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Deep Learning (Fall 2023)

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Linear Neural Networks

- Concise Implementation of Linear Regression

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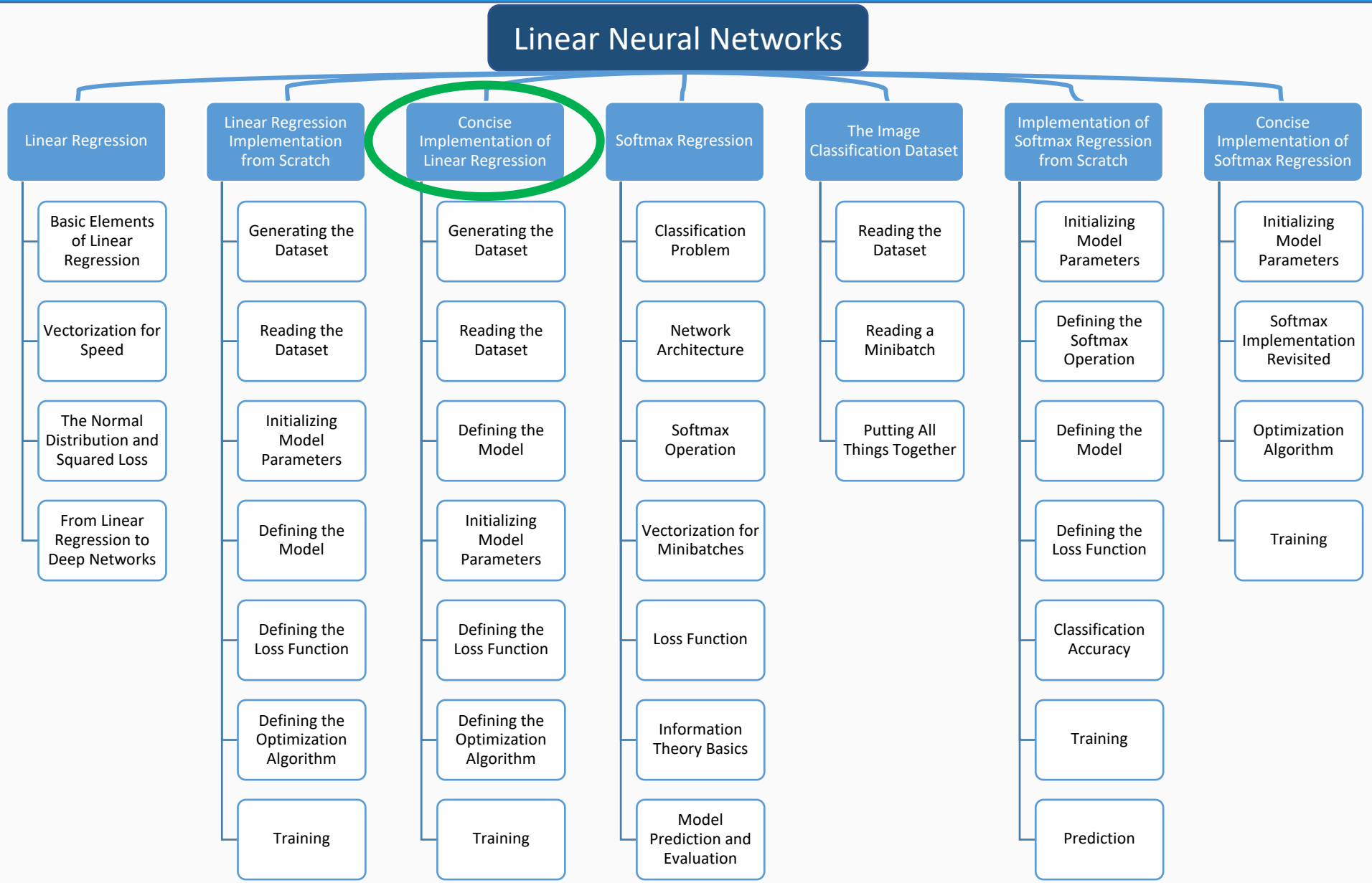
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Concise Implementation of Linear Regression

- We will learn how to implement the linear regression model concisely by using high-level APIs of DL frameworks.

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

Generating the Dataset

- We will generate the same dataset as in Section 3.2.

```
from d2l import mxnet as d2l
from mxnet import autograd, gluon, np, npx
npx.set_np()

true_w = np.array([2, -3.4])
true_b = 4.2
features, labels = d2l.synthetic_data(true_w, true_b, 1000)
```

$$\mathbf{X}$$

Reading the Dataset

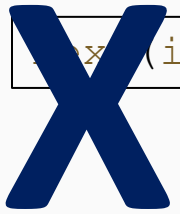
- Use the existing API in a framework to read data.
  - We pass in $features$ and $labels$ as arguments and specify batch_size when instantiating a data iterator object.
  - The boolean value is_train indicates whether or not to shuffle the data on each epoch.

```
def load_array(data_arrays, batch_size, is_train=True):  #@save
    """Construct a Gluon data iterator."""
    dataset = gluon.data.ArrayDataset(*data_arrays)
    return gluon.data.DataLoader(dataset, batch_size, shuffle=is_train)

batch_size = 10
data_iter = load_array((features, labels), batch_size)
```

- Now we can use $data\_iter$ in much the same way as we called the $data\_iter$ function in Section 3.2.
  - We use $iter$ to construct a Python iterator.
  - We use $next$ to obtain the first item from the iterator.

```
next(iter(data_iter))
```



Defining the Model

- We use a framework's predefined layers to focus on the layers used to construct the model rather than focusing on the implementation.

- The layer in a single-layer neural network (Fig. 3.1.2) is said to be $fully-connected$ because each of its inputs is connected to each of its outputs by means of a matrix-vector multiplication.
  - In PyTorch, the fully-connected layer is defined in the $Linear$ and $LazyLinear$ classes.
  - $LazyLinear$ allows users to specify merely the output dimension.
  - $Linear$ additionally asks for how many inputs go into this layer.
  - We will use such "lazy" layers whenever we can for simplicity.

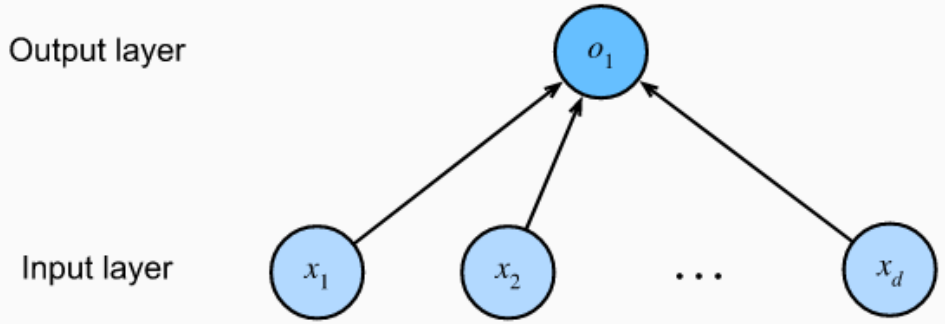


Fig. 3.1.2 Linear regression is a single-layer neural network.

Defining the Model

```
class LinearRegression(d2l.Module): #@save
    """The linear regression model implemented with high-level APIs."""
    def __init__(self, lr):
        super().__init__()
        self.save_hyperparameters()
        self.net = nn.LazyLinear(1)
        self.net.weight.data.normal_(0, 0.01)
        self.net.bias.data.fill_(0)
```

- In the *forward* method we just invoke the built-in __call__ method of the predefined layers to compute the outputs.

```
@d2l.add_to_class(LinearRegression) #@save
def forward(self, X):
    return self.net(X)
```

Defining the Loss Function

- The MSELoss class computes the mean squared error (without the 1/2 factor in (3.1.5)).
- By default, MSELoss returns the average loss over examples.
- It is faster (and easier to use) than implementing our own.
  - nn.MSELoss()

```
@d2l.add_to_class(LinearRegression) #@save
def loss(self, y_hat, y):
    fn = nn.MSELoss()
    return fn(y_hat, y)
```

Defining the Optimization Algorithm

- Minibatch SGD is a standard tool for optimizing neural networks and thus PyTorch supports it alongside a number of variations on this algorithm in the *optim* module. When instantiating an SGD instance, we will specify:
  - Parameters to optimize over (obtainable from our model via $self.parameters()$)
  - Learning rate (*self.lr*) required by our optimization algorithm

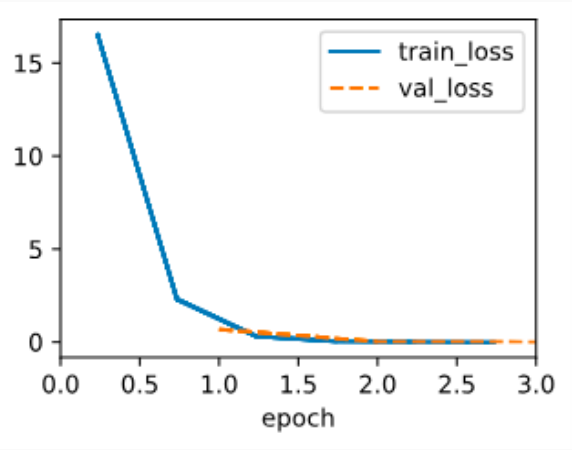
```
@d2l.add_to_class(LinearRegression) #@save
def configure_optimizers(self):
    return torch.optim.SGD(self.parameters(), self.lr)
```

Training

- Notice that expressing our model through high-level APIs of a DL framework requires fewer lines of code.
- We did not have to
  - allocate parameters individually
  - define our loss function
  - implement minibatch SGD
- Once we start working with much more complex models, the advantages of the high-level API will grow considerably.

- The training loop is the same as the one we implemented from scratch.
- We just call the *fit* method, which relies on the implementation of the *fit_epoch* method, to train our model.

```
model = LinearRegression(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)
```



Training

- We compare the model parameters learned by training and the actual parameters that generated our dataset.
- Our estimated parameters are close to their true counterparts.

```
@d2l.add_to_class(LinearRegression) #@save
def get_w_b(self):
        return (self.net.weight.data, self.net.bias.data)
w, b = model.get_w_b()

print(f'error in estimating w: {data.w - w.reshape(data.w.shape)}')
print(f'error in estimating b: {data.b - b}')
```

Summary

- Using PyTorch, we can implement models much more concisely.
- In PyTorch, the $data$ module provides tools for data processing.
- The nn module defines a large number of neural network layers and many common loss functions.
- We can initialize the parameters by replacing their values with methods ending with _.