

# Numpy for Vector and Matrix Operations

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# References/Reading

## NumPy user guide

This guide is an overview and explains the important features

- What is NumPy?
- Installation
- NumPy quickstart
- NumPy: the absolute basics for beginners
- NumPy fundamentals
- Miscellaneous
- NumPy for MATLAB users
- Building from source
- Using NumPy C-API
- NumPy Tutorials
- NumPy How Tos
- For downstream package authors

<https://numpy.org/doc/stable/user/index.html>

## Chapter 2

### Matrices

#### 2.1 Operations with Matrices

**Homework:** §2.1 (page 56): 7, 9, 13, 15, 17, 25, 27, 35, 37, 41, 46, 49, 67

**Main points in this section:**

1. We define a few concept regarding matrices. This would include addition of matrices, scalar multiplication and multiplication of matrices.
2. We also represent a system of linear equation as equation with matrices.

<https://mandal.ku.edu/math290/m290NotesChap2.pdf>

# Objective

## ❖ Traditional notation → Vectorized one

1) Pick a sample  $(x, y)$  from training data

2) Compute the output  $\hat{y}$

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

3) Compute loss

$$L = (\hat{y} - y)^2$$

4) Compute derivative

$$\frac{\partial L}{\partial w} = 2x(\hat{y} - y)$$

$$\frac{\partial L}{\partial b} = 2(\hat{y} - y)$$

5) Update parameters

$$w = w - \eta \frac{\partial L}{\partial w}$$

$$b = b - \eta \frac{\partial L}{\partial b}$$

$\eta$  is learning rate

Tradition

$$\mathbf{x} = \begin{bmatrix} 1 \\ x \end{bmatrix}$$

$$\boldsymbol{\theta} = \begin{bmatrix} b \\ w \end{bmatrix}$$

1) Pick a sample  $(x, y)$  from training data

2) Compute output  $\hat{y}$

$$\hat{y} = \boldsymbol{\theta}^T \mathbf{x} = \mathbf{x}^T \boldsymbol{\theta}$$

3) Compute loss

$$L = (\hat{y} - y)^2$$

4) Compute derivative

$$L'_{\boldsymbol{\theta}} = 2\mathbf{x}(\hat{y} - y)$$

5) Update parameters

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta L'_{\boldsymbol{\theta}}$$

$\eta$  is learning rate

Vectorization

# Objective

## ❖ Implementation (tradition)

1) Pick a sample  $(x, y)$  from training data

2) Compute the output  $\hat{y}$

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

3) Compute loss

$$L = (\hat{y} - y)^2$$

4) Compute derivative

$$\frac{\partial L}{\partial w} = 2x(\hat{y} - y) \qquad \frac{\partial L}{\partial b} = 2(\hat{y} - y)$$

5) Update parameters

$$w = w - \eta \frac{\partial L}{\partial w} \qquad b = b - \eta \frac{\partial L}{\partial b}$$

$\eta$  is learning rate

```
1 # forward
2 def predict(x, w, b):
3     return x*w + b
4
5 # compute gradient
6 def gradient(y_hat, y, x):
7     dw = 2*x*(y_hat-y)
8     db = 2*(y_hat-y)
9
10    return (dw, db)
11
12 # update weights
13 def update_weight(w, b, lr, dw, db):
14     w_new = w - lr*dw
15     b_new = b - lr*db
16
17    return (w_new, b_new)
```

# Objective

## ❖ Implementation (vectorization using numpy)

1) Pick a sample  $(x, y)$  from training data

2) Compute output  $\hat{y}$

$$\hat{y} = \theta^T x = x^T \theta$$

3) Compute loss

$$L = (\hat{y} - y)^2$$

4) Compute derivative

$$L'_\theta = 2x(\hat{y} - y)$$

5) Update parameters

$$\theta = \theta - \eta L'_\theta$$

$\eta$  is learning rate

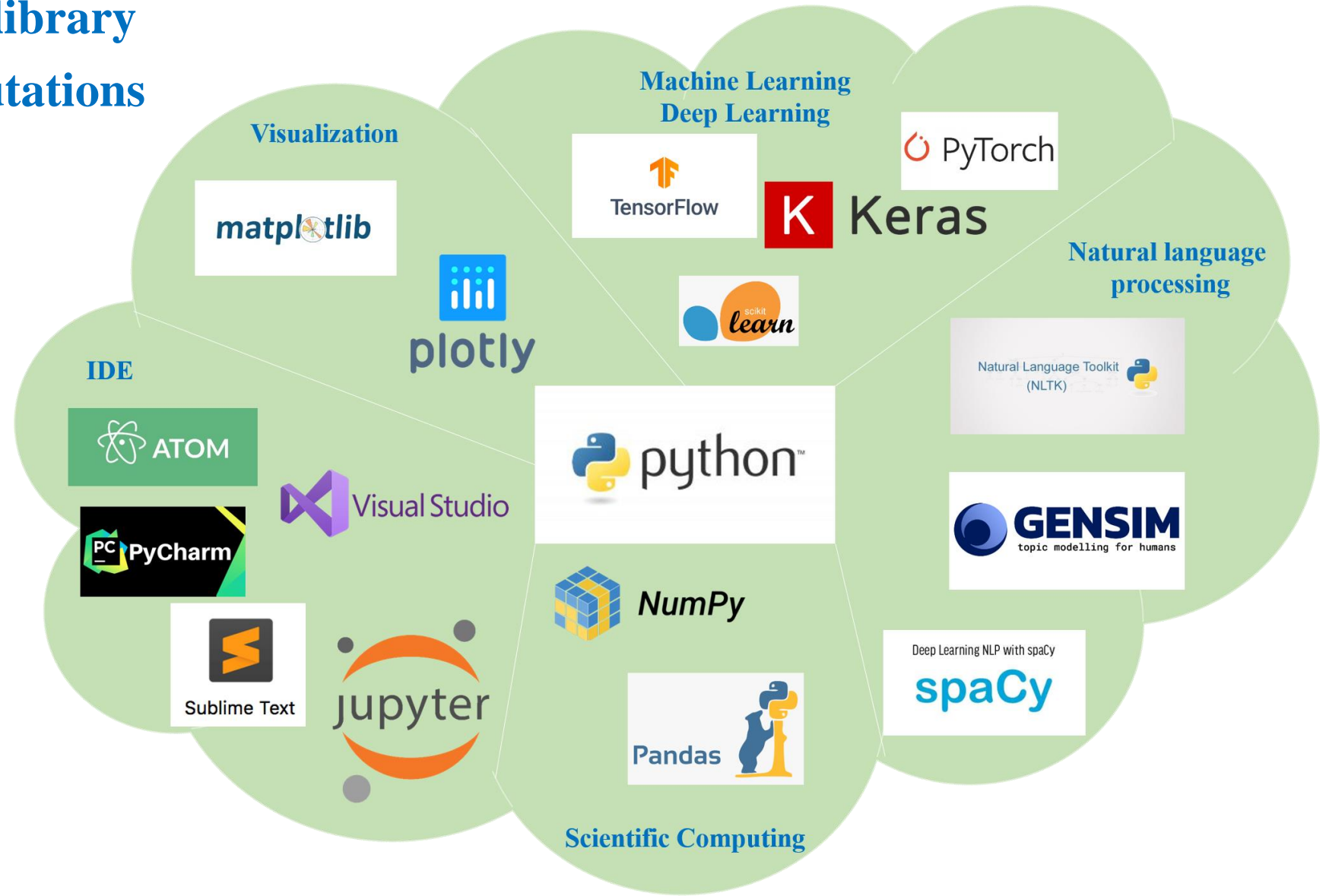
```
1 import numpy as np
2
3 # forward
4 def predict(x, theta):
5     return x.dot(theta)
6
7 # compute gradient
8 def gradient(y_hat, y, x):
9     dtheta = 2*x*(y_hat-y)
10
11     return dtheta
12
13 # update weights
14 def update_weight(theta, lr, dtheta):
15     dtheta_new = theta - lr*dtheta
16
17     return dtheta_new
```

# Outline

- **Introduction to Numpy**
- **Numpy Examples**
- **Introduction to Vector and Matrix**
- **Vectorize the Linear Regression (1-sample)**

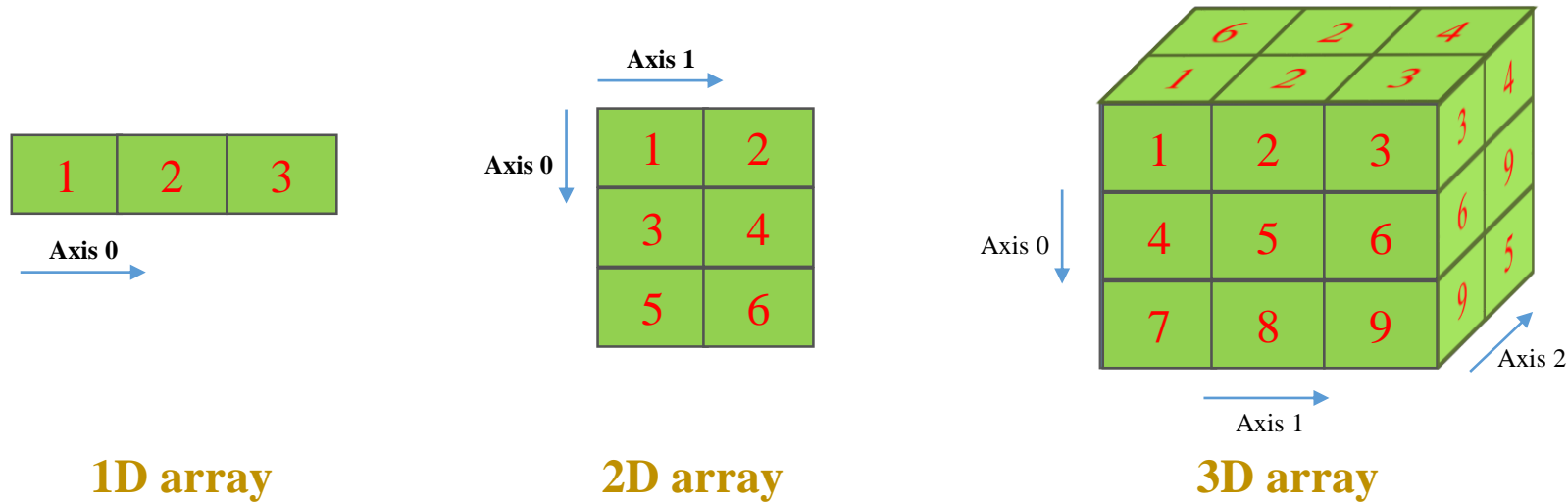
# Introduction to Numpy

- ❖ Numpy is a Python library
- ❖ For scientific computations



# Introduction to Numpy

- ❖ Numpy is a Python library
- ❖ For scientific computations
- ❖ Numpy array  $\leftrightarrow$  Tensor in Tensorflow and Pytorch
- ❖ Numpy arrays are multi-dimensional arrays



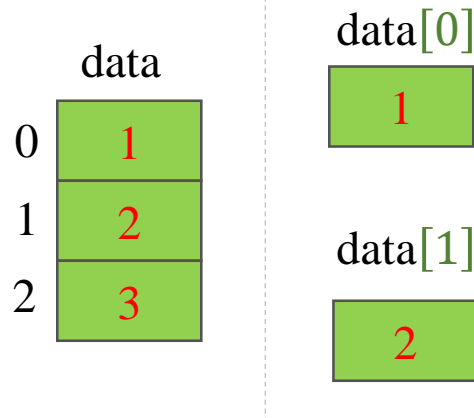


# Introduction to Numpy

## ❖ Create Numpy array

### ❖ From List

```
arr_np = np.array(python_list)
```



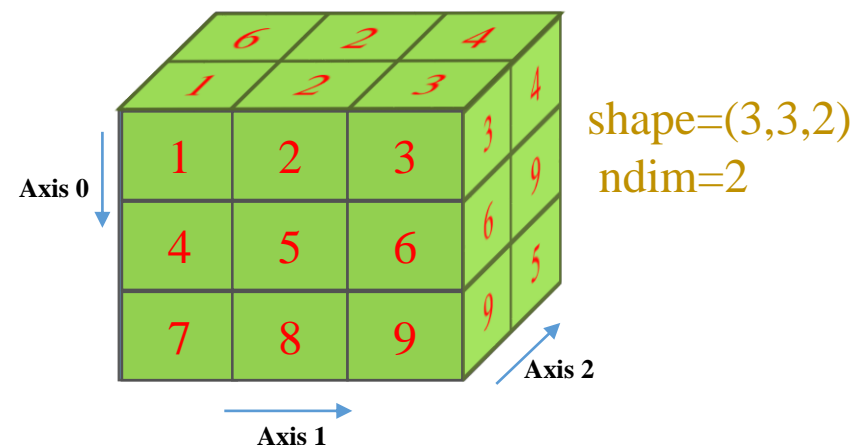
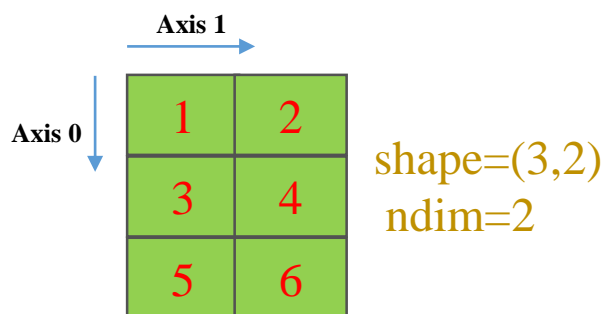
```
2 # tạo ndarray từ list
3
4 import numpy as np
5
6 # tạo list
7 l = list(range(1, 4))
8
9 # tạo ndarray
10 data = np.array(l)
11
12 print(data)
13 print(data[0])
14 print(data[1])
```

```
[1 2 3]
1
2
```

# Introduction to Numpy

## ❖ Common attributes

- ❖ dtype: data type
- ❖ shape: return a tuple of #elements in each dimension
- ❖ ndim: return #dimensions



```
2 # tạo ndarray từ list
3
4 import numpy as np
5
6 # tạo list
7 list1D = [1,2,3]
8
9 # tạo ndarray
10 data = np.array(list1D)
11
12 print(data)
13 print(data.shape)
```

```
[1 2 3]
(3,)
```

```
2 # tạo ndarray từ list
3
4 import numpy as np
5
6 # tạo list
7 list2D = [[1,2],[3,4],[5,6]]
8
9 # tạo ndarray
10 data = np.array(list2D)
11
12 print(data)
13 print(data.shape)
```

```
[[1 2]
 [3 4]
 [5 6]]
(3, 2)
```

```
2 # tạo ndarray từ list
3
4 import numpy as np
5
6 # tạo list
7 list3D = [[[1,6], [2,2], [3,4]],
8           [[4,7], [5,2], [6,9]],
9           [[7,7], [8,2], [9,5]]]
10
11 # tạo ndarray
12 data = np.array(list3D)
13
14 #print(data)
15 print(data.shape)
```

```
(3, 3, 2)
```

# Introduction to Numpy

## ❖ Common attributes

- ❖ dtype: data type
- ❖ shape: return a tuple of #elements in each dimension
- ❖ ndim: return #dimensions

### dtype example

```
4 import numpy as np
5
6 # tạo ndarray
7 data1 = np.array([1,2,3])
8 print(data1.dtype)
9
10 data2 = np.array([1.,2.,3.])
11 print(data2.dtype)
12
13 data3 = np.array([1,2,3], dtype=np.int64)
14 print(data3.dtype)
```

```
int32
float64
int64
```

### ndim example

```
4 import numpy as np
5
6 # tạo ndarray
7 data1 = np.array([1,2,3])
8 print(data1.ndim)
9
10 data2 = np.array([[1,2,3]])
11 print(data2.ndim)
12
13 data3 = np.array([[1],[2],[3]])
14 print(data3.ndim)
```

```
1
2
2
```

# Introduction to Numpy

## ❖ Create Numpy arrays

### zeros() function

	0	1	2
0	0	0	0
1	0	0	0

```
2 # Tạo một numpy array
3 # với tất cả phần tử là 0
4
5 import numpy as np
6
7 # shape: 2 dòng, 3 cột
8 arr = np.zeros((2,3))
9 print(arr)
```

```
[[0. 0. 0.]
 [0. 0. 0.]]
```

### ones() function

	0	1	2
0	1	1	1
1	1	1	1

```
2 # Tạo một numpy array với
3 # tất cả phần tử là 1
4
5 import numpy as np
6
7 # numpy.ones(shape)
8 # shape: 2 dòng, 3 cột
9 arr = np.ones((2,3))
10 print(arr)
```

```
[[1. 1. 1.]
 [1. 1. 1.]]
```

### full() function

	0	1	2
0	9	9	9
1	9	9	9

```
2 # Tạo một numpy array với tất
3 # cả phần tử là hằng số fill_value
4
5 import numpy as np
6
7 # numpy.full(shape, fill_value)
8 # shape: 2 dòng, 3 cột
9 arr = np.full((2,3), 9)
10 print(arr)
```

```
[[9 9 9]
 [9 9 9]]
```

# Introduction to Numpy

## ❖ Create Numpy arrays

### arange() function

	0	1	2	3	4
arr1 =	0	1	2	3	4

	0	1	2
arr2 =	0	2	4

### eye() function

	0	1	2
0	1	0	0
1	0	1	0
2	0	0	1

### random() function

	0	1	2
0	0.574	0.682	0.704
1	0.806	0.844	0.799

```
2 import numpy as np
3
4 # np.arange(start=0, stop, step=1)
5 arr1 = np.arange(5)
6 print(arr1)
7
8 arr2 = np.arange(0, 5, 2)
9 print(arr2)
```

```
[0 1 2 3 4]
[0 2 4]
```

```
2 # Tạo một numpy array với đường chéo là số 1
3 # số 0 được điền vào những ô phần tử còn lại
4
5 import numpy as np
6
7 # numpy.eye(N)
8 # shape: 3 dòng, 3 cột
9 arr = np.eye(3)
10 print(arr)
```

```
[[1. 0. 0.]
 [0. 1. 0.]
 [0. 0. 1.]]
```

```
2 # Tạo một numpy array với
3 # giá trị ngẫu nhiên
4
5 import numpy as np
6
7 # np.random.random(size)
8 # shape: 2 dòng, 3 cột; với
9 # phần tử có giá trị ngẫu nhiên
10 arr = np.random.random((2,3))
11 print(arr)
```

```
[[0.57488062 0.68266312 0.70438569]
 [0.80661973 0.84413356 0.79905247]]
```

# Introduction to Numpy

## ❖ Slicing

```
arr[for_axis_0, for_axis_1, ...]
```

	0	1	2	3	4	5
data =	1	2	3	4	5	6

	0	1	2	3	4	5
data[:,1] =	1	2	3	4	5	6

	0	1	2	3	4	5
data[::-1] =	6	5	4	3	2	1

	0	1	2	3	4	5
data[:] =	1	2	3	4	5	6

	0	1	2
data[2:5:1] =	3	4	5

	0	1	2
data[2:5:-1] =	6	5	4

	0	1	2
data[:3] =	1	2	3

':' - get all the elements

'start : stop : step'  
get the elements from  $a^{th}$  to  $(b^{th}-1)$

Could be ignored

step = 1

# Introduction to Numpy

## ❖ Slicing

```
arr[for_axis_0, for_axis_1, ...]
```

':' - get all the elements

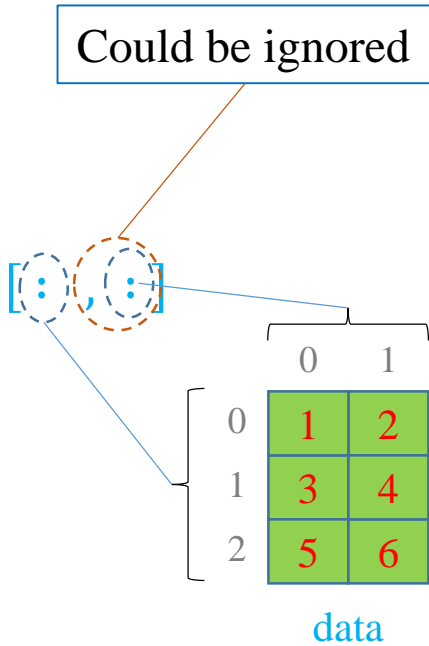
'start : stop : step'

get the elements from  $a^{th}$  to  $(b^{th}-1)$

Could be ignored

step = 1

Could be ignored



	0	1
0	1	2
1	3	4
2	5	6

data[:, :]

	0	1
0	3	4
1	5	6

data[1:3]

	0
0	1
1	3
2	5

data[:, :1]

	0
0	1
1	3
2	5

data[:, 1]

Feature

Label

	area	price
0	6.7	9.1
1	4.6	5.9
2	3.5	4.6
3	5.5	6.7

0 1

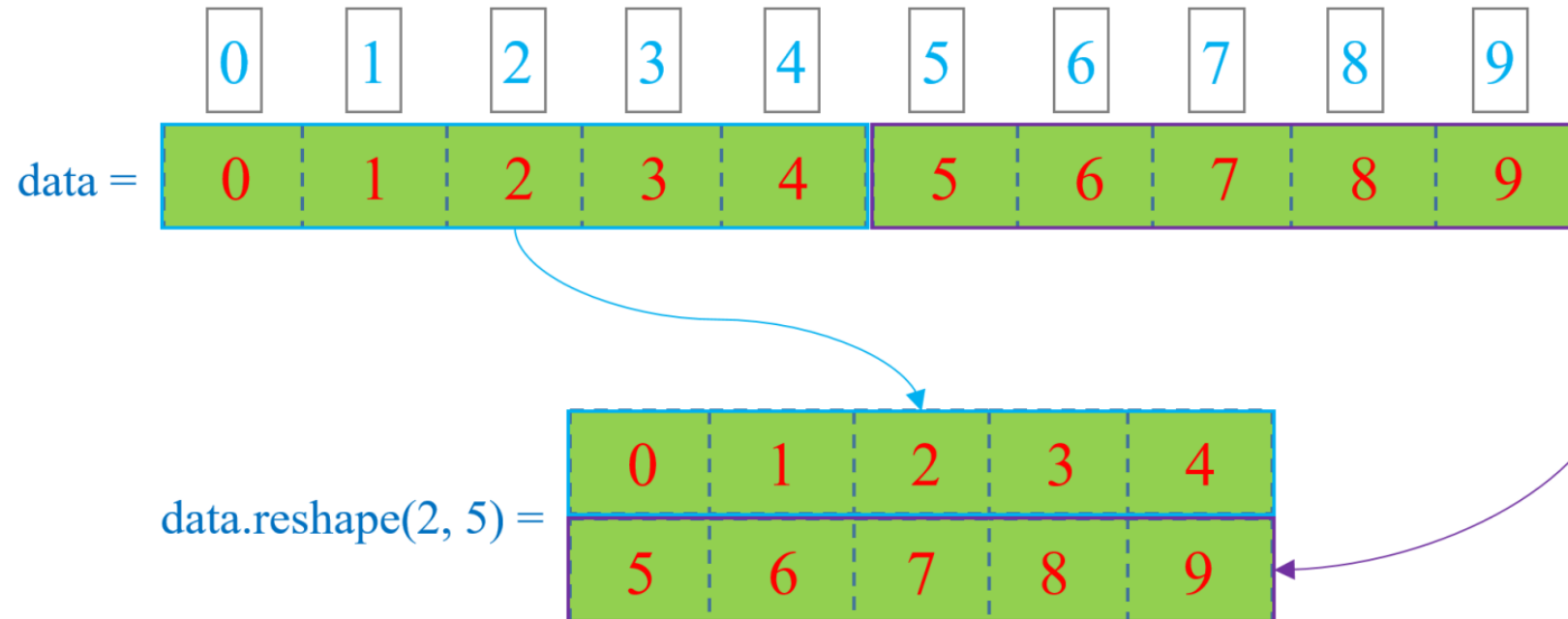
Get the area column as a matrix?

Get the price column as a vector?

## ❖ Reshape an array

```
1 # Python code
2 import numpy as np
3
4 # create a 1D ndarray from 0 to 9
5 data = np.arange(10)
6 print(data)
7
8 # reshape data to 2 rows and 5 columns
9 data_2d = data.reshape(2, 5)
10 print(data_2d)
```

```
===== Output =====
[0 1 2 3 4 5 6 7 8 9]
[[0 1 2 3 4]
 [5 6 7 8 9]]
=====
```





# Numpy

## Summation

## Square root

data		result
1	sqrt(data) =	1.0
2		1.4
3		1.7
4		2.0

```

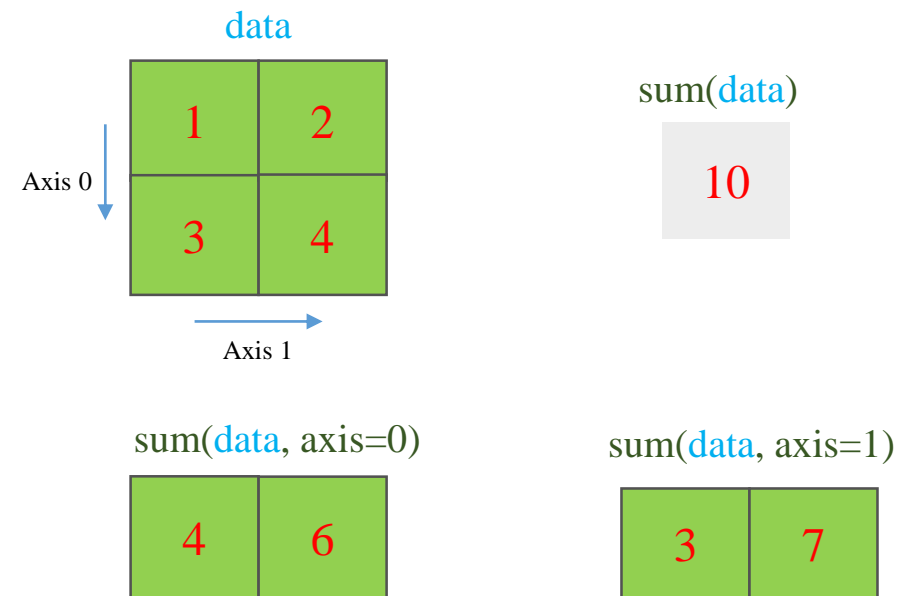
4 data = np.array([1,2,3,4])
5
6 print('data \n', data)
7
8 # Căn bậc 2 từng phần tử trong data
9 print('sqrt \n', np.sqrt(data))

```

```

data
[1 2 3 4]
sqrt
[1.         1.41421356 1.73205081 2.         ]

```



```

4 data = np.array([[1,2],
5                  [3,4]])
6
7 # Tổng các phần tử của mảng
8 print(np.sum(data))
9
10 # Tính tổng theo từng cột
11 print(np.sum(data, axis=0))
12
13 # Tính tổng theo từng dòng
14 print(np.sum(data, axis=1))

```

```

10
[4 6]
[3 7]

```

arr\_1 

1	2	3
---	---	---

**numpy.hstack()**

arr\_2 

4	5	6
---	---	---

`data = np.hstack((arr_1, arr_2))`

`np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])`

result 

1	2	3	4	5	6
---	---	---	---	---	---

```
4 import numpy as np
5
6 arr_1 = np.array([1, 2, 3])
7 print("arr_1: ", arr_1)
8
9 arr_2 = np.array([4, 5, 6])
10 print("arr_2: ", arr_2)
11
12 # kết hợp array theo chiều ngang
13 result = np.hstack((arr_1, arr_2))
14 print("result: ", result)
```

arr\_1: [1 2 3]  
arr\_2: [4 5 6]  
result: [1 2 3 4 5 6]

**numpy.vstack()**

arr\_1 

1	2	3
---	---	---

arr\_2 

4	5	6
---	---	---

`vstack((arr_1, arr_2))`

result 

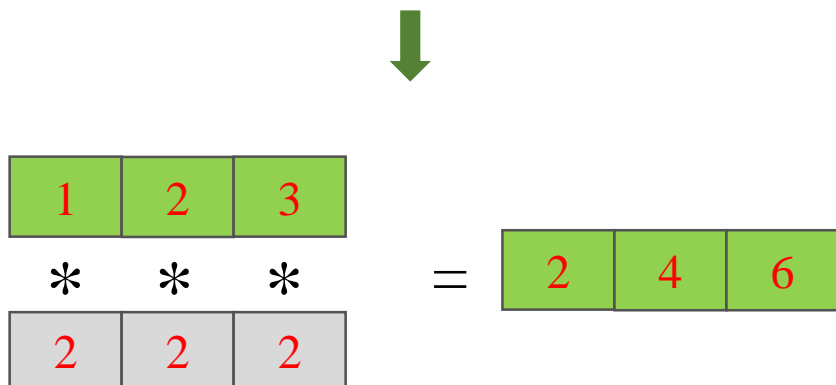
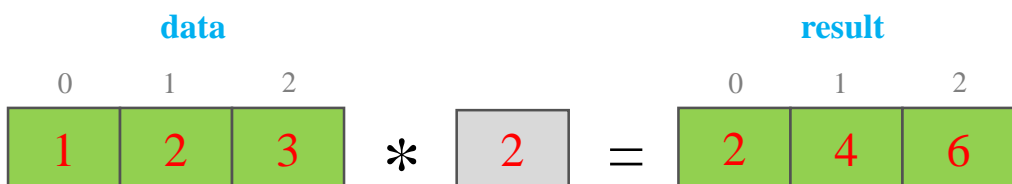
1	2	3
4	5	6

```
6 arr_1 = np.array([1, 2, 3])
7 print("arr_1: ", arr_1)
8
9 arr_2 = np.array([4, 5, 6])
10 print("arr_2: ", arr_2)
11
12 # kết hợp array theo chiều dọc
13 result = np.vstack((arr_1, arr_2))
14 print("result: \n", result)
```

arr\_1: [1 2 3]  
arr\_2: [4 5 6]  
result:  
[[1 2 3]  
[4 5 6]]

# Broadcasting

## ❖ Vector and a scalar

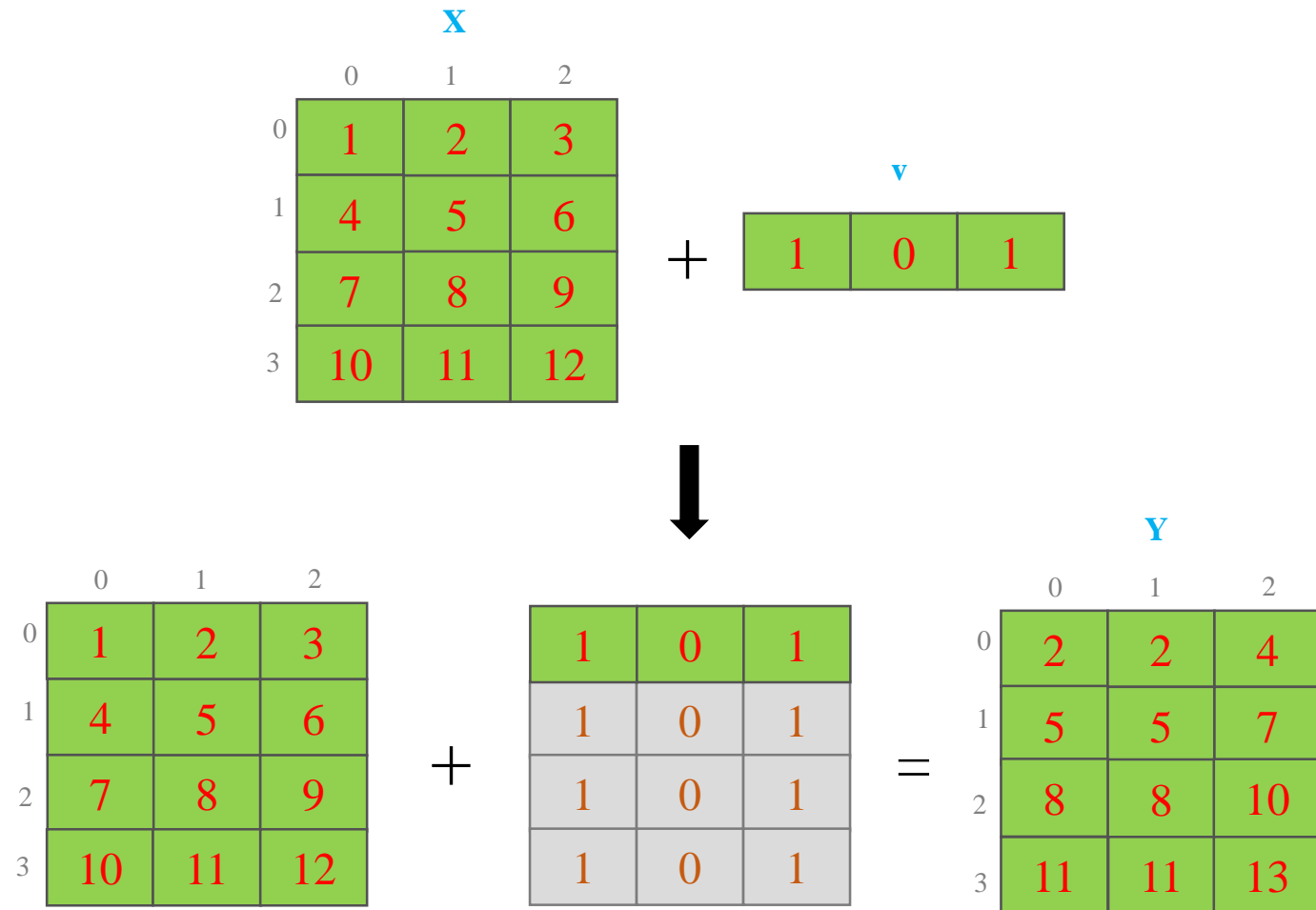


```
1 # aivietnam.ai
2 import numpy as np
3
4 # create data
5 data = np.array([1,2,3])
6 factor = 2
7
8 # broadcasting
9 result_multiplication = data*factor
10 result_minus = data - factor
11
12 print(data)
13 print(result_multiplication)
14 print(result_minus)
```

```
[1 2 3]
[2 4 6]
[-1  0  1]
```

# Broadcasting

## ❖ Matrix and vector



```
1 # aivietnam.ai
2 import numpy as np
3
4 X = np.array([[1, 2, 3],
5               [4, 5, 6],
6               [7, 8, 9],
7               [10, 11, 12]])
8 v = np.array([1, 0, 1])
9
10 Y = X + v
11 print(Y)
```

```
[[ 2  2  4]
 [ 5  5  7]
 [ 8  8 10]
 [11 11 13]]
```

# Outline

- Introduction to Numpy
- Numpy Examples
- Introduction to Vector and Matrix
- Vectorize the Linear Regression (1-sample)

# Vector & Matrix

## Vector

$n$  is a natural number

$\mathcal{R}$  is a set of real numbers

$\vec{v}$  has a length of  $n$  and contain real numbers

$$\vec{v} \in \mathcal{R}^n$$

$$\vec{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} \in \begin{bmatrix} \mathcal{R} \\ \mathcal{R} \\ \mathcal{R} \end{bmatrix} = \mathcal{R}^3$$

## Matrix

Matrix  $A$  has the shape of rectangle

Has  $m$  rows and  $n$  columns

Use capital letter

$$A \in \mathcal{R}^{m \times n}$$

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix} \in \begin{bmatrix} \mathcal{R} & \mathcal{R} \\ \mathcal{R} & \mathcal{R} \\ \mathcal{R} & \mathcal{R} \end{bmatrix} = \mathcal{R}^{3 \times 2}$$

# Vector Addition

$$\vec{v} = \begin{bmatrix} v_1 \\ \dots \\ v_3 \end{bmatrix} \quad \vec{u} = \begin{bmatrix} u_1 \\ \dots \\ u_3 \end{bmatrix}$$

$$\vec{v} + \vec{u} = \begin{bmatrix} v_1 \\ \dots \\ v_3 \end{bmatrix} + \begin{bmatrix} u_1 \\ \dots \\ u_3 \end{bmatrix} = \begin{bmatrix} v_1 + u_1 \\ \dots \\ v_3 + u_3 \end{bmatrix}$$

data x		data y		result
1		5		6
2		6		8
3	+	7	=	10
4		8		12

```
1 def add_vectors(vector1, vector2):  
2     '''  
3     Add corresponding elements between two vectors  
4     vector1 and vector2 are with list type  
5     output is a vector (list)  
6     '''  
7  
8     return [v1+v2 for v1, v2 in zip(vector1, vector2)]
```

```
2 import numpy as np  
3  
4 x = np.array([1,2,3,4])  
5 y = np.array([5,6,7,8])  
6  
7 print('data x \n', x)  
8 print('data y \n', y)  
9  
10 # Tổng của 2 mảng  
11 print('method 1 \n', x + y)  
12 print('method 2 \n', np.add(x, y))
```

```
data x  
[1 2 3 4]  
data y  
[5 6 7 8]  
method 1  
[ 6  8 10 12]  
method 2  
[ 6  8 10 12]
```

# Vector Operations

## Vector subtraction

$$\vec{v} = \begin{bmatrix} v_1 \\ \dots \\ v_n \end{bmatrix} \quad \vec{u} = \begin{bmatrix} u_1 \\ \dots \\ u_n \end{bmatrix}$$

$$\vec{v} - \vec{u} = \begin{bmatrix} v_1 \\ \dots \\ v_n \end{bmatrix} - \begin{bmatrix} u_1 \\ \dots \\ u_n \end{bmatrix} = \begin{bmatrix} v_1 - u_1 \\ \dots \\ v_n - u_n \end{bmatrix}$$

```
2 import numpy as np
3
4 x = np.array([5,6,7,8])
5 y = np.array([1,2,3,4])
6
7 print('data x \n', x)
8 print('data y \n', y)
9
10 # Hiệu 2 mảng
11 print('method 1 \n', x - y)
12 print('method 2 \n', np.subtract(x, y))
```

```
data x
[5 6 7 8]
data y
[1 2 3 4]
method 1
[4 4 4 4]
method 2
[4 4 4 4]
```

data x		data y		result
5		1		4
6		2		4
7	-	3	=	4
8		4		4



# Vector Operations

## Multiply with a number

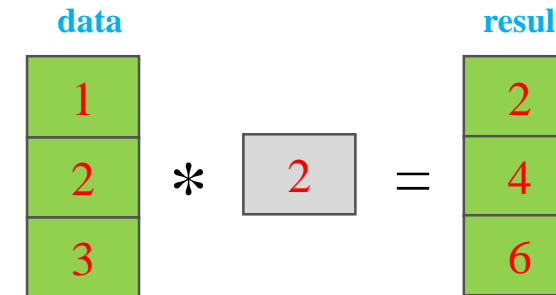
$$\alpha \vec{u} = \alpha \begin{bmatrix} u_1 \\ \dots \\ u_n \end{bmatrix} = \begin{bmatrix} \alpha u_1 \\ \dots \\ \alpha u_n \end{bmatrix}$$

## Length of a vector

$$\|\vec{u}\| = \sqrt{u_1^2 + \dots + u_n^2}$$

```
2 import numpy as np
3
4 # create data
5 data = np.array([1,2,3])
6 factor = 2
7
8 # broadcasting
9 result_multiplication = data*factor
```

```
[1 2 3]
[2 4 6]
```



```
1 # compute length of a vector
2
3 import numpy as np
4
5 data = np.array([1, 2, 4, 2])
6 length = np.linalg.norm(data)
7 print(length)
```

# Matrix Operations

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & \dots & b_{1n} \\ \dots & \dots & \dots \\ b_{m1} & \dots & b_{mn} \end{bmatrix}$$

## Addition

$$A + B = \begin{bmatrix} (a_{11} + b_{11}) & \dots & (a_{1n} + b_{1n}) \\ \dots & \dots & \dots \\ (a_{m1} + b_{m1}) & \dots & (a_{mn} + b_{mn}) \end{bmatrix}$$

## Subtraction

$$A - B = \begin{bmatrix} (a_{11} - b_{11}) & \dots & (a_{1n} - b_{1n}) \\ \dots & \dots & \dots \\ (a_{m1} - b_{m1}) & \dots & (a_{mn} - b_{mn}) \end{bmatrix}$$

```
1 import numpy as np
2
3 A = np.array([[4,2],
4               [9,8]])
5 B = np.array([[1,2],
6               [3,4]])
7
8 print(A+B)
9 print(A-B)
```

```
[[ 5  4]
 [12 12]]
[[ 3  0]
 [ 6  4]]
```

A		B		C												
<table><tr><td>4</td><td>2</td></tr><tr><td>9</td><td>8</td></tr></table>	4	2	9	8	+	<table><tr><td>1</td><td>2</td></tr><tr><td>3</td><td>4</td></tr></table>	1	2	3	4	=	<table><tr><td>5</td><td>4</td></tr><tr><td>12</td><td>12</td></tr></table>	5	4	12	12
4	2															
9	8															
1	2															
3	4															
5	4															
12	12															

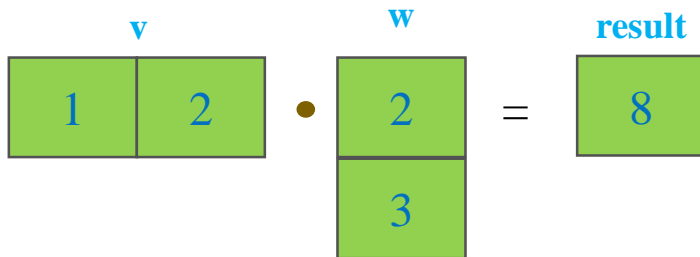
A		B		C												
<table><tr><td>4</td><td>2</td></tr><tr><td>9</td><td>8</td></tr></table>	4	2	9	8	-	<table><tr><td>1</td><td>2</td></tr><tr><td>3</td><td>4</td></tr></table>	1	2	3	4	=	<table><tr><td>3</td><td>0</td></tr><tr><td>6</td><td>4</td></tr></table>	3	0	6	4
4	2															
9	8															
1	2															
3	4															
3	0															
6	4															

# Vector Operations

## Dot product

$$\vec{v} = \begin{bmatrix} v_1 \\ \dots \\ v_n \end{bmatrix} \quad \vec{u} = \begin{bmatrix} u_1 \\ \dots \\ u_n \end{bmatrix}$$

$$\vec{v} \cdot \vec{u} = v_1 \times u_1 + \dots + v_n \times u_n$$



```
1 def dot_product(vector1, vector2):
2     '''
3     Compute dot product between two vectors
4     Output is a floating-point number
5     '''
6
7     return sum([v1*v2 for v1, v2 in zip(vector1, vector2)])
8
9 # test case
10 vector1 = [1, 2, 3]
11 vector2 = [2, 3, 4]
12
13 ouptut = dot_product(vector1, vector2)
14 print(ouptut)
20
```

```
2 import numpy as np
3
4 v = np.array([1, 2])
5 w = np.array([2, 3])
6
7 # Tính inner product giữa v và w
8 print('method 1 \n', v.dot(w))
9 print('method 2 \n', np.dot(v, w))
```

method 1  
8

method 2  
8

# Matrix Operations

## Matrix-vector multiplication

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \quad \vec{x} = \begin{bmatrix} x_1 \\ \dots \\ x_n \end{bmatrix}$$

$$A \in \mathcal{R}^{m \times n}$$

$$C = A\vec{x} \quad \text{where } c_i = \sum_{l=1}^n a_{il}x_l$$

```
1 # aivietnam.ai
2 import numpy as np
3
4 X = np.array([[1,2],
5               [3,4]])
6 v = np.array([1,2])
7
8 print('matrix X \n', X)
9 print('vector v \n', v)
10
11 # phép nhân giữa ma trận và vector
12 print('method 1: X.dot(v) \n', X.dot(v))
13 print('method 1: v.dot(X) \n', v.dot(X))
14 #print('\n method 2: X.dot(v) \n', np.dot(X, v))
15 #print('\n method 2: v.dot(X) \n', np.dot(v, X))
```

```
matrix X
[[1 2]
 [3 4]]
vector v
[1 2]
method 1: X.dot(v)
[ 5 11]
method 1: v.dot(X)
[ 7 10]
```

X			v		result
1	2	•	1	=	5
3	4		2		11

	X			result	
v	1	2	•	7	10
	3	4			

# Matrix Operations

## Matrix-matrix multiplication

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & \dots & b_{1k} \\ \dots & \dots & \dots \\ b_{n1} & \dots & b_{nk} \end{bmatrix}$$
$$A \in \mathcal{R}^{m \times n} \quad B \in \mathcal{R}^{n \times k}$$

$$C = AB$$

$$c_{ij} = \sum_{l=1}^n a_{il} b_{lj}$$

$$AB = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} b_{11} & \dots & b_{1k} \\ \dots & \dots & \dots \\ b_{n1} & \dots & b_{nk} \end{bmatrix} = \begin{bmatrix} (a_{11}b_{11} + \dots + a_{1n}b_{n1}) & \dots & (a_{1n}b_{1k} + \dots + a_{1n}b_{nk}) \\ \dots & \dots & \dots \\ (a_{m1}b_{11} + \dots + a_{mn}b_{n1}) & \dots & (a_{m1}b_{1k} + \dots + a_{mn}b_{nk}) \end{bmatrix}$$

# Matrix Operations

## Matrix-matrix multiplication

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & \dots & b_{1k} \\ \dots & \dots & \dots \\ b_{n1} & \dots & b_{nk} \end{bmatrix}$$
$$A \in \mathcal{R}^{m \times n} \quad B \in \mathcal{R}^{n \times k}$$

$$C = AB$$
$$c_{ij} = \sum_{l=1}^n a_{il} b_{lj}$$

```
1 def matrix_multiplication(matrix1, matrix2):
2     '''
3     This function does the multiplication between two matrices.
4     #columns of matrix1 == #rows of matrix2
5     '''
6     matrix1_nrows = len(matrix1)
7     matrix1_ncols = len(matrix1[0])
8
9     matrix2_nrows = len(matrix2)
10    matrix2_ncols = len(matrix2[0])
11
12    # tạo matrix kết quả
13    result = [[0]*matrix2_ncols for i in range(matrix1_nrows)]
14
15    for i in range(matrix1_nrows):
16        for j in range(matrix2_ncols):
17            for k in range(matrix2_nrows):
18                result[i][j] += matrix1[i][k] * matrix2[k][j]
19
20    return result
21
22    # test case
23    # 3x3 matrix
24    matrix1 = [[1, 2, 3],
25               [4, 5, 6],
26               [7, 8, 9]]
27
28    # 3x4 matrix
29    matrix2 = [[1, 1, 2, 1],
30               [1, 2, 1, 1],
31               [1, 1, 1, 2]]
32
33    result = matrix_multiplication(matrix1, matrix2)
34    print(result[0])
35    print(result[1])
36    print(result[2])
```

```
[6, 8, 7, 9]
[15, 20, 19, 21]
[24, 32, 31, 33]
```

# Matrix-matrix multiplication

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & \dots & b_{1k} \\ \dots & \dots & \dots \\ b_{n1} & \dots & b_{nk} \end{bmatrix}$$

$A \in \mathcal{R}^{m \times n}$        $B \in \mathcal{R}^{n \times k}$

$$C = AB$$

$$c_{ij} = \sum_{l=1}^n a_{il} b_{lj}$$

X			Y			result	
1	2	•	2	3	=	6	5
3	4		2	1		14	13

```
1 # aivietnam.ai
2 import numpy as np
3
4 X = np.array([[1,2],
5               [3,4]])
6 Y = np.array([[2,3],
7               [2,1]])
8
9 # Phép nhân giữa hai ma trận
10 print('method 1 \n', X.dot(Y))
11 print('method 1 \n', Y.dot(X))
12 #print('method 2 \n', np.dot(X, Y))
13 #print('method 2 \n', np.dot(Y, X))
```

```
method 1
[[ 6  5]
 [14 13]]
method 1
[[11 16]
 [ 5  8]]
```

Y			X			result	
2	3	•	1	2	=	11	16
2	1		3	4		5	8

# Hadamard product

$$\vec{v} = \begin{bmatrix} v_1 \\ \dots \\ v_n \end{bmatrix} \quad \vec{u} = \begin{bmatrix} u_1 \\ \dots \\ u_n \end{bmatrix}$$

$$\vec{v} \odot \vec{u} = \begin{bmatrix} v_1 \\ \dots \\ v_n \end{bmatrix} \odot \begin{bmatrix} u_1 \\ \dots \\ u_n \end{bmatrix} = \begin{bmatrix} v_1 \times u_1 \\ \dots \\ v_n \times u_n \end{bmatrix}$$

data x		data y		result
1		5		5
2		6		12
3	*	7	=	21
4		8		32

```
1 def Hadamard_product(vector1, vector2):
2     '''
3     Compute Hadamard product between two vectors
4     Output is a vector
5     '''
6     return [v1*v2 for v1, v2 in zip(vector1, vector2)]
```

```
2 import numpy as np
3
4 x = np.array([1,2,3,4])
5 y = np.array([5,6,7,8])
6
7 print('data x \n', x)
8 print('data y \n', y)
9
10 # Tích các phần tử tương ứng giữa x và y
11 print('method 1 \n', x*y)
12 print('method 2 \n', np.multiply(x, y))
```

```
data x
[1 2 3 4]
data y
[5 6 7 8]
method 1
[ 5 12 21 32]
method 2
[ 5 12 21 32]
```



# Numpy Array Operations

## ❖ Division

data x		data y		result
1	/	5	=	0.2
2		6		0.33
3		7		0.42
4		8		0.5

```
2 import numpy as np
3
4 x = np.array([1,2,3,4])
5 y = np.array([5,6,7,8])
6
7 print('data x \n', x)
8 print('data y \n', y)
9
10 # Phép chia các từng phần tương ứng x cho y
11 print('method 1 \n', x / y)
12 print('method 2 \n', x // y)
13 print('method 3 \n', np.divide(x, y))
```

```
data x
[1 2 3 4]
data y
[5 6 7 8]
method 1
[0.2          0.33333333 0.42857143 0.5          ]
method 2
[0 0 0 0]
method 3
[0.2          0.33333333 0.42857143 0.5          ]
```

# Matrix Operations

## Transpose

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{bmatrix}$$

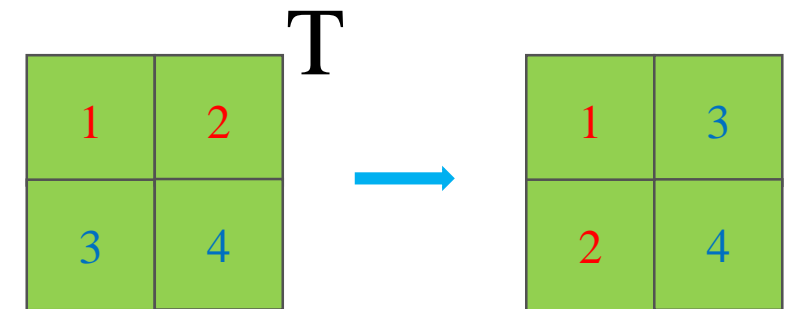
$$A^T = \begin{bmatrix} a_{11} & \dots & a_{m1} \\ \dots & \dots & \dots \\ a_{1n} & \dots & a_{mn} \end{bmatrix}$$

```
2 import numpy as np
3
4 X = np.array([[1,2],
5               [3,4]])
6 print(X)
7
8 #chuyển vị
9 print(X.T)
```

```
[[1 2]
 [3 4]]
[[1 3]
 [2 4]]
```

## Example

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix} \quad A^T = \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \end{bmatrix}$$



# Outline

- **Introduction to Numpy**
- **Numpy Examples**
- **Introduction to Vector and Matrix**
- **Vectorize the Linear Regression (1-sample)**

# Linear Regression

## ❖ Quick review

Linear regression models  $\leftarrow$  Linear equations

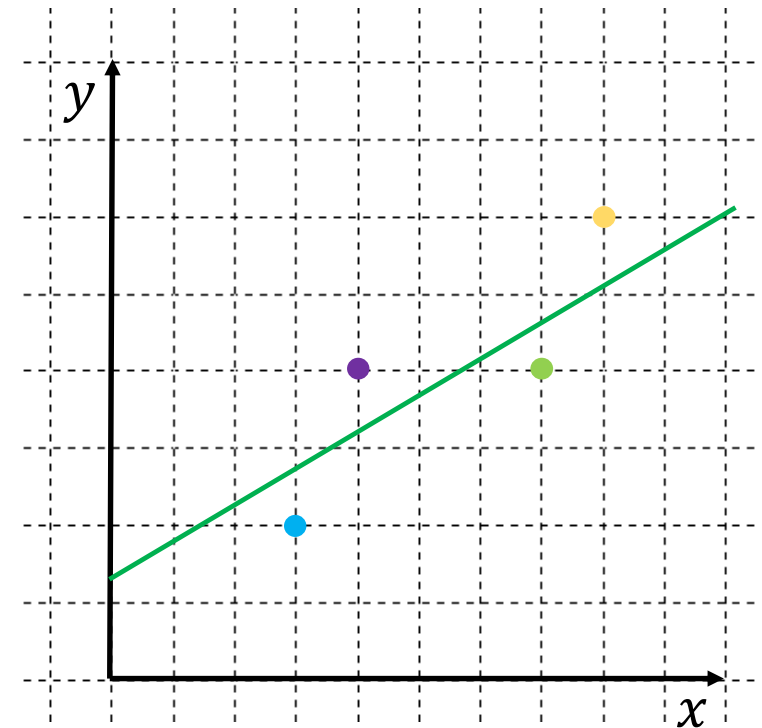
Linear equation =  $w_1x_1 + w_2x_2 + \dots + w_nx_n + b$

Feature	Label
area	price
6.7	9.1
4.6	5.9
3.5	4.6
5.5	6.7

House price data

Model:  $\hat{y} = w_1x_1 + b$

price = a \* area + b



# Linear Regression

## ❖ Quick review

### Linear equation

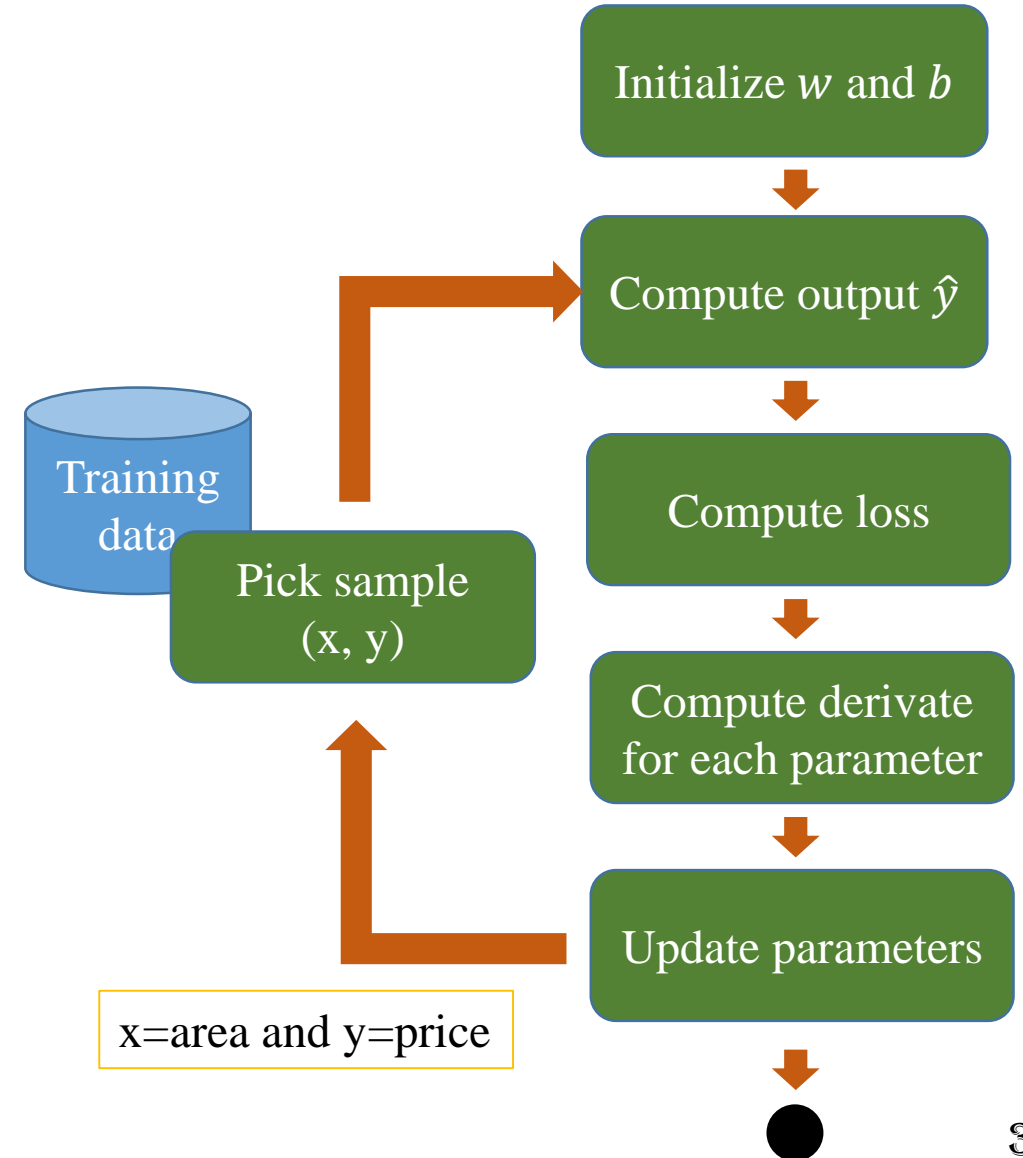
$$\hat{y} = wx + b$$

where  $\hat{y}$  is a predicted value,  
 $w$  and  $b$  are parameters  
and  $x$  is input feature

### Error (loss) computation

**Idea:** compare predicted values  $\hat{y}$  and label values  $y$   
Squared loss

$$L(\hat{y}, y) = (\hat{y} - y)^2$$



# Linear Regression

## ❖ Quick review

### Linear equation

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

where  $\hat{y}$  is a predicted value,

$w$  and  $b$  are parameters

and  $x$  is input feature

### Error (loss) computation

**Idea:** compare predicted values  $\hat{y}$  and label values  $y$

Squared loss

$$L(\hat{y}, y) = (\hat{y} - y)^2$$

Use gradient descent to minimize the loss function

Compute derivate for each parameter

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w} = 2x(\hat{y} - y)$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b} = 2(\hat{y} - y)$$

Update parameters

$$w = w - \eta \frac{\partial L}{\partial w}$$

$$b = b - \eta \frac{\partial L}{\partial b}$$

$\eta$  is learning rate

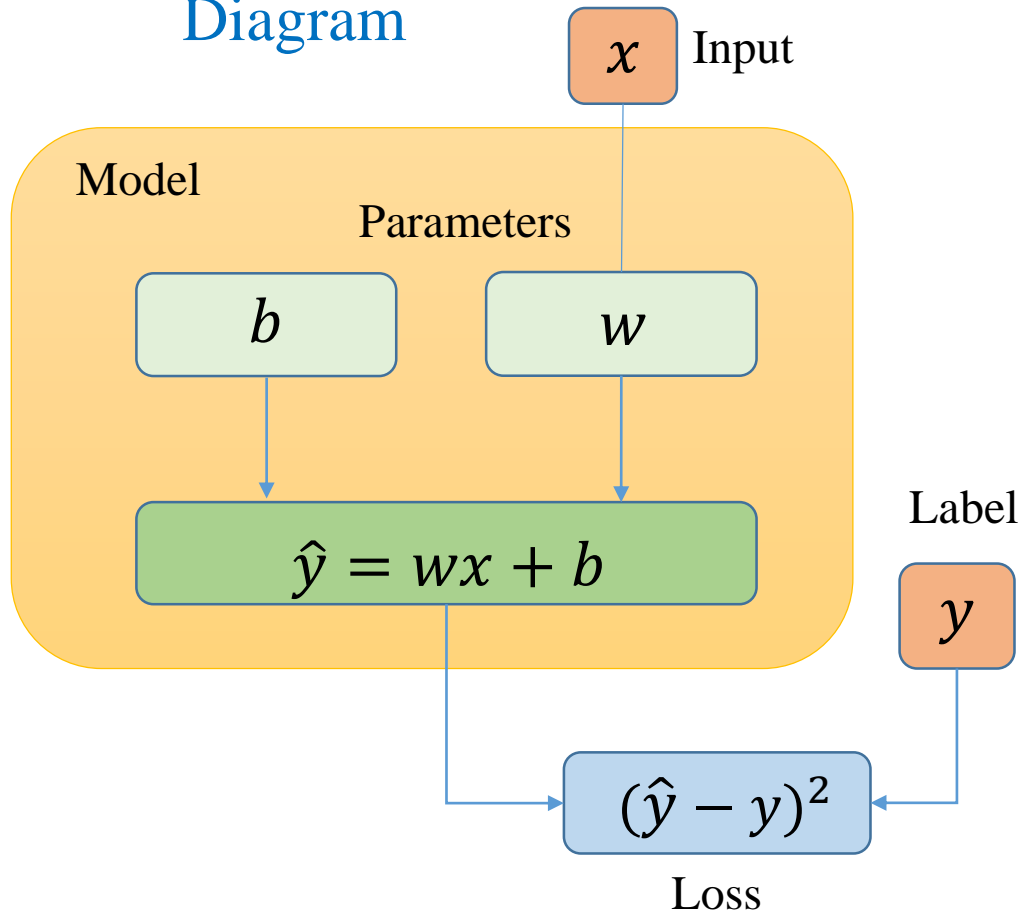
# Linear Regression

## ❖ Quick review

Feature	Label
area	price
6.7	9.1
4.6	5.9
3.5	4.6
5.5	6.7

House price data

### Diagram



### Cheat sheet

Compute the output  $\hat{y}$

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

Compute the loss

$$L = (\hat{y} - y)^2$$

Compute derivative

$$\frac{\partial L}{\partial w} = 2x(\hat{y} - y)$$

$$\frac{\partial L}{\partial b} = 2(\hat{y} - y)$$

Update parameters

$$w = w - \eta \frac{\partial L}{\partial w}$$

$$b = b - \eta \frac{\partial L}{\partial b}$$

# Linear Regression

## ❖ Quick review

1) Pick a sample  $(x, y)$  from training data

2) Tính output  $\hat{y}$

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

3) Tính loss

$$L = (\hat{y} - y)^2$$

4) Tính đạo hàm

$$\frac{\partial L}{\partial w} = 2x(\hat{y} - y) \quad \frac{\partial L}{\partial b} = 2(\hat{y} - y)$$

5) Cập nhật tham số

$$w = w - \eta \frac{\partial L}{\partial w} \quad b = b - \eta \frac{\partial L}{\partial b}$$

```
1 # forward
2 def predict(x, w, b):
3     return x*w + b
4
5 # compute gradient
6 def gradient(y_hat, y, x):
7     dw = 2*x*(y_hat-y)
8     db = 2*(y_hat-y)
9
10    return (dw, db)
11
12 # update weights
13 def update_weight(w, b, lr, dw, db):
14     w_new = w - lr*dw
15     b_new = b - lr*db
16
17    return (w_new, b_new)
```



# Linear Regression

## ❖ Quick review

1) Pick a sample  $(x, y)$  from training data

2) Tính output  $\hat{y}$

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

3) Tính loss

$$L = (\hat{y} - y)^2$$

4) Tính đạo hàm

$$\frac{\partial L}{\partial w} = 2x(\hat{y} - y) \quad \frac{\partial L}{\partial b} = 2(\hat{y} - y)$$

5) Cập nhật tham số

$$w = w - \eta \frac{\partial L}{\partial w} \quad b = b - \eta \frac{\partial L}{\partial b}$$

```
1 # init weights
2 b = 0.04
3 w = -0.34
4 lr = 0.01
5
6 # how long
7 epoch_max = 10
8 data_size = 4
9
10 for epoch in range(epoch_max):
11     for i in range(data_size):
12         # get a sample
13         x = areas[i]
14         y = prices[i]
15
16         # predict y_hat
17         y_hat = predict(x, w, b)
18
19         # compute loss
20         loss = (y_hat-y)*(y_hat-y)
21
22         # compute gradient
23         (dw, db) = gradient(y_hat, y, x)
24
25         # update weights
26         (w, b) = update_weight(w, b, lr, dw, db)
```

# Problem and solution?

House price data

Feature		Label	
	area	price	
	6.7	9.1	
	4.6	5.9	
	3.5	4.6	
	5.5	6.7	

$price = a * area + b$

Features			Label
TV	Radio	Newspaper	Sales
230.1	37.8	69.2	22.1
44.5	39.3	45.1	10.4
17.2	45.9	69.3	12
151.5	41.3	58.5	16.5
180.8	10.8	58.4	17.9

Advertising data

Model:  $\hat{y} = w_1x_1 + w_2x_2 + w_3x_3 + b$

$Sale = w_1 * TV + w_2 * Radio + w_3 * Newspaper + b$

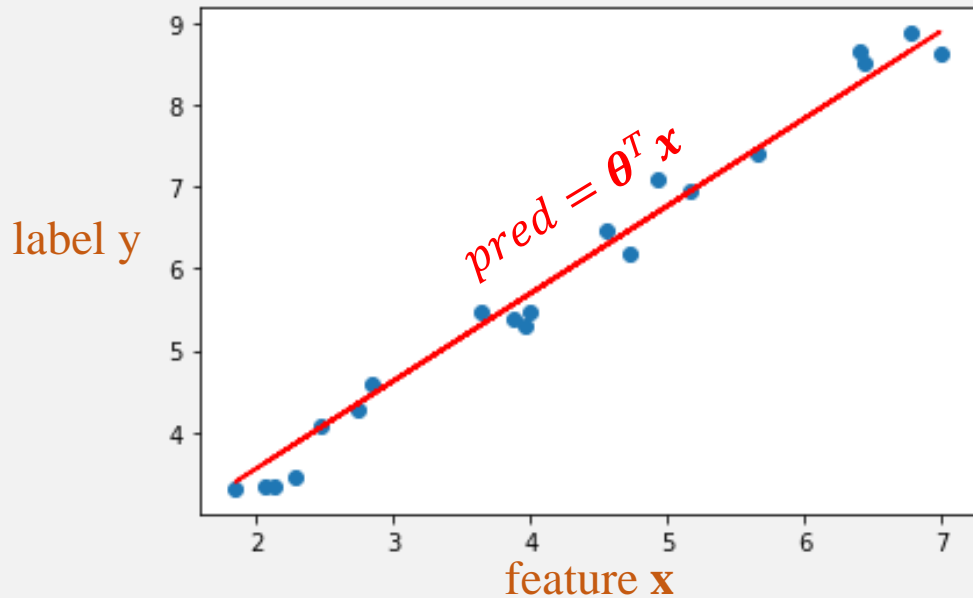
Boston House Price Data

Features													Label
crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
0.00632	18	2.31	0	0.538	6.575	65.2	4.09	1	296	15.3	396.9	4.98	24
0.02731	0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.9	9.14	21.6
0.03237	0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
0.06905	0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.9	5.33	36.2
0.08829	12.5	7.87	0	0.524	6.012	66.6	5.5605	5	311	15.2	395.6	12.43	22.9

$medv = w_1 * x_1 + \dots + w_{13} * x_{13} + b$

# Linear Regression

Model the relationship between  
feature  $x$  and label  $y$



Using a linear equation to fit data

Samples  $(x, y)$  are given in advance

Linear equation

$$\hat{y} = w_1x_1 + w_2x_2 + \dots + w_nx_n + b$$

where  $\hat{y}$  is a predicted value,

$\theta = [b \ w_1 \ w_2 \ \dots \ w_n]^T$  is parameter vector  
and  $x = [1 \ x_1 \ x_2 \ \dots \ x_n]^T$  is feature vector.

Error (loss) computation

**Idea:** compare predicted values  $\hat{y}$  and label values  $y$

Squared loss

$$L(\theta) = (\hat{y} - y)^2$$

# Linear Regression

## Linear equation

$$\hat{y} = w_1x_1 + w_2x_2 + \dots + w_nx_n + b$$

where  $\hat{y}$  is a predicted value,

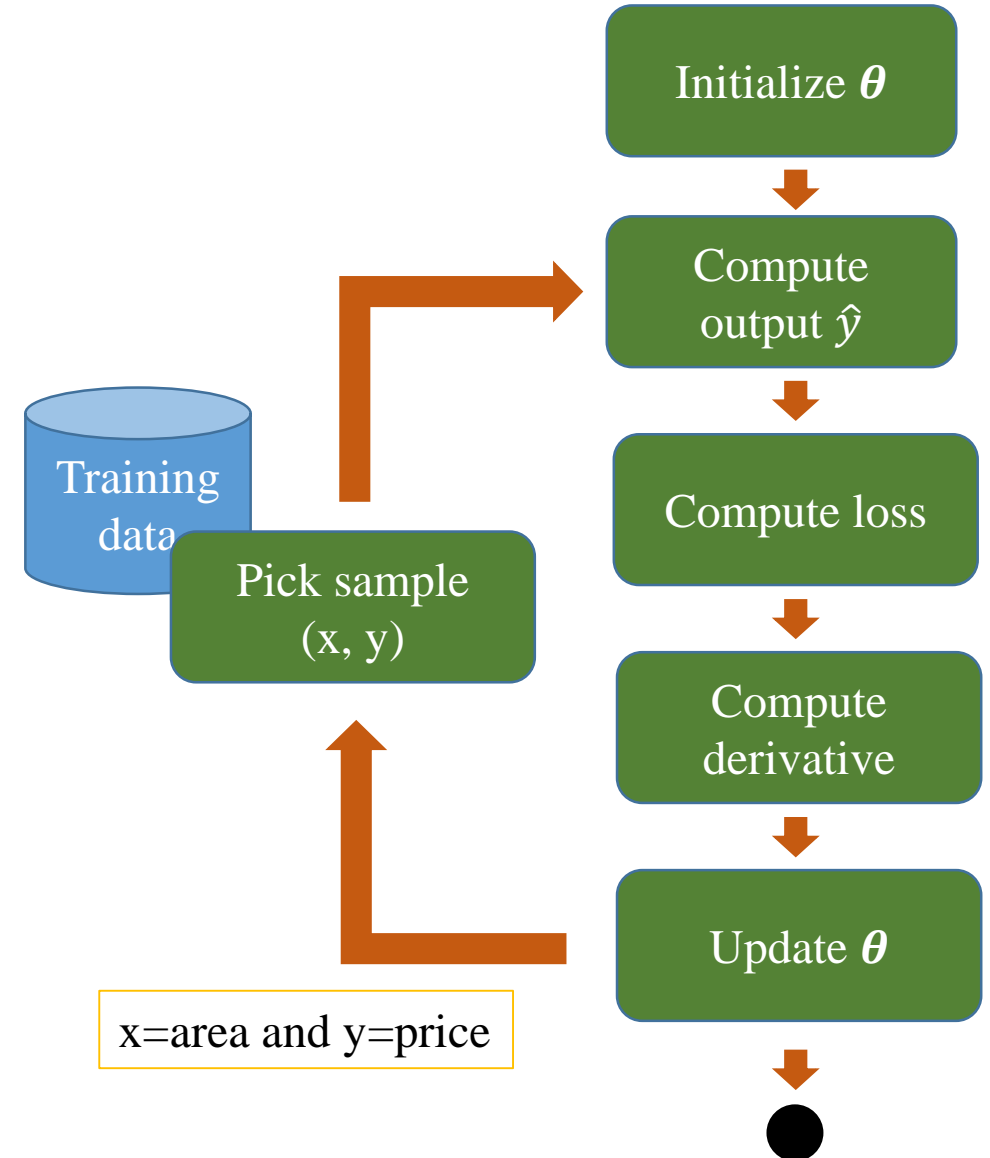
$\theta = [b \ w_1 \ w_2 \ \dots \ w_n]^T$  is parameter vector  
and  $x = [1 \ x_1 \ x_2 \ \dots \ x_n]^T$  is feature vector.

## Error (loss) computation

**Idea:** compare predicted values  $\hat{y}$  and label values  $y$

Squared loss

$$L(\theta) = (\hat{y} - y)^2$$



# Linear Regression: Vectorization

1) Pick a sample  $(x, y)$  from training data

2) Compute output  $\hat{y}$

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

3) Compute loss

$$L = (\hat{y} - y)^2$$

4) Compute derivative

$$\frac{\partial L}{\partial w} = 2x(\hat{y} - y) \quad \frac{\partial L}{\partial b} = 2(\hat{y} - y)$$

5) Update parameters

$$w = w - \eta \frac{\partial L}{\partial w} \quad b = b - \eta \frac{\partial L}{\partial b}$$

Normal version

1) Pick a sample  $(x, y)$  from training data

2) Compute output  $\hat{y}$

$$\hat{y} = \boldsymbol{\theta}^T \mathbf{x} = \mathbf{x}^T \boldsymbol{\theta}$$

3) Compute loss

$$L = (\hat{y} - y)^2$$

4) Compute derivative

$$L'_{\boldsymbol{\theta}} = 2\mathbf{x}(\hat{y} - y)$$

5) Update parameters

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta L'_{\boldsymbol{\theta}}$$

$\eta$  is learning rate

Vectorization

# Linear Regression: Vectorization

1) Pick a sample  $(x, y)$  from training data

2) Compute output  $\hat{y}$

$$\hat{y} = \theta^T x = x^T \theta$$

3) Compute loss

$$L = (\hat{y} - y)^2$$

4) Compute derivative

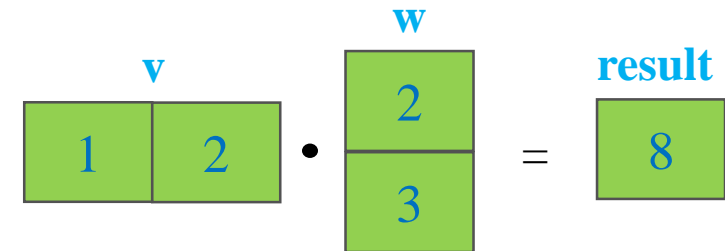
$$L'_\theta = 2x(\hat{y} - y)$$

5) Update parameters

$$\theta = \theta - \eta L'_\theta$$

$\eta$  is learning rate

## Vectorization



```
2 import numpy as np
3
4 v = np.array([1, 2])
5 w = np.array([2, 3])
6
7 # Tính inner product giữa v và w
8 print('method 1 \n', v.dot(w))
9 print('method 2 \n', np.dot(v, w))
```

method 1

8

method 2

8

# Linear Regression: Vectorization

1) Pick a sample  $(x, y)$  from training data

2) Compute output  $\hat{y}$

$$\hat{y} = \theta^T x = x^T \theta$$

3) Compute loss

$$L = (\hat{y} - y)^2$$

4) Compute derivative

$$L'_\theta = 2x(\hat{y} - y)$$

5) Update parameters

$$\theta = \theta - \eta L'_\theta$$

$\eta$  is learning rate

```
1 import numpy as np
2
3 # forward
4 def predict(x, theta):
5     return x.dot(theta)
6
7 # compute gradient
8 def gradient(y_hat, y, x):
9     dtheta = 2*x*(y_hat-y)
10
11     return dtheta
12
13 # update weights
14 def update_weight(theta, lr, dtheta):
15     dtheta_new = theta - lr*dtheta
16
17     return dtheta_new
```

# Linear Regression Vectorization

## ❖ Implementation

$\theta = ?$

```
1 import numpy as np
2
3 # forward
4 def predict(x, theta):
5     return x.dot(theta)
6
7 # compute gradient
8 def gradient(y_hat, y, x):
9     dtheta = 2*x*(y_hat-y)
10
11     return dtheta
12
13 # update weights
14 def update_weight(theta, lr, dtheta):
15     dtheta_new = theta - lr*dtheta
16
17     return dtheta_new
```

```
1 # test sample
2 x = np.array([6.7, 1])
3 y = np.array([9.1])
4
5 # init weight
6 lr = 0.01
7 theta = np.array([-0.34, 0.04]) #[w, b]
8 print('theta', theta)
9
10 # predict y_hat
11 y_hat = predict(x, theta)
12 print('y_hat: ', y_hat)
13
14 # compute loss
15 loss = (y_hat-y)*(y_hat-y)
16 print('Loss: ', loss)
17
18 # compute gradient
19 dtheta = gradient(y_hat, y, x)
20 print('dtheta: ', dtheta)
21
22 # update weights
23 theta = update_weight(theta, lr, dtheta)
24 print('theta_new: ', theta)
```



