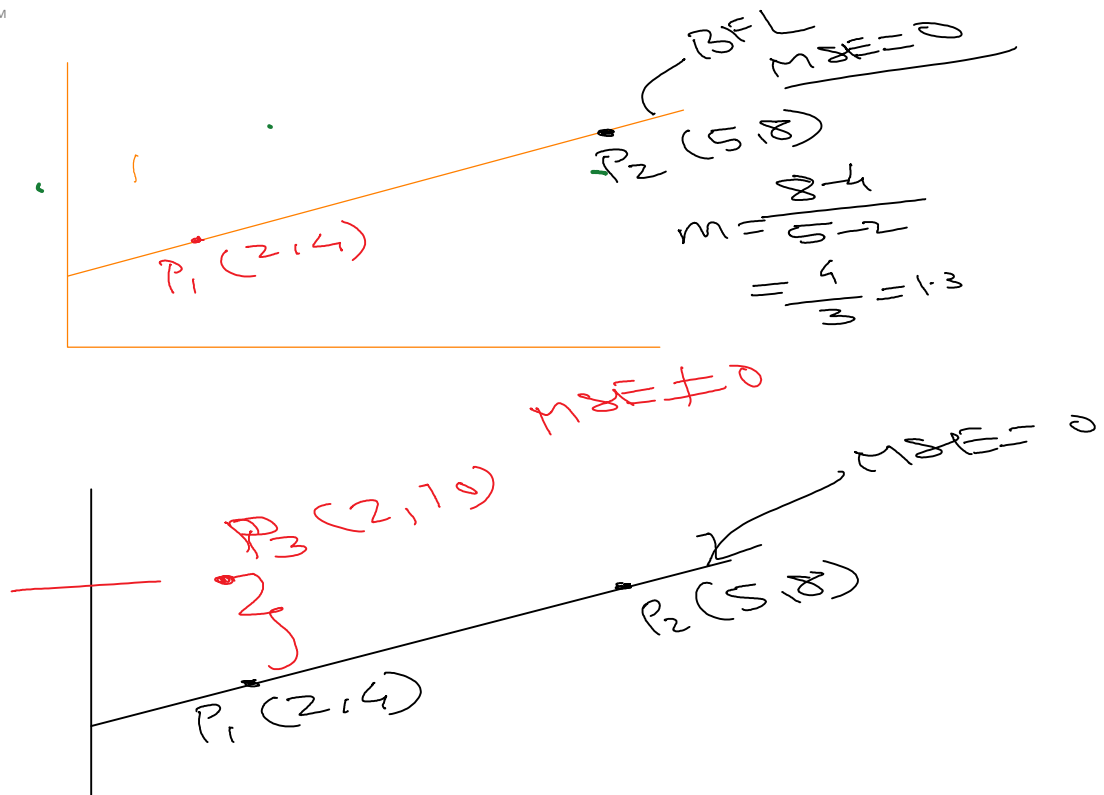


Regularization

Sunday, March 10, 2024 7:51 PM

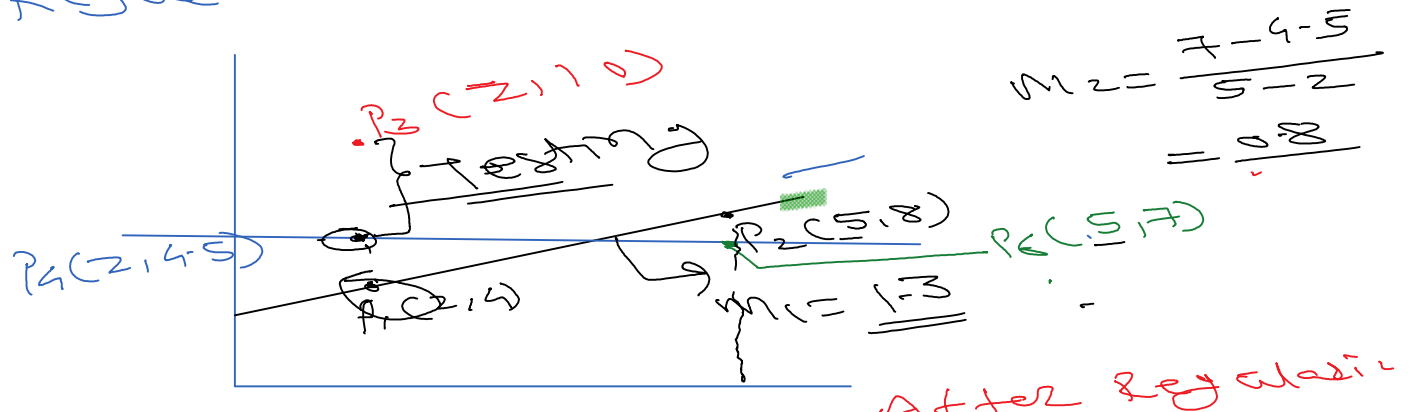


overfitting
 Training Accuracy / MSE
 100% 0

Testing Accuracy $\Rightarrow 80\%$
 $MSE \neq 0$

Low Bias High Variance

Regularization



conclusion

MSE[0] on training \Rightarrow MSE[40] ie MSE $\neq 0$

MSE[100] on testing \Rightarrow MSE[60]

After regularization

Types

① L1 Lasso

② L2 Ridge

Ridge Regression

$$\begin{aligned} CF &= SSE + 1 \times slope^2 \\ &= SSE + 1 \times [m_1^2 + m_2^2 + m_3^2 + m_4^2 + \dots] \end{aligned}$$

Case-I

$$SSE = 0$$

1 - Regularization parameter

$$\lambda = 1$$

Default

$$m_1 = 1.3$$

$$CF = 0 + 1 \times (1.3)^2$$

$$CF = 1.69 \Rightarrow \text{training}$$

Case-II

After regularization

$$m_2 = 0.8, SSE \neq 0, SSE = 0.5$$

$$CF = 0.5 + 1 \cdot (0.8)^2$$

$$CF = 1.14$$

$$= (1.3)^2$$

Let -

$$C-F = \uparrow SSE + \lambda \cdot (slope)^2 \downarrow$$

$\lambda = 1$ default
(regularization parameter)

range $\lambda = 0.01$ to ∞

Lasso (L1)

$$C-F = SSE + \lambda \cdot |slope|$$

$$= SSE + \lambda \cdot (|m_1| + |m_2| + |m_3| + \dots)$$

(1) use only in linear model

(2) Lasso \Rightarrow only 5 features
include small set features

Ridge \Rightarrow increase of large set features

(3) feature selection \Rightarrow Lasso is Best.

$$y = mx + c$$

$$\rightarrow y = m_1x_1 + m_2x_2 + \dots + c$$

$m_1 = 0$

$$C-F = SSE + \lambda \times [10.4 + 10 + 1.1]$$

$\hookrightarrow m_2$

$$C-F = SSE + r \times L \quad \underbrace{\quad}_{m_2}$$

(lasso)