How can I perform polynomial regression in Python?

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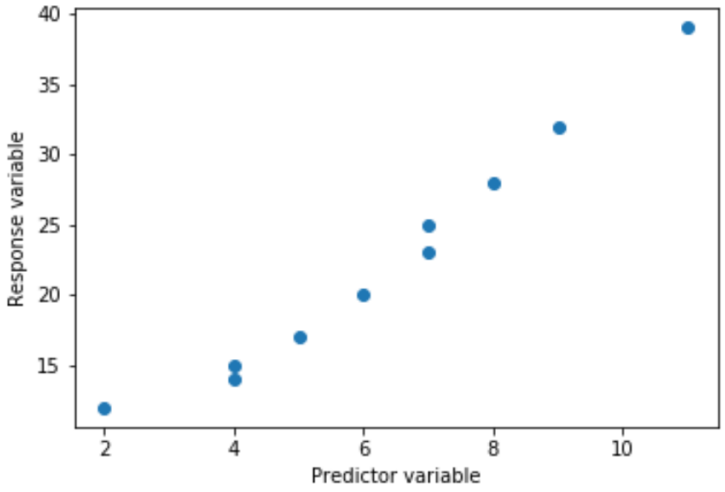
Polynomial regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables, by fitting a polynomial function to the observed data points. In order to perform polynomial regression in Python, one can use the "polyfit" function from the NumPy library, which allows for the calculation of the coefficients of the polynomial function. These coefficients can then be used to create a polynomial regression model using the "polyval" function, also from NumPy. Additionally, the "sklearn" library offers various tools and methods for polynomial regression, making it a convenient option for performing this type of analysis in Python. With the appropriate data preparation and utilization of these tools, one can easily perform polynomial regression in Python to model and predict relationships between variables.

Perform Polynomial Regression in Python

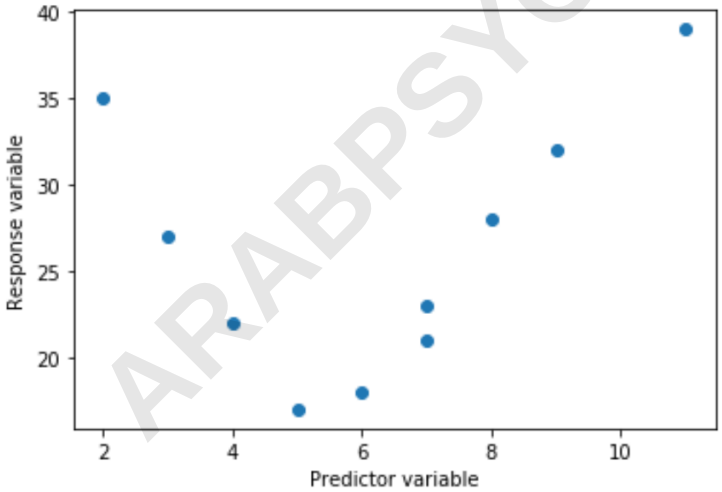
Regression analysis is used to quantify the relationship between one or more explanatory variables and a response variable.

The most common type of regression analysis is simple linear regression, which is used when a predictor variable and a response variable have a linear relationship.

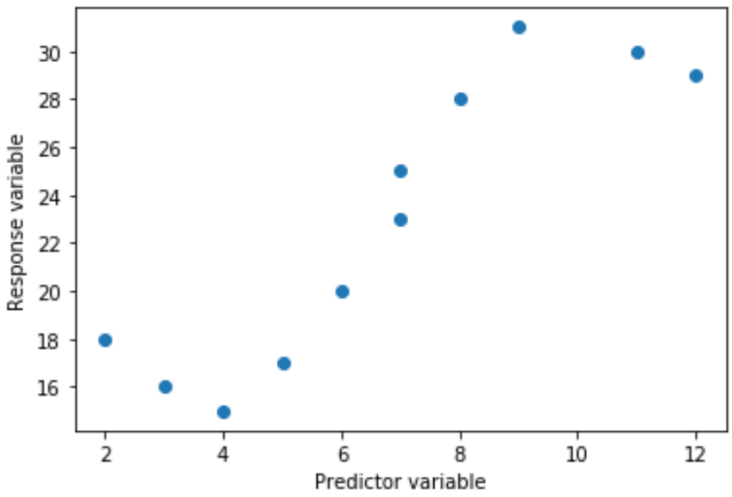


However, sometimes the relationship between a predictor variable and a response variable is nonlinear.

For example, the true relationship may be quadratic:



Or it may be cubic:



In these cases it makes sense to use polynomial regression, which can account for the nonlinear relationship between the variables.

This tutorial explains how to perform polynomial regression in Python.

Example: Polynomial Regression in Python

Suppose we have the following predictor variable (x) and response variable (y) in Python:

x =

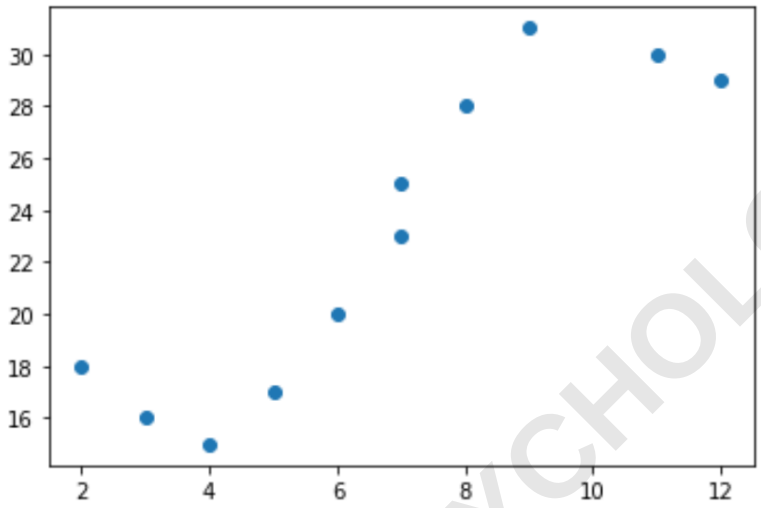
y =

If we create a simple scatterplot of this data, we can see that the relationship between x and y is clearly not

linear:

```
import matplotlib.pyplot as plt

#create scatterplot
plt.scatter(x, y)
```

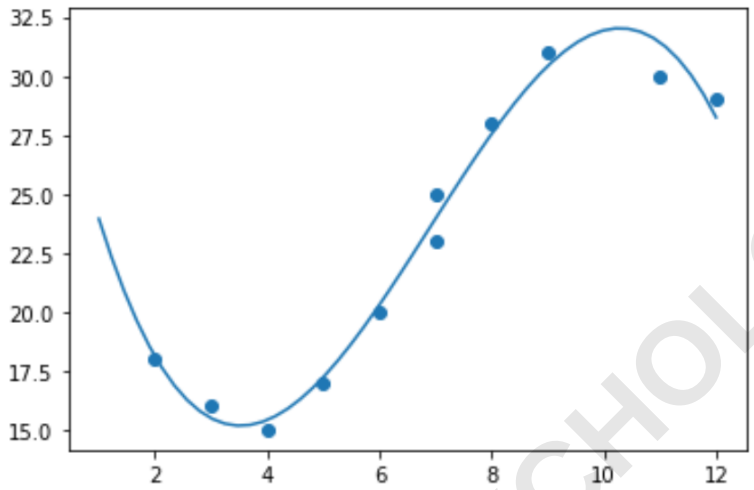


Thus, it wouldn't make sense to fit a linear regression model to this data. Instead, we can attempt to fit a polynomial regression model with a degree of 3 using the numpy.polyfit() function:

```
import numpy as np

#polynomial fit with degree = 3
model = np.poly1d(np.polyfit(x, y, 3))
```

```
#add fitted polynomial line to scatterplot
polyline = np.linspace(1, 12, 50)
plt.scatter(x, y)
plt.plot(polyline, model(polyline))
plt.show()
```



We can obtain the fitted polynomial regression equation by printing the model coefficients:

```
print(model)
```

poly1d()

The fitted polynomial regression equation is:

y = -0.109x3 + 2.256x2 - 11.839x + 33.626

This equation can be used to find the expected value for the response variable based on a given value for the explanatory variable.

For example, suppose x = 4. The expected value for the response variable, y, would be:

y = -0.109(4)3 + 2.256(4)2 - 11.839(4) + 33.626= 15.39.

We can also write a short function to obtain the R-squared of the model, which is the proportion of the variance in the response variable that can be explained by the predictor variables.

```
#define function to calculate r-squareddef polyfit(x, y, degree):
results = {}
coeffs = numpy.polyfit(x, y, degree)
p = numpy.poly1d(coeffs)
#calculate r-squared
yhat = p(x)
ybar = numpy.sum(y)/len(y)
ssreg = numpy.sum((yhat-ybar)**2)
sstot = numpy.sum((y - ybar)**2)
results = ssreg / sstot
```

return results

#find r-squared of polynomial model with degree = 3
polyfit(x, y, 3)

{'r_squared': 0.9841113454245183}

In this example, the R-squared of the model is 0.9841.

This means that 98.41% of the variation in the response variable can be explained by the predictor variables.