第五讲 PyTorch Tutorial

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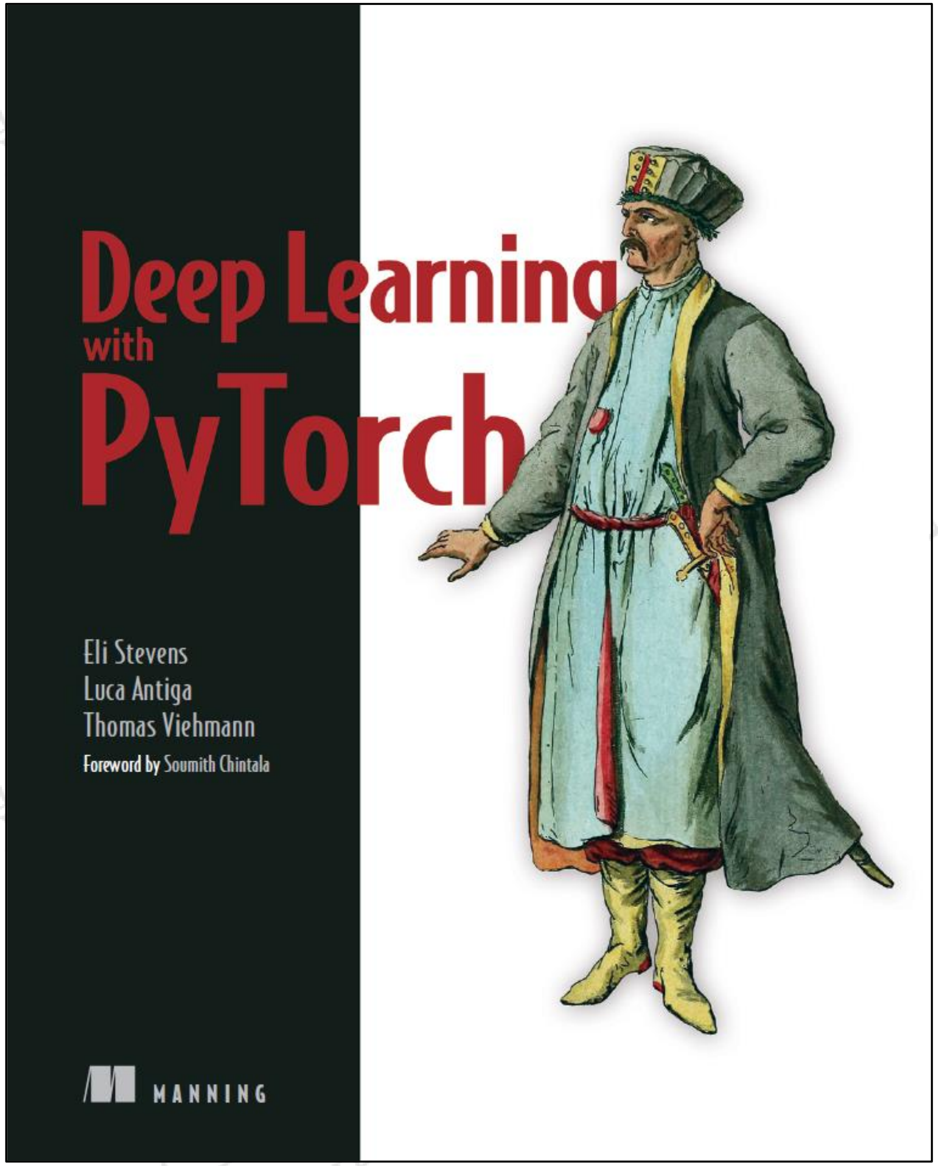
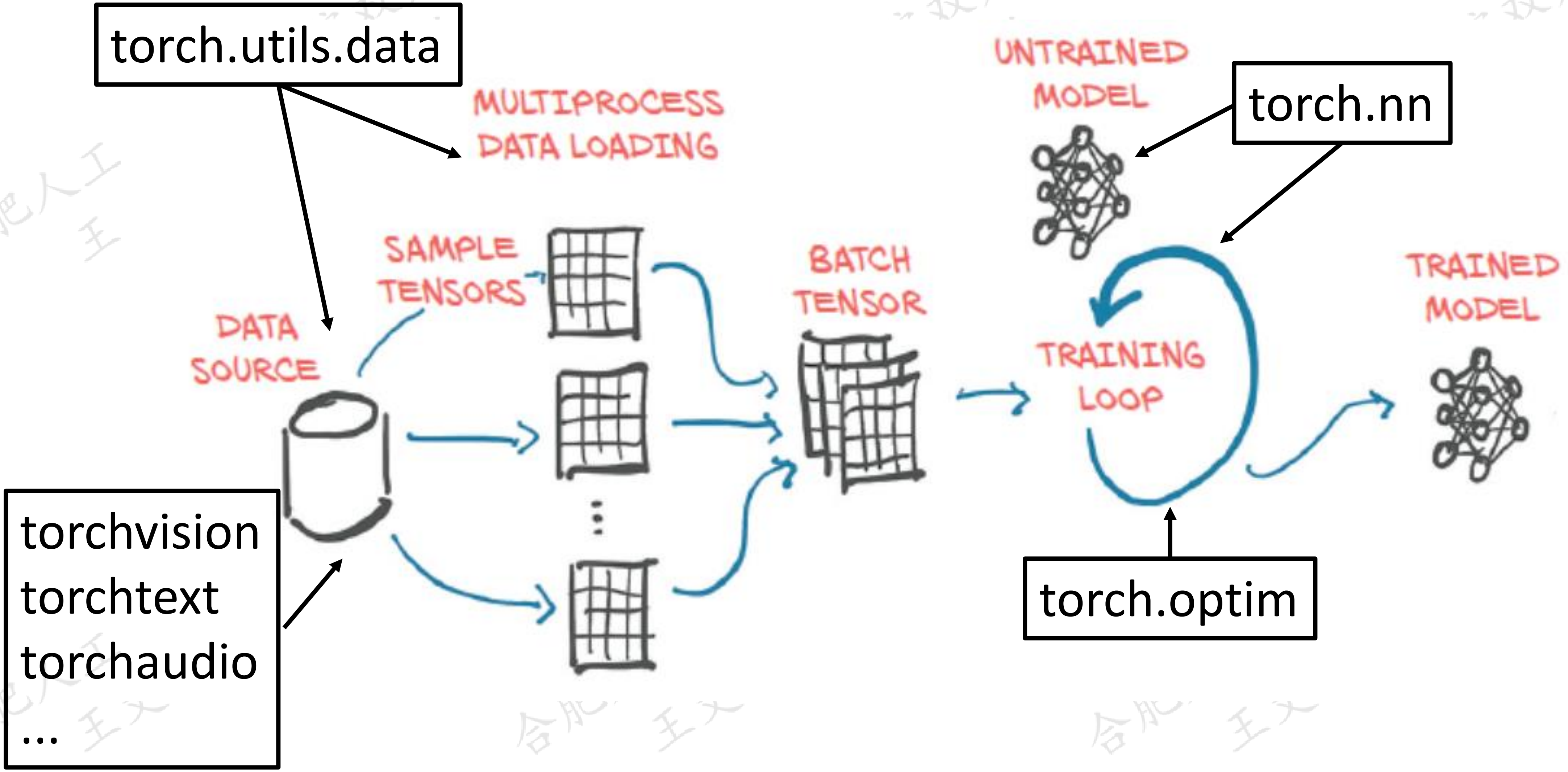


https://www.manning.com/books/deep-learning-with-pytorch

大纲

- 核心数据结构Tensor
- 多层感知机编程
- 卷积神经网络编程

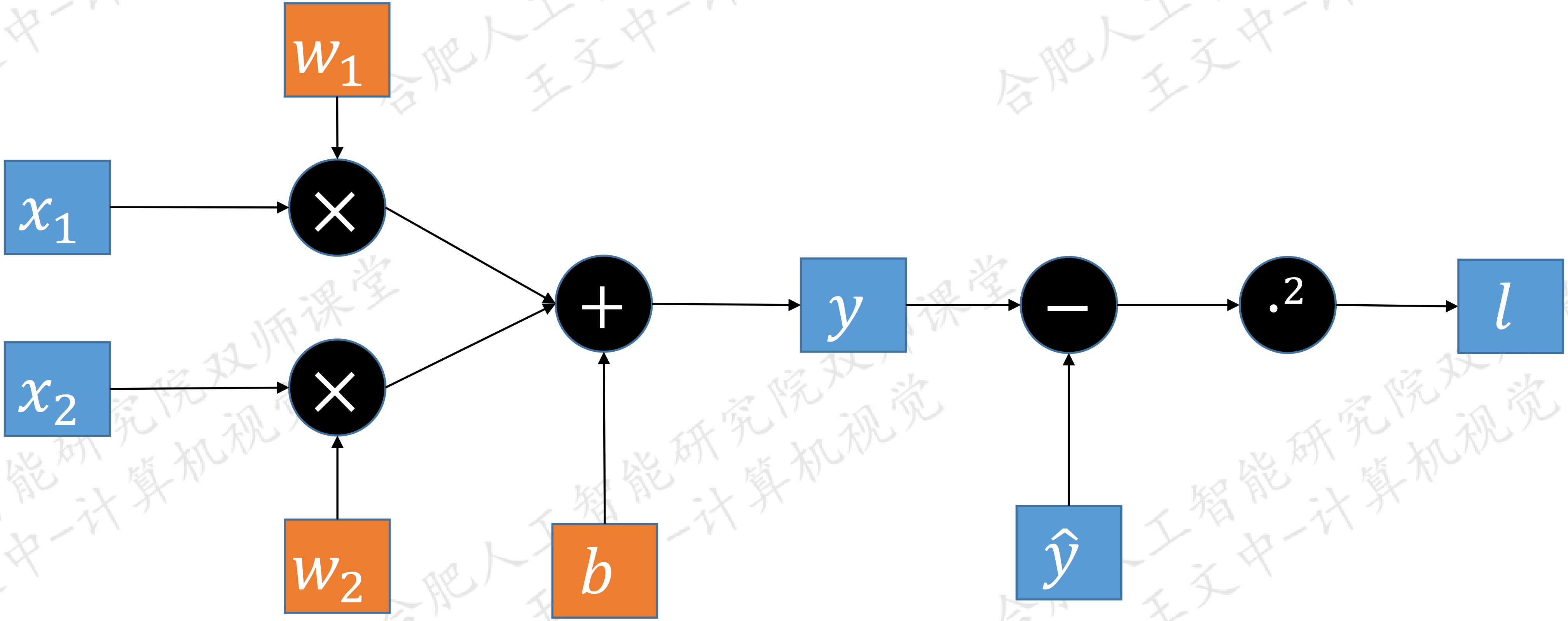
PyTorch



torch.utils.data
MULTIPROCESS DATA LOADING
UNTRAINED MODEL
torch.nn
SAMPLE TENSORS
DATA SOURCE
BATCH TENSOR
TRAINING LOOP
TRAINED MODEL
torchvision
torchtext
torchaudio
...
torch.optim

计算图

$$y = h(x; w, b) = w_1 \times x_1 + w_2 \times x_2 + b$$
$$l = (y - \hat{y})^2$$



用张量表示数据与参数

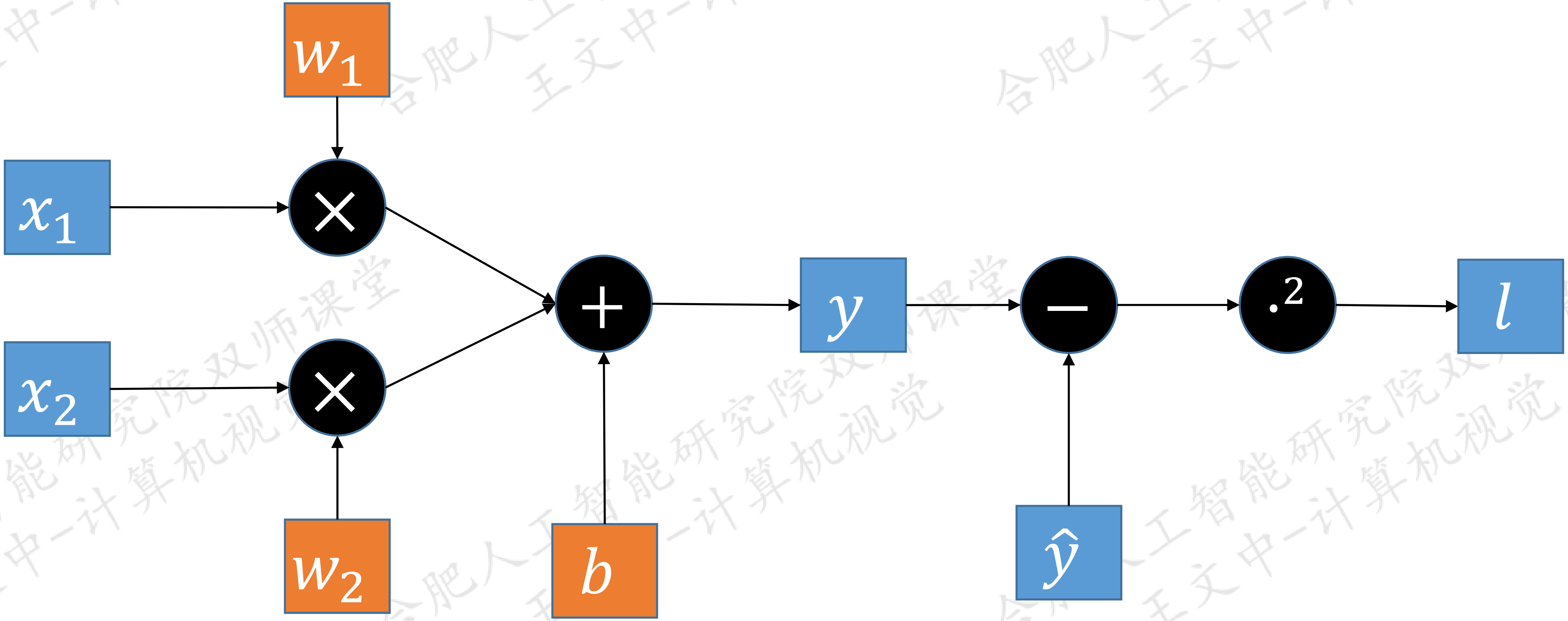
$$y = h(x; w, b) = w_1 \times x_1 + w_2 \times x_2 + b$$
$$l = (y - \hat{y})^2$$

$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \mathrm{w} = \begin{pmatrix} w_1 \\ w_2 \end{pmatrix}, b$$
$$y = w^T x + b$$
$$l = (y - \hat{y})^2$$

$$X = \left(x^{(1)}, x^{(2)}, \ldots, x^{(n)}\right)$$
$$\hat{Y} = \left(y^{(1)}, y^{(2)}, \ldots, y^{(n)}\right)$$
$$Y = w^T X + b$$
$$L = \left(Y - \hat{Y}\right)^2$$

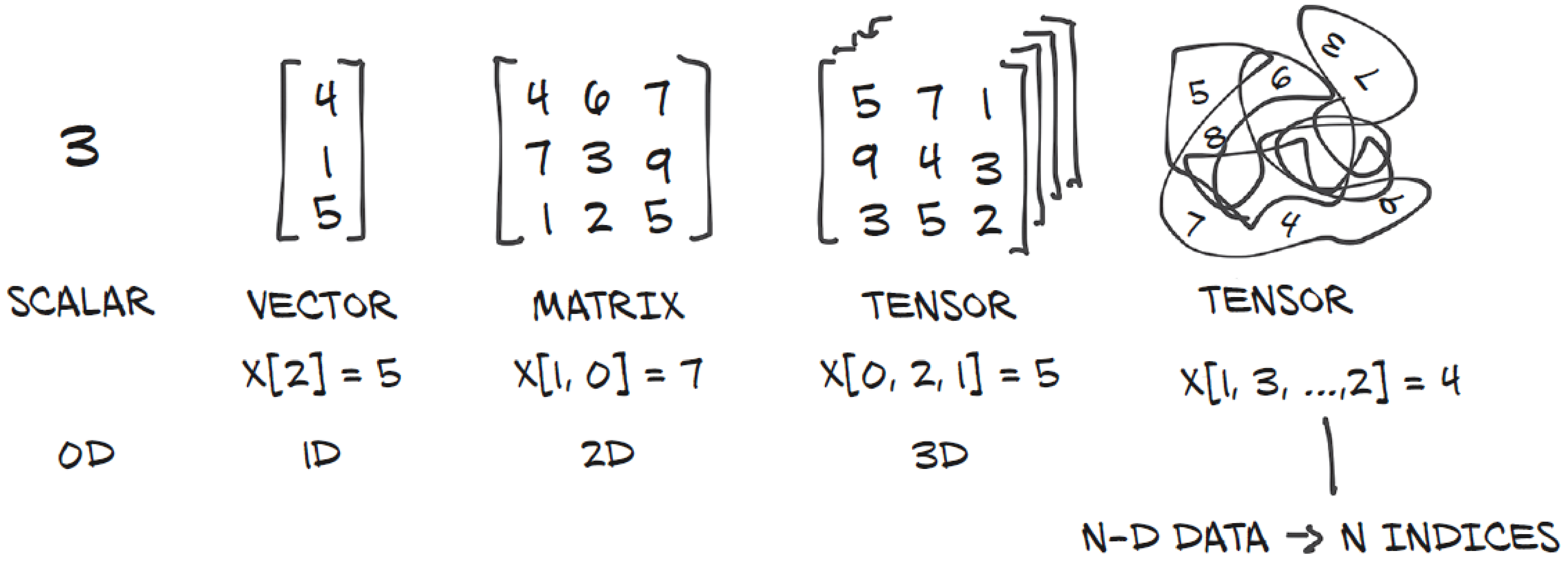
计算:张量流(Tensor Flow)

$$y = h(x; w, b) = w_1 \times x_1 + w_2 \times x_2 + b$$
$$l = (y - \hat{y})^2$$



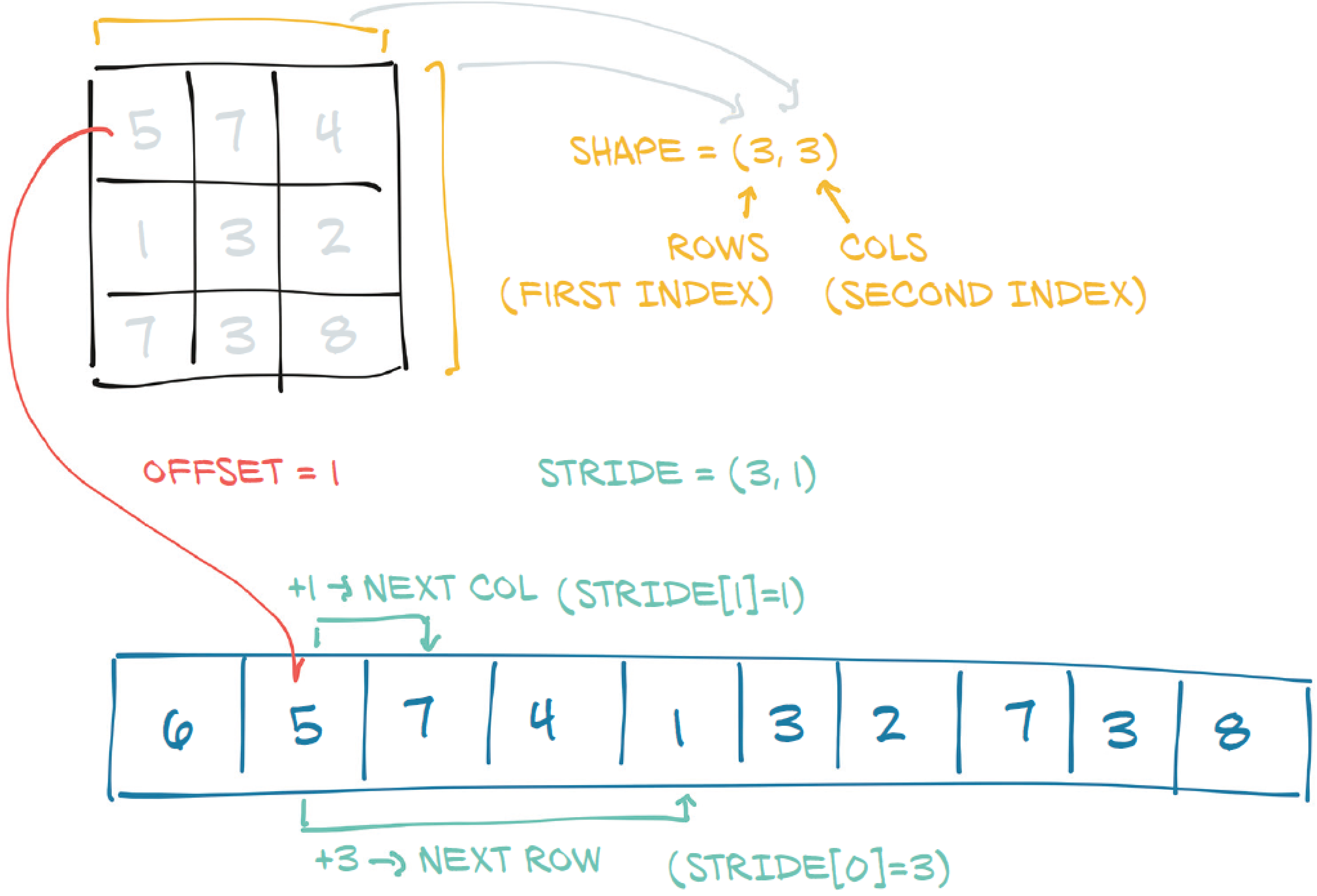
1.核心数据结构:Tensor

Tensor:多维数组


3
SCALAR
0D
4
1
5
VECTOR
X[2] = 5
1D
4 6 7
7 3 9
1 2 5
MATRIX
X[1, 0] = 7
2D
5 7 1
9 4 3
3 5 2
TENSOR
X[0, 2, 1] = 5
3D
TENSOR
X[1, 3, ...,2] = 4
N-D DATA → N INDICES

1.1 创建与操作Tensor

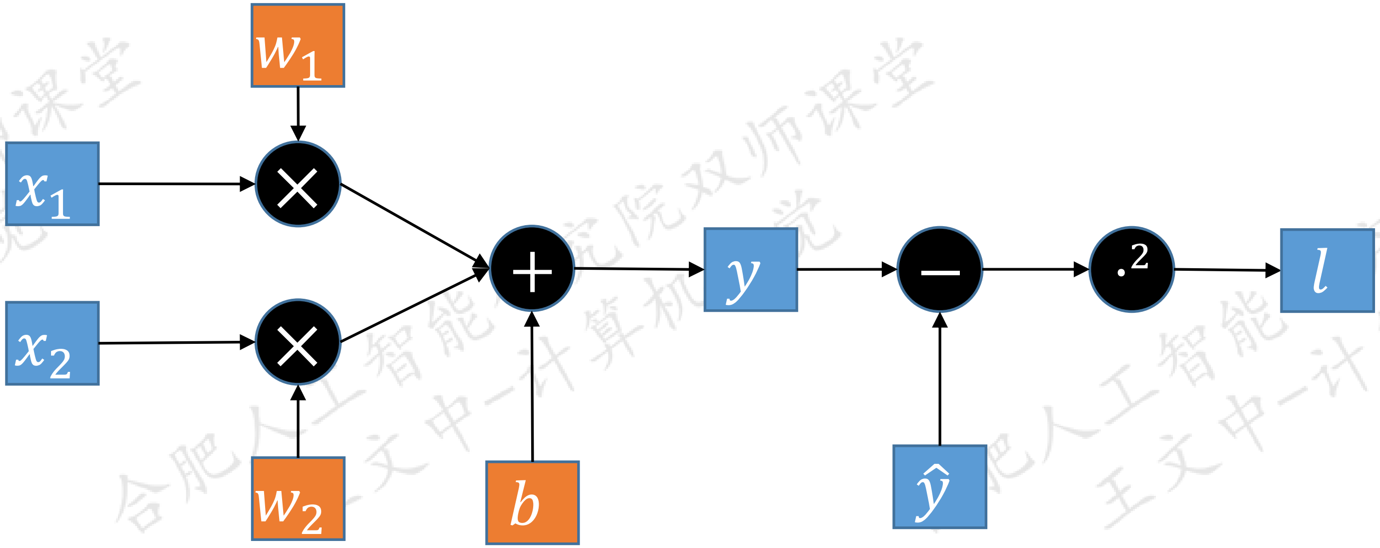
Tensor的属性



5 7 4
1 3 2
7 3 8
SHAPE = (3, 3)
ROWS
(FIRST INDEX)
COLS
(SECOND INDEX)
OFFSET = 1
STRIDE = (3, 1)
+1 → NEXT COL (STRIDE[1]=1)
6 5 7 4 1 3 2 7 3 8
+3 → NEXT ROW (STRIDE[0]=3)

创建一个Tensor

- 1.使用torch的创建算子(Creation Ops)
- 2.通过对Tensor的运算创建



创建一个Tensor

```
a = torch.tensor(1.0)
print(a)
print(a.dim())
print(a.shape)#print(a.size())
print(a.dtype)
print(a.item())
```

```
tensor(1.)
0
torch.Size([])
torch.float32
1.0
```

```
b = torch.tensor([1,2,3])
print(b)
print(b.dim())
print(b.shape)
print(b.dtype)
print(b.numpy())
```

```
tensor([1, 2, 3])
1
torch.Size([3])
torch.int64
[1 2 3]
```

```
x = np.array([0,1])
c = torch.from_numpy(x)
```

```
tensor([0, 1], dtype=torch.int32)
```

创建一个Tensor

```
c = torch.tensor([[1,2],[3,4],[5,6]],dtype = torch.int16)
print(c)
print(c.dim())
print(c.shape)
print(c.dtype)
print(c.numpy())
```

```
tensor([[1, 2],
        [3, 4],
        [5, 6]], dtype=torch.int16)
2
torch.Size([3, 2])
torch.int16
[[1 2]
 [3 4]
 [5 6]]
```

创建一个Tensor

```
d = torch.zeros((3,4))
```

```
tensor([[0., 0., 0., 0.],
        [0., 0., 0., 0.],
        [0., 0., 0., 0.]])
```

```
e = torch.randn((2,2,3,4))
```

```
tensor([[[[-1.0510,  0.3902,  0.1810,  1.0036],
          [-1.4556,  0.4581, -0.5105, -1.3028],
          [-0.8999,  0.3423,  0.0936,  1.3038]],

         [[-0.7691,  0.4797, -1.8662, -0.7550],
          [ 0.0411,  0.5273, -0.1488,  1.0463],
          [ 1.1466, -0.3363,  0.7472, -1.2813]]],


        [[[-0.3448,  0.3213,  0.2527,  1.2449],
          [ 0.7206, -1.5667,  0.2489, -1.9135],
          [ 0.0946, -0.1390,  0.1650,  1.1801]],

         [[-0.9789,  0.7678, -0.2877, -1.1634],
          [ 0.7762,  0.7401,  0.2081,  0.3059],
          [ 0.5780, -0.2145,  0.8056,  0.8838]]]])
```

```
e.stride()
```

```
(24, 12, 4, 1)
```

设置Tensor的设备属性

```
a = torch.tensor([1,2],device = 'cuda')

b = torch.tensor([1,2]).to(device='cuda')
```

访问Tensor的元素

```
a = torch.tensor(1.0)
a[0]
```

```
IndexError                                Traceback (most recent call last)
<ipython-input-68-292e29054dae> in <module>()
      1 a = torch.tensor(1.0)
----> 2 a[0]

IndexError: invalid index of a 0-dim tensor. Use tensor.item() to convert a 0-dim tensor to a Python number
```

```
a.item()
type(a.item())
```

```
1.0
float
```

```
a.numpy()
```

```
array(1., dtype=float32)
```

```
a = torch.tensor([1.0,2.0])
a.item()
```

```
a.numpy()
```

```
array([1., 2.], dtype=float32)
```

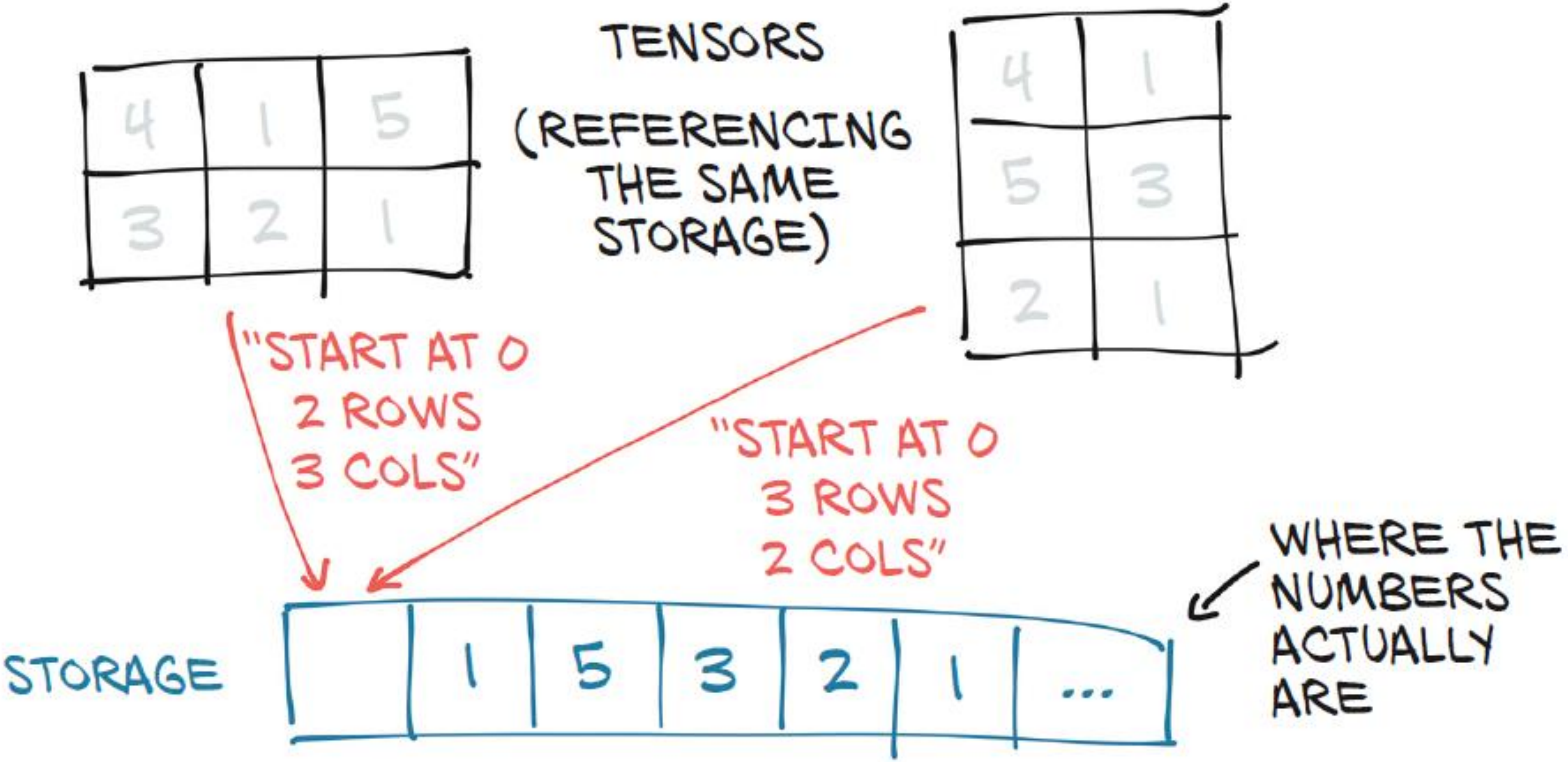
```
ValueError                                Traceback (most recent call last)
<ipython-input-121-cd1bda83583f> in <module>()
----> 1 a.item()

ValueError: only one element tensors can be converted to Python scalars
```

访问Tensor的元素

```
b = torch.tensor([[[1,2],[3,4]],
                  [[5,6],[7,8]],
                  [[9,10],[11,12]]
                 ],dtype = torch.int32)
```

```
b.shape       →  torch.Size([3, 2, 2])

b.storage()   →  1
                 2
                 3
                 4
                 5
                 6
                 7
                 8
                 9
                 10
                 11
                 12
                 [torch.LongStorage of size 12]

b[0]          →  tensor([[1, 2],
                         [3, 4]])

b[:1]         →  tensor([[[1, 2],
                          [3, 4]]])

b[:,0,0]      →  tensor([1, 5, 9])
```

访问Tensor的元素



访问Tensor的元素

```
a = torch.ones((3))
b = a[:2]
print(a)
print(b)
```

```
tensor([1., 1., 1.])
tensor([1., 1.])
```

```
b[0] = 2
print(a)
print(b)
```

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

```
c = a[:2].clone()
c[0] = 3
print(a)
print(c)
```

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

访问Tensor的元素:掩膜

```
X = torch.randn((2,3))
mask = torch.randn((2,3))>0
X1 = X[mask]
X2 = torch.masked_select(X,mask)
print('X=',X.numpy())
print('mask=',mask.numpy())
print('X1=',X1.numpy())
print('X2=',X2.numpy())
```

```
X= [[-1.7936143  -1.0867784   0.6989719 ]
 [ 0.32036787 -0.29389462  0.6172063 ]]

mask= [[False  True  True]
 [False  True  True]]

X1= [-1.0867784   0.6989719  -0.29389462  0.6172063 ]

X2= [-1.0867784   0.6989719  -0.29389462  0.6172063 ]
```

访问Tensor的元素:掩膜

```
col_mask = torch.randn((3))>0
print('col_mask=',col_mask.numpy())
X3 = X[:,col_mask]
X4 = torch.masked_select(X,col_mask)
print('X3=',X3.numpy())
print('X4=',X4.numpy())
```

```
X= [[-1.7936143  -1.0867784   0.6989719 ]
 [ 0.32036787 -0.29389462  0.6172063 ]]

col_mask= [False  True  True]

X3= [[-1.0867784   0.6989719 ]
 [-0.29389462  0.6172063 ]]

X4= [-1.0867784   0.6989719  -0.29389462  0.6172063 ]
```

访问Tensor的元素:条件选择

```
x = torch.randn(1, 3)
y = torch.randn(1, 3)
z = torch.where(x>y,x,y)
```

```
x tensor([[ 0.0684, -1.5483,  2.1476]])
y tensor([[-1.0761, -0.0047, -2.0822]])
z tensor([[ 0.0684, -0.0047,  2.1476]])
```

Transpose

```
a = torch.tensor([[[1,2],[3,4]],
                  [[5,6],[7,8]],
                  [[9,10],[11,12]]
                 ])
b = a.transpose(0,1)
print(a.stride())
print(b.stride())
```

```
(4, 2, 1)
(2, 4, 1)
```

```
tensor([[[ 1,  2],
         [ 5,  6],
         [ 9, 10]],

        [[ 3,  4],
         [ 7,  8],
         [11, 12]]])
```

1	2	3	4	5	6	7	8	9	10	11	12

Transpose

```
a = torch.tensor([[[1,2],[3,4]],
                  [[5,6],[7,8]],
                  [[9,10],[11,12]]
                 ])
b = a.transpose(0,2)
```

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

        [[5,6],[7,8]],

        [[9,10],[11,12]]])
```

```
tensor([[[ 1,  5,  9],
         [ 3,  7, 11]],

        [[ 2,  6, 10],
         [ 4,  8, 12]]])
```

Transpose

```
a = torch.tensor([[3,1,2],[4,1,7]])
b = a.transpose(0,1)
print(a[0,0])
b[0,0] = -1
print(a[0,0])
```

```
tensor(3)
```

```
tensor(-1)
```

```
a = torch.tensor([[3,1,2],[4,1,7]])
b = a.clone().transpose(0,1)
print(a[0,0])
b[0,0] = -1
print(a[0,0])
```

```
tensor(3)
```

```
tensor(3)
```

Squeeze/unsqueeze

```
a = torch.tensor([[[1,2,3]]])
b = a.squeeze(dim=0)
c = a.squeeze()
d = b.unsqueeze(dim=1)
a.size()        torch.Size([1, 1, 3])
b.size()        torch.Size([1, 3])
c.size()        torch.Size([3])
d.size()        torch.Size([3, 1])
```

cat

```
x = torch.randn(2, 3)
x1 = torch.cat((x,x),dim = 0)
x2 = torch.cat((x,x),dim = 1)
```

```
x
tensor([[-0.4173,  0.0633, -1.3320],
        [ 0.5852, -2.0193,  0.2838]])
```

```
x1
tensor([[-0.4173,  0.0633, -1.3320],
        [ 0.5852, -2.0193,  0.2838],
        [-0.4173,  0.0633, -1.3320],
        [ 0.5852, -2.0193,  0.2838]])
```

```
x2
tensor([[-0.4173,  0.0633, -1.3320, -0.4173,  0.0633, -1.3320],
        [ 0.5852, -2.0193,  0.2838,  0.5852, -2.0193,  0.2838]])
```

reshape

```
T = torch.arange(0,12)
V1 = T.reshape((2,6))#也可以用torch.reshape(T,(2,6))
V2 = T.reshape((3,4))
print('T=',T)
print('V1=',V1)
print('V2=',V2)
```

```
T= tensor([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])

V1= tensor([[ 0,  1,  2,  3,  4,  5],
        [ 6,  7,  8,  9, 10, 11]])

V2= tensor([[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11]])
```

permute

```python
A = torch.arange(24).reshape((2,3,4))
print(A.shape)
print('A=',A)

B = A.permute((2,1,0))
print(B.shape)
print('B=',B)

A[0,0,1] = -5
print('B=',B)#注意B[1,0,0]的值变为-5
```

```
torch.Size([2, 3, 4])
A= tensor([[[ 0,  1,  2,  3],
         [ 4,  5,  6,  7],
         [ 8,  9, 10, 11]],

        [[12, 13, 14, 15],
         [16, 17, 18, 19],
         [20, 21, 22, 23]]])
torch.Size([4, 3, 2])
B= tensor([[[ 0, 12],
         [ 4, 16],
         [ 8, 20]],

        [[ 1, 13],
         [ 5, 17],
         [ 9, 21]],

        [[ 2, 14],
         [ 6, 18],
         [10, 22]],

        [[ 3, 15],
         [ 7, 19],
         [11, 23]]])
```

```
B= tensor([[[ 0, 12],
         [ 4, 16],
         [ 8, 20]],

        [[-5, 13],
         [ 5, 17],
         [ 9, 21]],

        [[ 2, 14],
         [ 6, 18],
         [10, 22]],

        [[ 3, 15],
         [ 7, 19],
         [11, 23]]])
```

张量运算

```
A = torch.tensor([1,2,3],dtype = torch.float32)
B = torch.tensor([-1,1,-1],dtype = torch.float32)

C = A + B
D = A - B
E = A*B
F = A/B
```

```
A= [1. 2. 3.]
B= [-1.  1. -1.]
A+B= [0. 3. 2.]
A-B= [2. 1. 4.]
A*B= [-1.  2. -3.]
A/B= [-1.  2. -3.]
```

张量运算

```
A = torch.randn((2,3))
B = torch.randn((3,4))
C = A@B
print(A.shape)
print(B.shape)
print(C.shape)
```

```
torch.Size([2, 3])
torch.Size([3, 4])
torch.Size([2, 4])
```

张量运算

```
A = torch.tensor([[1,-1],[2,3],[4,5]])
B = A**2

print('A=',A.numpy())
print('B=',B.numpy())
```

```
A= [[ 1 -1]
 [ 2  3]
 [ 4  5]]
B= [[ 1  1]
 [ 4  9]
 [16 25]]
```

张量运算

```python
W = torch.randn((10,784))
b = torch.randn((10,1))

x = torch.randn((28,28)).reshape((784,1))
y = W@x + b

print(y)
```

```
tensor([[ 29.2908],
        [-43.5128],
        [-27.3771],
        [ 27.4112],
        [ 27.8641],
        [ 26.4428],
        [-36.5835],
        [  5.1869],
        [ 51.5410],
        [-20.5552]])
```

BroadCasting

```
x = torch.tensor([1,2,3])
y = torch.tensor([[-1],[0],[1]])
u = x * y
```

```
u: tensor([[-1, -2, -3],
        [ 0,  0,  0],
        [ 1,  2,  3]])
```

```
x: tensor([1, 2, 3])
y: tensor([[-1],
        [ 0],
        [ 1]])
```

```
x: torch.Size([3])
y: torch.Size([3, 1])

u: torch.Size([3, 3])
```

BroadCasting

```
x = torch.tensor([1,2,3])
z = torch.ones((2,3,3),dtype = torch.int64)
v = x * z
```

```
x: tensor([1, 2, 3])
z: tensor([[[1, 1, 1],
         [1, 1, 1],
         [1, 1, 1]],

        [[1, 1, 1],
         [1, 1, 1],
         [1, 1, 1]]])
```

```
x: torch.Size([3])
z: torch.Size([2, 3, 3])

v: torch.Size([2, 3, 3])
```

```
v: tensor([[[1, 2, 3],
         [1, 2, 3],
         [1, 2, 3]],

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

BroadCasting

```
y = torch.tensor([[-1],[0],[1]])
z = torch.ones((2,3,3),dtype = torch.int64)
w = y * z
```

```
y: tensor([[-1],
           [ 0],
           [ 1]])
z: tensor([[[1, 1, 1],
            [1, 1, 1],
            [1, 1, 1]],

           [[1, 1, 1],
            [1, 1, 1],
            [1, 1, 1]]])
```

```
y: torch.Size([3, 1])
z: torch.Size([2, 3, 3])

w: torch.Size([2, 3, 3])
```

```
w: tensor([[[-1, -1, -1],
            [ 0,  0,  0],
            [ 1,  1,  1]],

           [[-1, -1, -1],
            [ 0,  0,  0],
            [ 1,  1,  1]]])
```

例：彩色图像灰度化

```
from PIL import Image
img = np.asarray(Image.open('balloons.jpg'))
img_tensor = torch.tensor(img).to(dtype = torch.float32)
print(img_tensor.size())
```

```
torch.Size([605, 910, 3])
```

```
weights = torch.tensor([0.2126,0.7152,0.0722])
```

```
gray = torch.sum(weights * img_tensor,dim = 2)
```

```
torch.Size([605, 910])
```

```
img_tensor1 = img_tensor.permute([2,0,1])
```

```
torch.Size([3, 605, 910])
```

```
img_r,img_g,img_b = img_tensor1[0],img_tensor1[1],img_tensor1[2]
```

例2：图像标准化

```
img_files = ['balloons.jpg','happydog.jfif','sunflower.jpg','Woolsthorpe-Manor.jpg']

img_batch = torch.zeros(len(img_files),3,480,640,dtype = torch.uint8)

for i,f in enumerate(img_files):
    img = np.array(Image.open(f).resize((640,480)))
    img_tensor = torch.from_numpy(img)
    img_tensor = img_tensor.permute(2,0,1)
    img_batch[i] = img_tensor
```

```
img_batch : torch.Size([4, 3, 480, 640])
```

例2：图像标准化

```
img_batch = img_batch.float() / 255.0
mean = torch.tensor([0.485, 0.456, 0.406])
std = torch.tensor([0.229, 0.224, 0.225])

print('batch:',img_batch.size())
print('mean:',mean.size())
print('std:',std.size())
```

```
batch: torch.Size([4, 3, 480, 640])
mean: torch.Size([3])
std: torch.Size([3])
```

```
mean_unsqueezed = mean.unsqueeze(dim = 1).unsqueeze(dim=1)
std_unsqueezed = std.unsqueeze(dim = 1).unsqueeze(dim = 1)
print(mean_unsqueezed.size())
```

```
torch.Size([3, 1, 1])
```

```
img_batch_normalized = (img_batch - mean_unsqueezed) / std_unsqueezed
```

例3：使用张量编写神经元模型

```
class Neuron():
    def __init__(self, in_features):
        self.dim = in_features
        self.W = torch.zeros((1,self.dim))
        self.b = torch.zeros(1)

    def __sigmoid__(self, z):
        return 1/(1 + torch.exp(-z))

    def __transfer__(self, x):
        return self.W@x + self.b
```

例3：使用张量编写神经元模型

```
def __update__(self, dW,db,lr):
    self.W = self.W + lr * dW
    self.b = self.b + lr * db

def __calc_loss__(self, Y,rho):
    loss = -torch.log(rho[Y==1]).sum() - torch.log(1 - rho[Y==0]).sum()
    loss = loss / Y.shape[0]
    return loss
```

例3：使用张量编写神经元模型

```
def __backward__(self,Y,rho):
    err = Y - rho
    dW = err @ X.T/Y.shape[0]
    db = err.mean()
    return dW,db

def predict(self, x):
    z = self.__transfer__(x)
    rho = self.__sigmoid__(z)
    return rho
```

例3：使用张量编写神经元模型

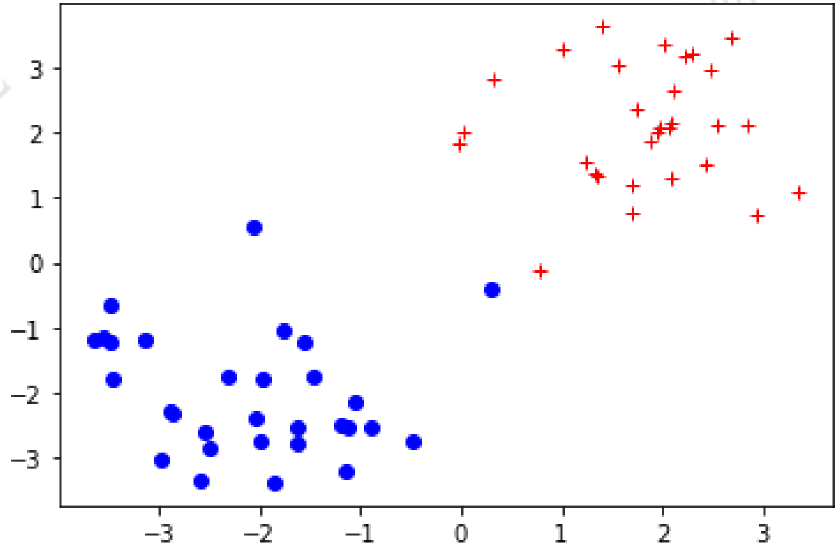
```
def fit(self, X,Y,max_iter=100,lr = 0.1):
    n = X.shape[1]
    assert(X.shape[0]==self.dim)
    assert(n==Y.shape[0])

    for iter in range(max_iter):
        rho = self.predict(X).squeeze()
        loss = self.__calc_loss__(Y,rho)
        print('iter=',iter,',loss=',loss.item())
        dW,db = self.__backward__(Y,rho)
        self.__update__(dW,db,lr)
```

例3：使用张量编写神经元模型

```
def GenerateSamples(n):
    x1 = torch.randn((2,n)) + 2
    x2 = torch.randn((2,n)) - 2
    y1 = torch.ones((n))
    y2 = torch.zeros((n))
    x = torch.cat((x1,x2),dim = 1)
    y = torch.cat((y1,y2),dim = 0)

    return x,y
```

例3：使用张量编写神经元模型

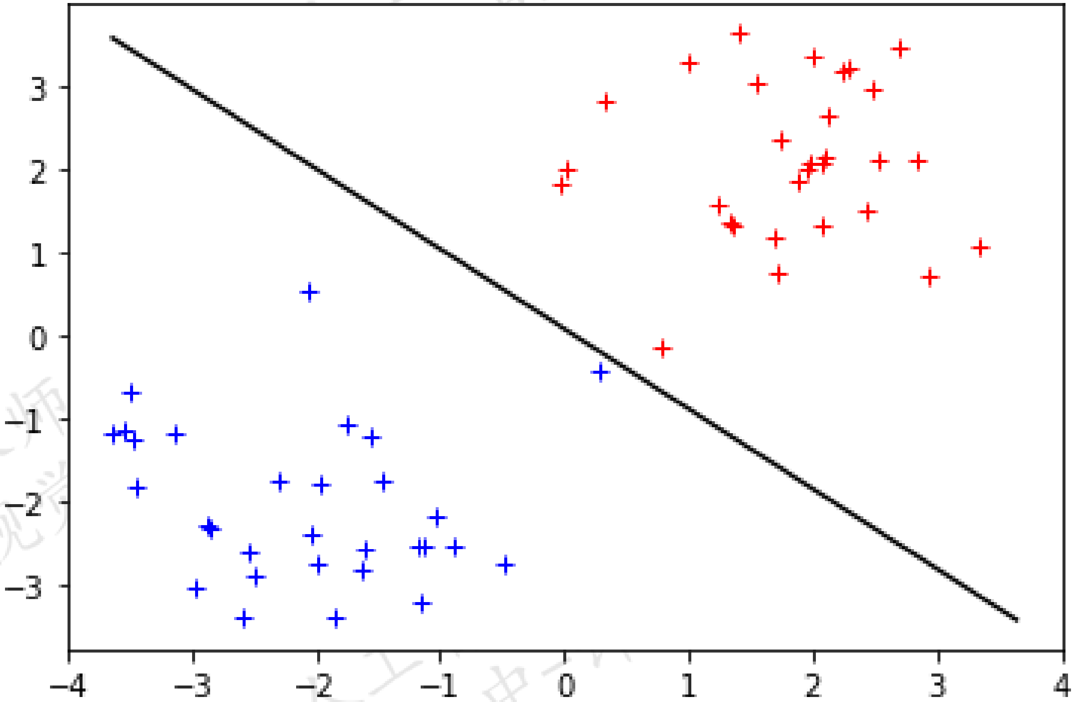
```
X,Y = GenerateSamples(30)
print(X.shape)
plt.plot(X[0,Y==1],X[1,Y==1],'r+')
plt.plot(X[0,Y==0],X[1,Y==0],'bo’)


cell = Neuron(2)
cell.fit(X,Y,100,1)
```




```
iter= 0 , loss= 0.6931470632553101
iter= 1 , loss= 0.04438574239611626
iter= 2 , loss= 0.041226837784051895
iter= 3 , loss= 0.038746096193790436
iter= 4 , loss= 0.036735840141773224
iter= 5 , loss= 0.03506697714328766
iter= 6 , loss= 0.0336545892059803
iter= 7 , loss= 0.032440345734357834
```

例3：使用张量编写神经元模型

```
w1,w2 = cell.W[0,0],cell.W[0,1]
b = cell.b
minx = torch.min(X,dim = 1)
maxx = torch.max(X,dim = 1)

xs = torch.cat((minx[0],maxx[0]))
ys = -(xs*w1+b)/w2

plt.plot(X[0,Y==1],X[1,Y==1],'r+')
plt.plot(X[0,Y==0],X[1,Y==0],'b+')
plt.plot(xs,ys,'k-')
```

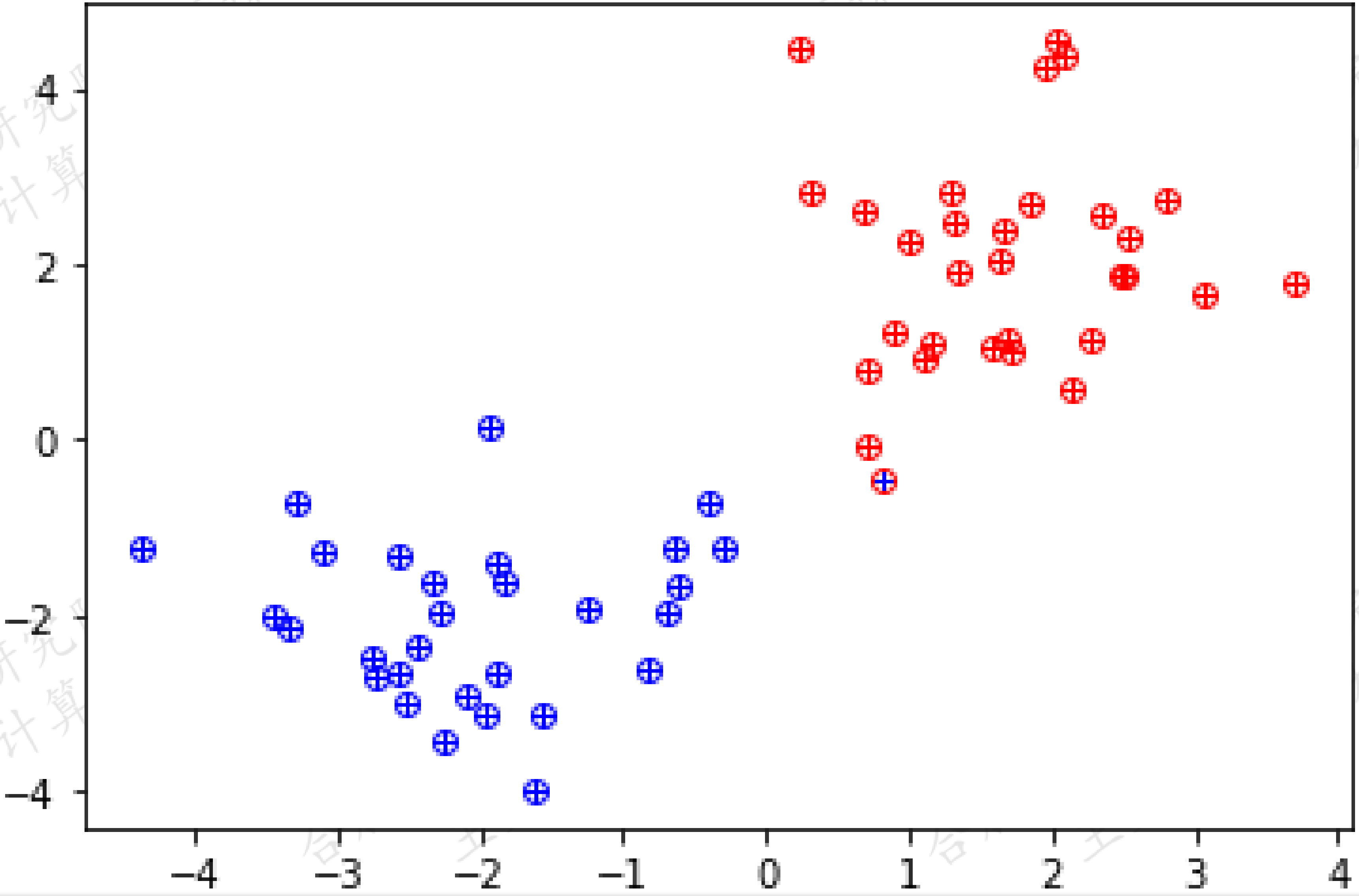


例3：使用张量编写神经元模型

```
#测试集预测效果
X_test,Y_test = GenerateSamples(30)
Y_hat = torch.where(cell.predict(X_test).squeeze()>0.5,1,0)


plt.plot(X_test[0,Y_test==1],X_test[1,Y_test==1],'r+')
plt.plot(X_test[0,Y_test==0],X_test[1,Y_test==0],'b+')
plt.plot(X_test[0,Y_hat==1],X_test[1,Y_hat==1],'ro',fillstyle='none')
plt.plot(X_test[0,Y_hat==0],X_test[1,Y_hat==0],'bo',fillstyle='none')


acc = torch.mean((Y_hat==Y_test).to(torch.float32)).item()
print('Test Acc = ',acc)
```

```
Test Acc = 0.9833333492279053
```

例3：使用张量编写神经元模型

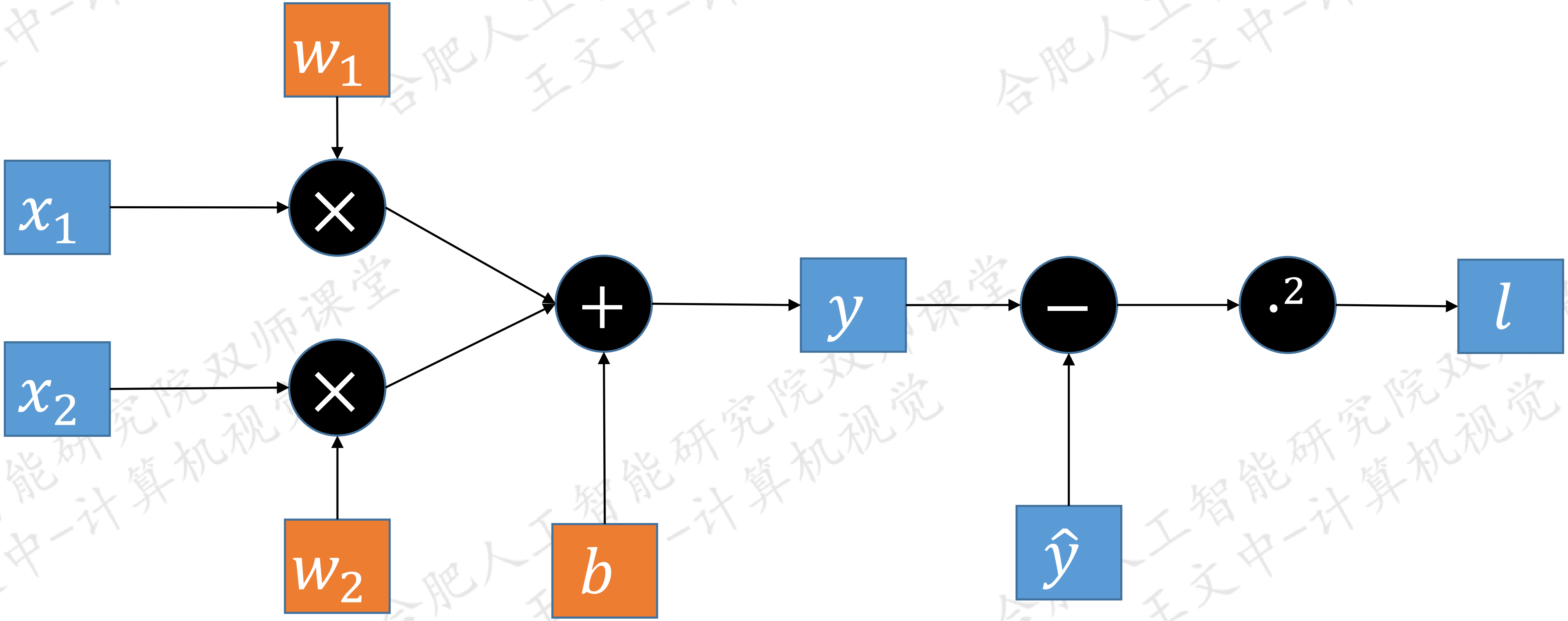


练习一：使用Tensor实现感知器模型

1.2 自动求导(AutoGrad)

计算图

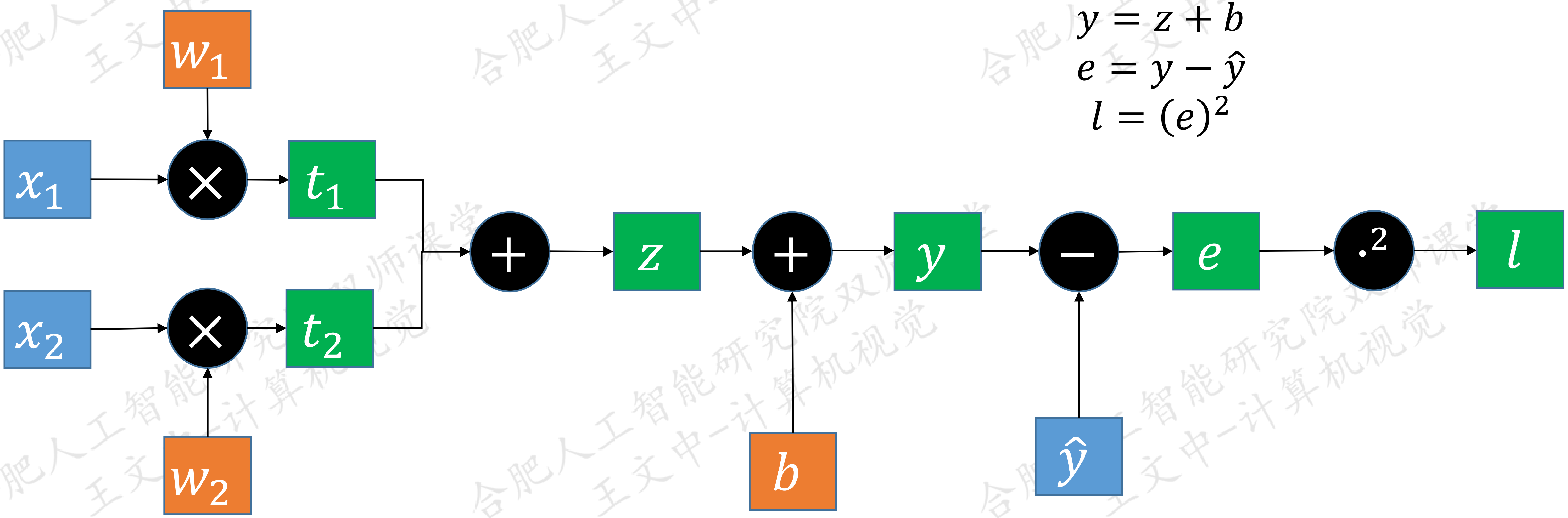
$$y = h(x; w, b) = w_1 \times x_1 + w_2 \times x_2 + b$$
$$l = (y - \hat{y})^2$$



计算图

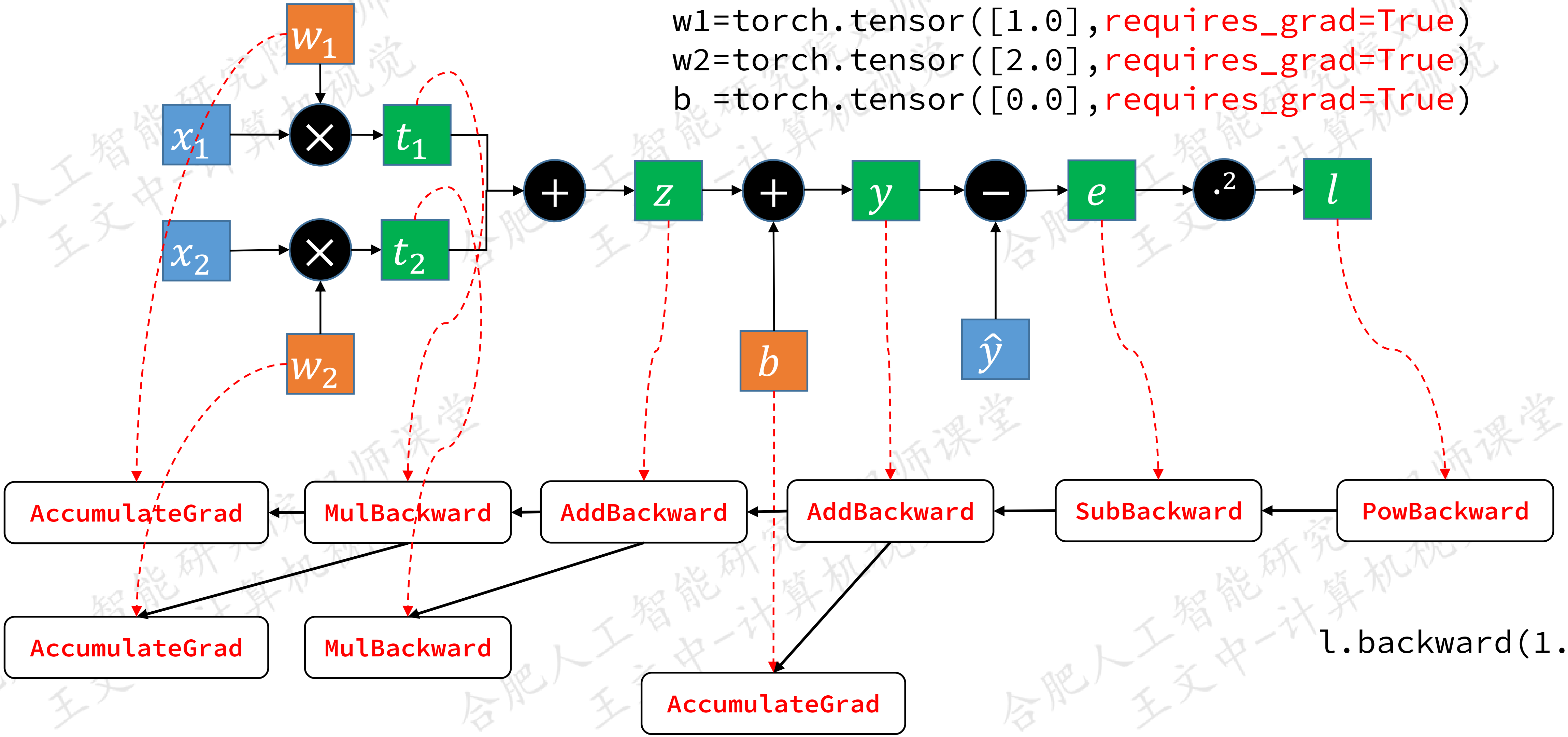
$$y = h(x; w, b) = w_1 \times x_1 + w_2 \times x_2 + b$$
$$l = (y - \hat{y})^2$$

$$t_1 = w_1 \times x_1$$
$$t_2 = w_2 \times x_2$$
$$z = t_1 + t_2$$
$$y = z + b$$
$$e = y - \hat{y}$$
$$l = (e)^2$$



计算图

```
w1=torch.tensor([1.0],requires_grad=True)
w2=torch.tensor([2.0],requires_grad=True)
b =torch.tensor([0.0],requires_grad=True)
```




```
l.backward(1.0)
```

$$y = h(x; w, b) = w * x + b$$
$$loss = (y - \hat{y})^2$$

```
x = torch.tensor([1.0])
w = torch.tensor([1.0],requires_grad = True)
y = w*x
print(y)
```

```
tensor([1.], grad_fn=<MulBackward0>)
```

```
loss = (y - 2)**2
print(loss)
```

```
tensor([1.], grad_fn=<PowBackward0>)
```

```
loss.backward()
print(w.grad)
```

```
tensor([-2.])
```

```
with torch.no_grad():
    w -= 0.1*w.grad
print(w)
```

```
tensor([1.2000], requires_grad=True)
```

```
x = torch.tensor([1.0])
w = torch.tensor([1.0],requires_grad = True)
y = w*x

for epoch in range(3):
    print('epoch:%d'%(epoch))
    loss = (y - 2)**2
    loss.backward()
    print(w.grad)
```

```
epoch:0
tensor([-2.])
epoch:1
```

```
RuntimeError: Trying to backward through
the graph a second time, but the buffers
have already been freed. Specify
retain_graph=True when calling backward
the first time.
```

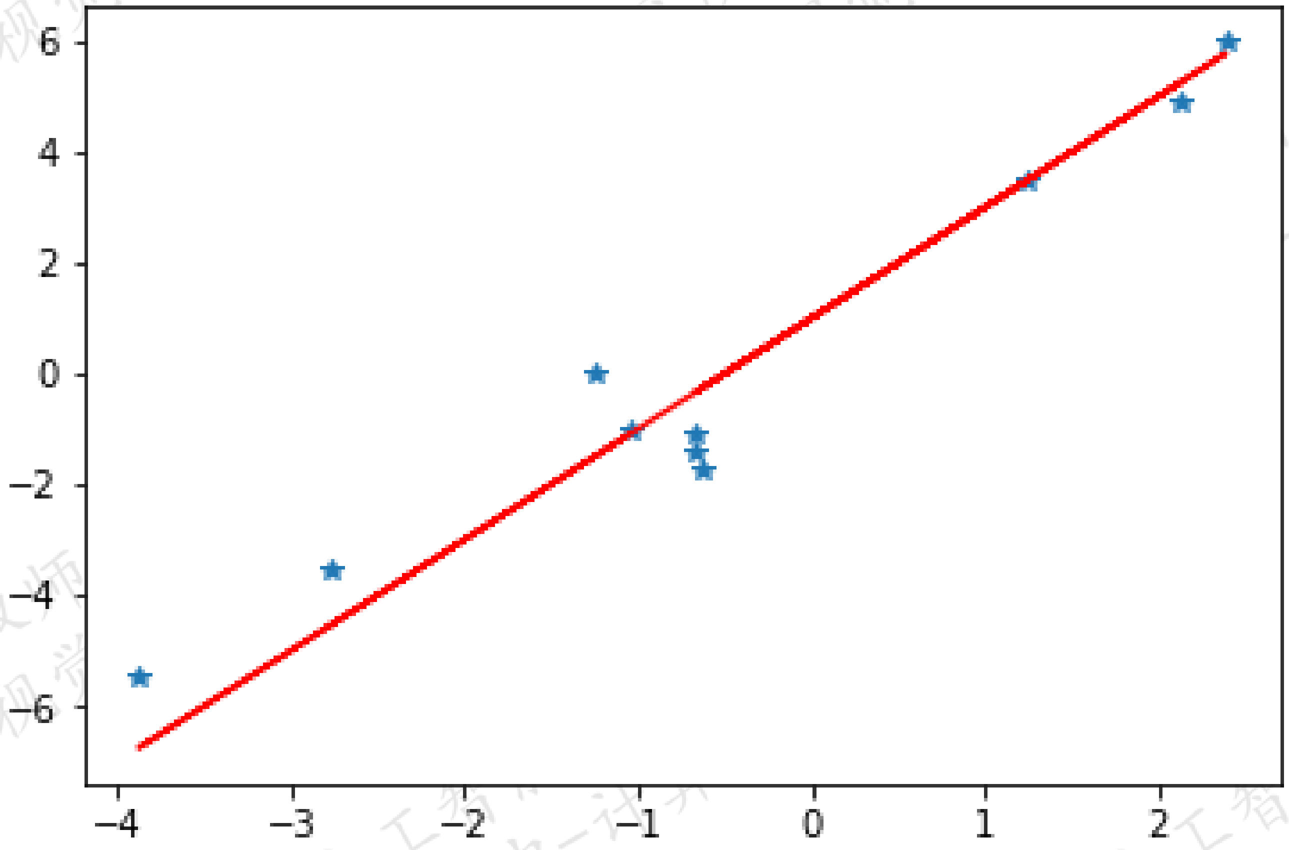
```python
x = torch.tensor([1.0])
w = torch.tensor([1.0],requires_grad = True)
y = w*x

for epoch in range(3):
    print('epoch:%d'%(epoch))
    loss = (y - 2)**2
    loss.backward(retain_graph=True)
    print(w.grad)
```

```
epoch:0
tensor([-2.])
epoch:1
tensor([-4.])
epoch:2
tensor([-6.])
```

```python
x = torch.tensor([1.0])
w = torch.tensor([1.0],requires_grad = True)
y = w*x

for epoch in range(3):
    print('epoch:%d'%(epoch))
    if w.grad is not None:
        w.grad.zero_()
    loss = (y - 2)**2
    print(w.grad)
    loss.backward(retain_graph=True)
    print(w.grad)
```

```
epoch:0
None
tensor([-2.])
epoch:1
tensor([0.])
tensor([-2.])
epoch:2
tensor([0.])
tensor([-2.])
```

例1：一个简单的一元线性回归问题



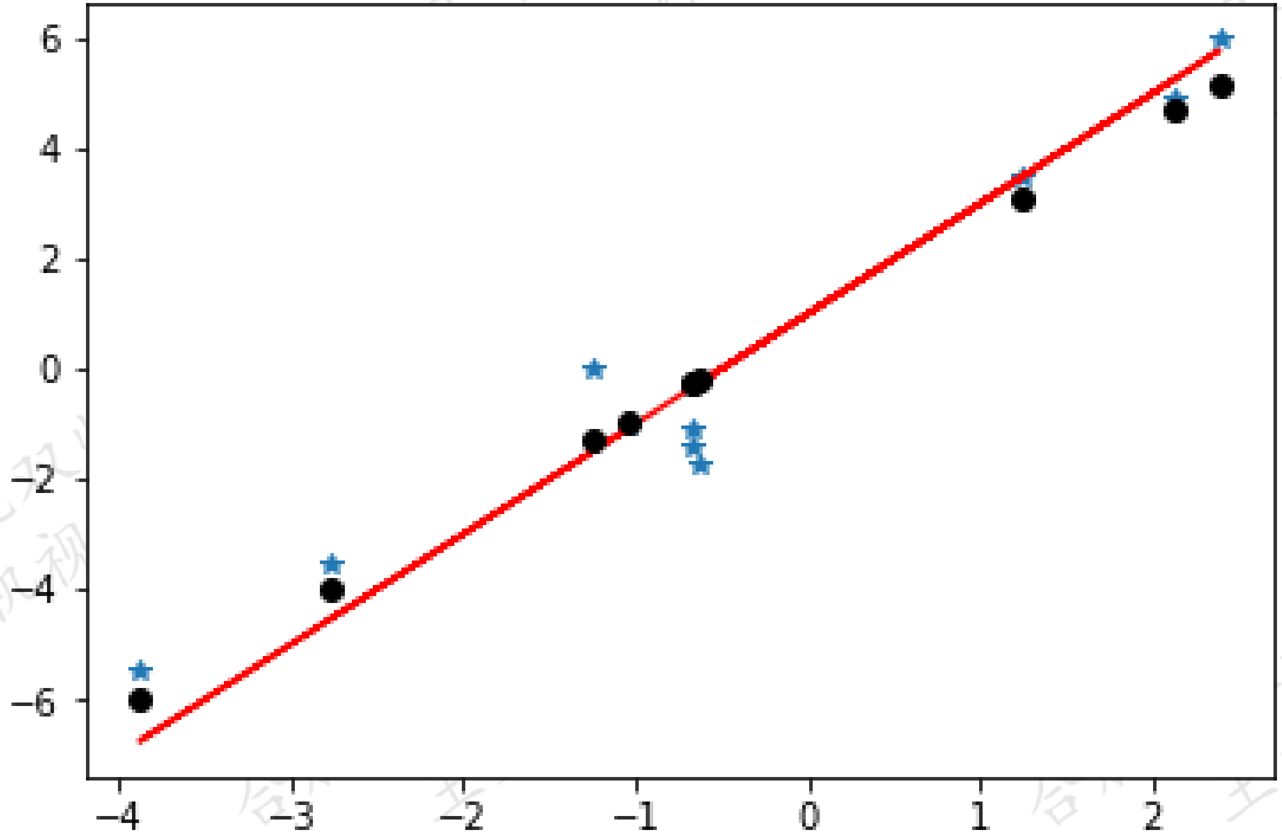
```python
#生成训练数据
x = torch.rand(10)*10 - 5 #[-5,5]上的均匀分布随机数
y = 2*x + 1 + torch.randn(10) #受随机噪声污染的y

#定义回归模型
def linearReg(x,w,b):
    y = w * x + b
    return y

#定义损失函数
def lossFn(y,y_hat):
    squared_errors = (y - y_hat)**2
    loss = squared_errors.mean()
    return loss
```

```
#定义训练函数
def trainModel(x,y,w,b,epochs,lr = 0.1):
    for epoch in range(1, epochs + 1):
        if w.grad is not None:
            w.grad.zero_()
        if b.grad is not None:
            b.grad.zero_()

        y_pred = linearReg(x,w,b)

        loss = lossFn(y_pred,y)

        loss.backward()

        with torch.no_grad():
            w -= lr * w.grad
            b -= lr * b.grad

        print('Epoch = %d, Loss = %f, w = %f,b = %f'%(
            epoch,loss.detach().numpy(),w.detach().numpy(),b.detach().numpy()))
    return w,b
```

```
#训练模型
#初始化参数w,b
w = torch.tensor([0.0],requires_grad = True)
b = torch.tensor([0.0],requires_grad = True)
w,b = trainModel(x,y,w,b,epochs = 10, lr = 0.2)
```

```
Epoch = 1, Loss = 12.116911, w = 2.548692,b = 0.003886
Epoch = 2, Loss = 4.572442, w = 1.183241,b = 0.532312
Epoch = 3, Loss = 2.037711, w = 2.024282,b = 0.567515
Epoch = 4, Loss = 1.181779, w = 1.580700,b = 0.762241
Epoch = 5, Loss = 0.891036, w = 1.858682,b = 0.787515
Epoch = 6, Loss = 0.791604, w = 1.714883,b = 0.860059
Epoch = 7, Loss = 0.757336, w = 1.806942,b = 0.873903
Epoch = 8, Loss = 0.745425, w = 1.760451,b = 0.901212
Epoch = 9, Loss = 0.741245, w = 1.791010,b = 0.908000
Epoch = 10, Loss = 0.739764, w = 1.776030,b = 0.918381
```

```
y_pred = linearReg(x,w,b)
plt.plot(x.numpy(),y.numpy(),'*')
plt.plot(x.numpy(),2*x.numpy()+1,'r-')
plt.plot(x.numpy(),y_pred.detach().numpy(),'ko')
plt.show()
```

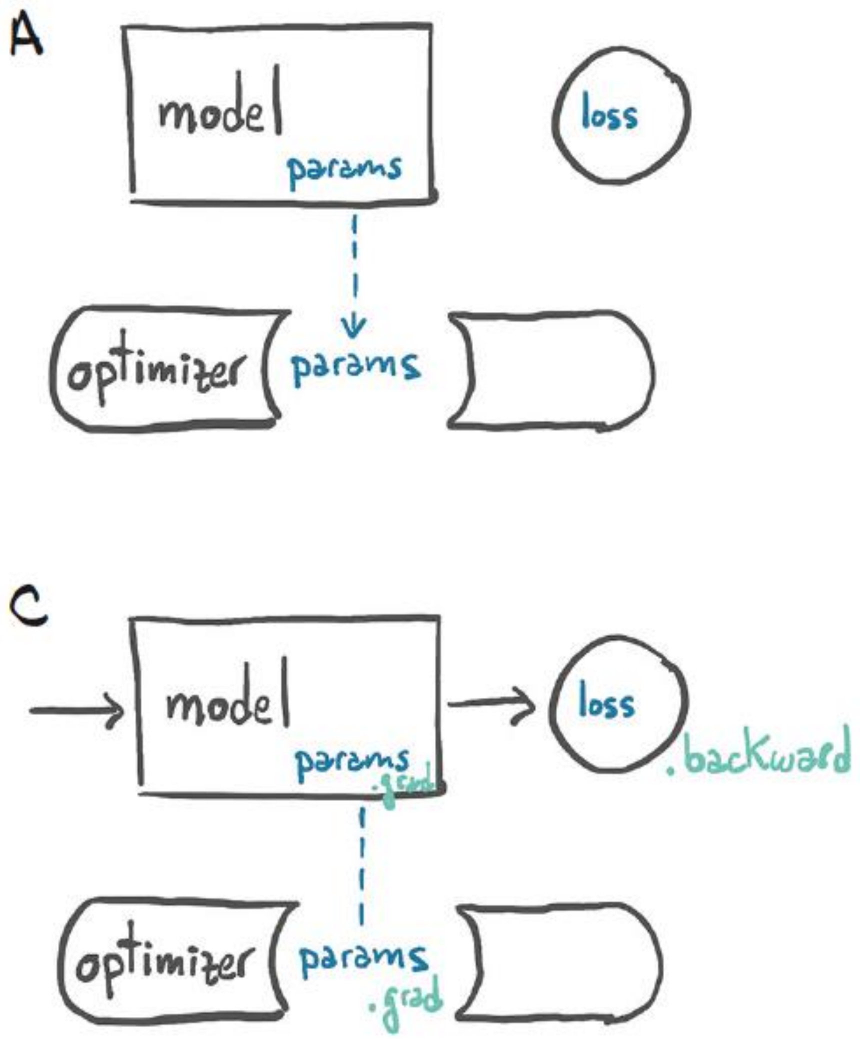


使用torch.optim训练模型

```
#定义训练函数
def trainModel(x,y,w,b,epochs,lr = 0.1):
    for epoch in range(1, epochs + 1):
        if w.grad is not None:
            w.grad.zero_()
        if b.grad is not None:
            b.grad.zero_()

        y_pred = linearReg(x,w,b)

        loss = lossFn(y_pred,y)

        loss.backward()

        with torch.no_grad():
            w -= lr * w.grad
            b -= lr * b.grad

    return w,b
```

```
import torch.optim as optim

def trainModel(x,y,w,b,epochs,lr = 0.1):

    optimizer = optim.SGD([w,b],lr = lr)

    for epoch in range(1, epochs + 1):

        optimizer.zero_grad()

        y_pred = linearReg(x,w,b)

        loss = lossFn(y_pred,y)

        loss.backward()

        optimizer.step()

    return w,b
```

使用torch.optim训练模型



练习二

- 使用Tensor和自动求导编写线性回归器

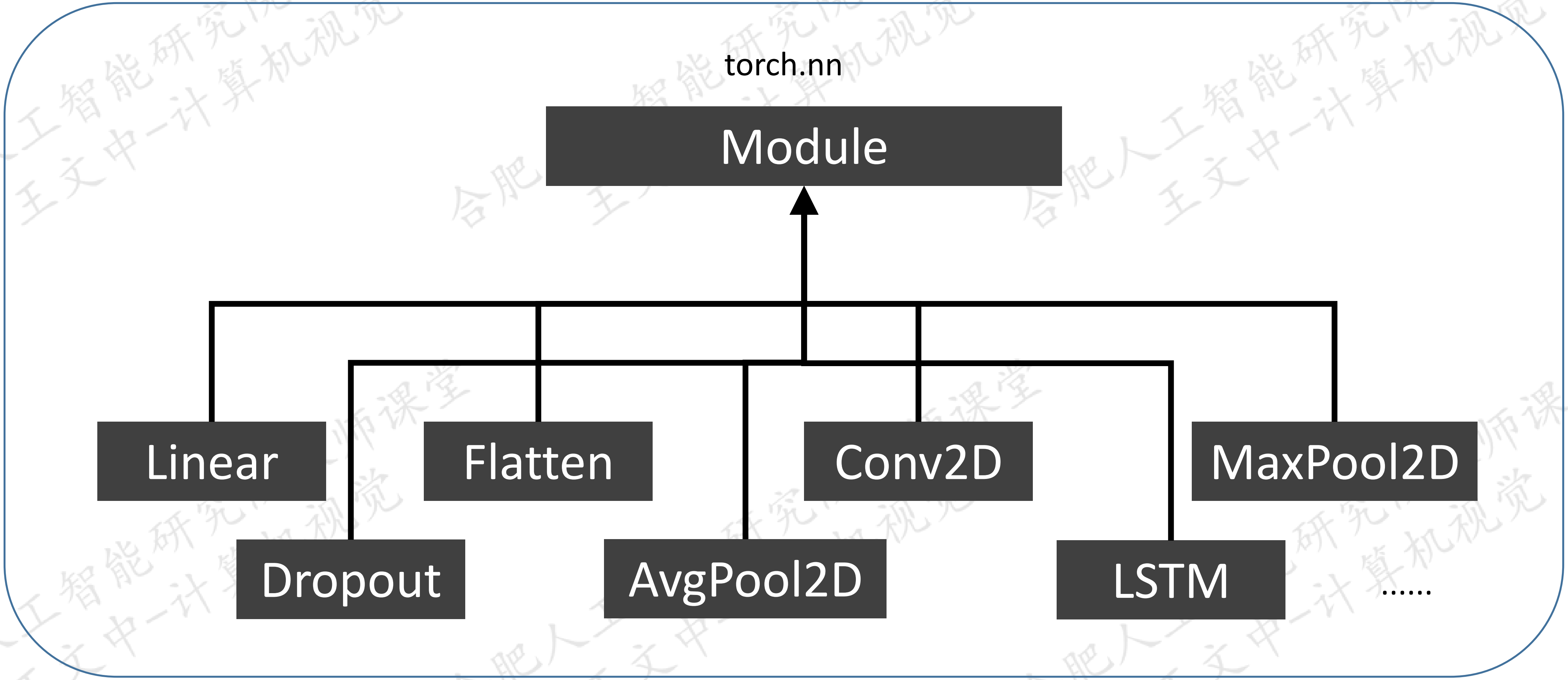
2. 多层感知器编程

torch.nn

多层感知器编程

- 编写网络模型
  - torch.nn.Sequential：编写简单的模型
  - torch.nn.Module：编写复杂的模型
- 训练模型：
  - 数据加载器
  - 损失函数：torch.nn
  - 优化器：torch.nn.optim

torch.nn.Module

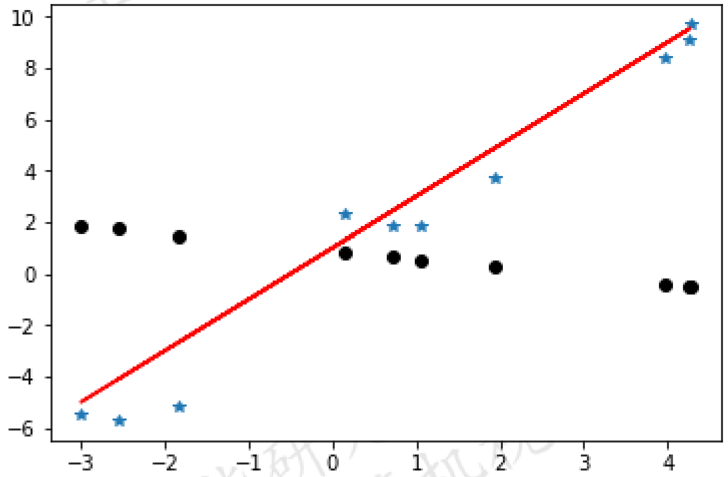


2.1 实现简单的模型

线性回归

```
torch.nn.Linear(in_features: int, out_features: int, bias: bool = True)
```

```
import torch.nn as nn
linReg = nn.Linear(1,1)


x = torch.rand(10)*10 - 5
y = 2*x + 1 + torch.randn(10)


y_pred = linReg(x.view(10,1))


plt.plot(x.numpy(),y.numpy(),'*')
plt.plot(x.numpy(),2*x.numpy()+1,'r-')
plt.plot(x.numpy(),y_pred.detach().numpy(),'ko')
plt.show()
```



线性回归

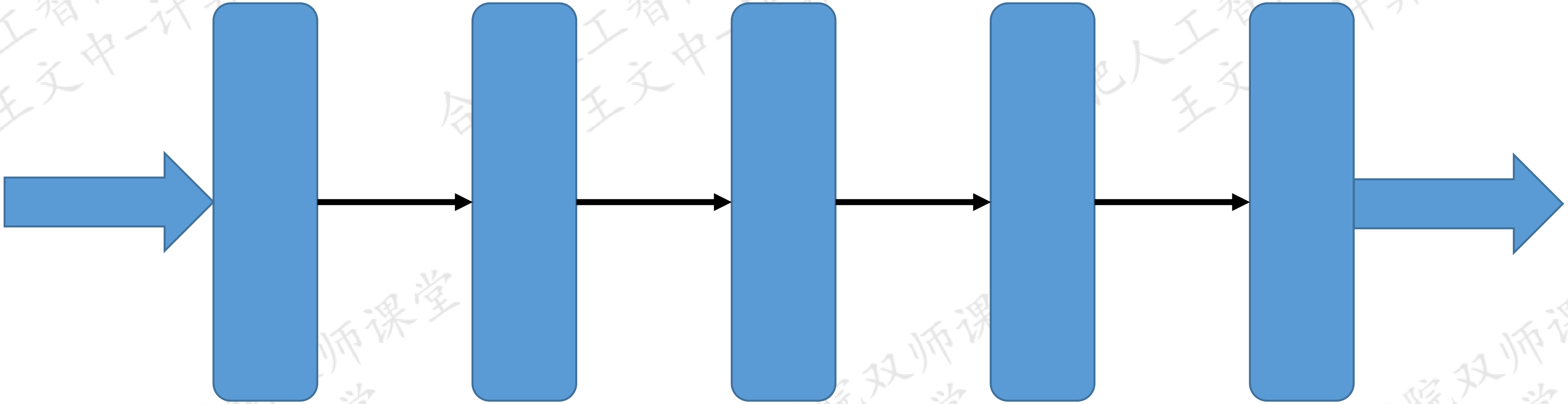
```
torch.nn.MSELoss(size_average=None, reduce=None, reduction: str = 'mean')
```

```
linReg = nn.Linear(1,1)
loss_fn = nn.MSELoss(reduction='mean')
linReg.train()
optimizer = optim.SGD(params = linReg.parameters(),lr = 0.1,momentum = 0.9)
for epoch in range(10):
    optimizer.zero_grad()
    y_pred = linReg(x.view(10,1))
    loss = loss_fn(y_pred, y)
    loss.backward()
    optimizer.step()
```

```python
x_train,y_train = readData('circle-train.csv')
x = torch.tensor(x_train,dtype = torch.float32)
y = torch.tensor(y_train[:,np.newaxis],dtype = torch.float)

logReg = nn.Linear(2,1)
loss_fn = nn.BCEWithLogitsLoss()

logReg.train()
optimizer = optim.SGD(params = logReg.parameters(),lr = 0.1,momentum = 0.9)
for epoch in range(10):
    optimizer.zero_grad()
    y_pred = logReg(x)
    loss = loss_fn(y_pred, y)
    loss.backward()
    optimizer.step()
```

2.2 使用Sequential构造神经网络模型

构造序列式神经网络模型

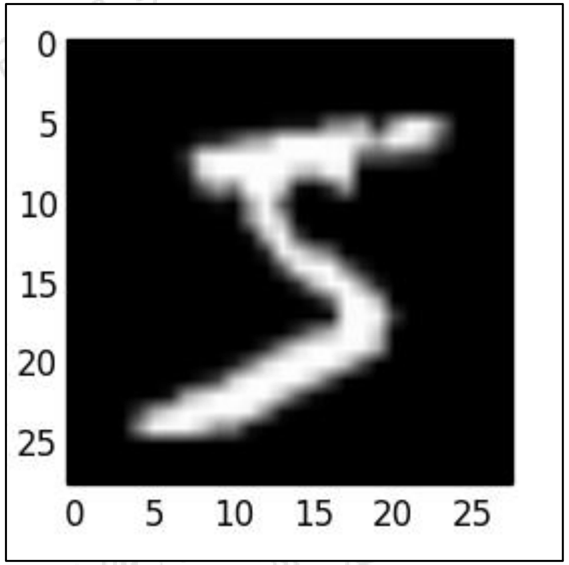


torch.nn.Sequential

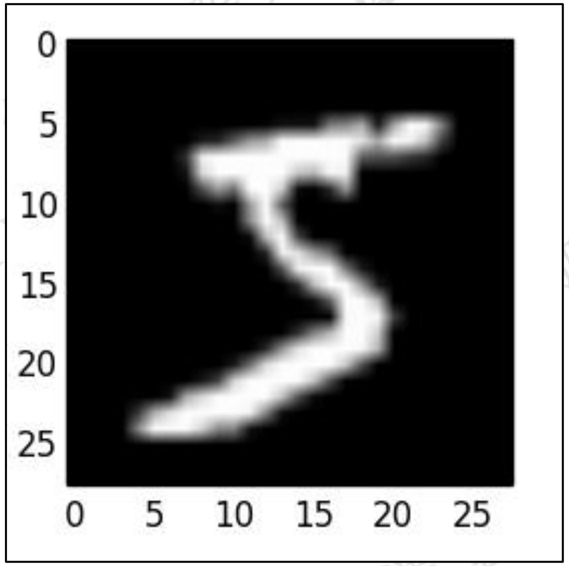
```
model = nn.Sequential(
          nn.Conv2d(1,20,5),
          nn.ReLU(),
          nn.Conv2d(20,64,5),
          nn.ReLU()
        )
```

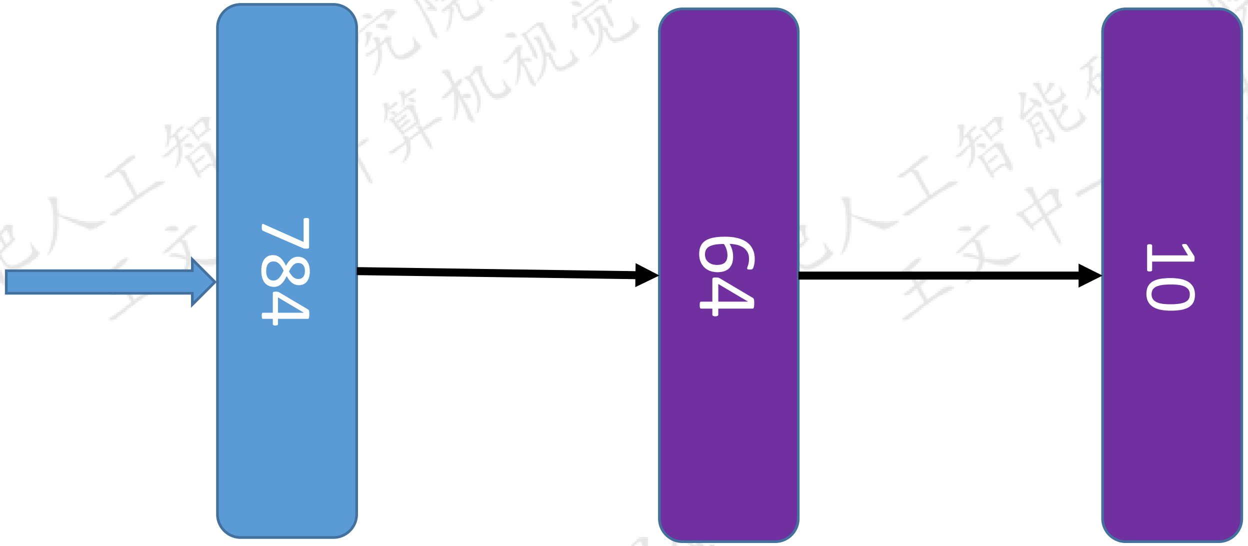
```
from collections import OrderedDict

model = nn.Sequential(OrderedDict([
          ('conv1', nn.Conv2d(1,20,5)),
          ('relu1', nn.ReLU()),
          ('conv2', nn.Conv2d(20,64,5)),
          ('relu2', nn.ReLU())
        ]))
```

MNIST手写体识别



MNIST手写体识别:设计一个单隐层神经网络





$h = \sigma(W_h x + b_h)$ $p = Softmax(W_o h + b_o)$

torch.nn.Linear

```
torch.nn.Linear(in_features, out_features, bias=True,
device=None, dtype=None)
```

$$out = W \times input + b$$

torch.nn.Linear

```
x = torch.tensor([1.0,2.0,3.0])
lin = torch.nn.Linear(3,2)
y = lin(x)
print(y)
```

```
tensor([-0.7312,  0.5305], grad_fn=<AddBackward0>)
```

```
for v in lin.parameters():
    print(v)
```

```
Parameter containing:
tensor([[-0.0212,  0.2302, -0.4544],
        [ 0.5579,  0.4064, -0.2442]], requires_grad=True)
Parameter containing:
tensor([ 0.1929, -0.1078], requires_grad=True)
```

torch.nn.Softmax

```
torch.nn.Softmax(dim=None)
```

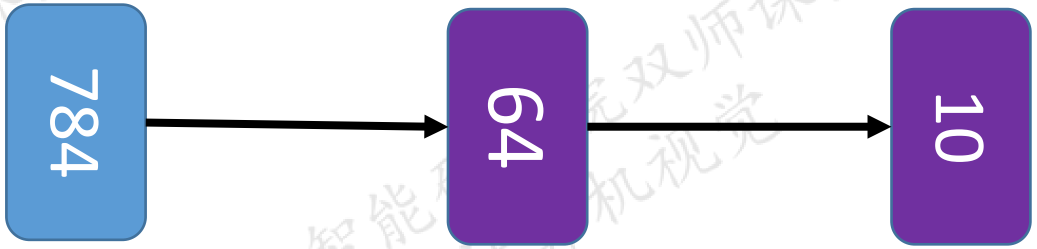
```
x = torch.tensor([[1.0,3.0,5.0],[4.0,5.0,1.0]])
prob1 = torch.nn.Softmax(dim=0)
y1 = prob1(x)
```

```
tensor([[0.0474, 0.1192, 0.9820],
        [0.9526, 0.8808, 0.0180]])
```

```
prob2 = torch.nn.Softmax(dim=1)
y2 = prob2(x)
```

```
tensor([[0.0159, 0.1173, 0.8668],
        [0.2654, 0.7214, 0.0132]])
```

MNIST手写体识别：构造神经网络



$h = \sigma(W_h x + b_h)$　　$z = W_o h + b_o$

```
mnist_mlp = nn.Sequential(nn.Linear(784,64),
                         nn.Sigmoid(),
                         nn.Linear(64,10))

optimizer = optim.SGD(mnist_mlp.parameters(), lr = 0.01)

loss_fn = nn.CrossEntropyLoss()
```

torch.nn.CrossEntropyLoss

$$l(\theta; z, y) = -\log\left(\frac{e^{z_y}}{\sum_{j=1}^{k} e^{z_j}}\right), z = h(x;\theta) = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_k \end{pmatrix}$$

torch.nn.NLLLoss

$$l(\theta; z, y) = -z_y, y \in \{1,2,\dots,k\}$$

$$z_j = \log(\rho_j), \rho_j = \frac{e^{z_j}}{\sum_{i=1}^{k} e^{z_i}}$$

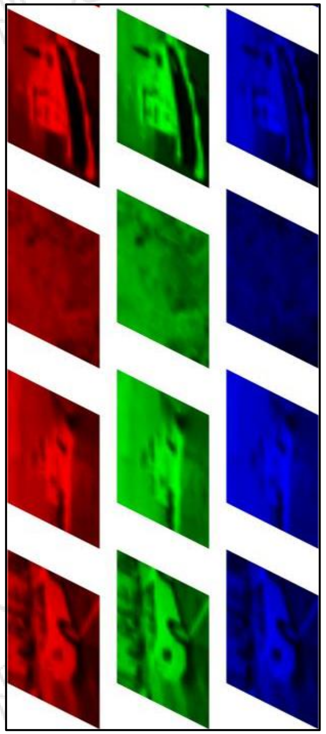
MNIST手写体识别：数据集与加载器

```
from torchvision import datasets,transforms


data_path = '../data/'
mnist = datasets.MNIST(data_path,download=True,
                       transform = transforms.ToTensor())
img,label = mnist[0]
img.shape                   torch.Size([1, 28, 28])
img = img.view(-1)
img.shape                   torch.Size([784])


mnist_loader = torch.utils.data.DataLoader(mnist, batch_size = 64,
                                           shuffle = True)
```

MNIST手写体识别：数据集与加载器

```
mnist_loader = torch.utils.data.DataLoader(mnist,
                                           batch_size = 64,
                                           shuffle = True)

for i,data in enumerate(mnist_loader):
    print(data[0].shape)
    print(data[1].shape)
    break
```

```
torch.Size([64, 1, 28, 28])
torch.Size([64])
```



MNIST手写体识别：训练神经网络

```
epochs = 10
mnist_mlp.train()
for epoch in range(epochs):
    for imgs, labels in mnist_loader:
        batch_size = imgs.shape[0]
        logits = mnist_mlp(imgs.view(batch_size,-1))
        loss = loss_fn(logits,labels)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

MNIST手写体识别：测试模型

```
test_loader = torch.utils.data.DataLoader(mnist_test,
                                          batch_size = 100, shuffle = False)
mnist_mlp.eval()
correct = 0
total = 0
with torch.no_grad():
    for imgs,labels in test_loader:
        batch_size = imgs.shape[0]
        logits = mnist_mlp(imgs.view(batch_size,-1))
        _,predicted = torch.max(logits.data,1)
        total += batch_size
        correct += (predicted == labels).sum().item()
acc = correct / total
```

2.2 子类化 torch.nn.Module

子类化torch.nn.Module

- 从torch.nn.Module派生一个子类
- 编写__init__函数
  - 初始化对象
  - 要调用父类的构造函数__init__
- 编写forward函数
  - 构造网络

使用nn.Module构造网络模型

```
class mlp(nn.Module):

    def __init__(self, in_dim, out_dim):
        super(mlp,self).__init__()
        self.lin1 = nn.Linear(in_features=in_dim, out_features=64)
        self.relu = nn.ReLU(inplace=True)
        self.lin2 = nn.Linear(in_features=64,out_features=out_dim)


    def forward(self, x):
        x = self.lin1(x)
        x = self.relu(x)
        x = self.lin2(x)

        return x
```

```
mnist_mlp = mlp(784,10)
print(mnist_mlp)
```

```
mlp(
  (lin1): Linear(in_features=784, out_features=64, bias=True)
  (relu): ReLU(inplace)
  (lin2): Linear(in_features=64, out_features=10, bias=True)
)
```

```
x = torch.randn((1,784),dtype = torch.float32)
y = F.softmax(mnist_mlp(x),dim=1)
print(y.detach().numpy())
```

```
[[0.07569709 0.11641571 0.12871902 0.10927621 0.05882455 0.12559932
  0.11405984 0.07417176 0.0880156  0.1092209 ]]
```

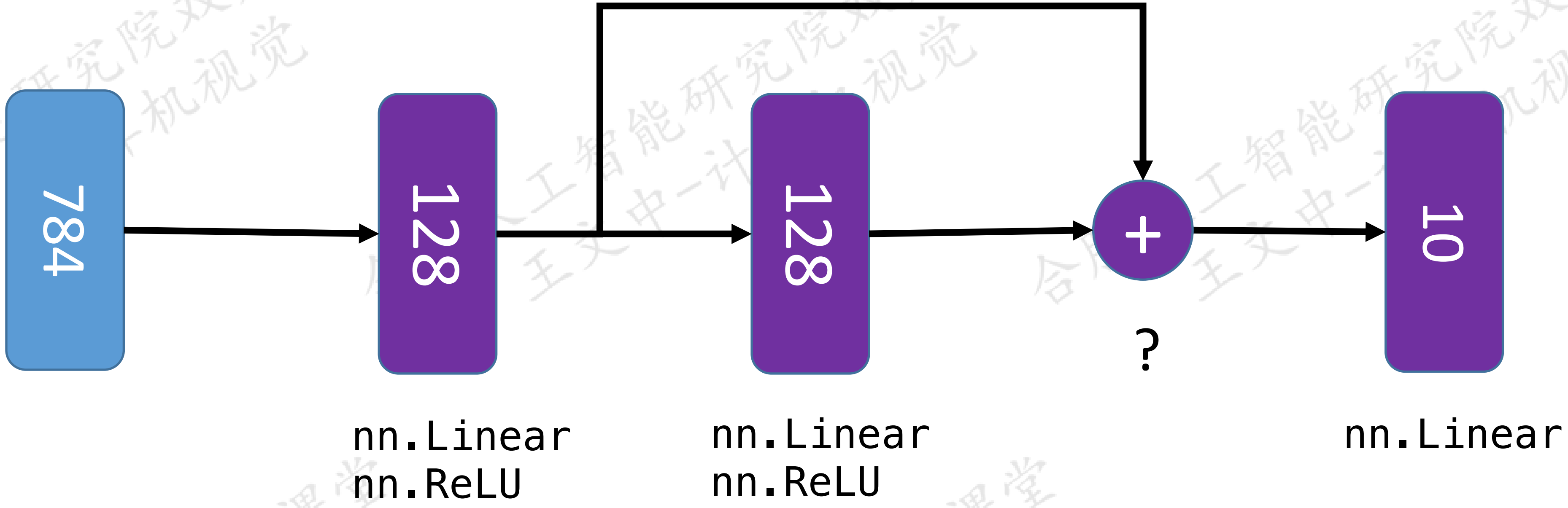
```
print(mnist_mlp._modules)
```

```
OrderedDict([('lin1', Linear(in_features=784, out_features=64,
bias=True)), ('relu', ReLU(inplace)), ('lin2', Linear(in_features=64,
out_features=10, bias=True))])
```

```
x = torch.randn((1,784),dtype = torch.float32)
y = mnist_mlp._modules['lin1'](x)
print(y.detach().numpy())
```

```
[[-0.01645807  0.12257674 -0.3842733  -0.10875969  0.16210961 -0.9262785
   0.3560028  -0.3479771  -0.4386911  -0.37093288 -0.0556463  -0.4703986
   0.54101855 -0.51167864  0.08044843  0.21852194  1.1178634   0.22886397
  -0.6046644  -0.36042506 -0.0121364  -0.37140787  0.41181365  0.9680239
  -0.44987577  0.11921623 -0.55106914  0.18517387  0.56142396 -0.59405994
   0.47401157  1.1164094   0.48247746  0.11364826  0.91904306  0.9782668
  -0.81544924  0.2937653  -1.3910329  -0.10774229 -0.03324178  0.54723066
  -0.43887684  0.12371415  0.03490007  0.62052786 -0.10143616 -0.43207315
   0.42250878  0.49805558 -0.69287837 -0.2873435  -0.5114934   0.6561675
   1.0234826   0.04920949  0.3638496   0.5078668   0.1270785  -0.18455932
  -1.1579272  -0.6274739  -0.23763435 -0.7309237 ]]
```

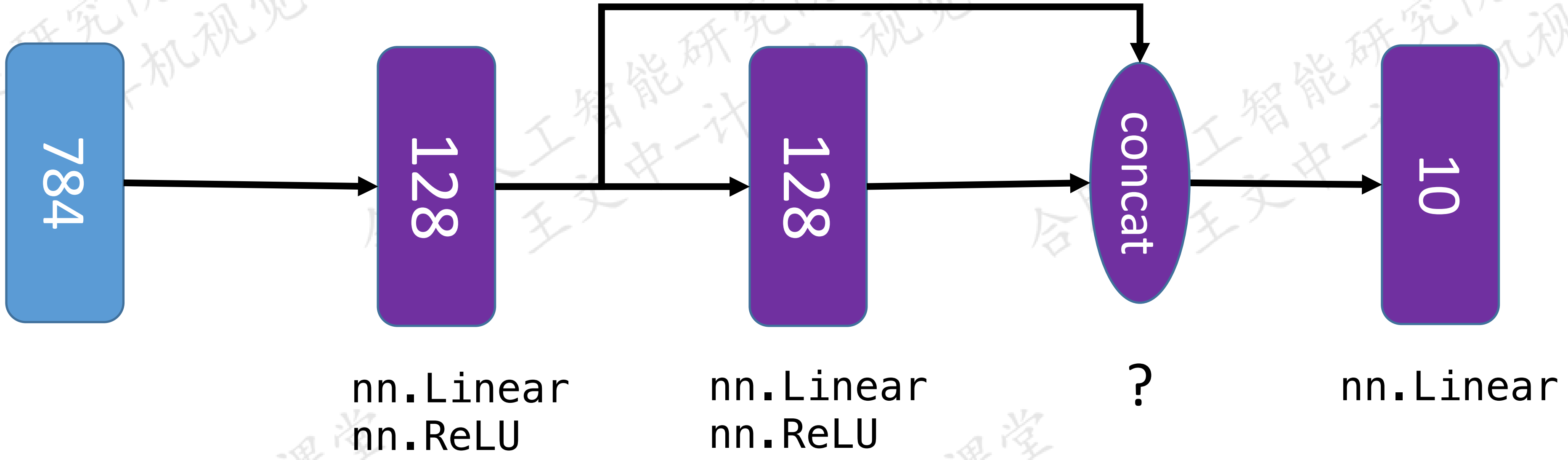
用Module实现复杂的模型



用Module实现复杂的模型

```python
import torch.nn.Functional as F

class mlp(nn.Module):
    def __init__(self, in_dim, out_dim):
        super(mlp,self).__init__()
        self.lin1 = nn.Linear(in_features=in_dim, out_features=128)
        self.lin2 = nn.Linear(in_features=128,out_features=128)
        self.lin3 = nn.Linear(in_features=128,out_features=out_dim)

    def forward(self, x):
        x1 = F.relu(self.lin1(x))
        x2 = F.relu(self.lin1(x1))
        x3 = x1+x2
        x4 = self.lin1(x3)
        return x4
```

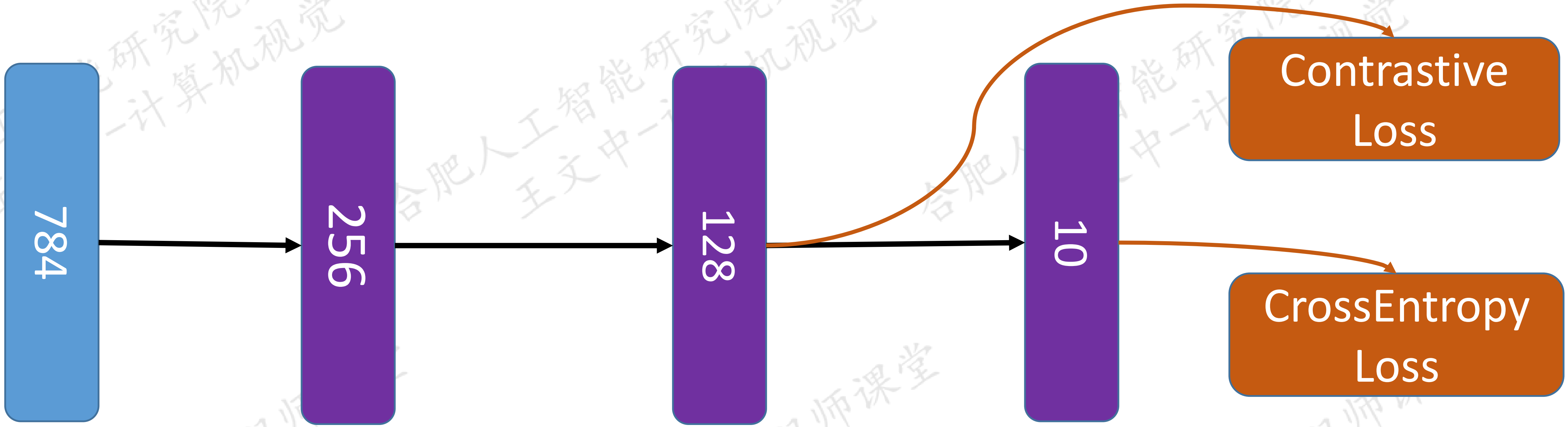
用Module实现复杂的模型



用Module实现复杂的模型

```
import torch.nn.Functional as F

class mlp(nn.Module):
    def __init__(self, in_dim, out_dim):
        super(mlp,self).__init__()
        self.lin1 = nn.Linear(in_features=in_dim, out_features=128)
        self.lin2 = nn.Linear(in_features=128,out_features=128)
        self.lin3 = nn.Linear(in_features=256,out_features=out_dim)

    def forward(self, x):
        x1 = F.relu(self.lin1(x))
        x2 = F.relu(self.lin1(x1))
        x3 = torch.cat((x1,x2),dim = 1)
        x4 = self.lin1(x3)
        return x4
```

用Module实现复杂的模型



$$h_1 = relu(W_{h1}x + b_{h1}) \quad h_2 = relu(W_{h2}h_1 + b_{h2}) \quad z = Softmax(W_o h_2 + b_o)$$

$$\|h_2\| = 1$$

$$contrastive\ loss(x_1, x_2, y) = y \times d(x_1, x_2) + (1 - y) \times \max(\alpha - d(x_1, x_2), 0)$$

用Module实现复杂的模型

```
def contrastive_loss(x,y, margin = 0.3):
    pair_dist = torch.cdist(x,features)

    l1 = torch.unsqueeze(y,dim=0)
    l2 = torch.unsqueeze(y,dim=1)
    pair_mask = torch.logical_not(torch.eye(y.shape[0],dtype=torch.bool))

    pos_mask = torch.logical_and(l1==l2, pair_mask)
    neg_mask = torch.logical_and(l1!=l2, pair_mask)

    pos_dist = torch.masked_select(pair_dist,pos_mask)
    neg_dist = torch.masked_select(pair_dist,neg_mask)

    pos_loss = torch.mean(pos_dist)
    margin = torch.tensor(margin)
    neg_loss = torch.mean(torch.max(margin - neg_dist,torch.tensor(0.0)))
    return pos_loss + neg_loss
```

用Module实现复杂的模型

```
labels = torch.tensor([0,1,2,0,2])
l1 = torch.unsqueeze(labels,dim=0)
l2 = torch.unsqueeze(labels,dim=1)
```

```
l1:tensor([[0, 1, 2, 0, 2]])

l2:tensor([[0],
        [1],
        [2],
        [0],
        [2]])
```

```
pair_mask = torch.logical_not(torch.eye(labels.shape[0],dtype=torch.bool))
pos_mask = torch.logical_and(l1==l2,pair_mask)
neg_mask = torch.logical_and(l1!=l2,pair_mask)
```

```
tensor([[False,  True,  True,  True,  True],
        [ True, False,  True,  True,  True],
        [ True,  True, False,  True,  True],
        [ True,  True,  True, False,  True],
        [ True,  True,  True,  True, False]])

tensor([[False, False, False,  True, False],
        [False, False, False, False, False],
        [False, False, False, False,  True],
        [ True, False, False, False, False],
        [False, False,  True, False, False]])

tensor([[False,  True,  True, False,  True],
        [ True, False,  True,  True,  True],
        [ True,  True, False,  True, False],
        [False,  True,  True, False,  True],
        [ True,  True, False,  True, False]])
```

```
sim = torch.randn((5,5))
```

```
tensor([[ 0.5344,  0.7295, -0.4729,  0.4417,  1.5117],
        [ 0.3096, -0.1728,  0.4240, -1.8273,  0.6577],
        [-0.0897, -0.8336, -0.2095,  0.4435,  1.1995],
        [-0.5547,  0.6684, -1.2100, -0.2603,  0.6245],
        [ 0.3822,  1.2045,  0.2586,  0.9755, -0.2574]])
```

```
pos_sim = torch.masked_select(sim,pos_mask)
neg_sim = torch.masked_select(sim,neg_mask)
```

```
tensor([ 0.4417,  1.1995, -0.5547,  0.2586])
tensor([ 0.7295, -0.4729,  1.5117,  0.3096,  0.4240, -1.8273,  0.6577, -0.0897,
        -0.8336,  0.4435,  0.6684, -1.2100,  0.6245,  0.3822,  1.2045,  0.9755])
```

用Module实现复杂的模型

```
class mlp(nn.Module):
    def __init__(self,in_features):
        super(mlp, self).__init__()

        self.fnet = nn.Sequential(OrderedDict([
            ('lin1',nn.Linear(in_features,256)),
            ('relu1',nn.ReLU()),
            ('lin2',nn.Linear(256,128)),
            ('relu2',nn.ReLU())]))

        self.fc = nn.Linear(128,10)
        self.softmax = nn.Softmax(dim=1)

    def forward(self, x):
        f = F.normalize(self.fnet(x),dim=1)
        logits = self.fc(f)
        p = self.softmax(logits)

        return f,logits,p
```

用Module实现复杂的模型

```
def train(model, data_loader,lr=0.01):
    epochs = 10
    model.train()
    optimizer = optim.RMSprop(model.parameters(), lr = lr)

    identity_loss = torch.nn.CrossEntropyLoss()

    for epoch in range(epochs):
        for imgs, labels in data_loader:
            batch_size = imgs.shape[0]
            features,logits, prob = model(imgs.view(batch_size,-1))

            contr_loss = contrastive_loss(features,labels)
            ident_loss = identity_loss(logits,labels)
            loss = contr_loss + ident_loss

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

小结

使用pytorch开发神经网络模型的基本步骤：

- 1. 构造模型：
  - torch.nn.Sequential类
  - torch.nn.Module类
- 2.训练模型：
  - 损失函数：torch.nn模块
  - 优化算法：torch.optim模块
  - 数据加载：torch.utils.data模块

练习三

- 1. 糖尿病预测（回归）

```
from sklearn.datasets import load_diabetes
diabetes_dataset = load_diabetes()
data = diabetes_dataset['data']
targets = diabetes_dataset['target']
print(data.shape)
print(targets.shape)
```

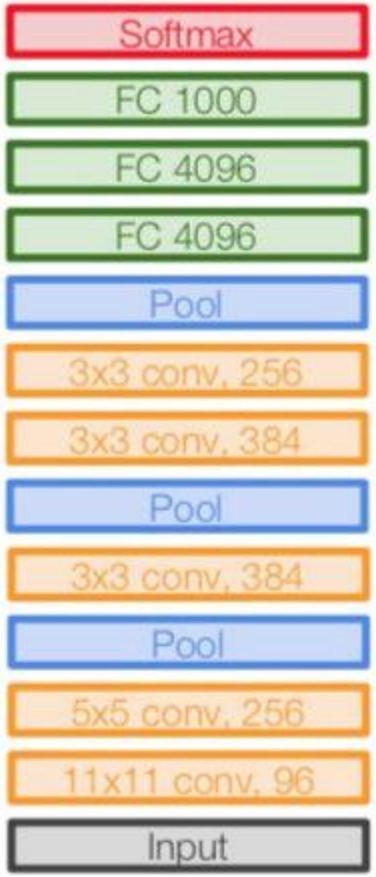
```
(442, 10)
(442,)
```

- 2. MNIST手写体识别（分类）

3.卷积神经网络编程

3.1 编写卷积网络模型

卷积神经网络



AlexNet

```
torch.nn.Conv2d
torch.nn.MaxPool2d
torch.nn.AvgPool2d
```

nn.Conv2d

```
torch.nn.Conv2d(in_channels: int,
out_channels: int,
kernel_size: Union[int, Tuple[int, int]],
stride: Union[int, Tuple[int, int]] = 1,
padding: Union[int, Tuple[int, int]] = 0,
dilation: Union[int, Tuple[int, int]] = 1,
groups: int = 1,
bias: bool = True,
padding_mode: str = 'zeros')
```

$input: N \times C_{in} \times H_{in} \times W_{in}$
$output: N \times C_{out} \times H_{out} \times W_{out}$

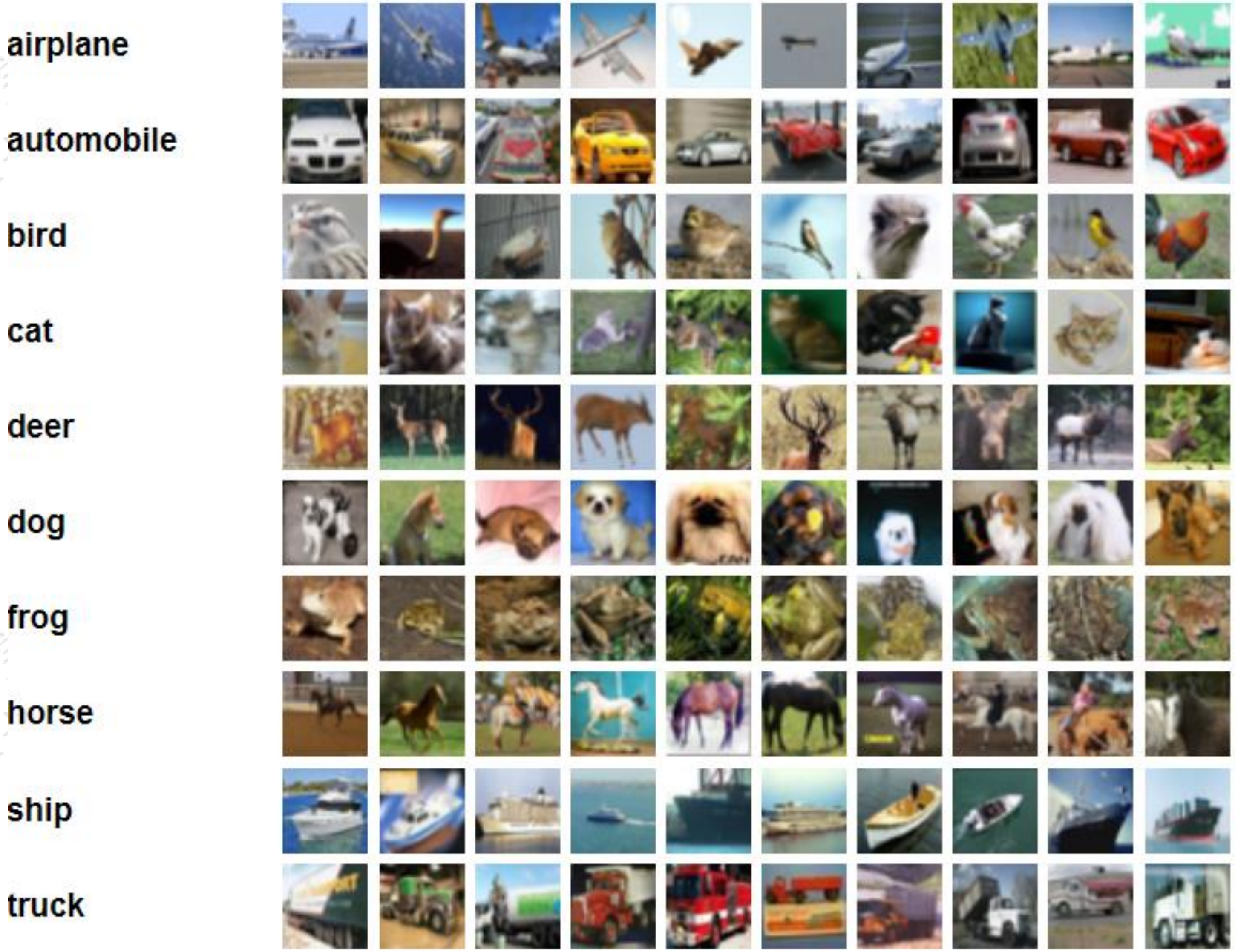
```
m = nn.Conv2d(16, 33, 3, stride=2)
m = nn.Conv2d(16, 33, (3, 5), stride=(2, 1), padding=(4, 2))
m = nn.Conv2d(16, 33, (3, 5), stride=(2, 1), padding=(4, 2), dilation=(3, 1))
```

nn.MaxPool2d

```
torch.nn.MaxPool2d(kernel_size,
stride=None,
padding=0,
dilation=1,
return_indices=False,
ceil_mode=False)
```

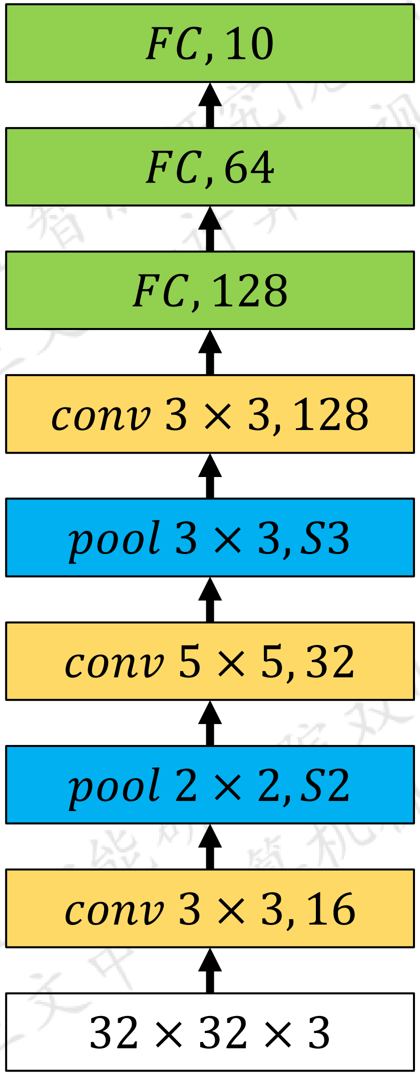
```
m1 = nn.MaxPool2d(2, 2)
m2 = nn.MaxPool2d((4, 2), stride=(2, 1), padding=(2, 1))
x = torch.rand((1,12,12))#x.dim==3 or 4
y1 = m1(x)          torch.Size([1, 6, 6])
y2 = m2(x)          torch.Size([1, 7, 13])
```

CIFAR10



$32 \times 32 \times 3$

CIFAR10


$FC, 10$
$FC, 64$
$FC, 128$
$conv\ 3 \times 3, 128$
$pool\ 3 \times 3, S3$
$conv\ 5 \times 5, 32$
$pool\ 2 \times 2, S2$
$conv\ 3 \times 3, 16$
$32 \times 32 \times 3$

```python
class CNN(nn.Module):
    def __init__(self):
        #注意：首先调用父类的初始化函数
        super(CNN, self).__init__()

        #定义卷积、池化以及全连接操作
```

$conv\ 3\times3, 16$	`self.conv1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3)`
$pool\ 2\times2, S2$	`self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)`
$conv\ 5\times5, 32$	`self.conv2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=5)`
$pool\ 3\times3, S3$	`self.pool2 = nn.MaxPool2d(kernel_size=3, stride=3)`
$conv\ 3\times3, 128$	`self.conv3 = nn.Conv2d(in_channels=32, out_channels=128, kernel_size=3)`
$FC, 128$	`self.fc1 = nn.Linear(128, 128)`
$FC, 64$	`self.fc2 = nn.Linear(128, 64)`
$FC, 10$	`self.fc3 = nn.Linear(64, 10)`

```
def forward(self, x):
        #在前向函数中构造出卷积网络
        #注意这里的x把不同层连接起来
        x = self.pool1(F.relu(self.conv1(x)))
        x = self.pool2(F.relu(self.conv2(x)))
        x = F.relu(self.conv3(x))

        #使用torch.Tensor.view函数，把一个多维张量拉直为一个1维张量（向量）
        x = x.view(-1, 128)

        #全连接层
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

组织训练样本datasets.ImageFolder

```
data/dog/0001.jpg
data/dog/0002.jpg
data/dog/harris.png
......
data/cat/0001.png
data/cat/ricky.png
data/cat/adam_1.png
```

```
data_set = torchvision.datasets.ImageFolder(root='./data')
```

样本预处理transforms

```
normalize = transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))

data_transform = transforms.Compose([
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),#把图像变换为张量
        normalize,#注意规范化要在ToTensor之后
    ])

data_set = torchvision.datasets.ImageFolder(root='./data',
                                            transform=data_transform)
```

数据加载器torch.utils.data.DataLoader

```
train_loader = torch.utils.data.DataLoader(dataset=train_set,
                                           batch_size=32,
                                           shuffle=True,
                                           num_workers=0)
test_loader = torch.utils.data.DataLoader(dataset=test_set,
                                          batch_size=32,
                                          shuffle=False,
                                          num_workers=0)
```

训练过程

```
net = CNN()
if torch.cuda.is_available():
    device = torch.device("cuda:0")
else:
    device = torch.device("cpu")

net.to(device)
xentropy = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.01, momentum=0.9)
net.train()
```

```python
for epoch in range(50):
    running_loss = 0.0
    for i, data in enumerate(train_loader):
        inputs, labels = data[0].to(device), data[1].to(device)
        optimizer.zero_grad()
        outputs = net(inputs)
        loss = xentropy(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

        if i % 10 == 9:
            print('[%d, %5d] loss = %.3f' % (epoch+1, i+1, running_loss/10))
            running_loss = 0.0
```

$input: N \times C \times H \times W$
$output: N \times K$

3.2 使用预训练模型

保存模型

```
model = CNN()
state_dict = model.state_dict()
print('State_dict of CNN model:')
for param_tensor in state_dict:
    print(param_tensor, '\t',state_dict[param_tensor].size())
```

```
State_dict of CNN model:
conv1.weight     torch.Size([16, 3, 3, 3])
conv1.bias       torch.Size([16])
conv2.weight     torch.Size([32, 16, 5, 5])
conv2.bias       torch.Size([32])
conv3.weight     torch.Size([128, 32, 3, 3])
conv3.bias       torch.Size([128])
fc1.weight       torch.Size([128, 128])
fc1.bias         torch.Size([128])
fc2.weight       torch.Size([64, 128])
fc2.bias         torch.Size([64])
fc3.weight       torch.Size([10, 64])
fc3.bias         torch.Size([10])
```

加载模型

```
model = CNN()
#训练模型......

#保存训练好的参数到文件my_model.pth中
state_dict = model.state_dict()
torch.save(state_dict,'my_model.pth')

#使用保存的模型参数:
state_dict = torch.load('my_model.pth')
#把读入的模型参数加载到模型model中:
model.load_state_dict(state_dict)
```

使用预训练模型

```
import torchvision.models as models
resnet18 = models.resnet18()
alexnet = models.alexnet()
vgg16 = models.vgg16()
squeezenet = models.squeezenet1_0()
densenet = models.densenet161()
inception = models.inception_v3()
googlenet = models.googlenet()
shufflenet = models.shufflenet_v2_x1_0()
mobilenet = models.mobilenet_v2()
resnext50_32x4d = models.resnext50_32x4d()
```

使用预训练模型

```
resnet50 = models.resnet50(pretrained=True)
```

```
resnet50 = models.resnet50()
#使用本地磁盘上的模型参数文件
state_dict = torch.load('resnet50.pth')
#把读入的模型参数加载到模型model中：
resnet50.load_state_dict(state_dict)
```

使用预训练模型

```
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
```

使用ResNet-50作为特征提取器

```
net = models.resnet50(pretrained=False)
state_dict = torch.load('./model/resnet50.pth')
net.load_state_dict(state_dict=state_dict)
for param in net.parameters():
    param.requires_grad=False
```

```
num_classes = 17
featureSize = net.fc.in_features
net.fc = nn.Linear(featureSize, num_classes)
```

微调ResNet-50

```
for name, _ in net.named_parameters():
    print(name)
```

```
layer4.2.conv1.weight
layer4.2.bn1.weight
layer4.2.bn1.bias
layer4.2.conv2.weight
layer4.2.bn2.weight
layer4.2.bn2.bias
layer4.2.conv3.weight
layer4.2.bn3.weight
layer4.2.bn3.bias
fc.weight
fc.bias
```

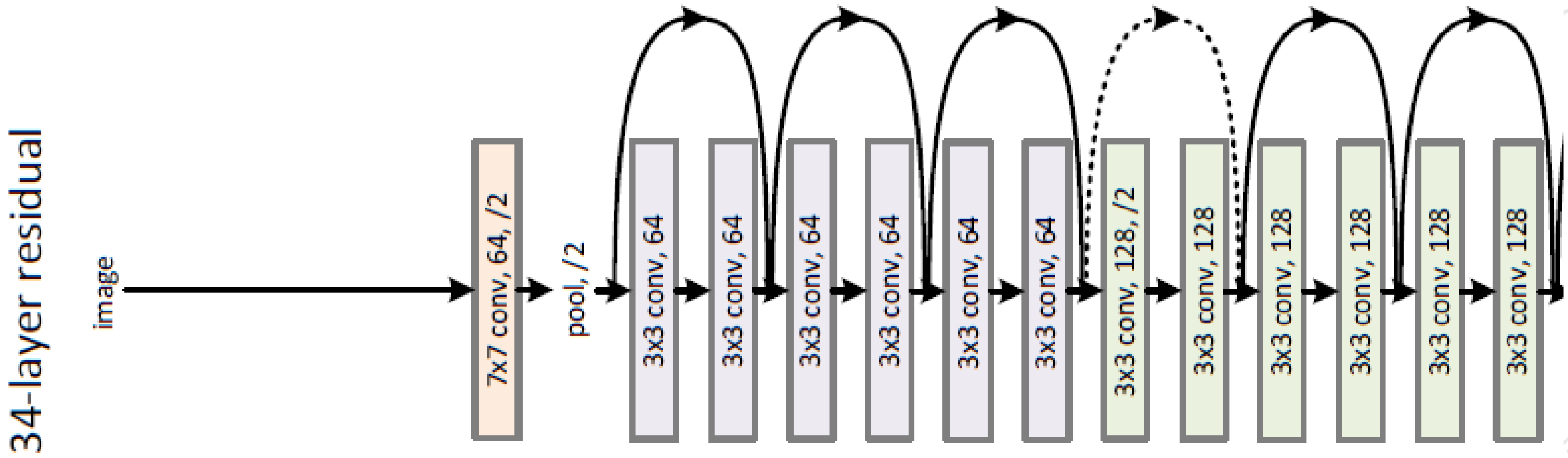
微调ResNet-50

```
#这些层不训练
exclude_layers = ['layer1', 'layer2', 'layer3’]
for name, param in net.named_parameters():
    for layer in exclude_layers:
        if name.startswith(layer):
            param.requires_grad = False
            break
```

```
layer4.2.conv1.weight
layer4.2.bn1.weight
layer4.2.bn1.bias
layer4.2.conv2.weight
layer4.2.bn2.weight
layer4.2.bn2.bias
layer4.2.conv3.weight
layer4.2.bn3.weight
layer4.2.bn3.bias
fc.weight
fc.bias
```

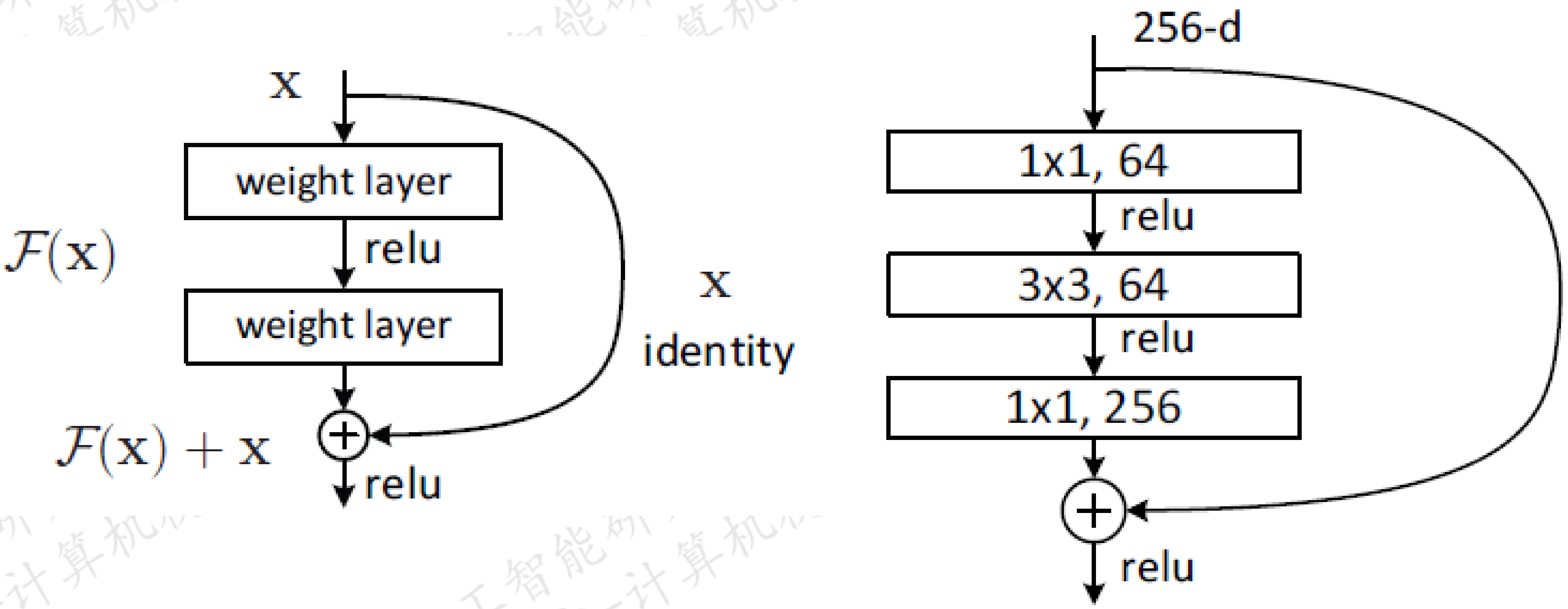
3.3 编写复杂的网络

ResNet



34-layer residual
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128

Residual Block



Conv Layer

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

```
class ResBlock(nn.Module):
    def __init__(self,in_channels,out_channels, downsample = False):
        super(ResBlock, self).__init__()
        stride = 2 if downsample else 1

        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size =
3,padding=1,stride = stride, bias = False)
        self.bn1 = nn.BatchNorm2d(num_features = out_channels)

        self.conv2 = nn.Conv2d(out_channels, out_channels,kernel_size =
3,padding=1,stride = 1, bias = False)
        self.bn2 = nn.BatchNorm2d(num_features = out_channels)

        self.relu = nn.ReLU(inplace = True)

        self.downsample = downsample
        if downsample:
            self.sampling_conv = nn.Conv2d(in_channels, out_channels,kernel_size=1,
stride = stride, padding = 0)
            self.sampling_bn = nn.BatchNorm2d(num_features=out_channels)
```

```python
    def forward(self, x):
        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu(out)

        out = self.conv2(out)
        out = self.bn2(out)

        identity = x
        if self.downsample:
            identity = self.sampling_conv(identity)
            identity = self.sampling_bn(identity)

        out += identity

        out = self.relu(out)
        return out
```

```python
class ResLayer(nn.Module):
    def __init__(self, in_channels, out_channels, n_blocks, downsample = True):
        super(ResLayer,self).__init__()
        blocks = [ResBlock(in_channels,out_channels,downsample)]
        for i in range(1,n_blocks):
            blocks.append(ResBlock(out_channels,out_channels))

        self.layer = nn.Sequential(*blocks)

    def forward(self,x):
        return self.layer(x)
```

```
class MyResnet(nn.Module):
    def __init__(self, blocks):
        super(MyResnet,self).__init__()
        channels = 64
        self.conv1 = nn.Conv2d(3,channels,kernel_size = 7,padding = 3, stride = 2, bias = False)
        self.bn1 = nn.BatchNorm2d(num_features = channels)
        self.pool1 = nn.MaxPool2d(kernel_size=3,stride=2)
        self.gPool = nn.AvgPool2d(kernel_size=7)

        self.layers = [ResLayer(in_channels=channels,out_channels=channels,n_blocks = blocks[0], downsample=False)]

        for b in blocks[1:]:
            self.layers.append(ResLayer(in_channels=channels,out_channels=2*channels,n_blocks = b))
            channels = channels * 2
        self.lin = nn.Linear(in_features=channels,out_features=1000)
```

```python
def forward(self,x):
    x = self.conv1(x)
    x = self.bn1(x)
    x = self.pool1(x)
    for l in self.layers:
        x = l(x)
    x = self.gPool(x)
    x = x.view(-1,x.shape[1])
    x = self.lin(x)

    return x
```

```python
def main():
    resnet = MyResnet([2,2,2,2])

    im = Image.open('Woolsthorpe-Manor.jpg')
    im = im.resize((224,224))
    im = np.array(im, dtype = np.float32) / 255.0
    im_tensor = torch.from_numpy(im)
    im_tensor = im_tensor.permute((2,0,1))
    im_tensor = im_tensor.unsqueeze(dim=0)
    print(im_tensor.size())

    out = resnet(im_tensor)
    print(out.size())

if __name__=='__main__':
    main()
```

```
torch.Size([1,3,224,224])
torch.Size([1,1000])
```

练习四

- 1. 复现Deep Residual Learning for Image Recognition论文中的CIFAR10分类识别
- 2. 使用ResNet-50迁移到hymenoptera_data进行蚂蚁与蜜蜂的识别，输出混淆矩阵，对识别结果进行分析。