Regularization & Feature Selection

Data Science Immersive



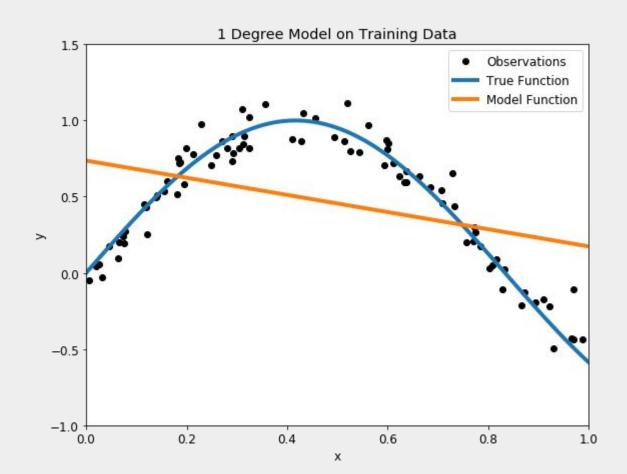
Learning Goals

After today, you'll be able to:

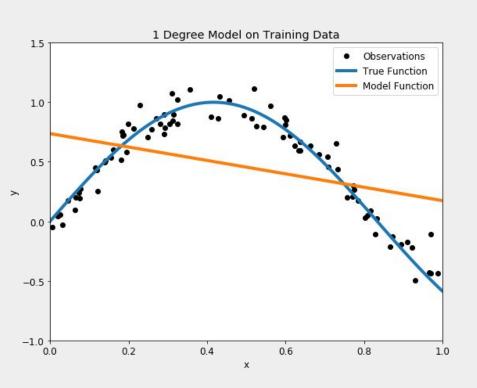
- Explain what the problems of over/underfitting are and how they relate to the bias/variance trade-off
- Explain how regularization addresses the over/underfitting problem
- Explain the differences between regularization methods and when it is appropriate to use them
- Explain the factors to consider when deciding which features to include
- Apply feature selection and regularization to prevent overfitting in a model

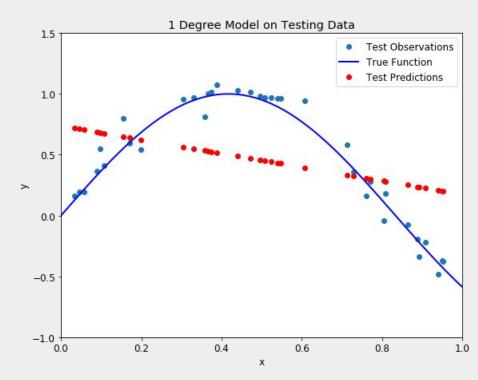
Question #1

- What would the problem be if our model looked like this?



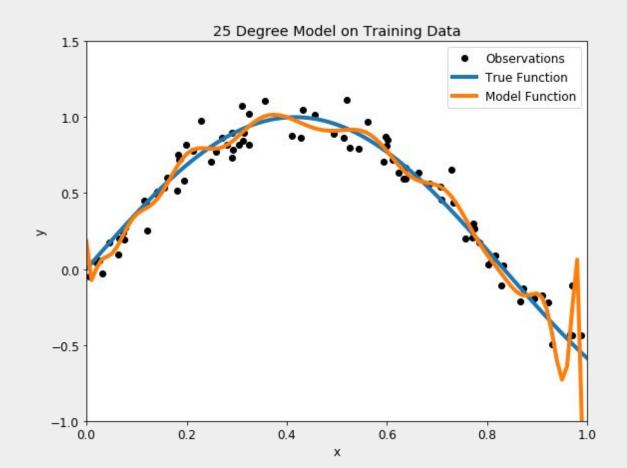
Question #1 - Review



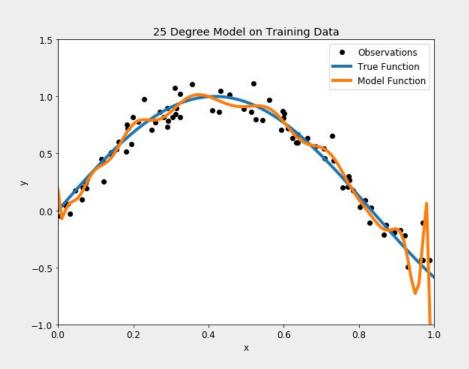


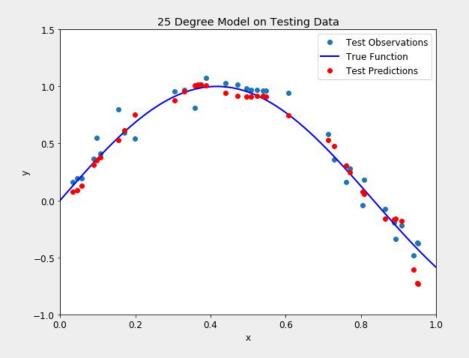
Question #2

- What would the problem be if our model looked like this?

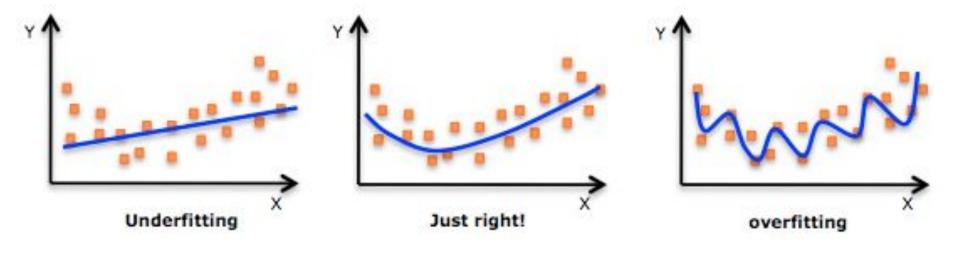


Question #2 - Review

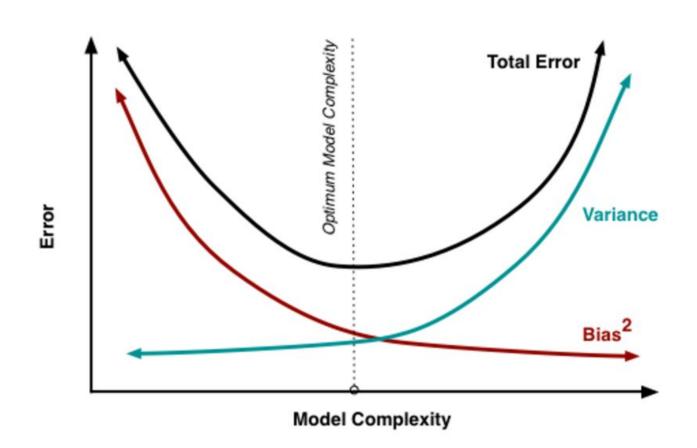




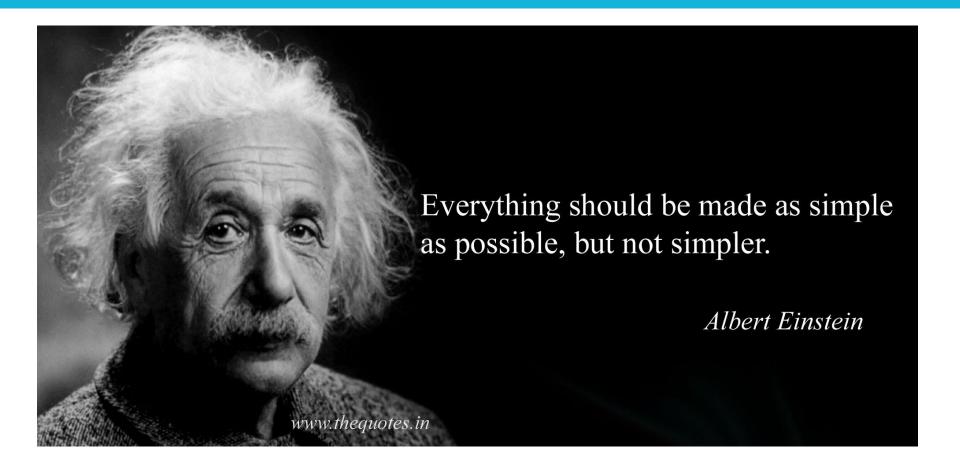
Underfitting vs. Overfitting



Bias Variance Trade-off



Regularization



Regularization

For simple linear regression, the cost function is represented as:

cost_function =
$$\sum_{i=1}^{n} (y_i - \hat{y})^2 = \sum_{i=1}^{n} (y_i - bx + b_0)^2$$

For linear regression with multiple predictors, the cost function is expressed as so:

cost_function =
$$\sum_{i=1}^{n} (y_i - \hat{y})^2 = \sum_{i=1}^{n} (y_i - \sum_{j=1}^{k} (m_j x_{ij}) + b)^2$$

Ridge

Ridge regression applies a penalizing parameter

cost_function_ridge =
$$\sum_{i=1}^{n} (y_i - \hat{y})^2 + \lambda \sum_{j=1}^{p} m_j^2$$

= $\sum_{i=1}^{n} (y_i - \sum_{j=1}^{k} (m_j x_{ij} + b))^2 + \lambda \sum_{j=1}^{p} m_j^2$

Lasso

Lasso regression applies a penalizing parameter

cost_function_lasso =
$$\sum_{i=1}^{n} (y_i - \hat{y})^2 + \lambda \sum_{j=1}^{p} |m_j|$$

= $\sum_{i=1}^{n} (y_i - \sum_{j=1}^{k} (m_j x_{ij} + b))^2 + \lambda \sum_{j=1}^{p} |m_j|$

Questions to ponder?

When should you use a regularized model instead of a normal model?

How do regularized models differ from normal linear regression?

How does a Ridge model differ from a Lasso Model?