

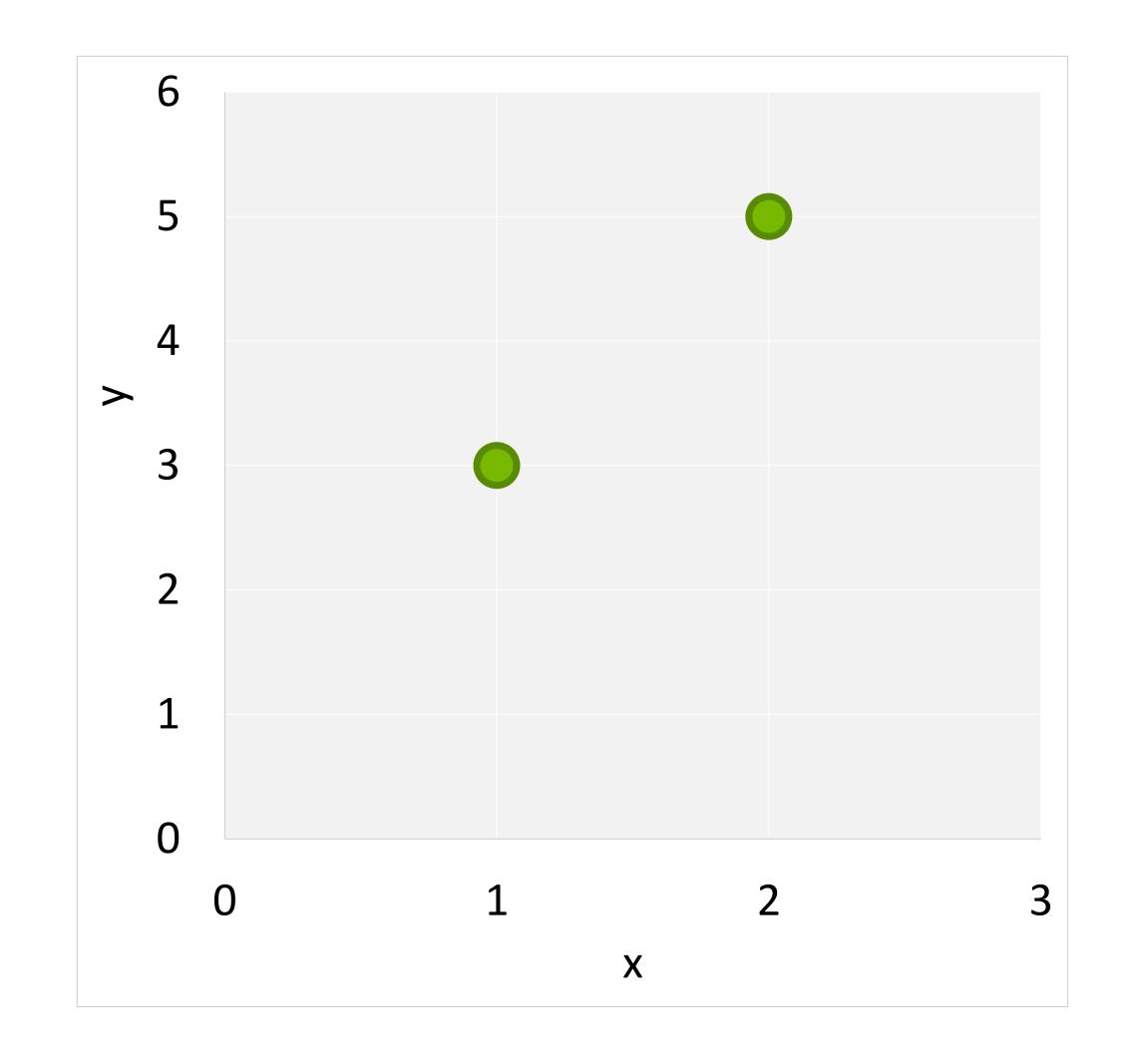
Agenda

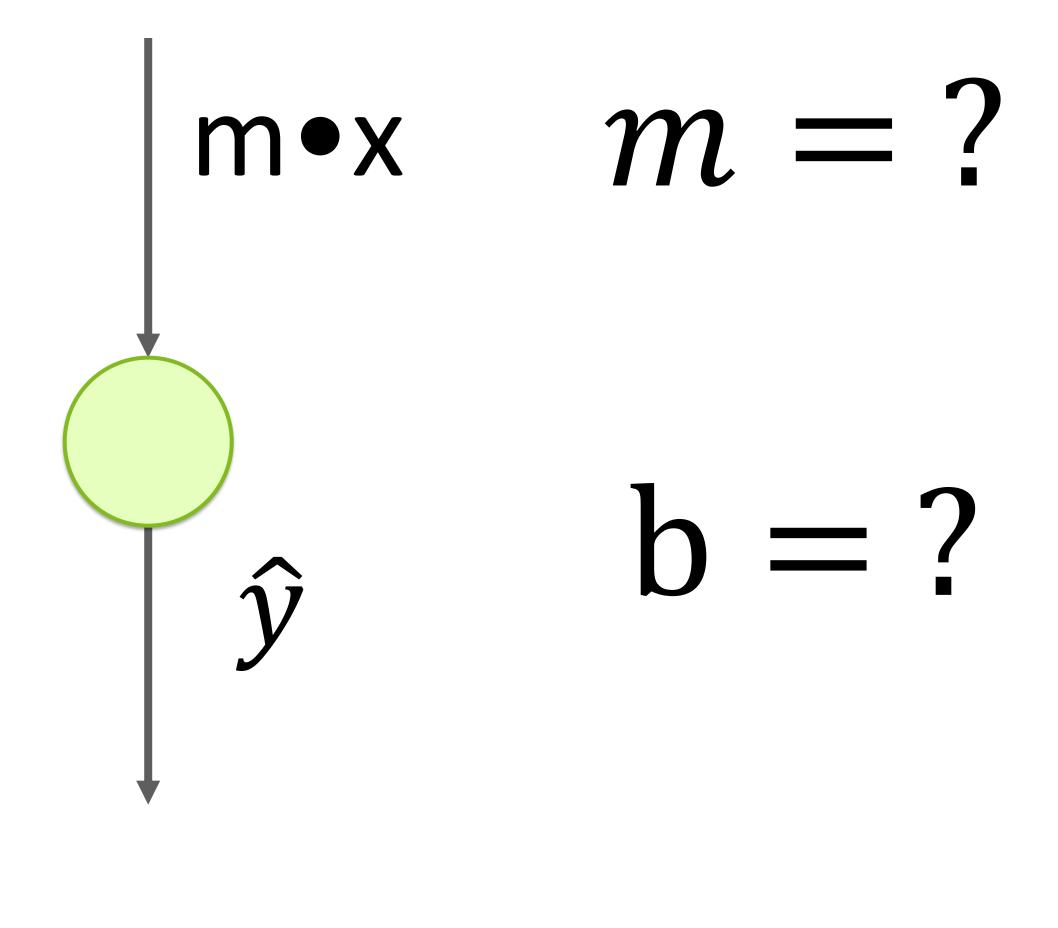
- Part 1: An Introduction to Deep Learning
- Part 2: How a Neural Network Trains
- Part 3: Convolutional Neural Networks
- Part 4: Data Augmentation and Deployment
- Part 5: Pre-Trained Models
- Part 6: Advanced Architectures



$$y = mx + b$$

X	y
1	3
2	5

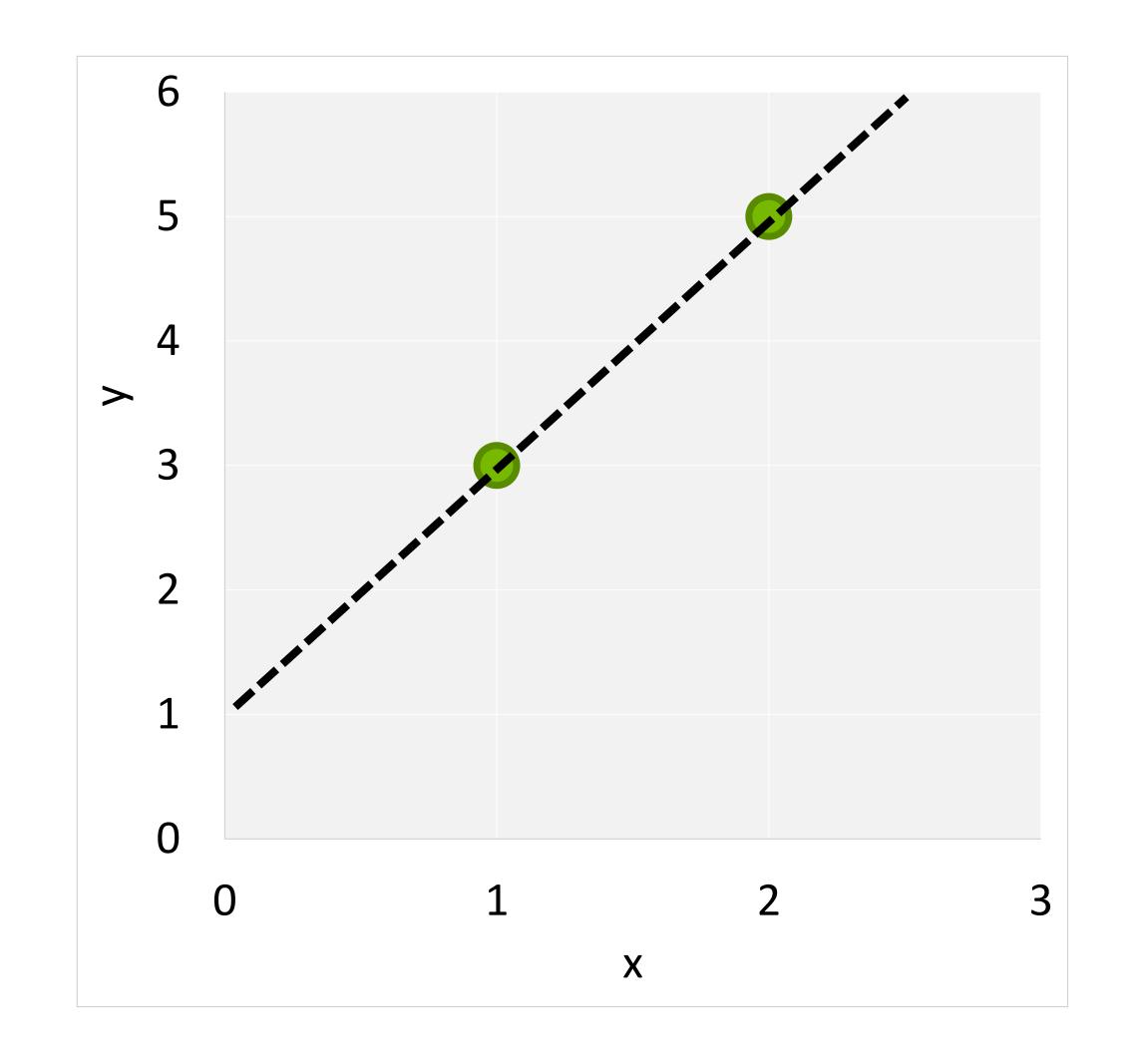


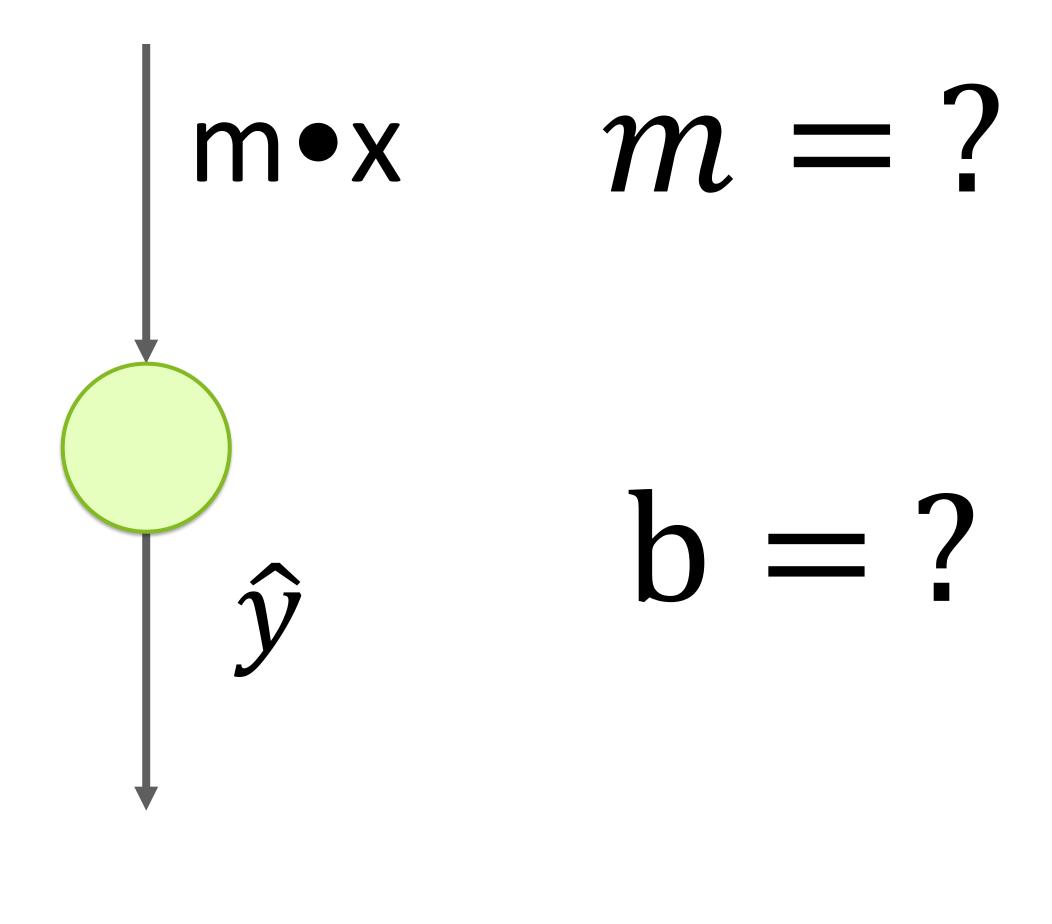




$$y = mx + b$$

X	y
1	3
2	5

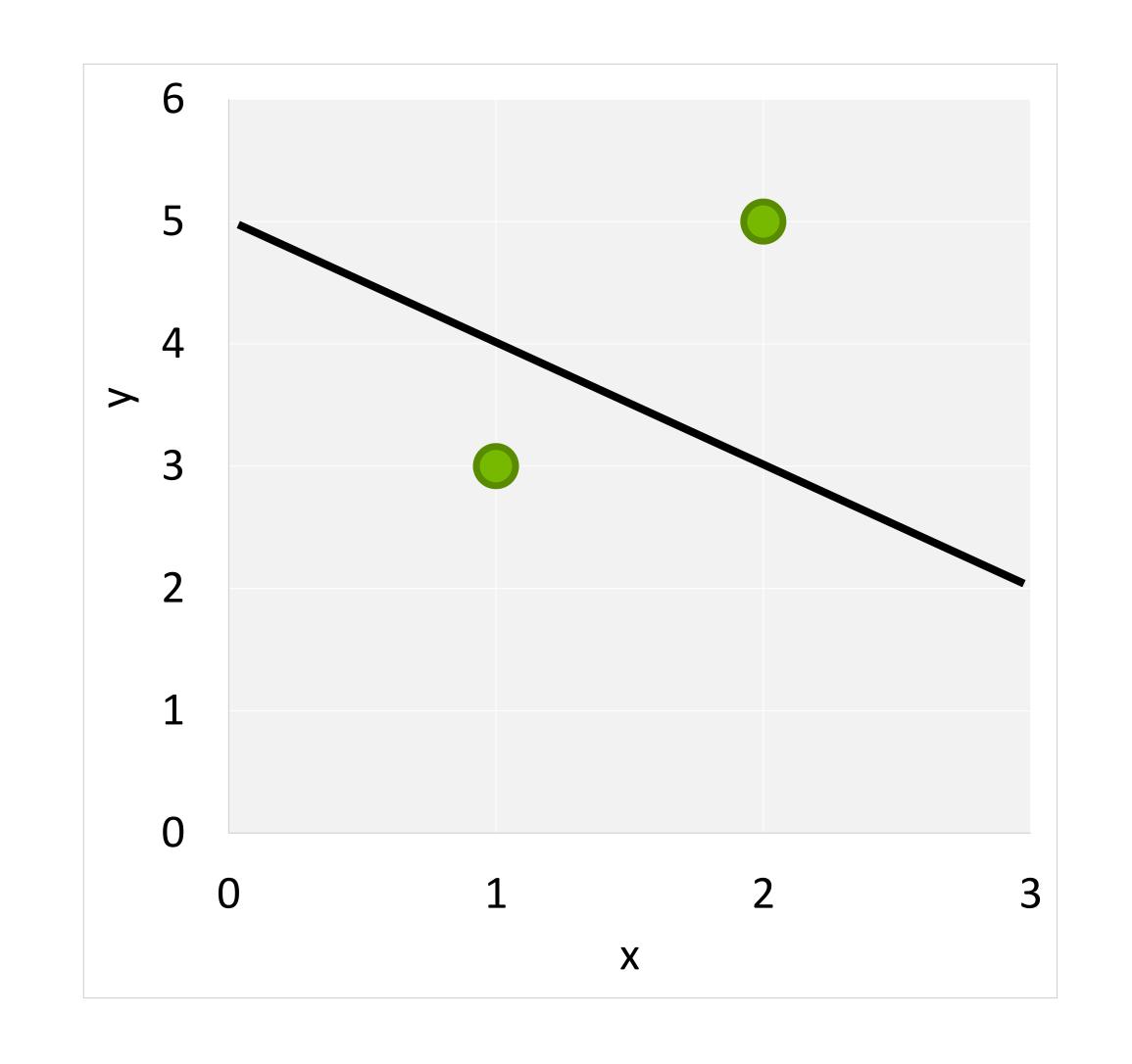


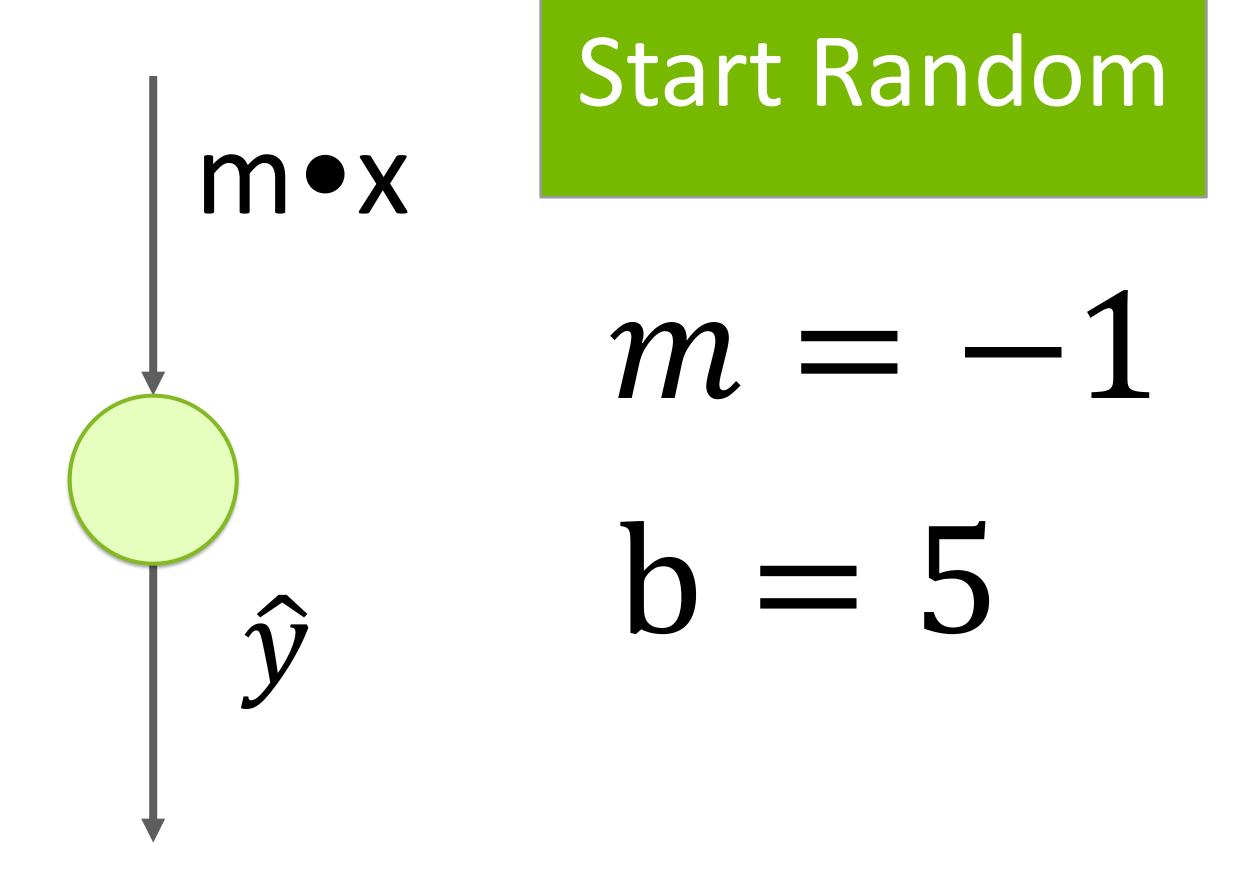




$$y = mx + b$$

X	y	$\widehat{\mathbf{y}}$
1	3	4
2	5	3

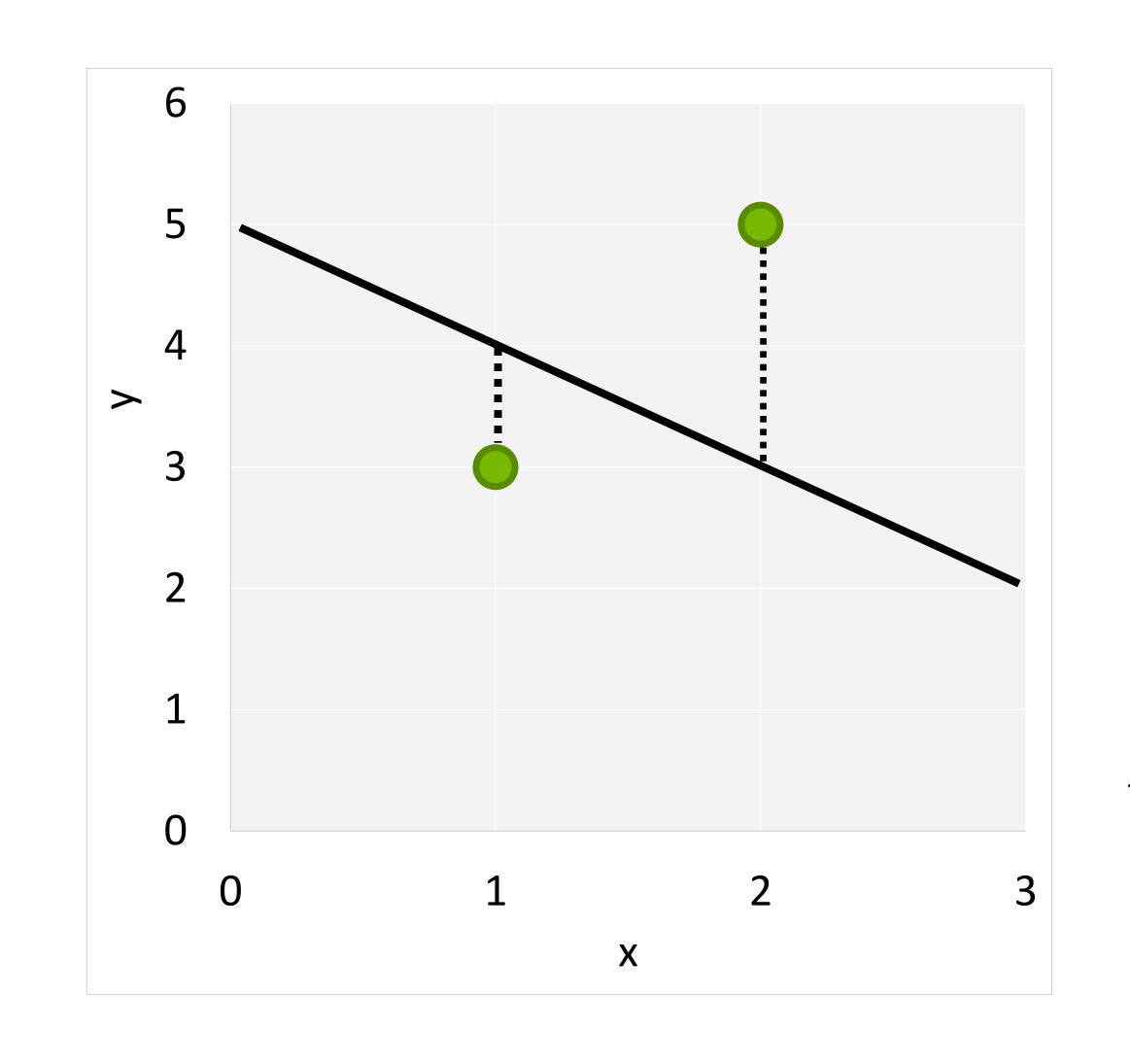






$$y = mx + b$$

X	y	ŷ	err ²
1	3	4	1
2	5	3	4
MSE =		2.5	
	RMSE =		1.6

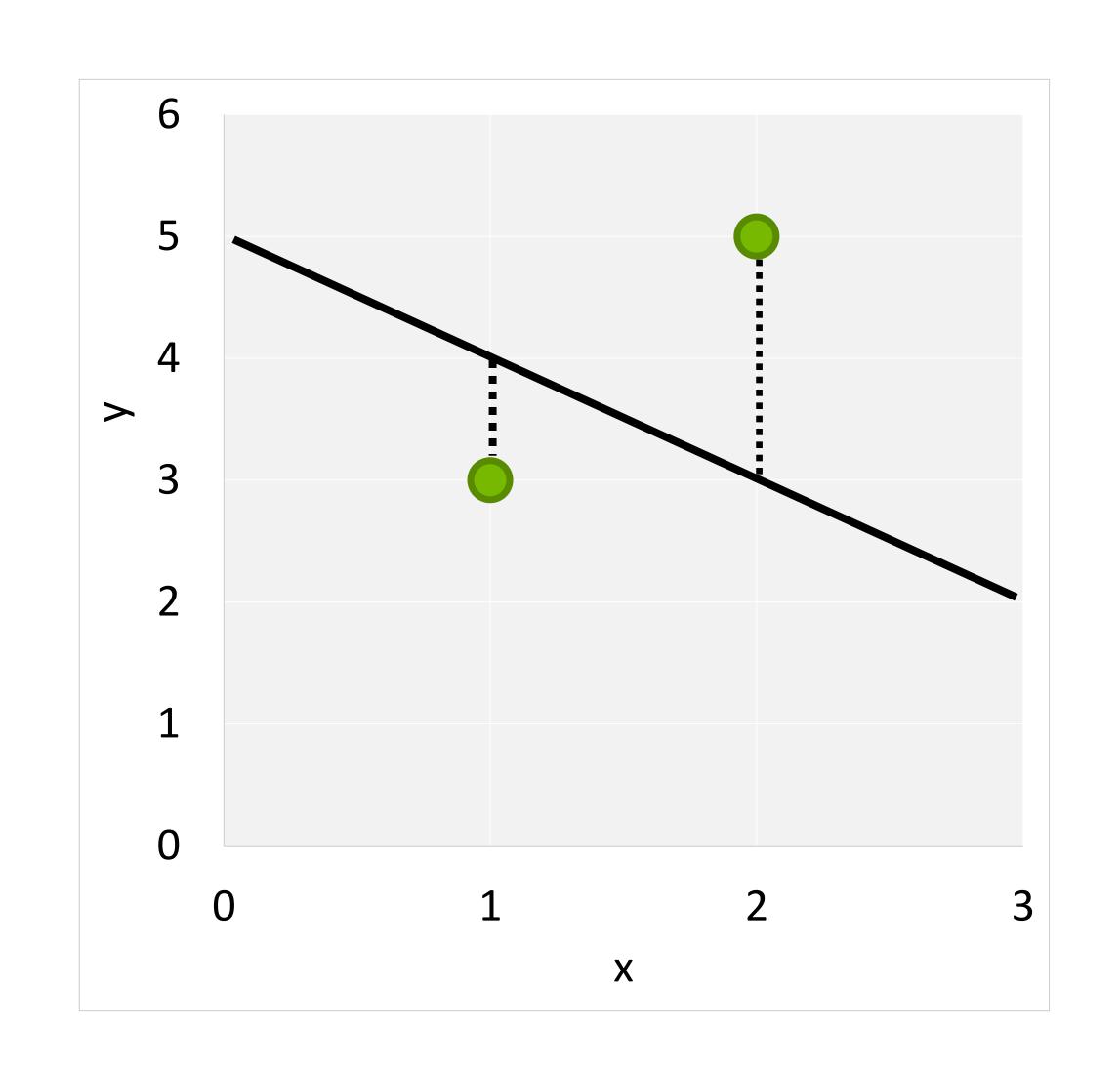


$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

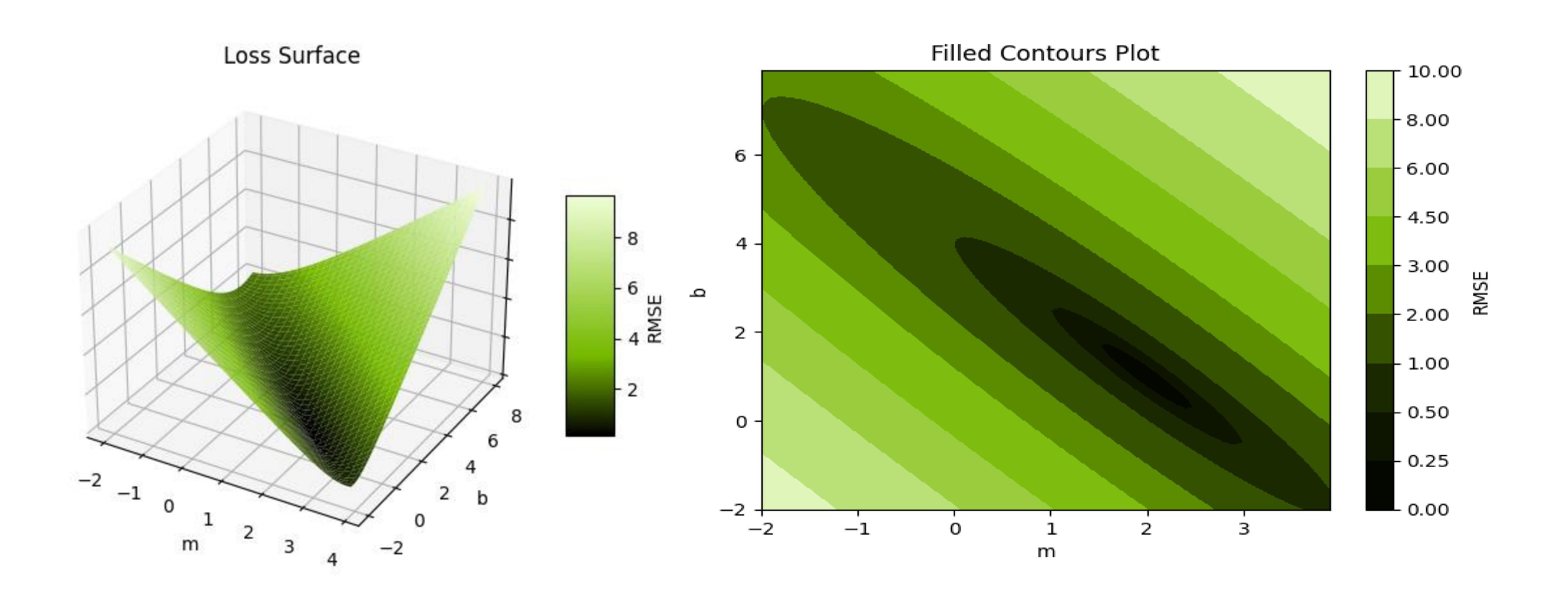
$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

$$y = mx + b$$

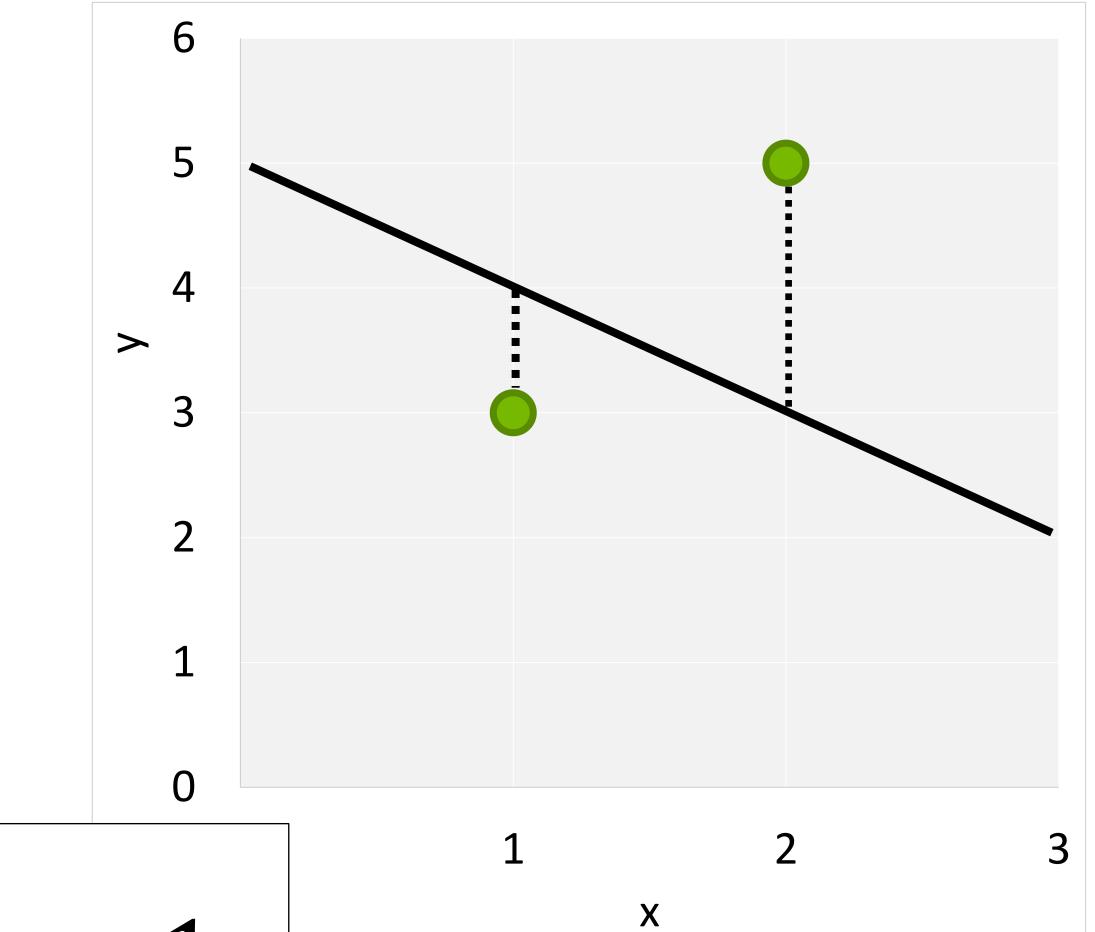
X	y	ŷ	err ²
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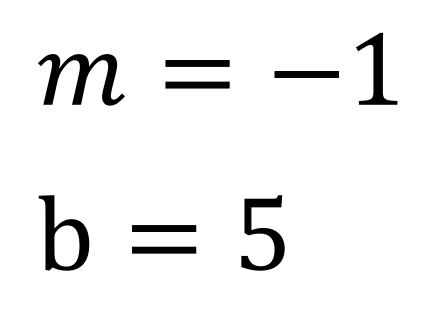


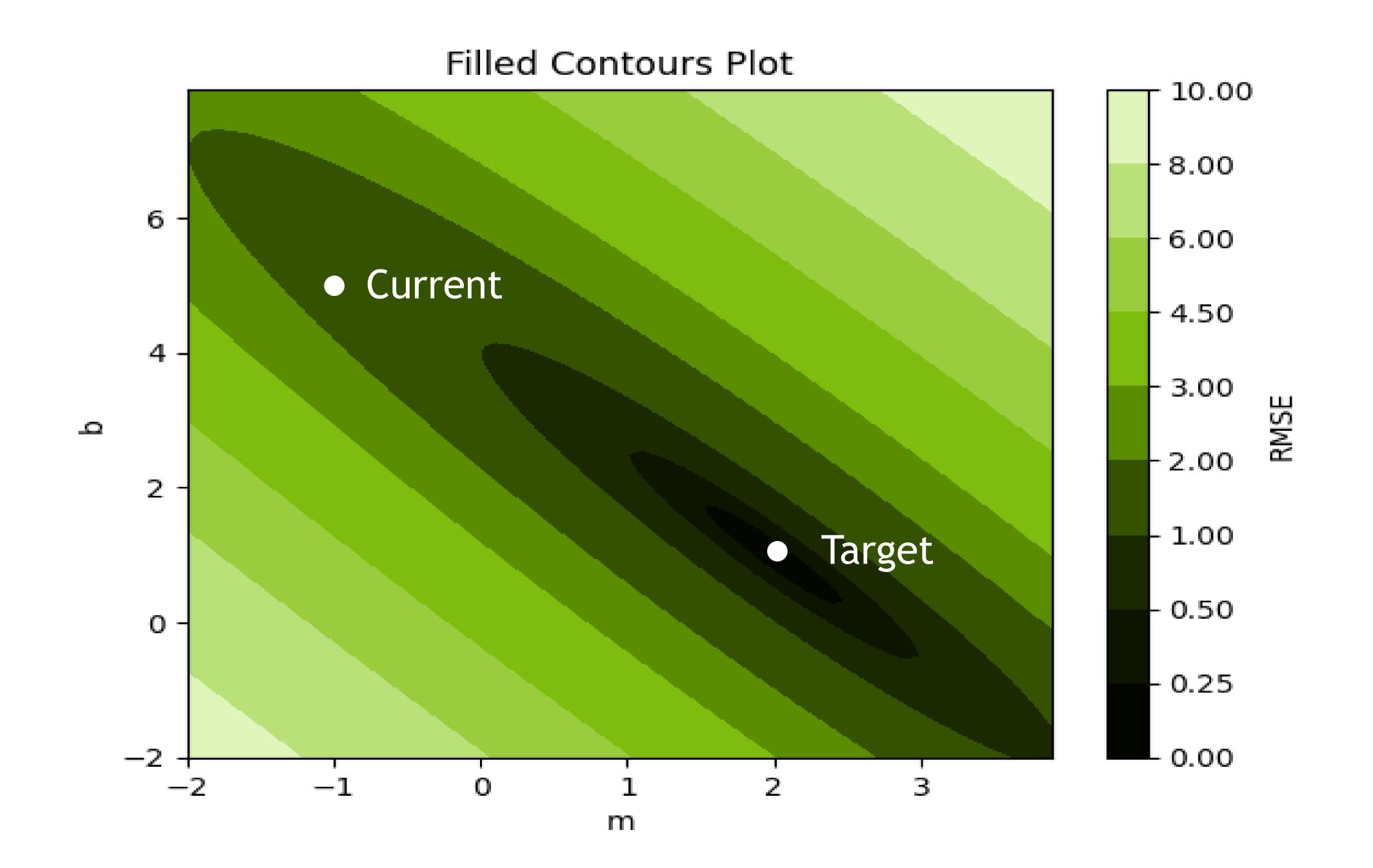
```
data = [(1, 3), (2, 5)]
    \mathbf{m} = -\mathbf{1}
    b = 5
 6 def get_rmse(data, m, b):
         """Calculates Mean Square Error"""
        n = len(data)
         squared_error = 0
         for x, y in data:
10 -
            # Find predicted y
11
             y_hat = m*x+b
12
             # Square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



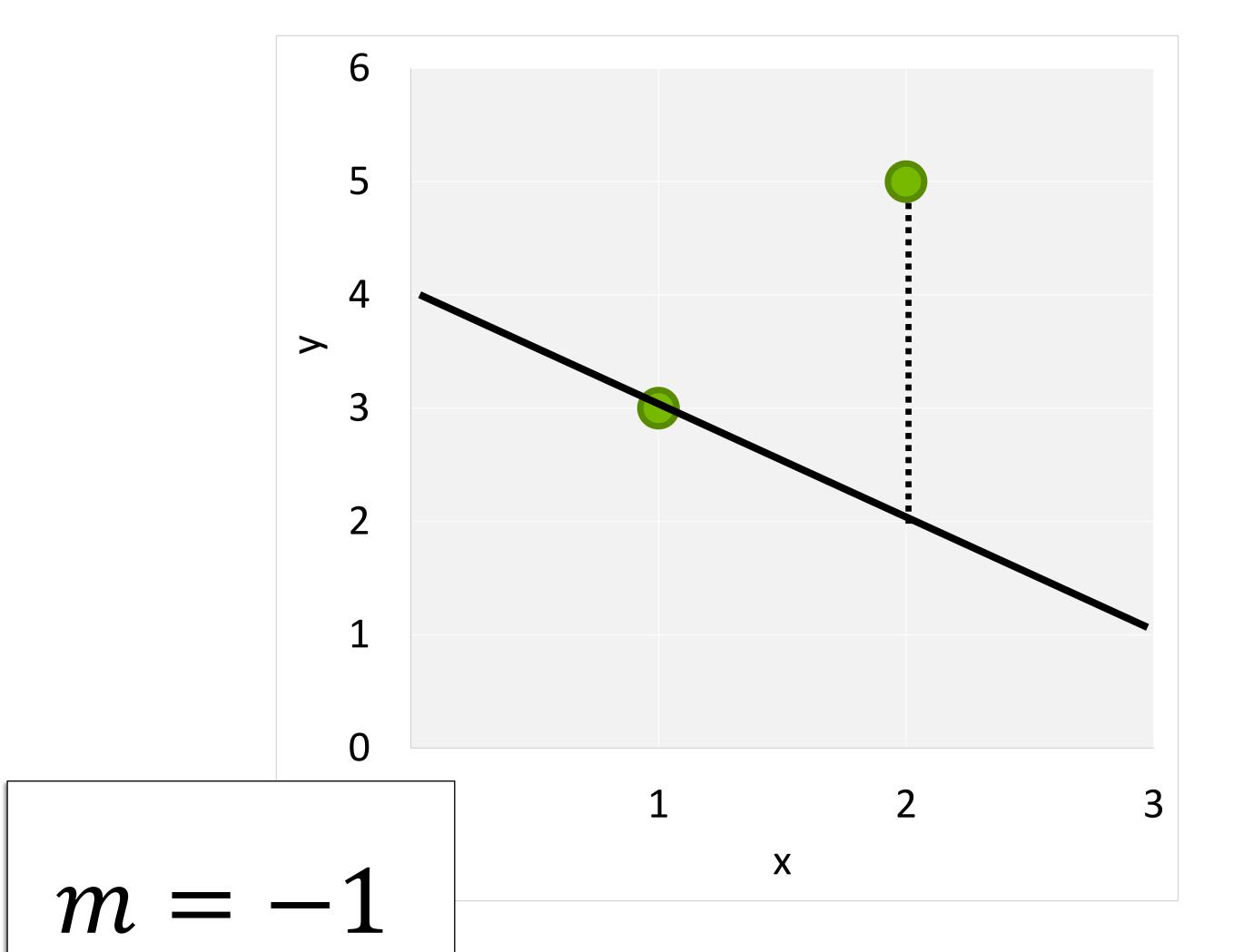


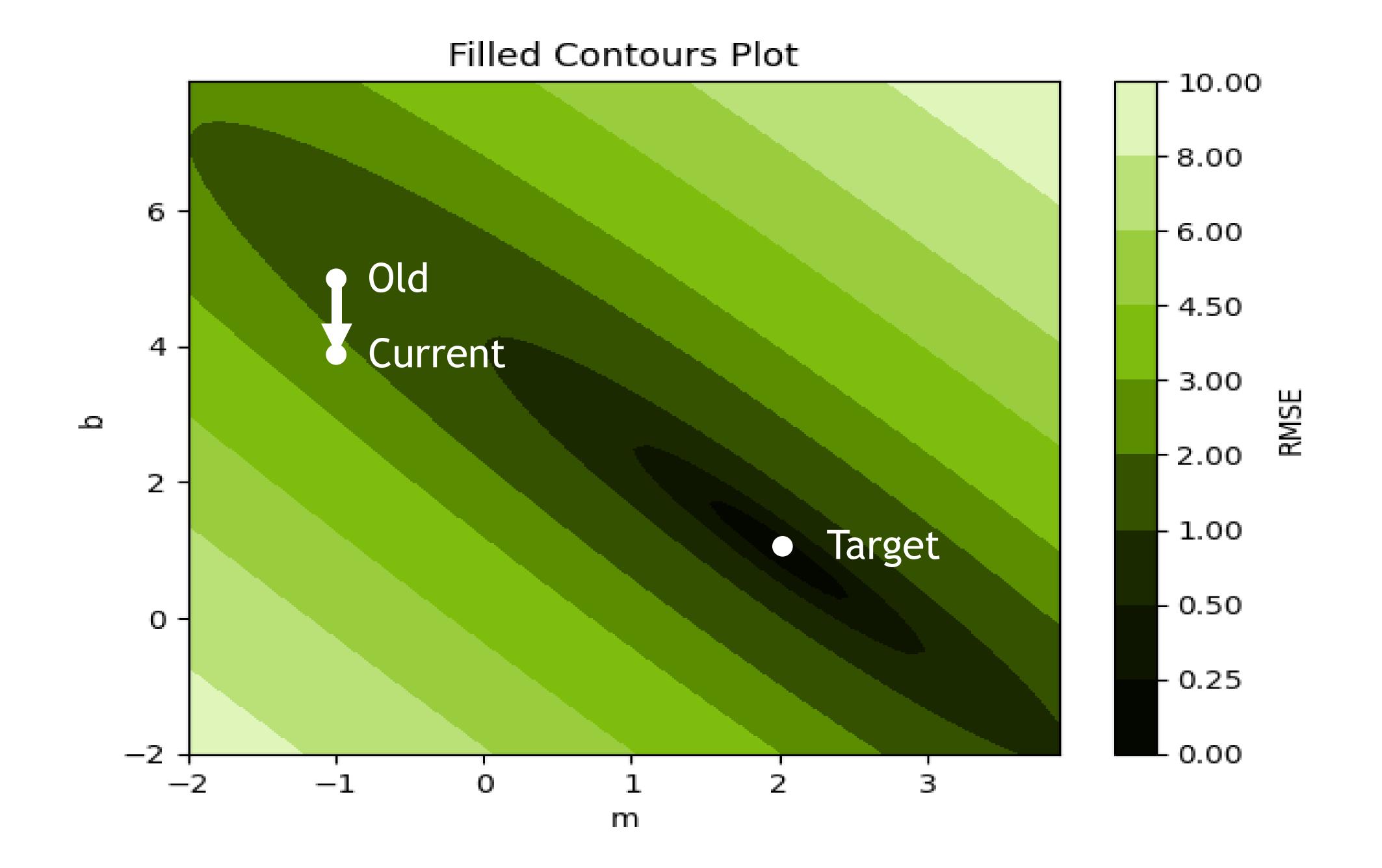


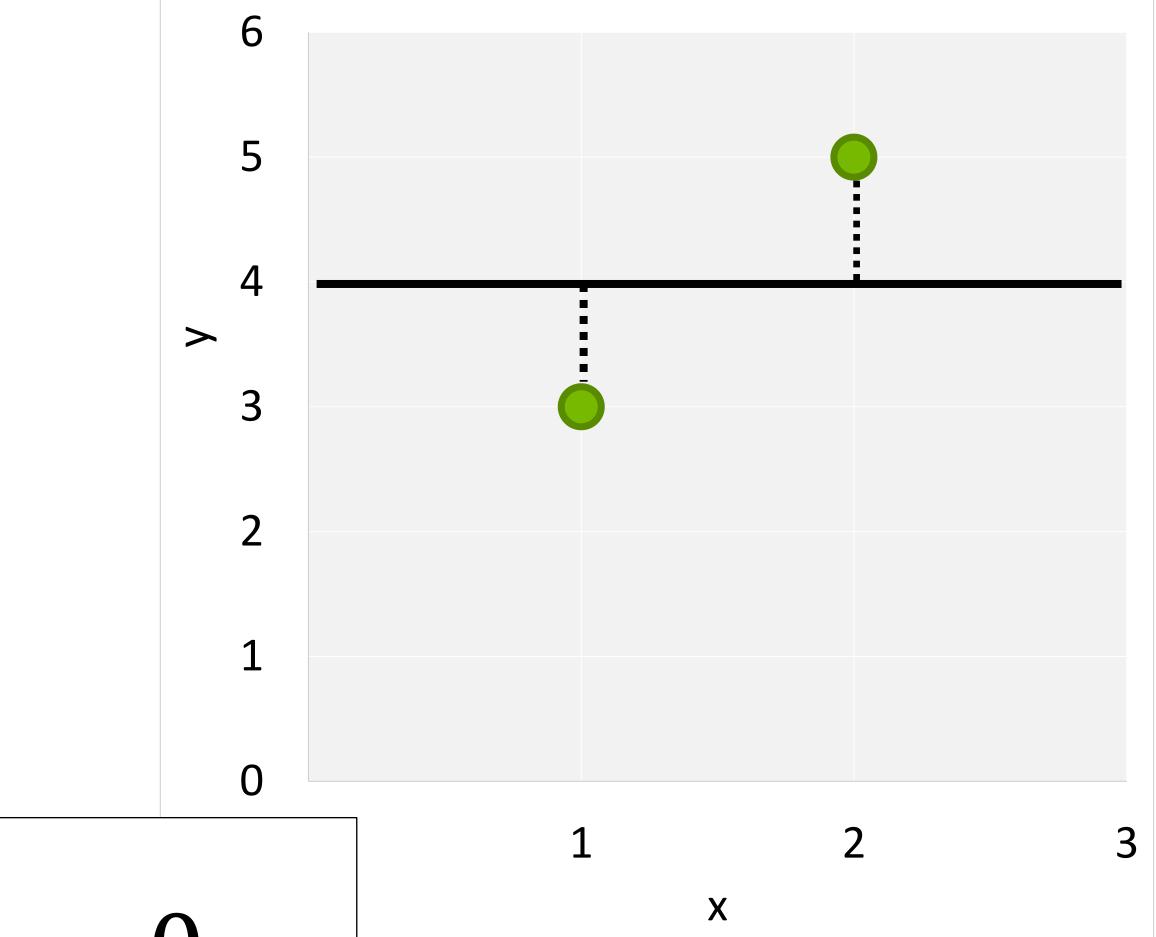


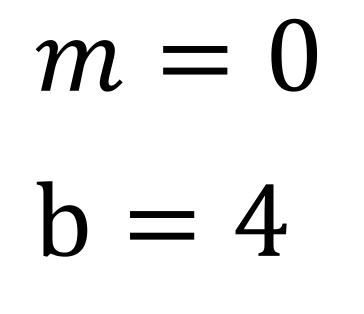


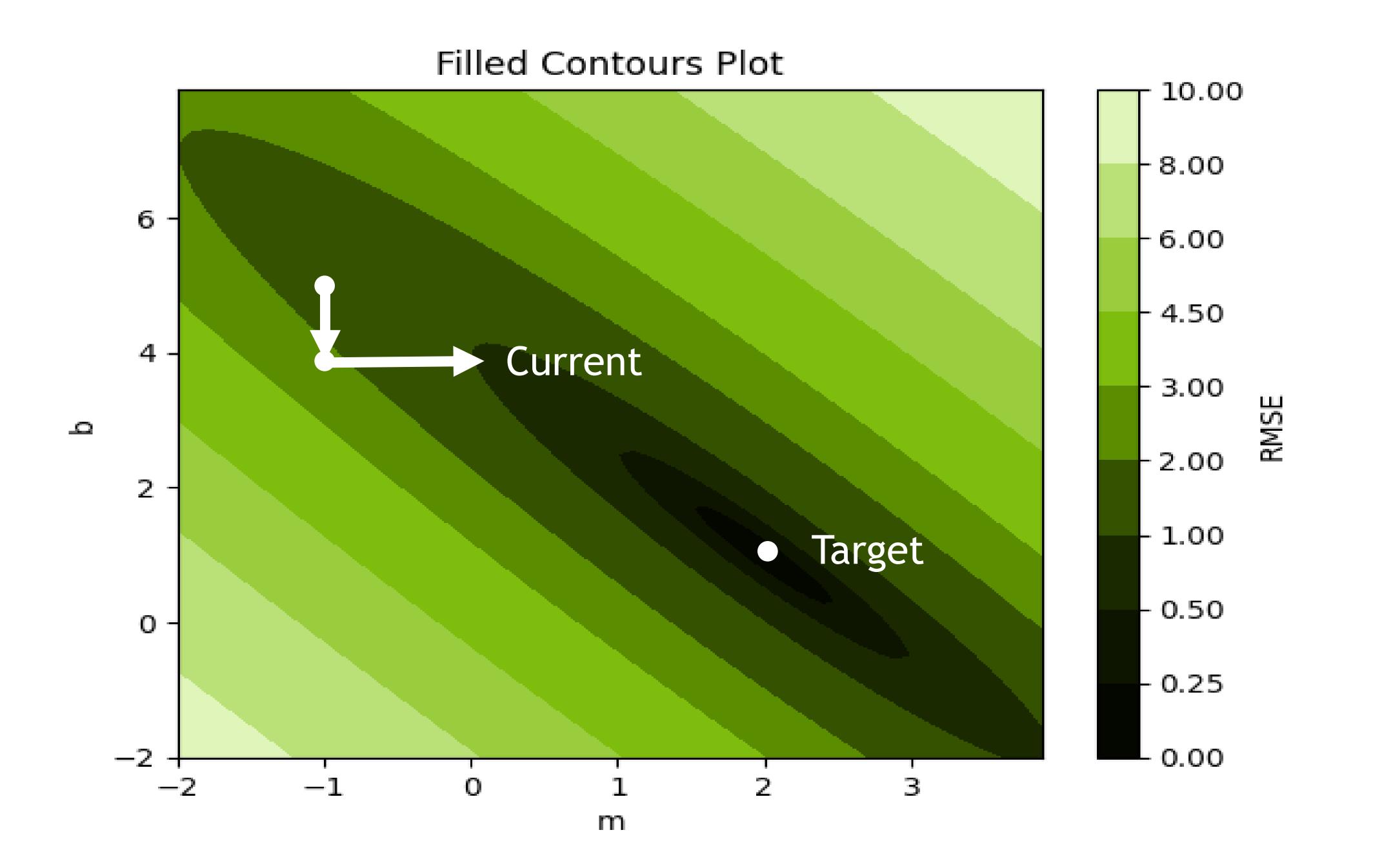




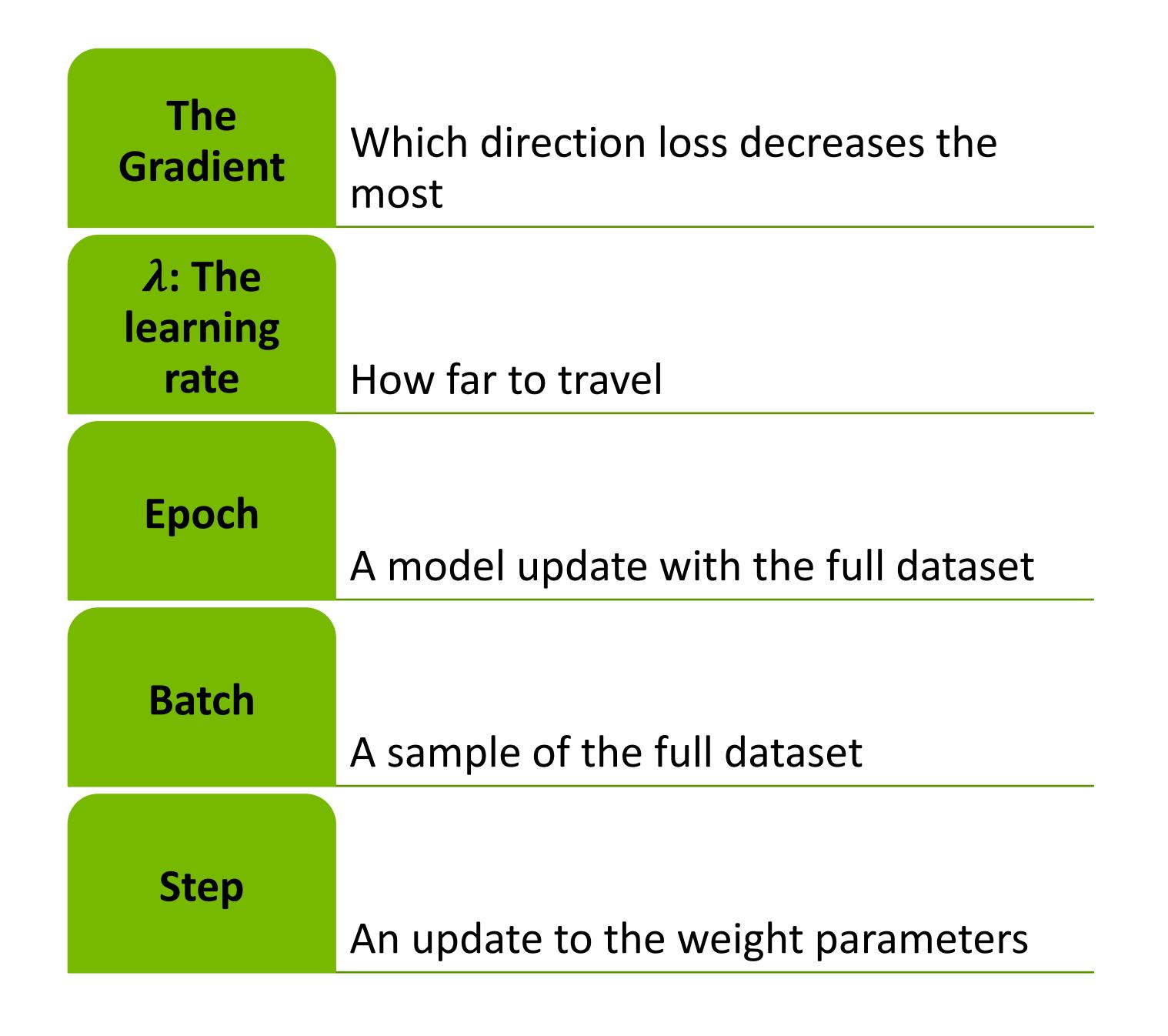


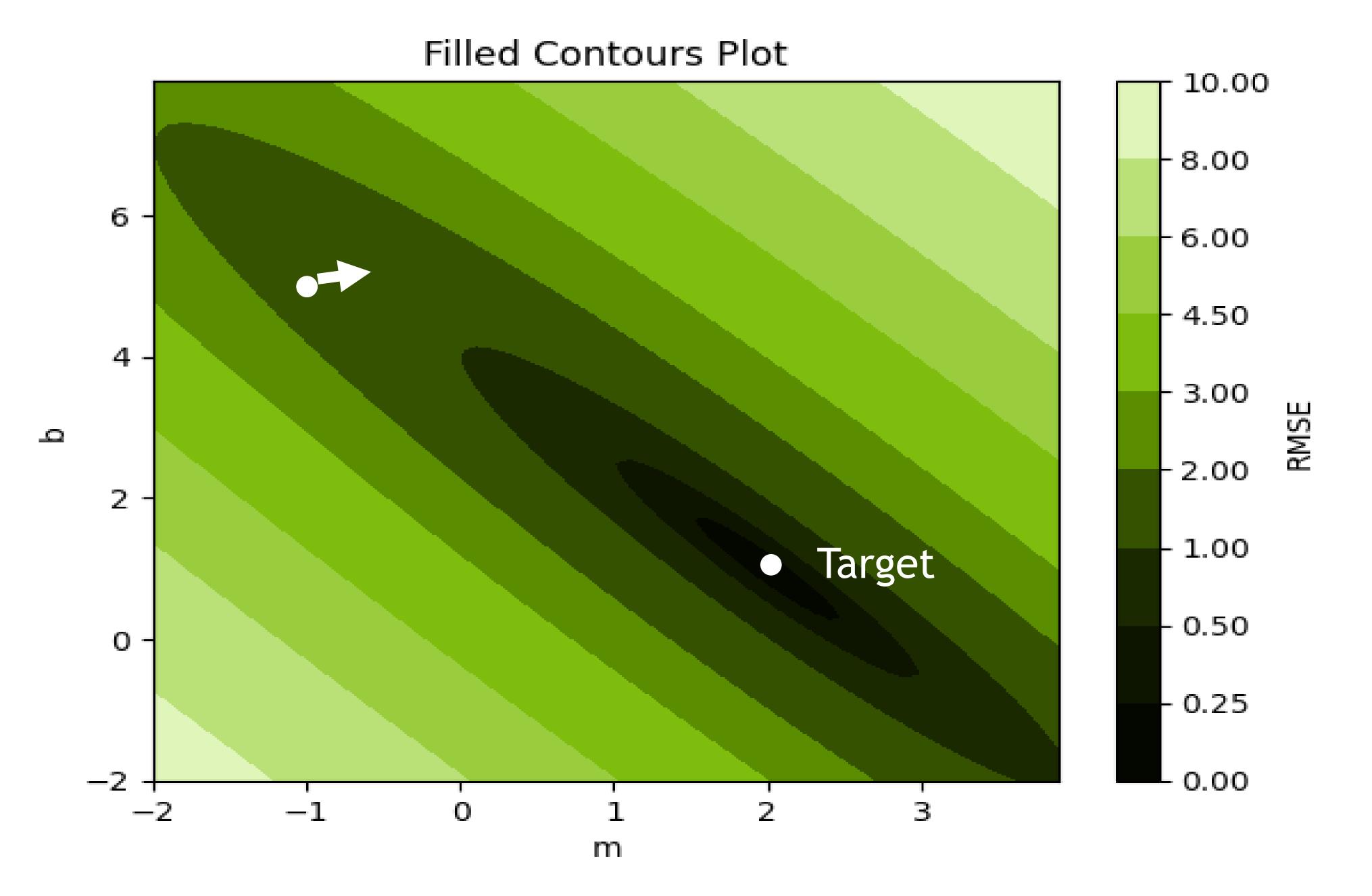




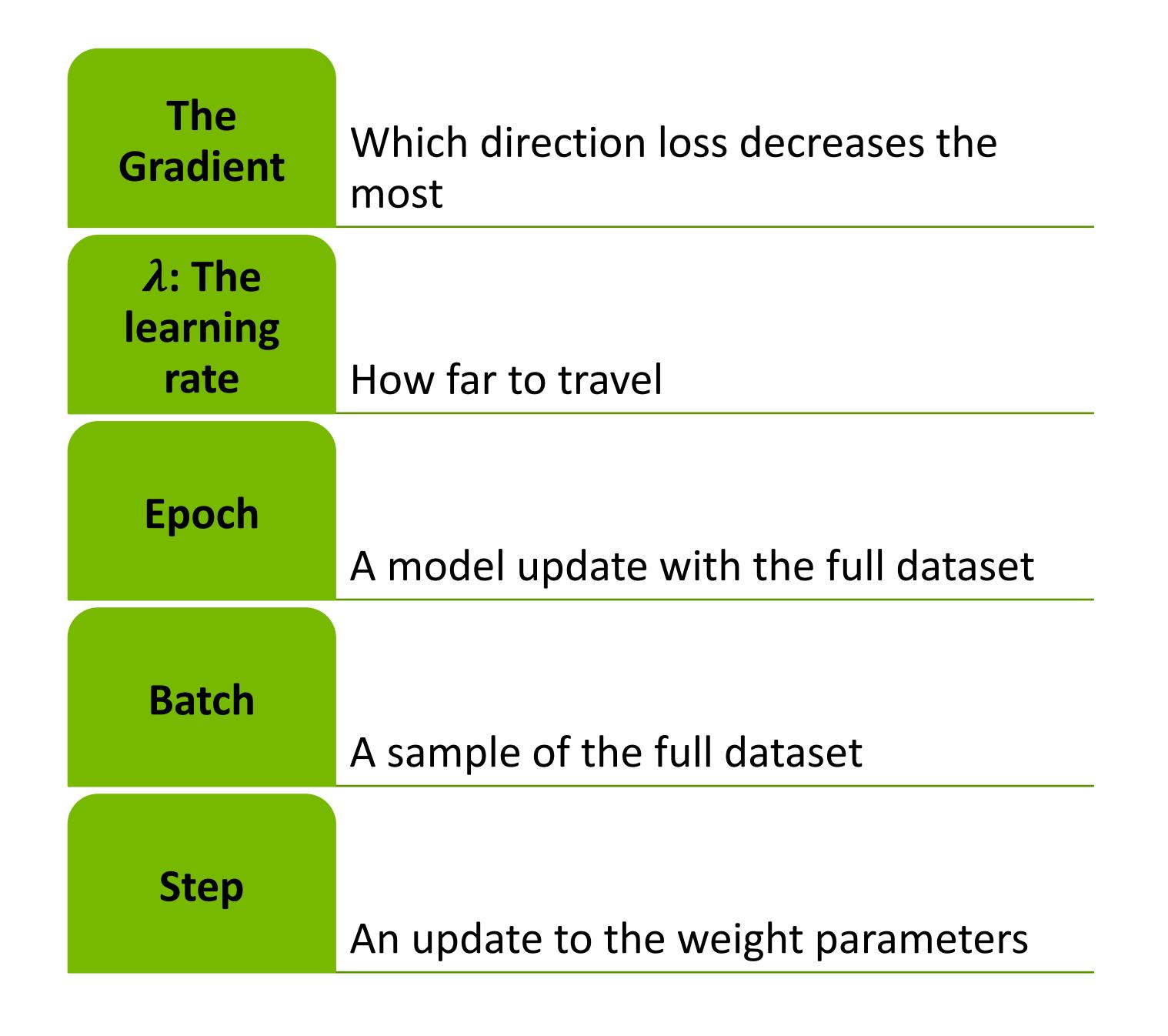


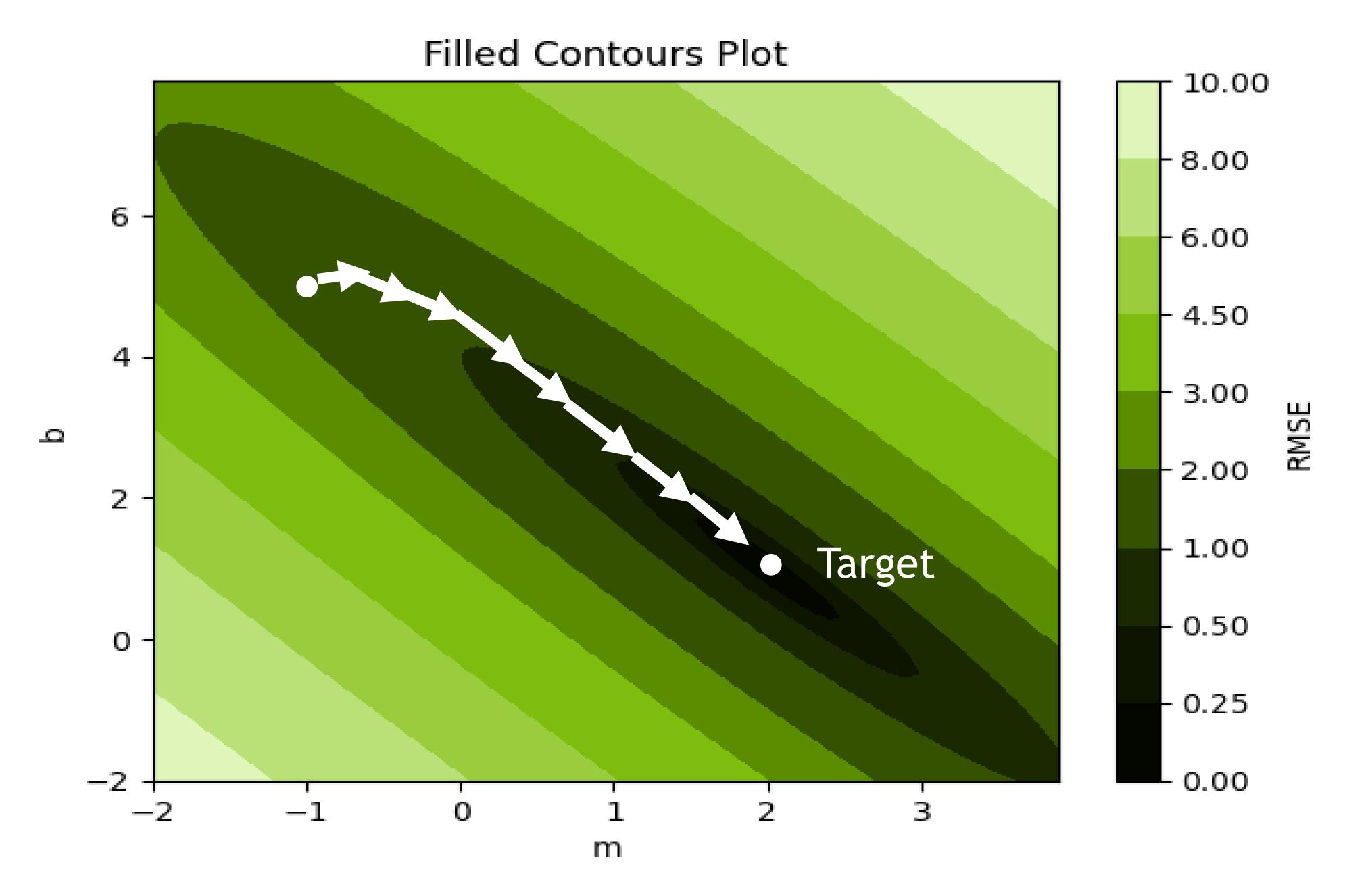












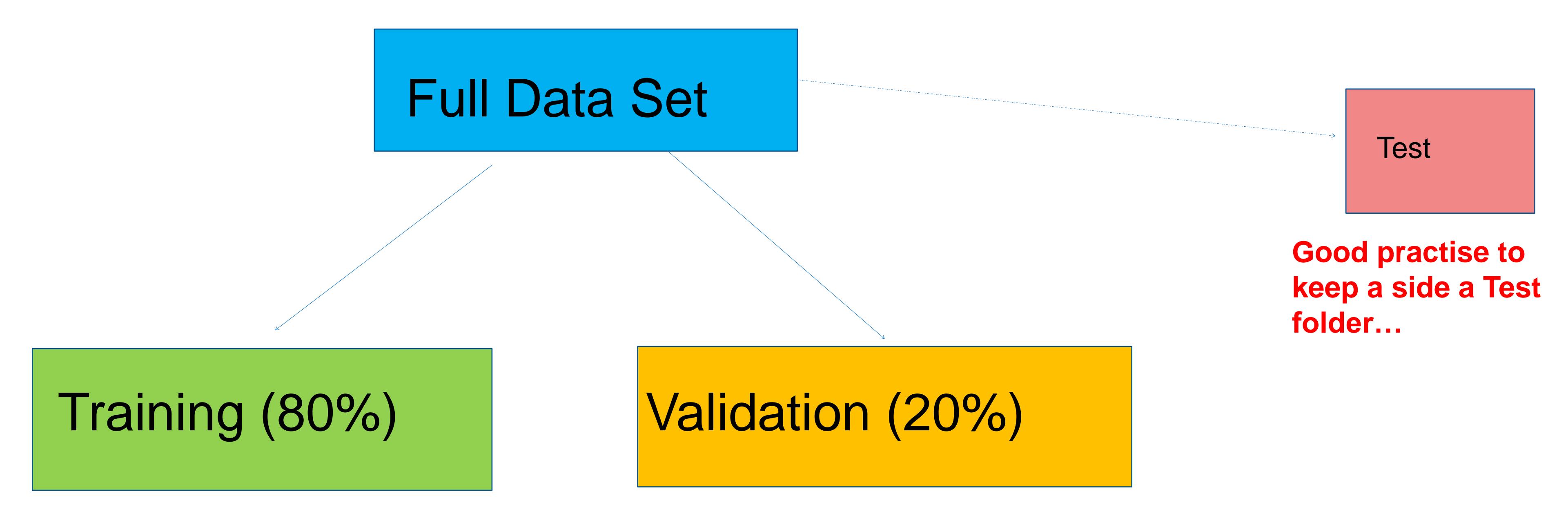


- 1 Iteration: 1 Forward pass + 1 Backward pass
- 1 Epoch: 1 Forward pass + 1 Backward pass for ALL training samples.
- Batch Size: Number of training samples
- Mini-batch (often called Batch Size!): Number of training samples used in 1 iteration
- Learning rate: determines to what extent newly acquired information overrides old information
- Loss: difference between prediction and correct output
- Accuracy: <u>number of correct predictions</u>
 total number of predictions

Full Data Set

Training (80%)

Validation (20%)

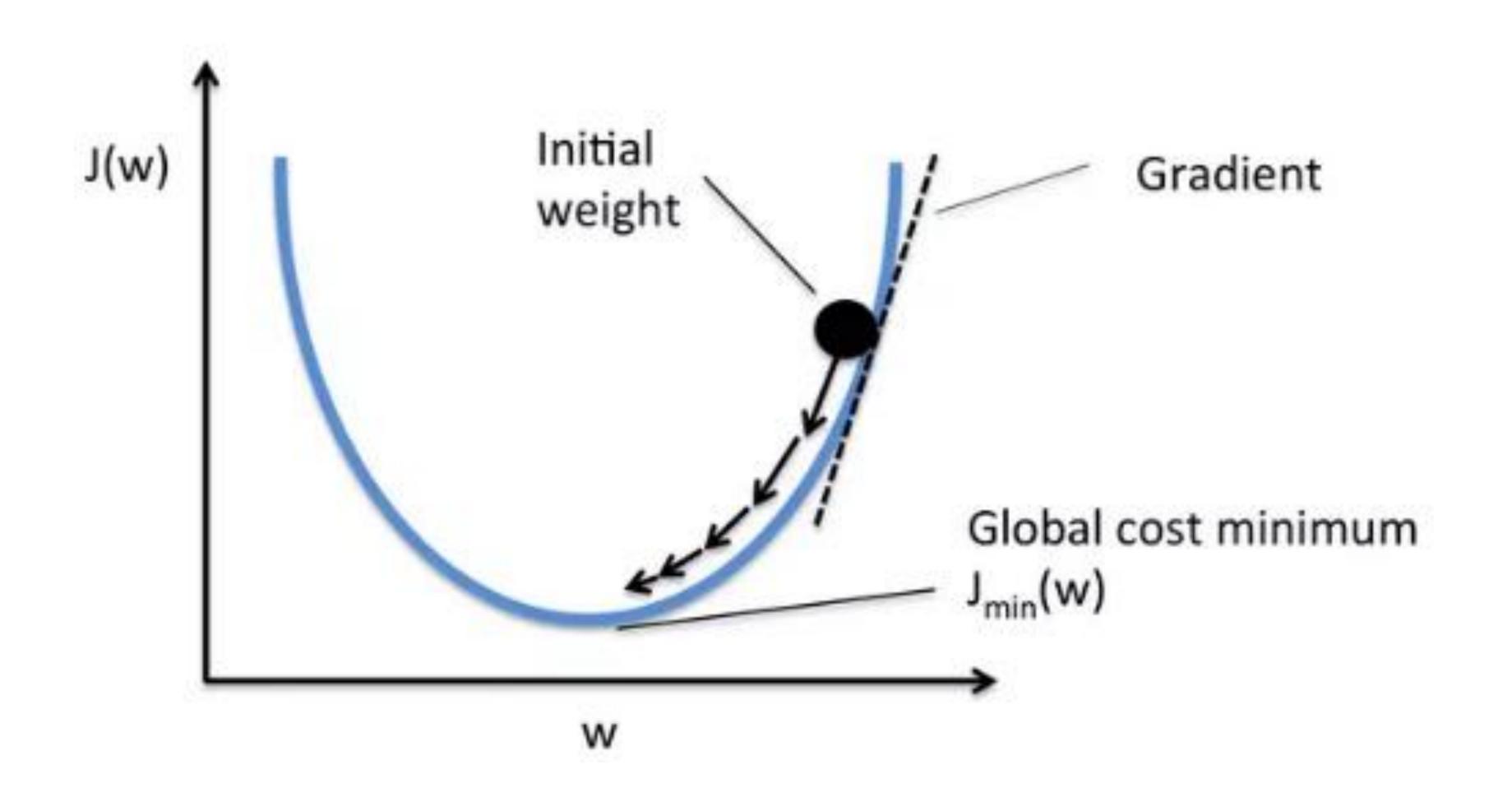


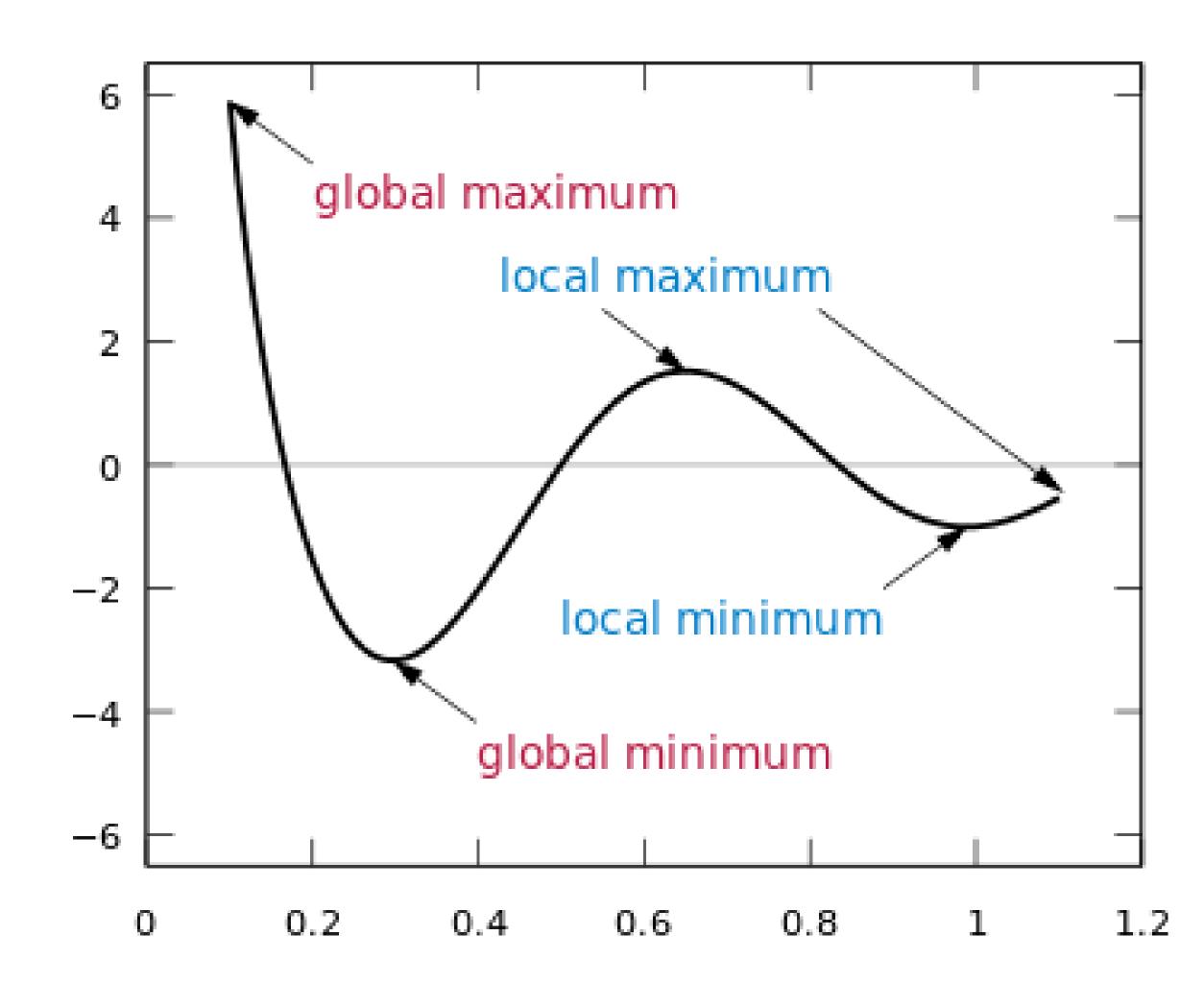
Parameters: weights of the Neural Network. Their values are derived via training

Hyper-parameters: are values set before the learning process begins.

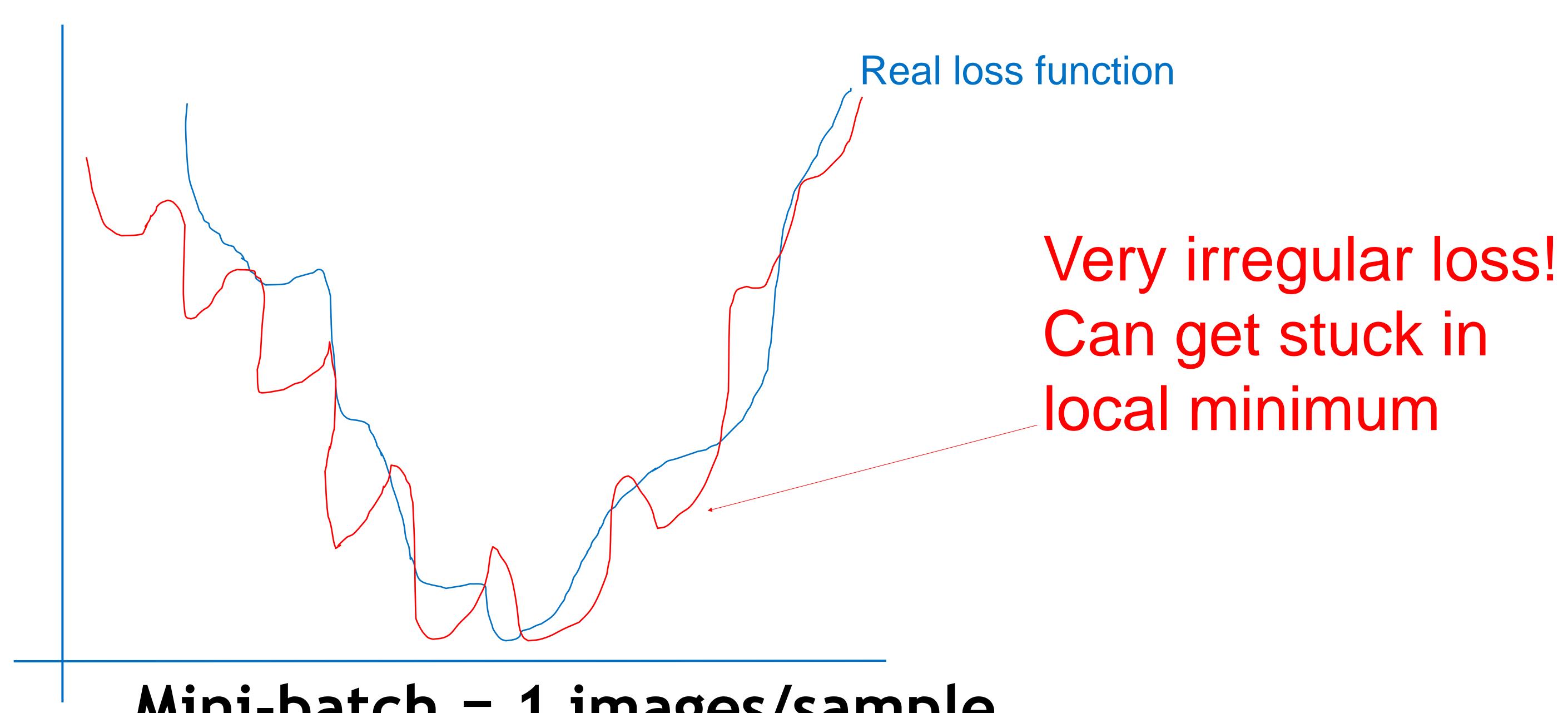
Ex: number of epochs mini-batch size learning rate

Non convex Cost functions





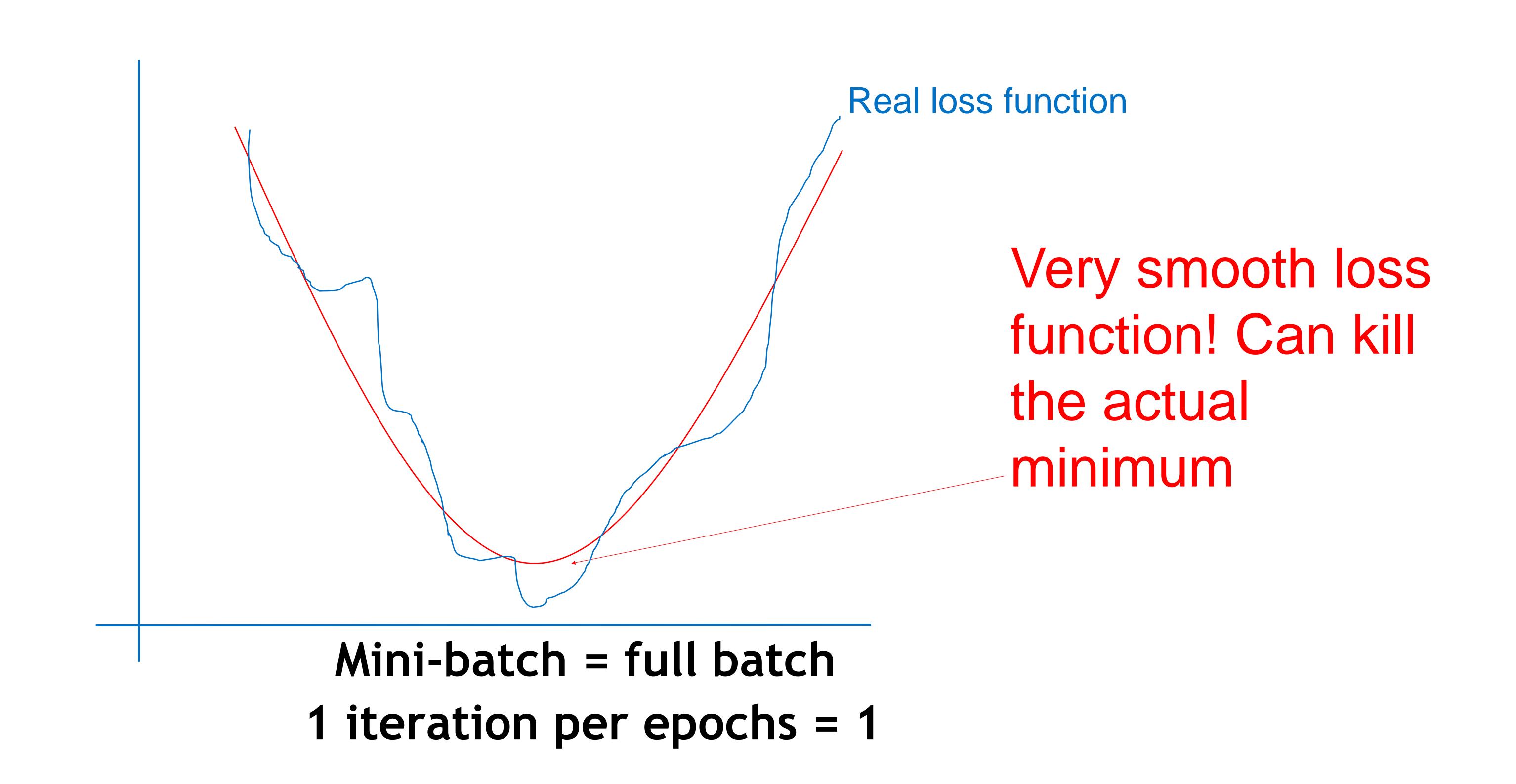
Stochastic Gradient Descent (SGD) method



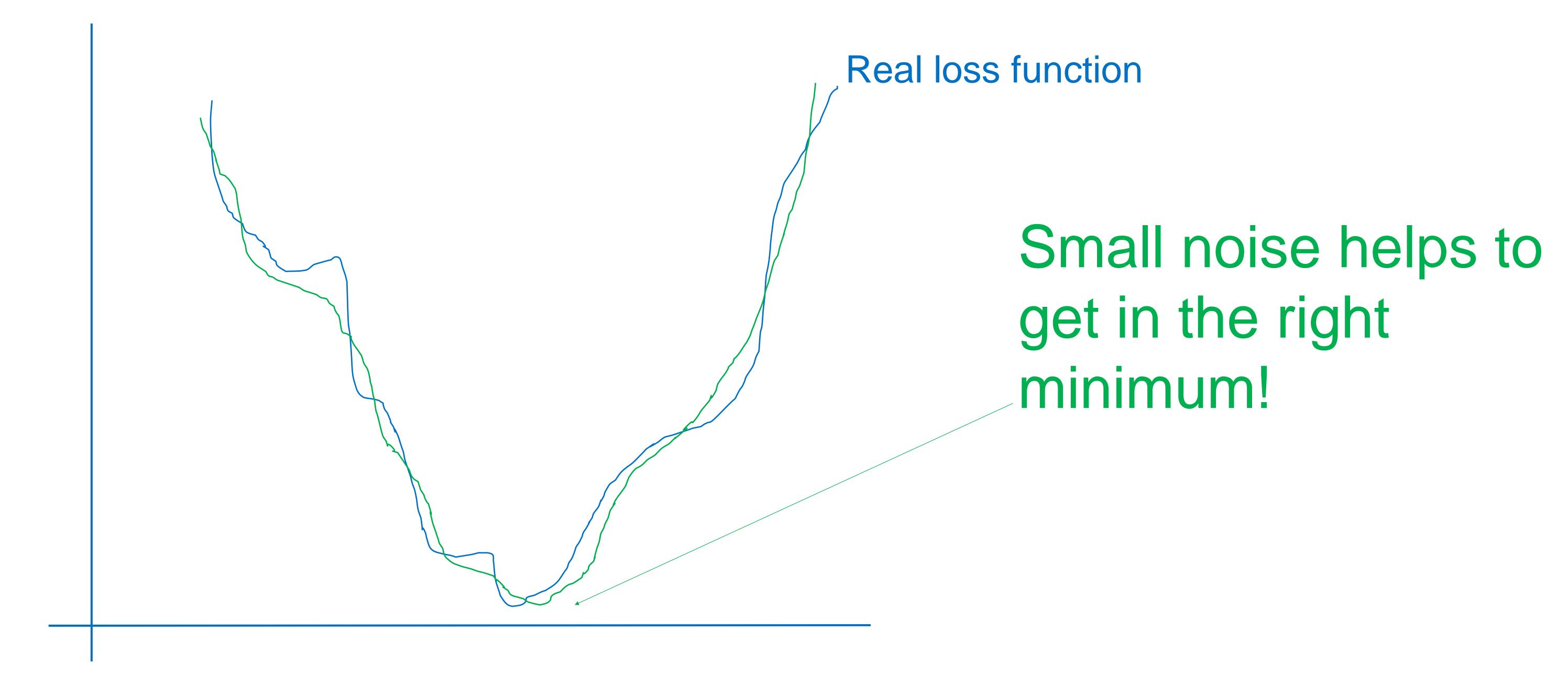
Mini-batch = 1 images/sample

N iterations per epochs = n samples in the batch

Batch Gradient Descent (BGD) method



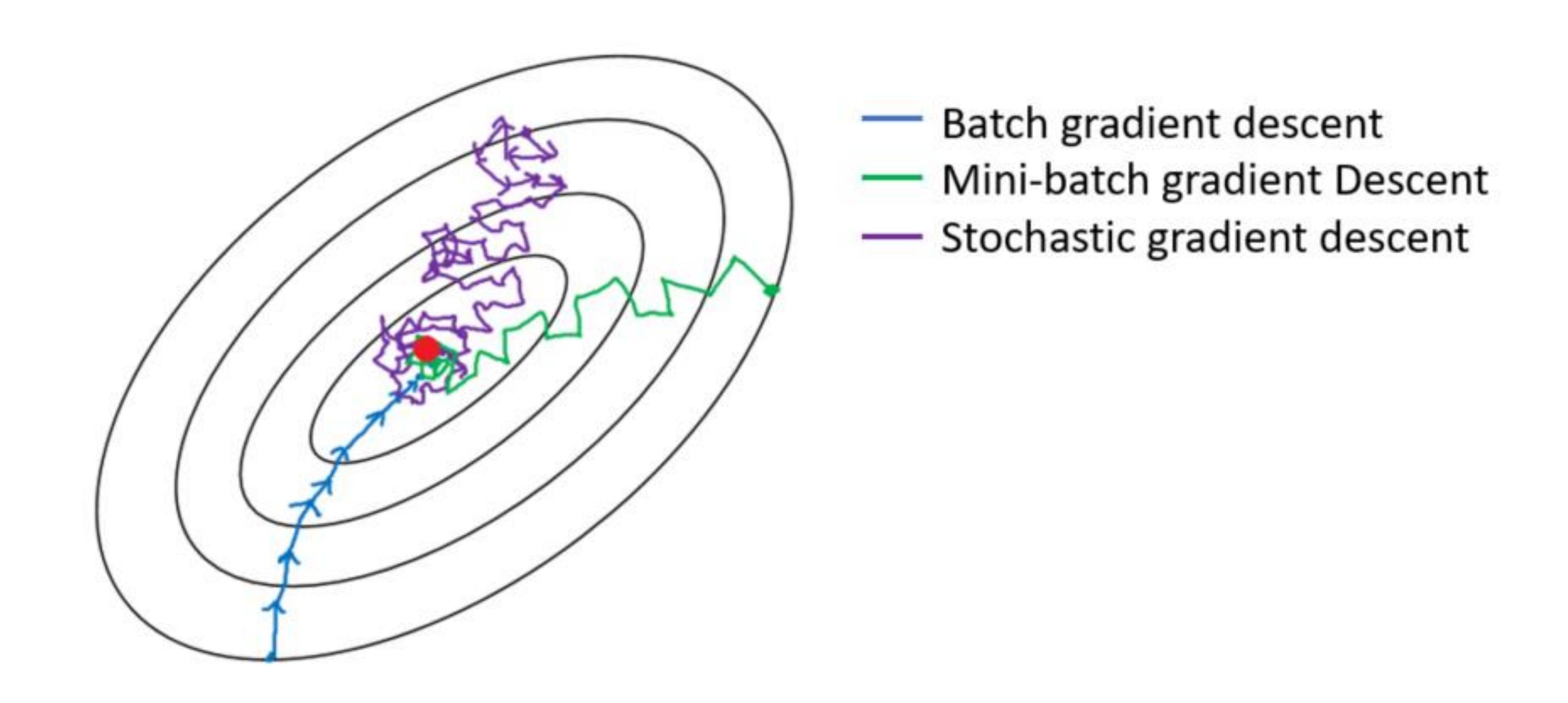
Mini-batch Stochastic Gradient Descent (mSGD) method



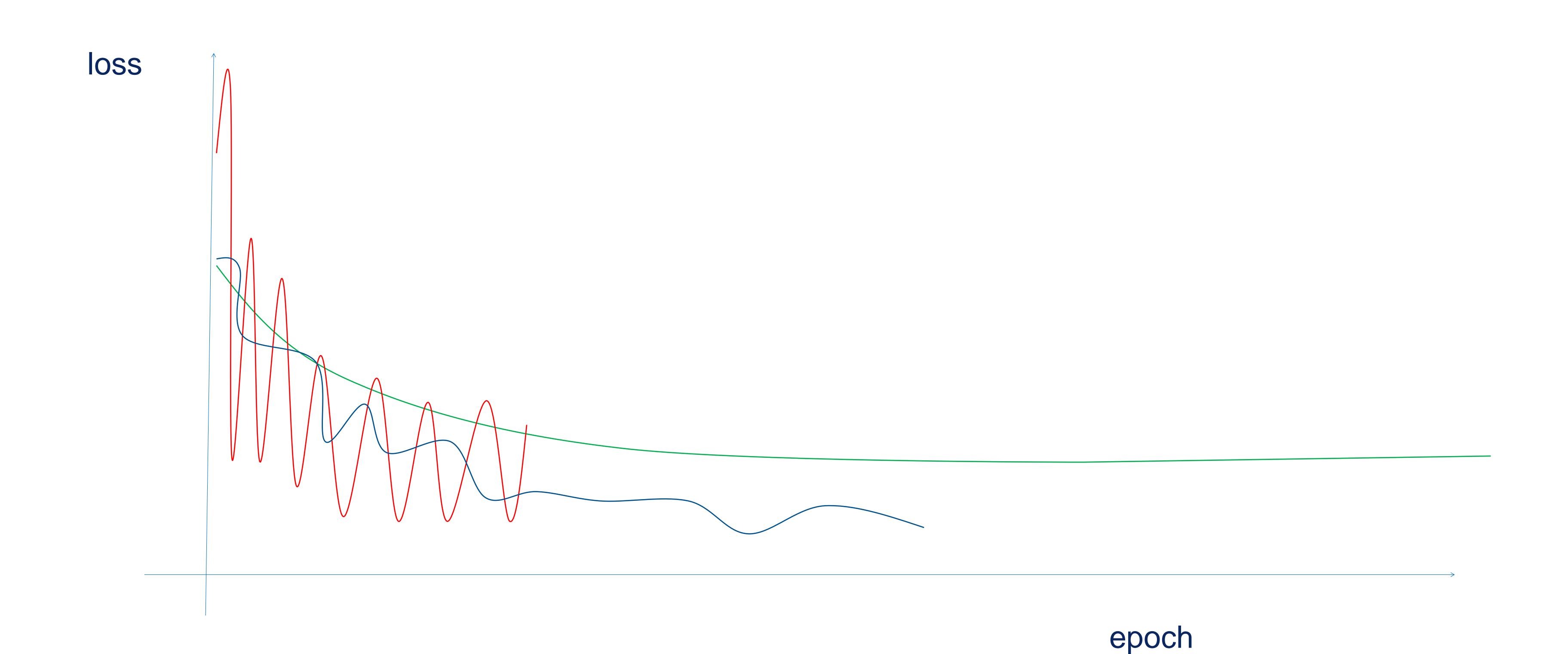
The mini-batch is equal to a subset of the batch size (usually 32/64/128...)

N iterations per epochs = N samples in the batch / mini-batch size

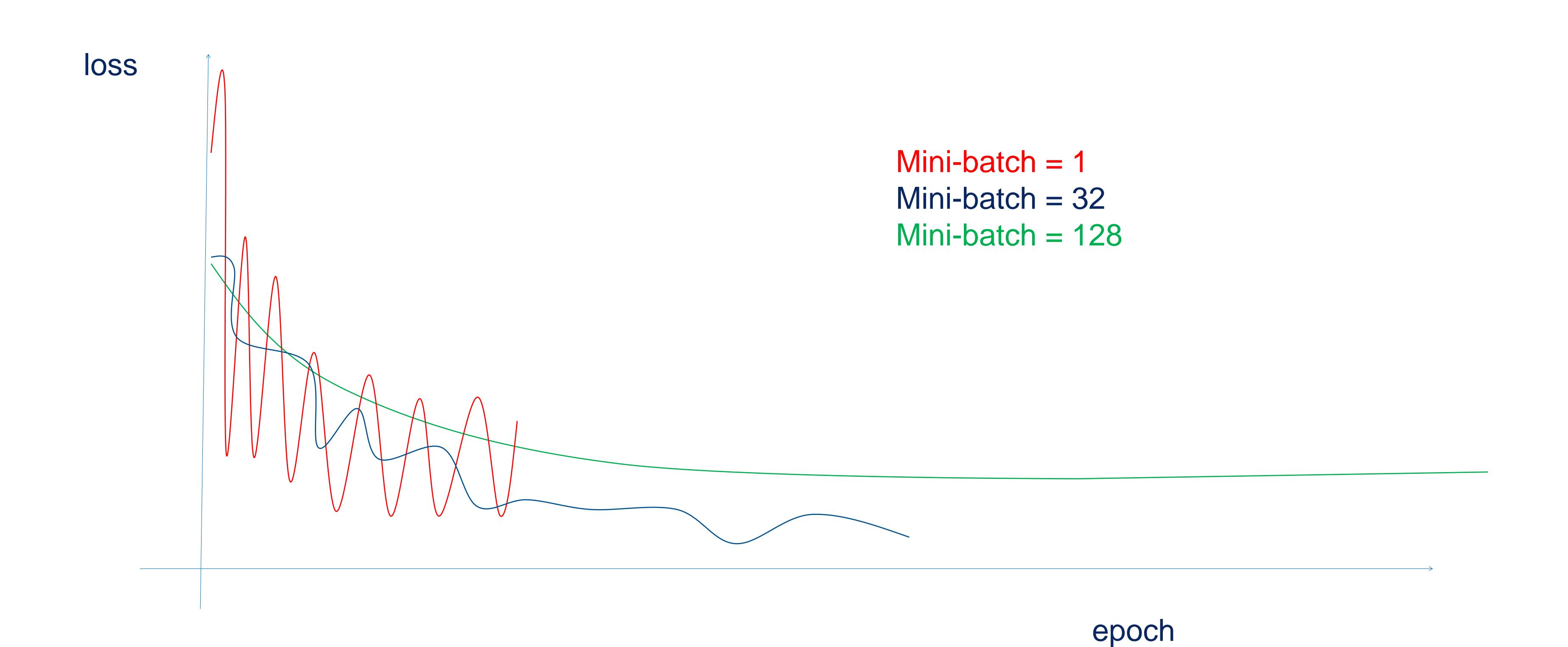
Effect of different mini-batch size



Which curve has the largest batch size?

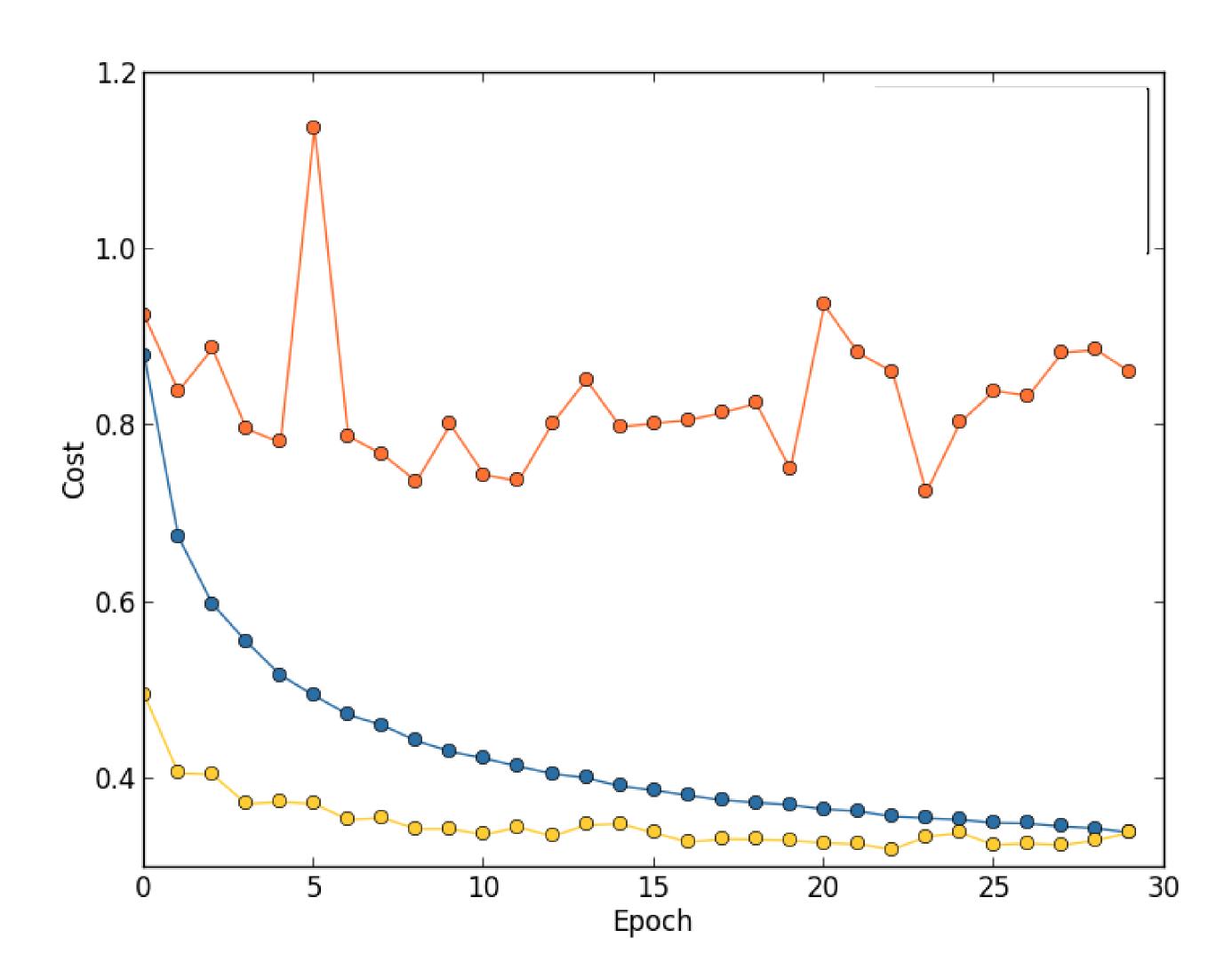


Which curve has the largest batch size?



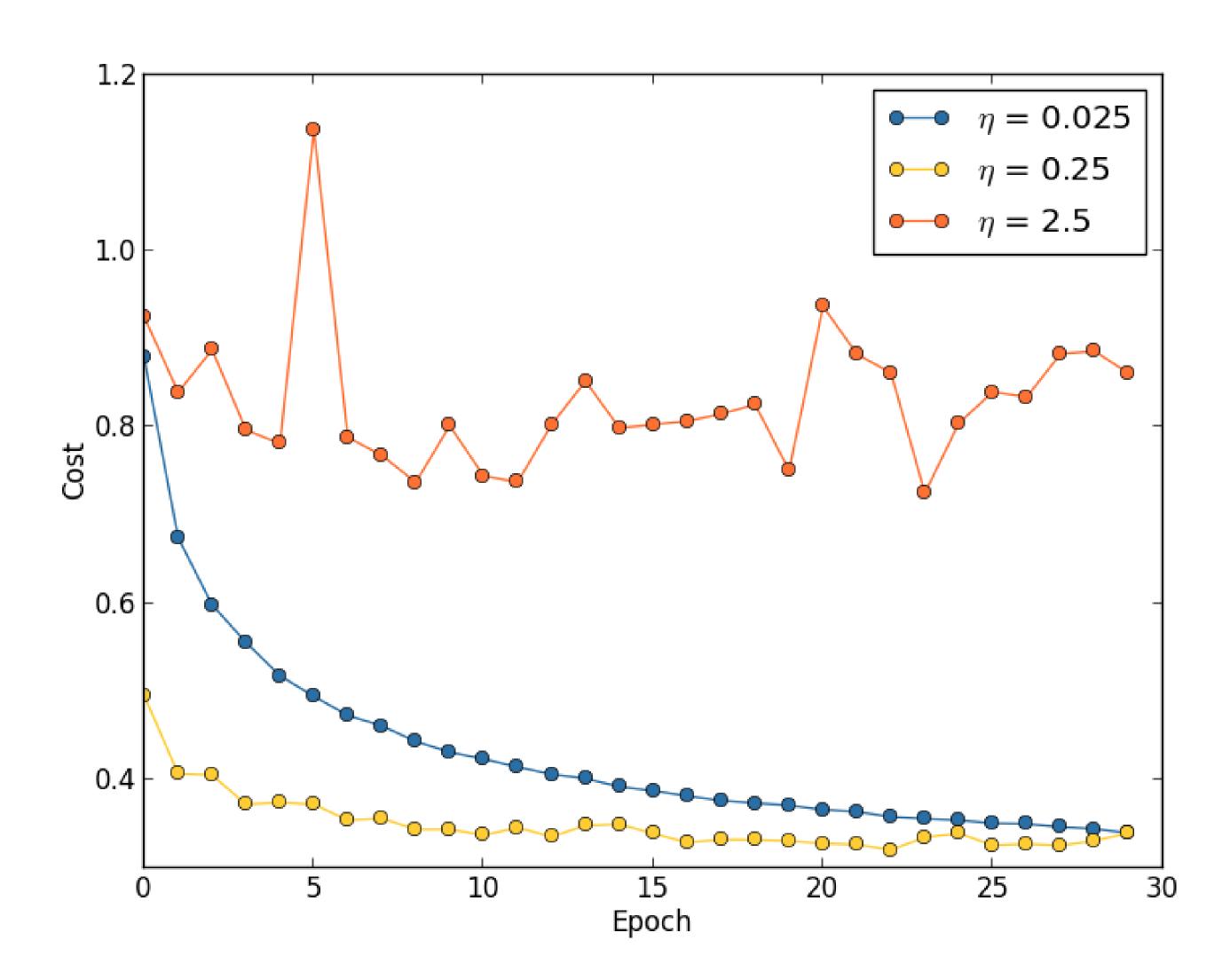
Which curve has the smallest learning rate?

$$w_t = w_{t-1} + \frac{dE}{dw_t}$$

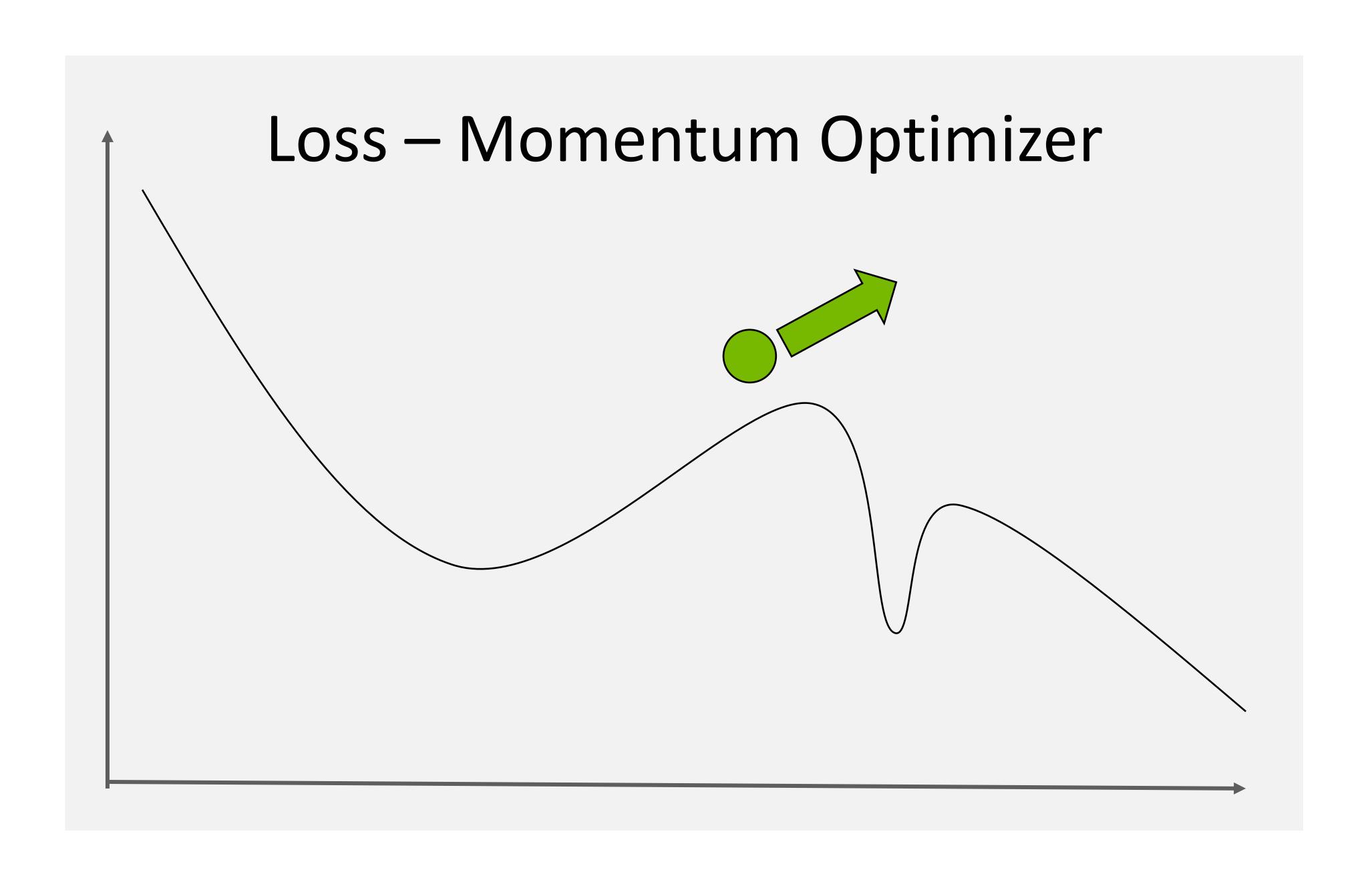


Which curve has the smallest learning rate?

$$w_t = w_{t-1} + \frac{dE}{dw_t}$$



Optimizers

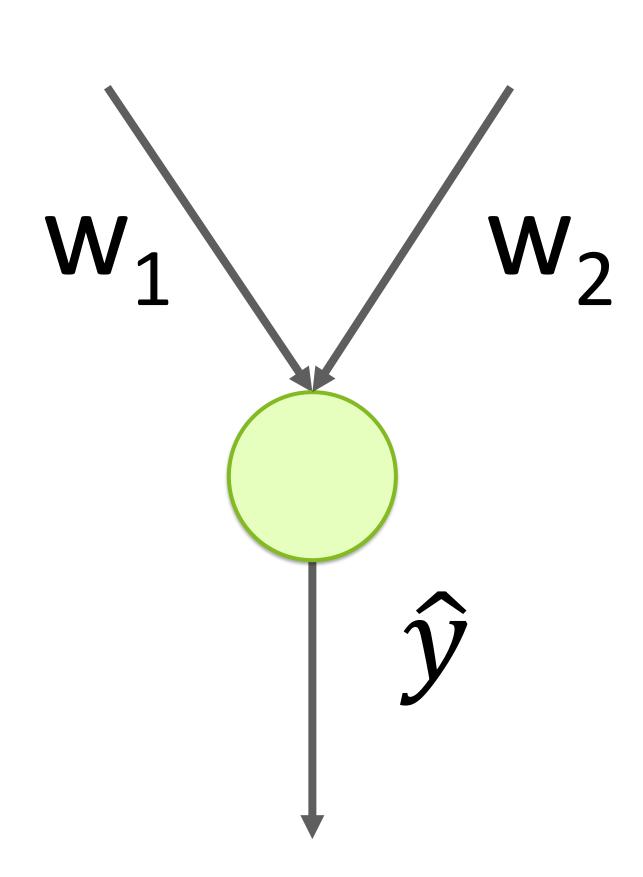


- Adam
- Adagrad
- RMSprop
- SGD



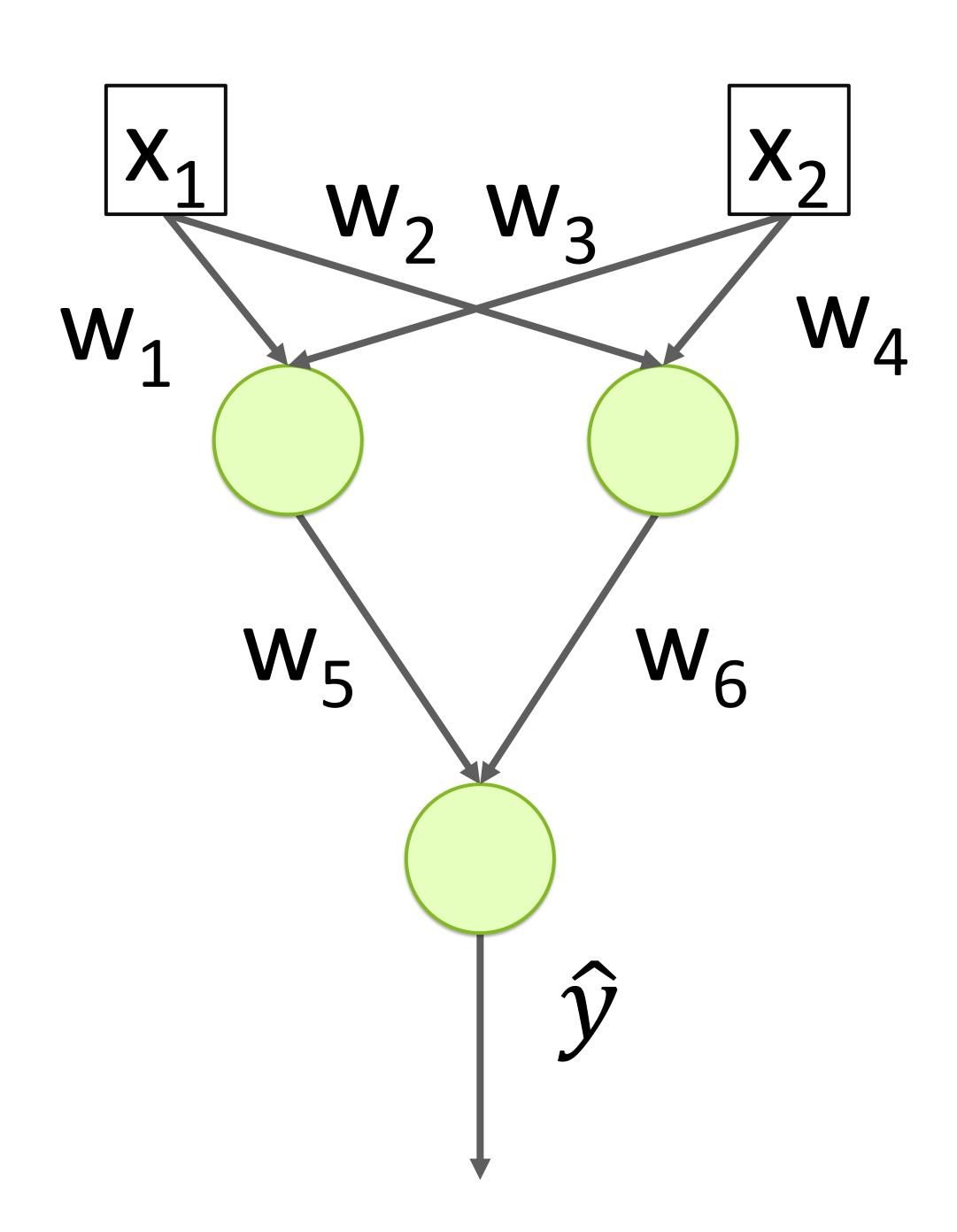


Building a Network



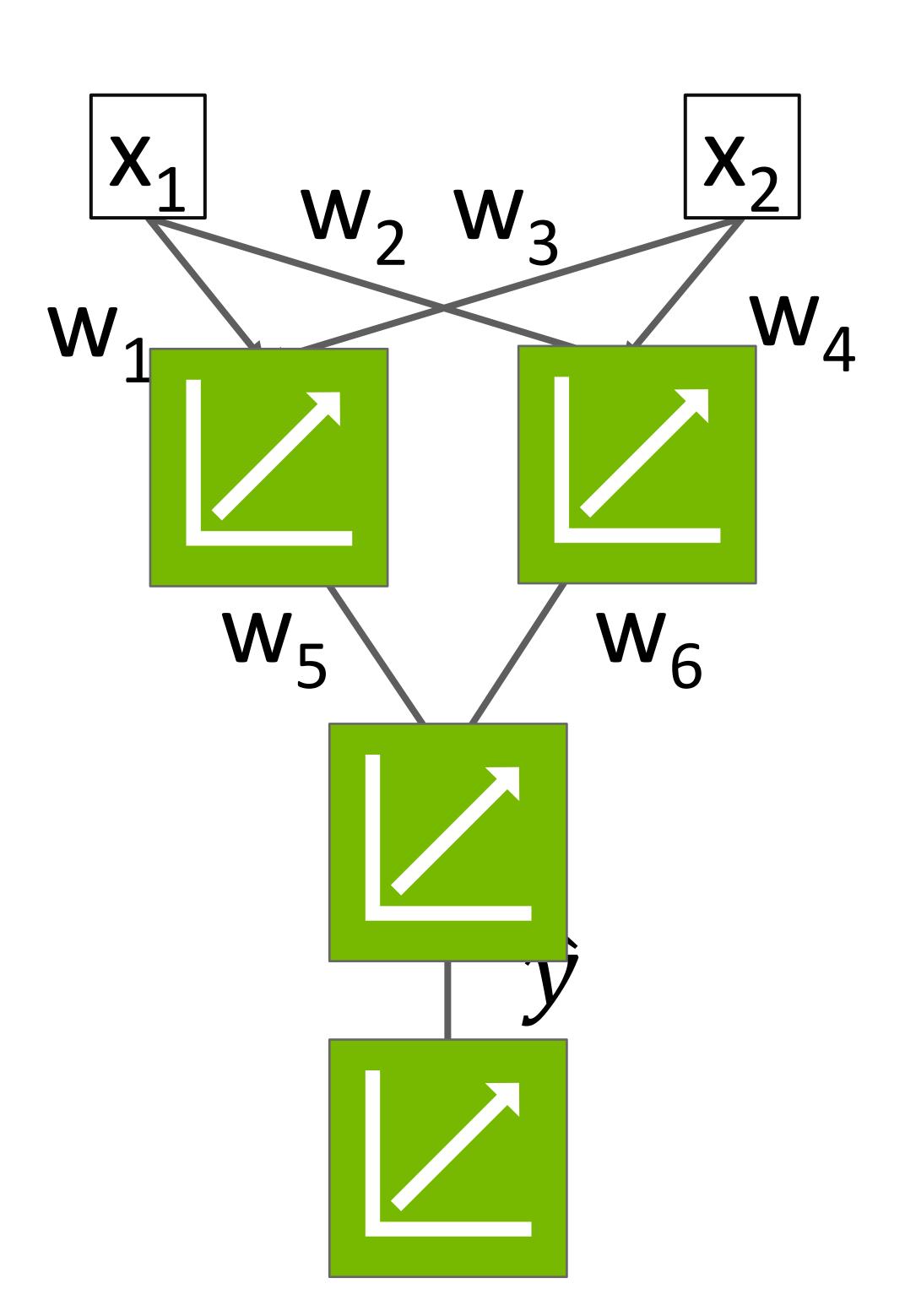
• Scales to more inputs

Building a Network



- Scales to more inputs
- Can chain neurons

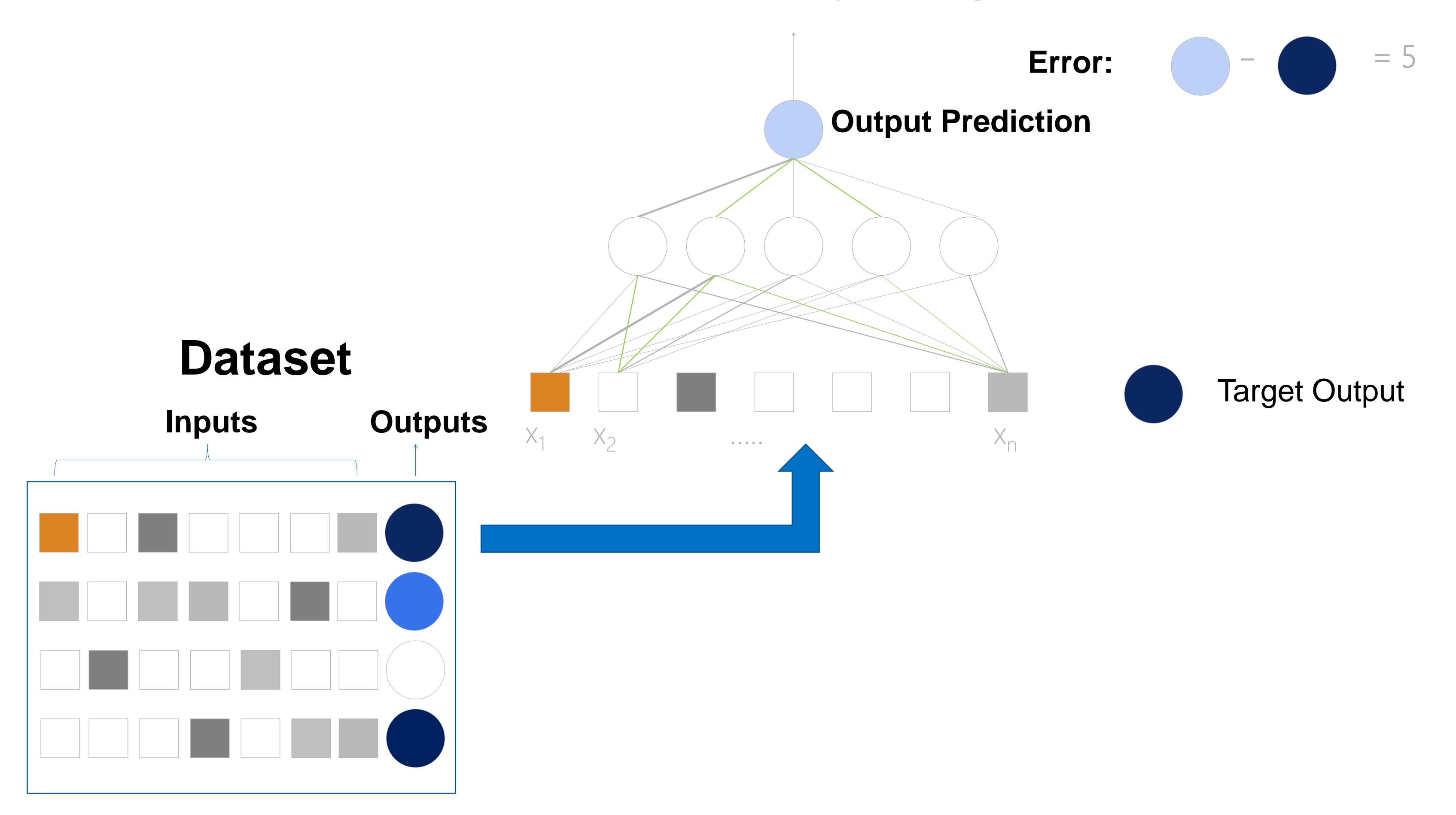
Building a Network



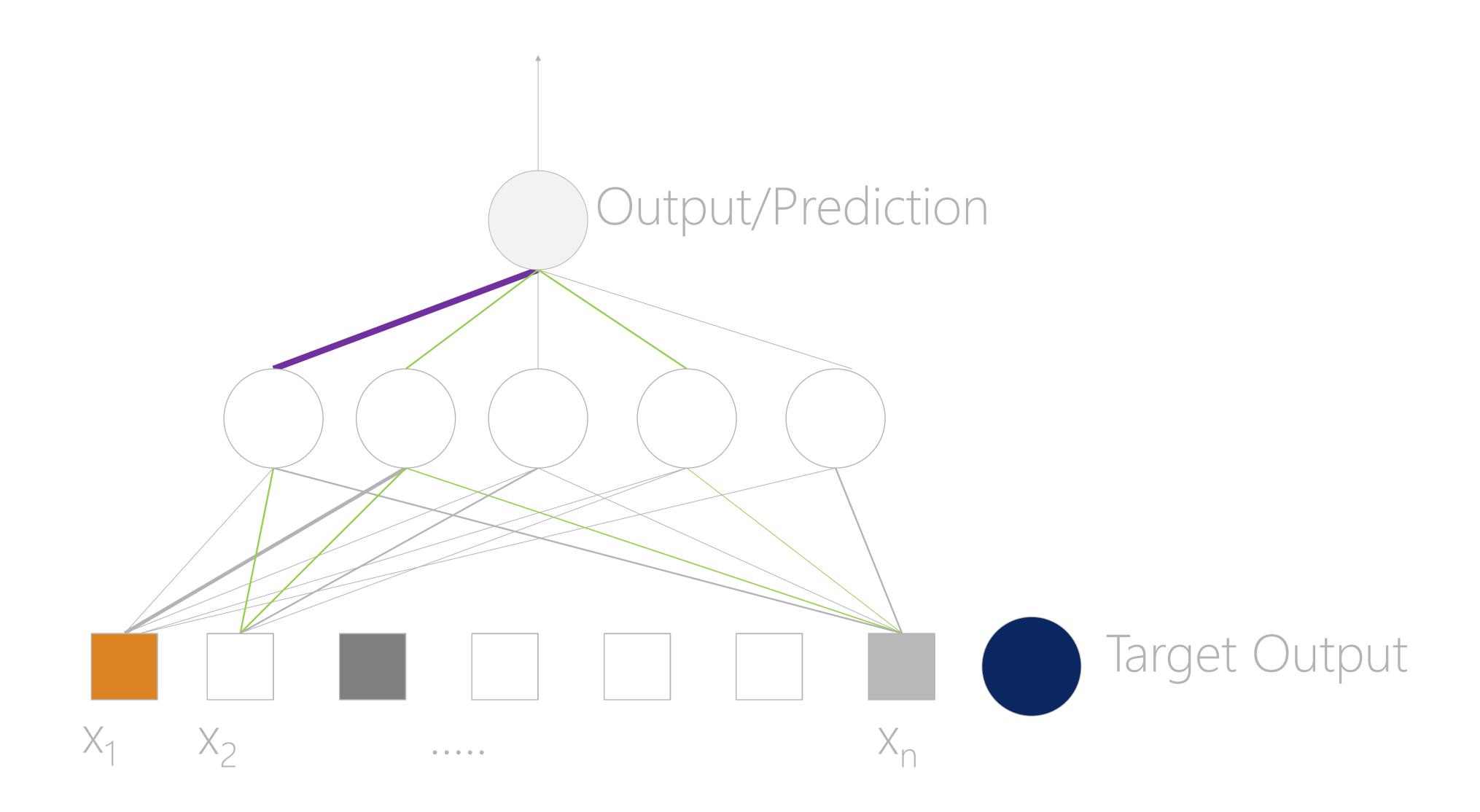
- Scales to more inputs
- Can chain neurons
- If all regressions are linear, then output will also be a linear regression



Learning Principle

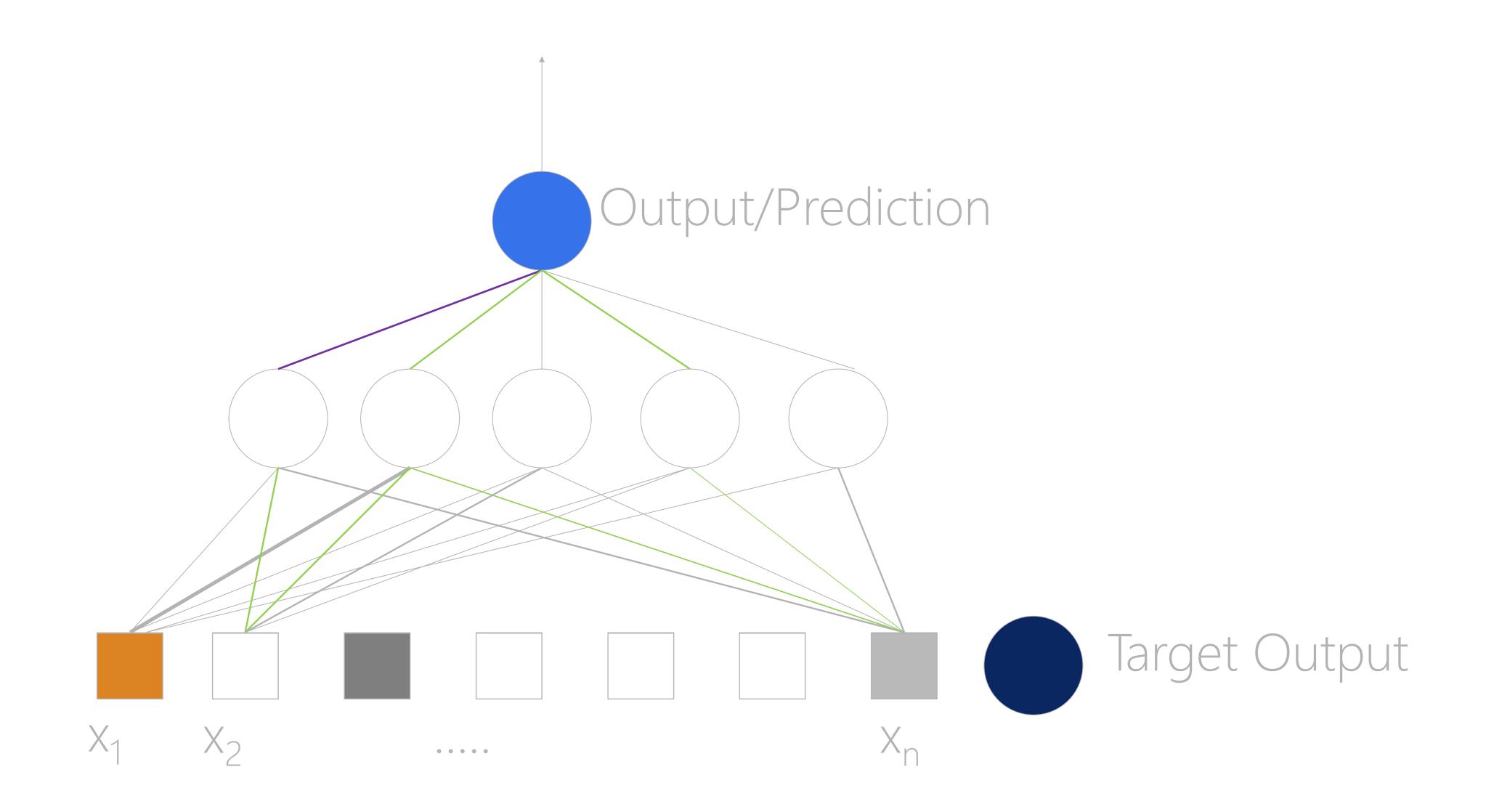


Learning Principle: adjust weigths





Learning Principle: adjust weights







Activation Functions

Linear

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

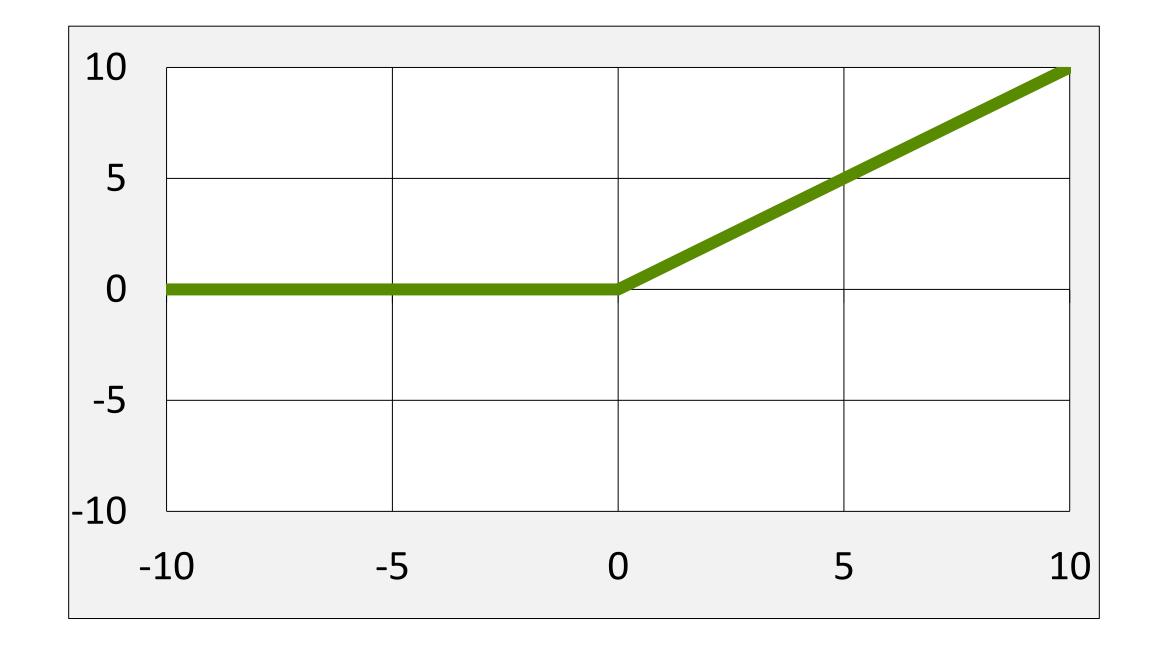
- 1 # Multiply each input
 2 # with a weight (w) and
- 3 # add intercept (b)
- $4 y_hat = wx+b$

10 5 0 -5 -10 -10 -5 0 5 10

ReLU

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

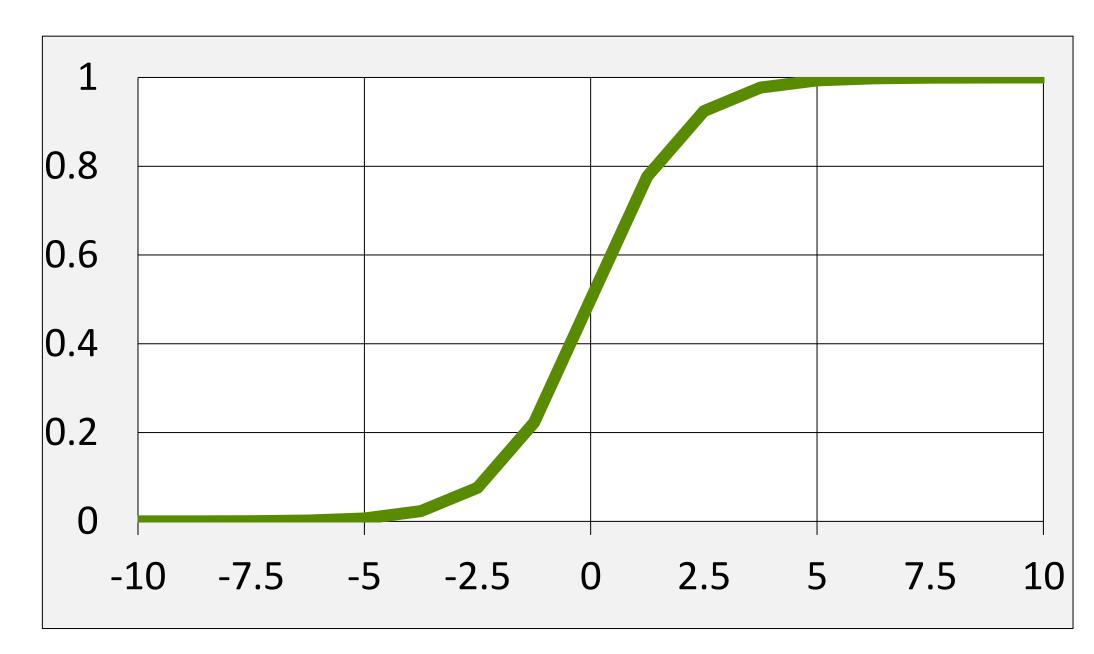
1 # Only return result
2 # if total is positive
3 linear = wx+b
4 y_hat = linear * (linear > 0)



Sigmoid

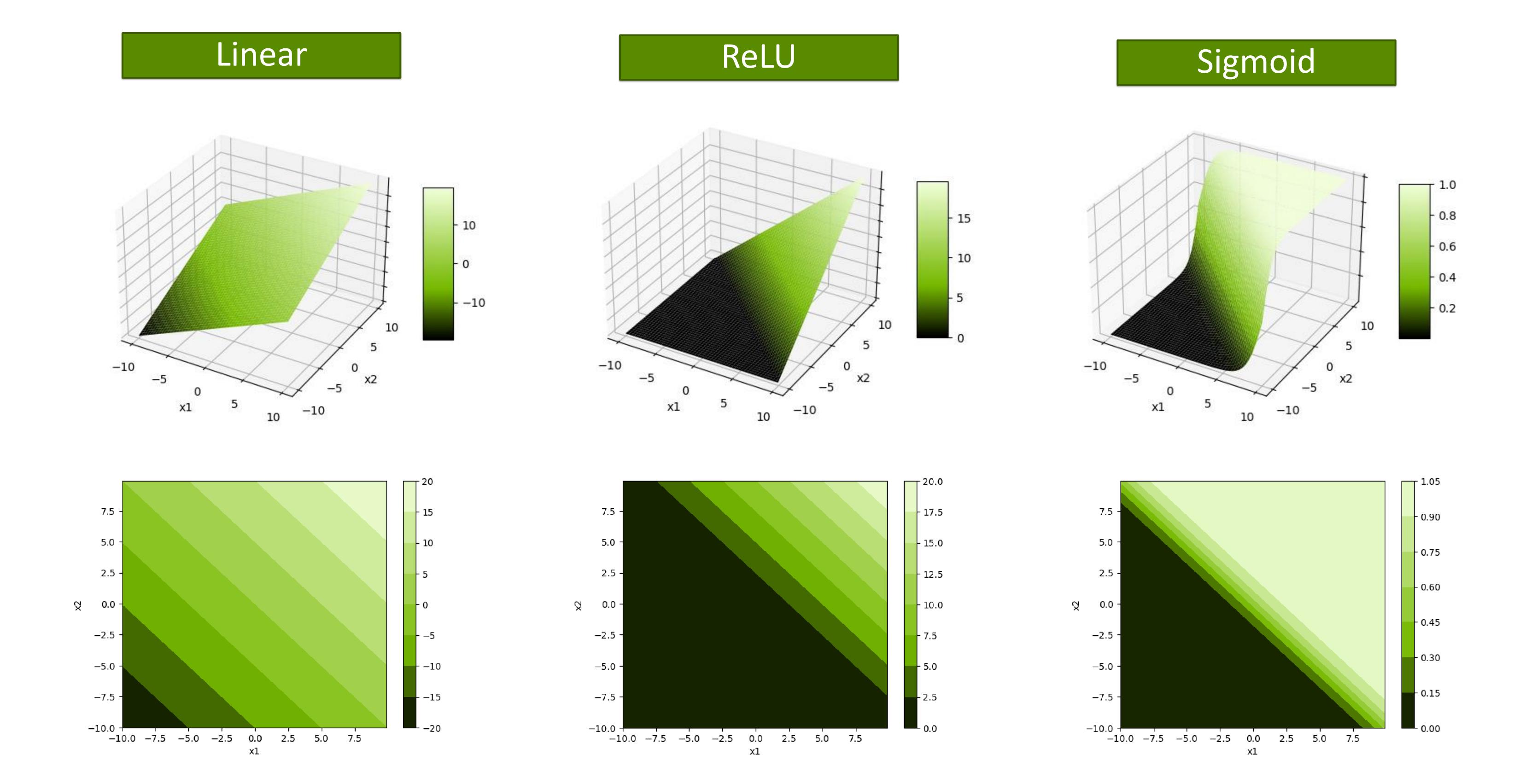
$$\hat{y} = \frac{1}{1 + e^{-(wx+b)}}$$

```
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)
```



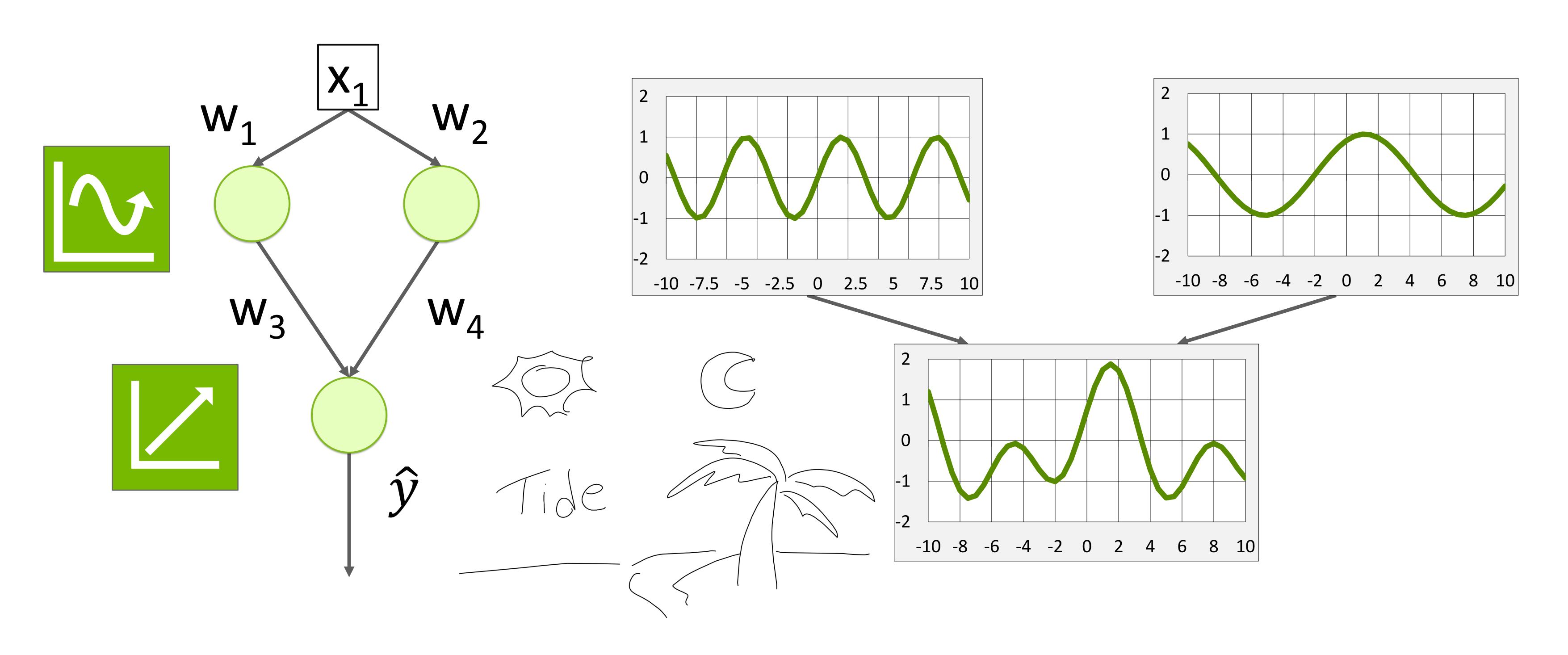


Activation Functions





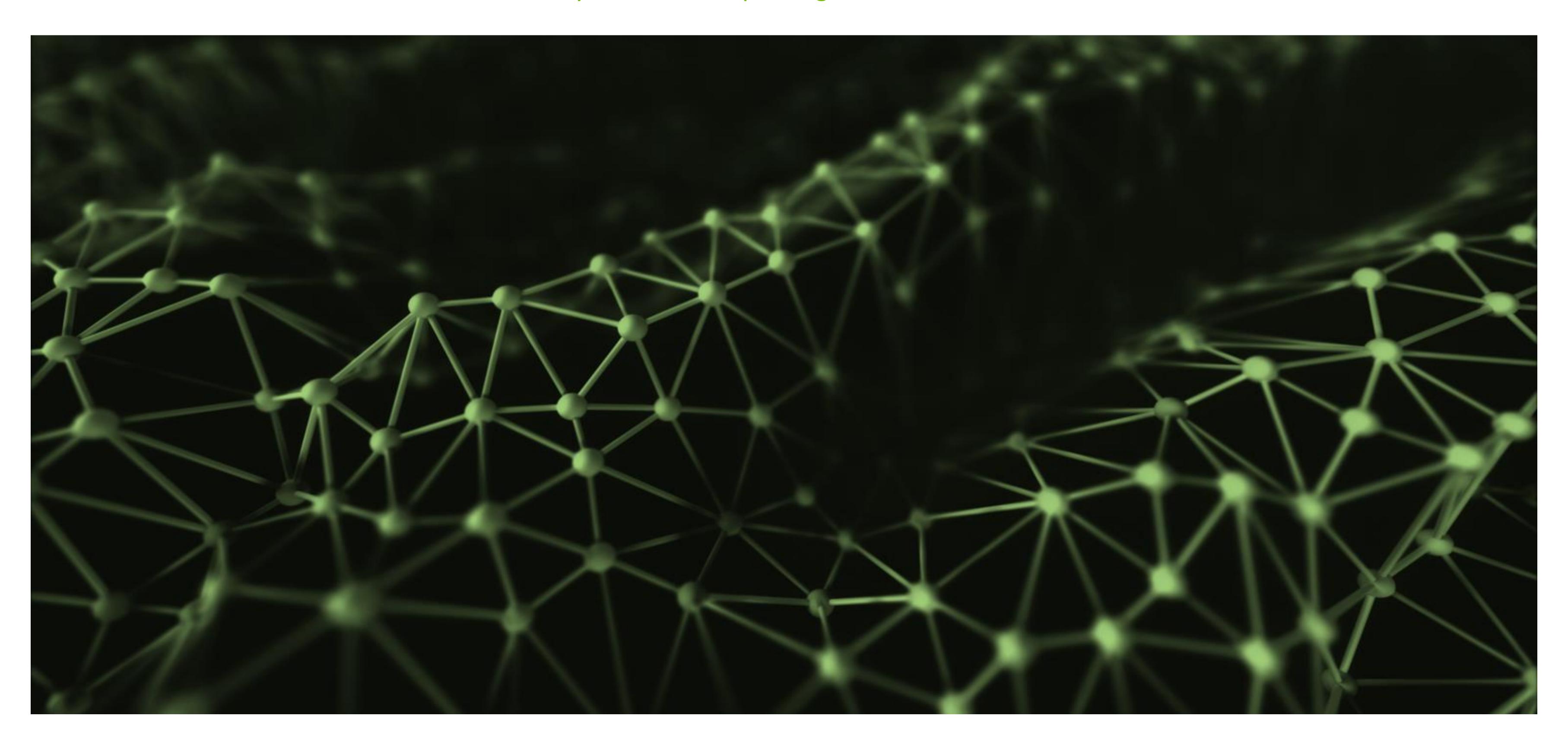
Activation Functions





Overfitting

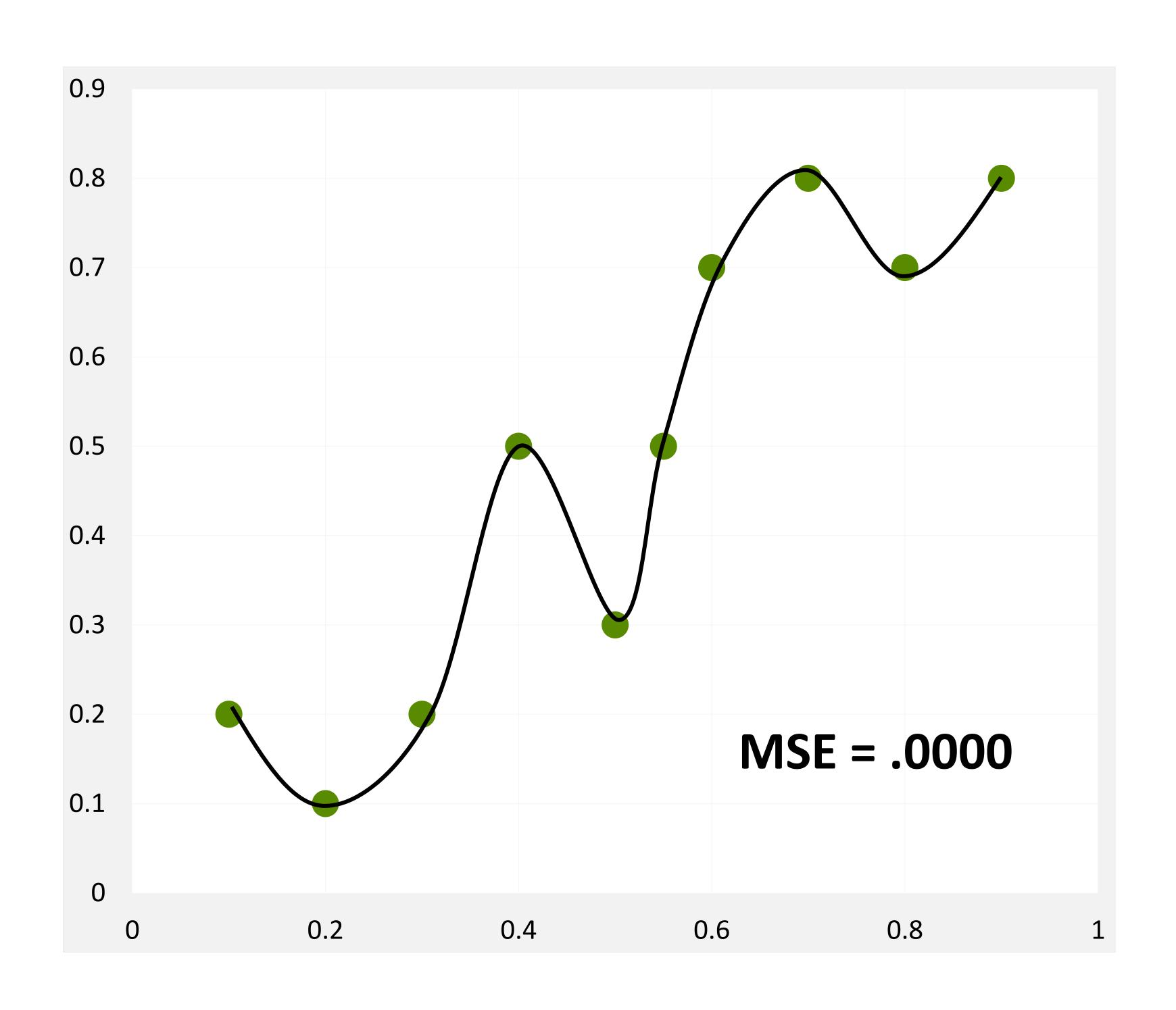
Why not have a super large neural network?

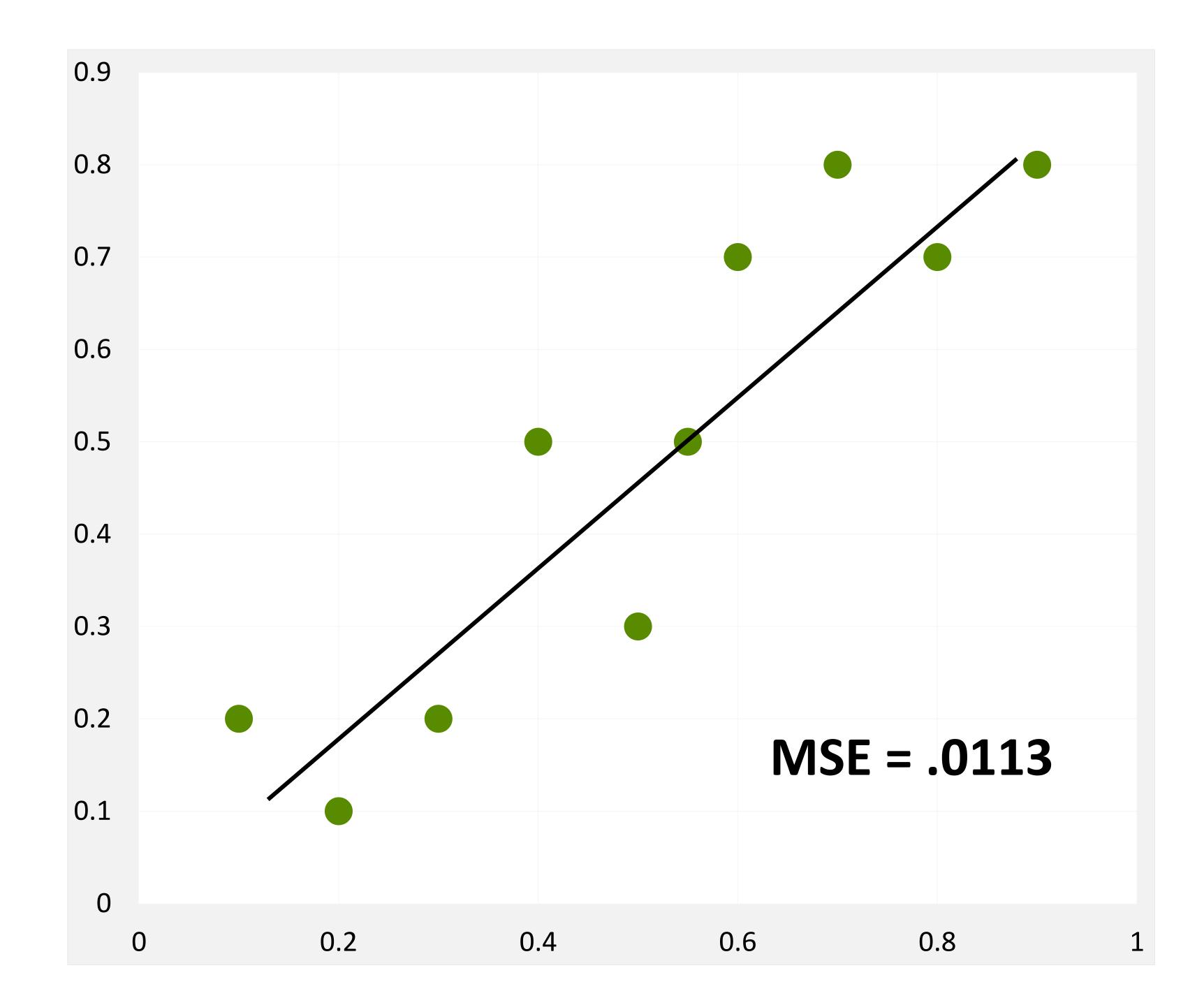




Overfitting

Which Trendline is Better?

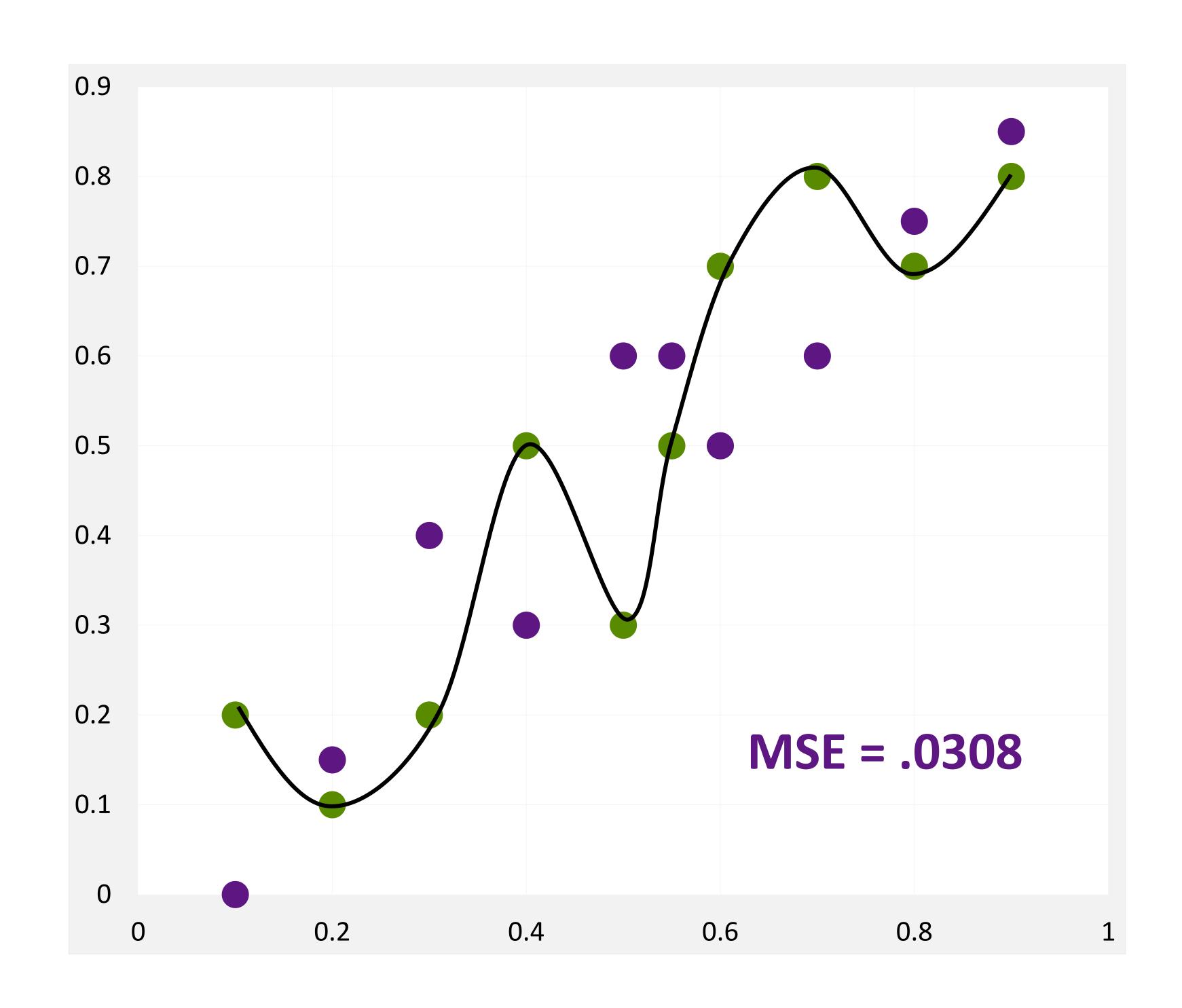


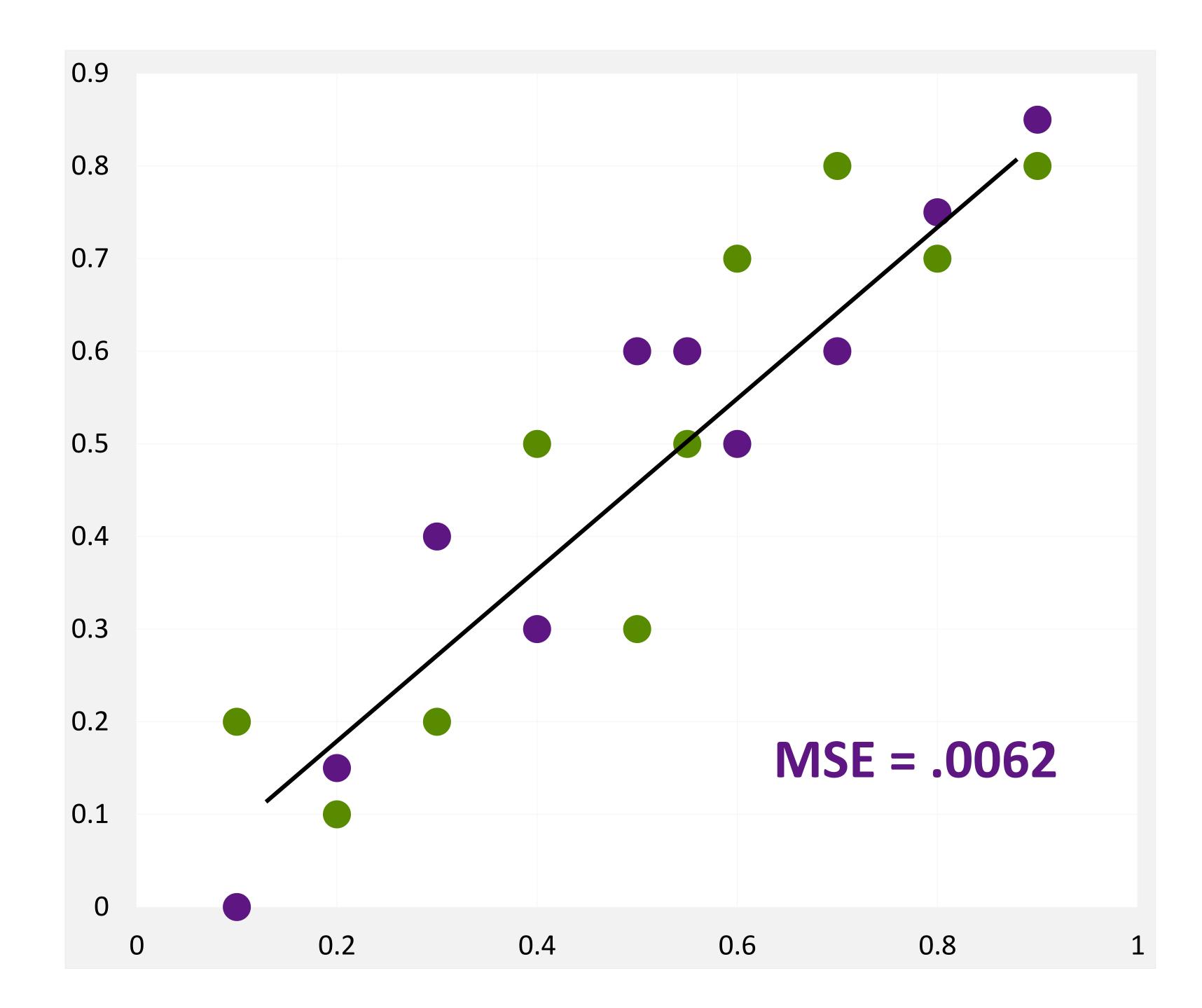




Overfitting

Which Trendline is Better?







Training vs Validation Data

Avoid memorization

Training data

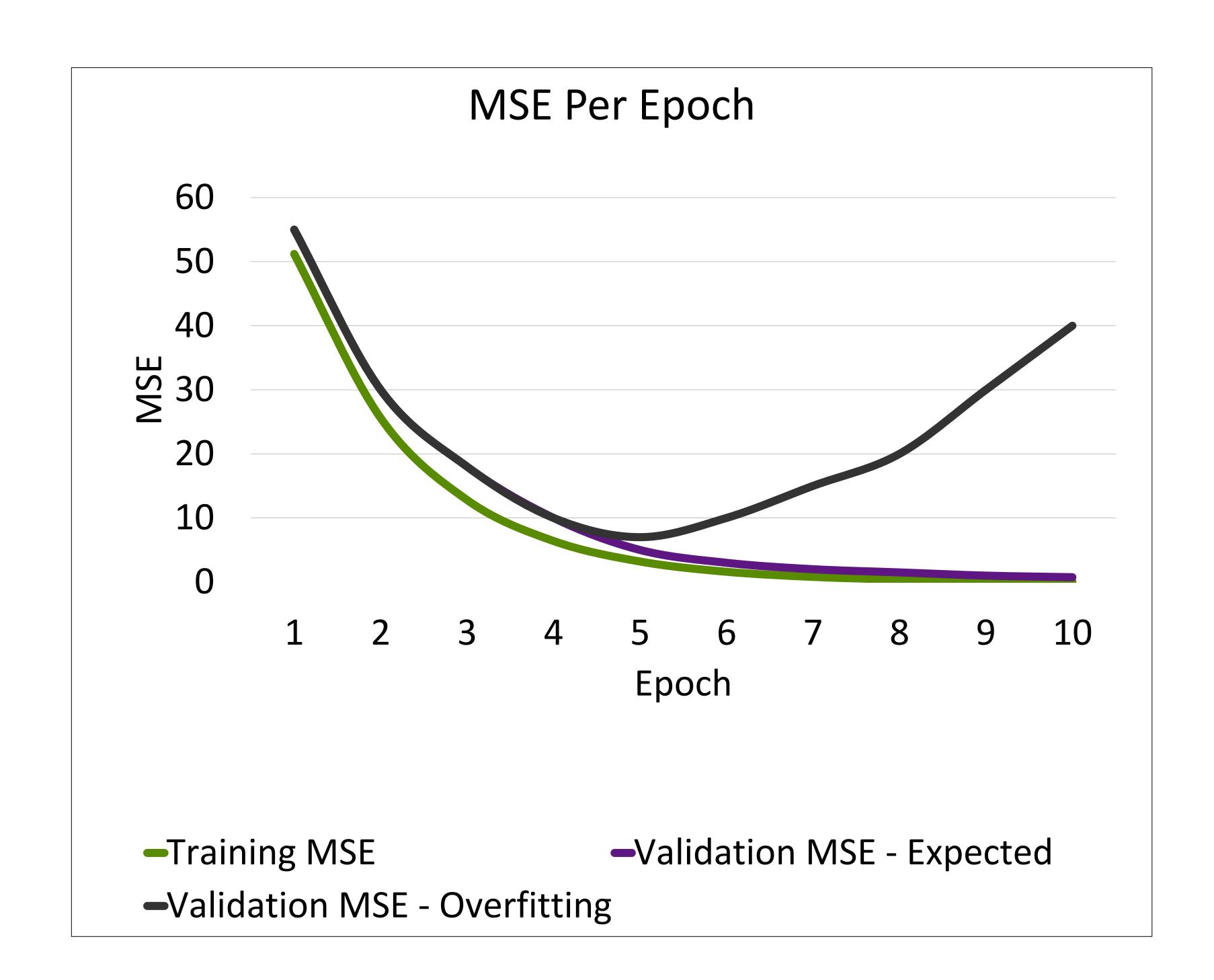
Core dataset for the model to learn on

Validation data

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

Overfitting

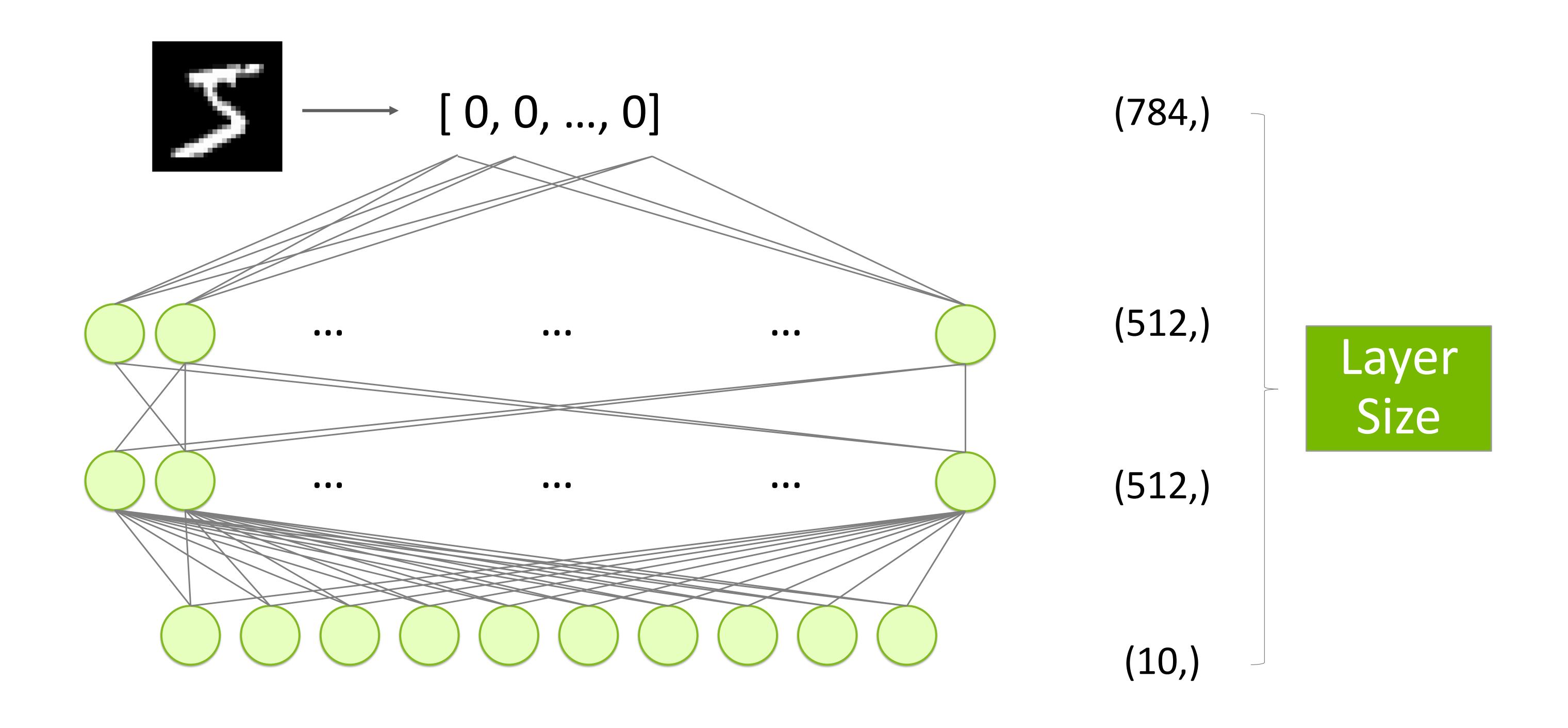
- •When model performs well on the training data, but not the validation data (evidence of memorization)
- Ideally the accuracy and loss should be similar between both datasets







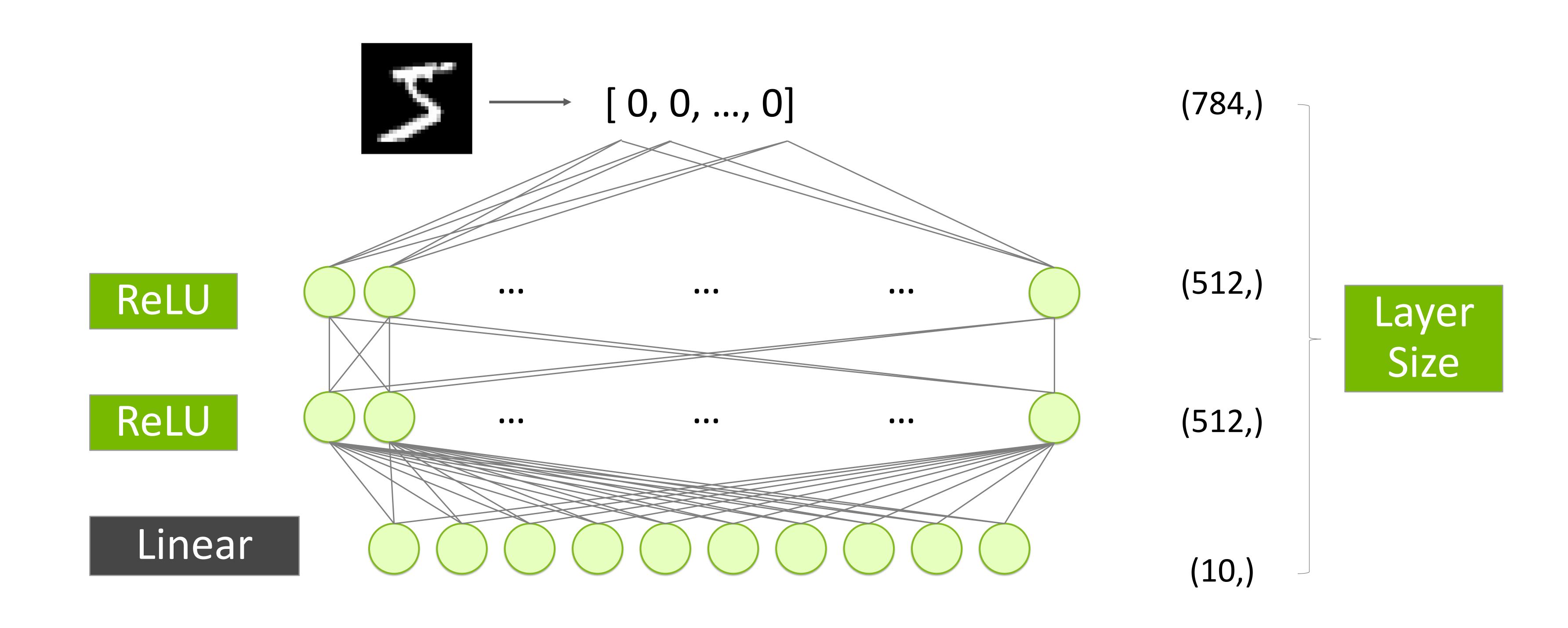
An MNIST Model





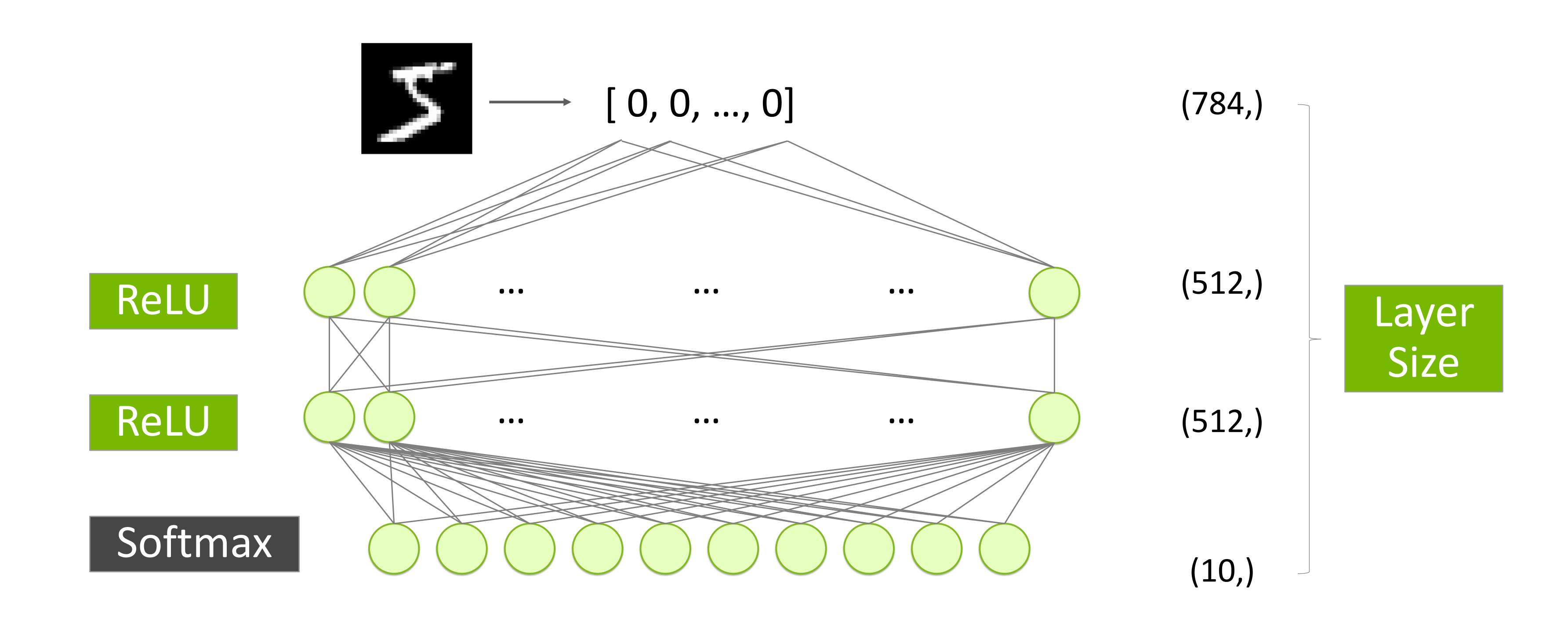
An MNIST Model

During Prediction

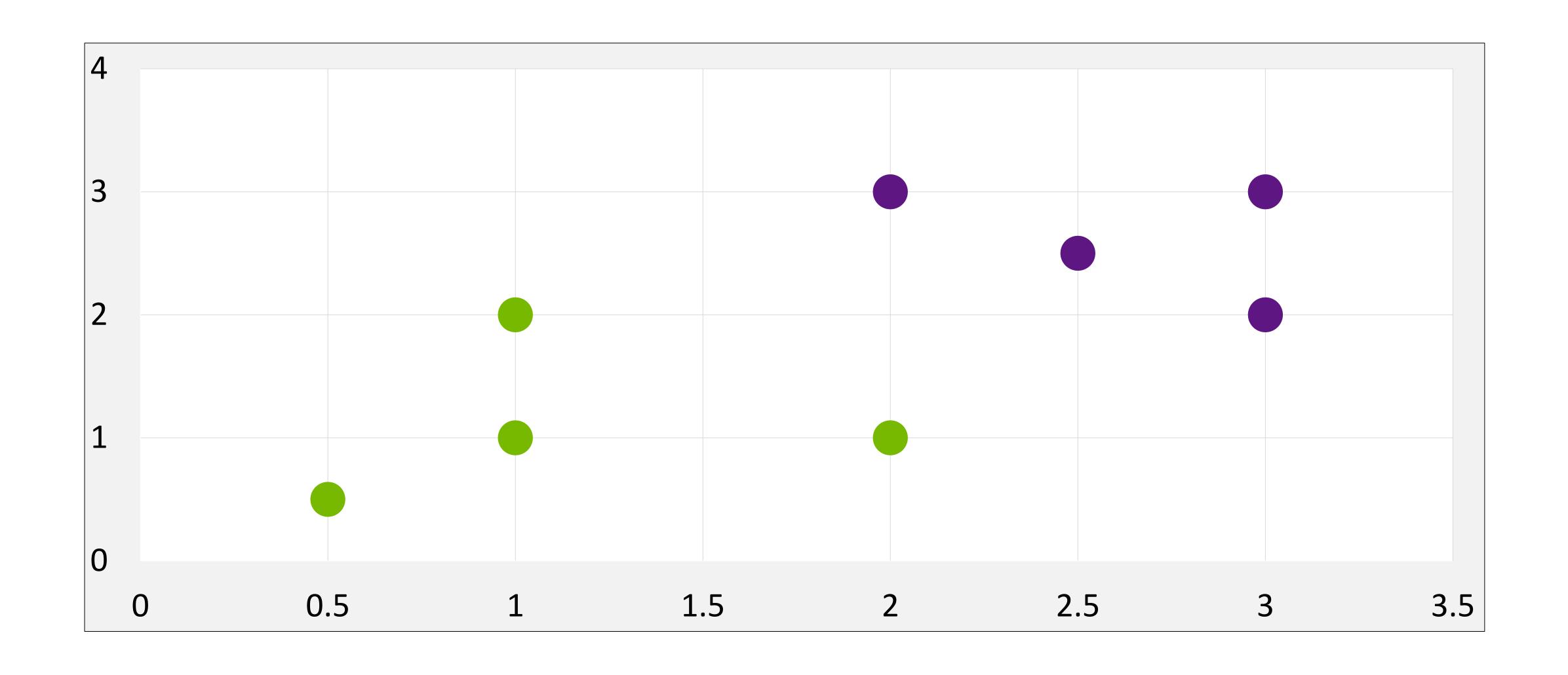


An MNIST Model

During Training

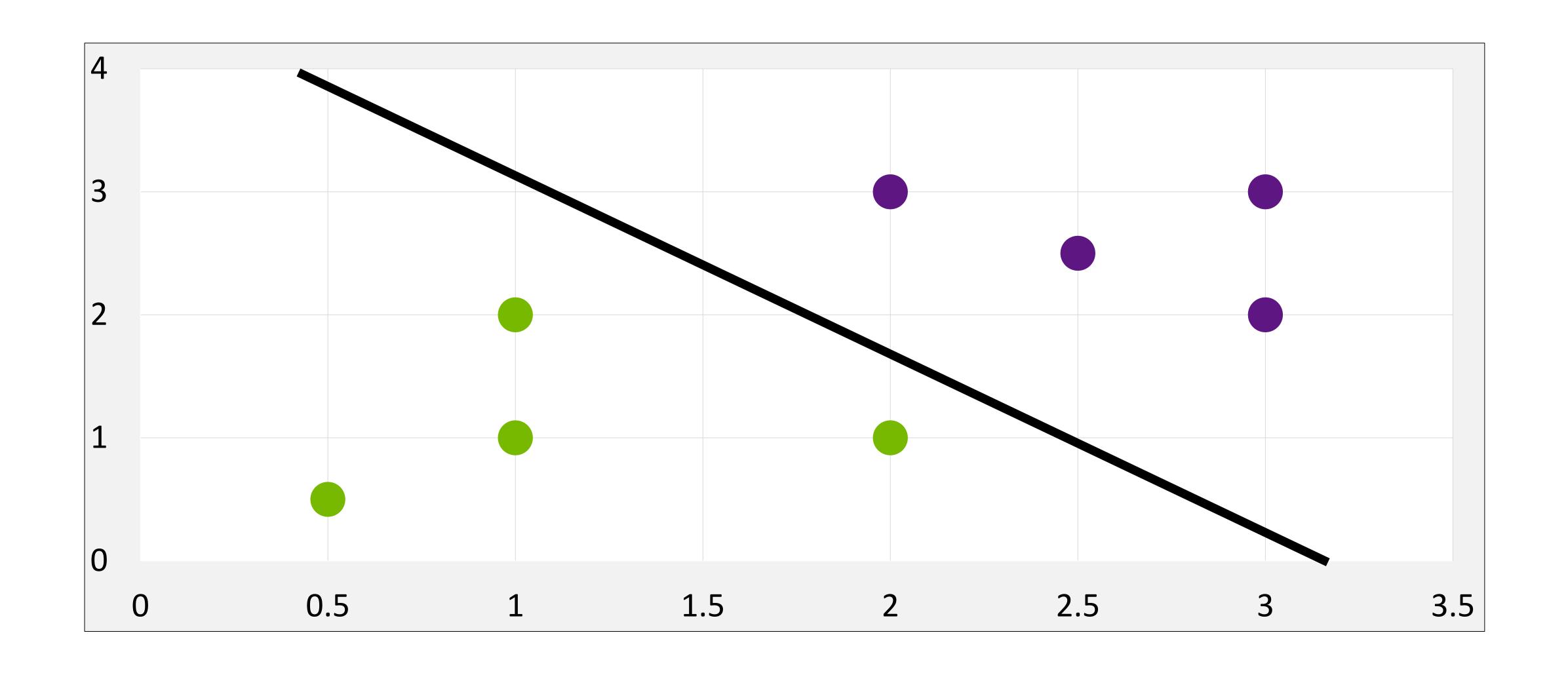


RMSE For Probabilities?



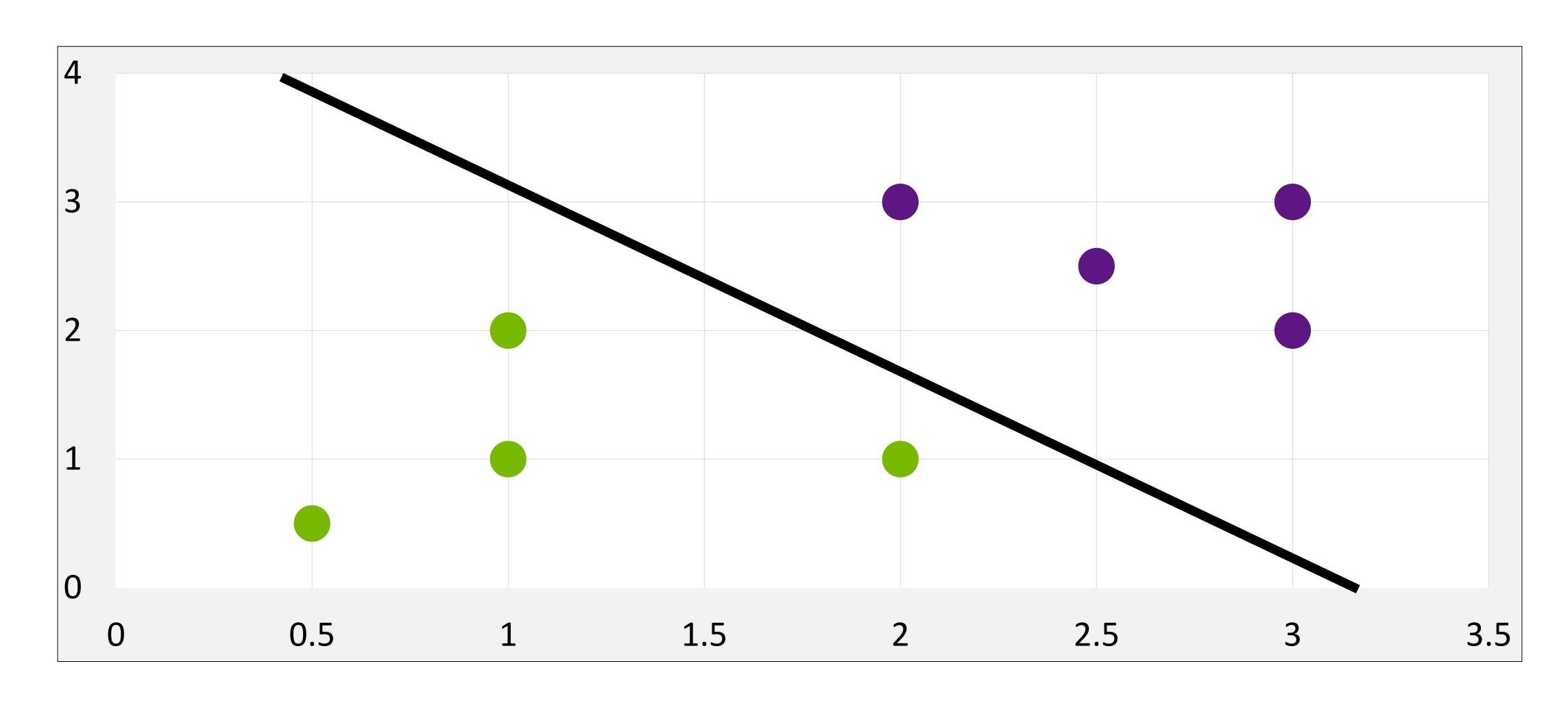


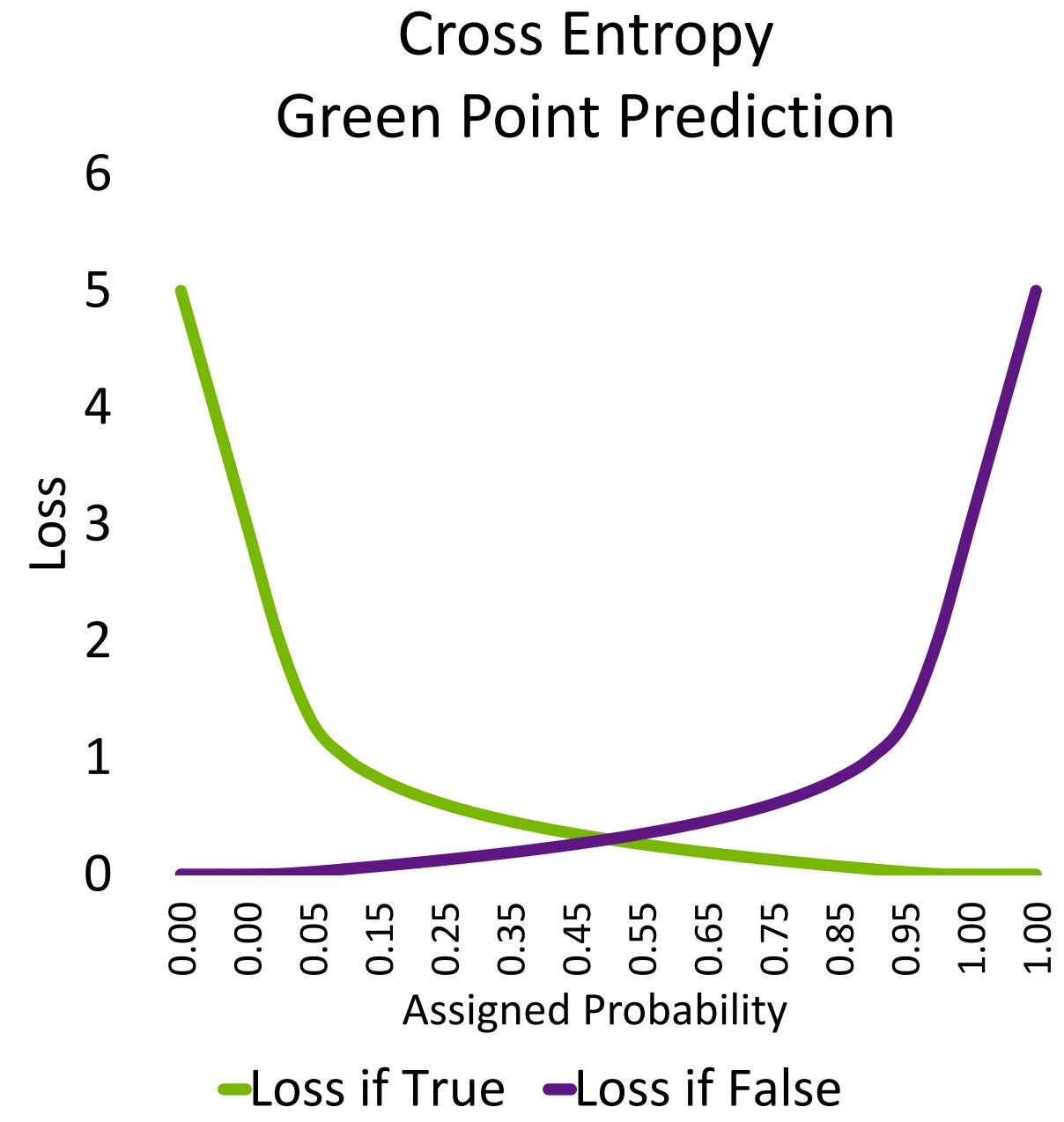
RMSE For Probabilities?





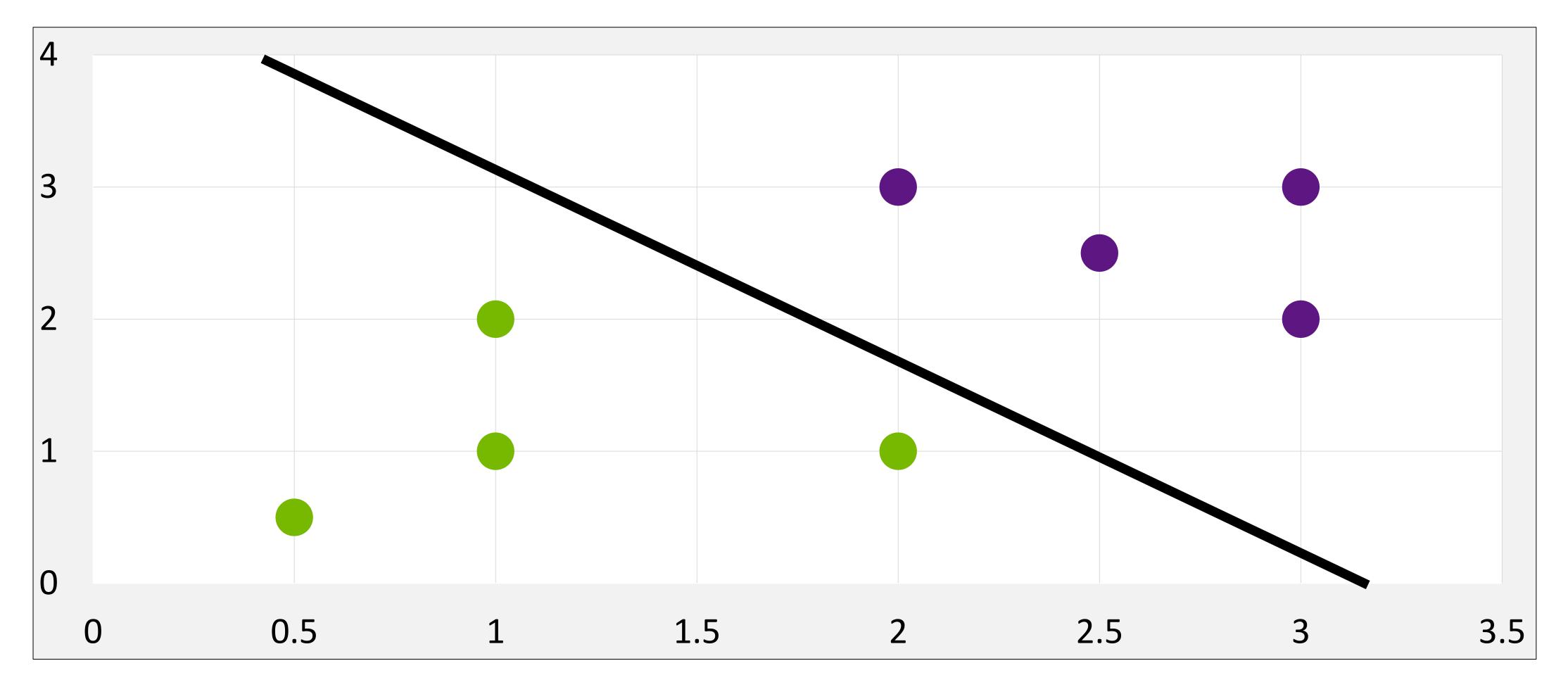
Cross Entropy

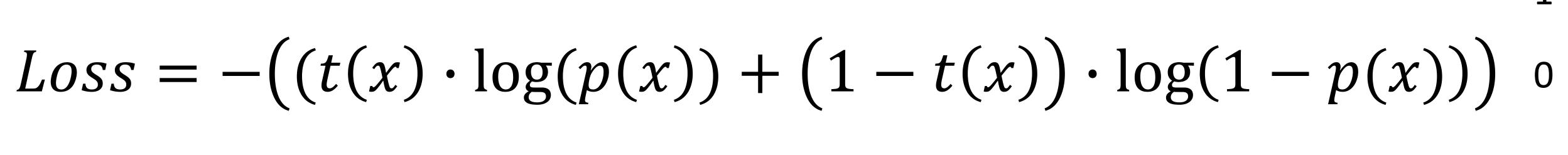






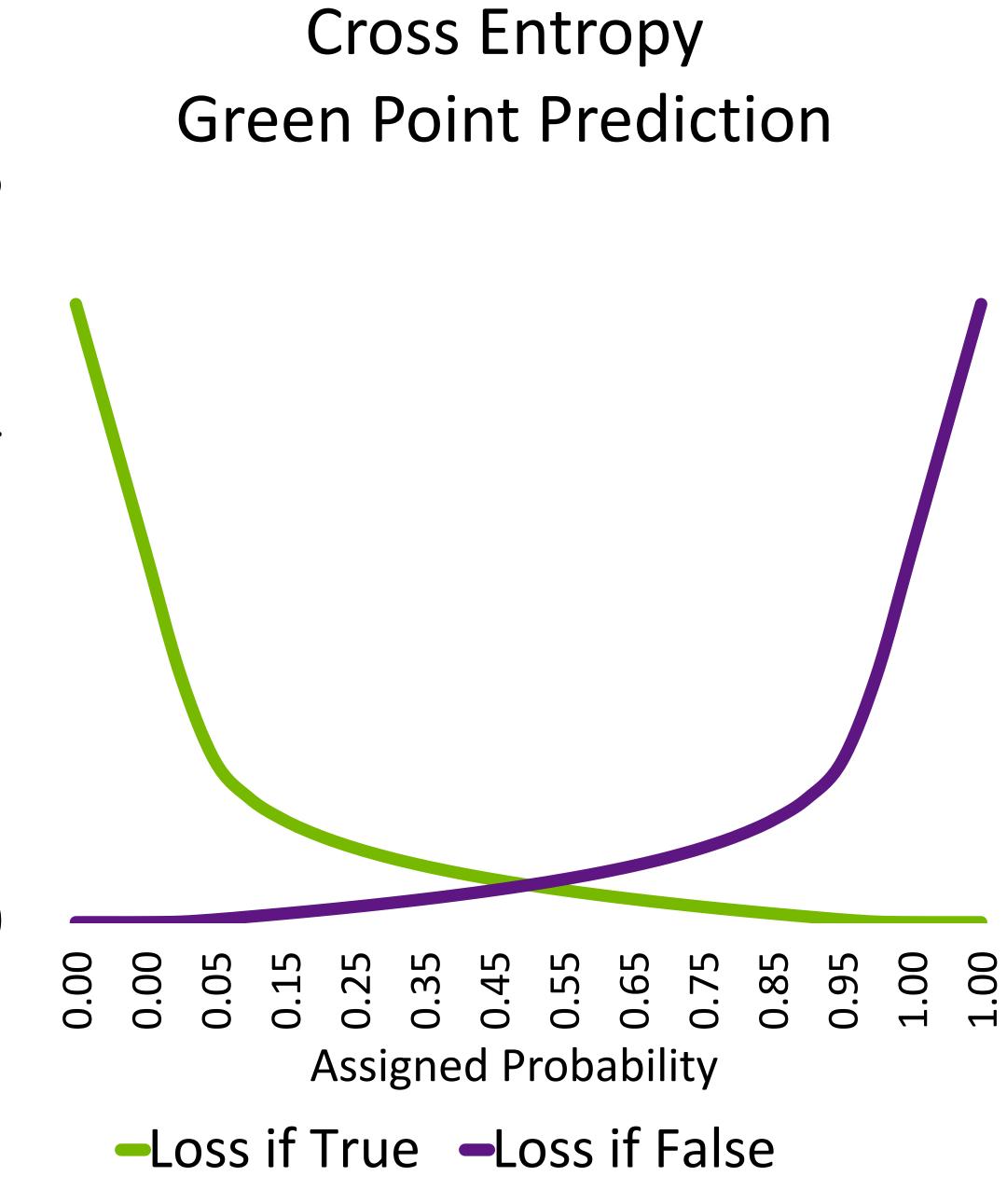
Cross Entropy



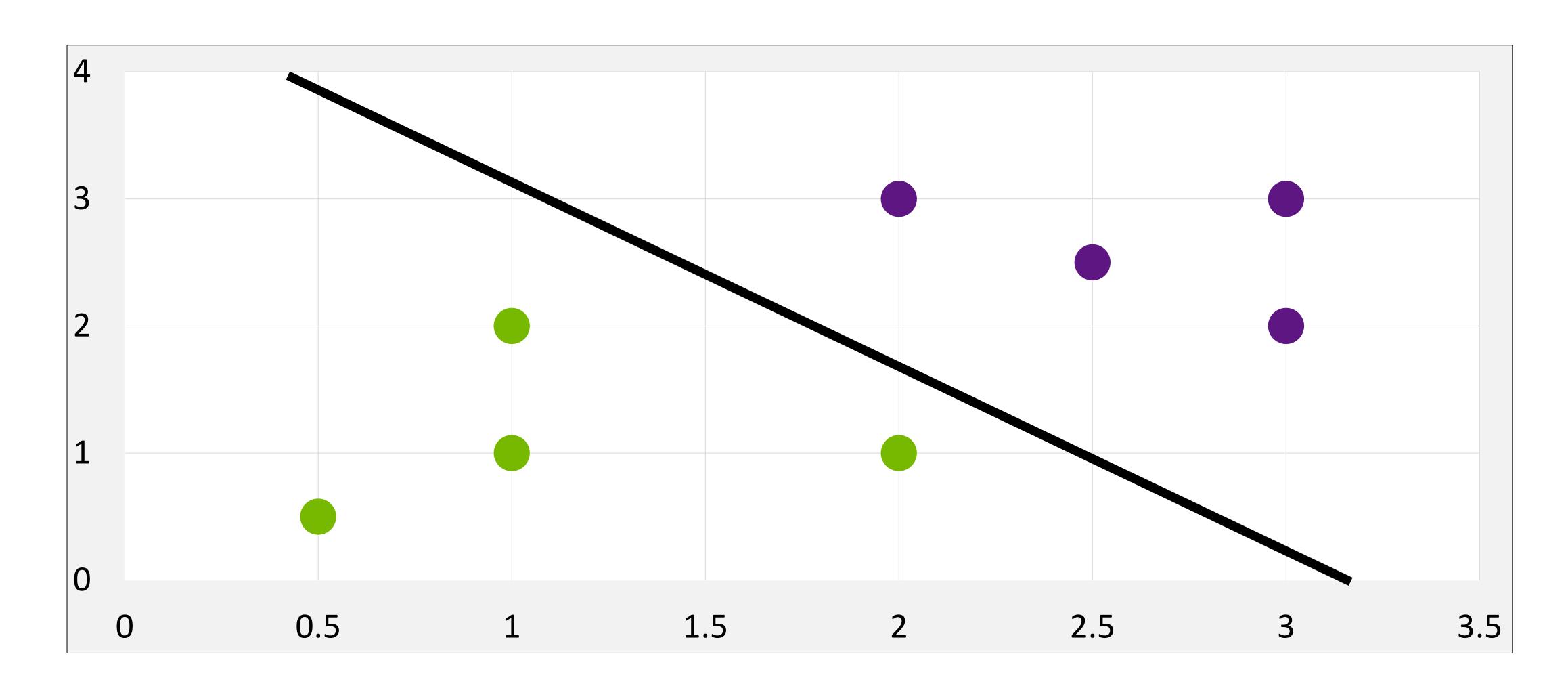


t(x) = target (0 if False, 1 if True)

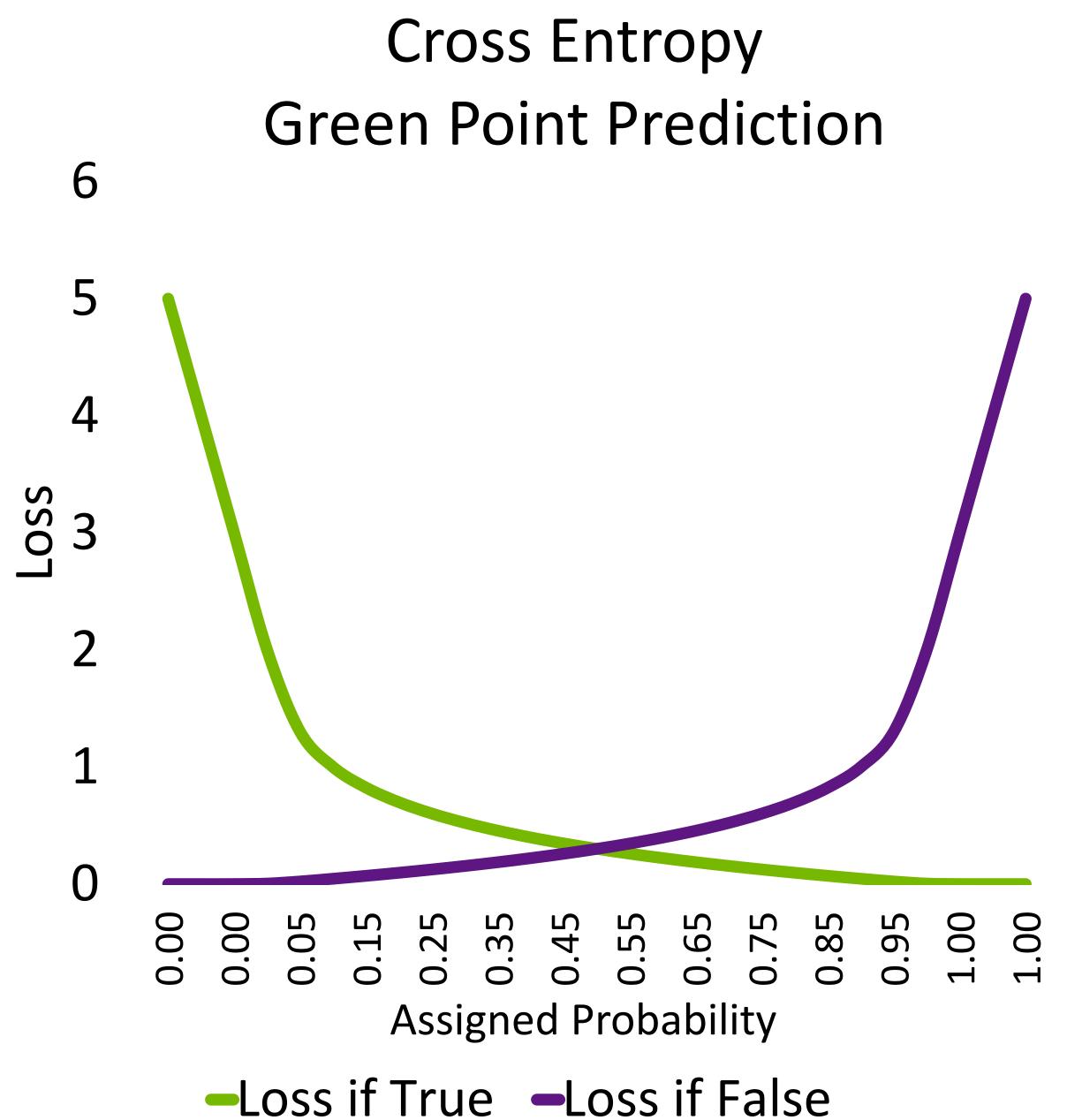
p(x) = probability prediction of point x



Cross Entropy



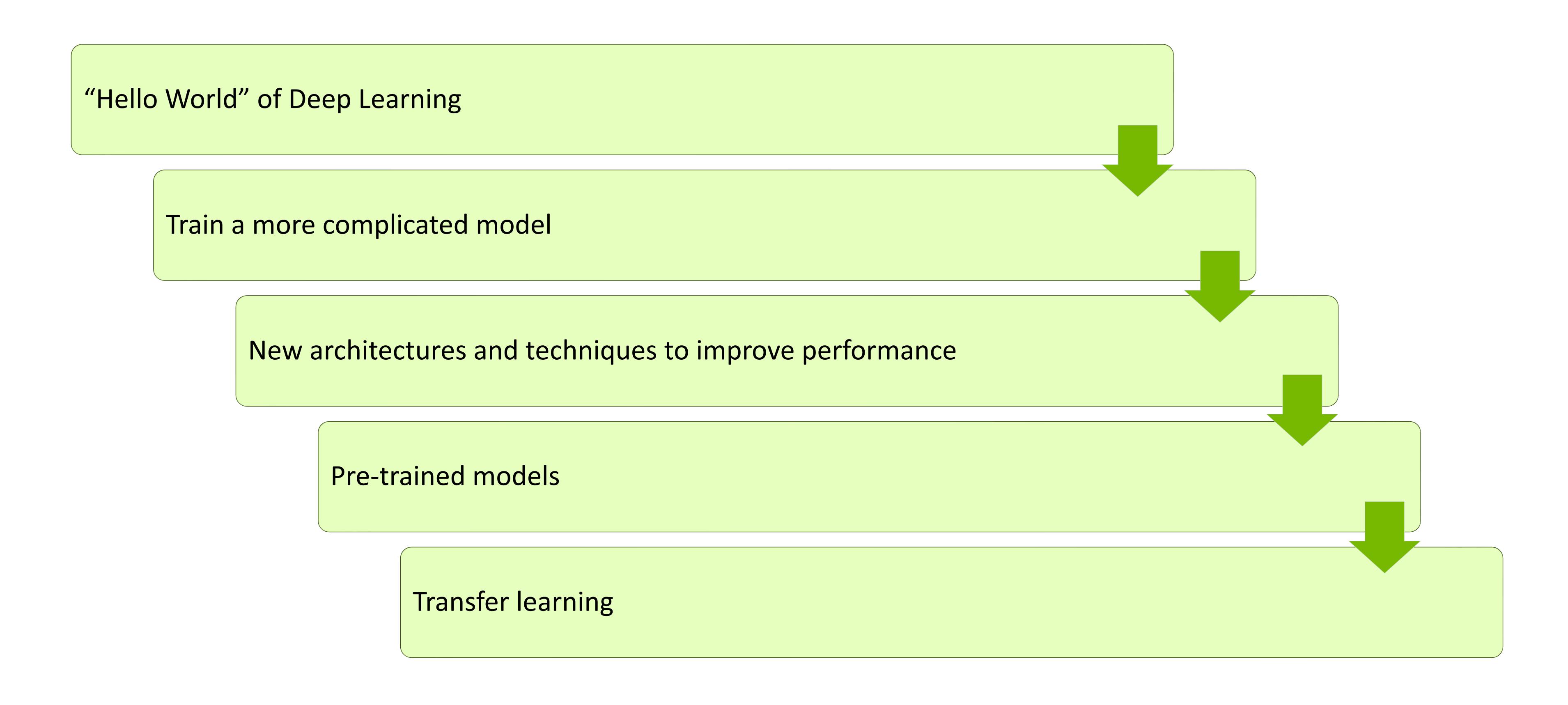
```
def cross_entropy(y_hat, y_actual):
    """Infinite error for misplaced confidence."""
    loss = log(y_hat) if y_actual else log(1-y_hat)
    return -1*loss
```



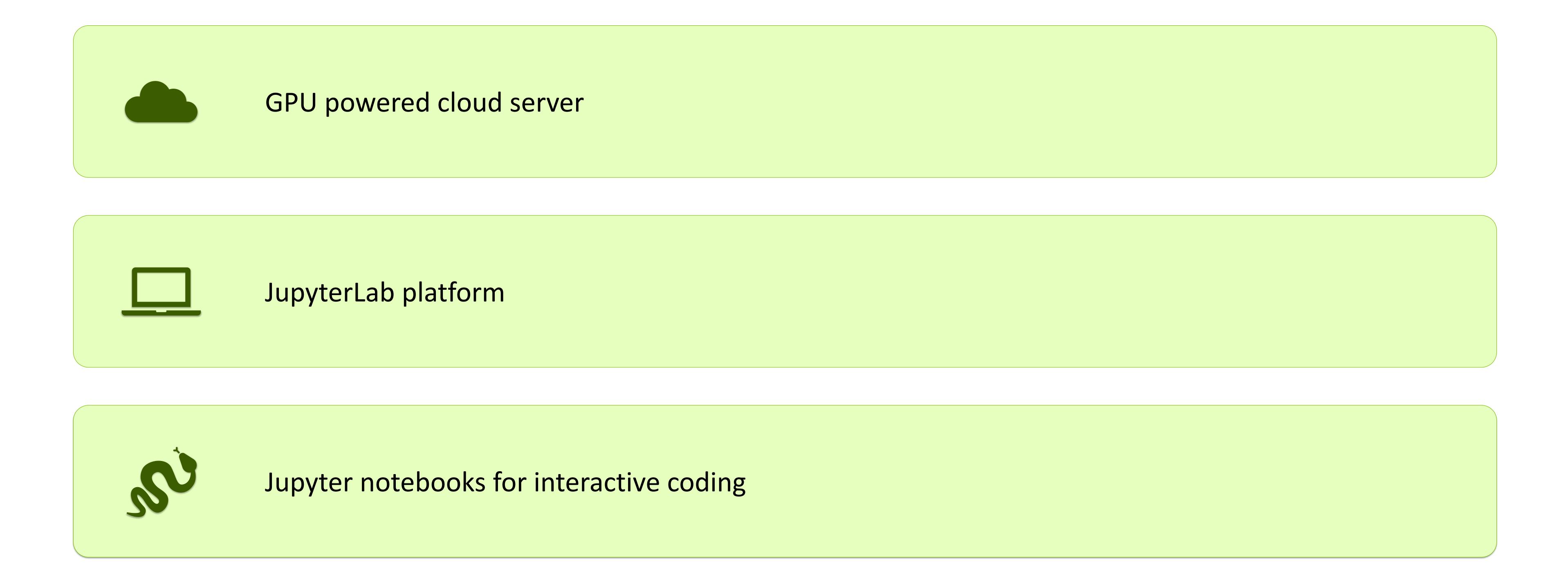




Structure of the Course



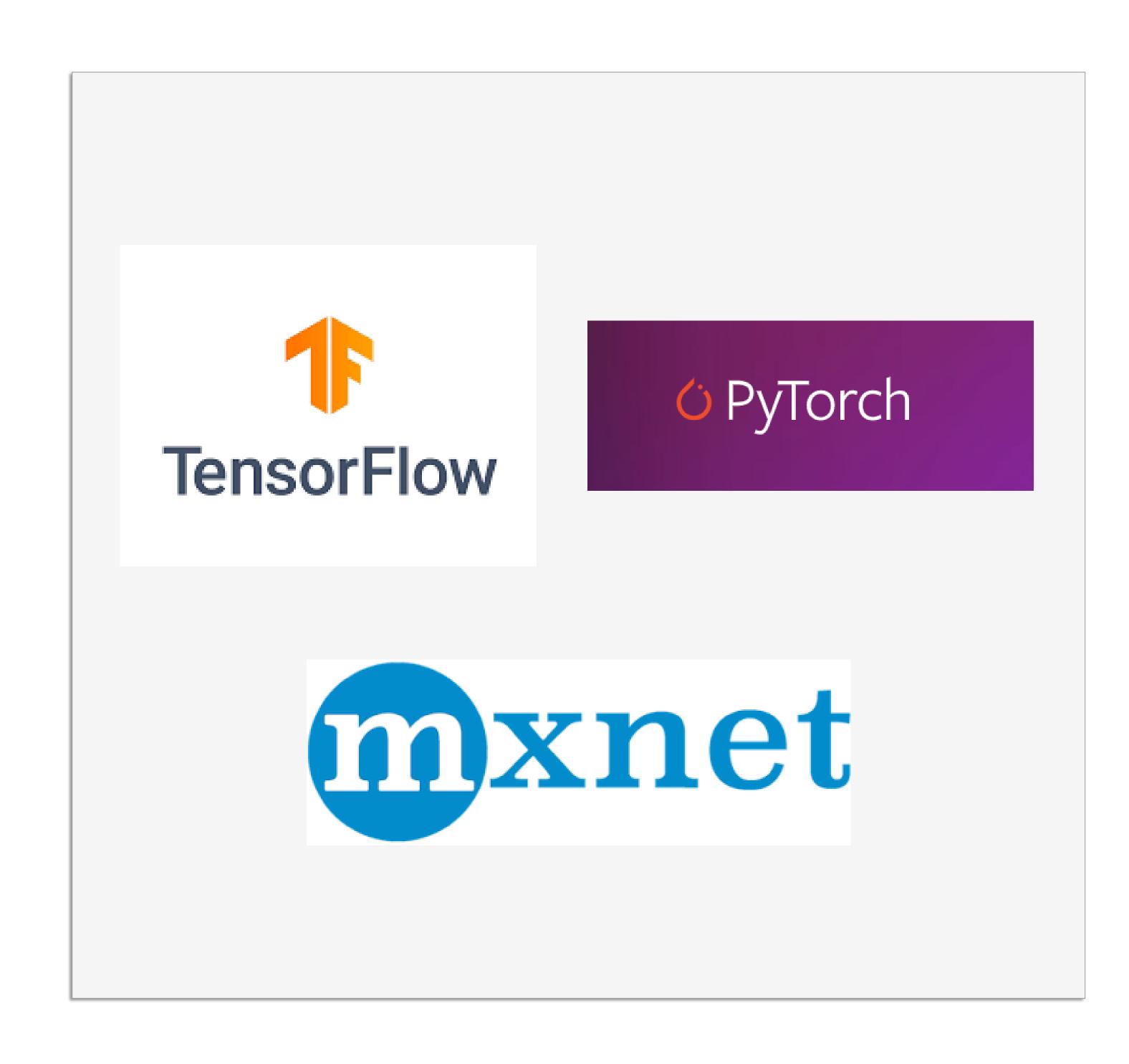
Platform of the Course





Software of This Course

- Major deep learning platforms:
 - TensorFlow + Keras (Google)
 - PyTorch (Meta)
 - MXNet (Apache)
- We'll be using PyTorch
- Good idea to gain exposure to others moving forward





Hands on Exercises

- Get comfortable with the process of deep learning
- Exposure to different models and datatypes
- Get a jump-start to tackle your own projects
- Have fun!!



Hands on: work through Introduction Section

- 1. WIFI Info: eduroam
- 2. Browser Recommendation: Chrome
- 3. websocketstest.courses.nvidia.com
- 4. https://learn.nvidia.com/dli-event
- 5. create an Account (if you have not done yet!)
- 6. event code:
- work through the Introduction Section and 'Start' launching your first GPU task

First exercise: MNSIT dataset classification (Hello Neural Networks)

Train a network to correctly classify handwritten digits

Historically important and difficult task for computers

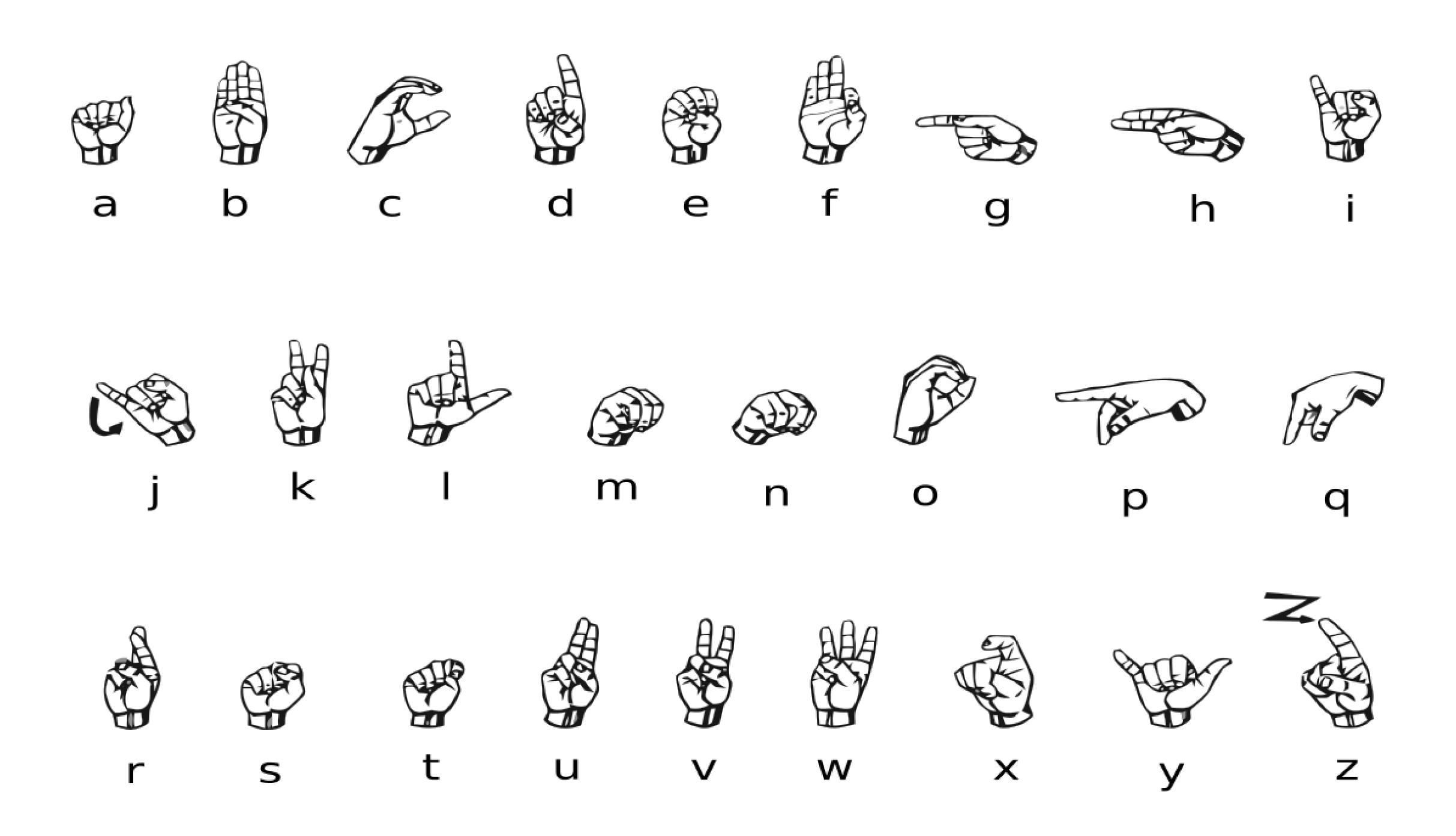
Try learning like a Neural Network

Get exposed to the example, and try to figure out the rules to how it works



Second Exercise

The American Sign Language Alphabet







Appendix: Gradient Descent

Helping the Computer Cheat Calculus

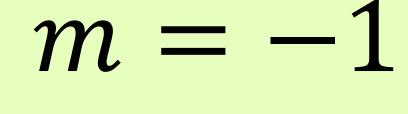
Learning from Error

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

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

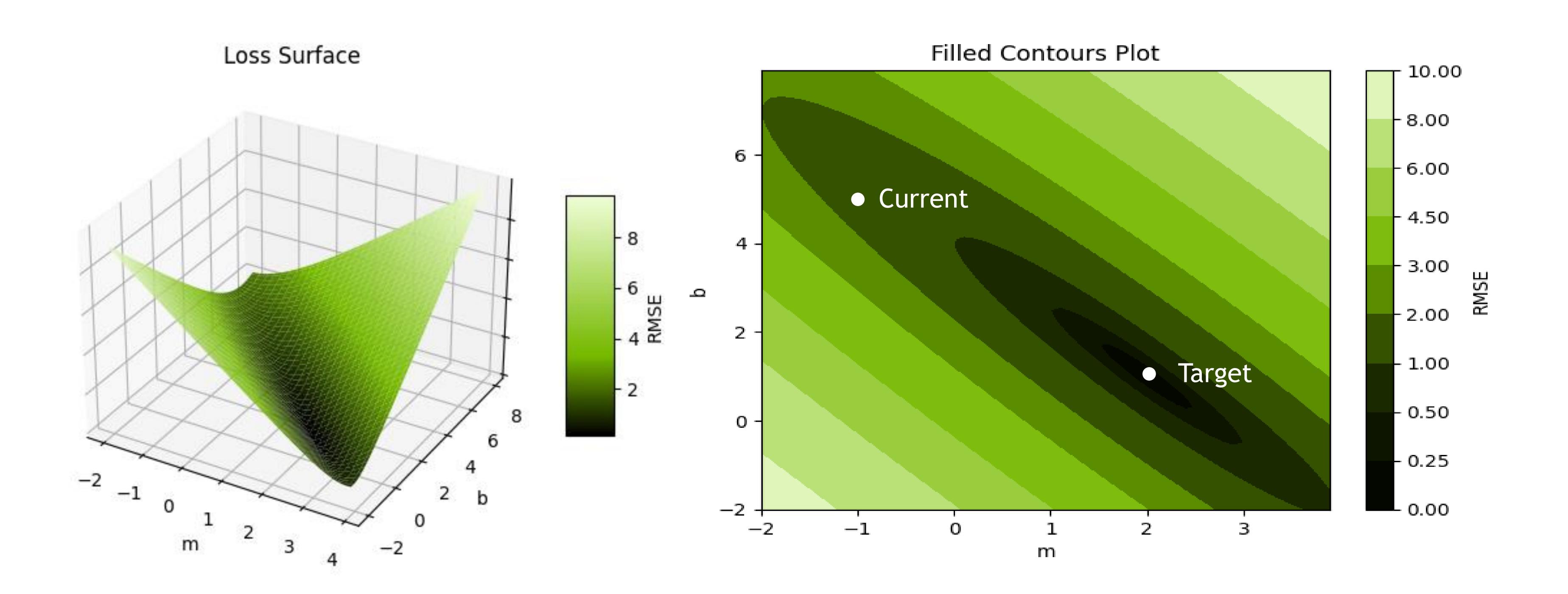
$$\frac{\partial MSE}{\partial m} = 5m + 3b - 13 \qquad \qquad \frac{\partial MSE}{\partial b} = 3m + 2b - 8$$

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



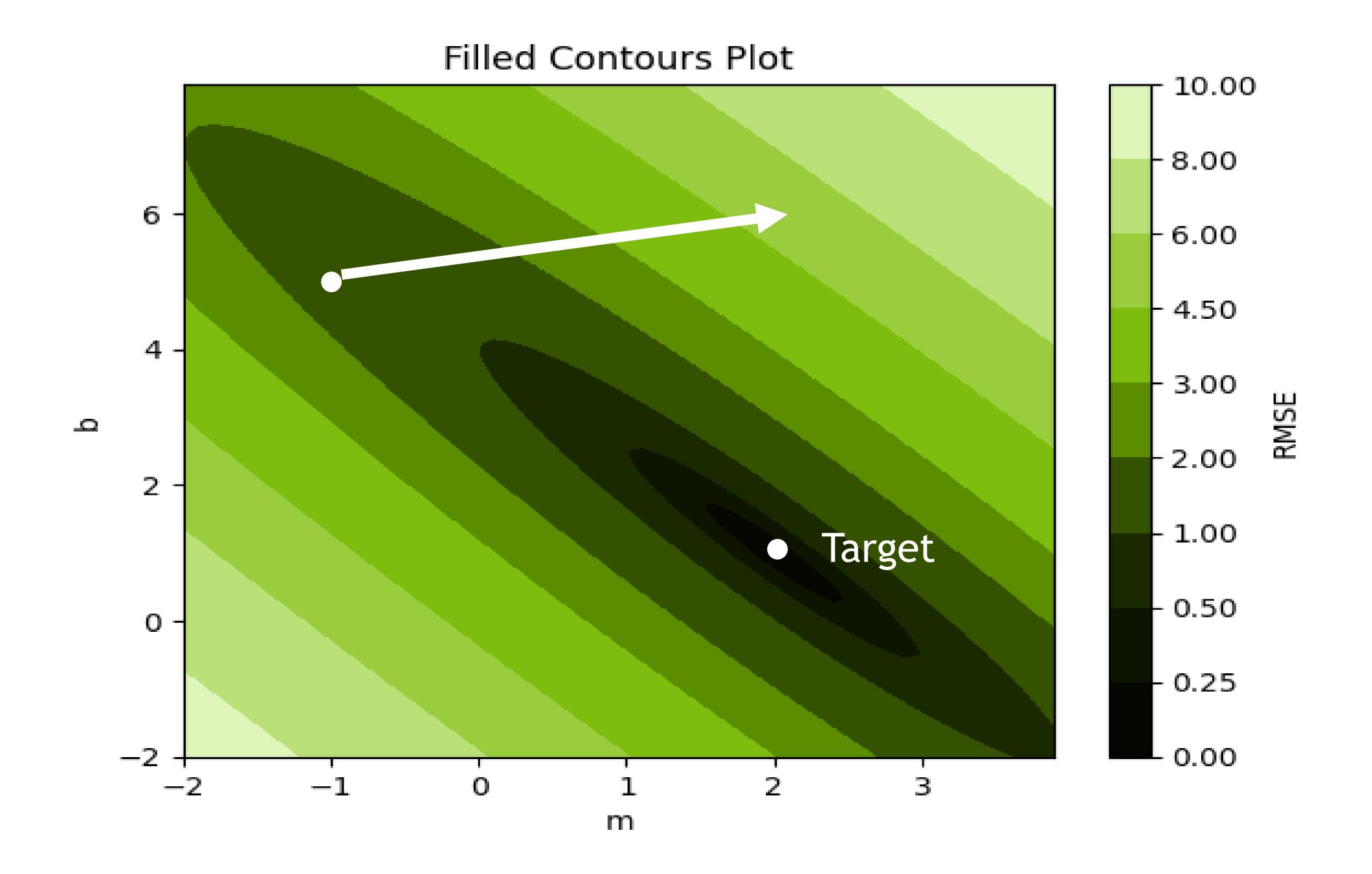
$$b = 5$$







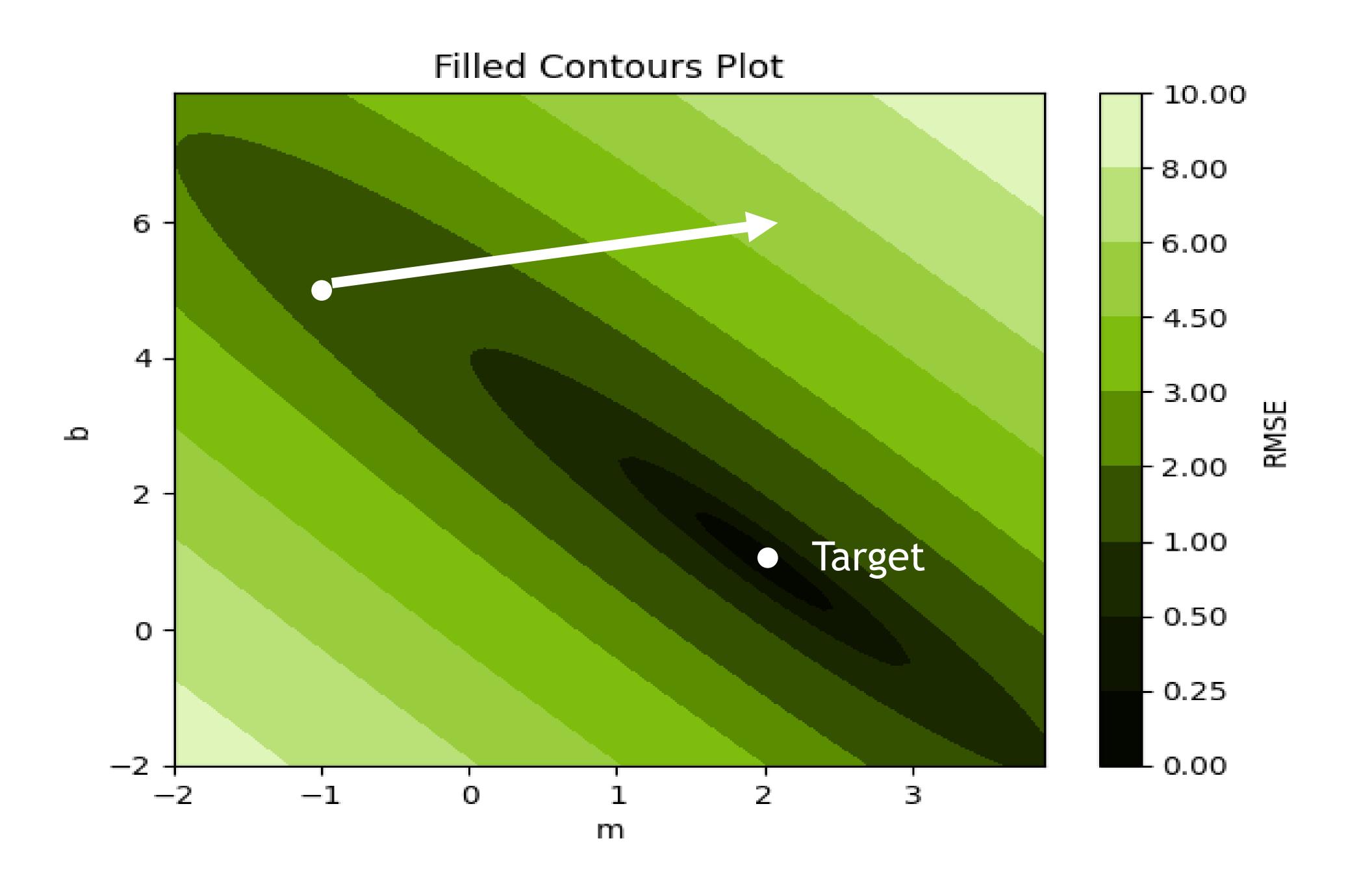
$$\frac{\partial MSE}{\partial m} = -3 \qquad \frac{\partial MSE}{\partial b} = -1$$



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

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

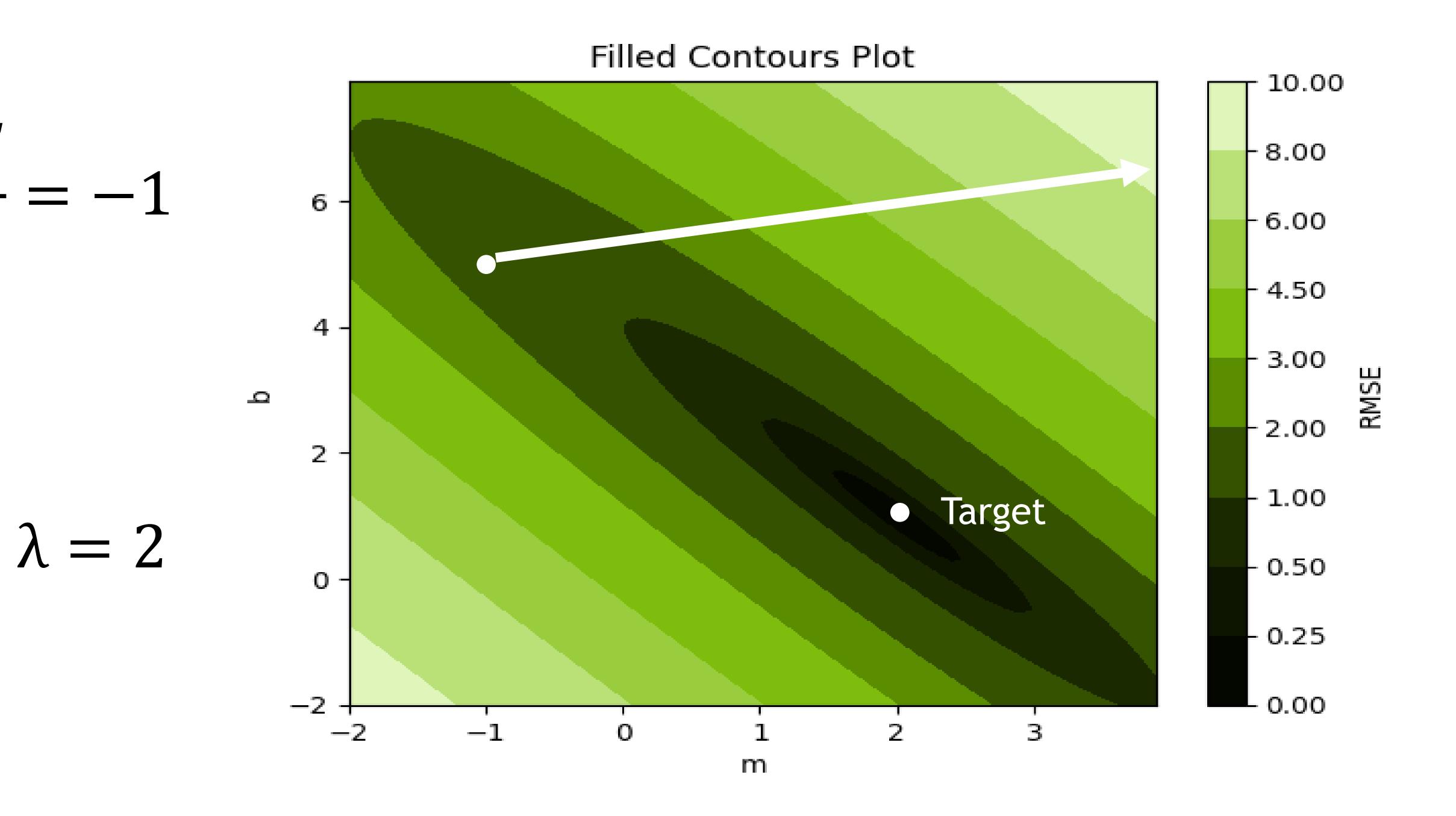
$$b := b - \lambda \frac{\partial MSE}{\partial b}$$



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

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

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

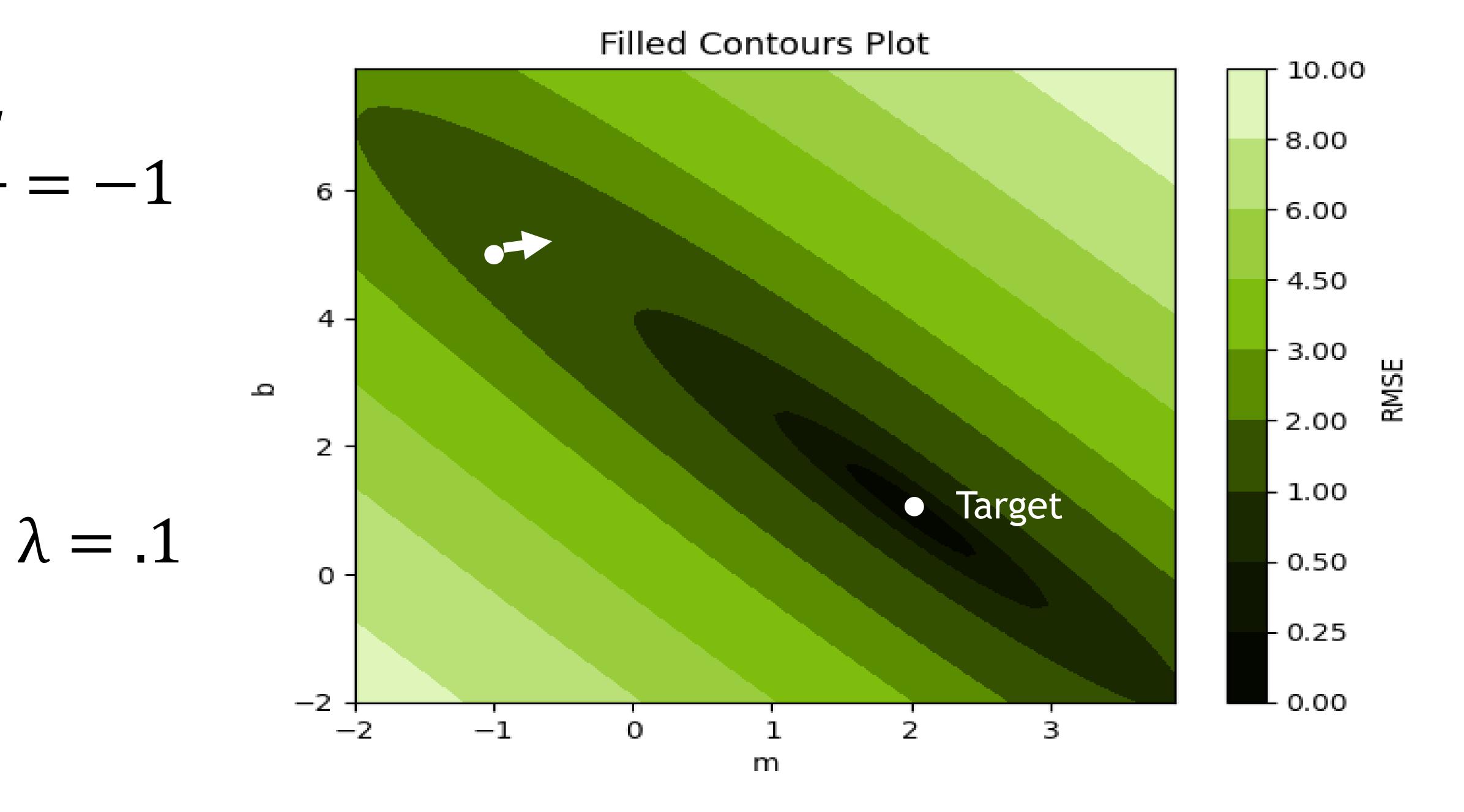




$$\frac{\partial MSE}{\partial m} = -3 \qquad \frac{\partial MSE}{\partial b} = -1$$

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

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

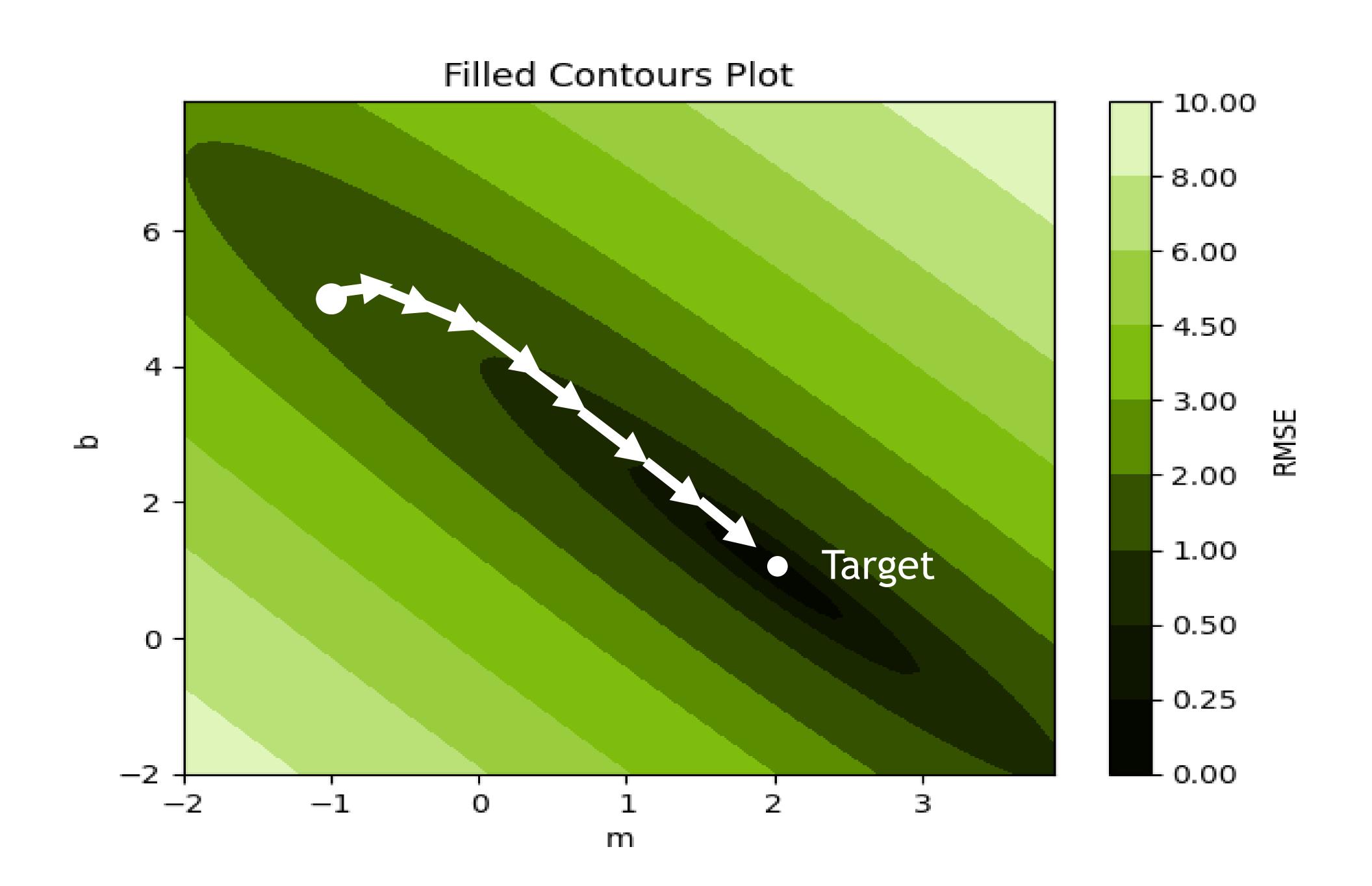




$$\lambda = .1$$

$$m := -1 + 3 \lambda = -0.7$$

$$b := 5 + \lambda = 5.1$$

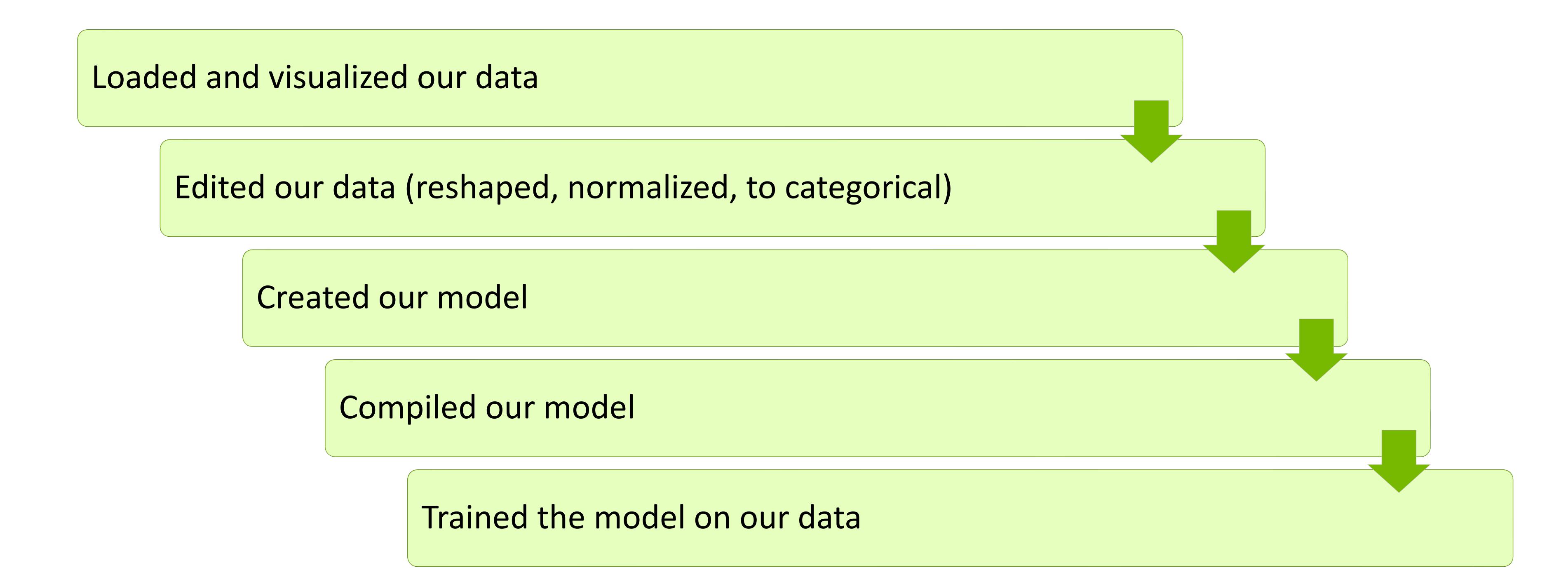






Recap of the Exercise

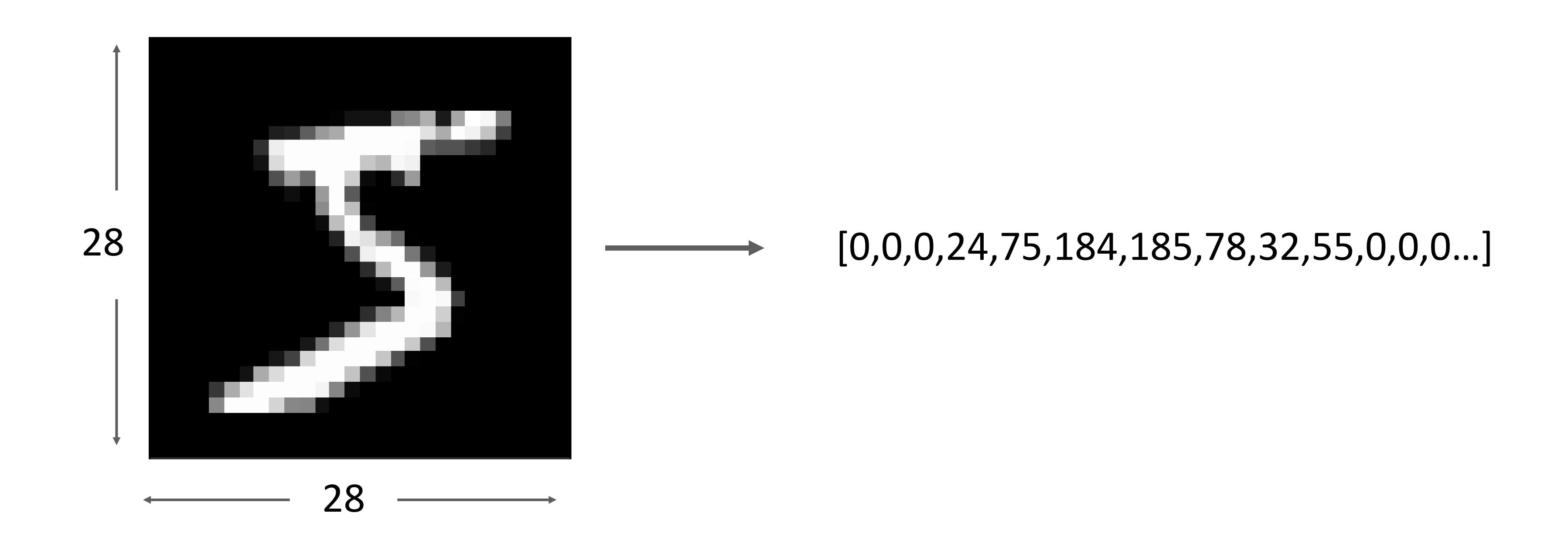
What just happened?





Data Preparation

Input as an Array





An Untrained Model

