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2.1 Data Manipulation

기본적인 텐서를 생성하고 조작하는 방법을 익힌다.

```
import torch
import numpy as np
```

```
x = torch.arange(16)
print(x)

x = torch.arange(16, dtype = torch.float32)
print(x)

# New tensor
```

```
tensor([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15])
tensor([ 0.,  1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9., 10., 11., 12., 13.,
        14., 15.])
```

```
print(x.numel())
print(x.shape)
# Number of elements / Tensor size
```

```
16
torch.Size([16])
```

```
X = x.reshape(4,4)
print(X)
# Reshape
```

```
tensor([[ 0.,  1.,  2.,  3.],
        [ 4.,  5.,  6.,  7.],
        [ 8.,  9., 10., 11.],
        [12., 13., 14., 15.]])
```

```
print(torch.zeros((2,3))) # All zeros
print(torch.ones((2,3))) # All ones
print(torch.randn((2,3))) # Random numbers
print(torch.tensor([[1,2,3],[4,5,6]])) # Tensor construction
```

```
tensor([[0., 0., 0.],
        [0., 0., 0.]])
tensor([[1., 1., 1.],
        [1., 1., 1.]])
tensor([[-0.0256, -1.1732,  0.6747],
        [ 0.4313, -1.4670,  0.2227]])
tensor([[1, 2, 3],
        [4, 5, 6]])
```

```
print("-----Original-----")
print(X)

print("-----Indexing-----")
```

```
print(X[1][2])
print(X[-1])

print("-----Slicing-----")
print(X[1:3])
print(X[:2, 1:])
```

```
-----Original-----
tensor([[ 0.,  1.,  2.,  3.],
        [ 4.,  5.,  6.,  7.],
        [ 8.,  9., 10., 11.],
        [12., 13., 14., 15.]])
-----Indexing-----
tensor(6.)
tensor([12., 13., 14., 15.])
-----Slicing-----
tensor([[ 4.,  5.,  6.,  7.],
        [ 8.,  9., 10., 11.]])
tensor([[1., 2., 3.],
        [5., 6., 7.]])
```

```
torch.exp(X)
# Exponential
```

```
tensor([1.0000e+00, 2.7183e+00, 7.3891e+00, 2.0086e+01, 5.4598e+01, 1.4841e+02,
        4.0343e+02, 1.0966e+03, 2.9810e+03, 8.1031e+03, 2.2026e+04, 5.9874e+04,
        1.6275e+05, 4.4241e+05, 1.2026e+06, 3.2690e+06])
```

```
x = torch.tensor([[1,2,3,4], [2,3,4,5]])
y = x+3
print(x)
print(y)
```

```
tensor([[1, 2, 3, 4],
        [2, 3, 4, 5]])
tensor([[4, 5, 6, 7],
        [5, 6, 7, 8]])
```

```
print(x+y)
print(x-y)
print(x*y)
print(x/y)
print(x**y)
# Operation
```

```
tensor([[ 5,  7,  9, 11],
        [ 7,  9, 11, 13]])
tensor([[-3, -3, -3, -3],
        [-3, -3, -3, -3]])
tensor([[ 4, 10, 18, 28],
        [10, 18, 28, 40]])
tensor([[0.2500, 0.4000, 0.5000, 0.5714],
        [0.4000, 0.5000, 0.5714, 0.6250]])
tensor([[     1,     32,    729,  16384],
        [    32,    729,  16384, 390625]])
```

```
print(torch.cat((x,y), dim = 0))
print(torch.cat((x,y), dim = 1))
# Concatenation
```

```
tensor([[1, 2, 3, 4],
        [2, 3, 4, 5],
        [4, 5, 6, 7],
        [5, 6, 7, 8]])
tensor([[1, 2, 3, 4, 4, 5, 6, 7],
        [2, 3, 4, 5, 5, 6, 7, 8]])
```

```
print(x==y)
print(x.sum())
```

```
tensor([[False, False, False, False],
        [False, False, False, False]])
tensor(24)
```

```
a = torch.arange(3).reshape((3, 1))
b = torch.arange(2).reshape((1, 2))
print(a+b)
# Dimension broadcasting
```

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

```
x = np.array([1,2,3,4])
y = torch.tensor([1,2,3,4])
print(type(x), type(y))

x = torch.from_numpy(x)
y = y.numpy()
print(type(x), type(y))

# Object conversion
```

```
<class 'numpy.ndarray'> <class 'torch.Tensor'>
<class 'torch.Tensor'> <class 'numpy.ndarray'>
```

2.2 Data Preprocessing

Pandas의 Dataframe을 다루고, 또 csv파일을 다루는 법을 익힌다.

의문점

pd.get_dummies(inputs, dummy_na=True)는 무엇인가?

인터넷 검색을 통해 해결. 예를 들어 'Color'라는 열에 'Red', 'Blue' 등 문자열 데이터가 있을 수 있다.
이를 컴퓨터가 처리할 수 있도록 Red 여부(0 or 1), Blue 여부(0 or 1)와 같이 더미 열을 만든다.
dummy_na=True는 NaN도 포함시킬 것이라는 의미이다.

```
import os
import pandas as pd
```

```
os.getcwd()
# Current directory
```

```
'/content'
```

```
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''')
```

```
data = pd.read_csv(data_file)
print(data)
# Pandas csv reading
```

```
   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] # Slicing
inputs = pd.get_dummies(inputs, dummy_na=True)
print(inputs)
# dummy_na = NaN도 분류할 것인가?
```

```
   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)
# Change NaN -> Mean value
```

```
   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
```

```
X = torch.tensor(inputs.to_numpy(dtype=float))
y = torch.tensor(targets.to_numpy(dtype=float))
X, y
# Pandas Dataframe to torch.tensor
```

```
(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

Vector, Matrix 등을 다루는데 이들 역시 Tensor의 일종이므로
2.1에서의 Data Manipulation과 상당 부분 겹치는 내용이다.

```
x = torch.tensor([[1,2,3],[4,5,6]], dtype=float)
print(x.T)
# Matrix Transpose
```

```
tensor([[1., 4.],
        [2., 5.],
        [3., 6.]], dtype=torch.float64)
```

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

```
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]]])
```

```
print(x.sum(axis=0))
print(x.sum(axis=1))
# Summation - Reduction
```

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

```
print(x.sum(axis=0, keepdim=True))
print(x.sum(axis=1, keepdim=True))
# Summation - Non-Reduction
```

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

```
a = torch.arange(3, dtype=float);
b = torch.ones(3, dtype=float);
print(torch.dot(a,b))
# Dot product
```

```
tensor(3., dtype=torch.float64)
```

```
torch.mv(x, a)
# Matrix-Vector product
```

```
tensor([ 8., 17.], dtype=torch.float64)
```

```
y = torch.tensor([[1,0,-1],[0,0,1],[1,1,1]], dtype=float)
torch.mm(x, y)
# Matrix-Matrix product
```

```
tensor([[ 4.,  3.,  4.],
        [10.,  6.,  7.]], dtype=torch.float64)
```

```
print(torch.norm(a))
# L2 Norm

print(abs(y))
# Absolute value
```

```
tensor(2.2361, dtype=torch.float64)
tensor([[1., 0., 1.],
        [0., 0., 1.],
        [1., 1., 1.]], dtype=torch.float64)
```

2.5 Automatic Differentiation

딥러닝에 있어서 필수적인 Backpropagation을 위해서는 Gradient 미분 계산이 필요하다.
Torch는 이러한 계산을 자동적으로 수행할 수 있도록 해 준다.
변수 x에 requires_grad=True를 설정하여 학습하는 Parameter임을 명시하면
y.backward() 함수 호출 시 x.grad에 미분계수가 축적된다.
이는 x.grad.zero_()로 초기화 할 수 있다.

```
x = torch.arange(4.0, requires_grad=True)
y = torch.dot(x, x)
```

```
y.backward()
x.grad
# (x^2)' = 2x
```

```
tensor([0., 2., 4., 6.])
```

```
x.grad.zero_() # Reset Gradient Buffer
y = x.sum() # Change y

y.backward()
x.grad
```

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

```
x.grad.zero_()
y = x * x
# y is vector

y.sum().backward()
x.grad
# Use sum for vector gradient
```

```
tensor([0., 2., 4., 6.])
```

```
x.grad.zero_()
y = x * x
u = y.detach()
z = u * x
# Detach => u has no ancestor

z.sum().backward()
x.grad
# (ux)' = u
```

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

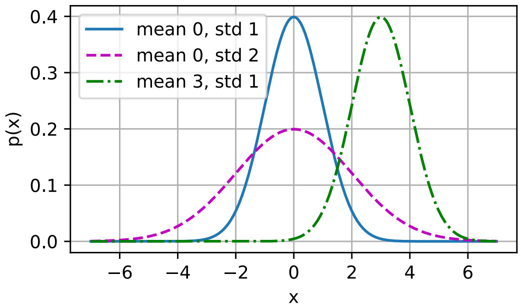
```
def f(a):
  b = a * 2
  while b.norm() < 1000:
        b = b * 2
  if b.sum() > 0:
        c = b
  else:
        c = 100 * b
  return c
# Function

a = torch.randn(size=(), requires_grad=True)
d = f(a)
d.backward()
# Function gradient

a.grad == d / a
# df/da
```

```
tensor(True)
```

3.1 Linear Regression

데이터에 가장 적합한 y=wx+b꼴의 w,b를 찾는다.
MSE Loss를 사용한다. (Gradient 계산이 쉬워지므로)

```
import math
from d2l import torch as d2l


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)
# Normal distribution


x = np.arange(-7, 7, 0.01)
params = [(0, 1), (0, 2), (3, 1)]
# mu, sigma

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

딥러닝 모델은 객체 지향(Object-Oriented)의 클래스로 정의된다.
그러나 클래스 코드는 길어지기 쉽다는 문제가 있다.
주피터 노트북, 구글 코랩 등은 코드를 짧고 간결하게 쓰는 것이 좋다.
그래서 클래스 선언 후 메소드를 이후 추가하는 등의 기능들을 만들 수 있다.

```
from torch import nn


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
# Class

a = A()
# Object


@add_to_class(A)
def do(self):
    print('Class attribute "b" is', self.b)
# Decorator(@) => Add new method

a.do()
```

```
Class attribute "b" is 1
```

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


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


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 inited'
        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'
```

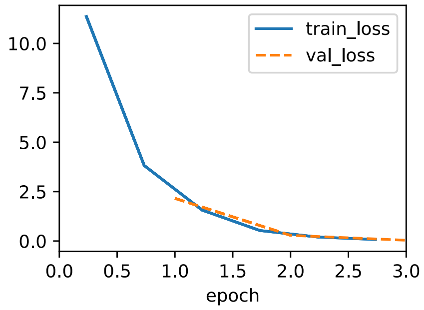
```
    def prepare_data(self, data):
        self.train_dataloader = data.train_dataloader()
        self.val_dataloader = data.val_dataloader()
        self.num_train_batches = len(self.train_dataloader)
        self.num_val_batches = (len(self.val_dataloader)
                                if self.val_dataloader 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

Stochastic Gradient Descent(SGD)를 실제로 구현해본다.

```
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

# -------------- Add methods --------------


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([ 0.1036, -0.1603])
error in estimating b: tensor([0.2145])
```

4.1 Softmax Regression

Softmax는 여러 변수들을, 확률처럼 합이 1이 되도록 만들어주는 함수이다.
딥러닝 이후 Output들은 임의의 실수 값이 될 수 있기에, Classification 등에 Softmax가 자주 쓰인다.

4.2 The Image Classification Dataset

MNIST란 사람이 쓴 숫자 이미지들을 모은 데이터셋으로, AI테스트용으로 많이 쓰여 유명하다.
여기서는 조금 더 난이도 높은 FashionMNIST라는 데이터셋을 알아본다.
셔츠, 바지, 신발 등 의류 이미지들의 데이터셋이고, 10개의 클래스로 분류를 해야 한다.

```
import torch
import torchvision
from torchvision import transforms
from d2l import torch as d2l


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()]) # Size를 조절
        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)
```

```
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz to ../data/FashionMNIST/raw/train-images-idx3-u
100%|██████████| 26421880/26421880 [00:07<00:00, 3711212.03it/s]
Extracting ../data/FashionMNIST/raw/train-images-idx3-ubyte.gz to ../data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz to ../data/FashionMNIST/raw/train-labels-idx1-u
100%|██████████| 29515/29515 [00:00<00:00, 280002.90it/s]
Extracting ../data/FashionMNIST/raw/train-labels-idx1-ubyte.gz to ../data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-ubyte.gz to ../data/FashionMNIST/raw/t10k-images-idx3-uby
100%|██████████| 4422102/4422102 [00:00<00:00, 4860642.99it/s]
Extracting ../data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to ../data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz to ../data/FashionMNIST/raw/t10k-labels-idx1-uby
100%|██████████| 5148/5148 [00:00<00:00, 12914041.26it/s]
Extracting ../data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to ../data/FashionMNIST/raw

(60000, 10000)
```

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

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

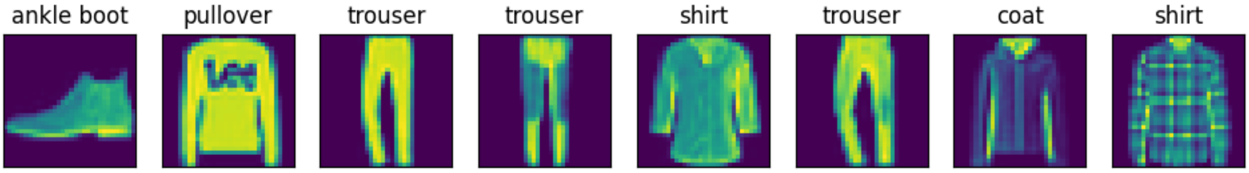
```python
@d2l.add_to_class(FashionMNIST)
def text_labels(self, indices):
    """Return text labels."""
    labels = ['t-shirt', 'trouser', 'pullover', 'dress', 'coat',
              'sandal', 'shirt', 'sneaker', 'bag', 'ankle boot']
    return [labels[int(i)] for i in indices]
```

```python
@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)
```

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

```python
@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)
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will create 4 worker processes in total
  warnings.warn(_create_warning_msg(
```



4.3 The Base Classification Model

이제 실제로 FashionMNIST의 Classifier model을 작성해 본다.
Accuracy를 통해 성능을 보여주는 코드도 작성한다.
Accuracy란 여러 성능 지표 중 하나로, (맞은 개수)/(전체 개수)로 정의된다.
가장 단순한 형태의 성능 지표이며, 데이터 편향 등 문제가 없을 때 사용할 수 있다.

```python
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

Softmax 및 CrossEntropy Loss의 코드를 작성한다.
Softmax는 변수들을 확률처럼, 0 이상이고 합계가 1이 되도록 변환해준다.
CrossEntropy는 딥러닝에서 자주 쓰이는 Loss로, 두 변수가 같을수록 엔트로피는 낮다.

```
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)

# Sum함수의 첫번째 인자는 어느 방향의 차원으로 더할지를 의미한다
```

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

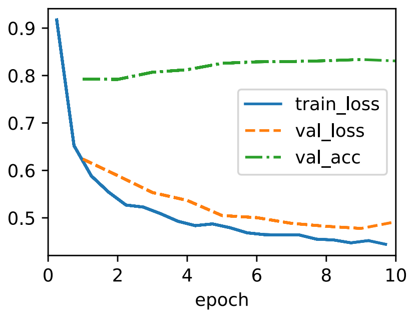
```
def softmax(X):
    X_exp = torch.exp(X)
    partition = X_exp.sum(1, keepdims=True)
    return X_exp / partition

# Softmax는 변수들을 확률의 형태로 변환해 준다.
```

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

# 확률처럼 전부 0 이상이고, 합계는 1인 것을 확인할 수 있다
```

```
(tensor([[0.2053, 0.2783, 0.1158, 0.1805, 0.2200],
         [0.1133, 0.1370, 0.2162, 0.2304, 0.3031]]),
 tensor([1., 1.]))
```

```
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]

# Classification에서, 최종 Output layer에 Softmax를 취하면,
# 각 Class일 확률을 나타내는 것으로 볼 수 있다.


@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)


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


@d2l.add_to_class(SoftmaxRegressionScratch)
def loss(self, y_hat, y):
    return cross_entropy(y_hat, y)
```

```
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)
```

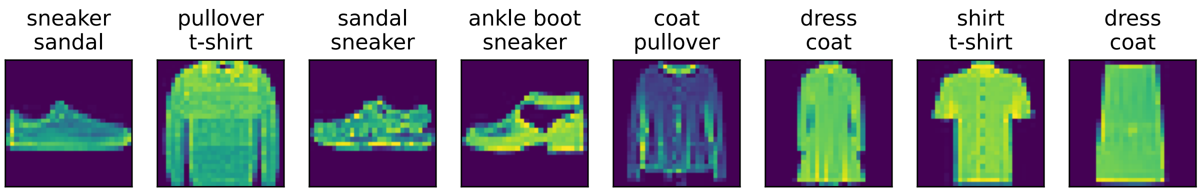



```
# ------------ 여기까지 Training ------------
```

```
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)
```



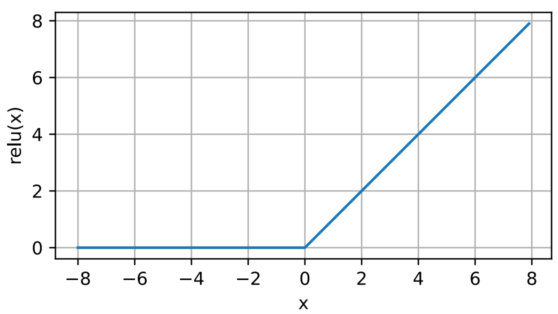

```
# ------------ 실제 Test ------------
```

5.1 Multilayer Perceptrons

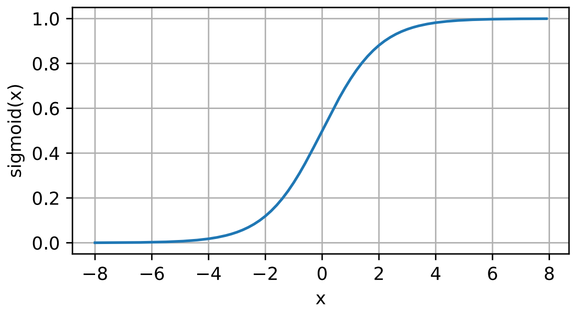
단순 Linear model은 단순한 만큼 단순한 문제만 해결할 수 있다.
Layer 수를 늘려 모델이 복잡해지면, 더 복잡한 문제도 해결할 수 있게 된다.
그러나 y=wx+b꼴의 Linear function만 있으면 아무리 여러 층이어도, 합성결과 여전히 Linear이다.
따라서 다양한 Nonlinear activation function들을 조합하는데, 이 함수들도 알아본다.

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

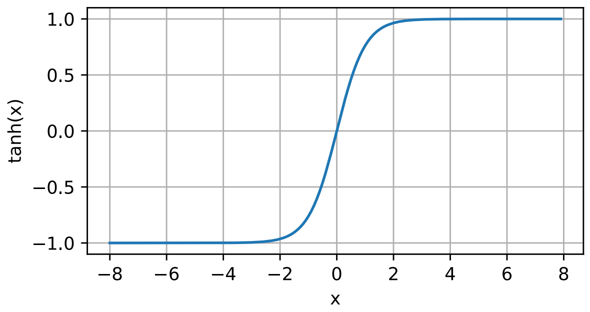
```
x = torch.arange(-8.0, 8.0, 0.1, requires_grad=True)
y = torch.relu(x)
d2l.plot(x.detach(), y.detach(), 'x', 'relu(x)', figsize=(5, 2.5))
```



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




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



5.2 Implementation of Multilayer Perceptrons

Torch의 nn(neural network)를 이용하여 실제로 구현을 해 본다.

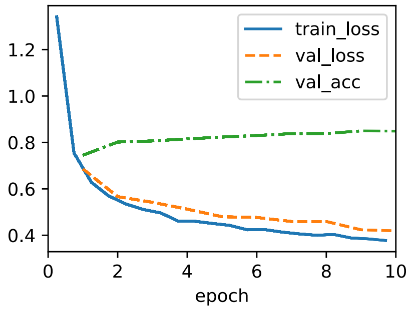
```
from torch import nn
```

```
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)
```

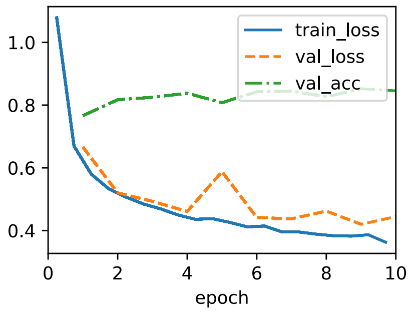
```
@d2l.add_to_class(MLPScratch)
def forward(self, X):
    X = X.reshape((-1, self.num_inputs))
    H = relu(torch.matmul(X, self.W1) + self.b1)
    return torch.matmul(H, self.W2) + self.b2
```

```
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

Forward pass는 딥러닝 모델이 계산을 하는 과정으로, 그래프 상에서 Input->Output 방향으로 이루어진다.
노드에 Input x가 들어오고, Weight를 곱하여 Activation(Wx+b)의 형태로 Output이 출력된다.
Backpropagation은 Output과 True value 사이 오차(Loss)를 통해 W를 업데이트한다.