

Lecture 5-1

Logistic (regression) classification

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Acknowledgement

- Andrew Ng's ML class
 - <https://class.coursera.org/ml-003/lecture>
 - <http://www.holehouse.org/mlclass/> (note)
- Convolutional Neural Networks for Visual Recognition
 - <http://cs231n.github.io/>
 - <http://cs231n.stanford.edu/>
- TensorFlow
 - <https://www.tensorflow.org>
 - <https://github.com/aymericdamien/TensorFlow-Examples>

Regression (HCG)

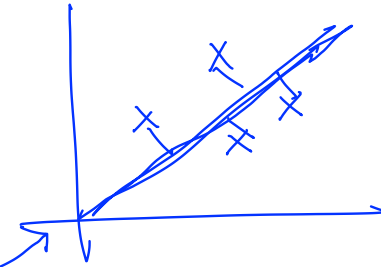
- H

| x1 (hours) | x2 (attendance) | y (score) |
|------------|-----------------|-----------|
| 10 | 5 | 90 |
| 9 | 5 | 80 |
| 3 | 2 | 50 |
| 2 | 4 | 60 |
| 11 | 1 | 40 |

- C

- G

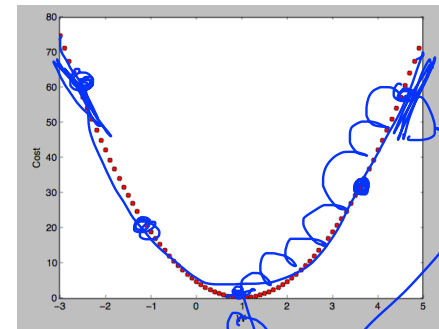
Regression



- Hypothesis: $H(X) = WX$

| x1 (hours) | x2 (attendance) | y (score) |
|------------|-----------------|-----------|
| 10 | 5 | 90 |
| 9 | 5 | 80 |
| 3 | 2 | 50 |
| 2 | 4 | 60 |
| 11 | 1 | 40 |

- Cost: $\text{cost}(W) = \frac{1}{m} \sum (WX - y)^2$



- Gradient decent: $W := W - \alpha \frac{\partial}{\partial W} \text{cost}(W)$

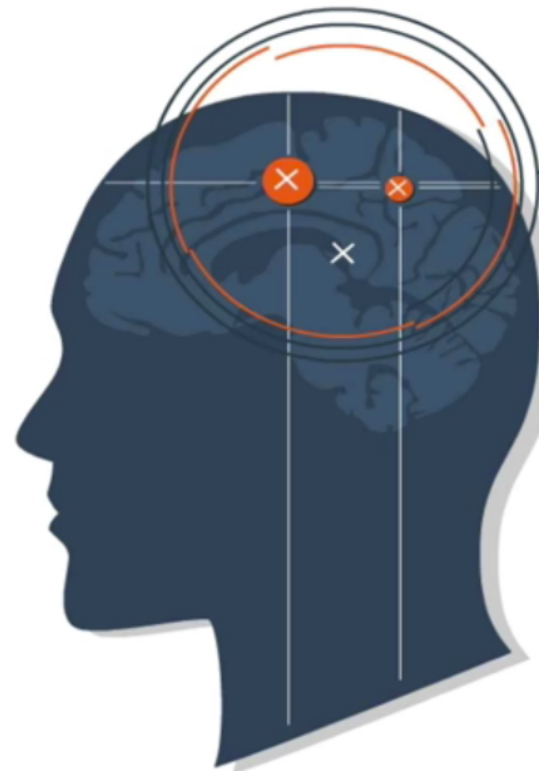
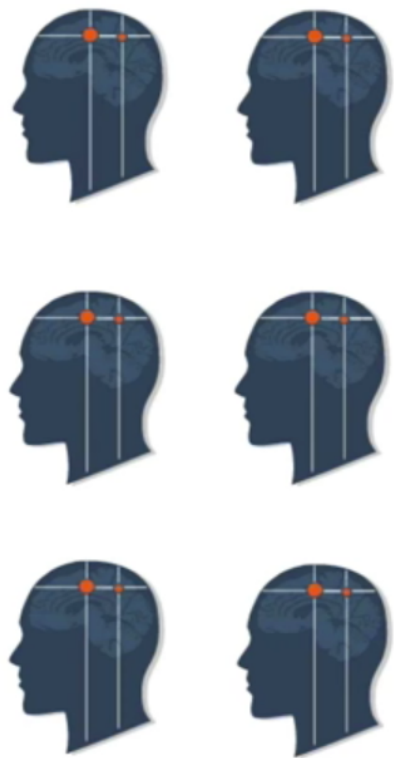
Classification

- Spam Detection: Spam or Ham
- Facebook feed: show or hide
- Credit Card Fraudulent Transaction detection: legitimate/fraud

0, 1 encoding

- Spam Detection: Spam (1) or Ham (0)
- Facebook feed: show(1) or hide(0)
- Credit Card Fraudulent Transaction detection: legitimate(0) or fraud (1)

Radiology



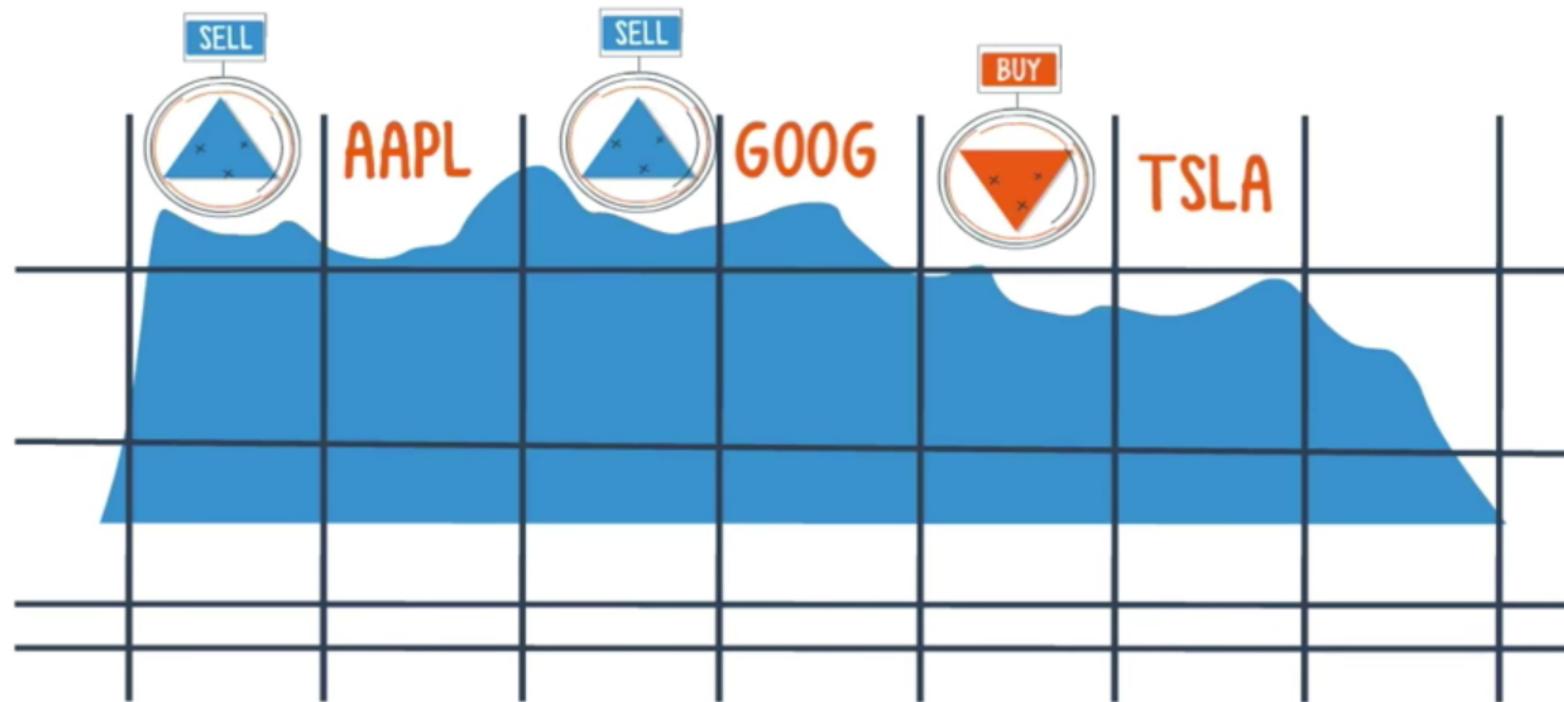
Malignant
tumor



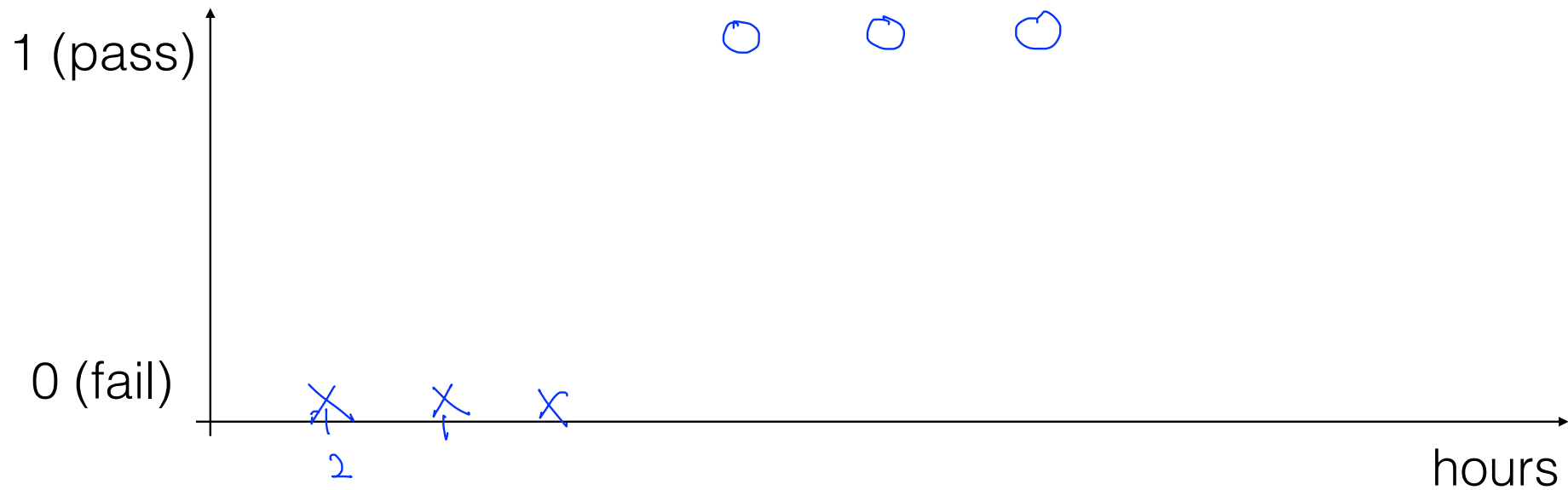
Benign
tumor

Finance

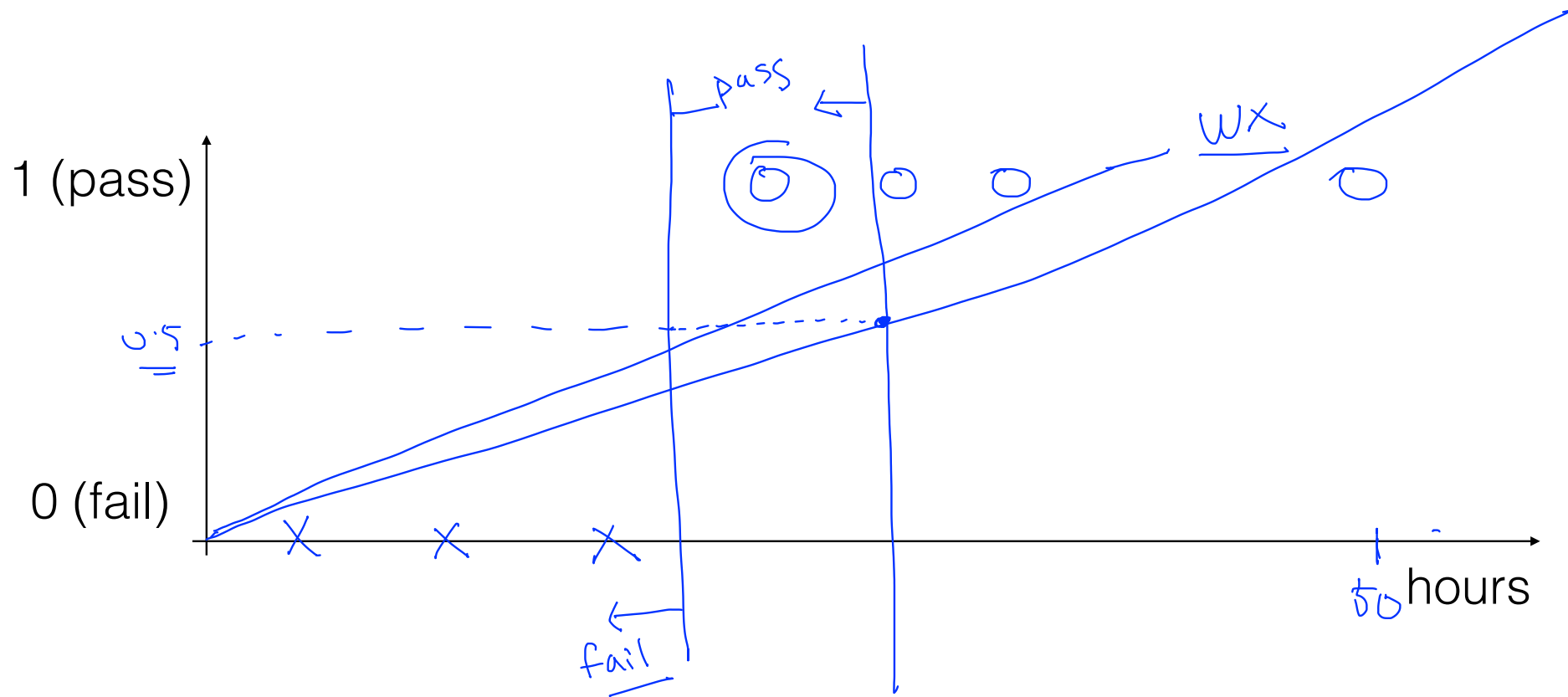
| | | |
|--------|-----------|---|
| DWJI | 17,499.10 | ▼ |
| SP500 | 2,025.51 | ▼ |
| NASDAQ | 4,976.9 | ▲ |
| AAPL | 107.71 | ▲ |
| GOOG | 750.06 | ▲ |
| TSLA | 234.24 | ▼ |



Pass(1)/Fail(0) based on study hours



Linear Regression?



Linear regression

- We know Y is 0 or 1

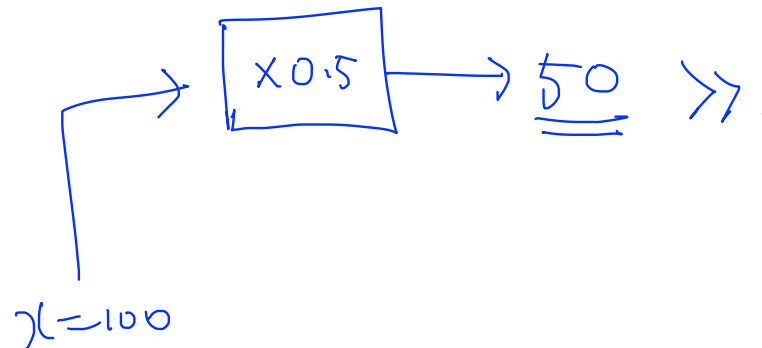
$$\underline{H(x) = Wx + b}$$

$$x = \begin{bmatrix} 1 \\ 2 \\ 5 \\ 10 \\ 11 \end{bmatrix}$$

$$W \approx 0.5, \quad b = 0$$

- Hypothesis can give values large than 1 or less than 0

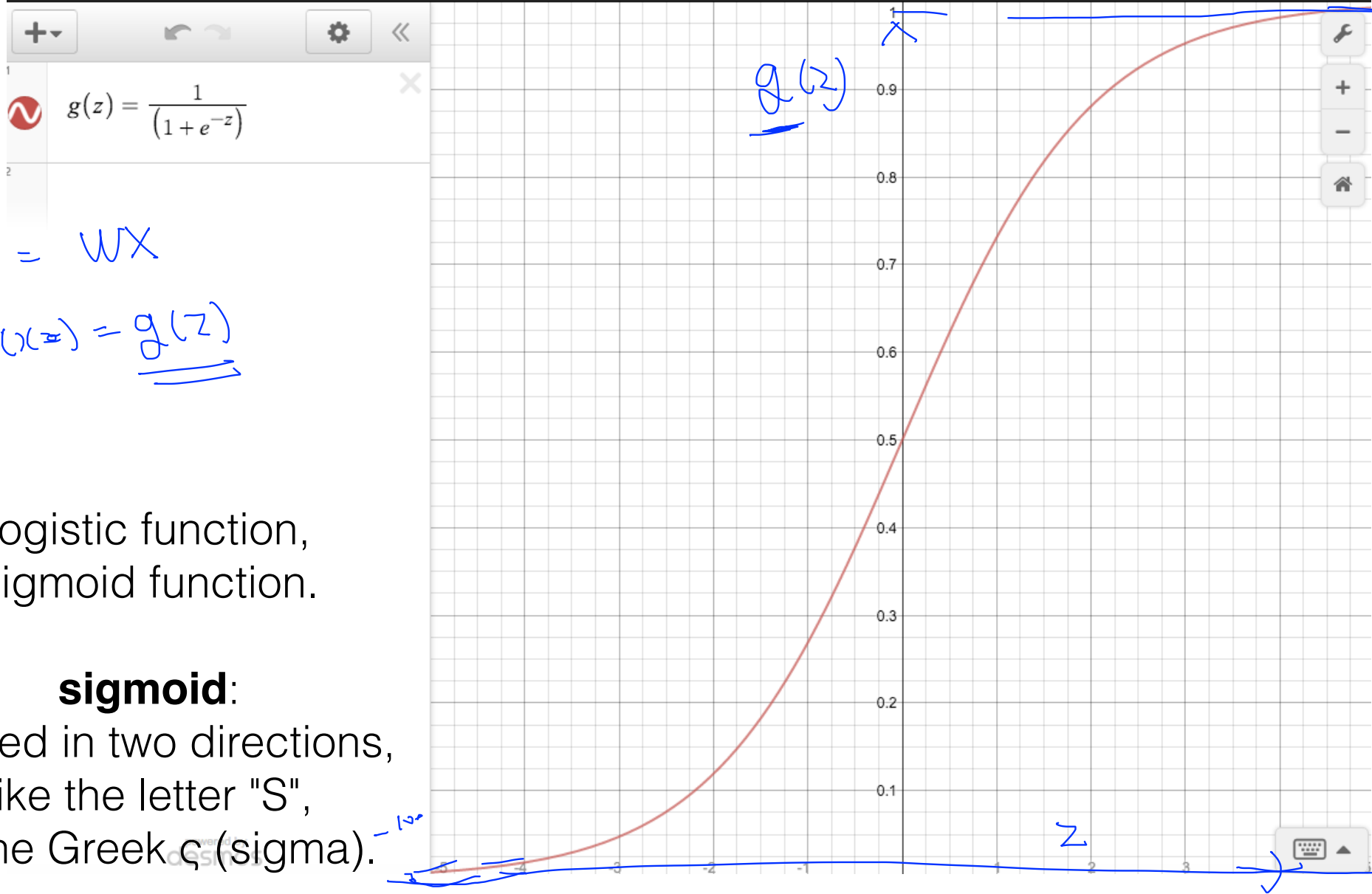
$$0 < \sim 1$$



Logistic Hypothesis

$$z \quad \cancel{H(x)} = \underline{Wx + b}$$

$$g(z) \rightarrow 0 \sim 1$$



$$z = WX$$

$$H(x) = \underline{\underline{g(z)}}$$

logistic function,
sigmoid function.

sigmoid:

Curved in two directions,
like the letter "S",
or the Greek ς (sigma).

Logistic Hypothesis

$$H(X) = \frac{1}{1 + e^{-W^T X}}$$

WX

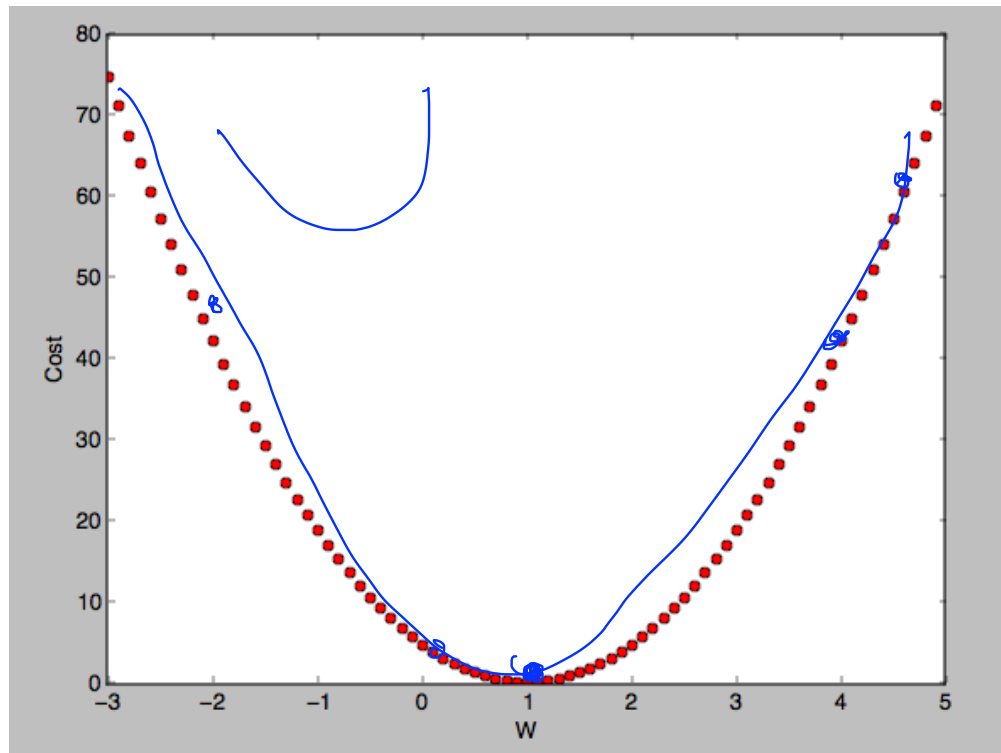
Lecture 5-2

Logistic (regression) classification:
cost function & gradient decent

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Cost

$$\text{cost}(W, b) = \frac{1}{m} \sum_{i=1}^m (H(x^{(i)}) - y^{(i)})^2 \quad \text{when} \quad \underline{H(x) = Wx + b}$$



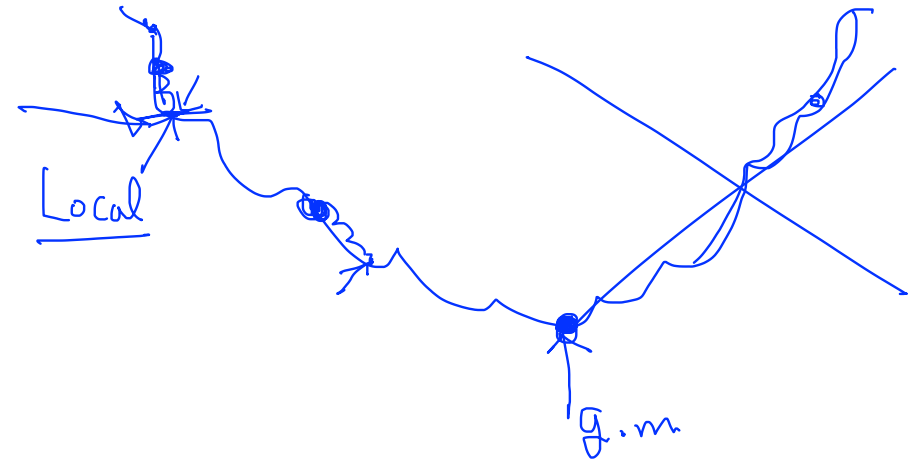
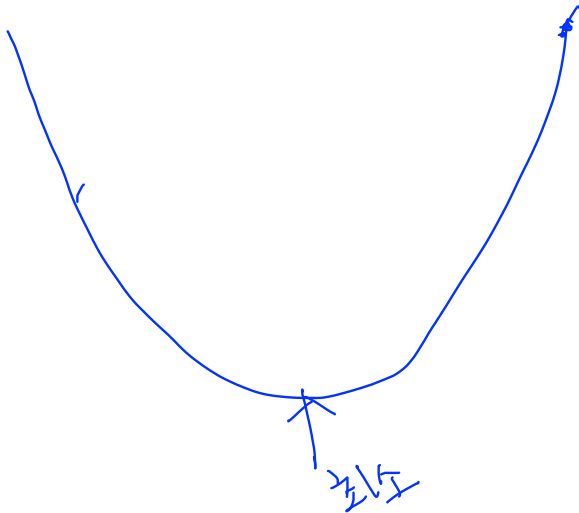
Cost function

$$\text{cost}(W, b) = \frac{1}{m} \sum_{i=1}^m (H(x^{(i)}) - y^{(i)})^2$$

$0 < \sim < 1$

$$\underline{H(x) = Wx + b}$$

$$\underline{H(X) = \frac{1}{1 + e^{-W^T X}}}$$



New cost function for logistic

$$\underline{cost}(W) = \frac{1}{m} \sum \quad \underline{c}(H(x), y)$$

$$\underline{c}(H(x), y) = \begin{cases} -\log(H(x)) & : y = 1 \\ -\log(1 - H(x)) & : y = 0 \end{cases}$$

understanding cost function

$$C(H(x), y) = \begin{cases} -\log(H(x)) & : y = 1 \\ -\log(1 - H(x)) & : y = 0 \end{cases}$$

Handwritten notes: $\frac{1}{1+e^{-z}}$ and \log with a squiggle arrow pointing to it.

Cost $y=1$

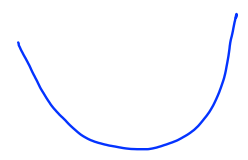
$H(x) = 1 \rightarrow \text{cost}(1) = 0$

$H(x) = 0 \rightarrow \text{cost} = \infty \uparrow$

$y=0$

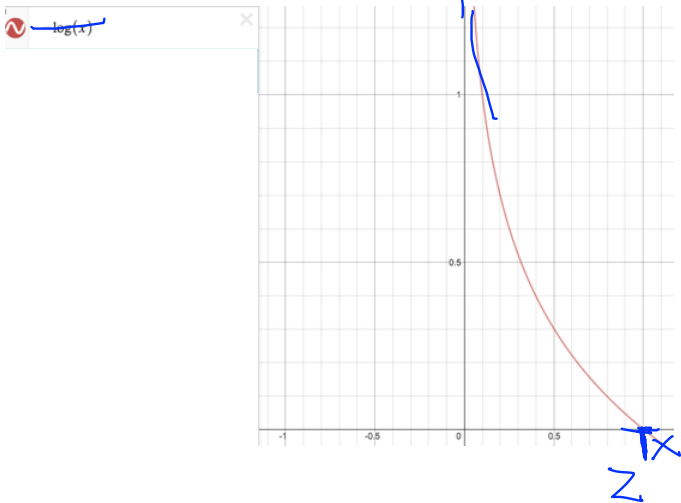
$H(x) = 0, \text{cost} = 0$

$H(x) = 1, \text{cost} = \infty \uparrow$

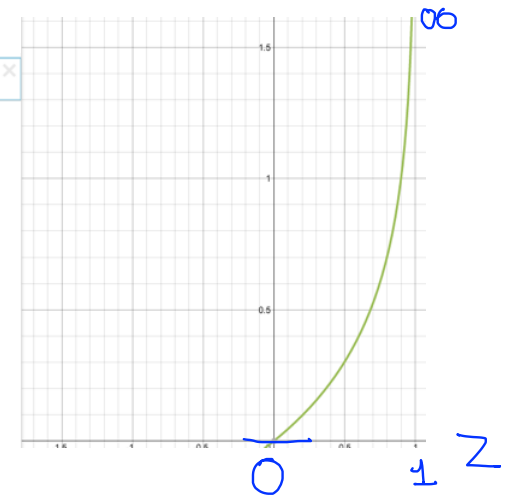
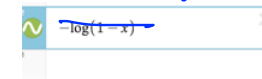


cost
//

$g(z) = -\log(z)$



$-g(1-z)$



Cost function

$$\text{cost}(W) = \frac{1}{m} \sum c(H(x), y)$$

$$C(H(x), y) = \begin{cases} -\log(H(x)) & : y = 1 \\ -\log(1 - H(x)) & : y = 0 \end{cases}$$

$$C(H(x), y) = -y \log(H(x)) - (1 - y) \log(1 - H(x))$$

$$y=1, c = -\log(H(x))$$



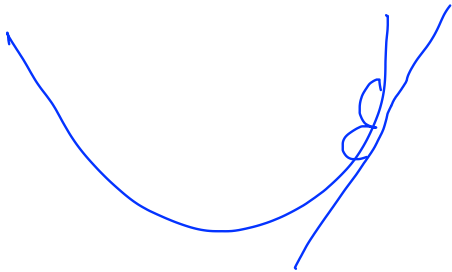
$$y=0,$$



$$c = -1 * \log(1 - H(x))$$

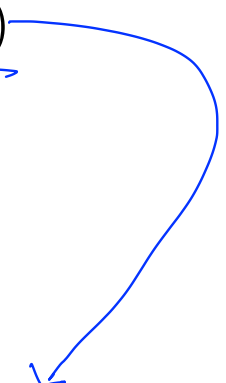
Minimize cost - Gradient decent algorithm

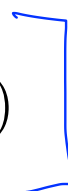
$$\underline{\text{cost}(W)} = -\frac{1}{m} \sum y \log(H(x)) + (1 - y) \log(1 - H(x))$$



$$W := W - \underbrace{\left[\alpha \frac{\partial}{\partial W} \text{cost}(W) \right]}$$

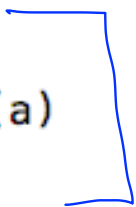
Gradient decent algorithm

$$\text{cost}(W) = -\frac{1}{m} \sum y \log(H(x)) + (1 - y) \log(1 - H(x))$$


$$W := W - \alpha \frac{\partial}{\partial W} \text{cost}(W)$$


```
# cost function
cost = tf.reduce_mean(-tf.reduce_sum(Y*tf.log(hypothesis) + (1-Y)*tf.log(1-hypothesis)))

# Minimize
a = tf.Variable(0.1) # Learning rate, alpha
optimizer = tf.train.GradientDescentOptimizer(a)
train = optimizer.minimize(cost)
```



Next
Multinomial
classification (Softmax)

