CPSC 425: Computer Vision

Assignment 6: Deep Learning

Attribution: This assignment is developed based on the example here (https://github.com/pytorch/examples/blob/master/mnist/main.py).

Preface

This assignment consists of three parts: In the first part, you will implement various PyTorch deep learning layers using Numpy; in part two, you will experiment with different hyper-parameters on a image classification task and find the best hyper-parameters; lastly, you will investigate a state-of-the-art neural architecture from the PyTorch model zoo.

IMPORTANT: Colab allows you to train your network in either a cpu or a **free** gpu. You can request a Colab GPU by clicking on the `Edit-Notebook Settings-HardwareAccelerator` and choose `GPU` . After you chose the GPU, the python program will restart from scratch. If you run the cell below, you will see whether a GPU has been assigned to you. If you cannot get a GPU on time, you can simply use a cpu, which should work for this assignment but slower.

IMPORTANT: Before proceeding, it is important to understand what is Google Colab notebooks. You can play around with this short tutorial here (https://colab.research.google.com/notebooks/intro.ipynb)

In [2]:
```
!nvidia-smi
```

```
Fri Apr  2 21:56:35 2021
+-----------------------------------------------------------------------------
-+
| NVIDIA-SMI 460.67       Driver Version: 460.32.03    CUDA Version: 11.2
|
|-------------------------------+----------------------+----------------------
-+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC
|
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M.
|
|                               |                      |               MIG M.
|
|===============================+======================+======================
=|
|   0  Tesla T4            Off  | 00000000:00:04.0 Off |                    0
|
| N/A   42C    P8    10W /  70W |      0MiB / 15109MiB |      0%      Default
|
|                               |                      |                  N/A
|
+-------------------------------+----------------------+----------------------
-+

+-----------------------------------------------------------------------------
-+
| Processes:
|
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory
|
|        ID   ID                                                   Usage
|
|=============================================================================
=|
|  No running processes found
|
+-----------------------------------------------------------------------------
-+
```

Implement Neural Network Layers

In this section, you are going to implement some fundamental deep learning layers of PyTorch using numpy arrays. Through this implementation, you will gain better understandings of the deep learning tools we introduced in class, such as activation functions, linear layers, max pooling layers and convolution layers. As we mentioned in class, each deep learning layer has two operators: `forward` and `backward`. In the forward pass, data are piped through a computational graph (each node is a deep learning layer) to obtain the final prediction. When comparing the prediction with a loss, gradients are backpropagated in the inverse direction of the graph, which allows us to compute the gradients with respect to the model parameters and we can follow the negative gradient to update the parameters (a.k.a. learning the parameters).

You will be implementing the `forward` pass of the `ReLU`, `MaxPool2d`, `Linear`, and `Conv2d` layers. Since the `backward` pass is quite intensive, we only require you to implement it for ther `ReLU` layer. Although in practice, most deep learning library (such as PyTorch) would compute the gradients for you automatically using the computational graph, which is called `AutoGrad`, sometimes you do need to implement your custom gradient backward.

Let's kick start by importing the following dependencies:

In [3]:
```
import torch
import torch.nn as nn
import numpy as np
import hw_utils
```

ReLU Activation `[2 marks]`

Implement the ReLU layer by filling in numpy code in between `START` and `END`. The assertions should tell you what we expect your input and output to be (such as the shape and the data type). Note that for ReLU, the input can be in any shape. Your solution should produce a numpy array that is very close to the outputs of a PyTorch implementations, which you can check by looking at the errors from the tests below. DO NOT remove the tests and include the errors in your final version upon submission.

In [4]:
```
class nn_ReLU():
    def __init__(self):
        pass
    def forward(self, X):
        assert isinstance(X, np.ndarray)
        in_shape = X.shape
        out = np.maximum(X, 0)
        assert isinstance(out, np.ndarray)
        assert out.shape == X.shape
        return out

    def backward(self, X):
        # compute the gradient of y with respect to X
        # where y = ReLU(X)
        grad = np.ones_like(X)
        grad[X<=0] = 0
        grad[X>0] = 1
        return grad

# Note: the following test cases only test for the forward function.
hw_utils.test_relu(in_shape=[7, 5, 3, 1], Layer=nn_ReLU)
hw_utils.test_relu(in_shape=[100], Layer=nn_ReLU)
hw_utils.test_relu(in_shape=[3, 4, 4], Layer=nn_ReLU)
```

```
norm(out_np - out_torch) = 0.000000
norm(out_np - out_torch) = 0.000000
norm(out_np - out_torch) = 0.000000
```

Maxpooling Layer [2 marks]

Implement the 2d pooling layer by filling in numpy code in between `START` and `END`. The assertions should tell you what we expect your input and output to be (such as the shape and the data type). Note that for 2d max pooling, you will work with inputs with shape `(N, C, size, size)` where `N` is the number of examples, `C` is the channel size, and `size` is the width and height of the feature map. The stride of this max pooling would be `size` as well. Your solution should produce a numpy array that is very close to the outputs of a PyTorch implementations, which you can check by looking at the errors from the tests below. DO NOT remove the tests and include the errors in your final version upon submission.

In [5]:
```
class nn_MaxPool2d():
    def __init__(self, kernel_size):
        self.kernel_size = kernel_size

    def forward(self, X):
        assert isinstance(X, np.ndarray)
        assert len(X.shape) == 4
        assert X.shape[2] == X.shape[3],\
            'You can assume width and height are the same'
        N, C, size, _ = X.shape
        assert size >= self.kernel_size,\
            'You can assume the feature map is always at least as big as the k
ernel size'
        kernel_size = self.kernel_size

        out_size = size // kernel_size
        window = out_size*kernel_size
        outFinal = np.zeros((N, C, out_size, out_size))
        for i in range(N):
          for j in range(C):
            # Filter image on window
            out = X[i, j, :window, :window]
            # Reshape and find max along 1st axis
            out = out.reshape((-1, kernel_size))
            out = out.max(axis=1)
            # Reshape and find max along 2nd axis
            out = out.reshape((out_size, kernel_size, out_size))
            outFinal[i,j] = out.max(axis=1)
        return outFinal

hw_utils.test_maxpool(N=3, C=6, size=4, kernel_size=1, Layer=nn_MaxPool2d)
hw_utils.test_maxpool(N=3, C=6, size=4, kernel_size=2, Layer=nn_MaxPool2d)
hw_utils.test_maxpool(N=3, C=6, size=4, kernel_size=4, Layer=nn_MaxPool2d)

hw_utils.test_maxpool(N=3, C=6, size=16, kernel_size=4, Layer=nn_MaxPool2d)
hw_utils.test_maxpool(N=3, C=6, size=16, kernel_size=8, Layer=nn_MaxPool2d)

hw_utils.test_maxpool(N=3, C=6, size=15, kernel_size=4, Layer=nn_MaxPool2d)
hw_utils.test_maxpool(N=3, C=6, size=15, kernel_size=8, Layer=nn_MaxPool2d)

hw_utils.test_maxpool(N=3, C=6, size=13, kernel_size=4, Layer=nn_MaxPool2d)
hw_utils.test_maxpool(N=3, C=6, size=13, kernel_size=8, Layer=nn_MaxPool2d)
```

```
norm(out_np - out_torch) = 0.000002
norm(out_np - out_torch) = 0.000002
norm(out_np - out_torch) = 0.000001
norm(out_np - out_torch) = 0.000005
norm(out_np - out_torch) = 0.000002
norm(out_np - out_torch) = 0.000003
norm(out_np - out_torch) = 0.000001
norm(out_np - out_torch) = 0.000003
norm(out_np - out_torch) = 0.000001
```

Linear Layer [2 marks]

Implement the linear layer by filling in numpy code in between `START` and `END`. The assertions should tell you what we expect your input and output to be (such as the shape and the data type). Note that for this layer, you will work with inputs with shape `(N, D)` where `N` is the number of examples, `D` is feature dimension. Your solution should produce a numpy array that is very close to the outputs of a PyTorch implementations, which you can check by looking at the errors from the tests below. DO NOT remove the tests and include the errors in your final version upon submission.

In [6]:
```
class nn_Linear():
    def __init__(self, in_features, out_features):
        self.W = np.random.rand(in_features, out_features)
        self.b = np.random.rand(1, out_features)

    def forward(self, X):
        assert isinstance(X, np.ndarray)
        assert len(X.shape) == 2
        N, D = X.shape

        y = np.dot(X,self.W) + self.b

        assert len(y.shape) == 2
        assert y.shape[0] == N
        return y

    def load_weights(self, W, b):
        W = W.T
        b = b.reshape(1, -1)
        assert W.shape == self.W.shape
        assert b.shape == self.b.shape
        self.W = W
        self.b = b

hw_utils.test_linear(N=3, D=4, K=5, Layer=nn_Linear)
hw_utils.test_linear(N=5, D=6, K=7, Layer=nn_Linear)
hw_utils.test_linear(N=1, D=4, K=5, Layer=nn_Linear)
hw_utils.test_linear(N=1, D=1, K=1, Layer=nn_Linear)
hw_utils.test_linear(N=2, D=1, K=1, Layer=nn_Linear)
hw_utils.test_linear(N=1, D=2, K=2, Layer=nn_Linear)
```

```
norm(out_np - out_torch) = 0.000000
norm(out_np - out_torch) = 0.000002
norm(out_np - out_torch) = 0.000000
norm(out_np - out_torch) = 0.000000
norm(out_np - out_torch) = 0.000000
norm(out_np - out_torch) = 0.000000
```

Convolution Layer `[4 marks]`

Implement the 2d convolution layer by filling in numpy code in between `START` and `END`. The assertions should tell you what we expect your input and output to be (such as the shape and the data type). Note that for this layer, you will work with inputs with shape `(N, D, size, size)` where `N` is the number of examples, `D` is channel dimension, `size` is the width/height. Your solution should produce a numpy array that is very close to the outputs of a PyTorch implementations, which you can check by looking at the errors from the tests below. DO NOT remove the tests and include the errors in your final version upon submission.

In [17]:
```
class nn_Conv2d():
    def __init__(self, in_channels, out_channels, kernel_size):
        assert kernel_size % 2  == 1, "We assume the kernel_size to be odd."
        self.in_channels = in_channels
        self.out_channels = out_channels
        self.kernel_size = kernel_size

        in_features = in_channels*kernel_size*kernel_size
        self.linear = nn_Linear(in_features, out_channels)

    def forward(self, X):
        assert isinstance(X, np.ndarray)
        assert len(X.shape) == 4
        assert X.shape[2] == X.shape[3]
        N, C, size, _ = X.shape
        assert size >= self.kernel_size
        kernel_size = self.kernel_size

        out_size = size - kernel_size + 1
        out = np.zeros((N, C, kernel_size, kernel_size, out_size, out_size))

        # Convolution
        for y in range(kernel_size):
          y_max = y + 1 * out_size
          for x in range(kernel_size):
              x_max = x + 1 * out_size
              out[:, :, y, x, :, :] = X[:, :, y:y_max:1, x:x_max:1]
        out = out.transpose(0, 4, 5, 1, 2, 3).reshape(N*out_size*out_size, -1)

        # Linear computation
        out = self.linear.forward(out)
        out = out.reshape(N, out_size, out_size, -1).transpose(0, 3, 1, 2)

        assert len(out.shape) == 4
        assert out.shape[0] == X.shape[0]
        assert out.shape[1] == self.out_channels
        assert out.shape[2] == out.shape[3]
        return out

    def load_weights(self, W, b):
        self.linear.load_weights(W, b)


hw_utils.test_conv2d(N=4, D=5, K=6, size=3, kernel_size=3, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=4, D=5, K=6, size=5, kernel_size=3, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=4, D=5, K=6, size=10, kernel_size=3, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=1, D=5, K=6, size=5, kernel_size=3, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=4, D=5, K=1, size=5, kernel_size=3, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=4, D=1, K=6, size=3, kernel_size=3, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=1, D=1, K=1, size=5, kernel_size=3, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=4, D=5, K=6, size=10, kernel_size=1, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=4, D=5, K=6, size=10, kernel_size=5, Layer=nn_Conv2d)
hw_utils.test_conv2d(N=4, D=5, K=6, size=10, kernel_size=7, Layer=nn_Conv2d)
```

```
norm(out_np - out_torch) = 0.000019
norm(out_np - out_torch) = 0.000052
norm(out_np - out_torch) = 0.000214
norm(out_np - out_torch) = 0.000033
norm(out_np - out_torch) = 0.000016
norm(out_np - out_torch) = 0.000008
norm(out_np - out_torch) = 0.000010
norm(out_np - out_torch) = 0.000090
norm(out_np - out_torch) = 0.000201
norm(out_np - out_torch) = 0.000169
```

Experimenting with a CNN classifier

Introducing the setup

In this section, you will be experimenting with various hyper-parameters of a CNN classifier on the CIFAR10 dataset. CIFAR10 is a dataset of images of objects in 10 categories. It is widely used for benchmarking image classification models. Since most students have very limited computational resources, to make the training and validation more feasible, we subsampled the dataset so that we have 5000 images for training, 5000 images for validation and 5000 images for testing.

As shown below, our neural network consists of two parts: `cnn` and `linear_layers`. Given an arbitray image from CIFAR10, the image will flow through the network in the same order shown in the printout. It first goes through a convolutional network and then flows into the linear layers for classifications.

In details, the `cnn` module is a sequence of 2d convolution layers and non-linear activation layers with 2d max pooling. You can fetch the CIFAR10 dataset and visualize the network structure by executing the lines below:

In [20]:
```
train_loader, val_loader, test_loader\
    = hw_utils.fetch_data()
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./dat
a/cifar-10-python.tar.gz


Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
len(train_set) = 5000, len(val_set) = 5000, len(test_set) = 5000
```

In [60]:
```
args = {
    'lr': 1e-3,
    'epoch': 10,
    'channel1': 32,
    'channel2': 128,
    'mid_dims': [256, 32],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(
    args, train_loader, val_loader, skip_train=True)
```

```
Net(
  (cnn): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1))
    (1): ReLU()
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=
False)
    (3): Conv2d(32, 128, kernel_size=(3, 3), stride=(1, 1))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=
False)
    (6): Conv2d(128, 64, kernel_size=(3, 3), stride=(1, 1))
    (7): ReLU()
  )
  (linear_layers): MLP(
    (model): ModuleList(
      (0): Linear(in_features=1024, out_features=256, bias=True)
      (1): ReLU()
      (2): Linear(in_features=256, out_features=32, bias=True)
      (3): ReLU()
      (4): Linear(in_features=32, out_features=10, bias=True)
    )
  )
)
```

The above printout is analogous to the interface you used in the first part of this assignment. For example, `Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1))` denotes a 2d convolution layer with an input channel of size 3, an output channel of size 32, a 2d convolution kernel size of 3 by 3, and a stride of 1. After the second convolution, we apply max pooling on the spatial dimension to reduce the resolution of the input feature map using `MaxPool2d(kernel_size=2, stride=2, padding=0)`. The `cnn` module outputs a feature map of shape `(N, 64, 4, 4)`, which denotes the number of examples, feature map channel depth, channel_width, and channel_height respectively. We then "flatten" the feature map in shape `(N, 64, 4, 4)` to single vectors in shape `(N, 64*4*4)=(N, 1024)` and let the vectors go through a feedforward classifier.

Since the purpose is for you to experiment with deep learning architectures, you are not required to manually create your own PyTorch network from scratch. Like our previous assignment, we have all of the boilerplate code written for you. **As a result, you only need to interact with the `args` object**, which stores the hyperparameters for creating the network and for training.

For example, `args['channel1']` and `args['channel2']` are the channel sizes of the convolution layers; `args['mid_dims']` stores the intermediate size of hidden layers. Compare the below network structure to the above to understand what eack key of `args` represents:

```
Net(
  (cnn): Sequential(
    (0): Conv2d(3, args['chanell1'], kernel_size=(3, 3), stride=(1, 1))
    (1): ReLU()
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(args['chanell1'], args['chanell2'], kernel_size=(3, 3), stride=(1,
 1))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(args['chanell2'], 64, kernel_size=(3, 3), stride=(1, 1))
    (7): ReLU()
  )
  (linear_layers): MLP(
    (model): ModuleList(
      (0): Linear(in_features=1024, out_features=args['mid_dims'][0], bias=True)
      (1): ReLU()
      (2): Linear(in_features=args['mid_dims'][0], out_features=args['mid_dims']
[1], bias=True)
      (3): ReLU()
      (4): Linear(in_features=args['mid_dims'][1], out_features=10, bias=True)
    )
  )
)
```

There are other hyper-parameters in `args`. For example, `args['lr']` is the learning rate at each iteration for training; `args['epoch']` is the number of times we train on the training set (if epoch is 2, you will go through the 5000 training examples for twice); `args['act_name']` is the activation function to use to introduce non-linearity.

IMPORTANT: Colab allows you to train your network in either a cpu or a **free** gpu. You can request a Colab GPU by clicking on the `Edit-Notebook Settings-HardwareAccelerator` and choose `GPU`. After you chose the GPU, the python program will restart from scratch. As to `args`, you can specify the device to use for training by setting `args['device'] = 'cpu'` or `args['device'] = 'cuda'`. We highly recommend you to use a GPU provided by Colab, which should speed up your development process.

First Deep Learning Model

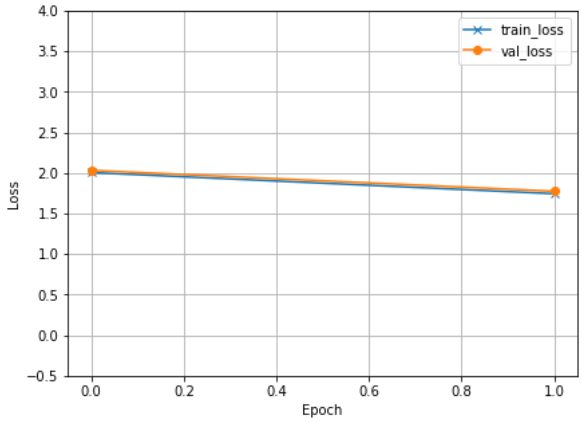
Now that the setup is done. Lets create and train our first deep learning model! The below cell specifies the arguments using `args`. The function `spawn_train_show` creates the model based on the configuration in `args`, trains the model, and plots the validation metrics as a figure. The left side of the figure shows the training and validation loss as we train the model across epochs; the right side shows the accuracies. It is normal that your accuracy is below `50%` because we are using a small fraction of the entire dataset and the default `args` is not optimal.

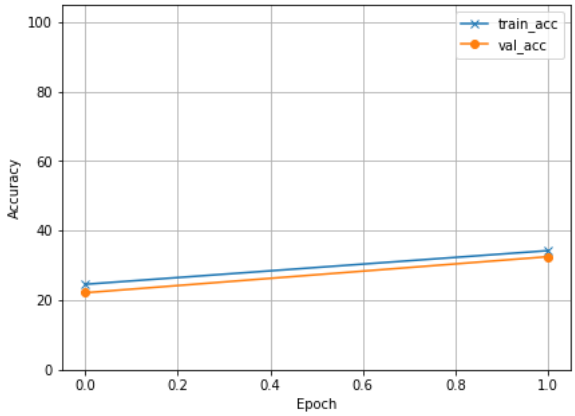
In [22]:
```
args = {
    'lr': 1e-3,
    'epoch': 2,
    'channel1': 16,
    'channel2': 16,
    'mid_dims': [16, 16],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(
    args, train_loader, val_loader, print_model=True, print_loss=True)
```

```
Net(
  (cnn): Sequential(
    (0): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1))
    (1): ReLU()
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=
False)
    (3): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=
False)
    (6): Conv2d(16, 64, kernel_size=(3, 3), stride=(1, 1))
    (7): ReLU()
  )
  (linear_layers): MLP(
    (model): ModuleList(
      (0): Linear(in_features=1024, out_features=16, bias=True)
      (1): ReLU()
      (2): Linear(in_features=16, out_features=16, bias=True)
      (3): ReLU()
      (4): Linear(in_features=16, out_features=10, bias=True)
    )
  )
)


Epoch 1: training loss = 2.0051, validation loss = 2.0324
Epoch 2: training loss = 1.7441, validation loss = 1.7746

The highest validation accuracy is 32.52 percent
```





Experiment: number of epochs [2 marks]

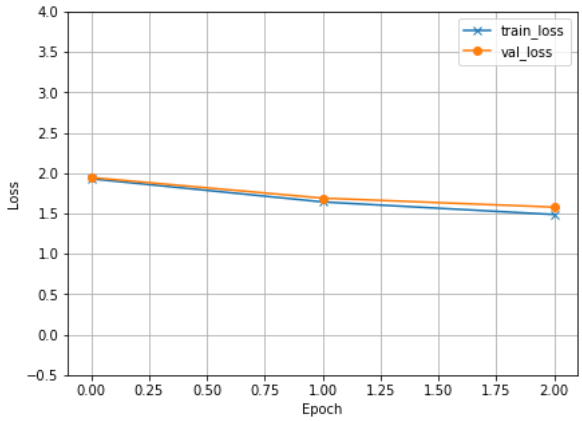
Use the following configuration as default (you may use either `cpu` or `cuda`):

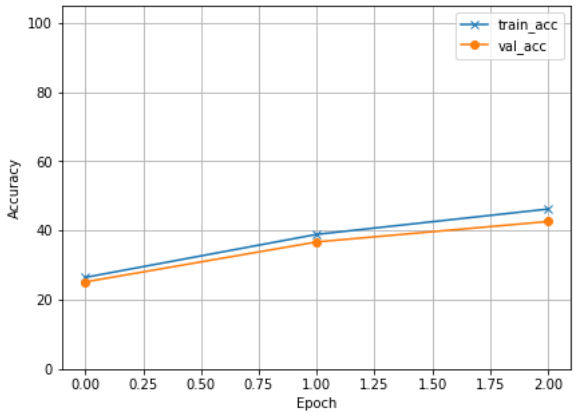
```
args = {
    'lr': 1e-3,
    'epoch': 10,
    'channel1': 128,
    'channel2': 256,
    'mid_dims': [512, 512],
    'act_name': 'relu',
    'device': 'cuda'
}
```

and experiment different `args['epoch']`. Report one configuration that underfit the network, and one configuration that overfits the network. Make sure you provide the `args` that you used, and the plots generated by that `args`. You can avoid printing the loss and models by setting `print_model=False`, `print_loss=False` in `spawn_train_show`.

In [64]:
```
args = {
    'lr': 1e-3,
    'epoch': 3,
    'channel1': 128,
    'channel2': 256,
    'mid_dims': [512, 512],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

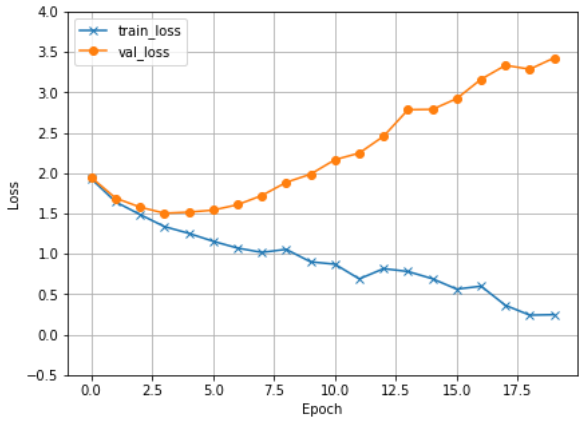
```
The highest validation accuracy is 42.62 percent
```

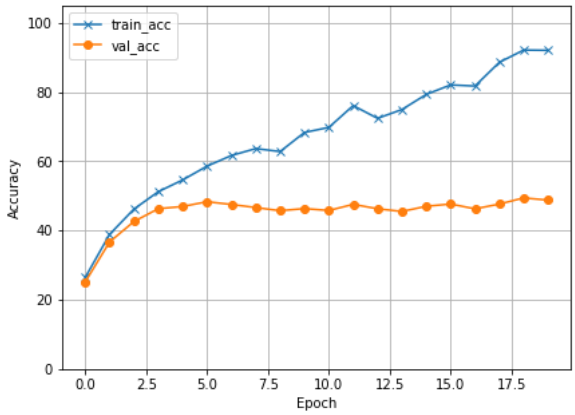




In [42]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 128,
    'channel2': 256,
    'mid_dims': [512, 512],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

```
The highest validation accuracy is 49.44 percent
```





Experiment: Channel Sizes [2 marks]

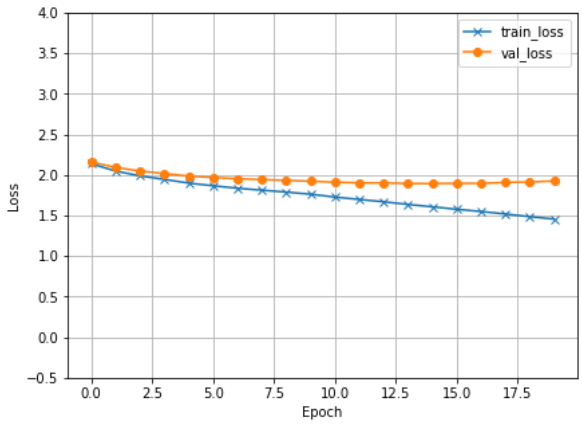
Use the following configuration as default (you may use either `cpu` or `cuda`):

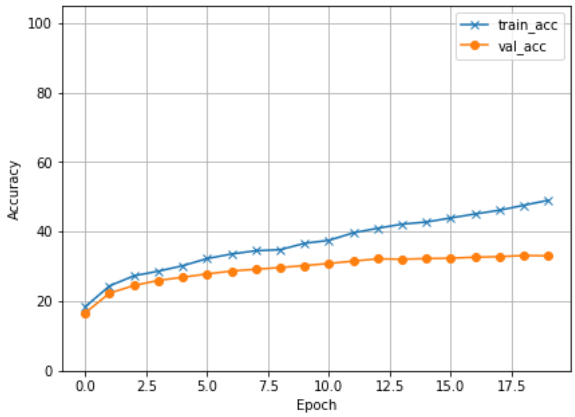
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 16,
    'channel2': 16,
    'mid_dims': [256, 256],
    'act_name': 'relu',
    'device': 'cuda'
}
```

and experiment different combinations of `args['channel1']` and `args['channel2']`. Report one configuration that underfit the network, and one configuration that overfits the network. Make sure you provide the `args` that you used, and the plots generated by that `args`. You can avoid printing the loss and models by setting `print_model=False`, `print_loss=False` in `spawn_train_show`.

In [32]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 1,
    'channel2': 1,
    'mid_dims': [256, 256],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

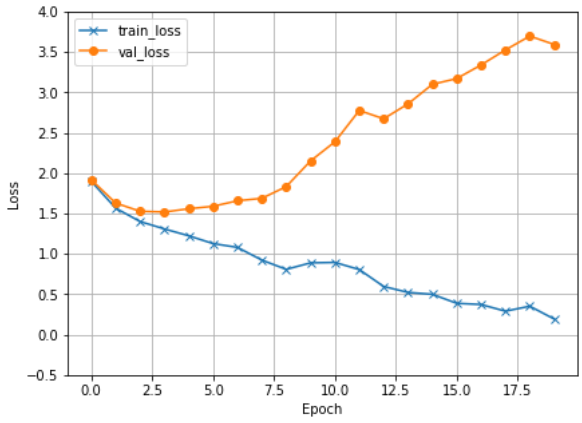
```
The highest validation accuracy is 33.14 percent
```

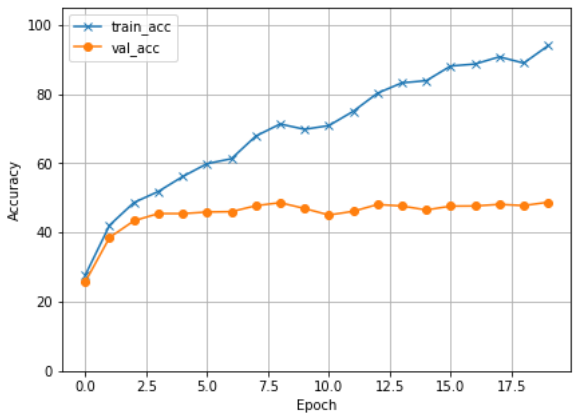




In [75]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 64,
    'channel2': 64,
    'mid_dims': [256, 256],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

```
The highest validation accuracy is 48.78 percent
```





Experiment: Linear Hidden Layer Width `[2 marks]`

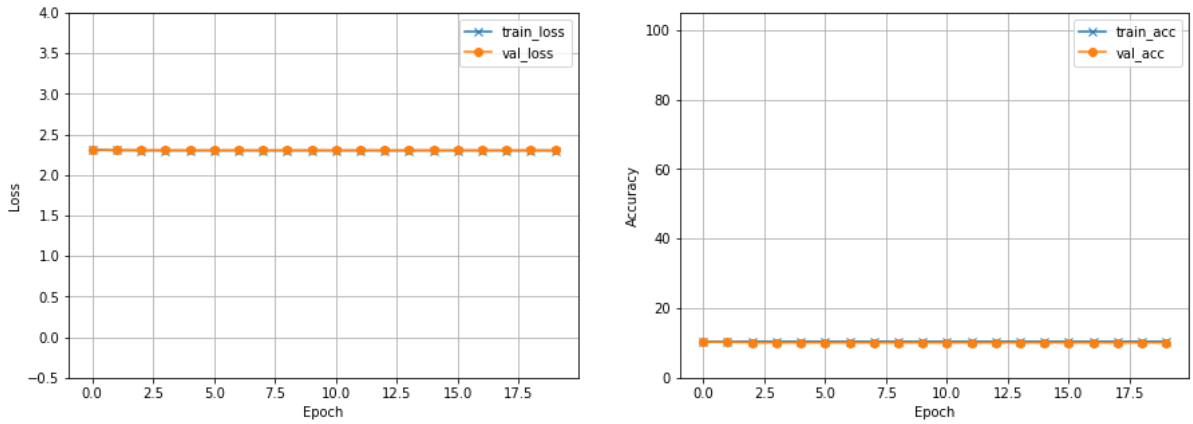
Use the following configuration as default (you may use either `cpu` or `cuda`):

```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 256,
    'channel2': 256,
    'mid_dims': [D, D],
    'act_name': 'relu',
    'device': 'cuda'
}
```

and experiment different `args['mid_dims'] = [D, D]` with different integer `D` (note that `args['mid_dims']` is a list of integers). Report one configuration that underfit the network, and one configuration that overfits the network. Make sure you provide the `args` that you used, and the plots generated by that `args`. You can avoid printing the loss and models by setting `print_model=False`, `print_loss=False` in `spawn_train_show`.

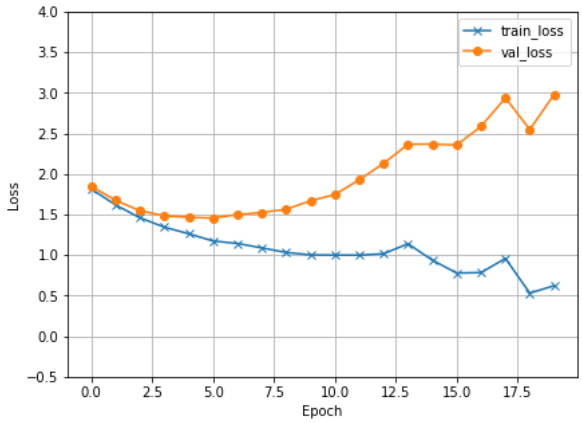
In [47]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 256,
    'channel2': 256,
    'mid_dims': [5, 5],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

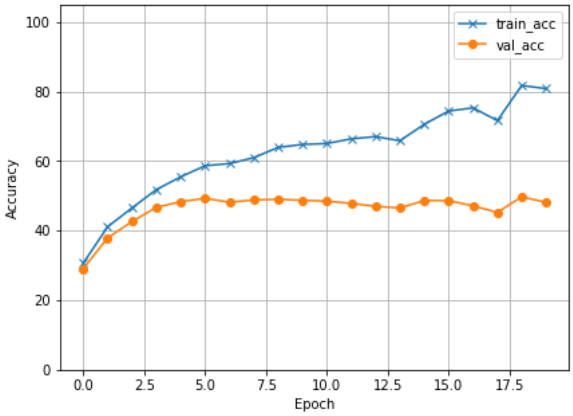
```
The highest validation accuracy is 10.26 percent
```



In [77]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 256,
    'channel2': 256,
    'mid_dims': [64, 64],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

```
The highest validation accuracy is 49.72 percent
```





Experiment: Linear Layer Depth [2 marks]

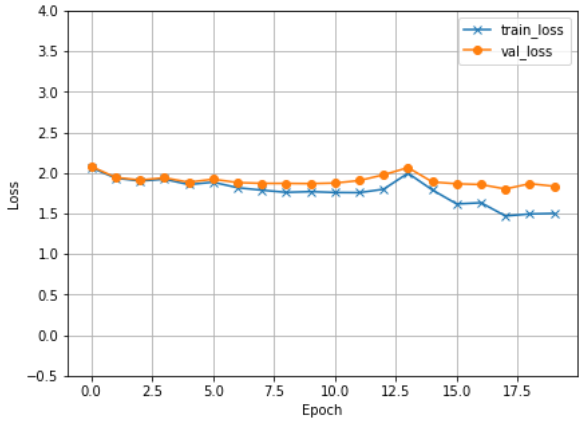
Use the following configuration as default (you may use either `cpu` or `cuda`):

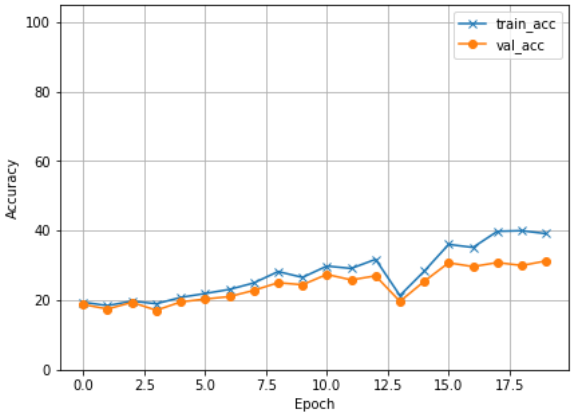
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 256,
    'channel2': 256,
    'mid_dims': [256]*K,
    'act_name': 'relu',
    'device': 'cuda'
}
```

and experiment different `args['mid_dims'] = [256]*K` with different integer `K` (note that `args['mid_dims']` is a list of integers). Report one configuration that underfit the network, and one configuration that overfits the network. Make sure you provide the `args` that you used, and the plots generated by that `args`. You can avoid printing the loss and models by setting `print_model=False`, `print_loss=False` in `spawn_train_show`.

In [39]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 256,
    'channel2': 256,
    'mid_dims': [256]*10,
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

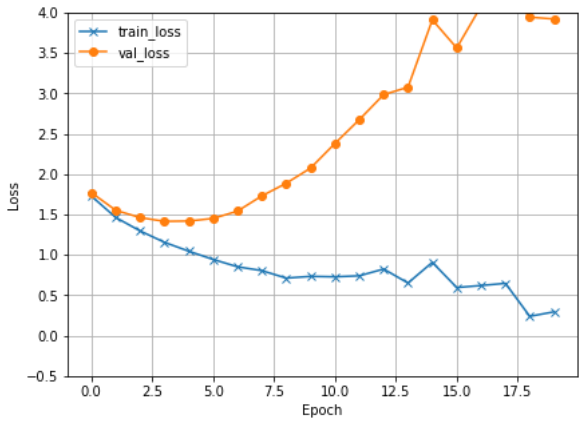
```
The highest validation accuracy is 31.30 percent
```

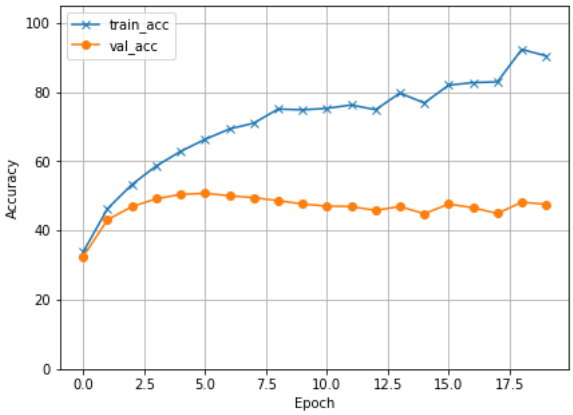




In [79]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 256,
    'channel2': 256,
    'mid_dims': [256]*1,
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

```
The highest validation accuracy is 50.76 percent
```





Experiment: Activations [2 marks]

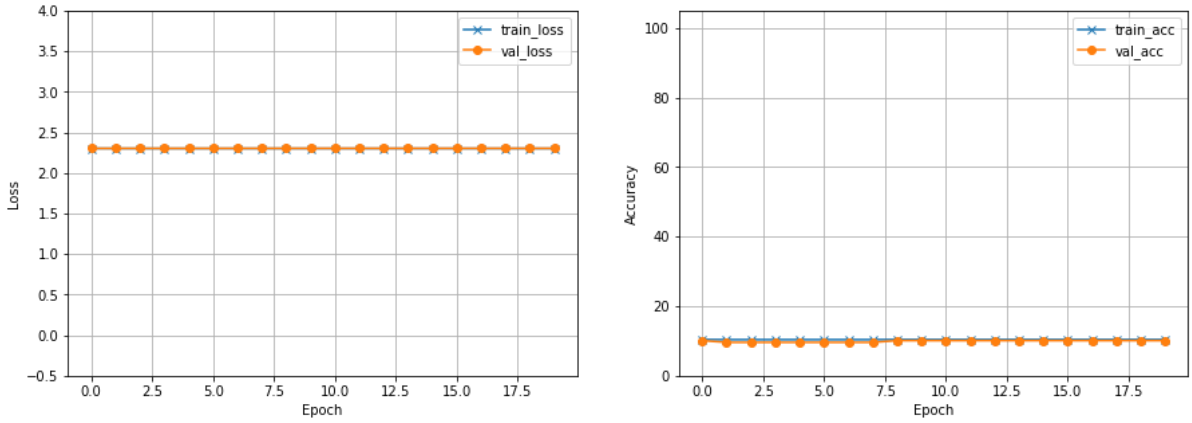
Use the following configuration as default (you may use either `cpu` or `cuda`):

```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 128,
    'channel2': 256,
    'mid_dims': [512, 512],
    'act_name': 'relu',
    'device': 'cuda'
}
```

and experiment on `args['act_name']` with the values `'relu', 'identity', 'tanh', 'sigmoid'`. Report one configuration that underfit the network, and one configuration that overfits the network. Make sure you provide the `args` that you used, and the plots generated by that `args`. You can avoid printing the loss and models by setting `print_model=False`, `print_loss=False` in `spawn_train_show`.

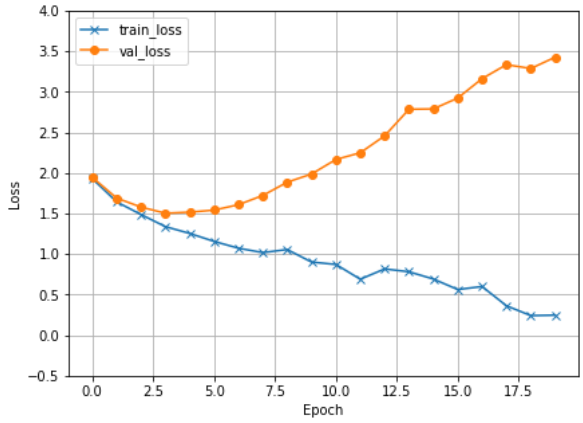
In [81]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 128,
    'channel2': 256,
    'mid_dims': [512, 512],
    'act_name': 'sigmoid',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

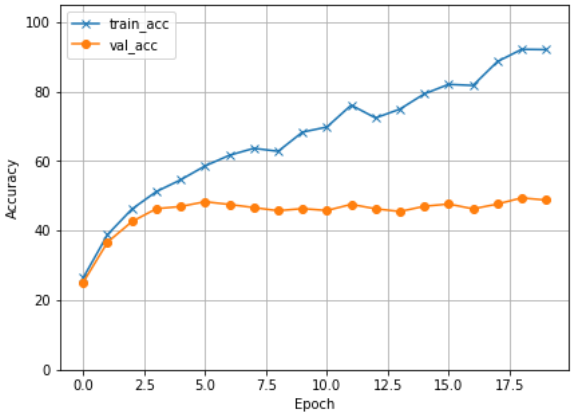
```
The highest validation accuracy is 10.10 percent
```



In [84]:
```
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 128,
    'channel2': 256,
    'mid_dims': [512, 512],
    'act_name': 'relu',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

```
The highest validation accuracy is 49.44 percent
```



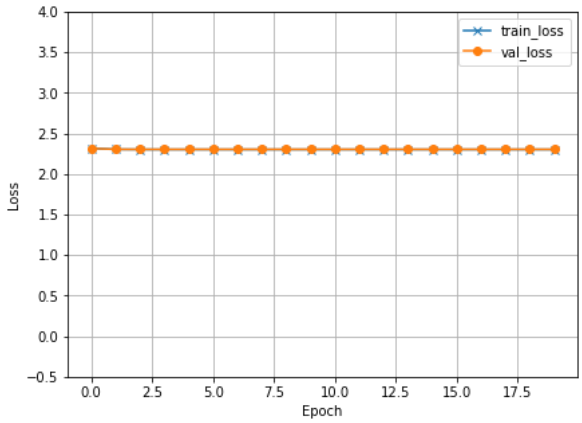


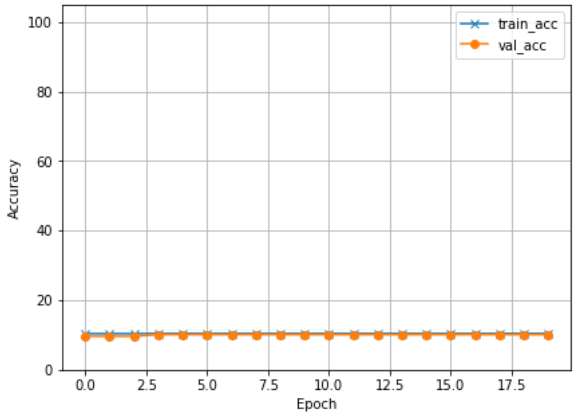
Creating the best model `[2 marks]`

After learning the effects of various hyper-parameters, it is time to create your final model. Experiment with different configurations in `args` and report your best hyperparameters, the training, validation accuracies. Provide the worst, and best configurations in terms of validation accuracies below:

In [50]:
```
# Worst
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 1,
    'channel2': 1,
    'mid_dims': [4]*10,
    'act_name': 'sigmoid',
    'device': 'cuda'
}
trained_model = hw_utils.spawn_train_show(args, train_loader, val_loader, prin
t_model=False, print_loss=False)
```

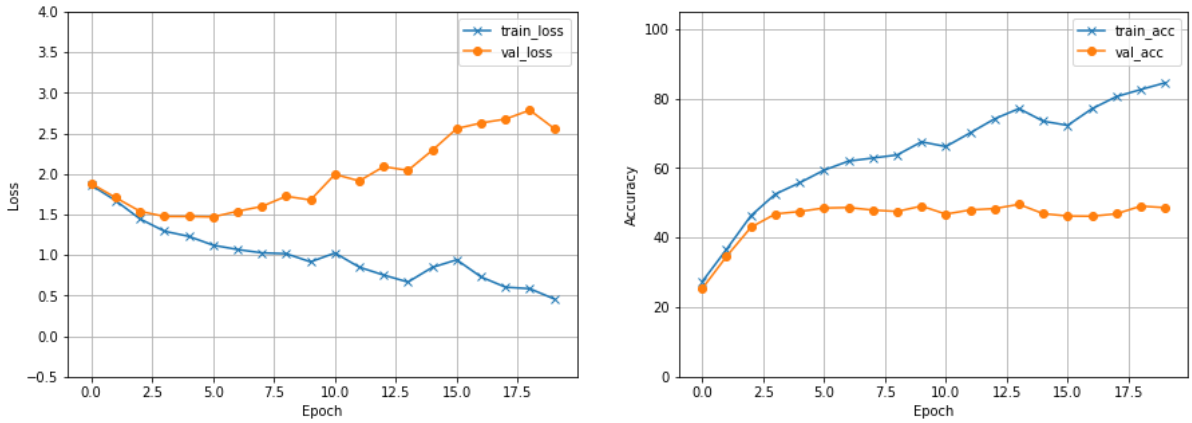
```
The highest validation accuracy is 10.10 percent
```





In [52]:
```
# Best
args = {
    'lr': 1e-3,
    'epoch': 20,
    'channel1': 256,
    'channel2': 256,
    'mid_dims': [64, 64, 64],
    'act_name': 'relu',
    'device': 'cuda'
}
best_model = hw_utils.spawn_train_show(args, train_loader, val_loader, print_m
odel=False, print_loss=False)
```

```
The highest validation accuracy is 49.60 percent
```



In machine learning, we often split the dataset into training, validation and test set. Your "best hyper-parameters" above should be chosen based on the model performance on the validation set. After choosing the best hyper-parameters, report your results on the test set.

In [53]:
```
_, test_acc = hw_utils.test(args, best_model, test_loader)
print('The test accuracy is %.2f percent' % (test_acc))
```

```
The test accuracy is 48.76 percent
```

Playing with SOTA [4 marks]

Mask R-CNN (https://arxiv.org/abs/1703.06870) is one of the state-of-the-art in the image segmentation task. Image segmentation is a more general version of an object detection task. Instead of labelling the class of a bouding box, a model needs to assign a label to each pixel. You are going to experiment Mask R-CNN with your own choice of images.

Lets import the model from the PyTorch model zoo:

In [10]:
```
import hw_utils
import torchvision
device = 'cuda'
model = torchvision.models.detection.maskrcnn_resnet50_fpn(pretrained=True).to
(device)
model.eval()
```

```
Downloading: "https://download.pytorch.org/models/maskrcnn_resnet50_fpn_coco-
bf2d0c1e.pth" to /root/.cache/torch/hub/checkpoints/maskrcnn_resnet50_fpn_coc
o-bf2d0c1e.pth
```

Out[10]:
```
MaskRCNN(
  (transform): GeneralizedRCNNTransform(
      Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
      Resize(min_size=(800,), max_size=1333, mode='bilinear')
  )
  (backbone): BackboneWithFPN(
    (body): IntermediateLayerGetter(
      (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3,
3), bias=False)
      (bn1): FrozenBatchNorm2d(64, eps=0.0)
      (relu): ReLU(inplace=True)
      (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ce
il_mode=False)
      (layer1): Sequential(
        (0): Bottleneck(
          (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=Fal
se)
          (bn1): FrozenBatchNorm2d(64, eps=0.0)
          (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(64, eps=0.0)
          (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
          (bn3): FrozenBatchNorm2d(256, eps=0.0)
          (relu): ReLU(inplace=True)
          (downsample): Sequential(
            (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
            (1): FrozenBatchNorm2d(256, eps=0.0)
          )
        )
        (1): Bottleneck(
          (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
          (bn1): FrozenBatchNorm2d(64, eps=0.0)
          (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(64, eps=0.0)
          (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
          (bn3): FrozenBatchNorm2d(256, eps=0.0)
          (relu): ReLU(inplace=True)
        )
        (2): Bottleneck(
          (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
          (bn1): FrozenBatchNorm2d(64, eps=0.0)
          (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=
(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(64, eps=0.0)
          (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
          (bn3): FrozenBatchNorm2d(256, eps=0.0)
          (relu): ReLU(inplace=True)
        )
      )
      (layer2): Sequential(
```

```
        (0): Bottleneck(
          (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
          (bn1): FrozenBatchNorm2d(128, eps=0.0)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(128, eps=0.0)
          (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
          (bn3): FrozenBatchNorm2d(512, eps=0.0)
          (relu): ReLU(inplace=True)
          (downsample): Sequential(
            (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=Fal
se)
            (1): FrozenBatchNorm2d(512, eps=0.0)
          )
        )
        (1): Bottleneck(
          (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
          (bn1): FrozenBatchNorm2d(128, eps=0.0)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(128, eps=0.0)
          (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
          (bn3): FrozenBatchNorm2d(512, eps=0.0)
          (relu): ReLU(inplace=True)
        )
        (2): Bottleneck(
          (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
          (bn1): FrozenBatchNorm2d(128, eps=0.0)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(128, eps=0.0)
          (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
          (bn3): FrozenBatchNorm2d(512, eps=0.0)
          (relu): ReLU(inplace=True)
        )
        (3): Bottleneck(
          (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
          (bn1): FrozenBatchNorm2d(128, eps=0.0)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(128, eps=0.0)
          (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
          (bn3): FrozenBatchNorm2d(512, eps=0.0)
          (relu): ReLU(inplace=True)
        )
      )
      (layer3): Sequential(
        (0): Bottleneck(
          (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=F
```

```
alse)
          (bn1): FrozenBatchNorm2d(256, eps=0.0)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(256, eps=0.0)
          (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn3): FrozenBatchNorm2d(1024, eps=0.0)
          (relu): ReLU(inplace=True)
          (downsample): Sequential(
            (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=Fa
lse)
            (1): FrozenBatchNorm2d(1024, eps=0.0)
          )
        )
        (1): Bottleneck(
          (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn1): FrozenBatchNorm2d(256, eps=0.0)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(256, eps=0.0)
          (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn3): FrozenBatchNorm2d(1024, eps=0.0)
          (relu): ReLU(inplace=True)
        )
        (2): Bottleneck(
          (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn1): FrozenBatchNorm2d(256, eps=0.0)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(256, eps=0.0)
          (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn3): FrozenBatchNorm2d(1024, eps=0.0)
          (relu): ReLU(inplace=True)
        )
        (3): Bottleneck(
          (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn1): FrozenBatchNorm2d(256, eps=0.0)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(256, eps=0.0)
          (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn3): FrozenBatchNorm2d(1024, eps=0.0)
          (relu): ReLU(inplace=True)
        )
        (4): Bottleneck(
          (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn1): FrozenBatchNorm2d(256, eps=0.0)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
```

```
          (bn2): FrozenBatchNorm2d(256, eps=0.0)
          (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn3): FrozenBatchNorm2d(1024, eps=0.0)
          (relu): ReLU(inplace=True)
        )
        (5): Bottleneck(
          (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn1): FrozenBatchNorm2d(256, eps=0.0)
          (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(256, eps=0.0)
          (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn3): FrozenBatchNorm2d(1024, eps=0.0)
          (relu): ReLU(inplace=True)
        )
      )
      (layer4): Sequential(
        (0): Bottleneck(
          (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn1): FrozenBatchNorm2d(512, eps=0.0)
          (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(512, eps=0.0)
          (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn3): FrozenBatchNorm2d(2048, eps=0.0)
          (relu): ReLU(inplace=True)
          (downsample): Sequential(
            (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=F
alse)
            (1): FrozenBatchNorm2d(2048, eps=0.0)
          )
        )
        (1): Bottleneck(
          (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn1): FrozenBatchNorm2d(512, eps=0.0)
          (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(512, eps=0.0)
          (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn3): FrozenBatchNorm2d(2048, eps=0.0)
          (relu): ReLU(inplace=True)
        )
        (2): Bottleneck(
          (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=
False)
          (bn1): FrozenBatchNorm2d(512, eps=0.0)
          (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1), bias=False)
          (bn2): FrozenBatchNorm2d(512, eps=0.0)
          (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=
```

```
False)
          (bn3): FrozenBatchNorm2d(2048, eps=0.0)
          (relu): ReLU(inplace=True)
        )
      )
    )
    (fpn): FeaturePyramidNetwork(
      (inner_blocks): ModuleList(
        (0): Conv2d(256, 256, kernel_size=(1, 1), stride=(1, 1))
        (1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1))
        (2): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1))
        (3): Conv2d(2048, 256, kernel_size=(1, 1), stride=(1, 1))
      )
      (layer_blocks): ModuleList(
        (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
        (1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
        (2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
        (3): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
      )
      (extra_blocks): LastLevelMaxPool()
    )
  )
  (rpn): RegionProposalNetwork(
    (anchor_generator): AnchorGenerator()
    (head): RPNHead(
      (conv): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
      (cls_logits): Conv2d(256, 3, kernel_size=(1, 1), stride=(1, 1))
      (bbox_pred): Conv2d(256, 12, kernel_size=(1, 1), stride=(1, 1))
    )
  )
  (roi_heads): RoIHeads(
    (box_roi_pool): MultiScaleRoIAlign(featmap_names=['0', '1', '2', '3'], ou
tput_size=(7, 7), sampling_ratio=2)
    (box_head): TwoMLPHead(
      (fc6): Linear(in_features=12544, out_features=1024, bias=True)
      (fc7): Linear(in_features=1024, out_features=1024, bias=True)
    )
    (box_predictor): FastRCNNPredictor(
      (cls_score): Linear(in_features=1024, out_features=91, bias=True)
      (bbox_pred): Linear(in_features=1024, out_features=364, bias=True)
    )
    (mask_roi_pool): MultiScaleRoIAlign(featmap_names=['0', '1', '2', '3'], o
utput_size=(14, 14), sampling_ratio=2)
    (mask_head): MaskRCNNHeads(
      (mask_fcn1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
      (relu1): ReLU(inplace=True)
      (mask_fcn2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
      (relu2): ReLU(inplace=True)
      (mask_fcn3): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
```

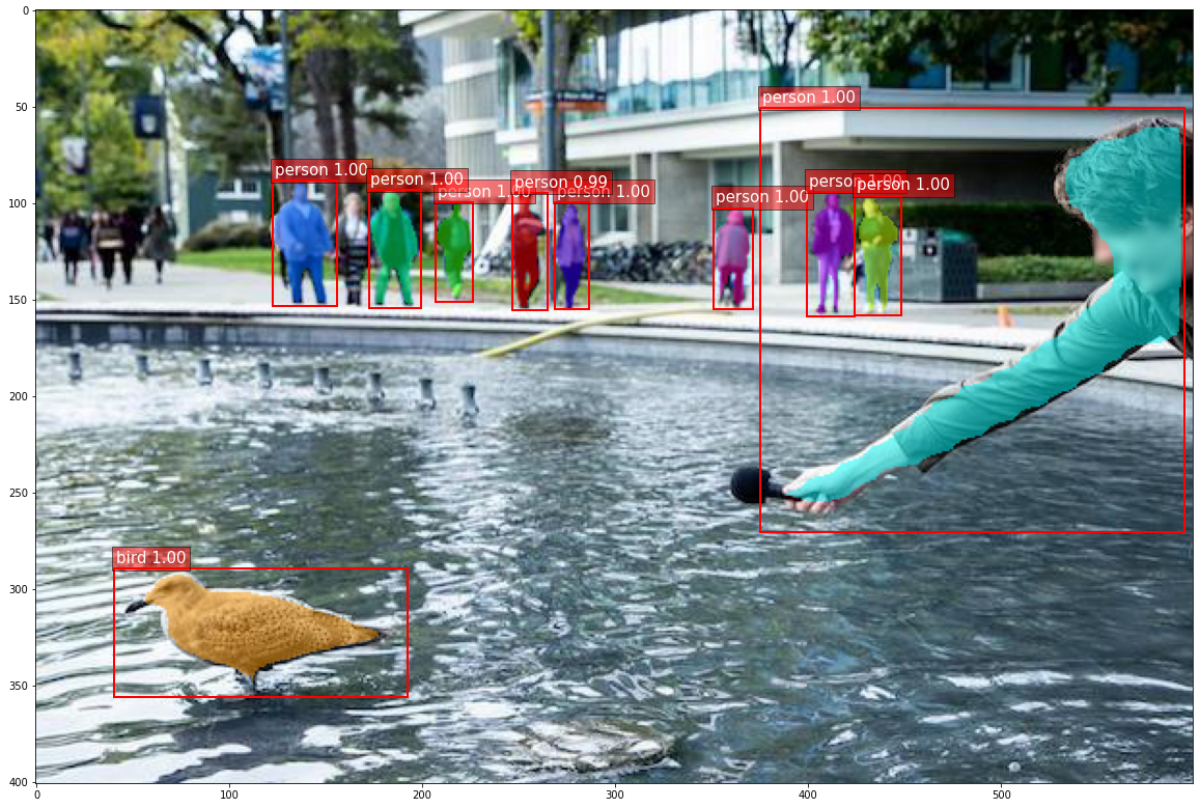
```
      (relu3): ReLU(inplace=True)
      (mask_fcn4): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), paddin
g=(1, 1))
      (relu4): ReLU(inplace=True)
    )
    (mask_predictor): MaskRCNNPredictor(
      (conv5_mask): ConvTranspose2d(256, 256, kernel_size=(2, 2), stride=(2,
2))
      (relu): ReLU(inplace=True)
      (mask_fcn_logits): Conv2d(256, 91, kernel_size=(1, 1), stride=(1, 1))
    )
  )
)
```

The following example shows you how to apply Mask R-CNN on your choice of images. The parameter `im_path` should point to an image path in your directory; `device` can be set above to either `cuda` or `cpu`; `topk` shows the topk most confident objects detected by the network.

The demo image is taken here (https://www.ubyssey.ca/blog/an-interview-with-the-birb/).

In [11]:
```
hw_utils.apply_mask_rcnn(im_path='birb.jpg', model=model, device=device, topk=
10)
```

```
Visualizing birb.jpg
Resized image size: 600, 401
```



Experiment with images of your choice and pick one image that this network would work and two images that this network will fail. Give two sentences to summarize when the model would work and when won't.

Positive Example: this network would work on this image

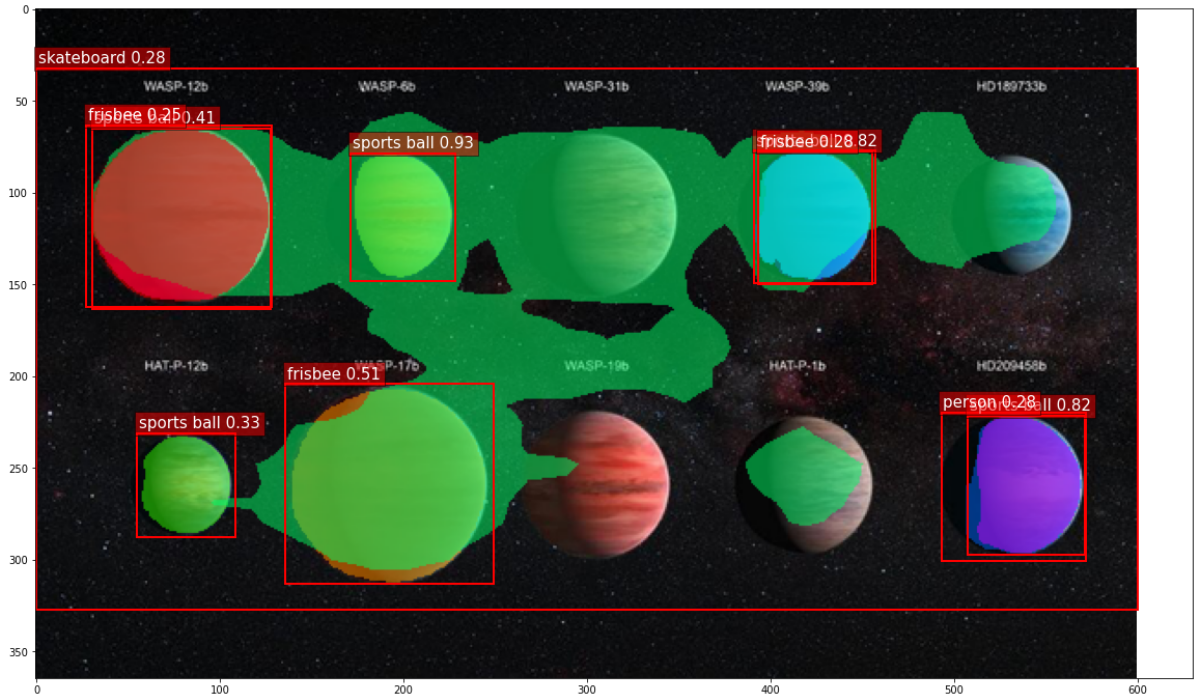
In [19]:
```
hw_utils.apply_mask_rcnn(im_path='freeway.jpg', model=model, device=device, topk=80)
```

```
Visualizing freeway.jpg
Resized image size: 600, 399
```

Negative Examples: this network would fail on two images

In [13]:
```
hw_utils.apply_mask_rcnn(im_path='planets.jpg', model=model, device=device, topk=10)
```

```
Visualizing planets.jpg
Resized image size: 600, 365
```



In [21]:
```
hw_utils.apply_mask_rcnn(im_path='scream.jpg', model=model, device=device, top
k=5)
```

```
Visualizing scream.jpg
Resized image size: 477, 600
```

When it will work?

- As you can see from the picture above, the model is able to identify objects that it was trained on. Even when it is a fairly crowded scene, the model segmented many of the cars and trucks on the congested freeway (albeit some with rather low confidence).

When it will fail?

- The model fails to identify objects that it was not trained on. In the first image, the model has no knowledge that the circles are planets. It makes guesses that they are frisbees and sports balls, due to the circular shape.
- In the second image, we can see that the model completely breaks down. All of the predictions are very low, and there is no obvious segmentation. This is because the painting is very abstract and does not contain any identifiable objects. It is too dissimilar to the data the model was trained on.