

Introduction to Machine Learning

Problems Unit 4: Model Order Selection

Prof. Sundeep Rangan

1. For each of the following pairs of true functions $f_0(\mathbf{x})$ and model classes $f(\mathbf{x}, \beta)$ determine: (i) if the model class is linear; (ii) if there is no under-modeling; and (iii) if there is no under-modeling, what is the true parameter?

(a) $f_0(x) = 1 + 2x$, $f(x, \beta) = \beta_0 + \beta_1 x + \beta_2 x^2$

(b) $f_0(x) = 1 + 1/(2 + 3x)$, $f(x, a_0, a_1, b_0, b_1) = (a_0 + a_1 x)/(b_0 + b_1 x)$.

(c) $f_0(x) = (x_1 - x_2)^2$ and

$$f(\mathbf{x}, a, b_1, b_2, c_1, c_2) = a + b_1 x_1 + b_2 x_2 + c_1 x_1^2 + c_2 x_2^2.$$

2. You want to fit an exponential model of the form,

$$y \approx \hat{y} = \sum_{j=0}^d \beta_j e^{-ju/d},$$

where the input u and output y are scalars. You are given python functions:

```
model = LinearRegression()
model.fit(X,y)           # Fits a linear model for a data matrix X
yhat = model.predict(X)  # Predicts values
```

Using these functions, write python code that, given vectors \mathbf{u} and \mathbf{y} :

- Splits the data into training and test using half the samples for each.
- Fits models of order $d_{\text{test}} = [1, 2, \dots, 10]$ on the training data.
- Selects the model with the lowest mean squared error.

3. Suppose we want to fit a model,

$$y \approx \hat{y} = f(x, \beta) = \beta x^2.$$

We get data (x_i, y_i) , $i = 1, \dots, N$ and compute the estimate,

$$\hat{\beta} = \frac{\sum_{i=1}^N y_i}{\sum_{i=1}^N x_i^2}.$$

Note: This is not optimal least-squares estimator. But, it is easier to analyze. For each case below compute the bias,

$$\text{Bias}(x) := \mathbb{E}(f(x, \hat{\beta})) - f(x, \beta_0),$$

as a function of the test point x , true parameter β_0 and training data x_i .

- (a) The training data has no noise: $y_i = f(x_i, \beta_0)$.
 - (b) The training data is $y_i = f(x_i, \beta_0) + \epsilon_i$ where the noise is i.i.d. $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$.
 - (c) The training data is $y_i = f(x_i + \epsilon_i, \beta_0)$ where the noise is i.i.d. $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$.
4. In this problem, we will see how to calculate the bias when there is undermodeling. Suppose that training data (x_i, y_i) , $i = 1, \dots, n$ is fit using a simple linear model of the form,

$$\hat{y} = f(x, \beta) = \beta_0 + \beta_1 x.$$

However, the true relation between x and y is given

$$y = f_0(x), \quad f_0(x) = \beta_{00} + \beta_{01}x + \beta_{02}x^2,$$

where the “true” function $f_0(x)$ is quadratic and $\beta_0 = (\beta_{00}, \beta_{01}, \beta_{02})$ is the vector of the true parameters. There is no noise.

- (a) Write an expression for the least-squares estimate $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1)$ in terms of the training data (x_i, y_i) , $i = 1, \dots, n$. These expressions will involve multiple steps. You do not need to simplify the equations. Just make sure you state clearly how one would compute $\hat{\beta}$ from the training values.
 - (b) Using the fact that $y_i = f_0(x_i)$ in the training data, write the expression for $\beta = (\hat{\beta}_0, \hat{\beta}_1)$ in terms of the values x_i and the true parameter values β_0 . Again, you do not need to simplify the equations. Just make sure you state clearly how one would compute $\hat{\beta}$ from the true parameter vector β_0 and \mathbf{x} .
 - (c) Suppose that the true parameters are $\beta_0 = (1, 2, -1)$ and the model is trained using 10 values x_i uniformly spaced in $[0, 1]$. Write a short python program to compute the estimate parameters $\hat{\beta}$. Plot the estimated function $f(x, \hat{\beta})$ and true function $f_0(x)$ for $x \in [0, 3]$.
 - (d) For what value x in this range $x \in [0, 3]$ is the bias $\text{Bias}^2(x) = (f(x, \hat{\beta}) - f_0(x))^2$ largest?
5. A medical researcher wishes to evaluate a new diagnostic test for cancer. A clinical trial is conducted where the diagnostic measurement y of each patient is recorded along with attributes of a sample of cancerous tissue from the patient. Three possible models are considered for the diagnostic measurement:
- Model 1: The diagnostic measurement y depends linearly only on the cancer volume.
 - Model 2: The diagnostic measurement y depends linearly on the cancer volume and the patient’s age.
 - Model 3: The diagnostic measurement y depends linearly on the cancer volume and the patient’s age, but the dependence (slope) on the cancer volume is different for two types of cancer – Type I and II.
- (a) Define variables for the cancer volume, age and cancer type and write a linear model for the predicted value \hat{y} in terms of these variables for each of the three models above. For Model 3, you will want to use one-hot coding.
 - (b) What are the numbers of parameters in each model? Which model is the most complex?

- (c) Since the models in part (a) are linear, given training data, we should have $\hat{\mathbf{y}} = \mathbf{A}\boldsymbol{\beta}$ where $\hat{\mathbf{y}}$ is the vector of predicted values on the training data, \mathbf{A} is a feature matrix and $\boldsymbol{\beta}$ is the vector of parameters. To test the different models, data is collected from 100 patients. The records of the first three patients are shown below:

Patient ID	Measurement y	Cancer type	Cancer volume	Patient age
12	5	I	0.7	55
34	10	II	1.3	65
23	15	II	1.6	70
\vdots	\vdots	\vdots	\vdots	\vdots

Based on this data, what would be the values of first three rows of the three \mathbf{A} matrices be for the three models in part (a)?

- (d) To evaluate the models, 10-fold cross validation is used with the following results.

Model	Mean training RSS	Mean test RSS	Test RSS std deviation
1	2.0	2.01	0.03
2	0.7	0.72	0.04
3	0.65	0.70	0.05

All RSS values are per sample, and the last column is the (biased) standard deviation – not the standard error. Which model should be selected based on the “one standard error rule”?