

# 머신러닝 스터디 4th week

## 보조 자료

20180125 김성현

# summary

- ch.7 Application & Tip

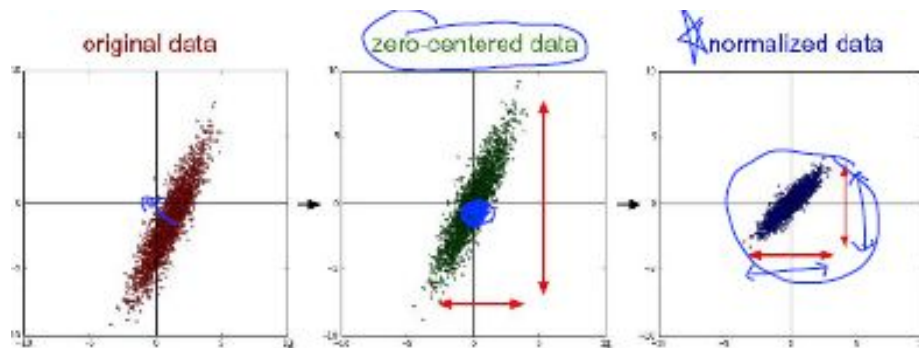
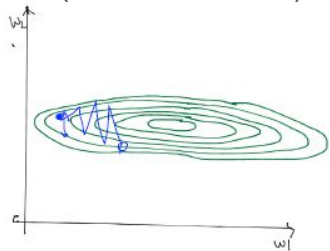
- Learning rate

- cost 함수의 값을 관찰하고 합리적인 rate를 찾아라. 0.01을 사용해보고 조금씩 조절해라.

- data preprocessing

- 특징 간 값 차이를 줄여라
    - normalization (Standardization)

x1	x2	y
1	9000	A
2	-5000	A
4	-2000	B
6	8000	B
9	9000	C



$$\underline{x'_j} = \frac{x_j - \mu_j}{\sigma_j} \quad \star$$

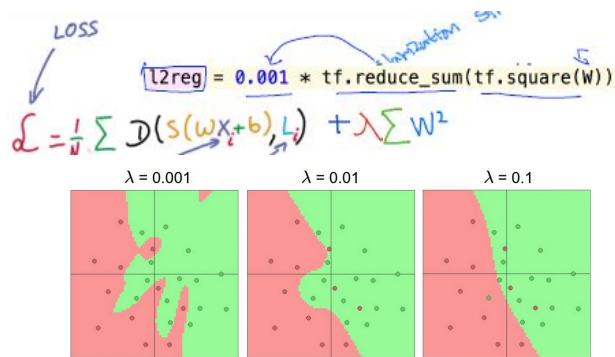
```
X_std[:,0] = (X[:,0] - X[:,0].mean()) / X[:,0].std()
```

# summary

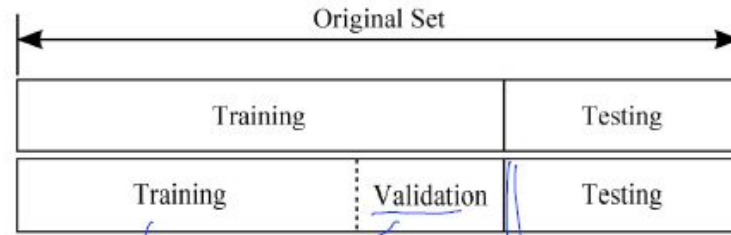
- ch.7 Application & Tip

- overfitting

- 더 많은 학습데이터를 사용해라
    - 특징의 수를 줄여라.
    - Regularization

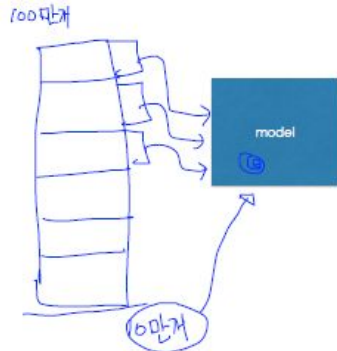


- Learning and test data sets



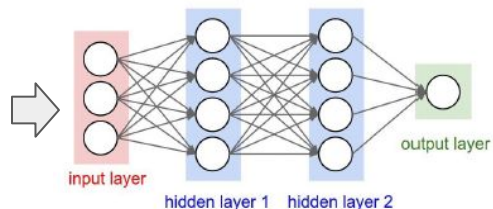
validation set으로  
학습 파라미터 튜닝 해라

- Online learning

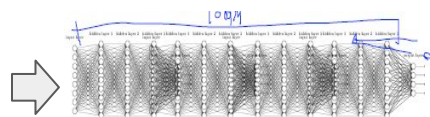


# summary

- ch.8 Neural Nets



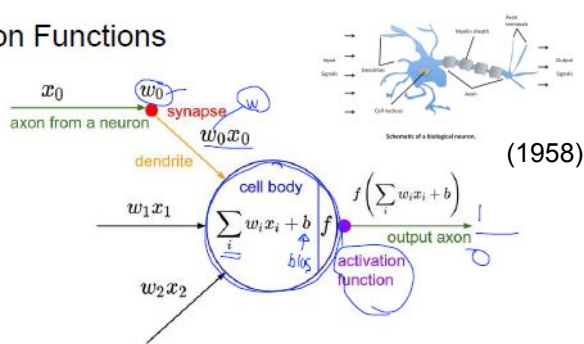
MLP를 사용하면 XOR을 풀수 있지만 학습이 어려워... Minsky(1969)



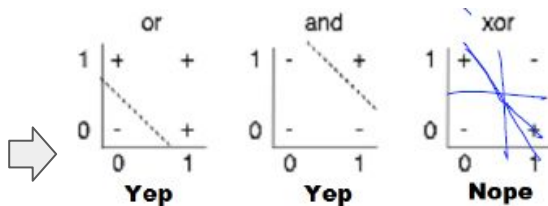
그런데 layer가 너무 많으니까 학습이 잘 안되.  
대신 SVM, RandomForest 등이 간단한 알고리즘으로 성능도 좋아.

w 초기값을 잘 주면 가능해..  
Hinton(2006)  
Deep Nets.  
Deep Learning  
으로 부르자

## Activation Functions

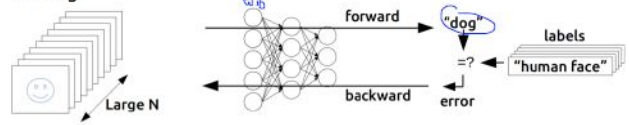


(1958)

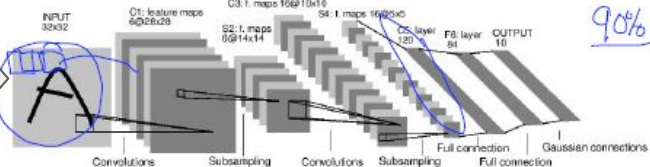


logistic regression unit 으로는 XOR를 못 푸네...

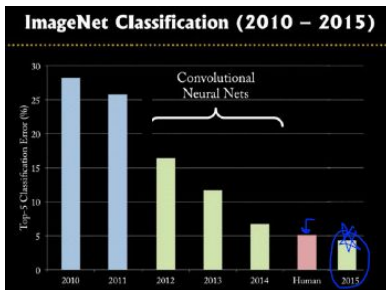
## Training



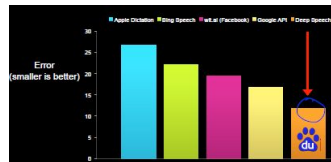
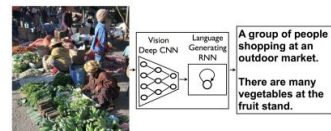
Backpropagation으로 학습 할 수 있잖아...  
Hinton(1986)



고양이 뇌처럼 필요한 뉴런만 사용해 보자.  
LeCun(1980)



Deep Nets은 성능이 정말  
좋잖아 (2012 ~)



## Deep API Learning\*



Figure 3: The Overall Workflow of Deep API Learning



# Data preprocessing 보충

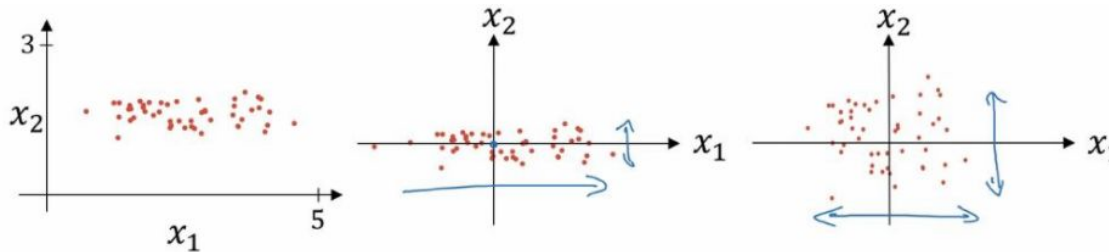
- Normalization

- 0~1 사이의 값으로 나타내는 척도법

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

- Standardization

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



# Regularization 보충

## 종류

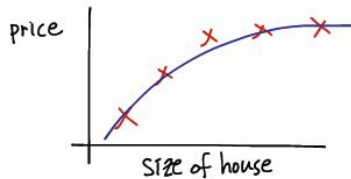
- L1:  $R(W) = \sum_k \sum_l |W_{k,l}|$
- L2:  $R(W) = \sum_k \sum_l W_{k,l}^2$
- Elastic:  $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$   
(L1과 L2의 혼합)

## Andrew Ng 자료

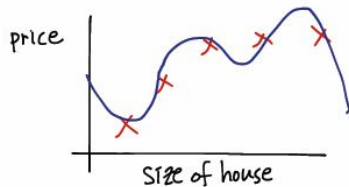
○

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 + \lambda \sum_{j=1}^{100} \theta_j^2$$

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



$$\theta_0 + \theta_1 x + \theta_2 x^2$$



$$\theta_0 + \theta_1 x + \theta_2 x^3 + \theta_3 x^3 + \theta_4 x^4$$

## Gradient Descent

Repeat {

$$\begin{aligned} \theta_0 &:= \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 x_0^{(i)} \\ \theta_j &:= \theta_j - \alpha \left[ \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 x_j^{(i)} + \frac{\lambda}{m} \theta_j \right] \end{aligned}$$

$$j = 1, \dots, n$$

$\theta_j$  값을 위해서 하면,

$$\theta_j := \theta_j (1 - \alpha \frac{\lambda}{m}) - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

< 1

for  $\alpha > 0, \lambda > 0, m > 0$

$\theta_j$  가 점점 작아지는 효과

$\theta_0$  는 regularize 안함, by convention

$\frac{\partial}{\partial \theta_j} J(\theta)$

원래 값에서 하던 역할 그대로