Learning Analytics- ML Model predictions

August 20, 2024

1 Learning Analytics and Model prediction

Goal is to predict the module completion rates using the courses, studentAssessment, and assessments datasets available on Open University Learning Analytics Dataset (OULAD) and investigate which model better predicts based on the model results.

Data Source: https://www.kaggle.com/rocki37/open-university-learning-analytics-dataset

Have used Python and SciKitLearn Machine Learning libraries for analyses of data from the OULAD Dataset, which contains data about courses, students and their interactions with Virtual Learning Environment (VLE) for seven selected courses (called modules).

Github repository# https://github.com/shirleymsassignments/Introduction-to-ML

[77]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪classification_report
from scipy import stats
```

[64]:

```
# Load datasets
courses = pd.read_csv('data/courses.csv')
student_assessments = pd.read_csv('data/studentAssessment.csv')
assessments = pd.read_csv('data/assessments.csv')
student_info = pd.read_csv('data/studentInfo.csv')

# Preview datasets
print("Courses data\n")
print(courses.head())
print("\nStudent_assessments data\n")
print(student_assessments.head())
print("\nAssessments data\n")
print(assessments.head())
```

```python
print("\nStudent_info data\n")
print(student_info.head())
```

```
Courses data

  code_module code_presentation  module_presentation_length
0         AAA              2013J                         268
1         AAA              2014J                         269
2         BBB              2013J                         268
3         BBB              2014J                         262
4         BBB              2013B                         240

Student_assessments data

   id_assessment  id_student  date_submitted  is_banked  score
0           1752       11391              18          0   78.0
1           1752       28400              22          0   70.0
2           1752       31604              17          0   72.0
3           1752       32885              26          0   69.0
4           1752       38053              19          0   79.0

Assessments data

  code_module code_presentation  id_assessment assessment_type   date  weight
0         AAA              2013J           1752             TMA   19.0    10.0
1         AAA              2013J           1753             TMA   54.0    20.0
2         AAA              2013J           1754             TMA  117.0    20.0
3         AAA              2013J           1755             TMA  166.0    20.0
4         AAA              2013J           1756             TMA  215.0    30.0

Student_info data

  code_module code_presentation  id_student gender                region  \
0         AAA              2013J       11391      M   East Anglian Region
1         AAA              2013J       28400      F              Scotland
2         AAA              2013J       30268      F  North Western Region
3         AAA              2013J       31604      F     South East Region
4         AAA              2013J       32885      F  West Midlands Region

       highest_education imd_band age_band  num_of_prev_attempts  \
0       HE Qualification  90-100%     55<=                     0
1       HE Qualification   20-30%    35-55                     0
2  A Level or Equivalent   30-40%    35-55                     0
3  A Level or Equivalent   50-60%    35-55                     0
4     Lower Than A Level   50-60%     0-35                     0

   studied_credits disability final_result
```

```
0              240          N         Pass
1               60          N         Pass
2               60          Y    Withdrawn
3               60          N         Pass
4               60          N         Pass
```

[26]:
```
###Merge the datasets based on relevant keys to create a unified dataset for␣
↪analysis.
```

[68]:
```
# Merge assessments with student assessments on assessment ID
merged_data = pd.merge(student_assessments, assessments, on='id_assessment')

# Merge the result with courses to get course information
merged_data = pd.merge(merged_data, courses, on=['code_module',␣
↪'code_presentation'])

merged_data = pd.merge(merged_data, student_info, on=['id_student',␣
↪'code_module', 'code_presentation'])
```

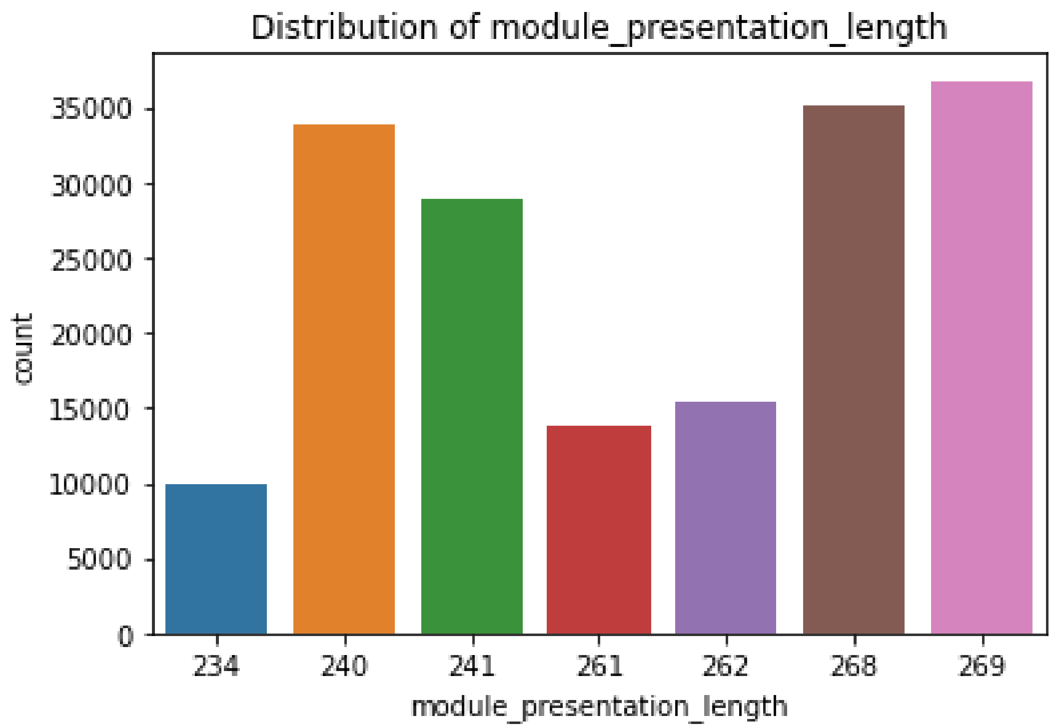
[69]:
```
print(merged_data.describe())
```

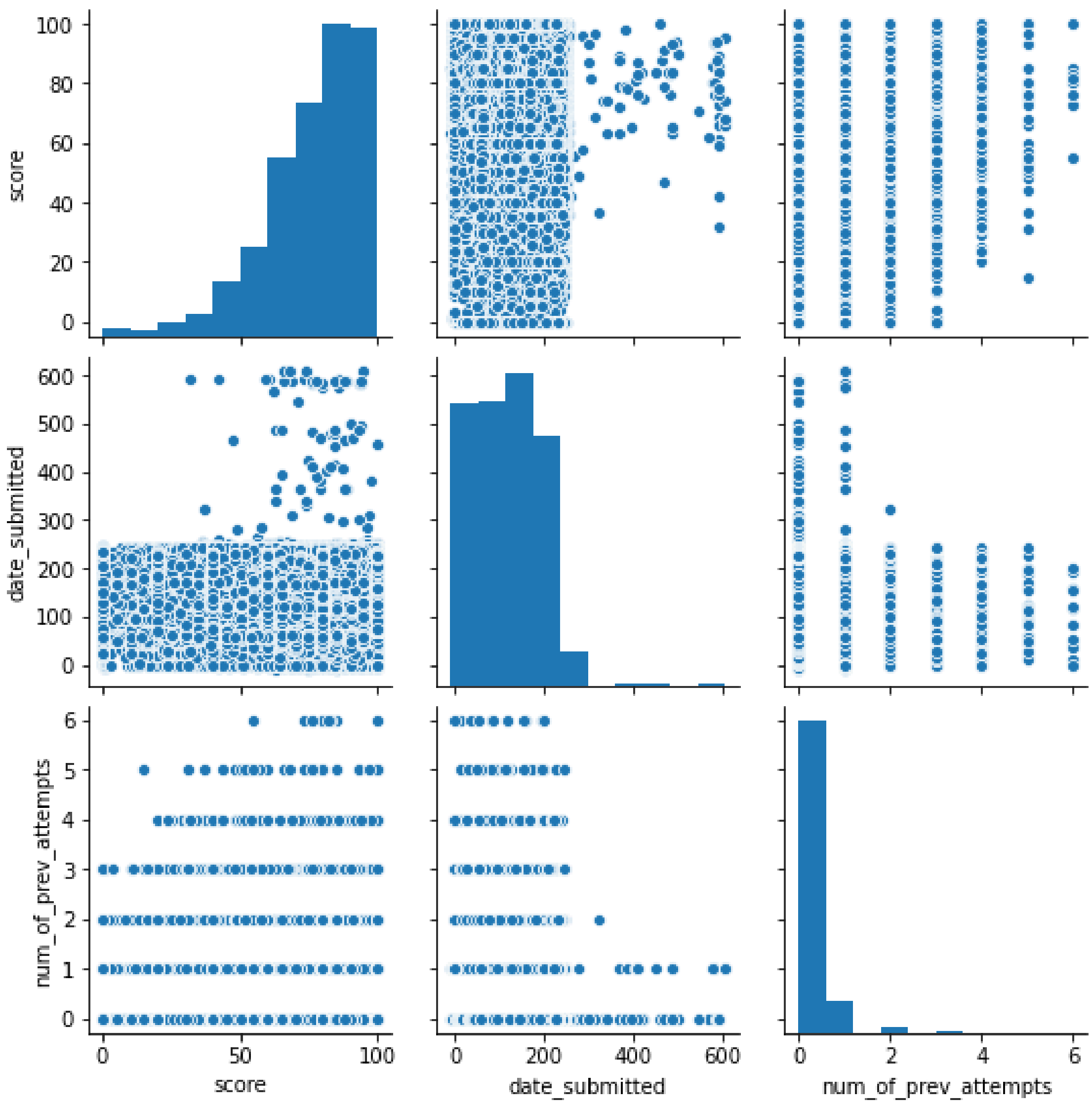
```
       id_assessment    id_student  date_submitted      is_banked  \
count  173912.000000  1.739120e+05   173912.000000  173912.000000
mean    26553.803556  7.051507e+05      116.032942       0.010977
std      8829.784254  5.523952e+05       71.484148       0.104194
min      1752.000000  6.516000e+03      -11.000000       0.000000
25%     15022.000000  5.044290e+05       51.000000       0.000000
50%     25359.000000  5.852080e+05      116.000000       0.000000
75%     34883.000000  6.344980e+05      173.000000       0.000000
max     37443.000000  2.698588e+06      608.000000       1.000000

               score           date         weight  \
count  173739.000000  171047.000000  173912.000000
mean       75.799573     130.605623      12.743899
std        18.798107      78.025175      17.877301
min         0.000000      12.000000       0.000000
25%        65.000000      54.000000       0.000000
50%        80.000000     129.000000       9.000000
75%        90.000000     214.000000      18.000000
max       100.000000     261.000000     100.000000

       module_presentation_length  num_of_prev_attempts  studied_credits
count               173912.000000         173912.000000    173912.000000
mean                   255.233831              0.144907        76.779147
std                     13.579401              0.445326        37.341741
min                    234.000000              0.000000        30.000000
25%                    240.000000              0.000000        60.000000
50%                    262.000000              0.000000        60.000000
```

75%	268.000000	0.000000	90.000000
max	269.000000	6.000000	630.000000

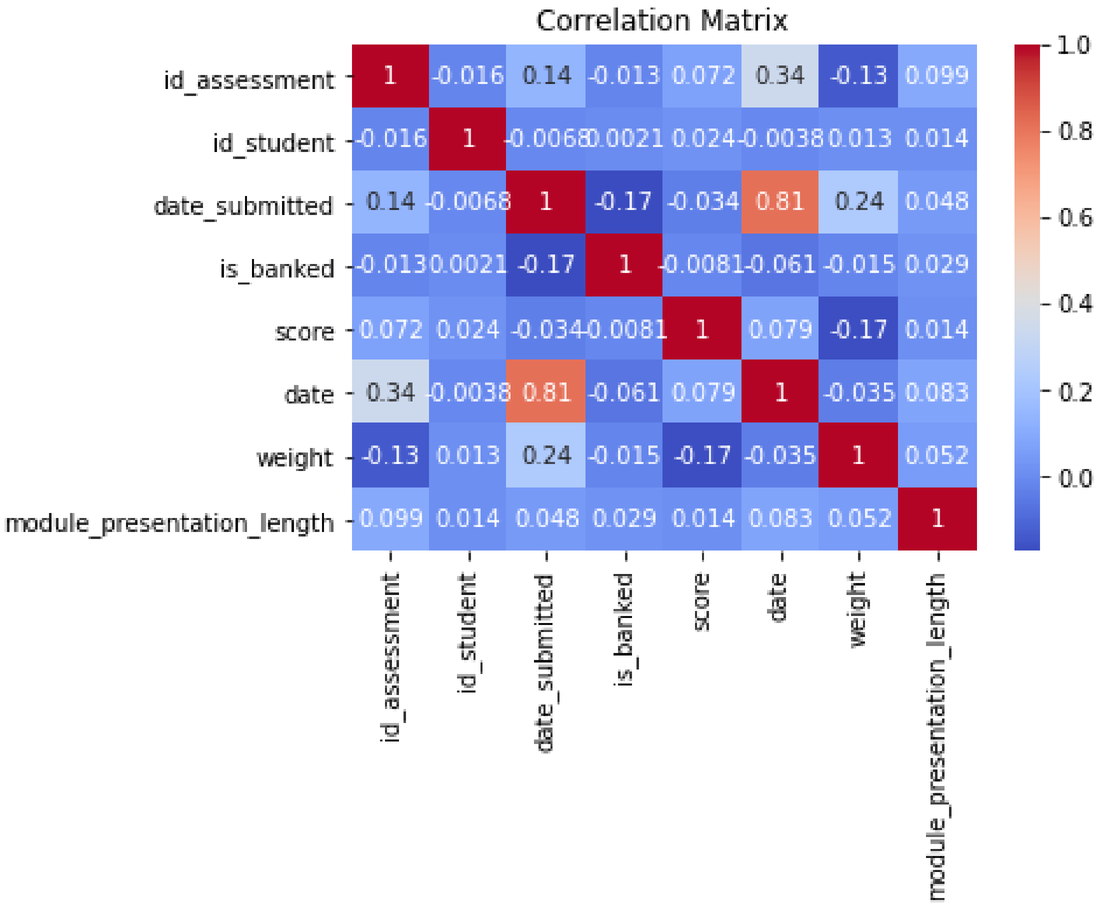
[70]:
```
### Exploratory Data Analysis (EDA)
```

[74]:
```
# Distribution of the target variable (e.g., 'final_result')
sns.countplot(merged_data['module_presentation_length'], data=merged_data)
plt.title('Distribution of module_presentation_length')
plt.show()

# Scatter plot for relationships
sns.pairplot(merged_data[['score', 'date_submitted', 'num_of_prev_attempts',␣
↪'final_result']])
plt.show()
```





[52]:
```
# Correlation matrix
corr_matrix = merged_data.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



The matrix suggests that factors like score, date_submitted, and weight have more substantial impacts on module completion rates

[53]:
```
###Data Cleaning
```

[75]:
```
# Check for missing values
print(merged_data.isnull().sum())

# Handle missing values
merged_data = merged_data.dropna()

# Feature Engineering: Create aggregated features
# For example, calculate the total score per course per student
merged_data['total_score'] = merged_data.groupby(['id_student', 'code_module',␣
↪'code_presentation'])['score'].transform('sum')

# Drop duplicates or redundant columns if any
merged_data = merged_data.drop_duplicates(subset=['id_student', 'code_module',␣
↪'code_presentation'])
```

```
id_assessment                    0
id_student                       0
date_submitted                   0
is_banked                        0
score                          173
code_module                      0
code_presentation                0
assessment_type                  0
date                          2865
weight                           0
module_presentation_length       0
gender                           0
region                           0
highest_education                0
imd_band                      7697
age_band                         0
num_of_prev_attempts             0
studied_credits                  0
disability                       0
final_result                     0
dtype: int64
```

[82]:

```
# One-hot encoding for categorical features
categorical_features = ['code_module', 'code_presentation', 'gender', 'region',␣
↪'highest_education']
encoded_data = pd.get_dummies(merged_data[categorical_features],␣
↪drop_first=True)

# Combine with the rest of the data
final_data = pd.concat([merged_data, encoded_data], axis=1)
final_data.drop(categorical_features, axis=1, inplace=True)
```

[56]:

```
## Data preparation
```

[83]:

```
# Select predictors and target variable
X = final_data[['total_score', 'date', 'weight']]  # Select relevant predictors
y = final_data['module_presentation_length']  # Continuous target: length of␣
↪the module presentation

# Train-test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Standardization (if necessary)
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[57]:
```
## Model Building: Linear Regression
```

[98]:
```
# LinearRegression model
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test) # prediction

# Model Evaluation
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')

# Coefficients interpretation
coefficients = pd.DataFrame(model.coef_, X.columns, columns=['Coefficient'])
print(coefficients)

# Logistic Regression Model
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_train, y_train)
y_pred_lr = log_reg.predict(X_test)

# Model Evaluation
print("\n\n\nLogistic Regression:\n\n")
print(f'Accuracy: {accuracy_score(y_test, y_pred_lr)}')
print(confusion_matrix(y_test, y_pred_lr))
print(classification_report(y_test, y_pred_lr))
```

```
Mean Squared Error: 168.54732316882414
R-squared: 0.020088379419650915
             Coefficient
total_score    -1.394672
date            0.808240
weight          1.014224



Logistic Regression:


Accuracy: 0.4300100704934542
[[244   0   0   0   0   0   0]
 [  0 278  52   0  77 252  55]
 [  0   0 156  29  79 161 434]
```

```
 [  0   0 176  32   0   0 240]
 [  0 103   3   0 504   0   3]
 [  0 292   1   2  93 431 181]
 [  0   0 154  29  99 315 490]]
              precision    recall  f1-score   support

         234       1.00      1.00      1.00       244
         240       0.41      0.39      0.40       714
         241       0.29      0.18      0.22       859
         261       0.35      0.07      0.12       448
         262       0.59      0.82      0.69       613
         268       0.37      0.43      0.40      1000
         269       0.35      0.45      0.39      1087

    accuracy                           0.43      4965
   macro avg       0.48      0.48      0.46      4965
weighted avg       0.41      0.43      0.41      4965
```

[99]:

```
# Random Forest Model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)

print("\n\n\nRandom Forest:\n\n")
print(f'Accuracy: {accuracy_score(y_test, y_pred_rf)}')
print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
```

```



Random Forest:


Accuracy: 0.611681772406848
[[244   0   0   0   0   0   0]
 [  0 408   0   1   0 304   1]
 [  0   1 306 167   0  33 352]
 [  0   0 135 278   0   0  35]
 [  0   0   0   0 612   0   1]
 [  0 289  27   0   0 563 121]
 [  0   0 289  69   0 103 626]]
              precision    recall  f1-score   support

         234       1.00      1.00      1.00       244
         240       0.58      0.57      0.58       714
         241       0.40      0.36      0.38       859
```

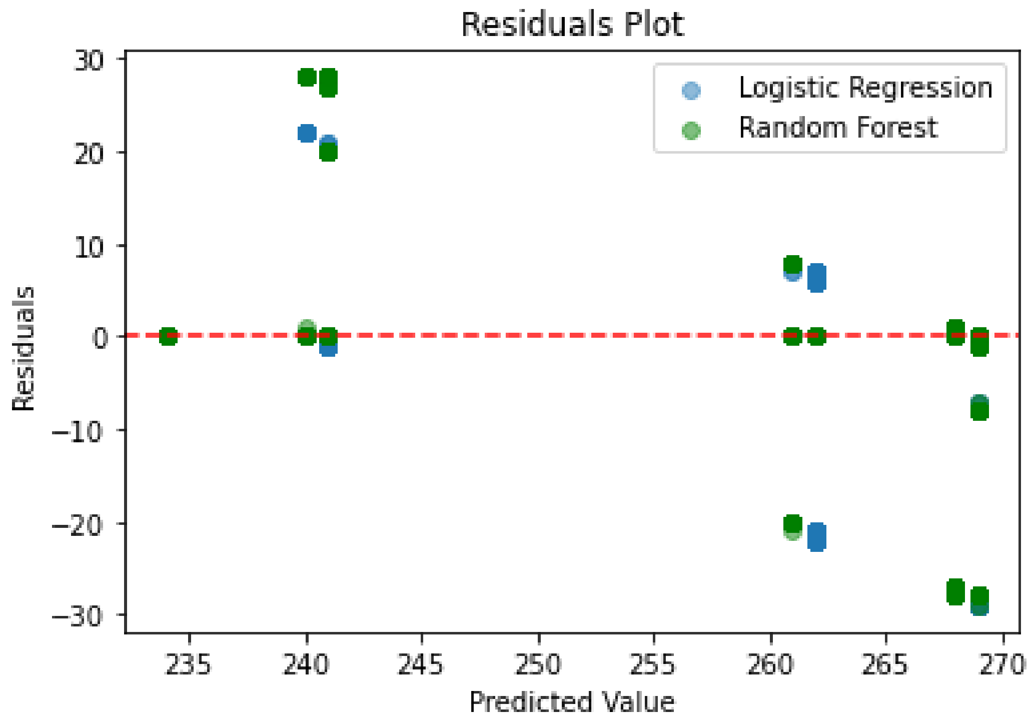
```
         261       0.54      0.62      0.58       448
         262       1.00      1.00      1.00       613
         268       0.56      0.56      0.56      1000
         269       0.55      0.58      0.56      1087

    accuracy                           0.61      4965
   macro avg       0.66      0.67      0.67      4965
weighted avg       0.61      0.61      0.61      4965
```

[97]:

```
### Residual Analysis
```

[96]:

```
# Residuals for Logistic Regression
residuals_lr = y_test - y_pred_lr

# Residuals for Random Forest
residuals_rf = y_test - y_pred_rf

# Plot Residuals
plt.figure()
plt.scatter(y_pred_lr, residuals_lr, alpha=0.5, label='Logistic Regression')
plt.scatter(y_pred_rf, residuals_rf, alpha=0.5, color='green', label='Random␣
 ↪Forest')
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Predicted Value')
plt.ylabel('Residuals')
plt.title('Residuals Plot')
plt.legend()
plt.show()
```



2 Analysis

3 Linear Regression

MSE indicates the average squared difference between predicted and actual values. A higher MSE suggests that the model's predictions are not close to the actual values. R-squared is very low (0.020), meaning the model explains only 2% of the variance in the target variable. This suggests that the linear regression model is not suitable for this data.

4 Logistic Regression

Accuracy is 0.43, which is quite low and suggests that the model performs poorly in predicting module completion.

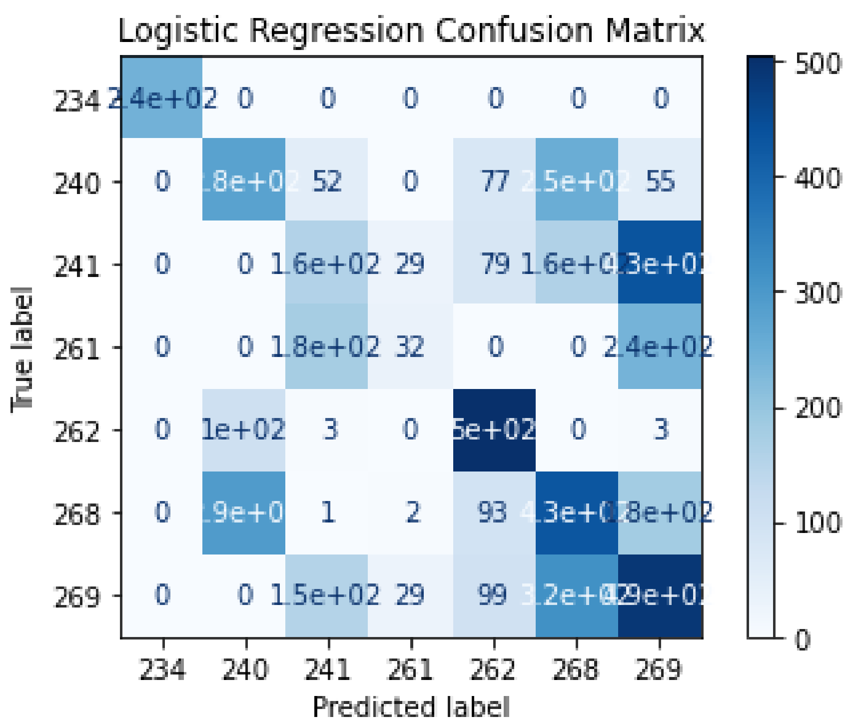
Precision and Recall vary significantly across classes, with high precision and recall for some classes (ex: Class 234) and very low for others (Ex: Class 261)

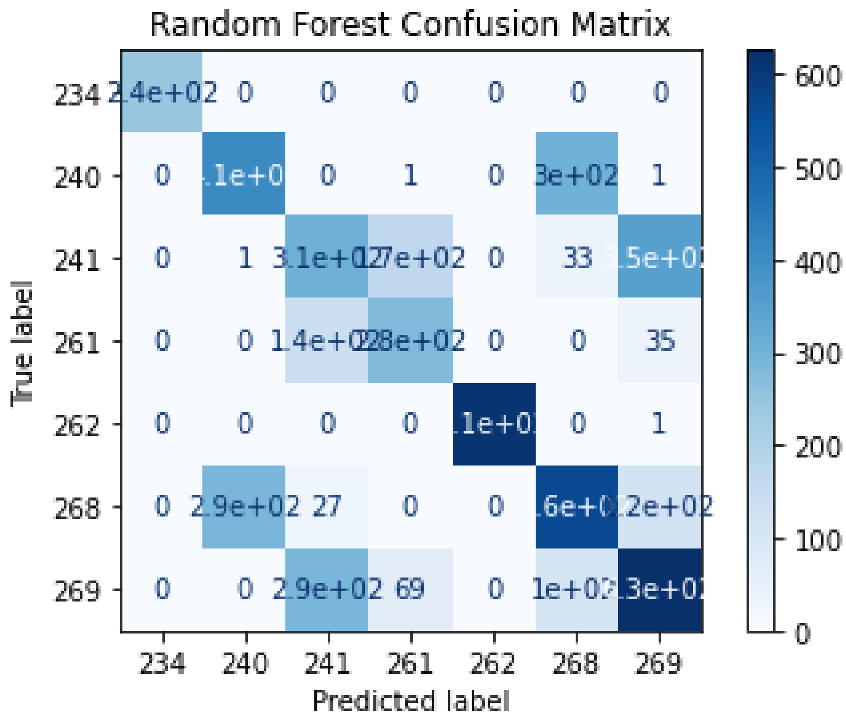
5 Random Forest

Accuracy is 0.61, indicating that the Random Forest model performs better than Logistic Regression. Precision and Recall are more balanced across classes compared to Logistic Regression.

6 Visualizing Model Performance

[101]:
```
from sklearn.metrics import ConfusionMatrixDisplay

# Logistic Regression Confusion Matrix
cm_lr = confusion_matrix(y_test, y_pred_lr)
disp_lr = ConfusionMatrixDisplay(confusion_matrix=cm_lr, display_labels=['234',␣
 ↪'240', '241', '261', '262', '268', '269'])
disp_lr.plot(cmap=plt.cm.Blues)
plt.title('Logistic Regression Confusion Matrix')
plt.show()

# Random Forest Confusion Matrix
cm_rf = confusion_matrix(y_test, y_pred_rf)
disp_rf = ConfusionMatrixDisplay(confusion_matrix=cm_rf, display_labels=['234',␣
 ↪'240', '241', '261', '262', '268', '269'])
disp_rf.plot(cmap=plt.cm.Blues)
plt.title('Random Forest Confusion Matrix')
plt.show()
```





7 Summary and Conclusion

Based on the model results, it concludes that the Logistic Regression model shows better performance than Linear Regression with an accuracy of 0.43. However, it struggles with class imbalance, and its precision/recall are inconsistent across classes. The Random Forest model has the highest accuracy (0.61) and provides more balanced precision and recall across different classes compared to Logistic Regression.

Random Forest is the best-performing model among the three for predicting module completion rates. It achieves the highest accuracy and shows more balanced performance across different classes.