In [1]: import pandas as pd import numpy as np import matplotlib.pyplot as plt from sklearn.model_selection import train_test_split from sklearn.preprocessing import PolynomialFeatures from sklearn.linear_model import LinearRegression from sklearn.metrics import mean_squared_error, r2_score # Step 1: Load the medical dataset # Replace 'medical_dataset.csv' with your actual dataset file data = pd.read_csv('data[1].csv') dob zipcode employment_status education marital_status children ancestry avg_commute daily_internet_use available_vehicles military_service Out[1]: id gender Amelia 1944-0 89136 2 female bachelors Portugal 13.38 2.53 retired married 1 03-09 Nixon Clara 1966-1 female 94105 Sweden 15.16 6.77 employed phd/md married 4 no 07-02 Hicks Mason 1981-89127 2 3.63 male employed masters married 2 Germany 23.60 no 05-31 Brown Michael 1945-5.00 44101 bachelors 2 19.61 male retired married Denmark no 02-13 Rice Eleanor 1939-4 female 89136 3 36.55 7.75 1 retired married Austria masters no 09-03 Ritter 1942-Ethan 1995 89127 1 Switzerland 28.48 5.88 male retired masters married no Johnson 04-13 Natalia 1963unemployed highschool female 60612 Denmark 21.09 5.92 1996 married no Dominguez 05-10 1965-Joseph 1997 94110 bachelors 2 Russia 30.80 4.91 2 male employed married no 07-12 Zuniga 1926-Daniel bachelors 1998 90015 3 Finland 2.69 male retired married 37.56 no 08-10 Murphy 1948-Samuel 1999 43210 bachelors Scotland 49.34 4.77 3 male retired married no 11-22 Harris 2000 rows × 14 columns In [2]: X= data[['daily_internet_use']] y=data['available_vehicles'] In [3]: # 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) In [4]: # Specify the degree of the polynomial (e.g., quadratic, cubic) degree = 2 # Create polynomial features poly_features = PolynomialFeatures(degree=degree) X_train_poly = poly_features.fit_transform(X_train) X_test_poly = poly_features.transform(X_test) In [5]: # Create a polynomial regression model model = LinearRegression() # Train the model on the polynomial features model.fit(X_train_poly, y_train) Out[5]: ▼ LinearRegression LinearRegression() In [6]: # Make predictions on the testing data y_pred = model.predict(x_test_poly) # Evaluate the model's performance mse = mean_squared_error(y_test, y_pred) r2 = r2_score(y_test, y_pred) # Print evaluation metrics print("Mean Squared Error (MSE):", mse) print("R-squared (R2):", r2) Mean Squared Error (MSE): 1.2090248183750671 R-squared (R2): -0.011080528004906443 In [7]: import pandas as pd import numpy as np import matplotlib.pyplot as plt from sklearn.model_selection import train_test_split from sklearn.preprocessing import PolynomialFeatures from sklearn.linear_model import LinearRegression from sklearn.metrics import mean_squared_error, r2_score # Step 1: Load the medical dataset # Replace 'medical_dataset.csv' with your actual dataset file data = pd.read_csv('city_temperature[1].csv') data C:\Users\nishi\AppData\Local\Temp\ipykernel_7736\2357946565.py:11: DtypeWarning: Columns (2) have mixed types. Specify dtype option on import or set low_memory=False. data = pd.read_csv('city_temperature[1].csv') **Region Country** City Month Day Year AvgTemperature Out[7]: **State** Africa Algeria NaN 1 1995 64.2 Algiers NaN 2 1995 49.4 1 Africa Algeria Algiers NaN 3 1995 48.8 2 Africa Algeria Algiers 3 Africa Algeria NaN Algiers 4 1995 46.4 4 Africa Algeria NaN Algiers 5 1995 47.9 ... 2906322 North America US Additional Territories San Juan Puerto Rico 27 2013 82.4 2906323 North America 28 2013 US Additional Territories San Juan Puerto Rico 81.6 2906324 North America Additional Territories San Juan Puerto Rico 29 2013 84.2 2906325 North America US Additional Territories San Juan Puerto Rico 30 2013 83.8 2906326 North America US Additional Territories San Juan Puerto Rico 31 2013 83.6 2906327 rows × 8 columns In [8]: X= data[['Day']] y=data['AvgTemperature'] In [9]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) In [10]: # Specify the degree of the polynomial (e.g., quadratic, cubic) degree = 2 # Create polynomial features poly_features = PolynomialFeatures(degree=degree) X_train_poly = poly_features.fit_transform(X_train) X_test_poly = poly_features.transform(X_test) In [11]: # Create a polynomial regression model model = LinearRegression() # Train the model on the polynomial features model.fit(X_train_poly, y_train) Out[11]: LinearRegression LinearRegression() In [12]: # Make predictions on the testing data y_pred = model.predict(X_test_poly) # Evaluate the model's performance mse = mean_squared_error(y_test, y_pred) r2 = r2_score(y_test, y_pred) # Print evaluation metrics print("Mean Squared Error (MSE):", mse) print("R-squared (R2):", r2) Mean Squared Error (MSE): 1028.5467147230481 R-squared (R2): 8.186790901754115e-06 **EXAMPLES** In [13]: import pandas as pd import numpy as np import matplotlib.pyplot as plt from sklearn.model_selection import train_test_split from sklearn .linear_model import LinearRegression from sklearn.preprocessing import PolynomialFeatures from sklearn.metrics import mean_squared_error In [14]: data=pd.read_csv('FuelConsumption[1].csv') data MODELYEAR MAKE MODEL VEHICLECLASS ENGINESIZE CYLINDERS TRANSMISSION FUELTYPE FUELCONSUMPTION_CITY FUELCONSUMPTION_HWY FUELCONSUM Out[14]: 0 2014 ACURA **ILX** COMPACT 2.0 4 AS5 Ζ 9.9 6.7 1 2014 ACURA **ILX** COMPACT 2.4 M6 Ζ 11.2 **ILX** 2014 ACURA COMPACT 2 1.5 4 AV7 Ζ 6.0 5.8 **HYBRID** MDX 2014 ACURA SUV - SMALL 3.5 AS6 12.7 9.1 4WD **RDX** SUV - SMALL Ζ 4 2014 ACURA 3.5 6 AS6 12.1 8.7 **AWD** XC60 1062 2014 VOLVO SUV - SMALL 6 9.8 3.0 AS6 Χ 13.4 **AWD** XC60 1063 2014 VOLVO SUV - SMALL 3.2 6 9.5 AS6 Χ 13.2 **AWD** XC70 1064 2014 VOLVO SUV - SMALL 6 9.8 3.0 AS6 Χ 13.4 **AWD** XC70 1065 2014 VOLVO SUV - SMALL 12.9 9.3 3.2 6 AS6 Χ **AWD** XC90 SUV -1066 2014 VOLVO 6 10.2 3.2 AS6 Χ 14.9 **AWD STANDARD** 1067 rows × 13 columns In [15]: X=data[['ENGINESIZE']] y=data['CO2EMISSIONS'] In [16]: X_train, X_test, y_train, y_test= train_test_split(X, y, test_size=0.2, random_state=42) In [17]: Degree=2 poly_feature=PolynomialFeatures(degree=degree) X_train_poly=poly_feature.fit_transform(X_train) X_test_poly=poly_feature.transform(X_test) In [18]: model = LinearRegression() model.fit(X_train_poly, y_train) Out[18]: ▼ LinearRegression LinearRegression() In [19]: y_pred=model.predict(X_test_poly) In [20]: mse=mean_squared_error(y_test,y_pred) r2=r2_score(y_test,y_pred) In [21]: | print(mse) print(r2) 960.8705832028328 0.7676219471812655 In [22]: # Step 9: Visualize the Regression Curve and Data plt.scatter(X_test, y_test, color='blue', label='Actual Data') plt.plot(X_test, y_pred, color='red', linewidth=2, label='Polynomial Regression') plt.xlabel('Engine Size') plt.ylabel('CO2 Emissions') plt.title('Polynomial Regression: Engine Size vs. CO2 Emissions') plt.legend() plt.show() Polynomial Regression: Engine Size vs. CO2 Emissions 450 Actual Data Polynomial Regression 400 350 CO2 Emissions 300 250 200 150 100 2 3 5 7 8 4 6 1 **Engine Size** Example In [23]: import pandas as pd import numpy as np import matplotlib.pyplot as plt from sklearn.model_selection import train_test_split from sklearn.preprocessing import PolynomialFeatures from sklearn.linear_model import LinearRegression from sklearn.metrics import mean_squared_error, r2_score In [24]: # Step 1: Load the Fuel Consumption Dataset data = pd.read_csv('FuelConsumption[1].csv') data MODELYEAR MAKE MODEL VEHICLECLASS ENGINESIZE CYLINDERS TRANSMISSION FUELTYPE FUELCONSUMPTION_CITY FUELCONSUMPTION_HWY FUELCONSUM Out[24]: 0 2014 ACURA **COMPACT** 2.0 AS5 Ζ 9.9 6.7 1 2014 ACURA COMPACT 11.2 7.7 2014 ACURA HYBRID **ILX** COMPACT 1.5 AV7 6.0 5.8 MDX 2014 ACURA SUV - SMALL AS6 Ζ 12.7 9.1 3.5 4WD RDX 4 2014 ACURA SUV - SMALL 3.5 6 AS6 Ζ 12.1 8.7 **AWD** XC60 2014 VOLVO SUV - SMALL 6 9.8 1062 3.0 AS6 Χ 13.4 **AWD** XC60 1063 2014 VOLVO SUV - SMALL 3.2 6 Χ 13.2 9.5 AS6 **AWD** XC70 1064 2014 VOLVO SUV - SMALL 6 Χ 13.4 9.8 3.0 AS6 **AWD** XC70 1065 2014 VOLVO SUV - SMALL 3.2 6 AS6 Χ 12.9 9.3 **AWD** XC90 SUV -1066 2014 VOLVO 6 Χ 14.9 10.2 3.2 AS6 **STANDARD AWD** 1067 rows × 13 columns In [25]: # Step 2: Select Features and Target Variable X = data[['ENGINESIZE']] # Feature (e.g., engine size) y = data['CO2EMISSIONS'] # Target variable (e.g., CO2 emissions) In [26]: # Step 3: 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) In [27]: degree = 2 # Adjust the degree as needed poly_features = PolynomialFeatures(degree=degree) X_train_poly = poly_features.fit_transform(X_train) X_test_poly = poly_features.transform(X_test) In [28]: # Step 5: Create and Train the Polynomial Regression Model model = LinearRegression() model.fit(X_train_poly, y_train) Out[28]: ▼ LinearRegression LinearRegression() In [29]: # Step 6: Make Predictions y_pred = model.predict(X_test_poly) In [30]: # Step 7: Evaluate the Model mse = mean_squared_error(y_test, y_pred) r2 = r2_score(y_test, y_pred) In [31]: # Step 8: Print Evaluation Metrics print("Mean Squared Error (MSE):", mse) print("R-squared (R2):", r2) Mean Squared Error (MSE): 960.8705832028328 R-squared (R2): 0.7676219471812655 In [32]: # Step 9: Visualize the Regression Curve and Data plt.scatter(X_test, y_test, color='pink', label='Actual Data') plt.plot(X_test, y_pred, color='red', linewidth=2, label='Polynomial Regression') plt.xlabel('Engine Size') plt.ylabel('CO2 Emissions') plt.title('Polynomial Regression: Engine Size vs. CO2 Emissions') plt.legend() plt.show() Polynomial Regression: Engine Size vs. CO2 Emissions 450 Actual Data Polynomial Regression 400 350 CO2 Emissions 300 250 200 150 100 3 5 7 **Engine Size EXAMPLE** In [34]: **import** pandas **as** pd import numpy as np from sklearn.model_selection import train_test_split from sklearn.preprocessing import PolynomialFeatures from sklearn.linear_model import LinearRegression from sklearn.metrics import mean_squared_error, r2_score # Load the Wine Quality Dataset data = pd.read_csv('WineQT[1].csv') data quality fixed acidity volatile acidity citric acid residual sugar chlorides free sulfur dioxide total sulfur dioxide density Id Out[34]: pH sulphates alcohol 0 7.4 0.700 0.00 1.9 0.076 11.0 34.0 0.99780 3.51 0.56 9.4 5 0 0.880 0.098 67.0 0.99680 3.20 1 7.8 0.00 2.6 25.0 0.68 9.8 5 1 2 7.8 0.760 0.04 2.3 0.092 15.0 54.0 0.99700 3.26 9.8 2 0.65 5 3 11.2 0.280 1.9 0.075 17.0 60.0 0.99800 3.16 0.58 3 0.56 9.8 4 7.4 0.700 1.9 0.076 11.0 34.0 0.99780 3.51 0.00 0.56 9.4 5 1138 6.3 0.510 0.13 2.3 0.076 29.0 40.0 0.99574 3.42 0.75 11.0 6 1592 1139 6.8 0.620 0.08 1.9 0.068 28.0 38.0 0.99651 3.42 0.82 9.5 6 1593 1140 6.2 0.600 0.08 2.0 0.090 32.0 44.0 0.99490 3.45 0.58 10.5 5 1594 1141 5.9 0.550 0.062 51.0 0.99512 3.52 0.10 2.2 39.0 0.76 11.2 6 1595 1142 5.9 0.645 0.12 2.0 0.075 32.0 44.0 0.99547 3.57 0.71 10.2 5 1597 1143 rows × 13 columns In [35]: # Select relevant features and target variable (e.g., 'alcohol' as a feature and 'quality' as the target) X = data[['alcohol']] # Feature y = data['quality'] # Target variable In [36]: # 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) In [37]: # Specify the degree of the polynomial degree = 2 # Create polynomial features poly_features = PolynomialFeatures(degree=degree) X_train_poly = poly_features.fit_transform(X_train) X_test_poly = poly_features.transform(X_test) In [38]: # Create a polynomial regression model model = LinearRegression() # Train the model on the polynomial features model.fit(X_train_poly, y_train) Out[38]: ▼ LinearRegression LinearRegression() In [39]: # Make predictions on the testing data y_pred = model.predict(X_test_poly) In [40]: # Evaluate the model's performance mse = mean_squared_error(y_test, y_pred) r2 = r2_score(y_test, y_pred) # Print evaluation metrics print("Mean Squared Error (MSE):", mse) print("R-squared (R2):", r2) Mean Squared Error (MSE): 0.41093136962180976 R-squared (R2): 0.26154300752733484 In [43]: plt.scatter(X_test, y_test, color='black', label='Actual Data') plt.plot(X_test, y_pred, color='pink', linewidth=2, label='Polynomial Regression') plt.xlabel('Alcohol Content') plt.ylabel('Quality') plt.title('Polynomial Regression: Alcohol Content vs. Quality') plt.legend() plt.show <function matplotlib.pyplot.show(close=None, block=None)> Out[43]: Polynomial Regression: Alcohol Content vs. Quality 8.0 Actual Data Polynomial Regression 7.5 7.0 6.5 Quality 6.0 5.5 5.0 4.5 4.0 10 11 12 13 14 15 Alcohol Content In [44]: **import** pandas **as** pd import numpy as np import matplotlib.pyplot as plt from sklearn.preprocessing import PolynomialFeatures from sklearn.linear_model import LinearRegression from sklearn.metrics import mean_squared_error, r2_score In [45]: data=pd.read_csv('concrete_data[1].csv') data Out[45]: cement blast_furnace_slag fly_ash water superplasticizer coarse_aggregate fine_aggregate age concrete_compressive_strength 540.0 0.0 162.0 1040.0 79.99 0 0.0 2.5 676.0 28 540.0 0.0 162.0 1055.0 61.89 0.0 2.5 676.0 28 0.0 2 332.5 142.5 0.0 228.0 932.0 594.0 270 40.27 142.5 0.0 228.0 932.0 41.05 332.5 0.0 594.0 365 825.5 360 198.6 132.4 0.0 192.0 0.0 978.4 44.30 4 1025 276.4 90.3 179.6 870.1 116.0 8.9 768.3 28 44.28 1026 322.2 0.0 115.6 196.0 10.4 817.9 813.4 28 31.18 108.6 192.7 1027 148.5 139.4 892.4 780.0 28 23.70 6.1 0.0 175.6 989.6 32.77 1028 159.1 186.7 11.3 788.9 28 1029 260.9 100.5 78.3 200.6 8.6 864.5 761.5 28 32.40 1030 rows × 9 columns In [47]: X = data[['cement']] # Feature y = data['concrete_compressive_strength'] # Target variable In [48]: # 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) In [49]: # Specify the degree of the polynomial degree = 2 # Create polynomial features poly_features = PolynomialFeatures(degree=degree) X_train_poly = poly_features.fit_transform(X_train) X_test_poly = poly_features.transform(X_test) In [50]: # Create a polynomial regression model model = LinearRegression() # Train the model on the polynomial features model.fit(X_train_poly, y_train) Out[50]: ▼ LinearRegression LinearRegression() In [51]: # Make predictions on the testing data y_pred = model.predict(X_test_poly) In [52]: # Evaluate the model's performance mse = mean_squared_error(y_test, y_pred) r2 = r2_score(y_test, y_pred) # Print evaluation metrics print("Mean Squared Error (MSE):", mse) print("R-squared (R2):", r2) Mean Squared Error (MSE): 193.14486285131377 R-squared (R2): 0.2504377882674438 In [53]: plt.scatter(X_test, y_test, color='blue', label='Actual Data') plt.plot(X_test, y_pred, color='red', linewidth=2, label='Polynomial Regression') plt.xlabel('Cement Content') plt.ylabel('Compressive Strength') plt.title('Polynomial Regression: Cement Content vs. Compressive Strength') plt.legend() plt.show() Polynomial Regression: Cement Content vs. Compressive Strength Actual Data Polynomial Regression 70 60 Compressive Strength 50 40 30 20 10 100 200 300 400 500 Cement Content