元智大學 卓越・務實・宏觀・圓融

Deep Learning – Concepts and PyTorch Development

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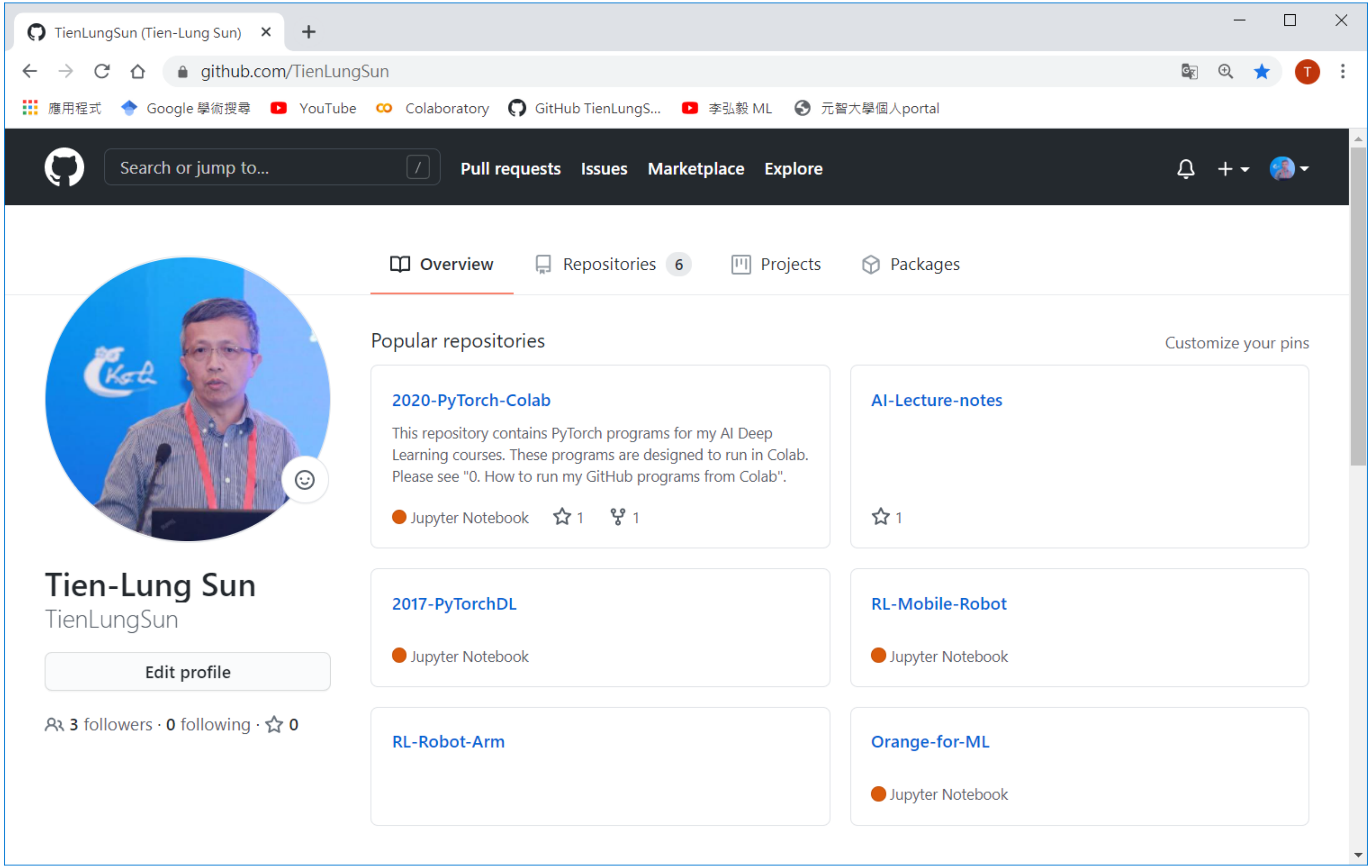
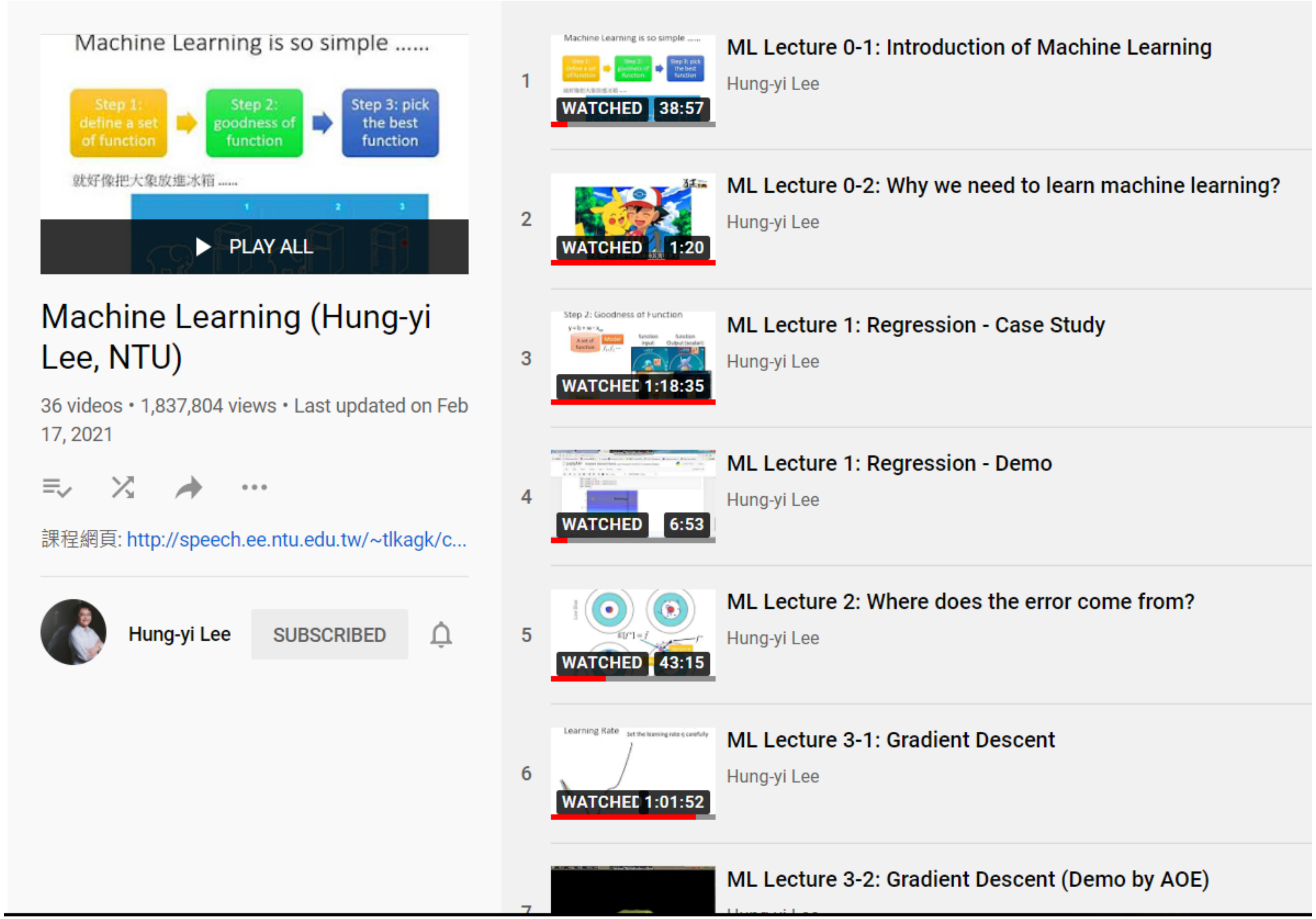
My GitHub



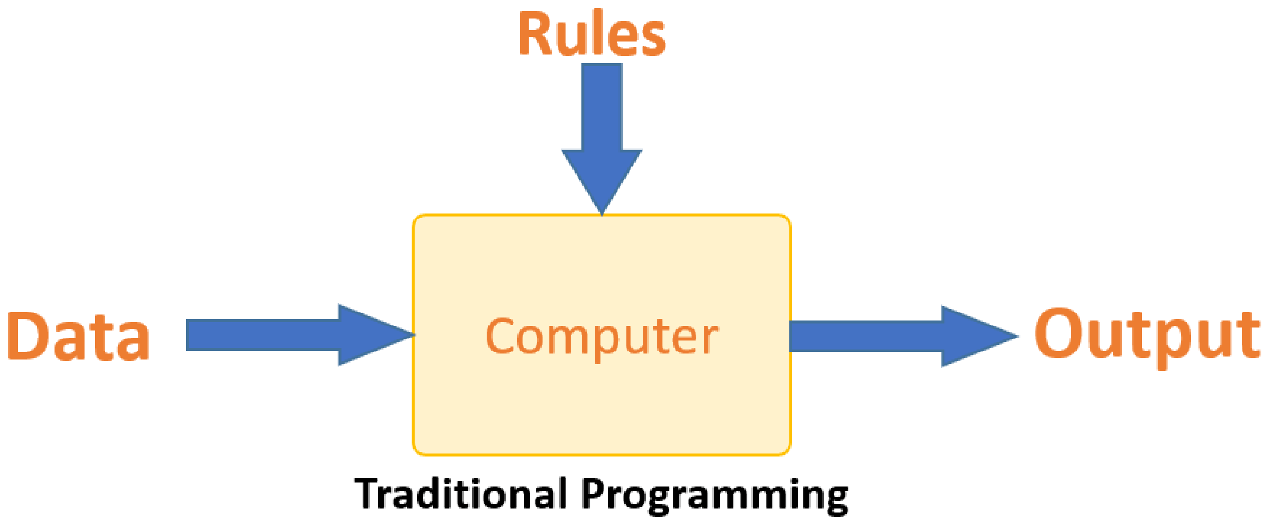
http://github.com/TienLungSun

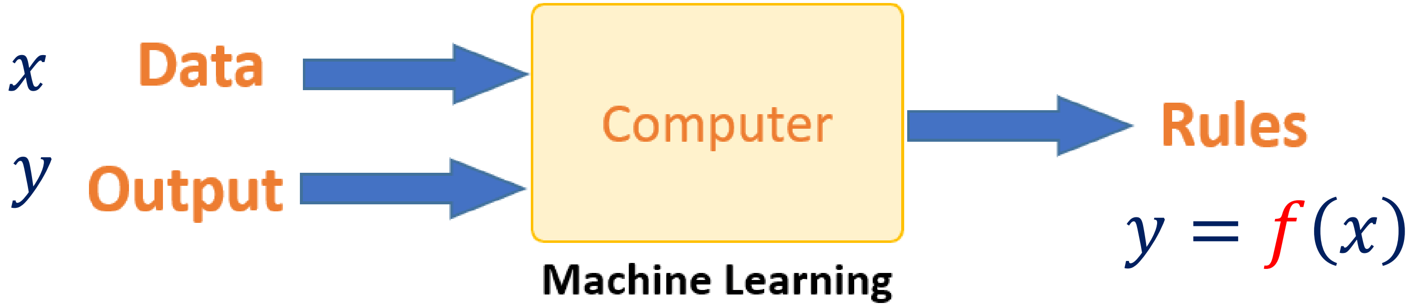
Acknowledgement



https://www.youtube.com/playlist?list=PLJV_el3uVTsPy9oCRY30oBPNLCo89yu49

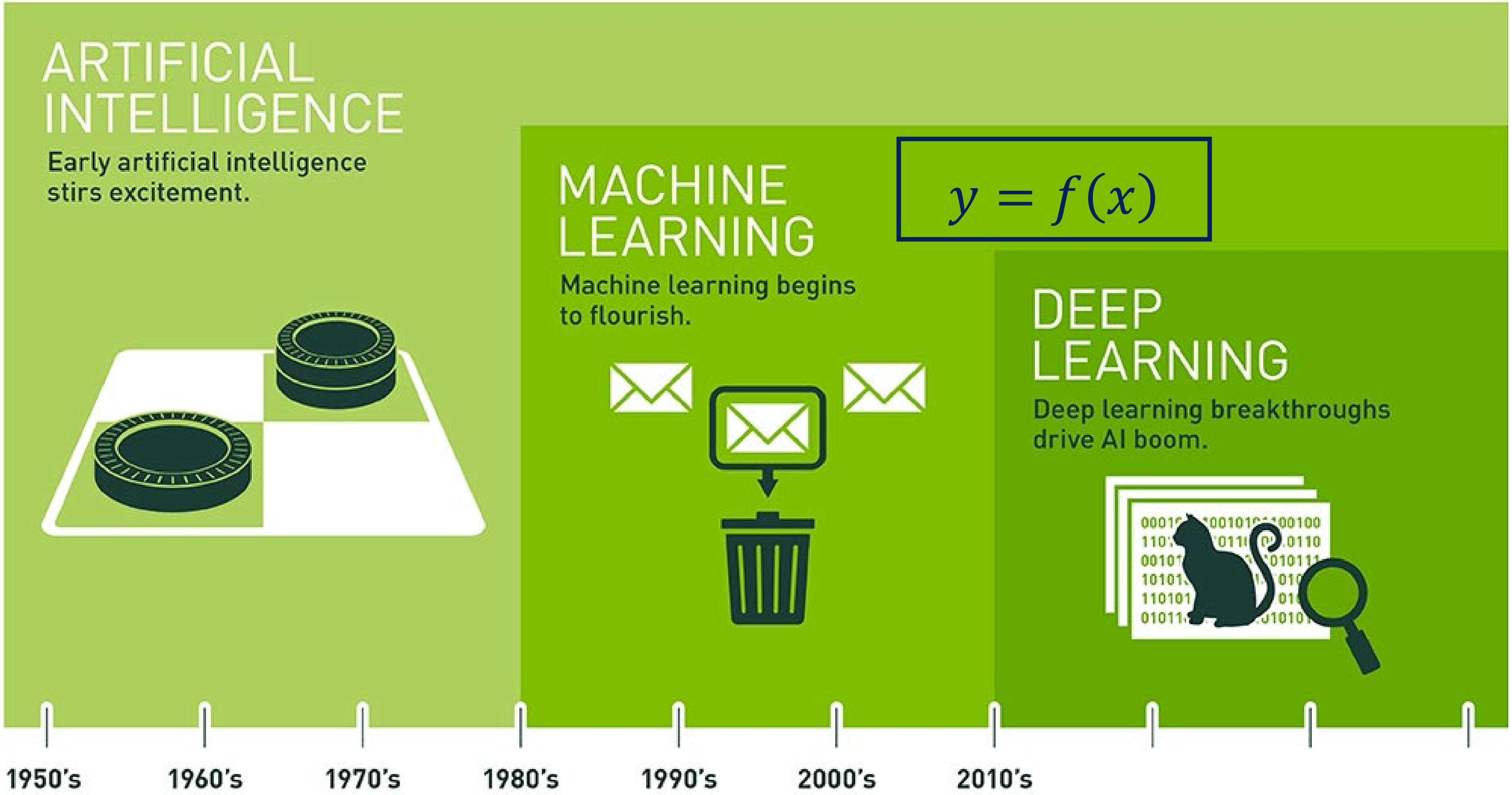
ML vs programming approach to let computer have intelligence





https://www.guru99.com/machine-learning-tutorial.html

AI, ML and DL



https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

Machine learning mechanism

1. Define a function to be learned: $y = f(x)$
2. Define a loss function $\mathcal{L}$ to describe the error between $y = f(x)$ and $\hat{y}$
3. Find the optimal parameters of f that minimize $\mathcal{L}$

Deep Learning - Machine learns a connected network

Geoffrey Hinton spent 30 years hammering away at an idea most other scientists dismissed as nonsense. Then, one day in 2012, he was proven right. Canada's most influential thinker in the field of artificial intelligence is far too classy to say I told you so

https://torontolife.com/tech/ai-superstars-google-facebook-apple-studied-guy/

For more than 30 years， Geoffrey Hinton hovered at the edges of artificial intelligence research，an outsider clinging to a simple proposition: that computers could think like humans do—using intuition rather than rules.

Geoffrey Hinton 多年來堅持着一個簡單的觀點：電腦可以像人類一樣思考-用直覺而不是規則。Hinton 一直好奇的是，電腦能不能像人類大腦一樣的工作：信息通過一個巨大的，由神經元圖譜連接起來的細胞網絡傳播，在多達十億條的路徑上發射、連接和傳輸。

Notations

x_i

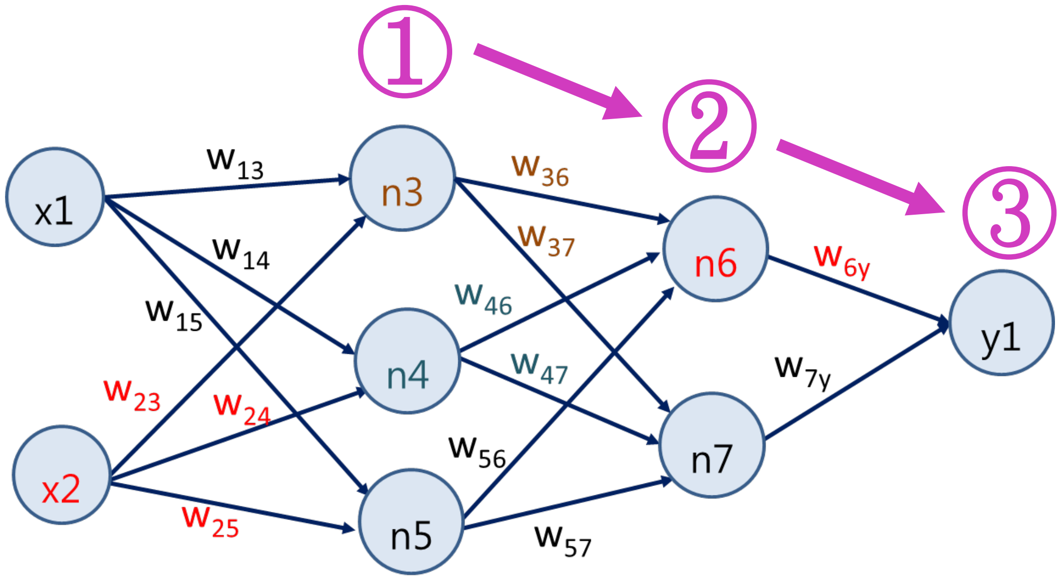
x^n x_i^n $\hat{y}^n$

No	age	t1	t2	t3	t4	t5	t6	time	Step frequency	n1	n2	n3	n4	n5	n6	px	py	pz	Steps	Gender	TUG	y1	BBS	y2
1	70	1.76	2.64	6.24	7.02	10	12.8	11	2.285	80	120	282	317	453	575	11.67	1.809	-1.99	13	F	11	0	26	0
2	86	1.64	2.6	5.82	7.27	10.4	12.6	11	1.934	75	118	263	328	470	570	11.14	2.302	-4.651	12	F	11	0	24	0
3	76	1.76	2.93	6.27	7.04	10.3	12.8	11	2.109	80	133	283	318	465	575	11.53	2.169	-3.253	14	F	11	0	22	1
4	70	2.38	3.29	5.58	6.47	9.02	10.4	8	2.461	108	149	252	292	407	468	11.6	1.838	-3.138	12	F	8	0	24	0
5	66	3.09	4.07	6.6	7.4	10.2	12.1	9	2.461	140	184	298	334	462	545	11.55	2.531	-2.742	12	F	9	0	26	0
6	79	1.76	2.91	5.87	6.6	10.2	12.8	11	2.109	80	132	265	298	462	575	[illegible]	1.788	-1.349	13	F	11	0	26	0
7	85	1.2	2.33	5.42	8.31	12.1	17.2	16	2.988	55	106	245	375	545	775	[illegible]	2.203	-4.89	17	M	16	1	18	1
8	81	1.64	2.93	5.98	7.47	10.9	13.6	12	1.758	75	133	270	337	493	615	11.1	2.667	-4.594	10	F	12	0	24	0
9	82	0.64	1.47	4.76	5.76	9.36	11.6	11	2.109	30	67	215	260	422	525	11.26	4.1	-2.693	14	M	11	0	24	0
10	69	1.64	2.49	5.02	5.98	9.82	12.6	11	2.637	75	113	227	270	443	570	11.27	3.292	-3.522	13	F	11	0	20	1
11	84	0.64	1.4	5.67	7.29	11.5	14.6	14	1.934	30	64	256	329	520	660	11.53	2.335	-2.999	15	M	14	1	26	0
12	69	1.09	1.98	5	5.62	8.38	10.1	9	2.109	50	90	226	254	378	455	11.15	1.919	-4.608	11	M	9	0	26	0
13	73	1.09	2.13	6.78	8.38	12.4	17.1	16	3.691	50	97	306	378	558	770	11.46	2.264	-3.333	16	F	16	1	14	1
14	81	0.64	1.87	9.24	11.2	19	22.6	22	1.934	30	85	417	507	857	1020	11.58	2.511	-2.157	27	M	22	1	24	0
15	80	0.76	1.71	3.98	5	7.58	9.76	9	2.109	35	78	180	226	342	440	11.33	2.821	-3.595	10	M	9	0	26	0
16	88	0.98	2.13	6.31	7.44	11.5	14	13	1.934	45	97	285	336	518	630	11.38	2.498	-3.702	16	M	14	1	26	0
17	81	1.09	2.09	4.18	5.16	7.76	10.1	9	2.285	50	95	189	233	350	455	11.21	2.241	-4.337	10	M	9	0	28	0
18	76	1.76	2.64	5.87	6.98	9.98	12.8	11	1.406	80	120	265	315	450	575	11.33	2.679	-3.736	10	M	11	0	26	0
19	69	0.36	3.76	13.3	16.7	24.2	29.4	29	3.691	17	170	598	753	1090	1322	11.31	1.361	-4.171	28	F	29	1	10	1
20	75	1.98	2.93	5.98	7.91	12.2	15	13	1.934	90	133	270	357	551	675	11.5	2.202	-1.495	14	M	13	0	28	0
21	87	1.53	3.2	10.9	13.8	21.3	26.5	25	2.9	70	145	492	624	960	1195	11.6	2.199	-2.54	19	F	25	1	16	1
22	72	0.2	1.02	3.36	4.11	7.42	10.2	10	1.758	10	47	152	186	335	460	11.52	2.658	-2.081	9	M	10	0	28	0
23	109	0.64	1.93	5.04	5.71	9.13	10.6	10	2.285	30	88	228	258	412	480	11.51	2.056	-3.158	15	F	10	0	28	0

Introduction to multi-layer perception (MLP)

Multiple-layer perception (MLP)

1. Define a function to be learned: $y^n = f(x^n)$



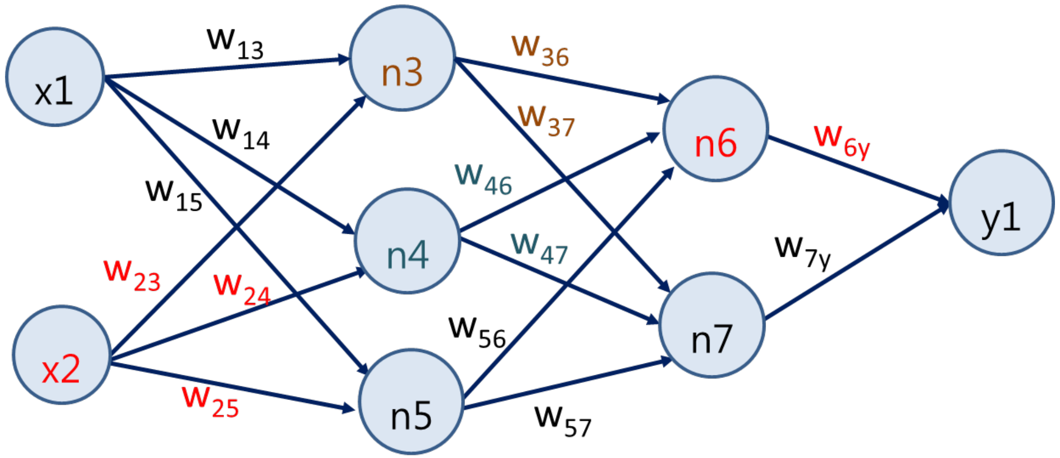
①
$$n_3 = \sigma(x_1 * w_{13} + x_2 * w_{23} + b_3)$$
$$n_4 = \sigma(x_1 * w_{14} + x_2 * w_{24} + b_4)$$
$$n_5 = \sigma(x_1 * w_{15} + x_2 * w_{25} + b_5)$$

②
$$n_6 = \sigma(n_3 * w_{36} + n_4 * w_{46} + n_5 * w_{56} + b_6)$$
$$n_7 = \sigma(n_3 * w_{37} + n_4 * w_{47} + n_5 * w_{57} + b_7)$$

③
$$y_1 = \sigma(n_6 * w_{6y} + n_7 * w_{7y} + b_y)$$

Calculate error

2. Define a loss function $\mathcal{L}(f)$ to describe the error between y^i and $\hat{y}^i$



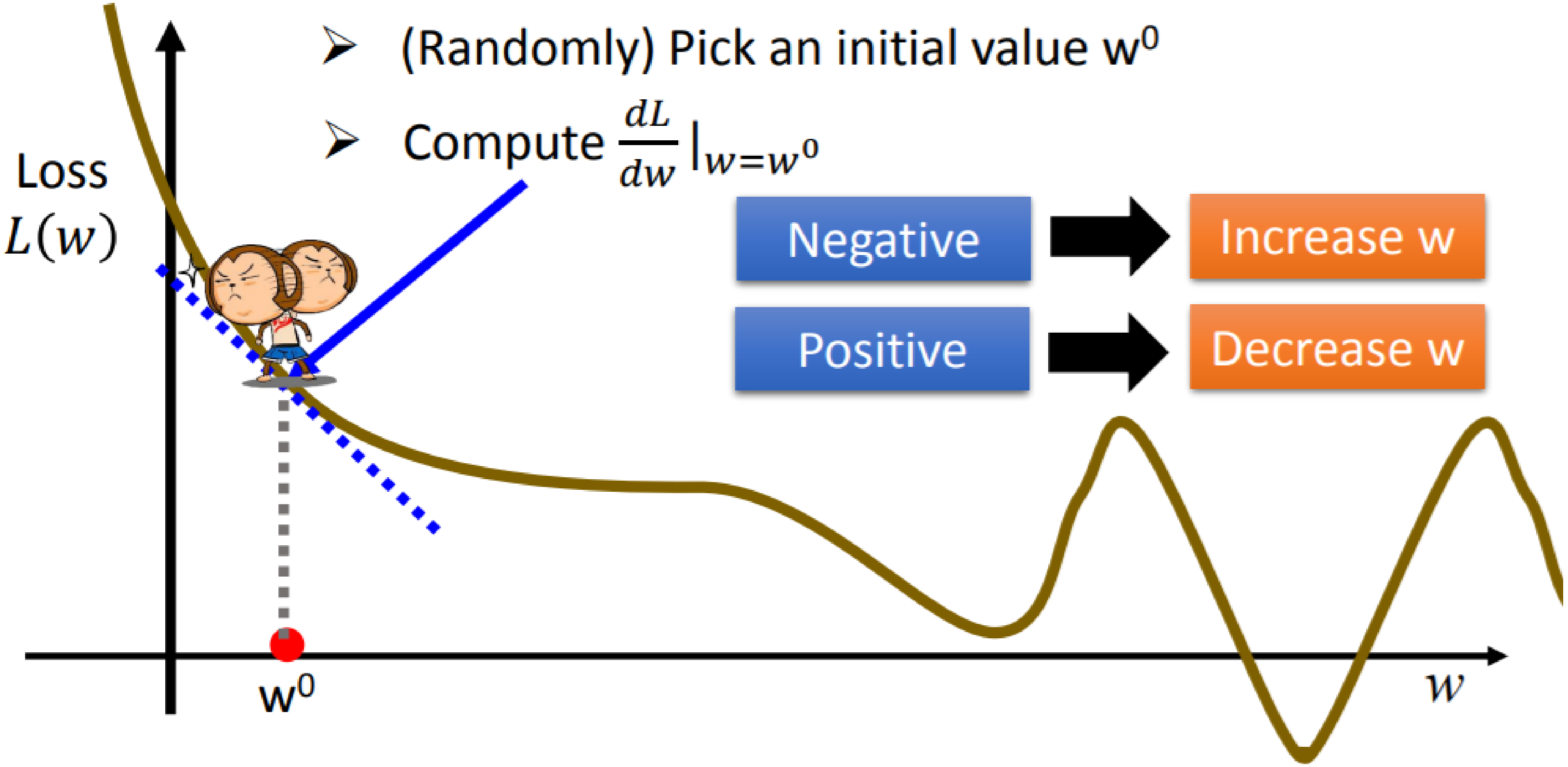
$$L = \frac{1}{N}\sum_{i=1}^{N}(y^i - \hat{y}^i)^2$$

Use gradient decent to find optimal parameters

3. Find the optimal parameters that minimize $\mathcal{L}(f)$

$$w^* = arg \min_{w} L(w)$$

- Consider loss function $L(w)$ with one parameter w:
  - (Randomly) Pick an initial value w^0
  - Compute $\frac{dL}{dw}|_{w=w^0}$



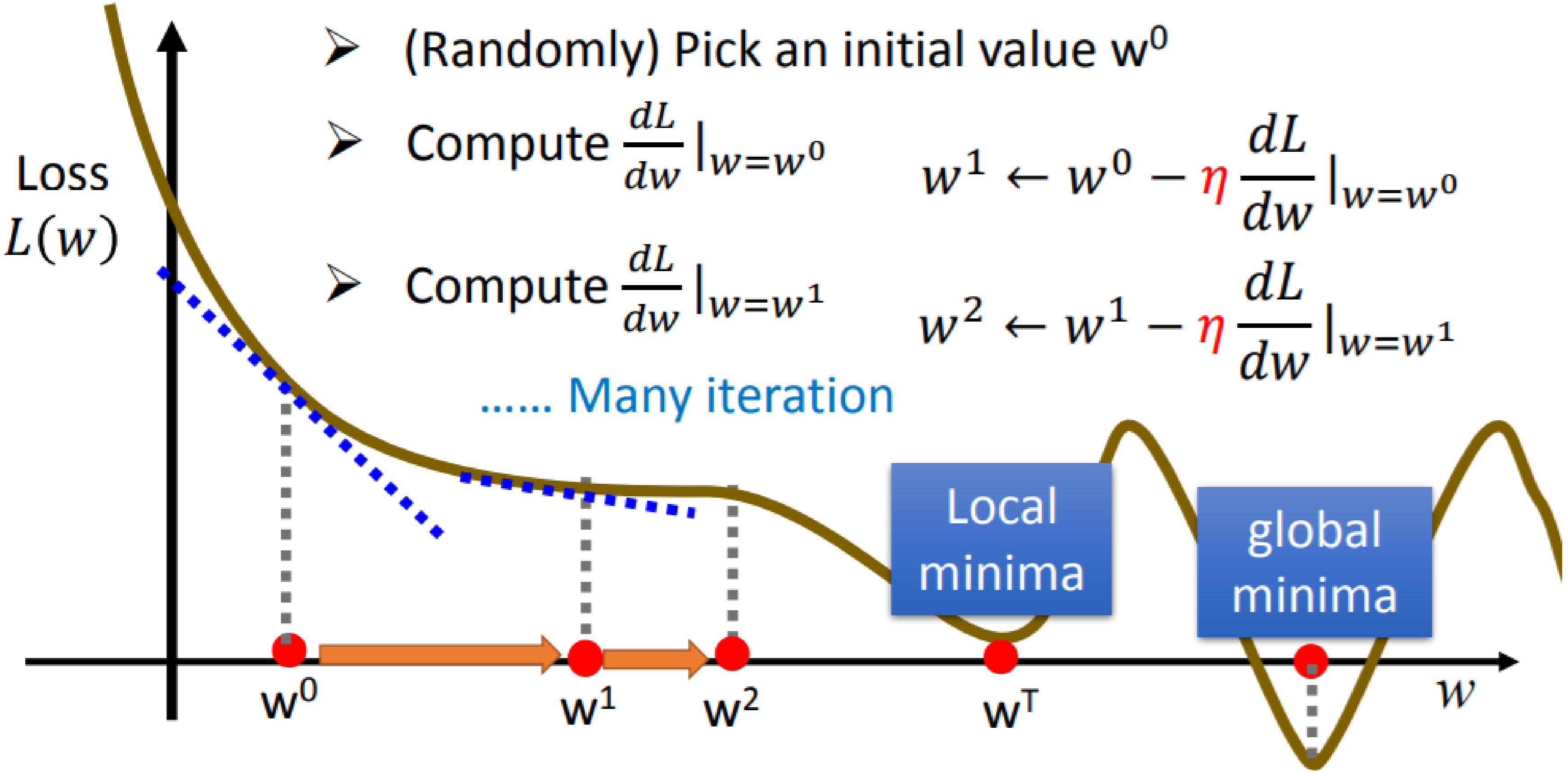
Reference: 李弘毅 ML Lecture 1 https://youtu.be/CXgbekl66jc

Use gradient decent to find optimal parameters

$$w^* = arg \min_w L(w)$$

- Consider loss function $L(w)$ with one parameter w:
  - ➢ (Randomly) Pick an initial value w^0
  - ➢ Compute $\frac{dL}{dw}|_{w=w^0}$ $\qquad w^1 \leftarrow w^0 - \eta \frac{dL}{dw}|_{w=w^0}$
  - ➢ Compute $\frac{dL}{dw}|_{w=w^1}$ $\qquad w^2 \leftarrow w^1 - \eta \frac{dL}{dw}|_{w=w^1}$

…… Many iteration



Gradient decent to find two parameters w^* and b^*

- How about two parameters? $w^*, b^* = arg \min_{w,b} L(w, b)$

  ➢ (Randomly) Pick an initial value w^0, b^0

  ➢ Compute $\frac{\partial L}{\partial w}|_{w=w^0, b=b^0}, \frac{\partial L}{\partial b}|_{w=w^0, b=b^0}$

$$\boxed{\begin{bmatrix} \frac{\partial L}{\partial w} \\ \frac{\partial L}{\partial b} \end{bmatrix} \text{gradient}}$$

$$w^1 \leftarrow w^0 - \eta \frac{\partial L}{\partial w}|_{w=w^0, b=b^0} \qquad b^1 \leftarrow b^0 - \eta \frac{\partial L}{\partial b}|_{w=w^0, b=b^0}$$

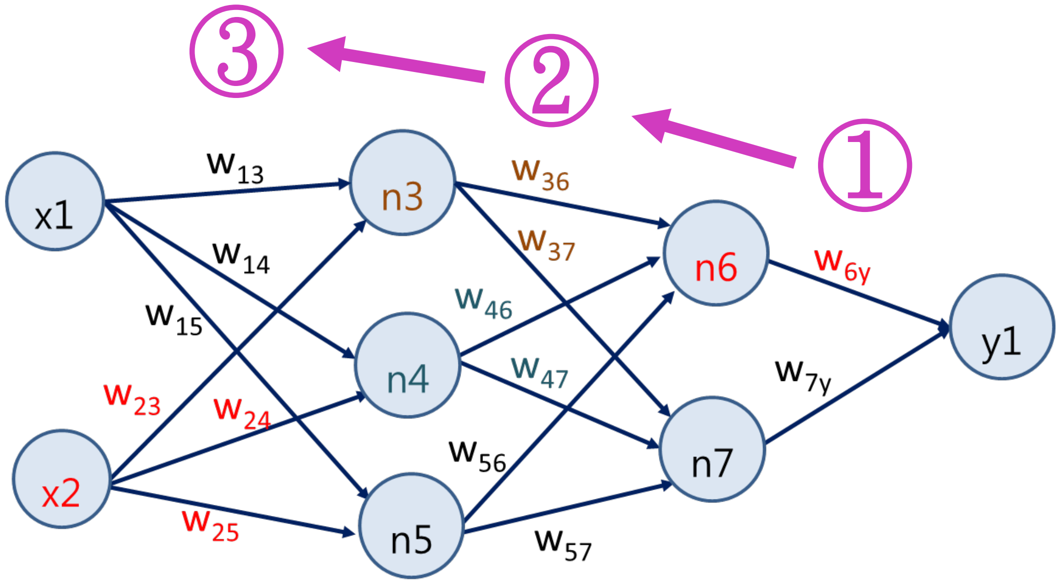
  ➢ Compute $\frac{\partial L}{\partial w}|_{w=w^1, b=b^1}, \frac{\partial L}{\partial b}|_{w=w^1, b=b^1}$

$$w^2 \leftarrow w^1 - \eta \frac{\partial L}{\partial w}|_{w=w^1, b=b^1} \qquad b^2 \leftarrow b^1 - \eta \frac{\partial L}{\partial b}|_{w=w^1, b=b^1}$$

Reference: 李弘毅 ML Lecture 1 https://youtu.be/CXgbekl66jc

Use gradient decent to find optimal NN weights

3. Find the optimal parameters that minimize $\mathcal{L}(f)$



$L = g(y - \hat{y})$ $\quad y = \sigma(n_6 * w_{6y} + n_7 * w_{7y} + b_y)$

①

$$w_{6y} \leftarrow w_{6y} - \eta \frac{\partial L}{\partial w_{6y}} \qquad \frac{\partial L}{\partial w_{6y}} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial w_{6y}}$$

$$w_{7y} \leftarrow w_{7y} - \eta \frac{\partial L}{\partial w_{7y}} \qquad \frac{\partial L}{\partial w_{7y}} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial w_{7y}}$$

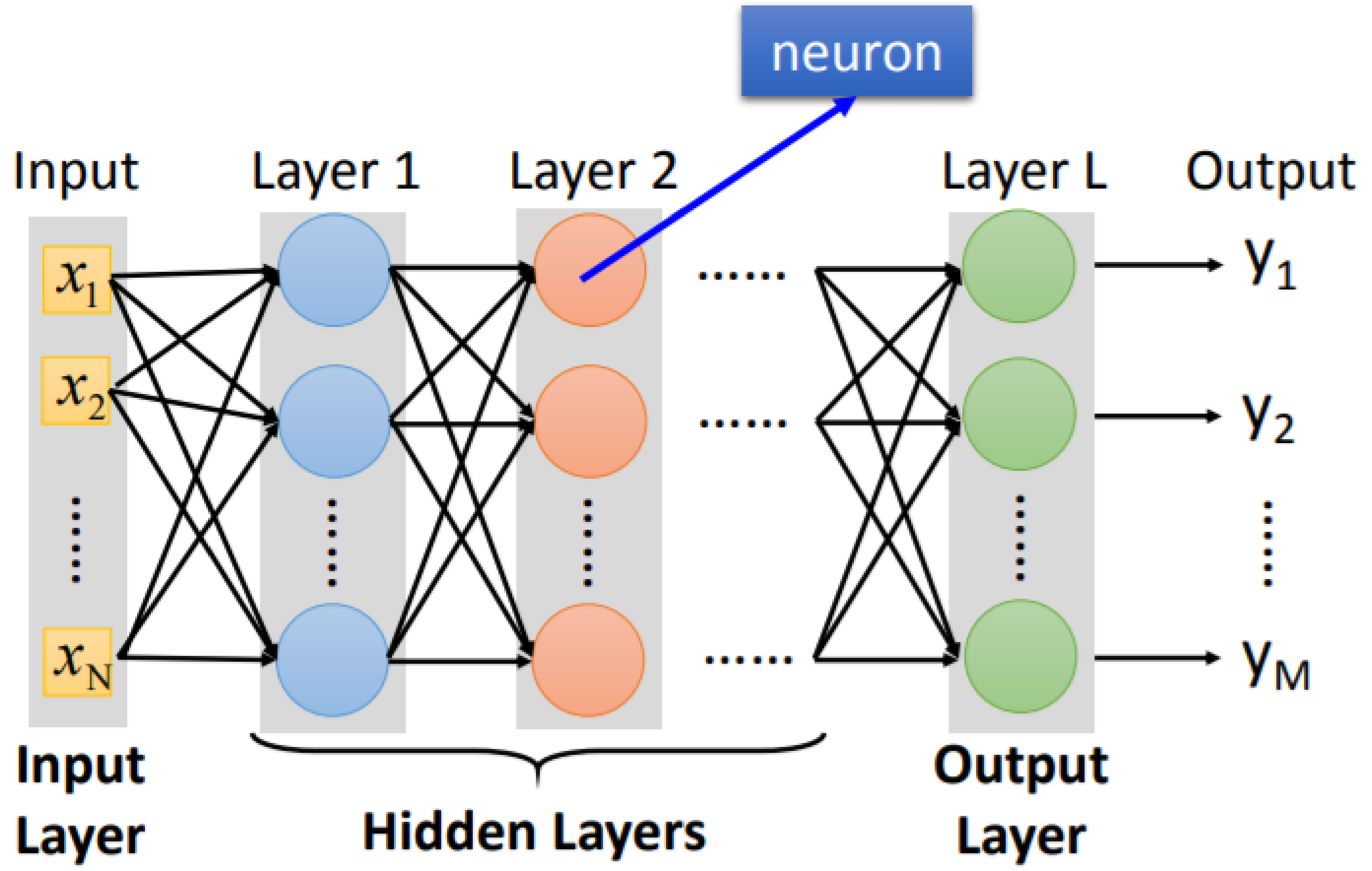
$$w_i \leftarrow w_i - \eta \frac{\partial e}{\partial w_i}$$

②

$$w_{57} \leftarrow w_{57} - \eta \frac{\partial L}{\partial w_{57}} \qquad \frac{\partial L}{\partial w_{57}} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial n_7}\frac{\partial n_7}{\partial w_{57}}$$

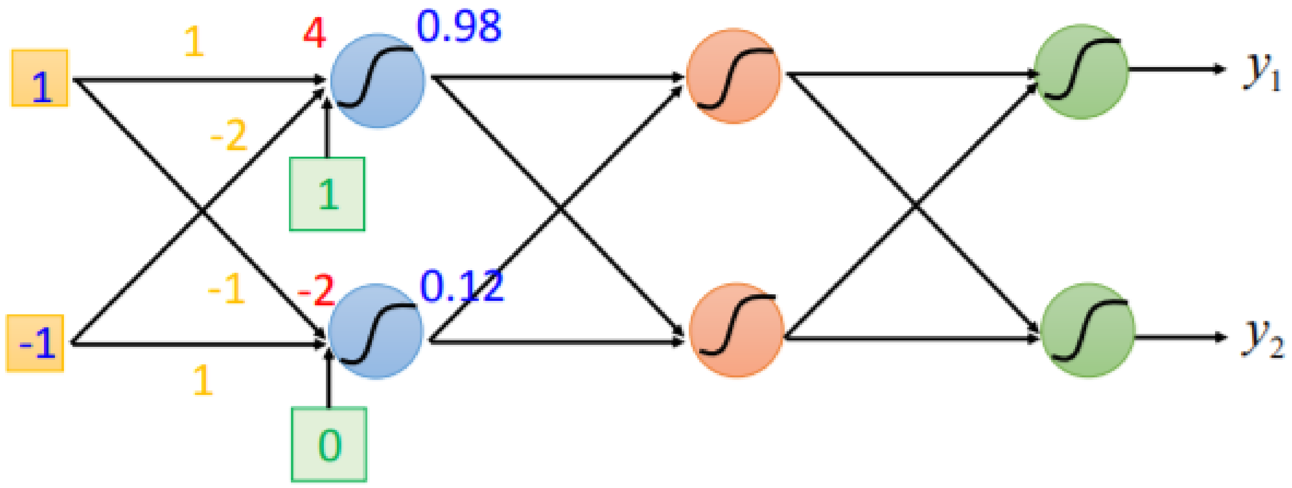
$$n_7 = f(n_3 * w_{37} + n_4 * w_{47} + n_5 * w_{57} + b_7)$$

MLP is a fully connected feedforward network



Reference: 李弘毅 ML Lecture 6 https://youtu.be/Dr-WRlEFefw

Fully connected feed forward network is implemented as matrix operation



$$y = \sigma(w \cdot x + b)$$

$$\sigma\Big(\underbrace{\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{\begin{bmatrix} 4 \\ -2 \end{bmatrix}}\Big) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

Reference: 李弘毅 ML Lecture 6 https://youtu.be/Dr-WRlEFefw

Practice

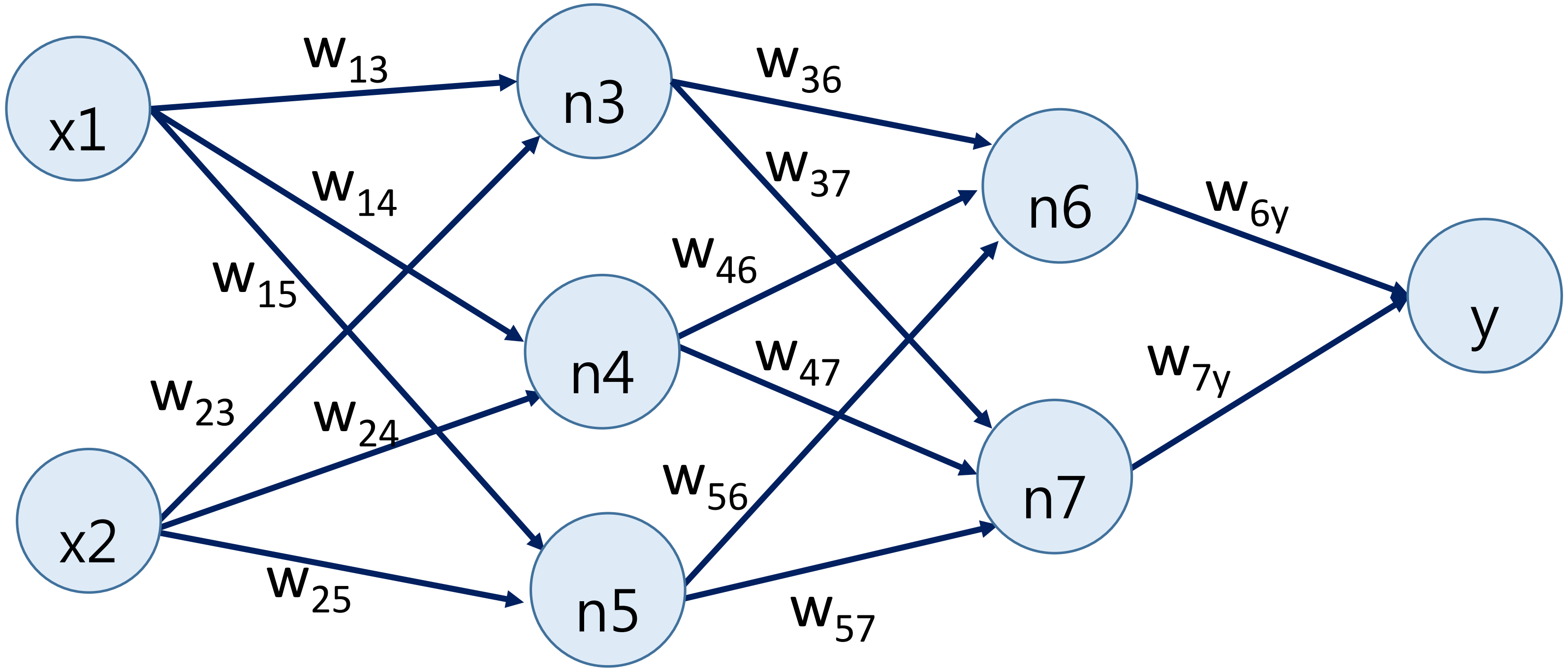
- Run "1.1 Matrix operation.ipynb"

Matrix operation

```
MyNet = nn.Sequential(
    nn.Linear(2, 3),
    nn.Linear(3, 2),
    nn.Linear(2, 1)
)
```

$$\vec{X} = \begin{array}{cc} x_1 & x_2 \\ \end{array}$$

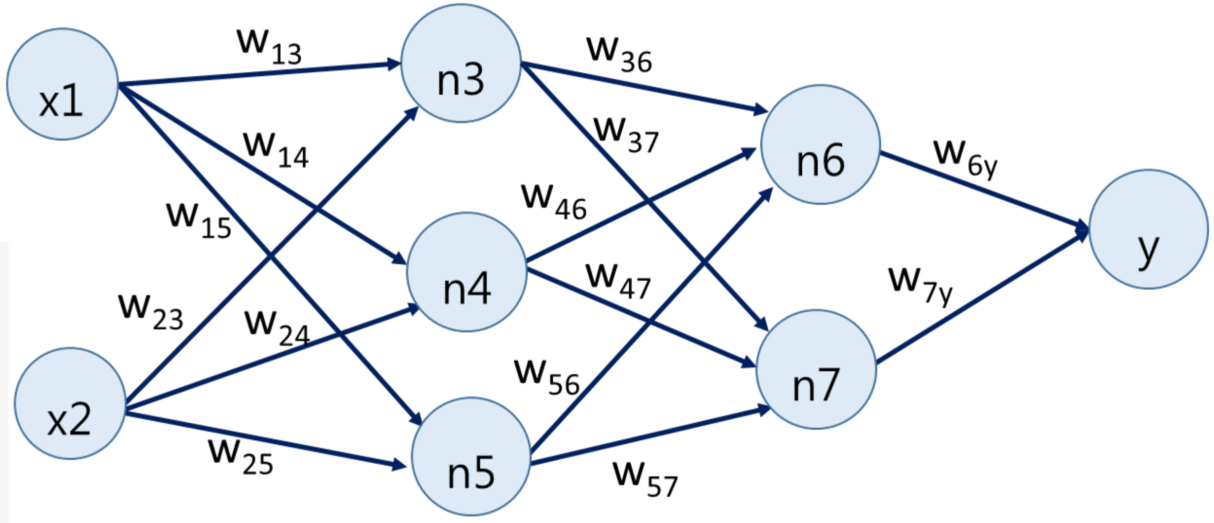
$$\vec{X} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 10 & 5 \end{bmatrix}$$



$$\hat{y} = \begin{bmatrix} 7 \\ 12 \\ 40 \end{bmatrix}$$

Matrix operation

```
for param in MyNet.parameters():
        if param.requires_grad:
                print(param.data)
```




```
tensor([[ 0.4727, -0.5188],
        [-0.5681, -0.6032],
        [-0.0252, -0.3011]])
tensor([-0.6986, -0.6602, -0.4860])
tensor([[-0.5549,  0.2550,  0.4584],
        [ 0.2930,  0.0849, -0.3146]])
tensor([0.1677, 0.0736])
tensor([[ 0.4106, -0.3618]])
tensor([-0.2270])
```

$$\begin{bmatrix} w_{13} & w_{23} \\ w_{14} & w_{24} \\ w_{15} & w_{25} \end{bmatrix}$$

$$[b_3 \quad b_4 \quad b_5]$$

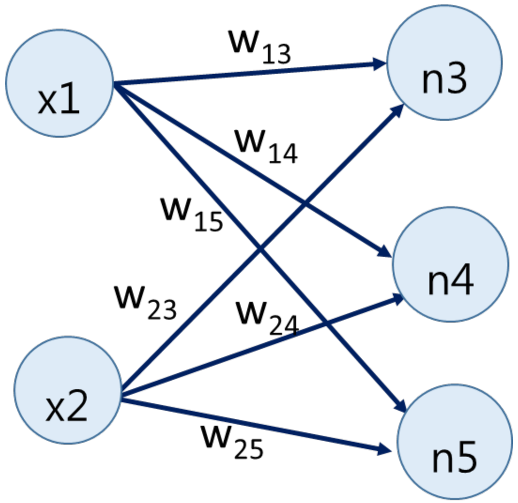
$$\begin{bmatrix} w_{36} & w_{46} & w_{56} \\ w_{37} & w_{47} & w_{57} \end{bmatrix}$$

$$[b_6 \quad b_7]$$

$$[w_{6y} \quad w_{7y}]$$

$$[b_y]$$

$$\vec{X} = \begin{array}{cc} x_1 & x_2 \\ \end{array}$$
$$\vec{X} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 10 & 5 \end{bmatrix}$$



$$\underbrace{\begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 10 & 5 \end{bmatrix}\begin{bmatrix} w_{13} & w_{14} & w_{15} \\ w_{23} & w_{24} & w_{25} \end{bmatrix}}_{\begin{bmatrix} k_3^1 & k_4^1 & k_5^1 \\ k_3^2 & k_4^2 & k_5^2 \\ k_3^3 & k_4^3 & k_5^3 \end{bmatrix}} + \begin{bmatrix} b_3 & b_4 & b_5 \end{bmatrix}$$

$$\underbrace{\begin{bmatrix} k_3^1 & k_4^1 & k_5^1 \\ k_3^2 & k_4^2 & k_5^2 \\ k_3^3 & k_4^3 & k_5^3 \end{bmatrix} + \begin{bmatrix} b_3 & b_4 & b_5 \\ b_3 & b_4 & b_5 \\ b_3 & b_4 & b_5 \end{bmatrix}}_{\boxed{\begin{bmatrix} n_3^1 & n_4^1 & n_5^1 \\ n_3^2 & n_4^2 & n_5^2 \\ n_3^3 & n_4^3 & n_5^3 \end{bmatrix}}}$$

Use Excel to verify

```
W1 = MyNet[0].weight
b1 = MyNet[0].bias
print(W1, W1.shape, b1)
```

```
Parameter containing:
tensor([[ 0.4727, -0.5188],
        [-0.5681, -0.6032],
        [-0.0252, -0.3011]],
tensor([-0.6986, -0.6602, -0.4860], r
```

$$\begin{bmatrix} w_{13} & w_{23} \\ w_{14} & w_{24} \\ w_{15} & w_{25} \end{bmatrix}$$

```
#Calculate n3, n4, n5
HiddenLayer1 = MyNet[0](tensorX)
print(HiddenLayer1)
```

```
tensor([[-1.2635, -2.4348, -1.1135],
        [-1.3097, -3.6061, -1.4398],
        [ 1.4340, -9.3577, -2.2441]],
```

```
#Calculate n3, n4, n5 using Pytorch matrix operation
HiddenLayer1 = tensorX.mm(torch.transpose(W1, 1, 0)) + b1
print(HiddenLayer1)
```

```
tensor([[-1.2635, -2.4348, -1.1135],
        [-1.3097, -3.6061, -1.4398],
        [ 1.4340, -9.3577, -2.2441]], grad_fn=<AddBackward0>)
```

```
#Calculate n6, n7 using PyTorch matrix operation
W2 = MyNet[1].weight
b2 = MyNet[1].bias
HiddenLayer2 = HiddenLayer1.mm(torch.transpose(W2, 1, 0)) +b2
print(HiddenLayer2)
```

```
tensor([[-0.2625, -0.1530],
        [-0.6852, -0.1632],
        [-4.0429,  0.4054]], grad_fn=<AddBackward0>)
```

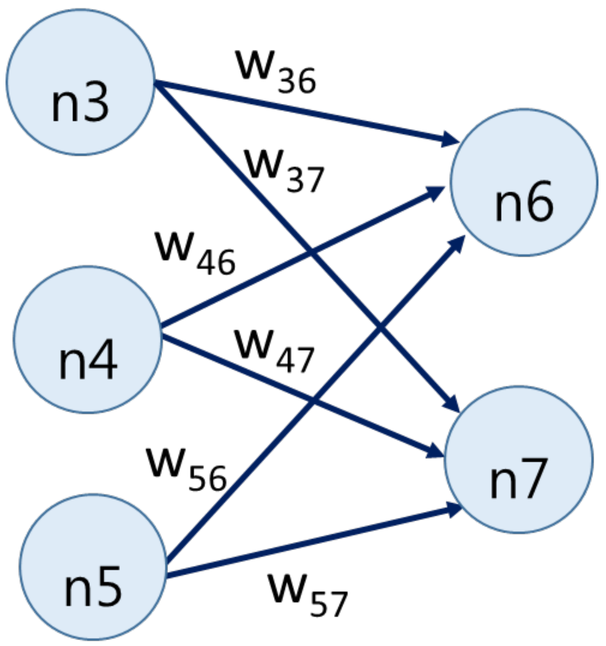
$$\begin{bmatrix} n_3^1 & n_4^1 & n_5^1 \\ n_3^2 & n_4^2 & n_5^2 \\ n_3^3 & n_4^3 & n_5^3 \end{bmatrix}$$

$$\underbrace{\begin{bmatrix} -1.2635 & -2.4348 & -1.1135 \\ -1.3097 & -3.6061 & -1.4398 \\ 1.4340 & -9.3577 & -2.2441 \end{bmatrix} \begin{bmatrix} w_{36} & w_{37} \\ w_{46} & w_{47} \\ w_{56} & w_{57} \end{bmatrix}} + \begin{bmatrix} b_6 & b_7 \end{bmatrix}$$

$$\underbrace{\begin{bmatrix} k_6^1 & k_7^1 \\ k_6^2 & k_7^2 \\ k_6^3 & k_7^3 \end{bmatrix} + \begin{bmatrix} b_6 & b_7 \\ b_6 & b_7 \\ b_6 & b_7 \end{bmatrix}}$$

$$\begin{bmatrix} n_6^1 & n_7^1 \\ n_6^2 & n_7^2 \\ n_6^3 & n_7^3 \end{bmatrix}$$

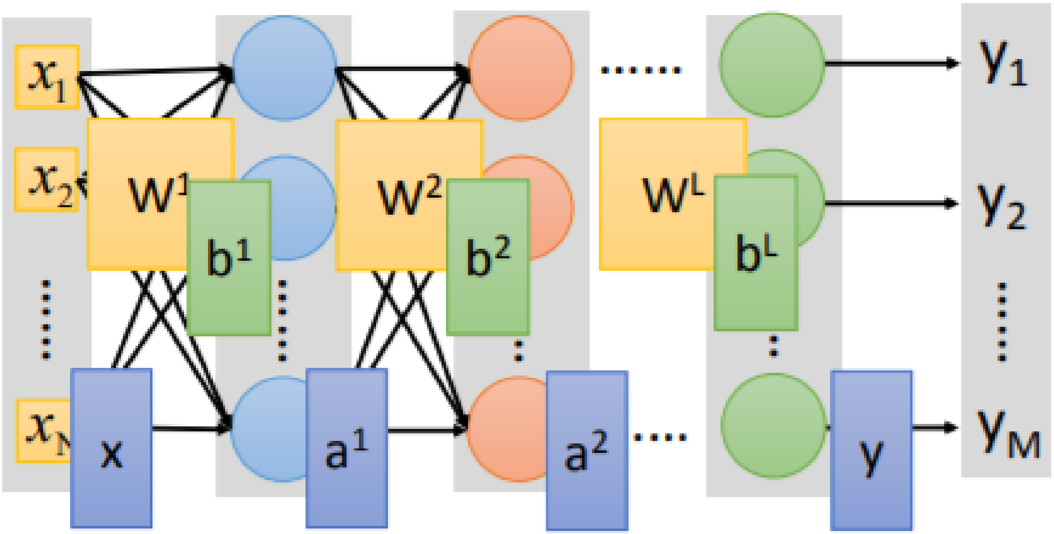
Use Excel to verify



Practice

- Run “1.2 Gradient decent.ipynb"

Use parallel computing to speed up matrix operation



$$y = f(x)$$

Using parallel computing techniques to speed up matrix operation

$$= \sigma(W^L \cdots \sigma(W^2\, \sigma(W^1 x + b^1) + b^2) \cdots + b^L)$$

Reference: 李弘毅 ML Lecture 6 https://youtu.be/Dr-WRlEFefw

Use parallel computing to speed up matrix operation

```
In [2]: if(torch.cuda.is_available()):
            device = torch.device("cuda")
            print(device, torch.cuda.get_device_name(0))
        else:
            device= torch.device("cpu")
            print(device)
```

```
cuda Tesla P100-PCIE-16GB
```

```
tensorX = torch.FloatTensor(trainX).to(device)
tensorY_hat = torch.FloatTensor(trainY_hat).to(device)
print(tensorX.shape, tensorY_hat.shape)
```

```
torch.Size([128, 2]) torch.Size([128, 1])
```

```
conv1_out = conv1(imageTensor.to(device))
conv1_out.shape
#output image (feature map) has 64 channels
```

```
torch.Size([1, 64, 55, 55])
```

How to learn? What intelligence learned?

Intelligence learned by supervision, self-supervision and reinforcement

	Supervised Learning	Self-supervised Learning	Reinforcement Learning
	Recognition		Act
1. Function to be learned	MLP, CNN families	AE/VAE, GAN	Actor
	$y = f(x)$	$\hat{x} = f(x)$	$a = f(s)$
2. Loss function $\mathcal{L}(f)$	MSE, CE	MSE, CE, KLD, JSD	MSE, KLD
3. Minimize $\mathcal{L}(f)$	Gradient decent, Maximum Likelihood		

Challenges in learning $a=f(s)$

- Define a function to be learned: $a = f(s)$
- Define a loss function $\mathcal{L}(f)$ to describe the error between y^n and $\hat{y}^n$

  Time-delayed answer – If at time *t* we perform action a_t under state s_t, we only know the immediate reward r_t and there is a time delay to know the total accumulated reward $\hat{y}$.

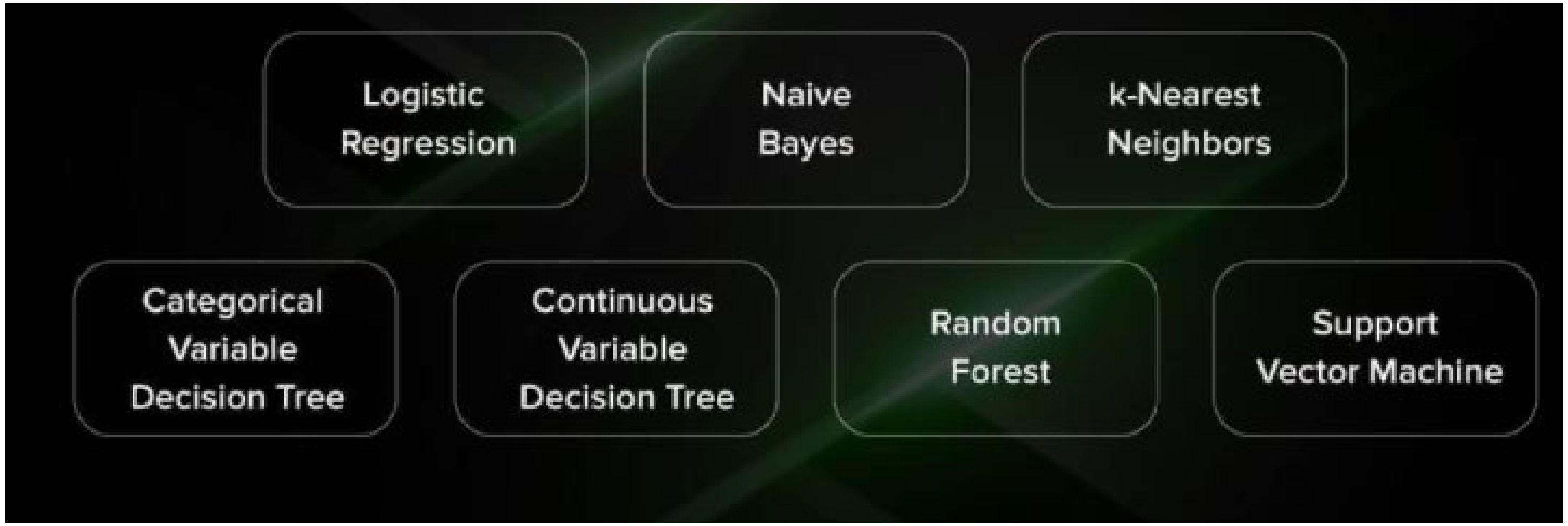
  Adversial interaction – After preforming a_t at state s_t, there are infinite number of possibilities for following state- actions $s_{t+1}, a_{t+1}, s_{t+2}, a_{t+2}, \cdots s_{t+T}, a_{t+T}$. It is difficult to estimate the true answer *y* (the true final reward).

- Find the optimal parameters that minimize $\mathcal{L}(f)$

AI applications we are working on

Classifier for vector data

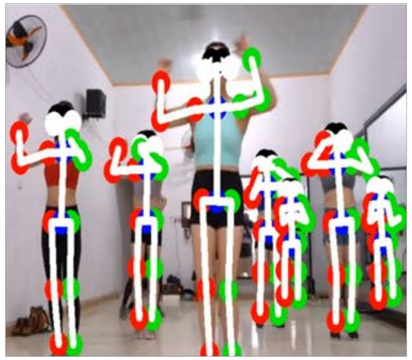
- Manufacturing and elderly-care applications (fall and dementia risk assessment)
- AI model is as good as its training data - study data and features (90% of the project time)
- Decision making based on multiple models
- Decision making with human in the loop



https://serokell.io/blog/classification-algorithms

Application of pre-trained CV neural networks

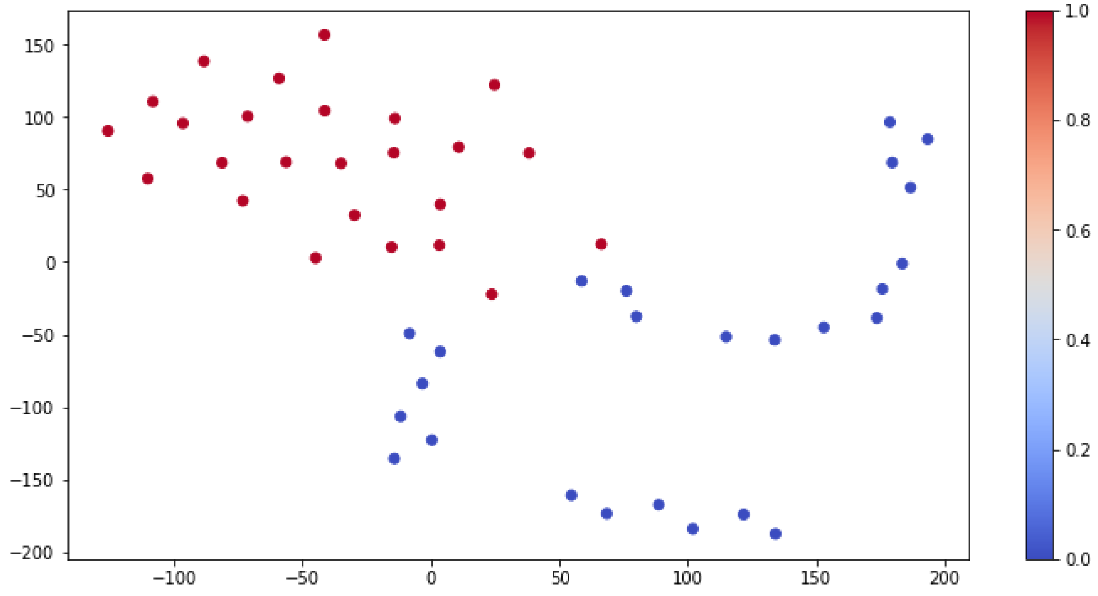
- Safety and elderly care applications
- Integrate with application software, e.g., flask, app
- Deployed to edge computing devices (Jetson Nano, Xavier)

Alex Net VGG16 Res Net	U Net	Faster RCNN	Mask RCNN	Keypoints RCNN	DeepSORT
Classification	Semantic Segmentation	Object Detection	Instance Segmentation	Joint detection	Object tracking
					
	GRASS, CAT, TREE, SKY	DOG, DOG, CAT	DOG, DOG, CAT		

Feature extraction for classification by AE/VAE

- Labelling cost concern
- Large-amount of data concern
- Unbalanced data concern

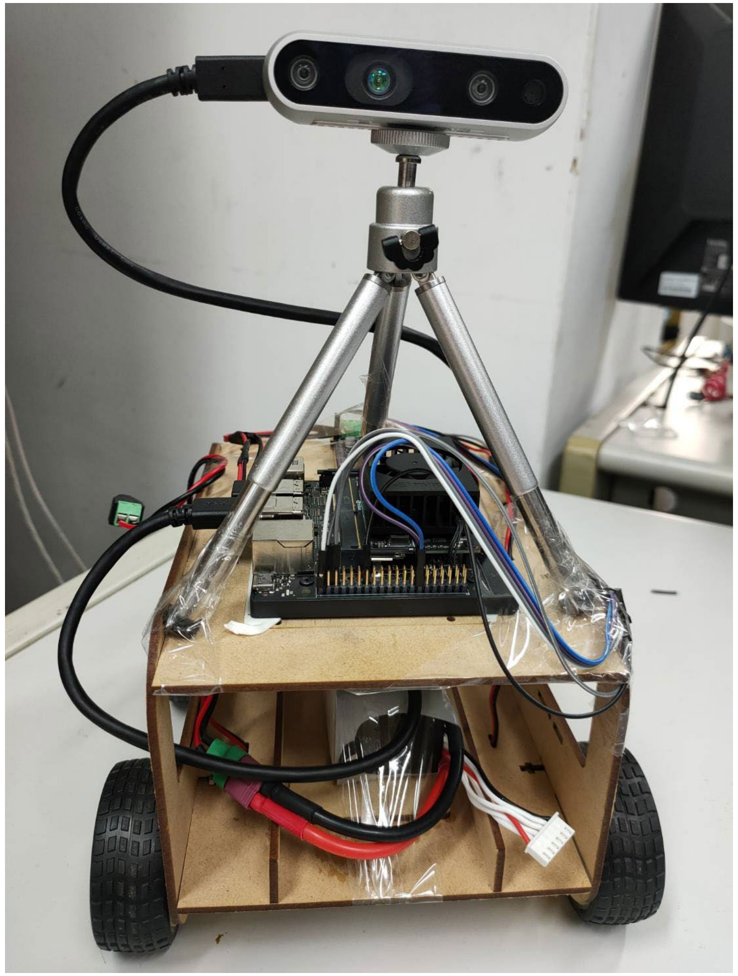
Visualization first



One class SVM

Classifier

Development of intelligent robot

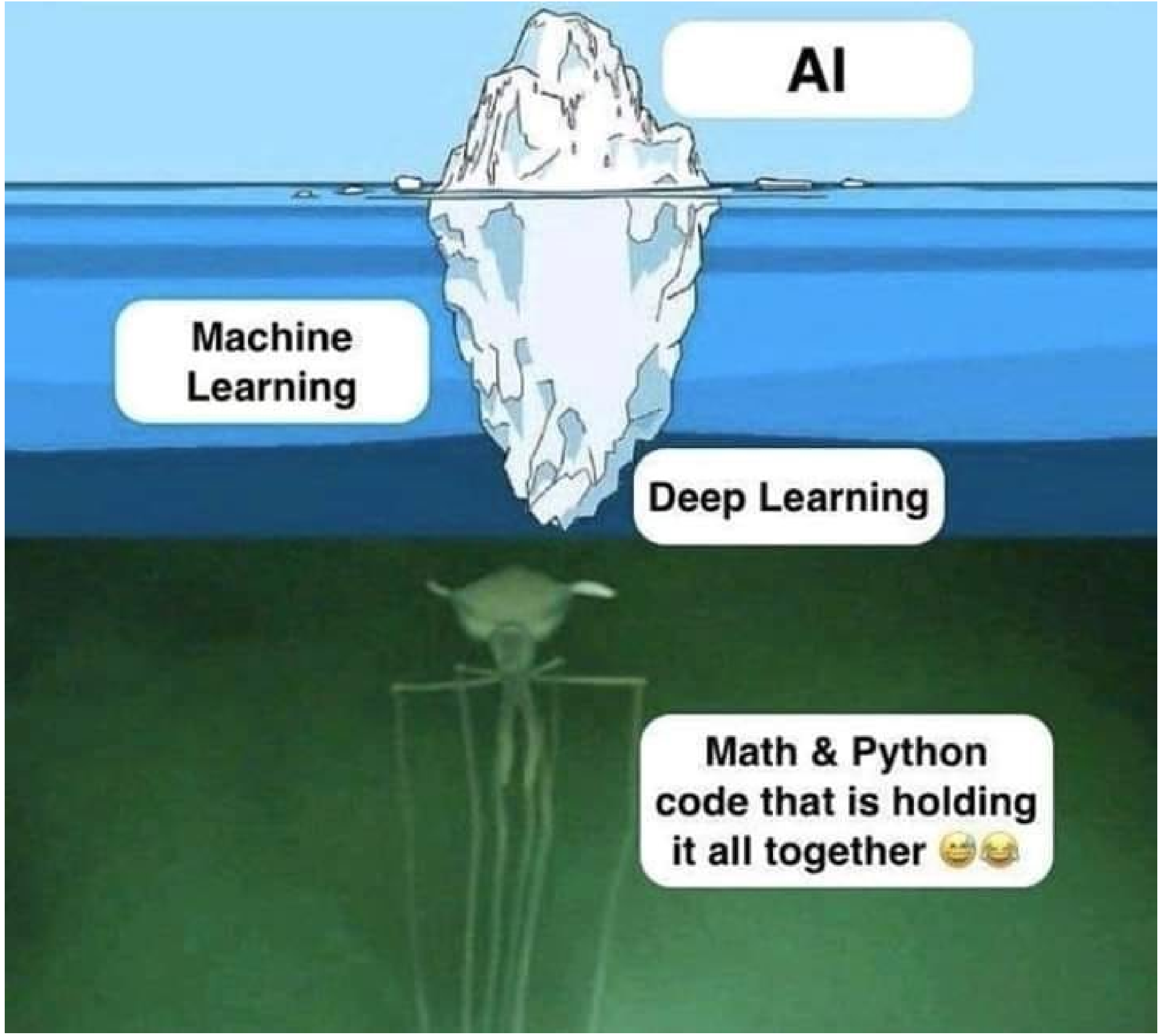


Applications of GAN families

- Image generation

AI development needs Math + coding

Math and coding



- Probability and statistics
- Non-linear optimization
- Linear algebra

https://www.facebook.com/257118421832544/photos/a.320314752179577/540486140162436/

Python

Run my PyTorch code in GitHub from Colab