

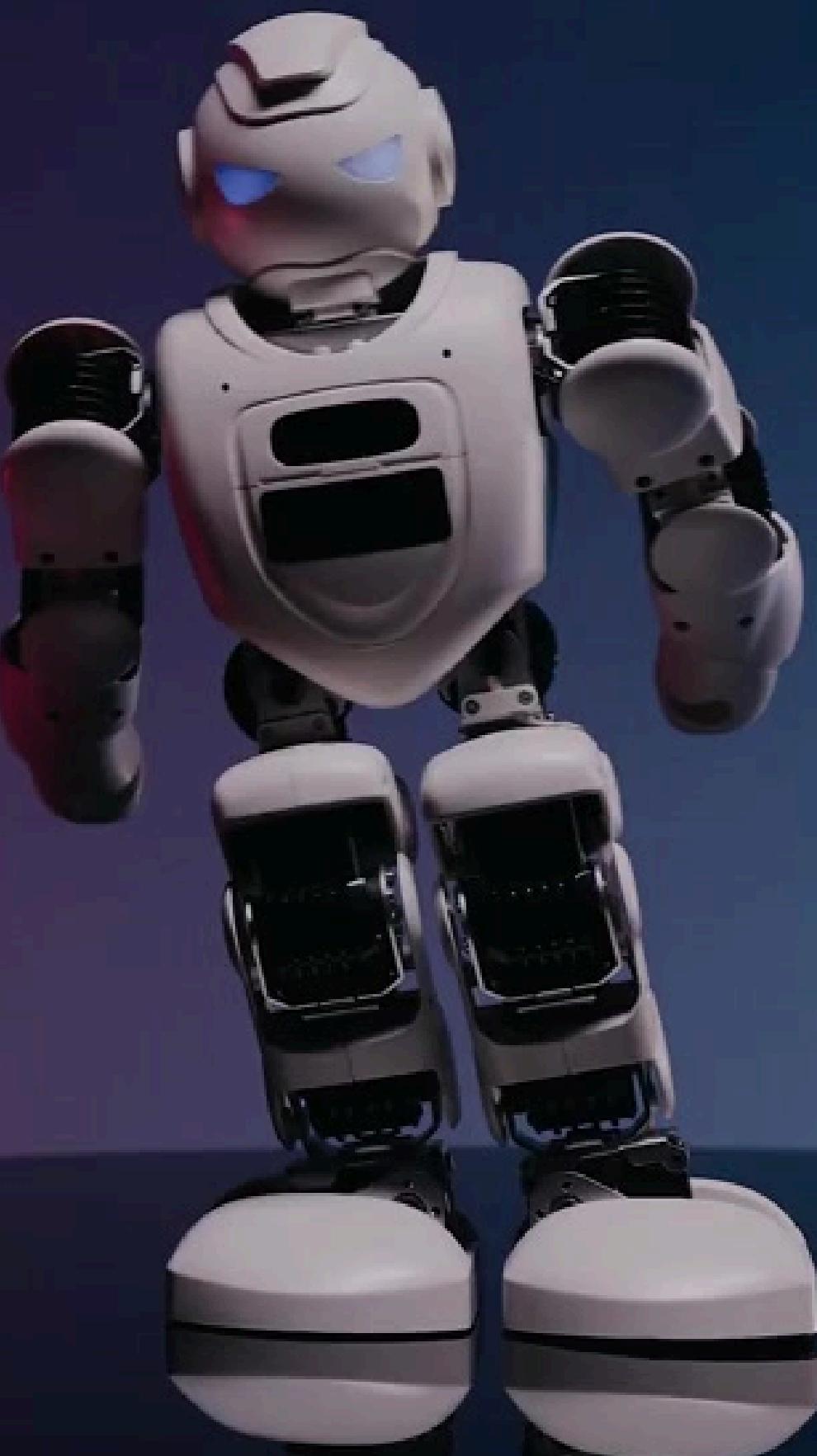


WEEK 1

DEEP LEARNING FOR COMPUTER VISION

UNLIMITED

Presented by **Asst. Prof. Dr. Tuchsanai Ploysuwan**



github.com/Tuchsanai/DL-FOR-COMPUTER-VISION

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Tuchsanai 00 d346e79 · 2 hours ago 259 Commits

week01	00	2 hours ago
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week04	g	10 months ago
week05	y	9 months ago
week06	aa	9 months ago
week07	zzz	9 months ago
week08	ss	9 months ago
week09	l	8 months ago
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week11	d	9 months ago
.gitattributes	Initial commit	2 years ago
.gitignore	11	7 months ago
README.md	Update README.md	last year

README

DL FOR COMPUTER VISION

Document



Course Learning Outcomes (CLOs)

Upon completion of this course, students are expected to be able to

CLO ID	CLO Description
CLO-1	ผู้เรียนเข้าใจหลักการพื้นฐานของงาน Deep learning สำหรับงาน Computer Vision
CLO-2	ผู้เรียนเข้าใจหลักการพื้นฐานในการใช้ Convolutional neural network (CNN) สำหรับงาน Image Classifications
CLO-3	ผู้เรียนสามารถอินพุตและเลือกใช้ Modern deep learning architectures ที่เหมาะสมสำหรับงาน Computer Vision ชนิดต่างๆ เช่น VGG, ResNet, and Efficientnet
CLO-4	ผู้เรียนเข้าใจหลักการการเลือกใช้งาน Loss function, activation functions และ stochastic optimization ได้อย่างเหมาะสม
CLO-5	ผู้เรียนเข้าใจหลักการในการใช้ Transfer learning และการ fine tuning ที่เหมาะสม
CLO-6	ผู้เรียนเข้าใจหลักการพื้นฐานในการใช้ Deep learning สำหรับการทำ Image Segmentation ในงาน Computer Vision
CLO-7	ผู้เรียนสามารถเข้าใจหลักการของ Object detection and Object Tracking ในงาน Computer Vision
CLO-8	ผู้เรียนสามารถเข้าใจหลักการของ Generative Adversarial Network

ลำดับที่	หัวข้อ	วิธีการเรียน	ผลการเรียนรู้	หมายเหตุ
1	The basic concept of deep learning and their applications in computer vision	บรรยาย	CLO-1	Chapter 1
2	Introduction to Images and Videos Basics with Python and OpenCV	บรรยาย	CLO-1	Chapter 1
3	Advance in OpenCV	บรรยาย	CLO-1	Chapter 1
4	Introduction to Pytorch	บรรยาย	CLO-2, CLO-3, CLO-4	Chapter 2
5	Fundamental Neural network	บรรยาย	CLO-2	Chapter 2
6	Stochastic optimization methods	บรรยาย	CLO-4	Chapter 2
7	Convolutional neural network for image classification	บรรยาย	CLO-2, CLO-3	Chapter 3
9	Modern architectures such as VGG, ResNet, and Efficientnet	บรรยาย	CLO-3,	Chapter 3
10	Transfer learning and fine tuning	บรรยาย	CLO-5	Chapter 3
11	Deep learning for Segmentation for images	บรรยาย	CLO-6	Chapter 4
12	Deep learning Object detection and Object Tracking	บรรยาย	CLO-7	Chapter 4
13	GAN architecture (Generative Adversarial Network) for photo-realistic images	บรรยาย	CLO-8	Chapter 5
14	Generative image from text CLIP model	บรรยาย	CLO-8	Chapter 5
15	Discussions	บรรยาย		

ການໃຫ້ຄະແນນ

Midterm Examination

30

Final Examination

30

Mini project, Kaggle

30

Participation

10

APPROACHING (ALMOST) ANY MACHINE LEARNING PROBLEM



ABHISHEK THAKUR

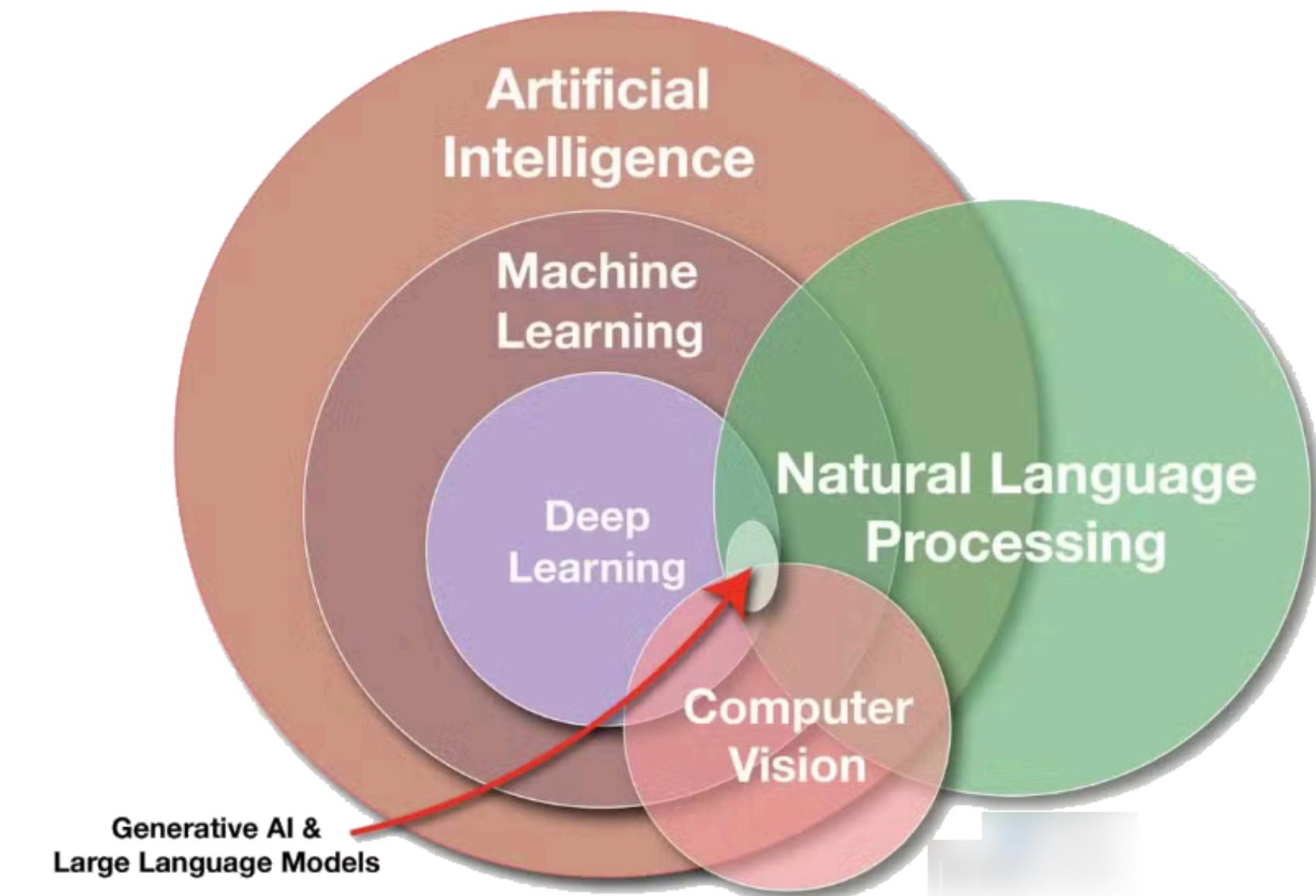
Books

<https://github.com/abhishekrthakur/approachingalmost>

Is Computer Vision Artificial Intelligence?

- Relation between Artificial Intelligence, Machine Learning and Deep Learning, Computer Vision.

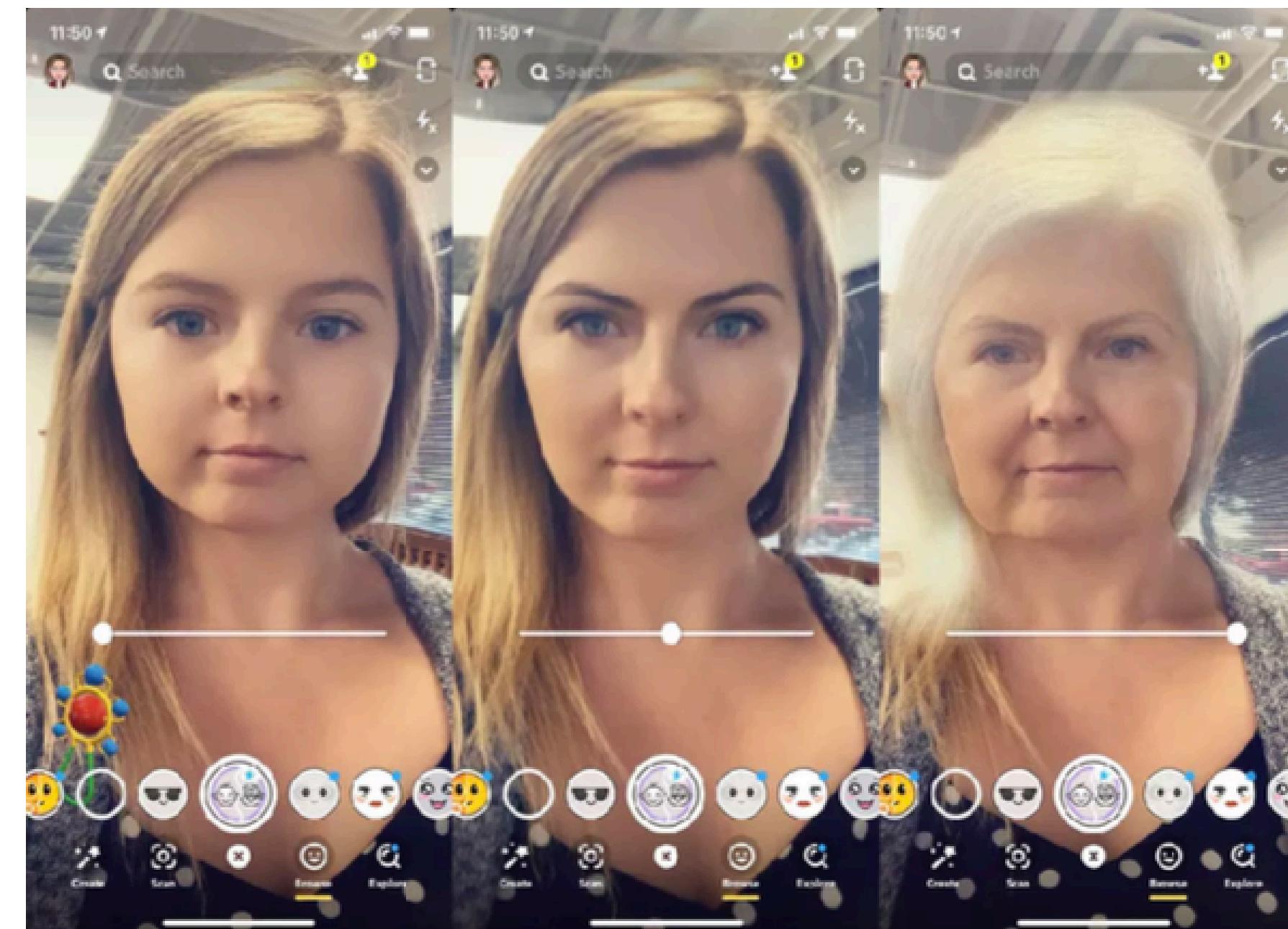
https://www.researchgate.net/figure/Relation-between-Artificial-Intelligence-Machine-Learning-and-Deep-Learning-Computer_fig1_342978934



So what can Computer Vision do?

You might be familiar with these...

- **Snapchat and Instagram filters**
- Optical Character Recognition (OCR)
- Licence Plate Reading
- Self-driving cars
- Sporting Analysis
- Facial Recognition

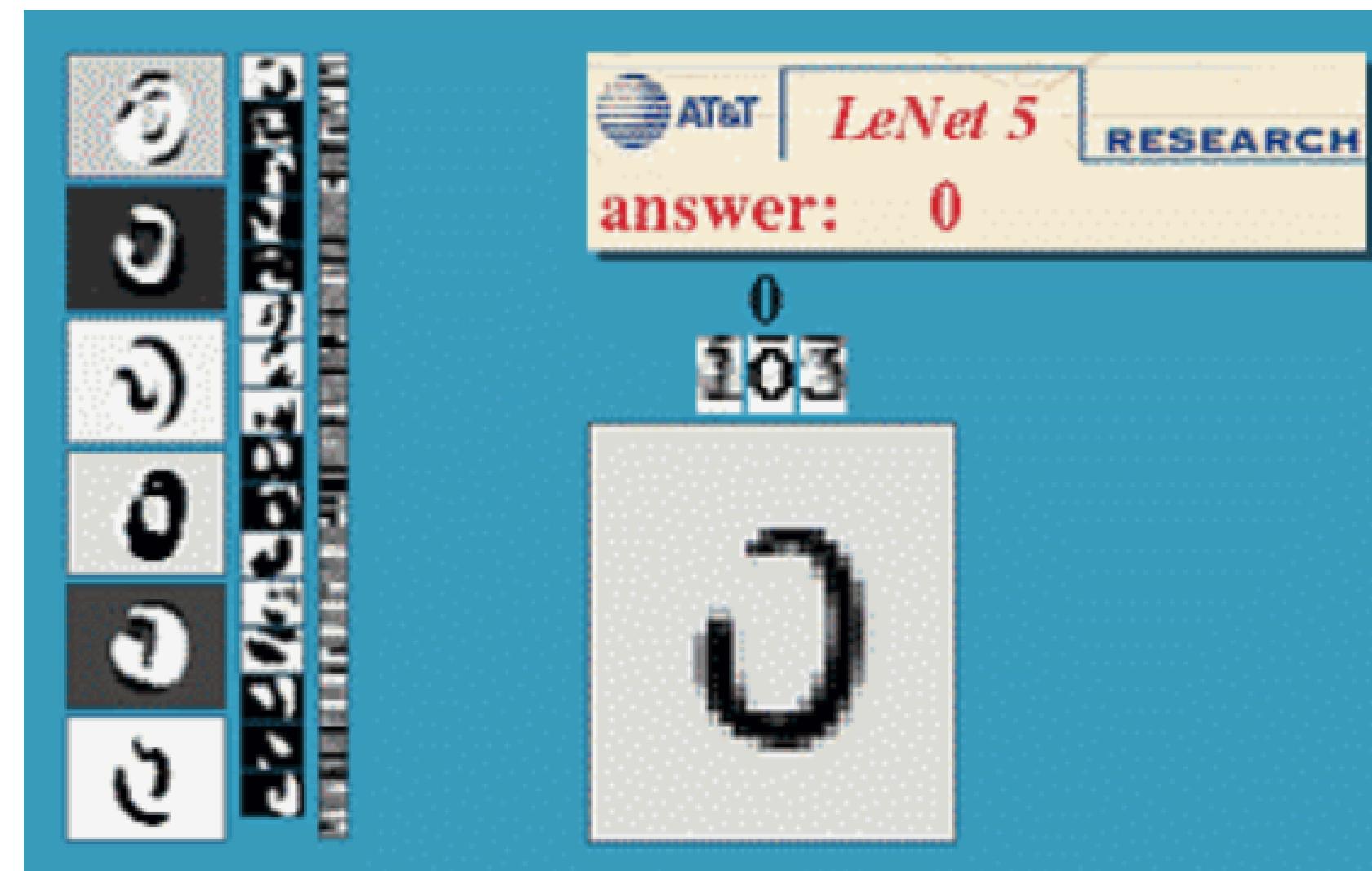


Source - Cnet - Snapchat's Time Machine AR lens creepily shows what you'll look like old

So what can Computer Vision do?

You might be familiar with these...

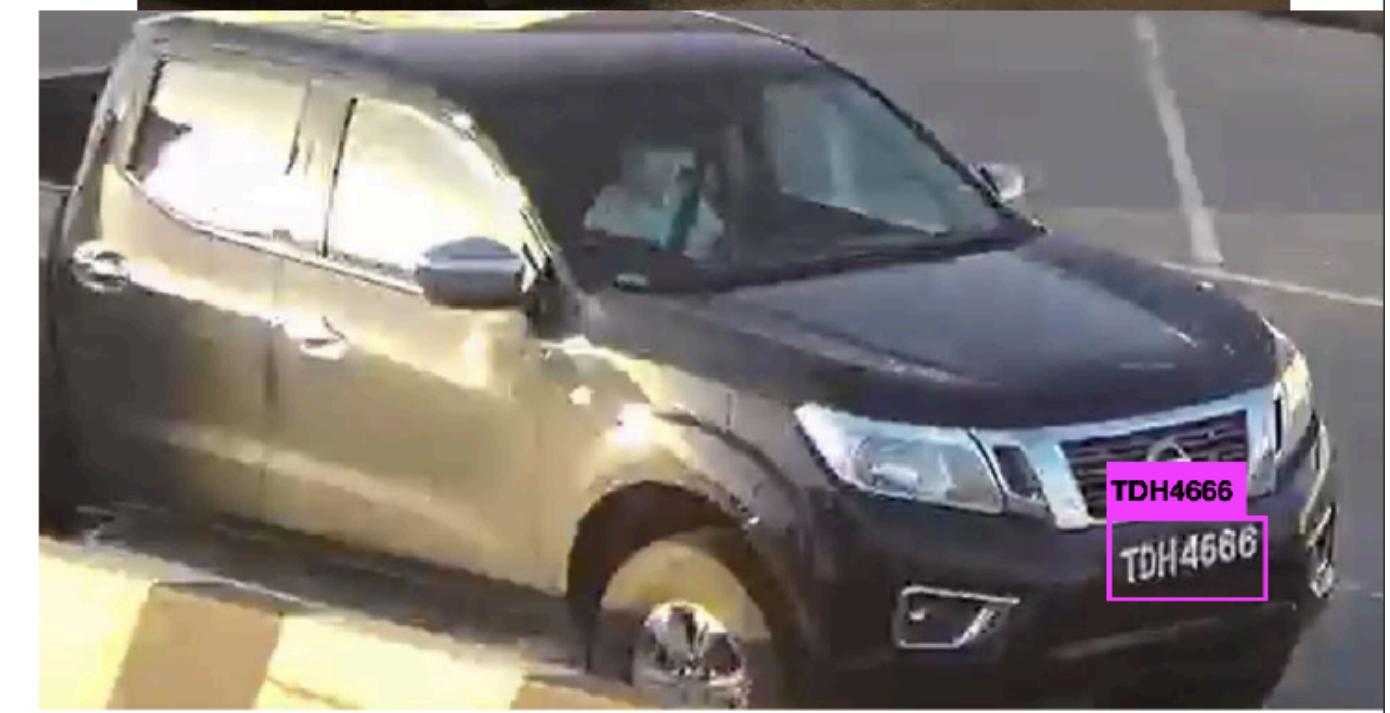
- Snapchat and Instagram filters
- **Optical Character Recognition (OCR)**
- Licence Plate Reading
- Self-driving cars
- Sporting Analysis
- Facial Recognition



Source -AT&T's LeNet OCR for Handwritten Digits

So what can Computer Vision do?

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- Facial Recognition

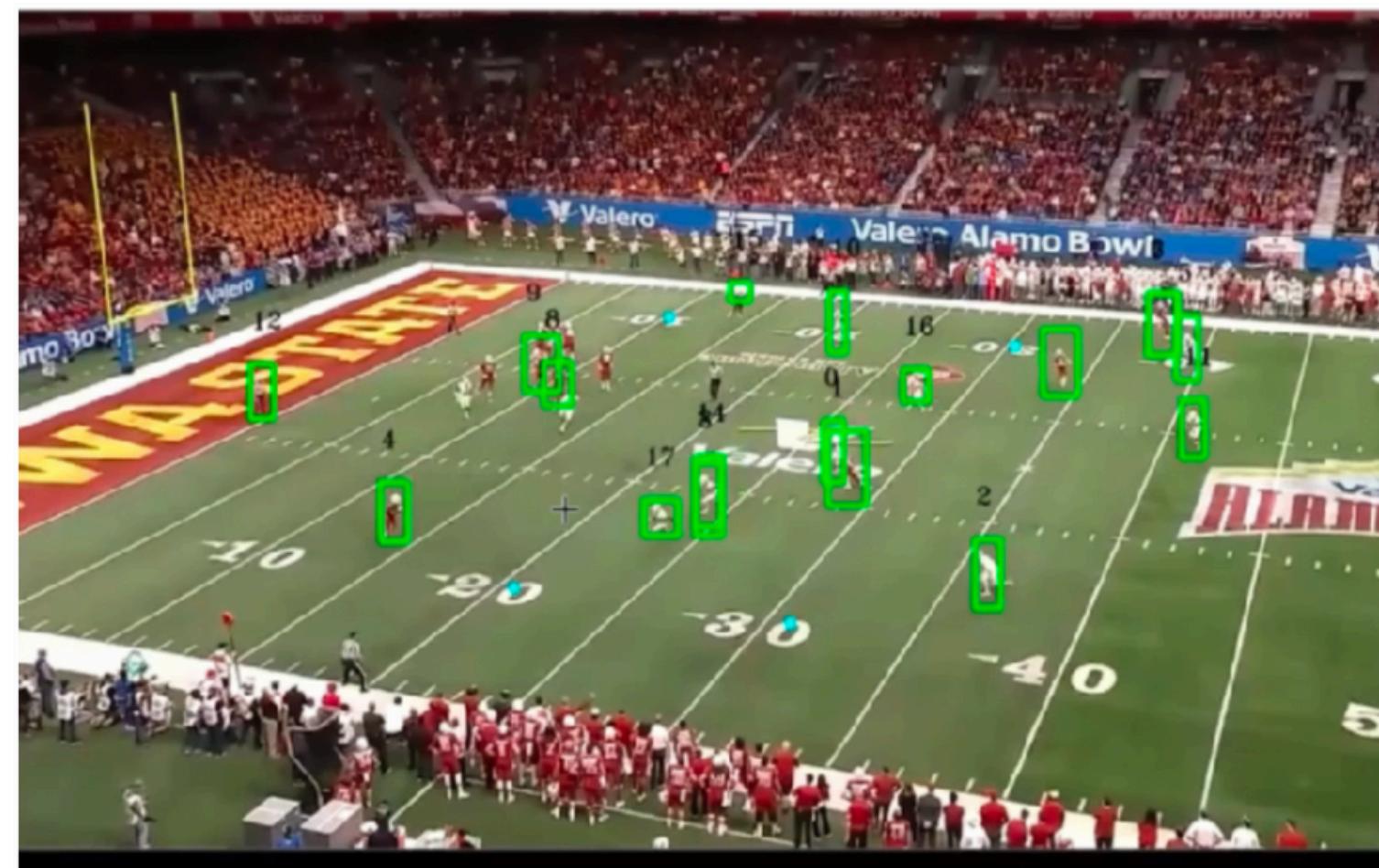
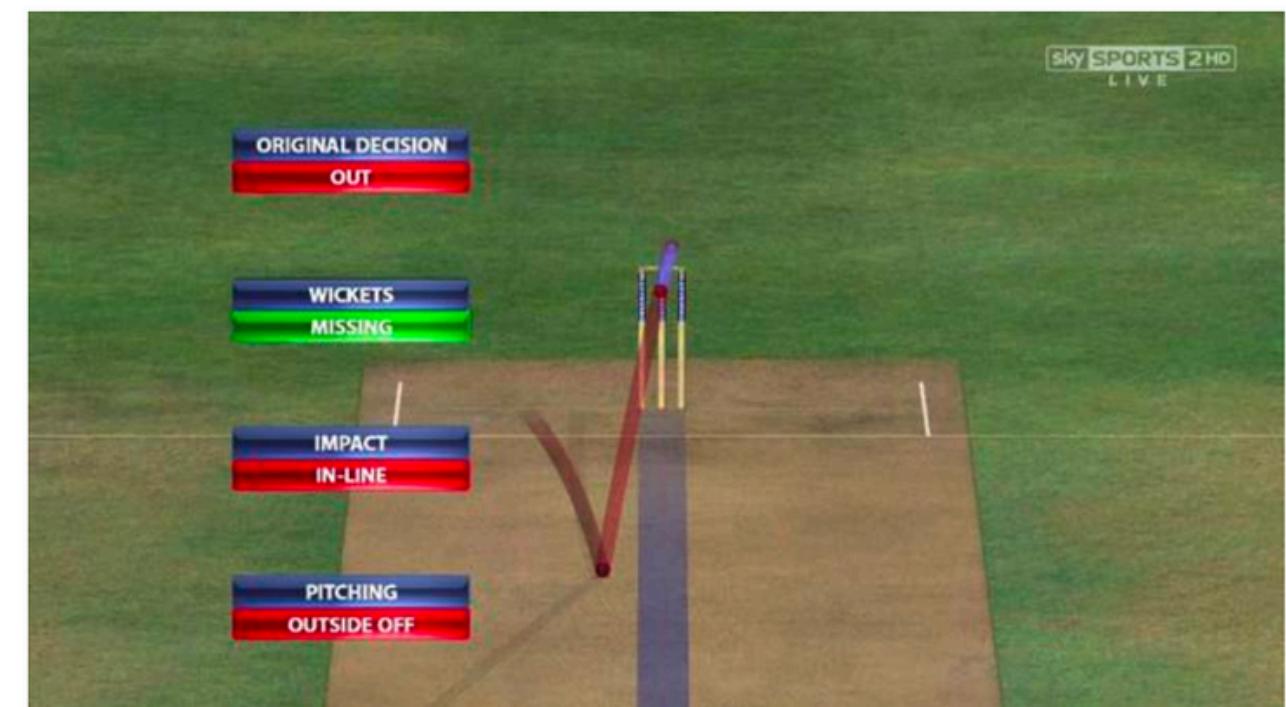


So what can Computer Vision do?

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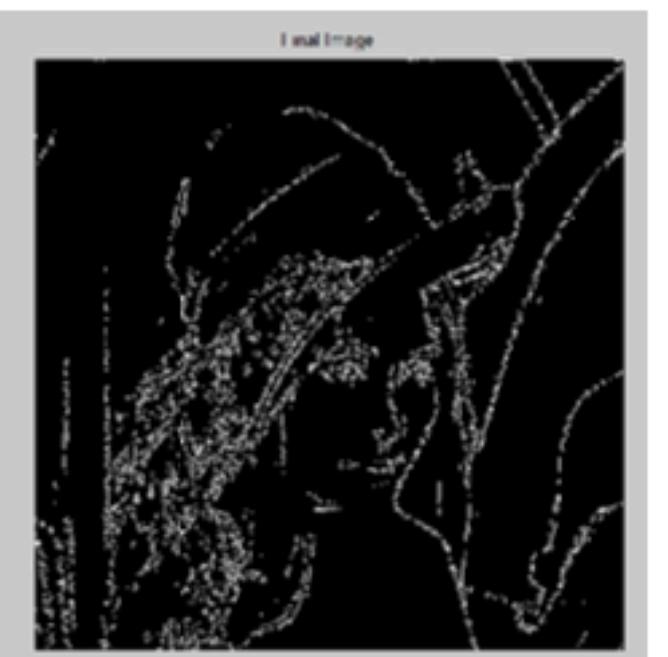
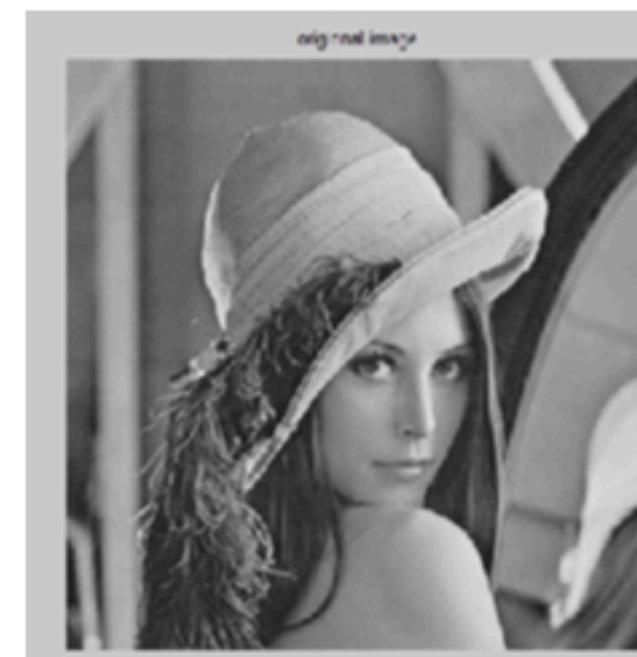
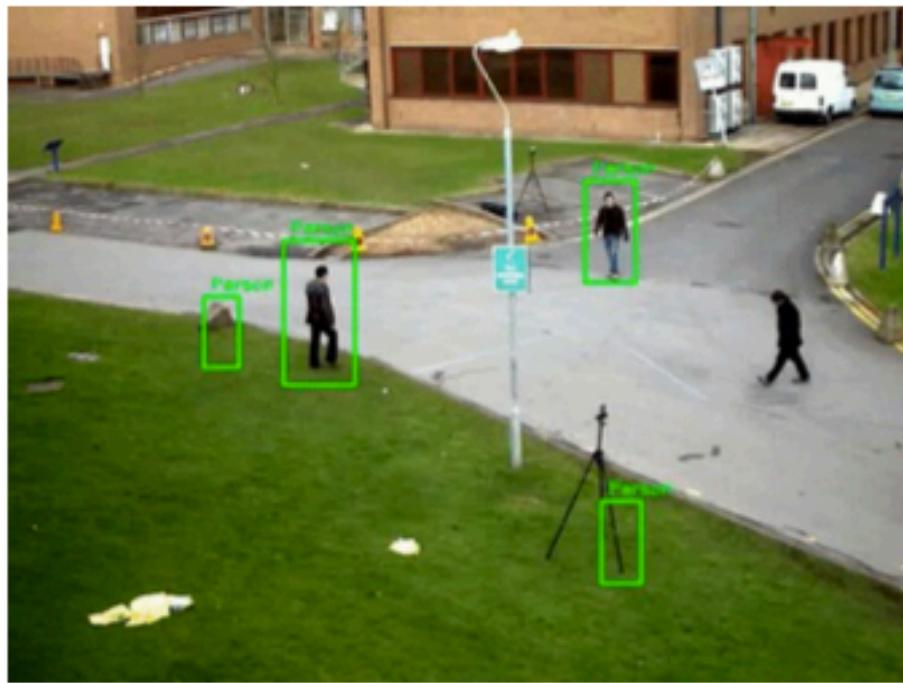
HawkEye in Cricket



Source -Roboflow - AI Coach

Classical Computer Vision?

- What is meant by **Classical Computer Vision?**
- It encompasses Computer Vision algorithms that **do not** involve Machine Learning
- Before the advent of Machine Learning and Deep Learning, Computer Vision was a deeply explored field and many useful algorithms were developed for things like **feature extraction, OCR, Segmentation and simple transformations.**
- **OpenCV** is the Classical Computer Vision library of choice!



Deep Learning Computer Vision

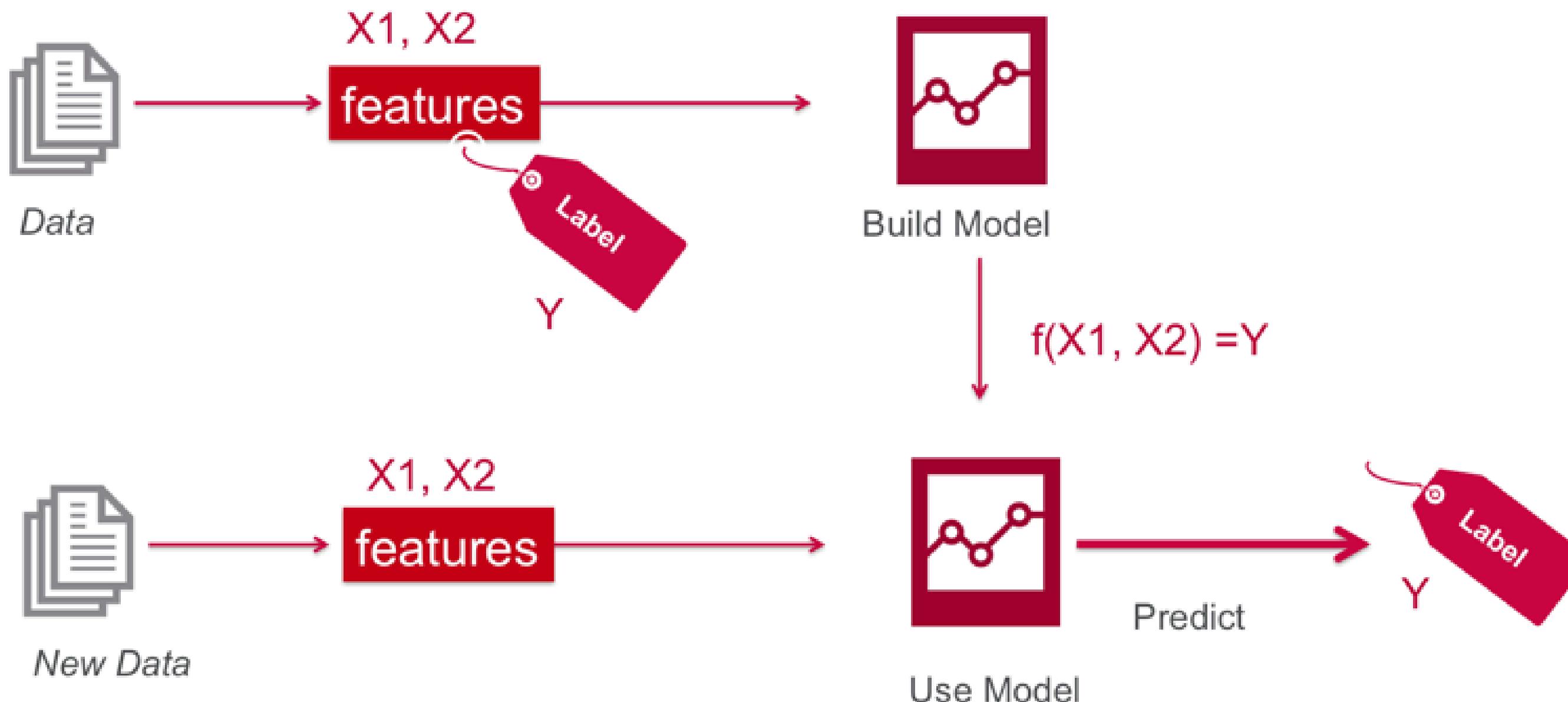
- Deep Learning was used in Computer Vision since the 1990s, however due to the computational requirements and intricate design, it remained on the sidelines for decades.
- Until the mid 2010s...which brought **two important building blocks** together.
 - **Accessible GPU processing** (NVIDIA's CUDA)



Deep Learning CV vs Classical CV

Deep Learning	Classical Computer Vision
Adapts to new images well (assuming it's similar to the data it was trained on)	Small changes can have big negative impacts
Requires Models to be trained	Doesn't require training and can be used once coded
Model weights learn to adapt to varying image conditions	Relies on hardcoded features and parameters
Requires GPU hardware (most times)	Can be run on CPU

Supervised Learning



Classification v.s. Regression

Classification

- Predict which category an item belongs to based on labeled examples of known items
- Use in classify a new data

Regression

- Predict a continuous value target.
- Linear regression predicts a numeric value
- Logistic regression predicts a probability

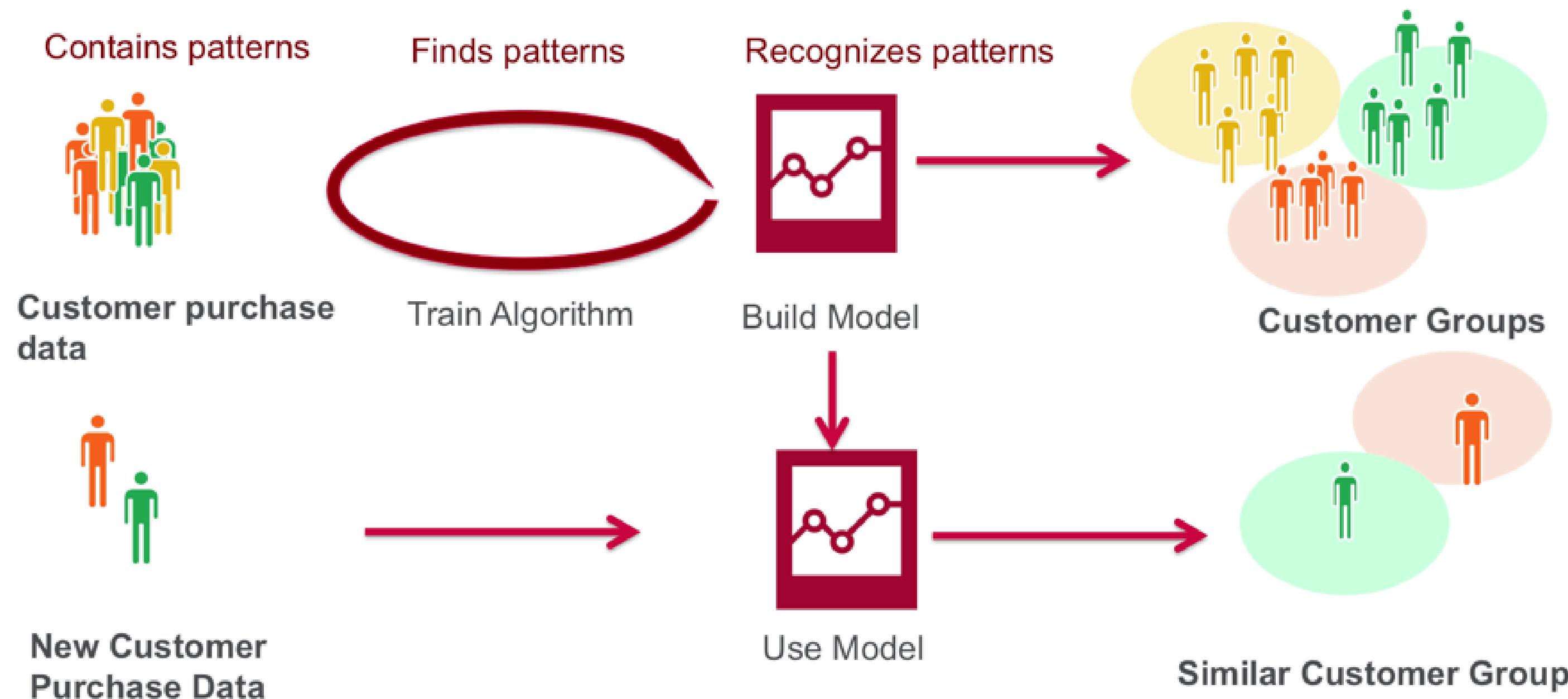
Examples of classification

- Credit card fraud detection (fraud, not fraud)
- Credit card application (good credit, bad credit)
- Email spam detection (spam, not spam)
- Text sentiment analysis (happy, not happy)
- Predicting patient risk (high risk patient, low risk patient)
- Classifying a tumor as malignant or not

Examples of regression

- Predicting the price of the house.
- Predicting age of a person
- Predicting the stock price for tomorrow.
- Predicting next year GDP.

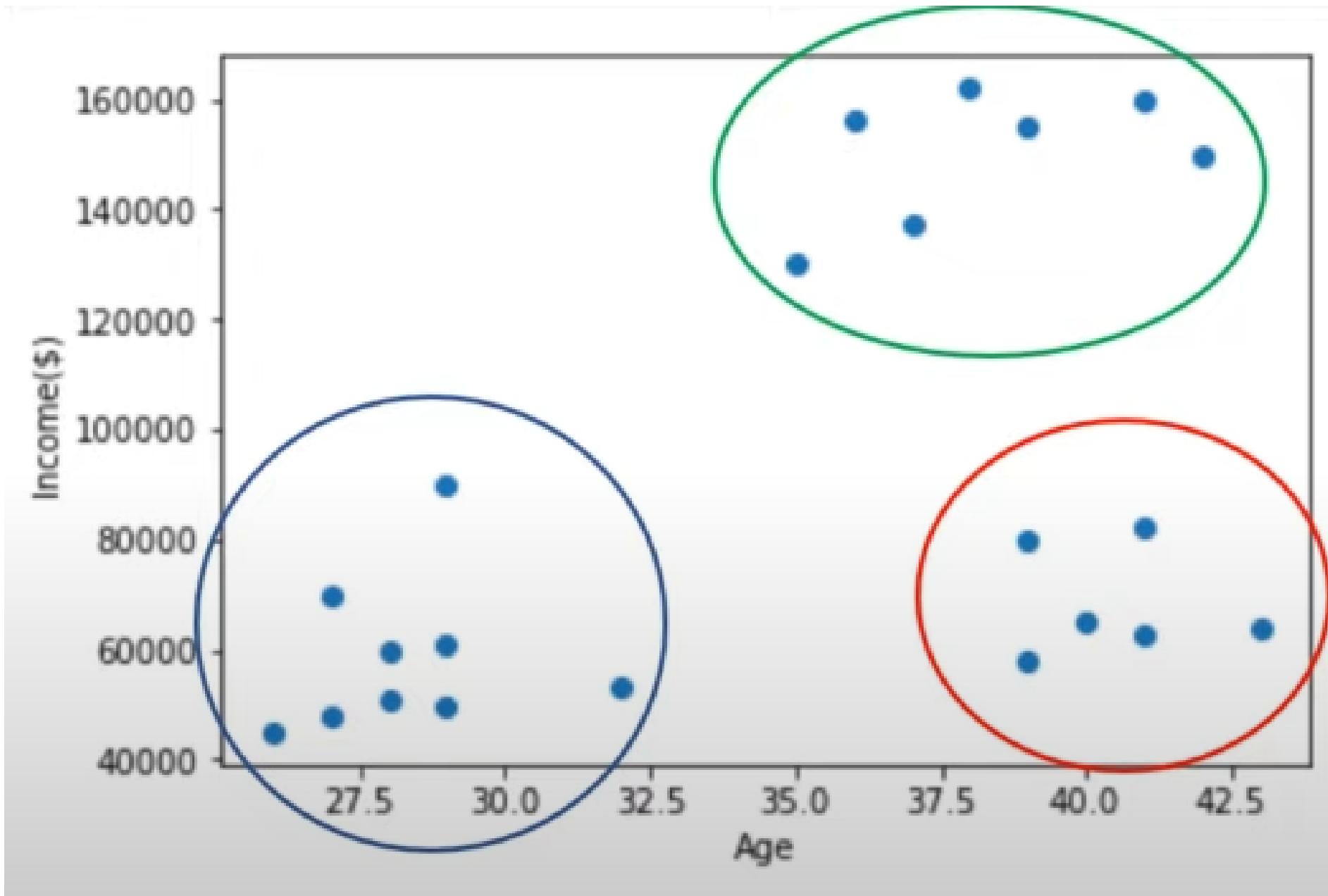
Unsupervised Learning | Self Supervised



Examples of clustering

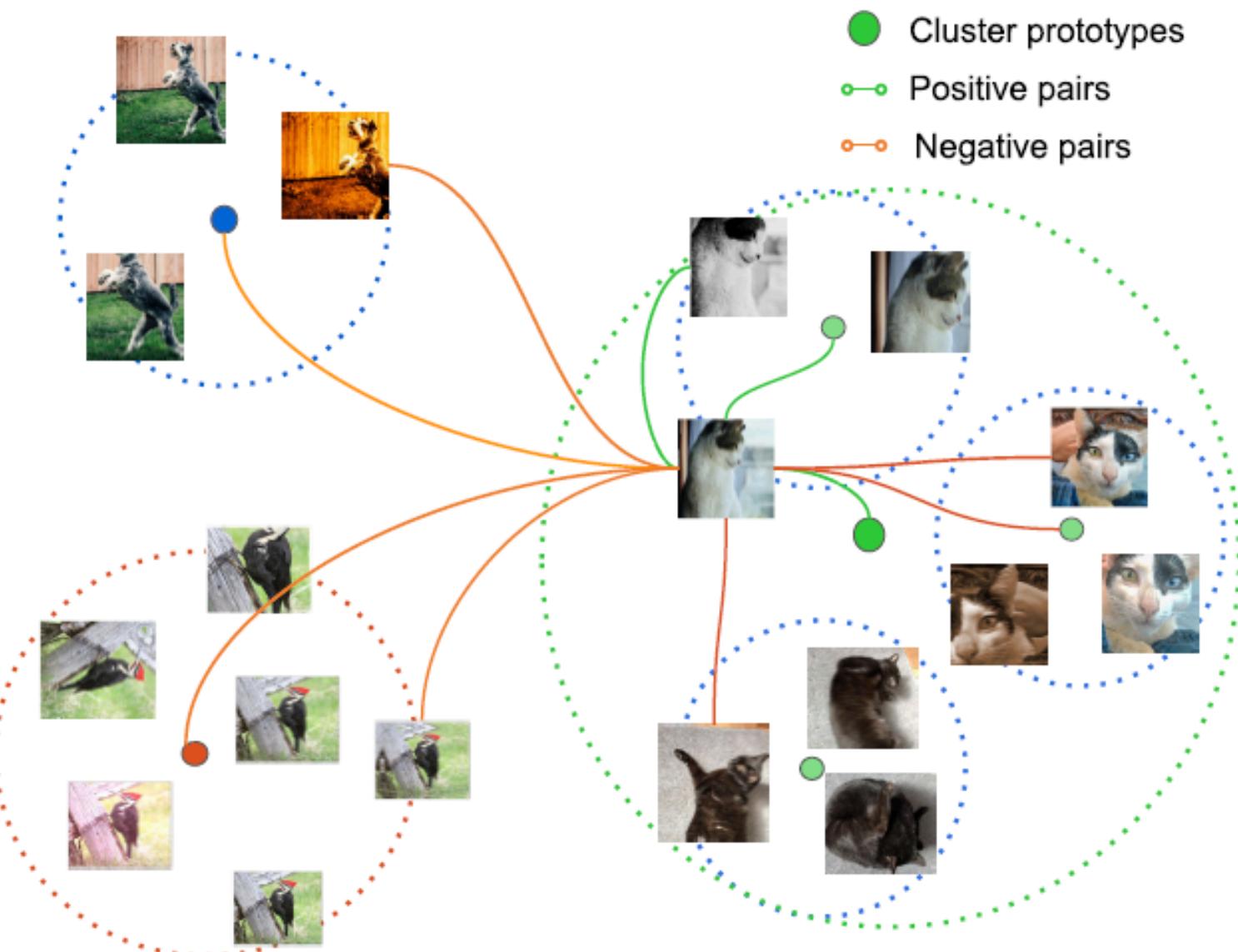
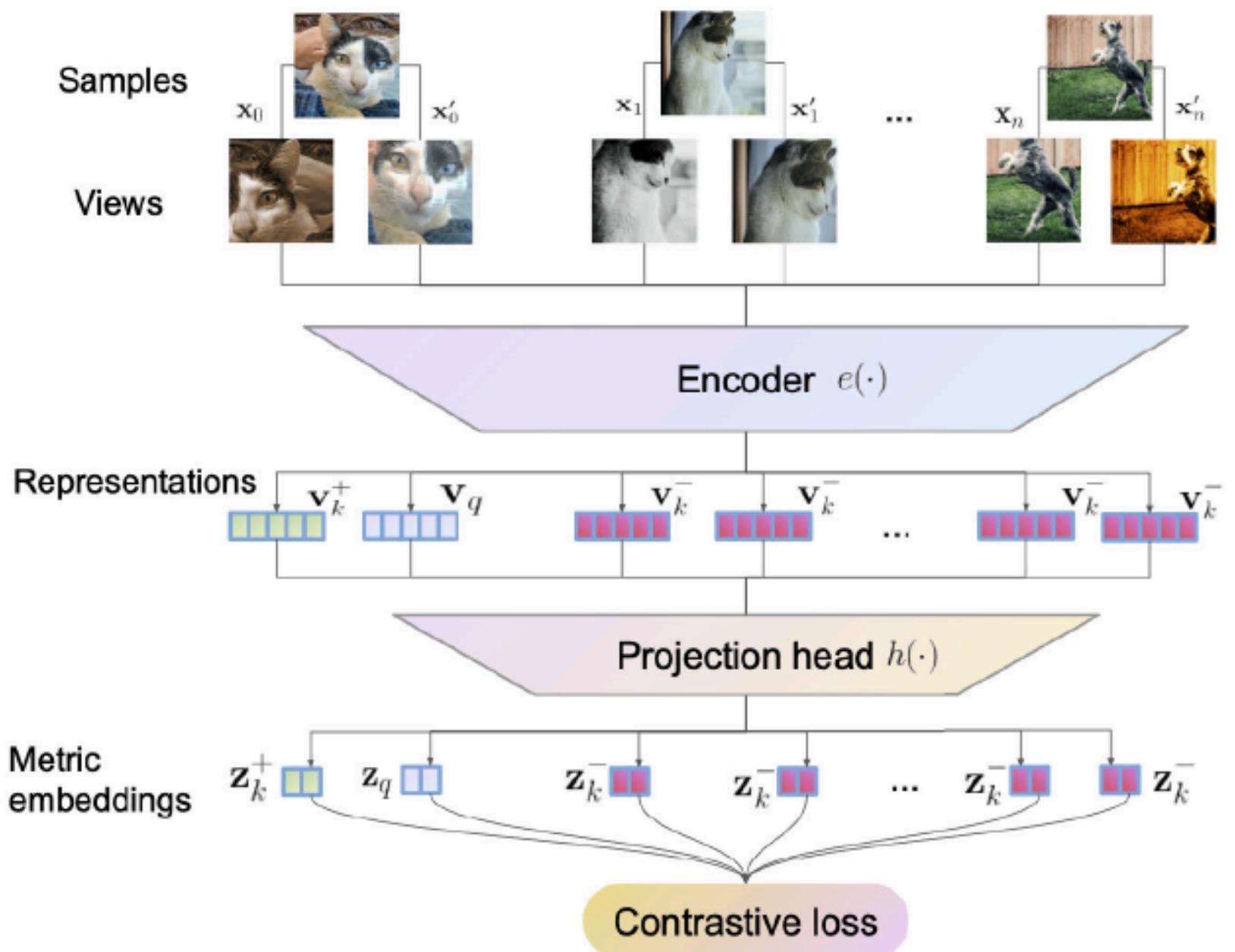
- Search results grouping
- Grouping similar customers
- Grouping similar patients
- Text categorization
- Network Security Anomaly detection

Unsupervised learning

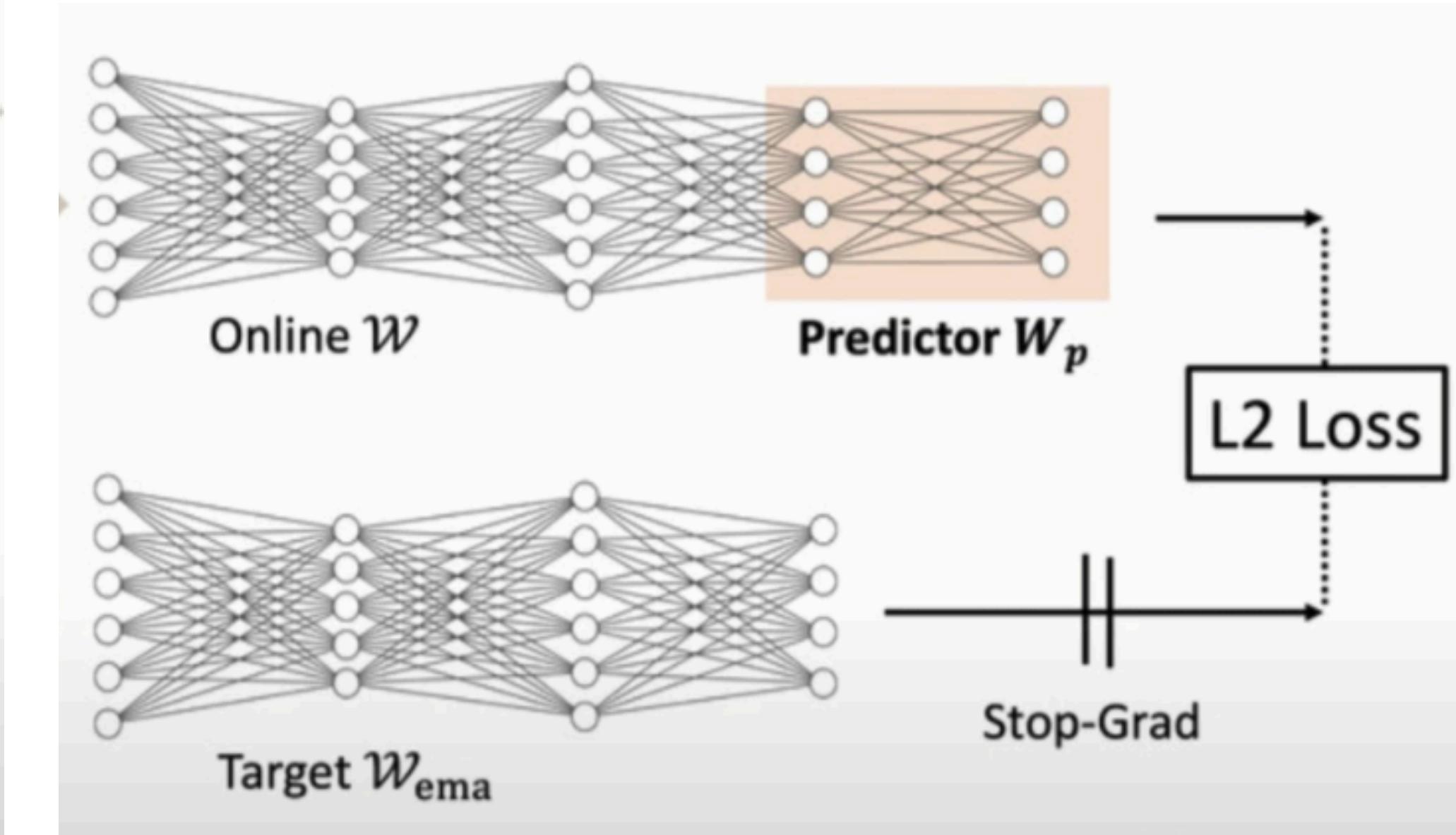
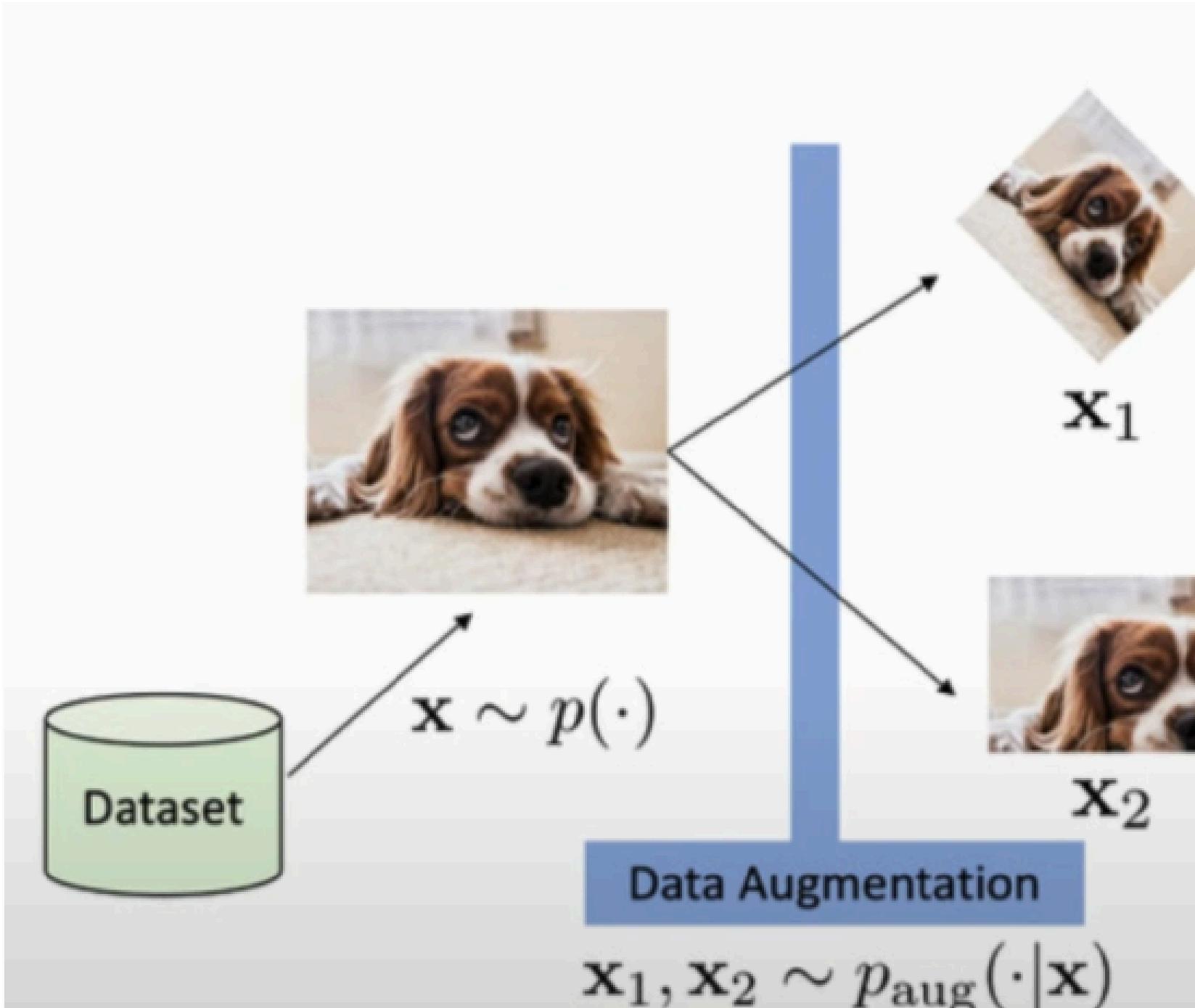


	A	B	C
1	Name	Age	Income(\$)
2	Rob	27	70000
3	Michael	29	90000
4	Mohan	29	61000
5	Ismail	28	60000
6	Kory	42	150000
7	Gautam	39	155000
8	David	41	160000
9	Andrea	38	162000
10	Brad	36	156000

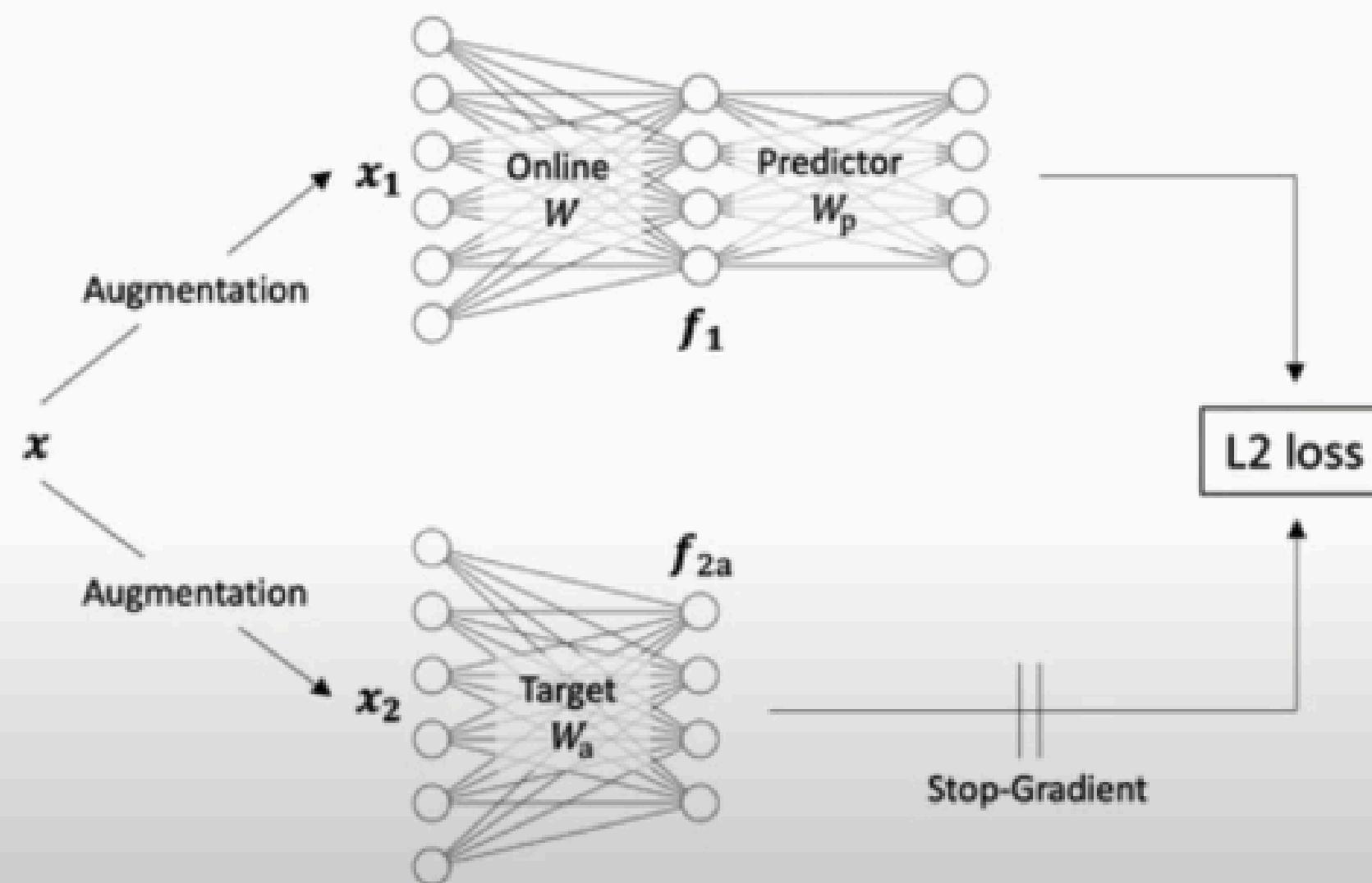
Self-Supervised



Easy review



A simple model



Objective:

$$J(W, W_p) := \frac{1}{2} \mathbb{E}_{x_1, x_2} [\|W_p f_1 - \text{StopGrad}(f_{2a})\|_2^2]$$

Linear online network W

Linear target network W_a

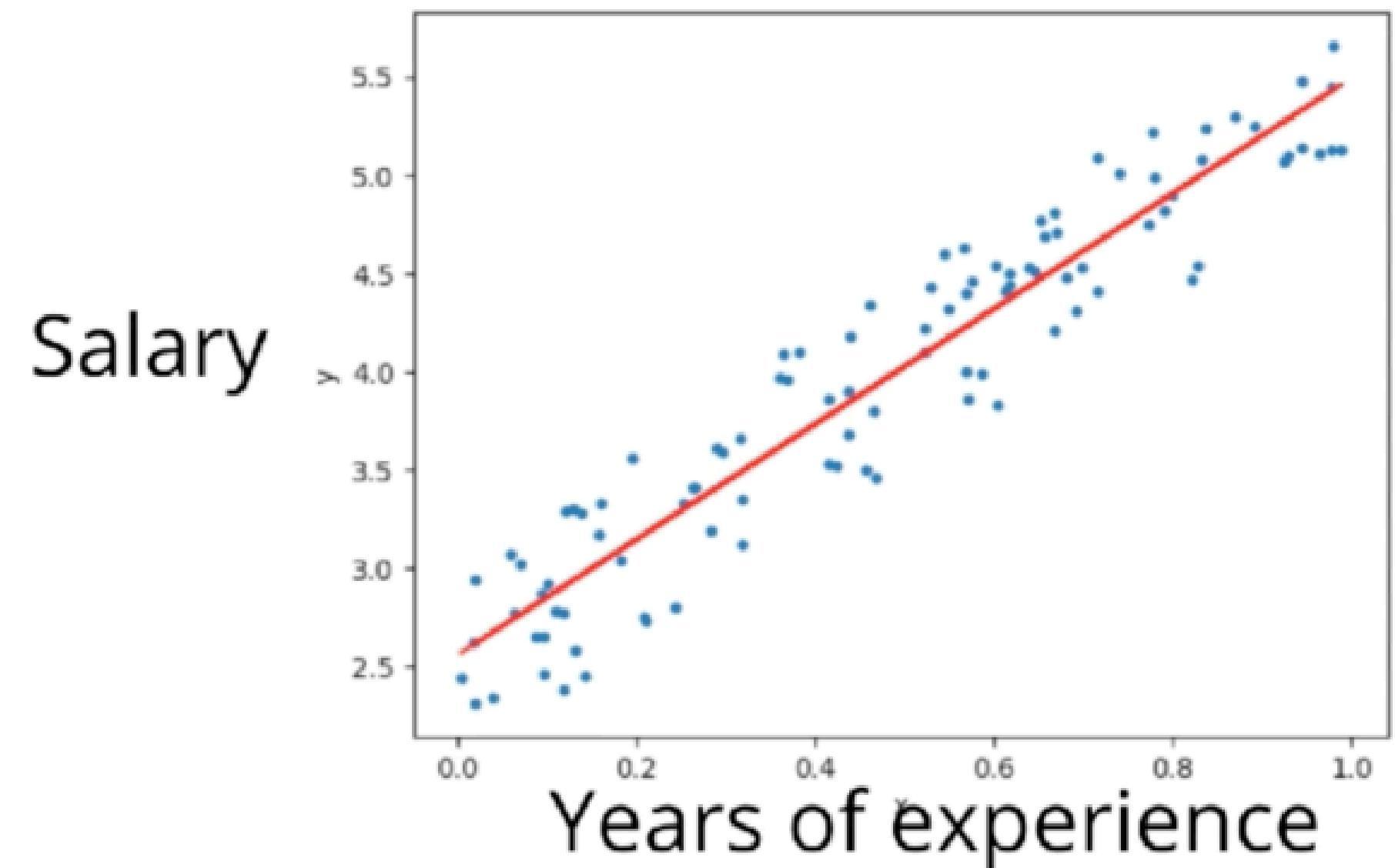
Linear predictor W_p

Example: Regression

- Fit a line or curve
- This is why grumpy old statisticians like to say: “machine learning is just glorified curve-fitting”

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

(sometimes we also use “a” for the slope)



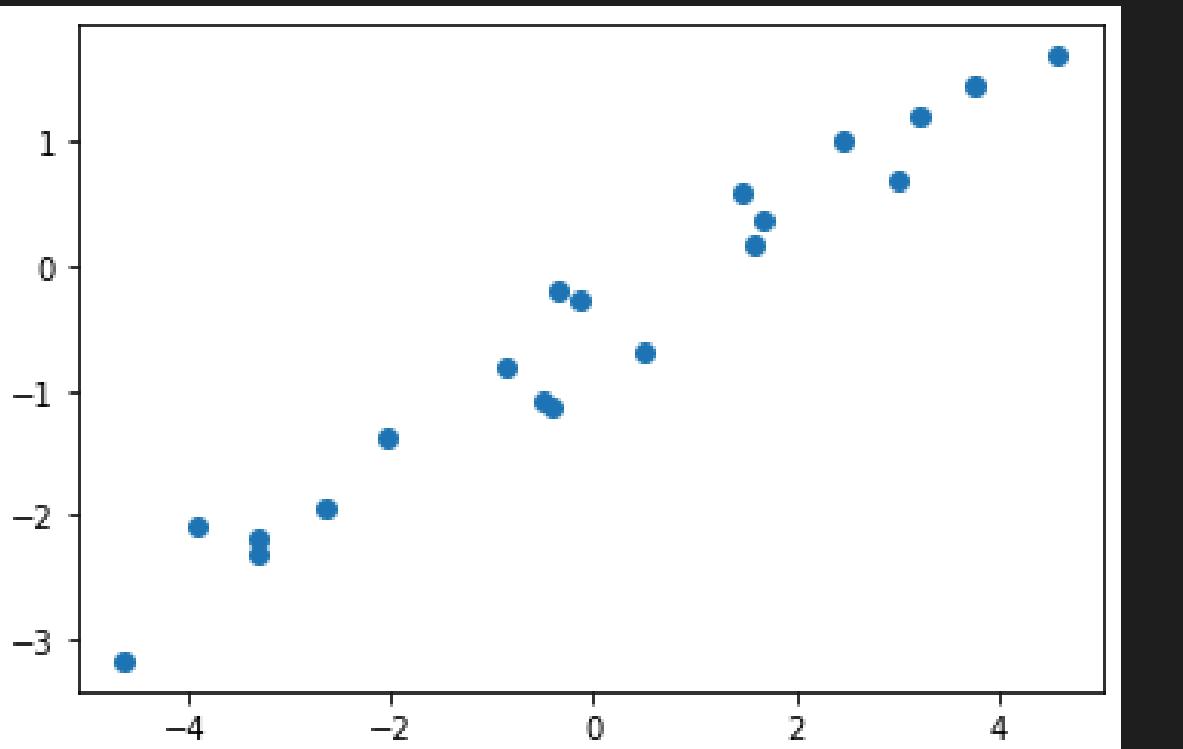
```
import matplotlib.pyplot as plt  
import numpy as np  
✓ 0.4s
```

```
# generate 20 data points  
N = 20  
  
#random data on x-axis  
x= np.random.rand(N)*10-5  
  
y = 0.5*x -1+ np.random.rand(N)
```

```
✓ 0.2s
```

```
plt.scatter(x,y)  
✓ 0.1s
```

```
<matplotlib.collections.PathCollection at 0x7fc1b147a410>
```



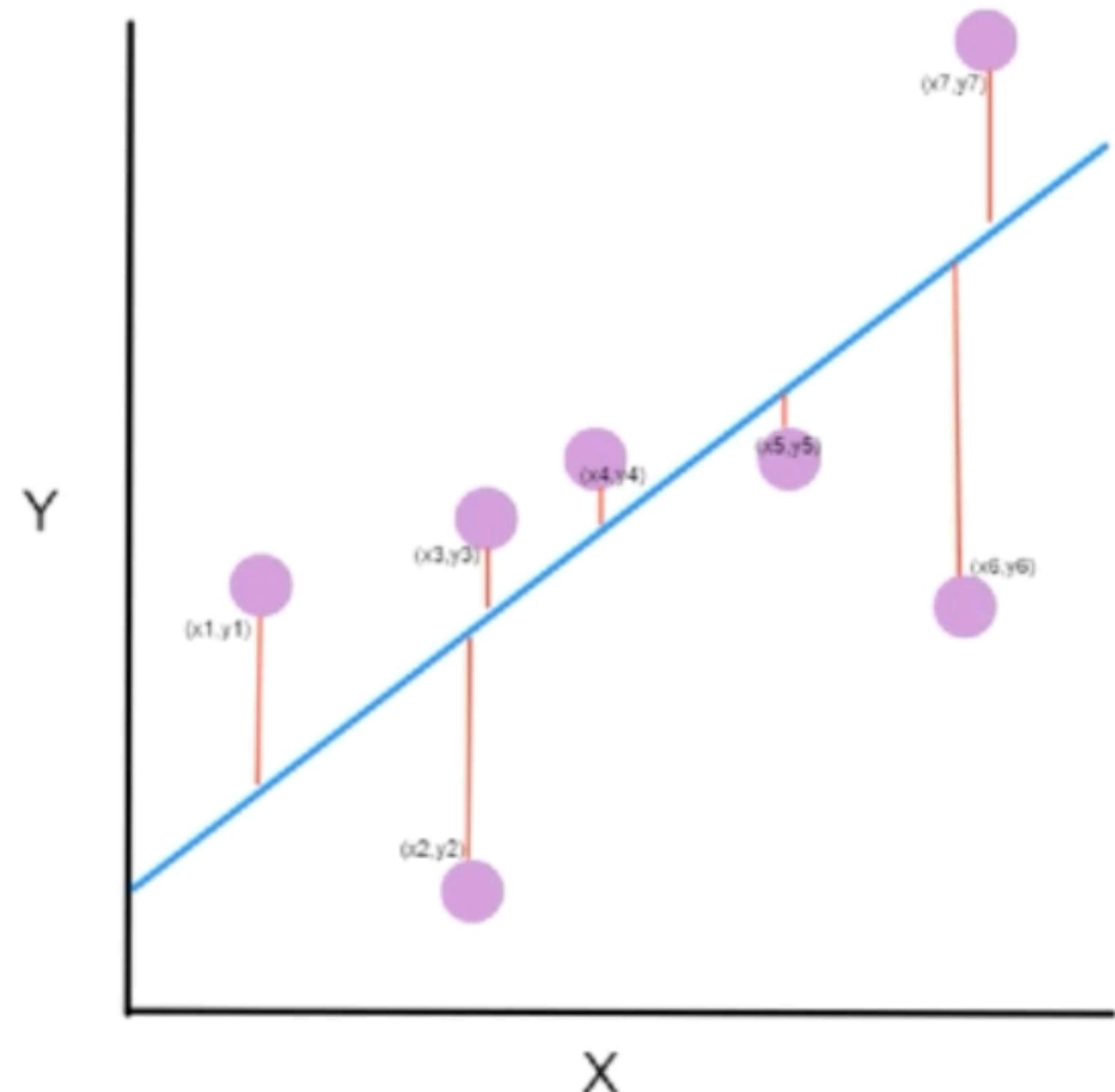
$$\hat{y} = mx + b$$

The Loss

- Data = $\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$
- N = number of samples in the dataset
- The line **cannot** perfectly pass through all the data points

MSE = Mean Squared Error

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



Applying the MSE to find slope / intercept

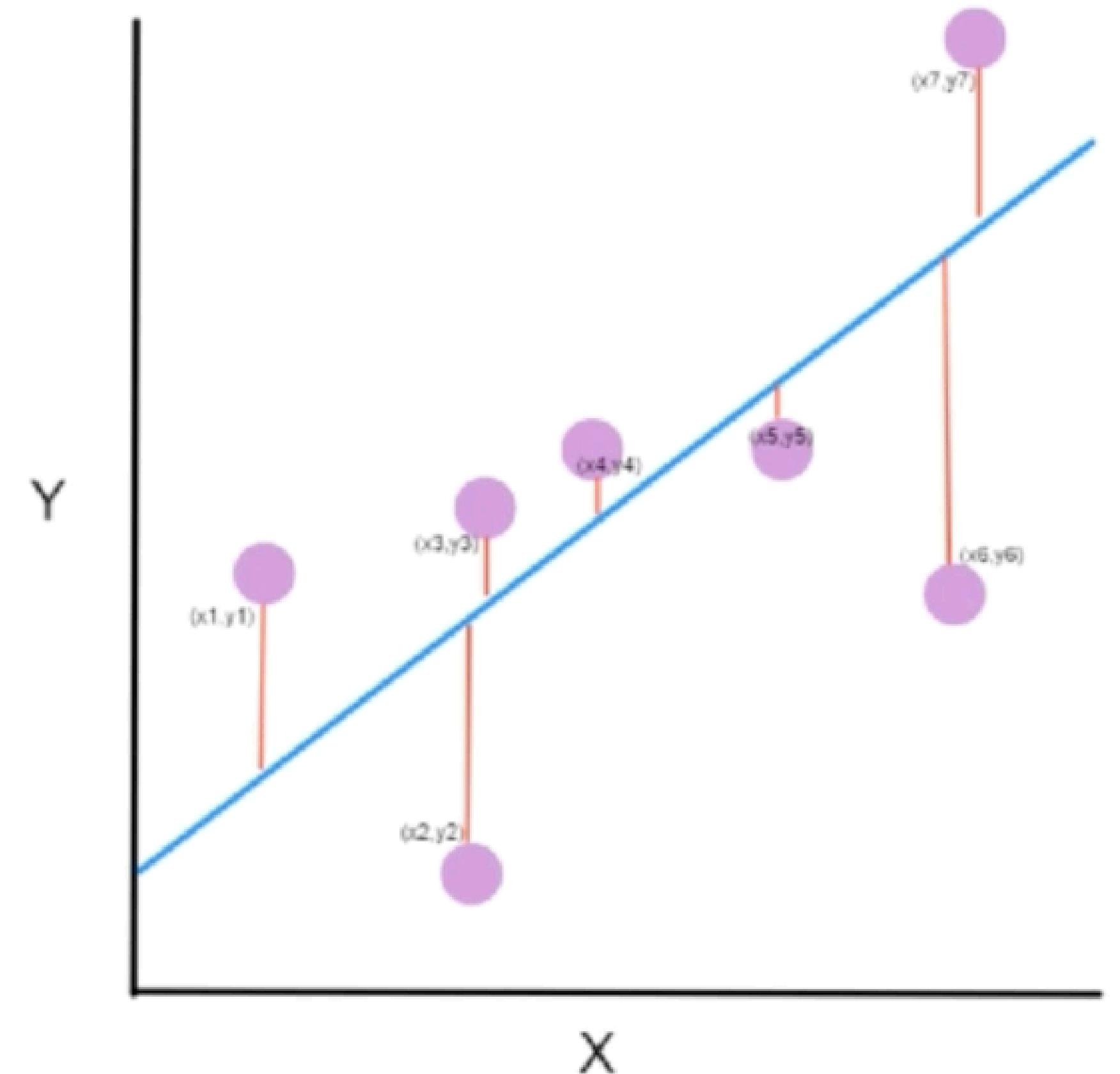
- Plug in the expression for the predictions (\hat{y}_i)
- Quiz: What are the **variables** in this expression?

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - (mx_i + b))^2$$

Applying the MSE to find slope / intercept

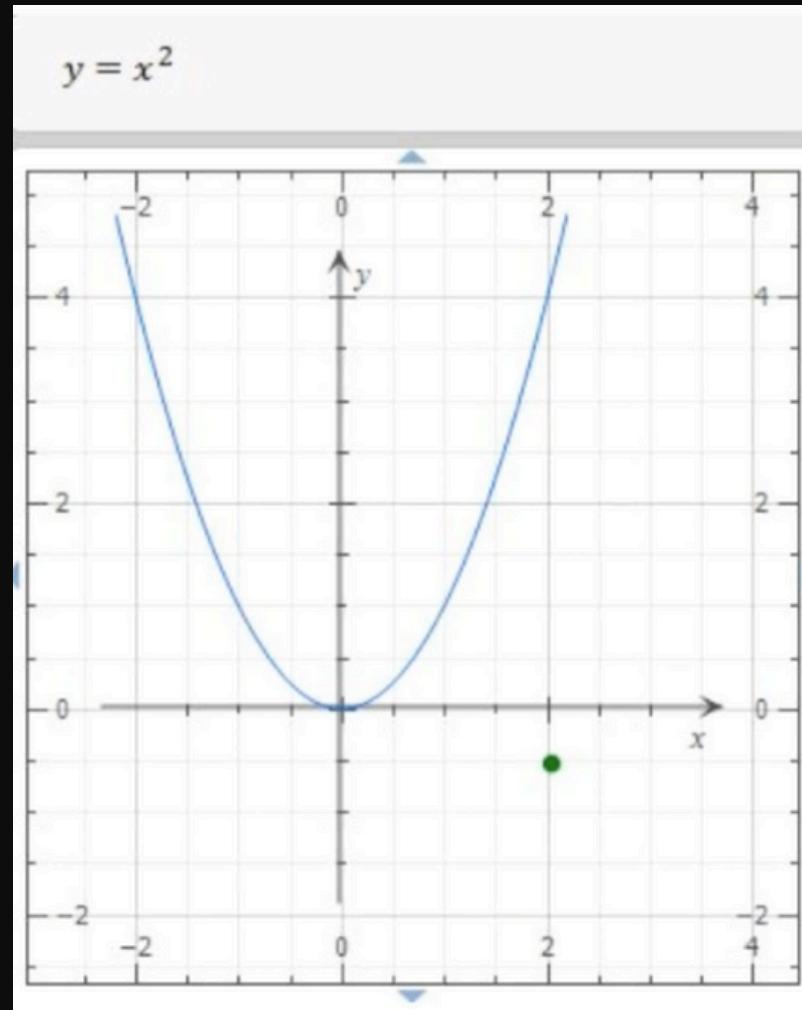
- Note: L (loss) = MSE
- We want to *minimize the loss* with respect to the parameters (m, b)

$$m^*, b^* = \arg \min_{m, b} L$$



First Solution

Minimize $f(x) = x^2$



- Use calculus!
- $df / dx = 2x = 0$
- Solve for x : $x = 0$

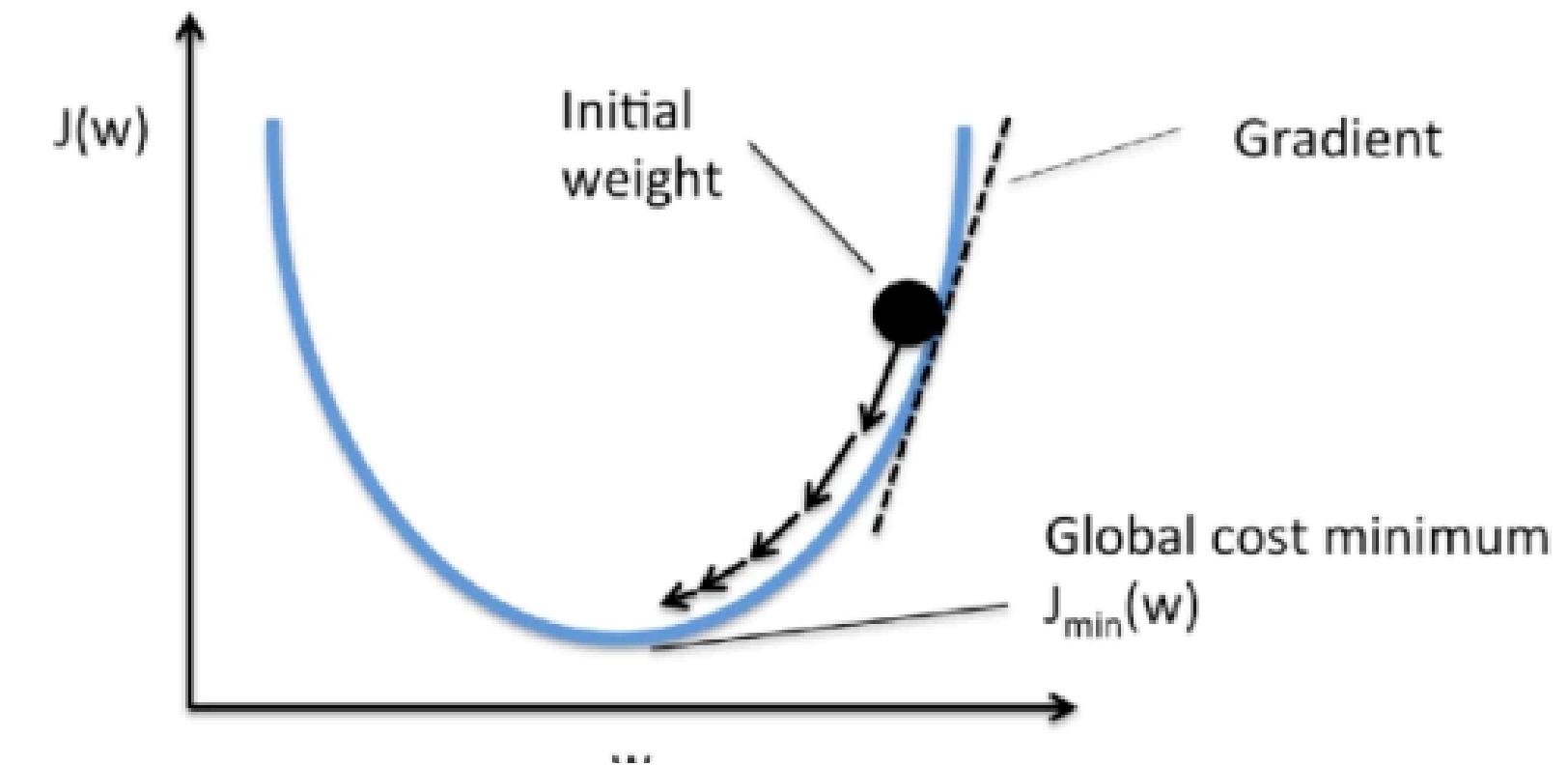
Second Solution : Gradient Descent

- Find the derivatives and set them to 0, solve for the parameters
- Yields 2 equations and 2 unknowns: can solve for (m, b)
- Try it as an exercise!: Should be in terms of $\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$

$$\partial L/\partial m = 0, \partial L/\partial b = 0$$

Gradient Descent to find hidden parameters

```
# gradient descent  
# pseudocode  
 $\theta$  = (m, b) = random()  
for i in range(n_epochs):  
     $\theta$  =  $\theta$  -  $\eta \nabla_{\theta} L$ 
```

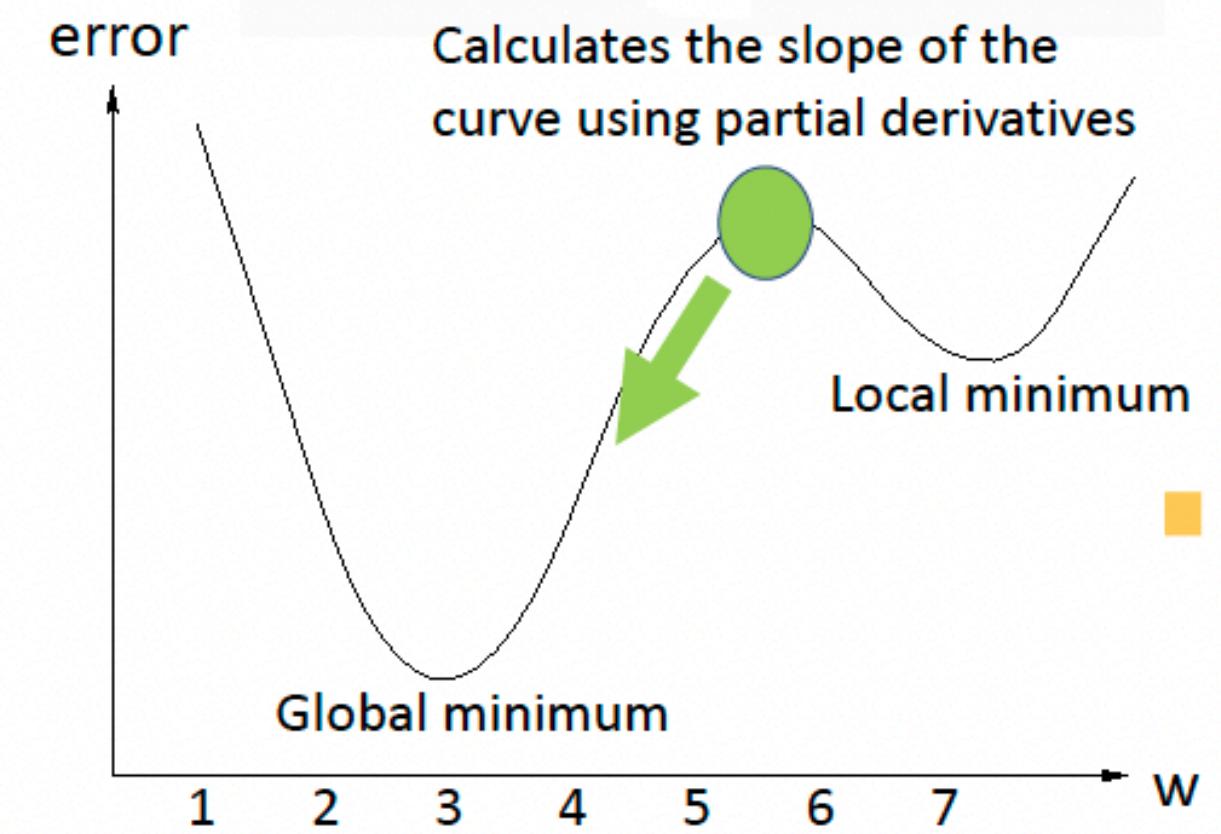
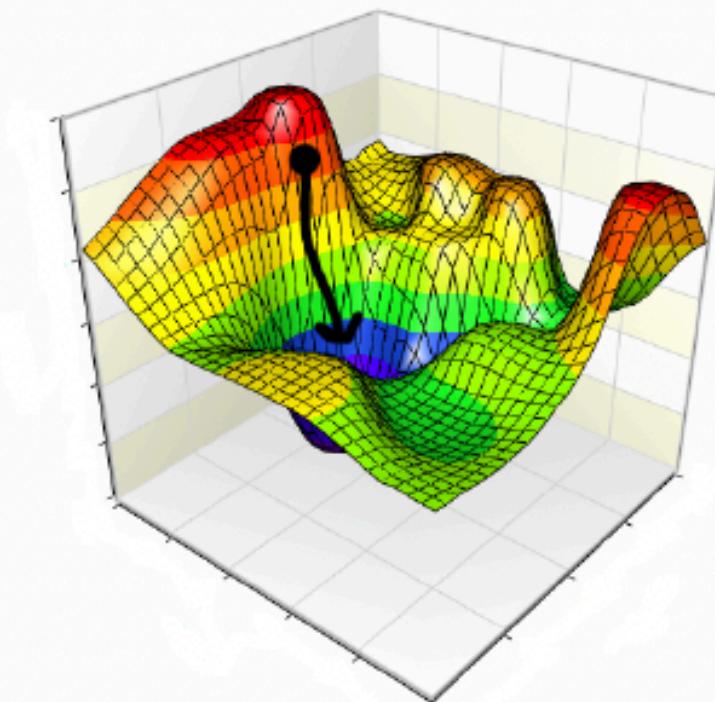
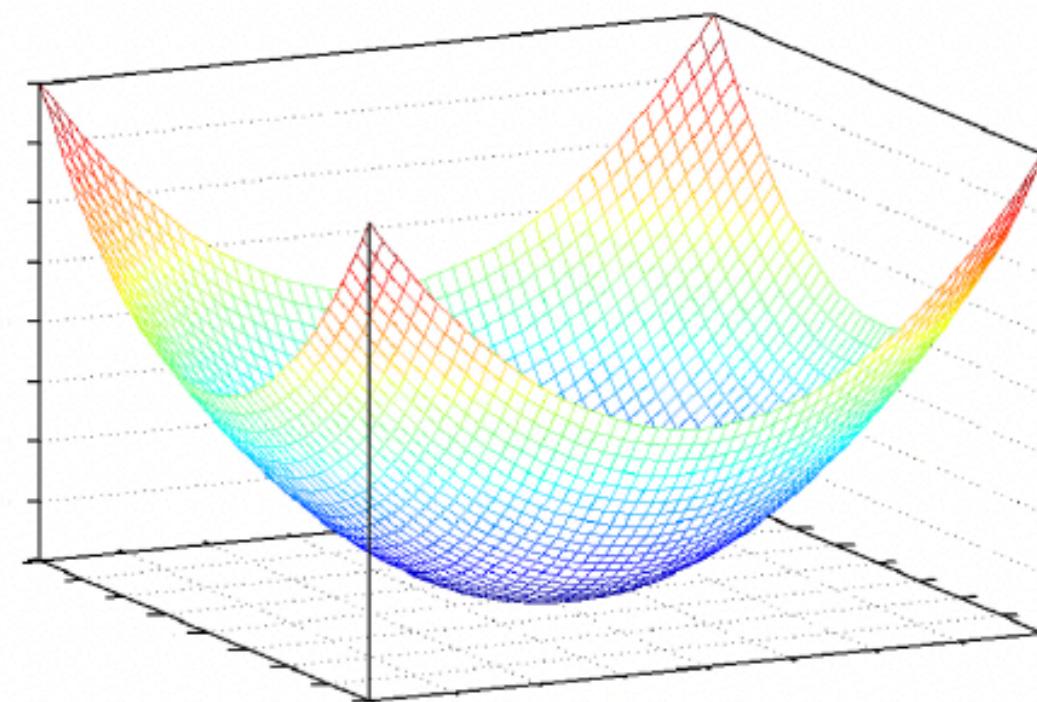


$$L = MSE = \frac{1}{N} \sum_{i=1}^N (y_i - (mx_i + b))^2$$

GRADIENT DESCENT

$$\min C(w_1, w_2 \dots w_n)$$

Calculate the partial derivative to move to the gradient direction



$$\frac{\partial}{\partial m} = \frac{2}{n} \sum_{i=1}^n -x_i(y_i - (mx_i + b))$$

$$\frac{\partial}{\partial b} = \frac{2}{n} \sum_{i=1}^n -(y_i - (mx_i + b))$$

```
def Gradient(m,b) :  
    grad_m = 0; grad_b = 0;  
  
    for i in range(N) :  
        grad_m += -X[i]*(Y[i]- (m*X[i]+b))  
        grad_b += - (Y[i]- (m*X[i]+b))  
  
    return grad_m, grad_b  
  
Gradient(-1,-1)  
✓ 0.3s  
(array([-209.28382035]), array([-10.12894605]))
```

```

# gradient descent
# pseudocode

θ = (m, b) = random()
for i in range(n_epochs):
    θ = θ - η∇_θ L

```

```

# Define the gradient function
def Gradient(m, b):
    grad_m = 0
    grad_b = 0
    for i in range(N):
        grad_m += -X[i] * (Y[i] - (m * X[i] + b))
        grad_b += -(Y[i] - (m * X[i] + b))
    return grad_m, grad_b

# Initialize m and b
m = 0
b = 0

# Set learning rate and number of iterations
learning_rate = 0.001
iterations = 1000

# Perform gradient descent
for _ in range(iterations):
    grad_m, grad_b = Gradient(m, b)
    m -= learning_rate * grad_m
    b -= learning_rate * grad_b

print("Estimated m:", m)
print("Estimated b:", b)

```

✓ 0.0s

```

Estimated m: 0.4860476543029485
Estimated b: -0.8921942796543206

```

```

# Gradient descent parameters
learning_rate = 0.001
iterations = 50000
m = 0 # Initial guess for m
b = 0 # Initial guess for b

# Lists to store parameters history
m_history = []
b_history = []
loss_history = []

# Gradient descent
for i in range(iterations):
    # Calculate gradients
    grad_m, grad_b = Gradient(m, b, X, Y)

    # Update parameters
    m = m - learning_rate * grad_m
    b = b - learning_rate * grad_b

    # Store parameters
    m_history.append(m)
    b_history.append(b)

    # Calculate and store loss
    loss = np.mean((Y - (m*X + b))**2)
    loss_history.append(loss)

print(f"Final parameters: m = {m:.4f}, b = {b:.4f}")
print(f"True parameters: m = 0.5000, b = -1.0000")

# Plotting
plt.figure(figsize=(15, 5))

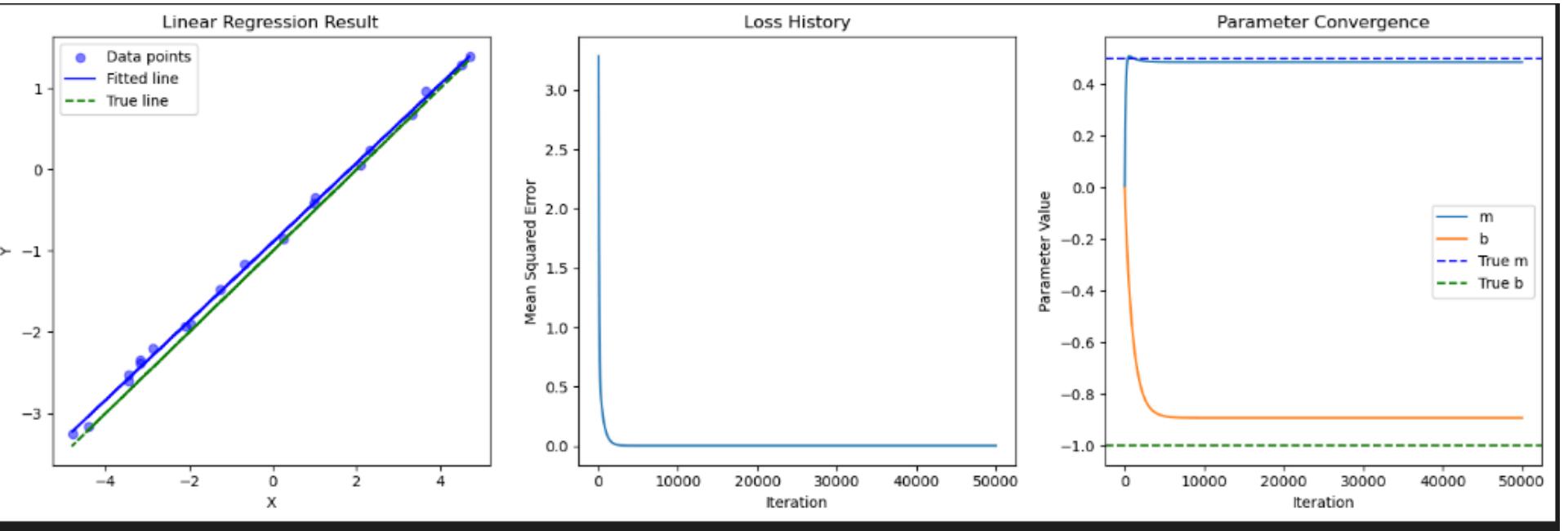
# Plot 1: Data and regression line
plt.subplot(131)
plt.scatter(X, Y, color='blue', alpha=0.5, label='Data points')
plt.plot(X, m*X + b, color='blue', label='Fitted line')
plt.plot(X, 0.5*X - 1, '--', color='green', label='True line')
plt.xlabel('X')
plt.ylabel('Y')
plt.title('Linear Regression Result')
plt.legend()

# Plot 2: Loss history
plt.subplot(132)
plt.plot(loss_history)
plt.xlabel('Iteration')
plt.ylabel('Mean Squared Error')
plt.title('Loss History')

# Plot 3: Parameter convergence
plt.subplot(133)
plt.plot(m_history, label='m')
plt.plot(b_history, label='b')
plt.axhline(y=0.5, color='b', linestyle='--', label='True m')
plt.axhline(y=-1, color='g', linestyle='--', label='True b')
plt.xlabel('Iteration')
plt.ylabel('Parameter Value')
plt.title('Parameter Convergence')
plt.legend()

plt.tight_layout()
plt.show()

```



Final parameters: $m = 0.4860$, $b = -0.8922$
 True parameters: $m = 0.5000$, $b = -1.0000$

Third Solution :Pytorch

SDG: Stochastic gradient
descent

$$\theta = \theta - \eta \nabla_{\theta} L$$

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

```
# Loss and optimizer
criterion = nn.MSELoss()
optimizer = torch.optim.SGD(model.parameters(), lr=0.1)
```

```
# gradient descent
# pseudocode

θ = (m, b) = random()
for i in range(n_epochs):
    θ = θ - η∇_θ L
```

```
# Train the model
n_epochs = 30
for it in range(n_epochs):
    # zero the parameter gradients
    optimizer.zero_grad()

    # Forward pass
    outputs = model(inputs)
    loss = criterion(outputs, targets)

    # Backward and optimize
    loss.backward()
    optimizer.step()
```

```

# Convert data to PyTorch tensors
X_train = torch.tensor(X, dtype=torch.float32).view(-1, 1)
Y_train = torch.tensor(Y, dtype=torch.float32).view(-1, 1)

# Initialize m and b as PyTorch parameters
m = torch.randn(1, requires_grad=True, dtype=torch.float32) # Random initialization for m
b = torch.randn(1, requires_grad=True, dtype=torch.float32) # Random initialization for b

# Define optimizer
learning_rate = 0.01
optimizer = torch.optim.SGD([m, b], lr=learning_rate) # Optimizer for m and b

# Training loop
epochs = 1000
for epoch in range(epochs):

    optimizer.zero_grad() # Clear gradients

    # Forward pass: Calculate y_pred using y = mx + b
    y_pred = m * X_train + b
    # Calculate Mean Squared Error (MSE) Loss
    loss = torch.mean((y_pred - Y_train) ** 2)

    # Backward pass: Compute gradients
    loss.backward() # Calculate new gradients

    # Update parameters using optimizer1
    optimizer.step()

    # Print the loss every 100 epochs
    if (epoch + 1) % 100 == 0:
        print(f'Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}')

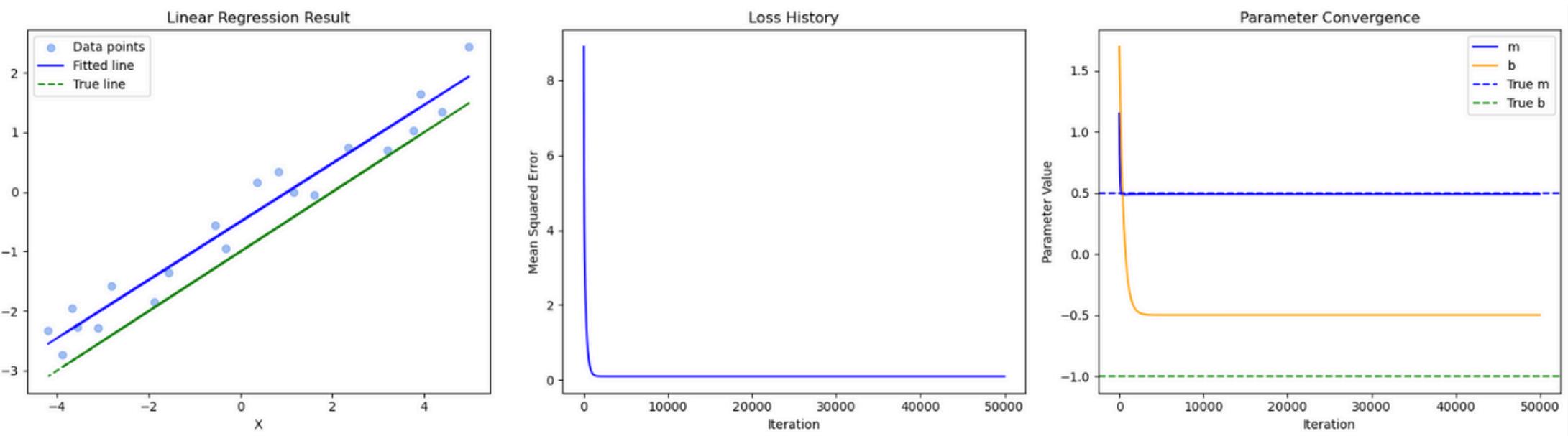
print("Estimated m:", m.item())
print("Estimated b:", b.item())

✓ 0.4s

Epoch [100/1000], Loss: 0.0752
Epoch [200/1000], Loss: 0.0240
Epoch [300/1000], Loss: 0.0230
Epoch [400/1000], Loss: 0.0230
Epoch [500/1000], Loss: 0.0230
Epoch [600/1000], Loss: 0.0230
Epoch [700/1000], Loss: 0.0230
Epoch [800/1000], Loss: 0.0230
Epoch [900/1000], Loss: 0.0230
Epoch [1000/1000], Loss: 0.0230
Estimated m: 0.48729196190834045
Estimated b: -0.7519025206565857

```

Pytorch Method 1

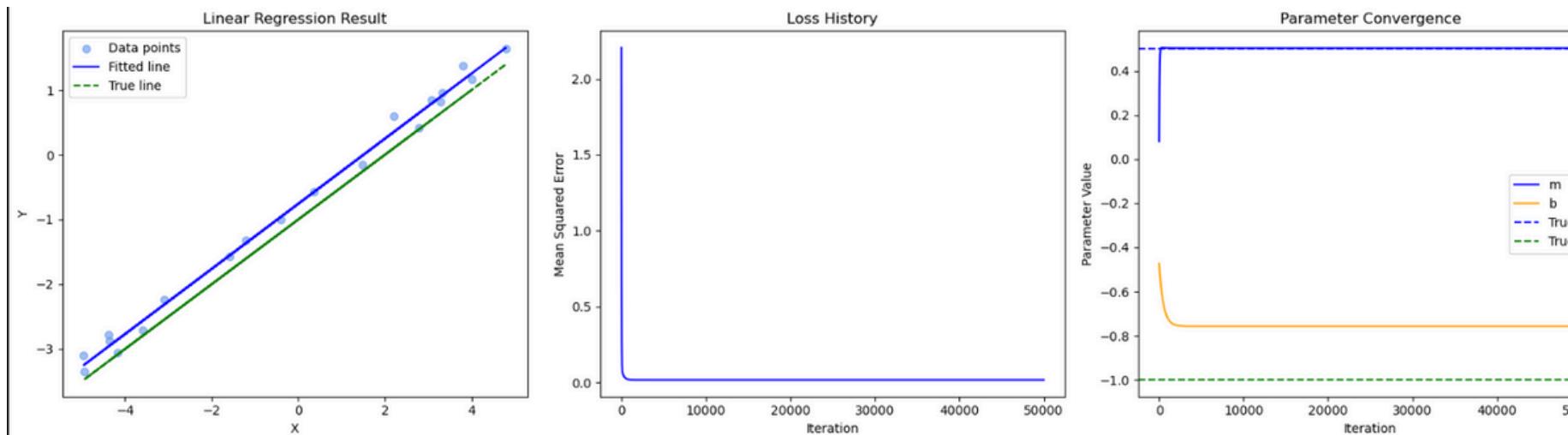


Pytorch Method 2

```
# Convert data to PyTorch tensors
X_train = torch.tensor(X, dtype=torch.float32).view(-1, 1)
Y_train = torch.tensor(Y, dtype=torch.float32).view(-1, 1)

# Define the model class
class LinearRegressionModel(nn.Module):
    def __init__(self):
        super(LinearRegressionModel, self).__init__()
        # Initialize m and b as parameters with random values
        self.m = nn.Parameter(torch.randn(1, dtype=torch.float32))
        self.b = nn.Parameter(torch.randn(1, dtype=torch.float32))

    def forward(self, x):
        # Apply the linear transformation y = mx + b
        return self.m * x + self.b
```



```
# Initialize model and optimizer
model = LinearRegressionModel()
learning_rate = 0.001
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

# Training loop with data recording for plots
epochs = 50000
loss_history = []
m_values, b_values = [], []

for epoch in range(epochs):
    # Forward pass
    y_pred = model(X_train)

    # Calculate Mean Squared Error (MSE) Loss
    loss = torch.mean((y_pred - Y_train) ** 2)
    loss_history.append(loss.item())
    m_values.append(model.m.item())
    b_values.append(model.b.item())

    # Backward pass and parameter update
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Pytorch Method 3

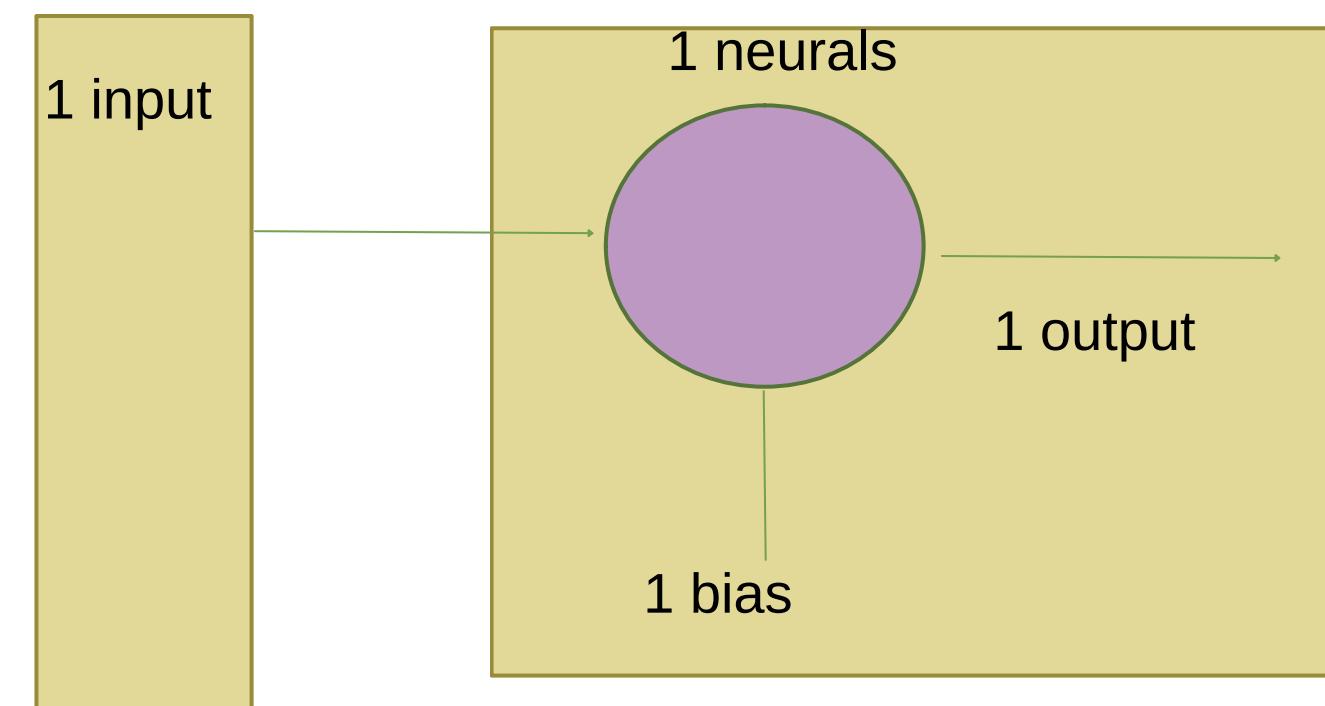
```
1 # Train the model
2 n_epochs = 30
3 losses = []
4 for it in range(n_epochs):
5     # zero the parameter gradients
6     optimizer.zero_grad()
7
8     # Forward pass
9     outputs = model(inputs)
10    loss = criterion(outputs, targets)
11
12    # keep the loss so we can plot it later
13    losses.append(loss.item())
14
15    # Backward and optimize
16    loss.backward()
17    optimizer.step()
18
19    print(f'Epoch {it+1}/{n_epochs}, Loss: {loss.item():.4f}')
```

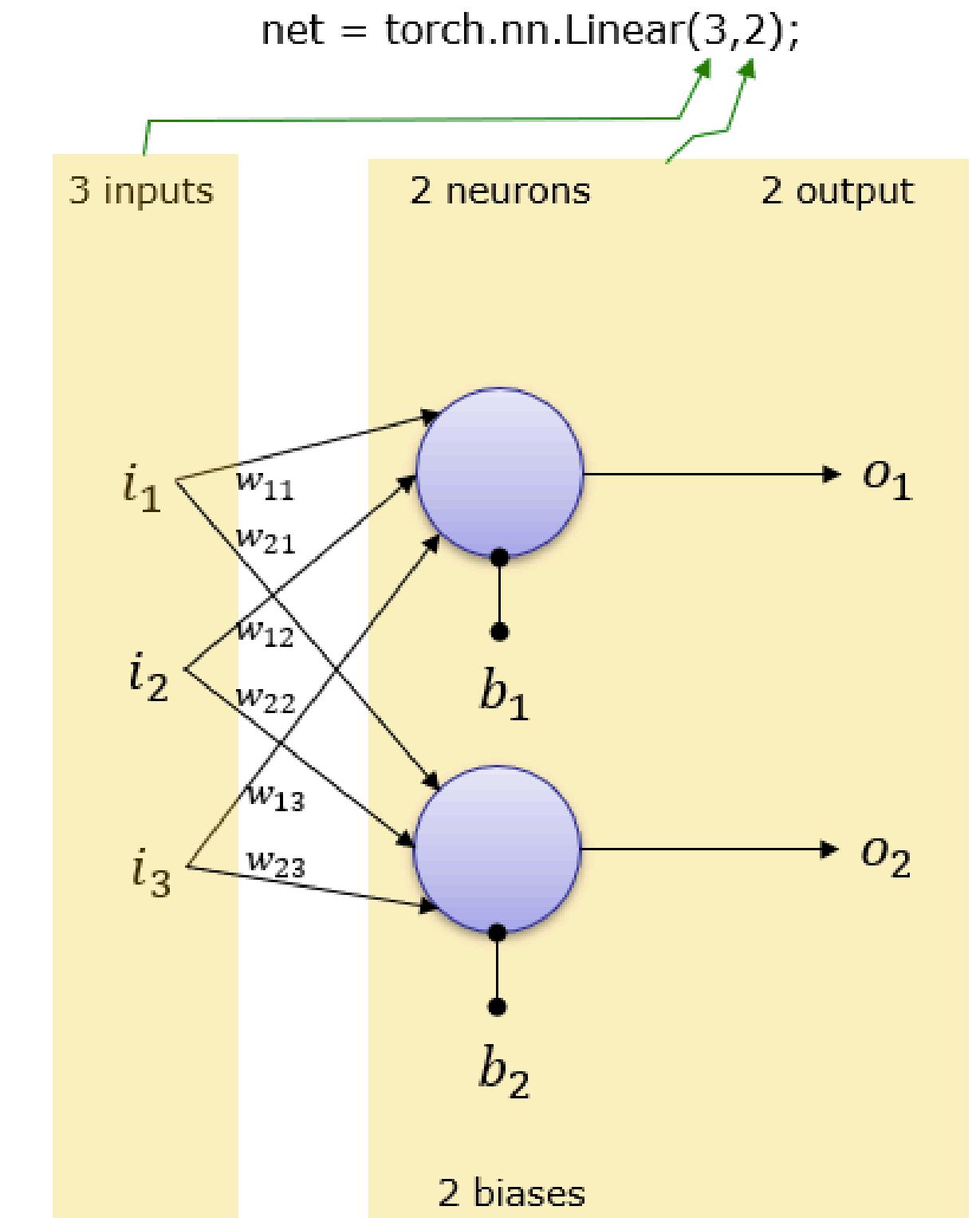
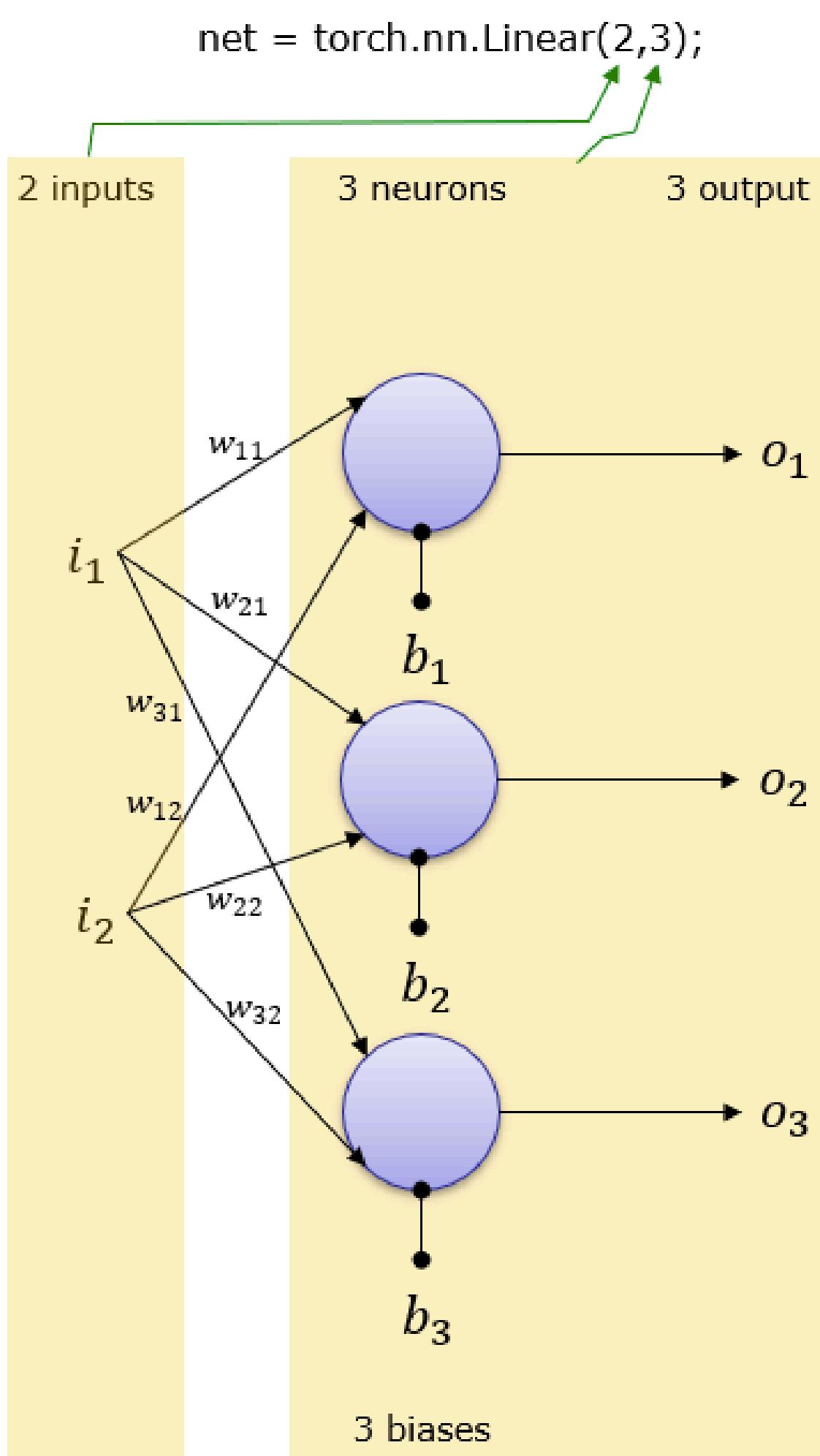
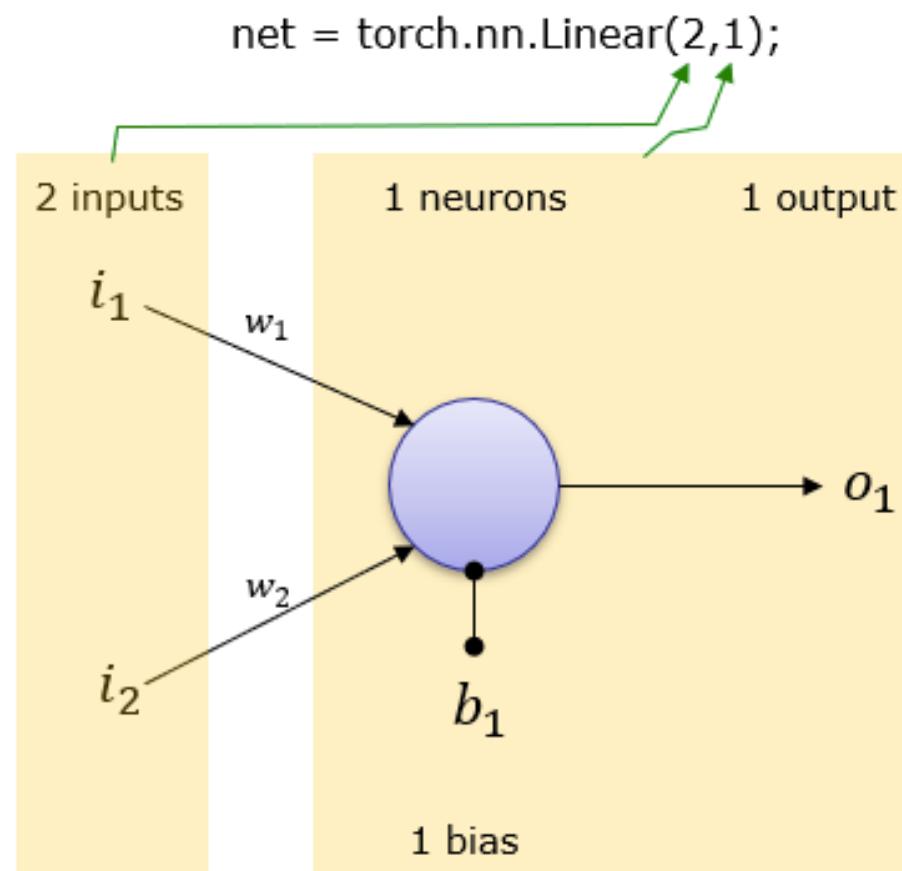
```
Epoch 1/30, Loss: 12.1352
Epoch 2/30, Loss: 2.8066
Epoch 3/30, Loss: 2.4554
Epoch 4/30, Loss: 2.1753
Epoch 5/30, Loss: 1.9483
Epoch 6/30, Loss: 1.7641
Epoch 7/30, Loss: 1.6148
```

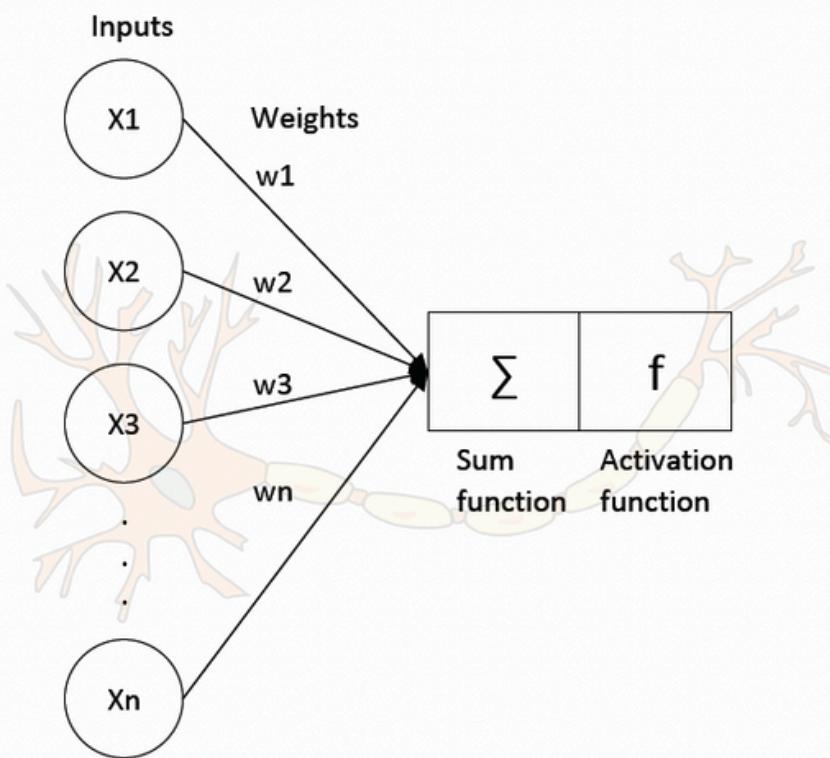
```
[ ] 1 # Create the linear regression model
[ ] 2 model = nn.Linear(1, 1)

[ ] 1 # Loss and optimizer
[ ] 2 criterion = nn.MSELoss()
[ ] 3 optimizer = torch.optim.SGD(model.parameters(), lr=0.05)

[ ] 1 # In ML we want our data to be of shape:
[ ] 2 # (num_samples x num_dimensions)
[ ] 3 X = X.reshape(N, 1)
[ ] 4 Y = Y.reshape(N, 1)
[ ] 5
[ ] 6 # PyTorch uses float32 by default
[ ] 7 # Numpy creates float64 by default
[ ] 8 inputs = torch.from_numpy(X.astype(np.float32))
[ ] 9 targets = torch.from_numpy(Y.astype(np.float32))
```

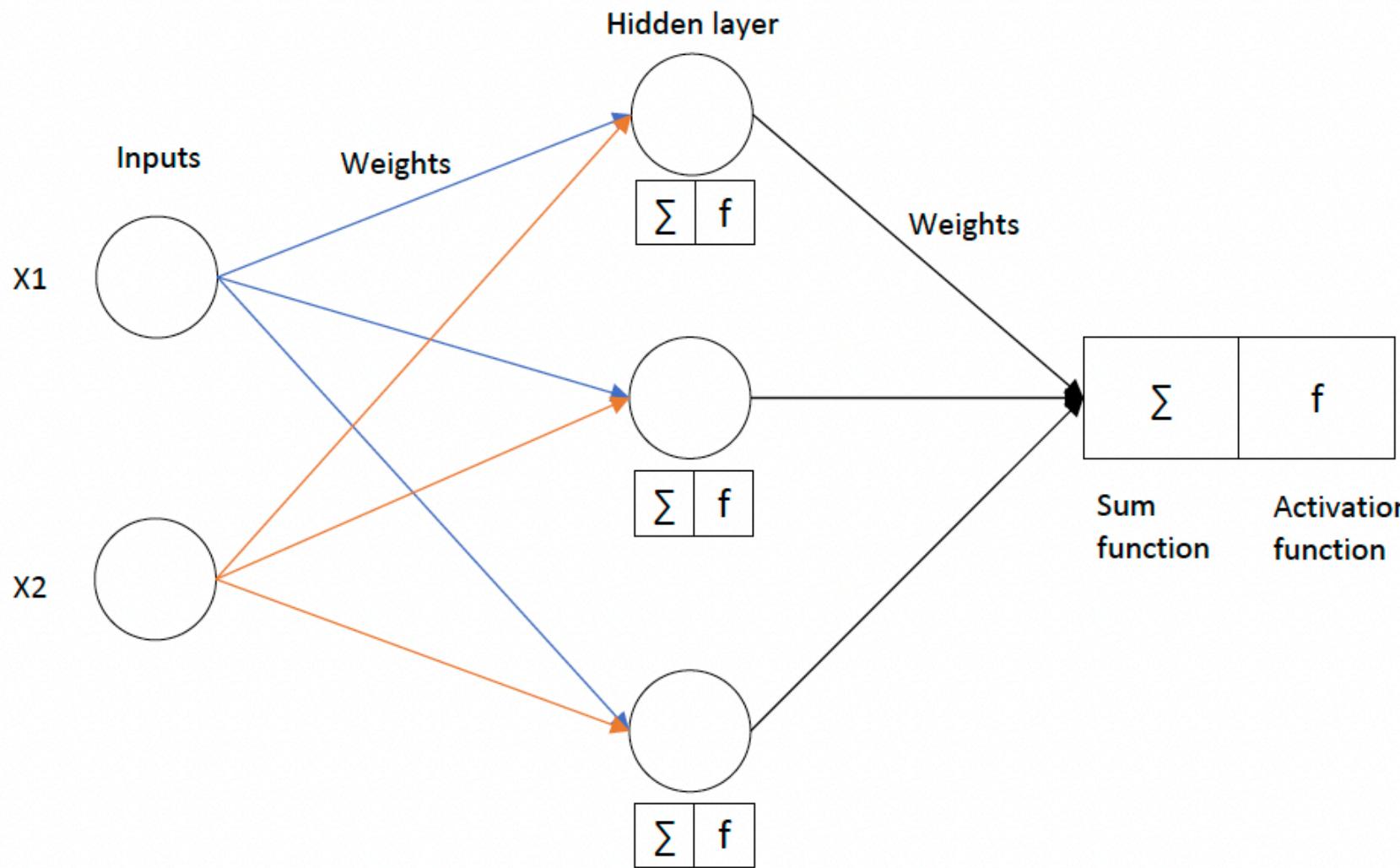






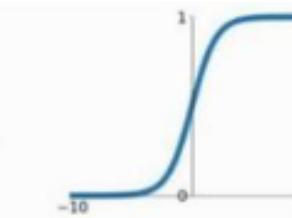
$$sum = \sum_{i=1}^n x_i * w_i$$

$$X_1 * w_1 + X_2 * w_2 + X_3 * w_3$$



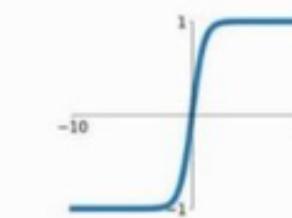
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



tanh

$$\tanh(x)$$



ReLU

$$\max(0, x)$$



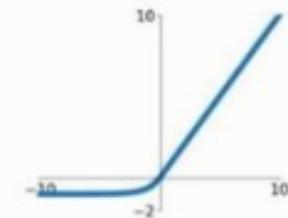
Leaky ReLU

$$\max(0.1x, x)$$



Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$



ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

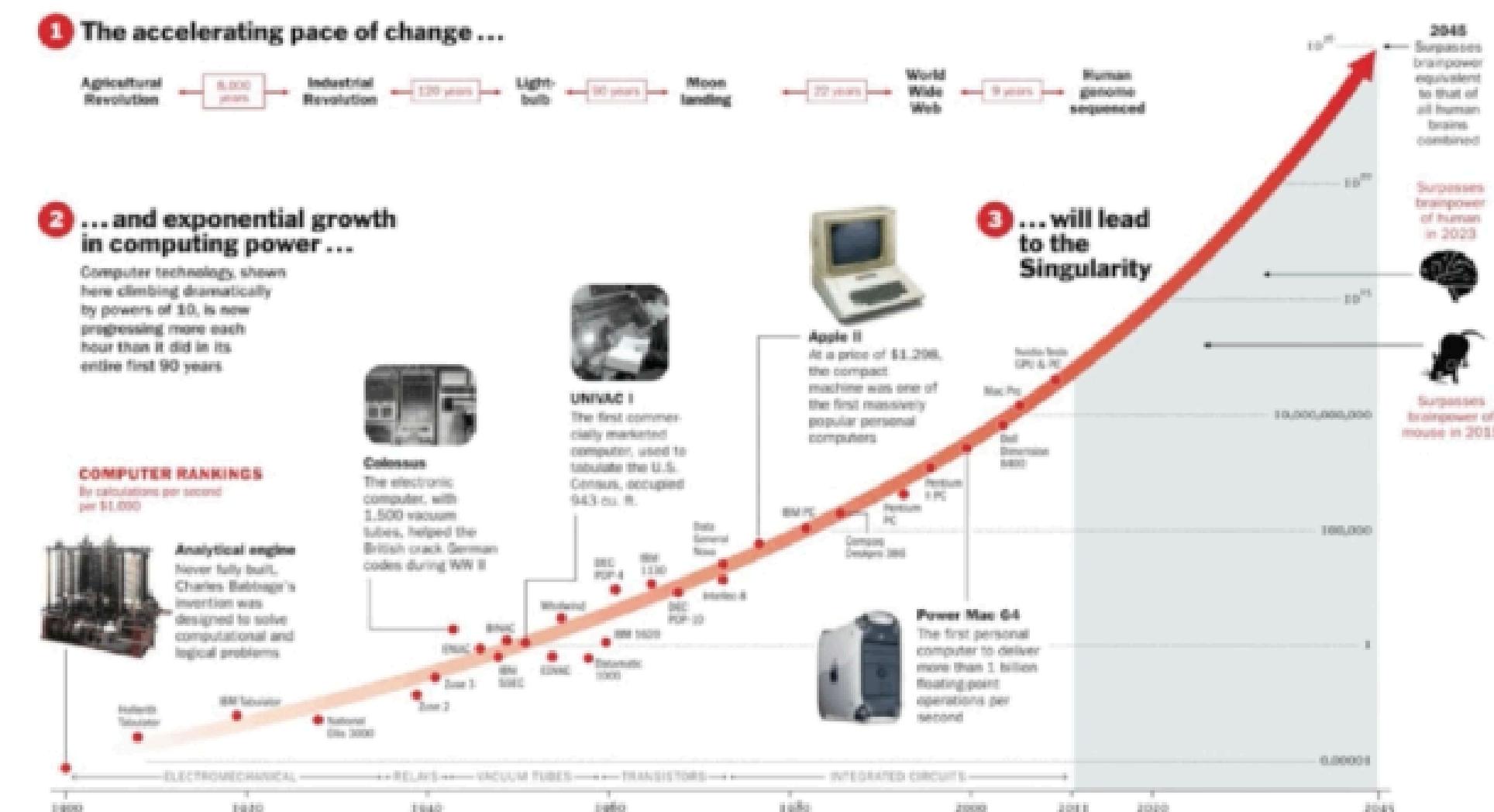
Home Work

Week 1

HOME WORK 2

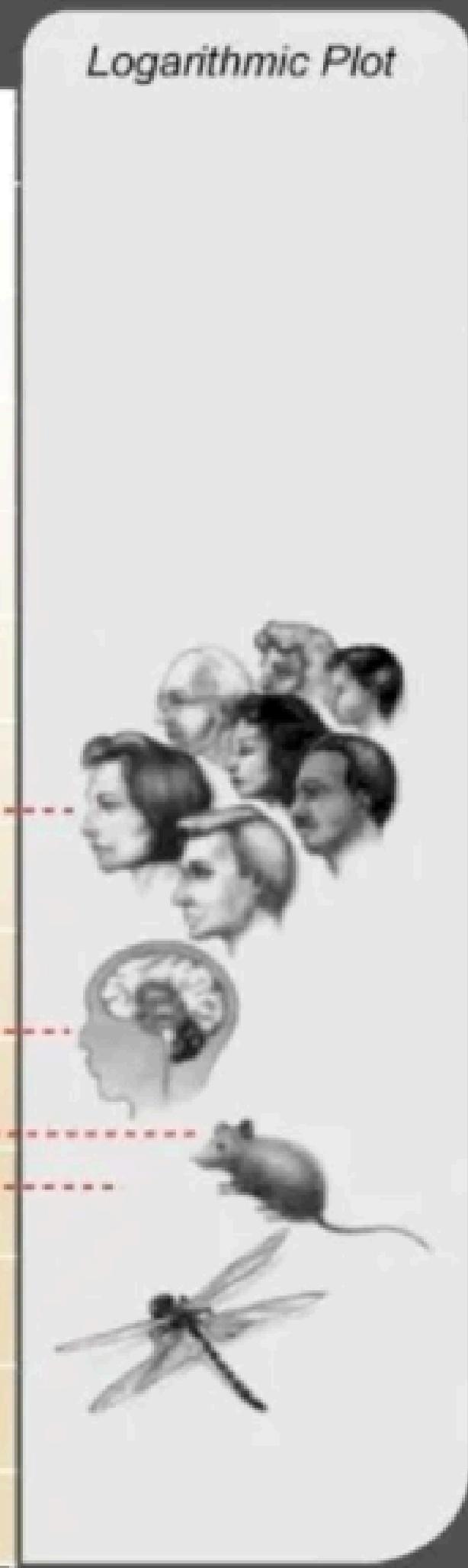
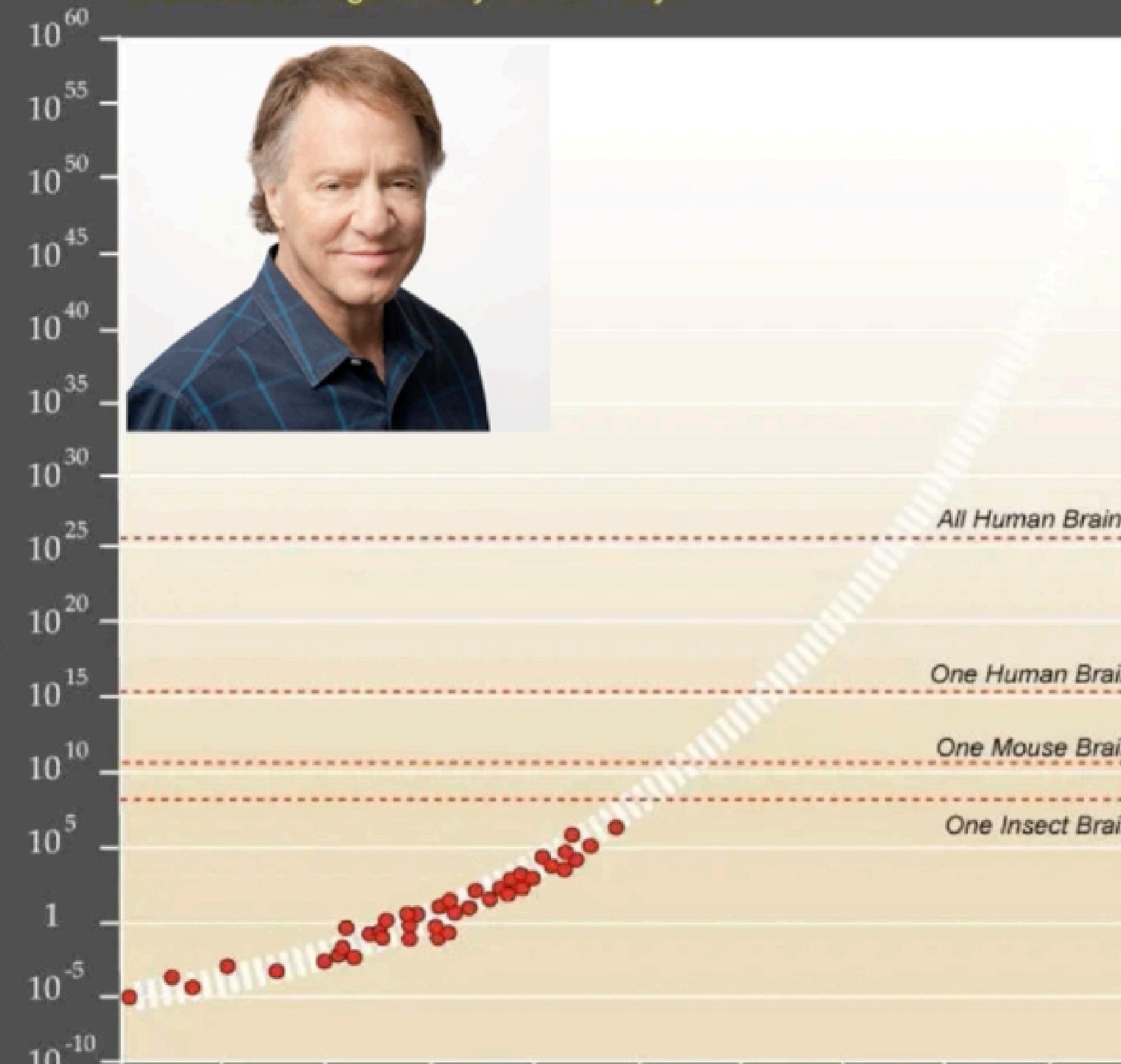
Real-World Dataset: Moore's Law

- The number of transistors per square inch on integrated circuits doubles approximately every 2 years



Exponential Growth of Computing

Twentieth through twenty first century



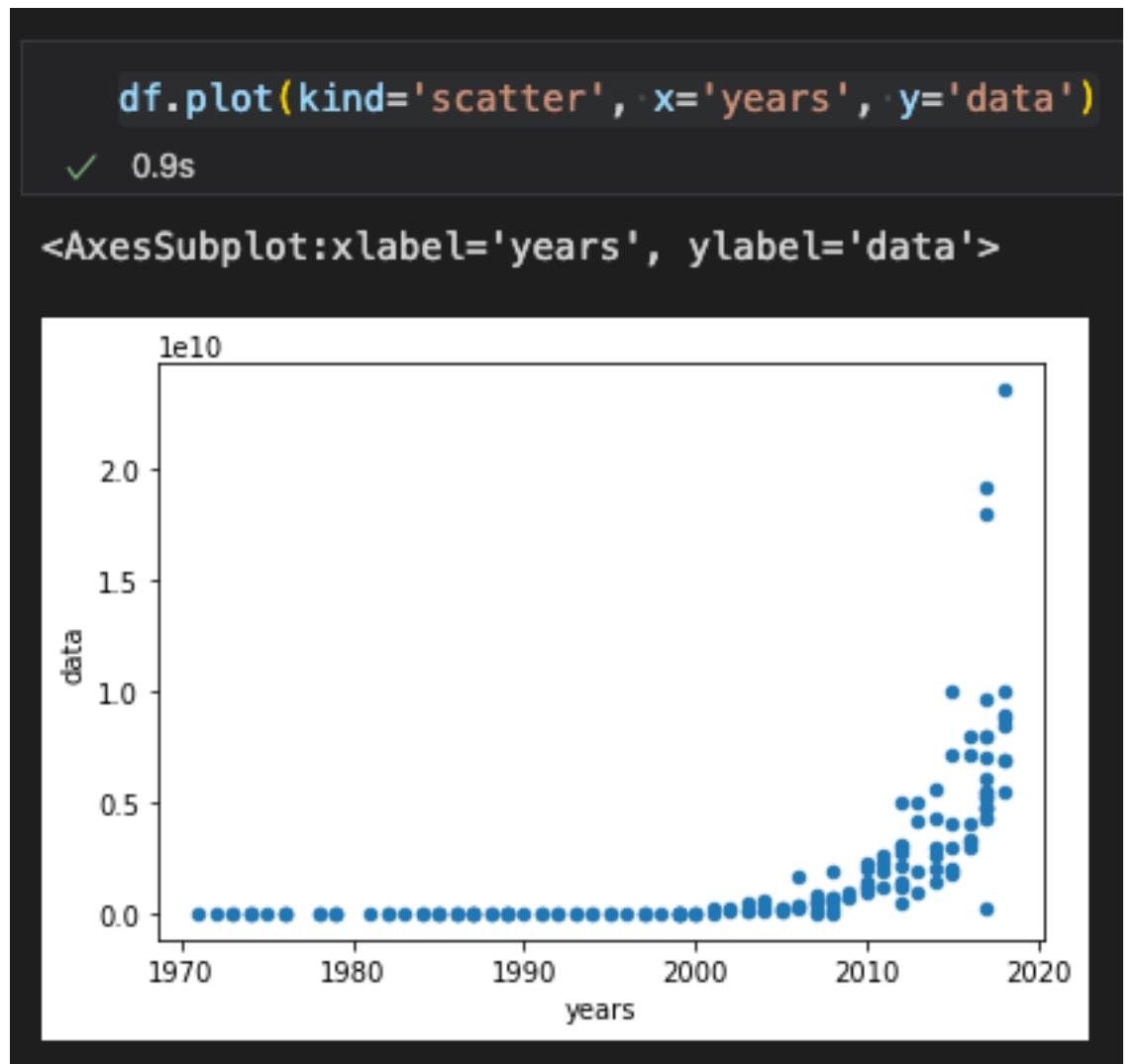
HOME WORK 2

```
df = pd.read_csv('https://raw.githubusercontent.com/lazyprogrammer/machine_learning_examples/master/tf2.0/moore.csv', header=None)
df= df.rename(columns={0: "years", 1: "data"})

df
✓ 0.2s
```

	years	data
0	1971	2300
1	1972	3500
2	1973	2500
3	1973	2500
4	1974	4100
...
157	2017	180000000000
158	2017	192000000000
159	2018	8876000000
160	2018	236000000000
161	2018	90000000000

162 rows x 2 columns



HOME WORK 2

$$y = A_1 \sin(f_1 t + \theta_1) + b_1 + A_2 \cos(f_2 t + \theta_2) + b_2$$

Parameters = $A_1, f_1, \theta_1, b_1, A_2, f_2, \theta_2, b_2$

```
t = np.arange(0, 10, 0.005)

#random data on x-axis
A1 = 5*np.random.rand()
f1 = 10*np.random.rand()+5
b1 = 20*np.random.rand()

ceta1 = 2*np.random.rand()*np.pi

signal1 = A1 * np.sin(f1 * t + ceta1) + b1

#random data on x-axis
A2 = 5*np.random.rand()
f2 = 10*np.random.rand()+20
b2 = 20*np.random.rand()
ceta2 = 2*np.random.rand()*np.pi

signal2 = A2 * np.cos(f2 * t + ceta2) + b2

y = signal1 + signal2

print(f"A1 = {A1}, f1 = {f1} , ceta1 = {ceta1} b1= {b1}")
print(f"A2 = {A2}, f1 = {f2} , ceta2 = {ceta2} b2= {b2}")

✓ 0.0s

A1 = 4.757400431132537, f1 = 14.982025297569715 , ceta1 = 4.532944447976331 b1= 4.804226285370636
A2 = 1.448664560946444, f1 = 24.567685969748283 , ceta2 = 2.764982500149891 b2= 19.881588370782723
```

