FUNDAMENTALS OF DEEP LEARNING

How a Neural Network Trains

Muljono

UNIVERSITAS DIAN NUSWANTORO

TENTANG SAYA

Latar Belakang Pendidikan:

- S1: Matematika Universitas Diponegoro Semarang
- S2: Teknik Informatika STTIBI Jakarta
- S3: Teknik Elektro ITS Surabaya

Riwayat/Pengalaman Pekerjaan:

- Anggota APTI (Asosiasi Profesi Telematika Indonesia)
- Dosen Universitas Dian Nuswantoro Semarang (Associate Professor)
- Post-Doctoral di Universtas Gadjah Mada Yogyakarta
- Sandwich Program di Tokyo University of Technology, Tokyo, Japan
- Teaching Mobility Program Erasmus + di University of Split, Croatia
- Workshop Big Data Analaysis dan IOT, Big Data Alibaba, Fozhou Polythechnic, Fouzhou China

TOP 20 JOB ROLES IN INCREASING AND DECREASING DEMAND

↗ Increasing demand

1	Data Analysts and Scientists
2	AI and Machine Learning Specialists
3	Big Data Specialists
4	Digital Marketing and Strategy Specialists
5	Process Automation Specialists
6	Business Development Professionals
7	Digital Transformation Specialists
8	Information Security Analysts
9	Software and Applications Developers
10	Internet of Things Specialists
11	Project Managers
12	Business Services and Administration Managers
13	Database and Network Professionals
14	Robotics Engineers
15	Strategic Advisors
16	Management and Organization Analysts
17	FinTech Engineers
18	Mechanics and Machinery Repairers
19	Organizational Development Specialists
20	Risk Management Specialists

↘ Decreasing demand

1	Data Entry Clerks
2	Administrative and Executive Secretaries
3	Accounting, Bookkeeping and Payroll Clerks
4	Accountants and Auditors
5	Assembly and Factory Workers
6	Business Services and Administration Managers
7	Client Information and Customer Service Workers
8	General and Operations Managers
9	Mechanics and Machinery Repairers
10	Material-Recording and Stock-Keeping Clerks
11	Financial Analysts
12	Postal Service Clerks
13	Sales Rep., Wholesale and Manuf., Tech. and Sci.Products
14	Relationship Managers
15	Bank Tellers and Related Clerks
16	Door-To-Door Sales, News and Street Vendors
17	Electronics and Telecoms Installers and Repairers
18	Human Resources Specialists
19	Training and Development Specialists
20	Construction Laborers

Source : Future of Jobs Survey 2020, World Economic Forum

TECHNOLOGY TREND:

- **Technology 5G**
- **Cyber Security**
- **AI (Artificial Intelligence)**

THE RISE OF TECHNOLOGY 5G

THE RISE OF CYBER SECURITY

THE GREAT ARTIFICIAL INTELLIGENCE AWAKENING

"AI is not the next big thing
— it’s the current big thing !

Welcome to the Artificial Intelligence era"


“KITA KEJAR-KEJARAN, SIAPA KUASAI AI BERPOTENSI KUASAI DUNIA”
Joko Widodo
President of Indonesia

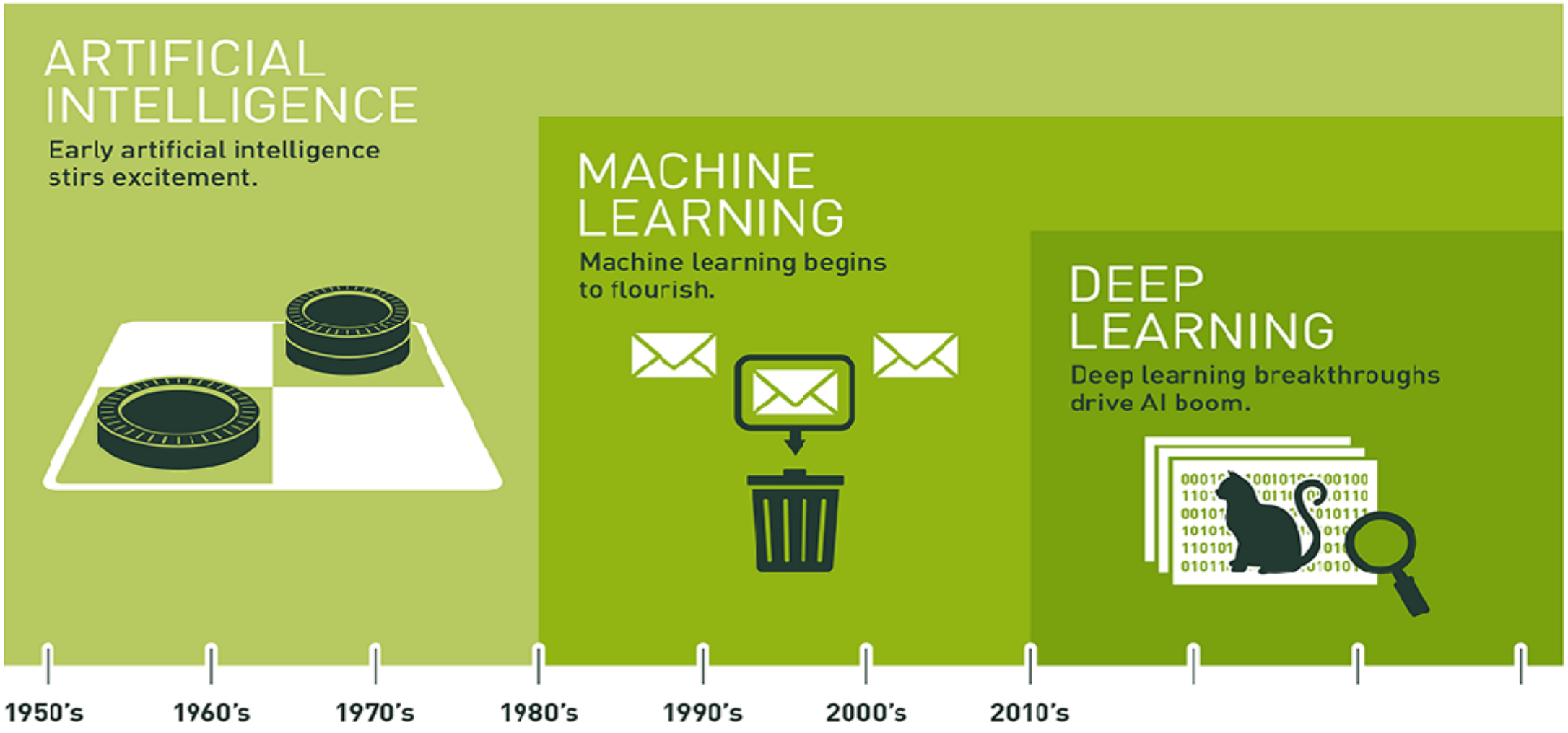
Robot AI Siap Geser Posisi PNS, Jokowi Sudah Ancang-ancang!

NEWS - Lidya Julita Sembiring, CNBC Indonesia | 26 November 2021 06:08

SHARE |

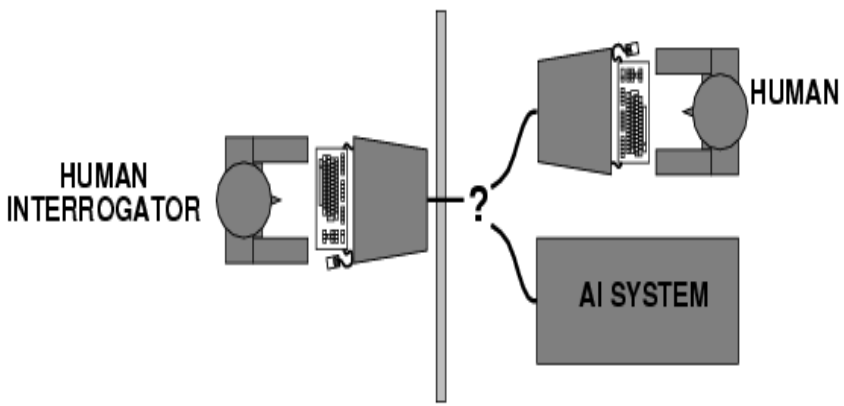
1. Robot AI Siap Geser Posisi PNS, Jokowi Sudah Ancang-ancang!

RELATIONSHIP BETWEEN AI, ML, DL



ARTIFICIAL INTELLIGENCE

Machines that think rationally.	Machines that act like humans
Machines that think like humans.	Machines that act rationally

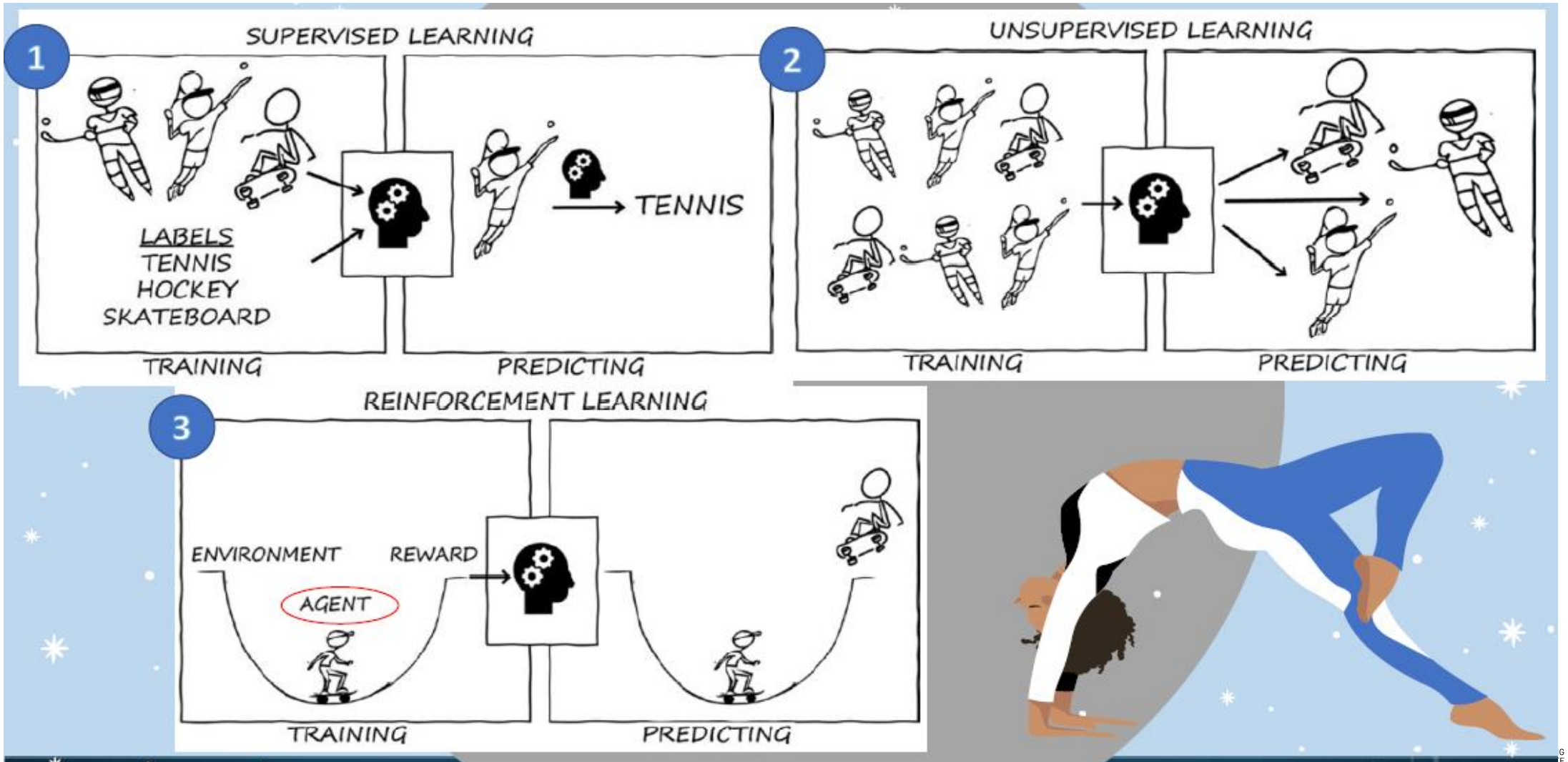


Turing (1950) "Computing machinery and intelligence”

MACHINE LEARNING

- Ability of computers to “learn” from “data” or “past experience”
- data: Comes from various sources such as sensors, domain knowledge, experimental runs, etc.
- learn: Make *intelligent* predictions or decisions based on data by optimizing a model

AREA MACHINE LEARNING



PRE-REQUISITE TO MACHINE LEARNING

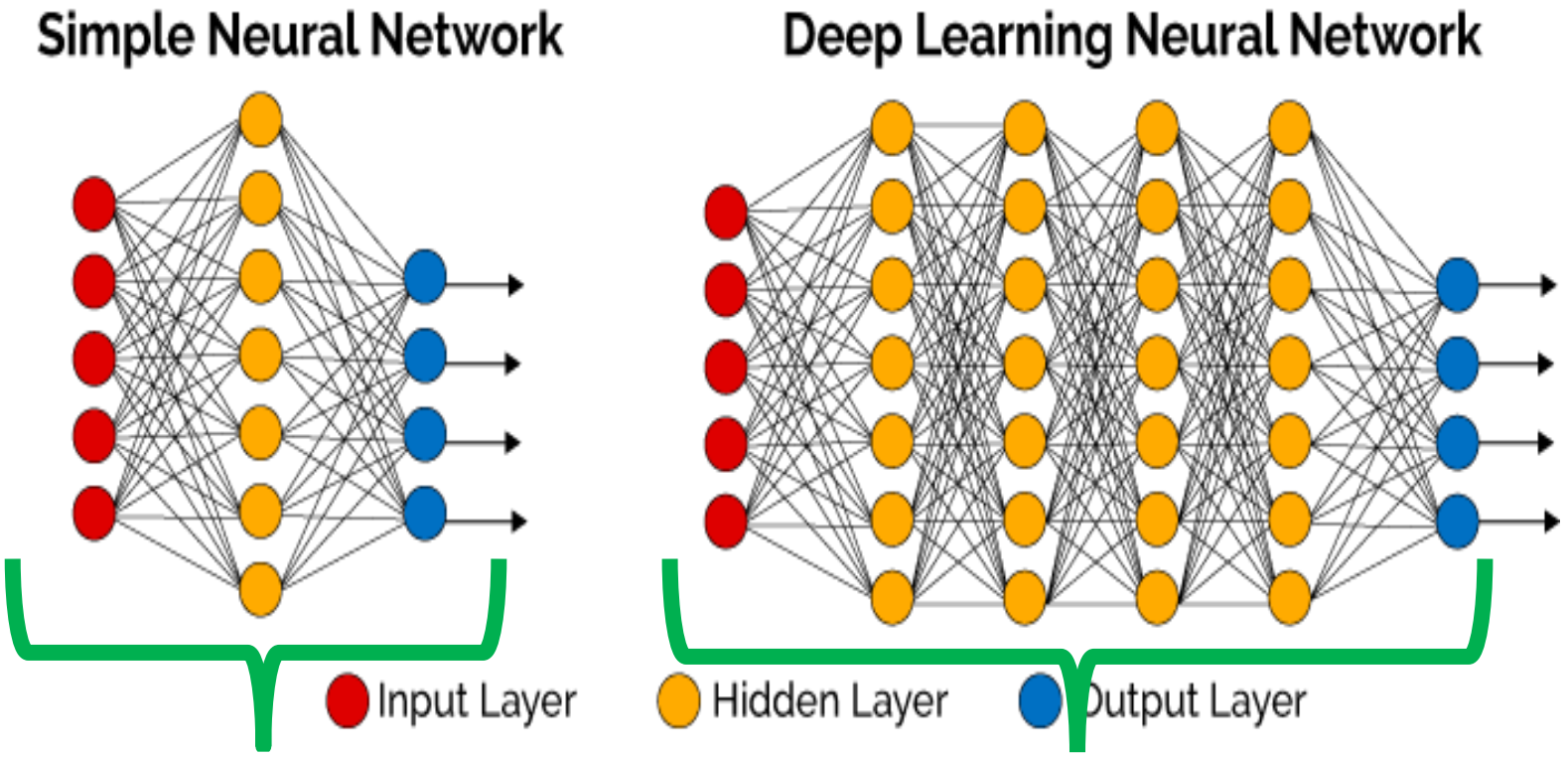
- Probability
  - distribution, random variable, expectation, conditional probability, variance, density
- Linear algebra
  - matrix multiplication
  - eigenvector
- Basic programming (in Python)

DEEP LEARNING

Deep learning is a subset of **machine learning** where artificial **neural networks**, algorithms inspired by the human brain, **learn** from large amounts of data.

Deep learning allows machines to solve complex problems even when using a data set that is very diverse, unstructured and inter-connected.

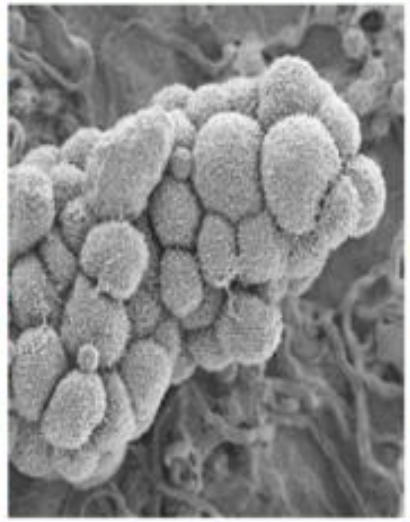
“DEEP” LEARNING ?



1 hidden layer

many hidden layers

DEEP LEARNING EVERYWHERE


INTERNET & CLOUD	MEDICINE & BIOLOGY	MEDIA & ENTERTAINMENT	SECURITY & DEFENSE	AUTONOMOUS MACHINES
Image Classification	Cancer Cell Detection	Video Captioning	Face Detection	Pedestrian Detection
Speech Recognition	Diabetic Grading	Video Search	Video Surveillance	Lane Tracking
Language Translation	Drug Discovery	Real Time Translation	Satellite Imagery	Recognize Traffic Sign
Language Processing				
Sentiment Analysis				
Recommendation				

Source : developer.nvidia.com/deep-leaning-course

UNSTRUCTURED DATA VS STRUCTURED DATA

unstructured data

Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
1	5.1	3.5	1.4	0.2	Iris-setosa
2	4.9	3.0	1.4	0.2	Iris-setosa
3	4.7	3.2	1.3	0.2	Iris-setosa
4	4.6	3.1	1.5	0.2	Iris-setosa
5	5.0	3.6	1.4	0.2	Iris-setosa
6	5.4	3.9	1.7	0.4	Iris-setosa
7	4.6	3.4	1.4	0.3	Iris-setosa
8	5.0	3.4	1.5	0.2	Iris-setosa
9	4.4	2.9	1.4	0.2	Iris-setosa
10	4.9	3.1	1.5	0.1	Iris-setosa
11	5.4	3.7	1.5	0.2	Iris-setosa

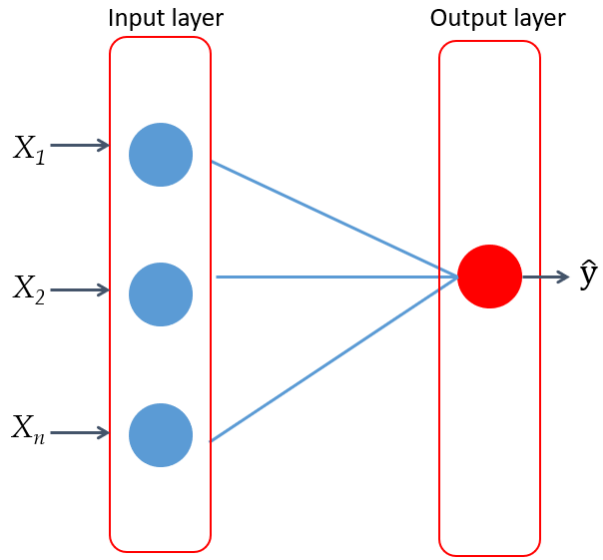
structured data

FUNDAMENTALS OF DEEP LEARNING

Artificial Neural Network

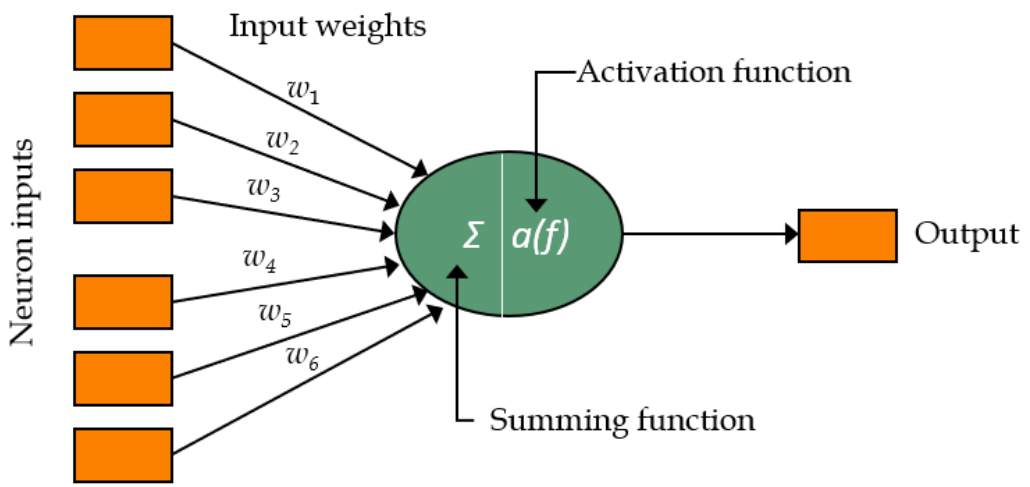
Arsitektur Single-layer Perceptron

Arsitektur single-layer ANN hanya terdiri dari input layer dan output layer



Unit pemrosesan informasi pada ANN sebagai berikut:

- Satu set link berupa neuron dan bobot w
- Fungsi penambah (penggabung linear) untuk mengitung jumlah perkalian bobot terhadap input X
- Fungsi aktivasi $a(\cdot)$



$$f = \sum_{i=1}^{m} w_i x_i + b$$

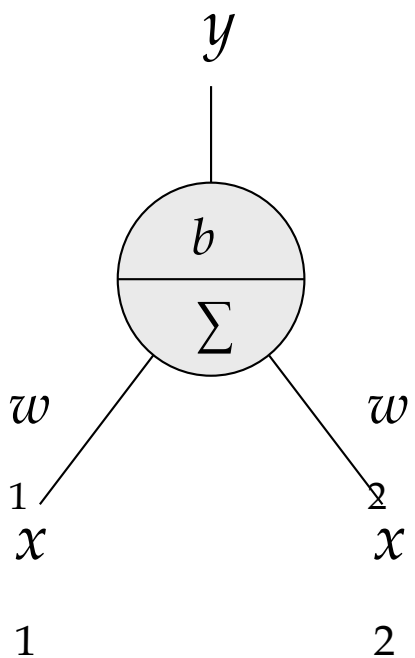
$$y = a(f)$$

Source : Microcredential Associate Data Science – Dikti 2021

Apa yang bisa dilakukan sebuah Neuron ?

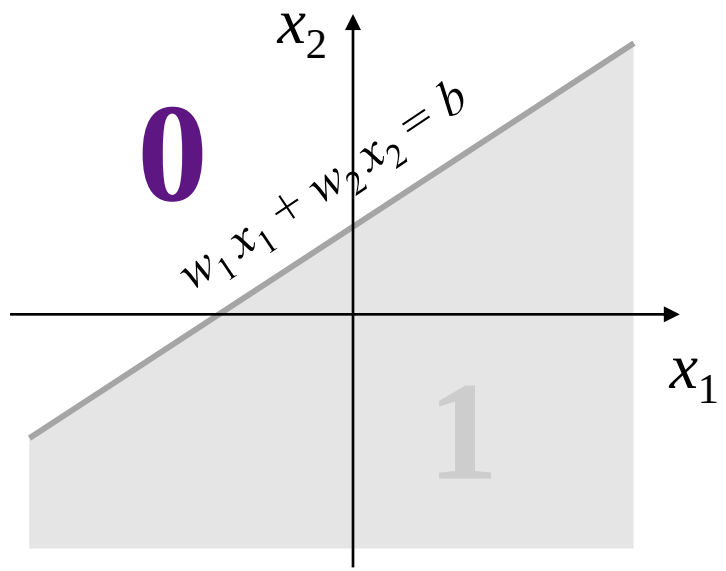
Sebuah neuron pada ANN dapat menyelesaikan permasalahan klasifikasi biner

- Sebagai fungsi pemisah (*hyperspace separation*)
- Sebagai *binary threshold*



$$f(x) = w_1 x_1 + w_2 x_2 - b$$

$$y = \begin{cases} 1 & f(x) \geq 0 \\ 0 & otherwise \end{cases}$$

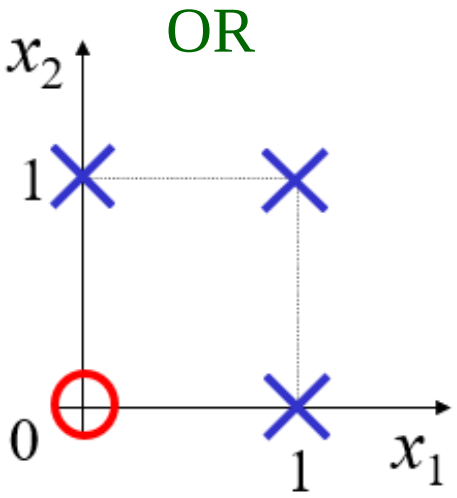


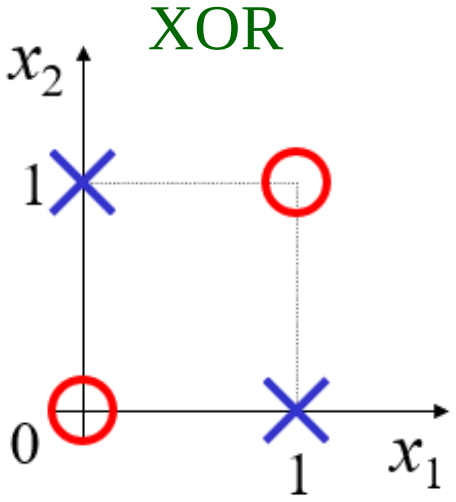
Source : Microcredential Associate Data Science – Dikti 2021

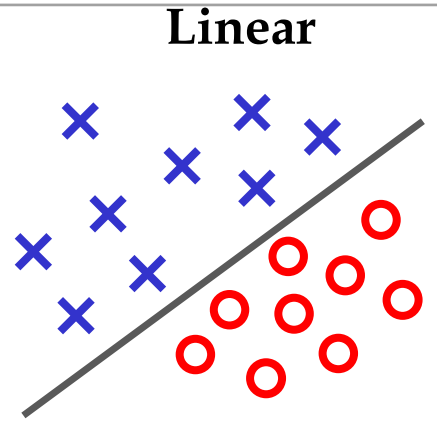
Permasalahan Linear dan Non-Linear

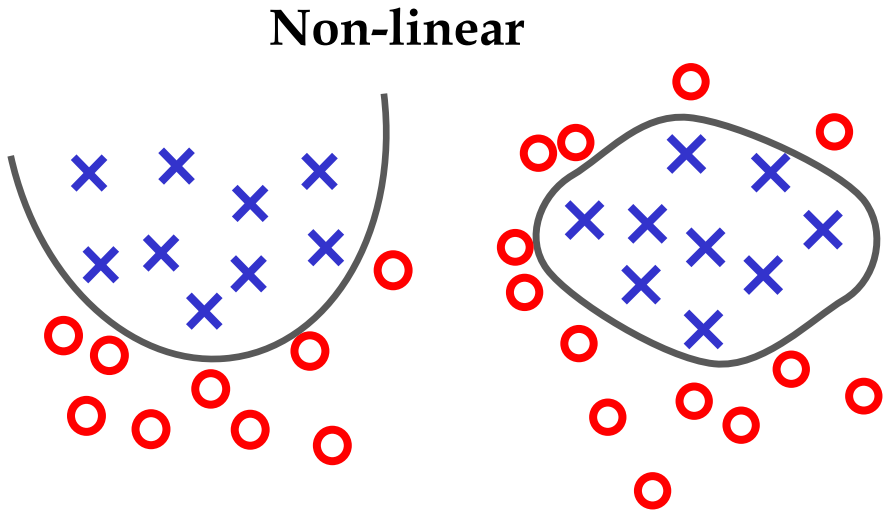
Permasalahan klasifikasi dapat dikategorikan sebagai:

- Permasalahan Linear, misalnya fungsi OR dan AND
- Permasalahan Non-Linear, misalnya fungsi XOR









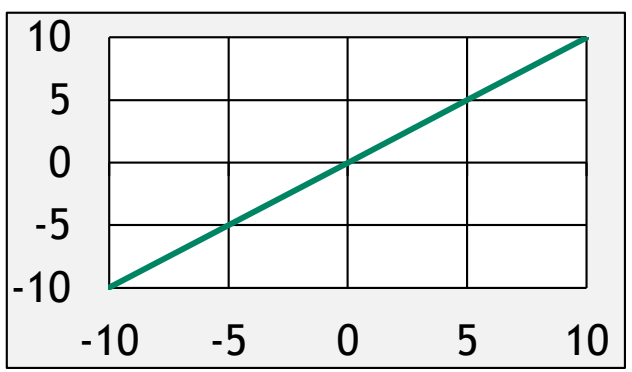
Source : Microcredential Associate Data Science – Dikti 2021

ACTIVATION FUNCTIONS

Linear

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

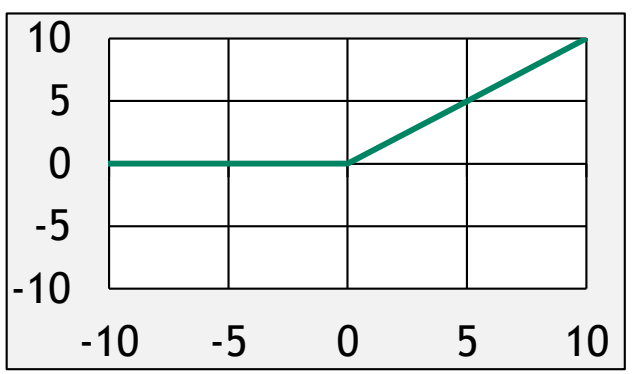
```
# Multiply each input
# with a weight (w) and
# add intercept (b)
y_hat = wx+b
```



ReLU

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

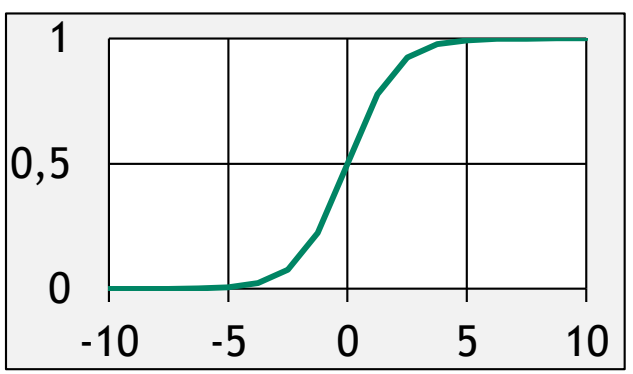
```
# Only return result
# if total is positive
linear = wx+b
y_hat = linear * (linear > 0)
```



Sigmoid

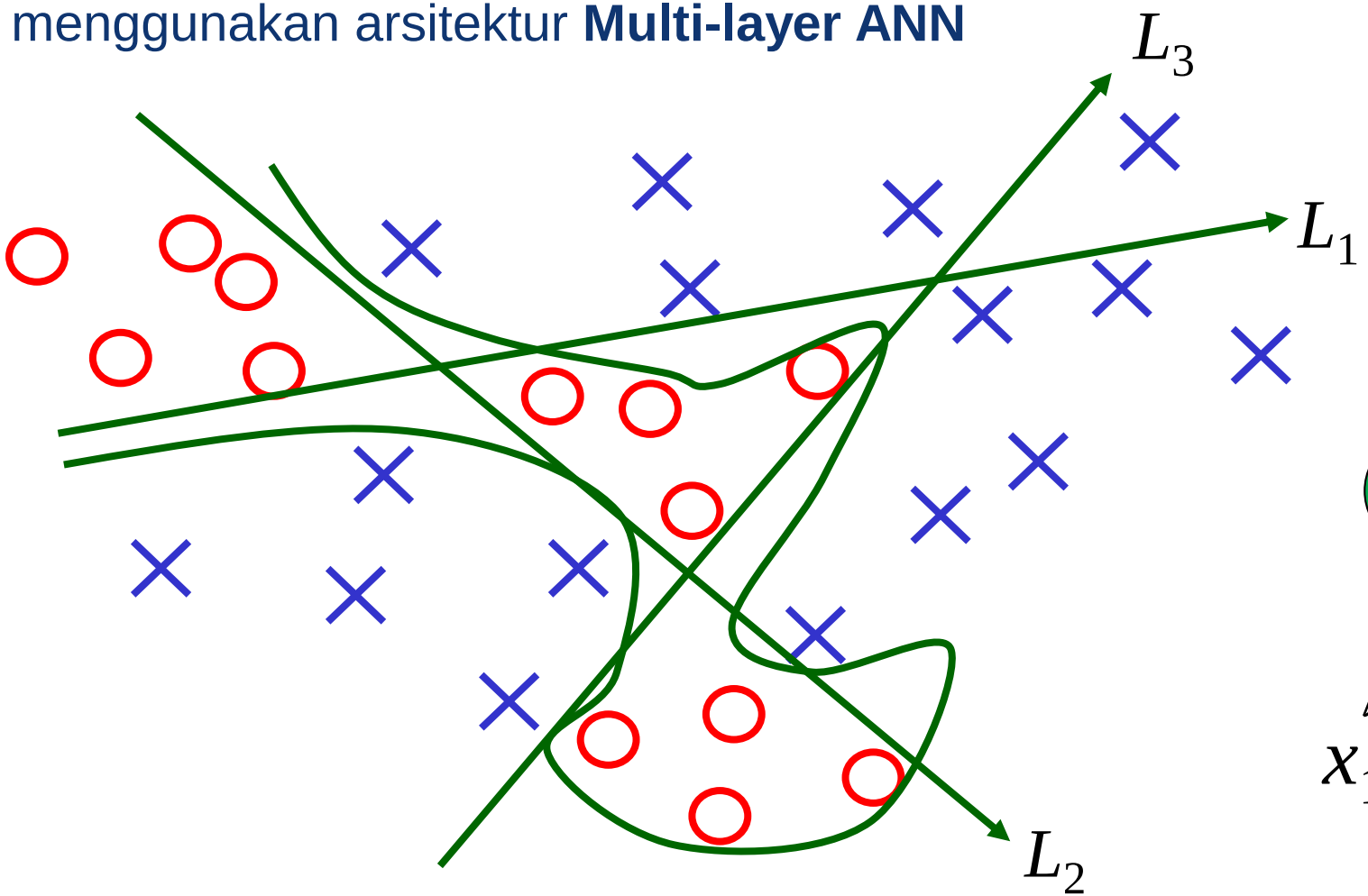
$$\hat{y} = \frac{1}{1 + e^{-(wx+b)}}$$

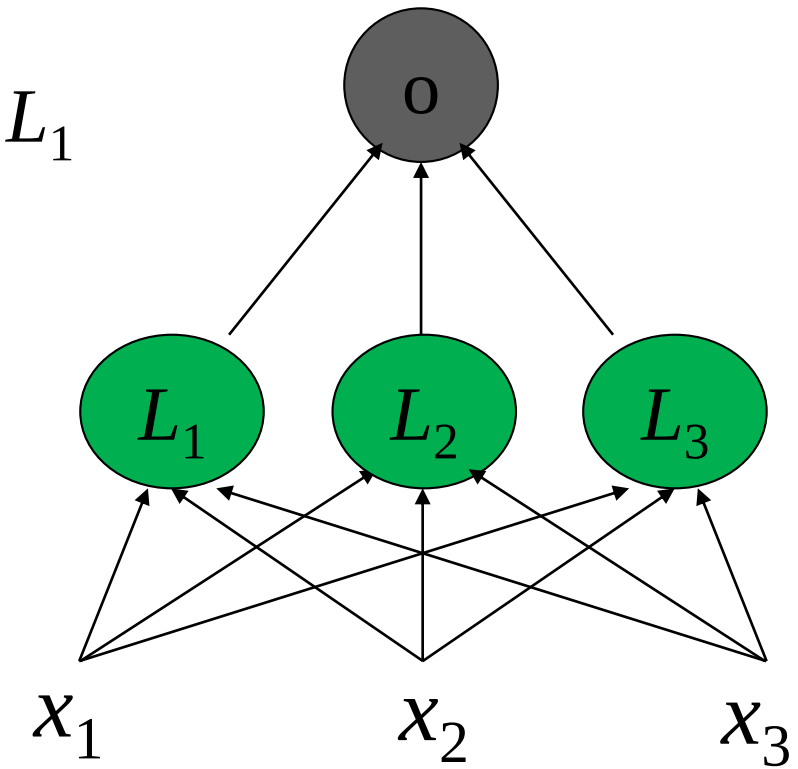
```
# Start with line
linear = wx + b
# Warp to - inf to 0
inf_to_zero = np.exp(-1 * linear)
# Squish to -1 to 1
y_hat = 1 / (1 + inf_to_zero)
```



Source : developer.nvidia.com/deep-leaning-course

Pada permasalahan non-linear dan permasalahan yang lebih kompleks, menggunakan arsitektur **Multi-layer ANN**

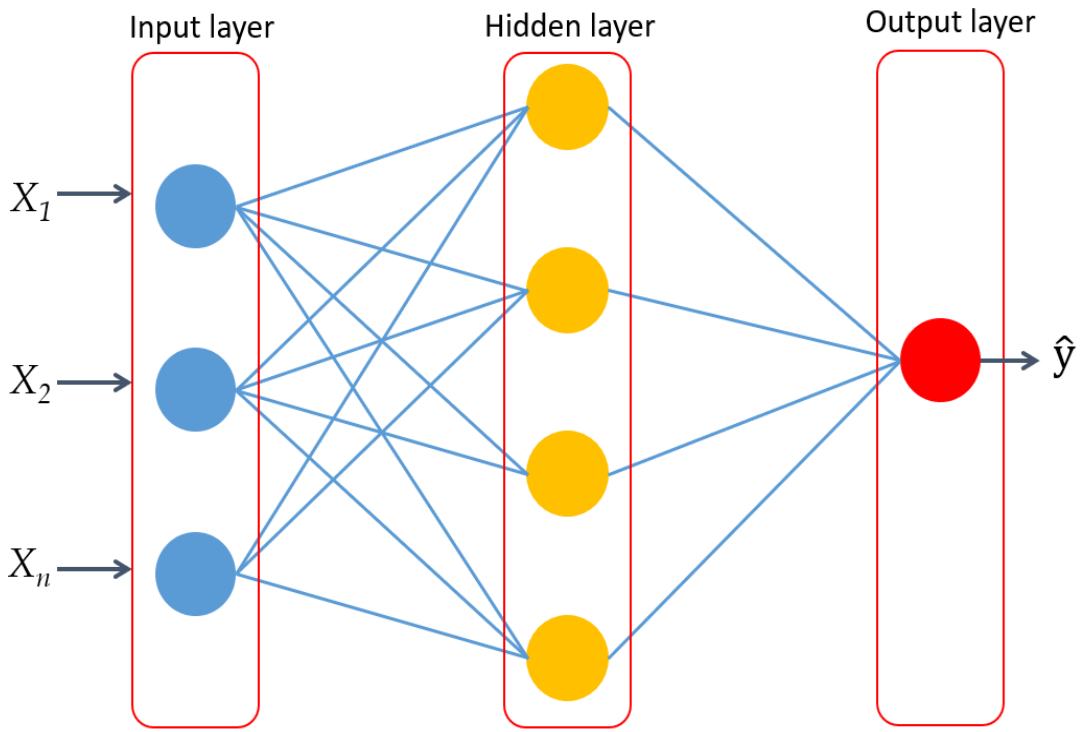




Source : Microcredential Associate Data Science – Dikti 2021

Arsitektur Multi-layer ANN

- Terdiri dari tiga layer yaitu:
  - input layer
  - hidden layer
  - output layer
- Hubungan antar neuron pada ANN merupakan ***fully connected network* (FCN)**
- **Jumlah *hidden layer*** sebaiknya disesuaikan dengan kompleksitas permasalahan
- **Jumlah neuron pada *hidden layer*** umumnya lebih banyak daripada jumlah *neuron* di *output layer*



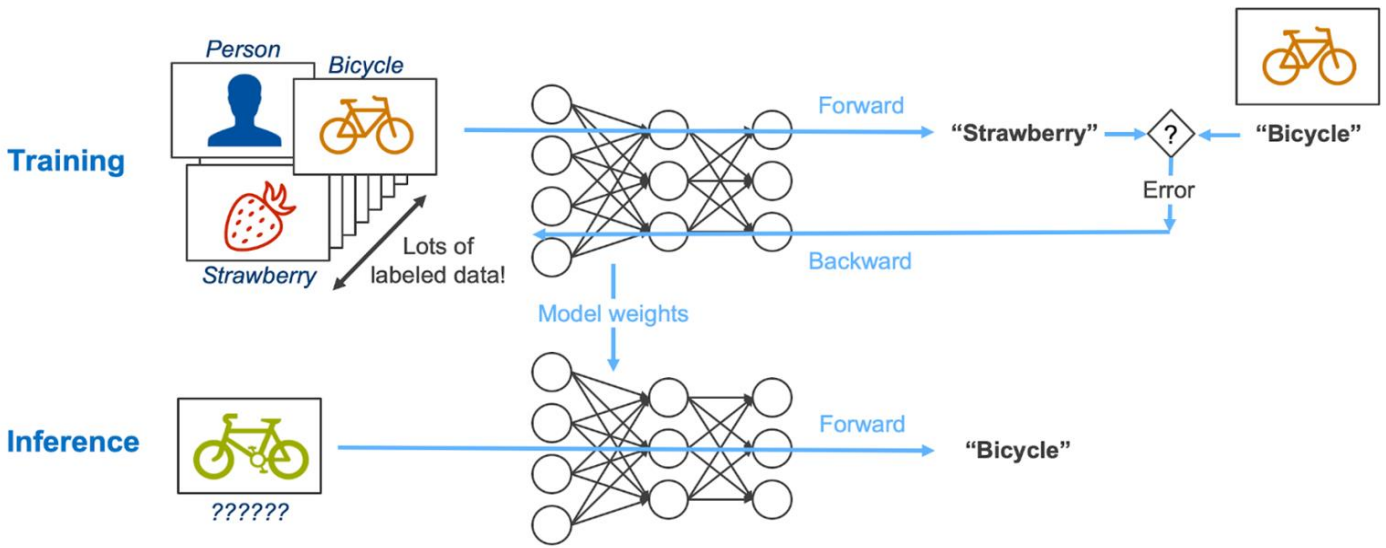
Source : Microcredential Associate Data Science – Dikti 2021

How a Neural Network Trains

Mekanisme Pembelajaran (*Learning*)

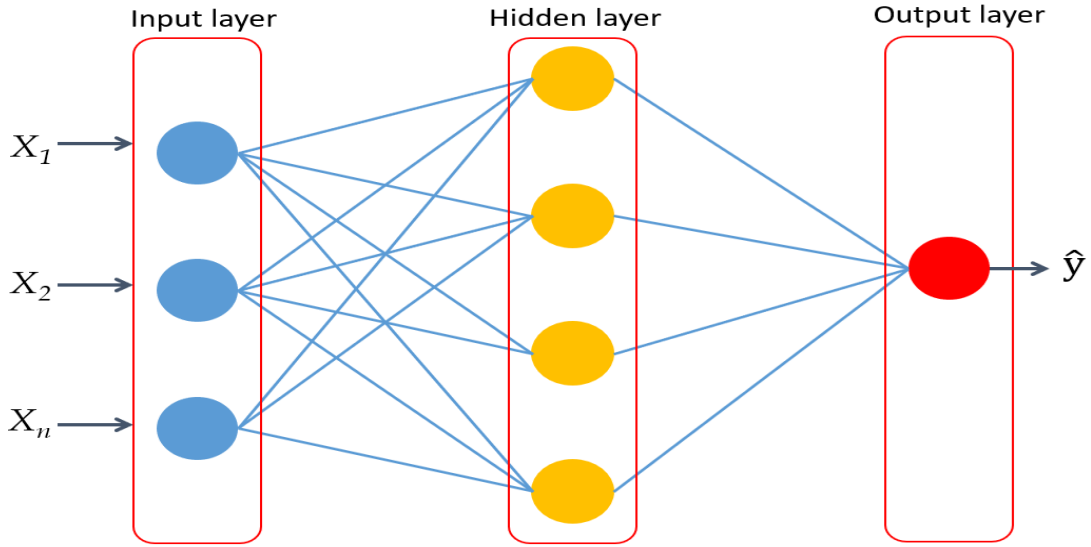
1. Training: learning pada saat pembentukan model.

2. Inferensi: learning saat menggunakan model NN.



Source : Microcredential Associate Data Science – Dikti 2021

Tahapan Pembelajaran Multi-layer Perceptron ANN



Langkah 0 – Inisialisasi bobot, learning rate, maksimum iterasi
Langkah 1 – Membaca vektor input *X*
Langkah 2 – Lakukan iterasi (*epoch*)
Langkah 3 – Hitung luaran neuron di hidden layer dan output layer
Langkah 4 – Hitung *back propagate error* (pada output layer dan hidden layer)
Langkah 5 – Perbarui semua bobot (pada output layer dan hidden layer)
Langkah 6 – Ulangi langkah 3 – 5 hingga bobot konvergen atau maksimum iterasi
Langkah 7 – Luaran berupa matrik bobot (pada output layer dan hidden layer)

https://machinelearningmastery.com/implement-backpropagation-algorithm-scratch-python/

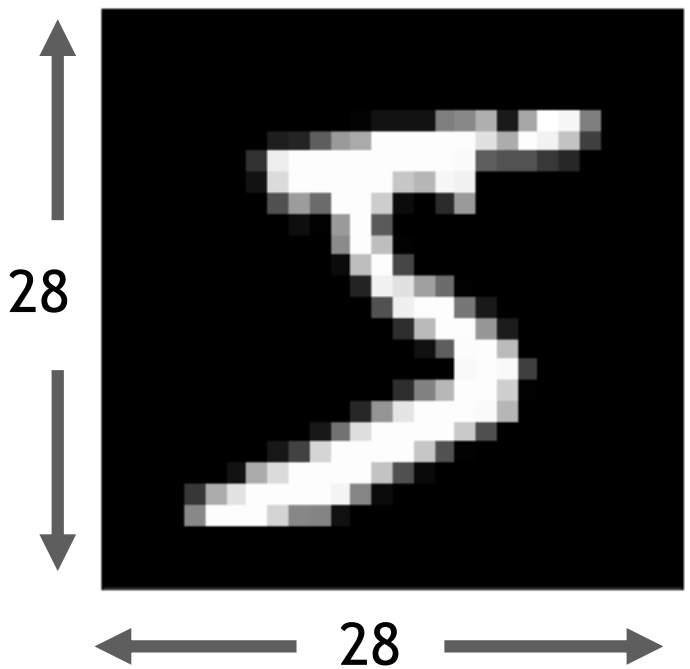
THE MNIST DATASET

Here are 40 of the images included in the MNIST dataset:

Source : developer.nvidia.com/deep-leaning-course

DATA PREPARATION

Input as an array

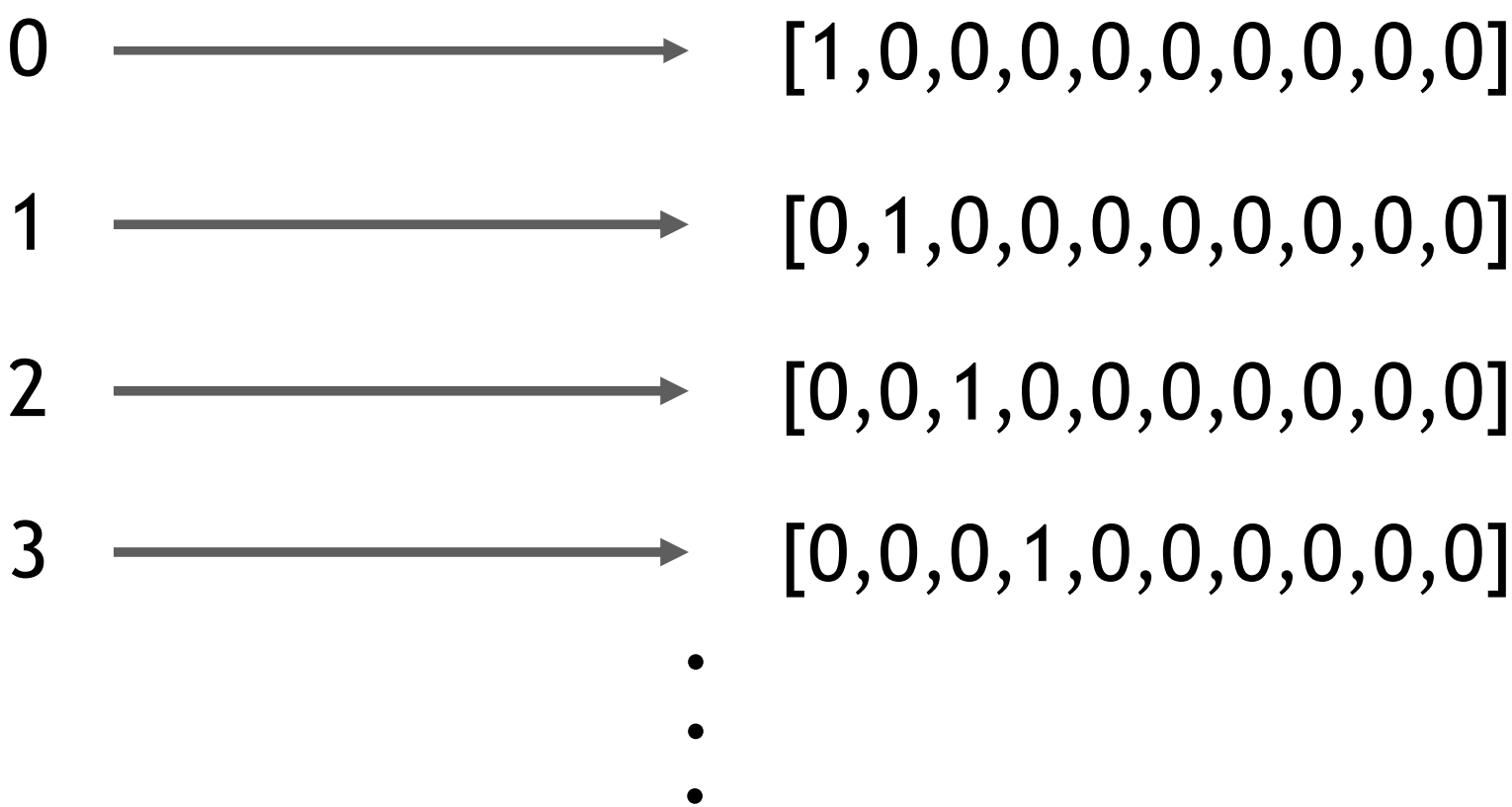


[0,0,0,24,75,184,185,78,32,55,0,0,0...]

Source : developer.nvidia.com/deep-leaning-course

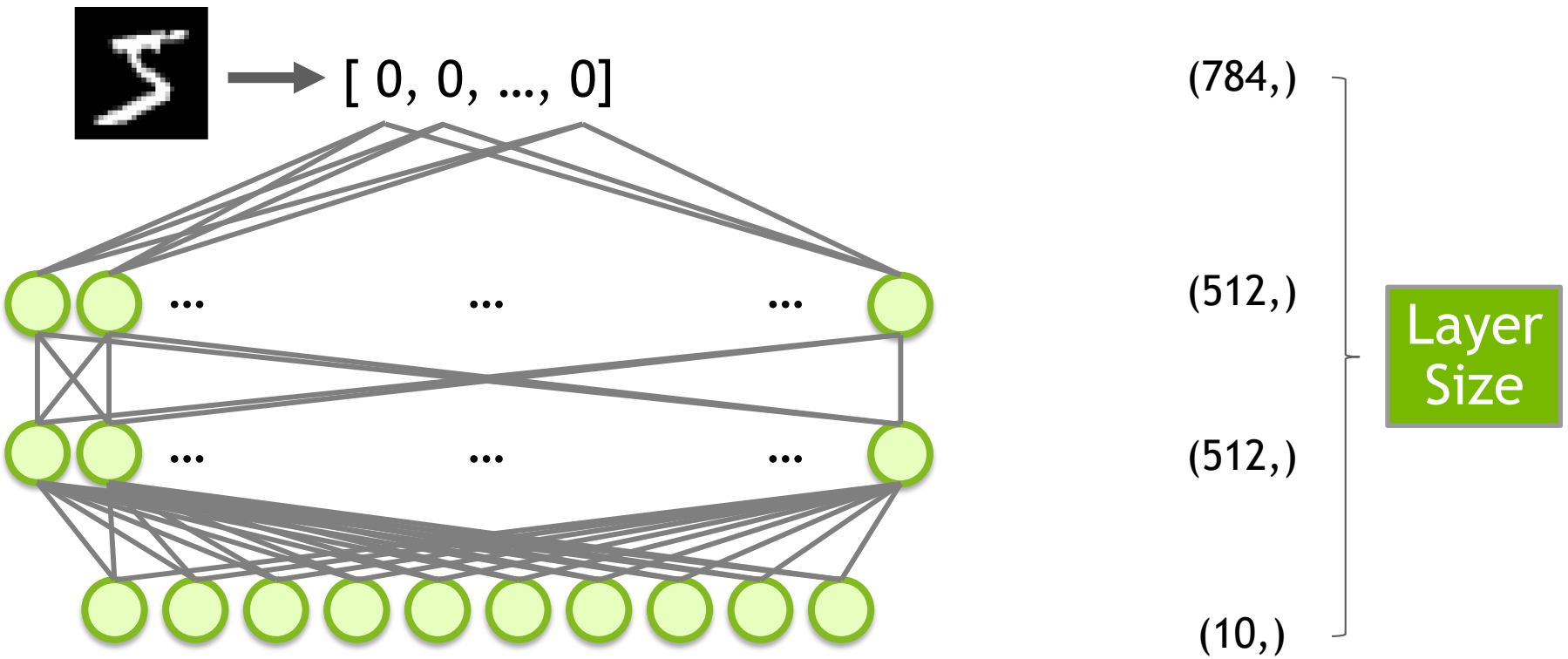
DATA PREPARATION

Targets as categories



Source : developer.nvidia.com/deep-leaning-course

AN UNTRAINED MODEL

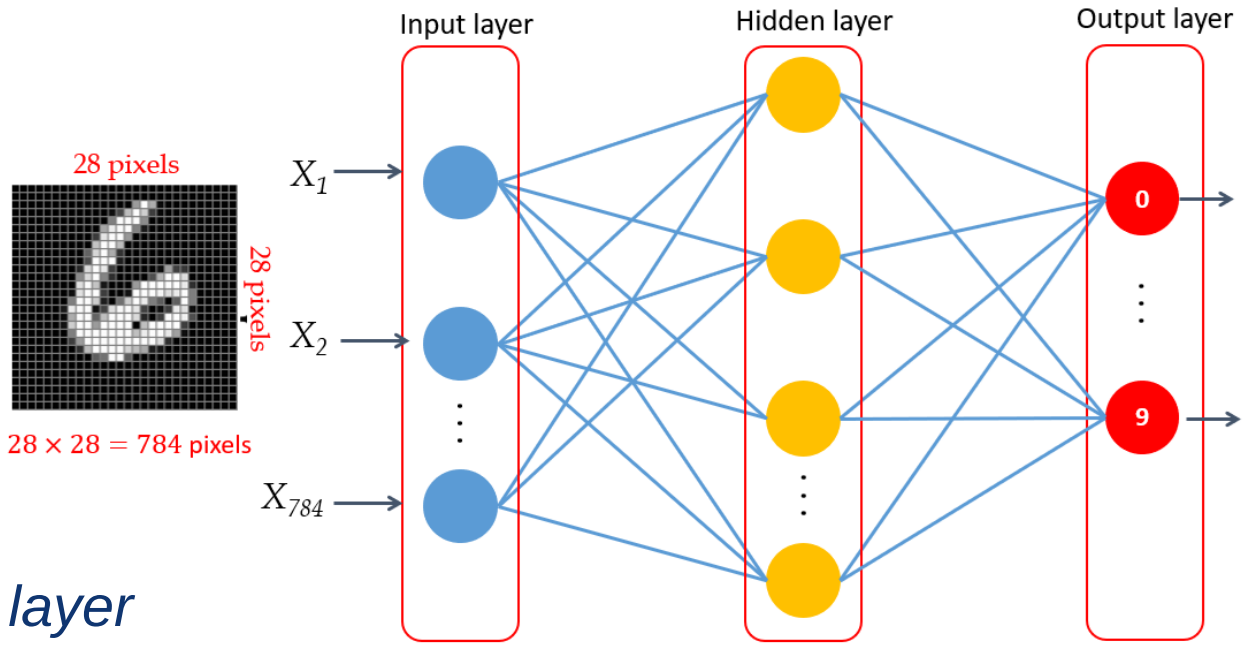


Source : developer.nvidia.com/deep-leaning-course

Desain arsitektur ANN

Penentuan jumlah *neuron* pada *input layer*

- Jumlah neuron sesuai dengan jumlah fitur pada data input



Penentuan jumlah *neuron* pada *output layer*

- Jumlah neuron sesuai dengan permasalahan
- Pada permasalahan klasifikasi biner dan regresi bisa menggunakan hanya satu *neuron*
- Pada permasalahan klasifikasi *multiclass* menggunakan jumlah *neuron* sesuai jumlah label kelasnya, misalnya: 10 neuron pada pengenalan angka

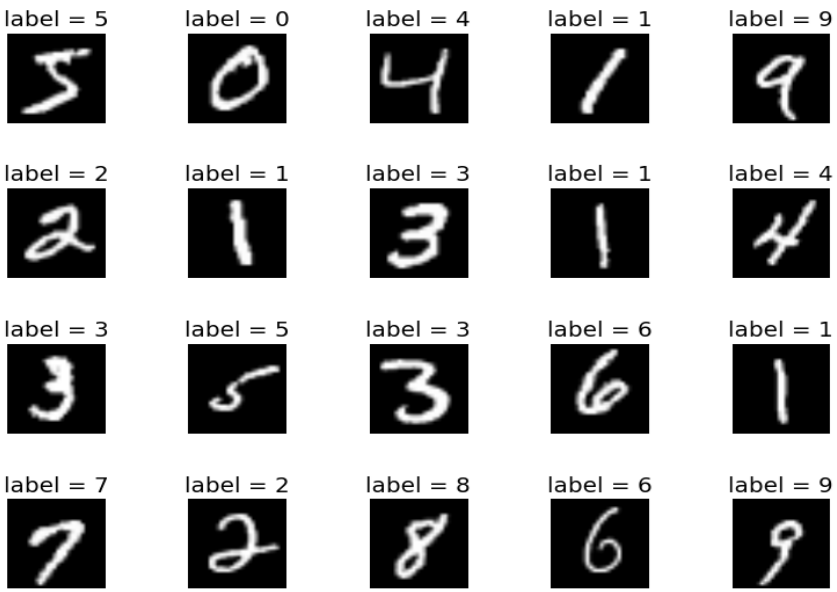
Source : Microcredential Associate Data Science – Dikti 2021

Contoh implementasi arsitektur *fully connected layer* pada pengenalan angka

Dataset MNIST *Handwritten Digit* dibagi menjadi 3:

- 55,000 training data
- 10,000 test data
- 5,000 validation data

Setiap citra berukuran 28 × 28 pixels dan label kelas diubah menjadi *one hot encoded*



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]
4	[0 0 0 0 1 0 0 0 0 0]
5	[0 0 0 0 0 1 0 0 0 0]
6	[0 0 0 0 0 0 1 0 0 0]
7	[0 0 0 0 0 0 0 1 0 0]

Source : Microcredential Associate Data Science – Dikti 2021

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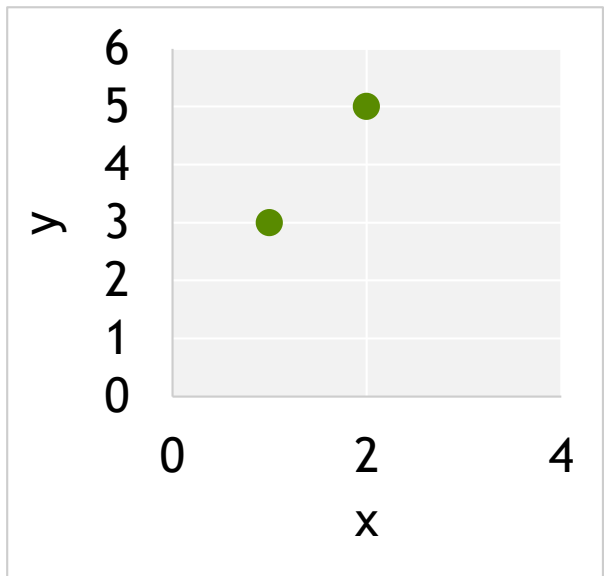
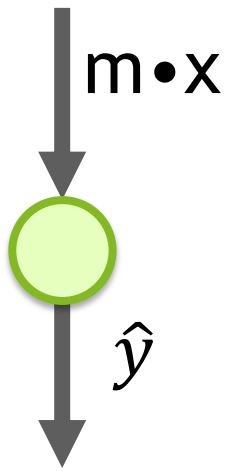
A SIMPLER MODEL

A SIMPLER MODEL

$$y = mx + b$$

x	y
1	3
2	5





$m = ?$

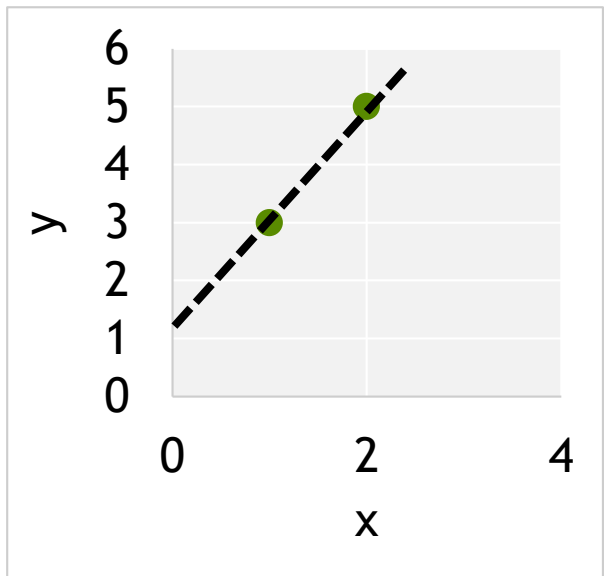
$b = ?$

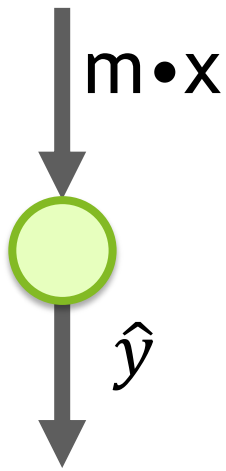
Source : developer.nvidia.com/deep-leaning-course

A SIMPLER MODEL

$$y = mx + b$$

x	y
1	3
2	5





$m = ?$

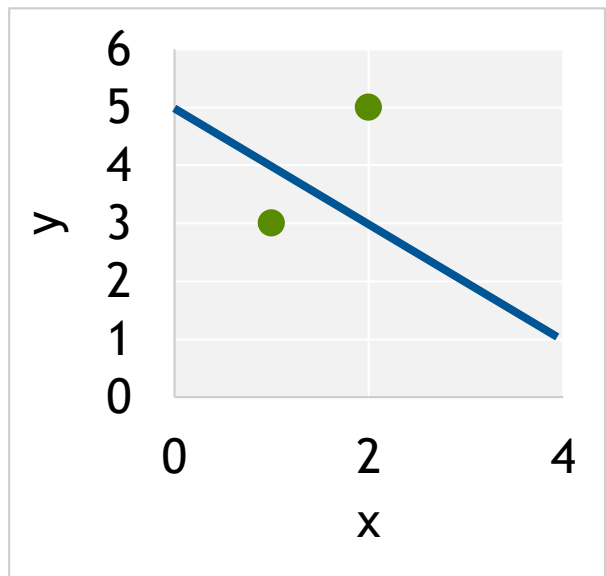
$b = ?$

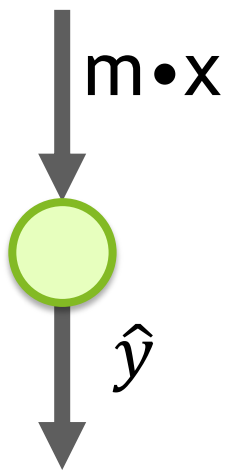
Source : developer.nvidia.com/deep-leaning-course

A SIMPLER MODEL

$$y = mx + b$$

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





Start Random

$$m = -1$$

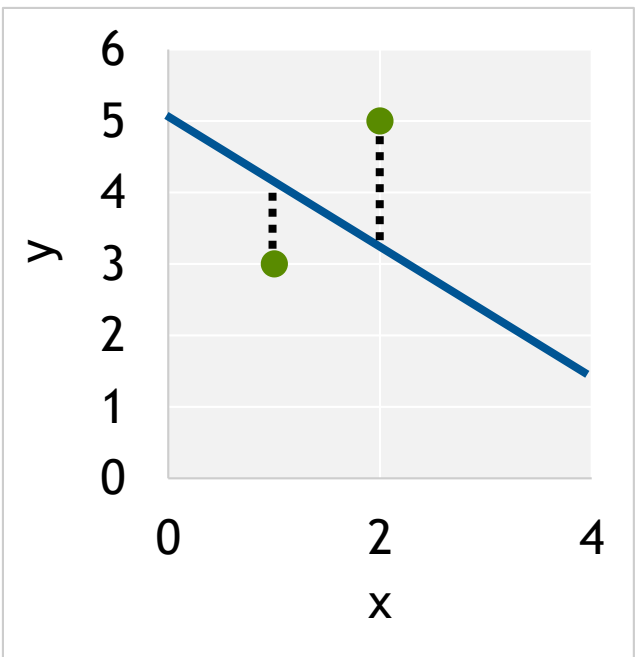
$$b = 5$$

Source : developer.nvidia.com/deep-leaning-course

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



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

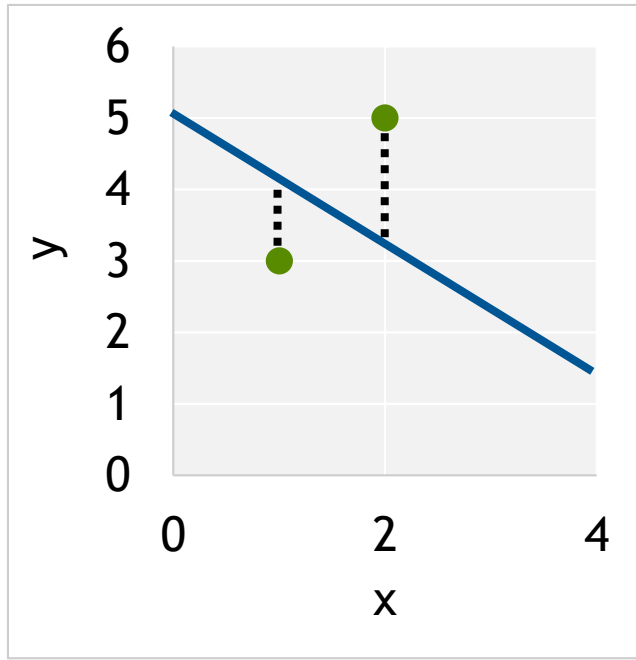
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Source : developer.nvidia.com/deep-leaning-course

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
```

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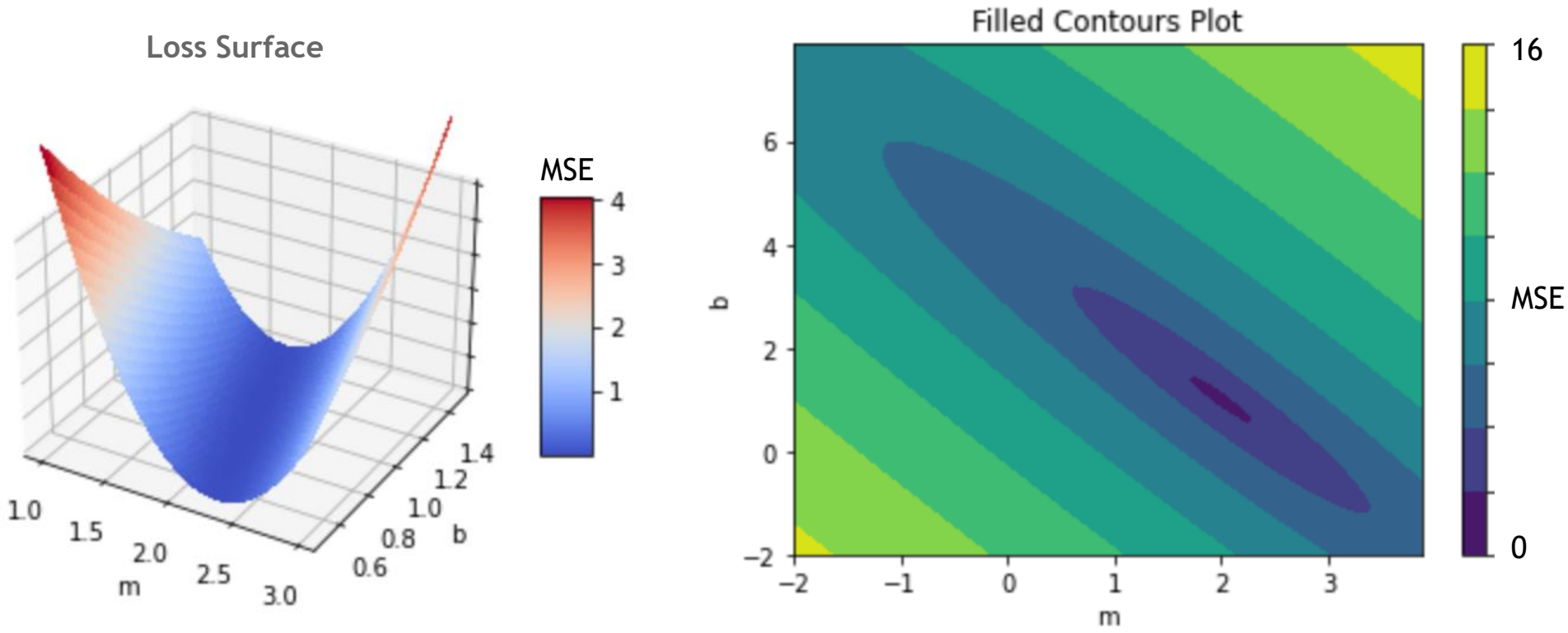
THE LOSS CURVE



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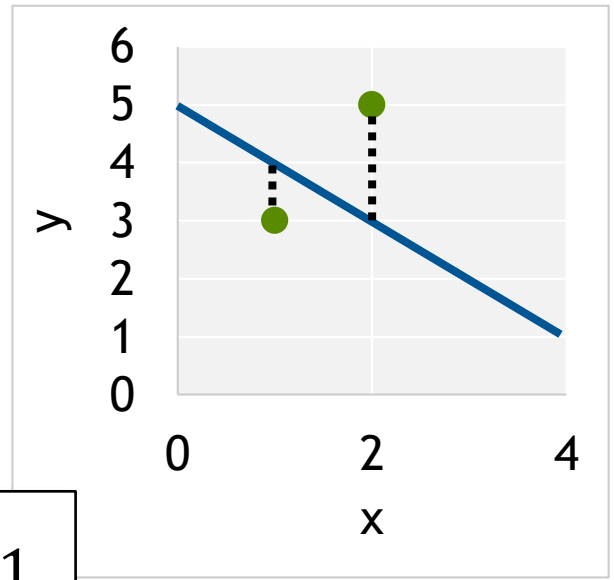
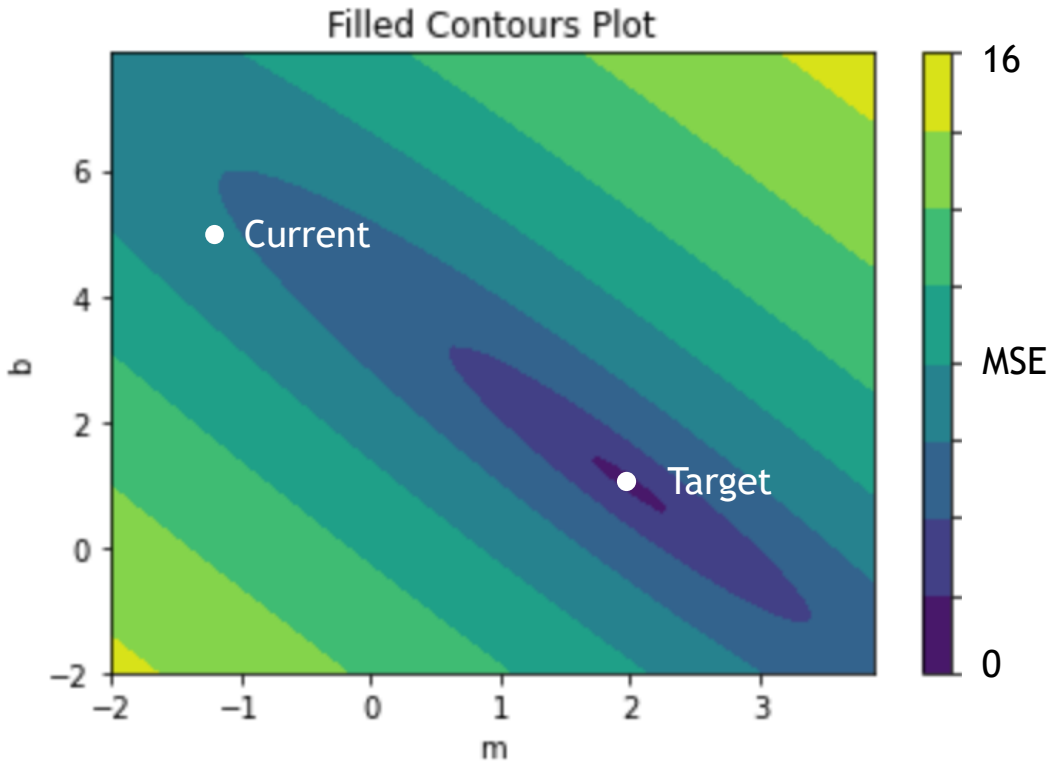
THE LOSS CURVE



$m = -1$

$b = 5$



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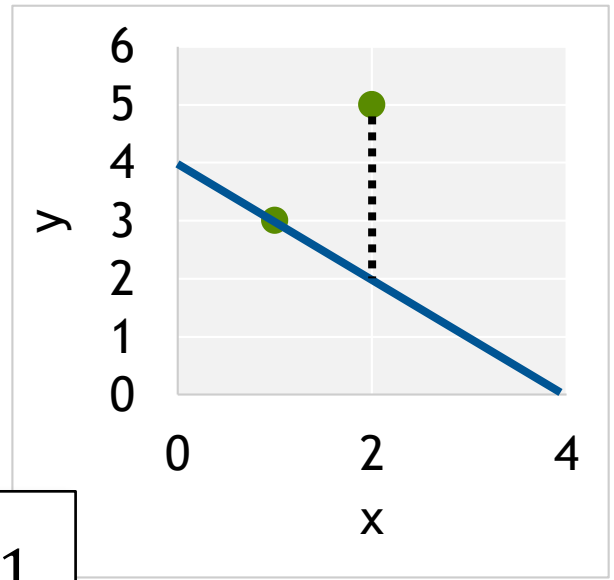
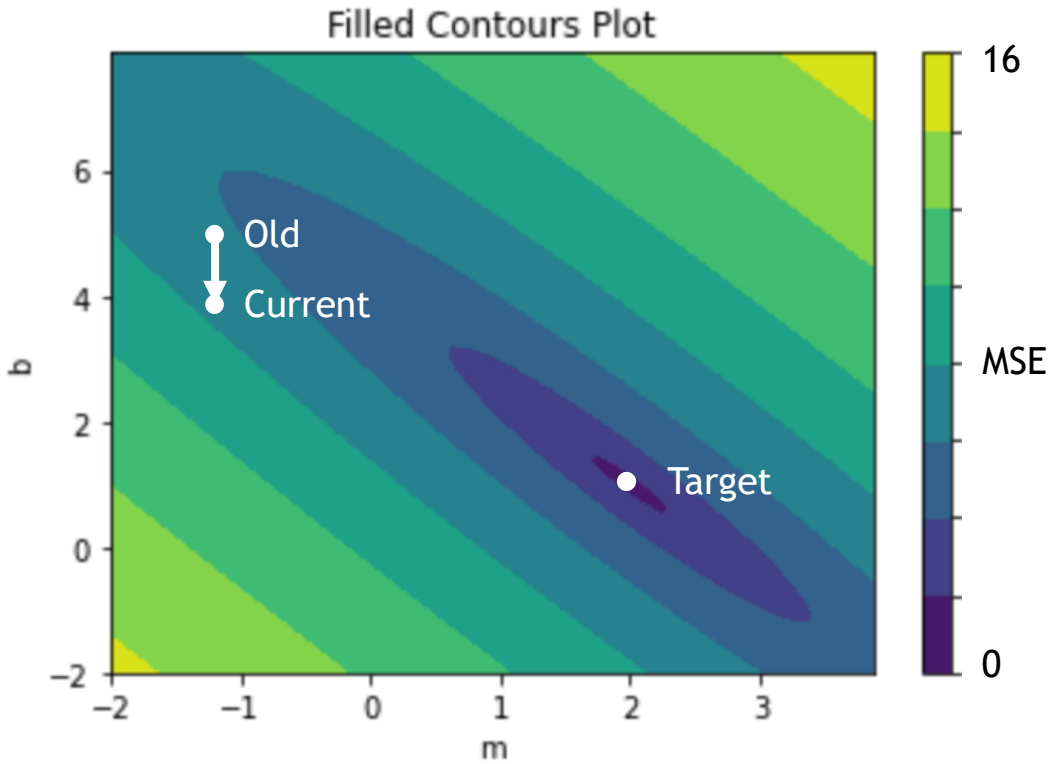
THE LOSS CURVE



$m = -1$

$b = 4$



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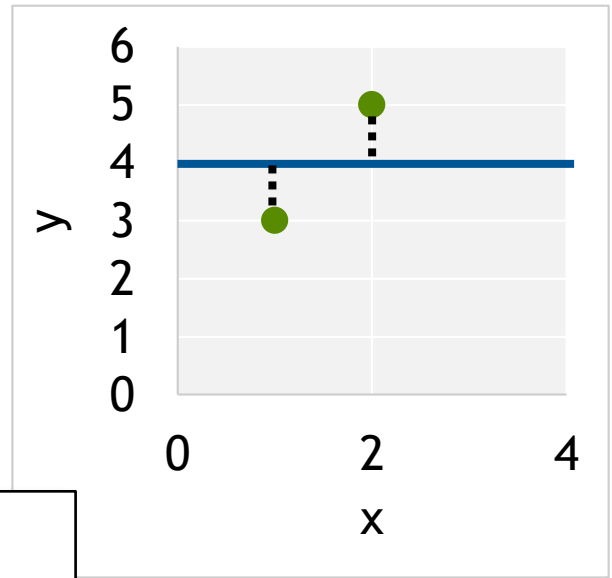
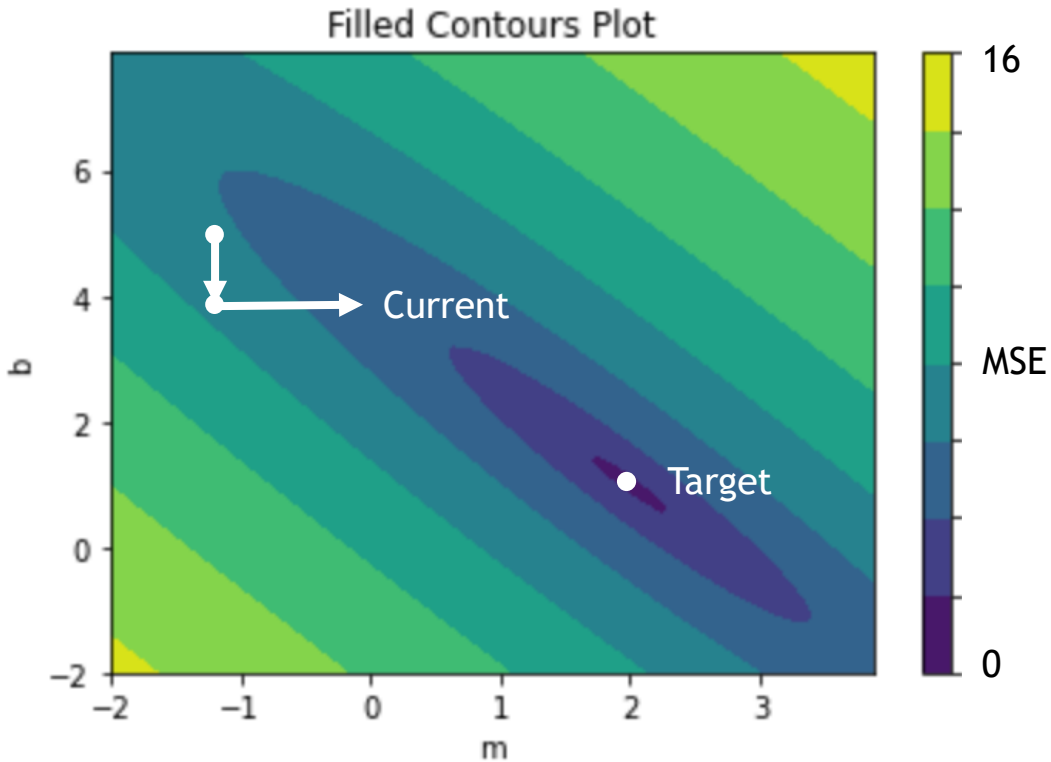
THE LOSS CURVE



$m = 0$

$b = 4$



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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

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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
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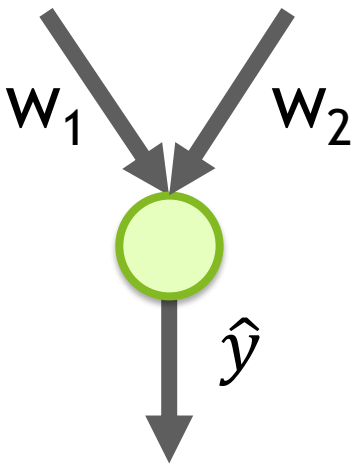
FROM NEURON TO
NETWORK

BUILDING A NETWORK



- Scales to more inputs

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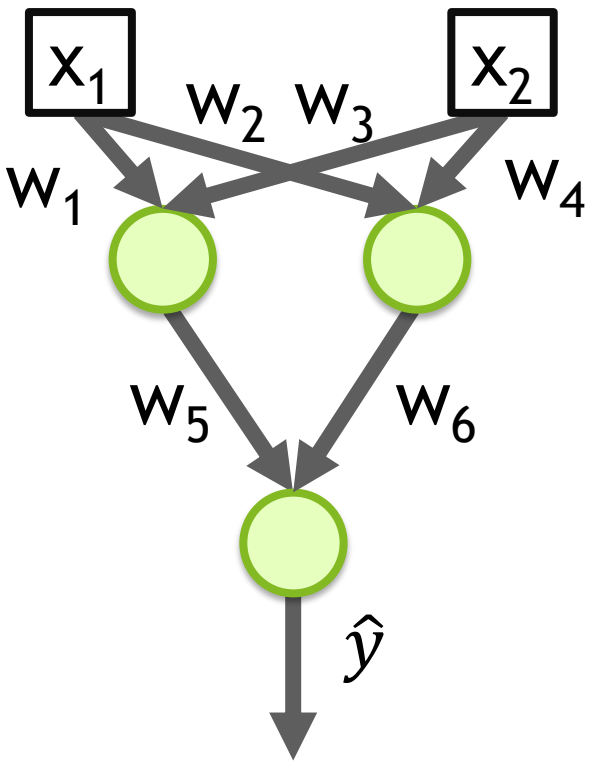
BUILDING A NETWORK



- Scales to more inputs
- Can chain neurons

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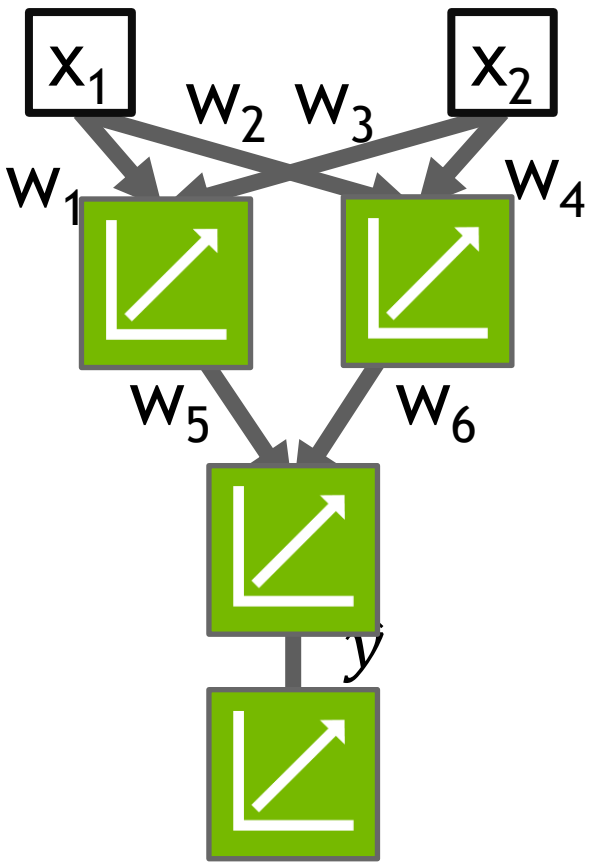
BUILDING A NETWORK



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

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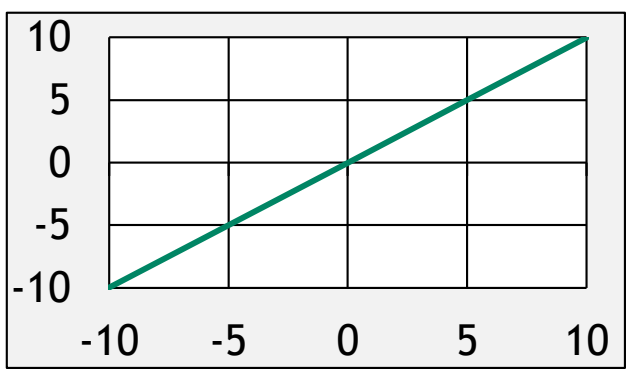
ACTIVATION FUNCTIONS

ACTIVATION FUNCTIONS

Linear

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

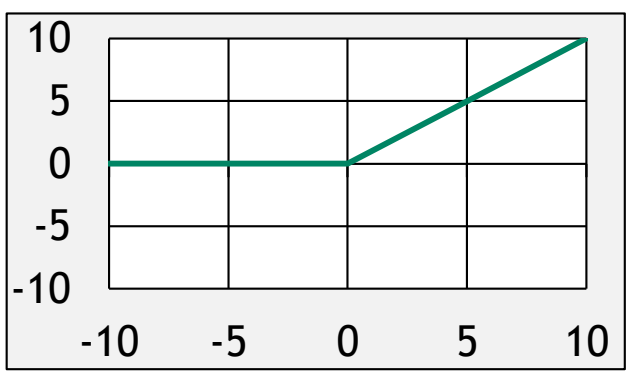
```
# Multiply each input
# with a weight (w) and
# add intercept (b)
y_hat = wx+b
```



ReLU

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

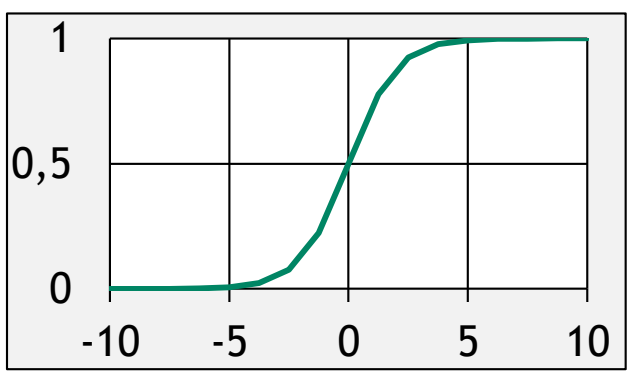
```
# Only return result
# if total is positive
linear = wx+b
y_hat = linear * (linear > 0)
```



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)
```



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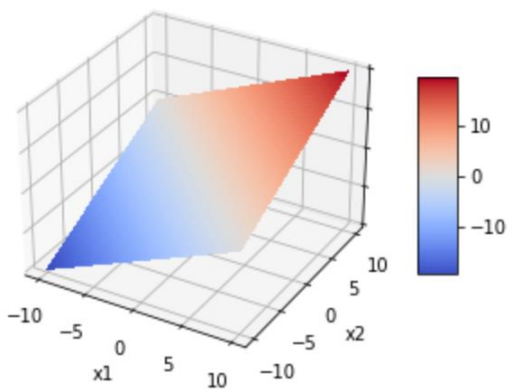
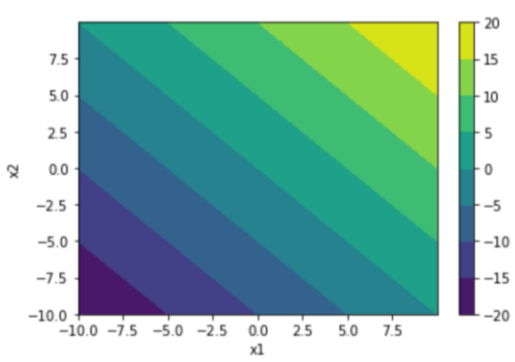
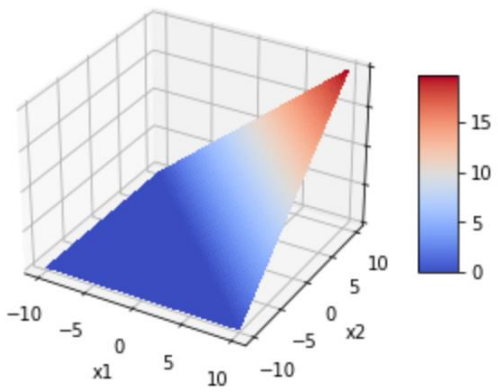
ACTIVATION FUNCTIONS

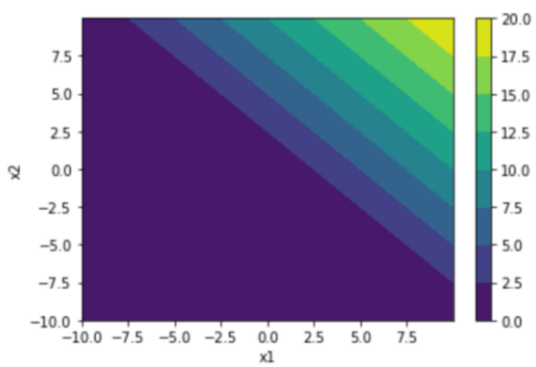
Linear



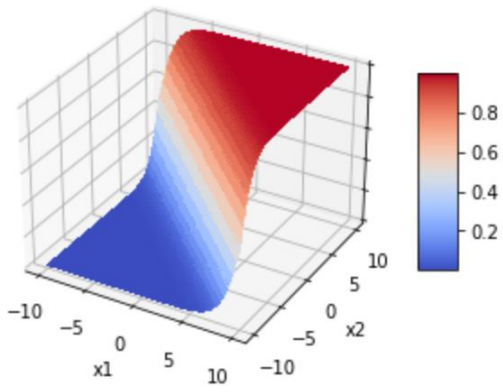


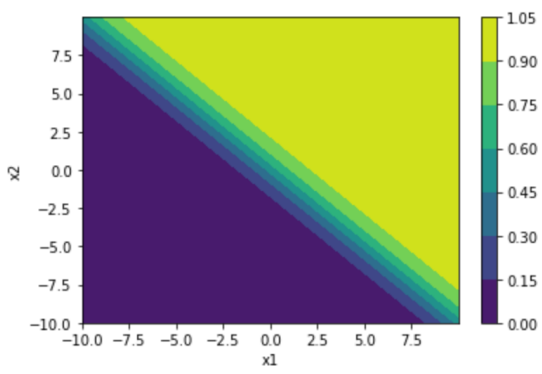
ReLU





Sigmoid





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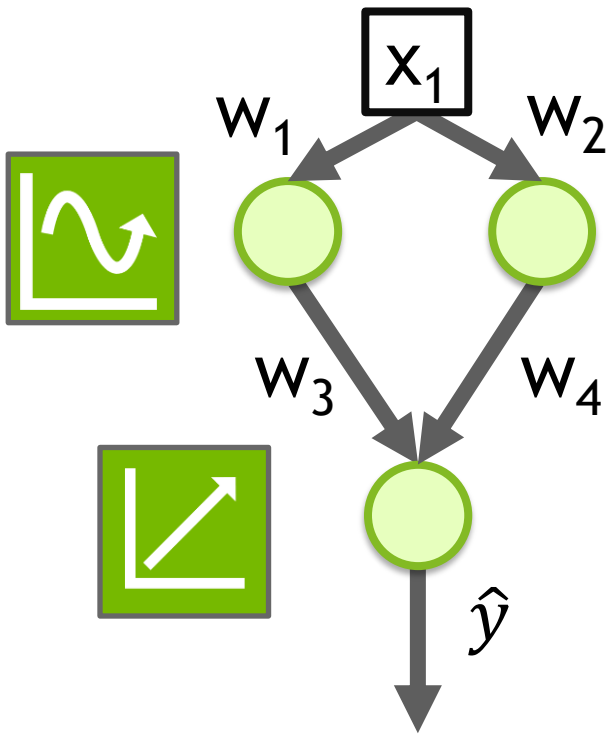
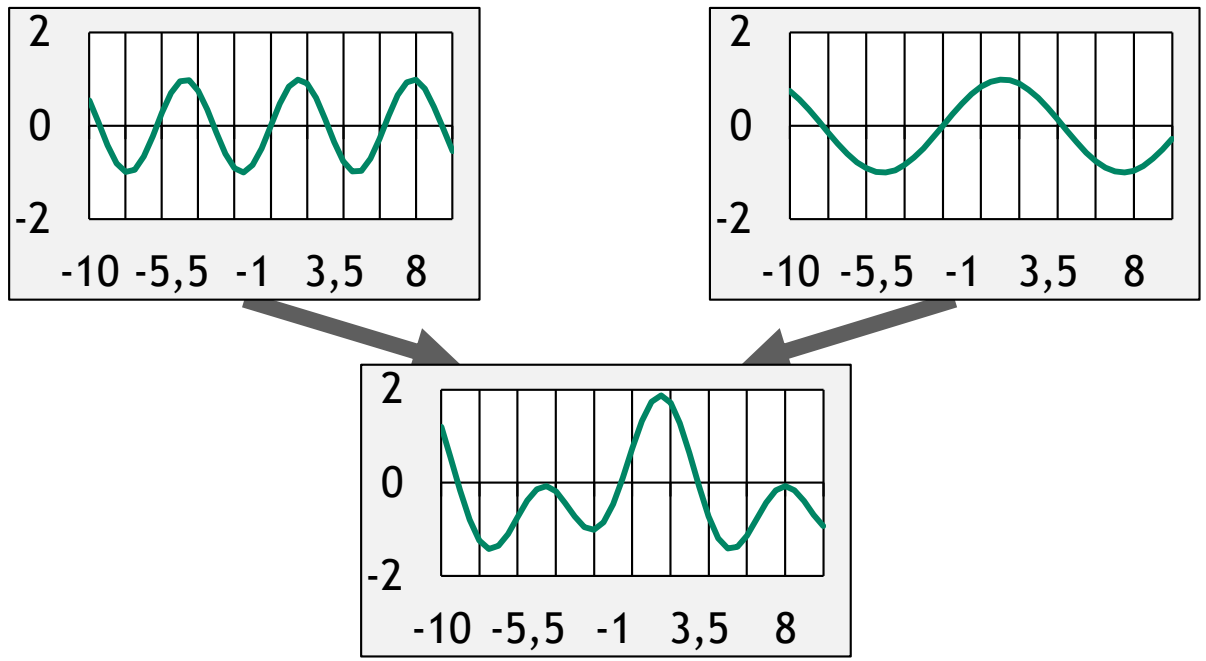
ACTIVATION FUNCTIONS





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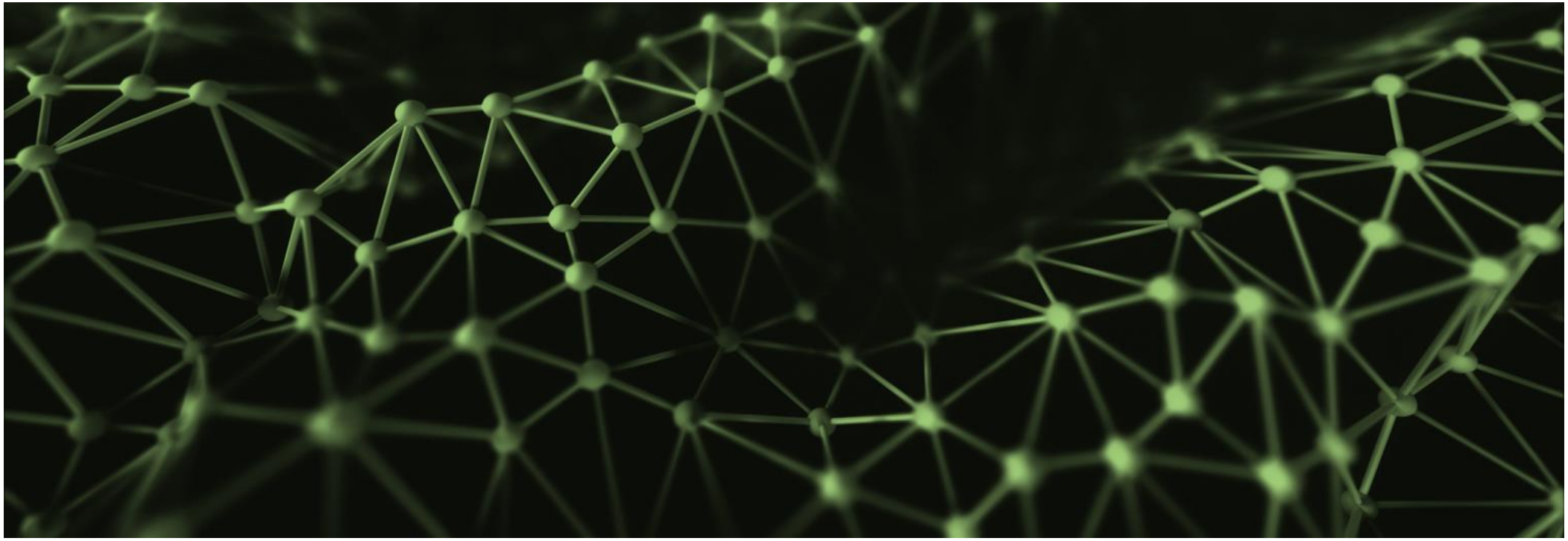
OVERFITTING

OVERFITTING

Why not have a super large neural network?



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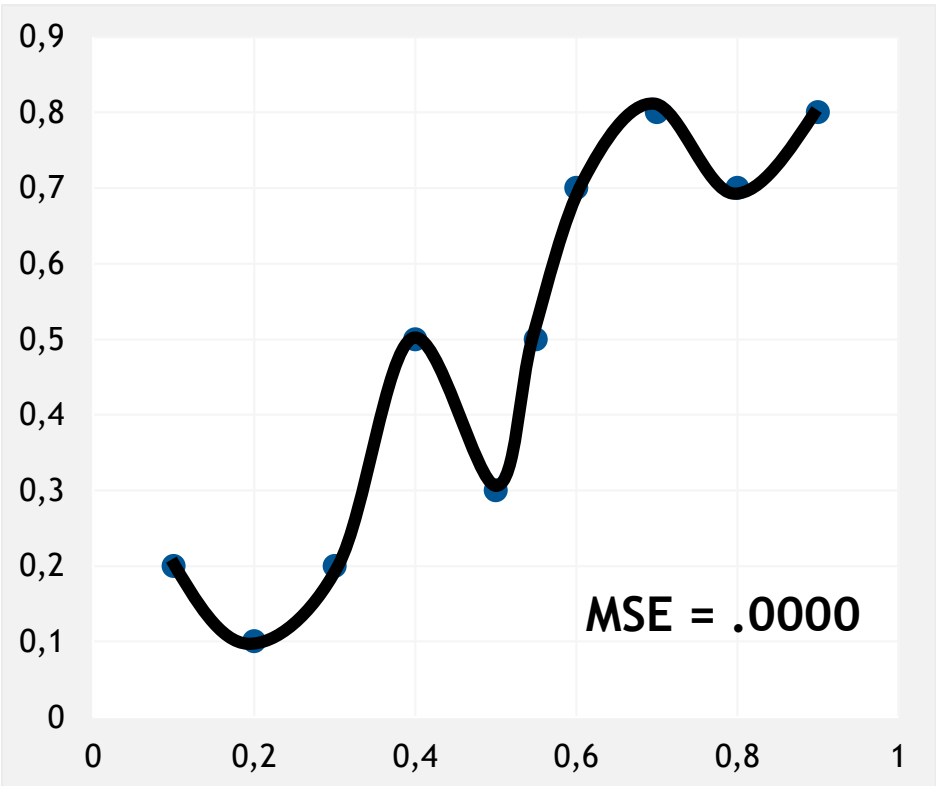
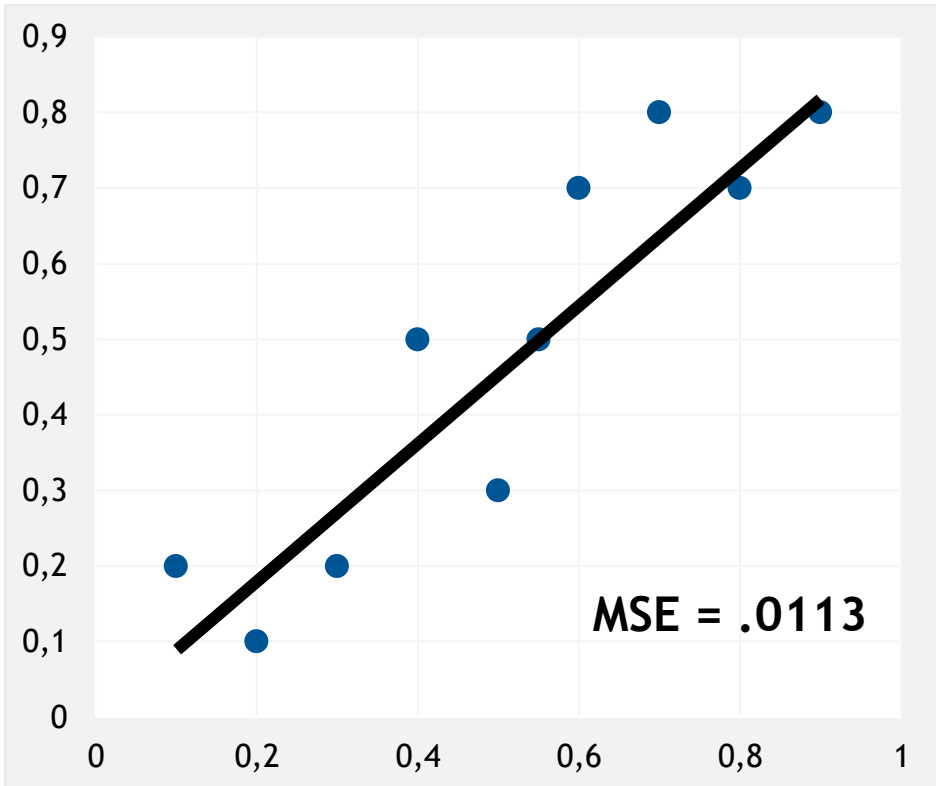
OVERFITTING

Which Trendline is Better?





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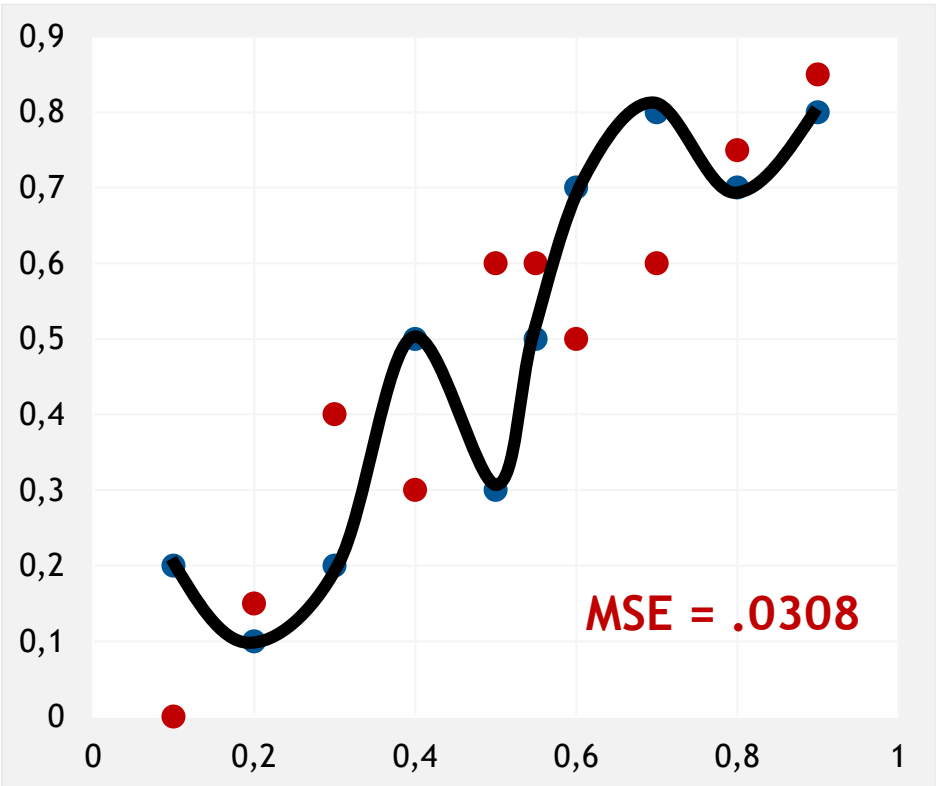
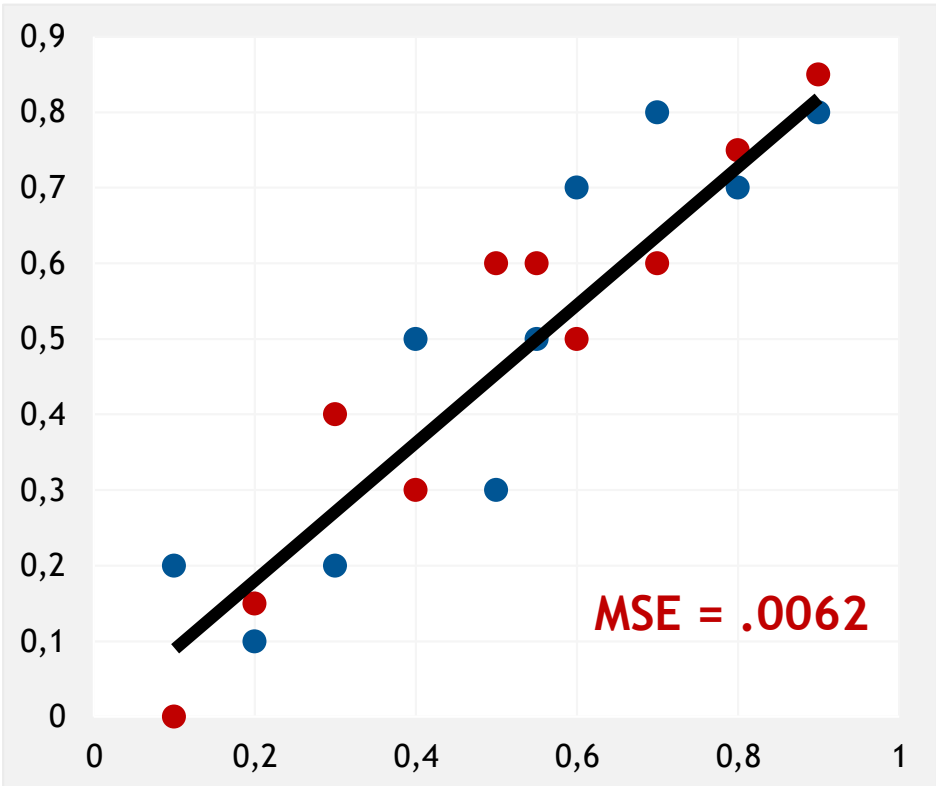
OVERFITTING

Which Trendline is Better?





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TRAINING VS VALIDATION DATA

Avoid memorization

Training data

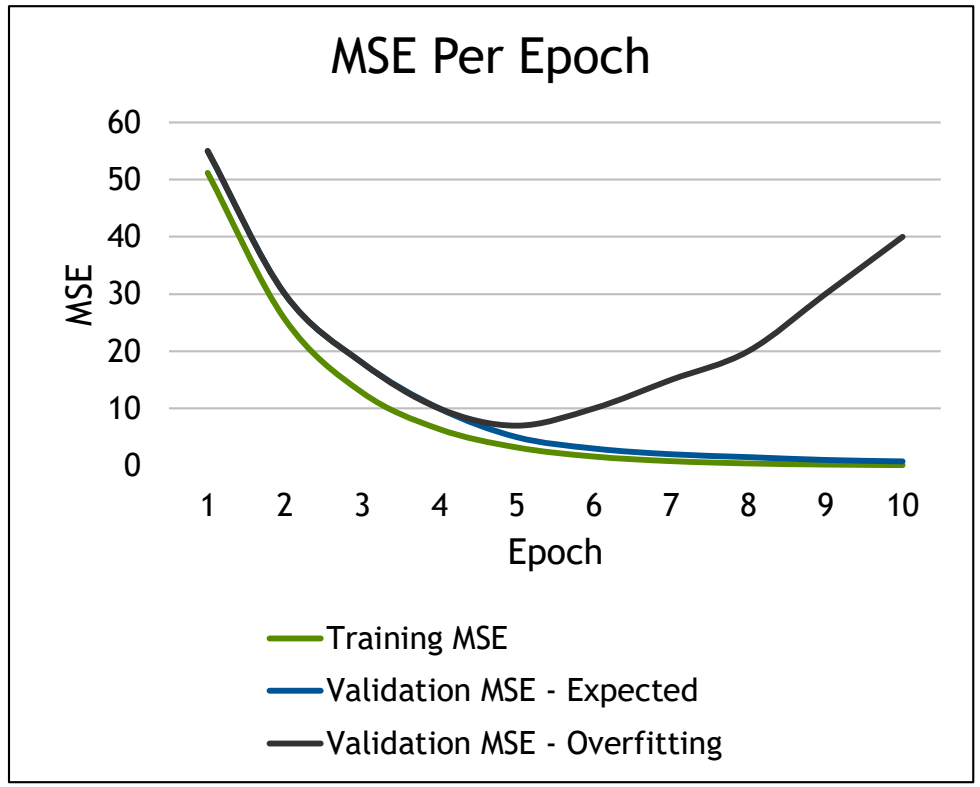
- Core dataset for the model to learn on

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



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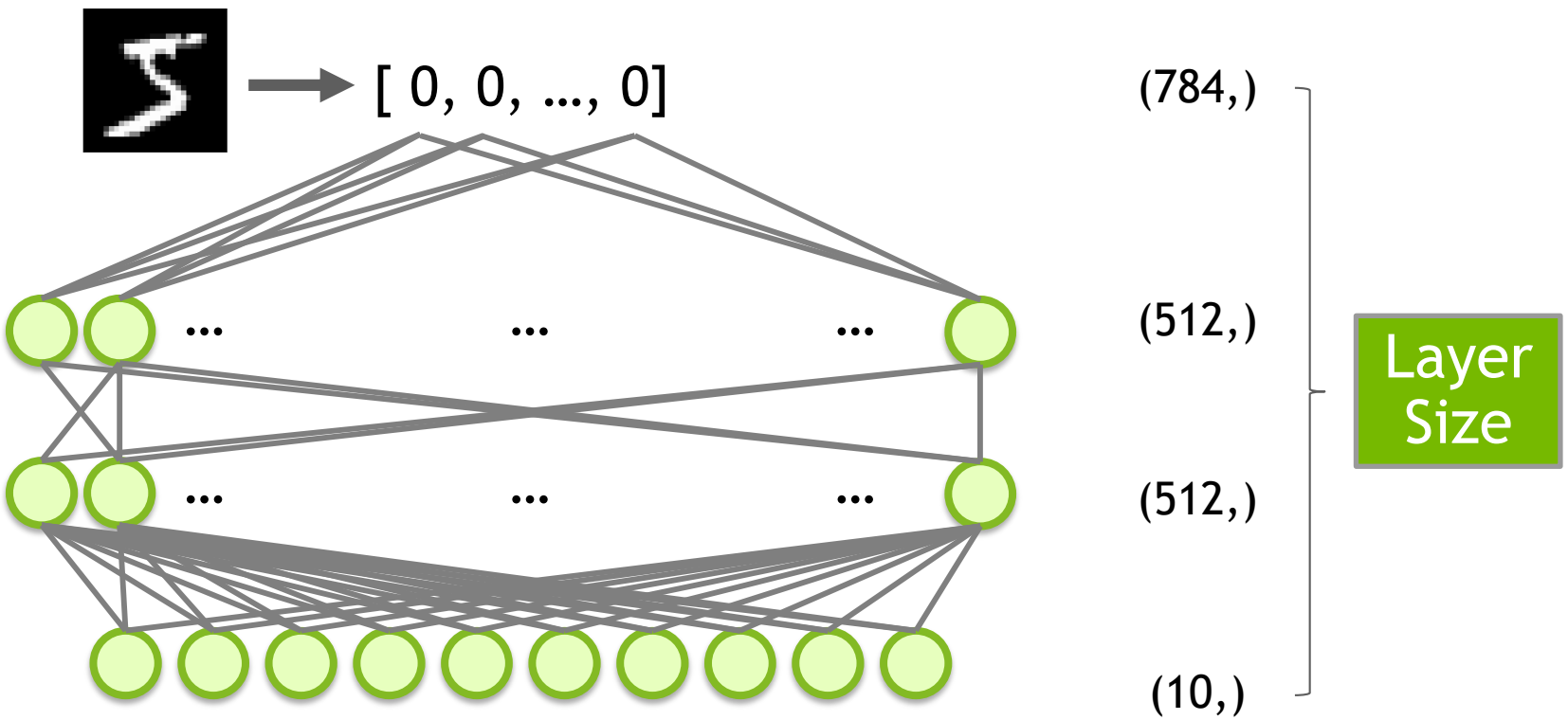
FROM REGRESSION TO CLASSIFICATION

AN MNIST MODEL



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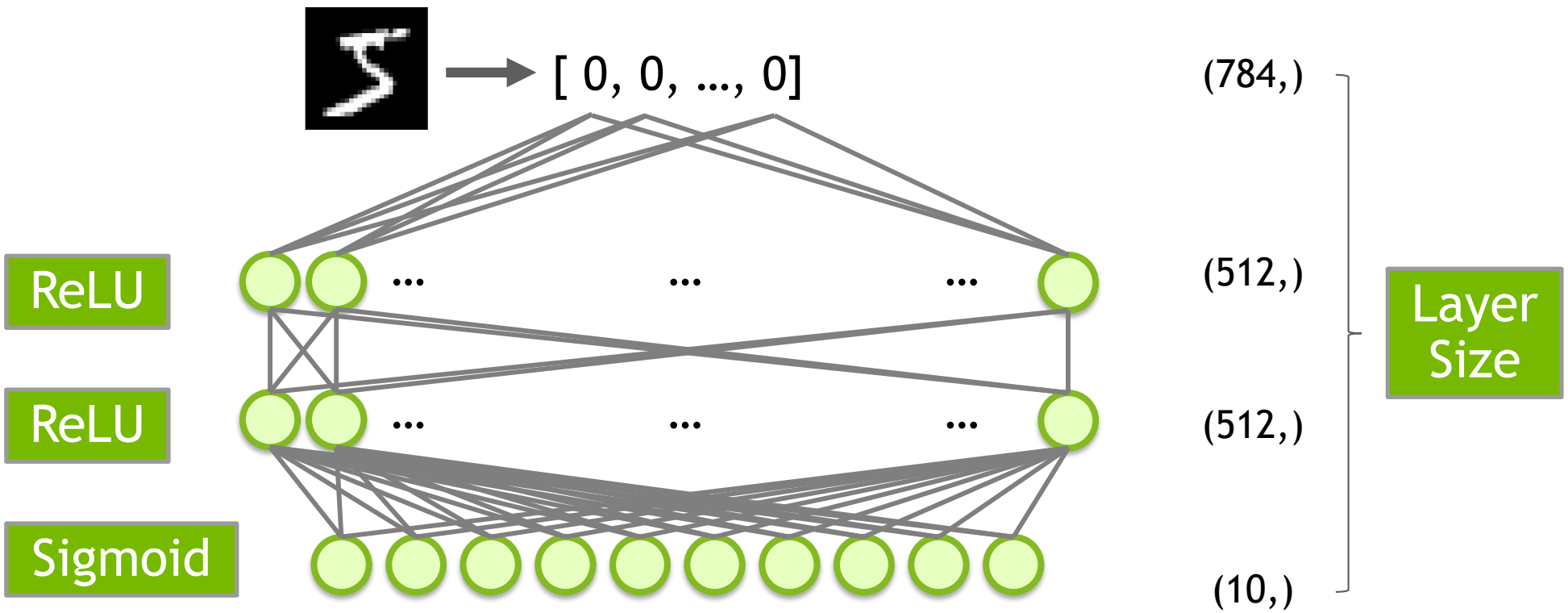
AN MNIST MODEL



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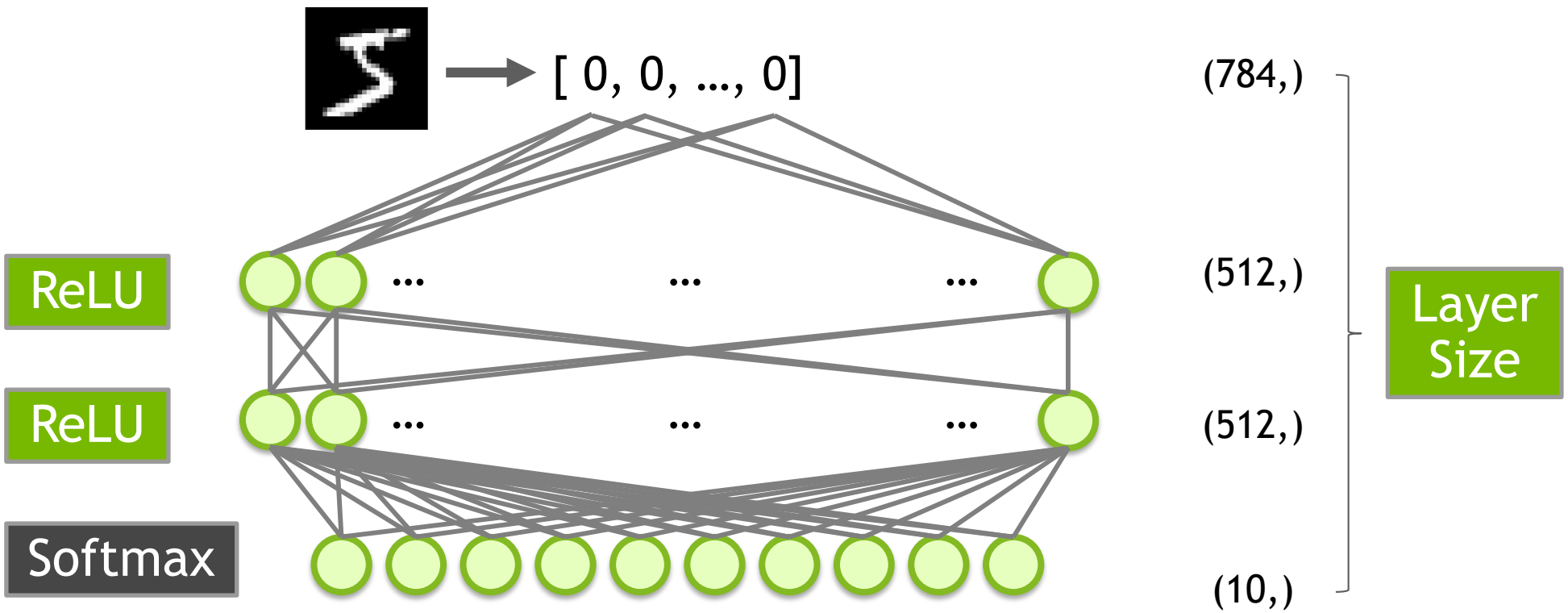
AN MNIST MODEL



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GRADIENT DESCENT

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

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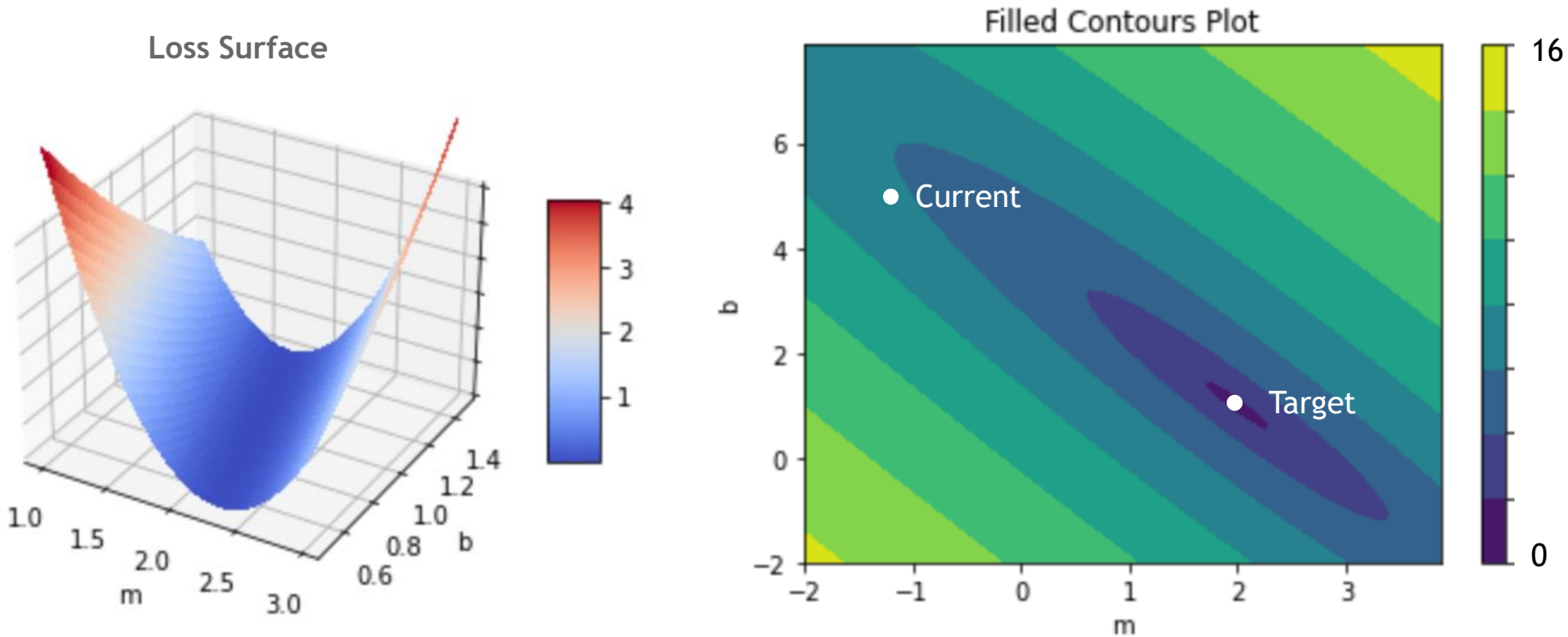
THE LOSS CURVE



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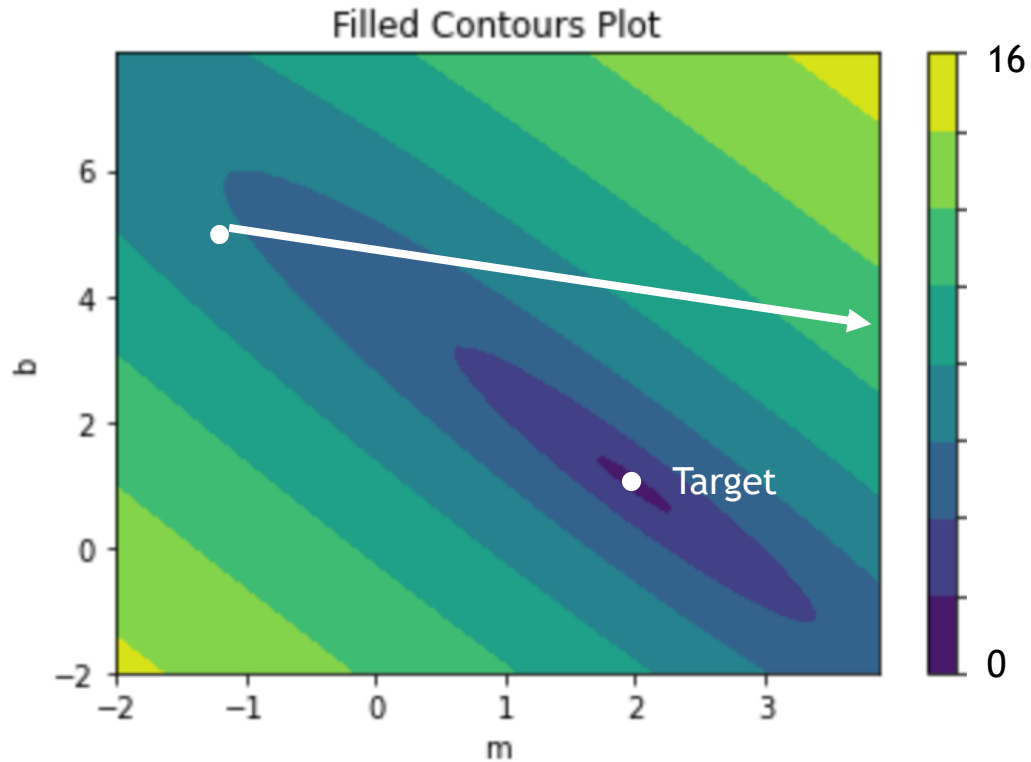
THE LOSS CURVE

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



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THE LOSS CURVE

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

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

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

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THE LOSS CURVE

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

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

$$\lambda = .6$$

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

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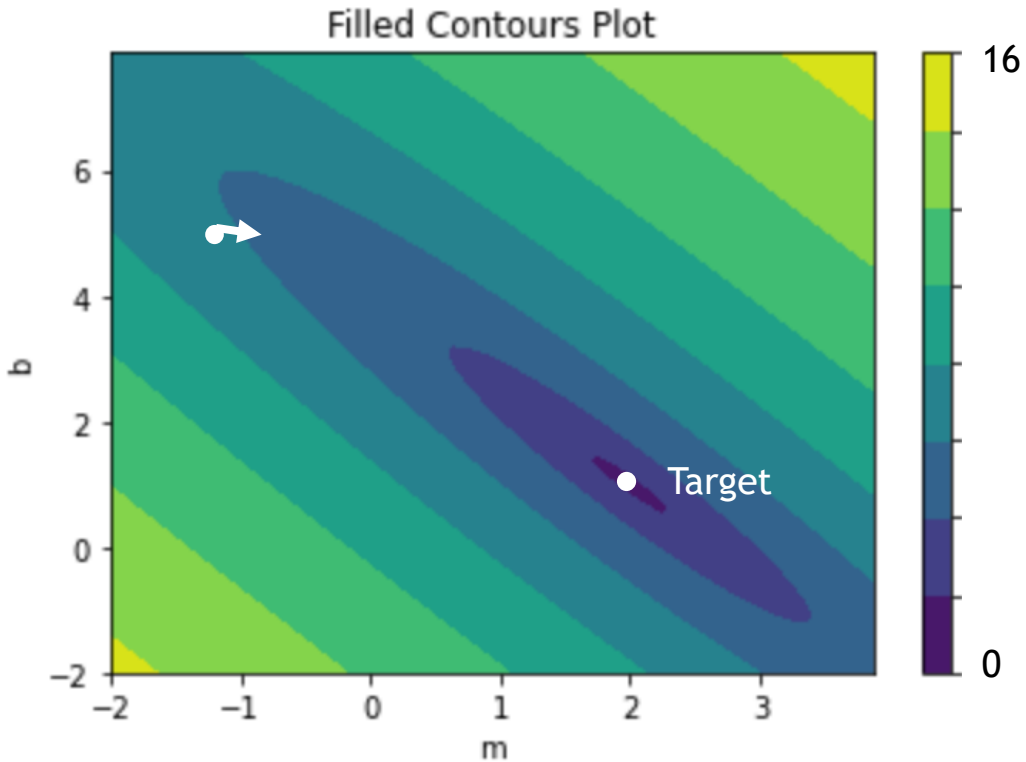
THE LOSS CURVE

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

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

$$\lambda = .005$$

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



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THE LOSS CURVE

$$\lambda = .1$$

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

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

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SEMOGA BERMANFAAT