

# PyTorch Tutorial

02. Linear Model

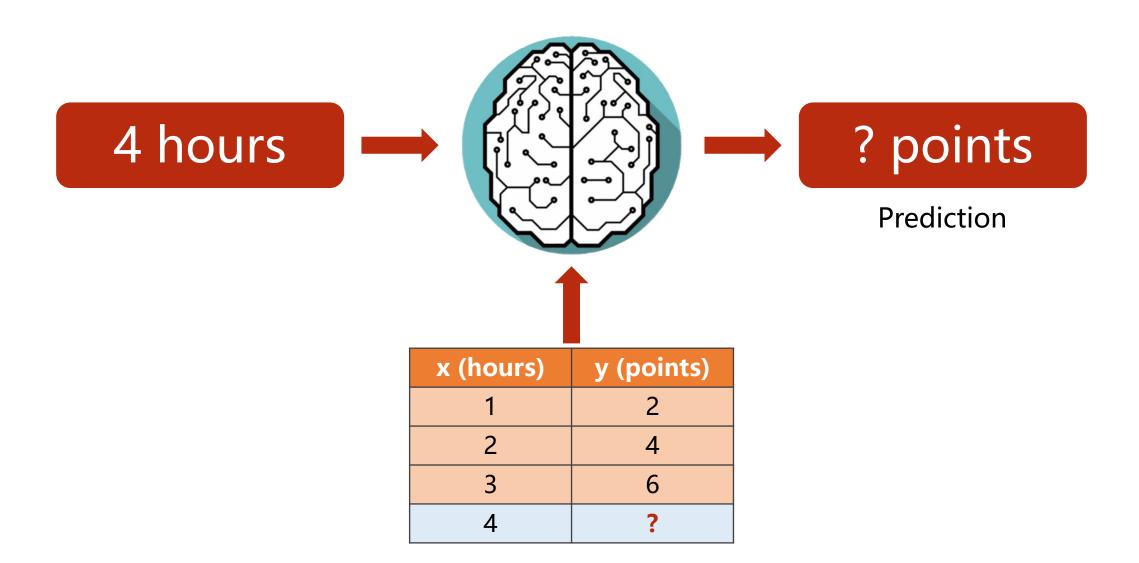
# Machine learning

• Suppose that students would get **y** points in final exam, if they spent **x** hours in paper *PyTorch Tutorial*.

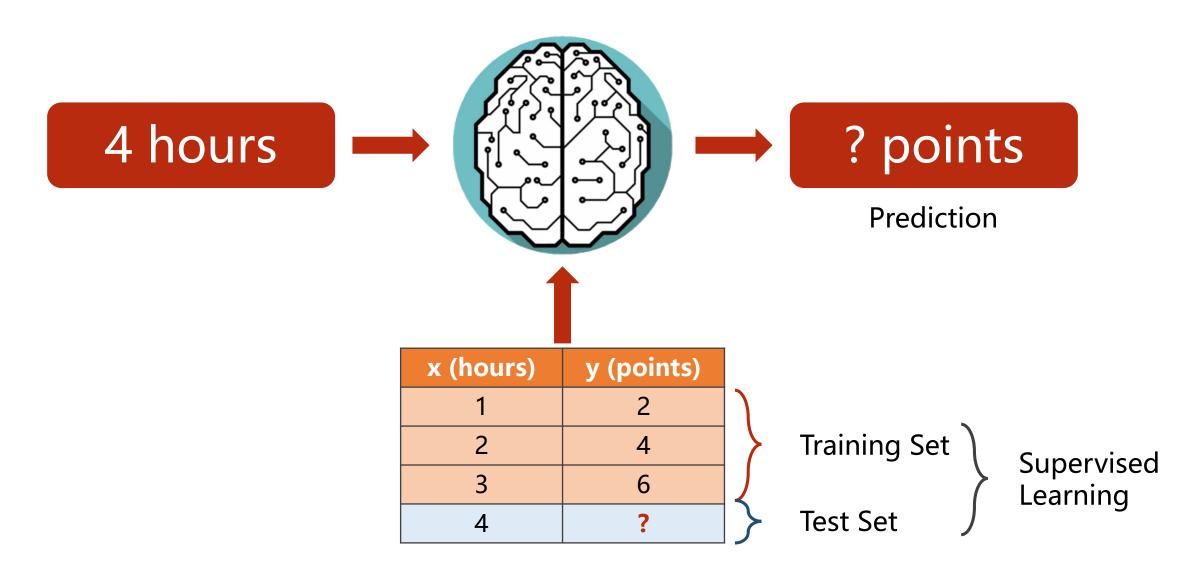
| x (hours) | y (points) |
|-----------|------------|
| 1         | 2          |
| 2         | 4          |
| 3         | 6          |
| 4         | ?          |

The question is what would be the grade if I study 4 hours?

# Machine Learning



# Machine Learning



# Model design

- What would be the best model for the data?
- Linear model?

| x (hours) | y (points) |
|-----------|------------|
| 1         | 2          |
| 2         | 4          |
| 3         | 6          |
| 4         | ?          |



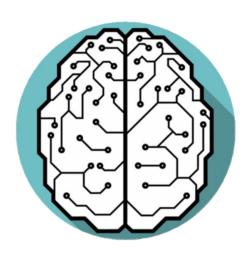
#### Linear Model

$$\hat{y} = x * \omega + b$$

# Model design

- What would be the best model for the data?
- Linear model?

| x (hours) | y (points) |
|-----------|------------|
| 1         | 2          |
| 2         | 4          |
| 3         | 6          |
| 4         | ?          |



#### Linear Model

$$\hat{y} = x * \omega$$

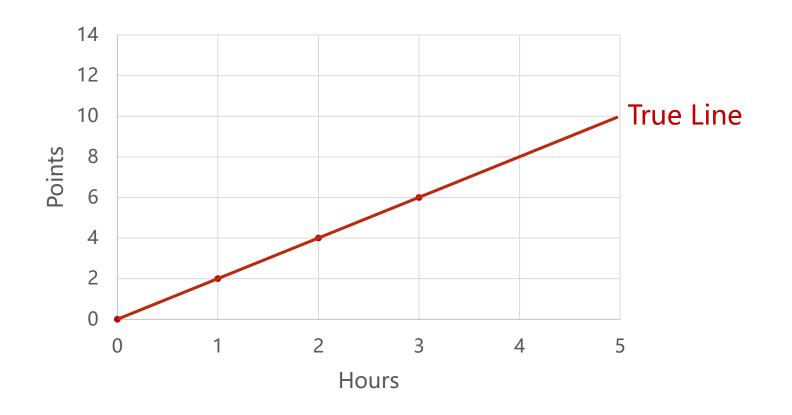
To simplify the model

#### **Linear Regression**

#### Linear Model

$$\hat{y} = x * \omega$$

| x (hours) | y (points) |
|-----------|------------|
| 1         | 2          |
| 2         | 4          |
| 3         | 6          |
|           |            |



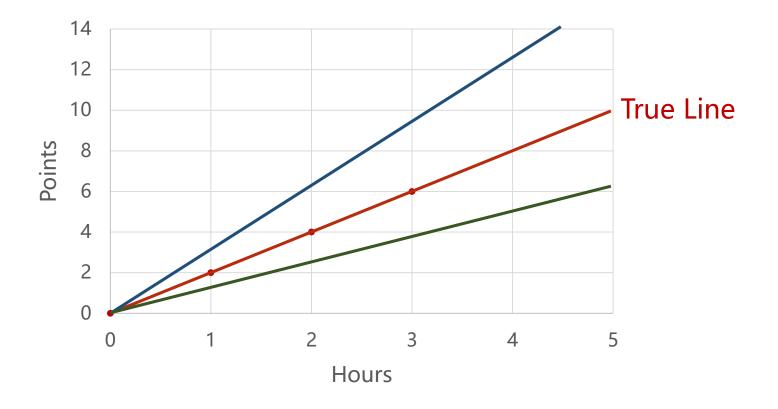
#### **Linear Regression**

#### Linear Model

$$\hat{y} = x * \omega$$

| x (hours) | y (points) |
|-----------|------------|
| 1         | 2          |
| 2         | 4          |
| 3         | 6          |
|           |            |

#### The machine starts with **a random guess**, $\omega$ = random value



$$loss = (\hat{y} - y)^2 = (x * \omega - y)^2$$

| x (Hours) | y (Points) | y_predict (w=3) | Loss (w=3)  |
|-----------|------------|-----------------|-------------|
| 1         | 2          | 3               | 1           |
| 2         | 4          | 6               | 4           |
| 3         | 6          | 9               | 9           |
|           |            |                 | mean = 14/3 |

$$loss = (\hat{y} - y)^2 = (x * \omega - y)^2$$

| x (Hours) | y (Points) | y_predict (w=4) | Loss (w=4)  |
|-----------|------------|-----------------|-------------|
| 1         | 2          | 4               | 4           |
| 2         | 4          | 8               | 16          |
| 3         | 6          | 12              | 36          |
|           |            |                 | mean = 56/3 |

$$loss = (\hat{y} - y)^2 = (x * \omega - y)^2$$

| x (Hours) | y (Points) | y_predict (w=0) | Loss (w=0)  |
|-----------|------------|-----------------|-------------|
| 1         | 2          | 0               | 4           |
| 2         | 4          | 0               | 16          |
| 3         | 6          | 0               | 36          |
|           |            |                 | mean = 56/3 |

$$loss = (\hat{y} - y)^2 = (x * \omega - y)^2$$

| x (Hours) | y (Points) | y_predict (w=1) | Loss (w=1)  |
|-----------|------------|-----------------|-------------|
| 1         | 2          | 1               | 1           |
| 2         | 4          | 2               | 4           |
| 3         | 6          | 3               | 9           |
|           |            |                 | mean = 14/3 |

$$loss = (\hat{y} - y)^2 = (x * \omega - y)^2$$

| x (Hours) | y (Points) | y_predict (w=2) | Loss (w=2) |
|-----------|------------|-----------------|------------|
| 1         | 2          | 2               | 0          |
| 2         | 4          | 4               | 0          |
| 3         | 6          | 6               | 0          |
|           |            |                 | mean = 0   |

#### Loss function & Cost function

#### Training Loss (Error)

$$loss = (\hat{y} - y)^2 = (x * \omega - y)^2$$



#### Mean Square Error

$$cost = \frac{1}{N} \sum_{n=1}^{N} (\hat{y}_n - y_n)^2$$

#### **Compute Cost**

#### Mean Square Error

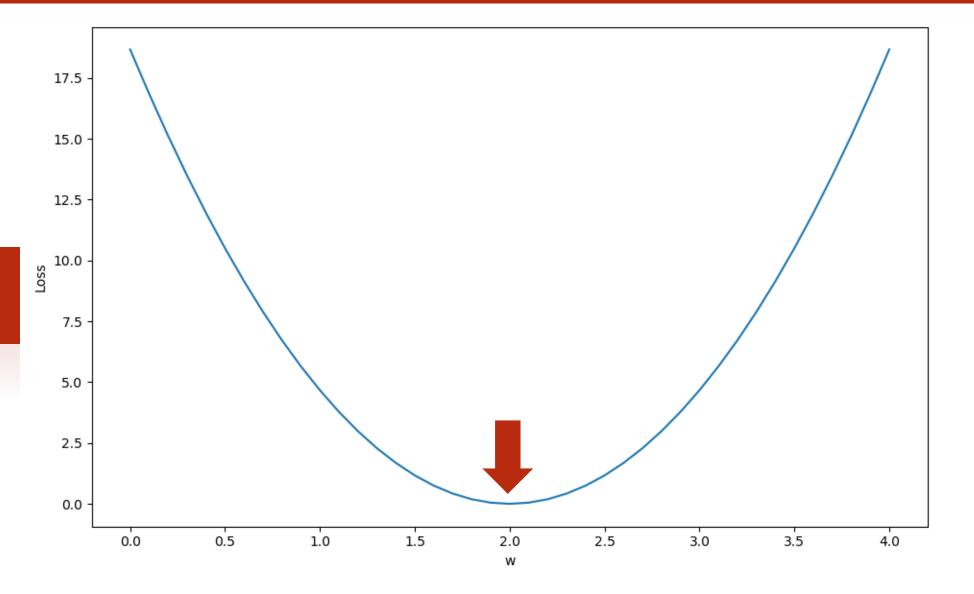
$$cost = \frac{1}{N} \sum_{n=1}^{N} (\hat{y}_n - y_n)^2$$

| x (Hours) | Loss (w=0) | Loss (w=1) | Loss (w=2) | Loss (w=3) | Loss (w=4) |
|-----------|------------|------------|------------|------------|------------|
| 1         | 4          | 1          | 0          | 1          | 4          |
| 2         | 16         | 4          | 0          | 4          | 16         |
| 3         | 36         | 9          | 0          | 9          | 36         |
| MSE       | 18.7       | 4.7        | 0          | 4.7        | 18.7       |

# **Linear Regression**

It can be found that when  $\omega = 2$ , the cost will be minimal.

will be minimal



```
import numpy as np
import matplotlib.pyplot as plt
x data = [1.0, 2.0, 3.0]
y data = [2.0, 4.0, 6.0]
def forward(x):
    return x * w
def loss(x, y):
    y \text{ pred} = forward(x)
    return (y pred - y) * (y pred - y)
w list = []
mse 1ist = []
for w in np. arange (0.0, 4.1, 0.1):
    print('w=', w)
    1 \text{ sum} = 0
    for x val, y_val in zip(x_data, y_data):
        y pred val = forward(x val)
        loss val = loss(x val, y val)
        1 \text{ sum} += 1 \text{ oss val}
        print('\t', x_val, y_val, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w_list.append(w)
    mse list.append(1 sum / 3)
```

```
import numpy as np
import matplotlib.pyplot as plt
```

Import necessary library to draw the graph.

```
import numpy as np
import matplotlib.pyplot as plt
x_{data} = [1.0, 2.0, 3.0]
y data = [2.0, 4.0, 6.0]
def forward(x):
    return x * w
def loss(x, y):
    y \text{ pred} = forward(x)
    return (y pred - y) * (y pred - y)
w list = []
mse 1ist = []
for w in np. arange (0.0, 4.1, 0.1):
    print('w=', w)
    1 \text{ sum} = 0
    for x_val, y_val in zip(x_data, y_data):
        y pred val = forward(x val)
        loss val = loss(x val, y val)
        1 \text{ sum} += 1 \text{ oss val}
        print('\t', x_val, y_val, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w list.append(w)
    mse_list.append(1 sum / 3)
```

```
x_data = [1.0, 2.0, 3.0]
y_data = [2.0, 4.0, 6.0]
```

Prepare the train set.

```
import numpy as np
import matplotlib.pyplot as plt
x data = [1.0, 2.0, 3.0]
y data = [2.0, 4.0, 6.0]
def forward(x):
    return x * w
def loss(x, y):
    y \text{ pred} = forward(x)
    return (y pred - y) * (y pred - y)
w list = []
mse list = []
for w in np. arange (0.0, 4.1, 0.1):
    print('w=', w)
    1 \text{ sum} = 0
    for x val, y_val in zip(x_data, y_data):
        y pred val = forward(x val)
        loss val = loss(x val, y val)
        1 \text{ sum} += 1 \text{ oss val}
        print('\t', x_val, y_val, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w list.append(w)
    mse list.append(1 sum / 3)
```

```
def forward(x):
    return x * w
```

#### Define the model:

#### Linear Model

$$\hat{y} = x * \omega$$

```
import numpy as np
import matplotlib.pyplot as plt
x data = [1.0, 2.0, 3.0]
y data = [2.0, 4.0, 6.0]
def forward(x):
    return x * w
def loss(x, y):
    y \text{ pred} = forward(x)
    return (y pred - y) * (y pred - y)
w list = []
mse 1ist = []
for w in np. arange (0.0, 4.1, 0.1):
    print('w=', w)
    1 \text{ sum} = 0
    for x val, y val in zip(x data, y data):
        y_pred_val = forward(x val)
        loss val = loss(x val, y val)
        1 sum += loss val
        print('\t', x_val, y_val, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w list.append(w)
    mse list.append(1 sum / 3)
```

```
def loss(x, y):
    y_pred = forward(x)
    return (y_pred - y) * (y_pred - y)
```

Define the loss function:

#### **Loss Function**

$$loss = (\hat{y} - y)^2 = (x * \omega - y)^2$$

```
import numpy as np
import matplotlib.pyplot as plt
x_{data} = [1.0, 2.0, 3.0]
y data = [2.0, 4.0, 6.0]
def forward(x):
    return x * w
def loss(x, y):
    y \text{ pred} = forward(x)
    return (y pred - y) * (y pred - y)
w list = []
mse 1ist = []
for w in np. arange (\hat{0}, \hat{0}, 4, \hat{1}, \hat{0}, \hat{1}):
    print('w=', w)
    1 \text{ sum} = 0
    for x_val, y_val in zip(x_data, y_data):
         y pred val = forward(x val)
         loss val = loss(x val, y val)
        1 \text{ sum} += 1 \text{ oss val}
         print('\t', x_val, y_val, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w_list.append(w)
    mse list.append(1 sum / 3)
```

```
w_list = []
mse_list = []
```

List  $w_l$  ist save the weights  $\omega$ . List  $mse_l$  ist save the cost values of each  $\omega$ .

```
import numpy as np
import matplotlib.pyplot as plt
x data = [1.0, 2.0, 3.0]
y data = [2.0, 4.0, 6.0]
def forward(x):
    return x * w
def loss(x, y):
    y \text{ pred} = forward(x)
    return (y pred - y) * (y pred - y)
w list = []
mse list = []
for w in np. arange (0.0, 4.1, 0.1):
    print('w=', w)
    1 \text{ sum} = 0
    for x val, y_val in zip(x_data, y_data):
        y pred val = forward(x val)
        loss val = loss(x val, y val)
        1 sum += loss val
        print('\t', x_val, y_val, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w_list.append(w)
    mse list.append(1 sum / 3)
```

```
for w in np. arange (0.0, 4.1, 0.1):
```

Compute cost value at [0.0, 0.1, 0.2, ..., 4.0]

```
import numpy as np
import matplotlib.pyplot as plt
x data = [1.0, 2.0, 3.0]
y_{data} = [2.0, 4.0, 6.0]
def forward(x):
    return x * w
def loss(x, y):
    y \text{ pred} = forward(x)
    return (y pred - y) * (y pred - y)
w 1 ist = []
mse 1ist = []
for w in np. arange (0.0, 4.1, 0.
    print ('w=', w)
    for x val, y val in zip(x data, y data):
        y_pred_val = forward(x val)
        loss val = loss(x val, y val)
        1 \text{ sum } += 1 \text{ oss val}
        print('\t', x_val, y_val, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w list.append(w)
    mse list.append(1 sum / 3)
```

```
for x_val, y_val in zip(x_data, y_data):
    y_pred_val = forward(x_val)
    loss_val = loss(x_val, y_val)
    l_sum += loss_val
    print('\t', x_val, y_val, y_pred_val, loss_val)
```

For each sample in train set, the loss function values were computed.

#### **ATTENTION:**

Value of cost function is the sum of loss function.

```
import numpy as np
import matplotlib.pyplot as plt
x_{data} = [1.0, 2.0, 3.0]
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def forward(x):
    return x * w
def loss(x, y):
    y \text{ pred} = forward(x)
    return (y pred - y) * (y pred - y)
w 1 ist = []
mse 1ist = []
for w in np. arange (0.0, 4.1, 0.1):
    print('w=', w)
    1 \text{ sum} = 0
    for x_val, y_val in zip(x_data, /y_data):
        y pred val = forward(x val)
        loss val = loss(x val, y val)
        1 \text{ sum} += 1 \text{oss val}
        print('\t', x_val, y_al, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w_list.append(w)
    mse_list.append(1 sum / 3)
```

```
w_list.append(w)
mse_list.append(l_sum / 3)
```

Save  $\omega$  and correspondence **MSE**.

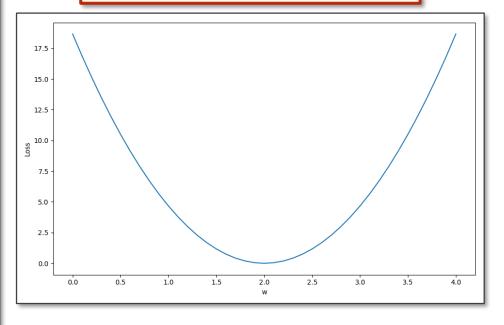
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    return (y pred - y) * (y pred - y)
w list = []
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for w in np. arange (0.0, 4.1, 0.1):
    print ('w=', w)
    1 \text{ sum} = 0
    for x val, y val in zip(x data, y data):
        y pred val = forward(x val)
        loss val = loss(x val, y val)
        1 \text{ sum } += 1 \text{ oss val}
        print('\t', x_val, y_val, y_pred_val, loss_val)
    print('MSE=', 1 sum / 3)
    w list.append(w)
    mse list.append(1 sum / 3)
```

#### Part of result

```
w = 0.0
        1.00 2.00 0.00 4.00
        2.00 4.00 0.00 16.00
        3.00 6.00 0.00 36.00
MSE= 18.6666666666668
w = 0.1
        1.00 2.00 0.10 3.61
        2.00 4.00 0.20 14.44
        3.00 6.00 0.30 32.49
MSE= 16.8466666666668
w = 0.2
        1.00 2.00 0.20 3.24
        2.00 4.00 0.40 12.96
        3.00 6.00 0.60 29.16
MSE= 15.1200000000000003
w= 0.30000000000000004
        1.00 2.00 0.30 2.89
        2.00 4.00 0.60 11.56
        3.00 6.00 0.90 26.01
MSE= 13.48666666666665
w = 0.4
        1.00 2.00 0.40 2.56
        2.00 4.00 0.80 10.24
        3.00 6.00 1.20 23.04
MSE= 11.946666666666667
w = 0.5
        1.00 2.00 0.50 2.25
        2.00 4.00 1.00 9.00
        3.00 6.00 1.50 20.25
MSE= 10.5
```

#### Draw the graph

```
plt.plot(w_list, mse_list)
plt.ylabel('Loss')
plt.xlabel('w')
plt.show()
```



#### Exercise

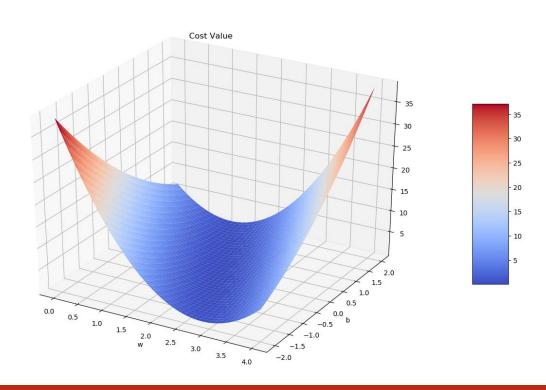
• Try to use the model in right-side, and draw the cost graph.

#### • Tips:

- You can read the material of how to draw 3d graph. [link]
- Function *np.meshgrid()* is very popular for drawing 3d graph, read the [docs] and utilize vectorization calculation.

#### Linear Model

$$\hat{y} = x * \omega + b$$





# PyTorch Tutorial

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