```
#Level 2 Implement the polynomial regression algorithm.
#Compare the learning curves of Polynomial and Linear Regression.
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import learning_curve
from sklearn.model_selection import train_test_split
```

```
#Import data
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/wine-quality/winequality-white.csv"
data = pd.read_csv(url, sep=';')
data
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	su
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.00100	3.00	
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	
...	...	...	...	...	...	...	...	...	...	
4893	6.2	0.21	0.29	1.6	0.039	24.0	92.0	0.99114	3.27	
4894	6.6	0.32	0.36	8.0	0.047	57.0	168.0	0.99490	3.15	
4895	6.5	0.24	0.19	1.2	0.041	30.0	111.0	0.99254	2.99	
4896	5.5	0.29	0.30	1.1	0.022	20.0	110.0	0.98869	3.34	
4897	6.0	0.21	0.38	0.8	0.020	22.0	98.0	0.98941	3.26	

```
# Count the number of missing values in each column
print(data.isnull().sum())
```

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

```
# Split the dataset into training and testing sets
X = data[['alcohol']].values
y = data['quality'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state=0)
```

```
# Fit a linear regression model to the data
lin_regressor = LinearRegression()
lin_regressor.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
# Fit a polynomial regression model to the data
poly = PolynomialFeatures(degree=2)
```

```
X_poly_train = poly.fit_transform(X_train)
X_poly_test = poly.transform(X_test)
poly_regressor = LinearRegression()
poly_regressor.fit(X_poly_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
X_poly_test
```

```
array([[  1.  ,  10.7 , 114.49],
       [  1.  ,   9.8 ,  96.04],
       [  1.  ,  10.8 , 116.64],
       ...,
       [  1.  ,   9.4 ,  88.36],
       [  1.  ,   9.5 ,  90.25],
       [  1.  ,   8.9 ,  79.21]])
```

```
# Predict the quality of the wine for the test data using both models
y_pred_lin = lin_regressor.predict(X_test)
y_pred_poly = poly_regressor.predict(X_poly_test)
```

```
# Print the performance metrics for both models
print('Linear Regression Metrics:')
mse_lin = mean_squared_error(y_test, y_pred_lin)
rmse_lin = np.sqrt(mse_lin)
r2_lin = r2_score(y_test, y_pred_lin)
print('Mean Squared Error: ', mse_lin)
print('Root Mean Squared Error: ', rmse_lin)
print('R-squared: ', r2_lin)
```

```
Linear Regression Metrics:
Mean Squared Error:  0.730644234019256
Root Mean Squared Error:  0.8547773008329457
R-squared:  0.1710201454832173
```

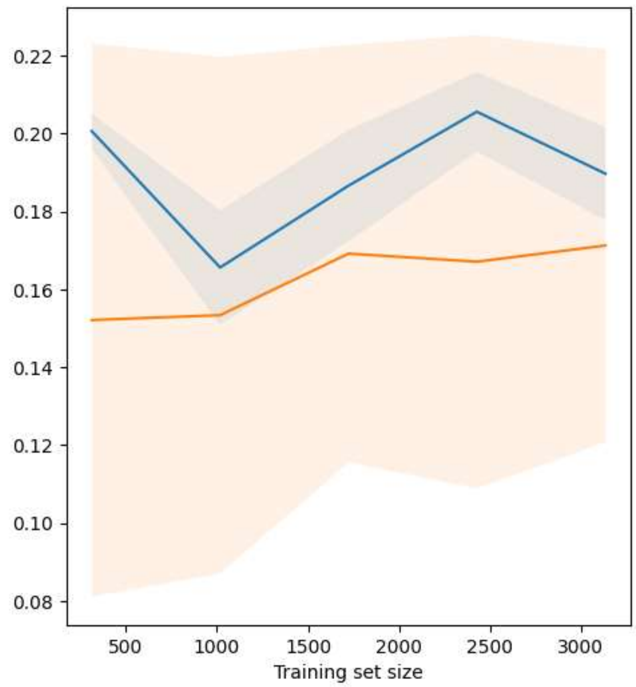
```
print('Polynomial Regression Metrics:')
mse_poly = mean_squared_error(y_test, y_pred_poly)
rmse_poly = np.sqrt(mse_poly)
r2_poly = r2_score(y_test, y_pred_poly)
print('Mean Squared Error: ', mse_poly)
print('Root Mean Squared Error: ', rmse_poly)
print('R-squared: ', r2_poly)
```

```
Polynomial Regression Metrics:
Mean Squared Error:  0.7321933575255222
Root Mean Squared Error:  0.8556829772325275
R-squared:  0.1692625292329819
```

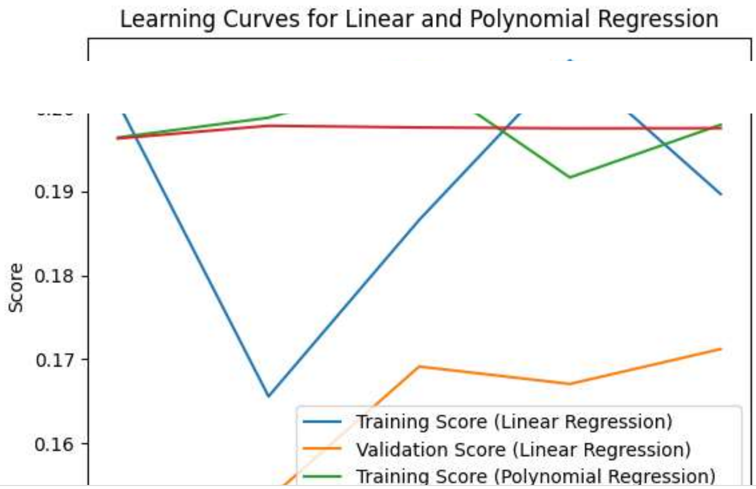
```
# Plot the learning curves for both models
train_sizes, train_scores_lin, test_scores_lin = learning_curve(lin_regressor,X, y, cv=5)
```

```
train_sizes, train_scores_poly, test_scores_poly = learning_curve(poly_regressor,X_poly_train, y_train, cv=5)
train_mean_lin = np.mean(train_scores_lin, axis=1)
train_std_lin = np.std(train_scores_lin, axis=1)
test_mean_lin = np.mean(test_scores_lin, axis=1)
test_std_lin = np.std(test_scores_lin, axis=1)
train_mean_poly = np.mean(train_scores_poly, axis=1)
train_std_poly = np.std(train_scores_poly, axis=1)
test_mean_poly = np.mean(test_scores_poly, axis=1)
test_std_poly = np.std(test_scores_poly, axis=1)
```

```
plt.figure(figsize=(12,6))
plt.subplot(1,2,1)
plt.plot(train_sizes, train_mean_lin, label='Training score')
plt.plot(train_sizes, test_mean_lin, label='Cross-validation score')
plt.fill_between(train_sizes, train_mean_lin - train_std_lin, train_mean_lin + train_std_lin, alpha=0.1)
plt.fill_between(train_sizes, test_mean_lin - test_std_lin,test_mean_lin + test_std_lin, alpha=0.1)
plt.xlabel('Training set size')
plt.show()
```




```
# Plot the learning curves for Linear Regression
plt.plot(train_sizes, train_mean_lin,label='Training Score (Linear Regression)')
plt.plot(train_sizes, test_mean_lin,label='Validation Score (Linear Regression)')
# Plot the learning curves for Polynomial Regression
plt.plot(train_sizes, train_mean_poly,label='Training Score (Polynomial Regression)')
plt.plot(train_sizes, test_mean_poly,label='Validation Score (Polynomial Regression)')
# Set the plot title and labels
plt.title("Learning Curves for Linear and Polynomial Regression")
plt.xlabel("Training examples")
plt.ylabel("Score")
# Set the legend
plt.legend(loc="best")
# Show the plot
plt.show()
```


Learning Curves for Linear and Polynomial Regression
0.19
0.18
0.17
0.16
Score
Training Score (Linear Regression)
Validation Score (Linear Regression)
Training Score (Polynomial Regression)