

성균관대학교 S / O / R

로봇학회



2022년 05월 00일

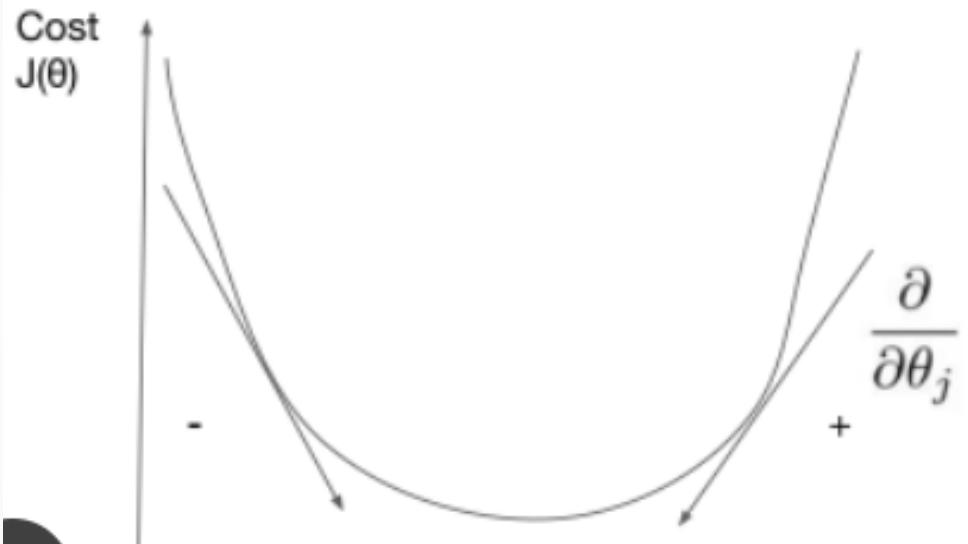
AI

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목차

- 1. Learning rate
- 2. Data preprocessing
- 3. Overfitting

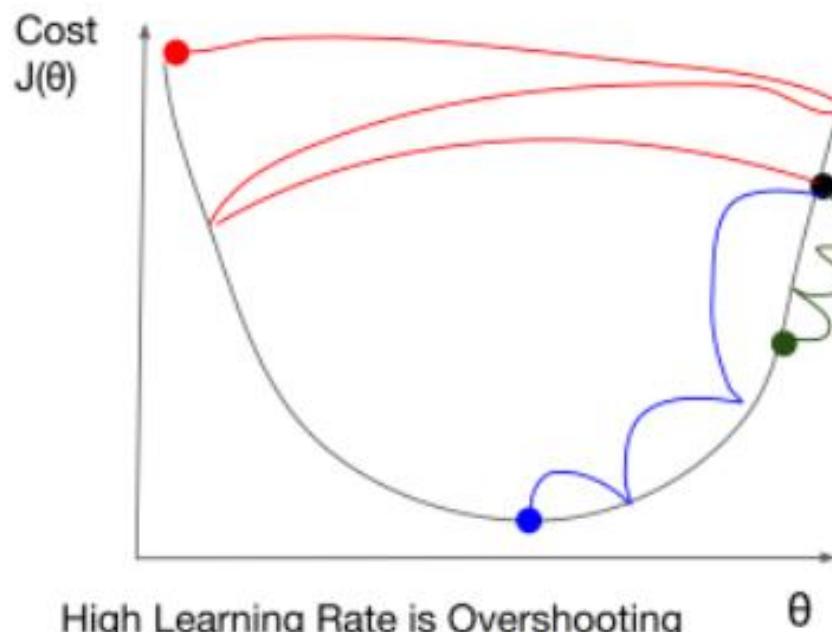
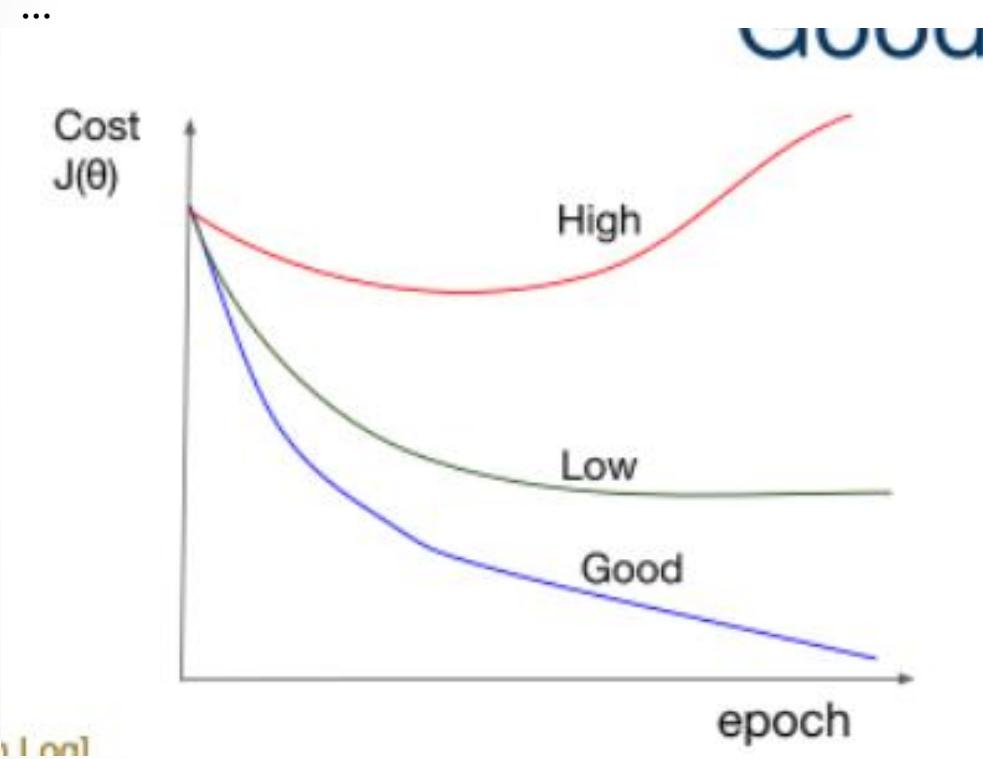
1. Learning rate



Repeat $\{ \theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \}$

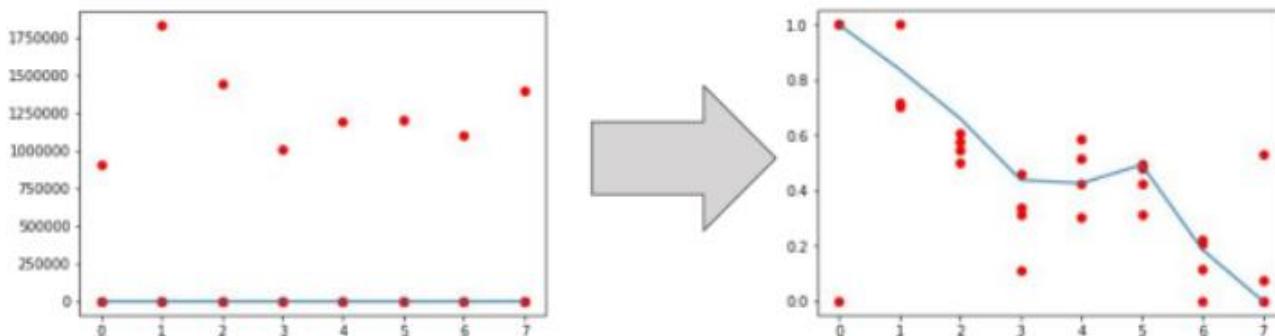
Learning rate is a hyper-parameter that controls how much we are adjusting the weights with respect the loss gradient

1. Learning rate



2. Data preprocessing

Feature Scaling



Standardization
(Mean Distance)

$$x_{new} = \frac{x - \mu}{\sigma}$$

[Python Code(numpy)]

```
Standardization = (data - np.mean(data)) / sqrt(np.sum((data - np.mean(data))^2) / np.count(data))
```

Normalization
(0~1)

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

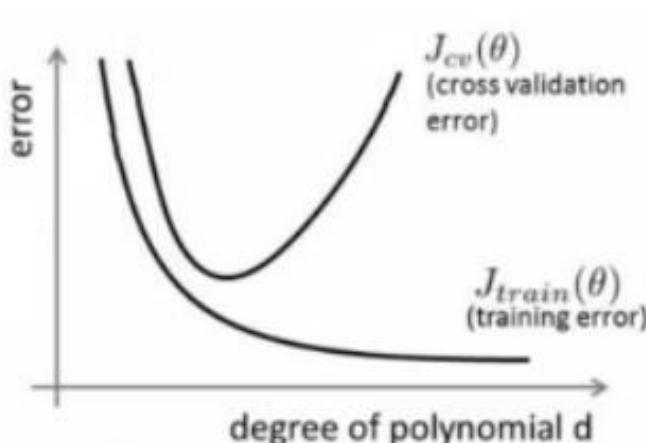
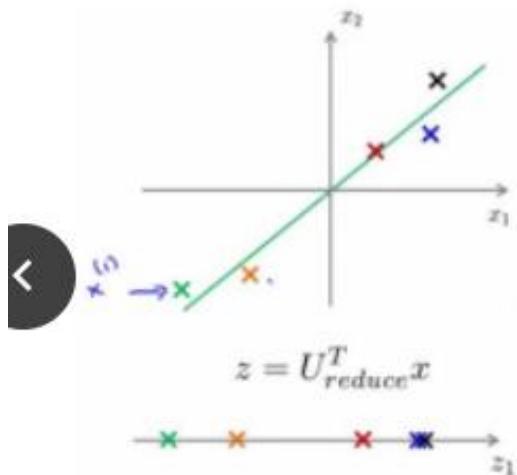
Normalization = (data - np.min(data, 0)) / (np.max(data, 0) - np.min(data, 0))

3. Overfitting

1.

Set a features

- Get more training data - more data will actually make a difference, (helps to fix high variance)
- Smaller set of features - dimensionality reduction(PCA) (fixes high variance)
- Add additional features - hypothesis is too simple, make hypothesis more specific (fixes high bias)



1. $h_\theta(x) = \theta_0 + \theta_1 x$
2. $h_\theta(x) = \theta_0 + \theta_1 x + \theta_2 x^2$
3. $h_\theta(x) = \theta_0 + \theta_1 x + \dots + \theta_3 x^3$
- ⋮
10. $h_\theta(x) = \theta_0 + \theta_1 x + \dots + \theta_{10} x^{10}$

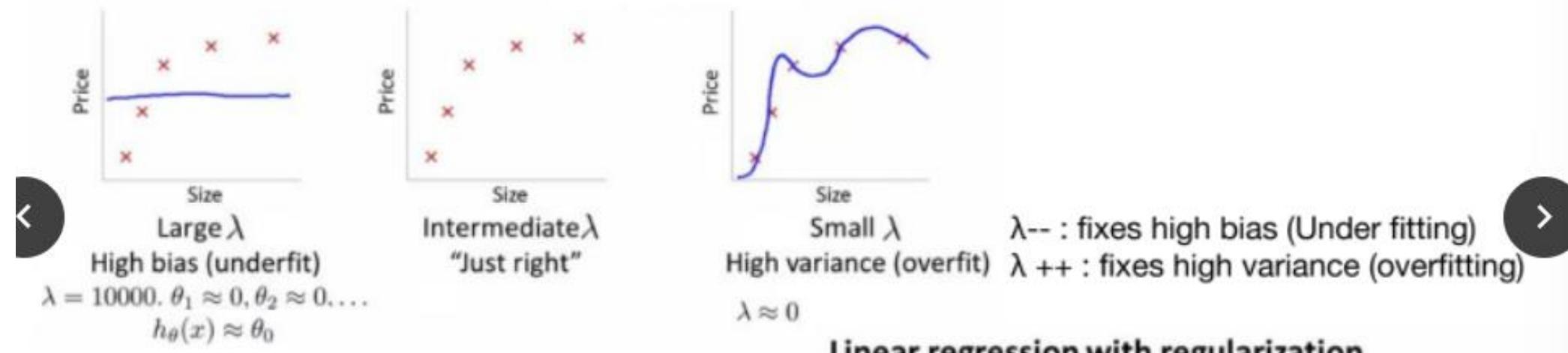
[sklearn Code]

```
from sklearn.decomposition import PCA
pca = decomposition.PCA(n_components=3)
pca.fit(X)
X = pca.transform(X)
```

3. Overfitting

2.

Regularization (Add term to loss)



Model: $h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 + \frac{\lambda}{2m} \sum_{j=1}^m \theta_j^2$$

[Tensorflow Code]

```
L2_loss = tf.nn.l2_loss(w) # output = sum(t ** 2) / 2
```

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Thank You

로 봇 동 아 리