

Homework 3

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1.

1. (a) the model is not linear and there is no under-modeling. $\beta = [1, 2, 0]$
- (b) the model is not linear and there is no under-modeling
 $a_0 = 3, a_1 = 3, b_0 = 2, b_1 = 3$
- (c) the model is not linear and it is under-modeling.

$$\begin{aligned}
 2. (a) \quad \bar{x} &= \frac{1}{N} \sum_{i=1}^N x_i & \bar{y} &= \frac{1}{N} \sum_{i=1}^N y_i \\
 S_{xy} &= \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y}) = \frac{1}{N} \sum x_i y_i - \bar{x} \bar{y} \\
 S_{x^2} &= \frac{1}{N} \sum (x_i - \bar{x})^2 = \frac{1}{N} \sum x_i^2 - \bar{x}^2 \\
 \hat{\beta}_1 &= \frac{S_{xy}}{S_{x^2}}, \quad \hat{\beta}_0 = \bar{y} - \beta_1 \bar{x} \\
 (b) \quad \bar{x} &= \frac{1}{N} \sum x_i & \bar{y} &= \frac{1}{N} \sum y_i = \frac{1}{N} \sum f_0(x_i) \\
 S_{xy} &= \frac{1}{N} \sum (x_i - \bar{x})(f_0(x_i) - \frac{1}{N} \sum f_0(x_i)) \\
 S_{x^2} &= \frac{1}{N} \sum x_i^2 - \bar{x}^2 \\
 \hat{\beta}_1 &= \frac{S_{xy}}{S_{x^2}}, \quad \hat{\beta}_0 = \bar{y} - \beta_1 \bar{x} = \frac{1}{N} \sum f_0(x_i) - \beta_1 \bar{x}
 \end{aligned}$$

2 (c)

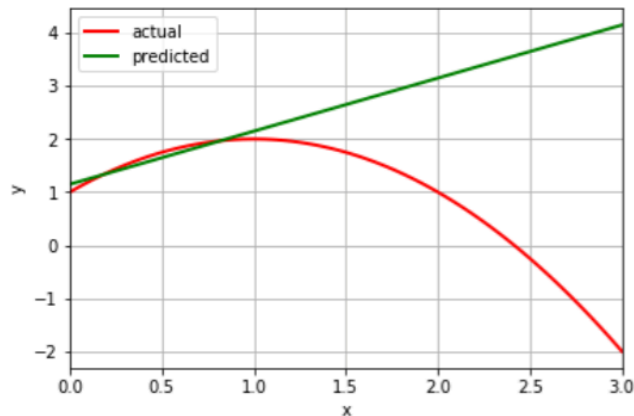
```
In [8]: 1 import numpy as np
2 import matplotlib
3 import matplotlib.pyplot as plt
4 from sklearn import datasets, linear_model, preprocessing
5 import numpy.polynomial.polynomial as poly
6 %matplotlib inline
7
8
9 beta = np.array([1, 2, -1])
10 nsamp = 10
11 xdat = np.linspace(0, 1, nsamp)
12 ydat = poly.polyval(xdat, beta)
13 d = 1
14 beta_hat = poly.polyfit(xdat, ydat, d)

[ 1.14814815  1.          ]
```

```
In [14]: 1 xp = np.linspace(0, 3, 100)
2 yp = poly.polyval(xp, beta)
3 yp_hat = poly.polyval(xp, beta_hat)
```

```
In [21]: 1 plt.xlim(0, 3)
2 plt.plot(xp, yp, 'r-', linewidth=2)
3 plt.plot(xp, yp_hat, 'g-', linewidth=2)
4 plt.legend(['actual', 'predicted'], loc = 'upper left')
5 plt.grid()
6 plt.xlabel('x')
7 plt.ylabel('y')
```

Out[21]: <matplotlib.text.Text at 0x1151fc400>



2(d)

```
In [22]: 1 bias = np.zeros(100)
2 for i in range(100):
3     bias[i] = (yp_hat[i] - yp[i])**2
4 bias_order = np.argsort(-bias)
5 print(xp[bias_order[0]])
```

3.0

3.

3. (a)

Model 1: cancer volume: x $\hat{y} = \beta_0 + \beta_1 x$

Model 2: cancer volume: x_1 , age: x_2 $\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$

Model 3: cancer I volume: x_1 , cancer II volume: x_2 , age: x_3

	Cancer I volume (x_1)	Cancer II volume (x_2)	Age (x_3)
Type I	1	0	1
Type II	0	1	1

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

(b)

Model 1: 2 parameters

Model 2: 3 parameters

Model 3: 4 parameters

Model 3 is the most complex one.

(c) Model 1: $A = \begin{bmatrix} 1 & 0.7 \\ 1 & 1.3 \\ 1 & 1.6 \end{bmatrix}$

Model 2: $A = \begin{bmatrix} 1 & 0.7 & 55 \\ 1 & 1.3 & 65 \\ 1 & 1.6 & 70 \end{bmatrix}$

Model 3: $A = \begin{bmatrix} 1 & 0.7 & 0 & 55 \\ 1 & 0 & 1.3 & 65 \\ 1 & 0 & 1.6 & 70 \end{bmatrix}$

(d) Model 2