LIBRARY SETTINGS

[ ] ↳ *2 cells hidden*

2 Prelimiaries

2.1 DATA MANIPULATION

```
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([[-2.5244, -0.0730, -0.7310,  0.6800],
        [ 0.0626,  1.0085, -1.0283,  0.2288],
        [-0.8688, -0.6578, -0.1008, -1.4014]])
```

```
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): 139868415165760
id(Z): 139868415165760
```

```
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)
```

Key Takeaways:

1. ndarray is essential for managing multi-dimensional data efficiently.
2. Basic operations include slicing, reshaping, and broadcasting.
3. ndarrays allow for fast mathematical operations and efficient memory use.

2.2 DATA PREPROCESSING

```
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)
```

```
   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
```

```
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))
```

Key Takeaways:

1. Pandas is essential for efficient data preprocessing and manipulation.
2. It helps handle missing data, perform filtering, and convert data types.
3. Pandas' DataFrames and Series provide powerful structures for working with large datasets.

2.3 LINEAR ALGEBRA

```
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])
```

```
print(x[2])
print(len(x))
x.shape
```

```
tensor(2)
3
torch.Size([3])
```

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

```
tensor([[0, 1],
        [2, 3],
        [4, 5]])
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()
print(A, A + B)
print(A*B)
```

```
tensor([[0., 1., 2.],
        [3., 4., 5.]]) tensor([[ 0.,  2.,  4.],
        [ 6.,  8., 10.]])
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)
print(x, x.sum())
print(A.shape, A.sum())
print(A.shape, A.sum(axis=0).shape)
print(A.shape, A.sum(axis=1).shape)
print(A.sum(axis=[0, 1]) == A.sum() )
print(A.mean(), A.sum() / A.numel())
print(A.mean(axis=0), A.sum(axis=0) / A.shape[0])
```

```
tensor([0., 1., 2.]) tensor(3.)
torch.Size([2, 3]) tensor(15.)
torch.Size([2, 3]) torch.Size([3])
torch.Size([2, 3]) torch.Size([2])
tensor(True)
tensor(2.5000) tensor(2.5000)
tensor([1.5000, 2.5000, 3.5000]) tensor([1.5000, 2.5000, 3.5000])
```

```
sum_A = A.sum(axis=1, keepdims=True)
print(sum_A)
print(sum_A.shape)
print(A / sum_A)
print(A.cumsum(axis=0))
```

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

```
tensor([[0.0000, 0.3333, 0.6667],
        [0.2500, 0.3333, 0.4167]])
tensor([[0., 1., 2.],
        [3., 5., 7.]])
```

```
y = torch.ones(3, dtype = torch.float32)
print(x, y, torch.dot(x, y))
print(torch.sum(x * y))
print(A.shape, x.shape, torch.mv(A, x), A@x)

B = torch.ones(3, 4)
torch.mm(A, B), A@B
```

```
tensor([0., 1., 2.]) tensor([1., 1., 1.]) tensor(3.)
tensor(3.)
torch.Size([2, 3]) torch.Size([3]) tensor([ 5., 14.]) tensor([ 5., 14.])
(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])
print(torch.norm(u))
print(torch.abs(u).sum())
torch.norm(torch.ones((4, 9)))
```

```
tensor(5.)
tensor(7.)
tensor(6.)
```

Key Takeaways:

1. Vectors and matrices are fundamental structures for storing and computing data.
2. Matrix operations like inversion and multiplication are vital for model calculations.

2.5 Automatic Differentiation

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

x.requires_grad_(True)
x.grad

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

y.backward()
```

```
print(x.grad)

print(x.grad == 4 * x)

x.grad.zero_()
y = x.sum()
y.backward()
print(x.grad)
```

```
tensor([0., 1., 2., 3.])
tensor(28., grad_fn=<MulBackward0>)
tensor([ 0.,  4.,  8., 12.])
tensor([True, True, True, True])
tensor([1., 1., 1., 1.])
```

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

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

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

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

Key Takeaways:

1. Autograd automates derivative computation, simplifying model training and it’s critical for backpropagation in neural networks.
2. It also tracks operations to create a computation graph for efficient optimization.

3 Linear Neural Networks for Regression

3.1 Linear Regression

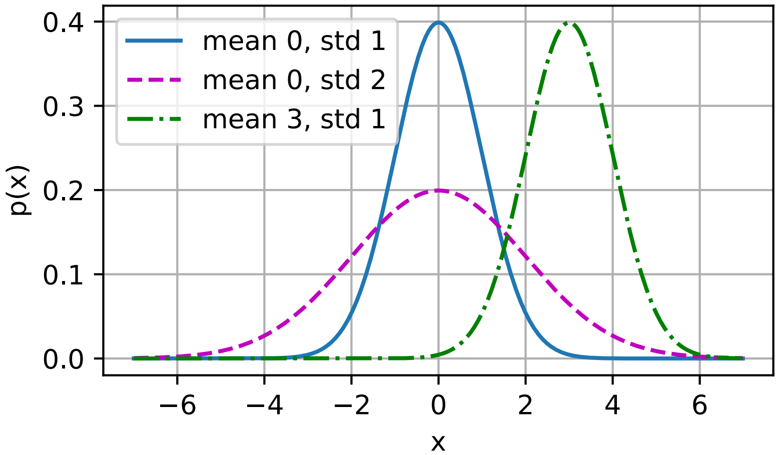
3.1.2. Vectorization for Speed

```
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]
print(f'{time.time() - t:.5f} sec')

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

```
0.12066 sec
'0.00121 sec'
```

3.1.3. The Normal Distribution and Squared Loss

```
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)

x = np.arange(-7, 7, 0.01)

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])
```



Key Takeaways:

1. Linear regression can predict continuous outcomes.
2. Techniques like gradient descent are crucial for finding the optimal parameters in linear regression, and they are also applicable to other machine learning algorithms.
3. Linear regression assumes a linear relationship between variables. In real-world scenarios, this may not always be the case, and more complex models may be needed.

3.2. Object-Oriented Design for Implementation

3.2.1 Utilities

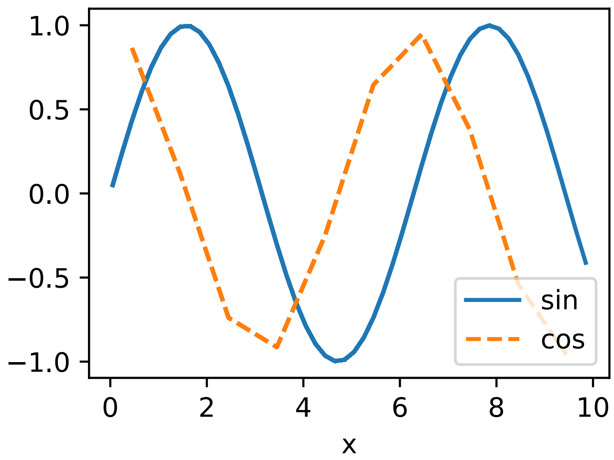
```
def add_to_class(Class):
    """Register functions as methods in created class."""
    def wrapper(obj):
        setattr(Class, obj.__name__, obj)
    return wrapper

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

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):
    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)
```



3.2.2 Models

```
class Module(nn.Module, d2l.HyperParameters):
    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):
        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
```

3.2.3 Data

```
class DataModule(d2l.HyperParameters):
    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)
```

3.2.4 Training

```
class Trainer(d2l.HyperParameters):
    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
```

Key Takeaways:

1. Object-oriented design promotes modularity by encapsulating the model's functionality within a class which stored in d2l library. This makes the code easier to understand, maintain, and extend.
2. The class-based design makes it easier to extend the model to include more features or functionalities. For example, you could add regularization methods or support for different types of regression.
3. Different aspects of the model like forward pass, loss calculation, and training are handled by separate methods. This separation helps in maintaining and debugging the code.

3.4 Linear Regression Implementation from Scratch

3.4.1. Defining the Model

```
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
```

3.4.2 Defining the Loss Function

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

3.4.3 Defining the Optimization Algorithm

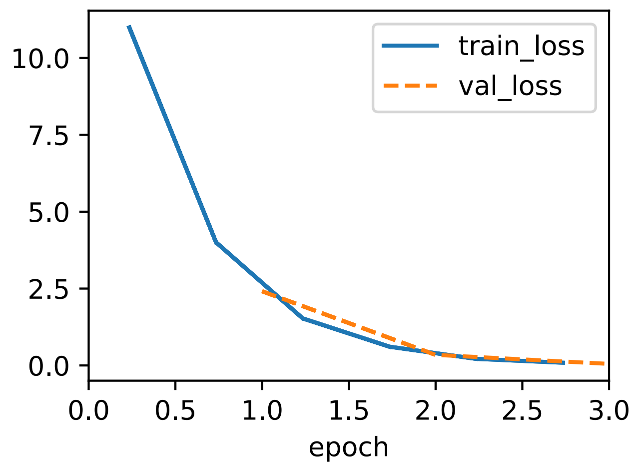
```
class SGD(d2l.HyperParameters):

    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)
```

3.4.4 Training

```
@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:
                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([ 0.1219, -0.1658])
error in estimating b: tensor([0.2384])
```

Key Takeaways:

1. While frameworks like PyTorch automate these steps, implementing it from scratch reveals how the core components work together and gives more control over the learning process.
2. During optimization, careful tuning of the learning rate is necessary to ensure the model converges to a good solution. If the learning rate is too high, the model may overshoot the optimal values.

4 Linear Neural Networks for Classification

4.1 Softmax Regression

Key Takeaways:

1. Softmax function converts model outputs into probabilities, allowing the model to predict which class an input belongs to. It's essential for classification tasks with more than two classes
2. Softmax regression is an extended version of binary logistic regression to handle multiple classes. This makes it suitable for tasks like image classification or text classification with multiple categories.
3. In Softmax regression, we rely on Maximum Likelihood Estimation, the same method when working on Mean Squared Error Loss

4.2 The Image Classification Dataset

4.2.1 Loading the Dataset

```
class FashionMNIST(d2l.DataModule):
    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)
```

```
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3
100%|██████████| 26421880/26421880 [00:02<00:00, 12928721.90it/s]
Extracting ../data/FashionMNIST/raw/train-images-idx3-ubyte.gz to ../data/FashionMNIST/r

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1
100%|██████████| 29515/29515 [00:00<00:00, 210352.35it/s]
Extracting ../data/FashionMNIST/raw/train-labels-idx1-ubyte.gz to ../data/FashionMNIST/r

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-
100%|██████████| 4422102/4422102 [00:01<00:00, 3916938.53it/s]
Extracting ../data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to ../data/FashionMNIST/ra
```

```
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-
100%|██████████| 5148/5148 [00:00<00:00, 5060294.58it/s]
Extracting ../data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to ../data/FashionMNIST/ra

(60000, 10000)
```

```
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]
```

4.2.2 Reading a Minibatch

```
@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)
```

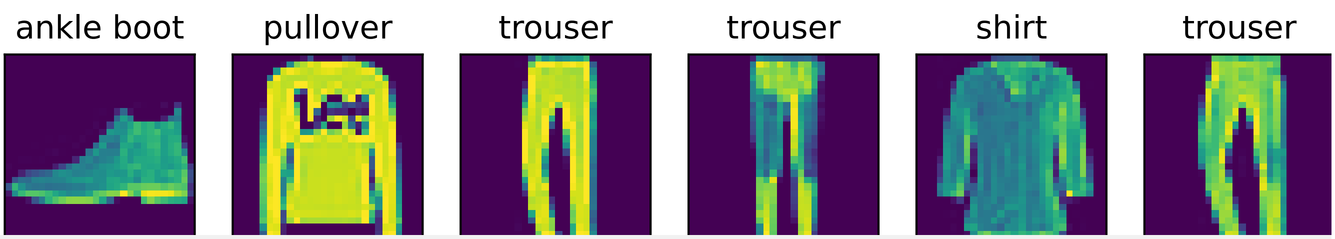
```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning:
  warnings.warn(_create_warning_msg(
torch.Size([64, 1, 32, 32]) torch.float32 torch.Size([64]) torch.int64
```

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

```
'13.09 sec'
```

4.2.3 Visualization

```
def show_images(imgs, num_rows, num_cols, titles=None, scale=1.5):

    raise NotImplementedErrors

@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)
```



Key Takeaways:

1. During Pre-processing, images will be resized to a uniform size and the pixels will be normalized to help the model to process them in more efficient and consistent way.
2. Enhancing the dataset with variations through augmentation helps the model generalize better by exposing it to a broader range of scenarios.
3. Splitting the dataset into training, validation, and test sets is important for assessing model performance and avoiding overfitting.

4.3 The Base Classification Model

4.3.1 The Classifier Class

```
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)
```

4.3.2 Accuracy

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

    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
```

Key Takeaways:

1. It is often the performance measure that we care about the most.
2. Although there will be probabilities estimated for one input, at the end, it will need to be chosen to be categorized among the classes given.

4.4 Softmax Regression Implementation from Scratch

4.4.1 The Softmax

```
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

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

```
(tensor([[0.2239, 0.2169, 0.1904, 0.2231, 0.1457],
         [0.1760, 0.1793, 0.1778, 0.1889, 0.2780]]),
```

```
tensor([1.0000, 1.0000]))
```

4.4.2 The Model

```
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()

print(cross_entropy(y_hat, y))

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

```
tensor(1.4979)
```

4.4.3 The Cross Entropy Loss

```
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])
```

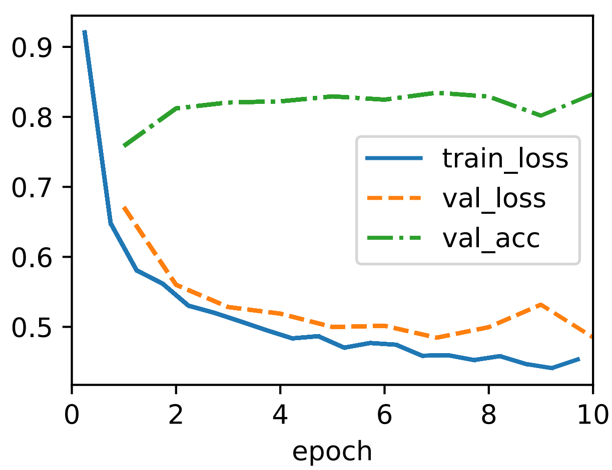
```
def cross_entropy(y_hat, y):
    return -torch.log(y_hat[list(range(len(y_hat))), y]).mean()

cross_entropy(y_hat, y)
```

```
tensor(1.4979)
```

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

4.4.4 Training

```
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)
```

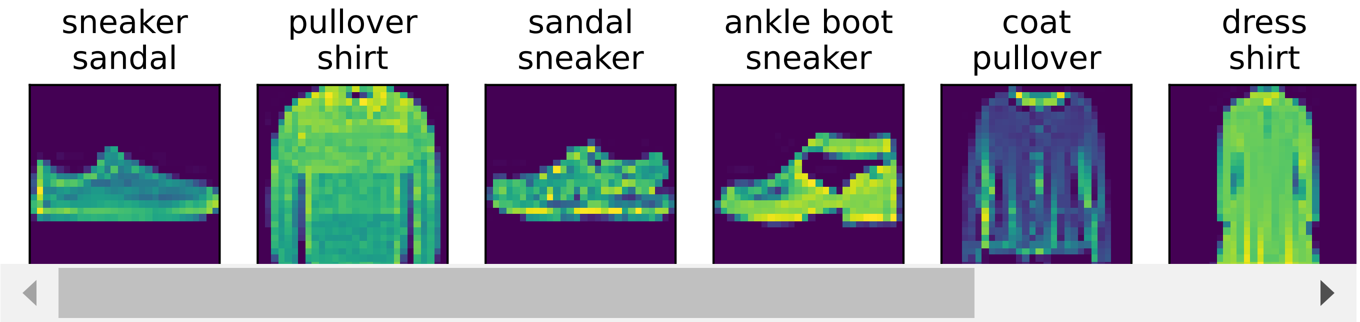


4.4.5 Prediction

```
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)
```



Key Takeaways:

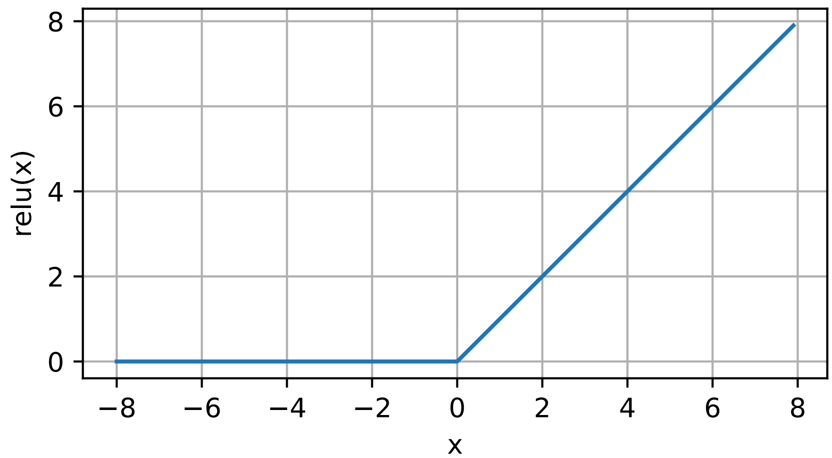
1. The softmax function converts raw scores (logits) into probabilities. For each class, it calculates the probability that an input belongs to that class. The probabilities are normalized so they sum up to 1.
2. The loss function used in softmax regression is cross-entropy loss.
3. The process involves multiple steps including initialization, forward pass, loss calculation, backward pass, and parameter updates.

5. Multilayer Perceptrons

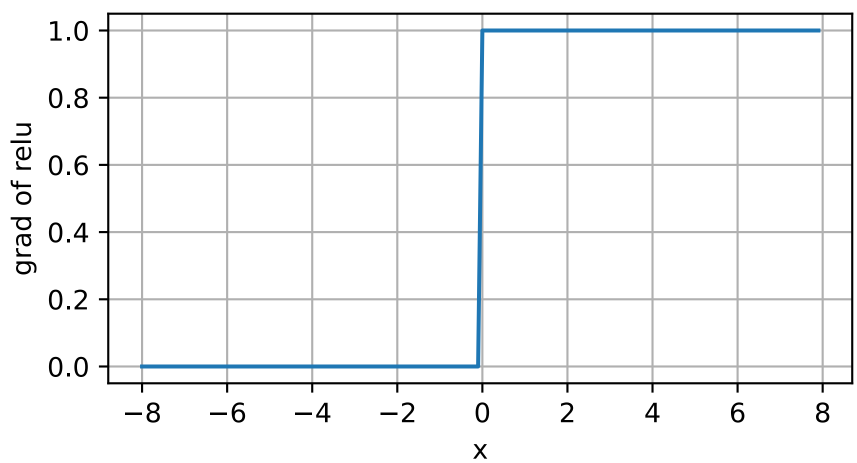
5.1.2 Hidden Layers

5.1.2.1 ReLU Function

```
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))
```

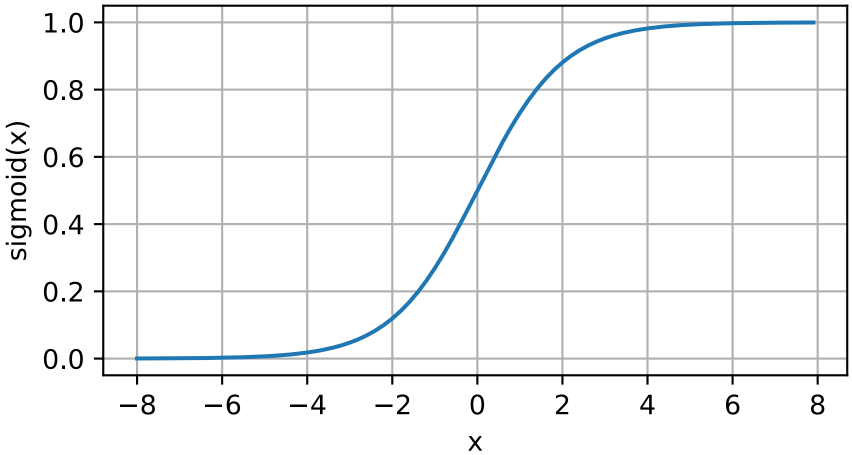



```
y.backward(torch.ones_like(x), retain_graph=True)
d2l.plot(x.detach(), x.grad, 'x', 'grad of relu', figsize=(5, 2.5))
```

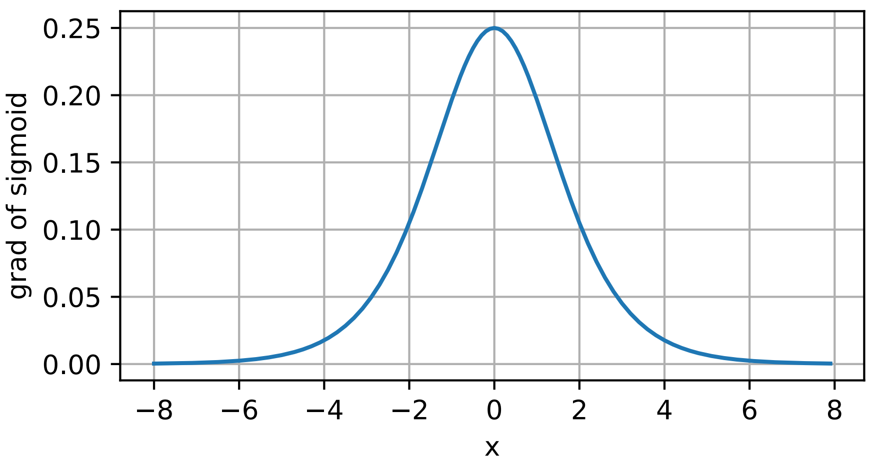


5.1.2.2 Sigmoid Function

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

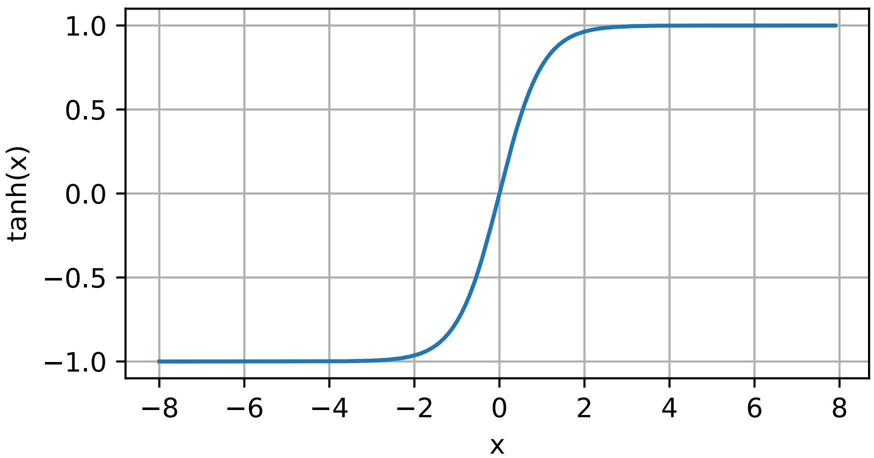



```
x.grad.data.zero_()
y.backward(torch.ones_like(x),retain_graph=True)
d2l.plot(x.detach(), x.grad, 'x', 'grad of sigmoid', figsize=(5, 2.5))
```

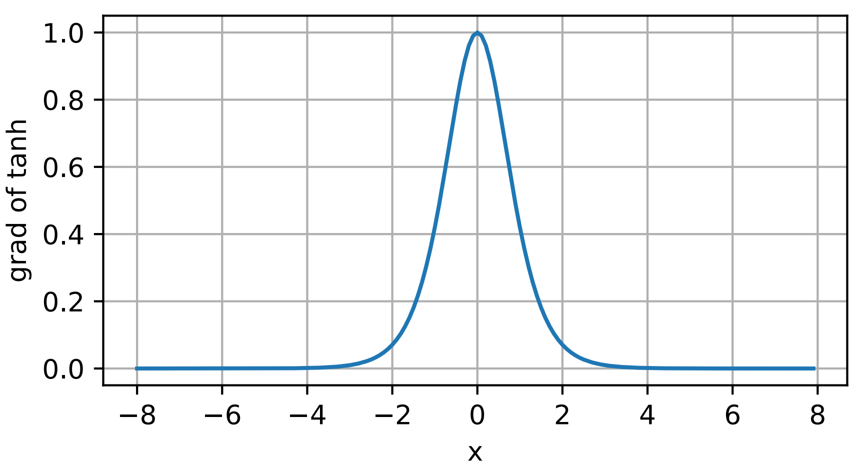


5.1.2.3 Tanh Function

```
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))
```



Key Takeaways:

1. Training an MLP involves iterating through many epochs, adjusting weights to minimize the loss. Effective training requires careful tuning of hyperparameters like learning rate, batch size, and number of epochs.
2. Neurons in hidden layers use activation functions to introduce non-linearity into the model.

5.2 Implementation of Multilayer Perceptrons

5.2.1 Implementation from Scratch

5.2.1.1. Initializing Model Parameters

```
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))
```

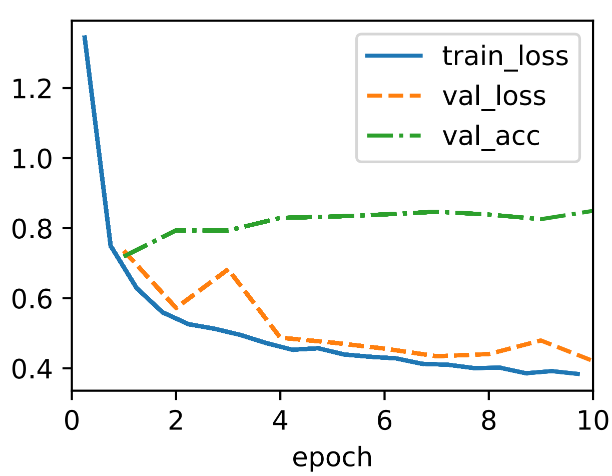
5.2.1.2 Model

```
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
```

5.2.1.3 Training

```
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)
```



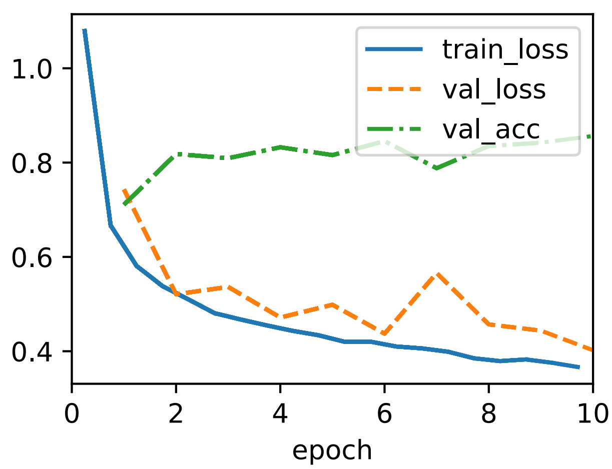
5.2.2 Concise Implementation

5.2.2.1 Model

```
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))
```

5.2.2.2 Training

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



Key Takeaways:

1. The training loop for MLP is exactly the same as for Softmax Regression.
2. Process of training includes: Define mode, data, trainer, then invoke the fitting method on model and data.
3. No forward method is defined, instead is now defined as a sequence of transformations via Sequential class.

5.3. Forward Propagation, Backward Propagation, and

Key Takeaways:

1. When it comes to calculate the gradients, we just invoke backpropagation function provided in framework.
2. Forward propagation and backpropagation are interdependent, and training requires significantly more memory than prediction.