Student Performance in Exam Analysis

Project Overview

This analysis assesses student exam performance using a variety of demographic and socioeconomic parameters. By examining the dataset, we hope to learn more about how gender, race/ethnicity, parental education level, lunch type, and test preparation affect students' math, reading, and writing scores.

The findings will assist in identifying crucial elements influencing academic achievement, which can then be used to inform educational practices and policies to improve student outcomes.

The dataset provides information on student exam performance. The critical user attributes or data elements that will be evaluated are:

1. Gender: Male or female. Gender analysis can provide insights into performance variations and preferences between male and female students, allowing for more individualized educational tactics and support services.
2. Race/Ethnicity: This categorical variable represents the student's race/ethnicity. Understanding racial and cultural backgrounds can assist in detecting educational discrepancies and inspire policies that promote equity and inclusion.
3. Parental Level of Education: This pertains to the highest level of education achieved by the student's parents. This statistic can shed light on the impact of parental education on student achievement, emphasizing the need for focused interventions.
4. Lunch: The meal the student received (regular, free, or reduced). Lunch kinds can disclose socioeconomic aspects that influence student achievement and guide resource allocation to help students from low-income homes.
5. Test Preparation Course: Indicates whether or not the student completed a test preparation course. Tracking the completion of test preparation courses can determine their effectiveness in improving student performance and informing educational program selections.
6. Math Score: A student's math exam score. This statistic is critical for evaluating students' math proficiency, finding areas for development, and customizing math training approaches.
7. Reading Score: A student's reading exam score. Analyzing reading scores assists in understanding students' literacy levels, guiding reading programs, and developing targeted reading interventions.
8. Writing Score: The student's score on the writing exam. This score provides information about students' writing ability, which informs writing training strategies and identifies the need for more writing support.

The primary goals of this project are to better understand demographic and socioeconomic determinants by examining how gender, race/ethnicity, parental education, lunch style, and test preparation courses affect exam results. The project also aims to identify performance trends by comparing trends across demographic groups and creating a model to predict student performance using the provided attributes.

This analysis is expected to provide insights into performance disparities among different gender and race/ethnicity groups, understanding how parents' educational level correlates with student performance, analyzing how receiving standard or free/reduced lunch and completing a course for test preparation affect exam scores, and predictions about future student performance to help identify at-risk students and provide targeted support.

Libraries and Data Handling

Importing Libraries

```
# Data Manipulation and Plotting
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import seaborn as sns

# Inferential Statistics
from scipy.stats import ttest_ind
import statsmodels.api as sm

# Machine Learning
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.metrics import mean_squared_error, r2_score
```

Importing Datasets

```
df = pd.read_csv('14_Student Performance in Exam Analysis.csv')
```

Data Analysis Techniques

Preliminary Analysis (Descriptive Analysis)

```
# Returns the first 5 rows of the DataFrame by default.
df.head()
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
0	female	group B	bachelor's degree	standard	none	72	72	74
1	female	group C	some college	standard	completed	69	90	88
2	female	group B	master's degree	standard	none	90	95	93
3	male	group A	associate's degree	free/reduced	none	47	57	44
4	male	group C	some college	standard	none	76	78	75

```
# Returns the last 5 rows of the DataFrame by default.
df.tail()
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
995	female	group E	master's degree	standard	completed	88	99	95
996	male	group C	high school	free/reduced	none	62	55	55
997	female	group C	high school	free/reduced	completed	59	71	65
998	female	group D	some college	standard	completed	68	78	77
999	female	group D	some college	free/reduced	none	77	86	86

```
# Returns a tuple representing the dimensionality of the DataFrame.
# The first element is the number of rows, and the second is the number of columns.
df.shape
```

```
(1000, 8)
```

```
# Generates descriptive statistics that summarize the central tendency, dispersion, and shape of a dataset’s distribution, excluding NaN values.
df.describe()
```

	math score	reading score	writing score
count	1000.00000	1000.000000	1000.000000
mean	66.08900	69.169000	68.054000
std	15.16308	14.600192	15.195657
min	0.00000	17.000000	10.000000
25%	57.00000	59.000000	57.750000
50%	66.00000	70.000000	69.000000
75%	77.00000	79.000000	79.000000
max	100.00000	100.000000	100.000000

```
# Returns the column labels of the DataFrame.
df.columns
```

```
Index(['gender', 'race/ethnicity', 'parental level of education', 'lunch',
       'test preparation course', 'math score', 'reading score',
       'writing score'],
      dtype='object')
```

```
# Returns the data types of each column in the DataFrame.
df.dtypes
```

```
gender                         object
race/ethnicity                 object
parental level of education    object
lunch                          object
test preparation course        object
math score                      int64
reading score                   int64
writing score                   int64
dtype: object
```

```
# Returns the number of missing values in each column.
df.isnull().sum()
```

```
gender                         0
race/ethnicity                 0
parental level of education    0
lunch                          0
test preparation course        0
math score                     0
reading score                  0
writing score                  0
dtype: int64
```

```
# Prints a concise summary of the DataFrame, including the index dtype and column dtypes, non-null values, and memory usage.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   gender                       1000 non-null   object
 1   race/ethnicity               1000 non-null   object
 2   parental level of education  1000 non-null   object
 3   lunch                        1000 non-null   object
 4   test preparation course      1000 non-null   object
 5   math score                   1000 non-null   int64 
 6   reading score                1000 non-null   int64 
 7   writing score                1000 non-null   int64 
dtypes: int64(3), object(5)
memory usage: 62.6+ KB
```

```
# Returns the number of unique values in each column.
df.nunique()
```

```
gender                          2
race/ethnicity                  5
parental level of education     6
lunch                           2
test preparation course         2
math score                     81
reading score                  72
writing score                  77
dtype: int64
```

Inferential Statistics

```
# Define numeric and categorical columns
numeric_columns = df.select_dtypes(exclude="object").columns.tolist()
categorical_columns = df.select_dtypes(include="object").columns.tolist()

# T-test for binary categorical variables
for num_col in numeric_columns:
    for cat_col in categorical_columns:
        unique_values = df[cat_col].unique()
        if len(unique_values) == 2:
            group1 = df[df[cat_col] == unique_values[0]][num_col]
            group2 = df[df[cat_col] == unique_values[1]][num_col]
            t_stat, p_value = ttest_ind(group1, group2)
            print(f'Numeric Column: {num_col}, Categorical Column: {cat_col}')
            print(f'T-statistic: {t_stat}, P-value: {p_value}')
            if p_value < 0.05:
                print(f"Reject the null hypothesis: There is a significant difference in {num_col} between {unique_values[0]} and {unique_values[1]}.\n")
            else:
                print(f"Fail to reject the null hypothesis: There is no significant difference in {num_col} between {unique_values[0]} and {unique_values[1]}.\n")

            print('\n' + '-' * 67 + '\n')
```

```
-------------------------------------------------------------------

Numeric Column: math score, Categorical Column: lunch
T-statistic: 11.837180472914612, P-value: 2.4131955993137074e-30
Reject the null hypothesis: There is a significant difference in math score between standard and free/reduced.


-------------------------------------------------------------------

Numeric Column: math score, Categorical Column: test preparation course
T-statistic: -5.704616417349102, P-value: 1.5359134607147415e-08
Reject the null hypothesis: There is a significant difference in math score between none and completed.


-------------------------------------------------------------------

Numeric Column: reading score, Categorical Column: gender
T-statistic: 7.959308005187657, P-value: 4.680538743933289e-15
Reject the null hypothesis: There is a significant difference in reading score between female and male.


-------------------------------------------------------------------

Numeric Column: reading score, Categorical Column: lunch
T-statistic: 7.451056467473455, P-value: 2.0027966545279011e-13
Reject the null hypothesis: There is a significant difference in reading score between standard and free/reduced.


-------------------------------------------------------------------

Numeric Column: reading score, Categorical Column: test preparation course
T-statistic: -7.871663538941468, P-value: 9.081783336892205e-15
Reject the null hypothesis: There is a significant difference in reading score between none and completed.


-------------------------------------------------------------------

Numeric Column: writing score, Categorical Column: gender
T-statistic: 9.979557910004507, P-value: 2.019877706867934e-22
Reject the null hypothesis: There is a significant difference in writing score between female and male.


-------------------------------------------------------------------

Numeric Column: writing score, Categorical Column: lunch
T-statistic: 8.009784197834758, P-value: 3.1861895831664765e-15
```

```
Numeric Column: writing score, Categorical Column: test preparation course
T-statistic: -10.409173436808748, P-value: 3.68529173524572e-24
Reject the null hypothesis: There is a significant difference in writing score between none and completed.


-------------------------------------------------------------------
```

Predictive Model (using Linear Regression)

```python
# Define features (X) and target (y)
# These variables will be used in all machine learning models belor
# Edit the column_name for other analysis
X = df.drop(['writing score'], axis=1)
y = df['writing score']

# Define numeric and categorical columns
numeric_columns = X.select_dtypes(exclude="object").columns.tolist()
categorical_columns = X.select_dtypes(include="object").columns.tolist()

# Preprocessing: OneHotEncoder for categorical columns and StandardScaler for numeric columns
numeric_transformer = StandardScaler()
oh_transformer = OneHotEncoder()
preprocessor = ColumnTransformer(
    transformers=[
        ("OneHotEncoder", oh_transformer, categorical_columns),
        ("StandardScaler", numeric_transformer, numeric_columns),
    ])

# Apply preprocessing to features
X = preprocessor.fit_transform(X)

# 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)

# Initialize and fit the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)

# Display the shapes of training and testing sets
print("\nTRAIN-TEST SPLIT: \n")

print("Training set shape:", X_train.shape)
print("Testing set shape:", X_test.shape)

print('\n' + '-' * 67 + '\n')

print("PREDICTIONS: \n")

print("y_train_pred: \n\n", y_train_pred)
print()
print("y_test_pred: \n\n", y_test_pred)

print('\n' + '-' * 67 + '\n')

mse = mean_squared_error(y_test, y_test_pred)
r2 = r2_score(y_test, y_test_pred)

print("EVALUATIONS: \n")
print("MSE: ", mse)
print("R2: ", r2)
```

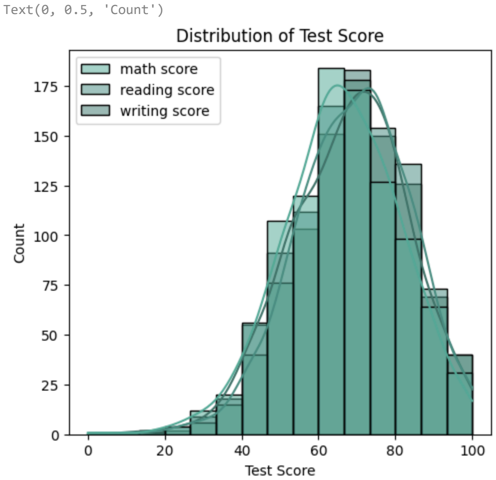
```
TRAIN-TEST SPLIT:

Training set shape: (800, 19)
Testing set shape: (200, 19)

-------------------------------------------------------------------

PREDICTIONS:

y_train_pred:

 [ 71.9375  83.9375  87.625   62.5625  59.5     22.1875 104.0625  76.125
  64.8125  56.      59.375   63.      63.25    68.4375  66.625   37.75
  65.5625  57.5625  88.      82.5     62.4375  56.375   81.125   80.875
  27.1875  94.75    68.      64.125   79.6875  57.375   71.5625  57.0625
  60.3125  49.6875  39.875   65.625   41.375   76.25    63.6875  76.5625
  49.5625  43.5     95.5625  56.875   86.75    66.      61.5625  78.1875
  37.25    83.125   47.125   79.75    64.5     61.25    60.8125  51.3125
  77.5625  97.25    63.8125  80.0625  43.375   86.75    72.125   74.5
  64.0625  72.125   56.875   84.6875  60.3125  94.0625  79.      61.5625
  82.      46.6875  55.3125  53.875   64.125   54.25    41.4375  62.9375
  61.     78.6875  76.6875  67.8125  27.875  100.      88.6875  70.625
  48.9375  71.5625  75.5625  65.8125  92.875   63.625   58.4375  86.625
  62.125   54.8125  38.5     87.4375  80.9375  81.375   63.6875  63.0625
  80.4375  71.125   92.125   53.1875  88.8125  75.625  102.875   72.8125
  76.375   57.3125  41.75    56.25    64.125   78.25    86.6875  57.
  67.375   80.625   83.625   52.0625  44.1875  63.125   77.      67.3125
  84.6875  83.6875  66.6875  59.25    87.4375  54.      74.5625  87.6875
  35.25    66.8125  81.625   59.125   68.8125  58.6875  85.75    91.25
  75.1875  93.75    48.125  104.0625  73.125   70.      60.4375  83.6875
  33.5     58.9375  72.4375  41.5     76.4375  36.1875  57.1875  74.1875
  79.5     92.5625  54.125   82.875   88.625   64.6875  76.0625  67.1875
  65.4375  84.1875  77.25    65.25    74.75    67.9375  96.0625  73.625
  66.      53.3125  44.3125  80.125   48.75    37.125   67.125   82.625
  69.6875  63.0625  81.375   74.5     77.8125  60.75    65.875   70.375
  84.6875  69.6875  62.9375  86.5     70.4375  68.0625  67.3125  71.3125
  73.75    65.6875  90.8125  53.375   82.9375  59.8125  52.8125  35.3125
  68.625   55.125   86.25    65.375   87.6875  69.5625  69.3125  85.125
  52.0625  58.125   79.1875  80.0625  45.3125  92.0625  48.6875  47.5
```

```
 55.375   62.0625  60.625   34.0625  72.3125  54.9375  80.      61.1875
 69.      89.5     79.3125  75.625   49.5     57.75    75.      66.3125
 77.0625  61.3125  99.5625  72.875   76.625   74.0625  83.75    55.75
 61.4375  83.0625  74.375   82.625   55.25    48.3125  64.5625  79.0625
 76.9375  75.1875  39.      64.875   44.8125  59.25    75.9375  54.5
 64.75    87.9375 102.8125  69.1875  56.5625  51.5     84.75    70.875
 70.75    83.      71.      45.375   49.0625  74.0625  67.4375  73.5
 60.875   84.      46.625   62.      87.5625  61.9375  58.5     51.625
 76.25    78.      78.      48.25    54.6875  65.875   80.625   70.5625
 73.9375  73.9375  53.125   70.      72.125   80.25    40.75    79.375
 80.75    58.625   63.6875  45.0625  80.875   64.375   76.4375  70.6875
 66.875   73.5     46.25    63.5625  62.625  102.625   87.4375  48.875
 57.125   74.75    84.5     55.1875  69.1875  88.25    83.25    66.8125
 62.125   45.0625  66.0625  54.8125  52.125   44.5625  62.875   62.9375
 50.25    38.75    78.625   63.8125  45.75    48.4375  63.75    72.
 84.625   59.0625  49.5     60.375   58.75    63.4375  83.8125  66.5
 79.5625  52.125   76.      65.625   81.6875  96.125   66.625   71.5625
 54.75    85.0625  48.625   78.375   91.9375  80.6875  64.625   79.8125
```

Visual Insights

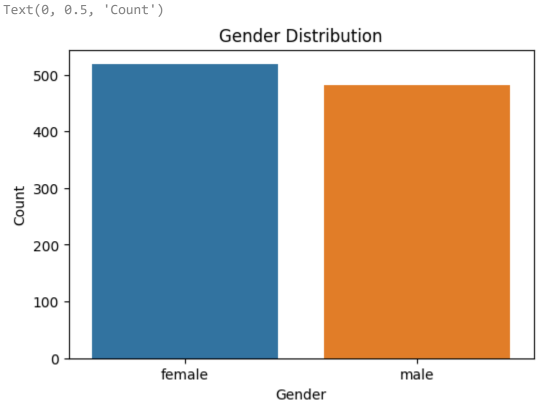
```
# Plot | Creates a figure
plt.figure(figsize = (12, 5)) # Size of the figure

# Subplot
plt.subplot(1, 2, 1)
sns.histplot(df[numeric_columns],
             bins = 15,
             kde = True)

plt.title('Distribution of Test Score')
plt.xlabel('Test Score')
plt.ylabel('Count')
```

```
Text(0, 0.5, 'Count')
```



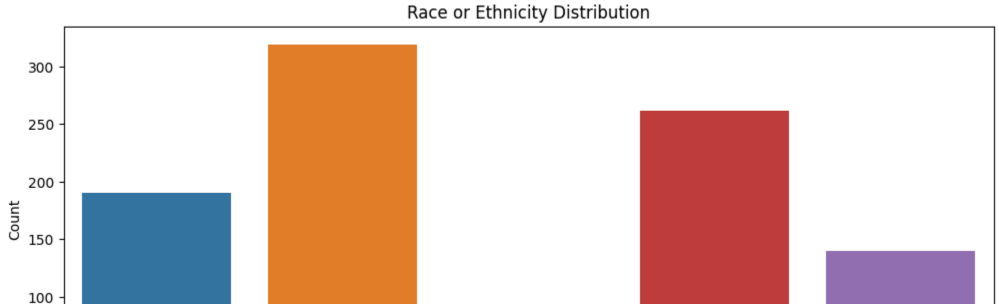

```
# Gender Figure
plt.figure(figsize = (6, 4))
sns.countplot(data = df,
              x = 'gender',
              hue = 'gender')
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
```

```
Text(0, 0.5, 'Count')
```



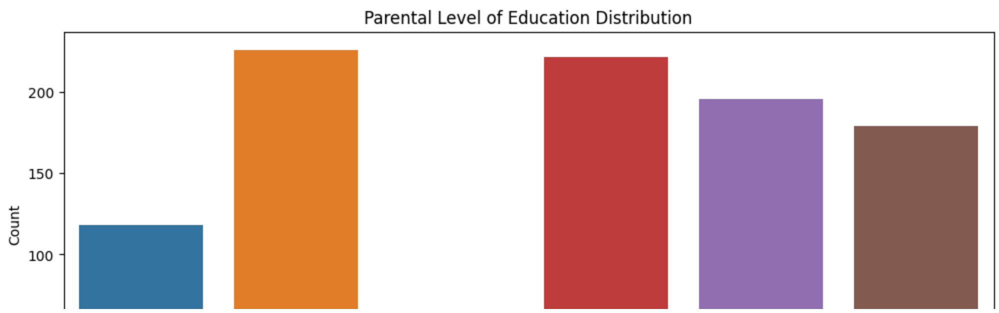

```
# Race/Ethnicity Figure
plt.figure(figsize = (12, 5))
sns.countplot(data = df,
              x = 'race/ethnicity',
              hue = 'race/ethnicity')
plt.title('Race or Ethnicity Distribution')
plt.xlabel('Race or Ethnicity')
plt.ylabel('Count')
```

```
Text(0, 0.5, 'Count')
```



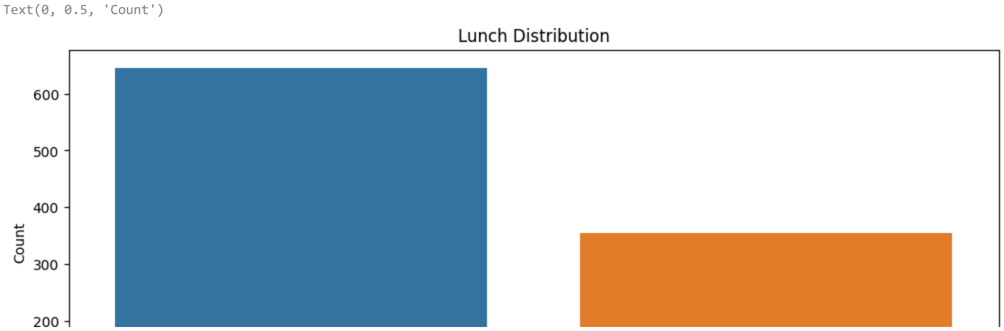

```
# Parental Level of Education Figure
plt.figure(figsize = (12, 5))
sns.countplot(data = df,
              x = 'parental level of education',
              hue = 'parental level of education')
plt.title('Parental Level of Education Distribution')
plt.xlabel('Degree')
plt.ylabel('Count')
```

```
Text(0, 0.5, 'Count')
```



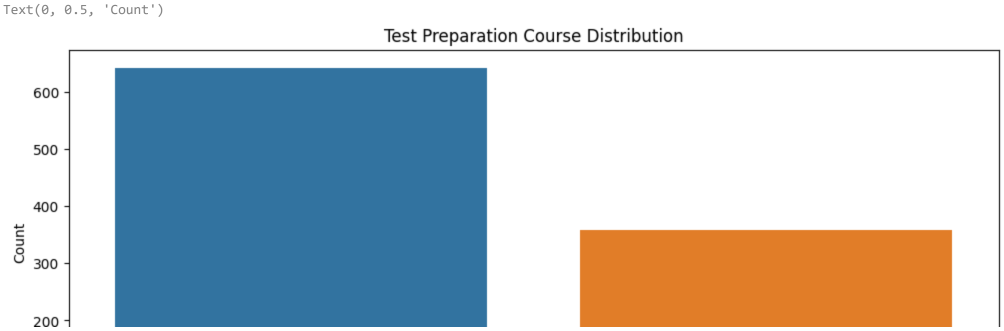

```
# Lunch Figure
plt.figure(figsize = (12, 5))
sns.countplot(data = df,
              x = 'lunch',
              hue = 'lunch')
plt.title('Lunch Distribution')
plt.xlabel('Lunch Type')
plt.ylabel('Count')
```

```
Text(0, 0.5, 'Count')
```

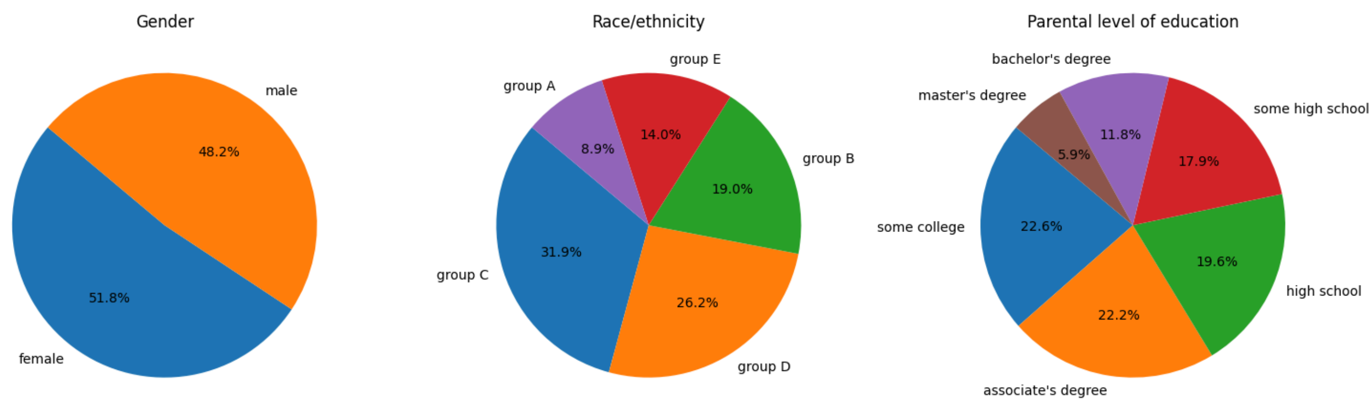



```
# Test Preparation Course Figure
plt.figure(figsize = (12, 5))
sns.countplot(data = df,
              x = 'test preparation course',
              hue = 'test preparation course')
plt.title('Test Preparation Course Distribution')
plt.xlabel('Test Preparation Course')
plt.ylabel('Count')
```

```
Text(0, 0.5, 'Count')
```

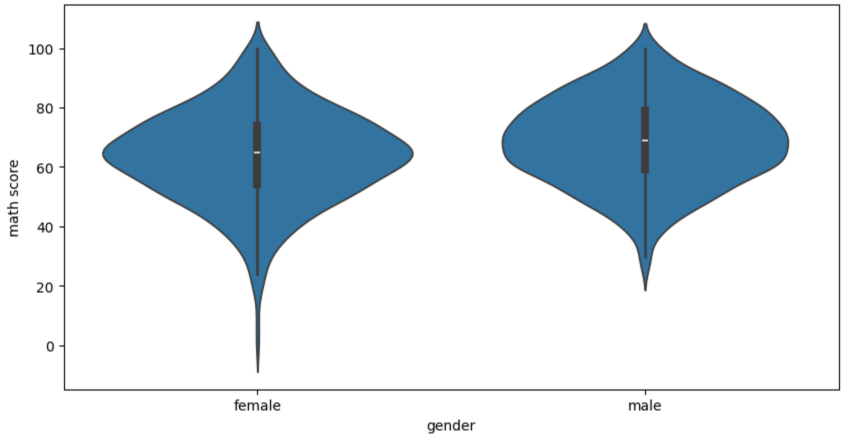


```
# Extarct numeric adn categorical features
numeric_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()


# Define the columns for multivariate analysis
columns_for_analysis = categorical_cols

# Define the number of rows and columns for subplots
num_plots = len(columns_for_analysis)
num_cols = 3
num_rows = (num_plots // num_cols) + (1 if num_plots % num_cols > 0 else 0)

# Create subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(15, 5*num_rows))

# Flatten the axes array to iterate over subplots
axes = axes.flatten()

# Iterate over columns for analysis and create pie plots
for i, column in enumerate(columns_for_analysis):
    # Get the value counts for the column
    value_counts = df[column].value_counts()

    # Plot the pie chart
    axes[i].pie(value_counts, labels=value_counts.index, autopct='%1.1f%%', startangle=140)
    axes[i].set_title(column.capitalize())  # Set subplot title

# Hide empty subplots
for i in range(num_plots, num_rows * num_cols):
    fig.delaxes(axes[i])

# Adjust layout
plt.tight_layout()

# Show the plots
plt.show()
```

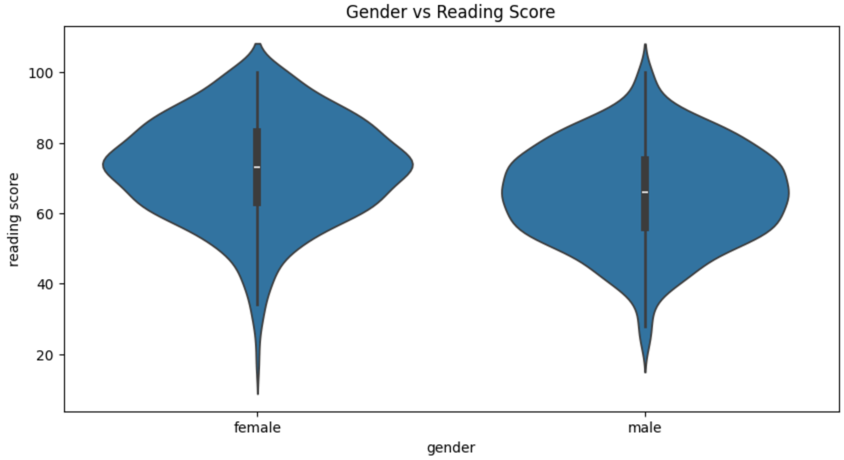



```
# Loop through each categorical variable
for feature in categorical_cols:
    # Create a box plot for each test score (math, reading, writing) against the current categorical variable
    plt.figure(figsize=(10, 5))
    sns.violinplot(x=feature, y='math score', data=df)
    plt.title(f'{feature.capitalize()} vs Math Score')
    plt.show()

    plt.figure(figsize=(10, 5))
    sns.violinplot(x=feature, y='reading score', data=df)
    plt.title(f'{feature.capitalize()} vs Reading Score')
    plt.show()

    plt.figure(figsize=(10, 5))
    sns.violinplot(x=feature, y='writing score', data=df)
    plt.title(f'{feature.capitalize()} vs Writing Score')
    plt.show()
```

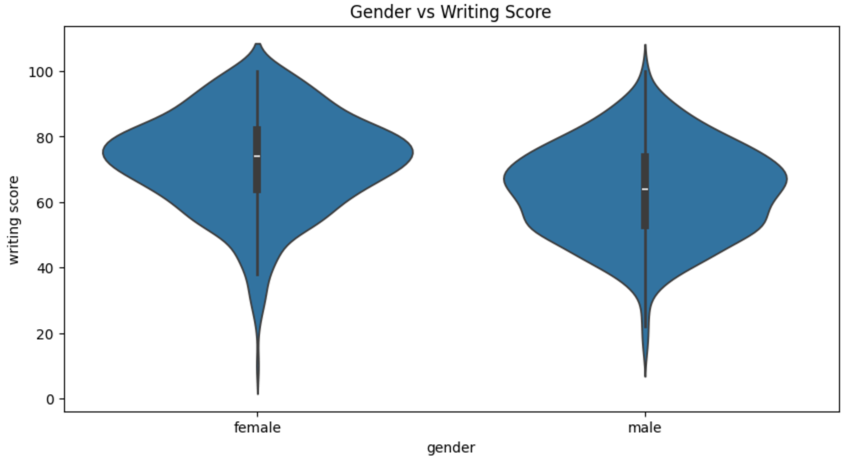
Gender vs Math Score



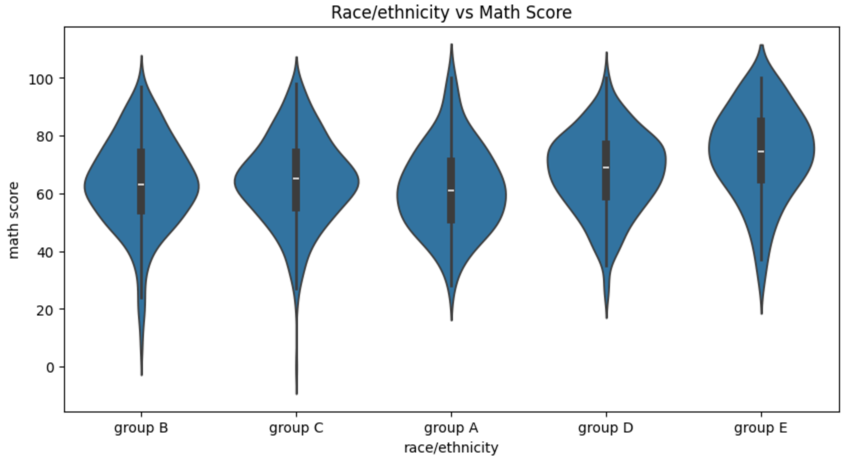
Gender vs Reading Score



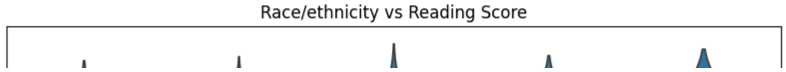
Gender vs Writing Score

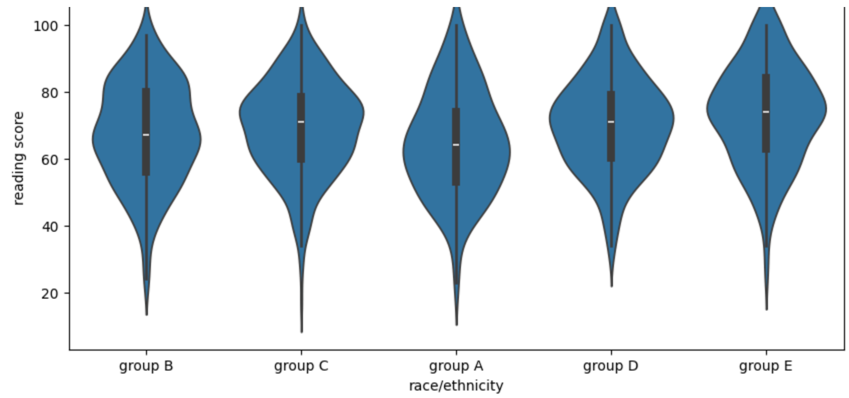


Race/ethnicity vs Math Score

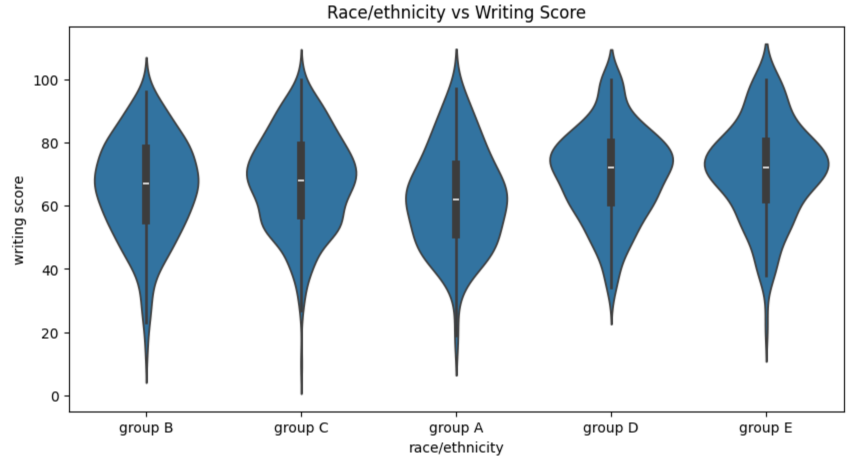


Race/ethnicity vs Reading Score

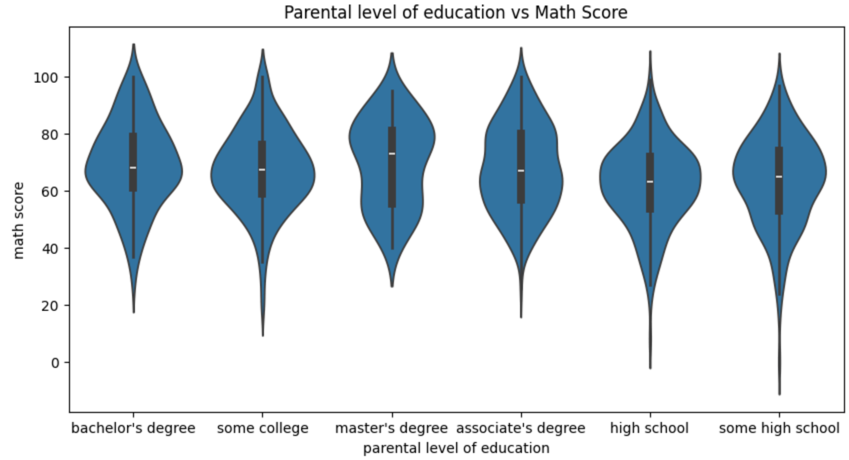




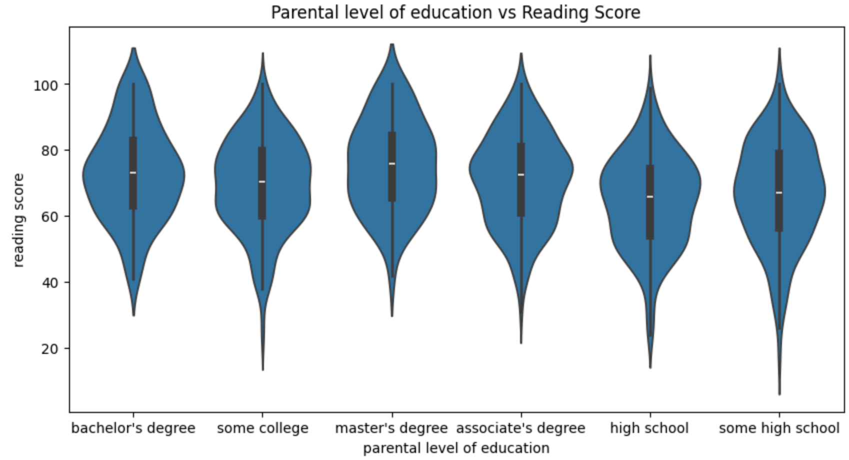
Race/ethnicity vs Writing Score



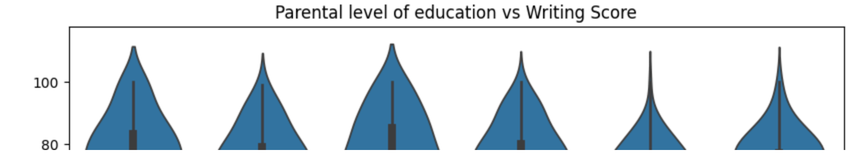
Parental level of education vs Math Score

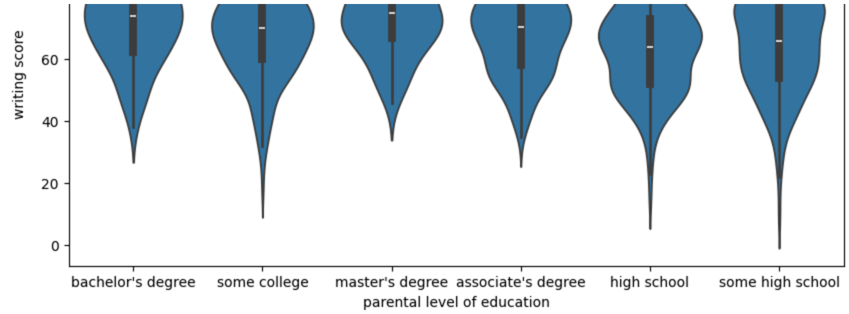


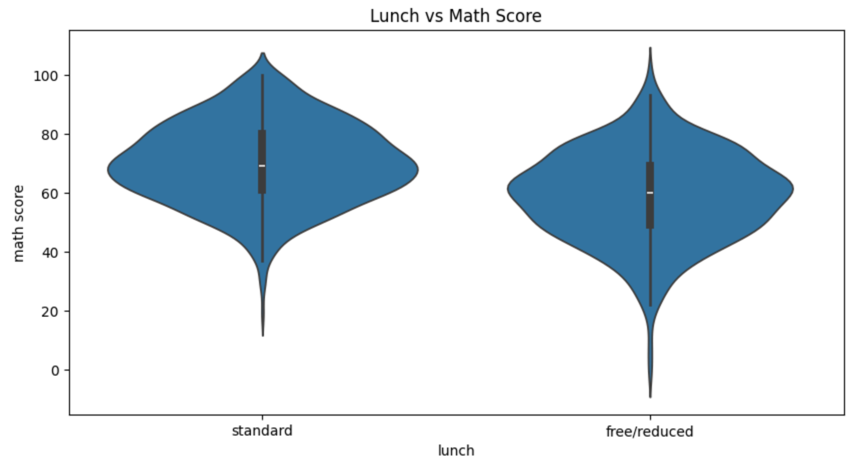
Parental level of education vs Reading Score

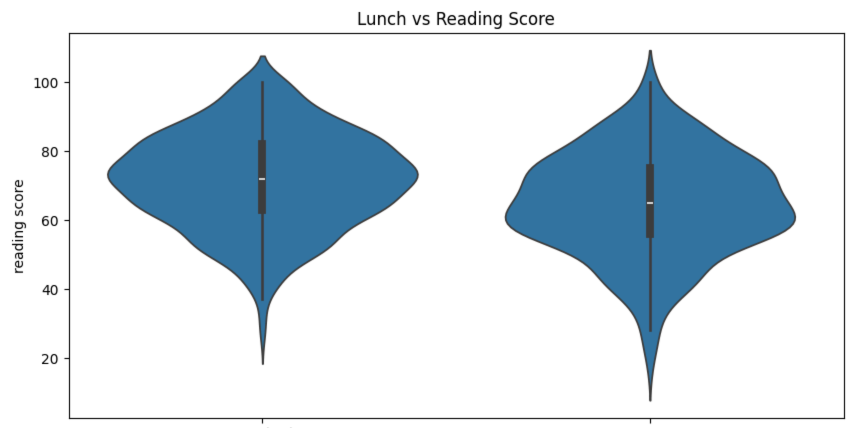


Parental level of education vs Writing Score









Key Findings and Business Impact

In the context of predictive modeling, MSE (Mean Squared Error) and R-squared (R2) are commonly used metrics to evaluate the performance of a model.

Mean Squared Error (MSE):

- MSE measures the average squared difference between the actual values (observed) and the predicted values (estimated) by the model. It quantifies the overall quality of predictions made by the model. Lower values of MSE indicate better predictive performance, as they reflect smaller errors between predicted and actual values.

R-squared (R2):

- R2 represents the proportion of variance in the dependent variable (target) that is explained by the independent variables (features) in the model. It ranges from 0 to 1, where: R2 = 0 indicates that the model does not explain any variability in the target variable. R2 = 1 indicates that the model perfectly explains the variability in the target variable. Higher values of R2 indicate better fit of the model to the data, suggesting that the independent variables are effective in explaining variation in the dependent variable.

EVALUATION (MATH SCORE):

Linear Regression: MSE: 29.0951698667155 R2: 0.8804332983749564

Ridge Regression: MSE: 29.056272192348306 R2: 0.8805931485028737

Lasso Regression: MSE: 28.821317118777714 R2: 0.8815586971937939

Random Forest Regressor: MSE: 36.212491241850906 R2: 0.8511846414628726

AdaBoost Regressor: MSE: 44.86818271598988 R2: 0.8156140472856324

EVALUATIONS (READING SCORE):

Linear Regression: MSE: 18.378046875 R2: 0.9187834030741185

Ridge Regression: MSE: 18.51373445853214 R2: 0.9181837700524743

Lasso Regression: MSE: 18.723078110804213 R2: 0.9172586348005504

Random Forest Regressor: MSE: 20.5123235 R2: 0.9093515692367182

AdaBoost Regressor: MSE: 24.23550121503363 R2: 0.8928980349834865

EVALUATIONS (WRITING SCORE):

Linear Regression: MSE: 14.94494140625 R2: 0.937992162559297

Ridge Regression: MSE: 14.9086590225526 R2: 0.9381427012659478

Lasso Regression: MSE: 15.23246410824539 R2: 0.9367992063287435

Random Forest Regressor: MSE: 20.382918513168935 R2: 0.9154295314130096

AdaBoost Regressor: MSE: 27.422427780826837 R2: 0.886222006641537

Findings:

• Linear Models (Linear Regression, Ridge Regression, Lasso Regression) consistently performed better than Non-Linear Models (Random Forest Regressor, AdaBoost Regressor) across all three score evaluations (math, reading, and writing).

• Among the linear models, Lasso Regression slightly outperformed the others for math scores, Linear Regression was best for reading scores, and Ridge Regression was best for writing scores.

• Random Forest Regressor and AdaBoost Regressor consistently showed higher prediction errors (higher MSE) and less explained variance (lower R2), making them less effective for these datasets.

Advanced Analysis

Feature Importance Analysis

```
numeric_columns = df.select_dtypes(exclude="object").columns.tolist()
categorical_columns = df.select_dtypes(include="object").columns.tolist()

# Separate features (X) and target (Y)
X = df.drop(numeric_columns, axis=1)
Y = df[numeric_columns]

# Define categorical columns
categorical_features = ['gender', 'race/ethnicity', 'parental level of education',

# Create a column transformer for preprocessing
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(drop='first'), categorical_features)
    ],
    remainder='passthrough'
)

# Apply preprocessing
X_processed = preprocessor.fit_transform(X)

print('TOP 3 FEATURES FOR EACH NUMERICAL COLUMNS:\n')

# Fit the Random Forest model separately for each target
for pred in numeric_columns:
    rf = RandomForestRegressor(random_state=42)
    rf.fit(X_processed, Y[pred])

    # Get feature importances
    importances = rf.feature_importances_
    feature_names = preprocessor.get_feature_names_out()
    feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance':
    feature_importance_df = feature_importance_df.sort_values(by='Importance', asc

    print(f"Feature importances for target: {pred}")
    print(feature_importance_df[:3])
    print()
```

```
TOP 3 FEATURES FOR EACH NUMERICAL COLUMNS:

Feature importances for target: math score
                               Feature  Importance
10                 cat__lunch_standard    0.251985
0                     cat__gender_male    0.101750
11  cat__test preparation course_none    0.097606

Feature importances for target: reading score
                               Feature  Importance
0                     cat__gender_male    0.149607
10                 cat__lunch_standard    0.132030
11  cat__test preparation course_none    0.131719

Feature importances for target: writing score
                               Feature  Importance
11  cat__test preparation course_none    0.184364
0                     cat__gender_male    0.182394
10                 cat__lunch_standard    0.140031
```

Implementation of Machine Learning

Fitting the Models (using Linear Regression, Ridge, Lasso, Random Forest Regressor, and Ada Boost Regressor)

```
# Initialize and fit the Linear Regression model
linear_model = LinearRegression()
linear_model.fit(X_train, y_train)

# Initialize and fit the Ridge model
ridge_model = Ridge(alpha=1.0)  # You can adjust the alpha value
ridge_model.fit(X_train, y_train)

# Initialize and fit the Lasso model
lasso_model = Lasso(alpha=0.1)  # You can adjust the alpha value
lasso_model.fit(X_train, y_train)

# Initialize and fit the Random Forest Regressor
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Initialize and fit the AdaBoost Regressor
adaboost_model = AdaBoostRegressor(n_estimators=50, learning_rate=0.1, random_state=42)
adaboost_model.fit(X_train, y_train)
```

```
▾ AdaBoostRegressor
AdaBoostRegressor(learning_rate=0.1, random_state=42)
```

Making Predictions

```
# Make predictions
y_test_pred_linear = linear_model.predict(X_test)
y_test_pred_ridge = ridge_model.predict(X_test)
y_test_pred_lasso = lasso_model.predict(X_test)
y_test_pred_rf = rf_model.predict(X_test)
y_test_pred_adaboost = adaboost_model.predict(X_test)
```

Mean Squared Error

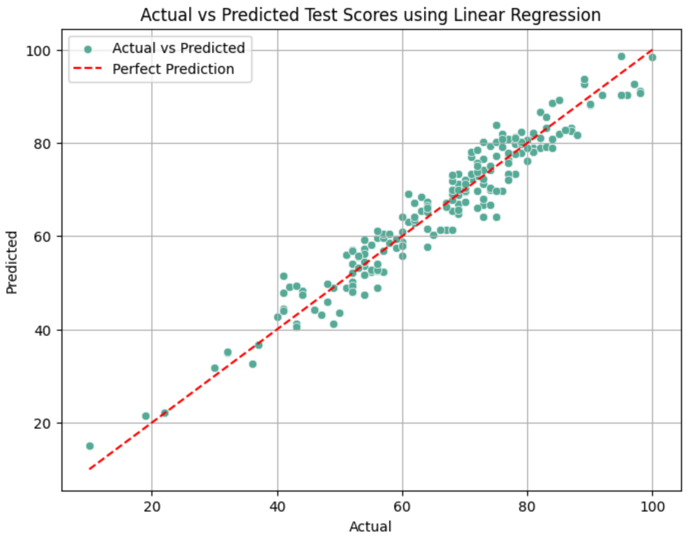
```
# Evaluate models
mse_linear = mean_squared_error(y_test, y_test_pred_linear)
r2_linear = r2_score(y_test, y_test_pred_linear)

mse_ridge = mean_squared_error(y_test, y_test_pred_ridge)
r2_ridge = r2_score(y_test, y_test_pred_ridge)

mse_lasso = mean_squared_error(y_test, y_test_pred_lasso)
r2_lasso = r2_score(y_test, y_test_pred_lasso)

mse_rf = mean_squared_error(y_test, y_test_pred_rf)
r2_rf = r2_score(y_test, y_test_pred_rf)

mse_adaboost = mean_squared_error(y_test, y_test_pred_adaboost)
r2_adaboost = r2_score(y_test, y_test_pred_adaboost)

print("Linear Regression:")
print("MSE:", mse_linear)
print("R2:", r2_linear)

print("\nRidge Regression:")
print("MSE:", mse_ridge)
print("R2:", r2_ridge)

print("\nLasso Regression:")
print("MSE:", mse_lasso)
print("R2:", r2_lasso)

print("\nRandom Forest Regressor:")
print("MSE:", mse_rf)
print("R2:", r2_rf)

print("\nAdaBoost Regressor:")
print("MSE:", mse_adaboost)
print("R2:", r2_adaboost)
```

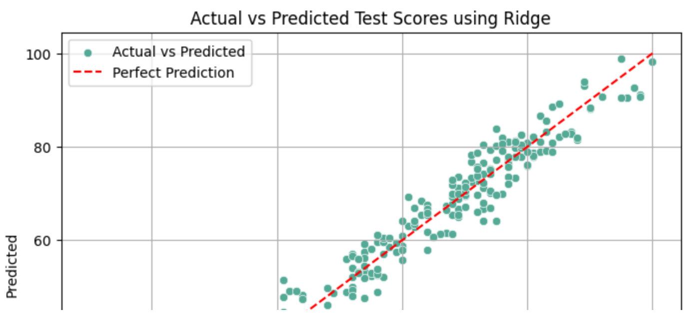
```
Linear Regression:
MSE: 14.94494140625
R2: 0.937992162559297

Ridge Regression:
MSE: 14.9086590225526
R2: 0.9381427012659478

Lasso Regression:
MSE: 15.23246410824539
R2: 0.9367992063287435

Random Forest Regressor:
MSE: 20.382918513168935
R2: 0.9154295314130096

AdaBoost Regressor:
MSE: 27.422427780826837
R2: 0.886222006641537
```

Plot Actual vs. Predicted Values for each Model

```
# Plot actual vs predicted values
def plot_actual_pred(actual, pred, model):
  plt.figure(figsize=(8, 6))
  sns.scatterplot(x=actual, y=pred, label='Actual vs Predicted')
  plt.plot([actual.min(), actual.max()], [actual.min(), actual.max()], color='red', linestyle='--', label='Perfect Prediction')
  plt.xlabel('Actual')
  plt.ylabel('Predicted')
  plt.title(f'Actual vs Predicted Test Scores using {model}')
  plt.legend()
  plt.grid(True)
  plt.show()
```

```
models = ['Linear Regression', 'Ridge', 'Lasso', 'Random Forest Regressor', 'Ada E
pred = [y_test_pred_linear, y_test_pred_ridge, y_test_pred_lasso, y_test_pred_rf,

for pred, model in zip(pred, models):
    plot_actual_pred(y_test, pred, model)
```





Conclusion

The analysis of the student performance dataset produced several important discoveries. According to descriptive statistics, the dataset has 1000 records, with comprehensive data on various performance and demographic characteristics. Significant variations in test preparation, lunch type, parental education, gender, and race/ethnicity were found using inferential statistics. Particularly, performance varied across racial and cultural groups, although males and females showed variations in math and writing scores. Higher parental education levels have been linked to improved student performance; test-preparation course completion and standard lunch recipients typically yielded higher scores. With high R2 values and low MSE, predictive modeling employing ridge regression, lasso regression, random forest regressor, and AdaBoost regressor revealed that ridge regression and linear regression were the most successful models. The most significant predictors of the three