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# FUNDAMENTALS OF DEEP LEARNING

## Part 2: How a Neural Network Trains

# AGENDA

- Part 1: An Introduction to Deep Learning
- Part 2: How a Neural Network Trains
- Part 3: Convolutional Neural Networks
- Part 4: Data Augmentation and Deployment
- Part 5: Pre-trained Models
- Part 6: Advanced Architectures

# AGENDA – PART 2

- Recap
- A Simpler Model
- From Neuron to Network
- Activation  Functions
- Overfitting
- From Neuron to Classification

# RECAP OF THE EXERCISE

## What just happened?

Loaded and visualized our data

Edited our data (reshaped, normalized, to categorical)

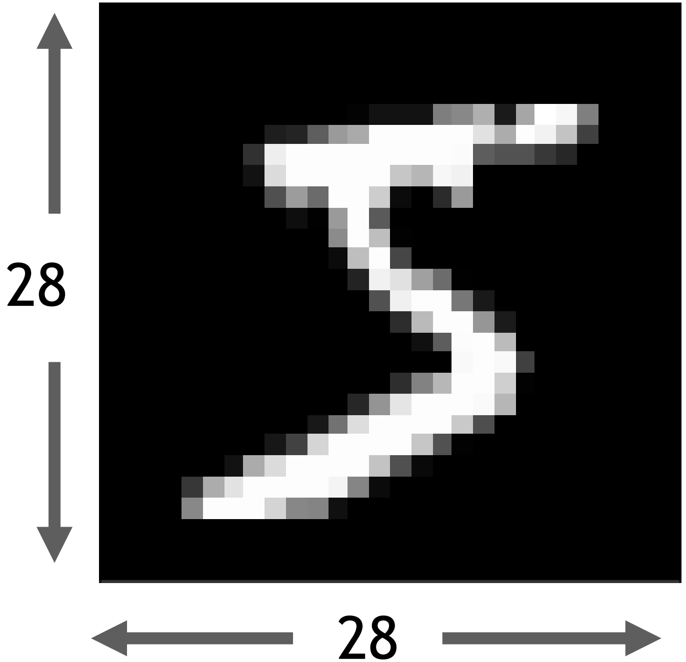
Created our model

Compiled our model

Trained the model on our data

# DATA PREPARATION

## Input as an array




[0,0,0,24,75,184,185,78,32,55,0,0,0...]

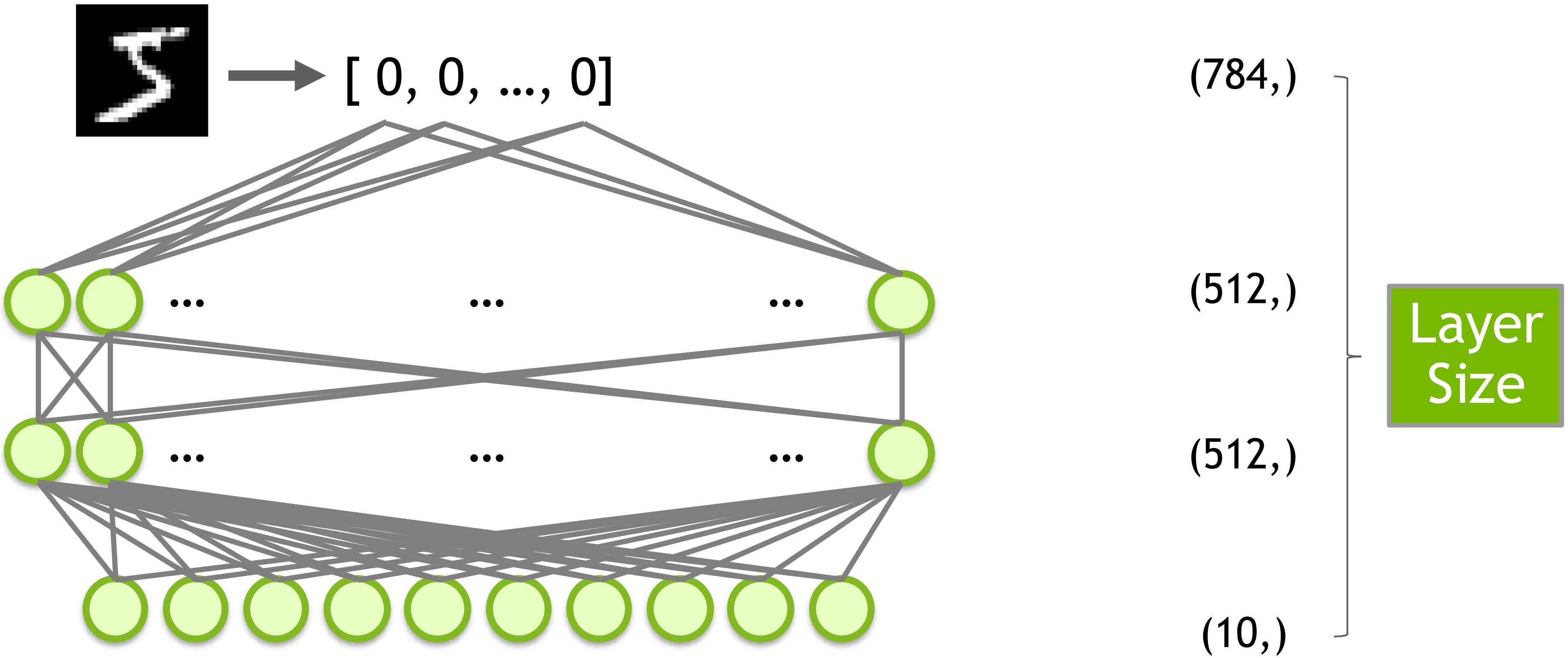
# DATA PREPARATION

Targets as categories

| | | |
|---|---|---|
| 0 | → | [1,0,0,0,0,0,0,0,0,0] |
| 1 | → | [0,1,0,0,0,0,0,0,0,0] |
| 2 | → | [0,0,1,0,0,0,0,0,0,0] |
| 3 | → | [0,0,0,1,0,0,0,0,0,0] |

⋮

# AN UNTRAINED MODEL

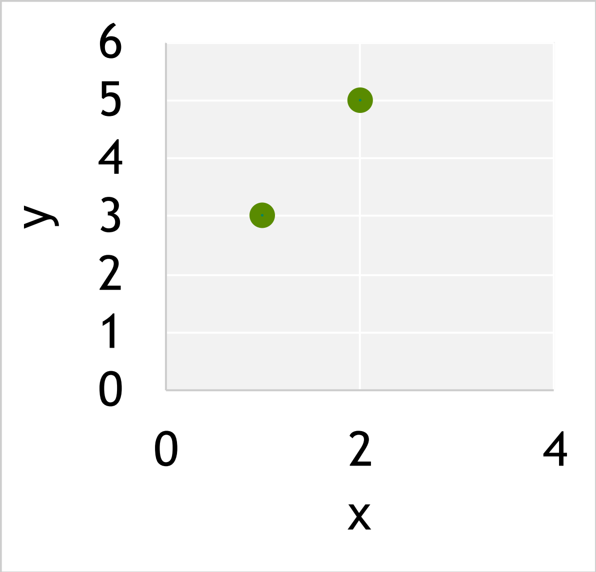


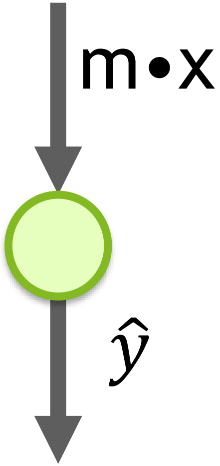
# A SIMPLER MODEL

# A SIMPLER MODEL

$$y = mx + b$$

| x | y |
|---|---|
| 1 | 3 |
| 2 | 5 |



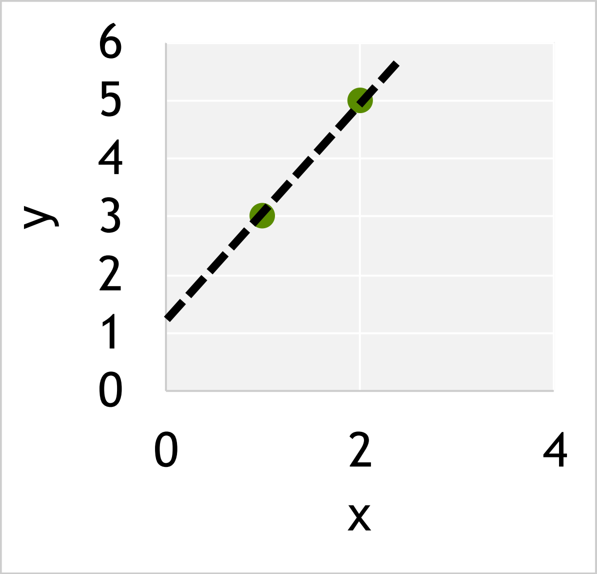

$m = ?$

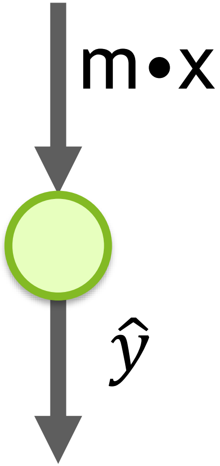
$b = ?$

# A SIMPLER MODEL

$$y = mx + b$$

| x | y |
|---|---|
| 1 | 3 |
| 2 | 5 |



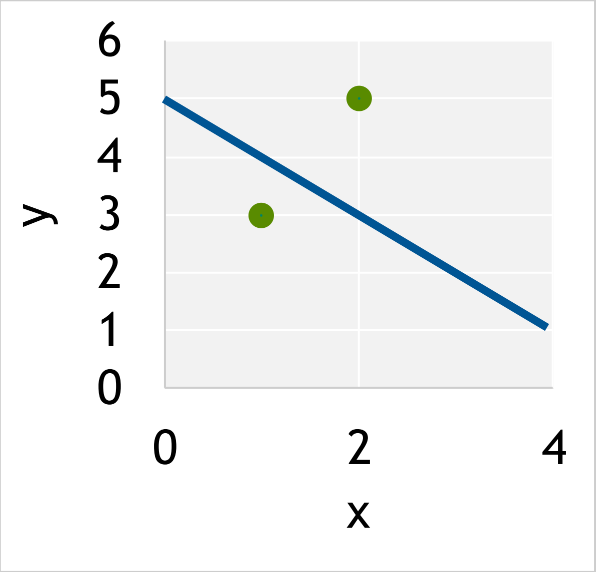

$$m = ?$$

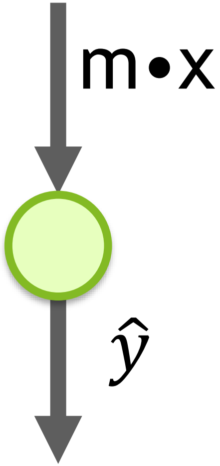
$$b = ?$$

# A SIMPLER MODEL

$$y = mx + b$$

| x | y | $\hat{y}$ |
|---|---|---|
| 1 | 3 | 4 |
| 2 | 5 | 3 |




Start Random

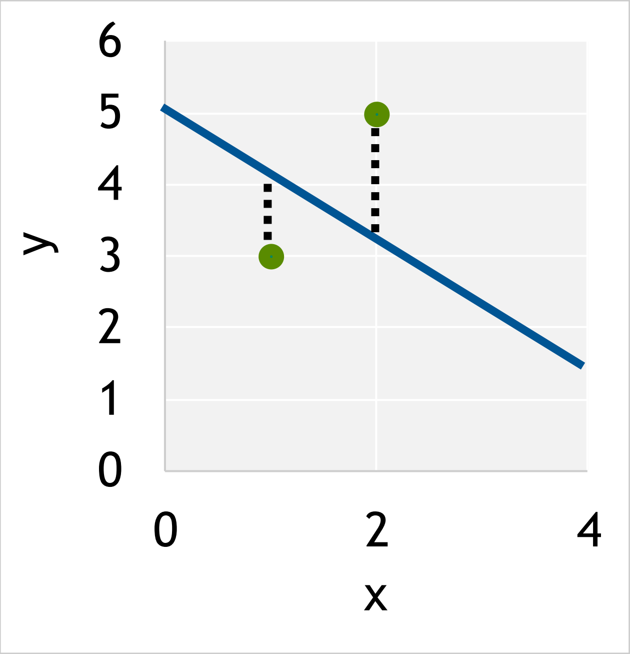
$$m = -1$$

$$b = 5$$

# A SIMPLER MODEL

$$y = mx + b$$

| x | y | $\hat{y}$ | $err^2$ |
|---|---|---|---|
| 1 | 3 | 4 | 1 |
| 2 | 5 | 3 | 4 |
| | | MSE = | 2.5 |
| | | RMSE = | 1.6 |



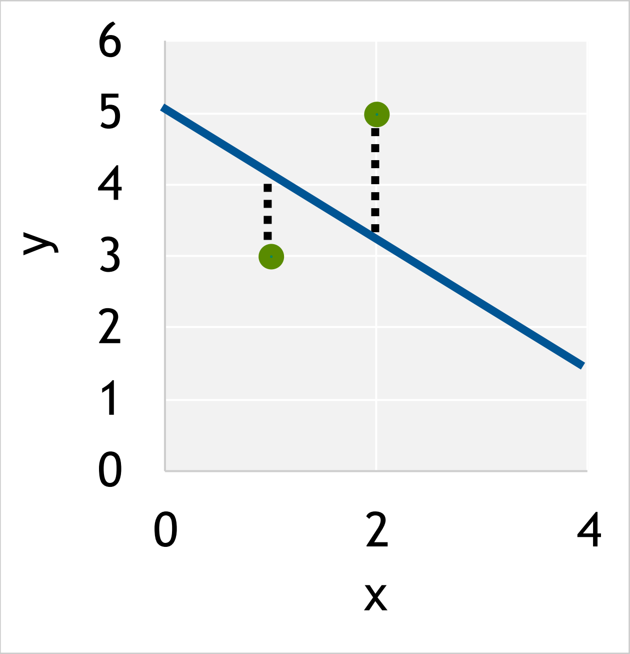

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

# A SIMPLER MODEL

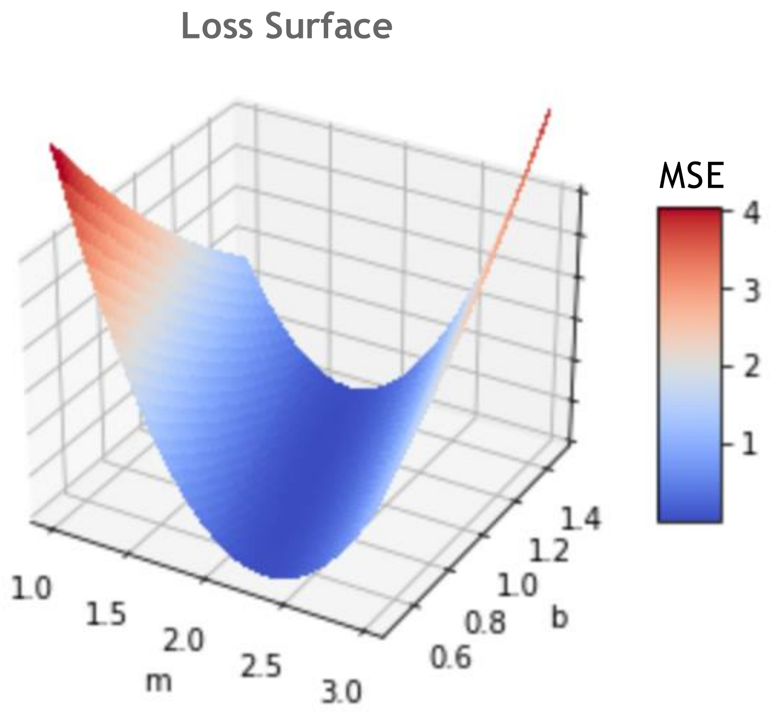
$$y = mx + b$$

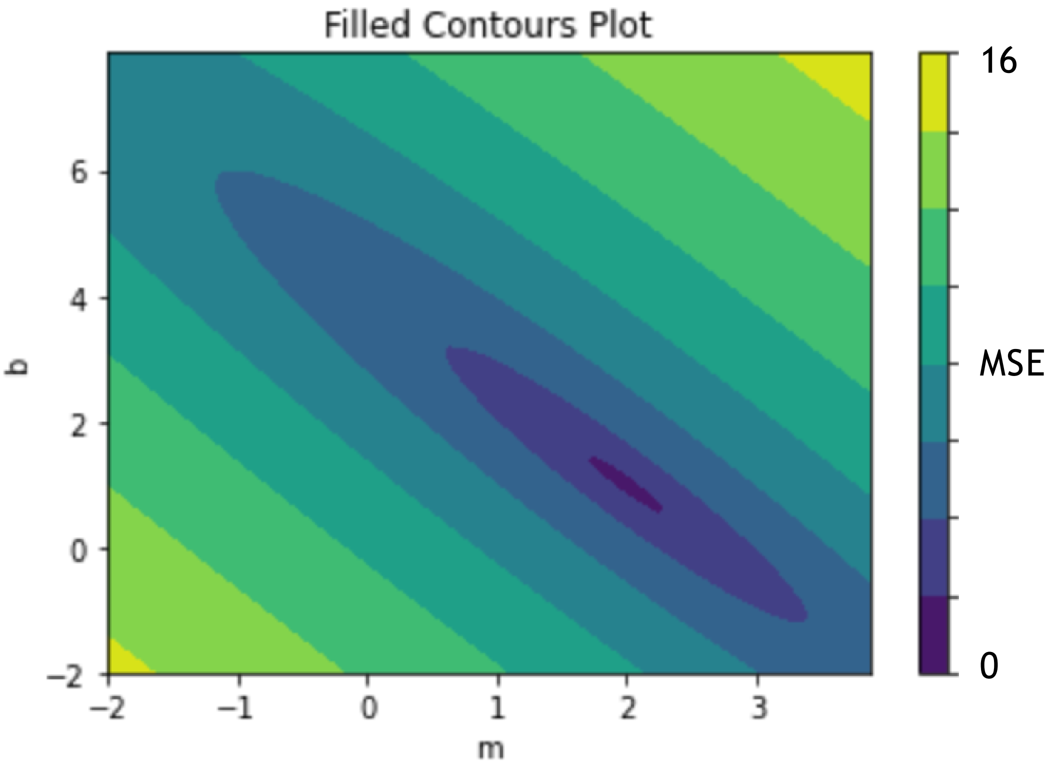
| x | y | $\hat{y}$ | $err^2$ |
|---|---|---|---|
| 1 | 3 | 4 | 1 |
| 2 | 5 | 3 | 4 |
| | | MSE = | 2.5 |
| | | RMSE = | 1.6 |



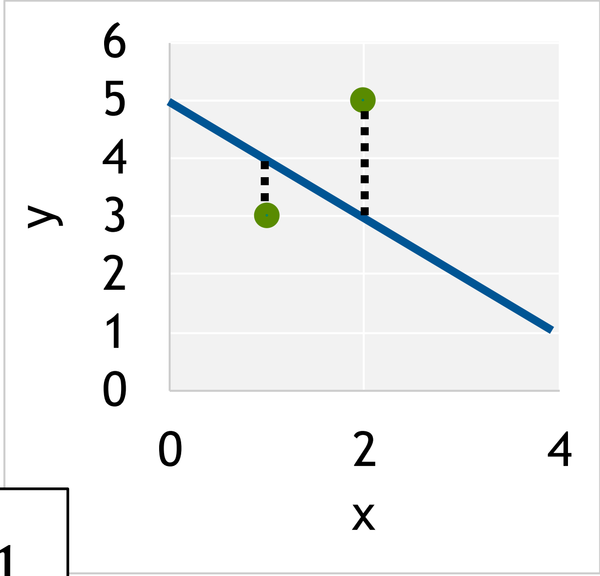

```python
data = [(1, 3), (2, 5)]
m = -1
b = 5


def get_rmse(data, m, b):
    """Calculates Mean Square Error"""
    n = len(data)
    squared_error = 0
    for x, y in data:
        # Find predicted y
        y_hat = m*x+b
        # Square difference between
        # prediction and true value
        squared_error += (
            y - y_hat)**2
    # Get average squared difference
    mse = squared_error / n
    # Square root for original units
    return mse ** .5
```

# THE LOSS CURVE



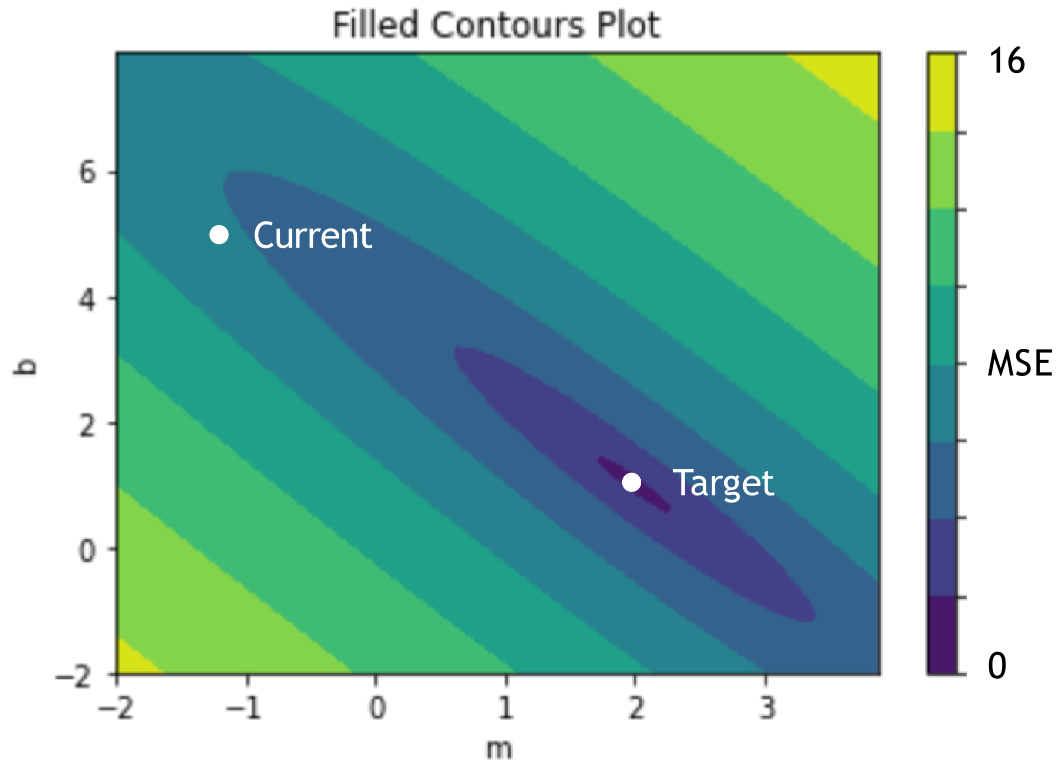



# THE LOSS CURVE

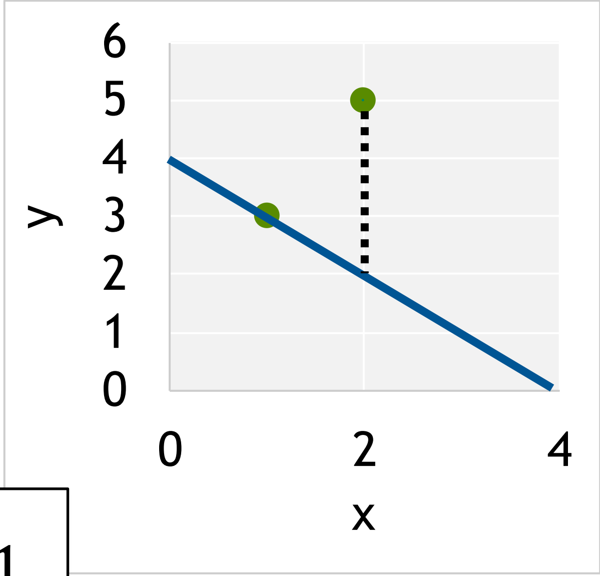



$$m = -1$$

$$b = 5$$

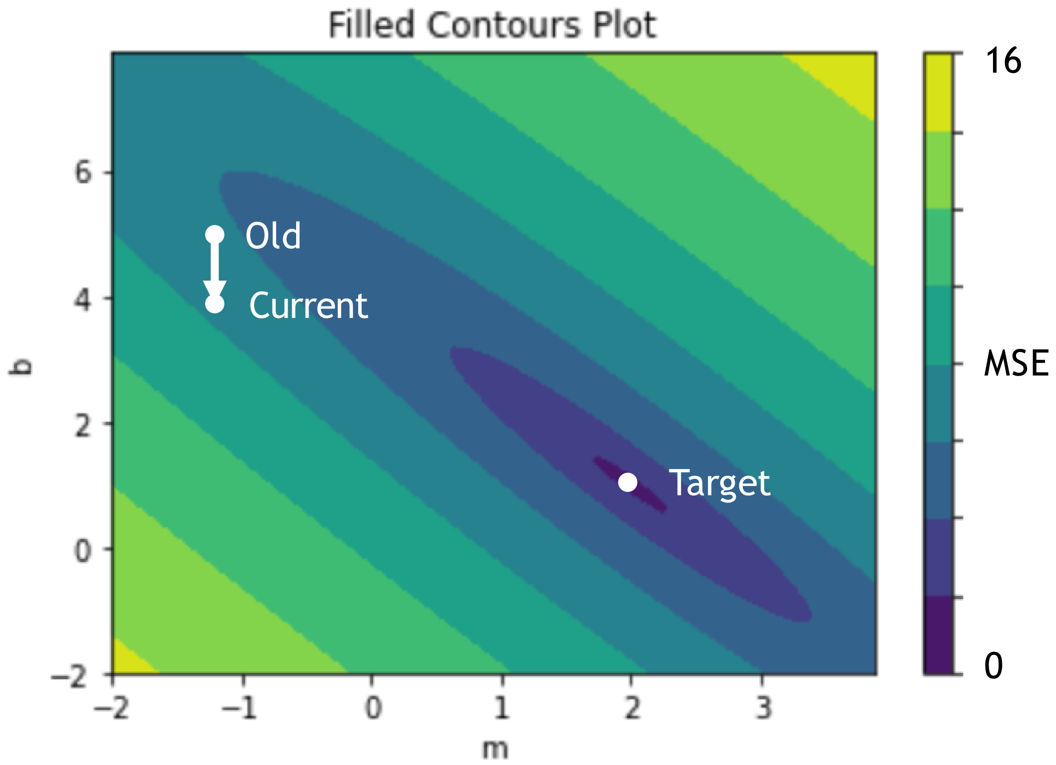


# THE LOSS CURVE

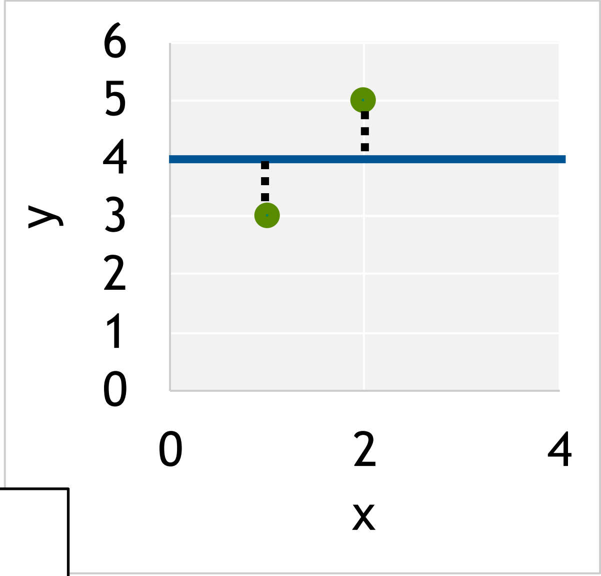



$m = -1$

$\mathrm{b} = 4$

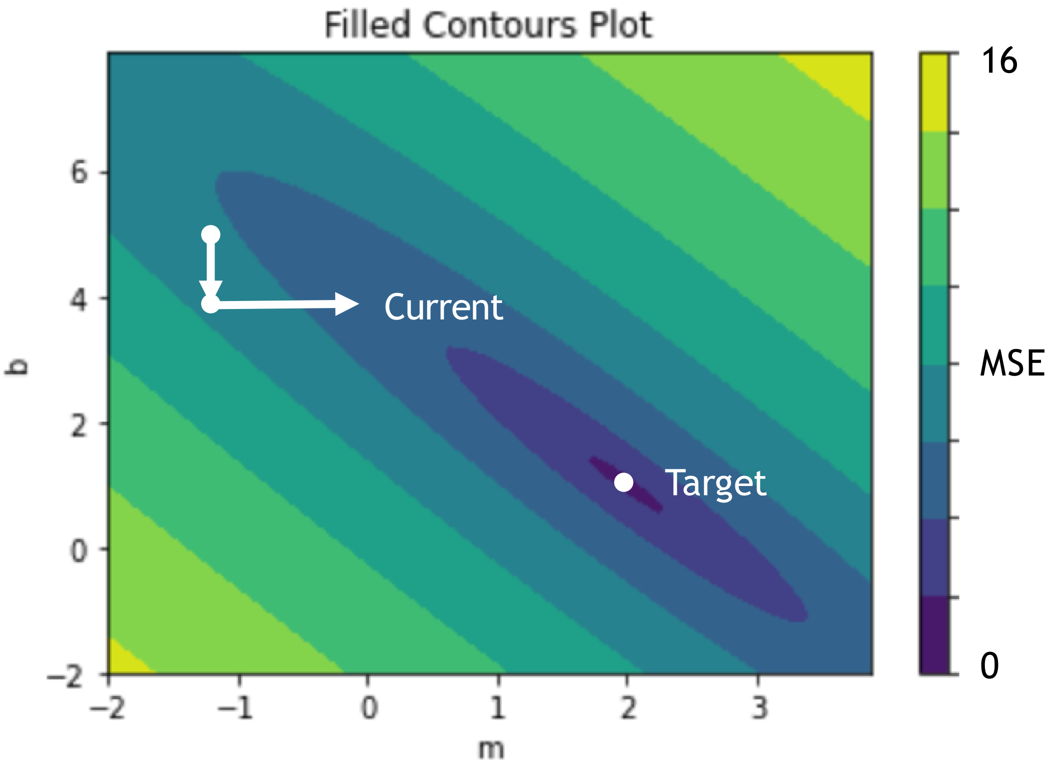


# THE LOSS CURVE



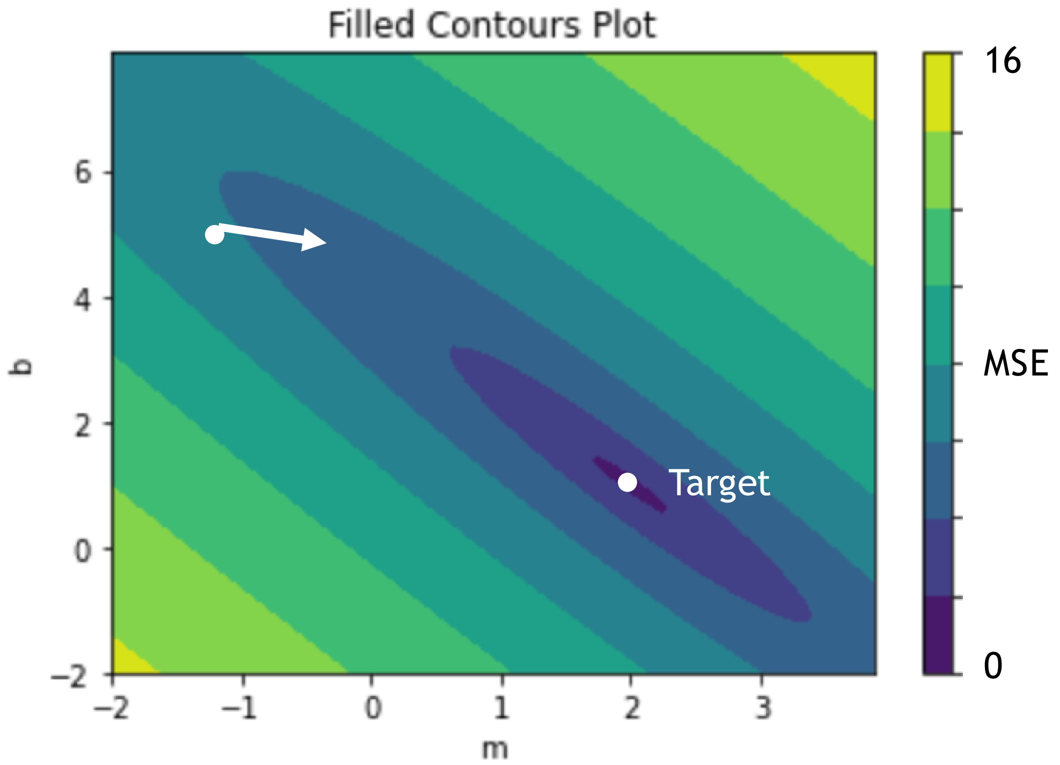

$m = 0$

$b = 4$



# THE LOSS CURVE

| | |
|---|---|
| The Gradient | Which direction loss decreases the most |
| λ: The learning rate | How far to travel |
| Epoch | A model update with the full dataset |
| Batch | A sample of the full dataset |
| Step | An update to the weight parameters |



# THE LOSS CURVE

| | |
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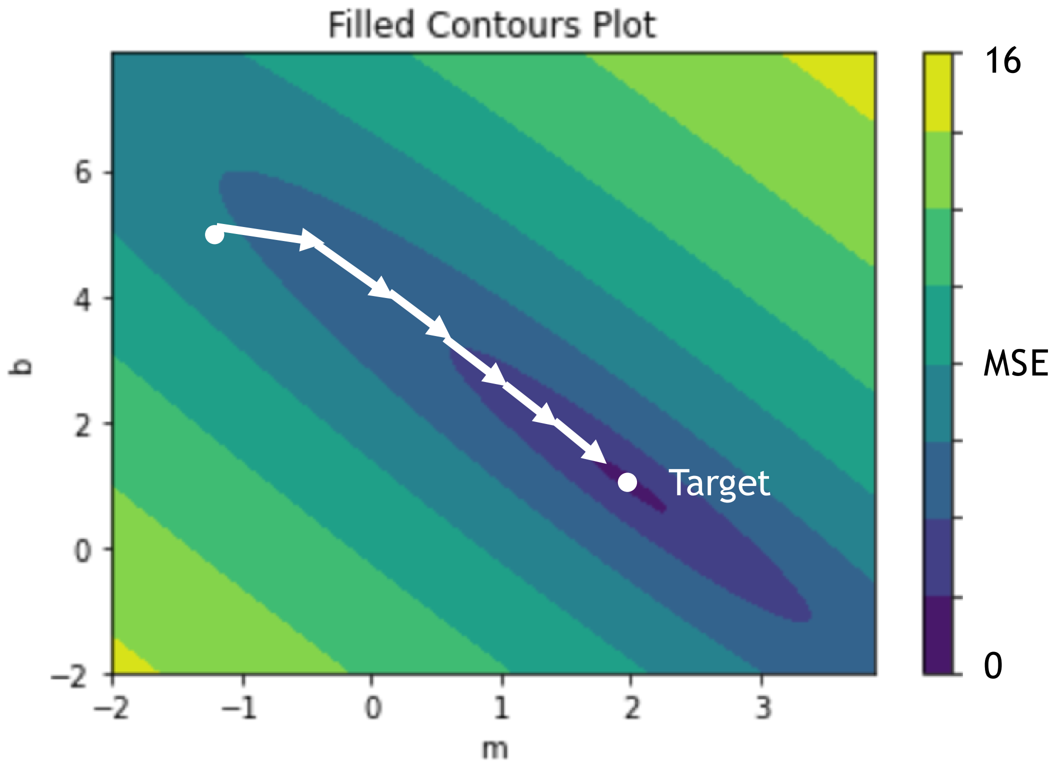
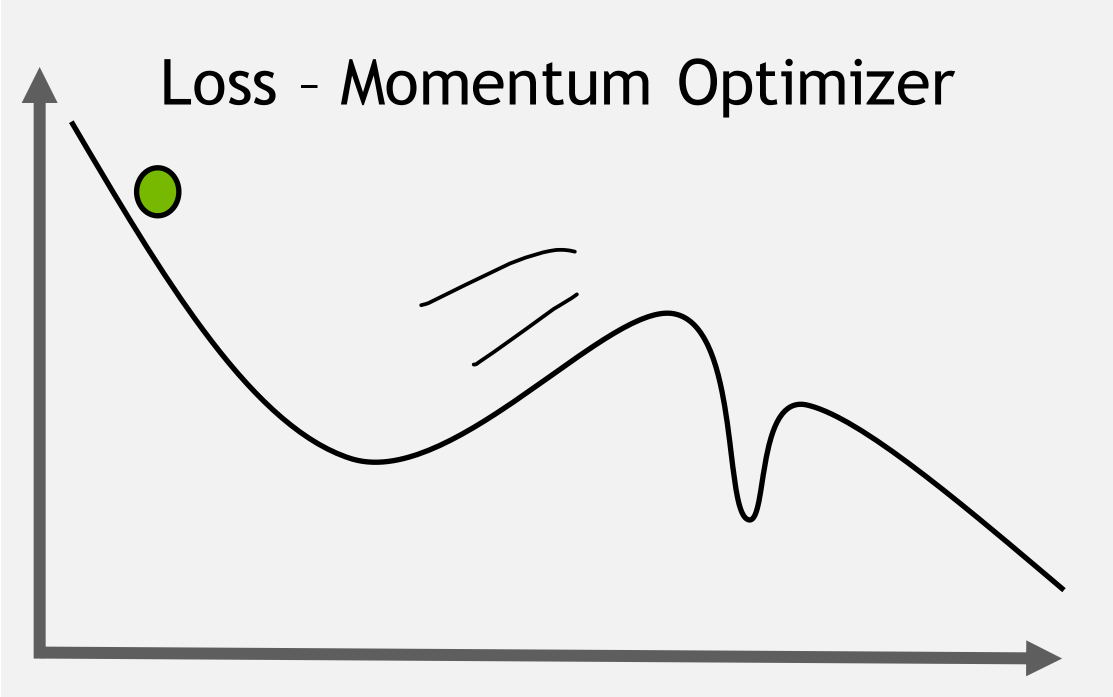


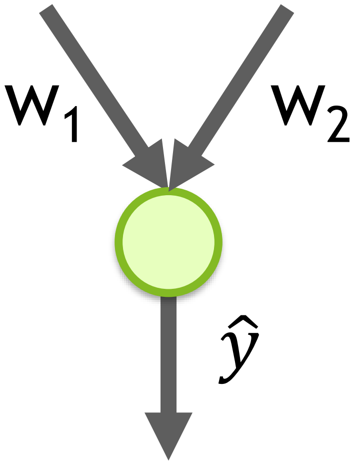
# OPTIMIZERS




- Adam
- Adagrad
- RMSprop
- SGD

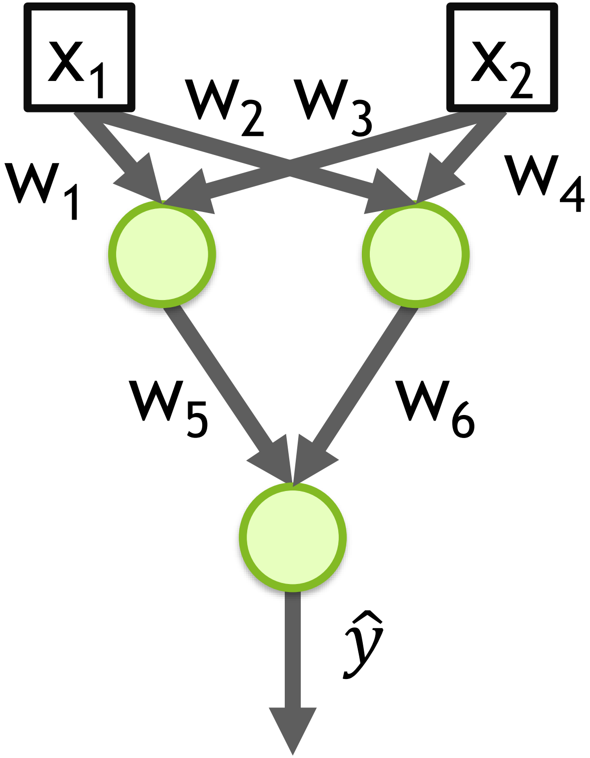
# FROM NEURON TO NETWORK

# BUILDING A NETWORK



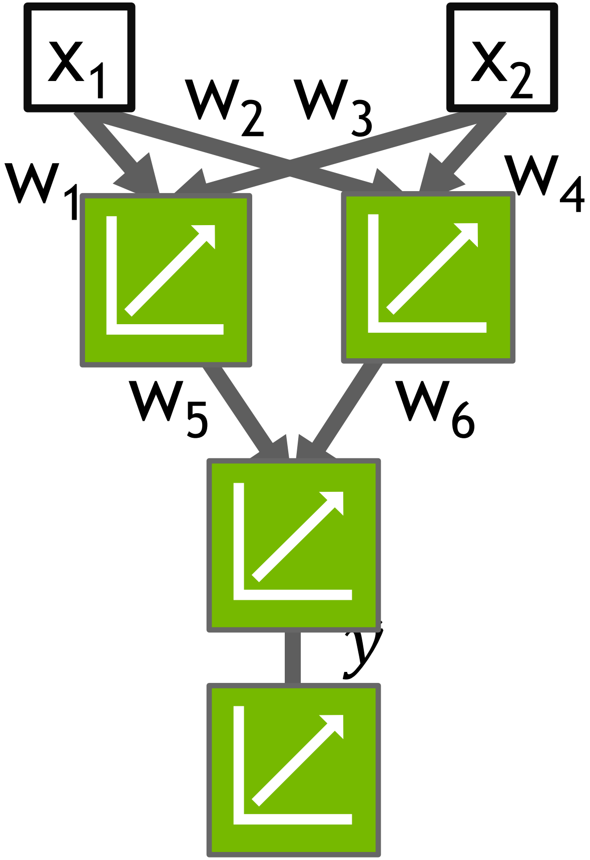

- Scales to more inputs

# BUILDING A NETWORK




- Scales to more inputs
- Can chain neurons

# BUILDING A NETWORK




- Scales to more inputs
- Can chain neurons
- If all regressions are linear, then output will also be a linear regression

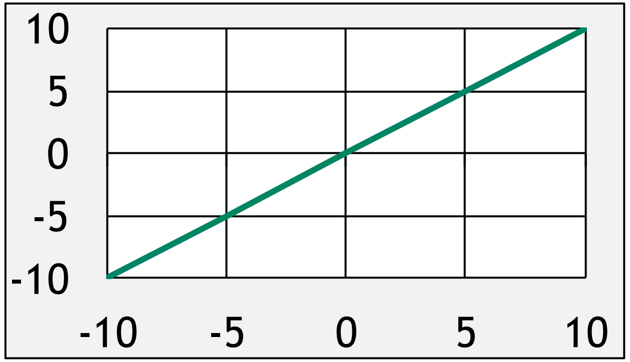
# ACTIVATION FUNCTIONS

# ACTIVATION FUNCTIONS

## Linear

$$\hat{y} = wx + b$$

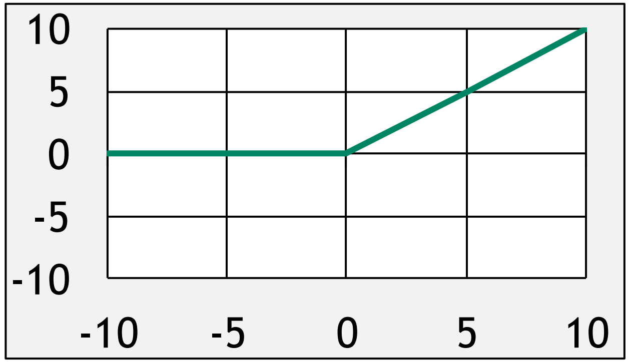
```
# Multiply each input
# with a weight (w) and
# add intercept (b)
y_hat = wx+b
```




## ReLU

$$\hat{y} = \begin{cases} wx + b \; if \; wx + b > 0 \\ 0 \;\; otherwise \end{cases}$$

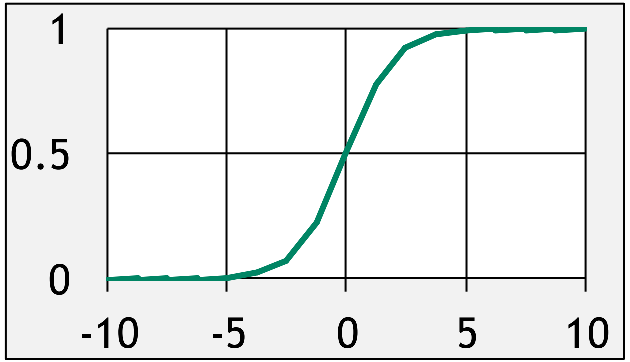
```
# Only return result
# if total is positive
linear = wx+b
y_hat = linear * (linear > 0)
```




## Sigmoid

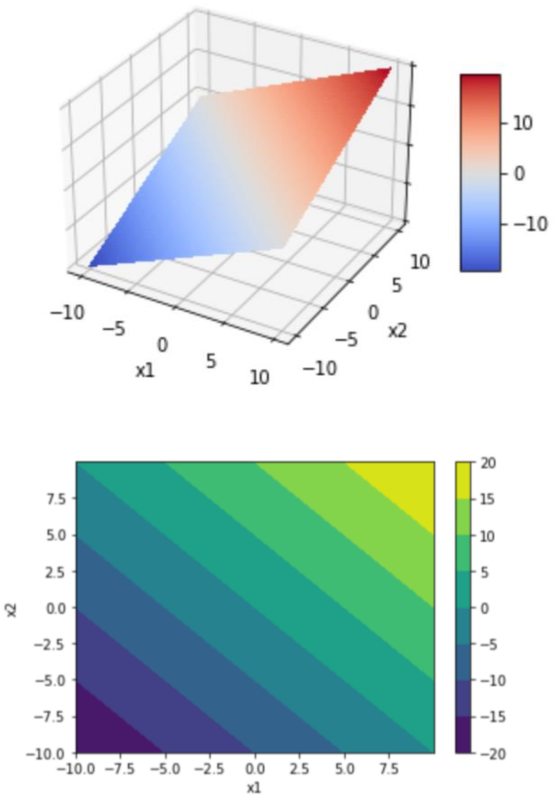
$$\hat{y} = \frac{1}{1 + e^{-(wx+b)}}$$

```
# Start with line
linear = wx + b
# Warp to - inf to 0
inf_to_zero = np.exp(-1 * linear)
# Squish to -1 to 1
y_hat = 1 / (1 + inf_to_zero)
```

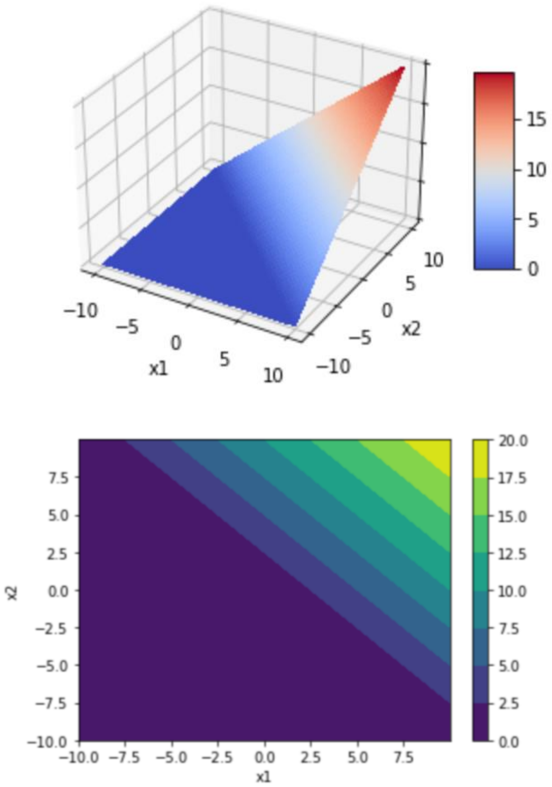


# ACTIVATION FUNCTIONS

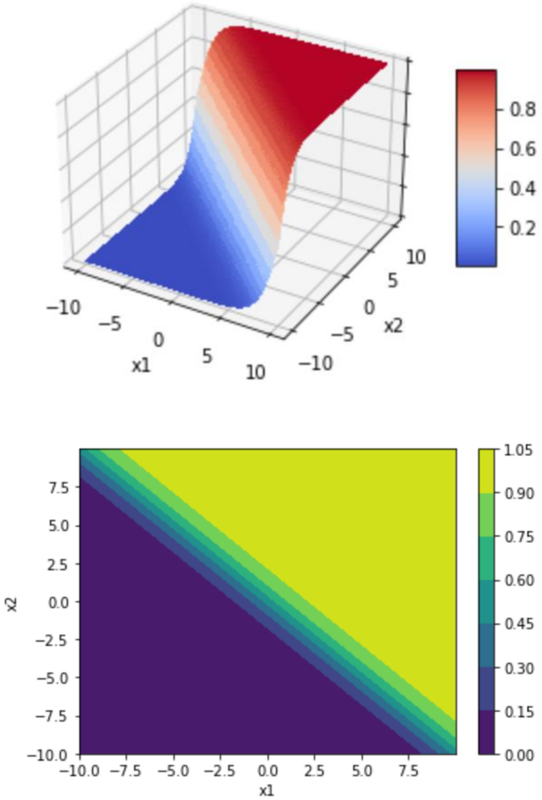
## Linear



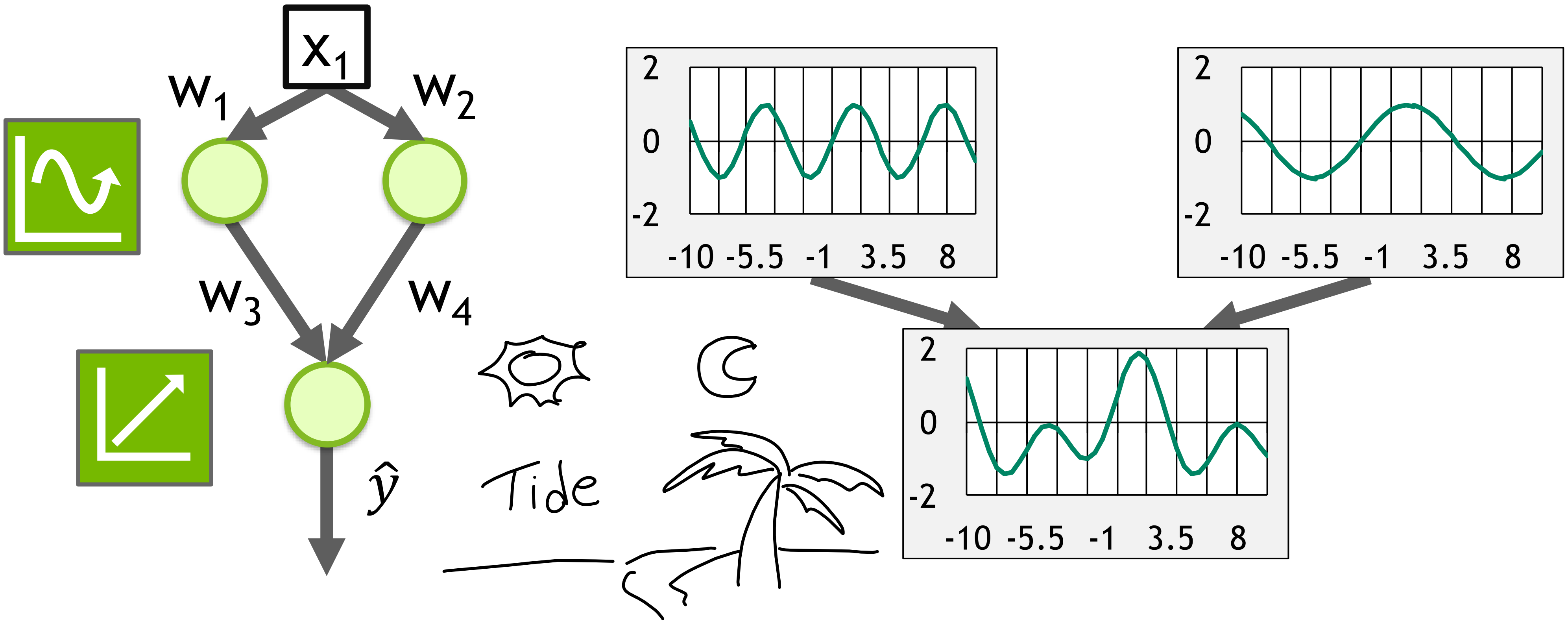

## ReLU




## Sigmoid



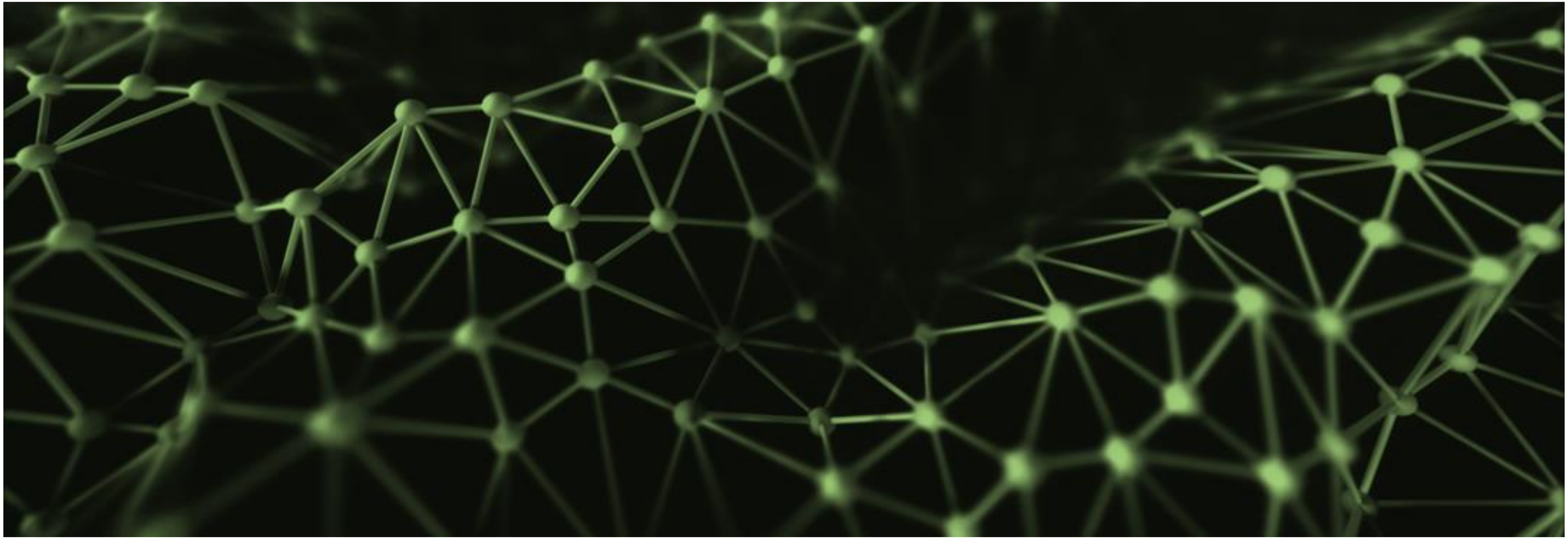
# ACTIVATION FUNCTIONS



# OVERFITTING

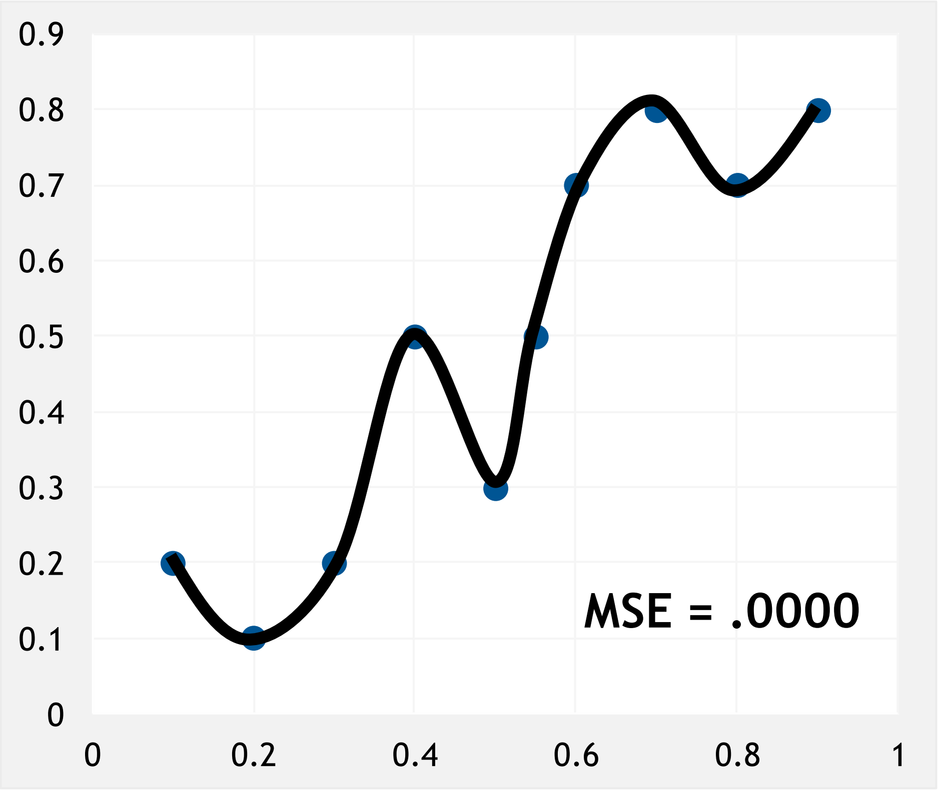
# OVERFITTING

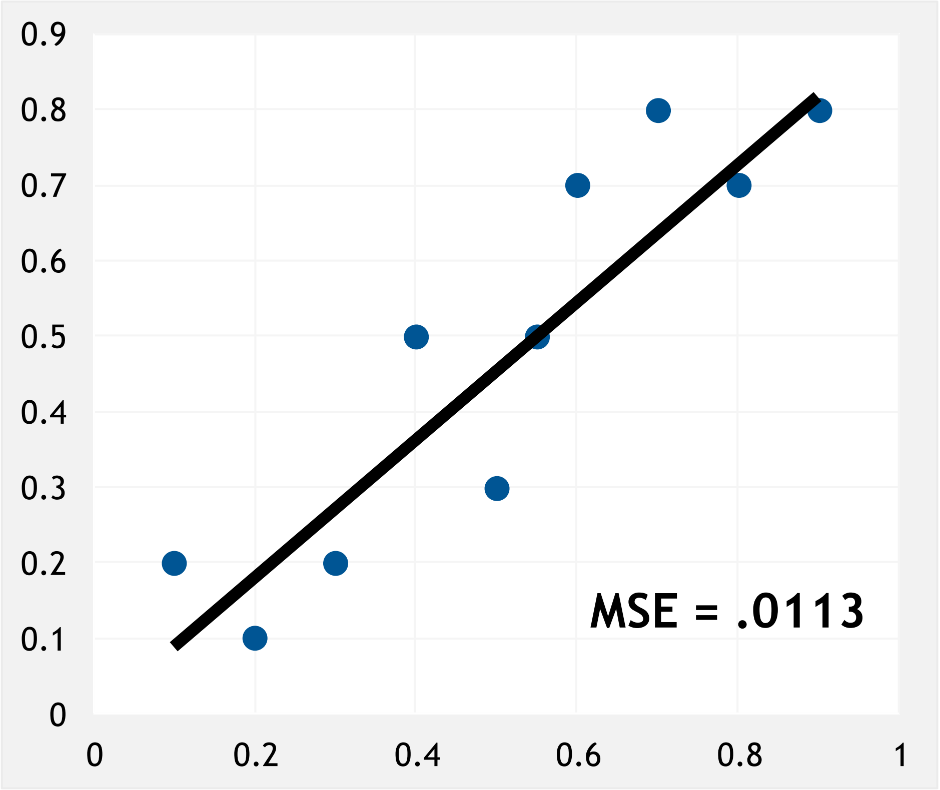
## Why not have a super large neural network?



# OVERFITTING

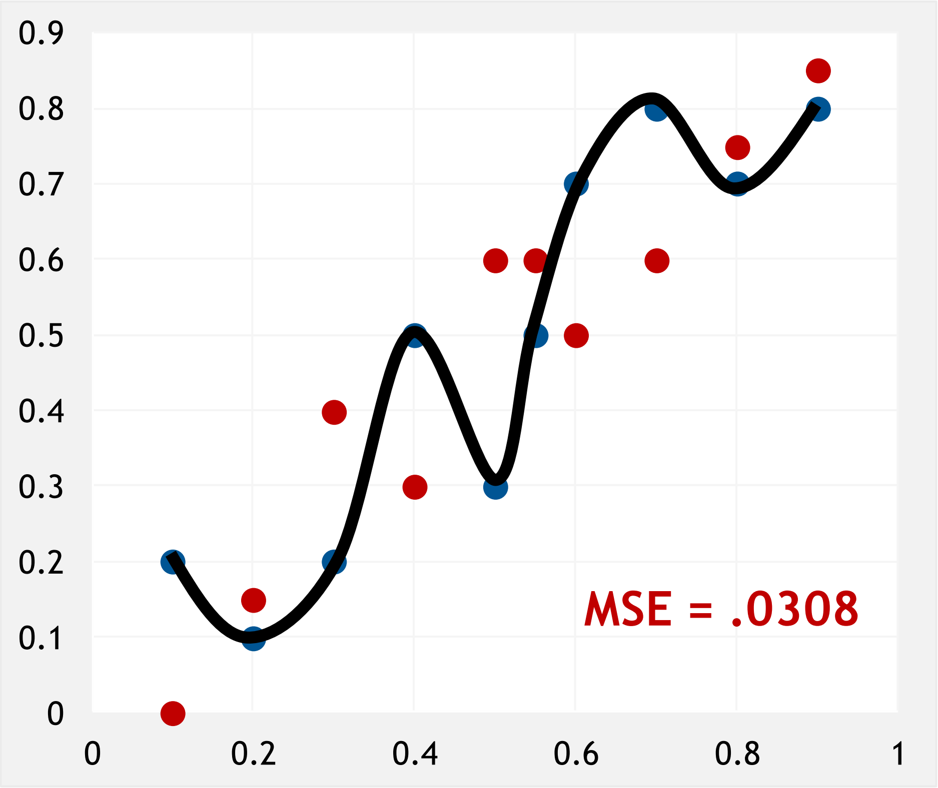
## Which Trendline is Better?

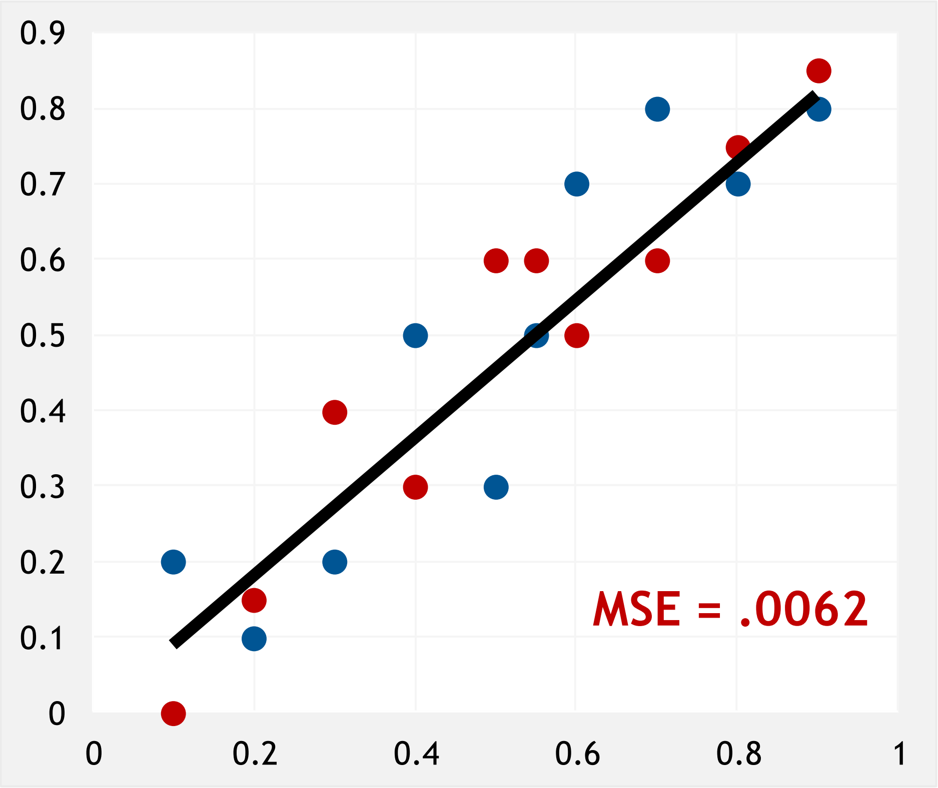


# OVERFITTING

## Which Trendline is Better?



# TRAINING VS VALIDATION DATA

## Avoid memorization

### Training data

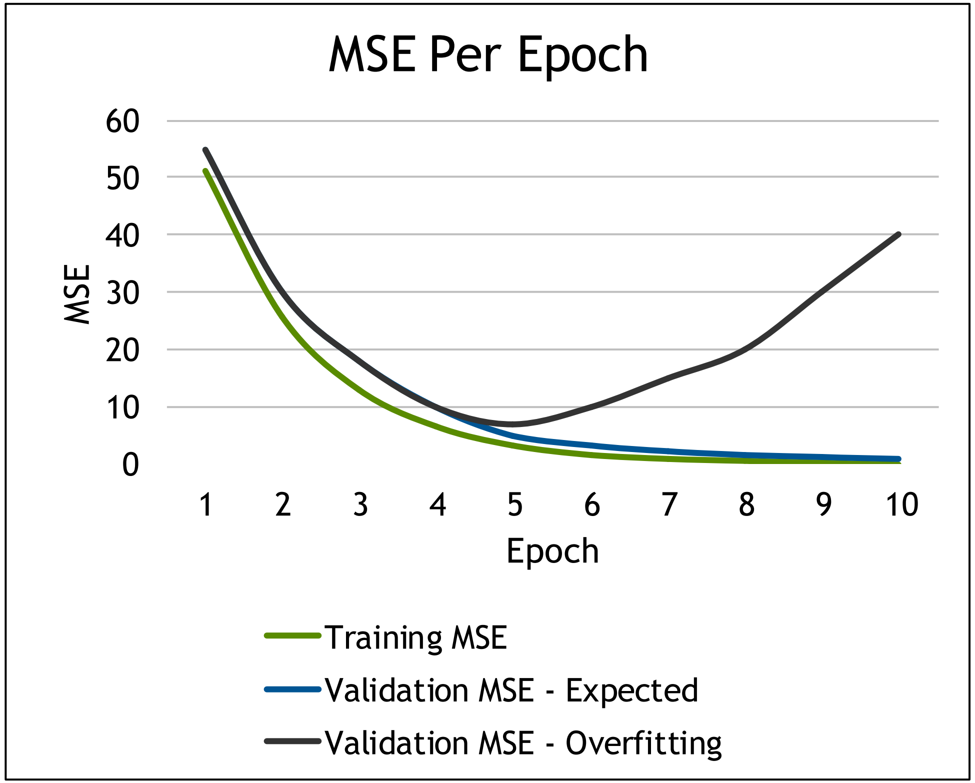
- Core dataset for the model to learn on

### Validation data

- New data for model to see if it truly understands (can generalize)

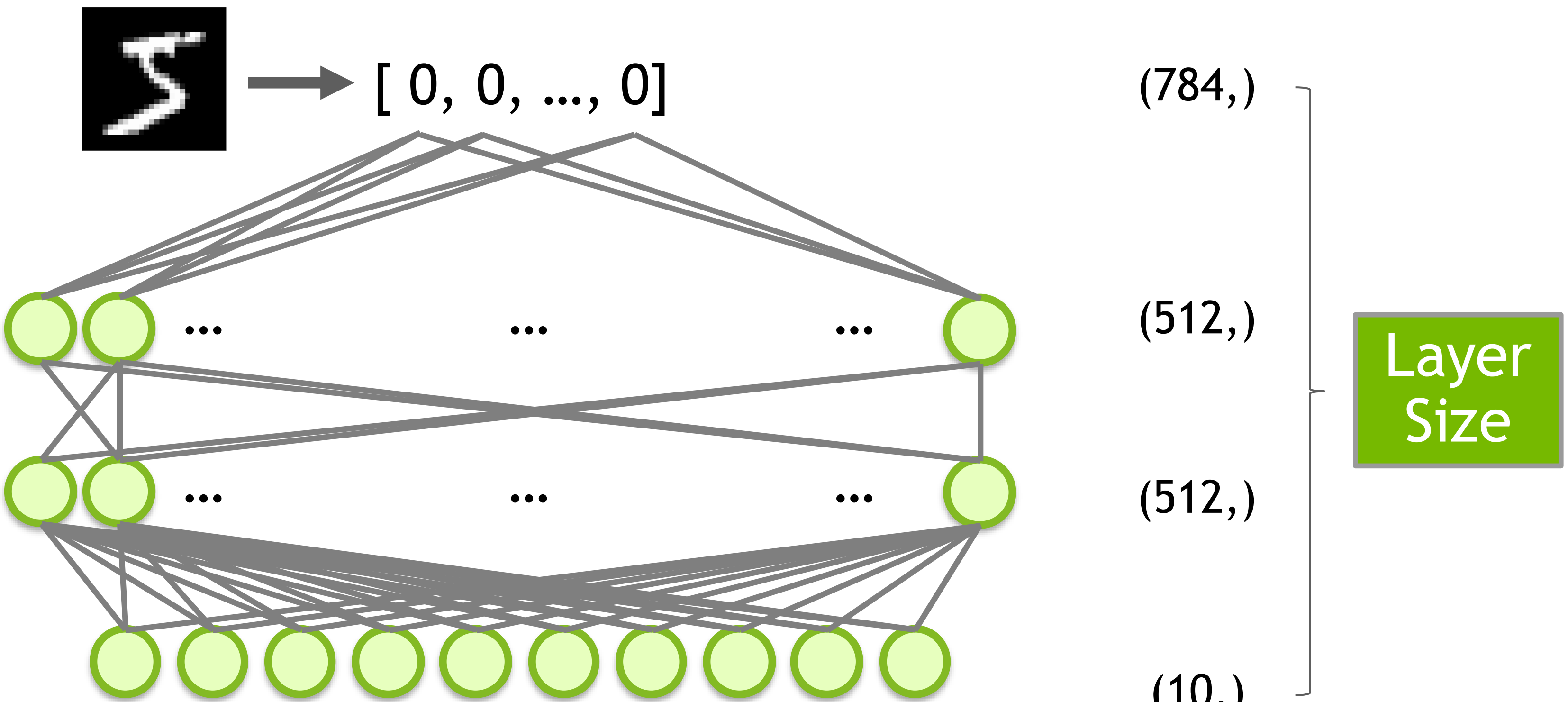
### Overfitting

- When model performs well on the training data, but not the validation data (evidence of memorization)
- Ideally the accuracy and loss should be similar between both datasets

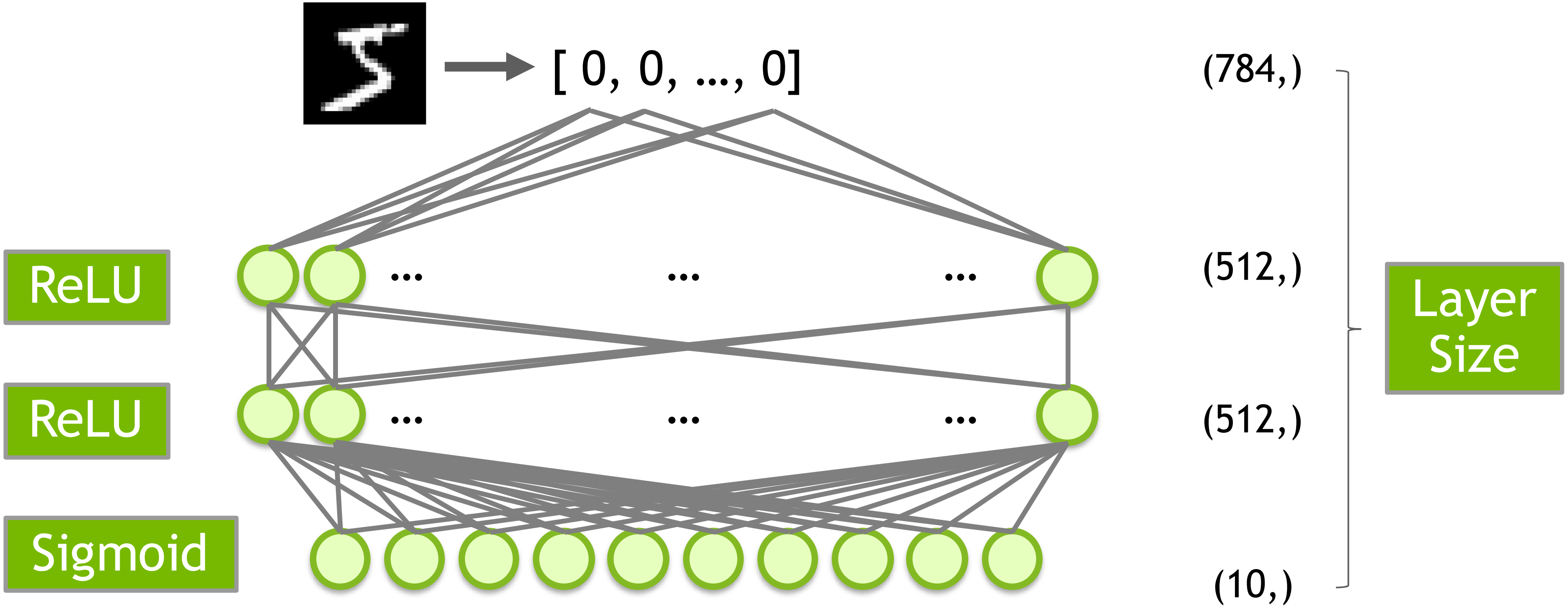


# FROM REGRESSION TO CLASSIFICATION

# AN MNIST MODEL



# AN MNIST MODEL



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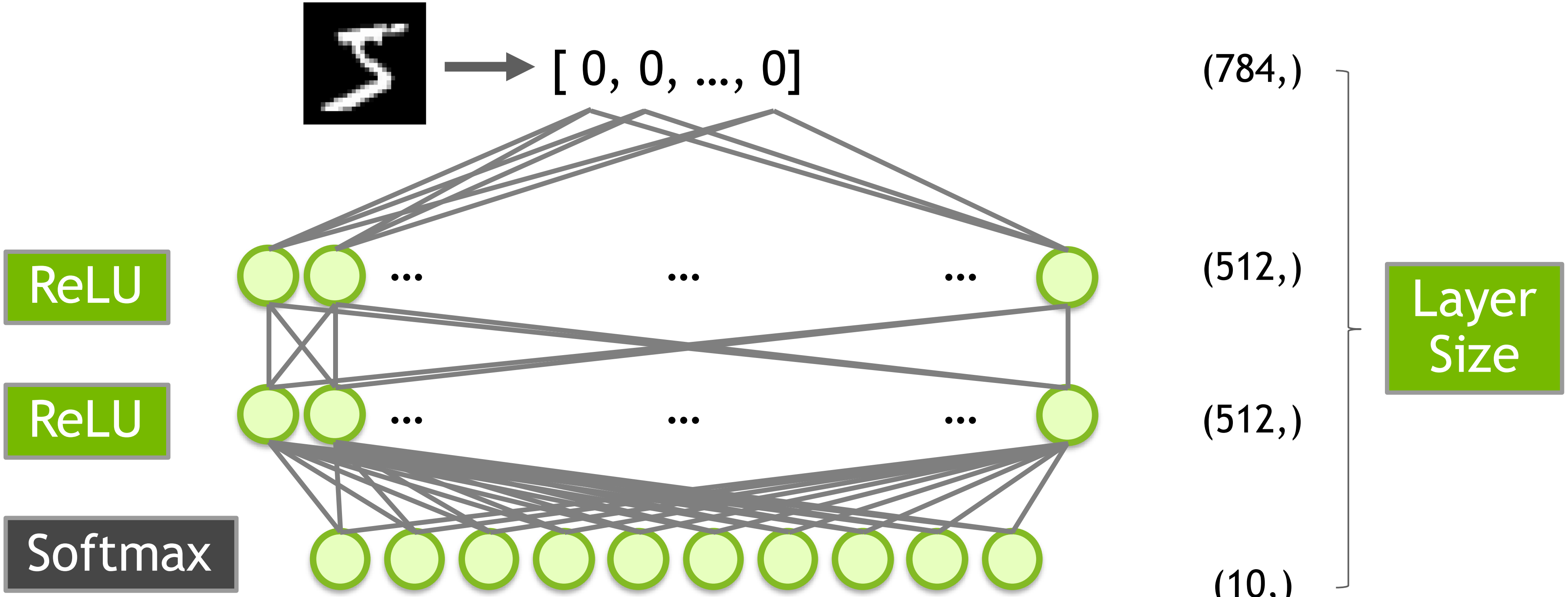
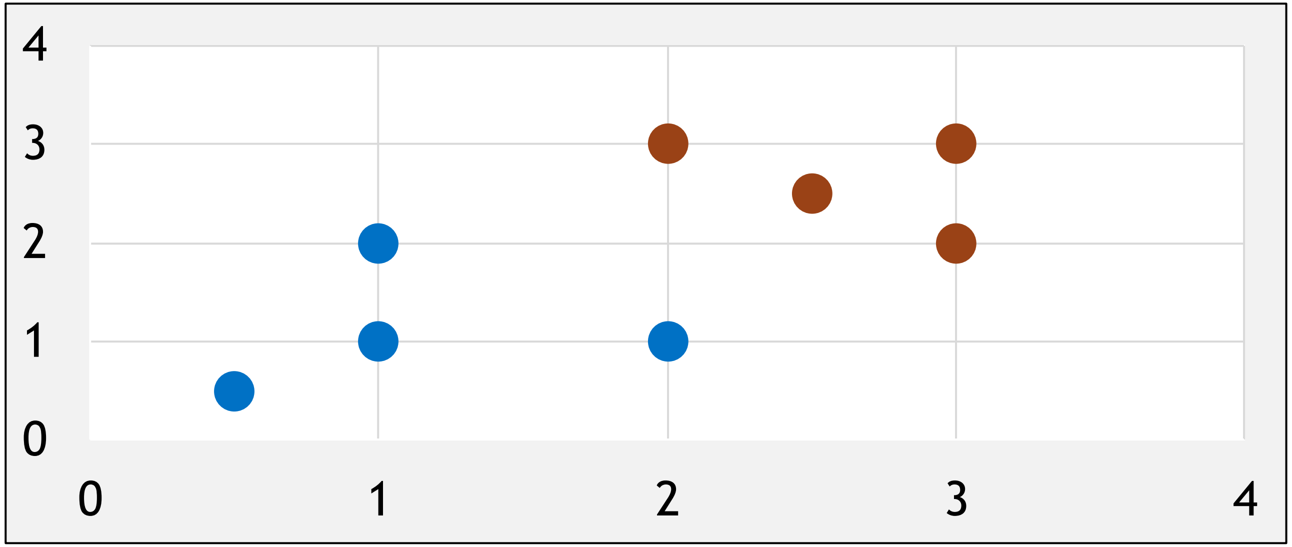
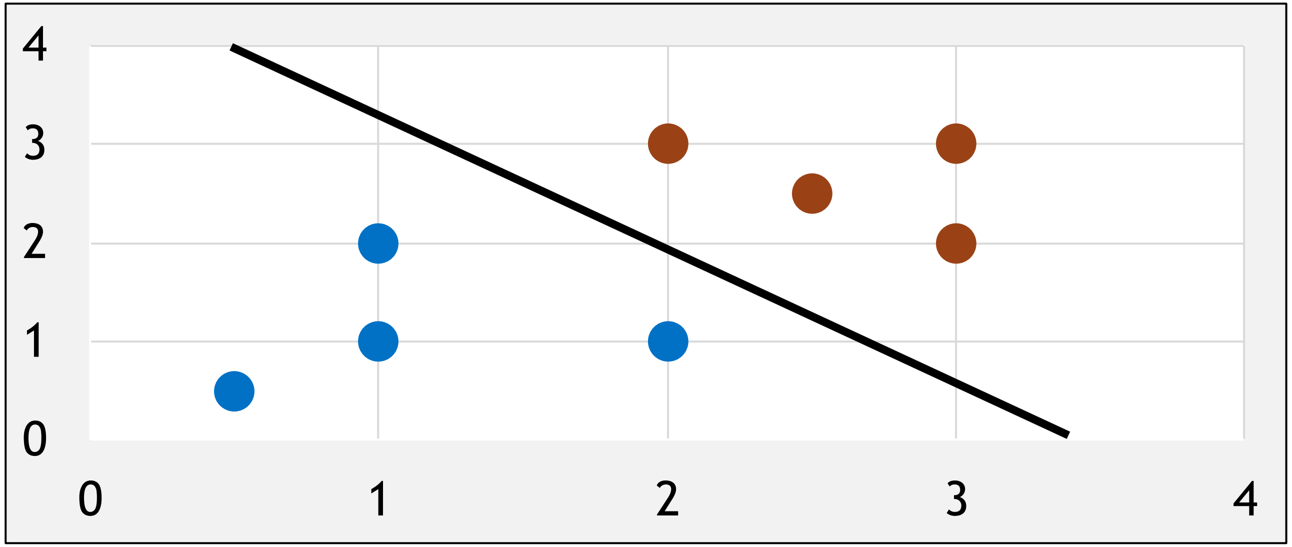


# RMSE FOR PROBABILITIES?



# RMSE FOR PROBABILITIES?

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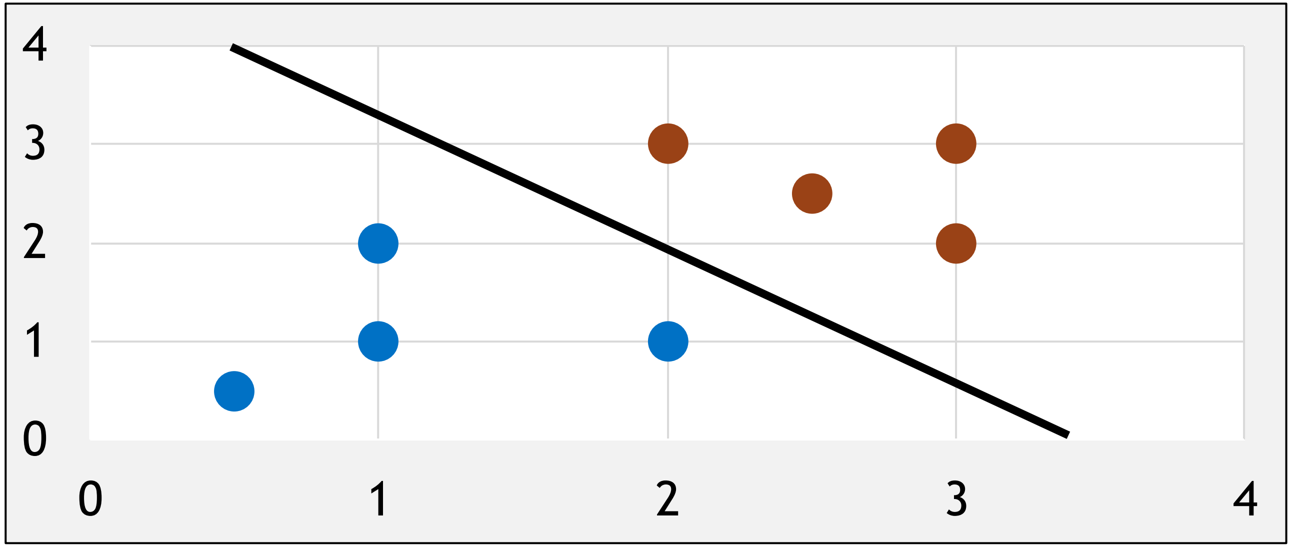
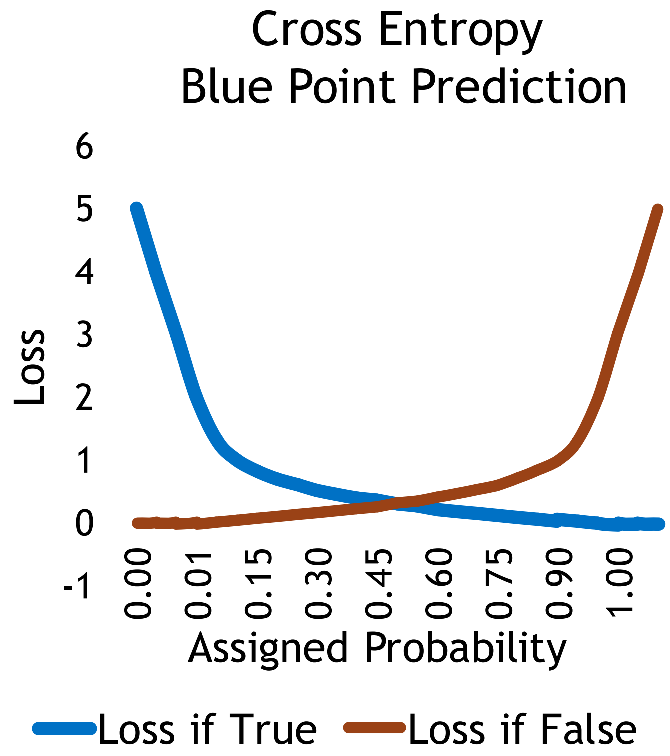
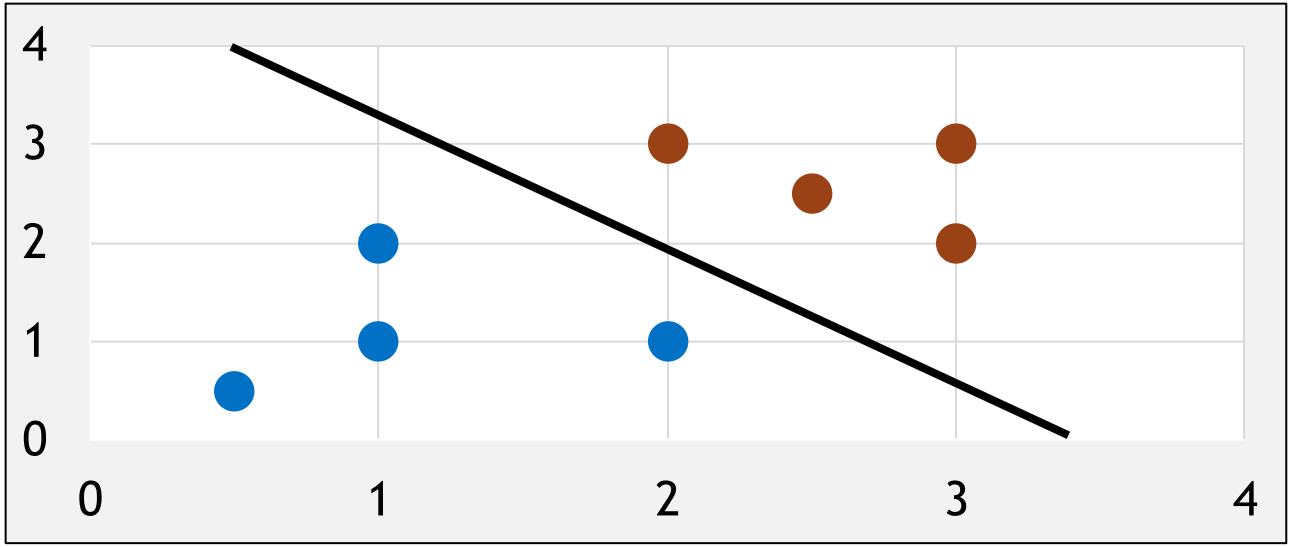
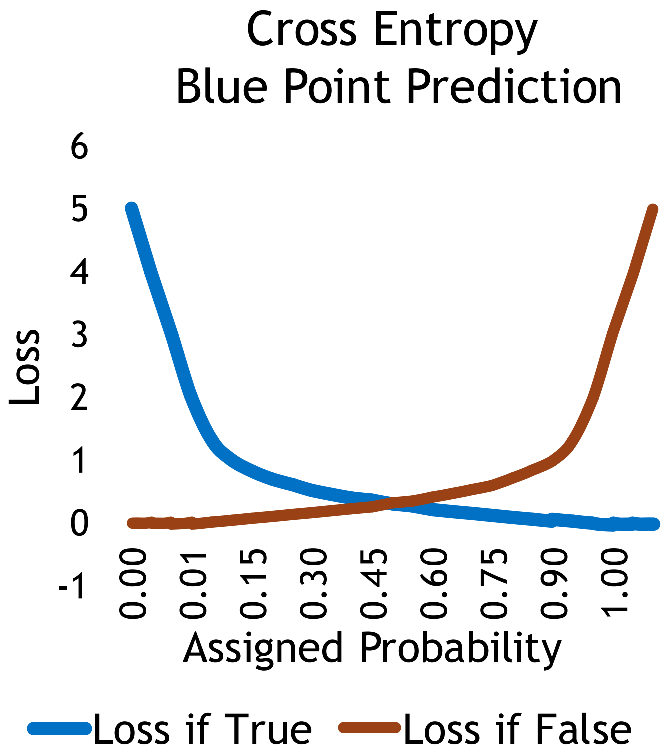
# CROSS ENTROPY



# CROSS ENTROPY



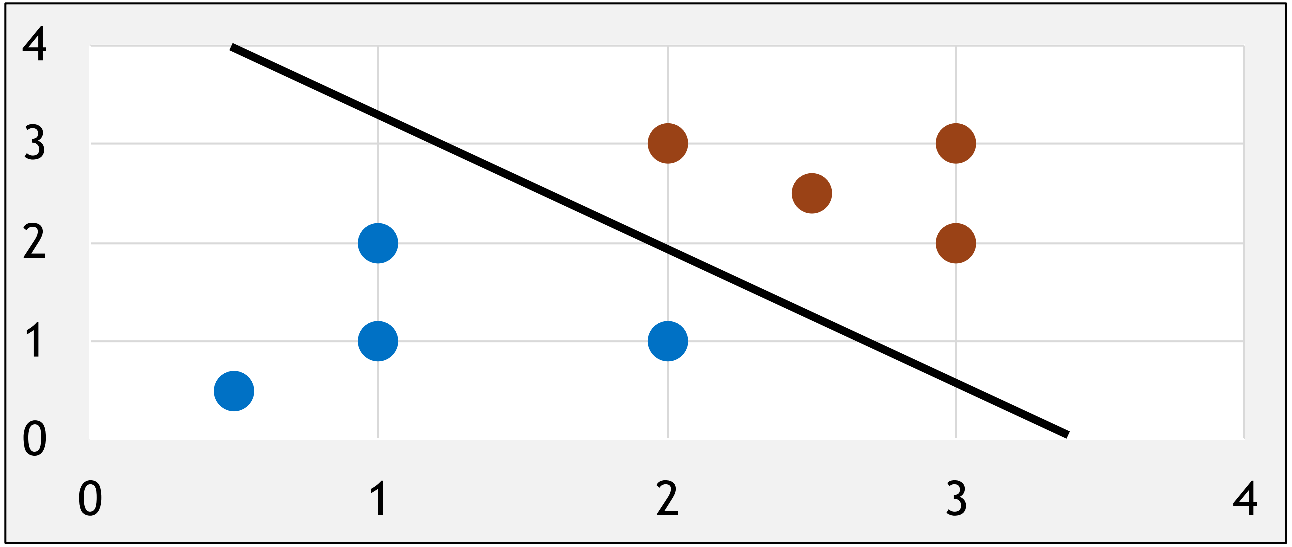




$$Loss = -\Big(\big(t(x) \cdot \log(p(x)\big) + \big(1 - t(x)\big) \cdot \log(1 - p(x)\big)\Big)$$

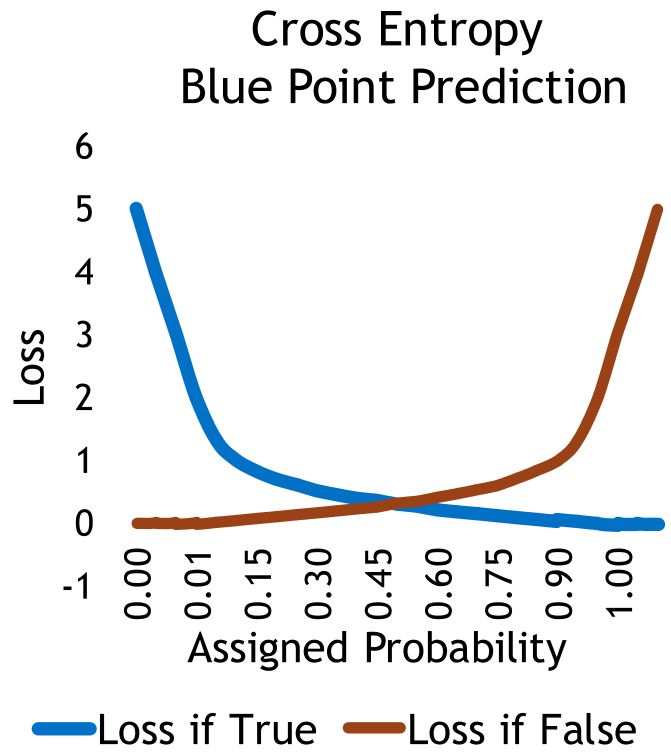
$$t(x) = target\ (0\ if\ False, 1\ if\ True)$$

$$p(x) = probability\ prediction\ of\ point\ x$$

# CROSS ENTROPY



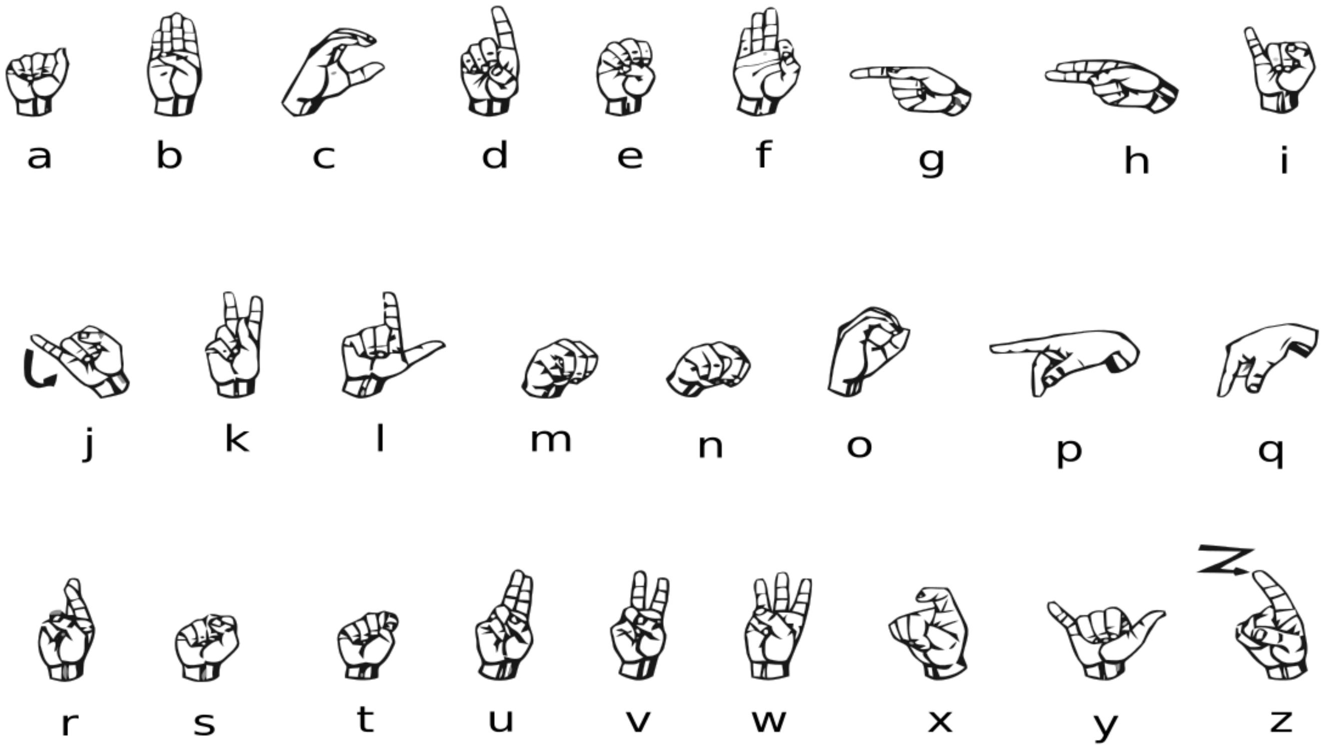
```
def cross_entropy(y_hat, y_actual):
    """Infinite error for misplaced confidence."""
    loss = log(y_hat) if y_actual else log(1-y_hat)
    return -1*loss
```



# BRINGING IT TOGETHER

# THE NEXT EXERCISE

## The American Sign Language Alphabet



# LET’S GO!

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# APPENDIX: GRADIENT DESCENT

## HELPING THE COMPUTER CHEAT CALCULUS

# Learning From Error

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y - \hat{y})^2 = \frac{1}{n}\sum_{i=1}^{n}(y - (mx + b))^2$$

$$MSE = \frac{1}{2}((3 - (m(1) + b))^2 + (5 - (m(2) + b))^2)$$

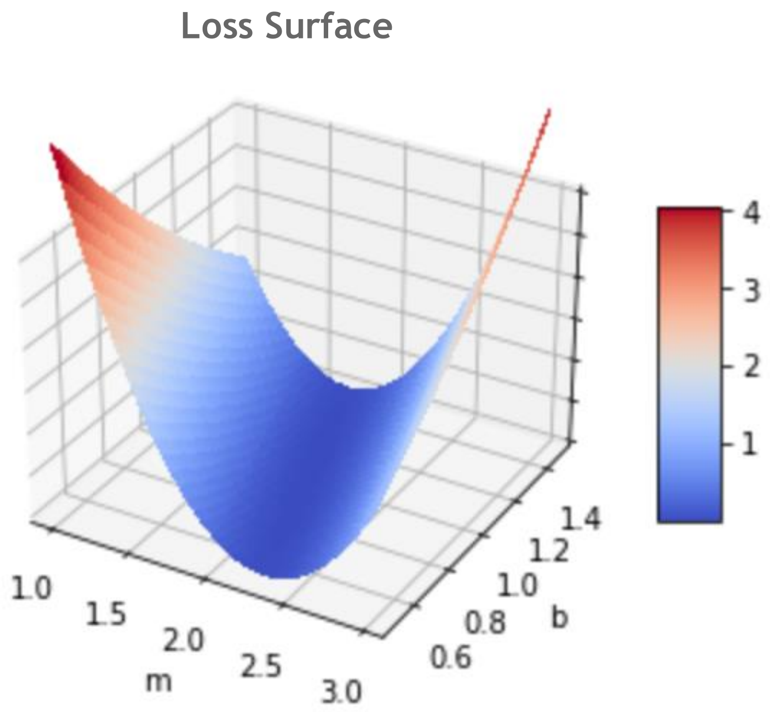
$$\frac{\partial MSE}{\partial m} = 5m + 3b - 13 \qquad \frac{\partial MSE}{\partial b} = 3m + 2b - 8$$

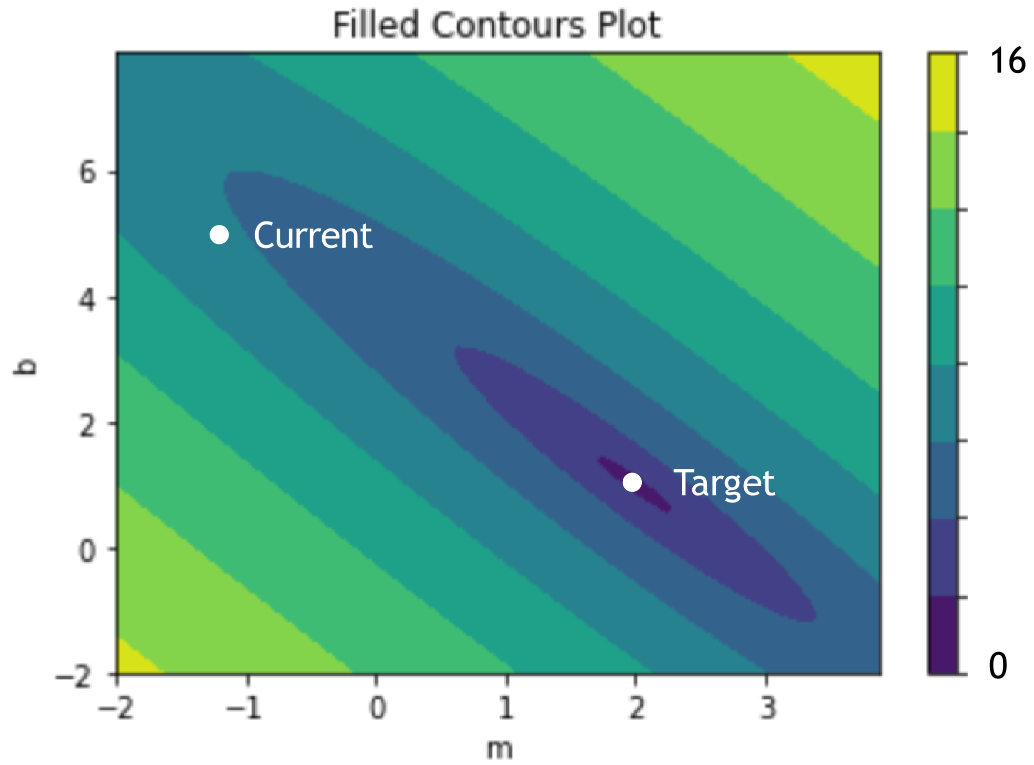
$$\frac{\partial MSE}{\partial m} = -3 \qquad \frac{\partial MSE}{\partial b} = -1$$

$m = -1$

b = 5

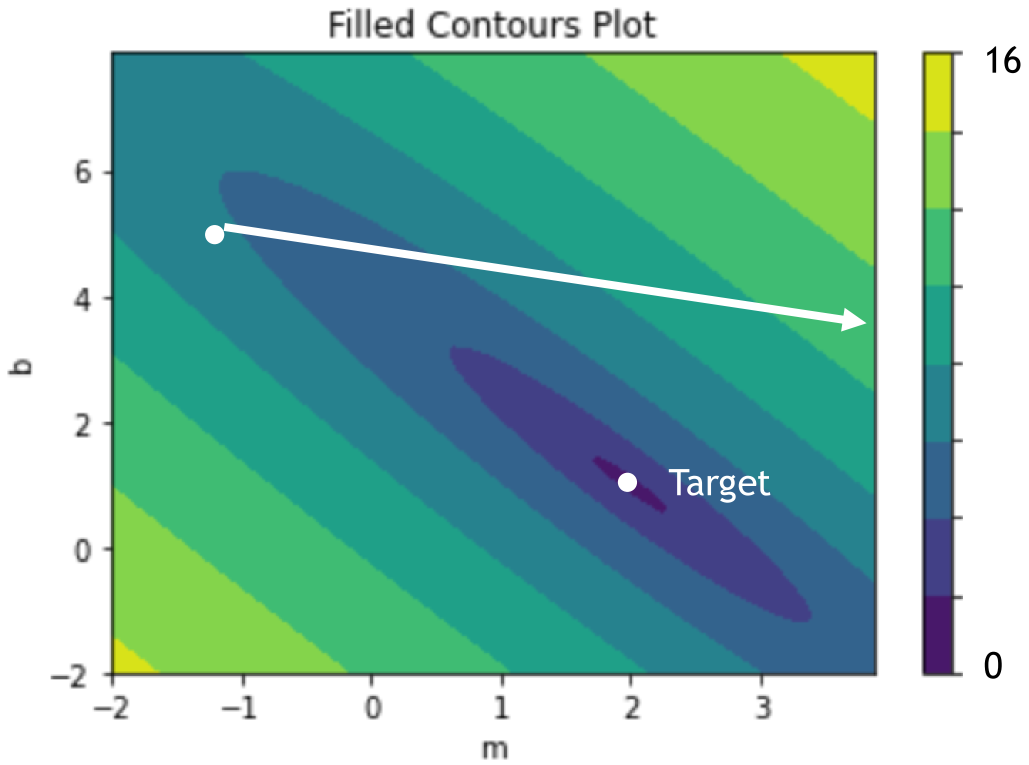
# THE LOSS CURVE



# THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7 \qquad \frac{\partial MSE}{\partial b} = -3$$

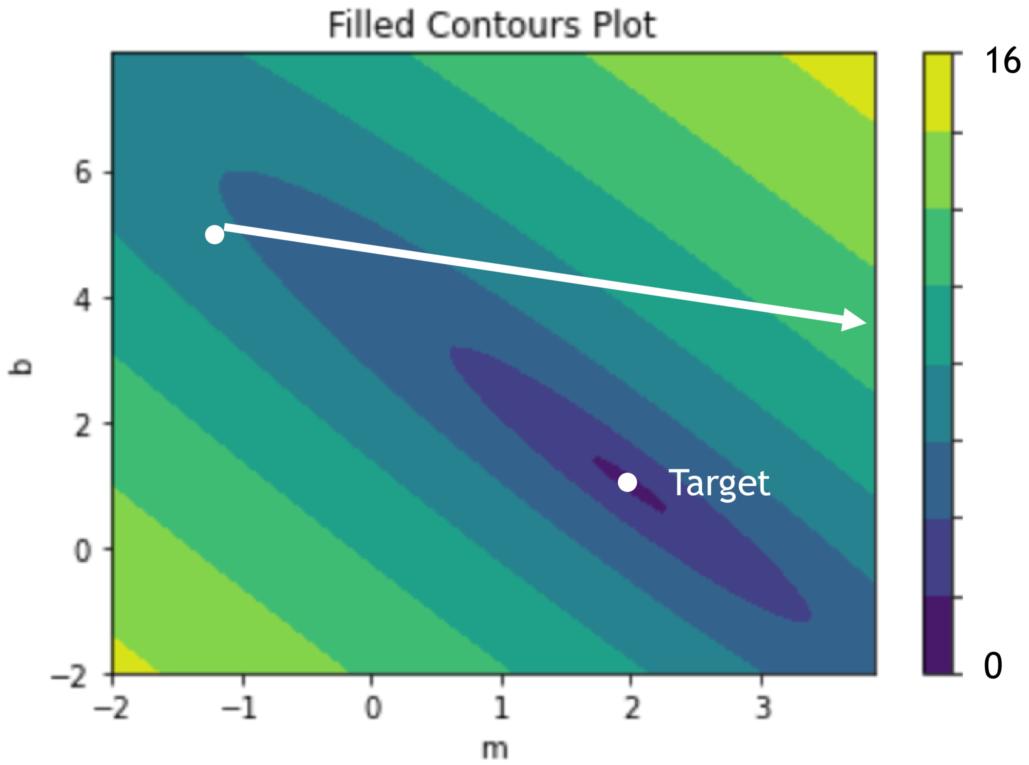


# THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7 \qquad \frac{\partial MSE}{\partial b} = -3$$

$$\mathrm{m} := \mathrm{m} - \lambda \frac{\partial MSE}{\partial m}$$

$$\mathrm{b} := b - \lambda \frac{\partial MSE}{\partial b}$$



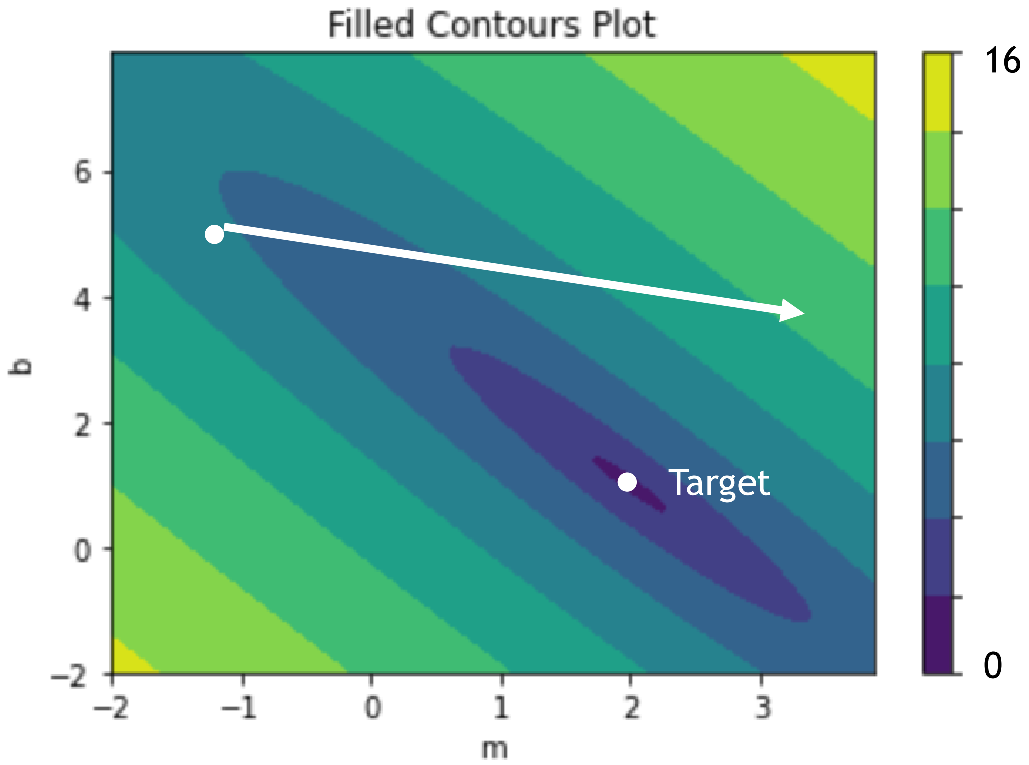
# THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7 \qquad \frac{\partial MSE}{\partial b} = -3$$

$$m := m - \lambda \frac{\partial MSE}{\partial m}$$

$$\lambda = .6$$

$$b := b - \lambda \frac{\partial MSE}{\partial b}$$



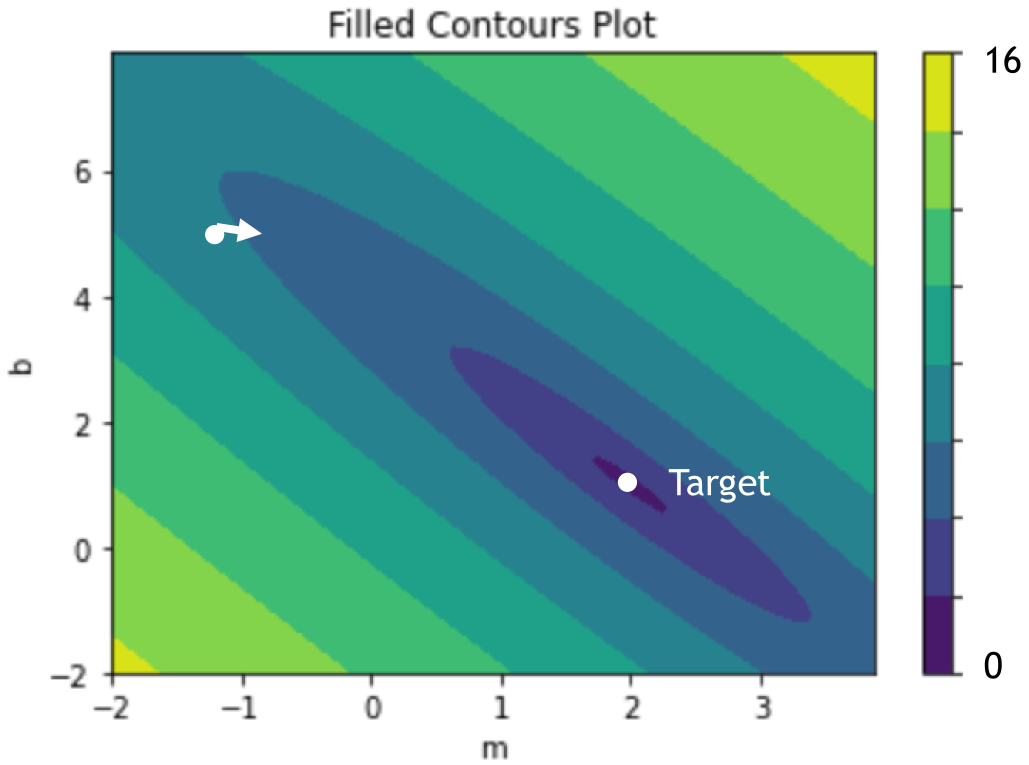
# THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7 \qquad \frac{\partial MSE}{\partial b} = -3$$

$$\mathrm{m} := \mathrm{m} - \lambda \frac{\partial MSE}{\partial m}$$

$$\lambda = .005$$

$$\mathrm{b} := b - \lambda \frac{\partial MSE}{\partial b}$$



# THE LOSS CURVE

$$\lambda = .1$$

$$m := -1 + 7\,\lambda = -0.3$$

$$b := 5 + 3\,\lambda = 4.7$$

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