## Polynomial Regression

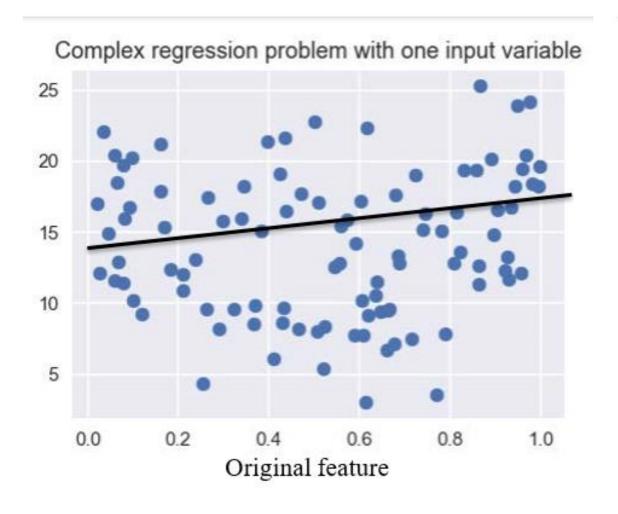
## Polynomial Features with Linear Regression

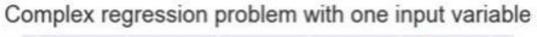
$$x = (x_0, x_1)$$
 Regression  $x' = (x_0, x_1, x_0^2, x_0 x_1, x_1^2)$ 

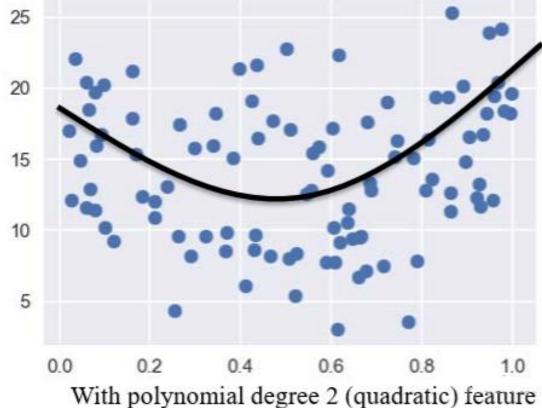
$$\hat{y} = \hat{w}_0 x_0 + \hat{w}_1 x_1 + \hat{w}_{00} x_0^2 + \hat{w}_{01} x_0 x_1 + \hat{w}_{11} x_1^2 + b$$

- Generate new features consisting of all polynomial combinations of the original two features  $(x_0, x_1)$ .
- The degree of the polynomial specifies how many variables participate at a time in each new feature (above example: degree 2)
- This is still a weighted linear combination of features, so it's <u>still a linear</u> model, and can use same least-squares estimation method for w and b.

## Least-Squares Polynomial Regression







## Polynomial Features with Linear Regression

- Why would we want to transform our data this way?
  - To capture interactions between the original features by adding them as features to the linear model.
  - To make a classification problem easier (we'll see this later).
- More generally, we can apply other non-linear transformations to create new features
  - (Technically, these are called non-linear basis functions)
- Beware of polynomial feature expansion with high as this can lead to complex models that overfit
  - Thus, polynomial feature expansion is often combined with a regularized learning method like ridge regression.