Comparing MLR and SLR

1. Is a lower MSE always implying a better fit?
   - Not necessarily.
2. MSE for an MLR model will be smaller than the MSE for an SLR model, since the errors of the data will decrease when more variables are included in the model
3. Polynomial regression will also have a smaller MSE then regular regression
4. A similar inverse relationship holds for R^2

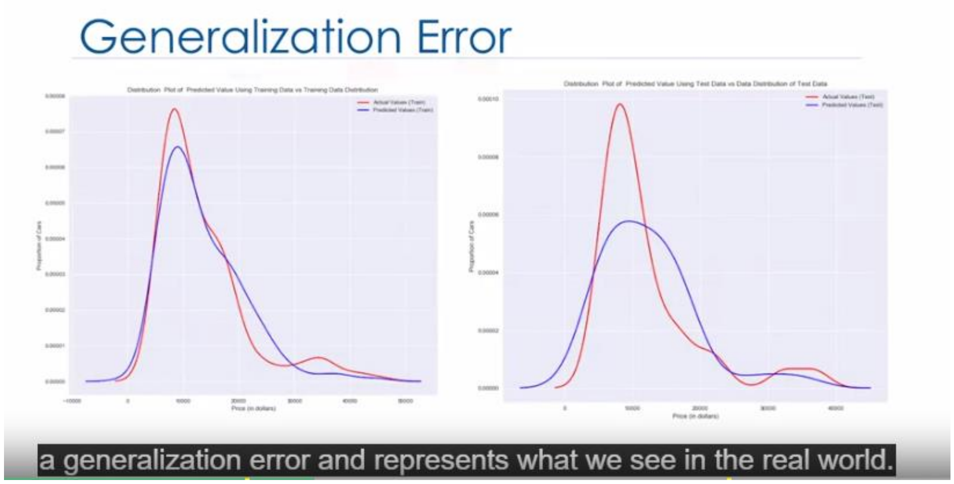
Model Evaluation

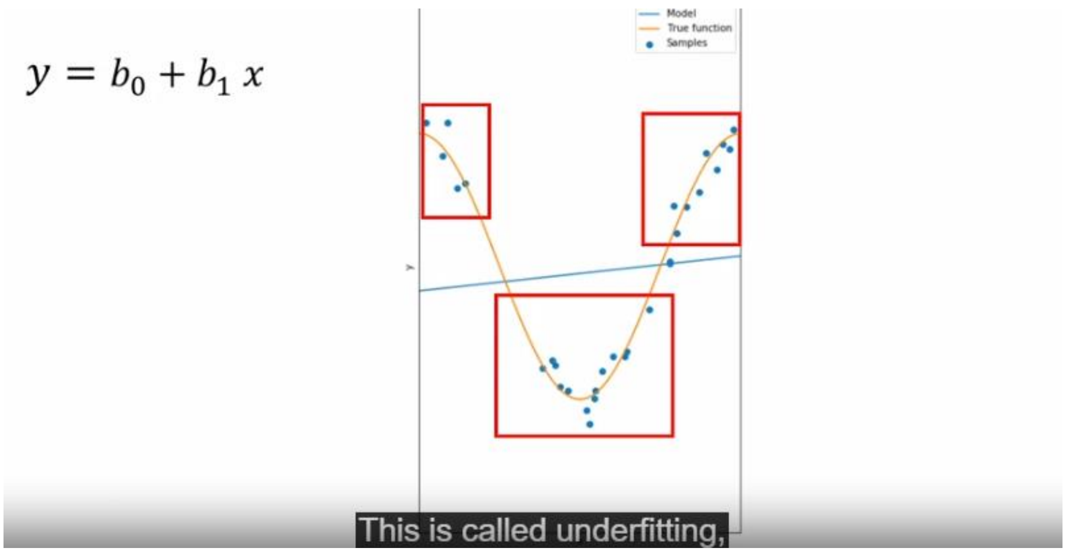
- In-sample evaluation tells us how well our model will fit the data used to train it
- Problem?
  - It does not tell us how well the trained model can be used to predict new data
- Solution?
  - In- sample data or training data
  - Out-of-sample evaluation or test set

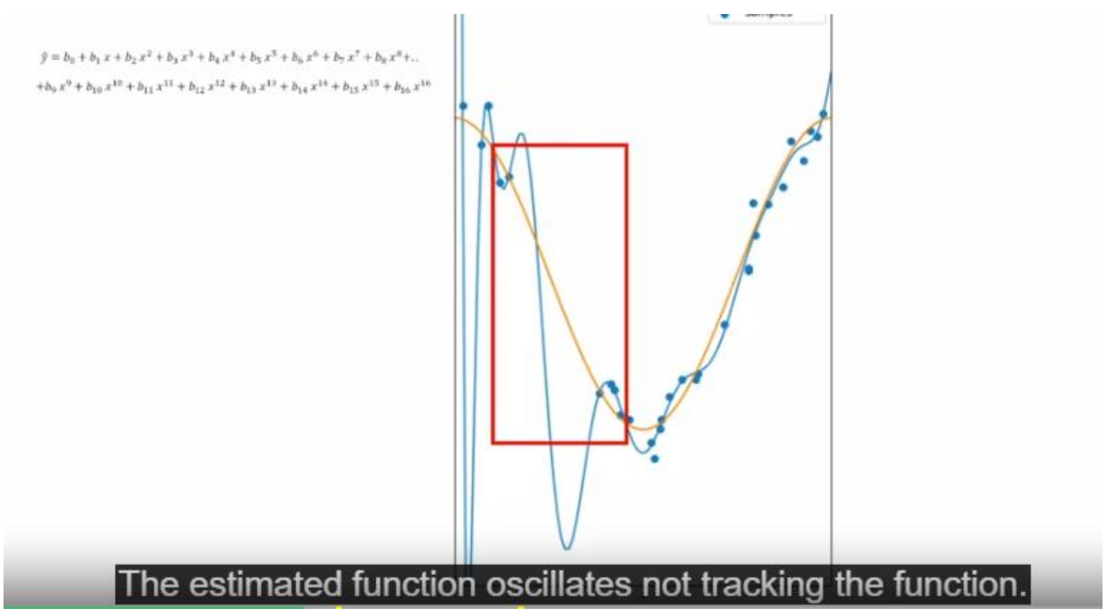
Training/Testing Sets

Data:

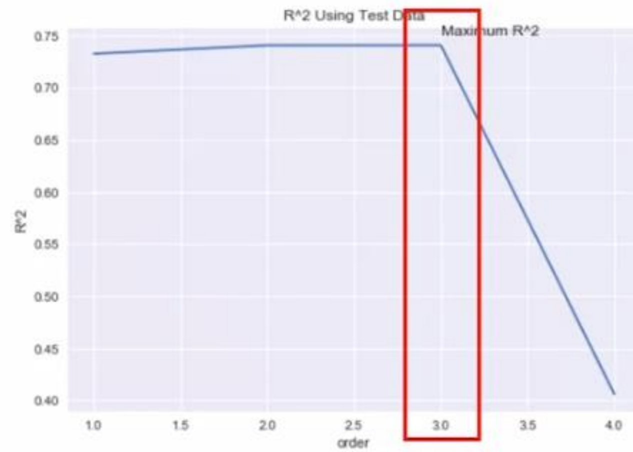
- Split dataset into:
  - Training set (70%),
  - Testing set (30%)
- Build and train the model with a training set
- Use testing set to assess the performance of a predictive model
- When we have completed testing our model we should use all the data to train the model to get the best performance


Generalization Error
a generalization error and represents what we see in the real world.

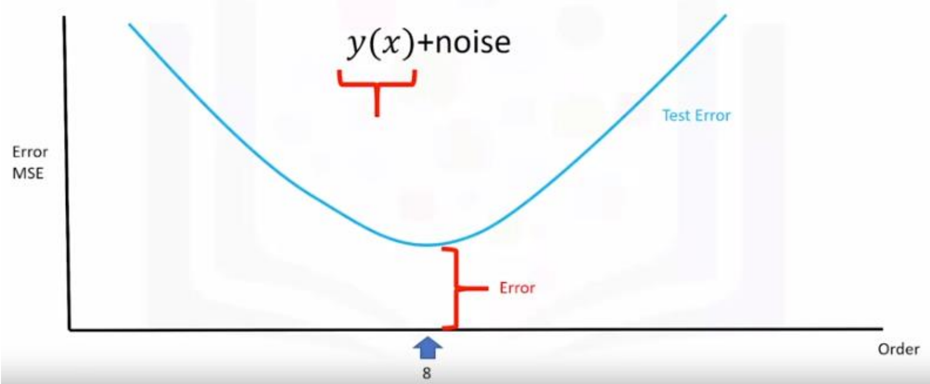

$y = b_0 + b_1 x$
Model
True function
Samples
This is called underfitting,


$\hat{y} = b_0 + b_1 x + b_2 x^2 + b_3 x^3 + b_4 x^4 + b_5 x^5 + b_6 x^6 + b_7 x^7 + b_8 x^8 + ..$
$+ b_9 x^9 + b_{10} x^{10} + b_{11} x^{11} + b_{12} x^{12} + b_{13} x^{13} + b_{14} x^{14} + b_{15} x^{15} + b_{16} x^{16}$
The estimated function oscillates not tracking the function.

Model Selection

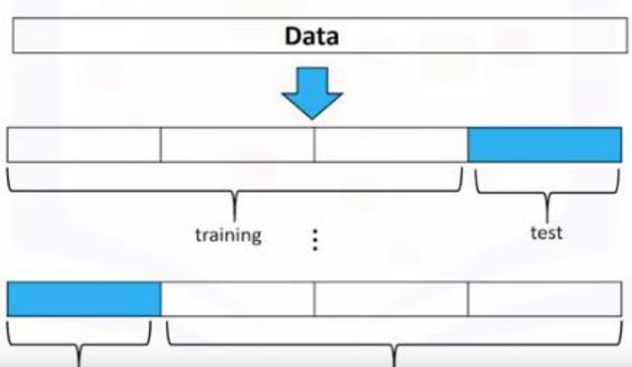


Model Selection



Cross Validation

- Most common out-of-sample evaluation metrics
- More effective use of data (each observation is used for both training and testing)



At the end, we use the average results as the estimate of out-of-sample error.