In [1]:
```
# Using ResNet-18 for image classification
# Data:
    # cinic10 --> https://www.kaggle.com/mengcius/cinic10
    # a subset of cinic10 containing only four classes - airplane, automobile, ship, and truck - is used
        # files from cinic10 'train' and 'val' folders are combined into one to provide 18000 training images from each class
        # test folders contain 9000 images from each class

# Note: here GPU processing is used --> running times with CPU would be greater
```

In [2]:
```
# import libraries

import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
from torchvision.utils import make_grid
import os

import numpy as np
import pandas as pd
import seaborn as sns  # for heatmaps
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style = "whitegrid", font_scale = 1.2)

# ignore non-critical warnings
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
# define transforms

cinic_mean = [0.4789, 0.4723, 0.4305] # from cinic10 'Readme' file
cinic_std = [0.2421, 0.2383, 0.2587] # from cinic10 'Readme' file

# we are using the same transforms for both train and test images
img_transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize(mean = cinic_mean, std = cinic_std)
])
```

In [4]:
```
# prepare train and test sets, loaders

# define root directory path
root = 'datasets/cinic10_classes4'

# batch size
b_size = 16

train_data = datasets.ImageFolder(os.path.join(root, 'train'), transform = img
_transform)
test_data = datasets.ImageFolder(os.path.join(root, 'test'), transform = img_t
ransform)

torch.manual_seed(42)
train_loader = DataLoader(train_data, batch_size = b_size, shuffle = True)
test_loader = DataLoader(test_data, batch_size = b_size, shuffle = True)

class_names = train_data.classes

print(class_names)
print(f'Training images available: {len(train_data)}')
print(f'Testing images available:  {len(test_data)}')
```

```
['airplane', 'automobile', 'ship', 'truck']
Training images available: 72000
Testing images available:  36000
```

In [5]:
```
# display a batch of images --> grab first batch of 16 images from train data

for images,labels in train_loader:
    break

images.shape
```

Out[5]:
```
torch.Size([16, 3, 32, 32])
```

In [6]:
```
# 16 images in one batch, 3 color channels (R-G-B), 32 x 32 pixels
```

In [7]:
```
# show images and their classes

# print labels
print('Label:', labels.numpy())
print('Class:', *np.array([class_names[i] for i in labels]))

im = make_grid(images)  # the default nrow is 8

# inverse normalize the images

inv_normalize = transforms.Normalize(
    mean=[-0.4789/0.2421, -0.4723/0.2383, -0.4305/0.2587],
    std=[1/0.2421, 1/0.2383, 1/0.2587]
)
im_inv = inv_normalize(im)

# print images
plt.figure(figsize=(16,6))
plt.imshow(np.transpose(im_inv.numpy(), (1, 2, 0)));
```

```
Label: [1 1 1 1 1 3 2 2 1 1 1 1 0 0 3 0]
Class: automobile automobile automobile automobile automobile truck ship ship
automobile automobile automobile automobile airplane airplane truck airplane
```

In [8]:
```
# everything works fine!
```

In [9]:
```
# select resnet18 model from torchvision models
ResNet18model = models.resnet18()
```

In [10]:
```
# display structure of resnet18
ResNet18model
```

Out[10]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), b
ias=False)
  (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_m
ode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=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_run
ning_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=512, out_features=1000, bias=True)
)
```

In [11]:
```
# modify last layer of model to have 4 outputs only --> we work with four clas
ses only
torch.manual_seed(42)

ResNet18model.fc = nn.Sequential(nn.Linear(512, 4),
                                 nn.LogSoftmax(dim=1))

ResNet18model
```

Out[11]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), b
ias=False)
  (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_m
ode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=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_run
ning_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=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_run
ning_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Sequential(
    (0): Linear(in_features=512, out_features=4, bias=True)
    (1): LogSoftmax()
  )
)
```

In [12]:
```
# last layer of model has been modified to meet our needs
```

In [13]:
```
# count model parameters

def count_parameters(model):
    params = [p.numel() for p in model.parameters() if p.requires_grad]
    for item in params:
        print(f'{item:>6}')
    print(f'______\n{sum(params):>6}')

count_parameters(ResNet18model)
```

```
  9408
    64
    64
 36864
    64
    64
 36864
    64
    64
 36864
    64
    64
 36864
    64
    64
 73728
   128
   128
147456
   128
   128
  8192
   128
   128
147456
   128
   128
147456
   128
   128
294912
   256
   256
589824
   256
   256
 32768
   256
   256
589824
   256
   256
589824
   256
   256
1179648
   512
   512
2359296
   512
   512
131072
   512
   512
2359296
   512
   512
```

```
2359296
   512
   512
  2048
     4
______
11178564
```

In [14]:

```
# approximately 11 million parameters which is not so large of a number
```

In [15]:

```
# check if GPU computing is available

# torch.cuda.is_available() checks and returns a Boolean True if a GPU with CU
DA is available, else it returns False
is_cuda = torch.cuda.is_available()

# set device to GPU or CPU depending on the outcome --> we will use this devic
e variable later on in our code!
if is_cuda:
    device = torch.device("cuda")
else:
    device = torch.device("cpu")
```

In [16]:

```
# set model to work with available device
ResNet18model.to(device)

# define optimizer --> optimizer needs to be defined after device for model is
selected!
optimizer = torch.optim.Adam(ResNet18model.parameters(), lr = 0.001)

# define loss function
criterion = nn.CrossEntropyLoss()
```

In [17]:
```
# start training

import time
start_time = time.time()

epochs = 40

# limit number of train and test images --> optional - saves time to run with
 small numbers first to see if model works
max_trn_batch = 1000
max_tst_batch = 500

# instantiate trackers for model performance
train_losses = []
test_losses = []
train_correct = []
test_correct = []

for i in range(epochs):
    trn_corr = 0
    tst_corr = 0

    # run the training batches
    for b, (X_train, y_train) in enumerate(train_loader):

        # limit the number of batches
        if b == max_trn_batch:
            break
        b+=1

        # apply the model
        y_pred = ResNet18model(X_train.to(device))
        loss = criterion(y_pred, y_train.to(device))

        # tally the number of correct predictions
        predicted = torch.max(y_pred.data, 1)[1]
        batch_corr = (predicted == y_train.to(device)).sum()
        trn_corr += batch_corr

        # update parameters
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # print interim results
        if b%max_trn_batch == 0:
            print(f'Epoch: {i+1:3}   Batch: {b:4}   Loss: {loss.item():10.4f}
Accuracy: {trn_corr.item()*100/(b_size*b):7.2f}% \
 Time Elapsed Since Start: {(time.time() - start_time)/60:7.2f} min')

    train_losses.append(loss)
    train_correct.append(trn_corr)

    # run the test batches
    with torch.no_grad():
        for b, (X_test, y_test) in enumerate(test_loader):
```

```
            # Limit the number of batches
            if b == max_tst_batch:
                break

            # apply the model
            y_val = ResNet18model(X_test.to(device))

            # tally the number of correct predictions
            predicted = torch.max(y_val.data, 1)[1]
            tst_corr += (predicted == y_test.to(device)).sum()

    loss = criterion(y_val, y_test.to(device))
    test_losses.append(loss)
    test_correct.append(tst_corr)
```

```
Epoch:   1   Batch: 1000   Loss:     1.0309   Accuracy:   49.45%  Time Elapse
d Since Start:    1.17 min
Epoch:   2   Batch: 1000   Loss:     1.2961   Accuracy:   56.84%  Time Elapse
d Since Start:    2.52 min
Epoch:   3   Batch: 1000   Loss:     0.9534   Accuracy:   61.48%  Time Elapse
d Since Start:    3.69 min
Epoch:   4   Batch: 1000   Loss:     1.1926   Accuracy:   63.99%  Time Elapse
d Since Start:    4.85 min
Epoch:   5   Batch: 1000   Loss:     0.5693   Accuracy:   66.62%  Time Elapse
d Since Start:    5.91 min
Epoch:   6   Batch: 1000   Loss:     0.8185   Accuracy:   67.78%  Time Elapse
d Since Start:    6.88 min
Epoch:   7   Batch: 1000   Loss:     0.5415   Accuracy:   70.53%  Time Elapse
d Since Start:    7.83 min
Epoch:   8   Batch: 1000   Loss:     0.5292   Accuracy:   71.11%  Time Elapse
d Since Start:    8.88 min
Epoch:   9   Batch: 1000   Loss:     0.8405   Accuracy:   72.19%  Time Elapse
d Since Start:    9.92 min
Epoch:  10   Batch: 1000   Loss:     0.4423   Accuracy:   73.97%  Time Elapse
d Since Start:   10.85 min
Epoch:  11   Batch: 1000   Loss:     0.9873   Accuracy:   74.79%  Time Elapse
d Since Start:   11.74 min
Epoch:  12   Batch: 1000   Loss:     0.6206   Accuracy:   76.16%  Time Elapse
d Since Start:   12.71 min
Epoch:  13   Batch: 1000   Loss:     0.9447   Accuracy:   76.58%  Time Elapse
d Since Start:   13.62 min
Epoch:  14   Batch: 1000   Loss:     0.3371   Accuracy:   77.47%  Time Elapse
d Since Start:   14.51 min
Epoch:  15   Batch: 1000   Loss:     0.4260   Accuracy:   77.65%  Time Elapse
d Since Start:   15.40 min
Epoch:  16   Batch: 1000   Loss:     0.4613   Accuracy:   78.91%  Time Elapse
d Since Start:   16.42 min
Epoch:  17   Batch: 1000   Loss:     0.5665   Accuracy:   79.36%  Time Elapse
d Since Start:   17.39 min
Epoch:  18   Batch: 1000   Loss:     0.7893   Accuracy:   80.25%  Time Elapse
d Since Start:   18.33 min
Epoch:  19   Batch: 1000   Loss:     0.7203   Accuracy:   80.09%  Time Elapse
d Since Start:   19.28 min
Epoch:  20   Batch: 1000   Loss:     0.5410   Accuracy:   81.17%  Time Elapse
d Since Start:   20.19 min
Epoch:  21   Batch: 1000   Loss:     0.3397   Accuracy:   82.08%  Time Elapse
d Since Start:   21.20 min
Epoch:  22   Batch: 1000   Loss:     0.4036   Accuracy:   82.18%  Time Elapse
d Since Start:   22.11 min
Epoch:  23   Batch: 1000   Loss:     0.9005   Accuracy:   83.06%  Time Elapse
d Since Start:   23.00 min
Epoch:  24   Batch: 1000   Loss:     0.4419   Accuracy:   83.28%  Time Elapse
d Since Start:   23.96 min
Epoch:  25   Batch: 1000   Loss:     0.3025   Accuracy:   84.07%  Time Elapse
d Since Start:   24.87 min
Epoch:  26   Batch: 1000   Loss:     0.2690   Accuracy:   84.34%  Time Elapse
d Since Start:   25.75 min
Epoch:  27   Batch: 1000   Loss:     0.5232   Accuracy:   85.41%  Time Elapse
d Since Start:   26.72 min
Epoch:  28   Batch: 1000   Loss:     0.2080   Accuracy:   85.51%  Time Elapse
d Since Start:   27.74 min
Epoch:  29   Batch: 1000   Loss:     0.3081   Accuracy:   86.44%  Time Elapse
```

```
d Since Start:   28.69 min
Epoch:  30   Batch: 1000   Loss:     0.3414   Accuracy:   86.39%  Time Elapse
d Since Start:   29.64 min
Epoch:  31   Batch: 1000   Loss:     0.5039   Accuracy:   86.93%  Time Elapse
d Since Start:   30.61 min
Epoch:  32   Batch: 1000   Loss:     0.1505   Accuracy:   87.88%  Time Elapse
d Since Start:   31.57 min
Epoch:  33   Batch: 1000   Loss:     0.3078   Accuracy:   87.53%  Time Elapse
d Since Start:   32.52 min
Epoch:  34   Batch: 1000   Loss:     0.1139   Accuracy:   89.03%  Time Elapse
d Since Start:   33.51 min
Epoch:  35   Batch: 1000   Loss:     0.1335   Accuracy:   88.74%  Time Elapse
d Since Start:   34.51 min
Epoch:  36   Batch: 1000   Loss:     0.1878   Accuracy:   89.14%  Time Elapse
d Since Start:   35.52 min
Epoch:  37   Batch: 1000   Loss:     0.2102   Accuracy:   89.54%  Time Elapse
d Since Start:   36.46 min
Epoch:  38   Batch: 1000   Loss:     0.1341   Accuracy:   89.88%  Time Elapse
d Since Start:   37.39 min
Epoch:  39   Batch: 1000   Loss:     0.4046   Accuracy:   89.99%  Time Elapse
d Since Start:   38.34 min
Epoch:  40   Batch: 1000   Loss:     0.1391   Accuracy:   90.60%  Time Elapse
d Since Start:   39.26 min
```

In [18]:

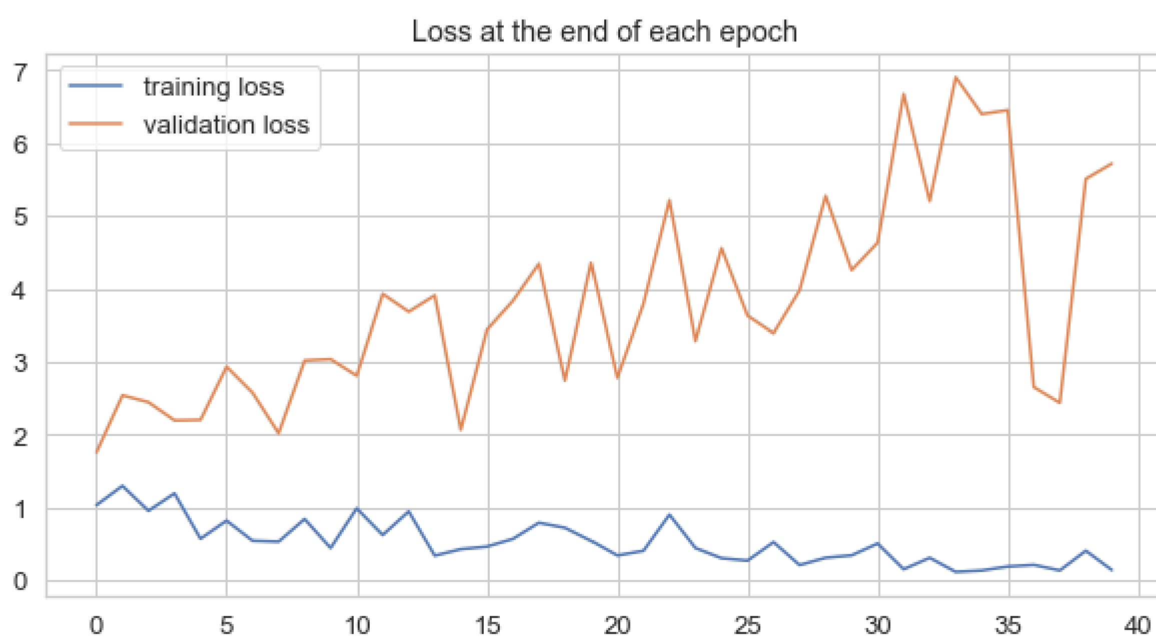
```python
# save the trained model

torch.save(ResNet18model.state_dict(), 'resnet18cinic10cl4.pt')
```

In [19]:

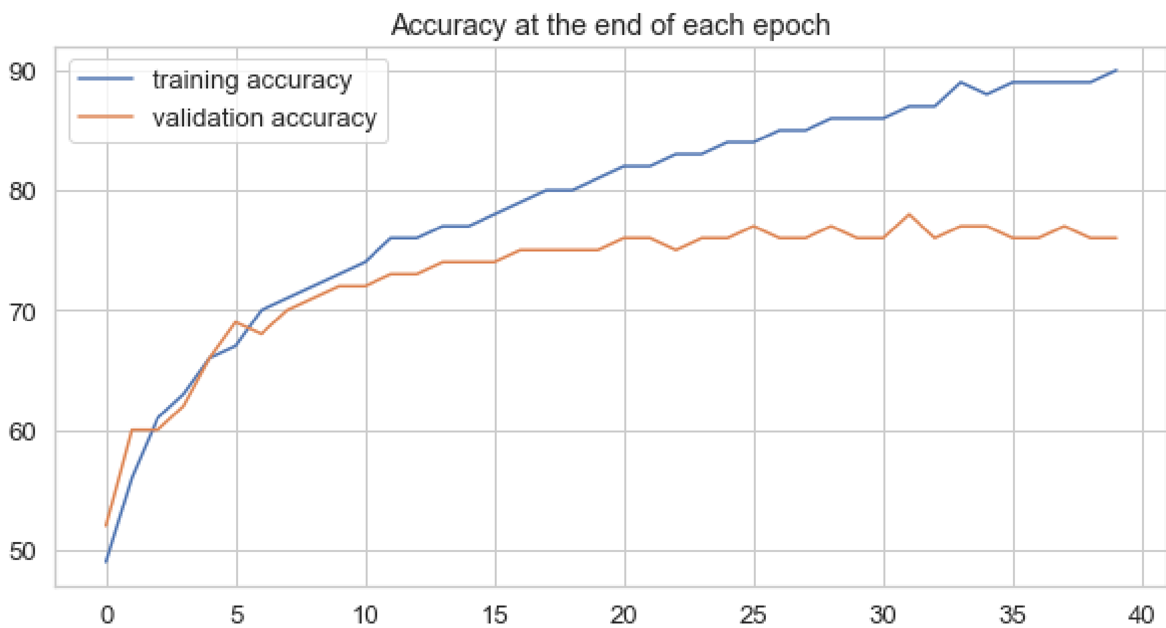
```python
# evaluate model performance

# plot losses
plt.figure(figsize = (10,5))
plt.plot(train_losses, label='training loss')
plt.plot(test_losses, label='validation loss')
plt.title('Loss at the end of each epoch')
plt.legend();
```



In [20]:
```
# train and test losses do not converge
```

In [21]:
```
# plot accuracy
plt.figure(figsize = (10,5))
plt.plot([t*100/(max_trn_batch*b_size) for t in train_correct], label='trainin
g accuracy')
plt.plot([t*100/(max_tst_batch*b_size) for t in test_correct], label='validati
on accuracy')
plt.title('Accuracy at the end of each epoch')
plt.legend();
```



In [22]:
```
# accuracy diverges as well
# model achieves 90% training accuracy and ~ 76% testing (validation) accuracy
# after ~ 30 epochs the validation accuracy reaches a plateau, while the train
ing accuracy continues to increase
    # if the number of epochs is increased, model could reach even higher trai
ning accuracy by "learning" the training set
    # this, however, will not lead to increase in validation accuracy which is
the true model accuracy
```

In [23]:
```
# print final test accuracy
print(f'Test accuracy: {test_correct[-1].item()*100/(max_tst_batch*b_size):.2
f}%') # take the value after the last epoch
```

```
Test accuracy: 76.05%
```

In [24]:
```
# test accuracy is 76%
```

In [25]:
```
# compare predictions against ground truth
# for better visualization we will use heatmap
```

In [26]:
```
# use all test images
test_load_all = DataLoader(test_data, batch_size = 36000, shuffle = False)
print(f'Testing images available:  {len(test_data)}')
```

```
Testing images available:  36000
```

In [27]:

```
# make predictions with all test images and show confusion matrix results as a heat map

# import confusion matrix
from sklearn.metrics import confusion_matrix

with torch.no_grad():
    correct = 0
    for X_test, y_test in test_load_all:
        y_val = ResNet18model(X_test.to(device))
        predicted = torch.max(y_val,1)[1]
        correct += (predicted == y_test.to(device)).sum()

# convert results to CPU tensors to be able to use them as numpy arrays!
device = torch.device("cpu")
y_test = y_test.to(device)
predicted = predicted.to(device)

# create heat map from confusion matrix and plot
arr = confusion_matrix(y_test.view(-1), predicted.view(-1))
df_cm = pd.DataFrame(arr, class_names, class_names)
plt.figure(figsize = (10,8))
sns.heatmap(df_cm, annot = True, fmt = "d", cmap = 'BuGn')
plt.xlabel("Prediction")
plt.ylabel("Label (ground truth)")
plt.show()
```

In [28]:
```
# Confusion matrix shows:
    # class 'ship' has highest prediction accuracy of 86.3% (7770/9000)
        # most often mistaken for 'airplane'
    # class 'airplane' has second highest prediction accuracy of 82.4% (7412/9
000)
        # most often mistaken for 'ship'
    # class 'automobile' is third in prediction accuracy with 74.8% (6736/900
0)
        # most often mistaken for 'truck'
    # class 'truck' has lowest prediction accuracy of 63.6% (5727/9000)
        # most often mistaken for 'automobile'
    # the corresponding classes causing highest confusion are neutral to expec
t due to the similarities between these classes

# In conclusion:
    # overall model accuracy is 76.8% (27645/36000) which is well above random
guess (25%)
    # given the similarity between the objects selected here and the small ima
ge resolution we consider this to be good accuracy
```