```
import pandas as pd
 In [7]:
          import numpy as np
          import matplotlib.pyplot as plt
          import seaborn as sns
          %matplotlib inline
          from sklearn.preprocessing import OneHotEncoder, StandardScaler
          from sklearn.compose import ColumnTransformer
          from sklearn.model_selection import train_test_split
          # Modelling
          from sklearn.neighbors import KNeighborsRegressor
          from sklearn.tree import DecisionTreeRegressor
          from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor
          from sklearn.svm import SVR
          from sklearn.linear_model import LinearRegression, Ridge, Lasso
          from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
          from sklearn.model_selection import RandomizedSearchCV
          from catboost import CatBoostRegressor
          from xgboost import XGBRegressor
          import warnings
          warnings.filterwarnings('ignore')
         df = pd.read_csv('data/stud.csv')
 In [4]:
          df.sample(2)
Out[4]:
              gender race_ethnicity parental_level_of_education
                                                                 lunch test_preparation_course math_score reading
          203
              female
                           group B
                                           associate's degree
                                                              standard
                                                                                      none
                                                                                                    57
          357
               female
                           group C
                                               some college free/reduced
                                                                                  completed
         X = df.drop(columns=['math_score'],axis=1)
 In [5]:
          y = df['math_score']
          num_features = X.select_dtypes(exclude="object").columns
 In [8]:
          cat_features = X.select_dtypes(include="object").columns
          numeric_transformer = StandardScaler()
          oh_transformer = OneHotEncoder()
          preprocessor = ColumnTransformer(
              [
                  ("OneHotEncoder", oh_transformer, cat_features),
                   ("StandardScaler", numeric_transformer, num_features),
 In [9]: X = preprocessor.fit_transform(X)
In [10]: X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=42)
          X train.shape, X test.shape
         ((800, 19), (200, 19))
Out[10]:
         def evaluate_model(true, predicted):
In [13]:
              mae = mean_absolute_error(true, predicted)
              mse = mean_squared_error(true, predicted)
              rmse = np.sqrt(mean_squared_error(true, predicted))
```

```
return mae, rmse, r2_square
In [14]: models = {
             "Linear Regression": LinearRegression(),
             "Lasso": Lasso(),
             "Ridge": Ridge(),
             "K-Neighbors Regressor": KNeighborsRegressor(),
             "Decision Tree": DecisionTreeRegressor(),
             "Random Forest Regressor": RandomForestRegressor(),
             "XGBRegressor": XGBRegressor(),
             "CatBoosting Regressor": CatBoostRegressor(verbose=False),
             "AdaBoost Regressor": AdaBoostRegressor()
         model_list = []
         r2_list =[]
         for i in range(len(list(models))):
             model = list(models.values())[i]
             model.fit(X_train, y_train) # Train model
             # Make predictions
             y_train_pred = model.predict(X_train)
             y_test_pred = model.predict(X_test)
             # Evaluate Train and Test dataset
             model_train_mae , model_train_rmse, model_train_r2 = evaluate_model(y_train, y_train_pred)
             model_test_mae, model_test_rmse, model_test_r2 = evaluate_model(y_test, y_test_pred)
             print(list(models.keys())[i])
             model_list.append(list(models.keys())[i])
             print('Model performance for Training set')
             print("- Root Mean Squared Error: {:.4f}".format(model_train_rmse))
             print("- Mean Absolute Error: {:.4f}".format(model_train_mae))
             print("- R2 Score: {:.4f}".format(model_train_r2))
             print('----')
             print('Model performance for Test set')
             print("- Root Mean Squared Error: {:.4f}".format(model_test_rmse))
             print("- Mean Absolute Error: {:.4f}".format(model_test_mae))
             print("- R2 Score: {:.4f}".format(model_test_r2))
             r2_list.append(model_test_r2)
             print('='*35)
             print('\n')
```

r2\_square = r2\_score(true, predicted)

## Lasso

Model performance for Training set

- Root Mean Squared Error: 6.5938

- Mean Absolute Error: 5.2063

- R2 Score: 0.8071

-----

Model performance for Test set

- Root Mean Squared Error: 6.5197

- Mean Absolute Error: 5.1579

- R2 Score: 0.8253

-----

## Ridge

Model performance for Training set

- Root Mean Squared Error: 5.3233

- Mean Absolute Error: 4.2650

- R2 Score: 0.8743

-----

Model performance for Test set

- Root Mean Squared Error: 5.3904

- Mean Absolute Error: 4.2111

- R2 Score: 0.8806

-----

## K-Neighbors Regressor

Model performance for Training set

- Root Mean Squared Error: 5.7088

- Mean Absolute Error: 4.5177

- R2 Score: 0.8554

-----

Model performance for Test set

- Root Mean Squared Error: 7.2494

- Mean Absolute Error: 5.6090

- R2 Score: 0.7840

## Decision Tree

Model performance for Training set

- Root Mean Squared Error: 0.2795

- Mean Absolute Error: 0.0187

- R2 Score: 0.9997

-----

Model performance for Test set

- Root Mean Squared Error: 8.0675

- Mean Absolute Error: 6.4550

- R2 Score: 0.7325

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Random Forest Regressor Model performance for Training set - Root Mean Squared Error: 2.3225 - Mean Absolute Error: 1.8622 - R2 Score: 0.9761 -----Model performance for Test set - Root Mean Squared Error: 6.0092 - Mean Absolute Error: 4.6202 - R2 Score: 0.8516 \_\_\_\_\_ XGBRegressor Model performance for Training set - Root Mean Squared Error: 1.0073 - Mean Absolute Error: 0.6875 - R2 Score: 0.9955 Model performance for Test set - Root Mean Squared Error: 6.4733 - Mean Absolute Error: 5.0577 - R2 Score: 0.8278 \_\_\_\_\_ CatBoosting Regressor Model performance for Training set - Root Mean Squared Error: 3.0427 - Mean Absolute Error: 2.4054 - R2 Score: 0.9589 -----Model performance for Test set - Root Mean Squared Error: 6.0086 - Mean Absolute Error: 4.6125 - R2 Score: 0.8516 \_\_\_\_\_ AdaBoost Regressor Model performance for Training set - Root Mean Squared Error: 5.7967 - Mean Absolute Error: 4.7360 - R2 Score: 0.8510 -----Model performance for Test set - Root Mean Squared Error: 6.0402

- Mean Absolute Error: 4.6618

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- R2 Score: 0.8501

In [15]: pd.DataFrame(list(zip(model\_list, r2\_list)), columns=['Model Name', 'R2\_Score']).sort\_values(by=

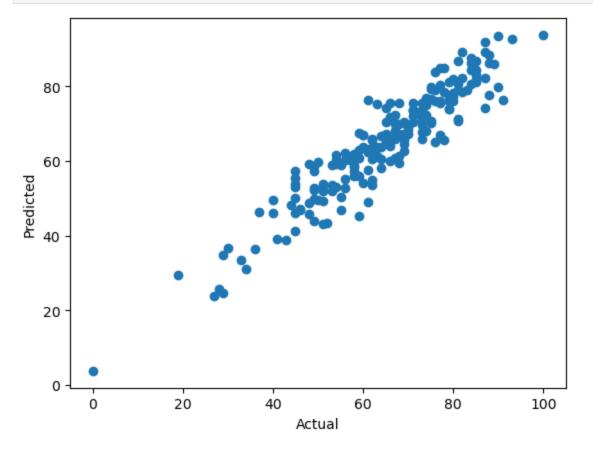
```
Model Name R2_Score
2
                            0.880593
                     Ridge
0
          Linear Regression
                            0.880433
7
      CatBoosting Regressor
                            0.851632
5
   Random Forest Regressor
                            0.851603
8
                            0.850071
        AdaBoost Regressor
6
                            0.827797
             XGBRegressor
1
                            0.825320
                     Lasso
3
     K-Neighbors Regressor
                            0.784030
4
              Decision Tree
                            0.732533
```

Out[15]:

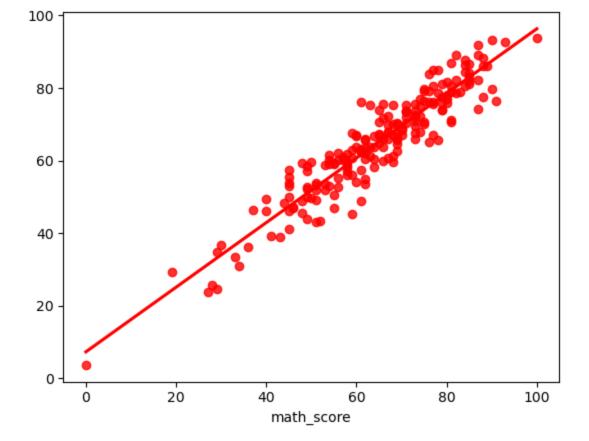
```
In [16]: lin_model = LinearRegression(fit_intercept=True)
lin_model = lin_model.fit(X_train, y_train)
y_pred = lin_model.predict(X_test)
score = r2_score(y_test, y_pred)*100
print(" Accuracy of the model is %.2f" %score)
```

Accuracy of the model is 88.04

```
In [17]: plt.scatter(y_test,y_pred);
    plt.xlabel('Actual');
    plt.ylabel('Predicted');
```



```
In [18]: sns.regplot(x=y_test,y=y_pred,ci=None,color ='red');
```



In [19]: pred\_df=pd.DataFrame({'Actual Value':y\_test,'Predicted Value':y\_pred,'Difference':y\_test-y\_pred}
pred\_df

Out[19]:		Actual Value	Predicted Value	Difference
	521	91	76.387970	14.612030
	737	53	58.885970	-5.885970
	740	80	76.990265	3.009735
	660	74	76.851804	-2.851804
	411	84	87.627378	-3.627378
	•••			
	408	52	43.409149	8.590851
	332	62	62.152214	-0.152214
	208	74	67.888395	6.111605
	613	65	67.022287	-2.022287
	78	61	62.345132	-1.345132

200 rows × 3 columns

In [ ]: