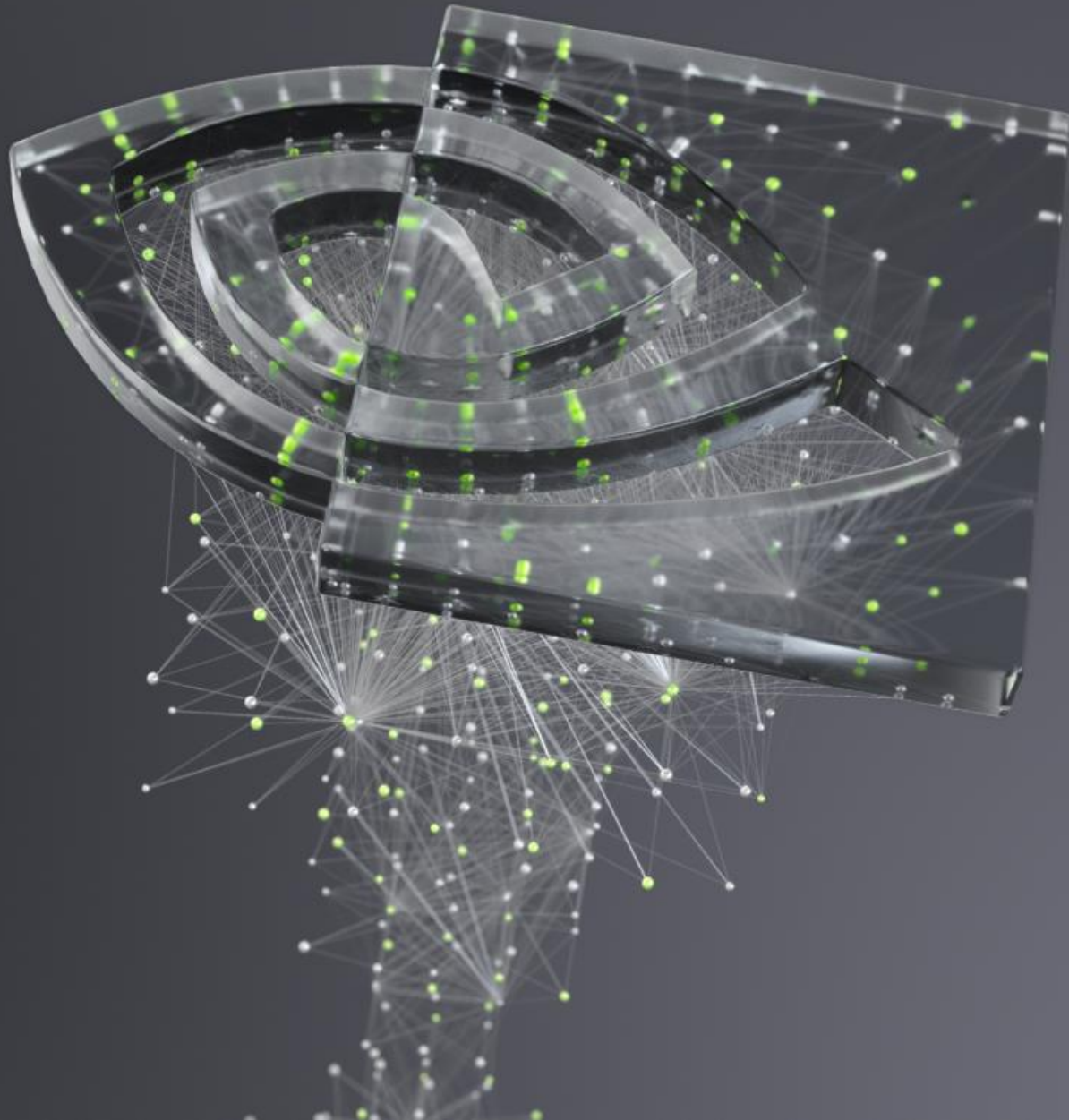




DEEP
LEARNING
INSTITUTE

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



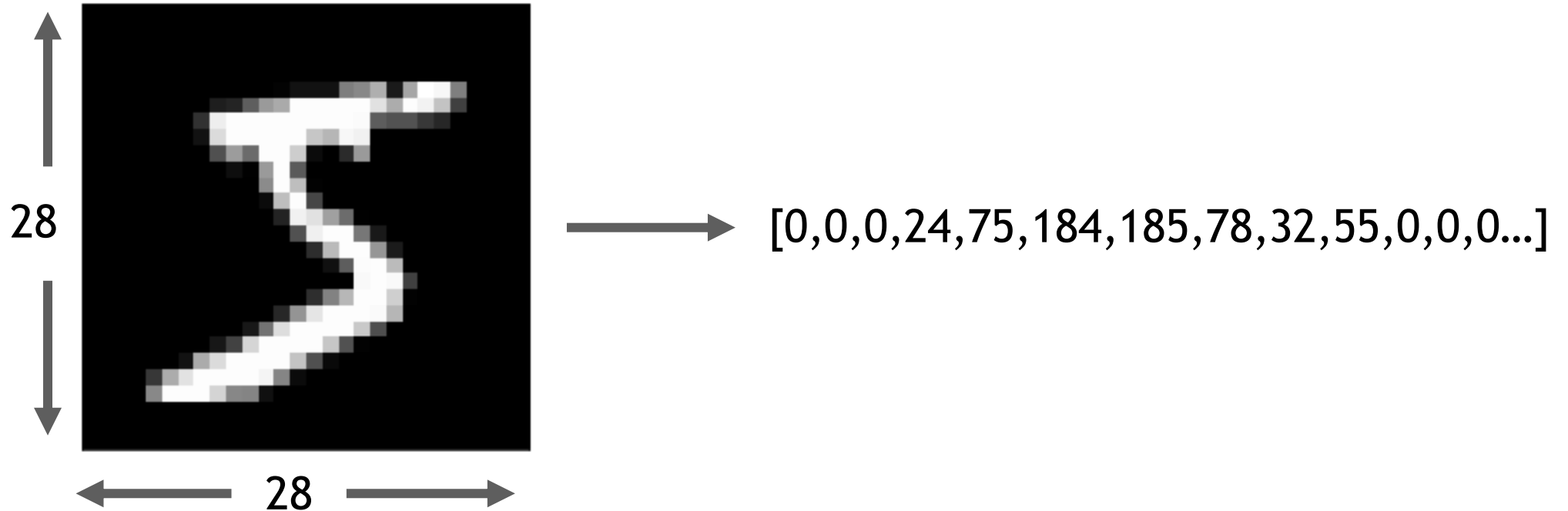
Compiled our model



Trained the model on our data

DATA PREPARATION

Input as an array

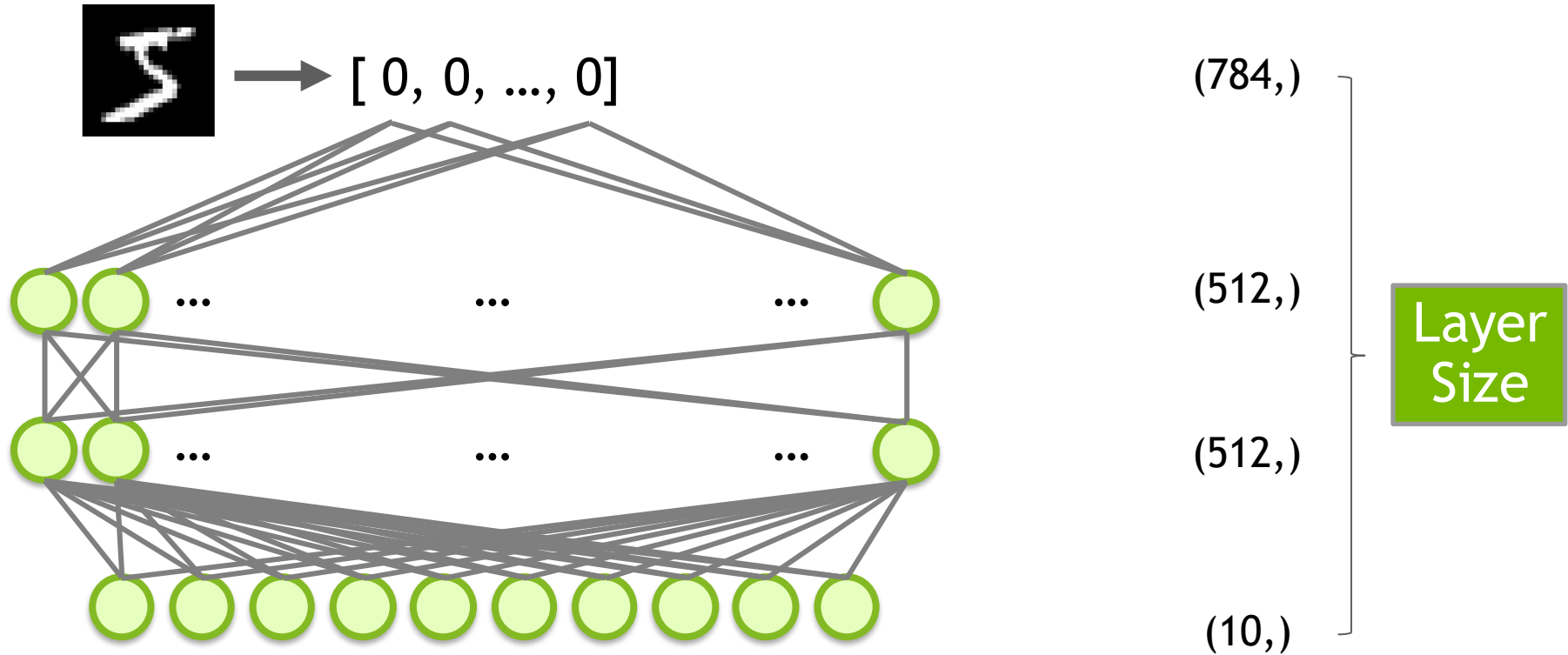


DATA PREPARATION

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



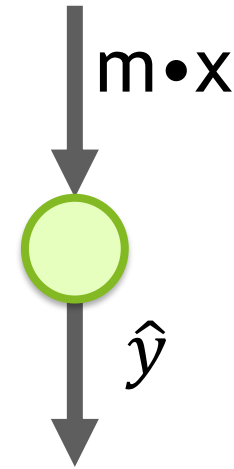
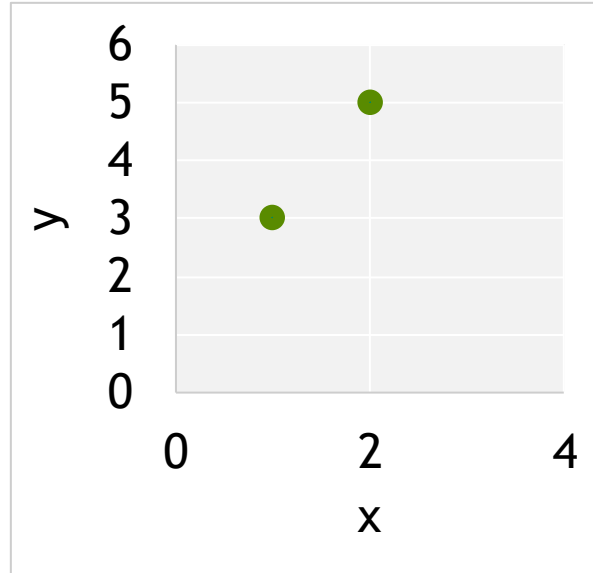


A SIMPLER MODEL

A SIMPLER MODEL

$$y = mx + b$$

x	y
1	3
2	5



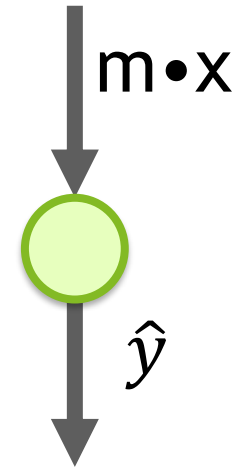
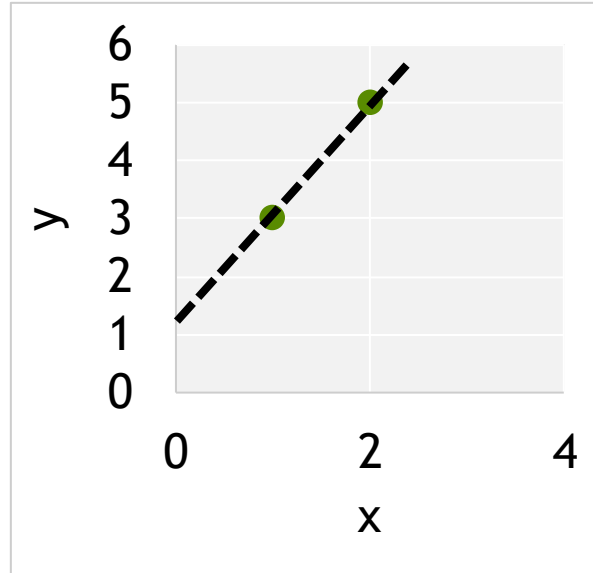
$$m = ?$$

$$b = ?$$

A SIMPLER MODEL

$$y = mx + b$$

x	y
1	3
2	5



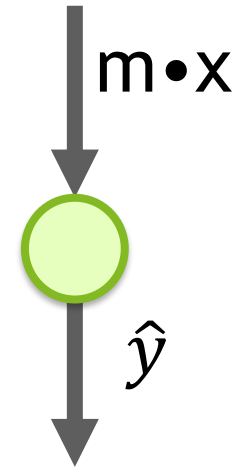
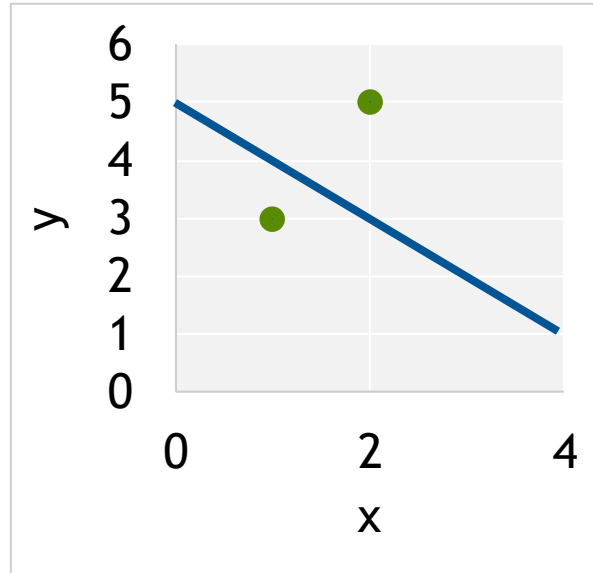
$$m = ?$$

$$b = ?$$

A SIMPLER MODEL

$$y = mx + b$$

x	y	\hat{y}
1	3	4
2	5	3



Start
Random

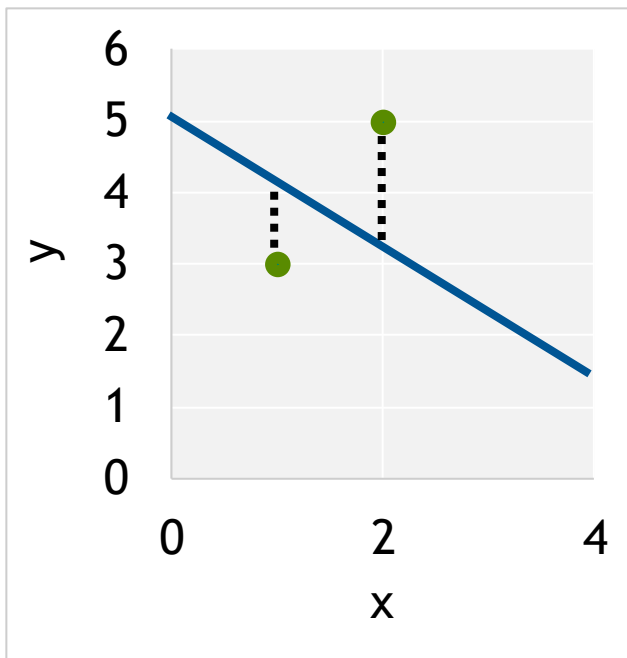
$$m = -1$$

$$b = 5$$

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



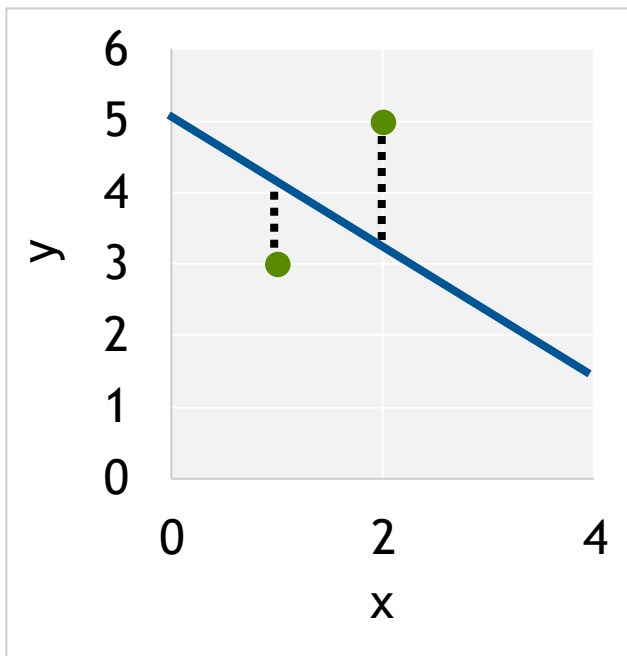
$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

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

A SIMPLER MODEL

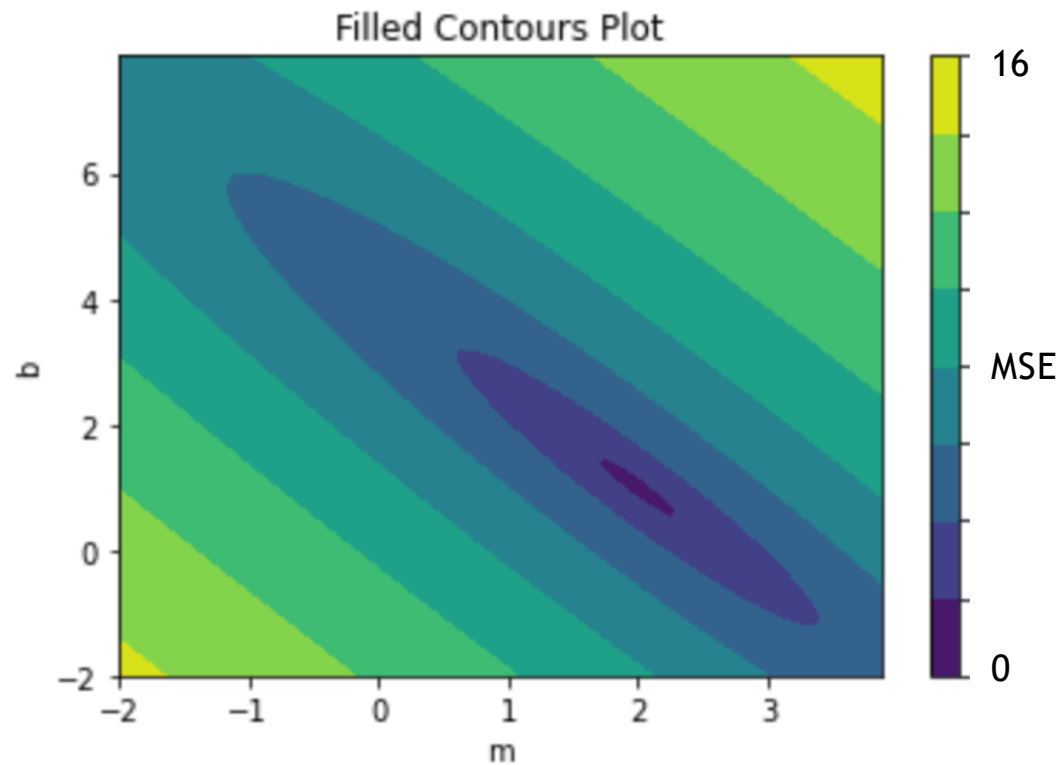
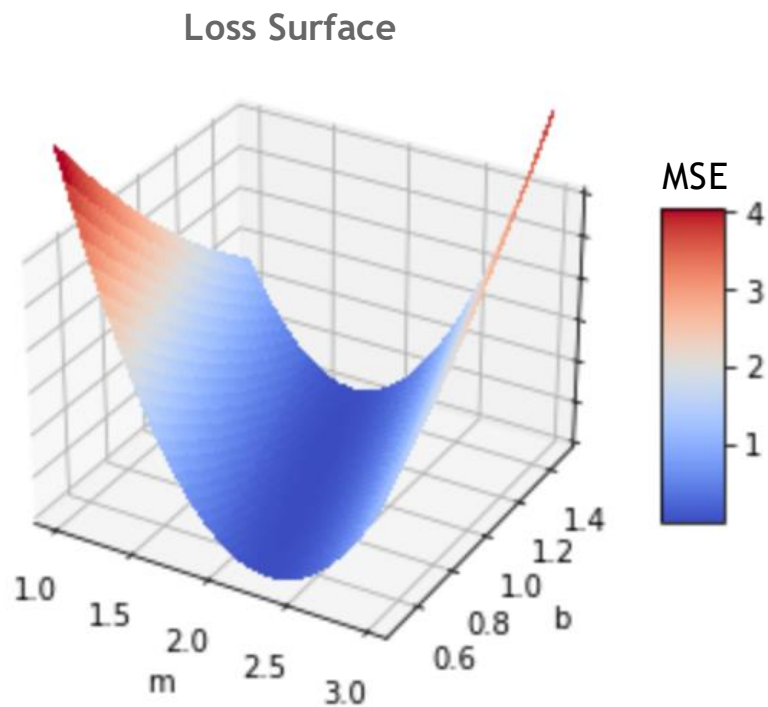
$$y = mx + b$$

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

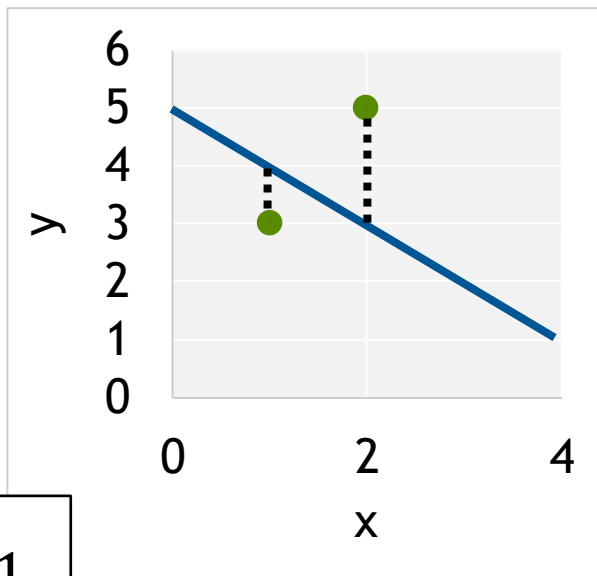


```
1 data = [(1, 3), (2, 5)]
2 m = -1
3 b = 5
4
5
6 def get_rmse(data, m, b):
7     """Calculates Mean Square Error"""
8     n = len(data)
9     squared_error = 0
10    for x, y in data:
11        # Find predicted y
12        y_hat = m*x+b
13        # Square difference between
14        # prediction and true value
15        squared_error += (
16            y - y_hat)**2
17    # Get average squared difference
18    mse = squared_error / n
19    # Square root for original units
20    return mse **.5
21
```

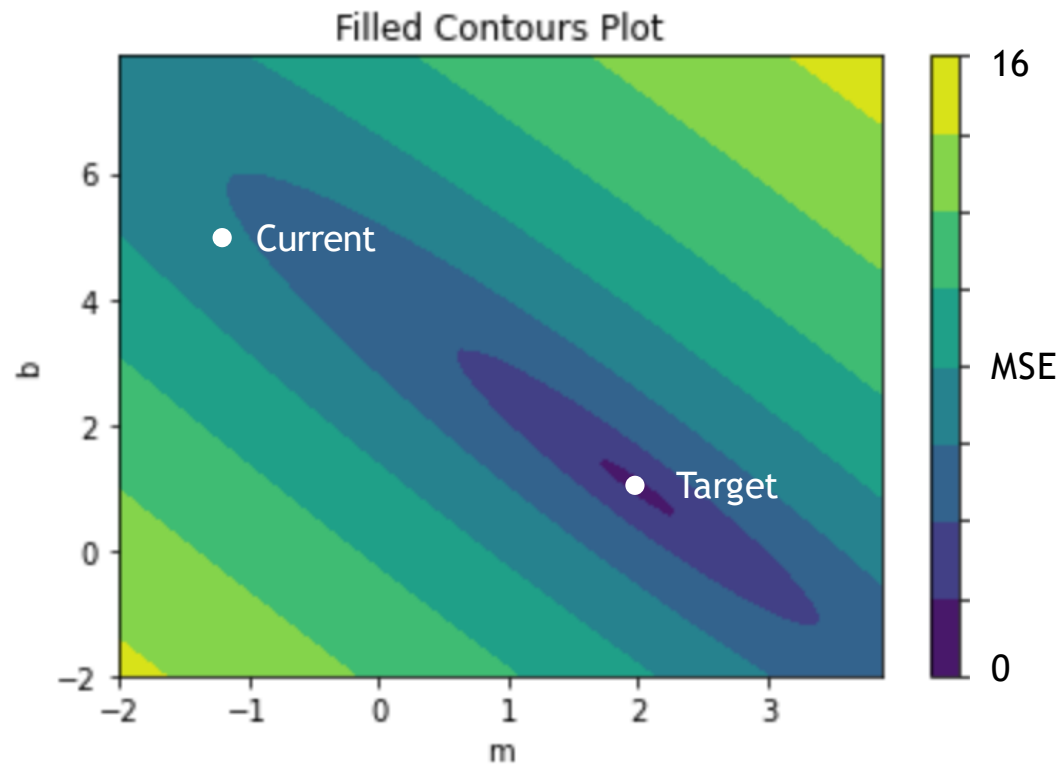
THE LOSS CURVE



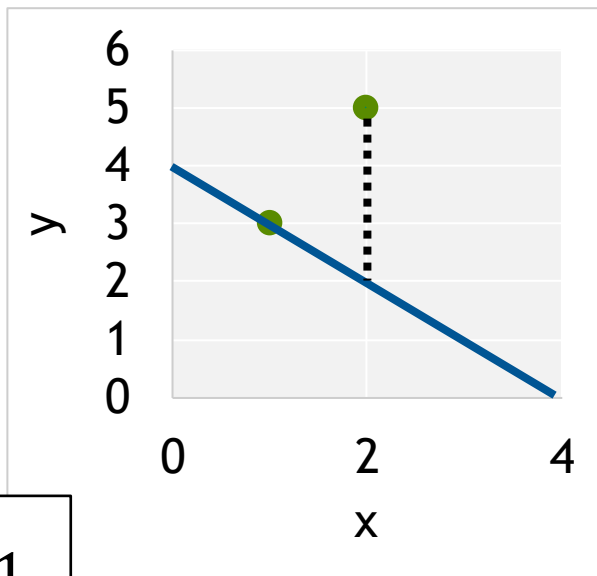
THE LOSS CURVE



$$m = -1$$
$$b = 5$$

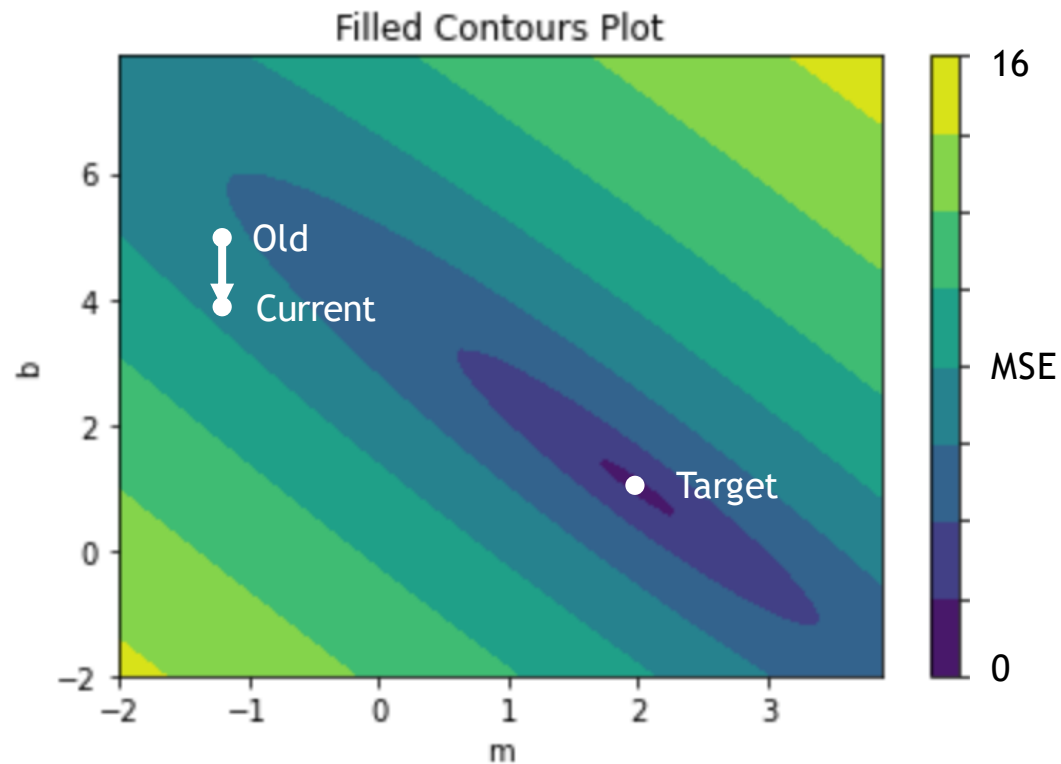


THE LOSS CURVE

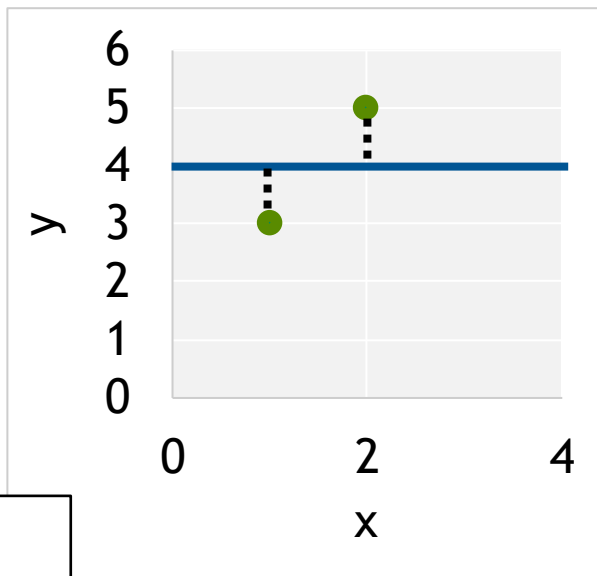


$$m = -1$$

$$b = 4$$

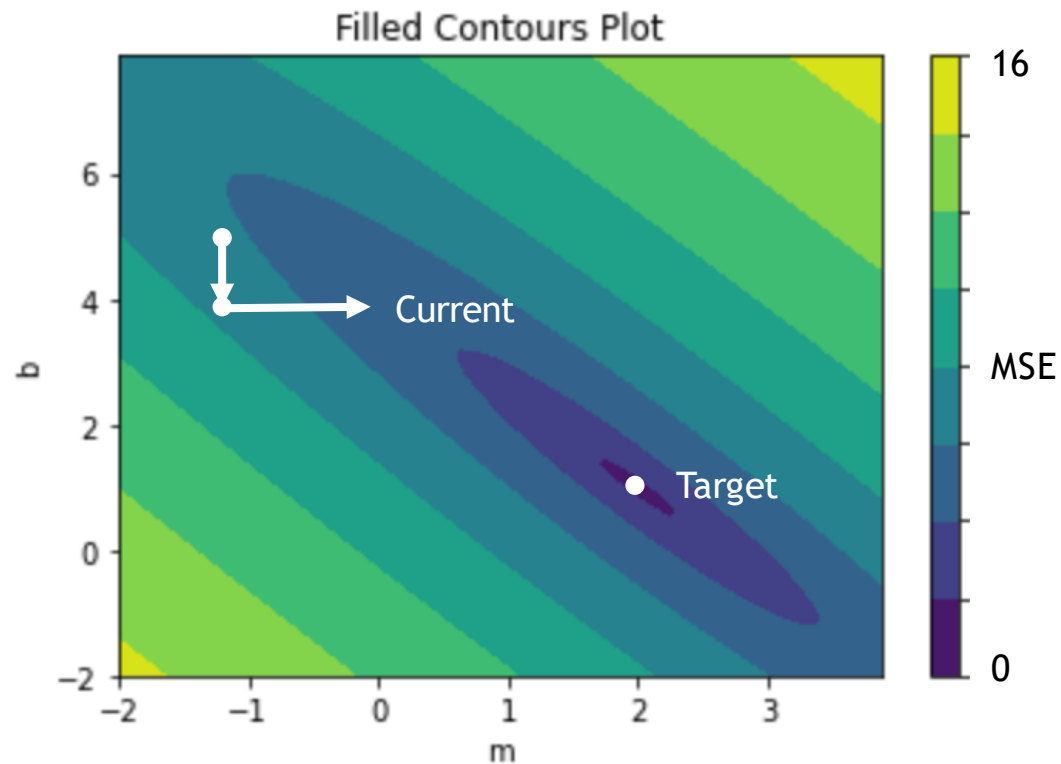


THE LOSS CURVE



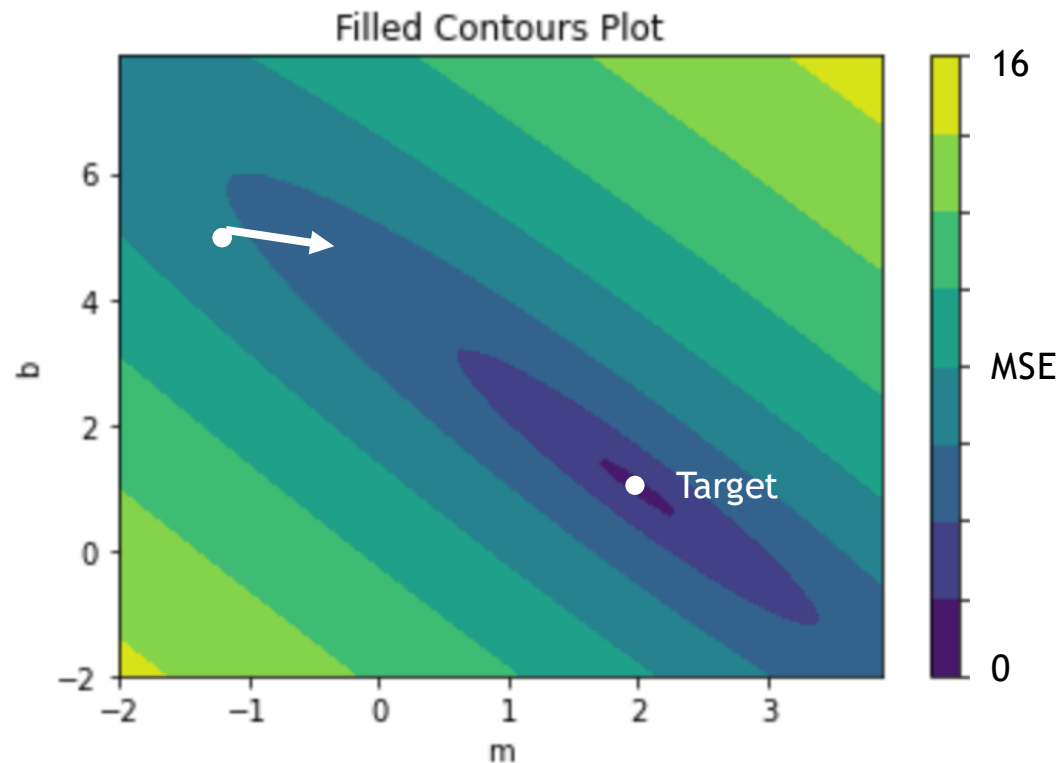
$$m = 0$$

$$b = 4$$



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

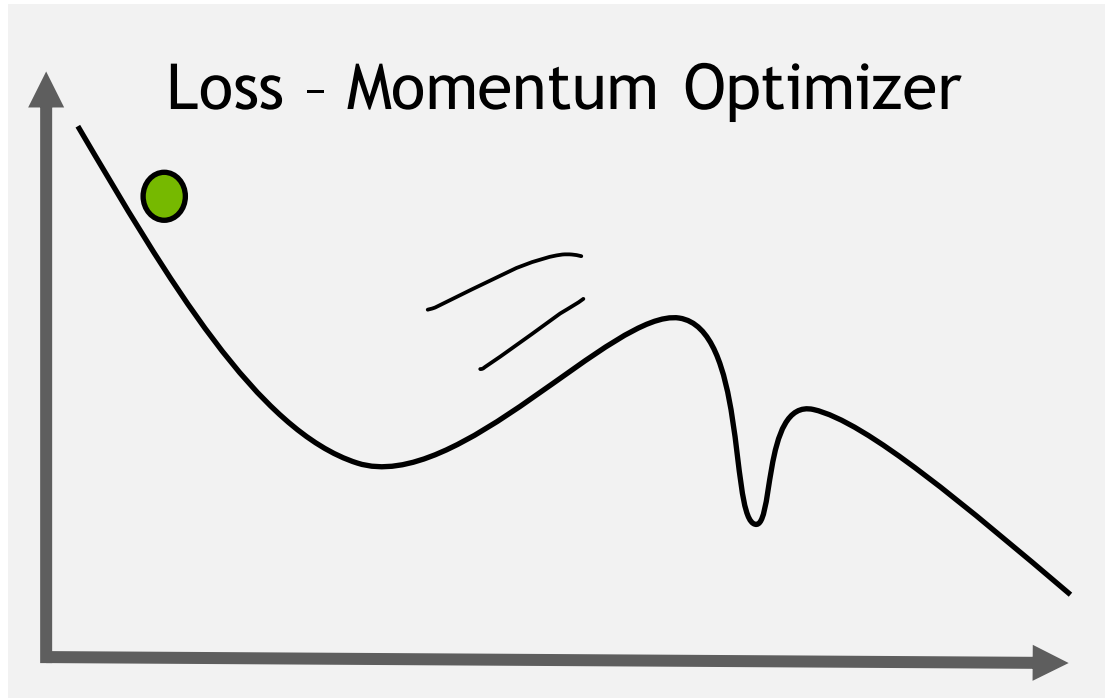


THE LOSS CURVE

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



OPTIMIZERS

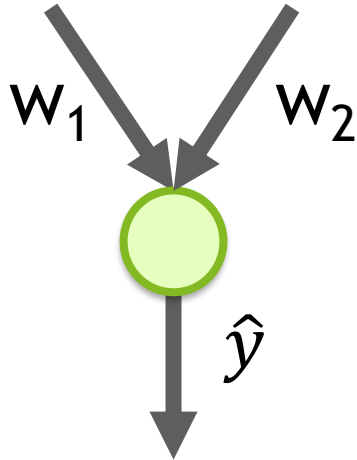


- Adam
- Adagrad
- RMSprop
- SGD



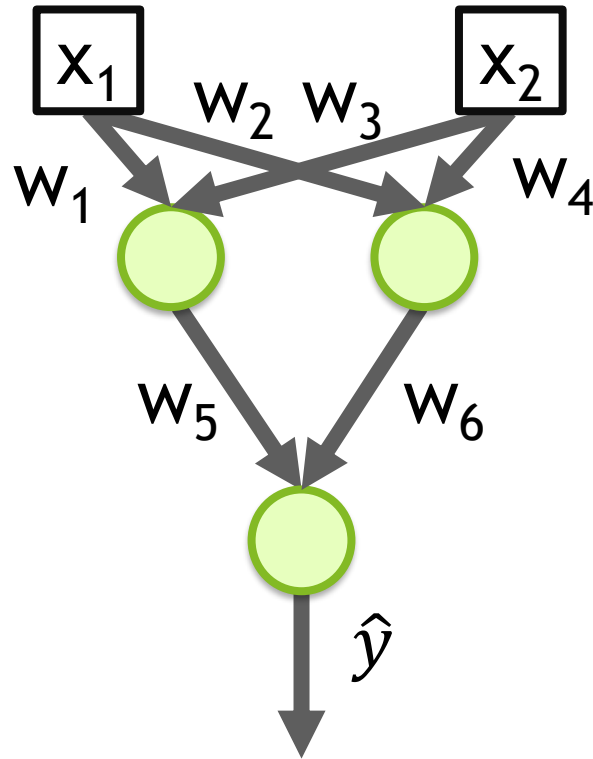
FROM NEURON TO NETWORK

BUILDING A NETWORK



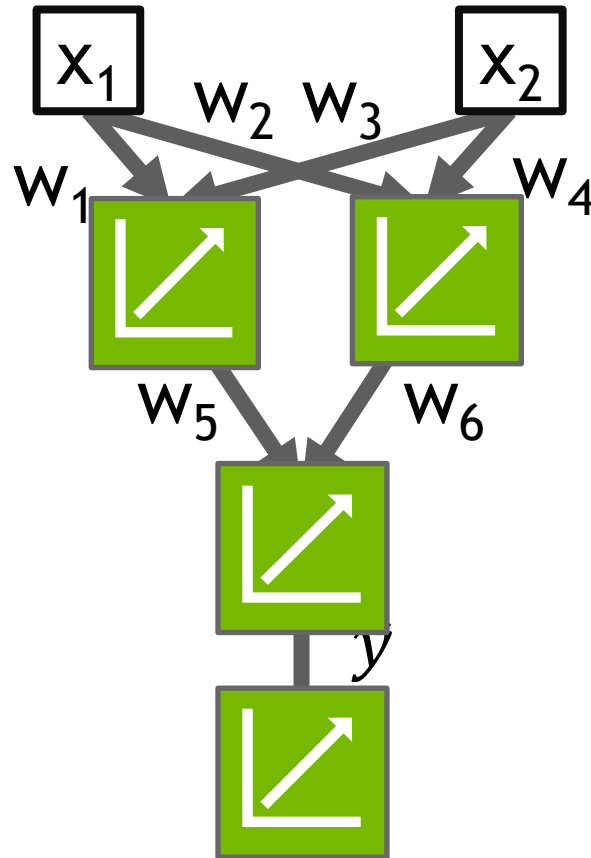
- Scales to more inputs

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



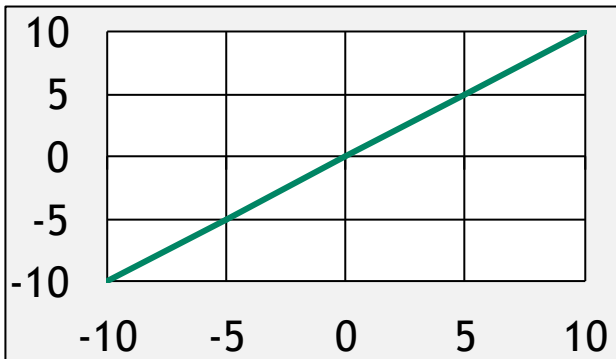
ACTIVATION FUNCTIONS

ACTIVATION FUNCTIONS

Linear

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

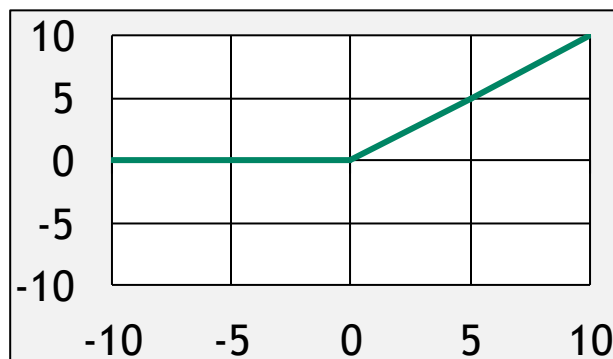
```
1 # Multiply each input
2 # with a weight (w) and
3 # add intercept (b)
4 y_hat = wx+b
```



ReLU

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

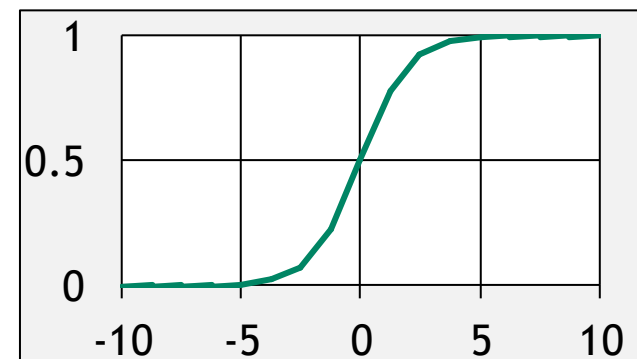
```
1 # Only return result
2 # if total is positive
3 linear = wx+b
4 y_hat = linear * (linear > 0)
```



Sigmoid

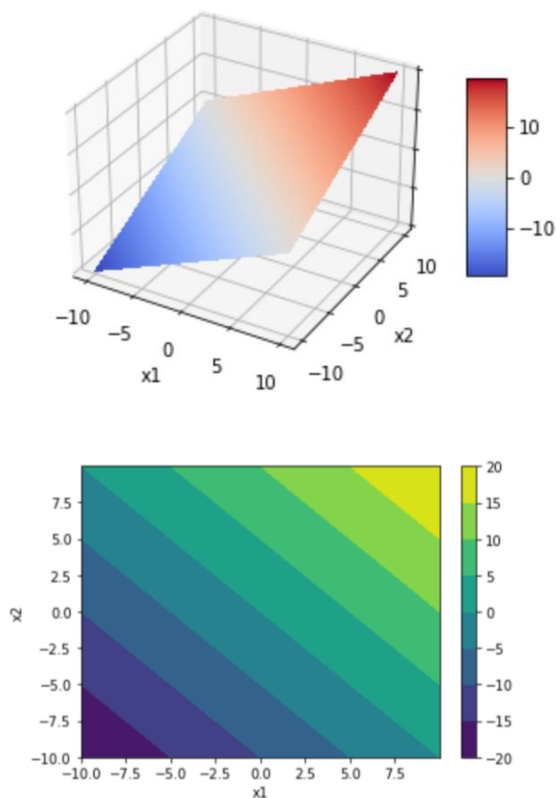
$$\hat{y} = \frac{1}{1 + e^{-(wx+b)}}$$

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

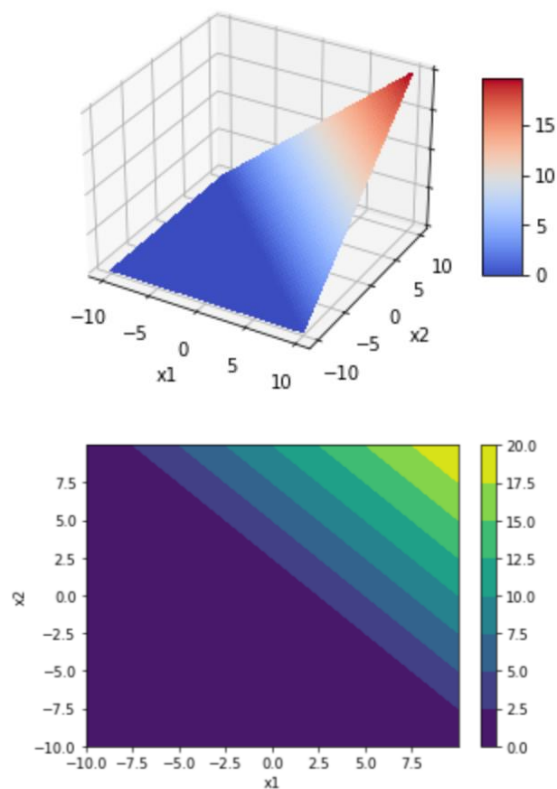


ACTIVATION FUNCTIONS

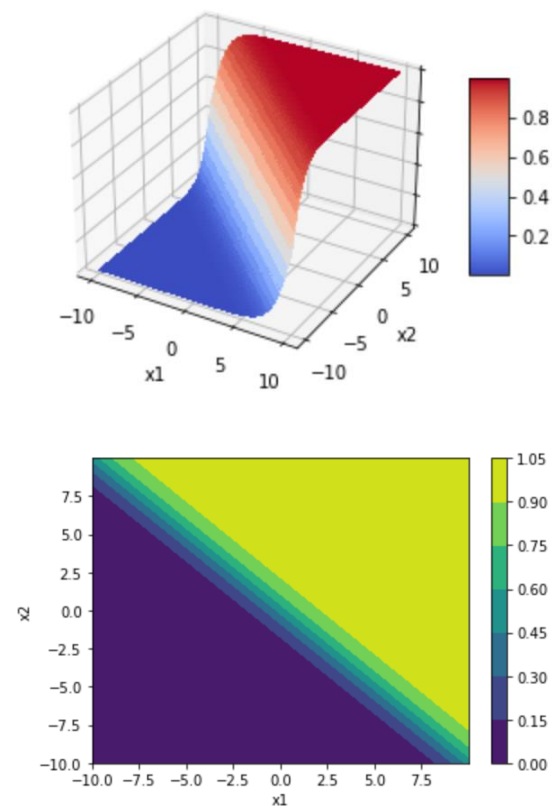
Linear



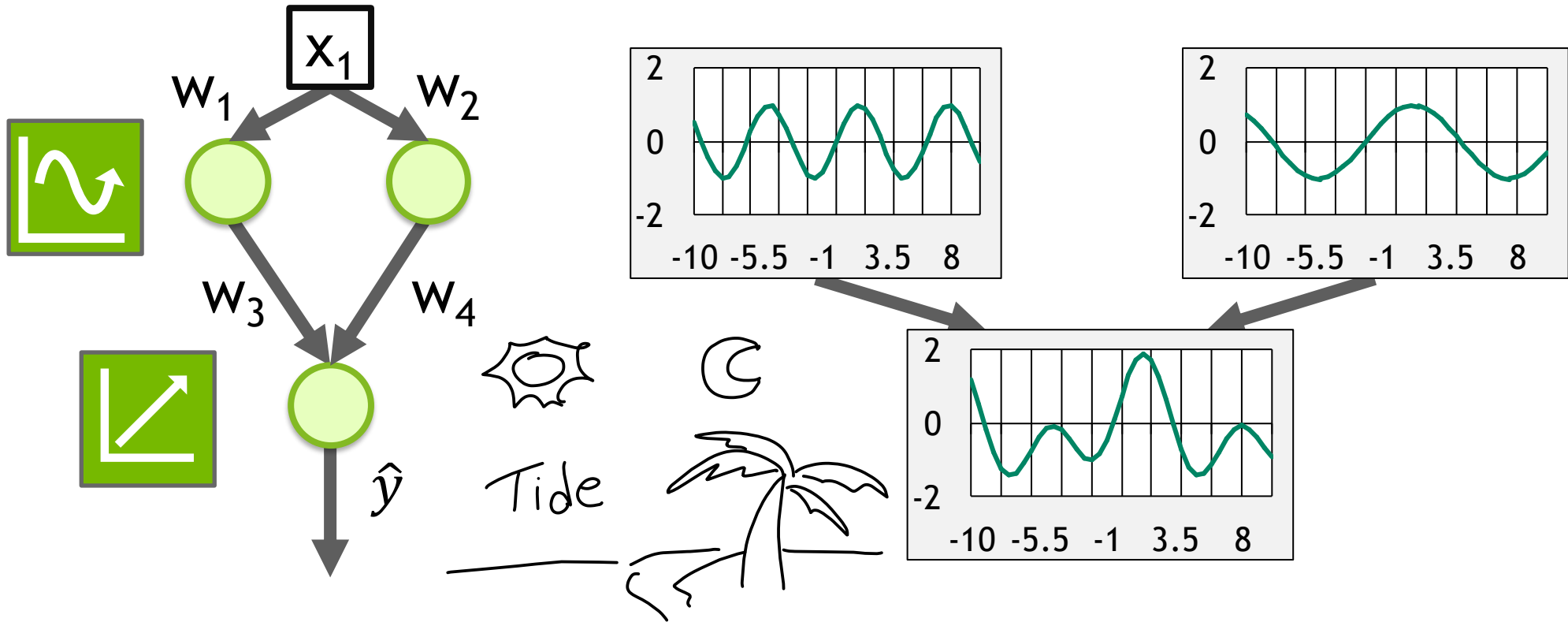
ReLU



Sigmoid



ACTIVATION FUNCTIONS





OVERFITTING

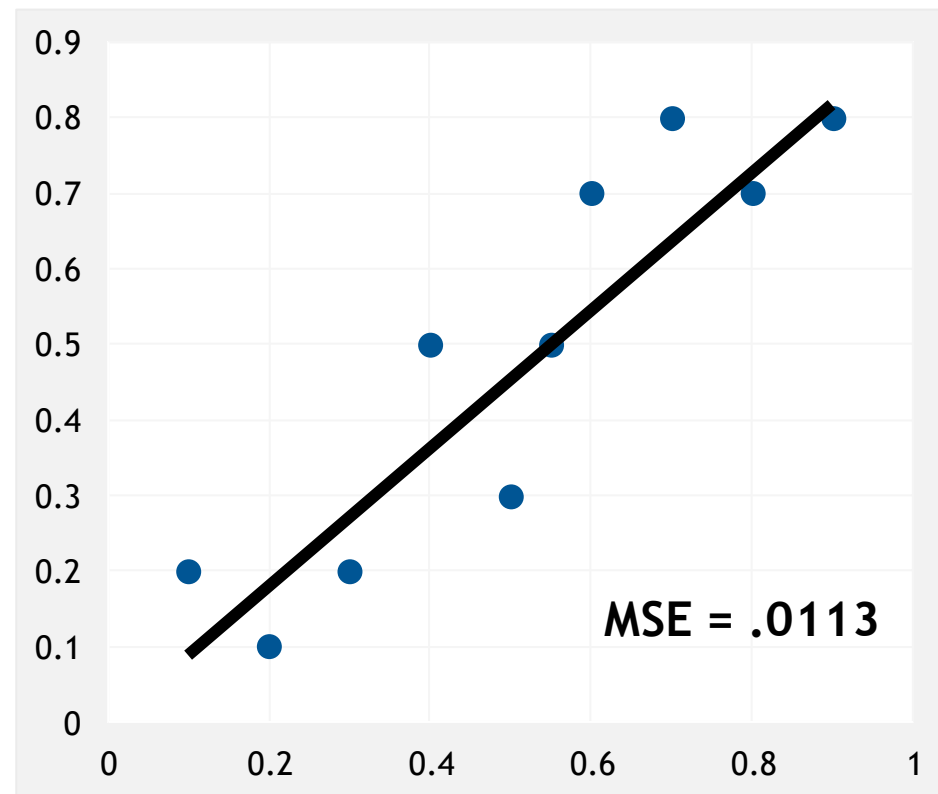
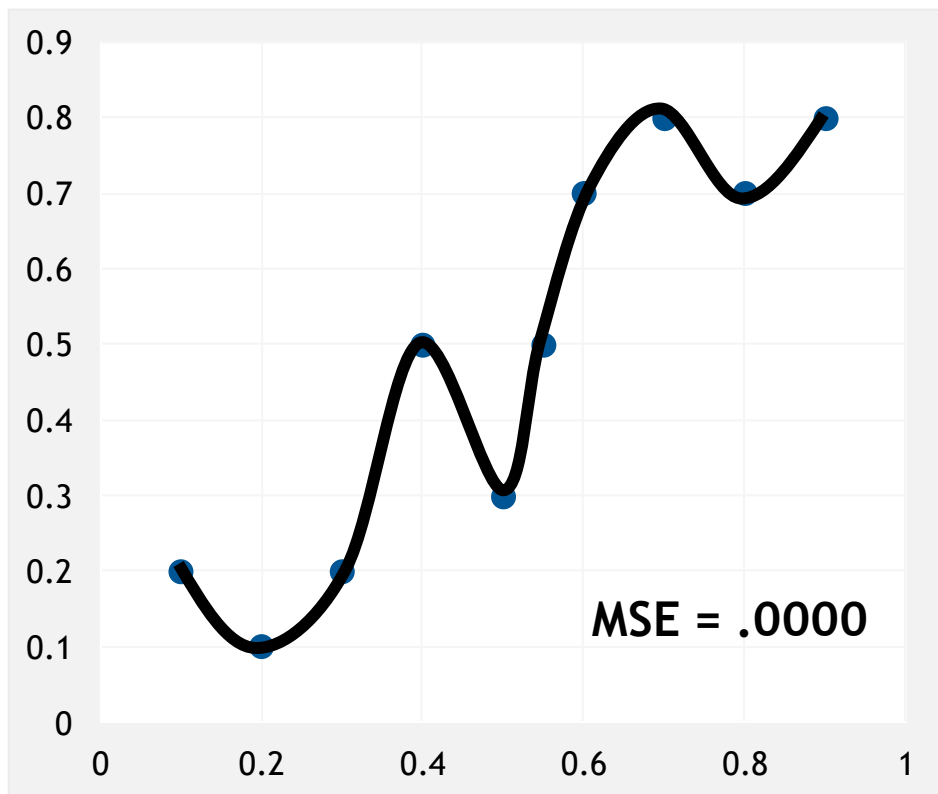
OVERFITTING

Why not have a super large neural network?



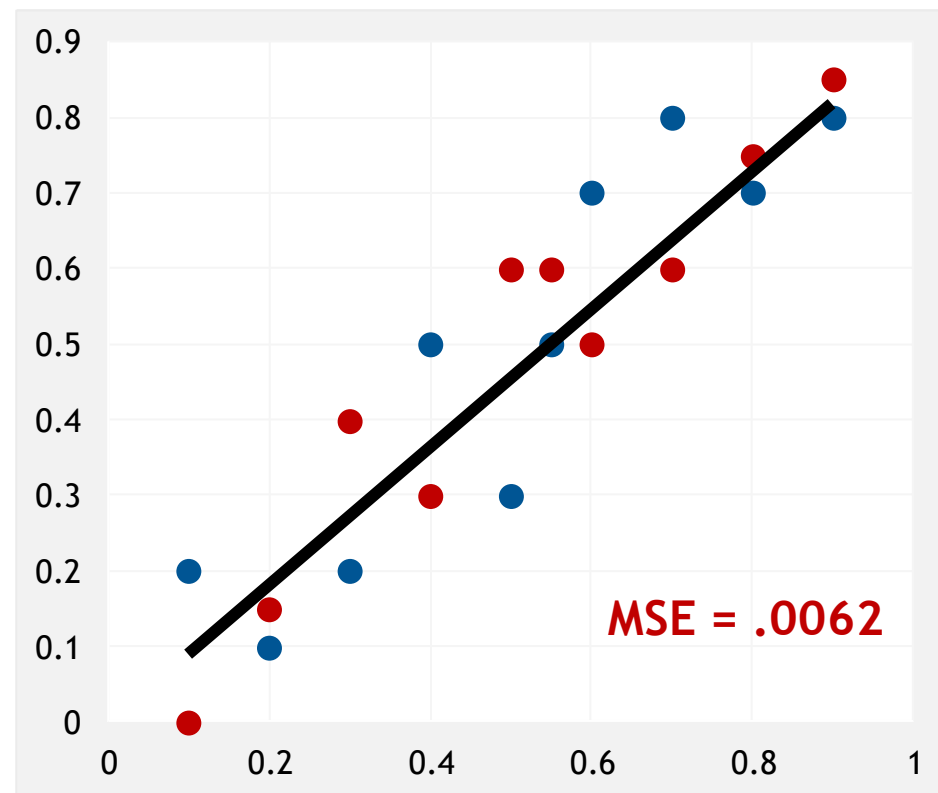
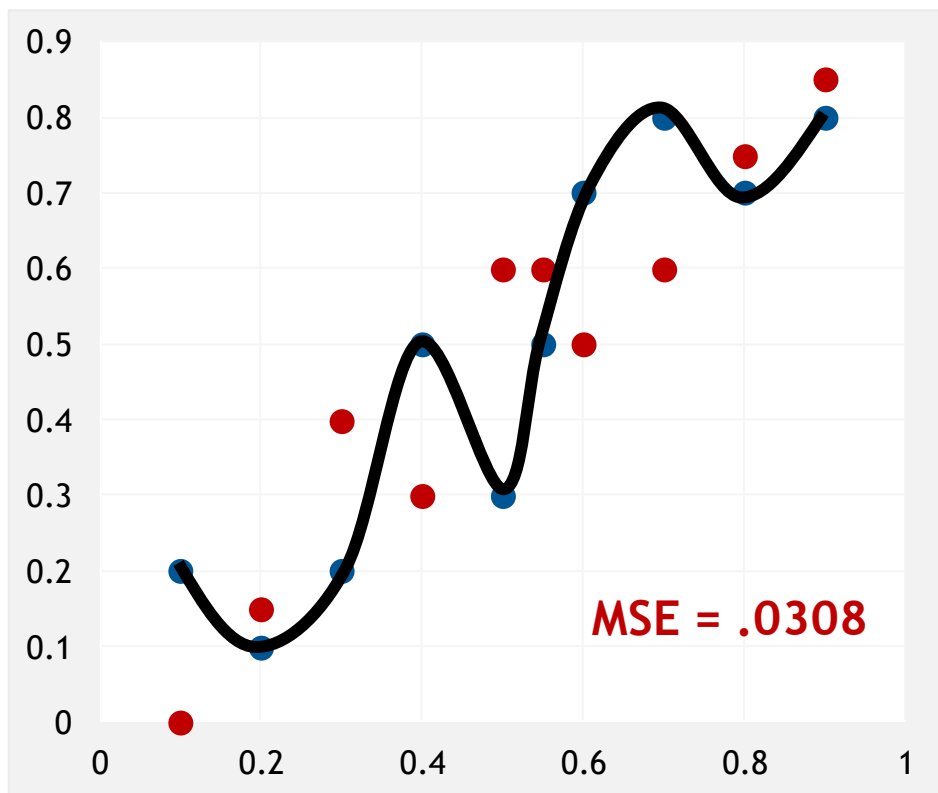
OVERFITTING

Which Trendline is Better?



OVERFITTING

Which Trendline is Better?



TRAINING VS VALIDATION DATA

Avoid memorization

Training data

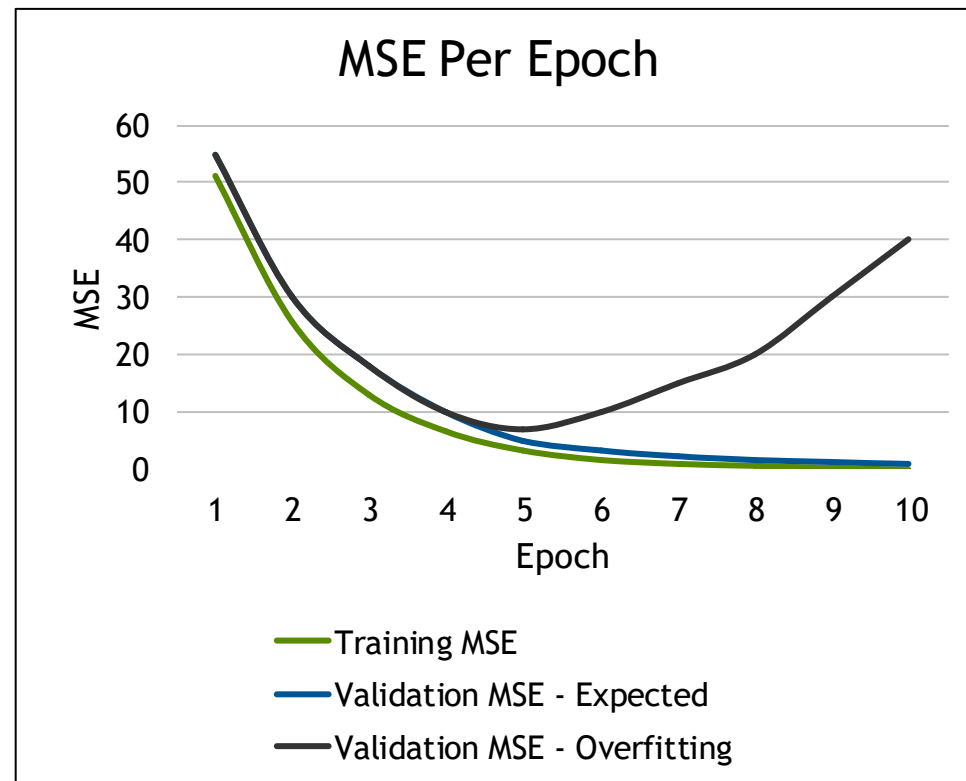
- Core dataset for the model to learn on

Validation data

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

Overfitting

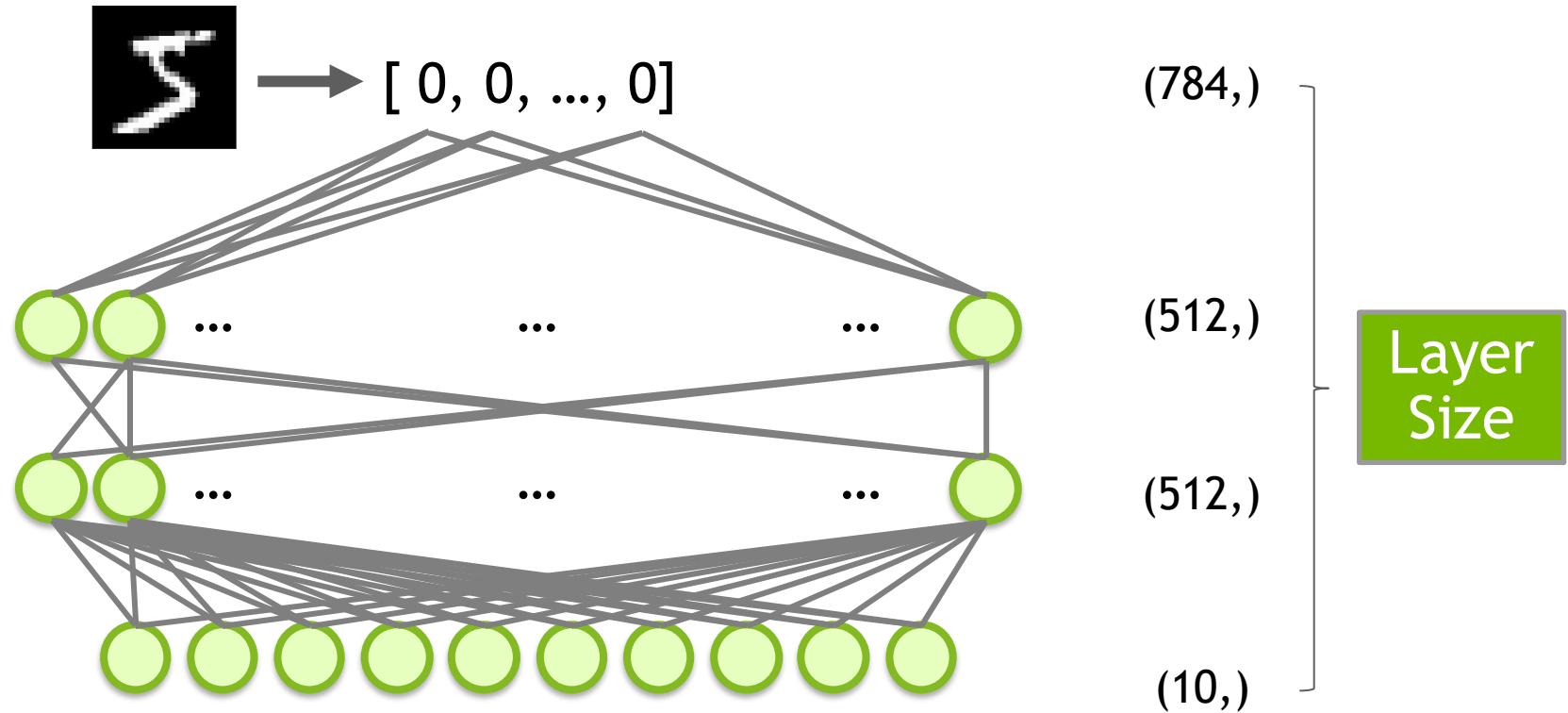
- When model performs well on the training data, but not the validation data (evidence of memorization)
- Ideally the accuracy and loss should be similar between both datasets



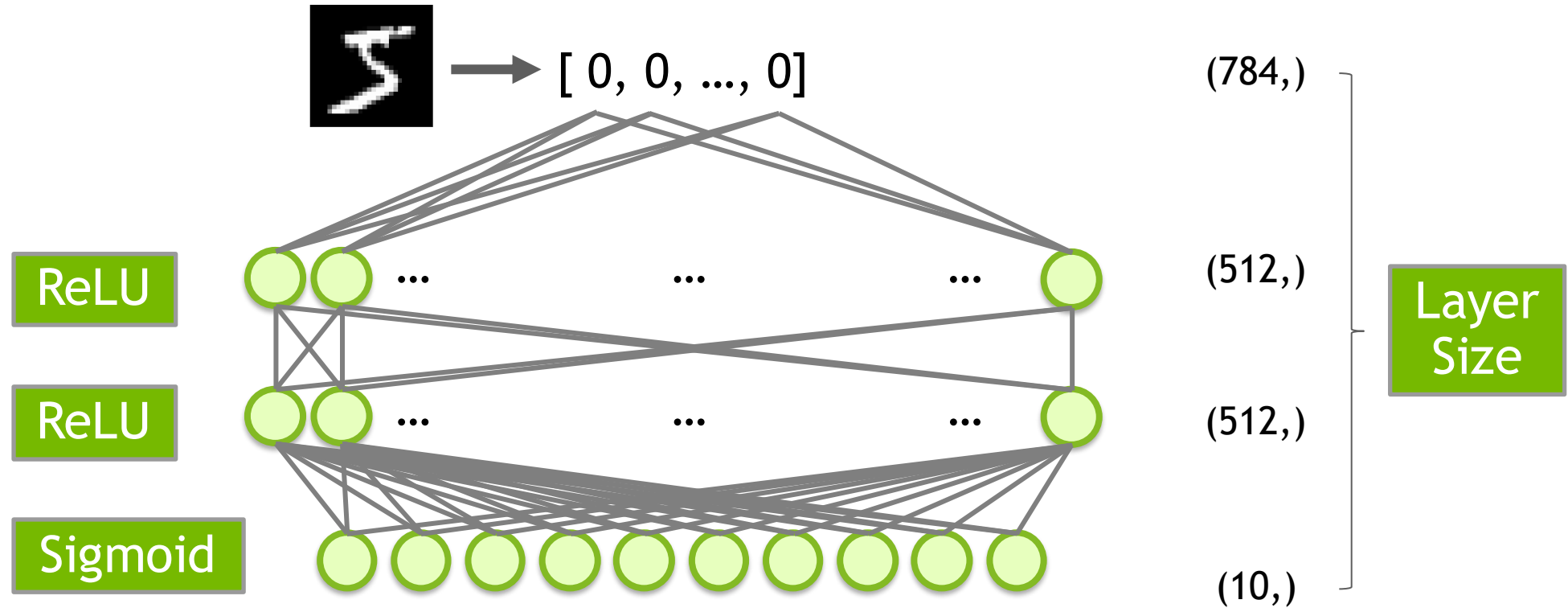


FROM REGRESSION TO CLASSIFICATION

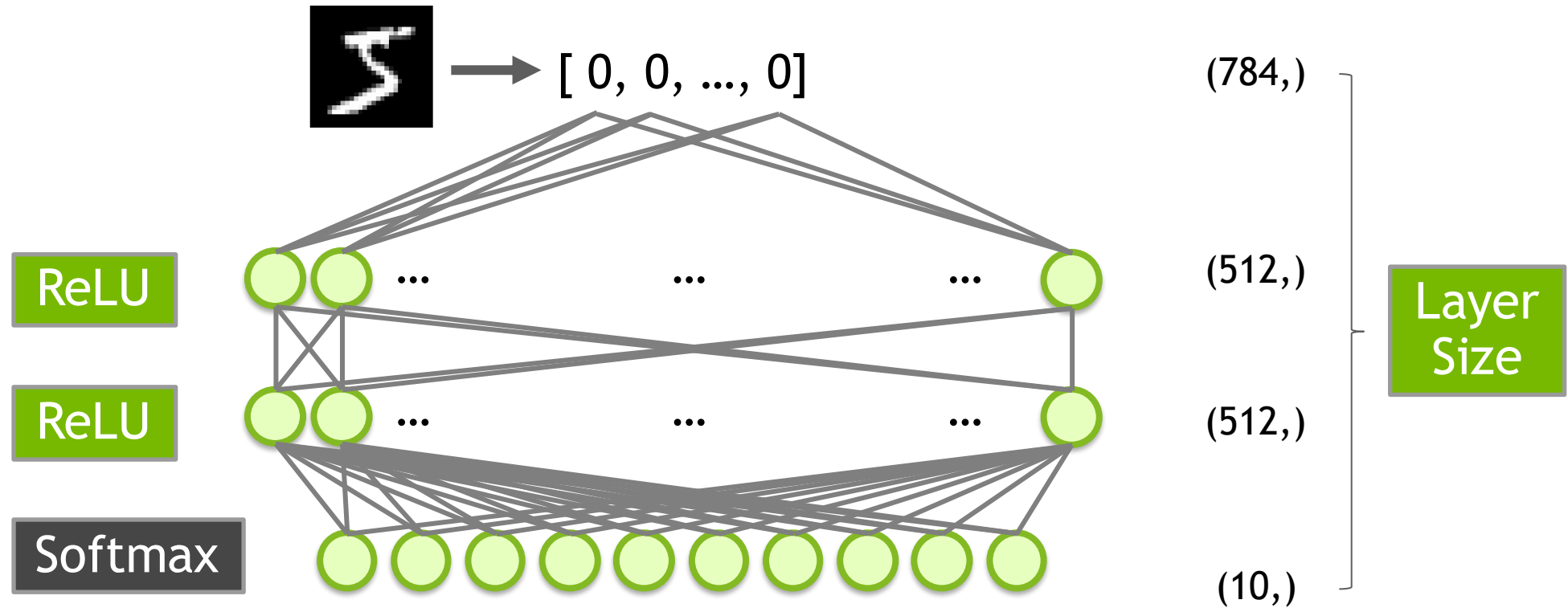
AN MNIST MODEL



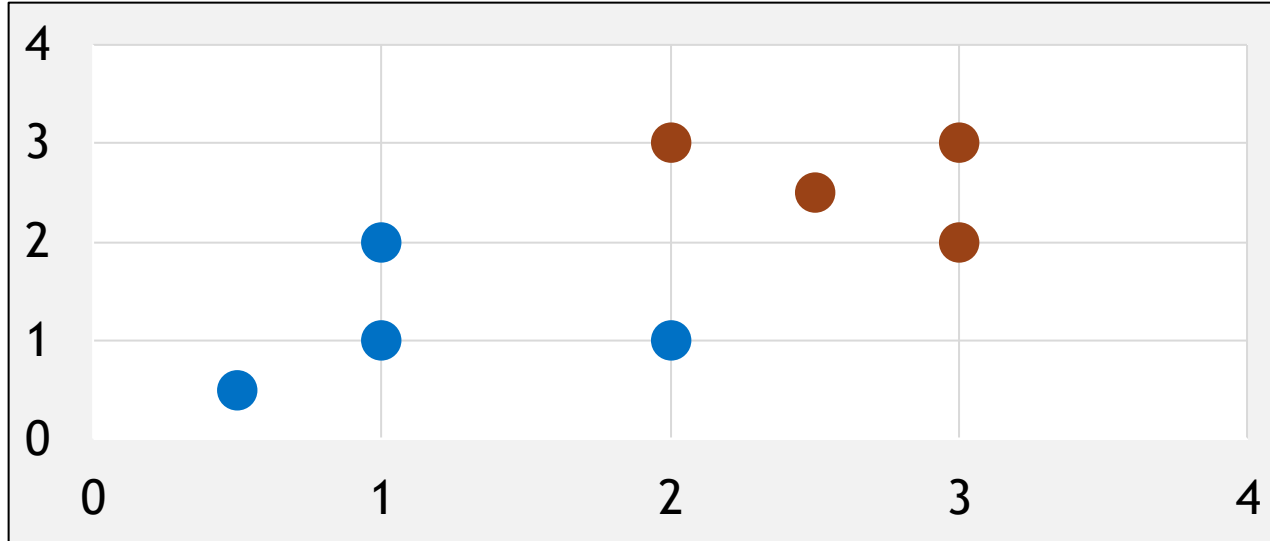
AN MNIST MODEL



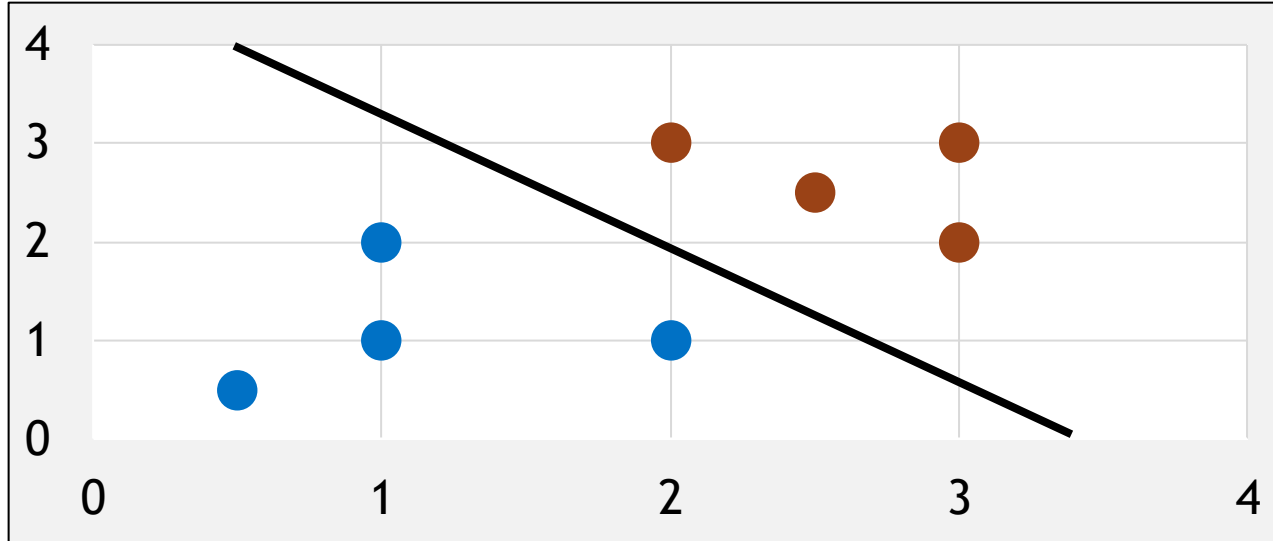
AN MNIST MODEL



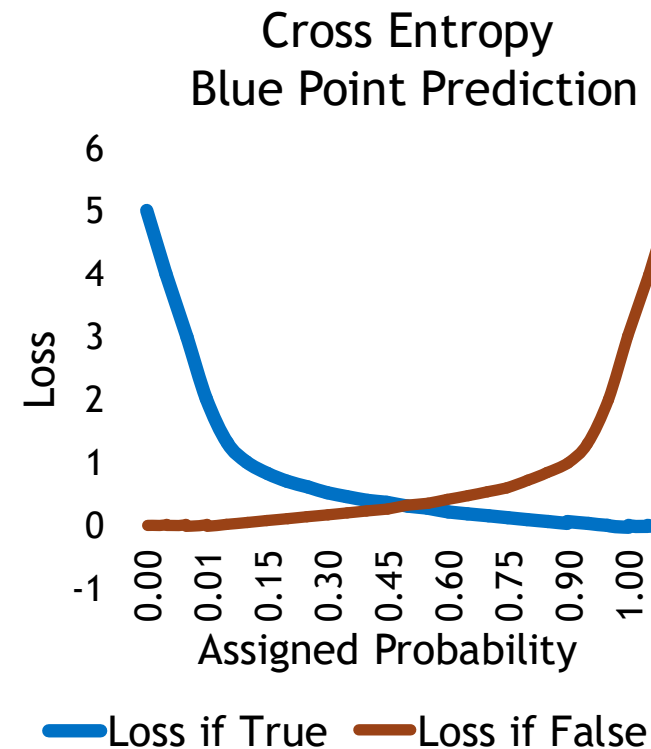
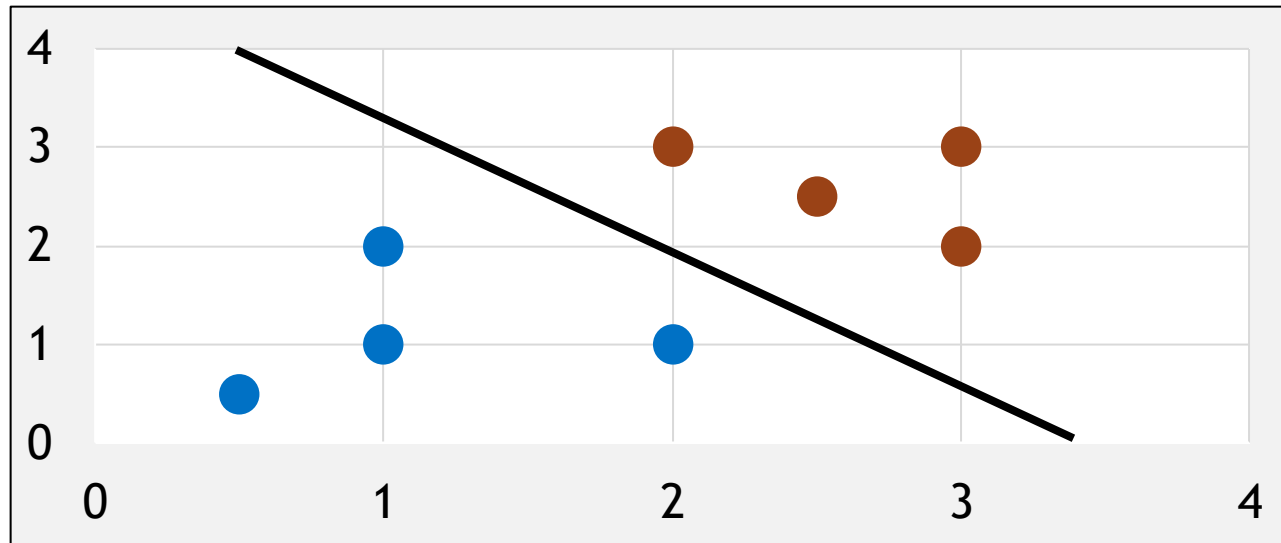
RMSE FOR PROBABILITIES?



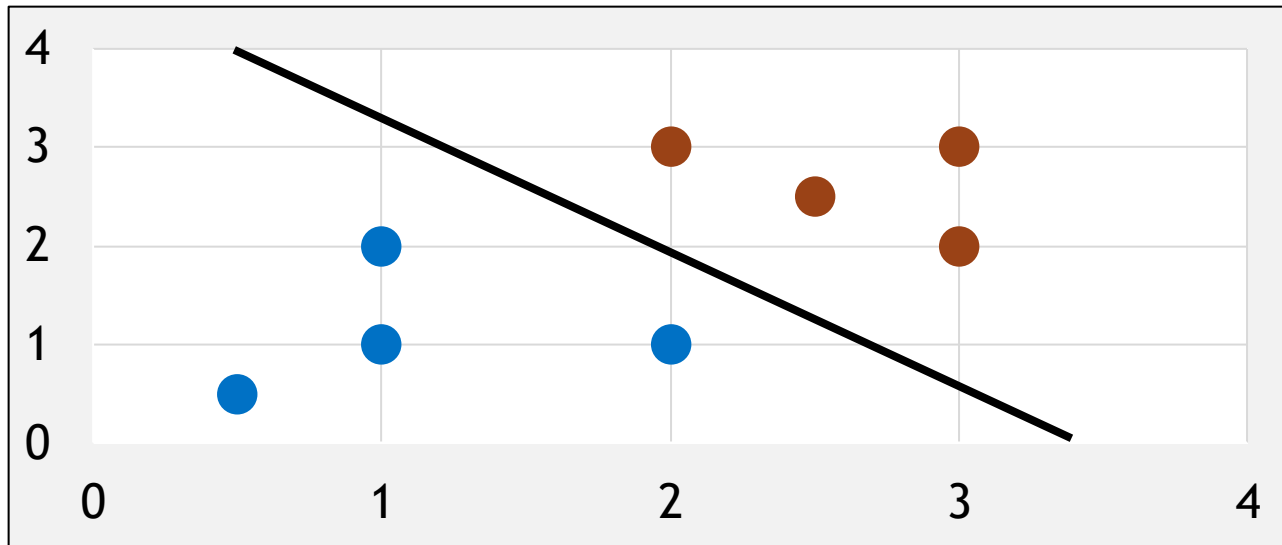
RMSE FOR PROBABILITIES?



CROSS ENTROPY



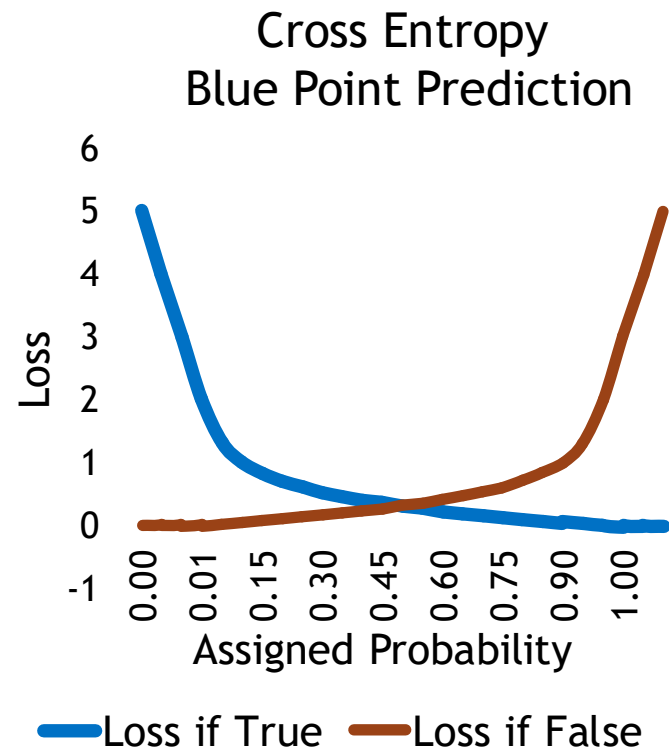
CROSS ENTROPY



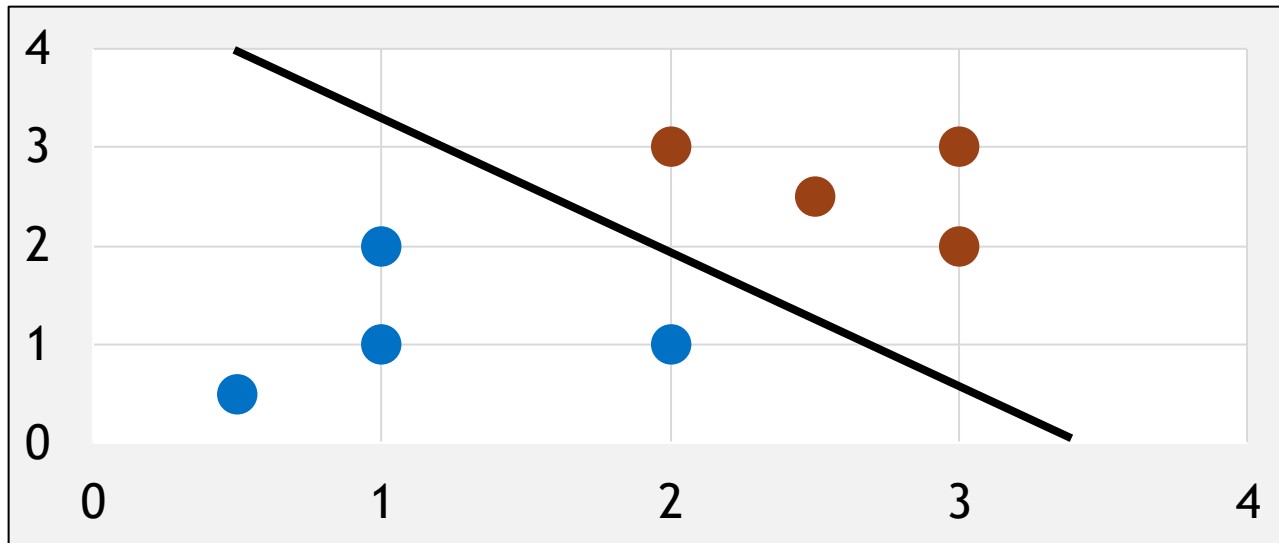
$$Loss = -((t(x) \cdot \log(p(x))) + (1 - t(x)) \cdot \log(1 - p(x)))$$

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

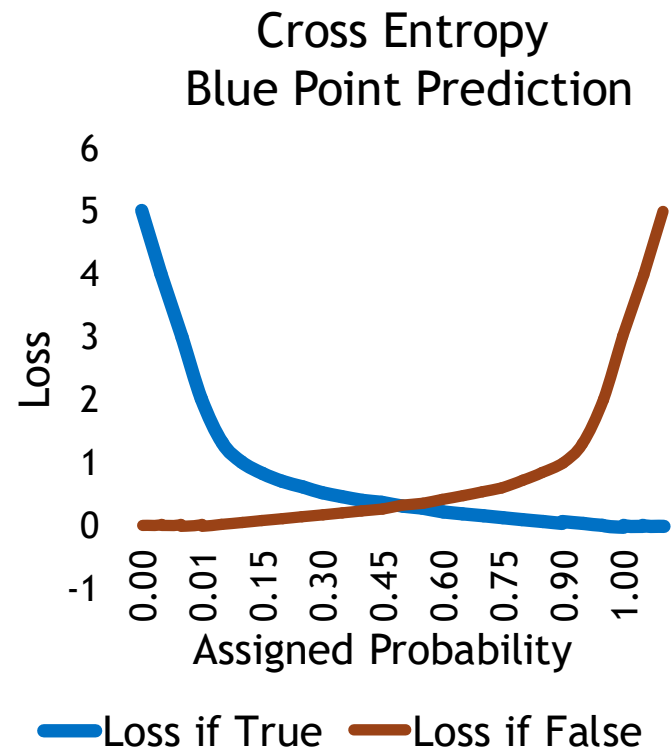
$p(x)$ = probability prediction of point x



CROSS ENTROPY



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

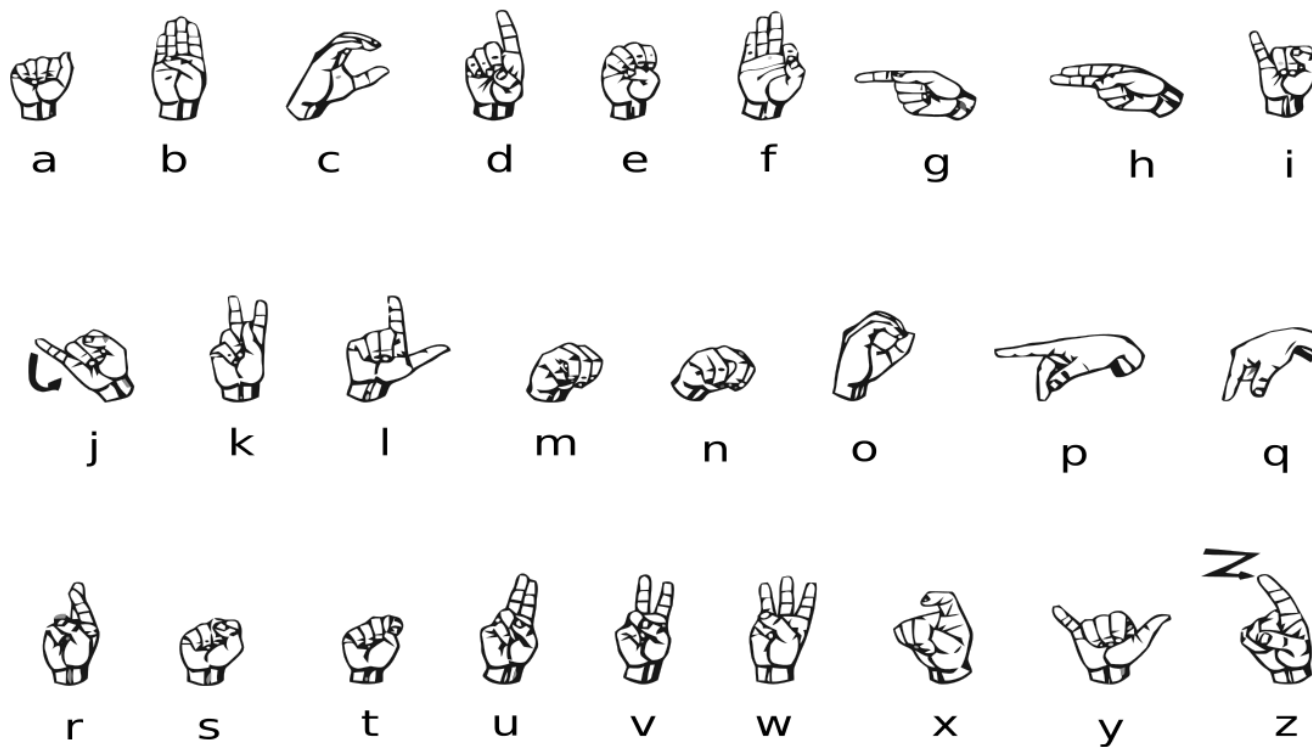




BRINGING IT TOGETHER

THE NEXT EXERCISE

The American Sign Language Alphabet





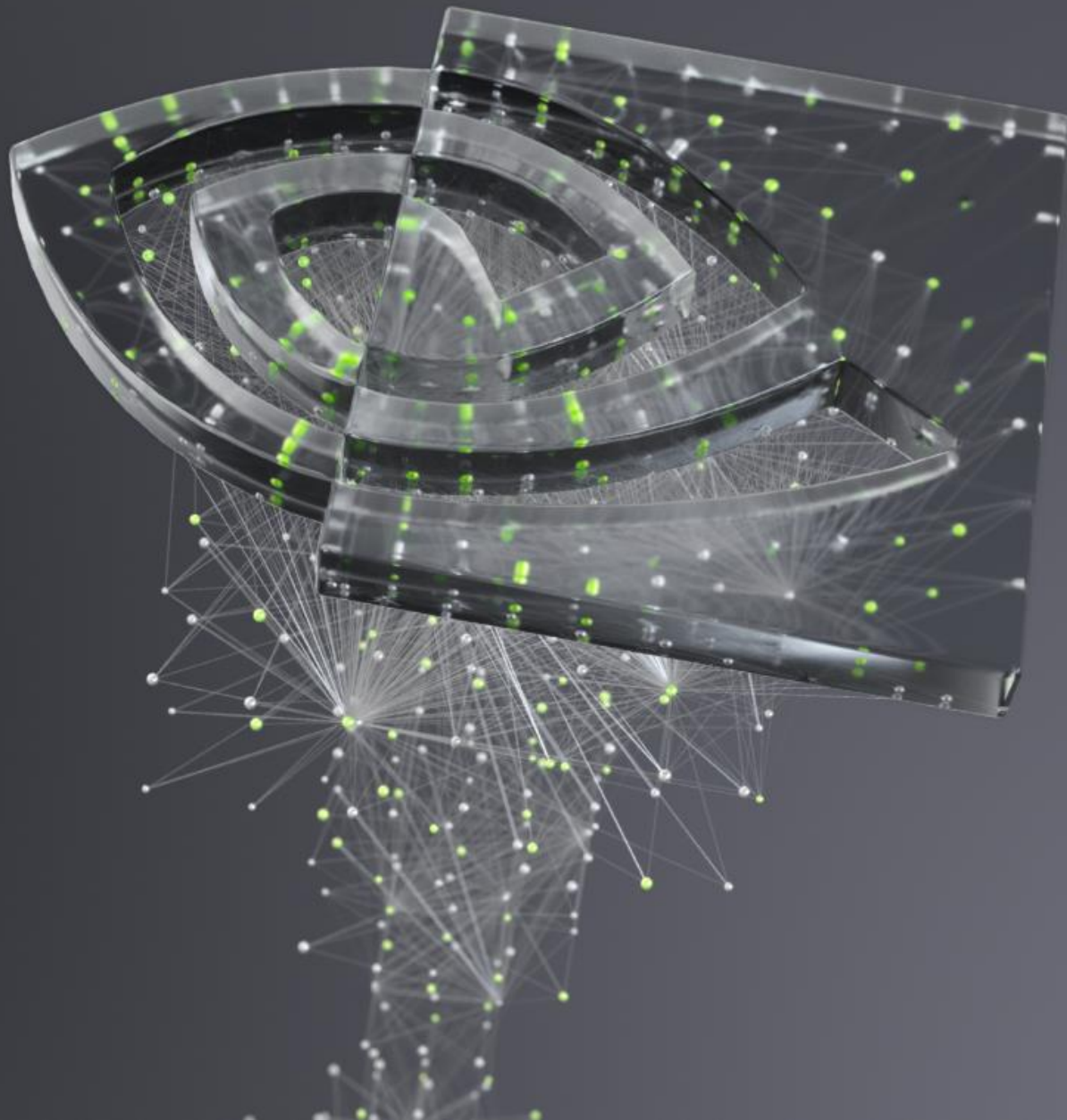
LET'S GO!



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APPENDIX: GRADIENT DESCENT

HELPING THE COMPUTER CHEAT CALCULUS



Learning From Error

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

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

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

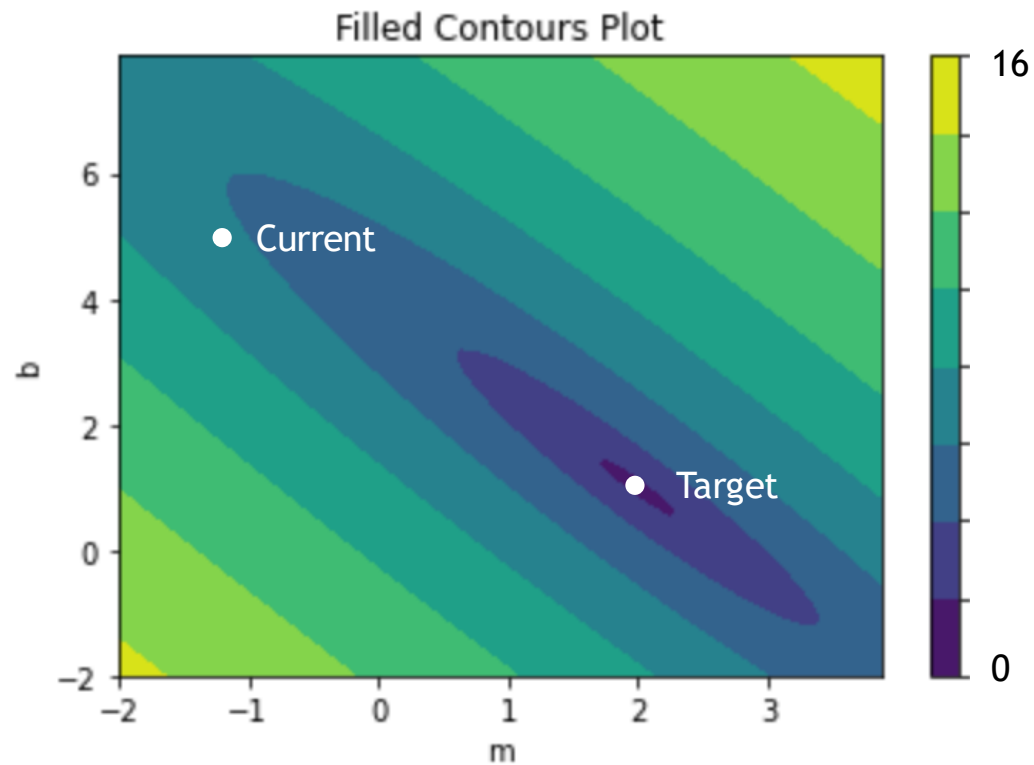
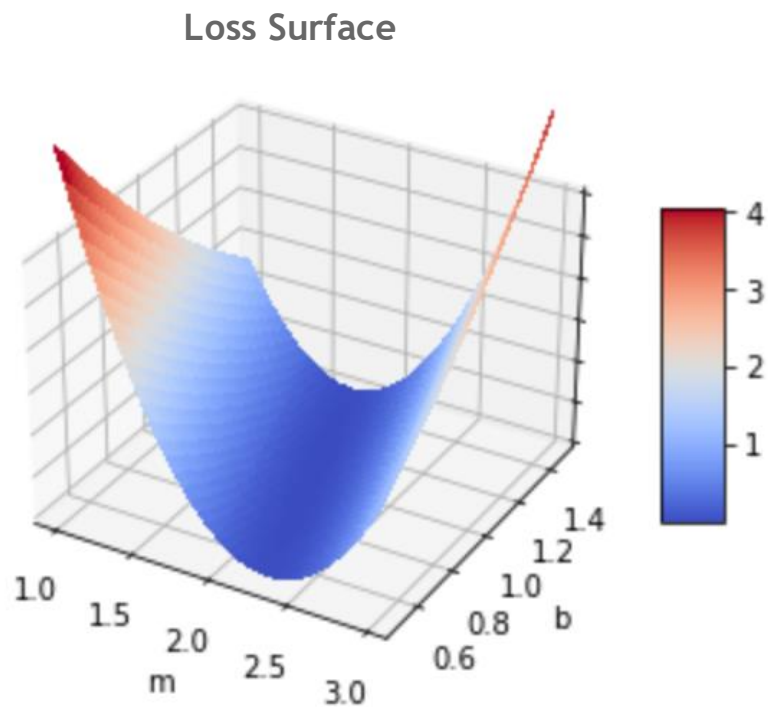
$$\frac{\partial MSE}{\partial b} = 3m + 2b - 8$$

$$\frac{\partial MSE}{\partial m} = -3$$

$$\frac{\partial MSE}{\partial b} = -1$$

$$m = -1$$
$$b = 5$$

THE LOSS CURVE



THE LOSS CURVE

$$\frac{\partial MSE}{\partial m} = -7$$

$$\frac{\partial MSE}{\partial b} = -3$$

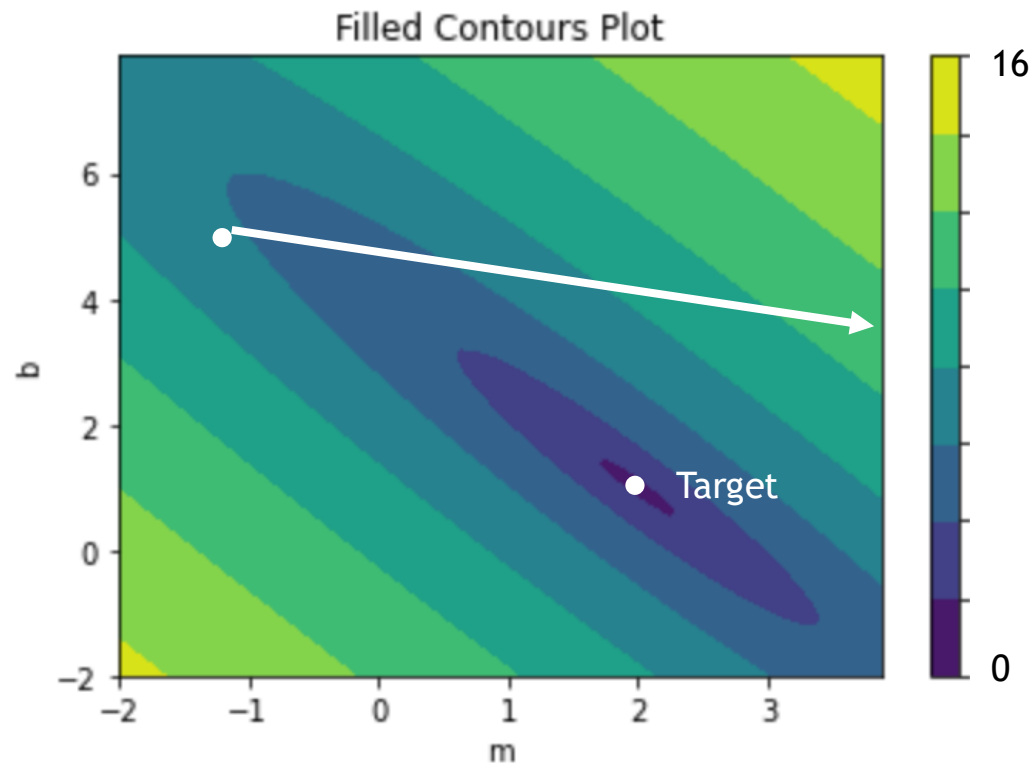


THE LOSS CURVE

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

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

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

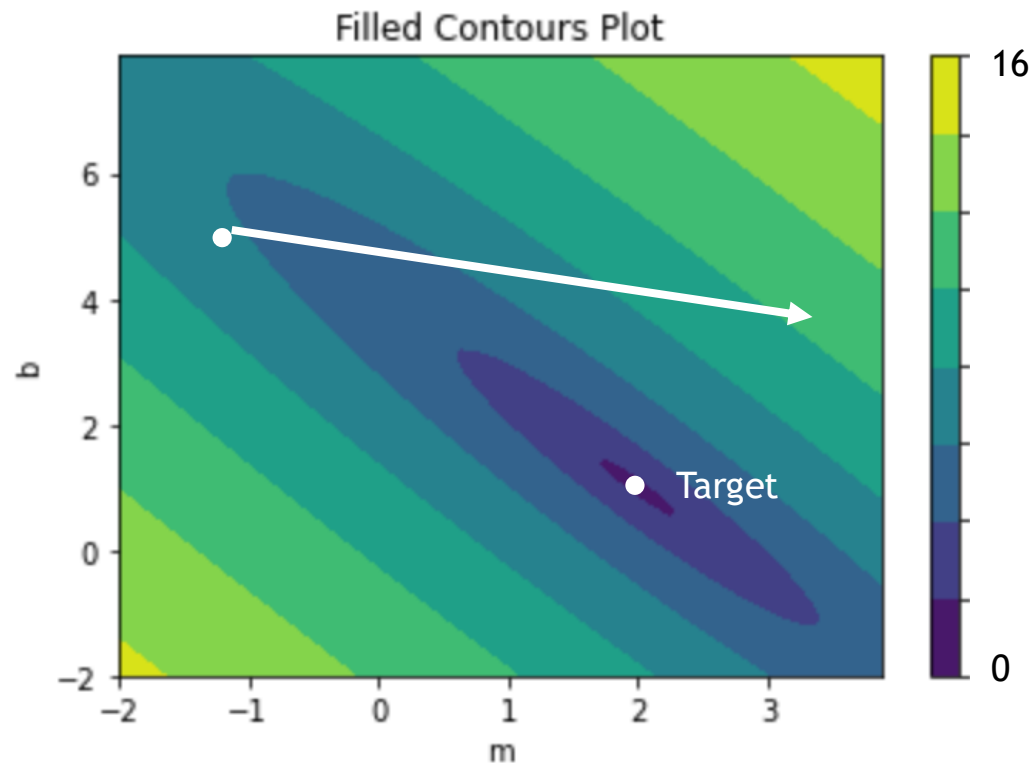


THE LOSS CURVE

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

$$m := m - \lambda \frac{\partial MSE}{\partial m} \quad \lambda = .6$$

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



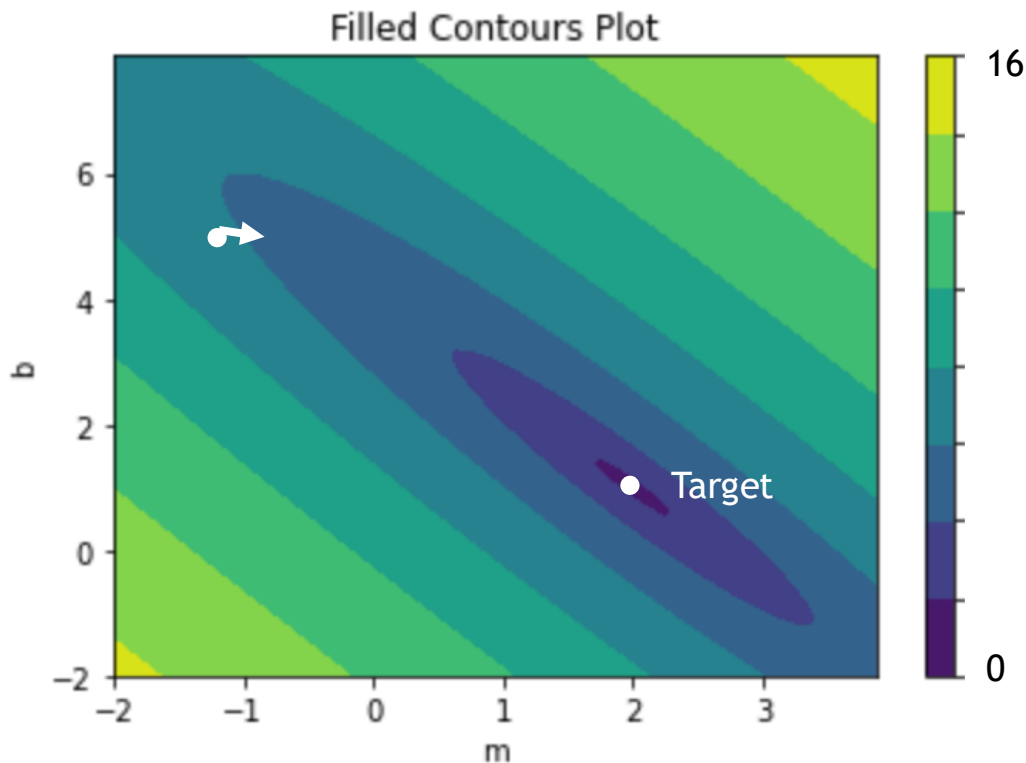
THE LOSS CURVE

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

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

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

$$\lambda = .005$$



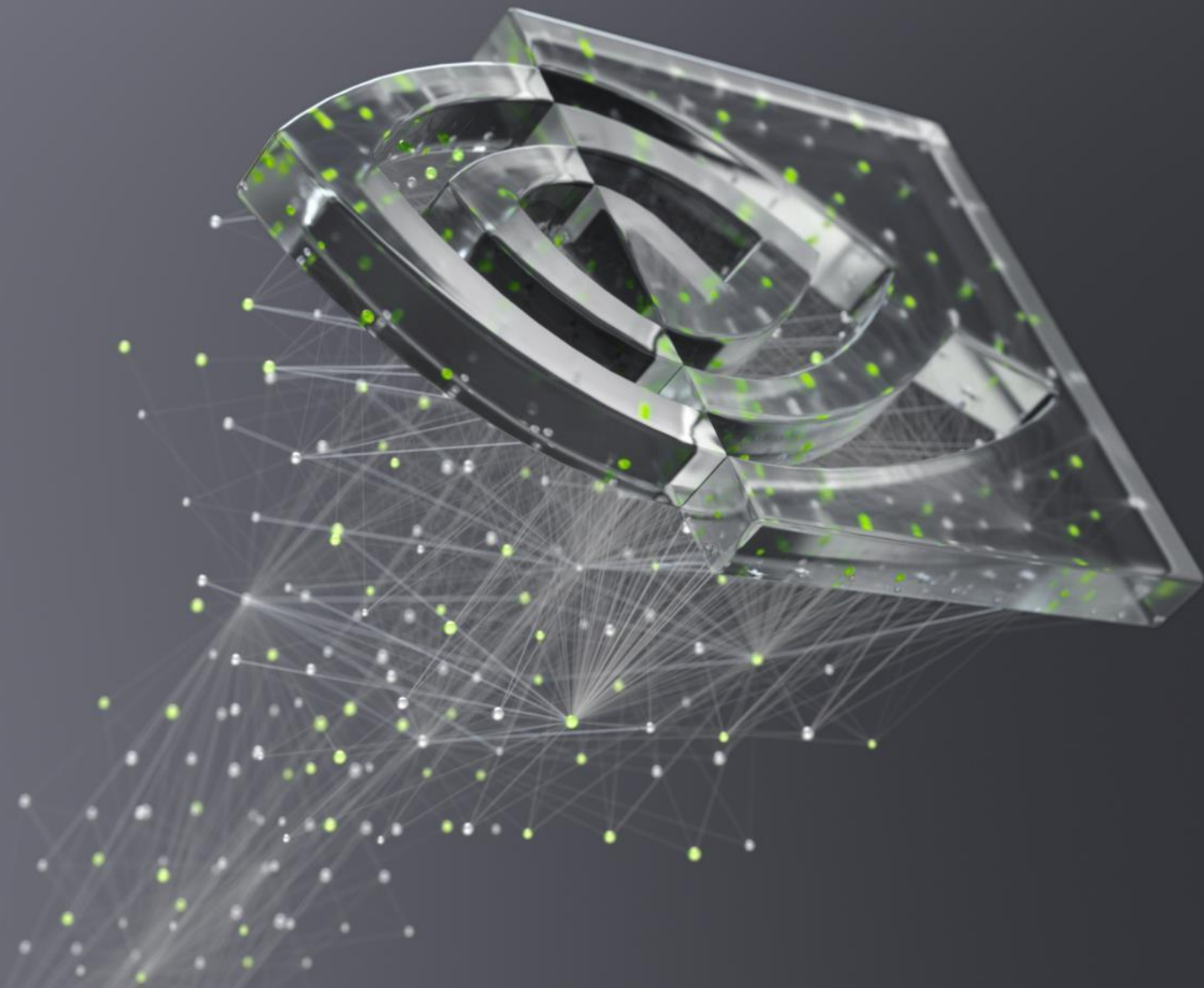
THE LOSS CURVE

$$\lambda = .1$$

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

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





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