Importing Necessary Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
```

```
df=pd.read_csv('/content/StudentsPerformance.csv')
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

Next steps: Generate code with df | View recommended plots | New interactive sheet

EDA (Explotry Data Analysis)

```
df.isna().sum()
```

	0
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

```
df.info()
df.describe()
```

```
<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
```

	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

```
df['parental level of education'].unique()
```

```
array(["bachelor's degree", 'some college', "master's degree",
       "associate's degree", 'high school', 'some high school'],
      dtype=object)
```

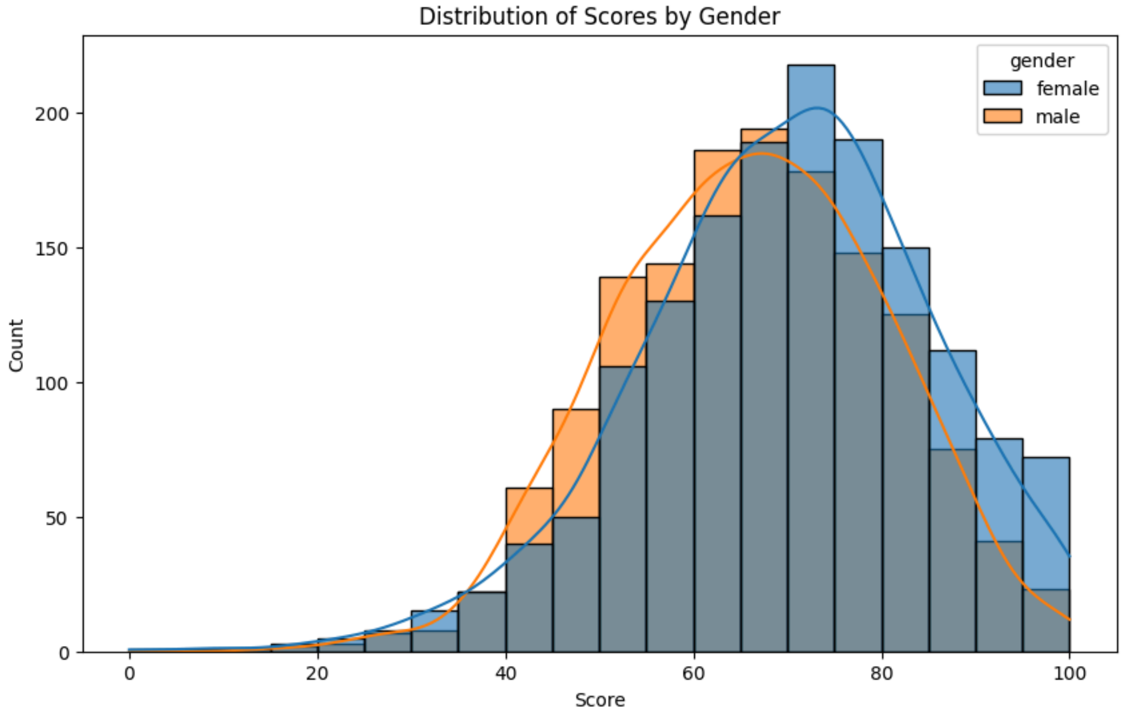
```
df['test preparation course'].unique()
```

```
array(['none', 'completed'], dtype=object)
```

Visulization

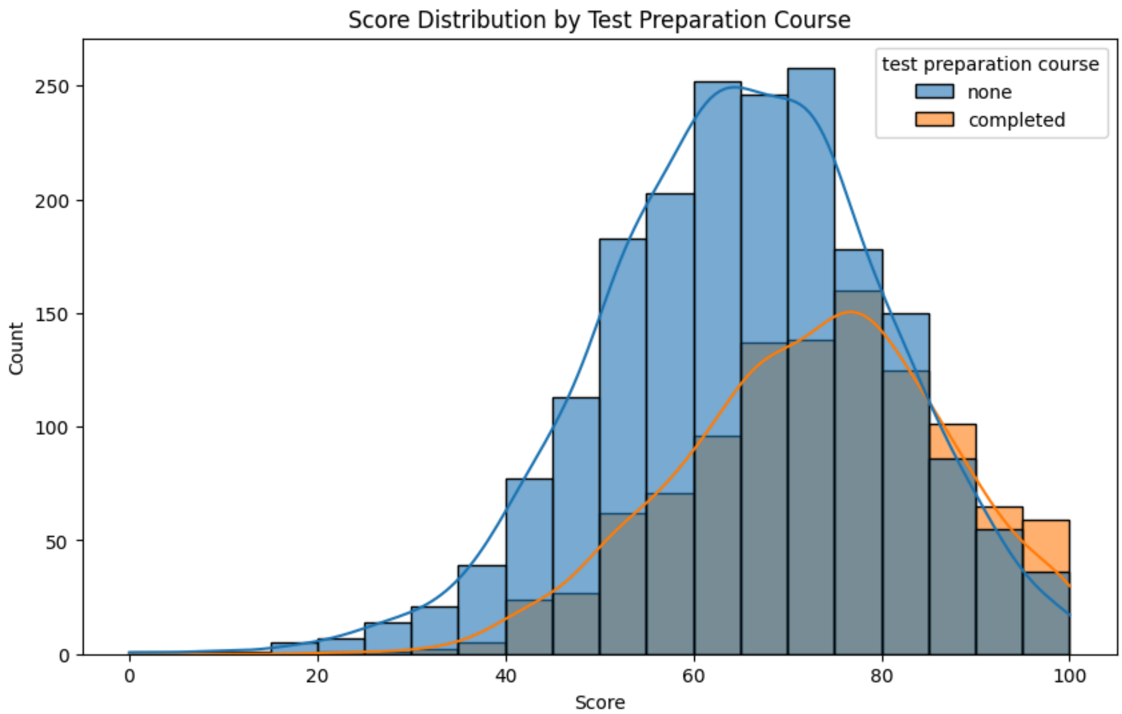
```
df_melted = df.melt(id_vars=['gender'],
                    value_vars=['math score', 'reading score', 'writing score'],
                    var_name='score_type',
                    value_name='score')

# Plot histograms with hue for gender
plt.figure(figsize=(10, 6))
sns.histplot(data=df_melted, x='score', hue='gender', bins=20, kde=True, alpha=0.6)
plt.title('Distribution of Scores by Gender')
plt.xlabel('Score')
plt.ylabel('Count')
plt.show()
```




```
df_melted = df.melt(id_vars=['test preparation course'],
                    value_vars=['math score', 'reading score', 'writing score'],
                    var_name='score_type',
                    value_name='score')

# Plot histograms
plt.figure(figsize=(10, 6))
sns.histplot(data=df_melted, x='score', hue='test preparation course', bins=20, kde=True, alpha=0.6)
plt.title('Score Distribution by Test Preparation Course')
plt.xlabel('Score')
plt.ylabel('Count')
plt.show()
```



Feature Engineering

```
df['Avg_Score']=df[['math score', 'reading score', 'writing score']].mean(axis=1)
df['Avg_Score']
```

	Avg_Score
0	72.666667
1	82.333333
2	92.666667
3	49.333333
4	76.333333
...	...
995	94.000000
996	57.333333
997	65.000000
998	74.333333
999	83.000000

1000 rows × 1 columns

dtype: float64

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df['test preparation course']=le.fit_transform(df['test preparation course'])
```

```
df['parental level of education']=le.fit_transform(df['parental level of education'])
```

```
df['gender']=le.fit_transform(df['gender'])
```

```
df[['parental level of education', 'test preparation course','gender']]
```

	parental level of education	test preparation course	gender
0	1	1	0
1	4	0	0
2	3	1	0
3	0	1	1
4	4	1	1
...	...	...	...
995	3	0	0
996	2	1	1
997	2	0	0
998	4	0	0
999	4	1	0

1000 rows × 3 columns

Model Training

Logistic Regression For Gender Prediction


```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
X=df[['math score','reading score','writing score','parental level of education','test preparation course']]
y=df['gender']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
lr=LogisticRegression()
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred)*100,'%')
print(classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Accuracy: 91.5 %
              precision    recall  f1-score   support

           0       0.90      0.93      0.91        97
           1       0.93      0.90      0.92       103

    accuracy                           0.92       200
   macro avg       0.92      0.92      0.91       200
weighted avg       0.92      0.92      0.92       200

Confusion Matrix:
 [[90  7]
 [10 93]]
```

Logistic Regression For test preparation course

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
X=df[['math score','reading score','writing score','parental level of education','gender']]
y=df['test preparation course']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
lr = LogisticRegression(class_weight='balanced', max_iter=1000)
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.71
              precision    recall  f1-score   support

           0       0.62      0.71      0.66        79
           1       0.79      0.71      0.75       121

    accuracy                           0.71       200
   macro avg       0.70      0.71      0.70       200
weighted avg       0.72      0.71      0.71       200
```