AI VIET NAM
@aivietnam.edu.vn

Pytorch

Deep Learning Framework

Quang-Vinh Dinh
Ph.D. in Computer Science

Year 2024

code&data

Objectives

Basic PyTorch

Mean Squared Error

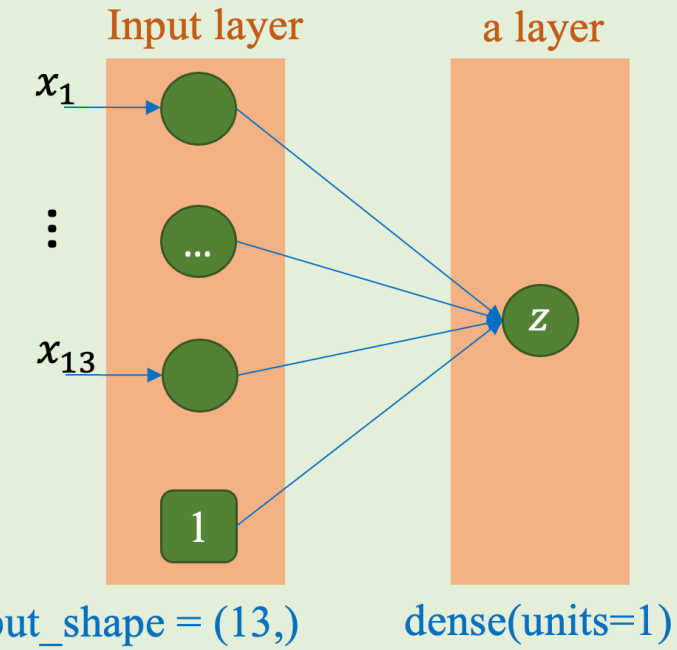
$$mse = \frac{1}{N}\sum_{i}(\boldsymbol{x}_i - \boldsymbol{y}_i)^2$$

```python
# Compute squared difference
import torch

# Create two tensors
x = torch.tensor([1.0, 2.0, 3.0, 4.0])
y = torch.tensor([5.0, 5.0, 5.0, 5.0])

# Compute squared difference
loss_fn = torch.nn.MSELoss()
mse = loss_fn(x,y)

print(f'x:\n {x}')
print(f'y = {y}')
print(f'mse:\n {mse}')
```

Model Construction

Model

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



Training&Inference

→ Tính output $\hat{y}$

$$\boldsymbol{z} = \boldsymbol{\theta}^T\boldsymbol{x} \qquad \hat{\boldsymbol{y}} = \frac{e^{\boldsymbol{z}}}{\sum_{i=1}^{k} e^{z_i}}$$

→ Tính loss (cross-entropy)

$$L(\boldsymbol{\theta}) = -\sum_{i=1}^{k} y_i \log \hat{y}_i$$

→ Tính đạo hàm $\frac{\partial L}{\partial \boldsymbol{\theta}_i} = \boldsymbol{x}(\hat{y}_i - y_i)$

→ Cập nhật tham số (Stochastic gradient descent)

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

Outline

SECTION 1

Basic PyTorch

SECTION 2

Model Construction

SECTION 3

Training&Inference

Mean Squared Error

$$mse = \frac{1}{N}\sum_{i}(\boldsymbol{x}_i - \boldsymbol{y}_i)^2$$

```python
# Compute squared difference
import torch

# Create two tensors
x = torch.tensor([1.0, 2.0, 3.0, 4.0])
y = torch.tensor([5.0, 5.0, 5.0, 5.0])

# Compute squared difference
loss_fn = torch.nn.MSELoss()
mse = loss_fn(x,y)

print(f'x:\n {x}')
print(f'y = {y}')
print(f'mse:\n {mse}')
```

Introduction

Create a tensor in PyTorch

```python
# From a list
import torch

data = [1, 2, 3]
data = torch.tensor(data)
print(data)
```

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

```python
# From a NumPy Array
import numpy as np

data = np.array([1, 2, 3])
data = torch.from_numpy(data)
print(data)
```

```
tensor([1, 2, 3], dtype=torch.int32)
```

```python
# random uniform
import torch

# Creates a 3x3 tensor with
# random values between 0 and 1
data = torch.rand(3, 3)
print(data)
```

```
tensor([[0.0615, 0.2716, 0.2160],
        [0.1595, 0.9780, 0.6053],
        [0.7718, 0.1605, 0.4205]])
```

```python
# random normal
import torch

# Creates a 3x3 tensor with values
# sampled from a standard normal distribution
data = torch.randn(3, 3)
print(data)
```

```
tensor([[-1.0891, -0.2750,  0.8105],
        [ 1.0836, -1.1107,  0.3683],
        [ 2.0638, -1.2075, -0.5610]])
```

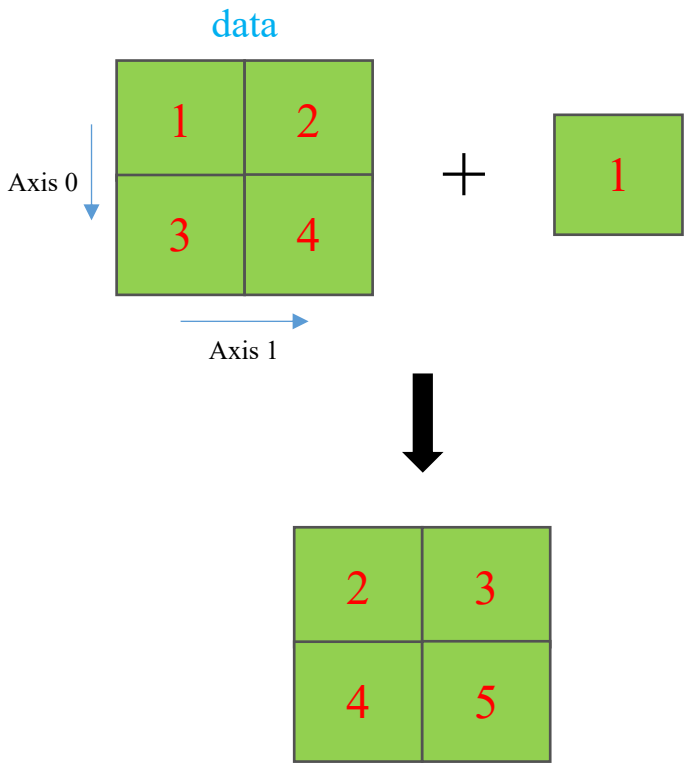
```python
# Using the arange function
import torch

# Creates a tensor [0, 1, 2, 3, 4]
data = torch.arange(start=0, end=5, step=1)
print(data)
```

```
tensor([0, 1, 2, 3, 4])
```

Introduction

❖ Tensor

❖ Broadcasting



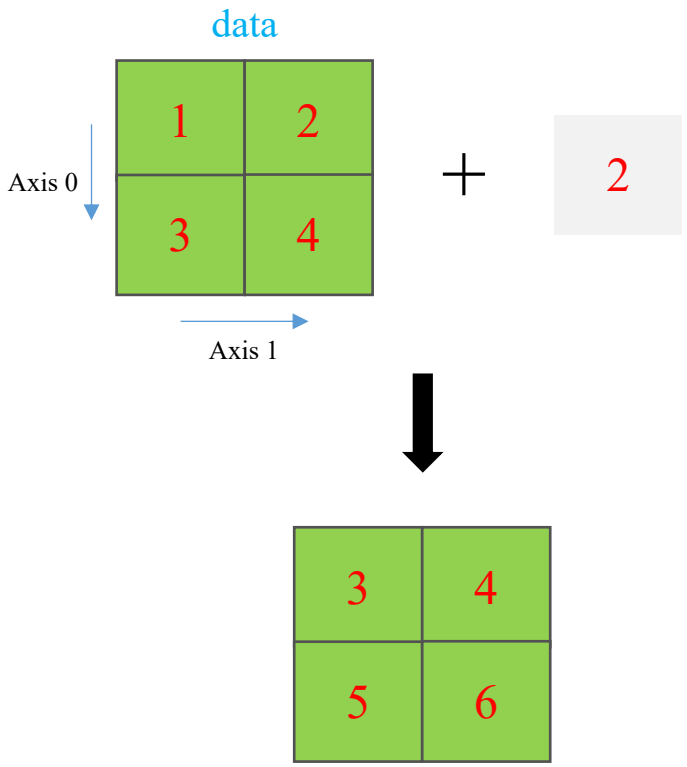

```python
# broadcasting
import numpy as np

# create a tensor
tensor1 = torch.tensor([[1, 2],
                        [3, 4]])
tensor2 = torch.tensor([1])
print(f'Tensor1:\n {tensor1}')
print(f'Tensor2:\n {tensor2}')

# Addition between two tensors
tensor3 = tensor1 + tensor2
print(f'Tensor3:\n {tensor3}')
```

```
Tensor1:
 tensor([[1, 2],
         [3, 4]])
Tensor2:
 tensor([1])
Tensor3:
 tensor([[2, 3],
         [4, 5]])
```

Introduction

❖ Tensor

❖ Broadcasting




```python
# broadcasting
import numpy as np

# create a tensor
tensor1 = torch.tensor([[1, 2],
                        [3, 4]])
print(f'Tensor1:\n {tensor1}')

# Between a tensor and a number
tensor2 = tensor1 + 2
print(f'Tensor2:\n {tensor2}')
```

```
Tensor1:
 tensor([[1, 2],
         [3, 4]])
Tensor2:
 tensor([[3, 4],
         [5, 6]])
```

Introduction

❖ Tensor

❖ Important functions

Squared Difference

$$sd = (x - y)^2$$

x	sd
1	16
2	9
3	4
4	1

$(x - y)^2 =$

```python
# Compute squared difference
import torch

# Create two tensors
x = torch.tensor([1.0, 2.0, 3.0, 4.0])
y = 5

# Compute squared difference
squared_diff = (x - y) ** 2

print(f'x:\n {x}')
print(f'y = {y}')
print(f'squared_diff:\n {squared_diff}')
```

```
x:
 tensor([1., 2., 3., 4.])
y = 5
squared_diff:
 tensor([16.,  9.,  4.,  1.])
```

Introduction

❖ Tensor

❖ Important functions

Mean Squared Error

$$mse = \frac{1}{N}\sum_{i}(\boldsymbol{x}_i - \boldsymbol{y}_i)^2$$

x
1
2
3
4

y
5
5
5
5

sd
16
9
4
1

$$\frac{1}{N}\sum_i(\boldsymbol{x}_i - \boldsymbol{y}_i)^2 = \frac{1}{N}\sum_i(\quad) = 7.5$$

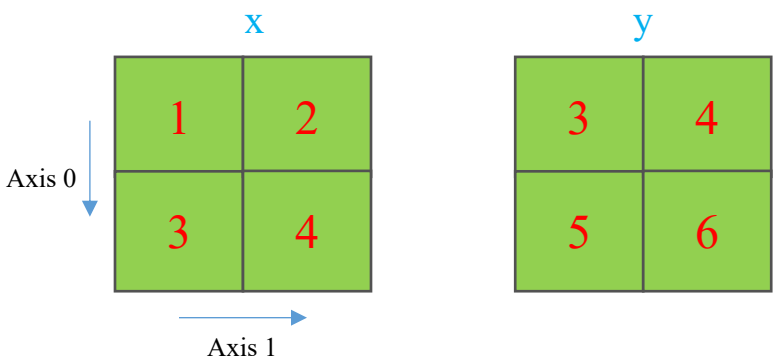
```python
# Compute squared difference
import torch

# Create two tensors
x = torch.tensor([1.0, 2.0, 3.0, 4.0])
y = torch.tensor([5.0, 5.0, 5.0, 5.0])

# Compute squared difference
loss_fn = torch.nn.MSELoss()
mse = loss_fn(x,y)

print(f'x:\n {x}')
print(f'y = {y}')
print(f'mse:\n {mse}')
```

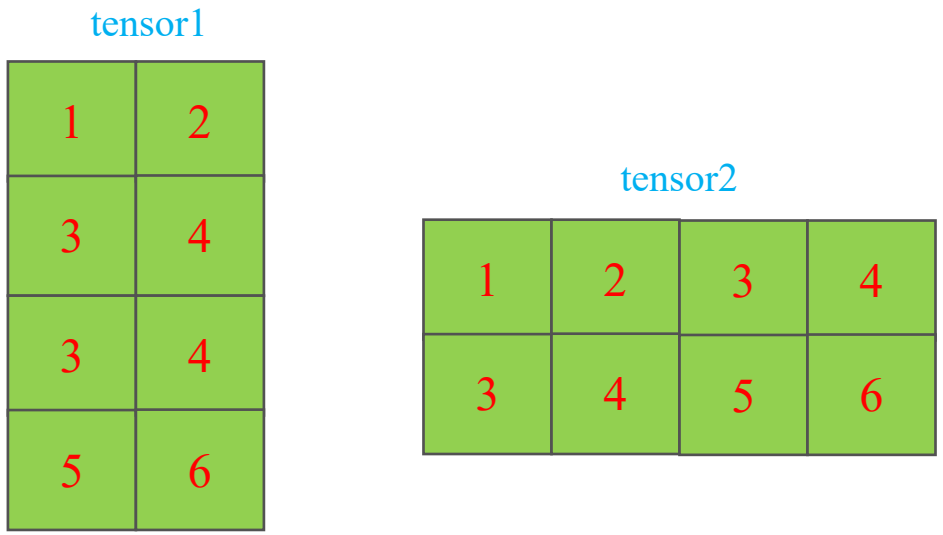
```
x:
 tensor([1., 2., 3., 4.])
y = tensor([5., 5., 5., 5.])
mse:
 7.5
```

Introduction

❖ Tensor

❖ Important functions






```python
# Concatenate tensors
import torch

# Create two tensors
x = torch.tensor([[1, 2],
                  [3, 4]])
y = torch.tensor([[3, 4],
                  [5, 6]])

# Concat tensors along the first dim
tensor1 = torch.cat((x, y), dim=0)
print(f'Tensor1:\n {tensor1}')

# Concat tensors along the second dim
tensor2 = torch.cat((x, y), dim=1)
print(f'Tensor2:\n {tensor2}')
```

```
Tensor1:
 tensor([[1, 2],
         [3, 4],
         [3, 4],
         [5, 6]])
Tensor2:
 tensor([[1, 2, 3, 4],
         [3, 4, 5, 6]])
```

Introduction

❖ Tensor

❖ Important functions

3	4
4	2
1	1

.argmax(axis=0) = | 1 | 0 |

3	4
4	2
1	1

.argmax(axis=1) = | 1 | 0 | 0 |

```python
# argmax
import torch

# Creates a 3x2 tensor
data = torch.randint(low=0, high=9, size=(3, 2))
print(f'data:\n {data}')

# Compute argmax across the rows (dimension 0)
argmax_dim0 = torch.argmax(data, dim=0)
print(f'argmax1:\n {argmax_dim0}')

# Compute argmax across the columns (dimension 1)
argmax_dim1 = torch.argmax(data, dim=1)
print(f'argmax1:\n {argmax_dim1}')
```

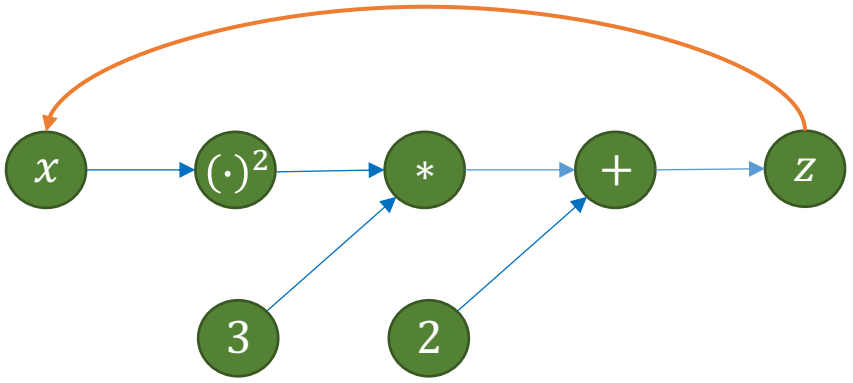
```
data:
 tensor([[3, 4],
         [4, 2],
         [1, 1]])
argmax1:
 tensor([1, 0])
argmax1:
 tensor([1, 0, 0])
```

Introduction

❖ Gradient computation

$$y = x^2$$

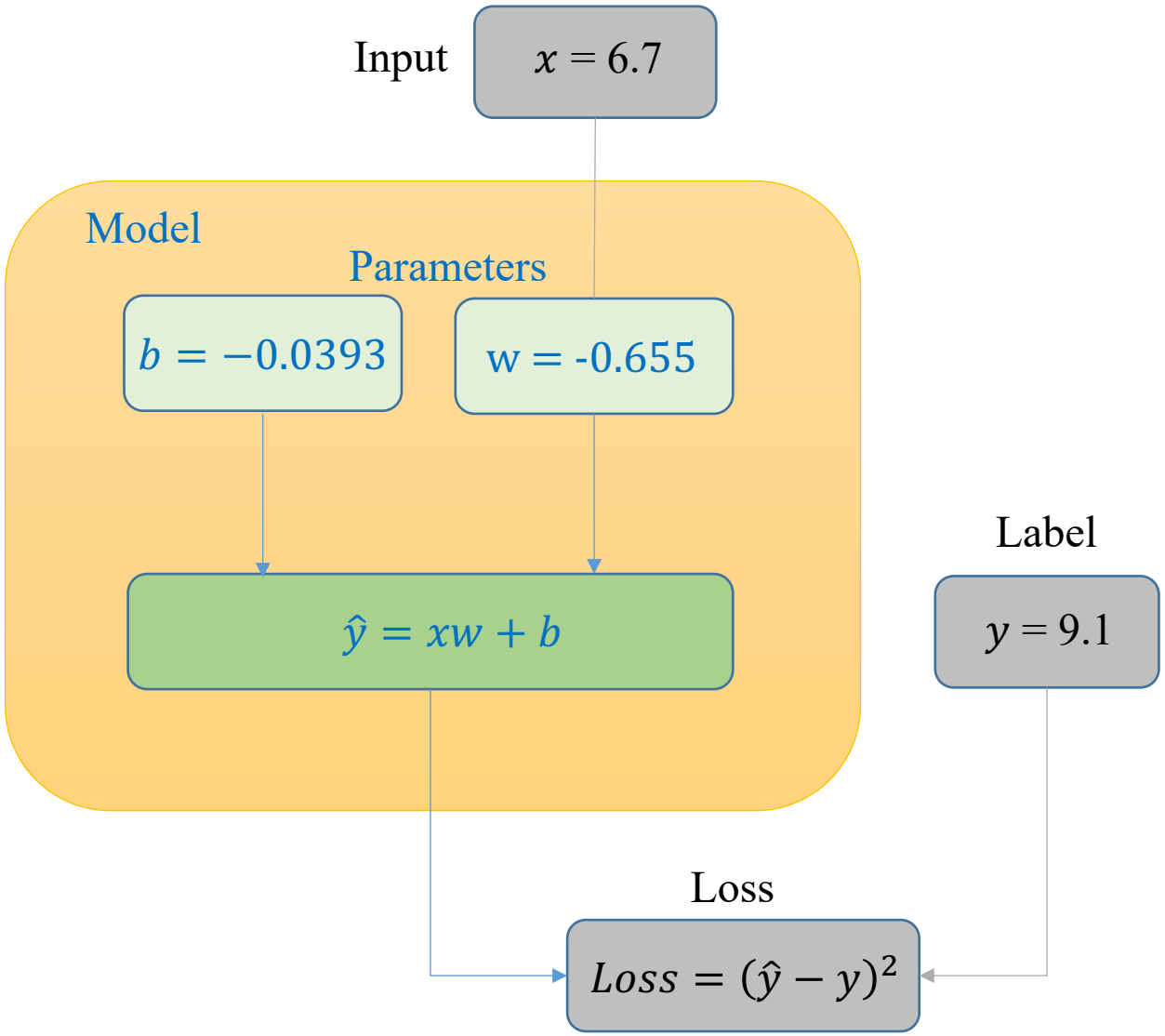
$$z = 3y + 2$$

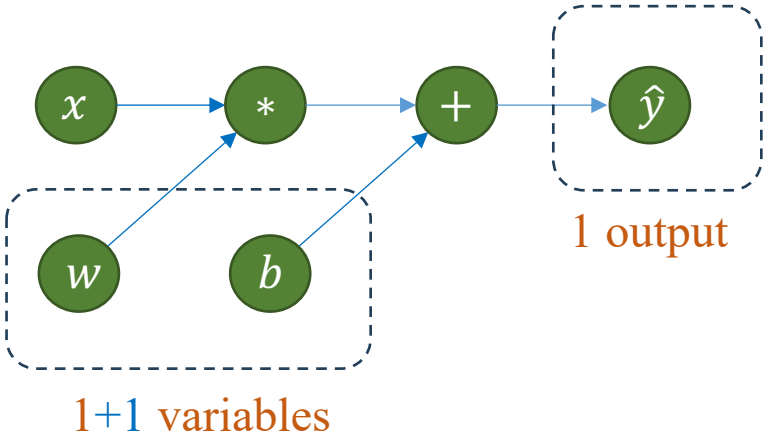



```python
# autograd
import torch

# Create a tensor to compute gradients
x = torch.tensor(2.0, requires_grad=True)

# operation
y = x ** 2
z = 3*y + 2
print(f'z: {z}')

# Backpropagate to compute gradients
z.backward()

# Print the gradient. dz/dx at x=2.0
print(f"Gradient of z w.r.t. x: {x.grad}")
```

```
z: 14.0
Gradient of z with respect to x: 12.0
```

Example 1

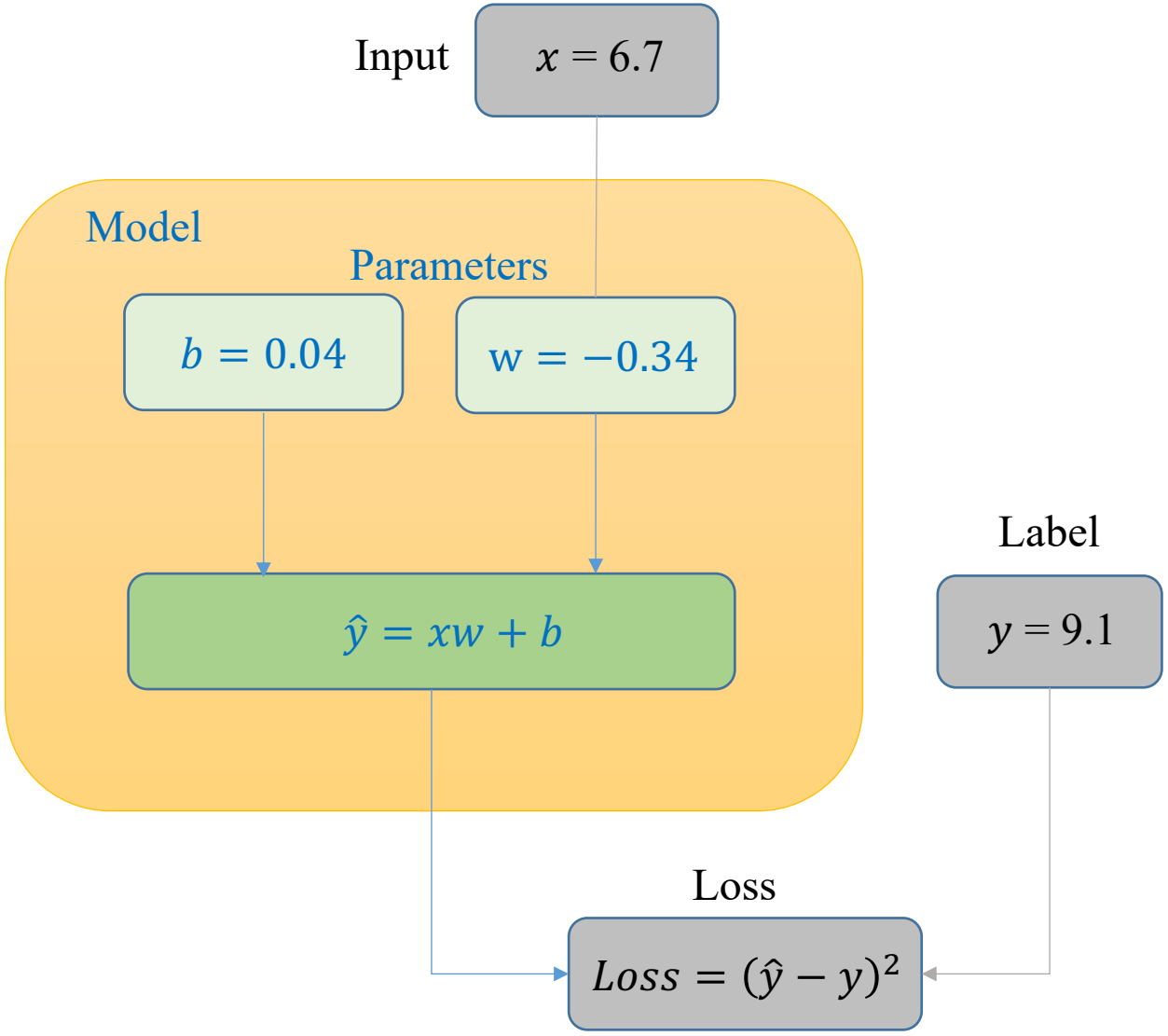


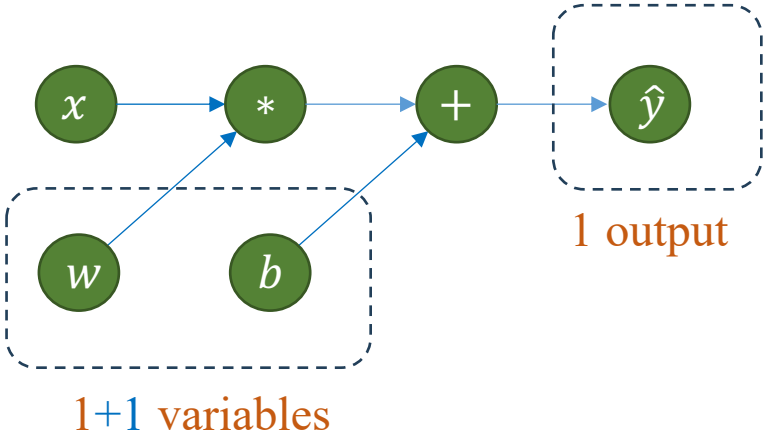



```python
import torch.nn as nn

# Create a linear layer
linear = nn.Linear(1, 1)

print(f'b - {linear.bias}')
print(f'w - {linear.weight}')
```

```
b - Parameter containing:
tensor([-0.0393], requires_grad=True)
w - Parameter containing:
tensor([[-0.6550]], requires_grad=True)
```

Example 1



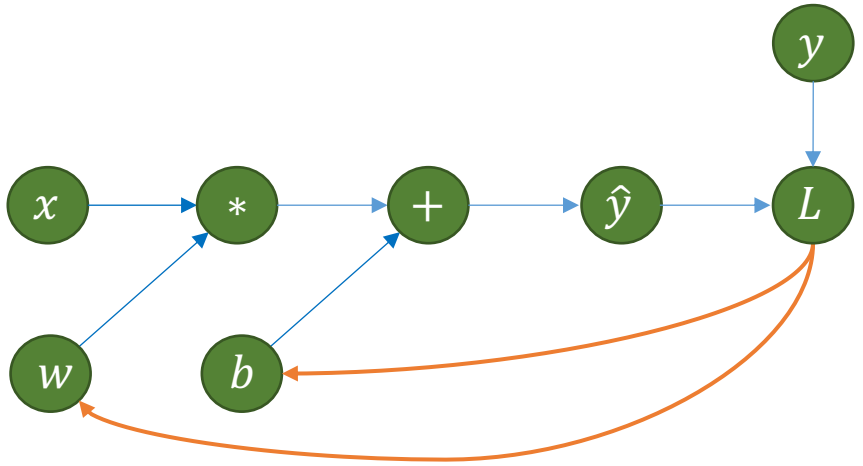



```python
import torch.nn as nn
import torch

# Create a linear layer
linear = nn.Linear(1, 1)

# set values
linear.bias.data = torch.Tensor([0.04])
linear.weight.data = torch.Tensor([[-0.34]])

print(f'b - {linear.bias}')
print(f'w - {linear.weight}')
```

```
b - Parameter containing:
tensor([0.0400], requires_grad=True)
w - Parameter containing:
tensor([[-0.3400]], requires_grad=True)
```

Example 1

L'_w L'_b



Input $x = 6.7$

Model

Parameters

$b = 0.04$

$w = -0.34$

$\hat{y} = xw + b$

Label

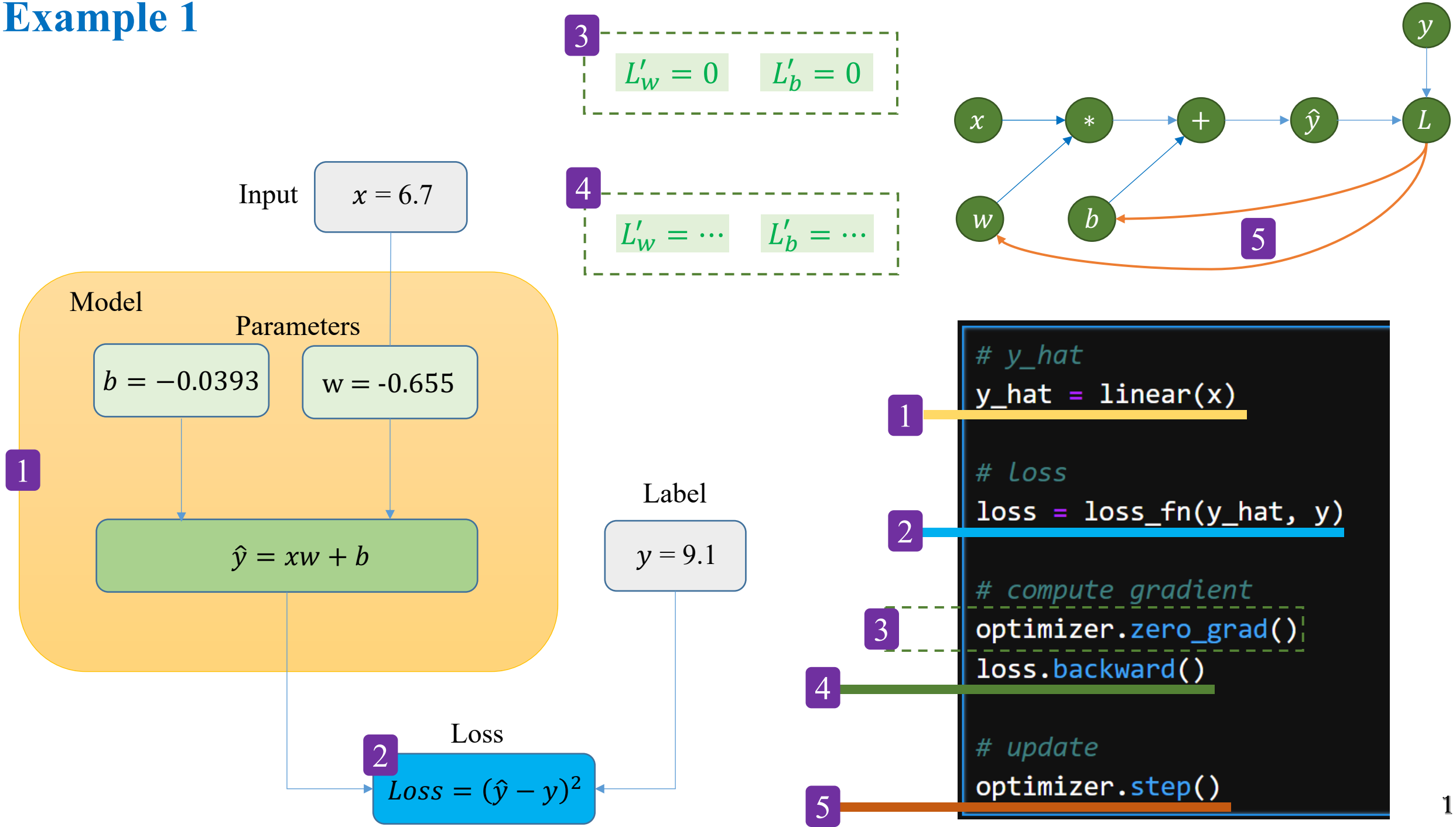
$y = 9.1$

Loss

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

```python
import torch.nn as nn
import torch

# Create a linear layer
linear = nn.Linear(1, 1)

# set values
linear.bias.data = torch.Tensor([0.04])
linear.weight.data = torch.Tensor([[-0.34]])

# loss function and optimizer
loss_fn = torch.nn.MSELoss()
optimizer = torch.optim.SGD(linear.parameters(),
                            lr=0.01)
```

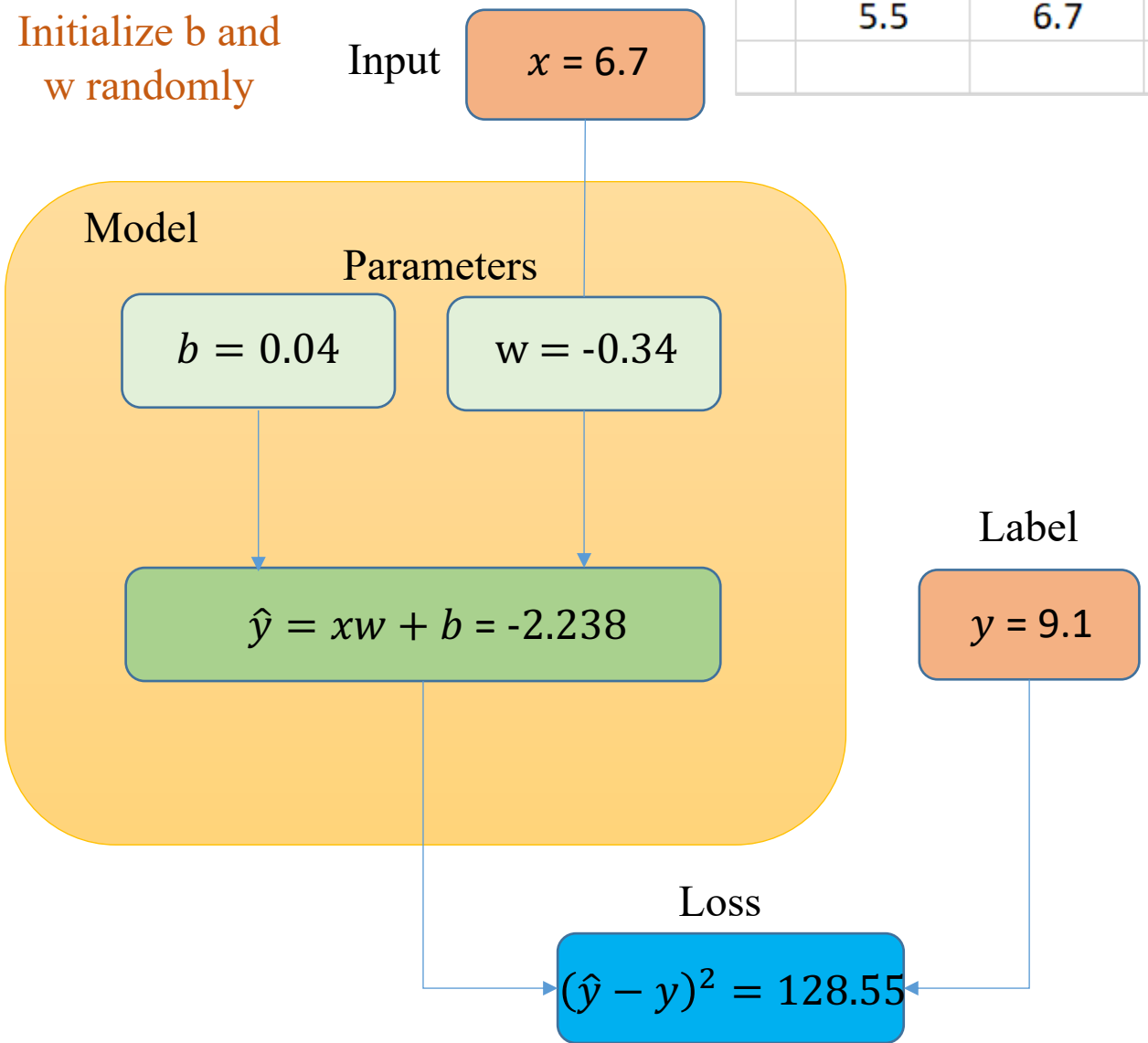
Example 1




```
# y_hat
y_hat = linear(x)

# loss
loss = loss_fn(y_hat, y)

# compute gradient
optimizer.zero_grad()
loss.backward()

# update
optimizer.step()
```

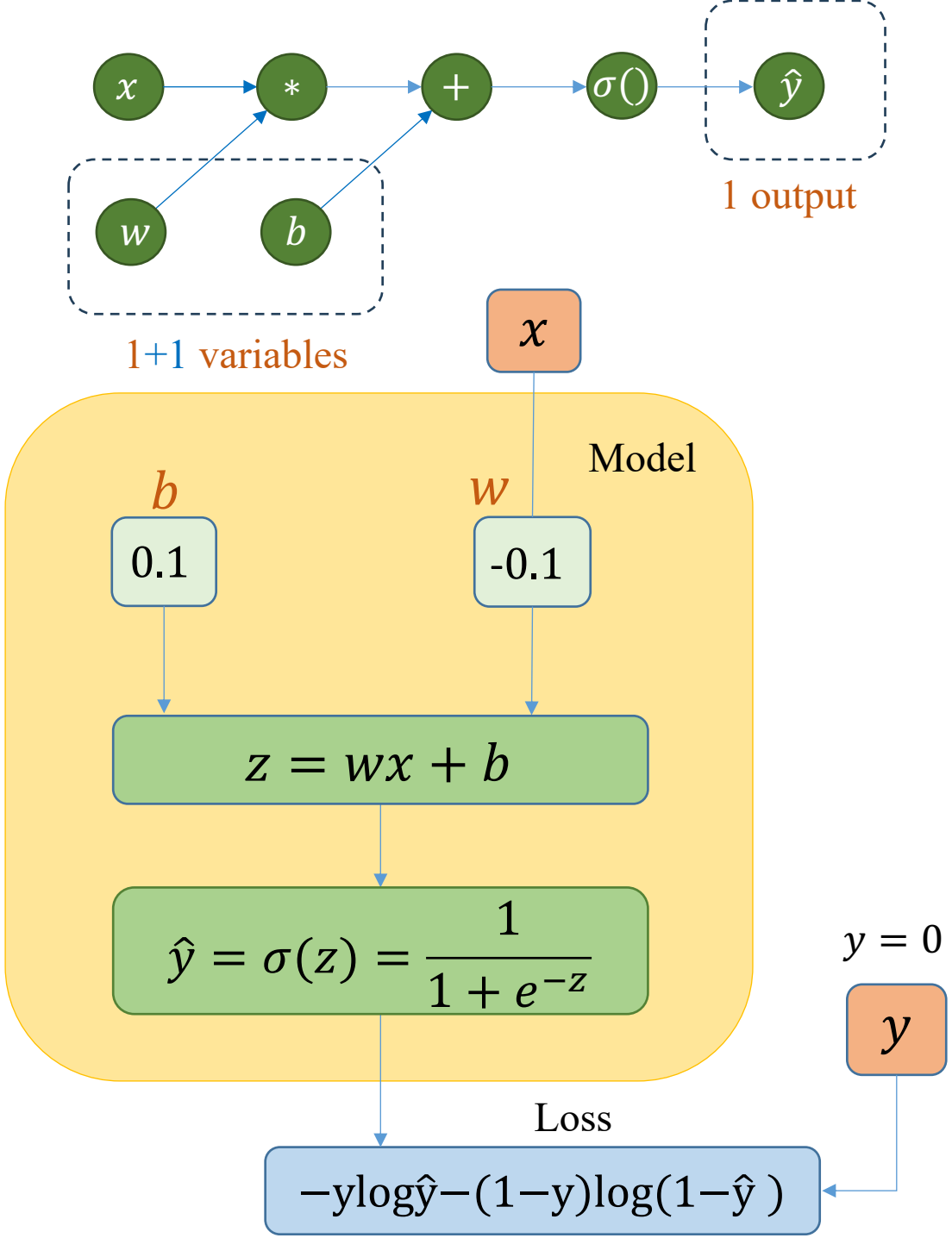
Example 1

area	price
6.7	9.1
4.6	5.9
3.5	4.6
5.5	6.7




```python
import numpy as np
import torch
import torch.nn as nn

### Data preparation
data = np.genfromtxt('data.csv', delimiter=',')
x_data = torch.from_numpy(data[:, 0:1]).float()
y_data = torch.from_numpy(data[:, 1:]).float()

# Create model, loss and optimizer
linear = nn.Linear(1, 1)
loss_fn = torch.nn.MSELoss()
optimizer = torch.optim.SGD(linear.parameters(),
                            lr=0.01)

# training
epochs = 100
for epoch in range(epochs):
    y_hat = linear(x_data)
    loss = loss_fn(y_hat, y_data)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Logistic Regression

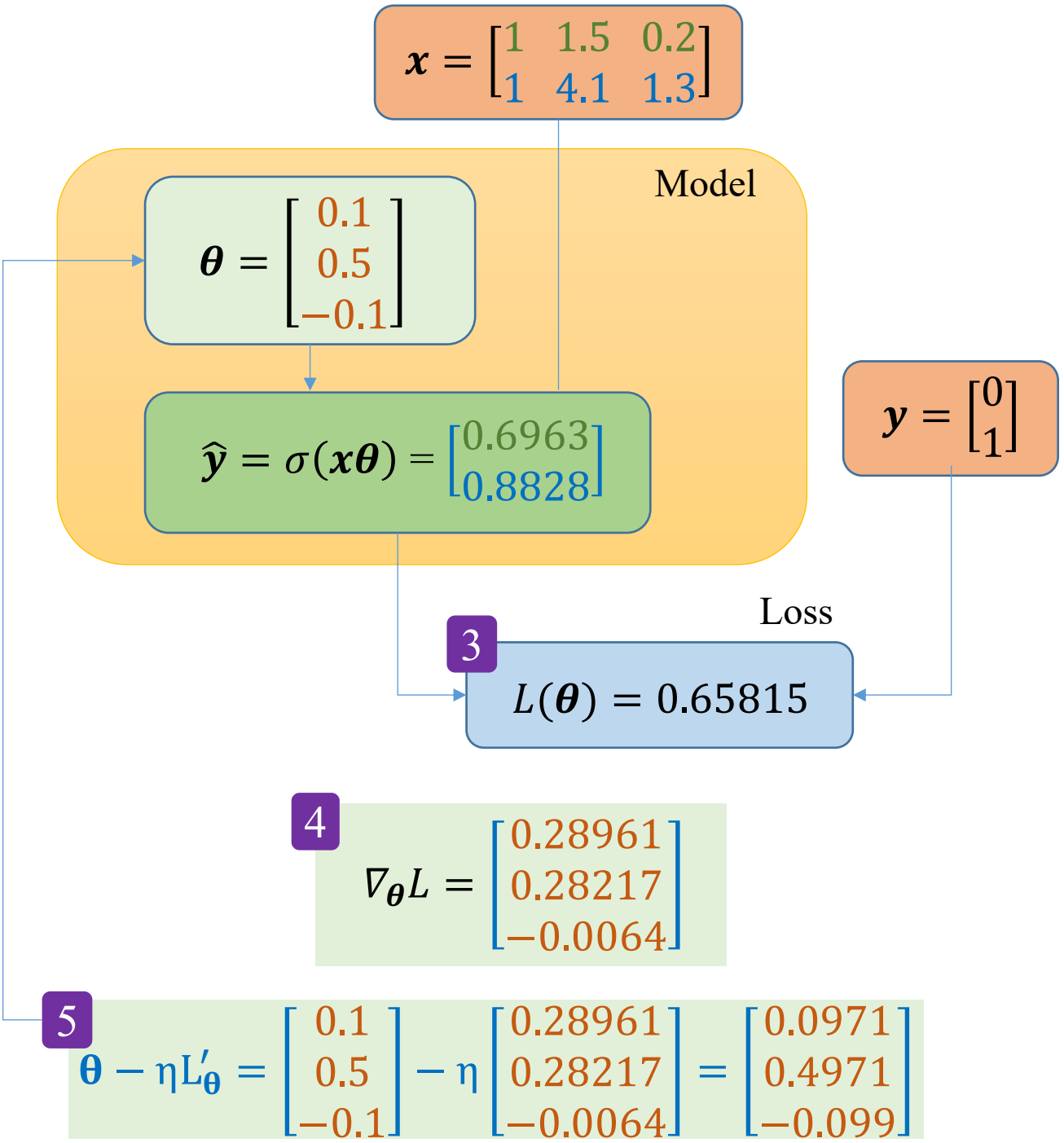



```python
data = np.genfromtxt('iris_1D.csv',
                     delimiter=',', skip_header=1)
X = torch.from_numpy(data[:,0:1]).float()
y = torch.from_numpy(data[:,1:]).float()
```

```python
# Create a linear layer
linear = nn.Linear(1, 1)

# loss and optimizer
loss_fn = torch.nn.BCELoss()
optimizer = torch.optim.SGD(linear.parameters(),
                            lr=0.01)
```

```python
# training
for epoch in range(epochs):
    y_hat = torch.sigmoid(linear(X))
    loss = loss_fn(y_hat, y)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Logistic Regression




```
data = np.genfromtxt('iris_2D_demo.csv',
                     delimiter=',', skip_header=1)
X = torch.from_numpy(data[:,0:2]).float()
y = torch.from_numpy(data[:,2:]).float()
```

```
# Create a linear layer
linear = nn.Linear(2, 1)

# loss and optimizer
loss_fn = torch.nn.BCELoss()
optimizer = torch.optim.SGD(linear.parameters(),
                            lr=0.01)
```

```
# training
for epoch in range(epochs):
    y_hat = torch.sigmoid(linear(X))
    loss = loss_fn(y_hat, y)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

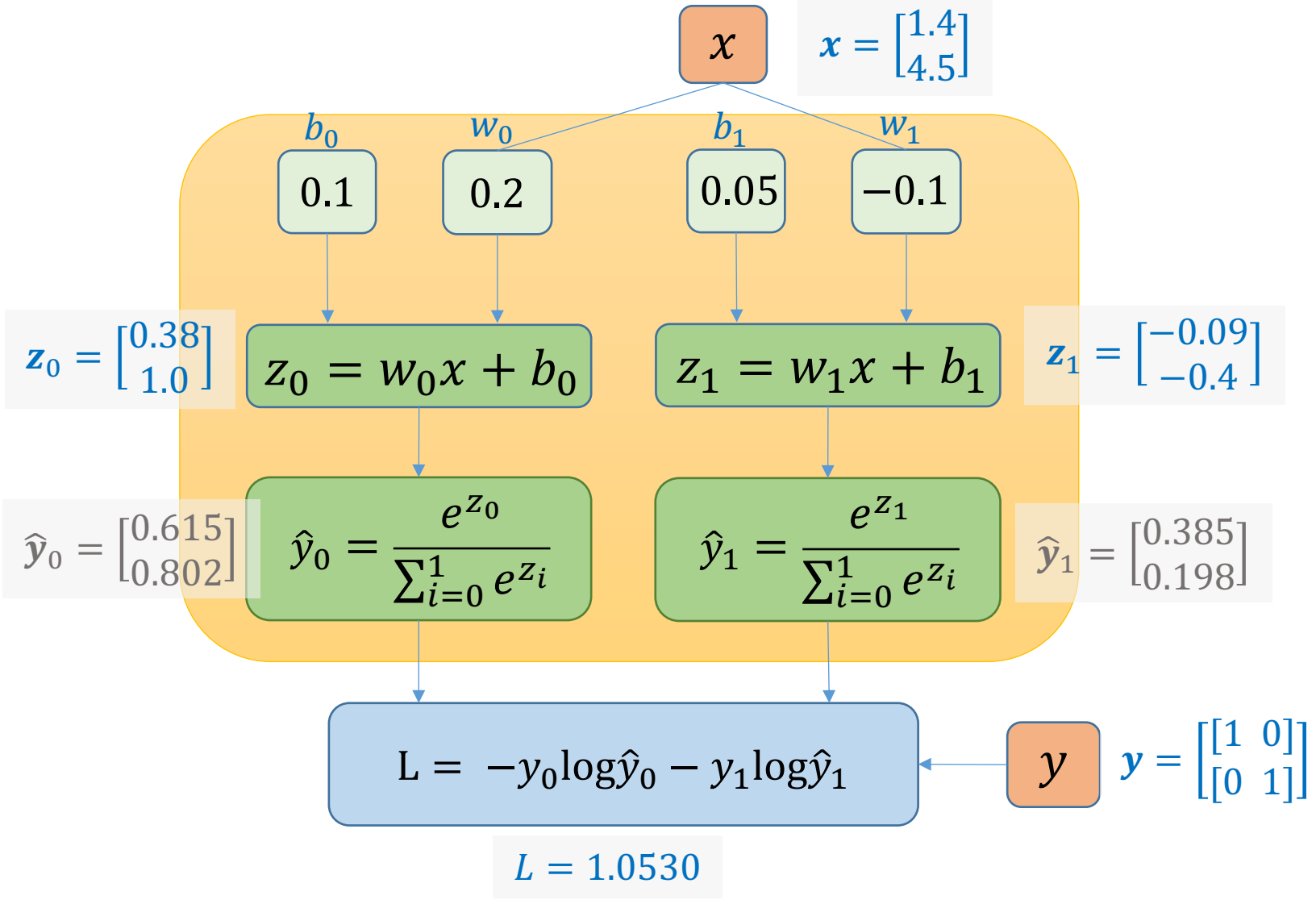
Loss Functions

❖ Cross-entropy

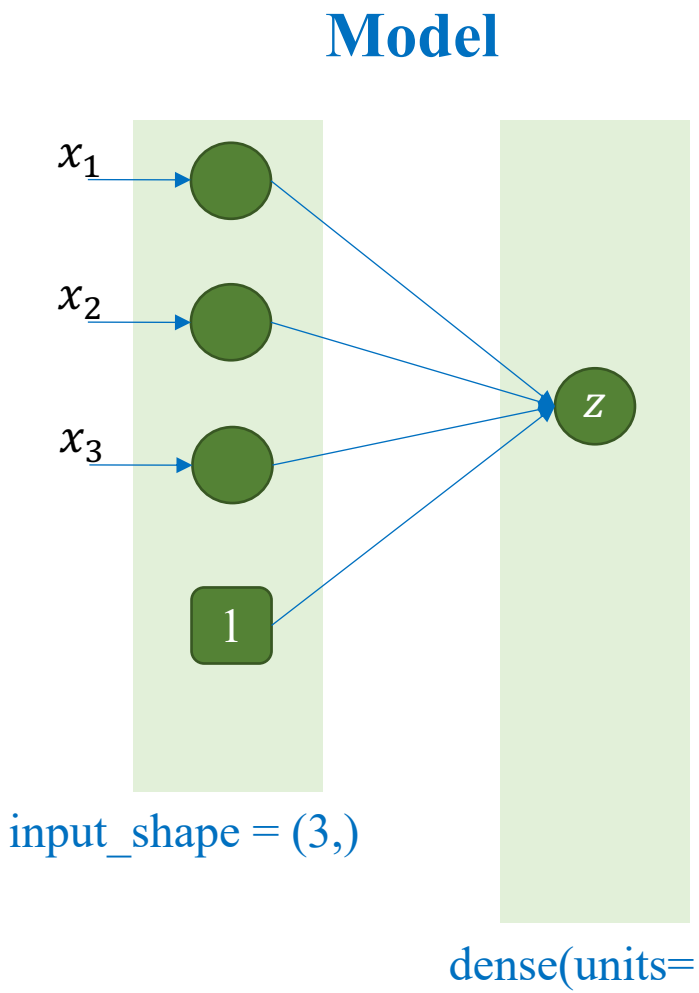
$$L(\hat{y}, y) = \sum_i -y^i \log(\hat{y}^i)$$

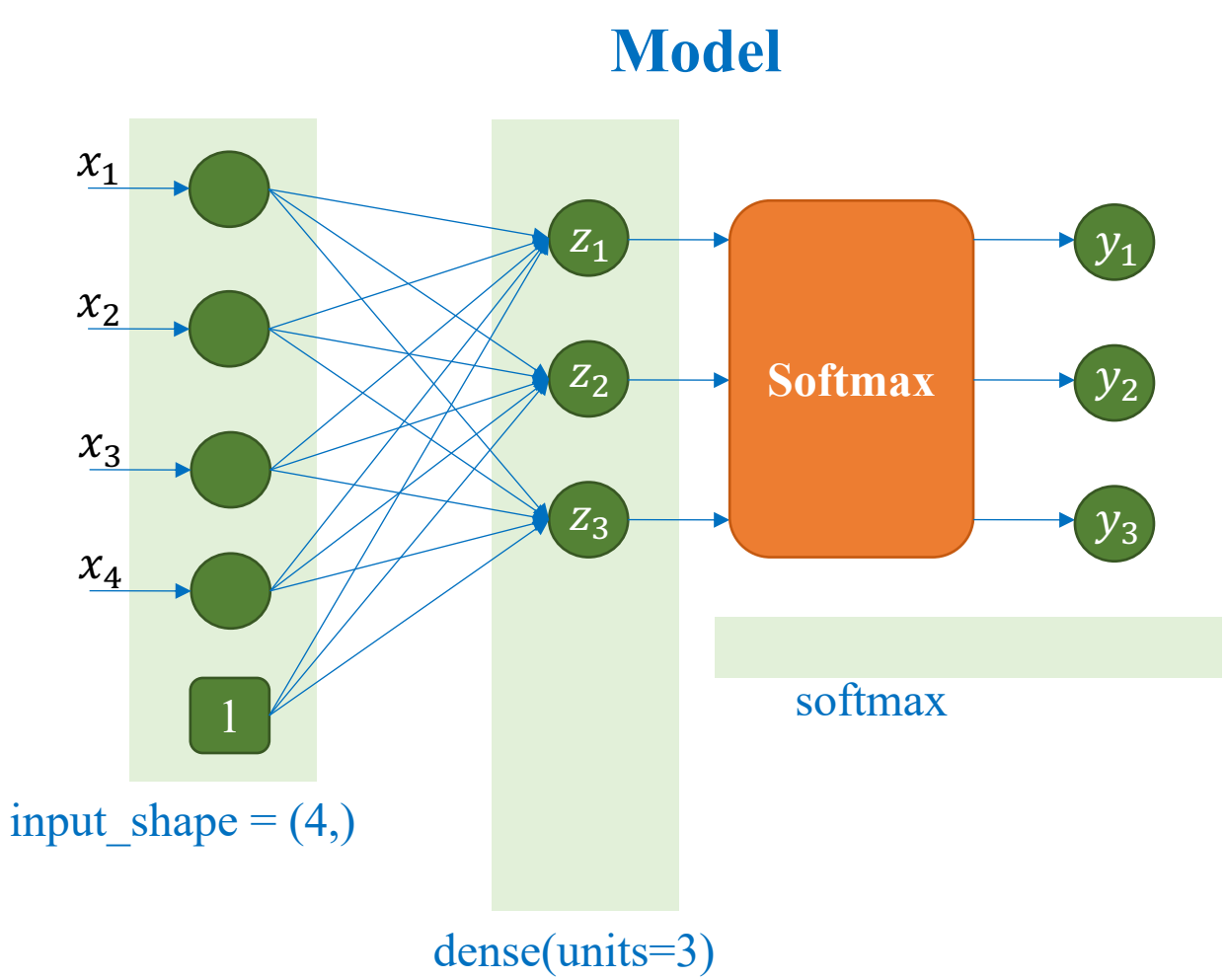
```
import torch.nn as nn
import torch

y_true = torch.Tensor([0, 1]).long()
logit_pred = torch.Tensor([[0.38, -0.09],
                           [1.0, -0.4]])

criterion = nn.CrossEntropyLoss()
loss = criterion(logit_pred, y_true)
print(loss)
```

```
tensor(1.0530)
```

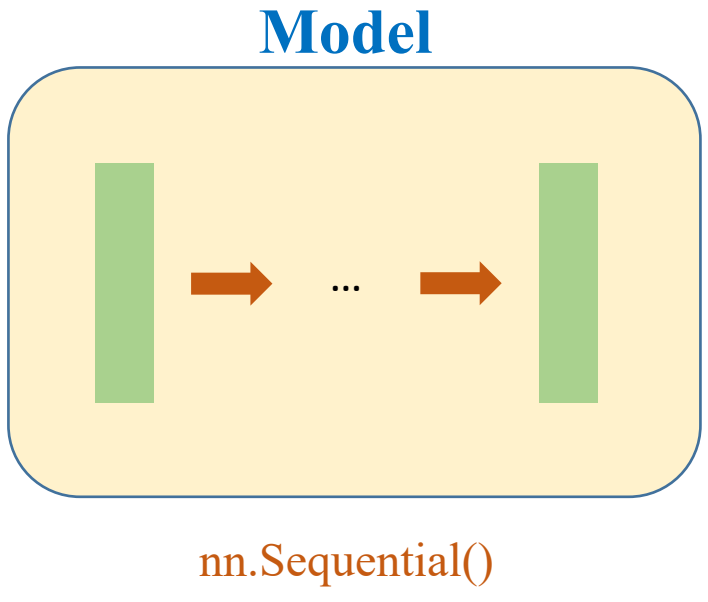


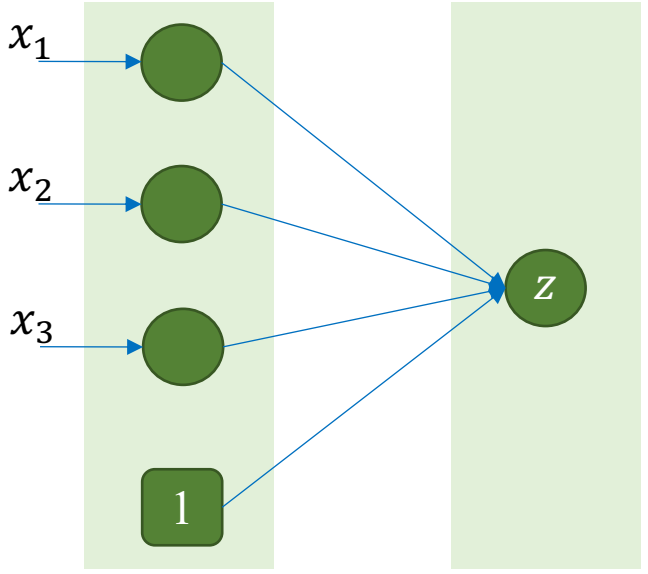
nn.Sequential()

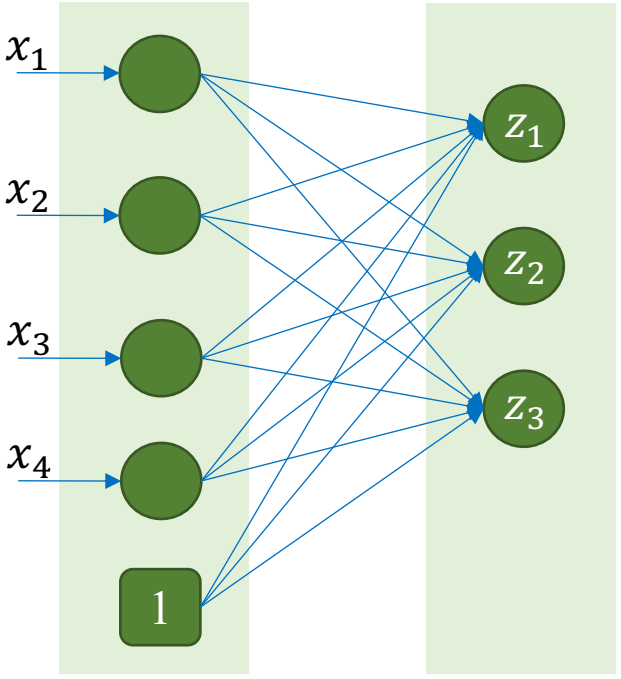




nn.Sequential()







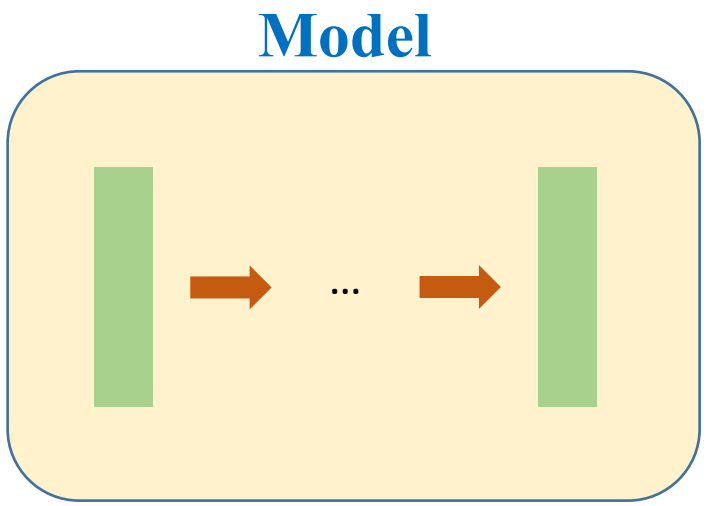

```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=3, out_features=1)
)
summary(model, input_size=(3,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                      [-1, 1]               4
================================================================
```

```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=4, out_features=3)
)
summary(model, input_size=(4,))
```

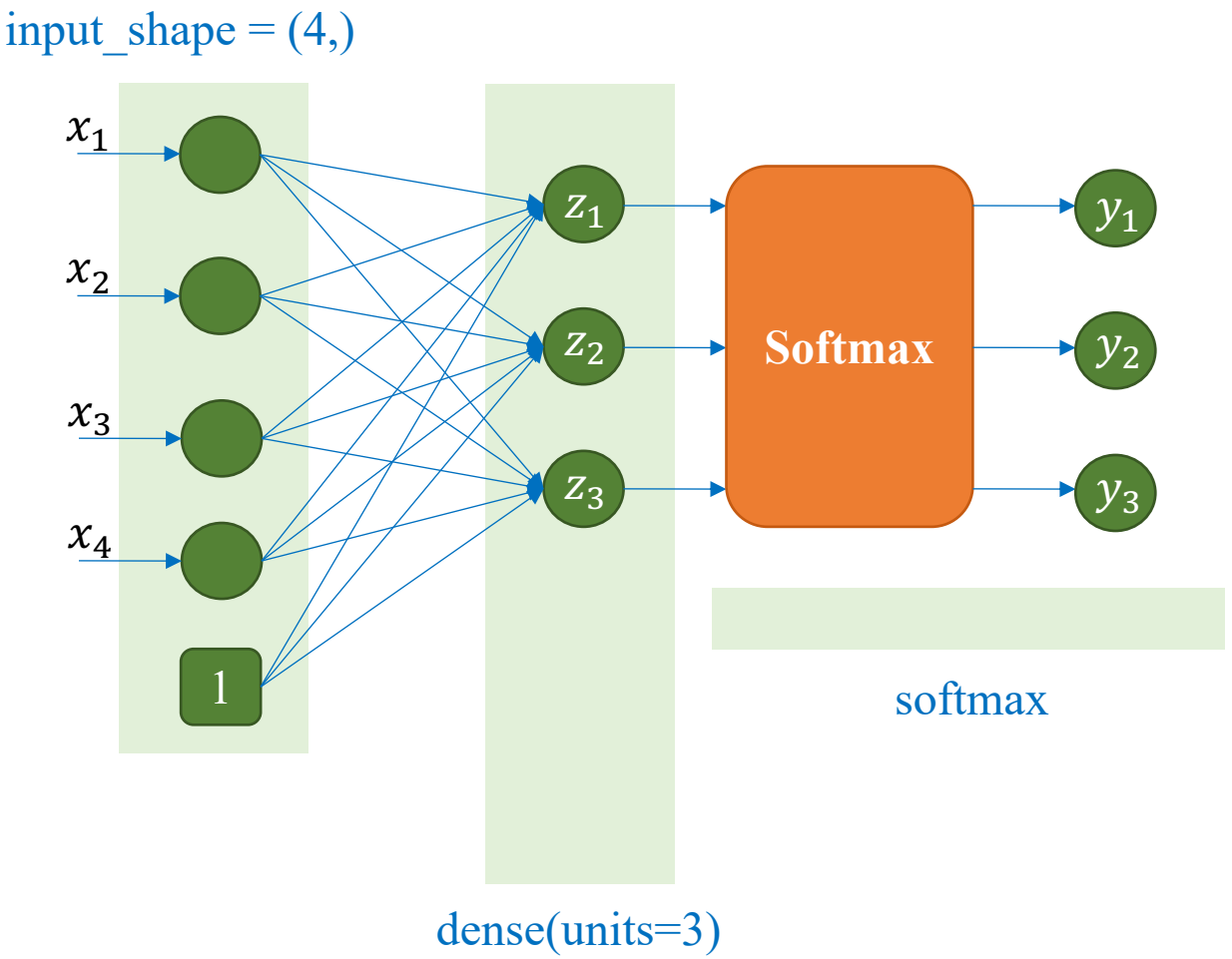
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                      [-1, 3]              15
================================================================
```

nn.Sequential()




```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=4, out_features=3)
    # don't include a softmax layer
)
summary(model, input_size=(4,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                      [-1, 3]              15
================================================================
```



Outline

SECTION 1

Basic PyTorch

SECTION 2

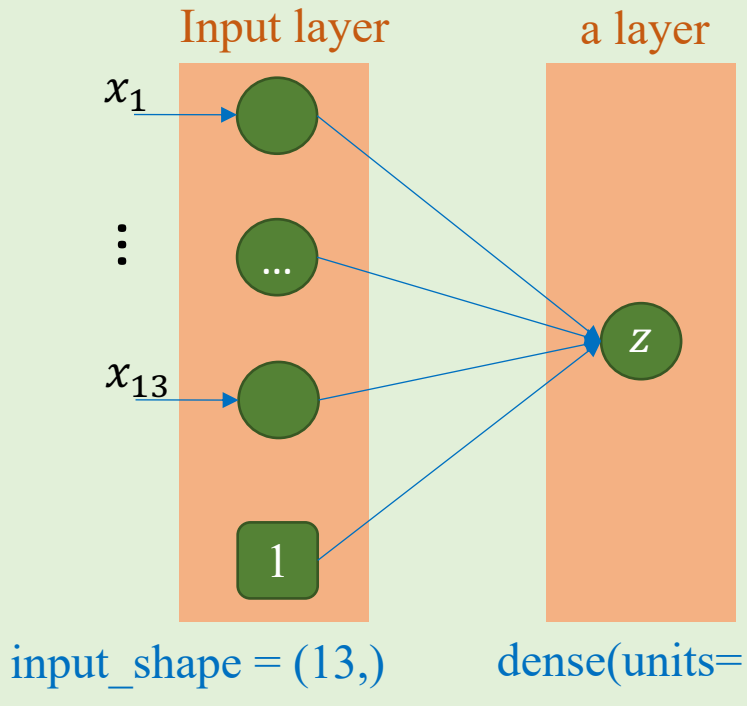
Model Construction

SECTION 3

Training&Inference

Model

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



Model Construction

❖ Linear regression

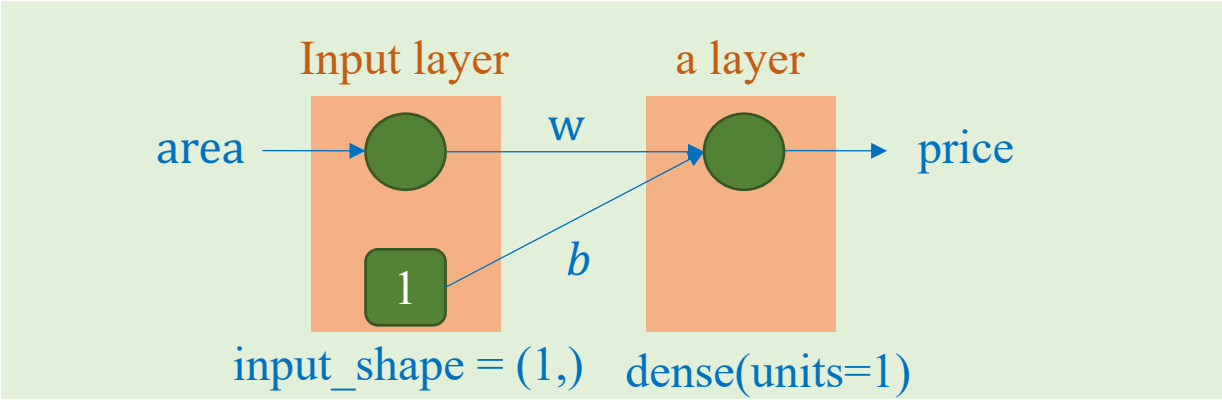
Feature	Label
area	price
6.7	9.1
4.6	5.9
3.5	4.6
5.5	6.7

House price data

Model

$$\text{price} = w * area + b$$

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




```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=1, out_features=1)
)
summary(model, input_size=(1,))
```

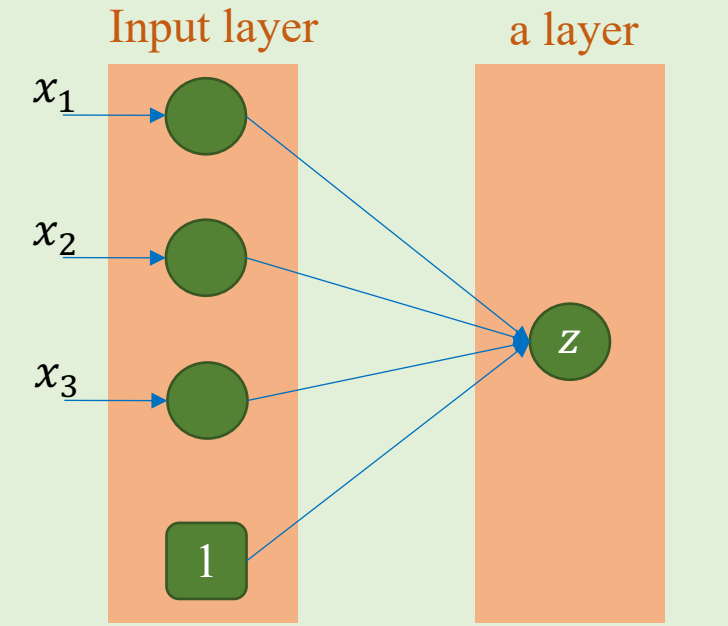
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                      [-1, 1]               2
================================================================
Total params: 2
Trainable params: 2
Non-trainable params: 0
----------------------------------------------------------------
```

Model Construction

❖ Linear regression

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-based sale data



Model

$$\text{Sale} = w_1 * TV + w_2 * Radio + w_3 * Newspaper + b$$

$$\hat{y} = w_1 x_1 + w_2 x_2 + w_3 x_3 + b$$

```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=3, out_features=1)
)
summary(model, input_size=(3,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                [-1, 1]               4
================================================================
```

Model Construction

❖ Linear regression

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

Model

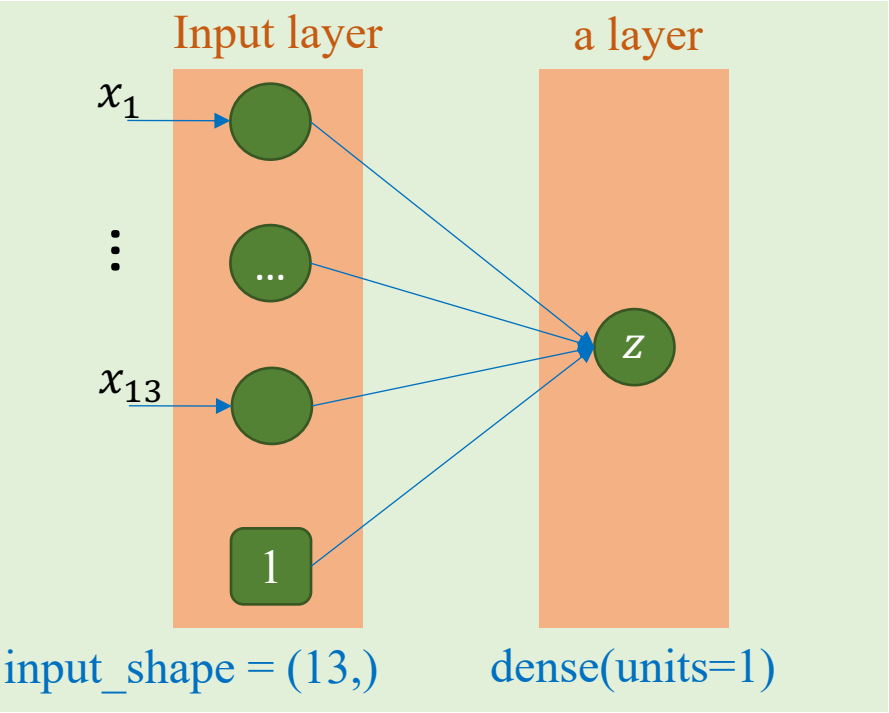
$$\text{medv} = w_1 * x_1 + \cdots + w_{13} * x_{13} + b$$

Model Construction

❖ Linear regression

Model

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




```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=13, out_features=1)
)
summary(model, input_size=(13,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                      [-1, 1]              14
================================================================
Total params: 14
Trainable params: 14
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.00
Estimated Total Size (MB): 0.00
----------------------------------------------------------------
```

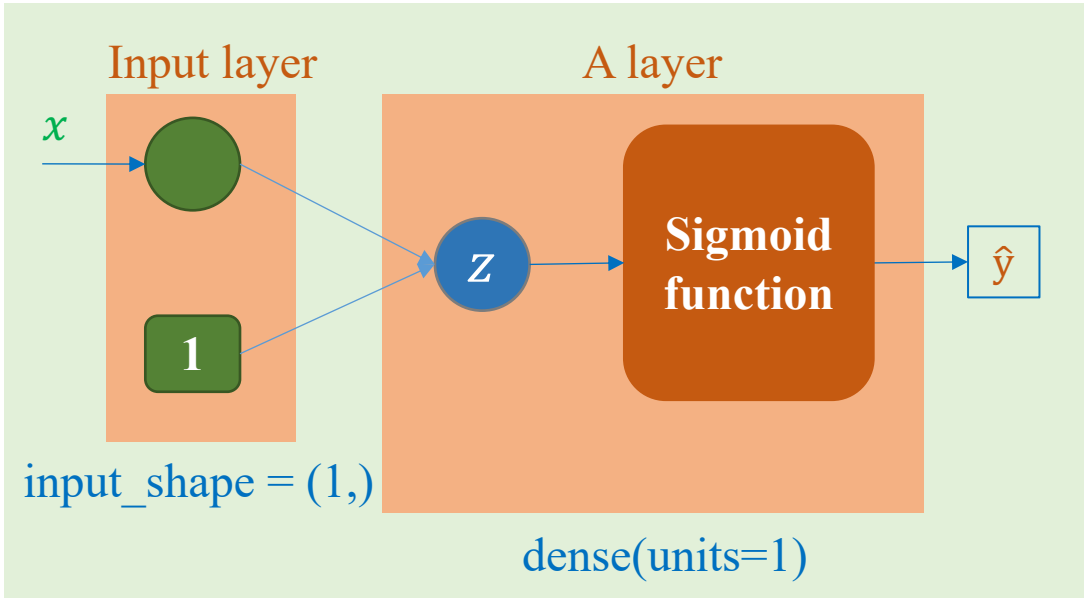
Model Construction

Feature	Label
Petal_Length	Category
1.4	0
1	0
1.5	0
3	1
3.8	1
4.1	1

Model

$$z = \theta^T x$$

$$\hat{y} = \frac{1}{1 + e^{-z}}$$



❖ Logistic regression

```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=1, out_features=1)
    # don't include a sigmoid layer
)
summary(model, input_size=(1,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                [-1, 1]               2
================================================================
Total params: 2
Trainable params: 2
Non-trainable params: 0
----------------------------------------------------------------
```

criterion = nn.BCEWithLogitsLoss()

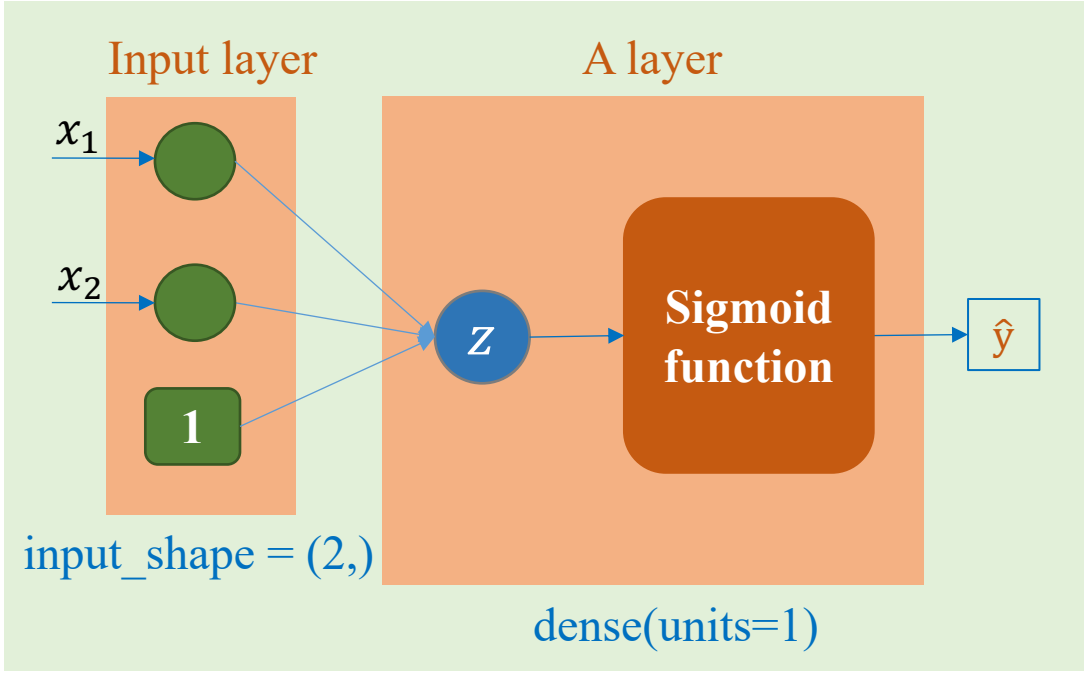
Model Construction

Feature		Label
Petal_Length	Petal_Width	Label
1.5	0.2	0
1.4	0.2	0
1.6	0.2	0
4.7	1.6	1
3.3	1.1	1
4.6	1.3	1

Model

$$z = \theta^T x$$

$$\hat{y} = \frac{1}{1 + e^{-z}}$$



❖ Logistic regression

```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=2, out_features=1)
    # don't include a sigmoid layer
)
summary(model, input_size=(2,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                [-1, 1]                   3
================================================================
Total params: 3
Trainable params: 3
Non-trainable params: 0
----------------------------------------------------------------
```

criterion = nn.BCEWithLogitsLoss()

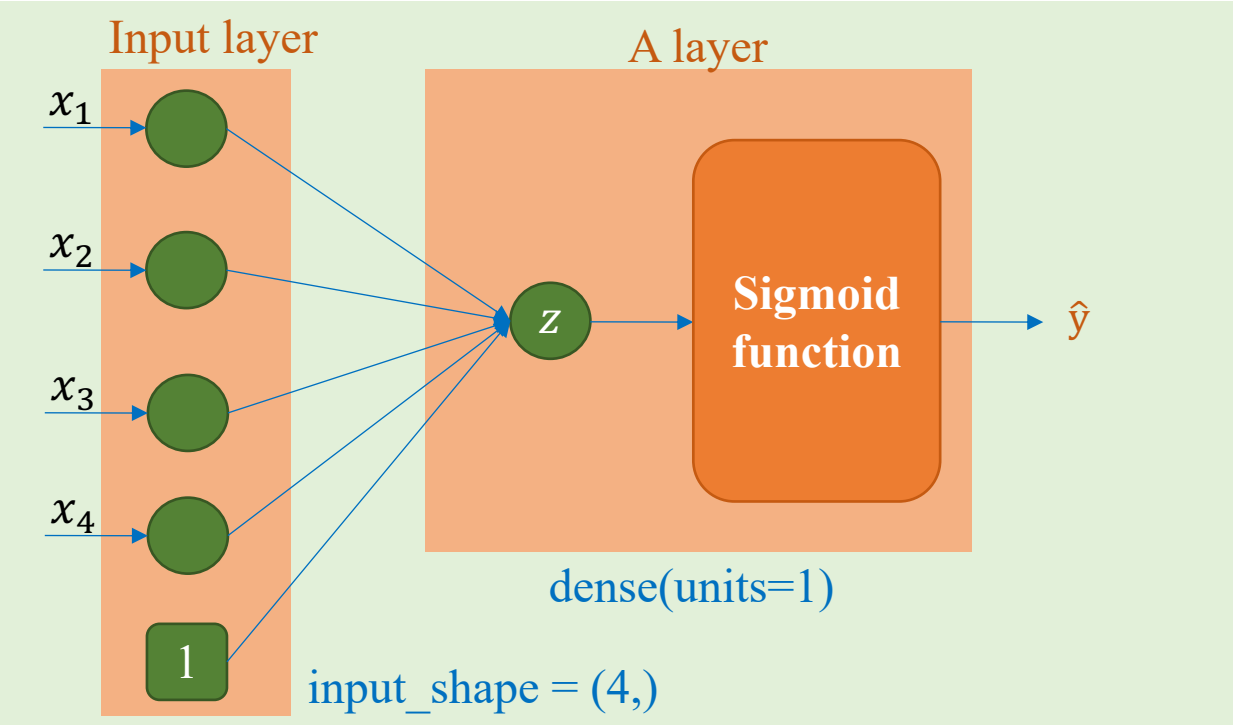
Model Construction

Feature				Label
Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	Label
5.2	3.5	1.5	0.2	0
5.2	3.4	1.4	0.2	0
4.7	3.2	1.6	0.2	0
6.3	3.3	4.7	1.6	1
4.9	2.4	3.3	1.1	1
6.6	2.9	4.6	1.3	1

Model

$$z = \theta^T x$$

$$\hat{y} = \frac{1}{1 + e^{-z}}$$



❖ Logistic regression

```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=4, out_features=1)
    # don't include a sigmoid layer
)
summary(model, input_size=(4,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                      [-1, 1]               5
================================================================
Total params: 5
Trainable params: 5
Non-trainable params: 0
----------------------------------------------------------------
```

criterion = nn.BCEWithLogitsLoss()

Model Construction

Feature	Label
Petal_Length	Label
1.4	1
1.3	1
1.5	1
4.5	2
4.1	2
4.6	2

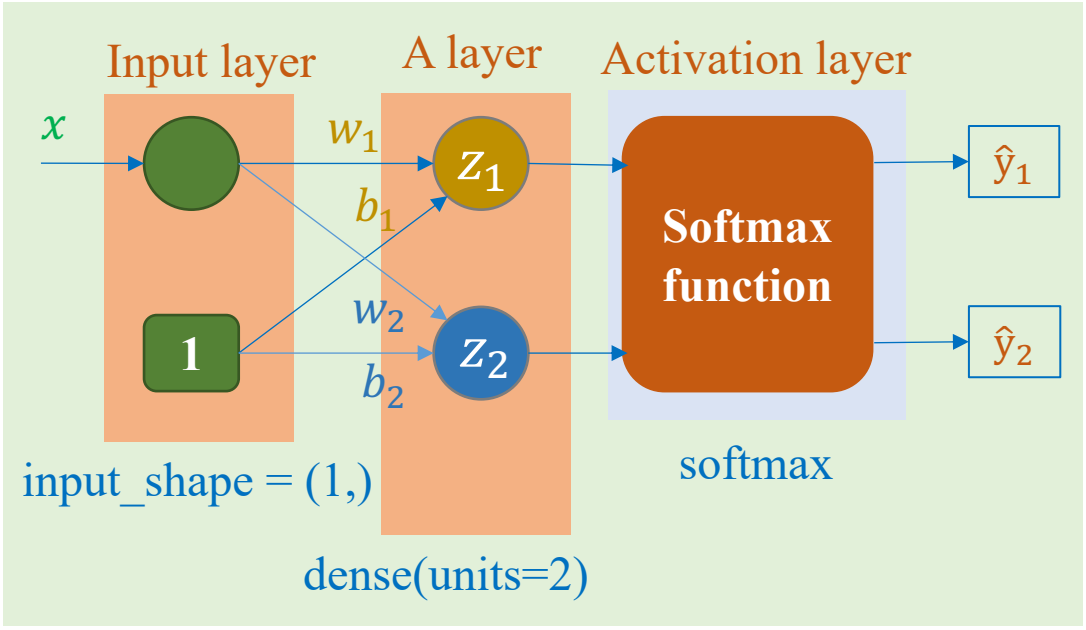
Iris Classification Data

$$z_1 = xw_1 + b_1$$

$$z_2 = xw_2 + b_2$$

$$\hat{y}_1 = \frac{e^{z_1}}{\sum_{j=1}^{2} e^{z_j}}$$

$$\hat{y}_2 = \frac{e^{z_1}}{\sum_{j=1}^{2} e^{z_j}}$$



❖ Softmax regression

```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=1, out_features=2)
    # don't include a softmax layer
)
summary(model, input_size=(1,))
```

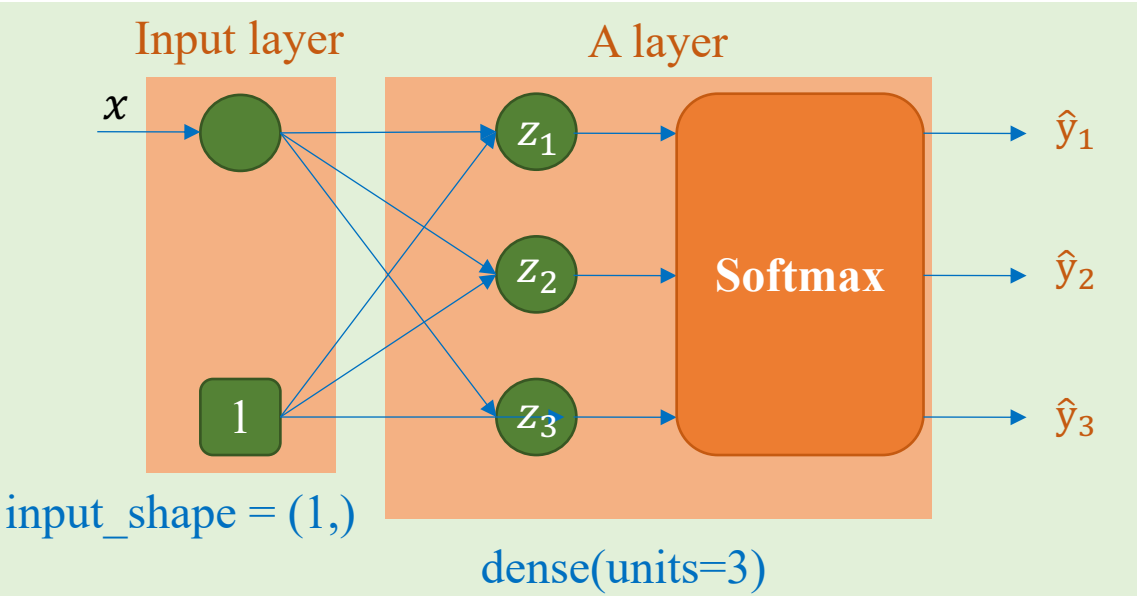
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                [-1, 2]               4
================================================================
Total params: 4
Trainable params: 4
Non-trainable params: 0
----------------------------------------------------------------
```

criterion = nn.CrossEntropyLoss()

Model Construction

❖ Softmax regression

Petal_Length	Label
1.4	1
1.3	1
1.5	1
4.5	2
4.1	2
4.6	2
5.2	3
5.6	3
5.9	3




```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=1, out_features=3)
    # don't include a softmax layer
)
summary(model, input_size=(1,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                      [-1, 3]               6
================================================================
Total params: 6
Trainable params: 6
Non-trainable params: 0
----------------------------------------------------------------
```

criterion = nn.CrossEntropyLoss()

AI VIET NAM
@aivietnam.edu.vn

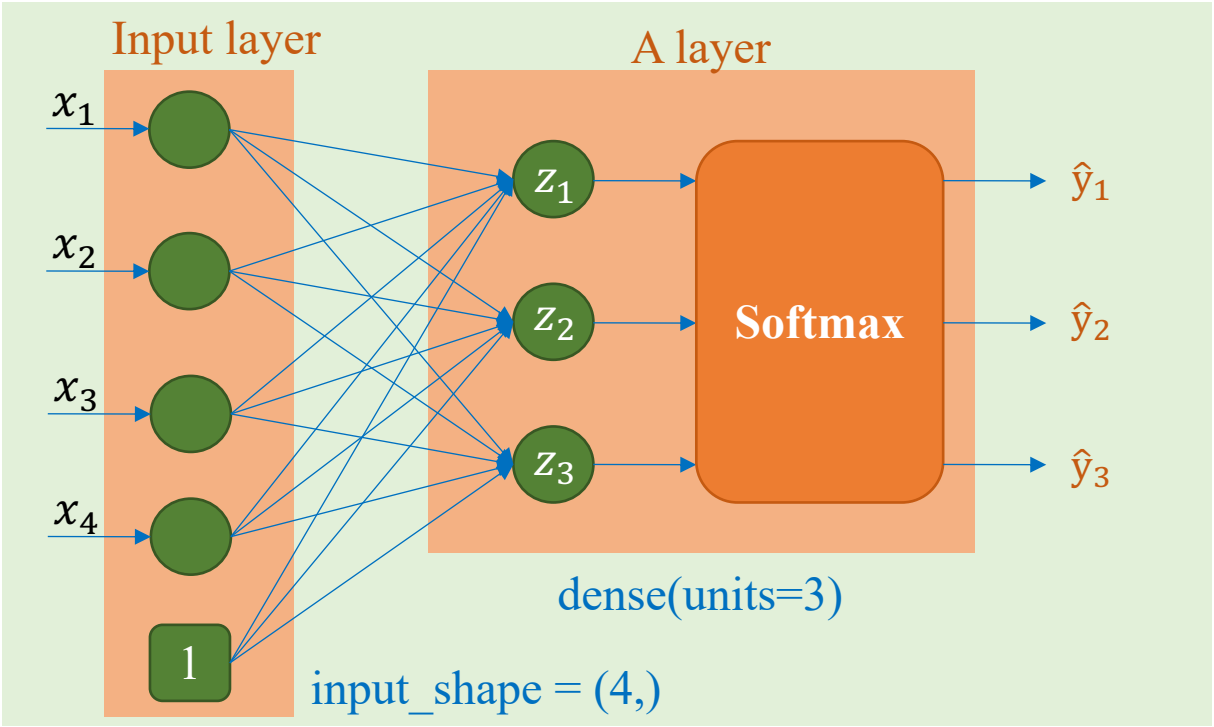
Model Construction

Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	Label
5.2	3.5	1.5	0.2	1
5.2	3.4	1.4	0.2	1
4.7	3.2	1.6	0.2	1
6.3	3.3	4.7	1.6	2
4.9	2.4	3.3	1.1	2
6.6	2.9	4.6	1.3	2
6.4	2.8	5.6	2.2	3
6.3	2.8	5.1	1.5	3
6.1	2.6	5.6	1.4	3

❖ Softmax regression

Forward computation

$$z = \theta^T x \qquad \hat{y} = \frac{e^z}{\sum_{i=1}^{k} e^{z_i}}$$




```
import torch.nn as nn
model = nn.Sequential(
    nn.Linear(in_features=4, out_features=3)
    # don't include a softmax layer
)
summary(model, input_size=(4,))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                      [-1, 3]              15
================================================================
Total params: 15
Trainable params: 15
Non-trainable params: 0
----------------------------------------------------------------
```

Outline

SECTION 1

Basic PyTorch

SECTION 2

Model Construction

SECTION 3

Training&Inference

→ Tính output $\hat{y}$

$$\boldsymbol{z} = \boldsymbol{\theta}^T \boldsymbol{x} \qquad \hat{\mathbf{y}} = \frac{e^{\boldsymbol{z}}}{\sum_{i=1}^{k} e^{z_i}}$$

→ Tính loss (cross-entropy)

$$L(\boldsymbol{\theta}) = -\sum_{i=1}^{k} y_i \log \hat{y}_i$$

→ Tính đạo hàm

$$\frac{\partial L}{\partial \boldsymbol{\theta}_i} = \boldsymbol{x}(\hat{y}_i - y_i)$$

→ Cập nhật tham số (Stochastic gradient descent)

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

Training

❖ Logistic regression

→ Tính output $\hat{y}$

$$z = \theta^T x$$
$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}}$$

→ Tính loss (binary cross-entropy)

$$L(\theta) = \left(-\mathbf{y}^{\mathrm{T}}\log\hat{\mathbf{y}} - (\mathbf{1}-\mathbf{y})^{\mathrm{T}}\log(1-\hat{\mathbf{y}})\right)$$

→ Tính đạo hàm

$$L'_{\theta} = \mathbf{x}^{\mathrm{T}}(\hat{\mathbf{y}} - \boldsymbol{y})$$

→ Cập nhật tham số (Stochastic gradient descent)

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

Declare optimizer and loss function

```
criterion = nn.BCEWithLogitsLoss()
optimizer = optim.SGD(model.parameters(),
                      lr=learning_rate)
```

Start training

```
for epoch in range(max_epoch):
    # Zero the gradients
    optimizer.zero_grad()

    # Forward pass
    outputs = model(X)

    # Compute loss
    loss = criterion(outputs, y)

    # Backward pass and optimization
    loss.backward()
    optimizer.step()
```

Training

❖ Softmax regression

→ Tính output $\hat{y}$

$$z = \theta^T x \qquad \hat{y} = \frac{e^z}{\sum_{i=1}^{k} e^{z_i}}$$

→ Tính loss (cross-entropy)

$$L(\theta) = -\sum_{i=1}^{k} y_i \log \hat{y}_i$$

→ Tính đạo hàm

$$\frac{\partial L}{\partial \theta_i} = x(\hat{y}_i - y_i)$$

→ Cập nhật tham số (Stochastic gradient descent)

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

Delaration and Training

```
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(),
                      lr=learning_rate)
```

```
for epoch in range(max_epoch):
    # Zero the gradients
    optimizer.zero_grad()

    # Forward pass
    outputs = model(X)

    # Compute loss
    loss = criterion(outputs, y)

    # Backward pass and optimization
    loss.backward()
    optimizer.step()
```

Training

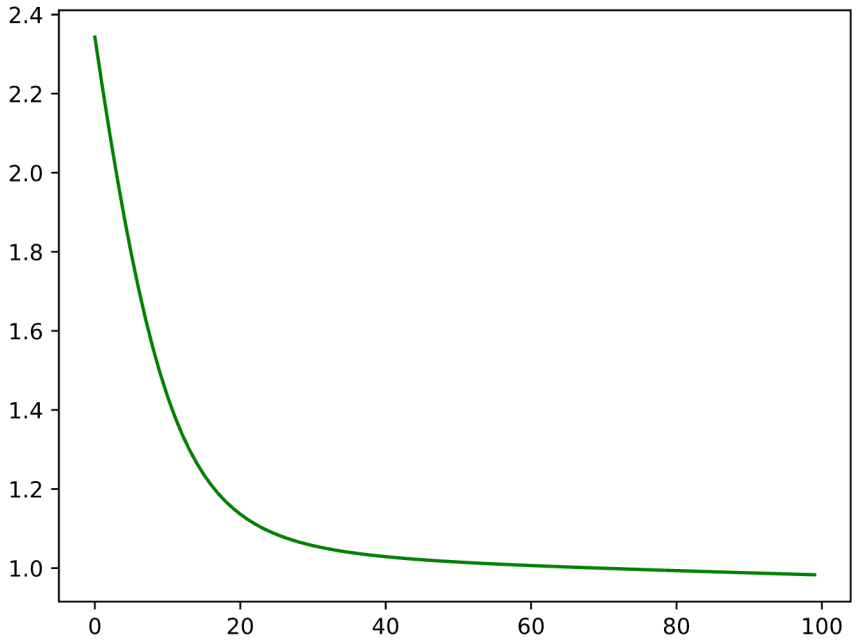
Petal_Length	Label
1.4	1
1.3	1
1.5	1
4.5	2
4.1	2
4.6	2
5.2	3
5.6	3
5.9	3

❖ Softmax regression

Model

$$z = \theta^T x$$

$$\hat{y} = \frac{e^z}{\sum_{i=1}^{k} e^{z_i}}$$




```python
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim

# Load data
iris = np.genfromtxt('iris_2D_3c.csv', dtype=None,
                     delimiter=',', skip_header=1)
X = torch.tensor(iris[:, 0:2], dtype=torch.float32)
y = torch.tensor(iris[:, 2], dtype=torch.int64)

# Define a simple Sequential model
input_dim = X.shape[1]
output_dim = len(torch.unique(y))
model = nn.Sequential(
    nn.Linear(in_features=input_dim, out_features=output_dim)
)

# Loss and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)
```

Training

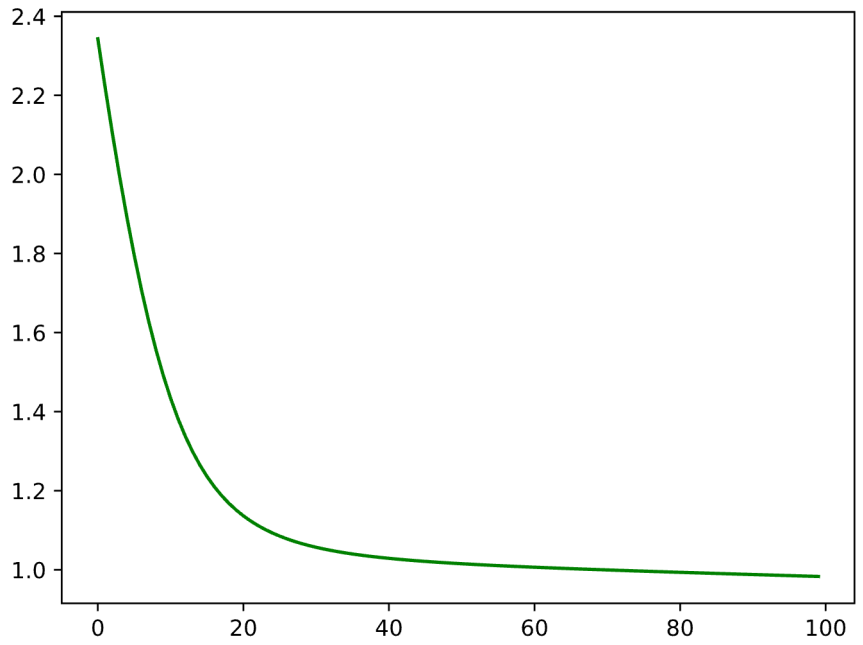
Petal_Length	Label
1.4	1
1.3	1
1.5	1
4.5	2
4.1	2
4.6	2
5.2	3
5.6	3
5.9	3

❖ Softmax regression

Model

$$z = \theta^T x$$

$$\hat{y} = \frac{e^z}{\sum_{i=1}^{k} e^{z_i}}$$



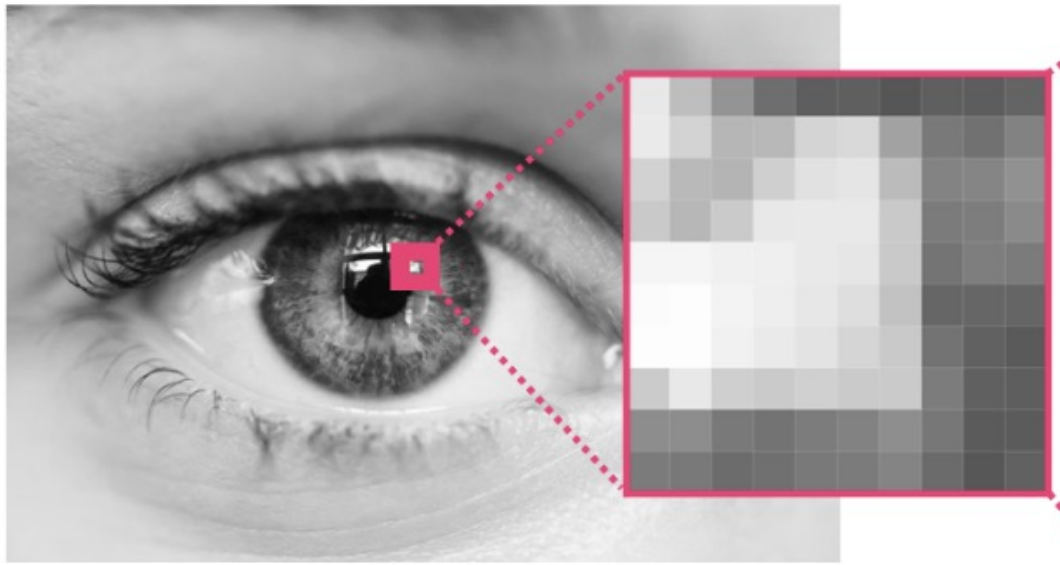

```python
# Training loop
max_epoch = 100
losses = []

for epoch in range(max_epoch):
    # Zero the gradients
    optimizer.zero_grad()

    # Forward pass
    outputs = model(X)

    # Compute loss
    loss = criterion(outputs, y)
    losses.append(loss.item())

    # Backward pass and optimization
    loss.backward()
    optimizer.step()
```

```python
import matplotlib.pyplot as plt
plt.plot(losses, 'g')
```

Extend to Image Data

Image Classification: Image Data

❖ Grayscale images



230	194	147	108	90	98	84	96	91	101
237	206	188	195	207	213	163	123	116	128
210	183	180	205	224	234	188	122	134	147
198	189	201	227	229	232	200	125	127	135
249	241	237	244	232	226	202	116	125	126
251	254	241	239	230	217	196	102	103	99
243	255	240	231	227	214	203	116	95	91
204	231	208	200	207	201	200	121	95	95
144	140	120	115	125	127	143	118	92	91
121	121	108	109	122	121	134	106	86	97

(Height, Width)

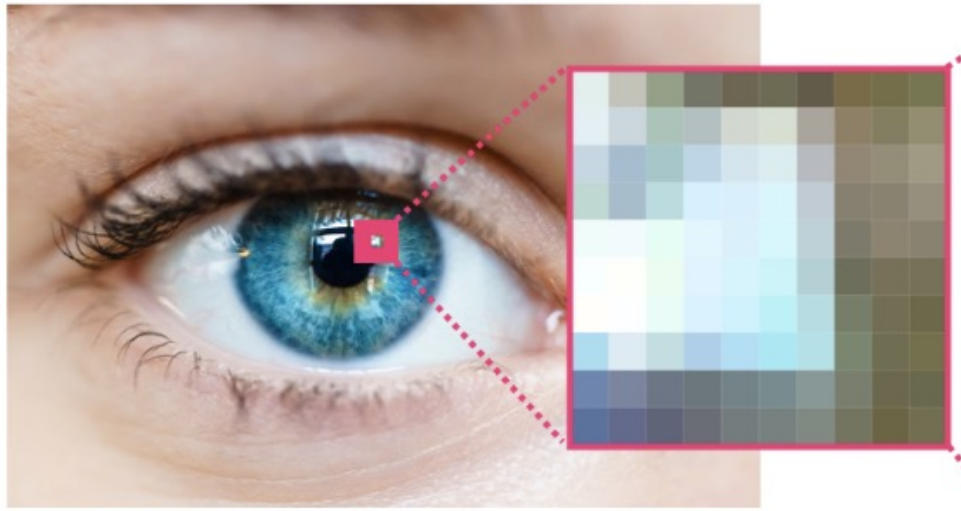
Pixel p = scalar

$0 \leq p \leq 255$

Resolution: #pixels
Resolution = HeightxWidth

Image Classification: Image Data

❖ Color images



	233	188	137	96	90	95	63	73	73	82
237	202	159	120	105	110	88	107	112	121	109
226	191	147	110	101	112	98	123	110	119	142	131
221	191	176	182	203	214	169	144	133	145	155	122
185	160	161	184	205	223	186	137	147	161	140	115
181	174	189	207	206	215	194	136	142	151	133	87
246	237	237	231	208	206	192	122	143	144	111	74
254	254	241	224	199	192	181	99	122	117	107	74
239	248	232	207	187	182	184	110	114	110	113	74
193	215	193	167	158	164	181	114	112	111	105	82
113	119	110	111	113	123	135	120	108	106	113	
93	97	91	103	107	111	122	112	104	114		

(Channel, Height, Width,)

RGB color image

Pixel $p = \begin{bmatrix} r \\ g \\ b \end{bmatrix}$

$0 \leq r,g,b \leq 255$

Resolution: #pixels
Resolution = HeightxWidth

Image Data

MNIST dataset

- Grayscale images
- Resolution=28x28
- Training set: 60000 samples
- Testing set: 10000 samples

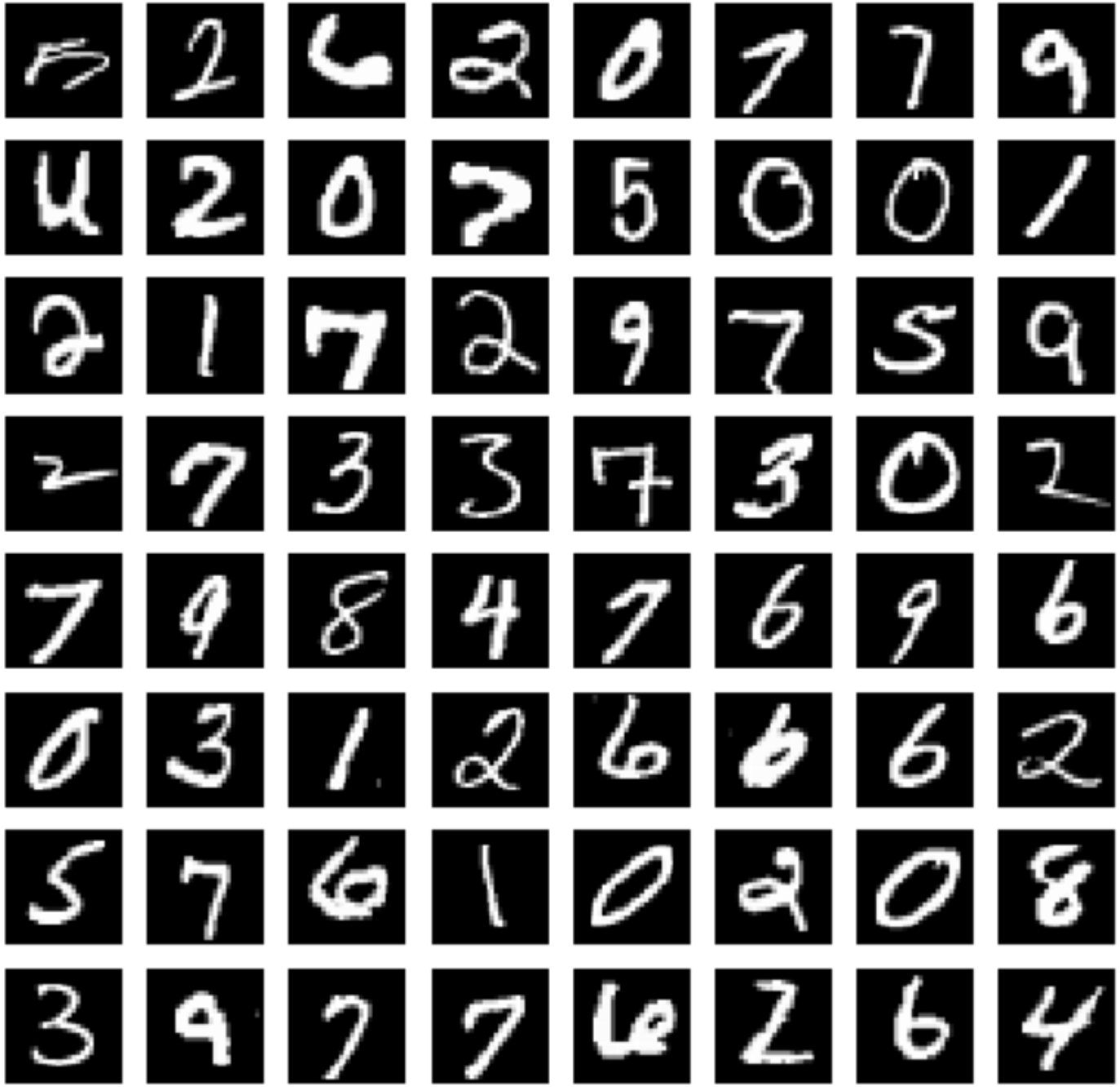
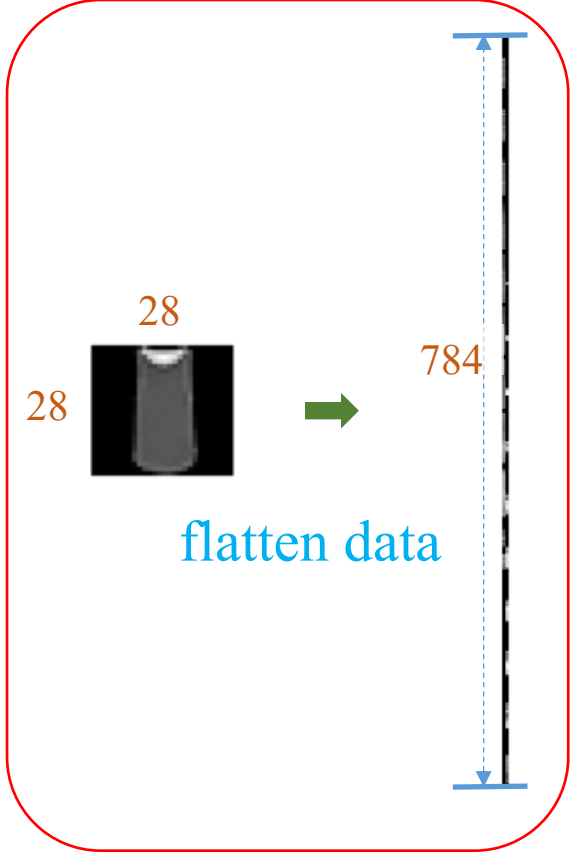


Image Data

Fashion-MNIST dataset

- Grayscale images
- Resolution=28x28
- Training set: 60000 samples
- Testing set: 10000 samples

Using Softmax Regression



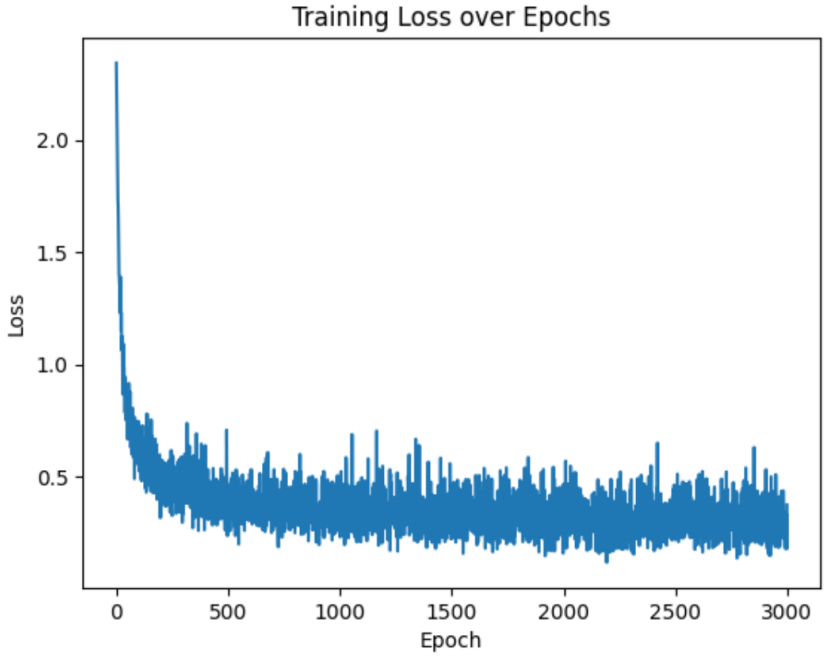

```
X_train: (60000, 784)
y_train: (60000,)
X_test: (10000, 784)
y_test: (10000,)
```

Data Sets

```python
class SoftmaxRegression(nn.Module):
    def __init__(self, input_dim, output_dim):
        super(SoftmaxRegression, self).__init__()
        self.linear = nn.Linear(input_dim, output_dim)
        self.flatten = nn.Flatten()

    def forward(self, x):
        x = self.flatten(x)
        return self.linear(x)
```

Demo

```python
# Testing the model
with torch.no_grad():
    correct = 0
    total = 0
    for images, labels in test_loader:
        outputs = model(images)
        predicted = torch.argmax(outputs.data, dim=1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
```



Test Accuracy
91.97%

```python
# Load MNIST dataset
train_loader = ...
test_loader = ...

# Input and output dimensions
input_dim = 28 * 28  # MNIST images are 28x28
output_dim = 10      # 10 classes for MNIST

# Create a Sequential model
model = nn.Sequential(nn.Flatten(),
                      nn.Linear(input_dim, output_dim))

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

# Training loop
num_epochs = 5
losses = []  # to store the average loss for each epoch

for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):
        outputs = model(images)
        loss = criterion(outputs, labels)
        losses.append(loss.item())

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

Summary

Basic PyTorch

Mean Squared Error

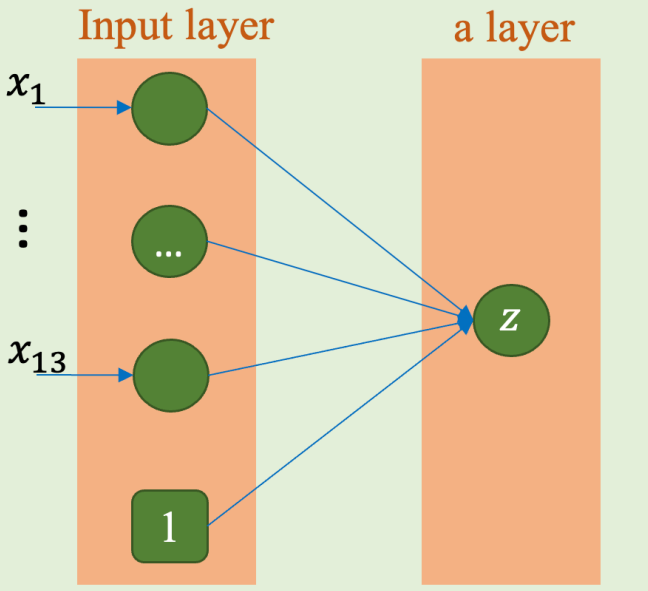
$$mse = \frac{1}{N}\sum_{i}(\boldsymbol{x}_i - \boldsymbol{y}_i)^2$$

```python
# Compute squared difference
import torch

# Create two tensors
x = torch.tensor([1.0, 2.0, 3.0, 4.0])
y = torch.tensor([5.0, 5.0, 5.0, 5.0])

# Compute squared difference
loss_fn = torch.nn.MSELoss()
mse = loss_fn(x,y)

print(f'x:\n {x}')
print(f'y = {y}')
print(f'mse:\n {mse}')
```

Model Construction

Model

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



Training&Inference

→ Tính output $\hat{y}$

$$\boldsymbol{z} = \boldsymbol{\theta}^T\boldsymbol{x} \qquad \hat{\boldsymbol{y}} = \frac{e^{\boldsymbol{z}}}{\sum_{i=1}^{k} e^{z_i}}$$

→ Tính loss (cross-entropy)

$$L(\boldsymbol{\theta}) = -\sum_{i=1}^{k} y_i \log \hat{y}_i$$

→ Tính đạo hàm $\frac{\partial L}{\partial \boldsymbol{\theta}_i} = \boldsymbol{x}(\hat{y}_i - y_i)$

→ Cập nhật tham số (Stochastic gradient descent)

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