

2020320064 문정민 컴퓨터학과

## ✓ 2.1. Data Manipulation

```
import torch
```

```
x = torch.arange(12, dtype=torch.float32)
```

```
x
```

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

```
x.numel()
```

```
→ 12
```

```
x.shape
```

```
→ torch.Size([12])
```

```
X = x.reshape(3, 4)
```

```
X
```

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

```
torch.zeros((2, 3, 4))
```

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

           [[0., 0., 0., 0.],
            [0., 0., 0., 0.],
            [0., 0., 0., 0.]])])
```

```
torch.ones((2, 3, 4))
```

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

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

```
torch.randn(3, 4)
```

```
→ tensor([[ -1.8280,  0.5906, -0.3446, -0.4376],
          [-0.7304, -0.6903, -0.5214, -0.6375],
          [ 1.4015,  0.4537, -0.5932,  0.9257]])
```

```
torch.tensor([[2, 1, 4, 3], [1, 2, 3, 4], [4, 3, 2, 1]])
```

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

```
X[-1], X[1:3]
```

```
→ (tensor([ 8.,  9., 10., 11.]),
   tensor([[ 4.,  5.,  6.,  7.],
           [ 8.,  9., 10., 11.])))
```

```
X[1, 2] = 17
```

```
X
```

```
→ tensor([[ 0.,  1.,  2.,  3.],
          [ 4.,  5., 17.,  7.],
          [ 8.,  9., 10., 11.]])
```

```
X[:2, :] = 12
```

```
X
```

```
→ tensor([[12., 12., 12., 12.],
          [12., 12., 12., 12.],
          [ 8.,  9., 10., 11.]])
```

```
torch.exp(x)
```

```
→ tensor([162754.7969, 162754.7969, 162754.7969, 162754.7969, 162754.7969,
          162754.7969, 162754.7969, 162754.7969, 2980.9580, 8103.0840,
          22026.4648, 59874.1406])
```

```
x = torch.tensor([1.0, 2, 4, 8])
```

```
y = torch.tensor([2, 2, 2, 2])
```

```
x + y, x - y, x * y, x / y, x ** y
```

```
→ (tensor([ 3.,  4.,  6., 10.]),
   tensor([-1.,  0.,  2.,  6.]),
   tensor([ 2.,  4.,  8., 16.]),
   tensor([0.5000, 1.0000, 2.0000, 4.0000]),
   tensor([ 1.,  4., 16., 64.]])
```

```
X = torch.arange(12, dtype=torch.float32).reshape((3,4))
```

```
Y = torch.tensor([[2.0, 1, 4, 3], [1, 2, 3, 4], [4, 3, 2, 1]])
```

```
torch.cat((X, Y), dim=0), torch.cat((X, Y), dim=1)
```

```
→ (tensor([[ 0.,  1.,  2.,  3.],
          [ 4.,  5.,  6.,  7.],
```

```

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

```

```
X == Y
```

```

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

```

```
X.sum()
```

```
⇒ tensor(66.)
```

```

a = torch.arange(3).reshape((3, 1))
b = torch.arange(2).reshape((1, 2))
a, b

```

```

⇒ (tensor([[0],
           [1],
           [2]]),
   tensor([[0, 1]]))

```

```
a + b
```

```

⇒ tensor([[0, 1],
          [1, 2],
          [2, 3]])

```

```

before = id(Y)
Y = Y + X
id(Y) == before

```

```
⇒ False
```

```

Z = torch.zeros_like(Y)
print('id(Z):', id(Z))
Z[:] = X + Y
print('id(Z):', id(Z))

```

```

⇒ id(Z): 139969559480656
   id(Z): 139969559480656

```

```

before = id(X)
X += Y
id(X) == before

```

```
⇒ True
```

```
A = X.numpy()
B = torch.from_numpy(A)
type(A), type(B)
```

→ (numpy.ndarray, torch.Tensor)

```
a = torch.tensor([3.5])
a, a.item(), float(a), int(a)
```

→ (tensor([3.5000]), 3.5, 3.5, 3)

## ✓ 2.2. Data Preprocessing

```
import os

os.makedirs(os.path.join '..', 'data'), exist_ok=True)
data_file = os.path.join '..', 'data', 'house_tiny.csv')
with open(data_file, 'w') as f:
    f.write('' NumRooms, RoofType, Price
NA, NA, 127500
2, NA, 106000
4, Slate, 178100
NA, NA, 140000'')
```

```
import pandas as pd
```

```
data = pd.read_csv(data_file)
print(data)
```

→

	NumRooms	RoofType	Price
0	NaN	NaN	127500
1	2.0	NaN	106000
2	4.0	Slate	178100
3	NaN	NaN	140000

```
inputs, targets = data.iloc[:, 0:2], data.iloc[:, 2]
inputs = pd.get_dummies(inputs, dummy_na=True)
print(inputs)
```

→

	NumRooms	RoofType_Slate	RoofType_nan
0	NaN	False	True
1	2.0	False	True
2	4.0	True	False
3	NaN	False	True

```
inputs = inputs.fillna(inputs.mean())
print(inputs)
```

```

➡ NumRooms  RoofType_Slate  RoofType_nan
0         3.0         False         True
1         2.0         False         True
2         4.0          True         False
3         3.0         False         True

```

```
import torch
```

```

X = torch.tensor(inputs.to_numpy(dtype=float))
y = torch.tensor(targets.to_numpy(dtype=float))
X, y

```

```

➡ (tensor([[3., 0., 1.],
           [2., 0., 1.],
           [4., 1., 0.],
           [3., 0., 1.]], dtype=torch.float64),
   tensor([127500., 106000., 178100., 140000.], dtype=torch.float64))

```

## ✓ 2.3. Linear Algebra

```
import torch
```

```

x = torch.tensor(3.0)
y = torch.tensor(2.0)

```

```
x + y, x * y, x / y, x**y
```

```
➡ (tensor(5.), tensor(6.), tensor(1.5000), tensor(9.))
```

```

x = torch.arange(3)
x

```

```
➡ tensor([0, 1, 2])
```

```
x[2]
```

```
➡ tensor(2)
```

```
len(x)
```

```
➡ 3
```

```
x.shape
```

```
➡ torch.Size([3])
```

```

A = torch.arange(6).reshape(3, 2)
A

```

```
→ tensor([[0, 1],
          [2, 3],
          [4, 5]])
```

A.T

```
→ tensor([[0, 2, 4],
          [1, 3, 5]])
```

```
A = torch.tensor([[1, 2, 3], [2, 0, 4], [3, 4, 5]])
A == A.T
```

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

```
torch.arange(24).reshape(2, 3, 4)
```

```
→ 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]]])
```

```
A = torch.arange(6, dtype=torch.float32).reshape(2, 3)
B = A.clone() # Assign a copy of A to B by allocating new memory
A, A + B
```

```
→ (tensor([[0., 1., 2.],
            [3., 4., 5.]]),
    tensor([[ 0.,  2.,  4.],
            [ 6.,  8., 10.])))
```

A \* B

```
→ tensor([[ 0.,  1.,  4.],
          [ 9., 16., 25.]])
```

```
a = 2
X = torch.arange(24).reshape(2, 3, 4)
a + X, (a * X).shape
```

```
→ (tensor([[[ 2,  3,  4,  5],
            [ 6,  7,  8,  9],
            [10, 11, 12, 13]],
          [[14, 15, 16, 17],
            [18, 19, 20, 21],
            [22, 23, 24, 25]]]),
    torch.Size([2, 3, 4]))
```

```
x = torch.arange(3, dtype=torch.float32)
x, x.sum()
```

```
⇒ (tensor([0., 1., 2.]), tensor(3.))
```

```
A.shape, A.sum()
```

```
⇒ (torch.Size([2, 3]), tensor(15.))
```

```
A.shape, A.sum(axis=0).shape
```

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

```
A.shape, A.sum(axis=1).shape
```

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

```
A.sum(axis=[0, 1]) == A.sum() # Same as A.sum()
```

```
⇒ tensor(True)
```

```
A.mean(), A.sum() / A.numel()
```

```
⇒ (tensor(2.5000), tensor(2.5000))
```

```
A.mean(axis=0), A.sum(axis=0) / A.shape[0]
```

```
⇒ (tensor([1.5000, 2.5000, 3.5000]), tensor([1.5000, 2.5000, 3.5000]))
```

```
sum_A = A.sum(axis=1, keepdims=True)
sum_A, sum_A.shape
```

```
⇒ (tensor([[ 3.],
           [12.]]),
    torch.Size([2, 1]))
```

```
A / sum_A
```

```
⇒ tensor([[0.0000, 0.3333, 0.6667],
          [0.2500, 0.3333, 0.4167]])
```

```
A.cumsum(axis=0)
```

```
⇒ tensor([[0., 1., 2.],
          [3., 5., 7.]])
```

```
y = torch.ones(3, dtype = torch.float32)
x, y, torch.dot(x, y)
```

```
→ (tensor([0., 1., 2.]), tensor([1., 1., 1.]), tensor(3.))
```

```
torch.sum(x * y)
```

```
→ tensor(3.)
```

```
A.shape, x.shape, torch.mv(A, x), A@x
```

```
→ (torch.Size([2, 3]), torch.Size([3]), tensor([ 5., 14.]), tensor([ 5., 14.]))
```

```
B = torch.ones(3, 4)
```

```
torch.mm(A, B), A@B
```

```
→ (tensor([[ 3.,  3.,  3.,  3.],
            [12., 12., 12., 12.]]),
    tensor([[ 3.,  3.,  3.,  3.],
            [12., 12., 12., 12.])))
```

```
u = torch.tensor([3.0, -4.0])
```

```
torch.norm(u)
```

```
→ tensor(5.)
```

```
torch.abs(u).sum()
```

```
→ tensor(7.)
```

```
torch.norm(torch.ones((4, 9)))
```

```
→ tensor(6.)
```

## ✓ 2.5. Automatic Differentiation

```
import torch
```

```
x = torch.arange(4.0)
```

```
x
```

```
→ tensor([0., 1., 2., 3.])
```

```
# Can also create x = torch.arange(4.0, requires_grad=True)
```

```
x.requires_grad_(True)
```

```
x.grad # The gradient is None by default
```

```
y = 2 * torch.dot(x, x)
```

```
y
```



```
→ tensor(28., grad_fn=<MulBackward0>)
```

```
y.backward()
x.grad
```

```
→ tensor([ 0.,  4.,  8., 12.])
```

```
x.grad == 4 * x
```

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

```
x.grad.zero_() # Reset the gradient
y = x.sum()
y.backward()
x.grad
```

```
→ tensor([1., 1., 1., 1.])
```

```
x.grad.zero_()
y = x * x
y.backward(gradient=torch.ones(len(y))) # Faster: y.sum().backward()
x.grad
```

```
→ tensor([0., 2., 4., 6.])
```

```
x.grad.zero_()
y = x * x
u = y.detach()
z = u * x
```

```
z.sum().backward()
x.grad == u
```

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

```
x.grad.zero_()
y.sum().backward()
x.grad == 2 * x
```

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

```
def f(a):
    b = a * 2
    while b.norm() < 1000:
        b = b * 2
    if b.sum() > 0:
        c = b
    else:
        c = 100 * b
    return c
```

```
a = torch.randn(size=(), requires_grad=True)
d = f(a)
d.backward()
```

```
a.grad == d / a
```

```
⇒ tensor(True)
```

## ✓ 3.1. Linear Regression

```
!pip install d2l==1.0.3
```

```
⇒ 숨겨진 출력 표시
```

```
%matplotlib inline
import math
import time
import numpy as np
import torch
from d2l import torch as d2l
```

```
n = 10000
a = torch.ones(n)
b = torch.ones(n)
```

```
c = torch.zeros(n)
t = time.time()
for i in range(n):
    c[i] = a[i] + b[i]
f'{time.time() - t:.5f} sec'
```

```
⇒ '0.15400 sec'
```

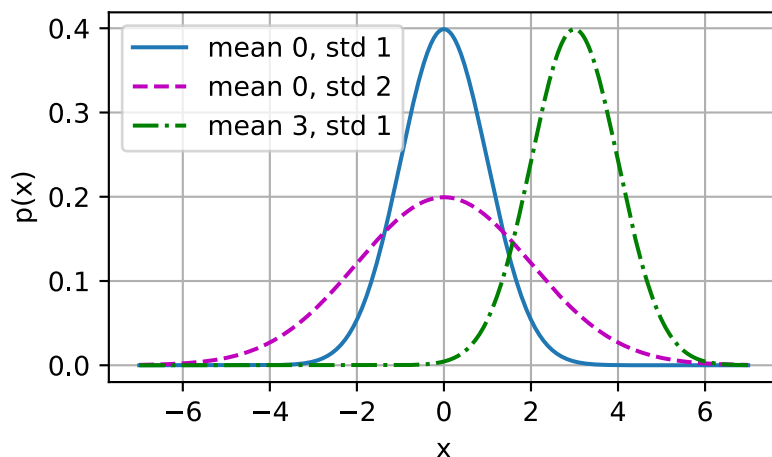
```
t = time.time()
d = a + b
f'{time.time() - t:.5f} sec'
```

```
⇒ '0.00016 sec'
```

```
def normal(x, mu, sigma):
    p = 1 / math.sqrt(2 * math.pi * sigma**2)
    return p * np.exp(-0.5 * (x - mu)**2 / sigma**2)
```

```
# Use NumPy again for visualization
x = np.arange(-7, 7, 0.01)
```

```
# Mean and standard deviation pairs
params = [(0, 1), (0, 2), (3, 1)]
d2l.plot(x, [normal(x, mu, sigma) for mu, sigma in params], xlabel='x',
         ylabel='p(x)', figsize=(4.5, 2.5),
         legend=[f'mean {mu}, std {sigma}' for mu, sigma in params])
```



## ✓ 3.2. Object-Oriented Design for Implementation

```
!pip install d2l==1.0.3
```



숨겨진 출력 표시

```
import time
import numpy as np
import torch
from torch import nn
from d2l import torch as d2l

def add_to_class(Class):
    """Register functions as methods in created class."""
    def wrapper(obj):
        setattr(Class, obj.__name__, obj)
    return wrapper

class A:
    def __init__(self):
        self.b = 1

a = A()

@add_to_class(A)
def do(self):
    print('Class attribute "b" is', self.b)
```

```
a.do()
```

```
⇒ Class attribute "b" is 1
```

```
class HyperParameters:
    """The base class of hyperparameters."""
    def save_hyperparameters(self, ignore=[]):
        raise NotImplemented

# Call the fully implemented HyperParameters class saved in d2l
class B(d2l.HyperParameters):
    def __init__(self, a, b, c):
        self.save_hyperparameters(ignore=['c'])
        print('self.a =', self.a, 'self.b =', self.b)
        print('There is no self.c =', not hasattr(self, 'c'))

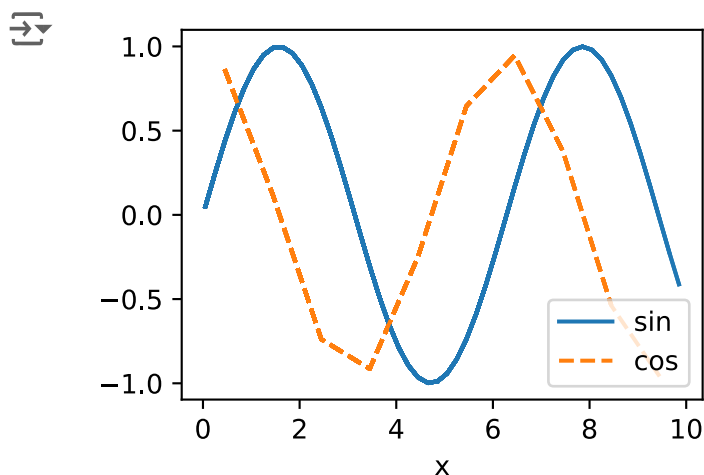
b = B(a=1, b=2, c=3)
```

```
⇒ self.a = 1 self.b = 2
   There is no self.c = True
```

```
class ProgressBoard(d2l.HyperParameters):
    """The board that plots data points in animation."""
    def __init__(self, xlabel=None, ylabel=None, xlim=None,
                  ylim=None, xscale='linear', yscale='linear',
                  ls=['-', '--', '-.', ':'], colors=['C0', 'C1', 'C2', 'C3'],
                  fig=None, axes=None, figsize=(3.5, 2.5), display=True):
        self.save_hyperparameters()

    def draw(self, x, y, label, every_n=1):
        raise NotImplemented

board = d2l.ProgressBoard('x')
for x in np.arange(0, 10, 0.1):
    board.draw(x, np.sin(x), 'sin', every_n=2)
    board.draw(x, np.cos(x), 'cos', every_n=10)
```



```

class Module(nn.Module, d2l.HyperParameters):
    """The base class of models."""
    def __init__(self, plot_train_per_epoch=2, plot_valid_per_epoch=1):
        super().__init__()
        self.save_hyperparameters()
        self.board = ProgressBoard()

    def loss(self, y_hat, y):
        raise NotImplementedError

    def forward(self, X):
        assert hasattr(self, 'net'), 'Neural network is defined'
        return self.net(X)

    def plot(self, key, value, train):
        """Plot a point in animation."""
        assert hasattr(self, 'trainer'), 'Trainer is not initied'
        self.board.xlabel = 'epoch'
        if train:
            x = self.trainer.train_batch_idx / \
                self.trainer.num_train_batches
            n = self.trainer.num_train_batches / \
                self.plot_train_per_epoch
        else:
            x = self.trainer.epoch + 1
            n = self.trainer.num_val_batches / \
                self.plot_valid_per_epoch
        self.board.draw(x, value.to(d2l.cpu()).detach().numpy(),
                        ('train_' if train else 'val_') + key,
                        every_n=int(n))

    def training_step(self, batch):
        l = self.loss(self(*batch[:-1]), batch[-1])
        self.plot('loss', l, train=True)
        return l

    def validation_step(self, batch):
        l = self.loss(self(*batch[:-1]), batch[-1])
        self.plot('loss', l, train=False)

    def configure_optimizers(self):
        raise NotImplementedError

class DataModule(d2l.HyperParameters):
    """The base class of data."""
    def __init__(self, root='../data', num_workers=4):
        self.save_hyperparameters()

    def get_dataloader(self, train):
        raise NotImplementedError

    def train_dataloader(self):
        return self.get_dataloader(train=True)

```

```

def val_dataloader(self):
    return self.get_dataloader(train=False)

class Trainer(d2l.HyperParameters):
    """The base class for training models with data."""
    def __init__(self, max_epochs, num_gpus=0, gradient_clip_val=0):
        self.save_hyperparameters()
        assert num_gpus == 0, 'No GPU support yet'

    def prepare_data(self, data):
        self.train_dataloader = data.train_dataloader()
        self.val_dataloader = data.val_dataloader()
        self.num_train_batches = len(self.train_dataloader)
        self.num_val_batches = (len(self.val_dataloader)
                                if self.val_dataloader is not None else 0)

    def prepare_model(self, model):
        model.trainer = self
        model.board.xlim = [0, self.max_epochs]
        self.model = model

    def fit(self, model, data):
        self.prepare_data(data)
        self.prepare_model(model)
        self.optim = model.configure_optimizers()
        self.epoch = 0
        self.train_batch_idx = 0
        self.val_batch_idx = 0
        for self.epoch in range(self.max_epochs):
            self.fit_epoch()

    def fit_epoch(self):
        raise NotImplementedError

```

## ✓ 3.4. Linear Regression Implementation from Scratch

```
!pip install d2l==1.0.3
```

 숨겨진 출력 표시

```

%matplotlib inline
import torch
from d2l import torch as d2l

```

```

class LinearRegressionScratch(d2l.Module):
    """The linear regression model implemented from scratch."""
    def __init__(self, num_inputs, lr, sigma=0.01):
        super().__init__()
        self.save_hyperparameters()

```

```
self.w = torch.normal(0, sigma, (num_inputs, 1), requires_grad=True)
self.b = torch.zeros(1, requires_grad=True)
```

```
@d2l.add_to_class(LinearRegressionScratch)
def forward(self, X):
    return torch.matmul(X, self.w) + self.b
```

```
@d2l.add_to_class(LinearRegressionScratch)
def loss(self, y_hat, y):
    l = (y_hat - y) ** 2 / 2
    return l.mean()
```

```
class SGD(d2l.HyperParameters):
    """Minibatch stochastic gradient descent."""
    def __init__(self, params, lr):
        self.save_hyperparameters()

    def step(self):
        for param in self.params:
            param -= self.lr * param.grad

    def zero_grad(self):
        for param in self.params:
            if param.grad is not None:
                param.grad.zero_()
```

```
@d2l.add_to_class(LinearRegressionScratch)
def configure_optimizers(self):
    return SGD([self.w, self.b], self.lr)
```

```
@d2l.add_to_class(d2l.Trainer)
def prepare_batch(self, batch):
    return batch
```

```
@d2l.add_to_class(d2l.Trainer)
def fit_epoch(self):
    self.model.train()
    for batch in self.train_dataloader:
        loss = self.model.training_step(self.prepare_batch(batch))
        self.optim.zero_grad()
        with torch.no_grad():
            loss.backward()
            if self.gradient_clip_val > 0: # To be discussed later
                self.clip_gradients(self.gradient_clip_val, self.model)
            self.optim.step()
        self.train_batch_idx += 1
    if self.val_dataloader is None:
        return
    self.model.eval()
    for batch in self.val_dataloader:
        with torch.no_grad():
```

```

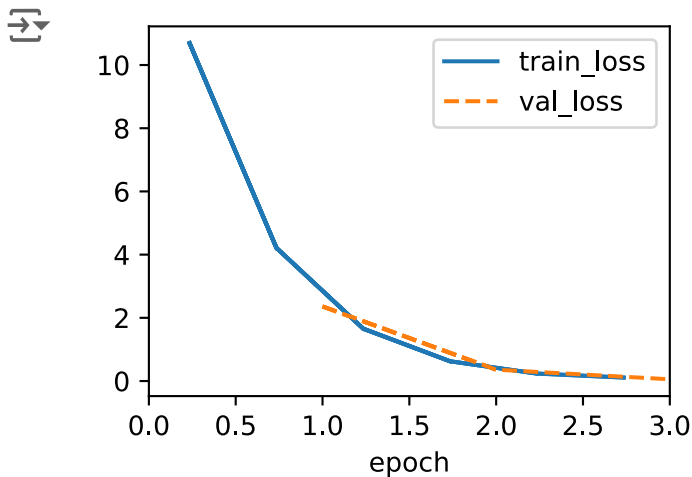
        self.model.validation_step(self.prepare_batch(batch))
    self.val_batch_idx += 1

```

```

model = LinearRegressionScratch(2, lr=0.03)
data = d2l.SyntheticRegressionData(w=torch.tensor([2, -3.4]), b=4.2)
trainer = d2l.Trainer(max_epochs=3)
trainer.fit(model, data)

```



```

with torch.no_grad():
    print(f'error in estimating w: {data.w - model.w.reshape(data.w.shape)}')
    print(f'error in estimating b: {data.b - model.b}')

```

```

error in estimating w: tensor([ 0.0917, -0.2013])
error in estimating b: tensor([0.2619])

```

## ✓ 4.1. Softmax Regression

# no code

## ✓ 4.2. The Image Classification Dataset

```
!pip install d2l==1.0.3
```

숨겨진 출력 표시

```

%matplotlib inline
import time
import torch
import torchvision
from torchvision import transforms
from d2l import torch as d2l

```



```
d2l.use_svg_display()
```

```
class FashionMNIST(d2l.DataModule):
    """The Fashion-MNIST dataset."""
    def __init__(self, batch_size=64, resize=(28, 28)):
        super().__init__()
        self.save_hyperparameters()
        trans = transforms.Compose([transforms.Resize(resize),
                                    transforms.ToTensor()])
        self.train = torchvision.datasets.FashionMNIST(
            root=self.root, train=True, transform=trans, download=True)
        self.val = torchvision.datasets.FashionMNIST(
            root=self.root, train=False, transform=trans, download=True)
```

```
data = FashionMNIST(resize=(32, 32))
len(data.train), len(data.val)
```

 숨겨진 출력 표시


```
data.train[0][0].shape
```

 torch.Size([1, 32, 32])

```
@d2l.add_to_class(FashionMNIST)
def text_labels(self, indices):
    """Return text labels."""
    labels = ['t-shirt', 'trouser', 'pullover', 'dress', 'coat',
              'sandal', 'shirt', 'sneaker', 'bag', 'ankle boot']
    return [labels[int(i)] for i in indices]

@d2l.add_to_class(FashionMNIST)
def get_dataloader(self, train):
    data = self.train if train else self.val
    return torch.utils.data.DataLoader(data, self.batch_size, shuffle=train,
                                       num_workers=self.num_workers)
```

```
X, y = next(iter(data.train_dataloader()))
print(X.shape, X.dtype, y.shape, y.dtype)
```

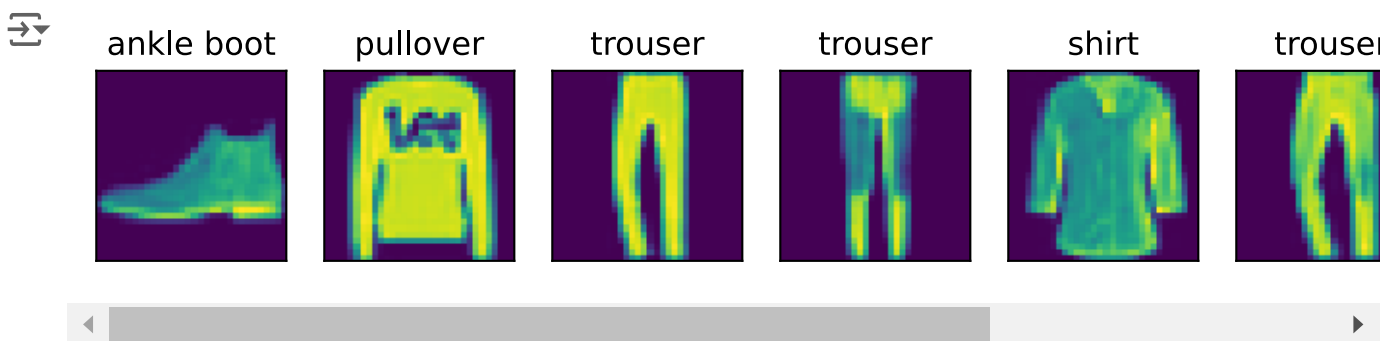
 /usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: The dataloader is not using a worker init method. This is deprecated in favor of torch.utils.data.\_utils.worker.\_init\_fn. Please use torch.utils.data.\_utils.worker.\_init\_fn instead. (Triggered at: /usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: The dataloader is not using a worker init method. This is deprecated in favor of torch.utils.data.\_utils.worker.\_init\_fn. Please use torch.utils.data.\_utils.worker.\_init\_fn instead.)

```
tic = time.time()
for X, y in data.train_dataloader():
    continue
f'{time.time() - tic:.2f} sec'
```

↩ '14.74 sec'

```
def show_images(imgs, num_rows, num_cols, titles=None, scale=1.5):
    """Plot a list of images."""
    raise NotImplementedError

@d2l.add_to_class(FashionMNIST)
def visualize(self, batch, nrows=1, ncols=8, labels=[]):
    X, y = batch
    if not labels:
        labels = self.text_labels(y)
    d2l.show_images(X.squeeze(1), nrows, ncols, titles=labels)
batch = next(iter(data.val_dataloader()))
data.visualize(batch)
```



## ✓ 4.3. The Base Classification Model

```
!pip install d2l==1.0.3
```

↩ 숨겨진 출력 표시

```
import torch
from d2l import torch as d2l

class Classifier(d2l.Module):
    """The base class of classification models."""
    def validation_step(self, batch):
        Y_hat = self(*batch[:-1])
        self.plot('loss', self.loss(Y_hat, batch[-1]), train=False)
        self.plot('acc', self.accuracy(Y_hat, batch[-1]), train=False)

@d2l.add_to_class(d2l.Module)
def configure_optimizers(self):
    return torch.optim.SGD(self.parameters(), lr=self.lr)

@d2l.add_to_class(Classifier)
def accuracy(self, Y_hat, Y, averaged=True):
```

```

"""Compute the number of correct predictions."""
Y_hat = Y_hat.reshape((-1, Y_hat.shape[-1]))
preds = Y_hat.argmax(axis=1).type(Y.dtype)
compare = (preds == Y.reshape(-1)).type(torch.float32)
return compare.mean() if averaged else compare

```

## ✓ 4.4. Softmax Regression Implementation from Scratch

```
!pip install d2l==1.0.3
```

 숨겨진 출력 표시

```


import torch
from d2l import torch as d2l

```

```

X = torch.tensor([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
X.sum(0, keepdims=True), X.sum(1, keepdims=True)

```

 (tensor([[5., 7., 9.]]),  
tensor([[ 6.],  
[15.])))

```


def softmax(X):
    X_exp = torch.exp(X)
    partition = X_exp.sum(1, keepdims=True)
    return X_exp / partition # The broadcasting mechanism is applied here

```

```

X = torch.rand((2, 5))
X_prob = softmax(X)
X_prob, X_prob.sum(1)

```

 (tensor([[0.1699, 0.1698, 0.2099, 0.2709, 0.1795],  
[0.2729, 0.1739, 0.1994, 0.1478, 0.2060]]),  
tensor([1.0000, 1.0000]))

```

class SoftmaxRegressionScratch(d2l.Classifier):
    def __init__(self, num_inputs, num_outputs, lr, sigma=0.01):
        super().__init__()
        self.save_hyperparameters()
        self.W = torch.normal(0, sigma, size=(num_inputs, num_outputs),
                                   requires_grad=True)
        self.b = torch.zeros(num_outputs, requires_grad=True)

    def parameters(self):
        return [self.W, self.b]

```

```
@d2l.add_to_class(SoftmaxRegressionScratch)
def forward(self, X):
    X = X.reshape((-1, self.W.shape[0]))
    return softmax(torch.matmul(X, self.W) + self.b)
```

```
y = torch.tensor([0, 2])
y_hat = torch.tensor([[0.1, 0.3, 0.6], [0.3, 0.2, 0.5]])
y_hat[[0, 1], y]
```

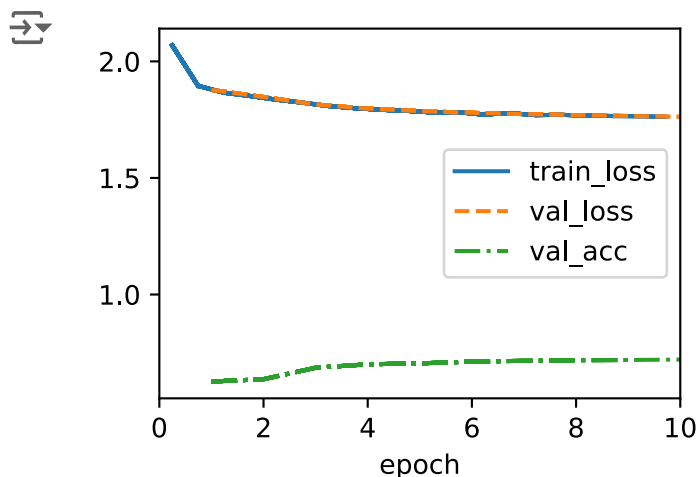
```
⇒ tensor([0.1000, 0.5000])
```

```
def cross_entropy(y_hat, y):
    return -torch.log(y_hat[list(range(len(y_hat))), y]).mean()
```

```
cross_entropy(y_hat, y)
```

```
⇒ tensor(1.4979)
```

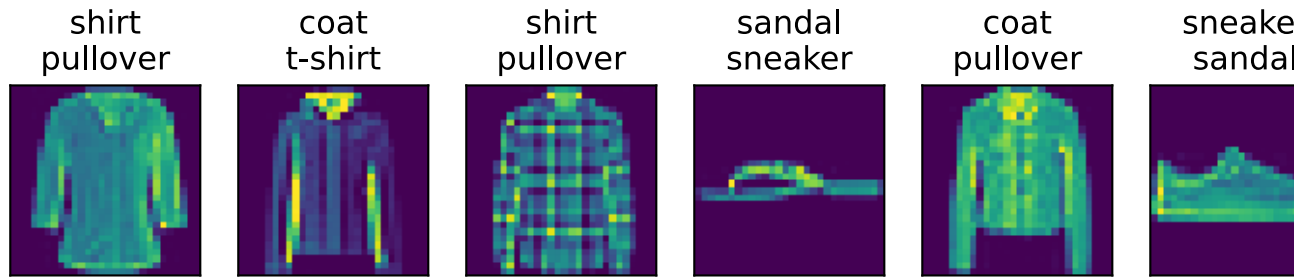
```
data = d2l.FashionMNIST(batch_size=256)
model = SoftmaxRegressionScratch(num_inputs=784, num_outputs=10, lr=0.1)
trainer = d2l.Trainer(max_epochs=10)
trainer.fit(model, data)
```



```
X, y = next(iter(data.val_dataloader()))
preds = model(X).argmax(axis=1)
preds.shape
```

```
⇒ torch.Size([256])
```

```
wrong = preds.type(y.dtype) != y
X, y, preds = X[wrong], y[wrong], preds[wrong]
labels = [a+'\n'+b for a, b in zip(
    data.text_labels(y), data.text_labels(preds))]
data.visualize([X, y], labels=labels)
```



## ✓ 5.1. Multilayer Perceptrons

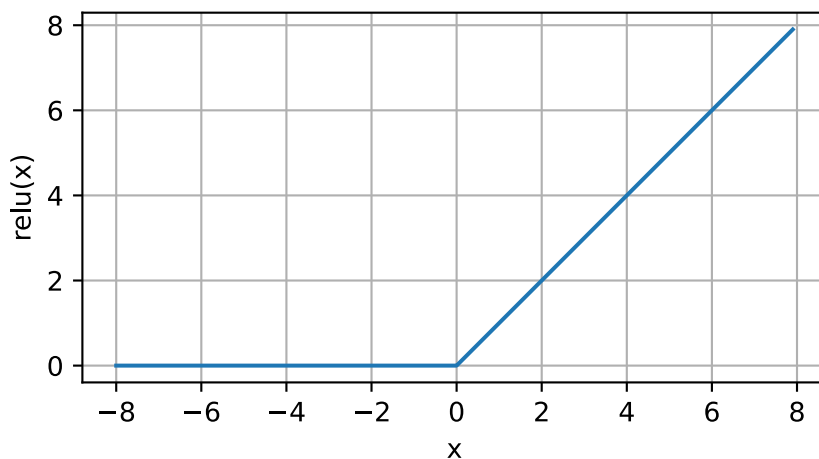
```
!pip install d2l==1.0.3
```



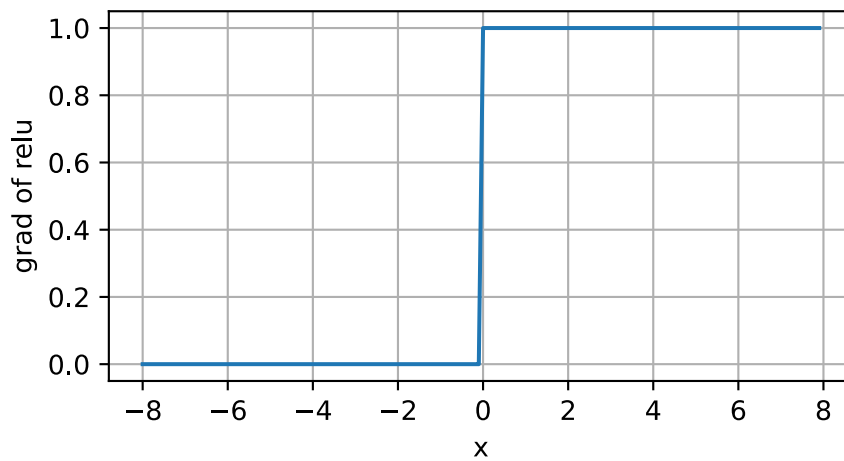
숨겨진 출력 표시

```
%matplotlib inline
import torch
from d2l import torch as d2l
```

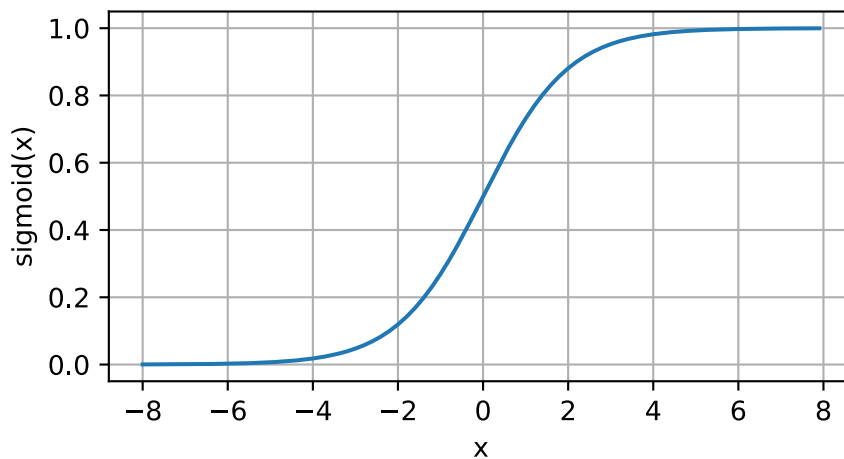
```
x = torch.arange(-8.0, 8.0, 0.1, requires_grad=True)
y = torch.relu(x)
d2l.plot(x.detach(), y.detach(), 'x', 'relu(x)', figsize=(5, 2.5))
```



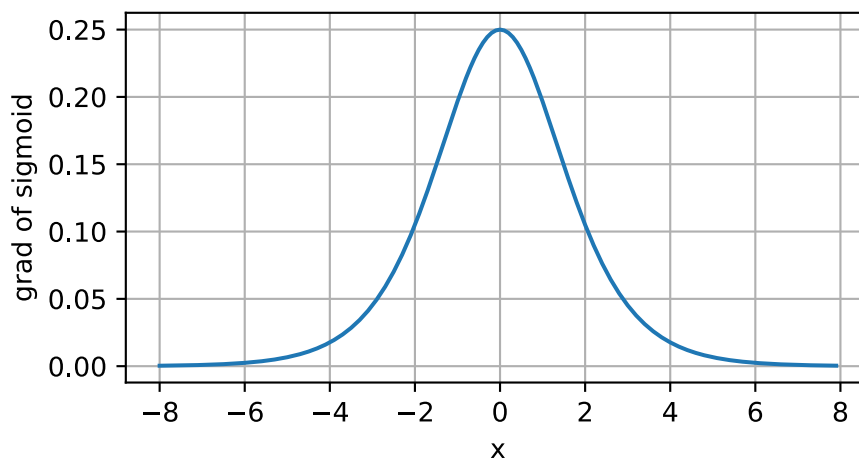
```
y.backward(torch.ones_like(x), retain_graph=True)
d2l.plot(x.detach(), x.grad, 'x', 'grad of relu', figsize=(5, 2.5))
```



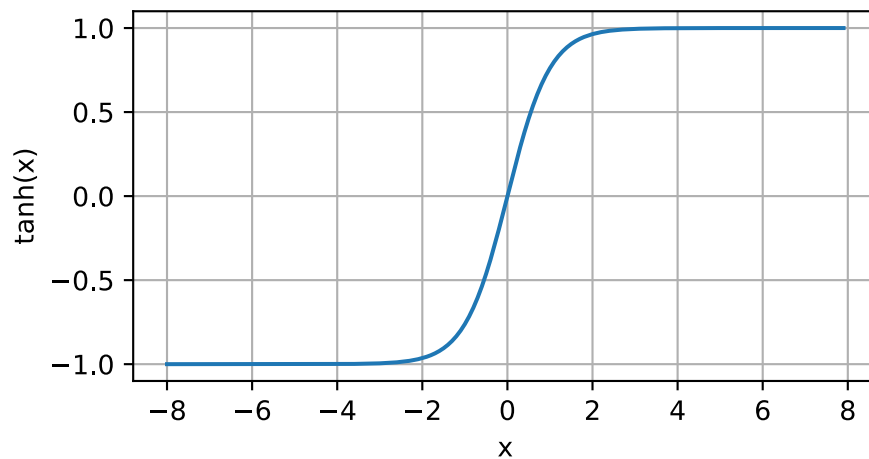
```
y = torch.sigmoid(x)
d2l.plot(x.detach(), y.detach(), 'x', 'sigmoid(x)', figsize=(5, 2.5))
```



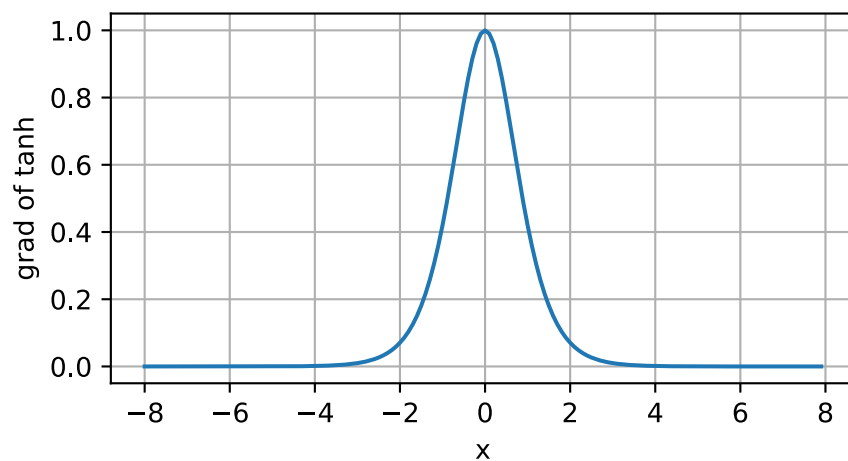
```
# Clear out previous gradients
x.grad.data.zero_()
y.backward(torch.ones_like(x), retain_graph=True)
d2l.plot(x.detach(), x.grad, 'x', 'grad of sigmoid', figsize=(5, 2.5))
```



```
y = torch.tanh(x)
d2l.plot(x.detach(), y.detach(), 'x', 'tanh(x)', figsize=(5, 2.5))
```



```
# Clear out previous gradients
x.grad.data.zero_()
y.backward(torch.ones_like(x), retain_graph=True)
d2l.plot(x.detach(), x.grad, 'x', 'grad of tanh', figsize=(5, 2.5))
```



## ✓ 5.2. Implementation of Multilayer Perceptrons

```
!pip install d2l==1.0.3
```



숨겨진 출력 표시

```
import torch
from torch import nn
from d2l import torch as d2l
```

```
class MLPScratch(d2l.Classifier):
    def __init__(self, num_inputs, num_outputs, num_hiddens, lr, sigma=0.01):
        super().__init__()
        self.save_hyperparameters()
        self.W1 = nn.Parameter(torch.randn(num_inputs, num_hiddens) * sigma)
```

```

self.b1 = nn.Parameter(torch.zeros(num_hiddens))
self.W2 = nn.Parameter(torch.randn(num_hiddens, num_outputs) * sigma)
self.b2 = nn.Parameter(torch.zeros(num_outputs))

```

```

def relu(X):
    a = torch.zeros_like(X)
    return torch.max(X, a)

```

```

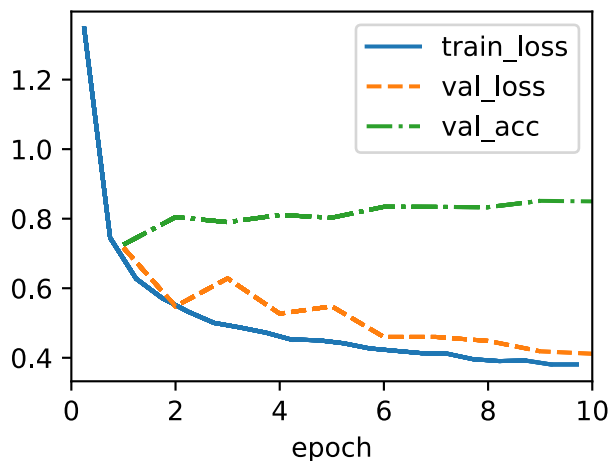
@d2l.add_to_class(MLPScratch)
def forward(self, X):
    X = X.reshape((-1, self.num_inputs))
    H = relu(torch.matmul(X, self.W1) + self.b1)
    return torch.matmul(H, self.W2) + self.b2

```

```

model = MLPScratch(num_inputs=784, num_outputs=10, num_hiddens=256, lr=0.1)
data = d2l.FashionMNIST(batch_size=256)
trainer = d2l.Trainer(max_epochs=10)
trainer.fit(model, data)

```



```

class MLP(d2l.Classifier):
    def __init__(self, num_outputs, num_hiddens, lr):
        super().__init__()
        self.save_hyperparameters()
        self.net = nn.Sequential(nn.Flatten(), nn.LazyLinear(num_hiddens),
                                  nn.ReLU(), nn.LazyLinear(num_outputs))

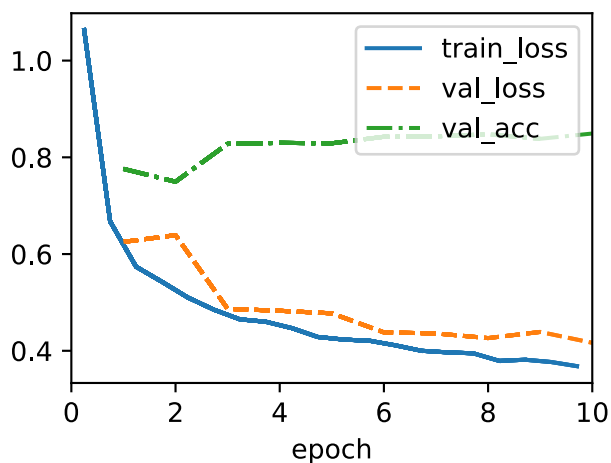
```

```

model = MLP(num_outputs=10, num_hiddens=256, lr=0.1)
trainer.fit(model, data)

```





## 5.3. Forward Propagation, Backward Propagation, and Computational Graphs

# no code

## Discussions & Exercises

### 2.1. Data Manipulation

What is the difference between reshape and transpose?

```
X = torch.tensor([[1, 2, 3, 4], [5, 6, 7, 8], [9, 0, 1, 2]])
print(f'original X:\n{X}\n')
print(f'reshape X to (4, 3):\n{X.reshape(4, 3)}\n')
print(f'transpose X to (4, 3):\n{X.transpose(0, 1)}\n')
```



```
original X:
tensor([[1, 2, 3, 4],
        [5, 6, 7, 8],
        [9, 0, 1, 2]])
```

```
reshape X to (4, 3):
tensor([[1, 2, 3],
        [4, 5, 6],
        [7, 8, 9],
        [0, 1, 2]])
```

```
transpose X to (4, 3):
tensor([[1, 5, 9],
        [2, 6, 0],
        [3, 7, 1],
        [4, 8, 2]])
```

```
[4, 8, 2]])
```

`torch.reshape` only changes the shape of a tensor. It doesn't change the order of the elements. On the other hand, if I use `torch.transpose`, then the order of the elements changes because it transposes the dimension of a tensor.

## ✓ 2.5. Automatic Differentiation

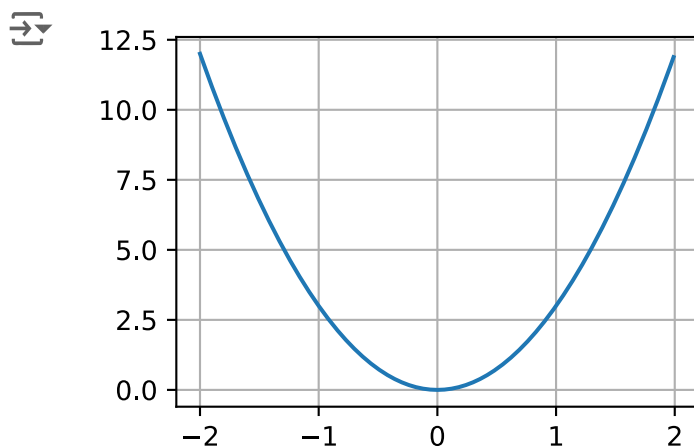
Plot a graph of  $y = 3x^2$  where  $-2 \leq x \leq 2$  using automatic differentiation of  $y = x^3$ .

```
x = torch.arange(-2, 2, 0.01, requires_grad=True)
```

```
y = x ** 3
```

```
for i in range(len(y)):
    y[i].backward(retain_graph=True) # when y = x^3, dy/dx = 3x^2
```

```
d2l.plot(x.detach().numpy(), x.grad.detach().numpy())
```



## ✓ 3.1. Linear Regression

Let's check speedups of vectorized codes!

### ✓ Element-wise multiplication of vectors

```

N = 1000
a = torch.randn(N)
b = torch.randn(N)

c = torch.zeros(N)
t = time.time()
for i in range(len(a)):
    c[i] = a[i] * b[i]
before = time.time() - t
print(f'Before vectorized: {round(before, 5)}')

```

⇒ Before vectorized: 0.01376

```

c = torch.zeros(N)
t = time.time()
c = a * b
after = time.time() - t
print(f'After vectorized: {round(after, 5)}')

```

⇒ After vectorized: 0.00014

```
print(f'Speedup: {round(before / after, 2)} times faster')
```

⇒ Speedup: 96.36 times faster

## ✓ Matrix multiplication

```

N = 50
a = torch.randn((N, N))
b = torch.randn((N, N))

c = torch.zeros((N, N))
t = time.time()
for i in range(a.shape[0]):
    for j in range(b.shape[1]):
        for k in range(len(a[i])):
            c[i, j] += a[i, k] * b[k, j]
before = time.time() - t
print(f'Before vectorized: {round(before, 5)}')

```

⇒ Before vectorized: 2.72773

```

c = torch.zeros(N)
t = time.time()
c = a @ b
after = time.time() - t
print(f'After vectorized: {round(after, 5)}')

```

⇒ After vectorized: 0.00016

```
print(f'Speedup: {round(before / after, 2)} times faster')
```

 Speedup: 16949.54 times faster

## ✓ Conclusion

Vectorization is very very important for speedup!

## ✓ 4.4. Softmax Regression Implementation from Scratch

### ✓ Numerically stable softmax function

Below code may be unstable because of the exponential function. Exponential function leads to large numbers, and dividing large numbers can be unstable.


```
def unstable_softmax(X):
    X_exp = torch.exp(X)
    partition = X_exp.sum(dim=1, keepdims=True)
    return X_exp / partition
```

Therefore, we can use a normalization trick. We subtract the largest value of a row from all values in the row, so that the largest value is 0, and the other values are less than 0.

```
def stable_softmax(X):
    X_max = torch.max(X, dim=1, keepdims=True).values
    X_exp = torch.exp(X - X_max)
    partition = X_exp.sum(dim=1, keepdims=True)
    return X_exp / partition
```

The results should be the same.

```
X = torch.randn((4, 3))
print(unstable_softmax(X))
print(stable_softmax(X))
```

 tensor([[0.0850, 0.5866, 0.3284],  
[0.1364, 0.3603, 0.5033],  
[0.8523, 0.0430, 0.1047],  
[0.4510, 0.3641, 0.1849]])  
tensor([[0.0850, 0.5866, 0.3284],  
[0.1364, 0.3603, 0.5033],  
[0.8523, 0.0430, 0.1047],  
[0.4510, 0.3641, 0.1849]])

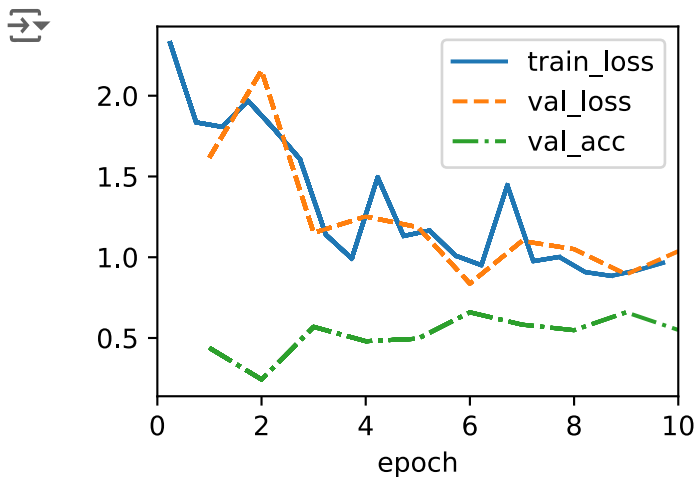
## ✓ 5.2. Implementation of Multilayer Perceptrons

What happens if we set the learning rate too high/low?

```
data = d2l.FashionMNIST(batch_size=256)
trainer = d2l.Trainer(max_epochs=10)
```

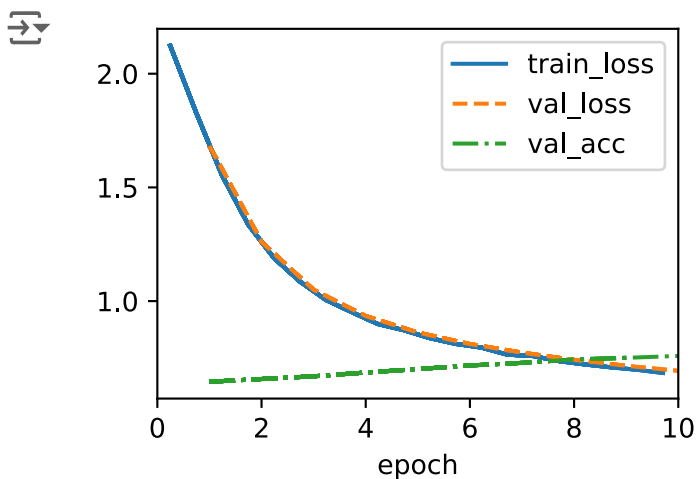
### ✓ High learning rate

```
model = MLP(num_outputs=10, num_hiddens=256, lr=1.0)
trainer.fit(model, data)
```



### ✓ Low learning rate

```
model = MLP(num_outputs=10, num_hiddens=256, lr=0.005)
trainer.fit(model, data)
```



## ✓ Conclusion

If we set the learning rate too high, the loss does not converge properly. It increases and decreases repeatedly, which means the training is unstable.

On the other hand, if the learning rate is too low, the model is not learning well. The loss is slightly reduced, but it is too slow.

Therefore, finding proper learning rate is essential for training a model.

-----