

Module-04, Python for Machine Learning

Regression Algorithms(Multiple, Polynomial Regressions)

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Data science and Artificial Intelligence
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at
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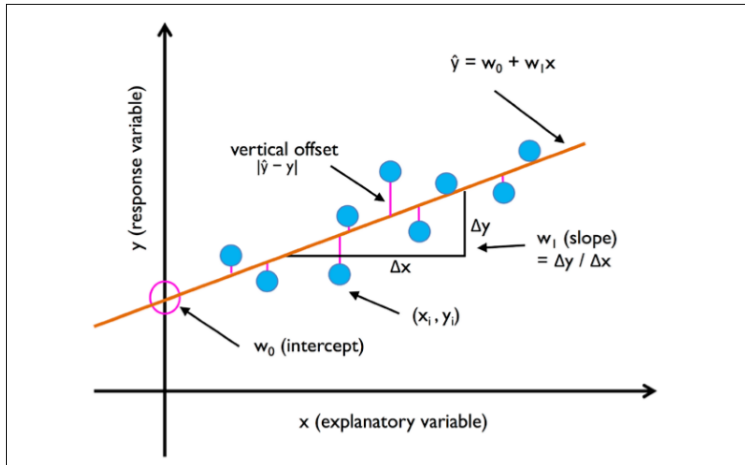
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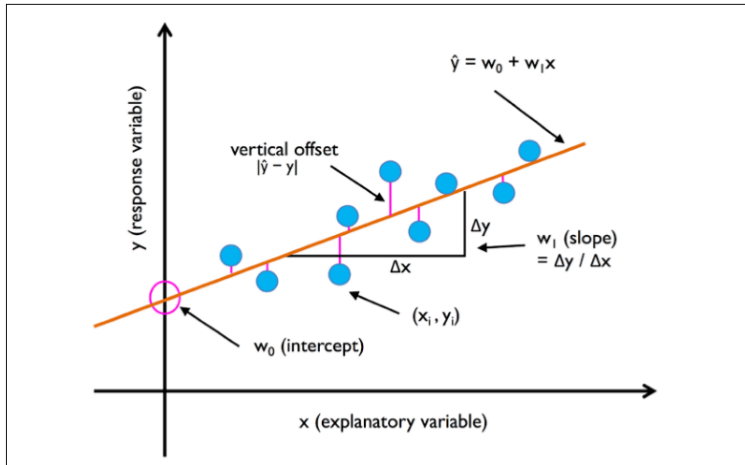


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Multi-linear regression

- The previous Lecture we introduced simple linear regression, a special case of linear regression with one explanatory variable. Of course, we can also generalize the linear regression model to multiple explanatory variables; this process is called multiple linear regression:
- Equation

$$y = w_0x_0 + w_1x_1 + w_2x_2 + \dots + w_nx_n = \sum_{i=0}^n w_ix_i = w^T x \quad (1)$$

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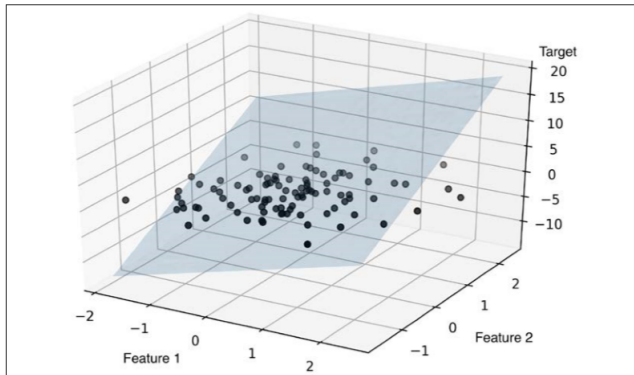
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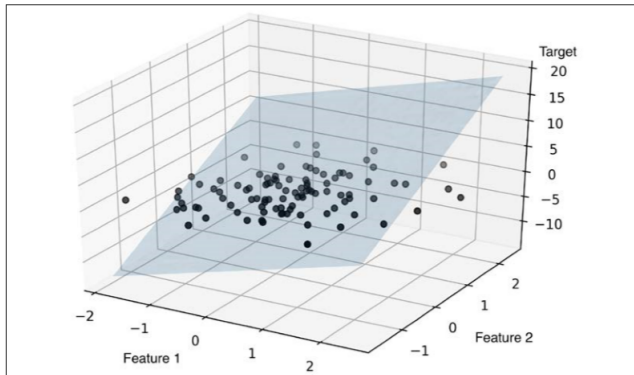
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Polynomial regression

- In the previous Lectures, we assumed a linear relationship between explanatory and response variables. One way to account for the violation of linearity assumption is to use a polynomial regression model by adding polynomial terms:

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$$y = w_0 + w_1x + w_2x^2 + \dots + w_dx^d \quad (2)$$

- Here, d denotes the degree of the polynomial. Although we can use polynomial regression to model a nonlinear relationship, it is still considered a multiple linear regression model because of the linear regression coefficients, w . In the following subsections, we will see how we can add such polynomial terms to an existing dataset conveniently and fit a polynomial regression model.



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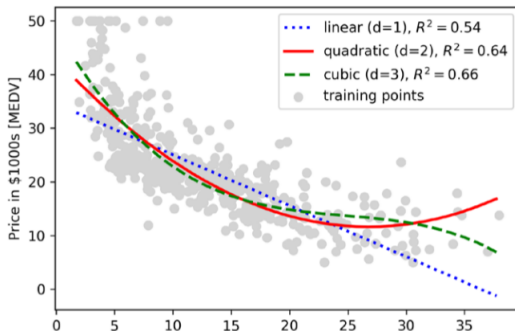
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Polynomial regression

- As you can see, the cubic fit captures the relationship between house prices and LSTAT better than the linear and quadratic fit. However, you should be aware that adding more and more polynomial features increases the complexity of a model and therefore increases the chance of overfitting. Thus, in practice, it is always recommended to evaluate the performance of the model on a separate test dataset to estimate the generalization performance.



Great Job
Thank you

