

PyTorch Tutorial

05. Linear Regression with PyTorch

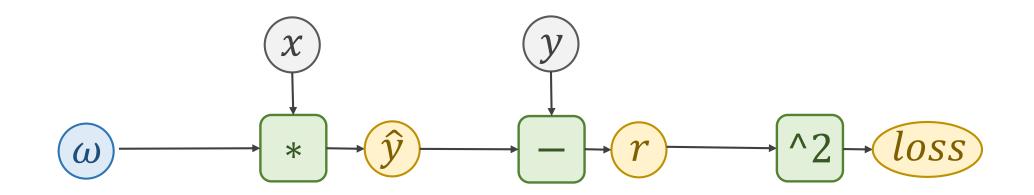
Revision

Linear Model

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

Loss Function

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



Revision

```
print("predict (before training)", 4, forward(4).item())
for epoch in range (100):
    for x, y in zip(x_data, y_data):
       1 = loss(x, y)
                         Forward
        1.backward()
                        Backward
        print('\tgrad:', x, y, w.grad.item())
        w. data = w. data - 0.01 * w. grad. data update
        w. grad. data. zero () 手动清零
    print("progress:", epoch, l.item())
print ("predict (after training)", 4, forward (4).item())
```

```
predict (before training) 4 4.0
        grad: 1.0 2.0 -2.0
        grad: 2.0 4.0 -7.840000152587891
        grad: 3.0 6.0 -16.228801727294922
progress: 0 7.315943717956543
        grad: 1.0 2.0 -1.478623867034912
        grad: 2.0 4.0 -5.796205520629883
        grad: 3.0 6.0 -11.998146057128906
progress: 1 3.9987640380859375
        grad: 1.0 2.0 -1.0931644439697266
        grad: 2.0 4.0 -4.285204887390137
        grad: 3.0 6.0 -8.870372772216797
progress: 2 2.1856532096862793
        grad: 1.0 2.0 -0.8081896305084229
        grad: 2.0 4.0 -3.1681032180786133
        grad: 3.0 6.0 -6.557973861694336
progress: 3 1.1946394443511963
        grad: 1.0 2.0 -0.5975041389465332
        grad: 2.0 4.0 -2.3422164916992188
        grad: 3.0 6.0 -4.848389625549316
progress: 4 0.6529689431190491
        grad: 1.0 2.0 -0.4417421817779541
        grad: 2.0 4.0 -1.7316293716430664
        grad: 3.0 6.0 -3.58447265625
progress: 5 0.35690122842788696
        grad: 1.0 2.0 -0.3265852928161621
        grad: 2.0 4.0 -1.2802143096923828
        grad: 3.0 6.0 -2.650045394897461
```

PyTorch Fashion

Prepare dataset
we shall talk about this later

Design model using Class inherit from nn.Module 计算 y_hat

Construct loss and optimizer using PyTorch API

Training cycle

forward, backward, update

PyTorch直接写"*"表示举证对应位置上元素相乘,矩阵乘法对应于torch.matmul.

Linear Regression – 1. Prepare dataset

In PyTorch, the computational graph is in mini-batch fashion, so X and Y are 3×1 Tensors.

$$\begin{bmatrix} y_{pred}^{(1)} \\ y_{pred}^{(2)} \\ y_{pred}^{(3)} \end{bmatrix} = \omega \cdot \begin{bmatrix} x^{(1)} \\ x^{(2)} \\ x^{(3)} \end{bmatrix} + b$$

```
import torch

x_data = torch. Tensor([[1.0], [2.0], [3.0]])
y_data = torch. Tensor([[2.0], [4.0], [6.0]])
```

Revision: Gradient Descent Algorithm

Derivative

$$\frac{\partial cost(\omega)}{\partial \omega} = \frac{\partial}{\partial \omega} \frac{1}{N} \sum_{n=1}^{N} (x_n \cdot \omega - y_n)^2$$

$$= \frac{1}{N} \sum_{n=1}^{N} \frac{\partial}{\partial \omega} (x_n \cdot \omega - y_n)^2$$

$$= \frac{1}{N} \sum_{n=1}^{N} 2 \cdot (x_n \cdot \omega - y_n) \frac{\partial (x_n \cdot \omega - y_n)}{\partial \omega}$$

$$= \frac{1}{N} \sum_{n=1}^{N} 2 \cdot x_n \cdot (x_n \cdot \omega - y_n)$$

Gradient

$$\frac{\partial cost}{\partial \omega}$$

Update

$$\omega = \omega - \alpha \frac{\partial cost}{\partial \omega}$$

Update

$$\omega = \omega - \alpha \frac{1}{N} \sum_{n=1}^{N} 2 \cdot x_n \cdot (x_n \cdot \omega - y_n)$$

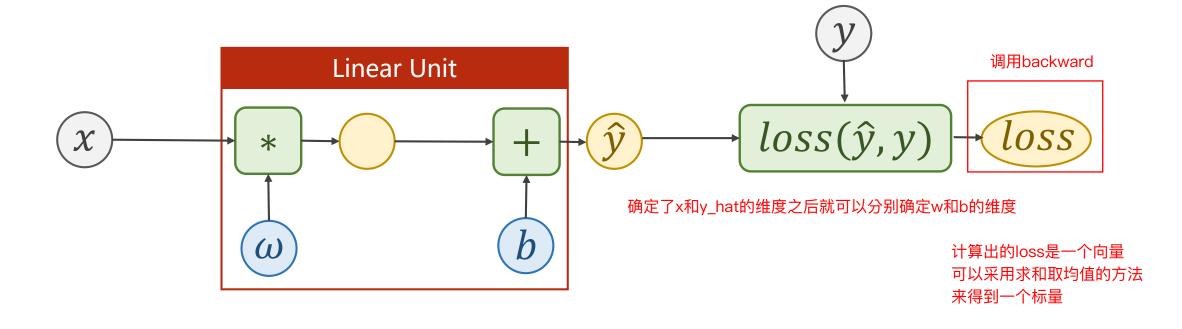
Affine Model = Linear Unit

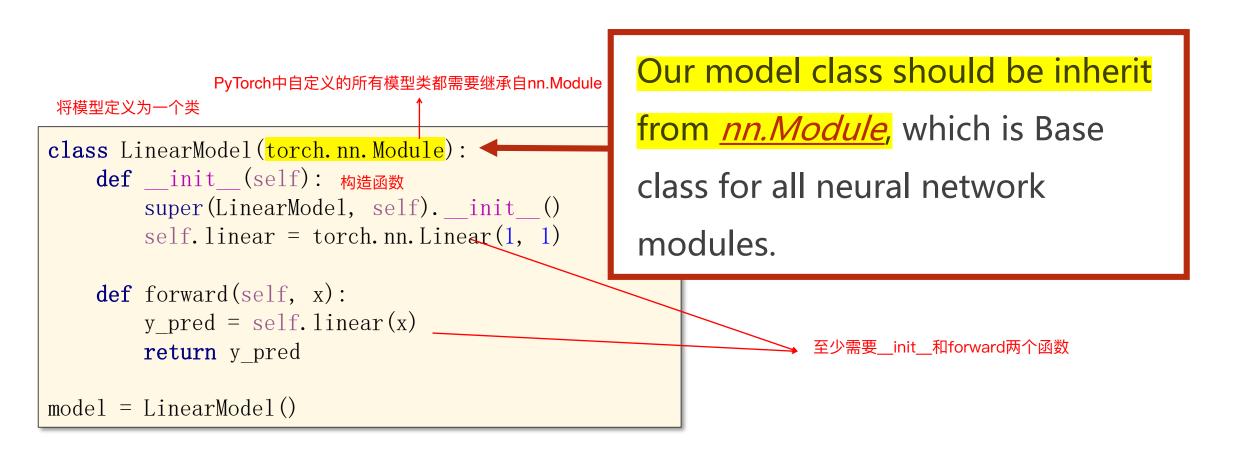
Affine Model

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

Loss Function

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





```
class LinearModel(torch.nn. Module):
    def __init__(self):
        super(LinearModel, self).__init__()
        self.linear = torch.nn. Linear(1, 1)

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

model = LinearModel()

Member methods __init__() and

forward() have to be implemented.
```

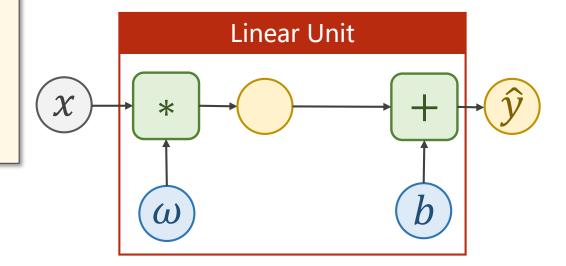
```
class LinearModel(torch.nn.Module):
    def __init__(self):
        super(LinearModel, self).__init__()
        self.linear = torch.nn.Linear(1, 1)

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

model = LinearModel()
```

Class *nn.Linear* contain two

member **Tensors**: weight and bias.



```
class torch.nn.Linear(in_features, out_features, bias=True)
                                                             [source]
  Applies a linear transformation to the incoming data: y = Ax + b
    Parameters:
                      • in_features – size of each input sample
                      • out_features - size of each output sample
                      • bias – If set to False, the layer will not learn an additive bias. Default: True
                                               是否需要偏置量
    Shape:
       • Input: (N, *, in\_features) where * means any number of additional dimensions
       • Output: (N,*,out\_features) where all but the last dimension are the same shape as
         the input.
    Variables:

    weight – the learnable weights of the module of shape (out_features x in_features)

                   • bias – the learnable bias of the module of shape (out features)
```

class torch.nn.Linear(in_features, out_features, bias=True) [source] Applies a linear transformation to the incoming data: y = Ax + bOutput $y_{pred}^{(1)}$ $= \omega \cdot \begin{bmatrix} \chi^{(1)} \\ \chi^{(2)} \end{bmatrix} + b$ Parameters: tive bias. Default: True Shape: • Input: $(N,*,in_features)$ where * means any number of additional dimensions • Output: $(N, *, out_features)$ where all but the last dimension are the same shape as the input. Variables: weight – the learnable weights of the module of shape (out_features x in_features) • bias – the learnable bias of the module of shape (out features)

Class <u>nn.Linear</u> has implemented the magic method <u>call</u>(), which enable the instance of the class can be called just like a function. Normally the *forward()* will be called.

Pythonic!!!

Linear Regression – 3. Construct Loss and Optimizer

构造损失函数和优化器

```
criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), 1r=0.01)
```

class torch.nn.MSELoss(size_average=True, reduce=True) [source]

Creates a criterion that measures the mean squared error betwee target y.

Also inherit from nn.Module.

The loss can be described as:

$$\ell(x,y) = L = \{l_1,\ldots,l_N\}^ op, \quad l_n = (x_n-y_n)^2,$$

where N is the batch size.

Linear Regression – 3. Construct Loss and Optimizer

```
criterion = torch.nn.MSELoss(size_average=False)

optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
|r=学习率

class torch.optim.SGD(params, lr=<object object>, momentum=0, dampening=0, weight_decay=0, nesterov=False)

[source]

Implements stochastic gradient descent (optionally with momentum).
```

Linear Regression – 3. Construct Loss and Optimizer

```
criterion = torch. nn. MSELoss (size_average=False)

optimizer = torch. optim. SGD (model. parameters (), lr=0.01)

Parameters:

• params (iterable) - iterable of parameters to optimize or dicts defining parameter groups

• lr (float) - learning rate 可以设置学习率为固定,也可以将学习率设置为先高后低
```

```
Loss虽然是一个tensor,但是在打印时会自动转换为str
for epoch in range (100):
    y_pred = model(x_data)
                                                    Forward: Loss
   loss = criterion(y_pred, y_data)
    print(epoch, loss)
    optimizer.zero_grad()所有权重归零
    loss.backward()
    optimizer.step()
```

```
for epoch in range(100):
    y_pred = model(x_data)
    loss = criterion(y_pred, y_data)
    print(epoch, loss)

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

NOTICE:

The grad computed by .backward() will be accumulated.

So before backward, remember set the grad to **ZERO**!!!

```
for epoch in range(100):
    y_pred = model(x_data)
    loss = criterion(y_pred, y_data)
    print(epoch, loss)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
Backward: Autograd
```

```
for epoch in range(100):
    y_pred = model(x_data)
    loss = criterion(y_pred, y_data)
    print(epoch, loss)

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

for x, y in zip(x_data, y_data):
    w. data = w. data - 0.01 * w. grad. data

Update
```

Linear Regression – Test Model

```
# Output weight and bias
print('w = ', model.linear.weight.item())
print('b = ', model.linear.bias.item())

# Test Model
x_test = torch.Tensor([[4.0]])
y_test = model(x_test)
print('y_pred = ', y_test.data)
```

```
86 0. 3036523759365082
87 0. 2992883026599884
88 0. 29498720169067383
89 0. 2907477021217346
90 0. 28656935691833496
91 0. 28245046734809875
92 0 27839142084121704
93 0. 27439042925834656
94 0. 2704470157623291
95 0. 2665606141090393
96 0. 262729674577713
97 0. 25895369052886963
98 0. 2552322745323181
99 0. 2515641450881958
w = 1.666100263595581
b = 0.7590328454971313
y_pred = tensor([[ 7.4234]])
```

```
986 3.594939812501252e-07
987 3.5411068211033125e-07
988 3.4917979974125046e-07
989 3.4428359185767476e-07
990 3.392528924450744e-07
991 3.3442694302721065e-07
992 3.294019847999152e-07
993 3.247135396122758e-07
994 3.199925231456291e-07
995 3.1540417921860353e-07
996 3.1097857799977646e-07
997 3.0668098816022393e-07
998 3.020934400410624e-07
999 2.977626536448952e-07
w = 1.9996366500854492
b = 0.0008257834706455469
y pred = tensor([[ 7.9994]])
```

100 Iterations

1000 Iterations

Linear Regression

```
import torch
x data = torch. Tensor([[1.0], [2.0], [3.0]])
y data = torch. Tensor([[2.0], [4.0], [6.0]])
class LinearModel (torch. nn. Module):
    def init (self):
        super(LinearModel, self). init ()
        self. linear = torch. nn. Linear (1, 1)
    def forward(self, x):
        y \text{ pred} = \text{self.linear}(x)
        return y pred
model = LinearModel()
criterion = torch.nn. MSELoss(size average=False)
optimizer = torch. optim. SGD (model. parameters (), 1r=0.01)
for epoch in range (1000):
    y pred = model(x data)
    loss = criterion(y pred, y data)
    print(epoch, loss.item())
    optimizer.zero grad()
    loss. backward()
    optimizer.step()
print('w = ', model.linear.weight.item())
print('b = ', model.linear.bias.item())
x test = torch. Tensor ([4.0])
y \text{ test} = \text{model}(x \text{ test})
print('y pred = ', y test.data)
```

Prepare dataset

we shall talk about this later

Design model using Class inherit from nn.Module

Construct loss and optimizer using PyTorch API

Training cycle forward, backward, update

Exercise 5-1: Try Different Optimizer in Linear Regression

- torch.optim.Adagrad
- torch.optim.Adam
- torch.optim.Adamax
- torch.optim.ASGD
- torch.optim.LBFGS
- torch.optim.RMSprop
- torch.optim.Rprop
- torch.optim.SGD

Exercise 5-2: Read more example from official tutorial

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https://pytorch.org/tutorials/beginner/pytorch_with_examples.html



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