CNN to Classify American Sign Language (ASL)

Group 9
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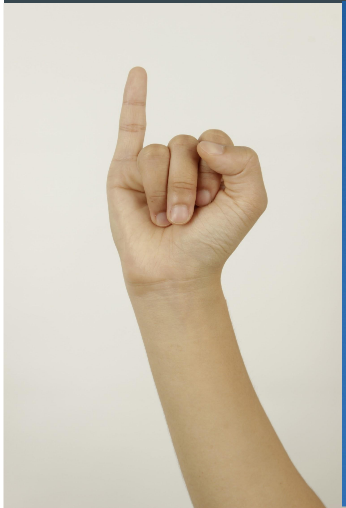


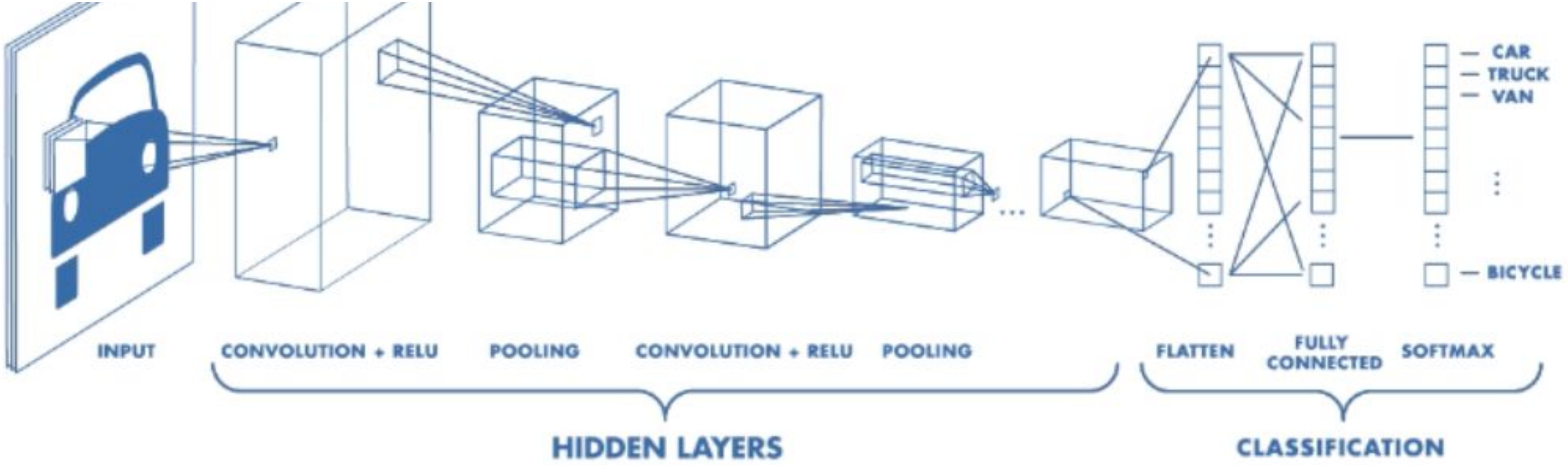
Overview

Problem: Classify American sign language images to letters of the alphabet

Method: Develop Convolutional Neural Network (CNN) within the Pytorch framework, and use two transfer learning models for comparison: VGG-16 and Resnet-50.

Data: Image data set for the American alphabet sign language

- Training: 87,000 images, 64 x 64 pixels
    - Classify into 29 classes, 26 letters A-Z and 3 for space, delete, and nothing
    - 3,000 files for each class
- Testing: 29 images, 64x64 pixels



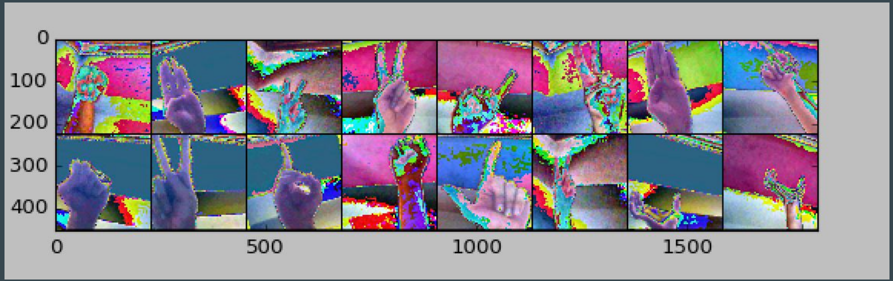
…hitecture of a CNN.—Source: https://www…

Convolutional Neural Network (CNN)

Method Specifics & Theory

- Mini-batch gradient descent
- 29 classes
- Classification organization

```
input_size = 64*64*3
num_classes = 29
num_epochs = 5
batch_size = 16
learning_rate = 0.0001
```

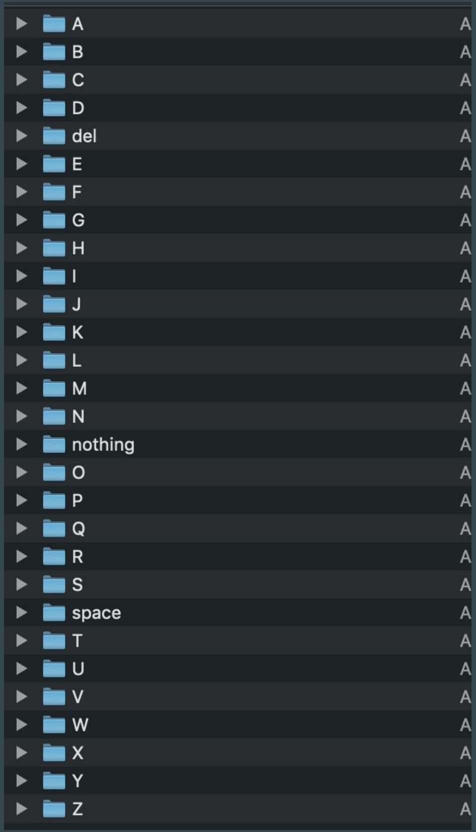



```
classes = ('A', 'B', 'C', 'D', 'del', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N',
    'nothing', 'O', 'P', 'Q', 'R', 'S', 'space', 'T', 'U', 'V', 'W', 'X', 'Y', 'Z')
```

Data Challenges

- Extremely large dataset.
- The names of the classes are based on the folder names of each image.
- Use the Pytorch function ImageFolder to handle this kind of data.

```
# Data augmentation and normalization for training
# Just normalization for validation
data_transforms = {
    'asl_alphabet_train': transforms.Compose([
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'asl_alphabet_test': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}

image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x),
                                          data_transforms[x])
                  for x in ['asl_alphabet_train', 'asl_alphabet_test']}


dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=batch_size,
                                              shuffle=True)
              for x in ['asl_alphabet_train', 'asl_alphabet_test']}

dataset_sizes = {x: len(image_datasets[x]) for x in ['asl_alphabet_train', 'asl_alphabet_test']}

class_names = image_datasets['asl_alphabet_train'].classes
```



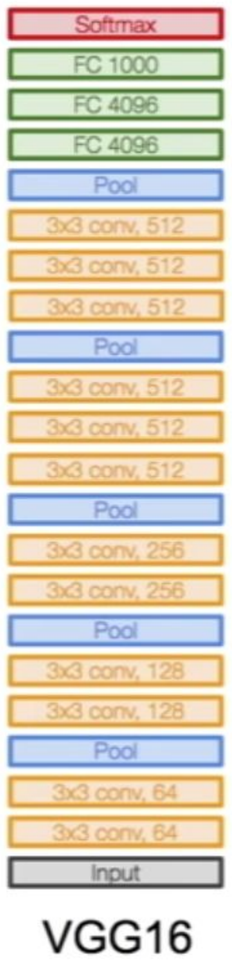
Training Images for “A”

Data augmentation and normalization for training

Normalization for validation

```
data_transforms = {
    'asl_alphabet_train': transforms.Compose([
        transforms.Grayscale(1),
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'asl_alphabet_test': transforms.Compose([
        transforms.Grayscale(1),
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}
```

Understanding the different networks

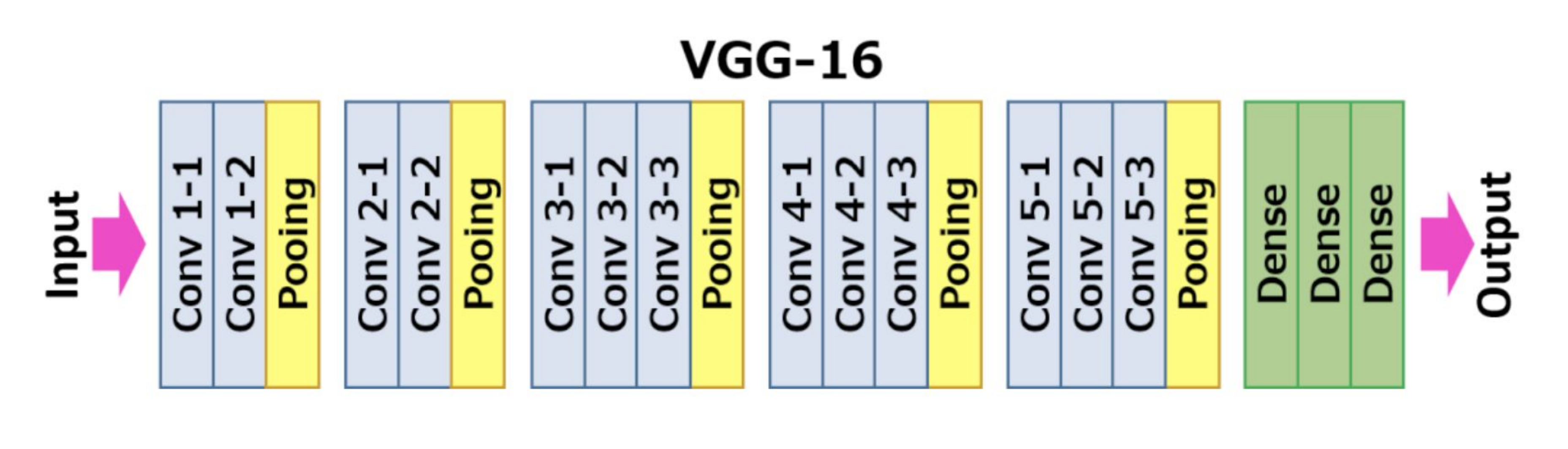


VGG-16

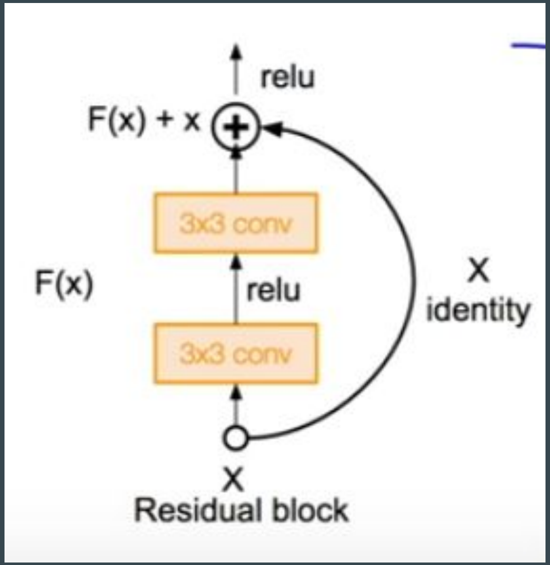
VGG-16:

- 2014 genesis, build from AlexNet, Oxford
- Competitor: GoogleNet
- Deeper but smaller filters, only 3 x 3 CONV all the way: 8 layers (AlexNet) to 16 layers

VGG-16 Network Diagram



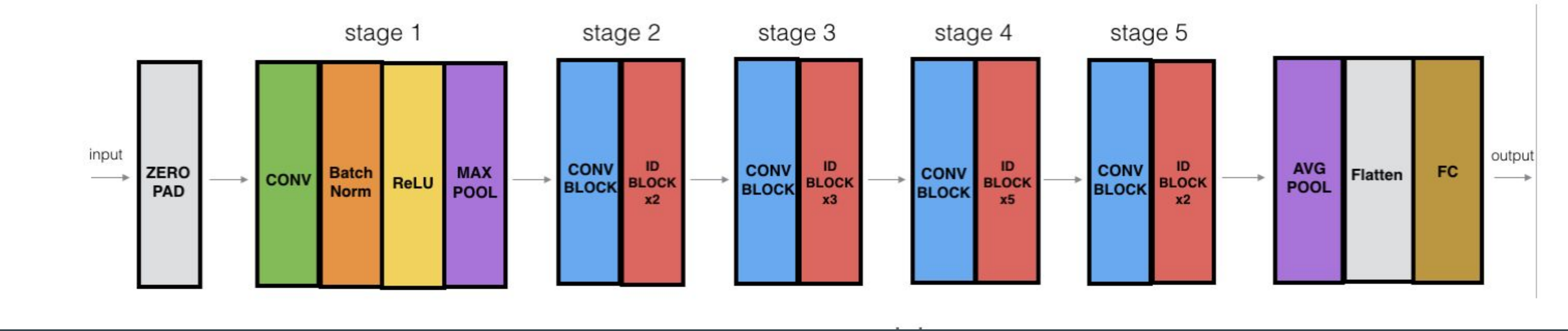
Resnet



Resnet:

- Follow up on Alexnet
- Stack resenet blocks
- Batch normalization after each layer
- Deeper than previous networks
- Residual connections
- Can train thousands of layers and still achieve good performance.

Resnet Network Diagram



Our Model

- Inspired by VGG
- Developed primarily in Keras then Pytorch
- It has six convolutional layers and two fully connected layers
- Used the Relu activation function

Code

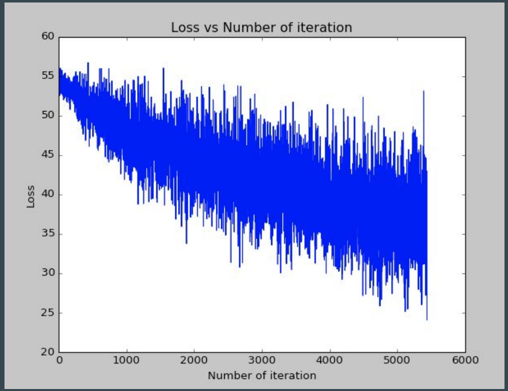
```python
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()

        self.conv1 = torch.nn.Conv2d(3 , 32, kernel_size=3, stride=1, padding=1)
        self.conv1_bn = nn.BatchNorm2d(32)
        self.relu = nn.ReLU()
        self.conv2 = torch.nn.Conv2d(32, 32, kernel_size=3, stride=1, padding=1)
        self.conv2_bn = nn.BatchNorm2d(32)
        self.relu = nn.ReLU()
        self.pool = torch.nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

        self.conv3 = torch.nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1)
        self.conv3_bn = nn.BatchNorm2d(64)
        self.relu = nn.ReLU()
        self.conv4 = torch.nn.Conv2d(64, 64, kernel_size=3, stride=1, padding=1)
        self.conv4_bn = nn.BatchNorm2d(64)
        self.relu = nn.ReLU()
        self.pool = torch.nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

        self.conv5 = torch.nn.Conv2d(64, 128, kernel_size=3, stride=1, padding=1)
        self.conv5_bn = nn.BatchNorm2d(128)
        self.conv6 = torch.nn.Conv2d(128, 128, kernel_size=3, stride=1, padding=1)
        self.conv6_bn = nn.BatchNorm2d(128)
        self.relu = nn.ReLU()

        self.fc1 = torch.nn.Linear(128 * 28 * 28, 128, bias= True)
        self.relu = nn.ReLU()
        self.dropout = nn.Dropout(0.2)
        self.out = nn.Linear(128, 29, bias = True)
        self.softmax = nn.LogSoftmax(dim=1)
```

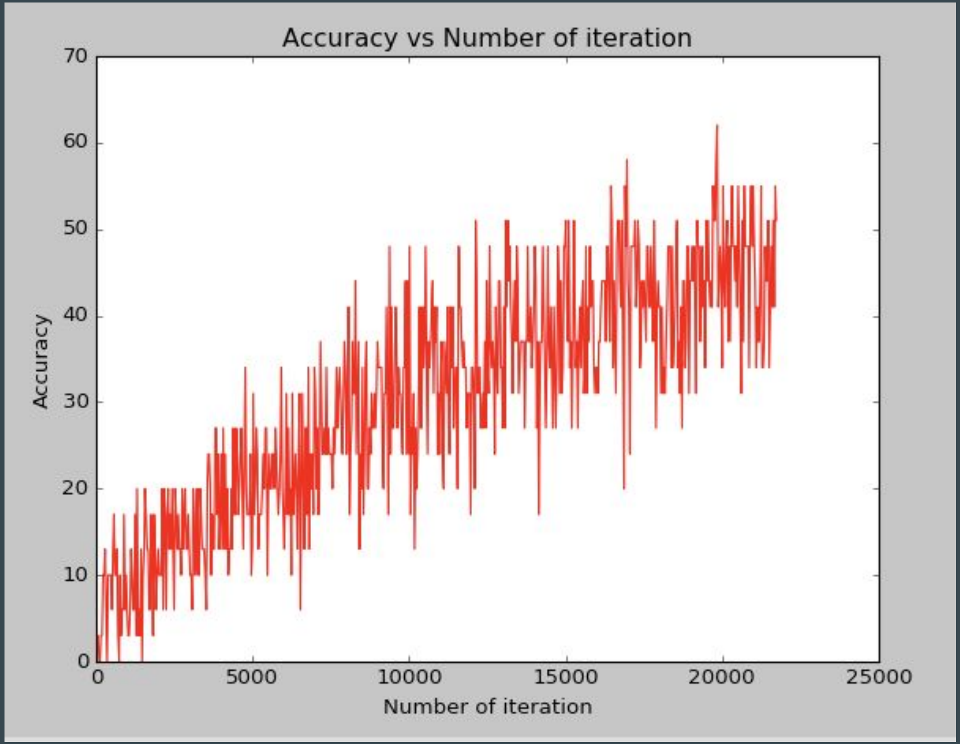
```python
def forward(self, x):
    out = self.conv1(x)
    out = self.conv1_bn(out)
    out = F.relu(out)
    out = F.relu(self.conv2_bn(self.conv2(out)))
    out = self.pool(out)

    out = F.relu(self.conv3_bn(self.conv3(out)))
    out = F.relu(self.conv4_bn(self.conv4(out)))
    out = self.pool(out)

    out = self.relu(self.conv5_bn(self.conv5(out)))
    out = self.relu(self.conv6_bn(self.conv6(out)))
    out = self.pool(out)

    #print(out.shape)

    out = out.view(-1, 128 * 28 * 28)

    out = self.dropout(F.relu(self.fc1(out)))
    out = self.softmax(self.out(out))

    return (out)
```

Accuracy and Loss Over Time for our Model

Results:

- Started off with very low accuracy
- Learned significantly over the lifetime of the model.
- Loss improved over time.
- Very slow performance

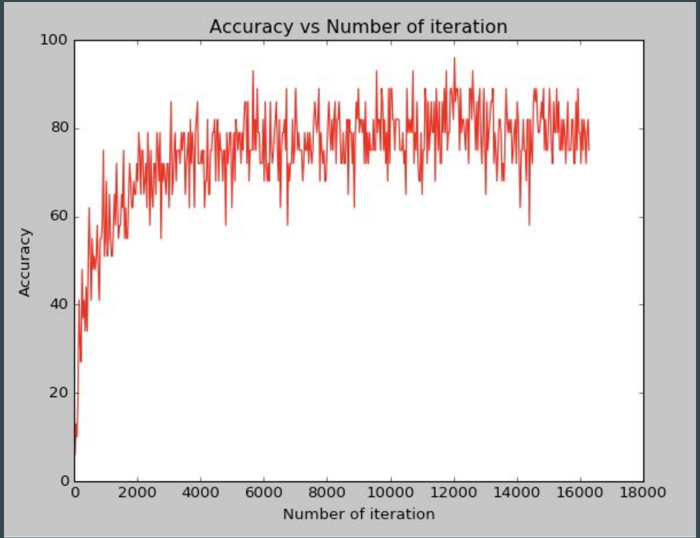




VGG-16 Network Code

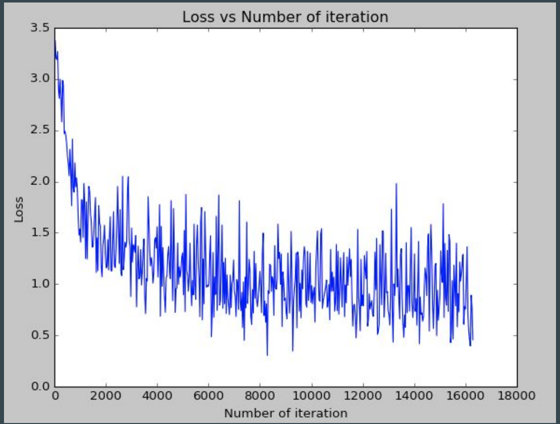
```
# Choose the right argument for x
net = models.vgg16(pretrained=True)
# Freeze model weights
for param in net.parameters():
    param.requires_grad = False

num_ftrs = net.classifier[6].in_features

# Add on classifier
net.classifier[6] = nn.Sequential(
                      nn.Linear(num_ftrs, 256),
                      nn.ReLU(),
                      nn.Dropout(0.4),
                      nn.Linear(256, num_classes),
                      nn.LogSoftmax(dim=1))
net.cuda()
net = nn.DataParallel(net)
#-----------------------------------------------
```

Accuracy and Loss Over Time for adapted VGG16



Results:

- Very slow.
- Performance is quite strong.
- Finished with around 80% accuracy.



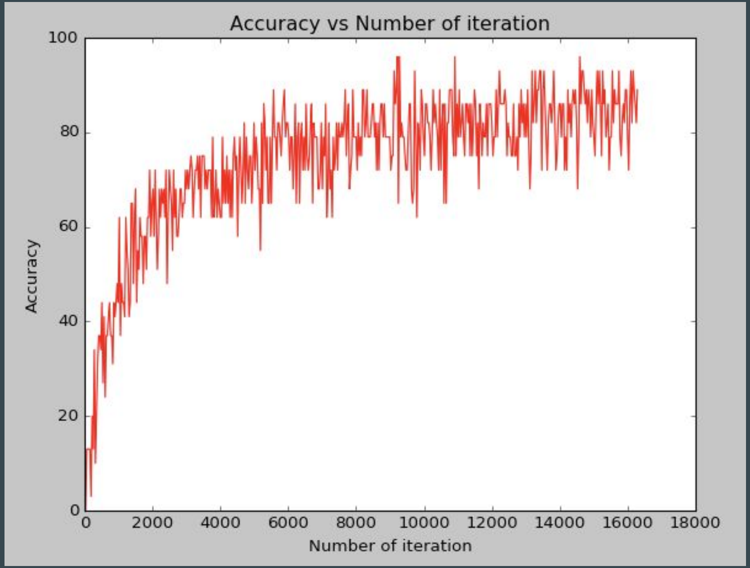
Resnet Network Code

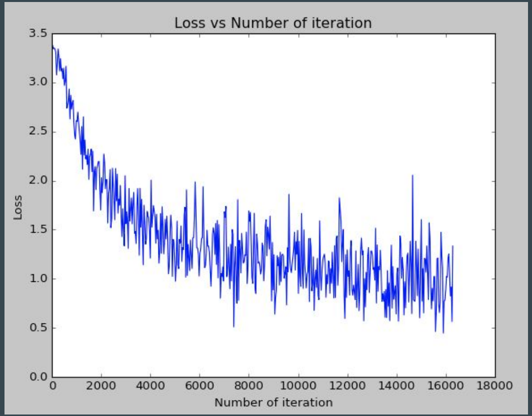
```
# ------------------------------------------------------------------------
net = models.resnet50(pretrained=True)
# Freeze model weights
for param in net.parameters():
    param.requires_grad = False

num_ftrs = net.fc.in_features

#Add on classifier
net.fc = nn.Sequential(
                      nn.Linear(num_ftrs, 256),
                      nn.ReLU(),
                      nn.Dropout(0.4),
                      nn.Linear(256, num_classes),
                      nn.LogSoftmax(dim=1))

net.cuda()
net = nn.DataParallel(net)
#-------------------------------------------------------------------------
criterion = nn.NLLLoss();
optimizer = torch.optim.Adam(net.parameters(), lr=learning_rate);

j = 0
loss_list = []
iteration_list = []
accuracy_list = []
```

Accuracy and Loss Over Time for adapted Resnet50

Results:

- Started off with very low accuracy
- Scaled rapidly
- Impressively quick performance
- Finished with around 90% accuracy





Conclusion

- Resnet-50 highest accuracy, 90%
- Our model did not perform well, could increase from 5 epochs or adjust model to achieve higher accuracy
- Computation time is a complexity of convolutional models

Questions?

Sources

- https://neurohive.io/en/popular-networks/vgg16/
- https://arxiv.org/abs/1512.03385
- **Akash. (2018, April 22). ASL Alphabet. Retrieved from https://www.kaggle.com/grassknoted/asl-alphabet**
- **Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. CoRR, abs/1409.1556 . Retrieved from http://arxiv.org/abs/ 1409.1556**
- **Stanford School of Engineering, CNN Architecture Lecture. Aug. 11, 2017. Retrieved from https://www.youtube.com/watch?v=DAOcjicFr1**