", "Issue Size",
      ↪"Altman Z Score", "Market to Book Prior to Issue (USD)"]

for variable in variables_of_interest:
    print("Descriptive Statistics for", variable)
    print(data["Firm Data"][variable].describe())
    print()
```

Descriptive Statistics for Total Assets Prior to Issue (USD)

```
count    1.960000e+02
mean     1.126371e+07
std      3.694185e+07
min      1.089870e+05
25%      5.670785e+05
50%      1.478326e+06
75%      4.457372e+06
max      2.456090e+08
```

Name: Total Assets Prior to Issue (USD), dtype: float64

Descriptive Statistics for Issue Size

```
count    1.950000e+02
mean     5.071033e+08
std      4.629155e+08
min      3.784875e+07
25%      2.012500e+08
50%      3.450000e+08
75%      6.633820e+08
max      3.000000e+09
```

Name: Issue Size, dtype: float64

Descriptive Statistics for Altman Z Score

```
count    196.000000
mean     0.730181
std      0.722560
min     -0.023878
25%      0.354975
50%      0.558901
75%      0.880198
max      7.386298
```

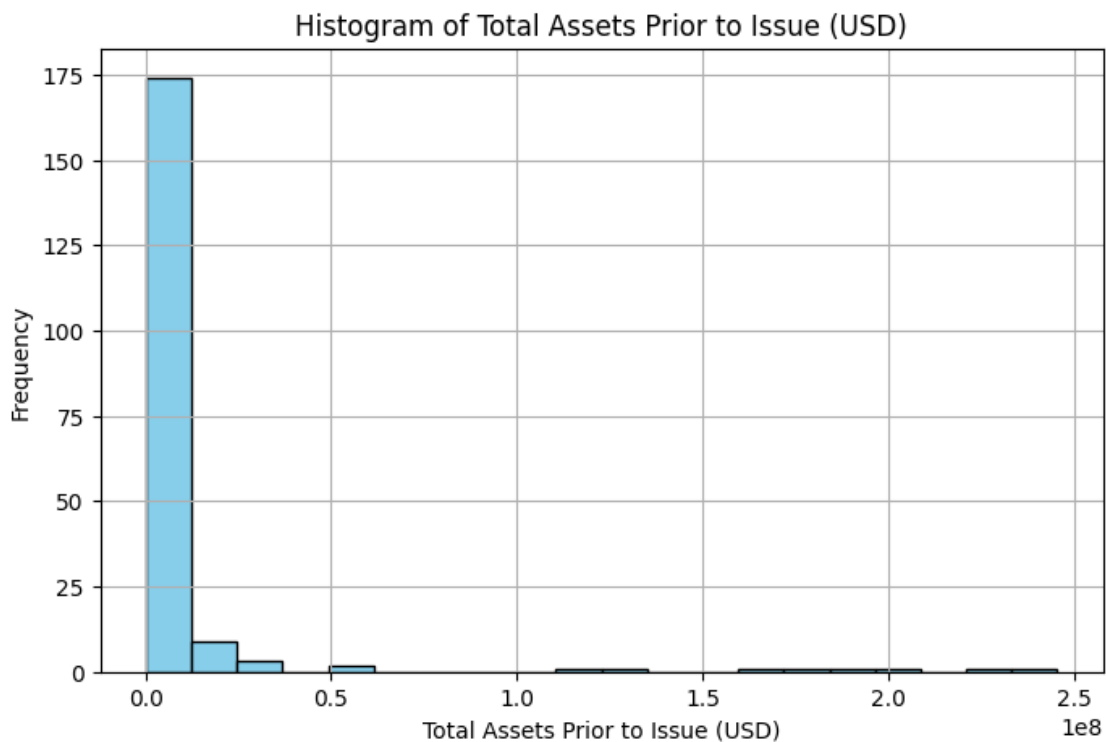
Name: Altman Z Score, dtype: float64

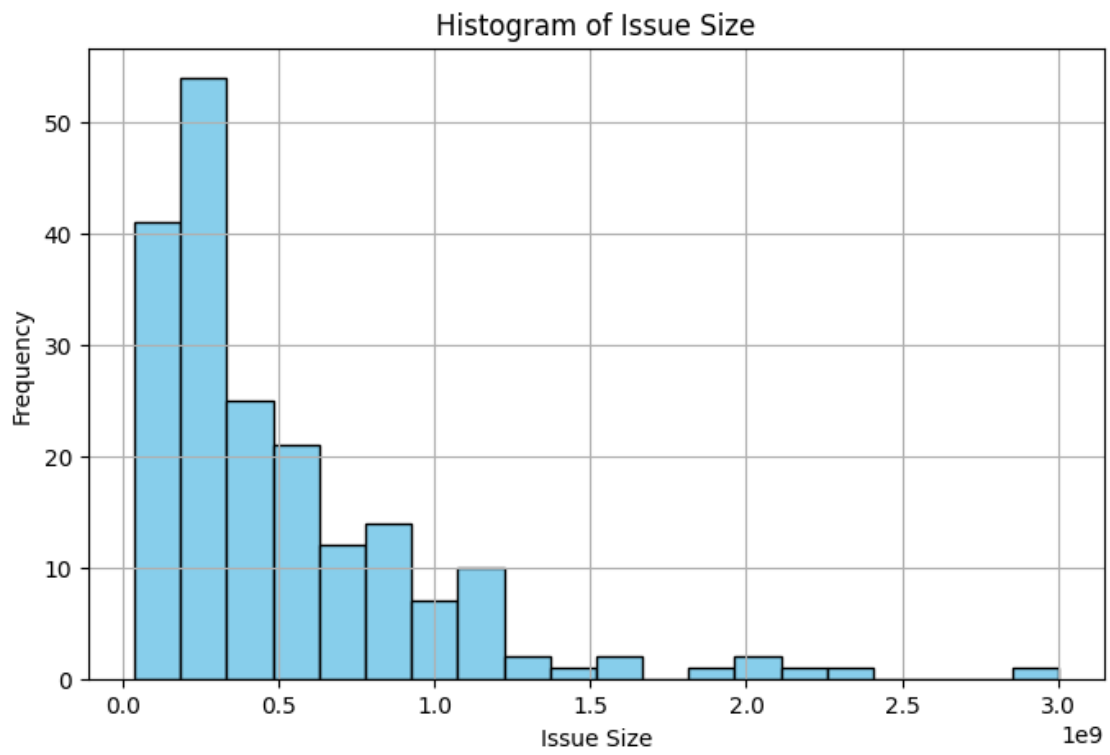
Descriptive Statistics for Market to Book Prior to Issue (USD)

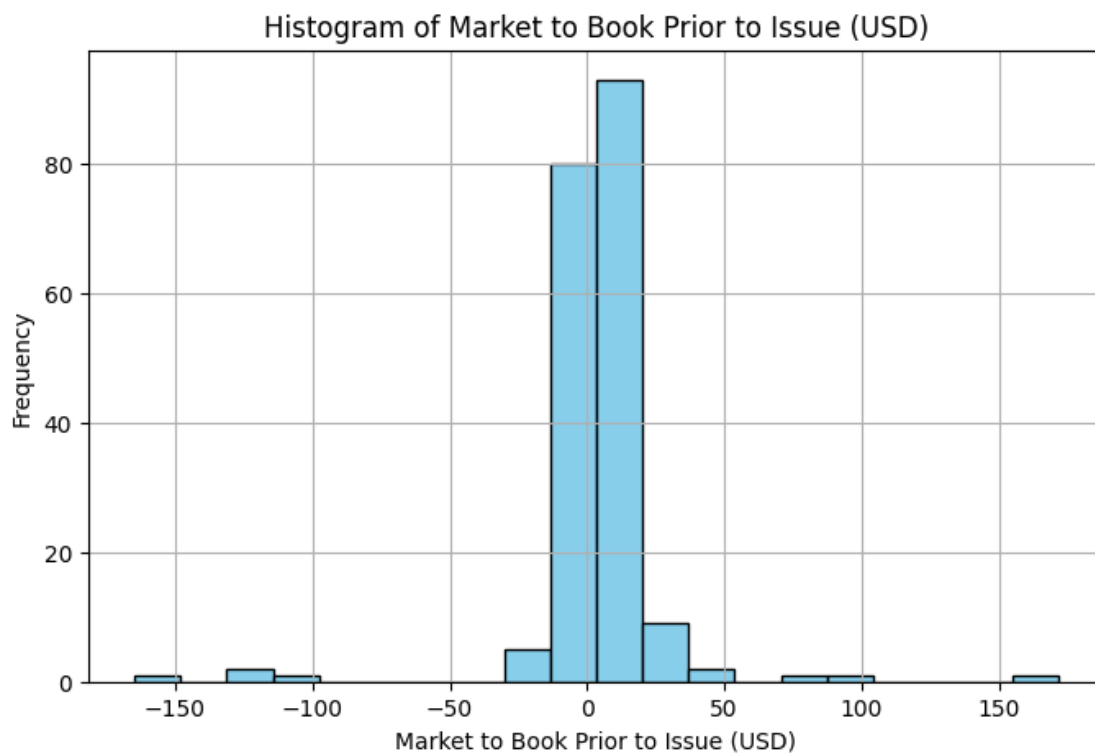
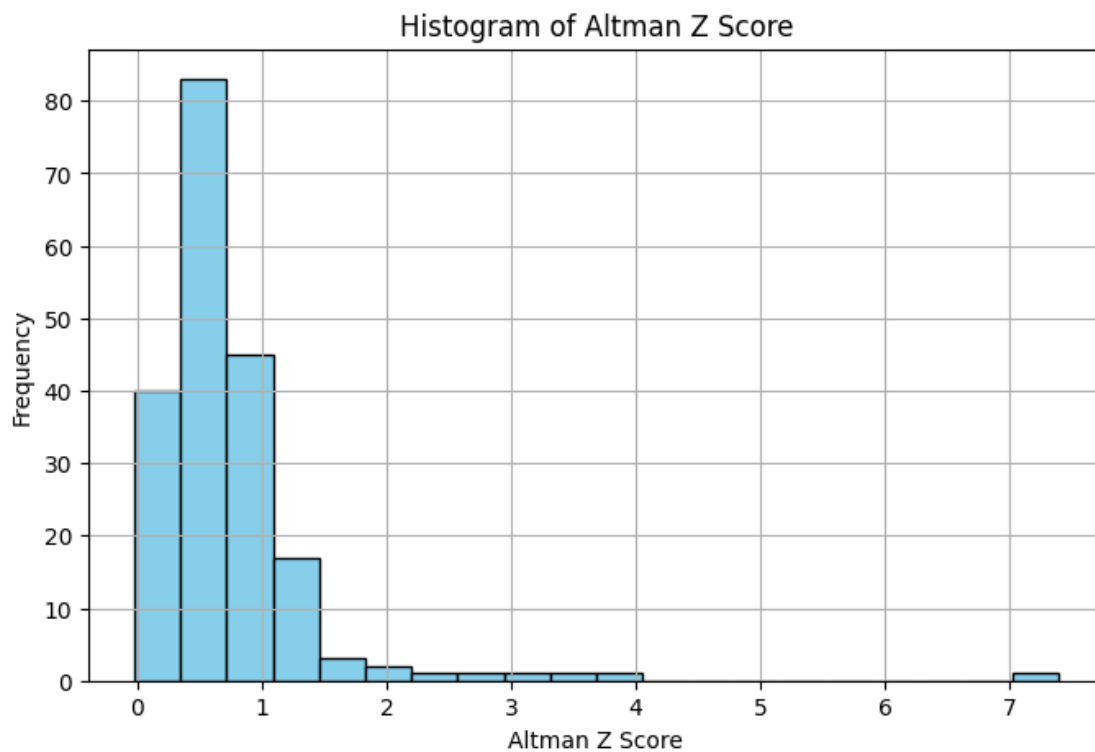
```
count    196.000000
mean      4.326888
std       26.024605
min      -164.890000
25%       1.455000
50%       3.690000
75%       8.157500
max       171.600000
Name: Market to Book Prior to Issue (USD), dtype: float64
```

```
[ ]: import matplotlib.pyplot as plt

# Univariate analysis: histograms for continuous variables
for variable in variables_of_interest:
    plt.figure(figsize=(8, 5))
    plt.hist(data["Firm Data"][variable], bins=20, color='skyblue',
             edgecolor='black')
    plt.title("Histogram of " + variable)
    plt.xlabel(variable)
    plt.ylabel("Frequency")
    plt.grid(True)
    plt.show()
```







```
[ ]: import statsmodels.api as sm

# Define independent variables and dependent variable
X = data["Firm Data"][["Total Assets Prior to Issue (USD)", "Issue Size",
    ↳ "Altman Z Score", "Market to Book Prior to Issue (USD)"]]
# Drop rows with NaN or inf values in the "Placement Type" column
data["Firm Data"] = data["Firm Data"][~data["Firm Data"]["Placement Type"].
    ↳ isna() & ~data["Firm Data"]["Placement Type"].isin([np.inf, -np.inf])]

# Convert "Placement Type" column to integers
y = data["Firm Data"]["Placement Type"].astype(int)

# Identify rows with non-finite values in the exog variables
rows_with_nans = np.isnan(X).any(axis=1) | np.isinf(X).any(axis=1)

# Remove rows with non-finite values
X_cleaned = X[~rows_with_nans]
y_cleaned = y[~rows_with_nans]

# Fit logistic regression model with cleaned data
logit_model = sm.Logit(y_cleaned, X_cleaned)
result = logit_model.fit()
print(result.summary())
```

Optimization terminated successfully.

Current function value: 0.500178

Iterations 6

Logit Regression Results

```
=====
Dep. Variable:          Placement Type    No. Observations:          195
Model:                  Logit             Df Residuals:           191
Method:                 MLE               Df Model:                3
Date:                  Sun, 18 Feb 2024    Pseudo R-squ.:           -0.01413
Time:                  11:28:05           Log-Likelihood:           -97.535
converged:              True              LL-Null:                  -96.176
Covariance Type:        nonrobust          LLR p-value:              1.000
=====
=====
```

	coef	std err	z	P> z
[0.025 0.975]				

Total Assets Prior to Issue (USD)	3.126e-10	4.88e-09	0.064	0.949
-9.26e-09 9.89e-09				
Issue Size	1.016e-09	4.38e-10	2.320	0.020

```

1.58e-10    1.87e-09
Altman Z Score          1.2148    0.345    3.526    0.000
0.540    1.890
Market to Book Prior to Issue (USD)    0.0034    0.008    0.452    0.651
-0.011    0.018
=====
=====

```

0.0.3 Assess model performance using confusion matrix and ROC curve

```

[ ]: import statsmodels.api as sm

# Define independent variables and dependent variable
X = data["Firm Data"][["Total Assets Prior to Issue (USD)", "Issue Size",
    ↪ "Altman Z Score", "Market to Book Prior to Issue (USD)"]]
y = data["Firm Data"]["Placement Type"]

# Add intercept term
X = sm.add_constant(X)

# Fit logistic regression model
logit_model = sm.Logit(y, X)
result = logit_model.fit()

# Print the summary of the logistic regression model
print(result.summary())

```

Optimization terminated successfully.

Current function value: 0.486423

Iterations 6

Logit Regression Results

```

=====
Dep. Variable:          Placement Type    No. Observations:          195
Model:                  Logit             Df Residuals:             190
Method:                 MLE               Df Model:                 4
Date:                  Sun, 18 Feb 2024    Pseudo R-squ.:           0.01376
Time:                  11:28:05           Log-Likelihood:          -94.852
converged:              True              LL-Null:                 -96.176
Covariance Type:        nonrobust          LLR p-value:             0.6185
=====
=====

```

		coef	std err	z	P> z

	[0.025 0.975]				

const		0.9213	0.387	2.379	0.017
0.162	1.680				
Total Assets Prior to Issue (USD)		-7.314e-10	4.74e-09	-0.154	0.877

-1e-08	8.55e-09				
Issue Size		4.266e-10	4.53e-10	0.942	0.346
-4.61e-10	1.31e-09				
Altman Z Score		0.4479	0.407	1.101	0.271
-0.349	1.245				
Market to Book Prior to Issue (USD)		-0.0002	0.008	-0.029	0.977
-0.015	0.015				

=====

=====

0.0.4 calculate the AIC and BIC values

```
[ ]: import numpy as np

# Log-likelihood values for the models
log_likelihood_current = -94.852
log_likelihood_previous = -97.535

# Number of parameters for each model
num_params_current = 5 # Including the intercept
num_params_previous = 4 # Including the intercept

# Number of observations
n = 195

# Calculate AIC for the current model
aic_current = -2 * log_likelihood_current + 2 * num_params_current

# Calculate BIC for the current model
bic_current = -2 * log_likelihood_current + num_params_current * np.log(n)

# Calculate AIC for the previous model
aic_previous = -2 * log_likelihood_previous + 2 * num_params_previous

# Calculate BIC for the previous model
bic_previous = -2 * log_likelihood_previous + num_params_previous * np.log(n)

print("AIC for current model:", aic_current)
print("BIC for current model:", bic_current)
print("AIC for previous model:", aic_previous)
print("BIC for previous model:", bic_previous)
```

```
AIC for current model: 199.704
BIC for current model: 216.06899779281875
AIC for previous model: 203.07
BIC for previous model: 216.16199823425498
```

0.0.5 Stochastic Gradient Descent (SGD) - Model

```
[ ]: from sklearn.linear_model import SGDClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪random_state=42)

# Feature scaling (optional but recommended for SGD)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize the SGDClassifier
sgd_clf = SGDClassifier(loss='log_loss', max_iter=1000, random_state=42)

# Train the model
sgd_clf.fit(X_train_scaled, y_train)

# Predictions on the test set
y_pred = sgd_clf.predict(X_test_scaled)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Accuracy: 0.6666666666666666

0.0.6 Model comparison

```
[ ]: # Extracting the intercept from the logistic regression results
logit_intercept = result.params[0]

# Using the coefficients and intercept to calculate the predicted probabilities
    ↪for logistic regression
logit_probs = 1 / (1 + np.exp(-(np.dot(X_test_scaled, logit_coefs) +
    ↪logit_intercept)))

# Converting probabilities to binary predictions for logistic regression
logit_pred = (logit_probs >= 0.5).astype(int)

# Calculating accuracy for logistic regression
logit_accuracy = accuracy_score(y_test, logit_pred)

# Printing the accuracy of both models
```

```
print("Logistic Regression Accuracy:", logit_accuracy)
print("SGDClassifier Accuracy:", accuracy)
```

Logistic Regression Accuracy: 0.8205128205128205

SGDClassifier Accuracy: 0.6666666666666666

/tmp/ipykernel_94736/1329026504.py:2: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`

```
logit_intercept = result.params[0]
```

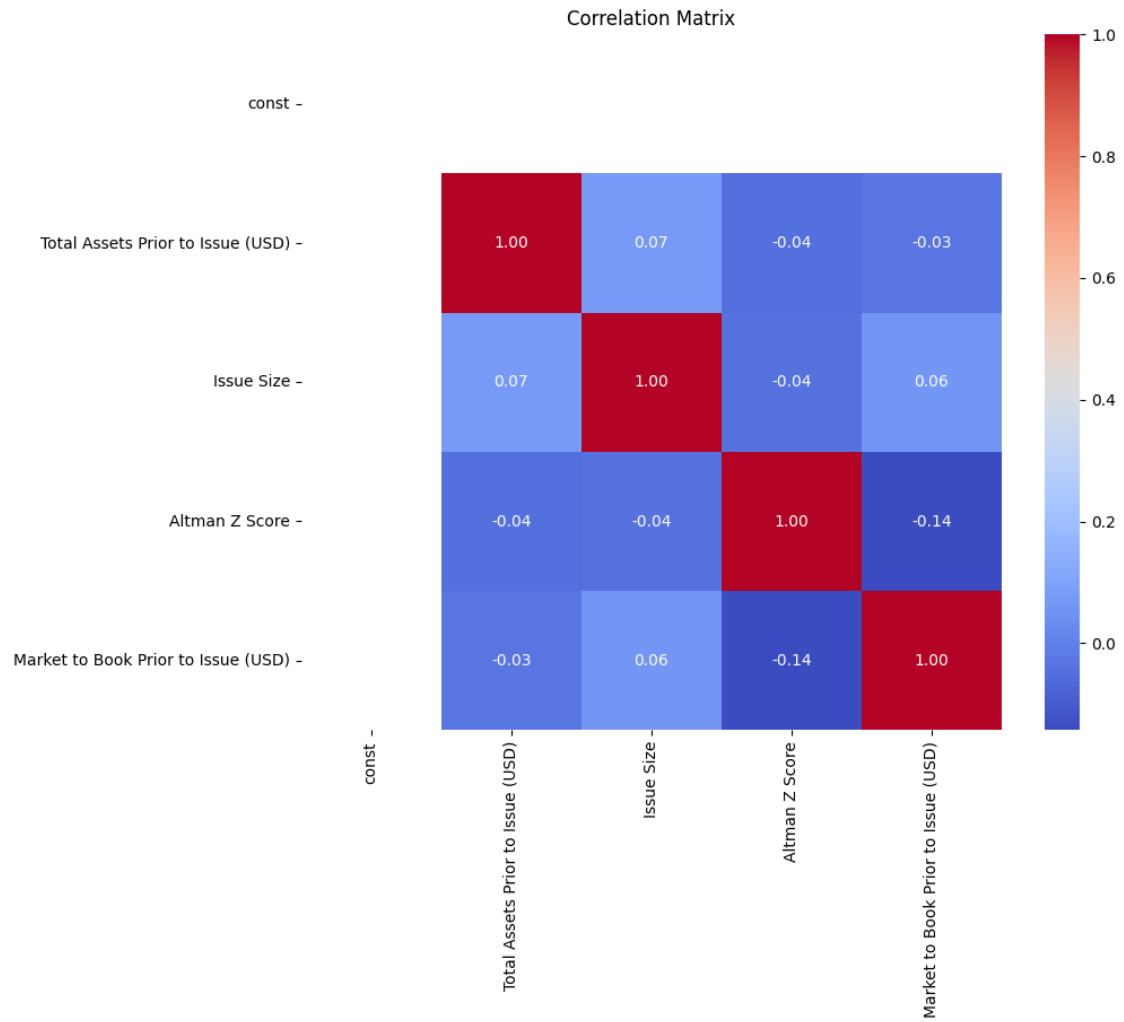
```
[ ]: import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_curve, precision_recall_curve, confusion_matrix

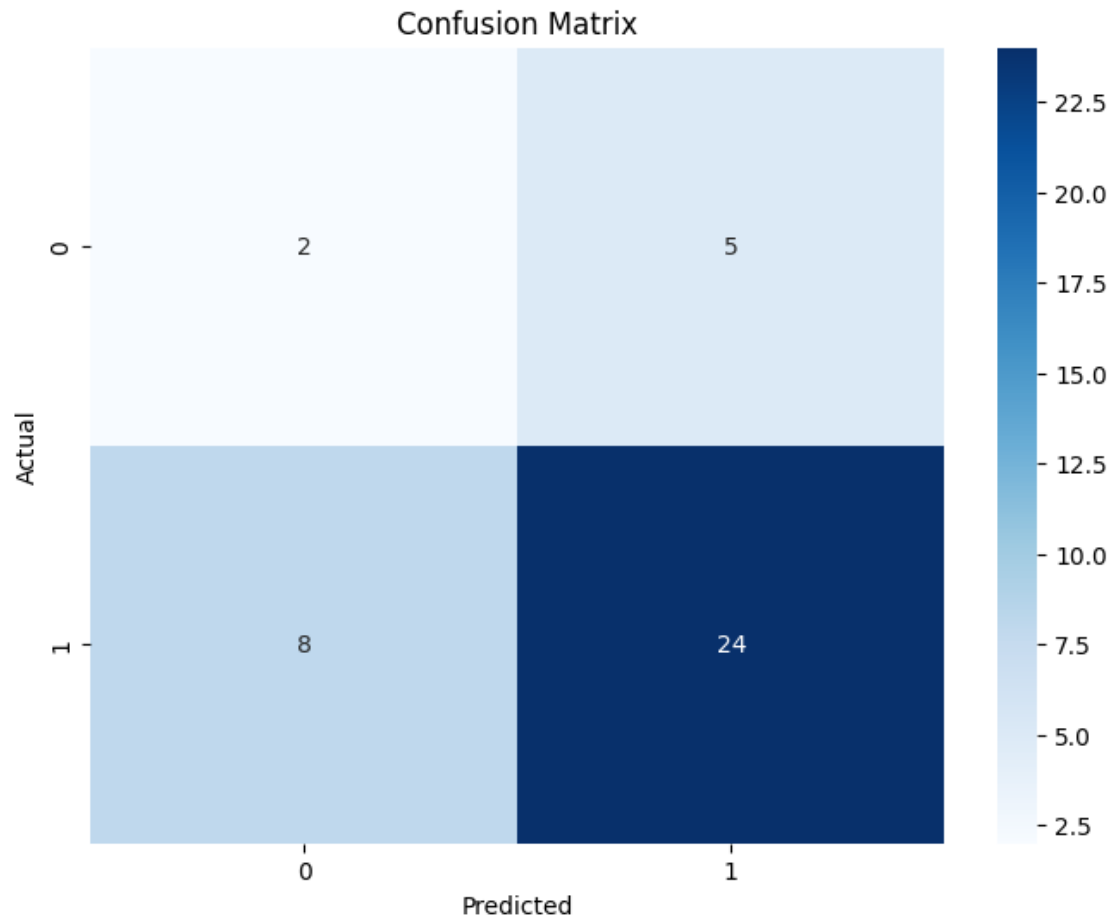
# Correlation Matrix
def plot_correlation_matrix(data):
    corr = data.corr()
    plt.figure(figsize=(10, 8))
    sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f")
    plt.title('Correlation Matrix')
    plt.show()

# Confusion Matrix
def plot_confusion_matrix(y_true, y_pred):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, cmap='Blues', fmt='g')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title('Confusion Matrix')
    plt.show()

# Call the functions with appropriate data
plot_correlation_matrix(X_train)

plot_confusion_matrix(y_test, y_pred)
```



```
[ ]:
```

```
[ ]: import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

def plot_feature_distribution(data):
    num_features = len(data.columns)
    num_rows = (num_features + 1) // 2
    plt.figure(figsize=(12, 6))
    for i, feature in enumerate(data.columns):
        plt.subplot(num_rows, 2, i+1)
        sns.histplot(data[feature], kde=True)
        plt.title(f'Distribution of {feature}')
    plt.tight_layout()
    plt.show()
```

```
# Call the function with appropriate data
```

```
# For example:  
plot_feature_distribution(X_train)
```

