实验三报告

一. 实验要求

1. 用多层感知机(MLP)和卷积网络(ConvNet)完成CIFAR图像分类

   使用PyTorch分别实现多层感知机(MLP)和卷积网络(ConvNet)，并完成CIFAR图像分类。本案例不提供初始代码，请自行配置网络和选取超参数，包括层数、卷积核数目、激活函数类型、损失函数类型、优化器等方面。

   提交所有代码和一份案例报告，要求如下：

   - 详细介绍所使用的模型及其结果，至少包括超参数选取，损失函数、准确率及其曲线；
   - 比较不同模型配置下的结果，至少从三个方面作比较和分析，例如层数、卷积核数目、激活函数类型、损失函数类型、优化器等。
2. 学习PyTorch ImageNet分类示例
   - 请自行学习PyTorch官方提供的ImageNet分类示例代码，以便更好地完成后续案例(https://github.com/pytorch/examples/tree/master/imagenet)，这部分无需提交代码和报告。

二. 数据加载与概览

2.1 数据加载

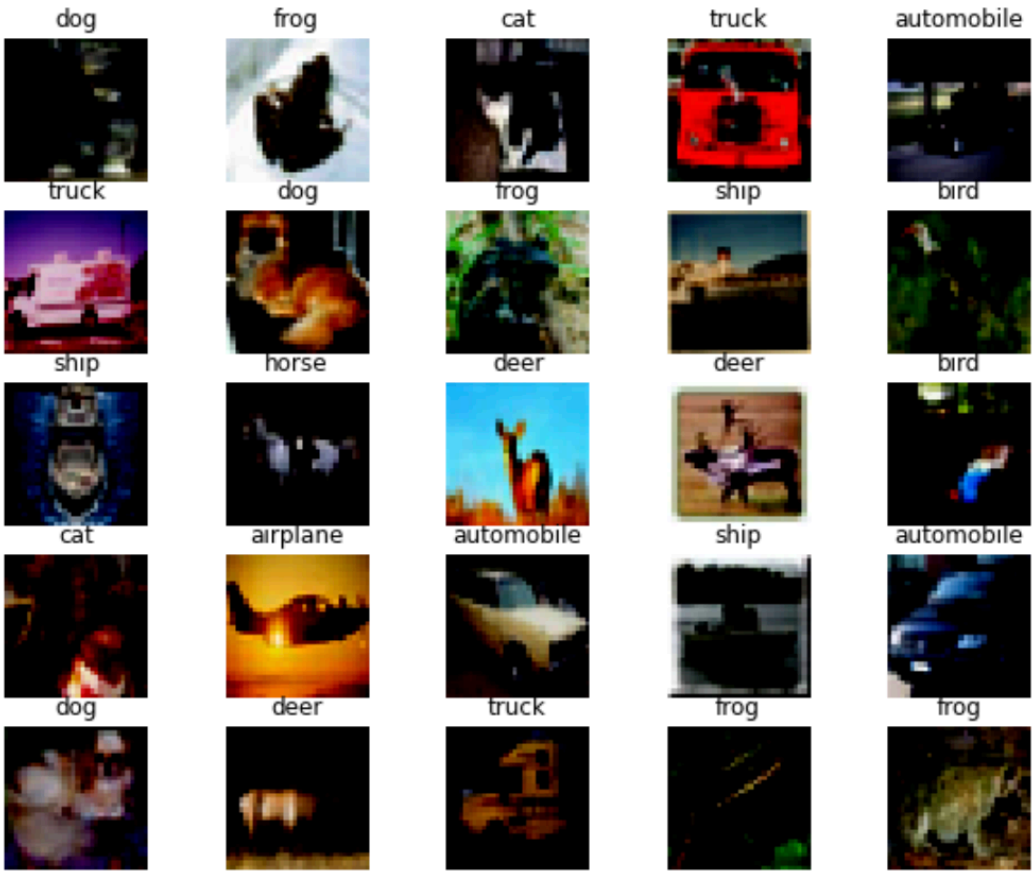
数据来自`torchvision.dataset`中的CIFAR10数据集。

```
train_data = datasets.CIFAR10(
    root = 'data',
    train = True,
    transform = transforms.Compose(
        [transforms.ToTensor(),
         transforms.Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))]
    ),
    download = True,
)

test_data = datasets.CIFAR10(
    root = 'data',
    train = False,
    transform = transforms.Compose(
          [transforms.ToTensor(),
           transforms.Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))]
    )
)
loaders = {
    'train' : torch.utils.data.DataLoader(train_data,
                                          batch_size=100,
                                          sampler = train_sampler,
                                          num_workers=3),
    'valid' : torch.utils.data.DataLoader(train_data,
```

```
                                            batch_size = 100,
                                            sampler = valid_sampler,
                                            num_workers=3),
    'test'  : torch.utils.data.DataLoader(test_data,
                                            batch_size=100,
                                            shuffle=True,
                                            num_workers=3),
}
```

2.2 数据预览

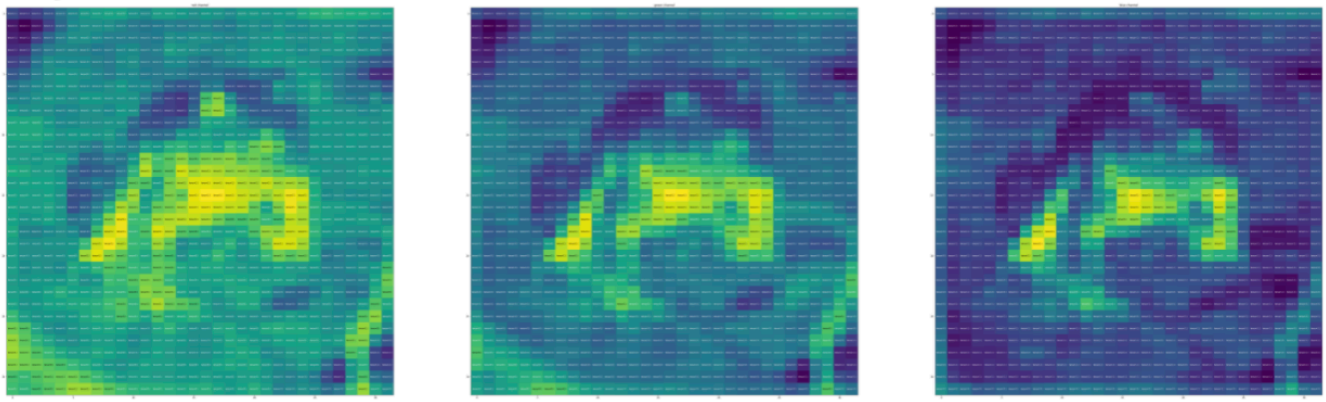
```
import matplotlib.pyplot as plt
import numpy as np

figure = plt.figure(figsize=(10, 8))
cols, rows = 5, 5
for i in range(1, cols * rows + 1):
    sample_idx = torch.randint(len(train_data), size=(1,)).item()
    img, label = train_data[sample_idx]
    ax = figure.add_subplot(rows, cols, i)
    plt.title(label)
    plt.axis("off")
    plt.imshow(np.transpose(img, (1, 2, 0)), interpolation='nearest')
    ax.set_title(classes[label])
plt.show()
```



我们可以将图片展开来观察。

```
image, label = train_data[0]
rgb_img = np.squeeze(image)
channels = ['red channel', 'green channel', 'blue channel']

fig = plt.figure(figsize=(100,100))
print(classes[label])
for idx in range(rgb_img.shape[0]):
  ax = fig.add_subplot(1,3,idx+1)
  img = rgb_img[idx]
  ax.imshow(img)
  ax.set_title(channels[idx])
  width, height = img.shape
  threshold = img.max()/2.5
  for x in range(width):
      for y in range(height):
          val = np.round(img[x][y]) if img[x][y] !=0 else 0
          ax.annotate(str(val), xy=(y,x),
                  horizontalalignment='center',
                  verticalalignment='center', size=8,
                  color='white' if img[x][y] < threshold else 'black')
```

```
frog
```



从上图观察中可以看到，每个channel的二维特征是不同。

三. ConvNet调试

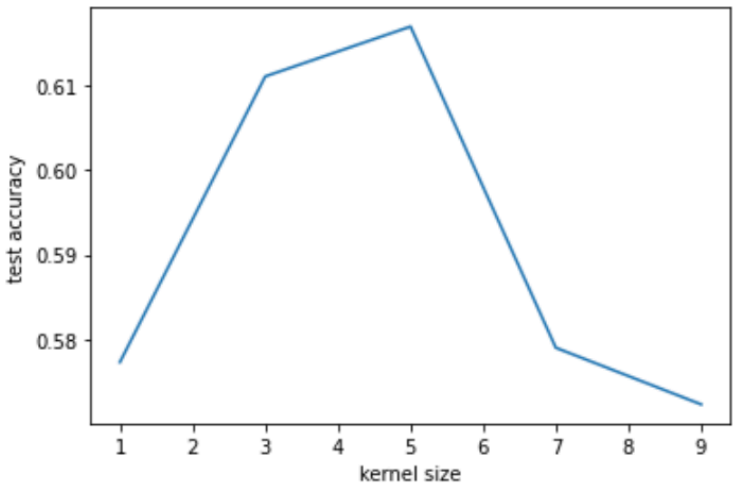
3.1 基本模型定义

```
class CNN(nn.Module):
  def __init__(self, kernel_size):
    super(CNN, self).__init__()
    self.conv1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=kernel_size)
    self.pool = nn.MaxPool2d(2, 2)
    self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=kernel_size)
    self.fc1 = nn.LazyLinear(out_features=120)
```

```
    self.fc2 = nn.Linear(in_features=120, out_features=84)
    self.fc3 = nn.Linear(in_features=84, out_features=10)

  def forward(self, x):
    x = self.pool(F.relu(self.conv1(x)))
    x = self.pool(F.relu(self.conv2(x)))
    x = x.view(x.size(0), -1)
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
    return x
```

3.2 调试卷积核数目

kernel size	1	3	5	7	9
test accuracy	0.5773	0.6111	0.6170	0.5790	0.5723



这里对卷积核大小进行了一个调整，kernel_size=3或5都是较优的选择。

3.3 调试层数

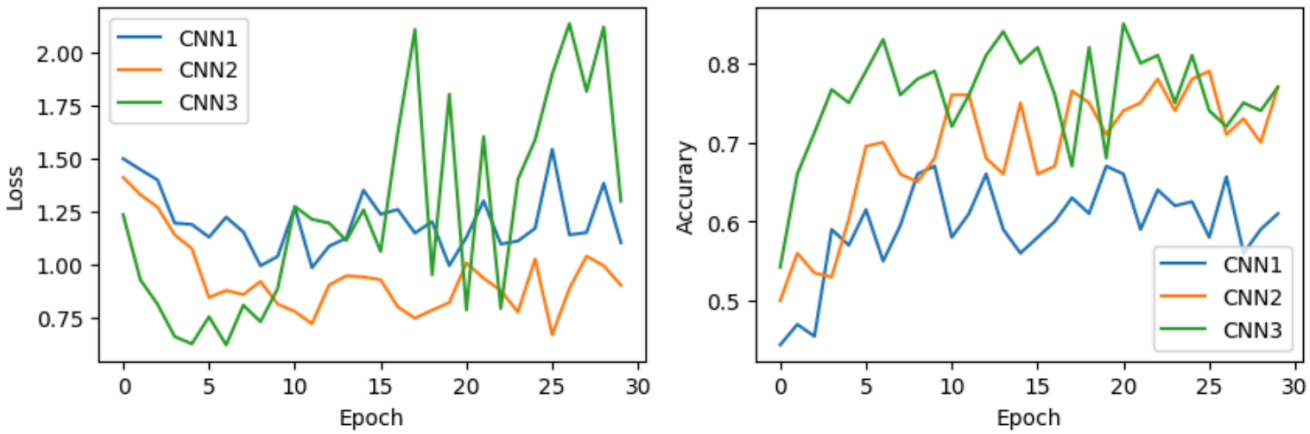
这里尝试了三个不同架构的CNN模型

```
# 模型一： 两层conv layer + 三层fc layer
class CNN1(nn.Module):
  def __init__(self):
    super(CNN1, self).__init__()
    self.conv1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=3)
    self.pool = nn.MaxPool2d(2, 2)
    self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=3)
    self.fc1 = nn.LazyLinear(120)
    self.fc2 = nn.Linear(120, 84)
```

```
    self.fc3 = nn.Linear(84, 10)

  def forward(self, x):
    x = self.pool(F.relu(self.conv1(x)))
    x = self.pool(F.relu(self.conv2(x)))
    x = x.view(x.size(0), -1)
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
    return x

# 模型二：三层conv layer + 三层fc layer
class CNN2(nn.Module):
  def __init__(self):
      super(CNN2, self).__init__()
      self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
      self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
      self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
      self.pool = nn.MaxPool2d(2, 2)
      self.fc1 = nn.Linear(64 * 4 * 4, 512)
      self.fc2 = nn.Linear(512, 64)
      self.fc3 = nn.Linear(64, 10)

  def forward(self, x):
      x = self.pool(F.relu(self.conv1(x)))
      x = self.pool(F.relu(self.conv2(x)))
      x = self.pool(F.relu(self.conv3(x)))
      x = x.view(-1, 64 * 4 * 4)
      x = self.dropout(F.relu(self.fc1(x)))
      x = self.dropout(F.relu(self.fc2(x)))
      x = self.fc3(x)
      return x

# 模型三：六层conv layer + 三层fc layer
class CNN3(nn.Module):
    def __init__(self):
        super(CNN3, self).__init__()
        self.conv_layer = nn.Sequential(
            # Conv Layer block 1
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
            # Conv Layer block 2
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.Conv2d(in_channels=128, out_channels=128, kernel_size=3, padding=1),
            nn.ReLU(),
```

```
            nn.MaxPool2d(kernel_size=2, stride=2),
            # Conv Layer block 3
            nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.Conv2d(in_channels=256, out_channels=256, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )
        self.fc_layer = nn.Sequential(
            nn.Linear(4096, 1024),
            nn.ReLU(),
            nn.Linear(1024, 512),
            nn.ReLU(),
            nn.Linear(512, 10)
        )

    def forward(self, x):
        x.view(-1, 3*32*32)
        x = self.conv_layer(x)
        x = x.view(x.size(0), -1)
        x = self.fc_layer(x)
        return x
```

	CNN1	CNN2	CNN3
Train Loss	0.4752	0.3567	0.0575
Train Accuracy		0.8754	0.9822
Validation Loss	1.1032	0.9035	
Validation Accuracy	0.6100	0.7700	0.7700

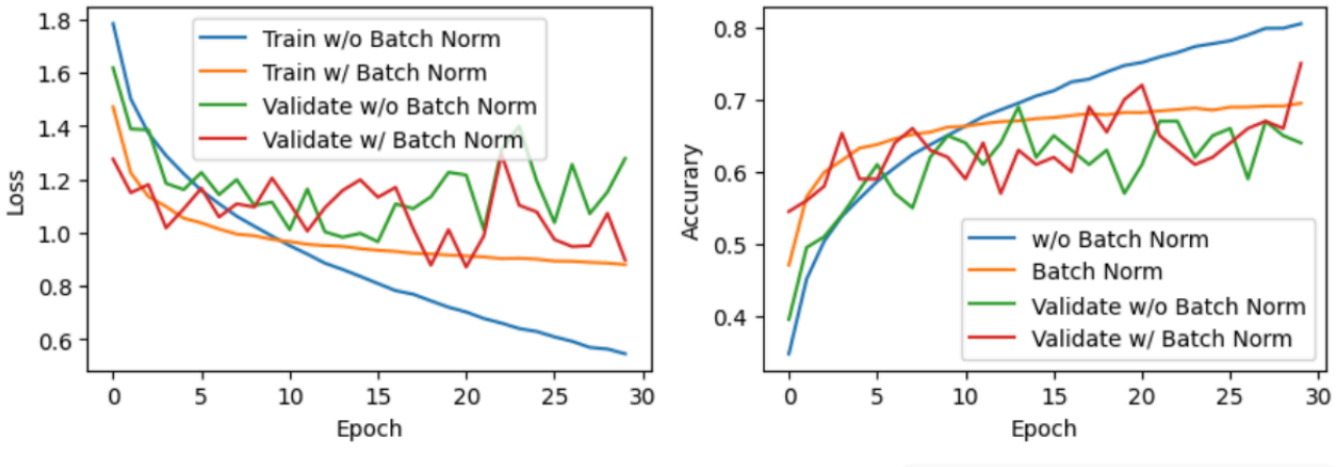


分析：总体来说，卷积层个数越多，效果更佳，但同时模型预测的效果并不是很稳定（上图为validation set上的结果）。

3.4 加入Batch Normalisation

```
# no batch norm
class CNN(nn.Module):
  def __init__(self):
    super(CNN, self).__init__()
    self.conv1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=5)
    self.pool = nn.MaxPool2d(2, 2)
    self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5)
    self.fc1 = nn.Linear(16 * 5 * 5, 120)
    self.fc2 = nn.Linear(120, 84)
    self.fc3 = nn.Linear(84, 10)

  def forward(self, x):
    x = self.pool(F.relu(self.conv1(x)))
    x = self.pool(F.relu(self.conv2(x)))
    x = x.view(-1, 16 * 5 * 5)
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
    return x

# batch norm
class CNN_batchnorm(nn.Module):
  def __init__(self):
    super().__init__()
    self.model = nn.Sequential(
        nn.Conv2d(in_channels=3, out_channels=6, kernel_size=5),
        nn.ReLU(),
        nn.MaxPool2d(2, 2),
        nn.BatchNorm2d(6),
        nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5),
        nn.ReLU(),
        nn.MaxPool2d(2, 2),
        nn.BatchNorm2d(16),
        nn.Flatten(),
        nn.Linear(16 * 5 * 5, 120),
        nn.Linear(120, 84),
        nn.Linear(84, 10)
    )

  def forward(self, x):
    return self.model(x)
```

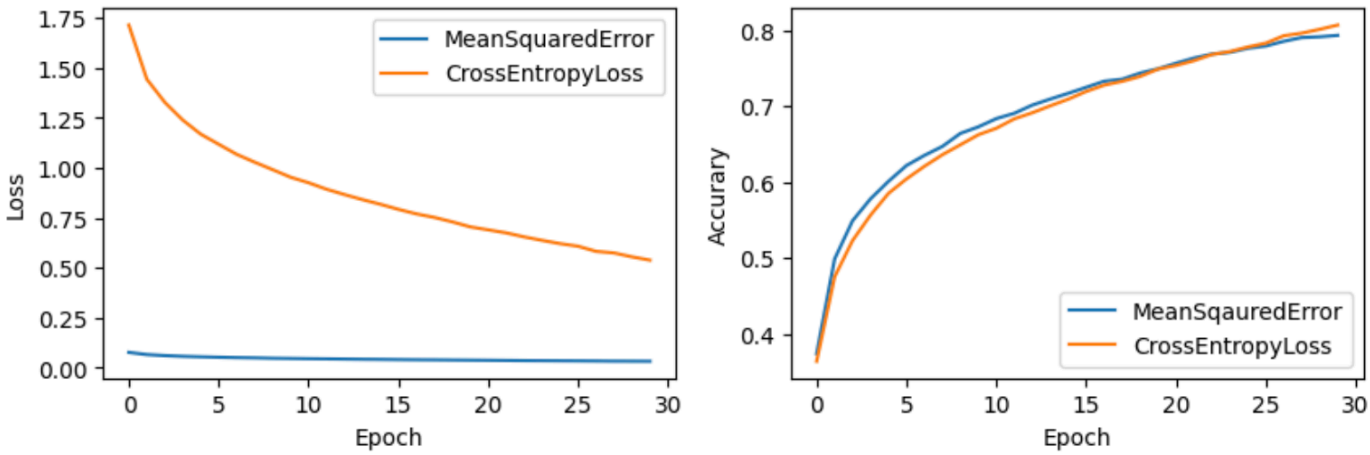
	batch norm	no batch norm
Train Loss	0.8802	0.5453
Train Accurarcy	0.6948	0.8051
Validation Loss	0.8973	1.2779
Validation Accuracy	0.7500	0.6400



分析：主要观察上图模型在validation set上的表现，可以看出加入batch normalization的模型比不加入batch normalization的模型在validation set上的总体效果更好。同时也反映了原cnn模型存在过拟合的情况。

3.5 调整损失函数类型

	MeanSquaredError	CrossEntropyLoss
Train Loss		0.5381
Train Accuracy	0.7931	0.8066
Validation Loss	0.0604	1.1379
Validation Accuracy	0.5700	0.6400

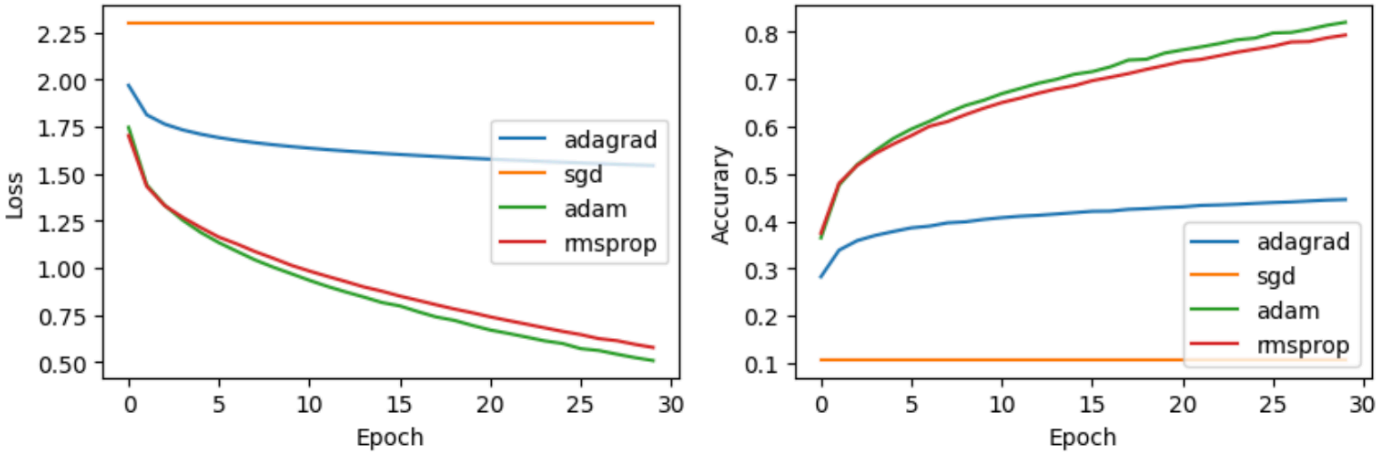


分析：对于accuracy这一衡量标准而言，MeanSquaredError与CrossEntropy并无显著差距。对于loss而言，由于其本身算法不同，loss的大小也不相同，这是自然的。

3.6 调整优化器

以下的learning rate均为0.001。

	sgd	adagrad	rmsprop	adam
Trian Loss	2.3054	1.5440	0.5772	0.5074
Train Accuracy	0.1052	0.4457	0.7936	0.8206
Validation Loss	2.2962	1.5225	1.3441	1.4153
Validation Accuracy	0.1050	0.3800	0.6500	0.6000



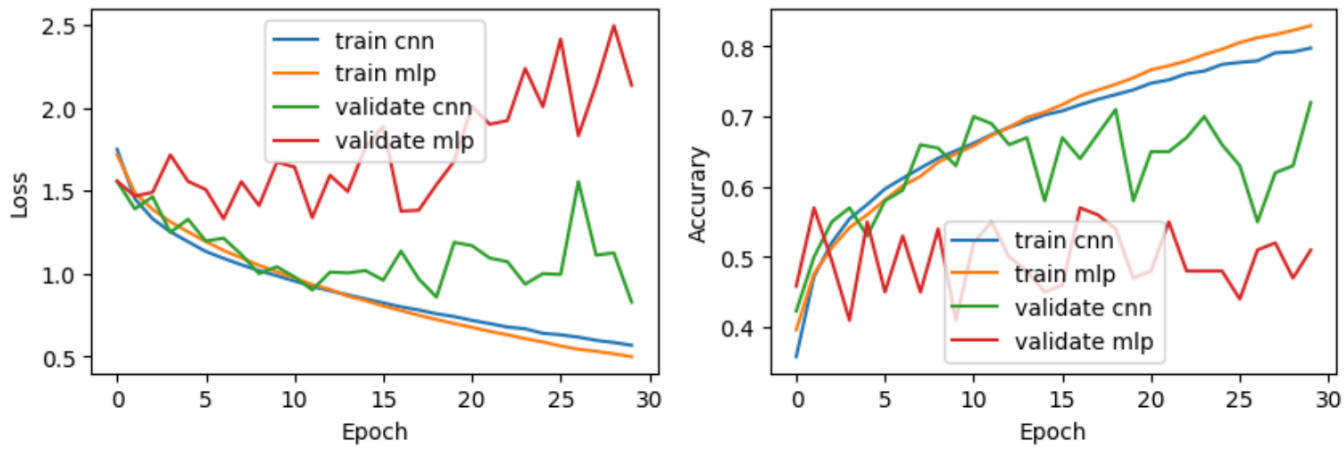
分析：从上图中可以看出sgd的表现最差，仅对学习率进行单调下降的adagrad其效果就已经有显著的提升，而RMSProp（动态调整学习率）和Adam（动态调整学习率并加上了动量）的效果相差并不是很多。

四. MLP与ConvNet 性能比较

```
# define mlp
class MLP(nn.Module):
  def __init__(self):
    super().__init__()
    self.fc1 = nn.Linear(3*32*32, 120)
    self.fc2 = nn.Linear(120, 84)
    self.fc3 = nn.Linear(84, 10)

  def forward(self, x):
    x = x.view(-1, 3*32*32)
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = F.relu(self.fc3(x))
    return x

```

```python
# define CNN
class CNN(nn.Module):
  def __init__(self):
    super(CNN, self).__init__()
    self.conv1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=5)
    self.pool = nn.MaxPool2d(2, 2)
    self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5)
    self.fc1 = nn.Linear(16 * 5 * 5, 120)
    self.fc2 = nn.Linear(120, 84)
    self.fc3 = nn.Linear(84, 10)

  def forward(self, x):
    x = self.pool(F.relu(self.conv1(x)))
    x = self.pool(F.relu(self.conv2(x)))
    x = x.view(-1, 16 * 5 * 5)
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
    return x
```

	MLP	CNN
Train Loss		
Train Accuracy		
Validation Loss		0.8272
Validation Accuracy	0.5100	0.7200



分析：对比两个模型，在fc layer个数相同的情况下，cnn的表现更佳，这完全可以归功于convolution layer对二维特征提取及描述的优越性。

五. 总结

最终模型

```
class CNN_final(nn.Module):
    def __init__(self):
        super(CNN_final, self).__init__()
        self.conv_layer = nn.Sequential(
            # Conv Layer block 1
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(32),
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),

            # Conv Layer block 2
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(128),
            nn.Conv2d(in_channels=128, out_channels=128, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
            # Conv Layer block 3
            nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(256),
            nn.Conv2d(in_channels=256, out_channels=256, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )
        self.fc_layer = nn.Sequential(
            nn.Dropout(p=0.1),
            nn.Linear(4096, 1024),
            nn.ReLU(),
            nn.Linear(1024, 512),
            nn.ReLU(),
            nn.Dropout(p=0.1),
            nn.Linear(512, 10)
        )

    def forward(self, x):
        x.view(-1, 3*32*32)
        x = self.conv_layer(x)
        x = x.view(x.size(0), -1)
        x = self.fc_layer(x)
        return x
```

结果：

```
Test Accuracy of the model on the 10000 test images: 0.8244
```

计算最终模型的置信区间：

一共$10,000$个测试样本，约有 0.8244 误分类的.

那么estimate of sample standard deviation $\sigma_{\bar{x}} \approx \sqrt{\frac{0.8244(1-0.8244)}{10000}} = 0.003804$

结论：本次模型的accuracy score 95%的置信区间$\approx 0.8244 \pm 1.96 \cdot 0.003804 \approx 0.8244 \pm 0.0075$