In this section we demonstrate how to ft the examples discussed in the text. We use the Python torch package, along with the pytorch_lightning torch pytorch_lightning package which provides utilities to simplify ftting and evaluating models. This code can be impressively fast with certain special processors, such as Apple's new M1 chip. The package is well-structured, fexible, and will feel comfortable to Python users. A good companion is the site pytorch.org/tutorials. Much of our code is adapted from there, as well as the pytorch_lightning documentation.

https://pytorch.org/tutorials/beginner/basics/intro.html and https://pytorch-lightning.readthedocs.io/en/latest/.

We start with several standard imports that we have seen before.

In [1]:
```
import numpy as np, pandas as pd
from matplotlib.pyplot import subplots
from sklearn.linear_model import \
(LinearRegression,
LogisticRegression,
Lasso)
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import KFold
from sklearn.pipeline import Pipeline
from ISLP import load_data
from ISLP.models import ModelSpec as MS
from sklearn.model_selection import \
(train_test_split,
GridSearchCV)
```

Torch-Specifc Imports

There are a number of imports for torch. (These are not included with ISLP, so must be installed separately.) First we import the main library and essential tools used to specify sequentially-structured networks

In [2]:
```
import torch
from torch import nn
from torch.optim import RMSprop
from torch.utils.data import TensorDataset
```

There are several other helper packages for torch. For instance, the torchmetrics package has utilities to compute various metrics to evaluate performance when fitting a model. The torchinfo package provides a useful summary of the layers of a model. We use the read_image() function when loading test images in Section 10.9.4.

In [3]:
```
from torchmetrics import (MeanAbsoluteError,R2Score)
from torchinfo import summary
from torchvision.io import read_image
```

The package pytorch_lightning is a somewhat higher-level interface to torch that simplifes the specifcation and ftting of models by reducing the amount of boilerplate code needed (compared to using torch alone).

In [4]:
```
from pytorch_lightning import Trainer
from pytorch_lightning.loggers import CSVLogger
```

In order to reproduce results we use seed_everything(). We will also instruct torch to use deterministic algorithms where possible.

In [5]:
```
from pytorch_lightning.utilities.seed import seed_everything
seed_everything(0, workers=True)
torch.use_deterministic_algorithms(True, warn_only=True)
```

```
C:\Users\ankit19.gupta\ankit\ankit\myenv\lib\site-packages\pytorch_lightning\utiliti
es\seed.py:48: LightningDeprecationWarning: `pytorch_lightning.utilities.seed.seed_e
verything` has been deprecated in v1.8.0 and will be removed in v1.10.0. Please use
`lightning_lite.utilities.seed.seed_everything` instead.
  rank_zero_deprecation(
Global seed set to 0
```

We will use several datasets shipped with torchvision for our examples: torchvision a pretrained network for image classifcation, as well as some transforms used for preprocessing.

In [6]:
```
from torchvision.datasets import MNIST, CIFAR100
from torchvision.models import (resnet50,ResNet50_Weights)
from torchvision.transforms import (Resize,Normalize,CenterCrop,ToTensor)
```

We have provided a few utilities in ISLP specifcally for this lab. The SimpleDataModule and SimpleModule are simple versions of objects used in pytorch_lightning, the high-level module for ftting torch models. Although more advanced uses such as computing on graphical processing units (GPUs) and parallel data processing are possible in this module, we will not be focusing much on these in this lab. The ErrorTracker handles collections of targets and predictions over each mini-batch in the validation or test stage, allowing computation of the metric over the entire validation or test data set

In [7]:
```
from ISLP.torch import (SimpleDataModule,SimpleModule,ErrorTracker,rec_num_workers)
```

In addition we have included some helper functions to load the IMDb database, as well as a lookup that maps integers to particular keys in the database. We’ve included a slightly modifed copy of the preprocessed IMDb data from keras, a separate package for ftting deep learning models. This saves us signifcant preprocessing and allows us to focus on specifying and ftting the models themselves.

In [8]:
```
from ISLP.torch.imdb import (load_lookup,load_tensor,load_sparse,load_sequential)
```

Finally, we introduce some utility imports not directly related to torch. The glob() function from the glob module is used to fnd all fles matching wildcard characters, which we will use in our example applying the ResNet50 model to some of our own images. The json module will be used to load a JSON fle for looking up classes to identify the labels of the pictures in the ResNet50 example.

In [9]:
```
from glob import glob
import json
```

10.9.1 Single Layer Network on Hitters Data

We start by ftting the models in Section 10.6 on the Hitters data.

In [10]:
```
Hitters = load_data('Hitters').dropna()
n = Hitters.shape[0]
```

We will ft two linear models (least squares and lasso) and compare their performance to that of a neural network. For this comparison we will use mean absolute error on a validation dataset.

We set up the model matrix and the response.

In [11]:
```
model = MS(Hitters.columns.drop('Salary'), intercept=False)
X = model.fit_transform(Hitters).to_numpy()
Y = Hitters['Salary'].to_numpy()
```

The to_numpy() method above converts pandas data frames or series to numpy arrays. We do this because we will need to use sklearn to ft the lasso model, and it requires this conversion. We also use a linear regression method from sklearn, rather than the method in Chapter 3 from statsmodels, to facilitate the comparisons.

We now split the data into test and training, fxing the random state used by sklearn to do the split.

In [12]:
```
(X_train,X_test,Y_train,Y_test) = train_test_split(X,Y,test_size=1/3,random_state=1
```

Linear Models

We ft the linear model and evaluate the test error directly.

In [13]:
```
hit_lm = LinearRegression().fit(X_train, Y_train)
Yhat_test = hit_lm.predict(X_test)
np.abs(Yhat_test - Y_test).mean()
```

```
Out[13]: 259.71528833146294
```

Next we ft the lasso using sklearn. We are using mean absolute error to select and evaluate a model, rather than mean squared error. The specialized solver we used in Section 6.5.2 uses only mean squared error. So here, with a bit more work, we create a cross-validation grid and perform the cross-validation directly.

We encode a pipeline with two steps: we frst normalize the features using a StandardScaler() transform, and then ft the lasso without further normalization

```
In [14]: scaler = StandardScaler(with_mean=True, with_std=True)
         lasso = Lasso(warm_start=True, max_iter=30000)
         standard_lasso = Pipeline(steps=[('scaler', scaler),('lasso', lasso)])
```

We need to create a grid of values for λ. As is common practice, we choose a grid of 100 values of λ, uniform on the log scale from lam_max down to 0.01*lam_max. Here lam_max is the smallest value of λ with an allzero solution. This value equals the largest absolute inner-product between any predictor and the (centered) response

```
In [15]: X_s = scaler.fit_transform(X_train)
         n = X_s.shape[0]
         lam_max = np.fabs(X_s.T.dot(Y_train - Y_train.mean())).max() / n
         param_grid = {'alpha': np.exp(np.linspace(0, np.log(0.01), 100))* lam_max}
```

Note that we had to transform the data frst, since the scale of the variables impacts the choice of λ. We now perform cross-validation using this sequence of λ values.

```
In [16]: cv = KFold(10,shuffle=True,random_state=1)
         grid = GridSearchCV(lasso,param_grid,cv=cv,scoring='neg_mean_absolute_error')
         grid.fit(X_train, Y_train);
```

We extract the lasso model with best cross-validated mean absolute error, and evaluate its performance on X_test and Y_test, which were not used in cross-validation.

```
In [17]: trained_lasso = grid.best_estimator_
         Yhat_test = trained_lasso.predict(X_test)
         np.fabs(Yhat_test - Y_test).mean()
```

```
Out[17]: 257.23820107995
```

This is similar to the results we got for the linear model ft by least squares. However, these results can vary a lot for diferent train/test splits; we encourage the reader to try a diferent seed in code block 12 and rerun the subsequent code up to this point.

Specifying a Network: Classes and Inheritance

To ft the neural network, we frst set up a model structure that describes the network. Doing so requires us to defne new classes specifc to the model we wish to ft. Typically this is done in pytorch by sub-classing a generic representation of a network, which is the approach we take here. Although this example is simple, we will go through the steps in some detail, since it will serve us well for the more complex examples to follow.

In [18]:
```python
class HittersModel(nn.Module):
    def __init__(self, input_size):
        super(HittersModel , self).__init__()
        self.flatten = nn.Flatten()
        self.sequential = nn.Sequential(
        nn.Linear(input_size, 50),
        nn.ReLU(),
        nn.Dropout(0.4),
        nn.Linear(50, 1))
    def forward(self, x):
        x = self.flatten(x)
        return torch.flatten(self.sequential(x))
```

The class statement identifes the code chunk as a declaration for a class HittersModel that inherits from the base class nn.Module. This base class is ubiquitous in torch and represents the mappings in the neural networks.

Indented beneath the class statement are the methods of this class: in this case $\_\_\text{init}\_\_$ and forward. The $\_\_\text{init}\_\_$ method is called when an instance of the class is created as in the cell below. In the methods, self always refers to an instance of the class. In the $\_\_\text{init}\_\_$ method, we have attached two objects to self as attributes: flatten and sequential. These are used in the forward method to describe the map that this module implements.

There is one additional line in the $\_\_\text{init}\_\_$ method, which is a call to super(). This function allows subclasses (i.e. HittersModel) to access meth- super() ods of the class they inherit from. For example, the class nn.Module has its own $\_\_\text{init}\_\_$ method, which is diferent from the HittersModel.$\_\_\text{init}\_\_$() method we've written above. Using super() allows us to call the method of the base class. For torch models, we will always be making this super() call as it is necessary for the model to be properly interpreted by torch.

The object nn.Module has more methods than simply $\_\_\text{init}\_\_$ and forward. These methods are directly accessible to HittersModel instances because of this inheritance. One such method we will see shortly is the eval() method, used to disable dropout for when we want to evaluate the model on test data.

In [19]:
```python
hit_model = HittersModel(X.shape[1])
```

The object self.sequential is a composition of four maps. The frst maps the 19 features of Hitters to 50 dimensions, introducing $50 \times 19 + 50$ parameters for the weights and intercept of the map (often called the bias). This layer is then mapped to a ReLU layer followed by a

40% dropout layer, and fnally a linear map down to 1 dimension, again with a bias. The total number of trainable parameters is therefore 50 × 19 + 50 + 50 + 1 = 1051.

The package torchinfo provides a summary() function that neatly summarizes this information. We specify the size of the input and see the size of each tensor as it passes through layers of the network.

In [20]:
```
summary(hit_model,input_size=X_train.shape,col_names=['input_size','output_size','n
```

Out[20]:
```
==================================================================================
=================================
Layer (type:depth-idx)                   Input Shape               Output Shape
Param #
==================================================================================
=================================
HittersModel                             [175, 19]                 [175]
--
├─Flatten: 1-1                           [175, 19]                 [175, 19]
--
├─Sequential: 1-2                        [175, 19]                 [175, 1]
--
│    └─Linear: 2-1                       [175, 19]                 [175, 50]
1,000
│    └─ReLU: 2-2                         [175, 50]                 [175, 50]
--
│    └─Dropout: 2-3                      [175, 50]                 [175, 50]
--
│    └─Linear: 2-4                       [175, 50]                 [175, 1]
51
==================================================================================
=================================
Total params: 1,051
Trainable params: 1,051
Non-trainable params: 0
Total mult-adds (M): 0.18
==================================================================================
=================================
Input size (MB): 0.01
Forward/backward pass size (MB): 0.07
Params size (MB): 0.00
Estimated Total Size (MB): 0.09
==================================================================================
=================================
```

We have truncated the end of the output slightly, here and in subsequent uses.

We now need to transform our training data into a form accessible to torch. The basic datatype in torch is a tensor, which is very similar to an ndarray from early chapters. We also note here that torch typically works with 32-bit (single precision) rather than 64-bit (double precision) foating point numbers. We therefore convert our data to np.float32 before forming the tensor. The X and Y tensors are then arranged into a Dataset recognized by torch using TensorDataset().

In [21]:
```
X_train_t = torch.tensor(X_train.astype(np.float32))
Y_train_t = torch.tensor(Y_train.astype(np.float32))
hit_train = TensorDataset(X_train_t, Y_train_t)
```

We do the same for the test data.

In [22]:
```
X_test_t = torch.tensor(X_test.astype(np.float32))
Y_test_t = torch.tensor(Y_test.astype(np.float32))
hit_test = TensorDataset(X_test_t, Y_test_t)
```

Finally, this dataset is passed to a DataLoader() which ultimately passes data into our network. While this may seem like a lot of overhead, this structure is helpful for more complex tasks where data may live on diferent machines, or where data must be passed to a GPU. We provide a helper function SimpleDataModule() in ISLP to make this task easier for standard usage. One of its arguments is num_workers, which indicates how many processes we will use for loading the data. For small data like Hitters this will have little efect, but it does provide an advantage for the MNIST and CIFAR100 examples below. The torch package will inspect the process running and determine a maximum number of workers.25 We've included a function rec_num_workers() to compute this so we know how many workers might be reasonable (here the max was 16).

In [23]:
```
max_num_workers = rec_num_workers()
```

The general training setup in pytorch_lightning involves training, validation and test data. These are each represented by diferent data loaders. During each epoch, we run a training step to learn the model and a validation step to track the error. The test data is typically used at the end of training to evaluate the model.

In this case, as we had split only into test and training, we'll use the test data as validation data with the argument validation=hit_test. The validation argument can be a foat between 0 and 1, an integer, or a Dataset. If a foat (respectively, integer), it is interpreted as a percentage (respectively number) of the training observations to be used for validation. If it is a Dataset, it is passed directly to a data loader.

In [24]:
```
hit_dm = SimpleDataModule(hit_train,hit_test,batch_size=32,num_workers=min(4, max_n
```

Next we must provide a pytorch_lightning module that controls the steps performed during the training process. We provide methods for our SimpleModule() that simply record the value of the loss function and any additional metrics at the end of each epoch. These operations are controlled by the methods SimpleModule.[training/test/validation]_step(), though we will not be modifying these in our examples.

In [25]:
```
hit_module = SimpleModule.regression(hit_model,metrics={'mae':MeanAbsoluteError()})
```

By using the SimpleModule.regression() method, we indicate that we will use squared-error loss as in 10.23). We have also asked for mean absolute error to be tracked as well in the metrics that are logged.

We log our results via CSVLogger(), which in this case stores the results in a CSV fle within a directory logs/hitters. After the ftting is complete, this allows us to load the results as a pd.DataFrame() and visualize them below. There are several ways to log the results within pytorch_lightning, though we will not cover those here in detail.

In [26]:
```
hit_logger = CSVLogger('logs', name='hitters')
```

Finally we are ready to train our model and log the results. We use the Trainer() object from pytorch_lightning to do this work. The argument datamodule=hit_dm tells the trainer how training/validation/test logs are produced, while the frst argument hit_module specifes the network architecture as well as the training/validation/test steps. The callbacks argument allows for several tasks to be carried out at various points while training a model. Here our ErrorTracker() callback will enable us to compute validation error while training and, fnally, the test error. We now ft the model for 50 epochs

In [27]:
```
hit_trainer = Trainer(deterministic=True,max_epochs=50,log_every_n_steps=5,logger=h
hit_trainer.fit(hit_module, datamodule=hit_dm)
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs

  | Name  | Type         | Params
---------------------------------------
0 | model | HittersModel | 1.1 K
1 | loss  | MSELoss      | 0
---------------------------------------
1.1 K     Trainable params
0         Non-trainable params
1.1 K     Total params
0.004     Total estimated model params size (MB)
Sanity Checking: 0it [00:00, ?it/s]
Training: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
```

```
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
`Trainer.fit` stopped: `max_epochs=50` reached.
```

At each step of SGD, the algorithm randomly selects 32 training observations for the computation of the gradient. Recall from Section 10.7 that an epoch amounts to the number of SGD steps required to process n observations. Since the training set has n = 175, and we specifed a batch_size of 32 in the construction of hit_dm, an epoch is 175/32 = 5.5 SGD steps.

After having ft the model, we can evaluate performance on our test data using the test() method of our trainer

In [28]:
```
hit_trainer.test(hit_module, datamodule=hit_dm)
```

```
Testing: 0it [00:00, ?it/s]
```

```
────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
       Test metric             DataLoader 0
────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
        test_loss            104098.5703125
        test_mae            229.50115966796875
────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
```

Out[28]:
```
[{'test_loss': 104098.5703125, 'test_mae': 229.50115966796875}]
```

The results of the ft have been logged into a CSV fle. We can fnd the results specifc to this run in the experiment.metrics_file_path attribute of our logger. Note that each time the model is ft, the logger will output results into a new subdirectory of our directory logs/hitters.

We now create a plot of the MAE (mean absolute error) as a function of the number of epochs. First we retrieve the logged summaries.

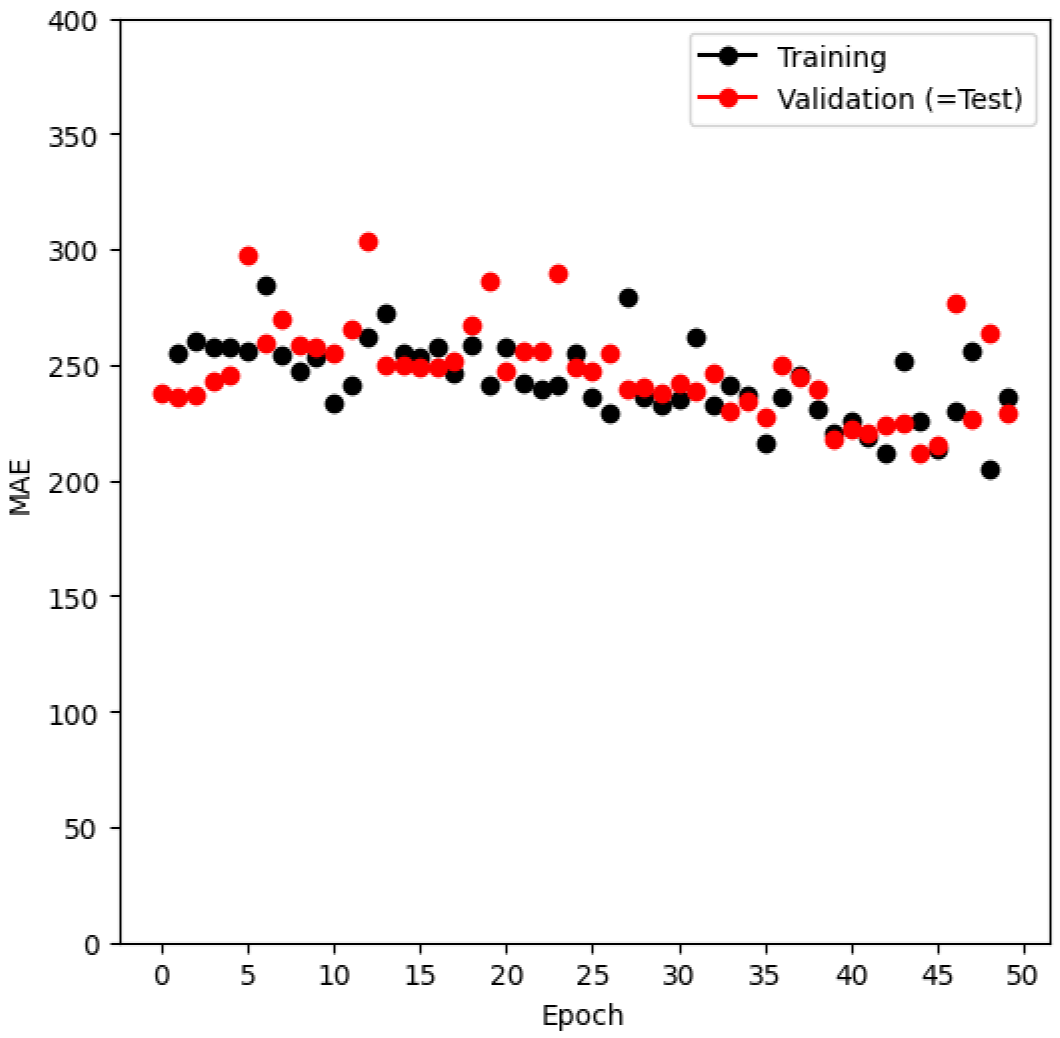
In [29]:
```python
hit_results = pd.read_csv(hit_logger.experiment.metrics_file_path)
```

Since we will produce similar plots in later examples, we write a simple generic function to produce this plot.

In [26]:
```python
def summary_plot(results,ax,col='loss',valid_legend='Validation',training_legend='T
    for (column,color,label) in zip([f'train_{col}_epoch',f'valid_{col}'],['black',
        results.plot(x='epoch',y=column,label=label,marker='o',color=color,ax=ax)
    ax.set_xlabel('Epoch')
    ax.set_ylabel(ylabel)
    return ax
```

We now set up our axes, and use our function to produce the MAE plot.

In [31]:
```python
fig, ax = subplots(1, 1, figsize=(6, 6))
ax = summary_plot(hit_results,ax,col='mae',ylabel='MAE',valid_legend='Validation (=
ax.set_ylim([0, 400])
ax.set_xticks(np.linspace(0, 50, 11).astype(int));
```



We can predict directly from the fnal model, and evaluate its performance on the test data. Before ftting, we call the eval() method of hit_model. This tells torch to efectively consider this model to be ftted, so that we can use it to predict on new data. For our model here, the biggest change is that the dropout layers will be turned of, i.e. no weights will be randomly dropped in predicting on new data.

In [32]:
```
hit_model.eval()
preds = hit_module(X_test_t)
torch.abs(Y_test_t - preds).mean()
```

Out[32]:
```
tensor(229.5011, grad_fn=<MeanBackward0>)
```

Cleanup

In setting up our data module, we had initiated several worker processes that will remain running. We delete all references to the torch objects to ensure these processes will be killed.

In [33]:
```
del(Hitters,
hit_model, hit_dm,
hit_logger,
hit_test, hit_train,
X, Y,
X_test, X_train,
Y_test, Y_train,
X_test_t, Y_test_t,
hit_trainer, hit_module)
```

10.9.2 Multilayer Network on the MNIST Digit Data

The torchvision package comes with a number of example datasets, including the MNIST digit data. Our frst step is to retrieve the training and test data sets; the MNIST() function within torchvision.datasets is provided for MNIST() this purpose. The data will be downloaded the frst time this function is executed, and stored in the directory data/MNIST.

In [36]:
```
(mnist_train,mnist_test) = [MNIST(root='data',train=train,download=True,transform=T
mnist_train
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to data\MNIS
T\raw\train-images-idx3-ubyte.gz
100%|██████████████████████████████████████████████████| 9912422/
9912422 [01:52<00:00, 87921.06it/s]
Extracting data\MNIST\raw\train-images-idx3-ubyte.gz to data\MNIST\raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to data\MNIS
T\raw\train-labels-idx1-ubyte.gz
100%|█████████████████████████████████████████████████████| 2888
1/28881 [00:00<00:00, 68639.86it/s]
Extracting data\MNIST\raw\train-labels-idx1-ubyte.gz to data\MNIST\raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to data\MNIST
\raw\t10k-images-idx3-ubyte.gz
100%|█████████████████████████████████████████████████| 1648877/1
648877 [00:06<00:00, 244260.85it/s]
Extracting data\MNIST\raw\t10k-images-idx3-ubyte.gz to data\MNIST\raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to data\MNIST
\raw\t10k-labels-idx1-ubyte.gz
100%|█████████████████████████████████████████████████████████
█████| 4542/4542 [00:00<?, ?it/s]
Extracting data\MNIST\raw\t10k-labels-idx1-ubyte.gz to data\MNIST\raw
```

Out[36]:
```
Dataset MNIST
    Number of datapoints: 60000
    Root location: data
    Split: Train
    StandardTransform
Transform: ToTensor()
```

There are 60,000 images in the training data and 10,000 in the test data. The images are 28 × 28, and stored as a matrix of pixels. We need to transform each one into a vector

Neural networks are somewhat sensitive to the scale of the inputs, much as ridge and lasso regularization are afected by scaling. Here the inputs are eight-bit grayscale values between 0 and 255, so we rescale to the unit interval.26 This transformation, along with some reordering of the axes, is performed by the ToTensor() transform from the torchvision.transforms package

As in our Hitters example, we form a data module from the training and test datasets, setting aside 20% of the training images for validation.

In [37]:
```
mnist_dm = SimpleDataModule(mnist_train,mnist_test,validation=0.2,num_workers=max_n
```

Let’s take a look at the data that will get fed into our network. We loop through the frst few chunks of the test dataset, breaking after 2 batches:

In [38]:
```
for idx, (X_ ,Y_) in enumerate(mnist_dm.train_dataloader()):
    print('X: ', X_.shape)
    print('Y: ', Y_.shape)
    if idx >= 1:
        break
```

```
X:  torch.Size([256, 1, 28, 28])
Y:  torch.Size([256])
X:  torch.Size([256, 1, 28, 28])
Y:  torch.Size([256])
```

We see that the X for each batch consists of 256 images of size 1x28x28. Here the 1 indicates a single channel (greyscale). For RGB images such as CIFAR100 below, we will see that the 1 in the size will be replaced by 3 for the three RGB channels.

Now we are ready to specify our neural network.

In [39]:
```
class MNISTModel(nn.Module):
    def __init__(self):
        super(MNISTModel, self).__init__()
        self.layer1 = nn.Sequential(
        nn.Flatten(),
        nn.Linear(28*28, 256),
        nn.ReLU(),
        nn.Dropout(0.4))
        self.layer2 = nn.Sequential(
        nn.Linear(256, 128),
        nn.ReLU(),
        nn.Dropout(0.3))
        self._forward = nn.Sequential(
        self.layer1,
        self.layer2,
        nn.Linear(128, 10))
    def forward(self, x):
        return self._forward(x)
```

We see that in the frst layer, each 1x28x28 image is fattened, then mapped to 256 dimensions where we apply a ReLU activation with 40% dropout. A second layer maps the frst layer's output down to 128 dimensions, applying a ReLU activation with 30% dropout. Finally, the 128 dimensions are mapped down to 10, the number of classes in the MNIST data.

In [40]:
```
mnist_model = MNISTModel()
```

We can check that the model produces output of expected size based on our existing batch X_ above.

In [41]:
```
mnist_model(X_).size()
```

Out[41]:
```
torch.Size([256, 10])
```

Let's take a look at the summary of the model. Instead of an input_size we can pass a tensor of correct shape. In this case, we pass through the fnal batched X_ from above.

In [42]:
```
summary(mnist_model,input_data=X_,col_names=['input_size','output_size','num_params
```

Out[42]:
```
================================================================================
=================================
Layer (type:depth-idx)                   Input Shape               Output Shape
Param #
================================================================================
=================================
MNISTModel                               [256, 1, 28, 28]          [256, 10]
--
├─Sequential: 1-1                        [256, 1, 28, 28]          [256, 10]
--
│    └─Sequential: 2-1                   [256, 1, 28, 28]          [256, 256]
--
│    │    └─Flatten: 3-1                 [256, 1, 28, 28]          [256, 784]
--
│    │    └─Linear: 3-2                  [256, 784]                [256, 256]
200,960
│    │    └─ReLU: 3-3                    [256, 256]                [256, 256]
--
│    │    └─Dropout: 3-4                 [256, 256]                [256, 256]
--
│    └─Sequential: 2-2                   [256, 256]                [256, 128]
--
│    │    └─Linear: 3-5                  [256, 256]                [256, 128]
32,896
│    │    └─ReLU: 3-6                    [256, 128]                [256, 128]
--
│    │    └─Dropout: 3-7                 [256, 128]                [256, 128]
--
│    └─Linear: 2-3                       [256, 128]                [256, 10]
1,290
================================================================================
=================================
Total params: 235,146
Trainable params: 235,146
Non-trainable params: 0
Total mult-adds (M): 60.20
================================================================================
=================================
Input size (MB): 0.80
Forward/backward pass size (MB): 0.81
Params size (MB): 0.94
Estimated Total Size (MB): 2.55
================================================================================
=================================
```

Having set up both the model and the data module, ftting this model is now almost identical to the Hitters example. In contrast to our regression model, here we will use the SimpleModule.classification() method which uses the cross-entropy loss function instead of mean squared error.

In [44]:
```
mnist_module = SimpleModule.classification(mnist_model,num_classes=10)
mnist_logger = CSVLogger('logs', name='MNIST')
```

Now we are ready to go. The fnal step is to supply training data, and ft the model.

In [45]:
```
mnist_trainer = Trainer(deterministic=True,max_epochs=30,logger=mnist_logger,callba
mnist_trainer.fit(mnist_module,datamodule=mnist_dm)
```

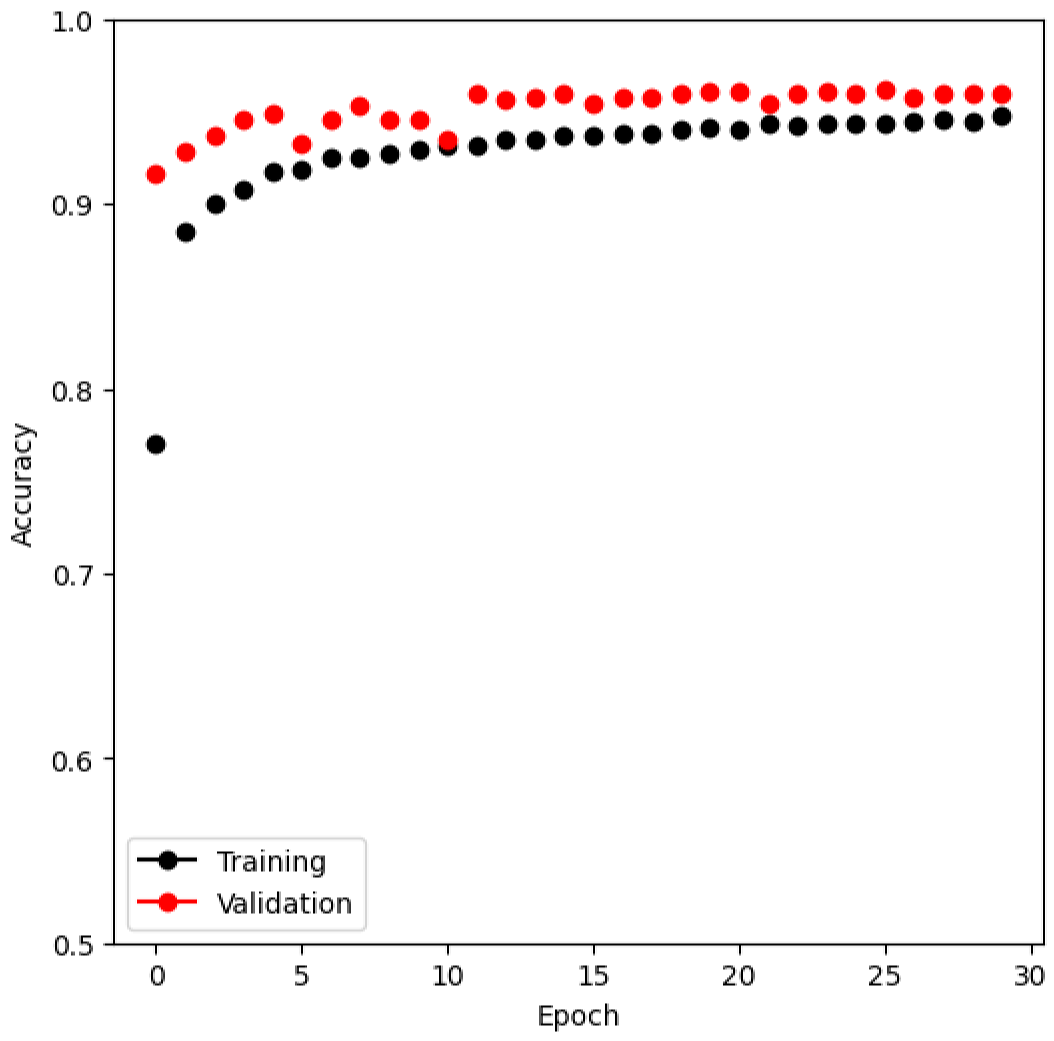
```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs
Missing logger folder: logs\MNIST

  | Name  | Type             | Params
-------------------------------------------
0 | model | MNISTModel       | 235 K
1 | loss  | CrossEntropyLoss | 0
-------------------------------------------
235 K     Trainable params
0         Non-trainable params
235 K     Total params
0.941     Total estimated model params size (MB)
Sanity Checking: 0it [00:00, ?it/s]
Training: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
`Trainer.fit` stopped: `max_epochs=30` reached.
```

We have suppressed the output here, which is a progress report on the ftting of the model, grouped by epoch. This is very useful, since on large datasets ftting can take time. Fitting this model took 245 seconds on a MacBook Pro with an Apple M1 Pro chip with 10 cores and 16 GB of RAM. Here we specifed a validation split of 20%, so training is actually performed on 80% of the 60,000 observations in the training set. This is an alternative to actually supplying validation data, like we did for the Hitters data. SGD uses batches of 256 observations in computing the gradient, and doing the arithmetic, we see that an epoch corresponds to 188 gradient steps.

SimpleModule.classification() includes an accuracy metric by default. Other classifcation metrics can be added from torchmetrics. We will use our summary_plot() function to display accuracy across epochs.

In [46]:
```
mnist_results = pd.read_csv(mnist_logger.experiment.metrics_file_path)
fig, ax = subplots(1, 1, figsize=(6, 6))
summary_plot(mnist_results,ax,col='accuracy',ylabel='Accuracy')
ax.set_ylim([0.5, 1])
ax.set_ylabel('Accuracy')
ax.set_xticks(np.linspace(0, 30, 7).astype(int));
```



Once again we evaluate the accuracy using the test() method of our trainer. This model achieves 97% accuracy on the test data.

In [47]:
```
mnist_trainer.test(mnist_module,datamodule=mnist_dm)
```

```
Testing: 0it [00:00, ?it/s]
────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
       Test metric             DataLoader 0
────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
      test_accuracy         0.9598000049591064
        test_loss           0.16626453399658203
────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
```

Out[47]:
```
[{'test_loss': 0.16626453399658203, 'test_accuracy': 0.9598000049591064}]
```

Table 10.1 also reports the error rates resulting from LDA (Chapter 4) and multiclass logistic regression. For LDA we refer the reader to Section 4.7.3. Although we could use the sklearn function LogisticRegression() to ft multiclass logistic regression, we are set up here to ft such a model with torch. We just have an input layer and an output layer, and omit the hidden layers!

In [49]:
```
class MNIST_MLR(nn.Module):
    def __init__(self):
        super(MNIST_MLR, self).__init__()
        self.linear = nn.Sequential(nn.Flatten(),nn.Linear(784, 10))
    def forward(self, x):
        return self.linear(x)
mlr_model = MNIST_MLR()
mlr_module = SimpleModule.classification(mlr_model,num_classes=10)
mlr_logger = CSVLogger('logs', name='MNIST_MLR')
```

In [50]:
```
mlr_trainer = Trainer(deterministic=True,max_epochs=30,
callbacks=[ErrorTracker()])
mlr_trainer.fit(mlr_module, datamodule=mnist_dm)
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs
Missing logger folder: C:\Users\ankit19.gupta\ankit\ankit\ML_Code\ISLP\lightning_log
s

  | Name  | Type             | Params
-------------------------------------------
0 | model | MNIST_MLR        | 7.9 K
1 | loss  | CrossEntropyLoss | 0
-------------------------------------------
7.9 K     Trainable params
0         Non-trainable params
7.9 K     Total params
0.031     Total estimated model params size (MB)
```

```
Sanity Checking: 0it [00:00, ?it/s]
Training: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
`Trainer.fit` stopped: `max_epochs=30` reached.
```

We ft the model just as before and compute the test results.

In [51]:
```
mlr_trainer.test(mlr_module,datamodule=mnist_dm)
```

```
Testing: 0it [00:00, ?it/s]
────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
       Test metric             DataLoader 0
────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
      test_accuracy         0.9142000079154968
        test_loss           0.3529835343360901
────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
```

Out[51]:
```
[{'test_loss': 0.3529835343360901, 'test_accuracy': 0.9142000079154968}]
```

The accuracy is above 90% even for this pretty simple model.

As in the Hitters example, we delete some of the objects we created above.

```
In [52]: del(mnist_test,mnist_train,mnist_model,mnist_dm,mnist_trainer,mnist_module,mnist_re
```

10.9.3 Convolutional Neural Networks

In this section we ft a CNN to the CIFAR100 data, which is available in the torchvision package. It is arranged in a similar fashion as the MNIST data.

```
In [53]: (cifar_train,cifar_test) = [CIFAR100(root="data",train=train,download=True) for tra
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-100-python.tar.gz to data\cifar-1
00-python.tar.gz
100%|████████████████████████████████████████████████| 169001437/1690
01437 [1:43:20<00:00, 27254.69it/s]
Extracting data\cifar-100-python.tar.gz to data
Files already downloaded and verified
```

```
In [54]: transform = ToTensor()
cifar_train_X = torch.stack([transform(x) for x in cifar_train.data])
cifar_test_X = torch.stack([transform(x) for x in cifar_test.data])
cifar_train = TensorDataset(cifar_train_X,torch.tensor(cifar_train.targets))
cifar_test = TensorDataset(cifar_test_X,torch.tensor(cifar_test.targets))
```

The CIFAR100 dataset consists of 50,000 training images, each represented by a three-dimensional tensor: each three-color image is represented as a set of three channels, each of which consists of 32 × 32 eight-bit pixels. We standardize as we did for the digits, but keep the array structure. This is accomplished with the ToTensor() transform.

Creating the data module is similar to the MNIST example.

```
In [55]: cifar_dm = SimpleDataModule(cifar_train,cifar_test,validation=0.2,num_workers=max_n
```

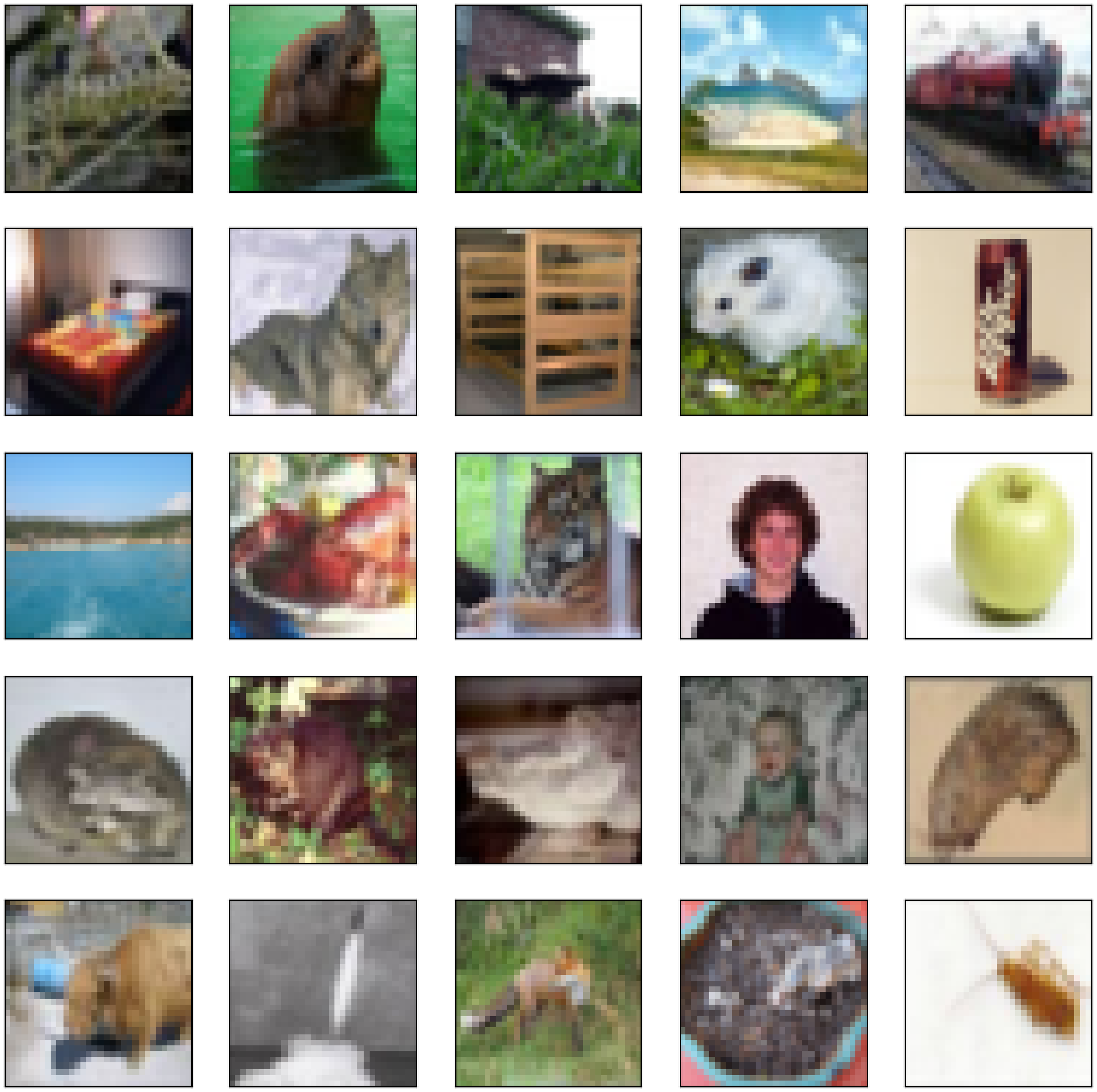
We again look at the shape of typical batches in our data loaders.

```
In [56]: for idx, (X_ ,Y_) in enumerate(cifar_dm.train_dataloader()):
    print('X: ', X_.shape)
    print('Y: ', Y_.shape)
    if idx >= 1:
        break
```

```
X:  torch.Size([128, 3, 32, 32])
Y:  torch.Size([128])
X:  torch.Size([128, 3, 32, 32])
Y:  torch.Size([128])
```

Before we start, we look at some of the training images; similar code produced Figure 10.5 on page 406. The example below also illustrates that TensorDataset objects can be indexed with integers — we are choosing random images from the training data by indexing cifar_train. In order to display correctly, we must reorder the dimensions by a call to np.transpose().

In [57]:
```
fig, axes = subplots(5, 5, figsize=(10,10))
rng = np.random.default_rng(4)
indices = rng.choice(np.arange(len(cifar_train)), 25,replace=False).reshape((5,5))
for i in range(5):
    for j in range(5):
        idx = indices[i,j]
        axes[i,j].imshow(np.transpose(cifar_train[idx][0],[1,2,0]),interpolation=No
        axes[i,j].set_xticks([])
        axes[i,j].set_yticks([])
```



Here the imshow() method recognizes from the shape of its argument that it is a 3-dimensional array, with the last dimension indexing the three RGB color channels.

We specify a moderately-sized CNN for demonstration purposes, similar in structure to Figure 10.8. We use several layers, each consisting of convolution, ReLU, and max-pooling steps. We frst defne a module that defnes one of these layers. As in our previous examples, we overwrite the __init__() and forward() methods of nn.Module. This user-defned module can now be used in ways just like nn.Linear() or nn.Dropout().

In [58]:
```
class BuildingBlock(nn.Module):
    def __init__(self,in_channels,out_channels):
        super(BuildingBlock , self).__init__()
        self.conv = nn.Conv2d(in_channels=in_channels,out_channels=out_channels,ker
        self.activation = nn.ReLU()
        self.pool = nn.MaxPool2d(kernel_size=(2,2))
    def forward(self, x):
        return self.pool(self.activation(self.conv(x)))
```

Notice that we used the padding = "same" argument to nn.Conv2d(), which ensures that the output channels have the same dimension as the input channels. There are 32 channels in the frst hidden layer, in contrast to the three channels in the input layer. We use a 3 × 3 convolution flter for each channel in all the layers. Each convolution is followed by a max-pooling layer over 2 × 2 blocks

In forming our deep learning model for the CIFAR100 data, we use several of our BuildingBlock() modules sequentially. This simple example illustrates some of the power of torch. Users can defne modules of their own,which can be combined in other modules. Ultimately, everything is ft by a generic trainer.

In [60]:
```
class CIFARModel(nn.Module):
    def __init__(self):
        super(CIFARModel, self).__init__()
        sizes = [(3,32),(32,64),(64,128),(128,256)]
        self.conv = nn.Sequential(*[BuildingBlock(in_, out_) for in_, out_ in sizes
        self.output = nn.Sequential(nn.Dropout(0.5),nn.Linear(2*2*256, 512),nn.ReLU
    def forward(self, x):
        val = self.conv(x)
        val = torch.flatten(val, start_dim=1)
        return self.output(val)
```

We build the model and look at the summary. (We had created examples of X_ earlier.)

In [61]:
```
cifar_model = CIFARModel()
summary(cifar_model,input_data=X_,col_names=['input_size','output_size','num_params
```

Out[61]:
```
==================================================================================
=================================
Layer (type:depth-idx)                   Input Shape               Output Shape
Param #
==================================================================================
=================================
CIFARModel                               [128, 3, 32, 32]          [128, 100]
--
├─Sequential: 1-1                        [128, 3, 32, 32]          [128, 256, 2,
2]           --
│    └─BuildingBlock: 2-1                [128, 3, 32, 32]          [128, 32, 16, 1
6]          --
│    │    └─Conv2d: 3-1                  [128, 3, 32, 32]          [128, 32, 32, 3
2]          896
│    │    └─ReLU: 3-2                    [128, 32, 32, 32]         [128, 32, 32, 3
2]          --
│    │    └─MaxPool2d: 3-3               [128, 32, 32, 32]         [128, 32, 16, 1
6]          --
│    └─BuildingBlock: 2-2                [128, 32, 16, 16]         [128, 64, 8, 8]
--
│    │    └─Conv2d: 3-4                  [128, 32, 16, 16]         [128, 64, 16, 1
6]          18,496
│    │    └─ReLU: 3-5                    [128, 64, 16, 16]         [128, 64, 16, 1
6]          --
│    │    └─MaxPool2d: 3-6               [128, 64, 16, 16]         [128, 64, 8, 8]
--
│    └─BuildingBlock: 2-3                [128, 64, 8, 8]           [128, 128, 4,
4]           --
│    │    └─Conv2d: 3-7                  [128, 64, 8, 8]           [128, 128, 8,
8]           73,856
│    │    └─ReLU: 3-8                    [128, 128, 8, 8]          [128, 128, 8,
8]           --
│    │    └─MaxPool2d: 3-9               [128, 128, 8, 8]          [128, 128, 4,
4]           --
│    └─BuildingBlock: 2-4                [128, 128, 4, 4]          [128, 256, 2,
2]           --
│    │    └─Conv2d: 3-10                 [128, 128, 4, 4]          [128, 256, 4,
4]           295,168
│    │    └─ReLU: 3-11                   [128, 256, 4, 4]          [128, 256, 4,
4]           --
│    │    └─MaxPool2d: 3-12              [128, 256, 4, 4]          [128, 256, 2,
2]           --
├─Sequential: 1-2                        [128, 1024]               [128, 100]
--
│    └─Dropout: 2-5                      [128, 1024]               [128, 1024]
--
│    └─Linear: 2-6                       [128, 1024]               [128, 512]
524,800
│    └─ReLU: 2-7                         [128, 512]                [128, 512]
--
│    └─Linear: 2-8                       [128, 512]                [128, 100]
51,300
==================================================================================
=================================
Total params: 964,516
Trainable params: 964,516
```

```
Non-trainable params: 0
Total mult-adds (G): 2.01
=================================================================================
=================================
Input size (MB): 1.57
Forward/backward pass size (MB): 63.54
Params size (MB): 3.86
Estimated Total Size (MB): 68.97
=================================================================================
=================================
```

The total number of trainable parameters is 964,516. By studying the size of the parameters, we can see that the channels halve in both dimensions after each of these max-pooling operations. After the last of these we have a layer with 256 channels of dimension 2 × 2. These are then fattened to a dense layer of size 1,024; in other words, each of the 2 × 2 matrices is turned into a 4-vector, and put side-by-side in one layer. This is followed by a dropout regularization layer, then another dense layer of size 512, and fnally, the output layer.

Up to now, we have been using a default optimizer in SimpleModule(). For these data, experiments show that a smaller learning rate performs better than the default 0.01. We use a custom optimizer here with a learning rate of 0.001. Besides this, the logging and training follow a similar pattern to our previous examples. The optimizer takes an argument params that informs the optimizer which parameters are involved in SGD (stochastic gradient descent).

We saw earlier that entries of a module's parameters are tensors. In passing the parameters to the optimizer we are doing more than simply passing arrays; part of the structure of the graph is encoded in the tensors themselves

In [64]:
```
cifar_optimizer = RMSprop(cifar_model.parameters(), lr=0.001)
cifar_module = SimpleModule.classification(cifar_model,optimizer=cifar_optimizer,nu
cifar_logger = CSVLogger('logs', name='CIFAR100')
```

In [65]:
```
cifar_trainer = Trainer(deterministic=True,max_epochs=30,logger=cifar_logger,callba
cifar_trainer.fit(cifar_module,datamodule=cifar_dm)
```

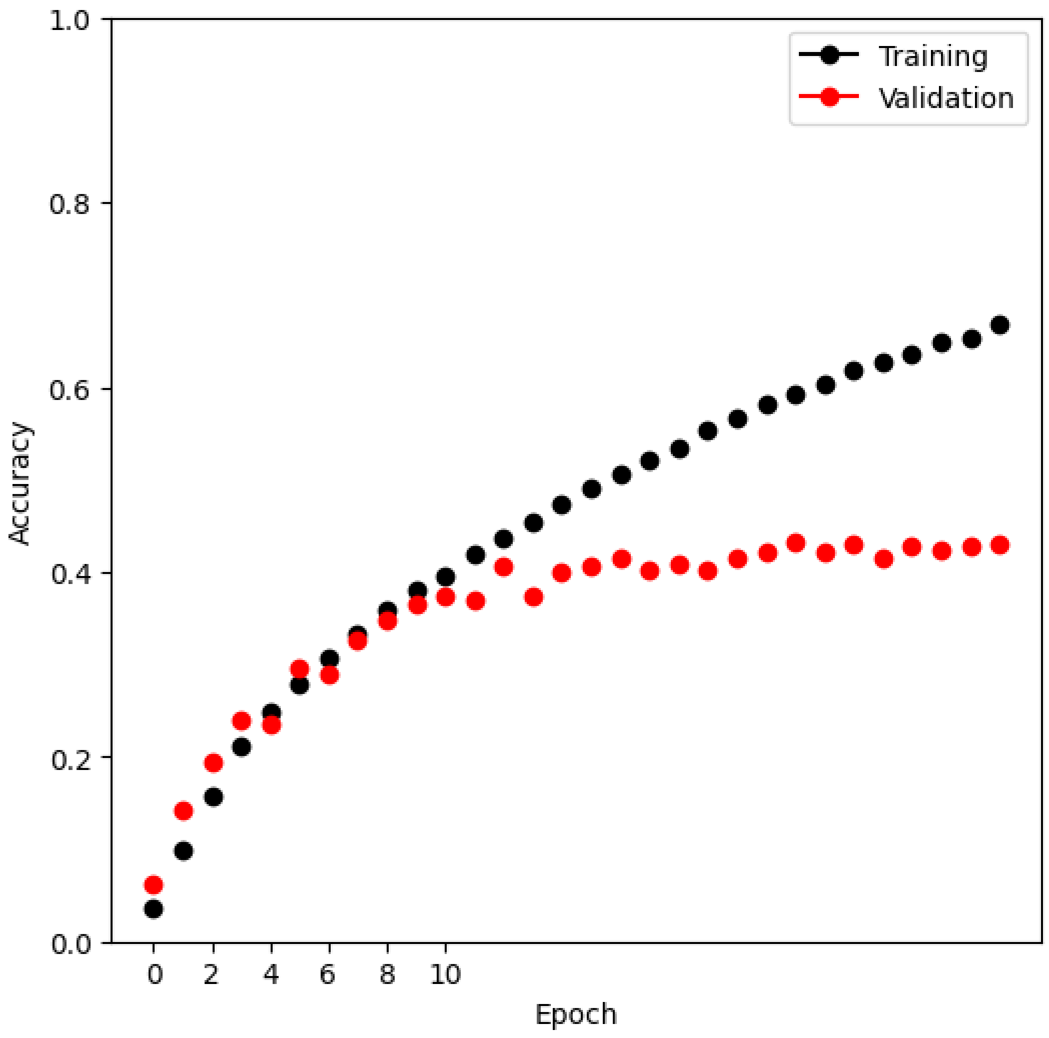
```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs
Missing logger folder: logs\CIFAR100

  | Name  | Type             | Params
-------------------------------------------
0 | model | CIFARModel       | 964 K
1 | loss  | CrossEntropyLoss | 0
-------------------------------------------
964 K     Trainable params
0         Non-trainable params
964 K     Total params
3.858     Total estimated model params size (MB)
Sanity Checking: 0it [00:00, ?it/s]
Training: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
`Trainer.fit` stopped: `max_epochs=30` reached.
```

This model takes 10 minutes or more to run and achieves about 42% accuracy on the test data. Although this is not terrible for 100-class data (a random classifer gets 1% accuracy), searching the web we see results around 75%. Typically it takes a lot of architecture carpentry, fddling with regularization, and time, to achieve such results.

Let's take a look at the validation and training accuracy across epochs.

In [66]:
```
log_path = cifar_logger.experiment.metrics_file_path
cifar_results = pd.read_csv(log_path)
fig, ax = subplots(1, 1, figsize=(6, 6))
summary_plot(cifar_results,ax,col='accuracy',ylabel='Accuracy')
ax.set_xticks(np.linspace(0, 10, 6).astype(int))
ax.set_ylabel('Accuracy')
ax.set_ylim([0, 1]);
```



Finally, we evaluate our model on our test data

In [67]:
```
cifar_trainer.test(cifar_module,datamodule=cifar_dm)
```

```
Testing: 0it [00:00, ?it/s]
```

```
────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
       Test metric             DataLoader 0
────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
      test_accuracy         0.4336000084877014
        test_loss            2.437638521194458
────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
```

Out[67]:
```
[{'test_loss': 2.437638521194458, 'test_accuracy': 0.4336000084877014}]
```

Hardware Acceleration

As deep learning has become ubiquitous in machine learning, hardware manufacturers have produced special libraries that can often speed up the gradient-descent steps.

For instance, Mac OS devices with the M1 chip may have the Metal programming framework enabled, which can speed up the torch computations. We present an example of how to use this acceleration.

The main changes are to the Trainer() call as well as to the metrics that will be evaluated on the data. These metrics must be told where the data will be located at evaluation time. This is accomplished with a call to the to() method of the metrics.

In [68]:
```python
try:
    for name, metric in cifar_module.metrics.items():
        cifar_module.metrics[name] = metric.to('mps')
        cifar_trainer_mps = Trainer(accelerator='mps',deterministic=True,max_epochs
        cifar_trainer_mps.fit(cifar_module,datamodule=cifar_dm)
        cifar_trainer_mps.test(cifar_module,datamodule=cifar_dm)
except:
    pass
```

This yields approximately two- or three-fold acceleration for each epoch. We have protected this code block using try: and except: clauses; if it works, we get the speedup, if it fails, nothing happens.

10.9.4 Using Pretrained CNN Models

We now show how to use a CNN pretrained on the imagenet database to classify natural images, and demonstrate how we produced Figure 10.10. We copied six JPEG images from a digital photo album into the directory book_images. These images are available from the data section of www. statlearning.com, the ISLP book website. Download book_images.zip; when clicked it creates the book_images directory.

The pretrained network we use is called resnet50; specifcation details can be found on the web. We will read in the images, and convert them into the array format expected by the torch software to match the specifcations in resnet50. The conversion involves a resize, a crop and then a predefned standardization for each of the three channels. We now read in the images and preprocess them

In [70]:
```
resize = Resize((232,232))
crop = CenterCrop(224)
normalize = Normalize([0.485,0.456,0.406],[0.229,0.224,0.225])
imgfiles = sorted([f for f in glob('book_images/*')])
imgs = torch.stack([torch.div(crop(resize(read_image(f))), 255) for f in imgfiles])
imgs = normalize(imgs)
imgs.size()
```

Out[70]:
```
torch.Size([5, 3, 224, 224])
```

We now set up the trained network with the weights we read in code block 6. The model has 50 layers, with a fair bit of complexity

In [71]:
```
resnet_model = resnet50(weights=ResNet50_Weights.DEFAULT)
summary(resnet_model,input_data=imgs,col_names=['input_size','output_size','num_par
```

```
Downloading: "https://download.pytorch.org/models/resnet50-11ad3fa6.pth" to C:\Users
\ankit19.gupta/.cache\torch\hub\checkpoints\resnet50-11ad3fa6.pth
100%|████████████████████████████████████████|
97.8M/97.8M [00:21<00:00, 4.73MB/s]
```

Out[71]:
```
==================================================================================
=================================
Layer (type:depth-idx)                   Input Shape               Output Shape
Param #
==================================================================================
=================================
ResNet                                   [5, 3, 224, 224]          [5, 1000]
--
├─Conv2d: 1-1                            [5, 3, 224, 224]          [5, 64, 112, 11
2]          9,408
├─BatchNorm2d: 1-2                       [5, 64, 112, 112]         [5, 64, 112, 11
2]          128
├─ReLU: 1-3                              [5, 64, 112, 112]         [5, 64, 112, 11
2]          --
├─MaxPool2d: 1-4                         [5, 64, 112, 112]         [5, 64, 56, 56]
--
├─Sequential: 1-5                        [5, 64, 56, 56]           [5, 256, 56, 5
6]           --
│    └─Bottleneck: 2-1                   [5, 64, 56, 56]           [5, 256, 56, 5
6]           --
│    │    └─Conv2d: 3-1                  [5, 64, 56, 56]           [5, 64, 56, 56]
4,096
│    │    └─BatchNorm2d: 3-2             [5, 64, 56, 56]           [5, 64, 56, 56]
128
│    │    └─ReLU: 3-3                    [5, 64, 56, 56]           [5, 64, 56, 56]
--
│    │    └─Conv2d: 3-4                  [5, 64, 56, 56]           [5, 64, 56, 56]
36,864
│    │    └─BatchNorm2d: 3-5             [5, 64, 56, 56]           [5, 64, 56, 56]
128
│    │    └─ReLU: 3-6                    [5, 64, 56, 56]           [5, 64, 56, 56]
--
│    │    └─Conv2d: 3-7                  [5, 64, 56, 56]           [5, 256, 56, 5
6]           16,384
│    │    └─BatchNorm2d: 3-8             [5, 256, 56, 56]          [5, 256, 56, 5
6]           512
│    │    └─Sequential: 3-9              [5, 64, 56, 56]           [5, 256, 56, 5
6]           16,896
│    │    └─ReLU: 3-10                   [5, 256, 56, 56]          [5, 256, 56, 5
6]           --
│    └─Bottleneck: 2-2                   [5, 256, 56, 56]          [5, 256, 56, 5
6]           --
│    │    └─Conv2d: 3-11                 [5, 256, 56, 56]          [5, 64, 56, 56]
16,384
│    │    └─BatchNorm2d: 3-12            [5, 64, 56, 56]           [5, 64, 56, 56]
128
│    │    └─ReLU: 3-13                   [5, 64, 56, 56]           [5, 64, 56, 56]
--
│    │    └─Conv2d: 3-14                 [5, 64, 56, 56]           [5, 64, 56, 56]
36,864
│    │    └─BatchNorm2d: 3-15            [5, 64, 56, 56]           [5, 64, 56, 56]
128
│    │    └─ReLU: 3-16                   [5, 64, 56, 56]           [5, 64, 56, 56]
--
│    │    └─Conv2d: 3-17                 [5, 64, 56, 56]           [5, 256, 56, 5
6]           16,384
```

```
│    │    └─BatchNorm2d: 3-18            [5, 256, 56, 56]          [5, 256, 56, 5
6]          512
│    │    └─ReLU: 3-19                   [5, 256, 56, 56]          [5, 256, 56, 5
6]          --
│    └─Bottleneck: 2-3                   [5, 256, 56, 56]          [5, 256, 56, 5
6]          --
│    │    └─Conv2d: 3-20                 [5, 256, 56, 56]          [5, 64, 56, 56]
16,384
│    │    └─BatchNorm2d: 3-21            [5, 64, 56, 56]           [5, 64, 56, 56]
128
│    │    └─ReLU: 3-22                   [5, 64, 56, 56]           [5, 64, 56, 56]
--
│    │    └─Conv2d: 3-23                 [5, 64, 56, 56]           [5, 64, 56, 56]
36,864
│    │    └─BatchNorm2d: 3-24            [5, 64, 56, 56]           [5, 64, 56, 56]
128
│    │    └─ReLU: 3-25                   [5, 64, 56, 56]           [5, 64, 56, 56]
--
│    │    └─Conv2d: 3-26                 [5, 64, 56, 56]           [5, 256, 56, 5
6]          16,384
│    │    └─BatchNorm2d: 3-27            [5, 256, 56, 56]          [5, 256, 56, 5
6]          512
│    │    └─ReLU: 3-28                   [5, 256, 56, 56]          [5, 256, 56, 5
6]          --
├─Sequential: 1-6                        [5, 256, 56, 56]          [5, 512, 28, 2
8]          --
│    └─Bottleneck: 2-4                   [5, 256, 56, 56]          [5, 512, 28, 2
8]          --
│    │    └─Conv2d: 3-29                 [5, 256, 56, 56]          [5, 128, 56, 5
6]          32,768
│    │    └─BatchNorm2d: 3-30            [5, 128, 56, 56]          [5, 128, 56, 5
6]          256
│    │    └─ReLU: 3-31                   [5, 128, 56, 56]          [5, 128, 56, 5
6]          --
│    │    └─Conv2d: 3-32                 [5, 128, 56, 56]          [5, 128, 28, 2
8]          147,456
│    │    └─BatchNorm2d: 3-33            [5, 128, 28, 28]          [5, 128, 28, 2
8]          256
│    │    └─ReLU: 3-34                   [5, 128, 28, 28]          [5, 128, 28, 2
8]          --
│    │    └─Conv2d: 3-35                 [5, 128, 28, 28]          [5, 512, 28, 2
8]          65,536
│    │    └─BatchNorm2d: 3-36            [5, 512, 28, 28]          [5, 512, 28, 2
8]          1,024
│    │    └─Sequential: 3-37             [5, 256, 56, 56]          [5, 512, 28, 2
8]          132,096
│    │    └─ReLU: 3-38                   [5, 512, 28, 28]          [5, 512, 28, 2
8]          --
│    └─Bottleneck: 2-5                   [5, 512, 28, 28]          [5, 512, 28, 2
8]          --
│    │    └─Conv2d: 3-39                 [5, 512, 28, 28]          [5, 128, 28, 2
8]          65,536
│    │    └─BatchNorm2d: 3-40            [5, 128, 28, 28]          [5, 128, 28, 2
8]          256
│    │    └─ReLU: 3-41                   [5, 128, 28, 28]          [5, 128, 28, 2
8]          --
```

```
│    │    └─Conv2d: 3-42                   [5, 128, 28, 28]          [5, 128, 28, 2
8]          147,456
│    │    └─BatchNorm2d: 3-43              [5, 128, 28, 28]          [5, 128, 28, 2
8]          256
│    │    └─ReLU: 3-44                     [5, 128, 28, 28]          [5, 128, 28, 2
8]          --
│    │    └─Conv2d: 3-45                   [5, 128, 28, 28]          [5, 512, 28, 2
8]          65,536
│    │    └─BatchNorm2d: 3-46              [5, 512, 28, 28]          [5, 512, 28, 2
8]          1,024
│    │    └─ReLU: 3-47                     [5, 512, 28, 28]          [5, 512, 28, 2
8]          --
│    └─Bottleneck: 2-6                     [5, 512, 28, 28]          [5, 512, 28, 2
8]          --
│    │    └─Conv2d: 3-48                   [5, 512, 28, 28]          [5, 128, 28, 2
8]          65,536
│    │    └─BatchNorm2d: 3-49              [5, 128, 28, 28]          [5, 128, 28, 2
8]          256
│    │    └─ReLU: 3-50                     [5, 128, 28, 28]          [5, 128, 28, 2
8]          --
│    │    └─Conv2d: 3-51                   [5, 128, 28, 28]          [5, 128, 28, 2
8]          147,456
│    │    └─BatchNorm2d: 3-52              [5, 128, 28, 28]          [5, 128, 28, 2
8]          256
│    │    └─ReLU: 3-53                     [5, 128, 28, 28]          [5, 128, 28, 2
8]          --
│    │    └─Conv2d: 3-54                   [5, 128, 28, 28]          [5, 512, 28, 2
8]          65,536
│    │    └─BatchNorm2d: 3-55              [5, 512, 28, 28]          [5, 512, 28, 2
8]          1,024
│    │    └─ReLU: 3-56                     [5, 512, 28, 28]          [5, 512, 28, 2
8]          --
│    └─Bottleneck: 2-7                     [5, 512, 28, 28]          [5, 512, 28, 2
8]          --
│    │    └─Conv2d: 3-57                   [5, 512, 28, 28]          [5, 128, 28, 2
8]          65,536
│    │    └─BatchNorm2d: 3-58              [5, 128, 28, 28]          [5, 128, 28, 2
8]          256
│    │    └─ReLU: 3-59                     [5, 128, 28, 28]          [5, 128, 28, 2
8]          --
│    │    └─Conv2d: 3-60                   [5, 128, 28, 28]          [5, 128, 28, 2
8]          147,456
│    │    └─BatchNorm2d: 3-61              [5, 128, 28, 28]          [5, 128, 28, 2
8]          256
│    │    └─ReLU: 3-62                     [5, 128, 28, 28]          [5, 128, 28, 2
8]          --
│    │    └─Conv2d: 3-63                   [5, 128, 28, 28]          [5, 512, 28, 2
8]          65,536
│    │    └─BatchNorm2d: 3-64              [5, 512, 28, 28]          [5, 512, 28, 2
8]          1,024
│    │    └─ReLU: 3-65                     [5, 512, 28, 28]          [5, 512, 28, 2
8]          --
├─Sequential: 1-7                          [5, 512, 28, 28]          [5, 1024, 14, 1
4]         --
│    └─Bottleneck: 2-8                     [5, 512, 28, 28]          [5, 1024, 14, 1
4]         --
```

```
│    │    └─Conv2d: 3-66                [5, 512, 28, 28]          [5, 256, 28, 2
8]        131,072
│    │    └─BatchNorm2d: 3-67           [5, 256, 28, 28]          [5, 256, 28, 2
8]        512
│    │    └─ReLU: 3-68                  [5, 256, 28, 28]          [5, 256, 28, 2
8]        --
│    │    └─Conv2d: 3-69                [5, 256, 28, 28]          [5, 256, 14, 1
4]        589,824
│    │    └─BatchNorm2d: 3-70           [5, 256, 14, 14]          [5, 256, 14, 1
4]        512
│    │    └─ReLU: 3-71                  [5, 256, 14, 14]          [5, 256, 14, 1
4]        --
│    │    └─Conv2d: 3-72                [5, 256, 14, 14]          [5, 1024, 14, 1
4]       262,144
│    │    └─BatchNorm2d: 3-73           [5, 1024, 14, 14]         [5, 1024, 14, 1
4]       2,048
│    │    └─Sequential: 3-74            [5, 512, 28, 28]          [5, 1024, 14, 1
4]       526,336
│    │    └─ReLU: 3-75                  [5, 1024, 14, 14]         [5, 1024, 14, 1
4]       --
│    └─Bottleneck: 2-9                  [5, 1024, 14, 14]         [5, 1024, 14, 1
4]       --
│    │    └─Conv2d: 3-76                [5, 1024, 14, 14]         [5, 256, 14, 1
4]        262,144
│    │    └─BatchNorm2d: 3-77           [5, 256, 14, 14]          [5, 256, 14, 1
4]        512
│    │    └─ReLU: 3-78                  [5, 256, 14, 14]          [5, 256, 14, 1
4]        --
│    │    └─Conv2d: 3-79                [5, 256, 14, 14]          [5, 256, 14, 1
4]        589,824
│    │    └─BatchNorm2d: 3-80           [5, 256, 14, 14]          [5, 256, 14, 1
4]        512
│    │    └─ReLU: 3-81                  [5, 256, 14, 14]          [5, 256, 14, 1
4]        --
│    │    └─Conv2d: 3-82                [5, 256, 14, 14]          [5, 1024, 14, 1
4]       262,144
│    │    └─BatchNorm2d: 3-83           [5, 1024, 14, 14]         [5, 1024, 14, 1
4]       2,048
│    │    └─ReLU: 3-84                  [5, 1024, 14, 14]         [5, 1024, 14, 1
4]       --
│    └─Bottleneck: 2-10                 [5, 1024, 14, 14]         [5, 1024, 14, 1
4]       --
│    │    └─Conv2d: 3-85                [5, 1024, 14, 14]         [5, 256, 14, 1
4]        262,144
│    │    └─BatchNorm2d: 3-86           [5, 256, 14, 14]          [5, 256, 14, 1
4]        512
│    │    └─ReLU: 3-87                  [5, 256, 14, 14]          [5, 256, 14, 1
4]        --
│    │    └─Conv2d: 3-88                [5, 256, 14, 14]          [5, 256, 14, 1
4]        589,824
│    │    └─BatchNorm2d: 3-89           [5, 256, 14, 14]          [5, 256, 14, 1
4]        512
│    │    └─ReLU: 3-90                  [5, 256, 14, 14]          [5, 256, 14, 1
4]        --
│    │    └─Conv2d: 3-91                [5, 256, 14, 14]          [5, 1024, 14, 1
4]       262,144
```

```
│    │    └─BatchNorm2d: 3-92           [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        2,048
│    │    └─ReLU: 3-93                  [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        --
│    └─Bottleneck: 2-11                 [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        --
│    │    └─Conv2d: 3-94                [5, 1024, 14, 14]        [5, 256, 14, 1
4]         262,144
│    │    └─BatchNorm2d: 3-95           [5, 256, 14, 14]         [5, 256, 14, 1
4]         512
│    │    └─ReLU: 3-96                  [5, 256, 14, 14]         [5, 256, 14, 1
4]         --
│    │    └─Conv2d: 3-97                [5, 256, 14, 14]         [5, 256, 14, 1
4]         589,824
│    │    └─BatchNorm2d: 3-98           [5, 256, 14, 14]         [5, 256, 14, 1
4]         512
│    │    └─ReLU: 3-99                  [5, 256, 14, 14]         [5, 256, 14, 1
4]         --
│    │    └─Conv2d: 3-100               [5, 256, 14, 14]         [5, 1024, 14, 1
4]        262,144
│    │    └─BatchNorm2d: 3-101          [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        2,048
│    │    └─ReLU: 3-102                 [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        --
│    └─Bottleneck: 2-12                 [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        --
│    │    └─Conv2d: 3-103               [5, 1024, 14, 14]        [5, 256, 14, 1
4]         262,144
│    │    └─BatchNorm2d: 3-104          [5, 256, 14, 14]         [5, 256, 14, 1
4]         512
│    │    └─ReLU: 3-105                 [5, 256, 14, 14]         [5, 256, 14, 1
4]         --
│    │    └─Conv2d: 3-106               [5, 256, 14, 14]         [5, 256, 14, 1
4]         589,824
│    │    └─BatchNorm2d: 3-107          [5, 256, 14, 14]         [5, 256, 14, 1
4]         512
│    │    └─ReLU: 3-108                 [5, 256, 14, 14]         [5, 256, 14, 1
4]         --
│    │    └─Conv2d: 3-109               [5, 256, 14, 14]         [5, 1024, 14, 1
4]        262,144
│    │    └─BatchNorm2d: 3-110          [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        2,048
│    │    └─ReLU: 3-111                 [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        --
│    └─Bottleneck: 2-13                 [5, 1024, 14, 14]        [5, 1024, 14, 1
4]        --
│    │    └─Conv2d: 3-112               [5, 1024, 14, 14]        [5, 256, 14, 1
4]         262,144
│    │    └─BatchNorm2d: 3-113          [5, 256, 14, 14]         [5, 256, 14, 1
4]         512
│    │    └─ReLU: 3-114                 [5, 256, 14, 14]         [5, 256, 14, 1
4]         --
│    │    └─Conv2d: 3-115               [5, 256, 14, 14]         [5, 256, 14, 1
4]         589,824
│    │    └─BatchNorm2d: 3-116          [5, 256, 14, 14]         [5, 256, 14, 1
4]         512
```

```
│    │    └─ReLU: 3-117                 [5, 256, 14, 14]          [5, 256, 14, 1
4]          --
│    │    └─Conv2d: 3-118               [5, 256, 14, 14]          [5, 1024, 14, 1
4]         262,144
│    │    └─BatchNorm2d: 3-119          [5, 1024, 14, 14]         [5, 1024, 14, 1
4]         2,048
│    │    └─ReLU: 3-120                 [5, 1024, 14, 14]         [5, 1024, 14, 1
4]         --
├─Sequential: 1-8                       [5, 1024, 14, 14]         [5, 2048, 7, 7]
--
│    └─Bottleneck: 2-14                 [5, 1024, 14, 14]         [5, 2048, 7, 7]
--
│    │    └─Conv2d: 3-121               [5, 1024, 14, 14]         [5, 512, 14, 1
4]          524,288
│    │    └─BatchNorm2d: 3-122          [5, 512, 14, 14]          [5, 512, 14, 1
4]          1,024
│    │    └─ReLU: 3-123                 [5, 512, 14, 14]          [5, 512, 14, 1
4]          --
│    │    └─Conv2d: 3-124               [5, 512, 14, 14]          [5, 512, 7, 7]
2,359,296
│    │    └─BatchNorm2d: 3-125          [5, 512, 7, 7]            [5, 512, 7, 7]
1,024
│    │    └─ReLU: 3-126                 [5, 512, 7, 7]            [5, 512, 7, 7]
--
│    │    └─Conv2d: 3-127               [5, 512, 7, 7]            [5, 2048, 7, 7]
1,048,576
│    │    └─BatchNorm2d: 3-128          [5, 2048, 7, 7]           [5, 2048, 7, 7]
4,096
│    │    └─Sequential: 3-129           [5, 1024, 14, 14]         [5, 2048, 7, 7]
2,101,248
│    │    └─ReLU: 3-130                 [5, 2048, 7, 7]           [5, 2048, 7, 7]
--
│    └─Bottleneck: 2-15                 [5, 2048, 7, 7]           [5, 2048, 7, 7]
--
│    │    └─Conv2d: 3-131               [5, 2048, 7, 7]           [5, 512, 7, 7]
1,048,576
│    │    └─BatchNorm2d: 3-132          [5, 512, 7, 7]            [5, 512, 7, 7]
1,024
│    │    └─ReLU: 3-133                 [5, 512, 7, 7]            [5, 512, 7, 7]
--
│    │    └─Conv2d: 3-134               [5, 512, 7, 7]            [5, 512, 7, 7]
2,359,296
│    │    └─BatchNorm2d: 3-135          [5, 512, 7, 7]            [5, 512, 7, 7]
1,024
│    │    └─ReLU: 3-136                 [5, 512, 7, 7]            [5, 512, 7, 7]
--
│    │    └─Conv2d: 3-137               [5, 512, 7, 7]            [5, 2048, 7, 7]
1,048,576
│    │    └─BatchNorm2d: 3-138          [5, 2048, 7, 7]           [5, 2048, 7, 7]
4,096
│    │    └─ReLU: 3-139                 [5, 2048, 7, 7]           [5, 2048, 7, 7]
--
│    └─Bottleneck: 2-16                 [5, 2048, 7, 7]           [5, 2048, 7, 7]
--
│    │    └─Conv2d: 3-140               [5, 2048, 7, 7]           [5, 512, 7, 7]
1,048,576
```

```
│    │    └─BatchNorm2d: 3-141           [5, 512, 7, 7]            [5, 512, 7, 7]
1,024
│    │    └─ReLU: 3-142                  [5, 512, 7, 7]            [5, 512, 7, 7]
--
│    │    └─Conv2d: 3-143                [5, 512, 7, 7]            [5, 512, 7, 7]
2,359,296
│    │    └─BatchNorm2d: 3-144           [5, 512, 7, 7]            [5, 512, 7, 7]
1,024
│    │    └─ReLU: 3-145                  [5, 512, 7, 7]            [5, 512, 7, 7]
--
│    │    └─Conv2d: 3-146                [5, 512, 7, 7]            [5, 2048, 7, 7]
1,048,576
│    │    └─BatchNorm2d: 3-147           [5, 2048, 7, 7]           [5, 2048, 7, 7]
4,096
│    │    └─ReLU: 3-148                  [5, 2048, 7, 7]           [5, 2048, 7, 7]
--
├─AdaptiveAvgPool2d: 1-9                 [5, 2048, 7, 7]           [5, 2048, 1, 1]
--
├─Linear: 1-10                           [5, 2048]                 [5, 1000]
2,049,000
==========================================================================================
=================================
Total params: 25,557,032
Trainable params: 25,557,032
Non-trainable params: 0
Total mult-adds (G): 20.45
==========================================================================================
=================================
Input size (MB): 3.01
Forward/backward pass size (MB): 889.16
Params size (MB): 102.23
Estimated Total Size (MB): 994.40
==========================================================================================
=================================
```

We set the mode to eval() to ensure that the model is ready to predict on new data

In [72]:
```
resnet_model.eval()
```

Out[72]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=F
alse)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats
=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=F
alse)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), b
ias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), b
ias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), b
ias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer3): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
    )
    (4): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
    )
    (5): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1),
bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=2048, out_features=1000, bias=True)
)
```

Inspecting the output above, we see that when setting up the resnet_model, the authors defned a Bottleneck, much like our BuildingBlock module.

We now feed our six images through the ftted network.

In [73]:
```
img_preds = resnet_model(imgs)
```

Let’s look at the predicted probabilities for each of the top 3 choices. First we compute the probabilities by applying the softmax to the logits in img_preds. Note that we have had to call the detach() method on the tensor img_preds in order to convert it to our a more familiar ndarray.

In [74]:
```
img_probs = np.exp(np.asarray(img_preds.detach()))
img_probs /= img_probs.sum(1)[:,None]
```

In order to see the class labels, we must download the index fle associated with imagenet.

In [76]:
```
labs = json.load(open('imagenet_class_index.json'))
class_labels = pd.DataFrame([(int(k), v[1]) for k, v in labs.items()], columns=['id
class_labels = class_labels.set_index('idx')
class_labels = class_labels.sort_index()
```

We’ll now construct a data frame for each image fle with the labels with the three highest probabilities as estimated by the model above.

In [77]:
```
for i, imgfile in enumerate(imgfiles):
    img_df = class_labels.copy()
    img_df['prob'] = img_probs[i]
    img_df = img_df.sort_values(by='prob', ascending=False)[:3]
    print(f'Image: {imgfile}')
    print(img_df.reset_index().drop(columns=['idx']))
```

```
Image: book_images\Cape_Weaver.jpg
      label      prob
0   jacamar  0.297500
1     macaw  0.068107
2  lorikeet  0.051104
Image: book_images\Hawk_Fountain.jpg
            label      prob
0            kite  0.184716
1           robin  0.084018
2  great_grey_owl  0.061267
Image: book_images\Hawk_cropped.jpg
            label      prob
0            kite  0.453834
1  great_grey_owl  0.015914
2             jay  0.012210
Image: book_images\Lhasa_Apso.jpg
             label      prob
0            Lhasa  0.260317
1         Shih-Tzu  0.097196
2  Tibetan_terrier  0.032820
Image: book_images\Sleeping_Cat.jpg
        label      prob
0  Persian_cat  0.163070
1        tabby  0.074143
2    tiger_cat  0.042578
```

We see that the model is quite confdent about Flamingo.jpg, but a little less so for the other images.

We end this section with our usual cleanup.

In [78]:
```
del(cifar_test,cifar_train,cifar_dm,cifar_module,cifar_logger,cifar_optimizer,cifar
```

10.9.5 IMDB Document Classifcation

We now implement models for sentiment classifcation (Section 10.4) on the IMDB dataset. As mentioned above code block 8, we are using a preprocessed version of the IMDB dataset found in the keras package. As keras uses tensorflow, a diferent tensor and deep learning library, we have converted the data to be suitable for torch. The code used to convert from keras is available in the module ISLP.torch._make_imdb. It requires some of the keras packages to run. These data use a dictionary of size 10,000.

We have stored three diferent representations of the review data for this lab:

• load_tensor(), a sparse tensor version usable by torch;

• load_sparse(), a sparse matrix version usable by sklearn, since we will compare with a lasso ft;

• load_sequential(), a padded version of the original sequence representation, limited to the last 500 words of each review.

```
In [10]: (imdb_seq_train,imdb_seq_test) = load_sequential(root='data/IMDB')
         padded_sample = np.asarray(imdb_seq_train.tensors[0][0])
         sample_review = padded_sample[padded_sample > 0][:12]
         sample_review[:12]
```

```
Out[10]: array([   1,   14,   22,   16,   43,  530,  973, 1622, 1385,   65,  458,
                4468])
```

The datasets imdb_seq_train and imdb_seq_test are both instances of the class TensorDataset. The tensors used to construct them can be found in the tensors attribute, with the frst tensor the features X and the second the outcome Y. We have taken the frst row of features and stored it as padded_sample. In the preprocessing used to form these data, sequences were padded with 0s in the beginning if they were not long enough, hence we remove this padding by restricting to entries where padded_sample > 0. We then provide the frst 12 words of the sample review.

We can fnd these words in the lookup dictionary from the ISLP.torch.imdb module

```
In [11]: lookup = load_lookup(root='data/IMDB')
         ' '.join(lookup[i] for i in sample_review)
```

```
Out[11]: "<START> this film was just brilliant casting location scenery story direction eve
         ryone's"
```

For our frst model, we have created a binary feature for each of the 10,000 possible words in the dataset, with an entry of one in the i, j entry if word j appears in review i. As most reviews are quite short, such a feature matrix has over 98% zeros. These data are accessed using load_tensor() from the ISLP library.

```
In [12]: max_num_workers=10
         (imdb_train,imdb_test) = load_tensor(root='data/IMDB')
         imdb_dm = SimpleDataModule(imdb_train,imdb_test,validation=2000,num_workers=min(6,
```

We'll use a two-layer model for our frst model.

In [13]:
```
class IMDBModel(nn.Module):
    def __init__(self, input_size):
        super(IMDBModel, self).__init__()
        self.dense1 = nn.Linear(input_size, 16)
        self.activation = nn.ReLU()
        self.dense2 = nn.Linear(16, 16)
        self.output = nn.Linear(16, 1)
    def forward(self, x):
        val = x
        for _map in [self.dense1,self.activation,self.dense2,self.activation,self.o
            val = _map(val)
        return torch.flatten(val)
```

We now instantiate our model and look at a summary (not shown).

In [14]:
```
imdb_model = IMDBModel(imdb_test.tensors[0].size()[1])
summary(imdb_model,input_size=imdb_test.tensors[0].size(),col_names=['input_size','
```

Out[14]:
```
==================================================================================
=================================
Layer (type:depth-idx)                   Input Shape               Output Shape
Param #
==================================================================================
=================================
IMDBModel                                [25000, 10003]            [25000]
--
├─Linear: 1-1                            [25000, 10003]            [25000, 16]
160,064
├─ReLU: 1-2                              [25000, 16]               [25000, 16]
--
├─Linear: 1-3                            [25000, 16]               [25000, 16]
272
├─ReLU: 1-4                              [25000, 16]               [25000, 16]
--
├─Linear: 1-5                            [25000, 16]               [25000, 1]
17
==================================================================================
=================================
Total params: 160,353
Trainable params: 160,353
Non-trainable params: 0
Total mult-adds (G): 4.01
==================================================================================
=================================
Input size (MB): 1000.30
Forward/backward pass size (MB): 6.60
Params size (MB): 0.64
Estimated Total Size (MB): 1007.54
==================================================================================
=================================
```

We'll again use a smaller learning rate for these data, hence we pass an optimizer to the SimpleModule. Since the reviews are classifed into positive or negative sentiment, we use SimpleModule.binary_classification()

In [15]:
```
imdb_optimizer = RMSprop(imdb_model.parameters(), lr=0.001)
imdb_module = SimpleModule.binary_classification(imdb_model,optimizer=imdb_optimize
```

Having loaded the datasets into a data module and created a SimpleModule, the remaining steps are familiar.

In [17]:
```
imdb_logger = CSVLogger('logs', name='IMDB')
imdb_trainer = Trainer(deterministic=True,max_epochs=30,logger=imdb_logger,callback
imdb_trainer.fit(imdb_module,datamodule=imdb_dm)
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs

  | Name  | Type              | Params
--------------------------------------------
0 | model | IMDBModel         | 160 K
1 | loss  | BCEWithLogitsLoss | 0
--------------------------------------------
160 K     Trainable params
0         Non-trainable params
160 K     Total params
0.641     Total estimated model params size (MB)
Sanity Checking: 0it [00:00, ?it/s]
Training: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
```

```
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
`Trainer.fit` stopped: `max_epochs=30` reached.
```

Evaluating the test error yields roughly 86% accuracy.

In [18]:
```
test_results = imdb_trainer.test(imdb_module, datamodule=imdb_dm)
test_results
```

```
Testing: 0it [00:00, ?it/s]
────────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
       Test metric             DataLoader 0
────────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
      test_accuracy         0.8487600088119507
        test_loss           1.4336767196655273
────────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
```

Out[18]:
```
[{'test_loss': 1.4336767196655273, 'test_accuracy': 0.8487600088119507}]
```

Comparison to Lasso

We now ft a lasso logistic regression model using LogisticRegression() from sklearn. Since sklearn does not recognize the sparse tensors of torch, we use a sparse matrix that is recognized by sklearn.

In [19]:
```
((X_train, Y_train),(X_valid, Y_valid),(X_test, Y_test)) = load_sparse(validation=2
```

```
Retrieving "IMDB_X_test.npz" from "http://imdb.jtaylor.su.domains/jtaylor/data/".
Retrieving "IMDB_X_train.npz" from "http://imdb.jtaylor.su.domains/jtaylor/data/".
```

Similar to what we did in Section 10.9.1, we construct a series of 50 values for the lasso reguralization parameter λ.

In [20]:
```
lam_max = np.abs(X_train.T * (Y_train - Y_train.mean())).max()
lam_val = lam_max * np.exp(np.linspace(np.log(1),np.log(1e-4), 50))
```

With LogisticRegression() the regularization parameter C is specifed as the inverse of λ. There are several solvers for logistic regression; here we use liblinear which works well with the sparse input format.

In [21]:
```
logit = LogisticRegression(penalty='l1',C=1/lam_max,solver='liblinear',warm_start=T
```

The path of 50 values takes approximately 40 seconds to run.

In [22]:
```
coefs = []
intercepts = []
for l in lam_val:
    logit.C = 1/l
    logit.fit(X_train, Y_train)
    coefs.append(logit.coef_.copy())
    intercepts.append(logit.intercept_)
```

The coefcient and intercepts have an extraneous dimension which can be removed by the np.squeeze() function

In [23]:
```
coefs = np.squeeze(coefs)
intercepts = np.squeeze(intercepts)
```

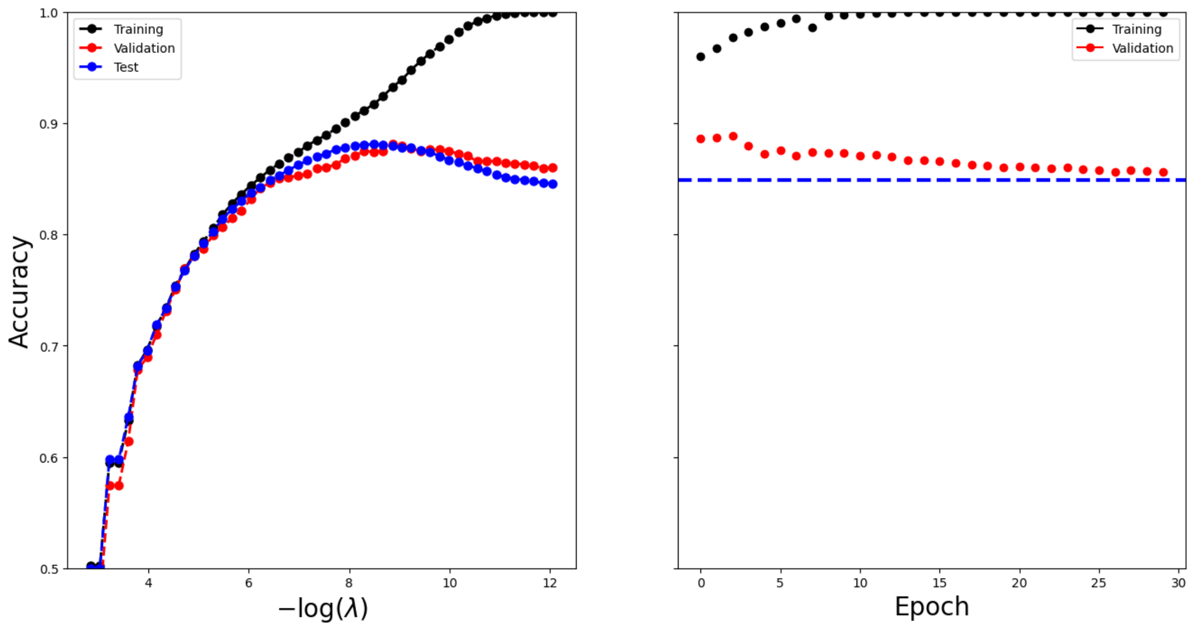
We'll now make a plot to compare our neural network results with the lasso.

In [24]:
```
%%capture
fig, axes = subplots(1, 2, figsize=(16, 8), sharey=True)
for ((X_, Y_),data_,color) in zip([(X_train, Y_train),(X_valid, Y_valid),(X_test, Y
    linpred_ = X_ * coefs.T + intercepts[None,:]
    label_ = np.array(linpred_ > 0)
    accuracy_ = np.array([np.mean(Y_ == l) for l in label_.T])
    axes[0].plot(-np.log(lam_val / X_train.shape[0]),accuracy_,'.--',color=color,ma
axes[0].legend()
axes[0].set_xlabel(r'$-\log(\lambda)$', fontsize=20)
axes[0].set_ylabel('Accuracy', fontsize=20)
```

Notice the use of %%capture, which suppresses the displaying of the partially completed fgure. This is useful when making a complex fgure, since the steps can be spread across two or more cells. We now add a plot of the lasso accuracy, and display the composed fgure by simply entering its name at the end of the cell.

In [27]:
```
imdb_results = pd.read_csv(imdb_logger.experiment.metrics_file_path)
summary_plot(imdb_results,axes[1],col='accuracy',ylabel='Accuracy')
axes[1].set_xticks(np.linspace(0, 30, 7).astype(int))
axes[1].set_ylabel('Accuracy', fontsize=20)
axes[1].set_xlabel('Epoch', fontsize=20)
axes[1].set_ylim([0.5, 1]);
axes[1].axhline(test_results[0]['test_accuracy'],color='blue',linestyle='--',linewi
fig
```

Out[27]:



From the graphs we see that the accuracy of the lasso logistic regression peaks at about 0.88, as it does for the neural network.

Once again, we end with a cleanup.

In [28]:
```
del(imdb_model,imdb_trainer,imdb_logger,imdb_dm,imdb_train,imdb_test)
```

10.9.6 Recurrent Neural Networks

Sequential Models for Document Classifcation

Here we ft a simple LSTM RNN for sentiment prediction to the IMDb movie-review data, as discussed in Section 10.5.1. For an RNN we use the sequence of words in a document, taking their order into account. We loaded the preprocessed data at the beginning of Section 10.9.5. A script that details the preprocessing can be found in the ISLP library. Notably, since more than 90% of the documents had fewer than 500 words, we set the document length to 500. For longer documents, we used the last 500 words, and for shorter documents, we padded the front with blanks

In [29]:
```
imdb_seq_dm = SimpleDataModule(imdb_seq_train,imdb_seq_test,validation=2000,batch_s
```

The frst layer of the RNN is an embedding layer of size 32, which will be learned during training. This layer one-hot encodes each document as a matrix of dimension 500×10, 003, and then maps these 10, 003 dimensions down to 32. 29 Since each word is represented by an integer, this is efectively achieved by the creation of an embedding matrix of size 10, 003 × 32; each of the 500 integers in the document are then mapped to the appropriate 32 real numbers by indexing the appropriate rows of this matrix.

The second layer is an LSTM with 32 units, and the output layer is a single logit for the binary classifcation task. In the last line of the forward() method below, we take the last 32-dimensional output of the LSTM and map it to our response.

In [30]:
```
class LSTMModel(nn.Module):
    def __init__(self, input_size):
        super(LSTMModel, self).__init__()
        self.embedding = nn.Embedding(input_size, 32)
        self.lstm = nn.LSTM(input_size=32,
        hidden_size=32,
        batch_first=True)
        self.dense = nn.Linear(32, 1)
    def forward(self, x):
        val, (h_n, c_n) = self.lstm(self.embedding(x))
        return torch.flatten(self.dense(val[:,-1]))
```

We instantiate and take a look at the summary of the model, using the frst 10 documents in the corpus.

In [31]:
```
lstm_model = LSTMModel(X_test.shape[-1])
summary(lstm_model,input_data=imdb_seq_train.tensors[0][:10],
col_names=['input_size','output_size','num_params'])
```

Out[31]:
```
==================================================================================
=================================
Layer (type:depth-idx)                   Input Shape               Output Shape
Param #
==================================================================================
=================================
LSTMModel                                [10, 500]                 [10]
--
├─Embedding: 1-1                         [10, 500]                 [10, 500, 32]
320,096
├─LSTM: 1-2                              [10, 500, 32]             [10, 500, 32]
8,448
├─Linear: 1-3                            [10, 32]                  [10, 1]
33
==================================================================================
=================================
Total params: 328,577
Trainable params: 328,577
Non-trainable params: 0
Total mult-adds (M): 45.44
==================================================================================
=================================
Input size (MB): 50.00
Forward/backward pass size (MB): 2.56
Params size (MB): 1.31
Estimated Total Size (MB): 53.87
==================================================================================
=================================
```

The 10,003 is suppressed in the summary, but we see it in the parameter count, since 10, 003 × 32 = 320, 096.

In [32]:
```
lstm_module = SimpleModule.binary_classification(lstm_model)
lstm_logger = CSVLogger('logs', name='IMDB_LSTM')
```

In [33]:
```
lstm_trainer = Trainer(deterministic=True,max_epochs=20,logger=lstm_logger,callback
lstm_trainer.fit(lstm_module,datamodule=imdb_seq_dm)
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs
Missing logger folder: logs\IMDB_LSTM

  | Name  | Type              | Params
--------------------------------------------
0 | model | LSTMModel         | 328 K
1 | loss  | BCEWithLogitsLoss | 0
--------------------------------------------
328 K     Trainable params
0         Non-trainable params
328 K     Total params
1.314     Total estimated model params size (MB)
Sanity Checking: 0it [00:00, ?it/s]
Training: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
`Trainer.fit` stopped: `max_epochs=20` reached.
```

The rest is now similar to other networks we have ft. We track the test performance as the network is ft, and see that it attains 85% accuracy

In [34]:
```
lstm_trainer.test(lstm_module, datamodule=imdb_seq_dm)
```

```
Testing: 0it [00:00, ?it/s]
```

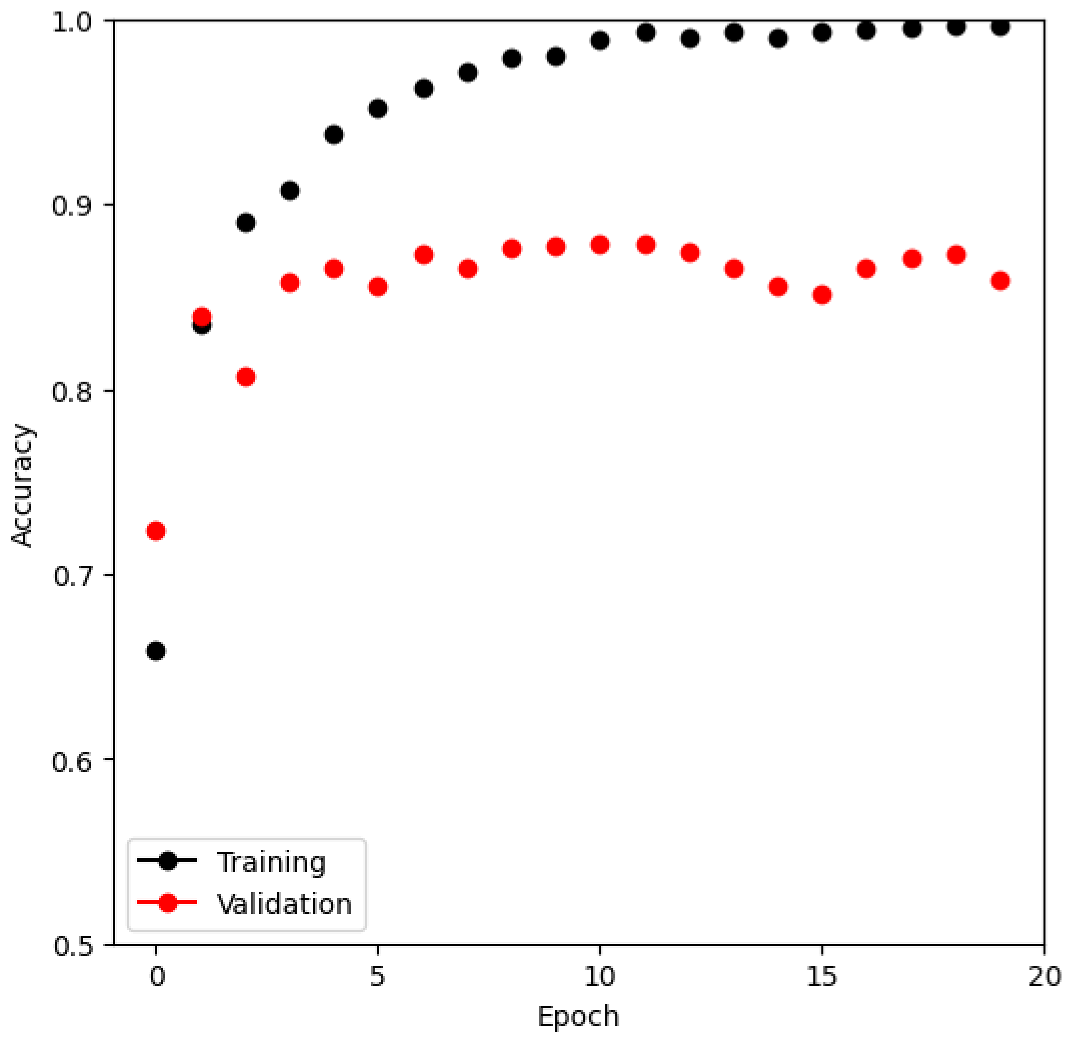
```
────────────────────────────────────────────────────────────────────────────────
────────────────────────────
       Test metric             DataLoader 0
────────────────────────────────────────────────────────────────────────────────
────────────────────────────
      test_accuracy         0.8510800004005432
        test_loss           0.7619530558586121
────────────────────────────────────────────────────────────────────────────────
────────────────────────────
```

Out[34]:
```
[{'test_loss': 0.7619530558586121, 'test_accuracy': 0.8510800004005432}]
```

We once again show the learning progress, followed by cleanup

In [35]:
```python
lstm_results = pd.read_csv(lstm_logger.experiment.metrics_file_path)
fig, ax = subplots(1, 1, figsize=(6, 6))
summary_plot(lstm_results,ax,col='accuracy',ylabel='Accuracy')
ax.set_xticks(np.linspace(0, 20, 5).astype(int))
ax.set_ylabel('Accuracy')
ax.set_ylim([0.5, 1])
```

Out[35]:
```
(0.5, 1.0)
```



In [36]:
```python
del(lstm_model,lstm_trainer,lstm_logger,imdb_seq_dm,imdb_seq_train,imdb_seq_test)
```

Time Series Prediction

We now show how to ft the models in Section 10.5.2 for time series prediction. We frst load and standardize the data.

In [37]:
```
NYSE = load_data('NYSE')
cols = ['DJ_return', 'log_volume', 'log_volatility']
X = pd.DataFrame(StandardScaler(with_mean=True,with_std=True).fit_transform(NYSE[co
```

Next we set up the lagged versions of the data, dropping any rows with missing values using the dropna() method.

In [38]:
```
for lag in range(1, 6):
    for col in cols:
        newcol = np.zeros(X.shape[0]) * np.nan
        newcol[lag:] = X[col].values[:-lag]
        X.insert(len(X.columns), "{0}_{1}".format(col, lag), newcol)
X.insert(len(X.columns), 'train', NYSE['train'])
X = X.dropna()
```

Finally, we extract the response, training indicator, and drop the current day's DJ_return and log_volatility to predict only from previous day's data.

In [39]:
```
Y, train = X['log_volume'], X['train']
X = X.drop(columns=['train'] + cols)
X.columns
```

Out[39]:
```
Index(['DJ_return_1', 'log_volume_1', 'log_volatility_1', 'DJ_return_2',
       'log_volume_2', 'log_volatility_2', 'DJ_return_3', 'log_volume_3',
       'log_volatility_3', 'DJ_return_4', 'log_volume_4', 'log_volatility_4',
       'DJ_return_5', 'log_volume_5', 'log_volatility_5'],
      dtype='object')
```

We frst ft a simple linear model and compute the R2 on the test data using the score() method.

We reft this model, including the factor variable day_of_week. For a categorical series in pandas, we can form the indicators using the get_dummies() method

In [40]:
```
X_day = pd.merge(X,pd.get_dummies(NYSE['day_of_week']),on='date')
```

Note that we do not have to reinstantiate the linear regression model as its fit() method accepts a design matrix and a response directly.

In [41]:
```
M.fit(X_day[train], Y[train])
M.score(X_day[~train], Y[~train])
```

```
  Cell In[41], line 2
    M.score(X_day[~train], Y[~train])
                  ^
SyntaxError: invalid character '~' (U+223C)
```

This model achieves an R2 of about 46%.

To ft the RNN, we must reshape the data, as it will expect 5 lagged versions of each feature as indicated by the input_shape argument to the layer nn.RNN() below. We frst ensure the columns of our data frame are such that a reshaped matrix will have the variables correctly lagged. We use the reindex() method to do this.

For an input shape (5,3), each row represents a lagged version of the three variables. The nn.RNN() layer also expects the frst row of each observation to be earliest in time, so we must reverse the current order. Hence we loop over range(5,0,-1) below, which is an example of using a slice() to index iterable objects. The general notation is start:end:step.

In [42]:
```
ordered_cols = []
for lag in range(5,0,-1):
    for col in cols:
        ordered_cols.append('{0}_{1}'.format(col, lag))
X = X.reindex(columns=ordered_cols)
X.columns
```

Out[42]:
```
Index(['DJ_return_5', 'log_volume_5', 'log_volatility_5', 'DJ_return_4',
       'log_volume_4', 'log_volatility_4', 'DJ_return_3', 'log_volume_3',
       'log_volatility_3', 'DJ_return_2', 'log_volume_2', 'log_volatility_2',
       'DJ_return_1', 'log_volume_1', 'log_volatility_1'],
      dtype='object')
```

We now reshape the data.

In [43]:
```
X_rnn = X.to_numpy().reshape((-1,5,3))
X_rnn.shape
```

Out[43]:
```
(6046, 5, 3)
```

By specifying the frst size as -1, numpy.reshape() deduces its size based on the remaining arguments.

Now we are ready to proceed with the RNN, which uses 12 hidden units, and 10% dropout. After passing through the RNN, we extract the fnal time point as val[:,-1] in forward() below. This gets passed through a 10% dropout and then fattened through a linear layer.

In [44]:
```
class NYSEModel(nn.Module):
    def __init__(self):
        super(NYSEModel, self).__init__()
        self.rnn = nn.RNN(3,
        12,
        batch_first=True)
        self.dense = nn.Linear(12, 1)
        self.dropout = nn.Dropout(0.1)
    def forward(self, x):
        val, h_n = self.rnn(x)
        val = self.dense(self.dropout(val[:,-1]))
        return torch.flatten(val)
nyse_model = NYSEModel()
```

We ft the model in a similar fashion to previous networks. We supply the fit function with test data as validation data, so that when we monitor its progress and plot the history function we can see the progress on the test data. Of course we should not use this as a basis for early stopping, since then the test performance would be biased.

We form the training dataset similar to our Hitters example

In [50]:
```
datasets = []
for mask in [train, ~train]:
    X_rnn_t = torch.tensor(X_rnn[mask].astype(np.float32))
    Y_t = torch.tensor(Y[mask].astype(np.float32))
    datasets.append(TensorDataset(X_rnn_t, Y_t))
nyse_train, nyse_test = datasets
```

Following our usual pattern, we inspect the summary.

In [51]:
```
summary(nyse_model,input_data=X_rnn_t,col_names=['input_size','output_size','num_pa
```

Out[51]:
```
===================================================================================
=================================
Layer (type:depth-idx)                  Input Shape               Output Shape
Param #
===================================================================================
=================================
NYSEModel                               [1770, 5, 3]              [1770]
--
├─RNN: 1-1                              [1770, 5, 3]              [1770, 5, 12]
204
├─Dropout: 1-2                          [1770, 12]                [1770, 12]
--
├─Linear: 1-3                           [1770, 12]                [1770, 1]
13
===================================================================================
=================================
Total params: 217
Trainable params: 217
Non-trainable params: 0
Total mult-adds (M): 1.83
===================================================================================
=================================
Input size (MB): 0.11
Forward/backward pass size (MB): 0.86
Params size (MB): 0.00
Estimated Total Size (MB): 0.97
===================================================================================
=================================
```

We again put the two datasets into a data module, with a batch size of 64.

```
In [52]: nyse_dm = SimpleDataModule(nyse_train,nyse_test,num_workers=min(4, max_num_workers)
```

We run some data through our model to be sure the sizes match up correctly

```
In [53]: for idx, (x, y) in enumerate(nyse_dm.train_dataloader()):
             out = nyse_model(x)
             print(y.size(), out.size())
             if idx >= 2:
                 break
```

```
torch.Size([64]) torch.Size([64])
torch.Size([64]) torch.Size([64])
torch.Size([64]) torch.Size([64])
```

We follow our previous example for setting up a trainer for a regression problem, requesting the R2 metric to be be computed at each epoch.

```
In [54]: nyse_optimizer = RMSprop(nyse_model.parameters(),lr=0.001)
         nyse_module = SimpleModule.regression(nyse_model,optimizer=nyse_optimizer,metrics={
```

Fitting the model should by now be familiar. The results on the test data are very similar to the linear AR model.

```
In [55]: nyse_trainer = Trainer(deterministic=True,max_epochs=200,callbacks=[ErrorTracker()]
         nyse_trainer.fit(nyse_module,datamodule=nyse_dm)
         nyse_trainer.test(nyse_module,datamodule=nyse_dm)
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs

  | Name  | Type      | Params
------------------------------------
0 | model | NYSEModel | 217
1 | loss  | MSELoss   | 0
------------------------------------
217       Trainable params
0         Non-trainable params
217       Total params
0.001     Total estimated model params size (MB)
Sanity Checking: 0it [00:00, ?it/s]
Training: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
```

```
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
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Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
Validation: 0it [00:00, ?it/s]
```

```
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`Trainer.fit` stopped: `max_epochs=200` reached.
Testing: 0it [00:00, ?it/s]
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       Test metric             DataLoader 0
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────────────────────────────────────
        test_loss           0.6153677105903625
         test_r2            0.4159860610961914
────────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
```

Out[55]:
```
[{'test_loss': 0.6153677105903625, 'test_r2': 0.4159860610961914}]
```

We could also ft a model without the nn.RNN() layer by just using a nn.Flatten() layer instead. This would be a nonlinear AR model. If in addition we excluded the hidden layer, this would be equivalent to our earlier linear AR model.

Instead we will ft a nonlinear AR model using the feature set X_day that includes the day_of_week indicators. To do so, we must frst create our test and training datasets and a corresponding data module. This may seem a little burdensome, but is part of the general pipeline for torch.

In [57]:
```python
datasets = []
for mask in [train, ~train]:
    X_day_t = torch.tensor(np.asarray(X_day[mask]).astype(np.float32))
    Y_t = torch.tensor(np.asarray(Y[mask]).astype(np.float32))
    datasets.append(TensorDataset(X_day_t, Y_t))
day_train, day_test = datasets
```

Creating a data module follows a familiar pattern.

In [58]:
```
day_dm = SimpleDataModule(day_train,day_test,num_workers=min(4, max_num_workers),va
```

We build a NonLinearARModel() that takes as input the 20 features and a hidden layer with 32 units. The remaining steps are familiar.

In [59]:
```
class NonLinearARModel(nn.Module):
    def __init__(self):
        super(NonLinearARModel , self).__init__()
        self._forward = nn.Sequential(nn.Flatten(),nn.Linear(20, 32),nn.ReLU(),nn.D
    def forward(self, x):
        return torch.flatten(self._forward(x))
```

In [60]:
```
nl_model = NonLinearARModel()
nl_optimizer = RMSprop(nl_model.parameters(),lr=0.001)
nl_module = SimpleModule.regression(nl_model,optimizer=nl_optimizer,metrics={'r2':R
```

We continue with the usual training steps, ft the model, and evaluate the test error. We see the test R2 is a slight improvement over the linear AR model that also includes day_of_week.

In [61]:
```
nl_trainer = Trainer(deterministic=True,max_epochs=20,
callbacks=[ErrorTracker()])
nl_trainer.fit(nl_module, datamodule=day_dm)
nl_trainer.test(nl_module, datamodule=day_dm)
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs

  | Name  | Type             | Params
-------------------------------------------
0 | model | NonLinearARModel | 705
1 | loss  | MSELoss          | 0
-------------------------------------------
705       Trainable params
0         Non-trainable params
705       Total params
0.003     Total estimated model params size (MB)
Sanity Checking: 0it [00:00, ?it/s]
Training: 0it [00:00, ?it/s]
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`Trainer.fit` stopped: `max_epochs=20` reached.
Testing: 0it [00:00, ?it/s]
────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
       Test metric             DataLoader 0
────────────────────────────────────────────────────────────────────────────────────
────────────────────────────────────
        test_loss           0.5610806941986084
         test_r2             0.467507004737854
────────────────────────────────────────────────────────────────────────────────────
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```

Out[61]:
```
[{'test_loss': 0.5610806941986084, 'test_r2': 0.467507004737854}]
```

In [ ]:

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In [ ]:

In [ ]: