# modeling-for-business-forecasting

February 7, 2024

**Data Collection and Preprocessing:**

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
from sklearn.impute import SimpleImputer
```

[ ]:
```
data = pd.read_csv("/content/Financial Distress.csv")
data.head()
```

[ ]:
```
   Company  Time  Financial Distress      x1        x2       x3       x4  \
0        1     1            0.010636  1.2810  0.022934  0.87454  1.21640
1        1     2           -0.455970  1.2700  0.006454  0.82067  1.00490
2        1     3           -0.325390  1.0529 -0.059379  0.92242  0.72926
3        1     4           -0.566570  1.1131 -0.015229  0.85888  0.80974
4        2     1            1.357300  1.0623  0.107020  0.81460  0.83593

         x5        x6       x7  …      x74    x75     x76     x77   x78  \
0  0.060940  0.188270  0.52510  …   85.437  27.07  26.102  16.000  16.0
1 -0.014080  0.181040  0.62288  …  107.090  31.31  30.194  17.000  16.0
2  0.020476  0.044865  0.43292  …  120.870  36.07  35.273  17.000  15.0
3  0.076037  0.091033  0.67546  …   54.806  39.80  38.377  17.167  16.0
4  0.199960  0.047800  0.74200  …   85.437  27.07  26.102  16.000  16.0

   x79  x80       x81  x82  x83
0  0.2   22  0.060390   30   49
1  0.4   22  0.010636   31   50
2 -0.2   22 -0.455970   32   51
3  5.6   22 -0.325390   33   52
4  0.2   29  1.251000    7   27

[5 rows x 86 columns]
```

[ ]:
```
print(data.isnull().sum())
```

```
Company              0
Time                 0
```

```
Financial Distress    0
x1                    0
x2                    0
                     ..
x79                   0
x80                   0
x81                   0
x82                   0
x83                   0
Length: 86, dtype: int64
```

**Feature Selection and Engineering:**

[ ]:
```
#correlation_matrix
correlation_matrix = data.corr().abs()
upper_tri = correlation_matrix.where(np.triu(np.ones(correlation_matrix.shape),␣
↪k=1).astype(np.bool))
to_drop = [column for column in upper_tri.columns if any(upper_tri[column] > 0.
↪95)]
data.drop(to_drop, axis=1, inplace=True)
```

```
<ipython-input-19-891450e28ae9>:3: DeprecationWarning: `np.bool` is a deprecated
alias for the builtin `bool`. To silence this warning, use `bool` by itself.
Doing this will not modify any behavior and is safe. If you specifically wanted
the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  upper_tri =
correlation_matrix.where(np.triu(np.ones(correlation_matrix.shape),
k=1).astype(np.bool))
```

[ ]:
```
# Define the features (X) and target variable (y)
X = data.drop(columns=['Financial Distress'])
y = data['Financial Distress']
```

[ ]:
```
# Handle missing values by imputing them with the mean of each column
imputer = SimpleImputer(strategy='mean')
X_imputed = imputer.fit_transform(X)

# Feature engineering: Creating new features that might improve the model's␣
↪predictive power
poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(X_imputed)
```

[ ]:
```
data['month'] = pd.to_datetime(data['Time']).dt.month
data['day'] = pd.to_datetime(data['Time']).dt.day
data['hour'] = pd.to_datetime(data['Time']).dt.hour
```

```
[ ]: data['x1_lag1'] = data['x1'].shift(1)
```

**Model Selection:**

```
[ ]: from sklearn.model_selection import train_test_split
     from sklearn.linear_model import LinearRegression
     from sklearn.ensemble import RandomForestRegressor
     from sklearn.metrics import mean_squared_error
     from sklearn.impute import SimpleImputer
```

```
[ ]: # Split the data into training and testing sets
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
      ↪random_state=42)
```

```
[ ]: # Handle missing values in the features
     imputer = SimpleImputer(strategy='mean')
     X_train_imputed = imputer.fit_transform(X_train)
     X_test_imputed = imputer.transform(X_test)
```

```
[ ]: # Model selection: Choose appropriate regression models
     models = {
         "Linear Regression": LinearRegression(),
         "Random Forest Regressor": RandomForestRegressor(random_state=42)
     }
```

```
[ ]: # Train and evaluate each model
     for name, model in models.items():
         model.fit(X_train_imputed, y_train)
         y_pred = model.predict(X_test_imputed)
         mse = mean_squared_error(y_test, y_pred)
         print(f"{name}: Mean Squared Error = {mse:.2f}")
```

```
Linear Regression: Mean Squared Error = 1003.63
Random Forest Regressor: Mean Squared Error = 1.14
```

**Model Development and Evaluation:**

```
[ ]: from sklearn.model_selection import train_test_split
     from sklearn.ensemble import RandomForestRegressor
     from sklearn.impute import SimpleImputer
     from sklearn.metrics import mean_squared_error
```

```
[ ]: # Split the data into training and testing sets
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
      ↪random_state=42)
```

```
[ ]: # Handle missing values in the features
     imputer = SimpleImputer(strategy='mean')
```

```
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)
```

[ ]:
```
# Define the model
model = RandomForestRegressor(random_state=42)
```

[ ]:
```
# Train the model
model.fit(X_train_imputed, y_train)
```

[ ]:
```
RandomForestRegressor(random_state=42)
```

[ ]:
```
# Make predictions on the testing data
y_pred = model.predict(X_test_imputed)
```

[ ]:
```
# Evaluate the model using Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse:.2f}")
```

```
Mean Squared Error: 1.14
```

**Predictive Insights:**

[ ]:
```
# Get feature importances
feature_importance = model.feature_importances_

# Sort feature importances in descending order
sorted_idx = np.argsort(feature_importance)[::-1]

# Print feature names and their importance scores
for i in sorted_idx:
    print(f"{X.columns[i]}: {feature_importance[i]}")
```

```
x48: 0.3090087194062596
x41: 0.163136481522076
x25: 0.14561107025407827
x10: 0.04382329461971983
x73: 0.017246554441904243
x19: 0.015594210974306778
x9: 0.015144994870977339
x83: 0.010487358954927717
x3: 0.00891042212655669
x28: 0.008371355916789953
x14: 0.007770702679828272
x47: 0.007670687128422793
x30: 0.007654078740588396
x58: 0.007427739314997659
x39: 0.007114408382947107
x59: 0.007058183524293813
```

```
x22: 0.006987261700509246
x21: 0.0068025684156600204
x32: 0.006608977269191928
x68: 0.006439945229182956
x20: 0.0062812419490220605
x24: 0.0061139003514323
x54: 0.006013698947933399
x36: 0.005988819716260606
x46: 0.005668338677229048
x66: 0.005658450546249864
x16: 0.005499047953228381
x40: 0.00527019042111605
x12: 0.005175151527174476
x45: 0.005141277201464576
x18: 0.005139162472876233
x71: 0.004953625676704989
x61: 0.004786823114997776
x55: 0.004723718066318178
x37: 0.004660609151906636
x57: 0.004633516060501674
x79: 0.004587664183173071
x63: 0.004247660829974798
x5: 0.003946581653934656
x53: 0.003924205272744166
x17: 0.003787997113625004
x31: 0.0037141194773741533
x74: 0.0036646564860900693
x65: 0.0036126862164825076
x27: 0.0033884080396323845
x60: 0.0032770944007498855
x56: 0.0031738224919303764
x38: 0.003155396543887233
Company: 0.0029481489006722684
x33: 0.0028328049504060334
x51: 0.002802768096463701
x23: 0.0026232040416876885
x26: 0.0025735433340151738
x62: 0.002549688068575275
x11: 0.0025192702926476822
x43: 0.002518549728735546‌4
x64: 0.0025171437207263335
x80: 0.002496805505393409
x44: 0.0024832000490814256
x4: 0.0024805509735338306
x82: 0.0024366758203886777
x2: 0.0024125354015970017
x69: 0.00235748688058591
x8: 0.0022836939218970984
```

```
x70: 0.0020375484276274O4
x15: 0.002016925409720O874
x67: 0.0020091791483752737
Time: 0.0019642868670897273
x42: 0.0019554510512905495
x7: 0.001909992801898369
x35: 0.0016277879489805971
x6: 0.0014914246773651393
x29: 0.0014912068788452888
x1: 0.0014718832262057494
x72: 0.000851730491901645
x78: 0.0007274716320505119
x77: 0.0005521617350094228
```

[ ]:
```
# Calculate residuals
residuals = y_test - y_pred
```

[ ]:
```
# Find instances with high prediction errors
high_error_indices = np.argsort(np.abs(residuals))[::-1][:10]  # Adjust the␣
↪number of instances as needed

# Print feature values and their corresponding actual and predicted values for␣
↪high-error instances
for idx in high_error_indices:
    print(f"Instance {idx}:")
    print(f"Actual Value: {y_test.iloc[idx]}")
    print(f"Predicted Value: {y_pred[idx]}")
    print(f"Features: {X_test.iloc[idx]}")
```

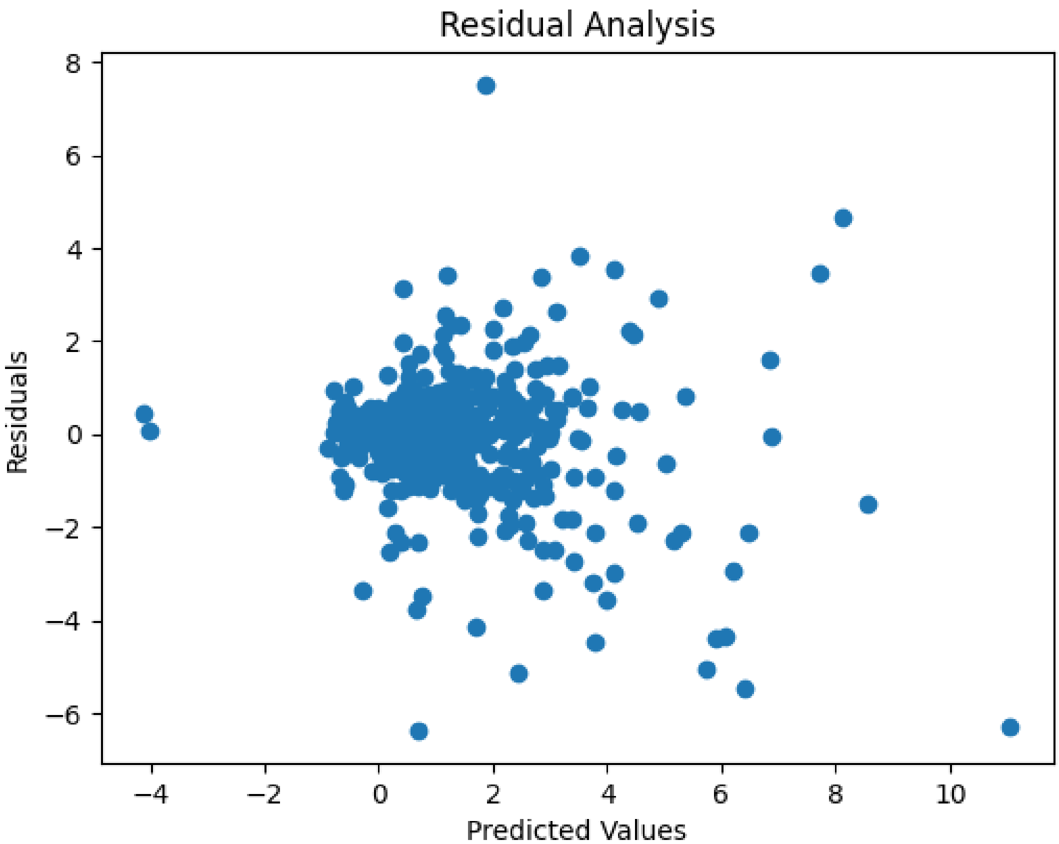
```
Instance 347:
Actual Value: 9.3749
Predicted Value: 1.8606840999999992
Features: Company    96.00000
Time        4.00000
x1          0.70861
x2          0.58095
x3          0.84753
             …
x78        16.00000
x79         5.60000
x80        18.00000
x82         4.00000
x83        15.00000
Name: 1073, Length: 77, dtype: float64
Instance 665:
Actual Value: -5.6838
Predicted Value: 0.6850457449999996
Features: Company    89.000000
```

```
Time        1.000000
x1          1.125600
x2          0.028183
x3          0.860420
              …
x78        16.000000
x79         0.200000
x80        23.000000
x82         3.000000
x83        20.000000
Name: 1006, Length: 77, dtype: float64
Instance 154:
Actual Value: 4.7789
Predicted Value: 11.0579138
Features: Company    284.00000
Time        11.00000
x1           6.84810
x2           0.74941
x3           0.20403
              …
x78         14.50000
x79        -13.75000
x80         25.00000
x82          2.00000
x83          9.00000
Name: 2893, Length: 77, dtype: float64
Instance 128:
Actual Value: 0.96119
Predicted Value: 6.404533899999997
Features: Company    360.000000
Time         9.000000
x1           0.726020
x2           0.068228
x3           0.787430
               …
x78         12.750000
x79          0.750000
x80         29.000000
x82         16.000000
x83         50.000000
Name: 3261, Length: 77, dtype: float64
Instance 240:
Actual Value: -2.7031
Predicted Value: 2.4237075520000007
Features: Company    15.000000
Time        6.000000
x1          0.989490
x2          0.080388
```

```
x3          0.762280
             …
x78        12.000000
x79        -6.400000
x80        18.000000
x82        12.000000
x83        41.000000
Name: 139, Length: 77, dtype: float64
Instance 676:
Actual Value: 0.71129
Predicted Value: 5.744179399999999
Features: Company    249.00000
Time        11.00000
x1           1.22220
x2           0.18870
x3           0.51988
             …
x78         14.50000
x79        -16.00000
x80         19.00000
x82         16.00000
x83         55.00000
Name: 2599, Length: 77, dtype: float64
Instance 492:
Actual Value: 12.772
Predicted Value: 8.124106099999995
Features: Company    284.00000
Time        10.00000
x1           1.28090
x2           0.52497
x3           0.38903
             …
x78         14.12500
x79         -5.10000
x80         25.00000
x82          1.00000
x83          8.00000
Name: 2892, Length: 77, dtype: float64
Instance 545:
Actual Value: -0.72071
Predicted Value: 3.7704444399999995
Features: Company    263.00000
Time         7.00000
x1           1.11090
x2           0.11228
x3           0.83831
             …
x78         12.00000
```

```
x79        -13.40000
x80         22.00000
x82          6.00000
x83         18.00000
Name: 2742, Length: 77, dtype: float64
Instance 46:
Actual Value: 1.5174
Predicted Value: 5.888393099999999
Features: Company    294.00000
Time        14.00000
x1           0.41990
x2           0.13382
x3           0.68937
             …
x78         20.50000
x79          8.60000
x80         16.00000
x82          1.00000
x83          8.00000
Name: 2917, Length: 77, dtype: float64
Instance 399:
Actual Value: 1.7354
Predicted Value: 6.063268899999998
Features: Company    186.00000
Time        11.00000
x1           2.07540
x2           0.51572
x3           0.24060
             …
x78         14.50000
x79        -16.00000
x80          4.00000
x82          1.00000
x83         17.00000
Name: 1992, Length: 77, dtype: float64
```

[ ]:
```
# Plot residuals
plt.scatter(y_pred, residuals)
plt.xlabel("Predicted Values")
plt.ylabel("Residuals")
plt.title("Residual Analysis")
plt.show()
```


Residual Analysis
Residuals
Predicted Values
8
6
4
2
0
−2
−4
−6
−4
−2
0
2
4
6
8
10