You can find my results on my github: https://github.com/Barrel-Titor/homework-MLDL

Data preparation

`caltech_dataset.py` given by https://github.com/MachineLearning2020/Homework2-Caltech101 is incomplete. Quindi the complete code is as follows:

```
 class Caltech(VisionDataset):
     def __init__(self, root, split='train', transform=None, target_transform=None):
         super(Caltech, self).__init__(root, transform=transform, target_transform=target_transform)

         if split != 'train' and split != 'test':
             raise ValueError("should take 'train' or 'test' as value of 'split'")

         self.split = split # This defines the split you are going to use
                            # (split files are called 'train.txt' and 'test.txt')

+        self.root = root
+        self.transform = transform
+        self.target_transform = target_transform
+        self.img_list = []
+
+        self.label_list = [x.name for x in os.scandir(self.root)]
+        self.label_list.sort()
+        self.label_list.remove('BACKGROUND_Google')
+
+        self.split_ = os.path.join(self.root, '..', self.split + '.txt')
+
+        with open(self.split_, 'r') as f:
+            for line in f:
+                line = line.strip('\n')
+                label = line.split('/')[0]
+                if label != 'BACKGROUND_Google':
+                    self.img_list.append((line, self.label_list.index(label)))

     def __getitem__(self, index):
-        image, label = ...
+        path, label = self.img_list[index]
+        image = pil_loader(os.path.join(self.root, path))

         if self.transform is not None:
             image = self.transform(image)

         return image, label

     def __len__(self):
-        length = ...
```

```
+        length = len(self.img_list)
         return length
```

If any string, except 'train' and 'test', is provided for the argument `split`, it will raise an error.

`BACKGROUND_Google` is removed from the label_list. Besides, whenever a line in `train.txt` and `test.txt` is started with `BACKGROUND_Google`, that line is ignored.

Training from scratch

A. Split training set in training and validation sets

In order to balance the number of images of each folder in train set and validation set, `train_indexes` and `val_indexes` are selected as [0, 2, 4, ...] and [1, 3, 5, ...]

```
train_val_dataset = Caltech(DATA_DIR, split='train', transform=train_transform)
test_dataset = Caltech(DATA_DIR, split='test', transform=eval_transform)

train_indexes = list(range(0, len(train_val_dataset), 2))
val_indexes = list(range(1, len(train_val_dataset), 2))

train_dataset = Subset(train_val_dataset, train_indexes)
val_dataset = Subset(train_val_dataset, val_indexes)
```

B. Model selection with validation

Since I have to evaluate the model every training epoch, I combine the train part and validation part given by the template in one epoch.

Hyperparameters are the default ones:

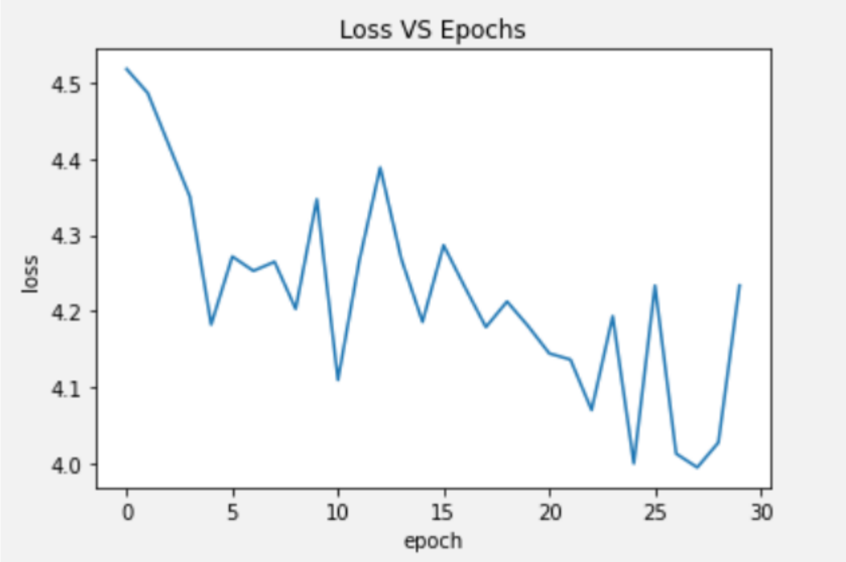
Current hyperparameters	Value
Initial learning rate	0.001
Decaying policy	StepLR
Decaying step size	20 epochs
Decaying factor	0.1
Optimizer	SGD
Epochs	30

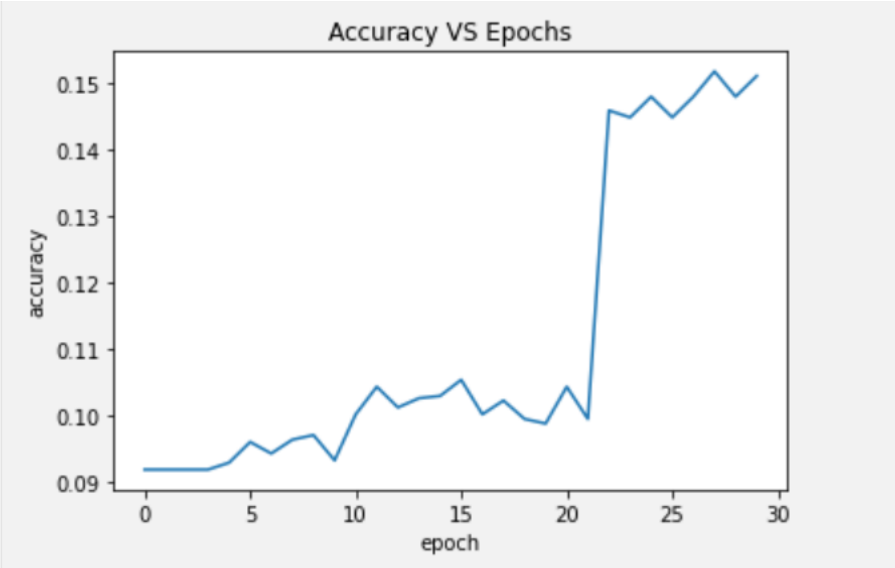
Use only the best performing model on the validation set for testing

```
# Start iterating over the epochs
for epoch in range(NUM_EPOCHS):
```

```
    print('Starting epoch {}/{}, LR = {}'.format(epoch+1, NUM_EPOCHS, scheduler.get_last_lr()))

    # Train part
    net.train() # Sets module in training mode

    # Iterate over the dataset
    for images, labels in train_dataloader:
        # Bring data over the device of choice
        images = images.to(DEVICE)
        labels = labels.to(DEVICE)

        # PyTorch, by default, accumulates gradients after each backward pass
        # We need to manually set the gradients to zero before starting a new iteration
        optimizer.zero_grad() # Zero-ing the gradients

        # Forward pass to the network
        outputs = net(images)

        # Compute loss based on output and ground truth
        loss = criterion(outputs, labels)

        # Log loss
        if current_step % LOG_FREQUENCY == 0:
            print('Step {}, Loss {}'.format(current_step, loss.item()))

        # Compute gradients for each layer and update weights
        loss.backward()  # backward pass: computes gradients
        optimizer.step() # update weights based on accumulated gradients

        current_step += 1

    # Step the scheduler
    scheduler.step()

    # Use the best model for validation
    if not loss_hist or loss.item() < min(loss_hist):
        best_net = deepcopy(net)

    # Validation part
    best_net.train(False) # Set Network to evaluation mode

    running_corrects = 0
    with torch.no_grad():
        for images, labels in val_dataloader:
            images = images.to(DEVICE)
            labels = labels.to(DEVICE)

            # Forward Pass
            outputs = best_net(images)

            # Get predictions
            _, preds = torch.max(outputs.data, 1)

            # Update Corrects
            running_corrects += torch.sum(preds == labels.data).data.item()
```

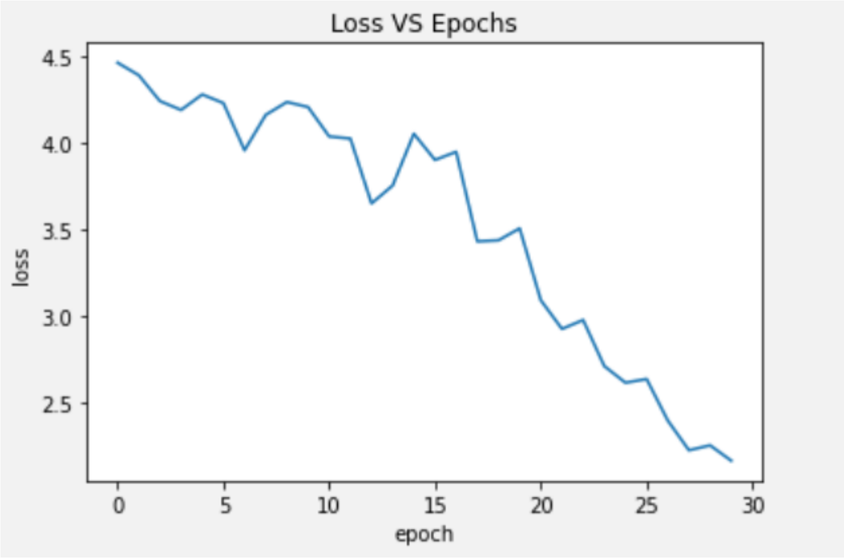
```
    # Calculate Accuracy
    accuracy = running_corrects / float(len(val_dataset))
    print('Accuracy {}\n'.format(accuracy))

    # Record loss and accuracy after each epoch
    loss_hist.append(loss.item())
    acc_hist.append(accuracy)
```

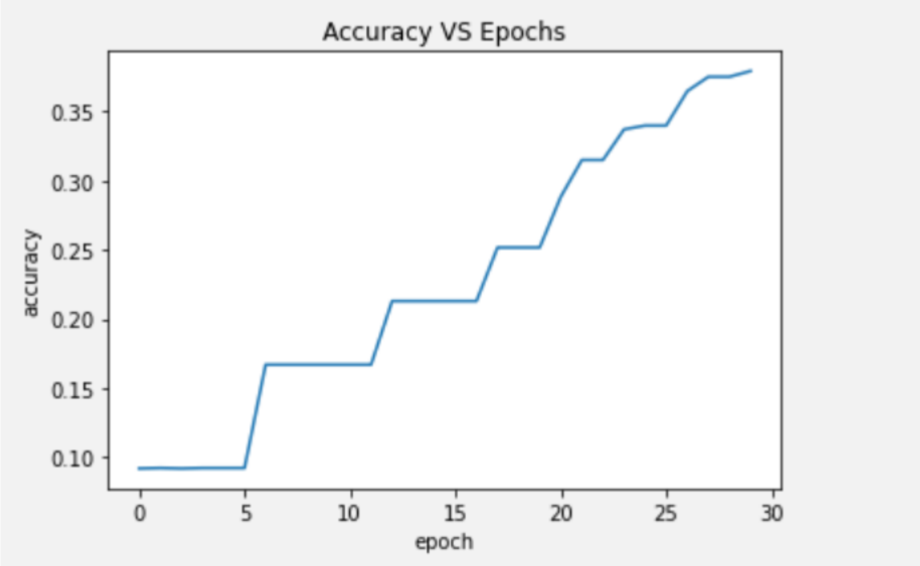




C. Try 2 sets of hyperparameters

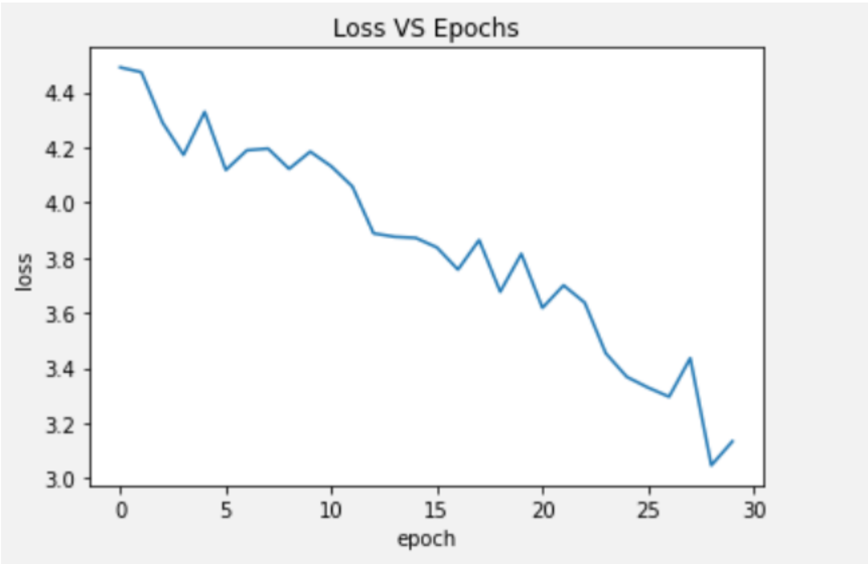
Current hyperparameters	Value
Initial learning rate	0.1
Decaying policy	StepLR
Decaying step size	20 epochs
Decaying factor	0.1
Optimizer	SGD
Epochs	30

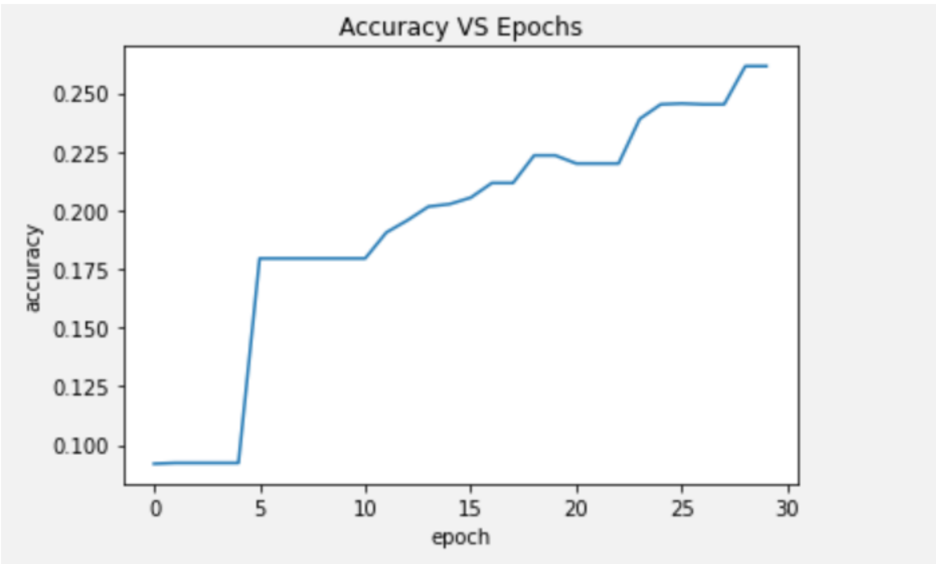





```
test_accuracy    # 0.39094365710335294
```

Current hyperparameters	Value
Initial learning rate	0.1
Decaying policy	StepLR
Decaying step size	10 epochs
Decaying factor	0.3
Optimizer	SGD
Epochs	30






```
test_accuracy    # 0.27134462495679224
```

Transfer learning and Data augmentation

A. Load AlexNet with weights trained on ImageNet

Pytorch already provides methods to load weights

```
net = alexnet(pretrained=True)
```

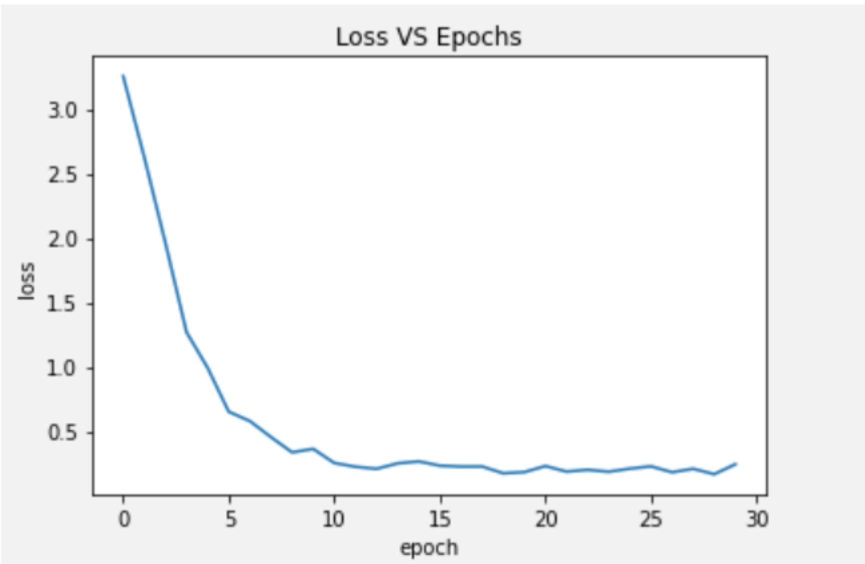
B. Change the normalize function

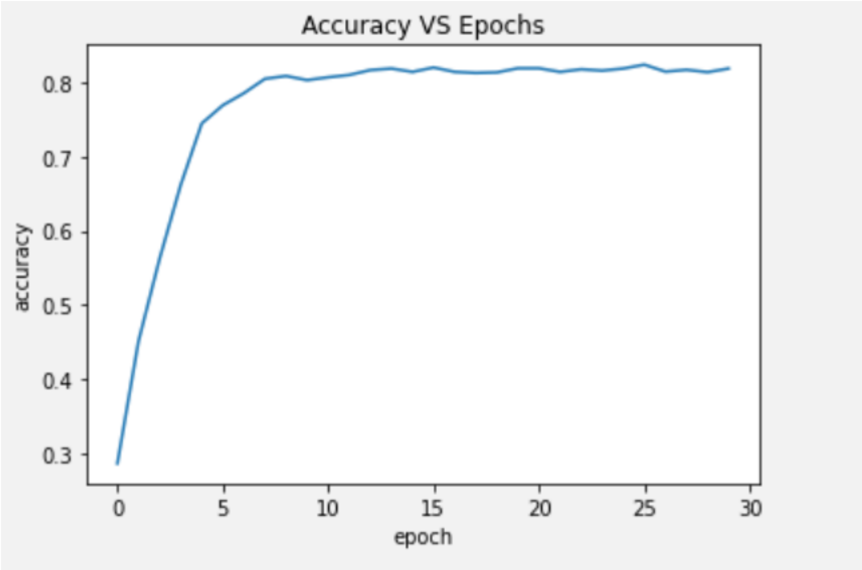
Reading Pytorch documents, I find that mean of ImageNet is [0.485, 0.456, 0.406], and standard deviation [0.229, 0.224, 0.225]

C. Try 3 sets of hyperparameters

Since this is the procedure of fine tuning, I set the initial learning rate a small number.

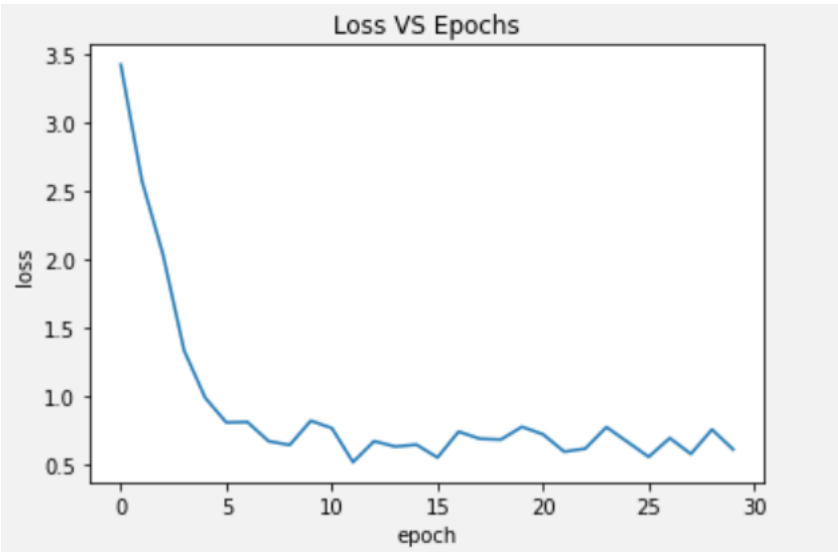
Current hyperparameters	Value
Initial learning rate	0.001
Decaying policy	StepLR
Decaying step size	10 epochs
Decaying factor	0.1
Optimizer	SGD
Epochs	30

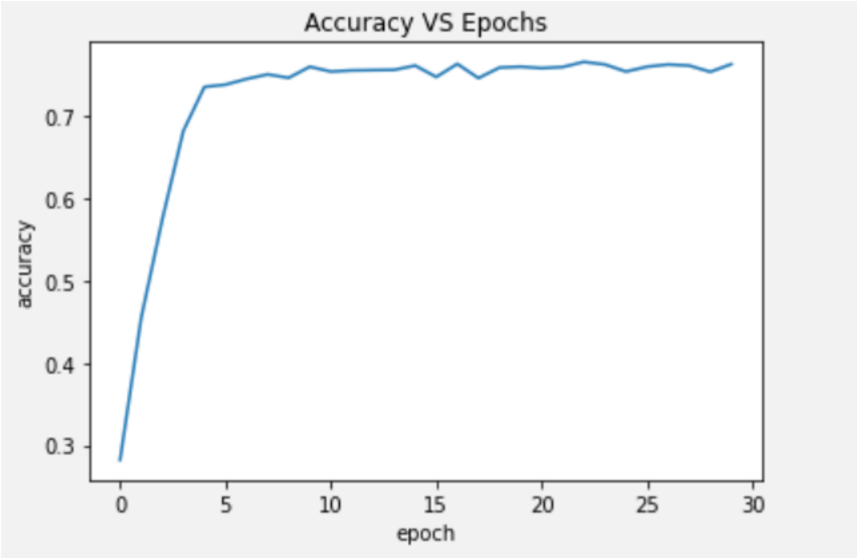





```
test_accuracy    # 0.8212927756653993
```

Current hyperparameters	Value
Initial learning rate	0.001
Decaying policy	StepLR
Decaying step size	5 epochs
Decaying factor	0.1
Optimizer	SGD
Epochs	30



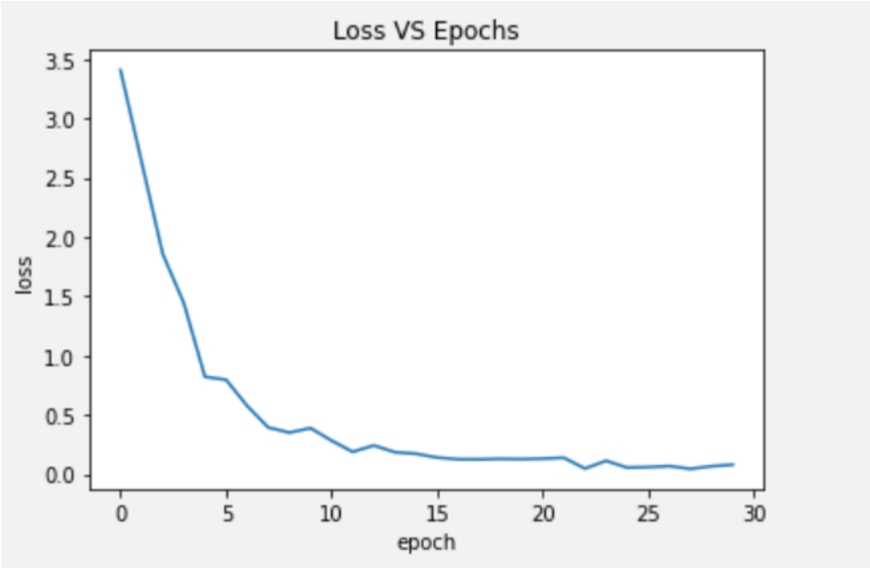


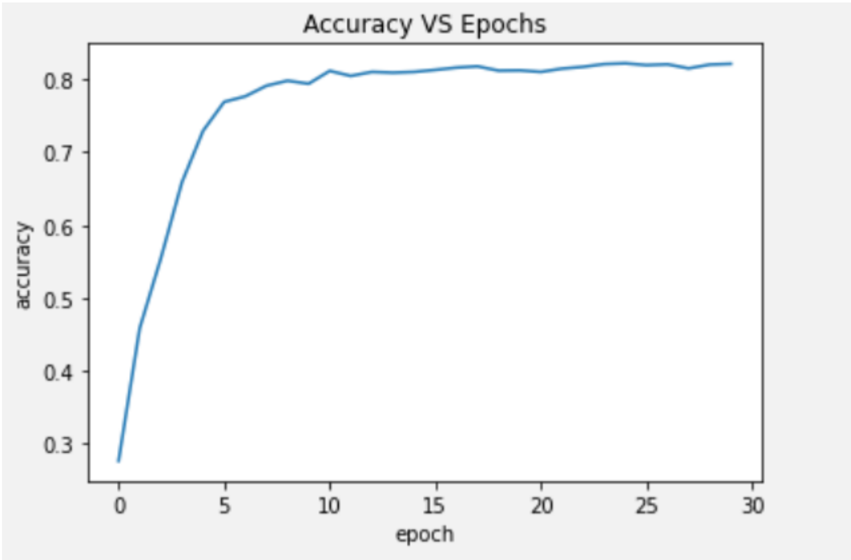

```
test_accuracy    # 0.7684064984445212
```

I also try different scheduler `torch.optim.lr_scheduler.ReduceLROnPlateau`

> Reduce learning rate when a metric has stopped improving. Models often benefit from reducing the learning rate by a factor of 2-10 once learning stagnates. This scheduler reads a metrics quantity and if no improvement is seen for a 'patience' number of epochs, the learning rate is reduced.

Current hyperparameters	Value
Initial learning rate	0.001
Decaying policy	ReduceLROnPlateau
Decaying factor	0.1
Decaying patience	3 epochs
Optimizer	SGD
Epochs	30





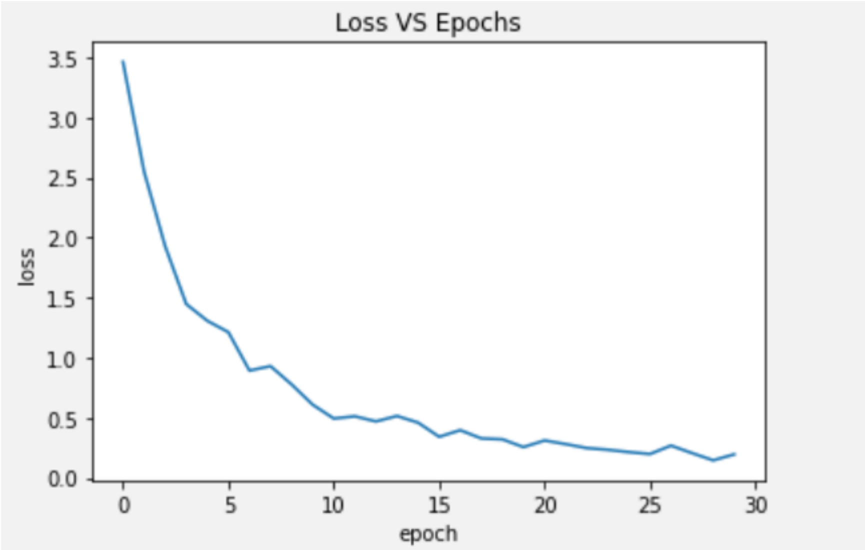

```
test_accuracy   # 0.832353957829243
```

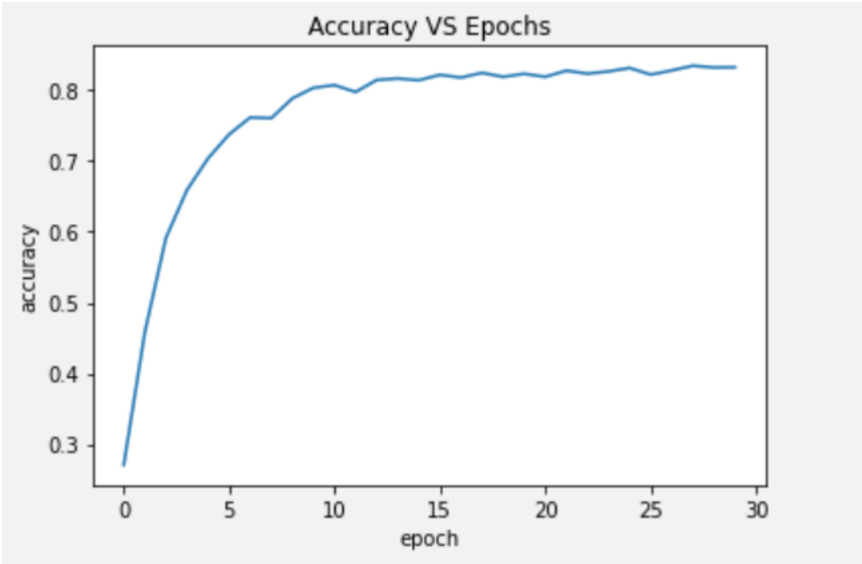
This set of hyperparameters performs best, so I use it in the following sections.

D. Experiment by training only the FC layers

Only one line needs to be modified compared with above:

```
  criterion = nn.CrossEntropyLoss()
- parameters_to_optimize = net.parameters()
+ parameters_to_optimize = net.classifier.parameters()
  optimizer = optim.SGD(parameters_to_optimize, lr=LR, momentum=MOMENTUM, weight_decay=WEIGHT_DECAY)
  scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, factor=FACTOR, patience=PATIENCE)
```



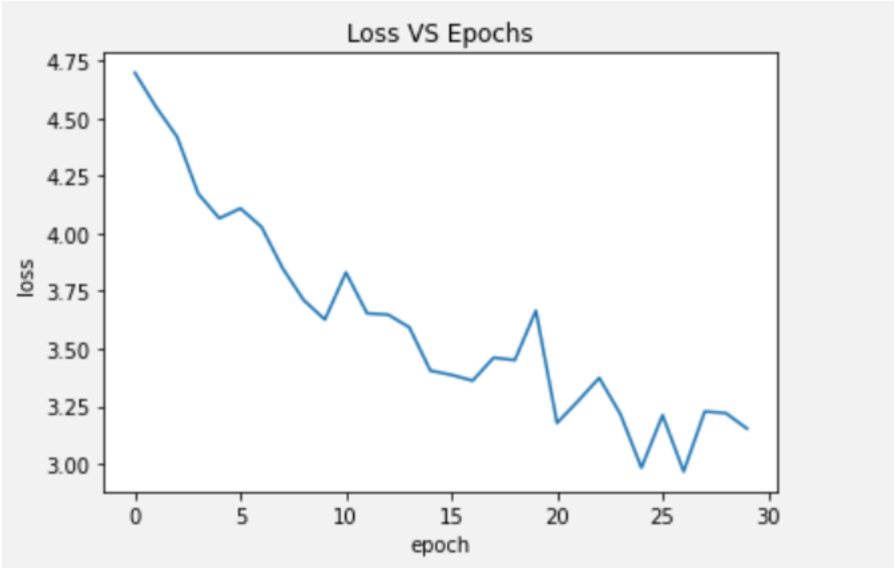


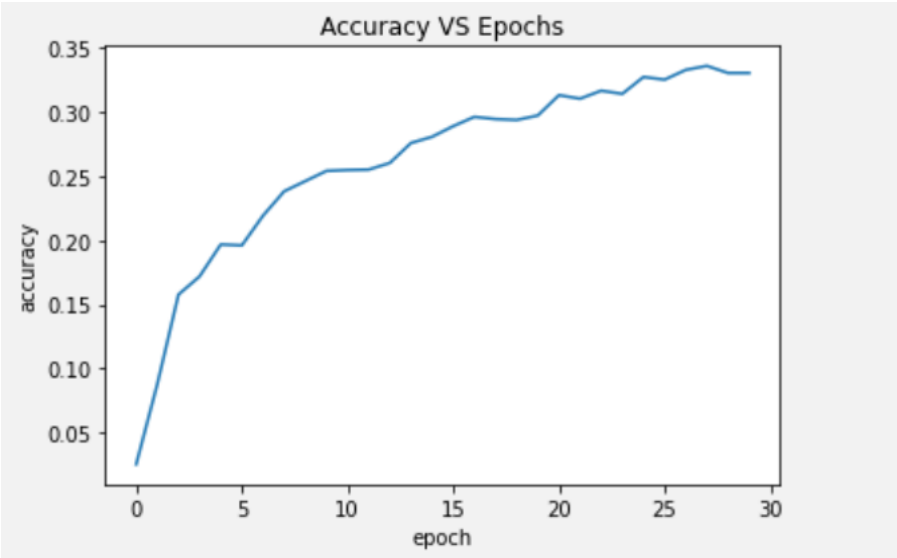

```
test_accuracy    # 0.8354649153128241
```

The result doesn't vary much, but the speed up is obvious

E. Experiment by training only the Conv layers

```
  criterion = nn.CrossEntropyLoss()
- parameters_to_optimize = net.parameters()
+ parameters_to_optimize = net.features.parameters()
  optimizer = optim.SGD(parameters_to_optimize, lr=LR, momentum=MOMENTUM, weight_decay=WEIGHT_DECAY)
  scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, factor=FACTOR, patience=PATIENCE)
```






```
test_accuracy   # 0.3328724507431732
```

The result seems awful, but at least better than that not using transfer learning.

Data Augmentation

Checking Pytorch documentation, I select 3 sets of transforms for training images:

- transforms.RandomCrop(224)
- transforms.RandomHorizontalFlip()
- transforms.ColorJitter()

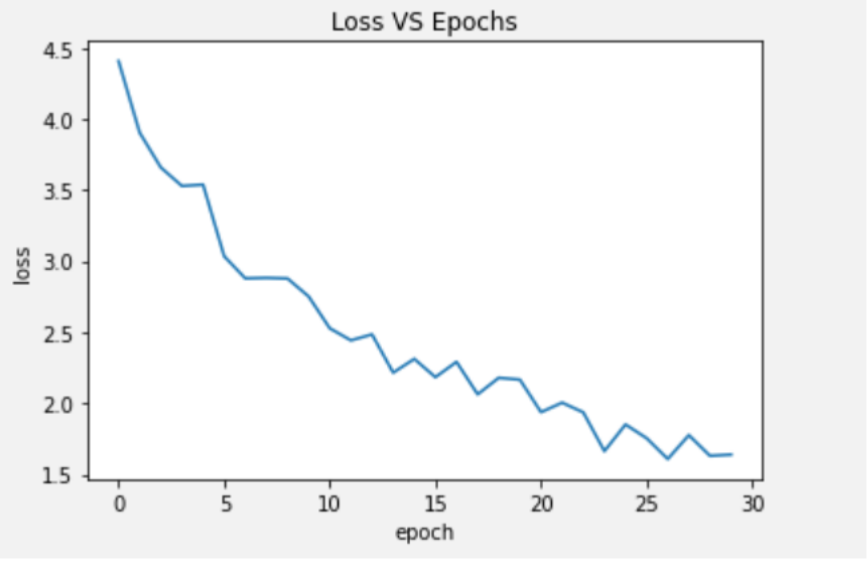
And I don't use data augmentation methods on test images.

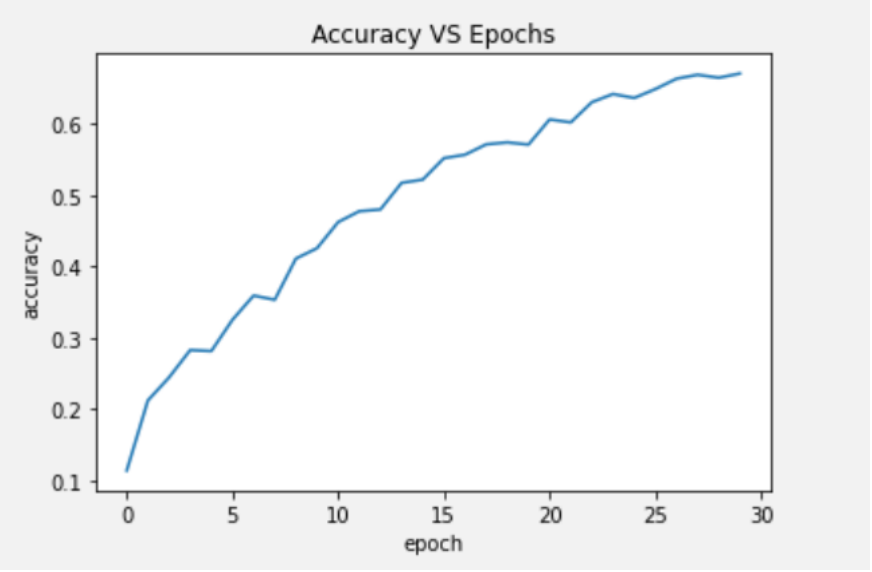
Therefore the code is as follows:

```
train_transform = transforms.Compose([transforms.Resize(256),
                                     transforms.RandomCrop(224),
                                     transforms.RandomHorizontalFlip(),
                                     transforms.ColorJitter(),
                                     transforms.ToTensor(),
                                     transforms.Normalize([0.485, 0.456,
0.406], [0.229, 0.224, 0.225])

eval_transform = transforms.Compose([transforms.Resize(256),
                                    transforms.CenterCrop(224),
                                    transforms.ToTensor(),
                                    transforms.Normalize([0.485, 0.456,
0.406], [0.229, 0.224, 0.225])
```

Try ResNet18

Fortunately the input size of ResNet18 is also 224 * 224, thus there aren't much differences in code.






```
test_accuracy    # 0.6864846180435534
```