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**Implementing VGG16 with PyTorch: A Comprehensive Guide to Data Preparation and Model Training**

Image: ImageNet Challenge, 2010–2017, CS231n.*
**What's in here:**

**1. Introduction**
VGG16, developed by the Visual Geometry Group at the University of Oxford, is an influential architecture in the field of deep learning. It comprises 16 layers with learnable parameters (hence the name), primarily using 3x3 convolutional filters, followed by max pooling layers. This architecture has shown impressive performance in various image classification benchmarks.

The VGG network won in the 2014 ImageNet competition for classification and localization tasks. VGG established new ideas for the design of ConvNets, many of which remain standard today, and it possessed greater depth than AlexNet. This pattern demonstrated that deep networks consistently outperform shallow networks.

**2. VGG Architecture**
The VGG architecture comprises 16 layers (VGG-16) and 19 layers (VGG-19).

This quantity is double the number of layers in AlexNet.

**The key design tenets of the VGG network are outlined below:**

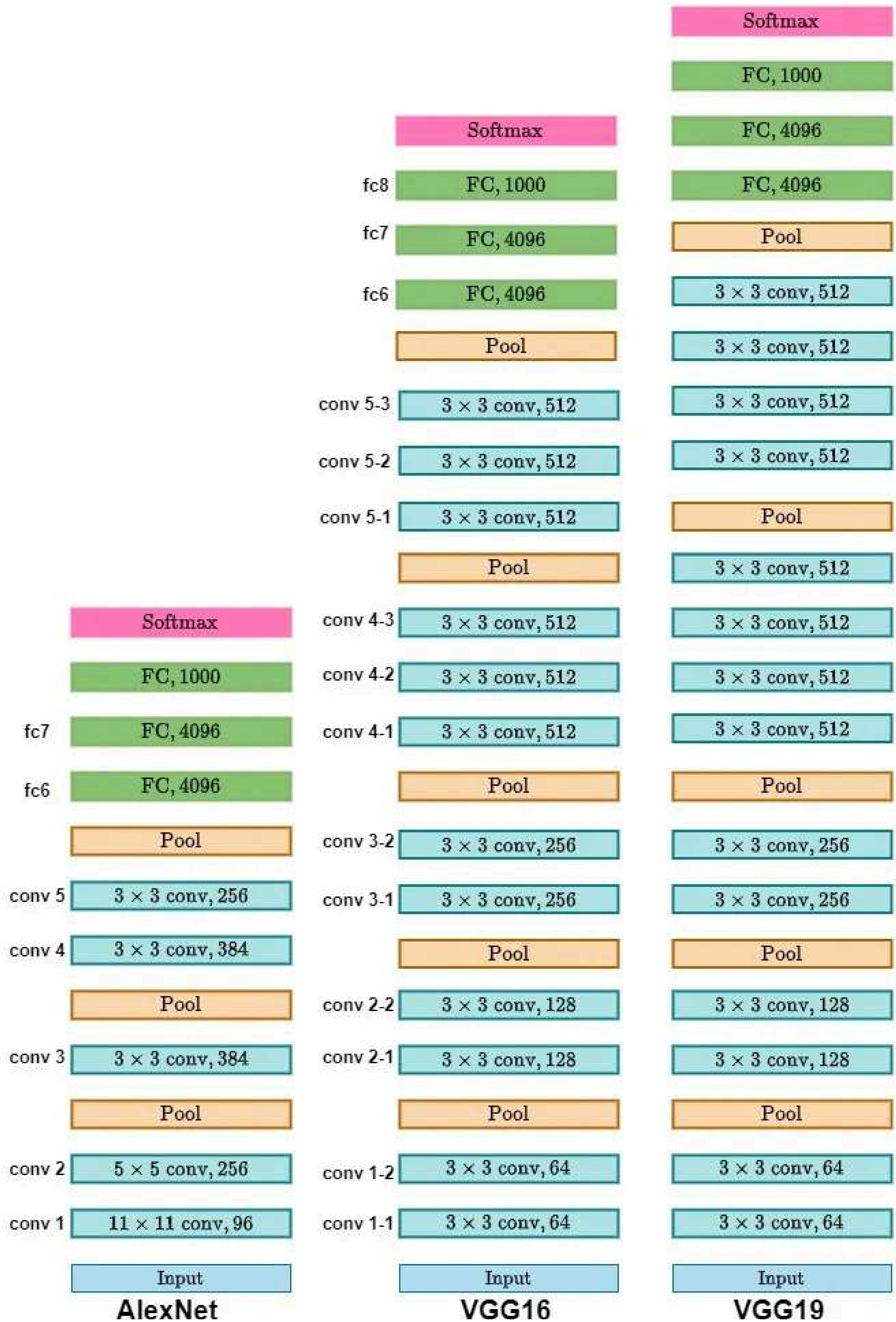
Each convolutional layer employs a kernel size 3x3 and utilizes zero padding to ensure that the output maintains the same height and width as the input. The stride is configured to one. Convolutional layers are arranged in stages, with each level succeeded by a pooling layer. All convolutional layers employ the ReLU activation function. All max pooling layers utilize a pooling size of 2 and a stride of 2. After the pooling layer, the ensuing convolutional step featured double the amount of filters compared to the preceding stages. If the initial convolutional layer comprises 64 filters, the subsequent layer will consist of 128 filters. This design concept is still extensively utilized today in the development of convolutional neural networks. The initial convolutional stage comprises 64 filters, the second stage contains 128 filters, the fourth stage includes 256 filters, and the fifth stage consists of 512 filters.

The convolutional layers in VGG-16 are structured as follows:

* Stage 1: conv — conv — pool
* Stage 2: conv — conv — pool
* Stage 3: conv — conv — conv — pool
* Stage 4: conv — conv — conv — pool
* Stage 5: conv — conv — conv — pool

In VGG-19, the 4th and 5th stages have 4 convolutional layers.

Same as AlexNet, VGG has also 3 fully connected layers with the exact same configurations: 4096 units in the first two fully connected layers, and 1000 units in the last connected layers. The last layer has a softmax activation function for classification purposes.



Softmax
FC, 1000
fc7 FC, 4096
fc6 FC, 4096
Pool
conv 5 3 × 3 conv, 256
conv 4 3 × 3 conv, 384
Pool
conv 3 3 × 3 conv, 384
Pool
conv 2 5 × 5 conv, 256
conv 1 11 × 11 conv, 96
Input
AlexNet
Softmax
fc8 FC, 1000
fc7 FC, 4096
fc6 FC, 4096
Pool
conv 5-3 3 × 3 conv, 512
conv 5-2 3 × 3 conv, 512
conv 5-1 3 × 3 conv, 512
Pool
conv 4-3 3 × 3 conv, 512
conv 4-2 3 × 3 conv, 512
conv 4-1 3 × 3 conv, 512
Pool
conv 3-2 3 × 3 conv, 256
conv 3-1 3 × 3 conv, 256
Pool
conv 2-2 3 × 3 conv, 128
conv 2-1 3 × 3 conv, 128
Pool
conv 1-2 3 × 3 conv, 64
conv 1-1 3 × 3 conv, 64
Input
VGG16
Softmax
FC, 1000
FC, 4096
FC, 4096
Pool
3 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
Pool
3 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
Pool
3 × 3 conv, 256
3 × 3 conv, 256
Pool
3 × 3 conv, 128
3 × 3 conv, 128
Pool
3 × 3 conv, 64
3 × 3 conv, 64
Input
VGG19

Image by designed author

Justin Johnson has also a great side-by-side comparison of AlexNet and VGG in his Deep Learning for Computer Vision course.

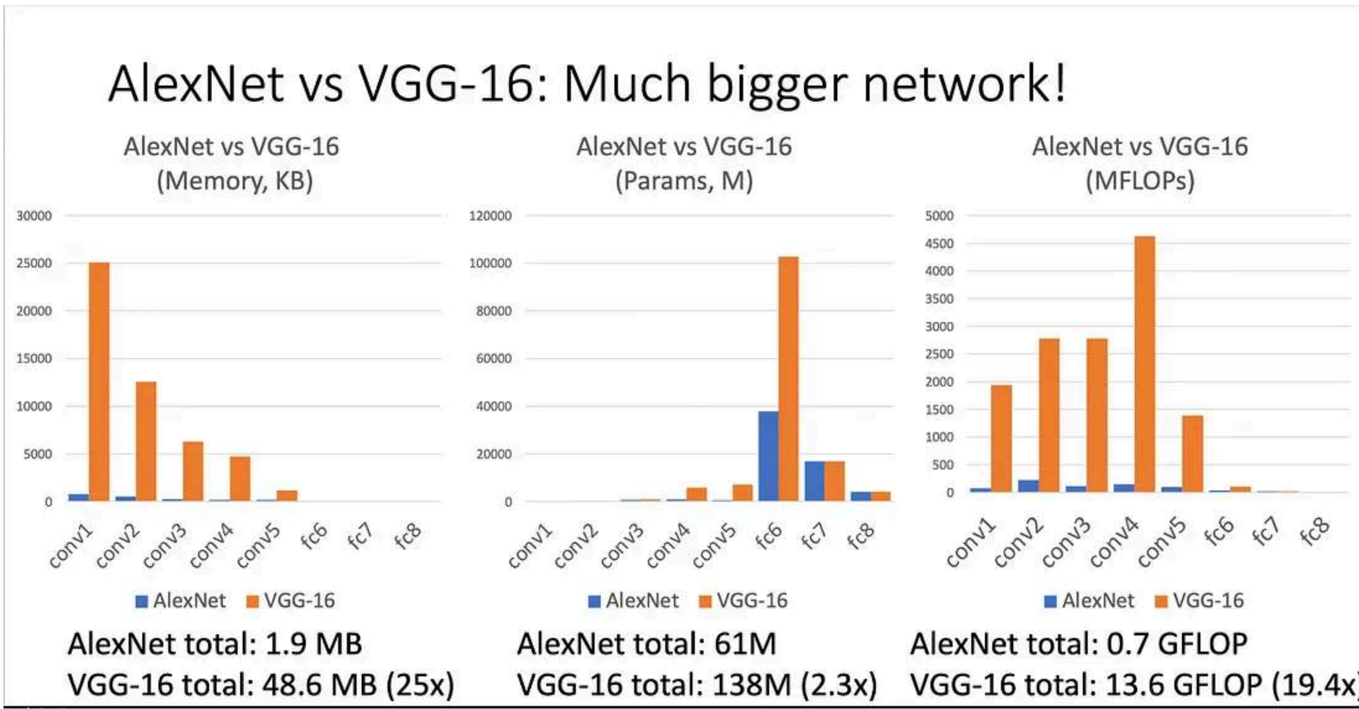



Image by Justin Johnson

**3. VGG Implementation**

As we now understand the ins and outs of the VGG network, let's implement it. There are many versions of VGG such as VGG-11, VGG-16, and VGG-19. We will implement VGG-16 but the process is similar to how you would implement other versions.

The quickest way to implement VGG is to stack all layers with their respective hyperparameters, block after block. A fancier and cleaner way would be to build a convolutional block as a function that takes several convolutional layers and filters and reuses it for each block.

**The CIFAR-10 Dataset**

The CIFAR-10 dataset consists of 60,000 32x32 color images across 10 classes: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. While VGG16 is often used with larger datasets like ImageNet, we can adapt it for CIFAR-10 by resizing the images.

**Setting Up the Environment**

Before we start, make sure you have PyTorch and torchvision installed. If you have not done so yet, you can install them using:

```
pip install torch torchvision
```

**Step 1: Import Necessary Libraries**

First, we need to import the required libraries, including PyTorch and torchvision

```
import torch
import torchvision
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
import torchvision.transforms as transforms
```

**Step 2: Define the VGG16 Model**

Next, we define the VGG16 model. This model contains several convolutional layers followed by fully connected layers



```
        # Define convolutional blocks (features)
        self.features = nn.Sequential(
            # Block 1
            nn.Conv2d(3, 64, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            # Block 2
            nn.Conv2d(64, 128, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            # Block 3
            nn.Conv2d(128, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            # Block 4
            nn.Conv2d(256, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            # Block 5
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
```

```
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2)
        )

        # Fully connected layers (classifier)
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(512 * 7 * 7, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(4096, num_classes),
            nn.Softmax(dim=1)
        )

    def forward(self, x):
        x = self.features(x)
        x = self.classifier(x)
        return x

if __name__ == "__main__":
  vgg_16 = VGG16(num_classes=1000)

  # Create a random input tensor with shape (batch_size, channels, height, width
  # For example, batch size = 1, channels = 3 (RGB), height = 224, width = 224
  input_tensor = torch.rand(1, 3, 224, 224) # random imput tensor
  output = vgg_16(input_tensor)
  print("Output shape:", output.shape) # print the shape
```

### Step 3: Load and Preprocess the Dataset

We need to load the CIFAR-10 dataset and apply the necessary transformations. We'll resize the images to 224x224 (the input size for VGG16) and normalize them.

```
def load_cifar10_dataset(batch_size=32):
    # Define data transformations
```

```
    transform = transforms.Compose([
        transforms.Resize((224, 224)),  # Resize images to 224x224
        transforms.ToTensor(),  # Convert images to tensors
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.22
    ])

    # Load CIFAR-10 dataset
    train_dataset = torchvision.datasets.CIFAR10(root='./data', train=True, tran
    test_dataset = torchvision.datasets.CIFAR10(root='./data', train=False, tran

    train_loader = DataLoader(dataset=train_dataset, batch_size=batch_size, shuf
    test_loader = DataLoader(dataset=test_dataset, batch_size=batch_size, shuffl

    return train_loader, test_loader
```

### Step 4: Define the Loss Function and Optimizer

Next, we need to set up our loss function and optimizer. We will use the CrossEntropyLoss for multi-class classification and the Adam optimizer: The VGG-16 network, trained on the ImageNet dataset, contains about 138 million parameters. The network is quite extensive.

```
vgg_16 = VGG16(num_classes=10)  # num_classes = 10 for CIFAR-10

train_loader, test_loader = load_cifar10_dataset(batch_size=32)

learning_rate = 0.001

# Define loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(vgg_16.parameters(), lr=learning_rate)
```

### Step 5: Train the Model

We will now implement the training loop. For each epoch, we'll perform a forward pass, compute the loss, backpropagate the gradients, and update the weights

```
# Training the model
for epoch in range(num_epochs):
    for images, labels in train_loader:
        # Forward pass
        outputs = vgg_16(images)
        loss = criterion(outputs, labels)

        # Backward pass and optimization
        optimizer.zero_grad()  # Zero the gradients
        loss.backward()  # Backpropagate
        optimizer.step()  # Update weights

    print(f'Epoch [{epoch + 1}/{num_epochs}], Loss: {loss.item():.4f}')
```

**Evaluate the Model**
After training, we need to evaluate the model's performance on the test set. We will calculate the accuracy.

**Concluding Remarks**
The VGG network is among the pioneering architectures of ConvNets that established architectural principles for visual recognition systems; yet, it possesses a substantial number of parameters, rendering it computationally inefficient. The subsequent architectures we shall examine, including GoogLeNet, tackled the difficulty of creating efficient designs suitable for mobile devices.

We successfully trained and tested a VGG16 model on the CIFAR-10 dataset. We covered all the necessary steps, from defining the model to evaluating its performance. While the VGG16 architecture is relatively simple, its depth allows it to learn complex features from images, making it a powerful tool for image classification tasks.

Feel free to modify the hyperparameters or explore different datasets to further your understanding of deep learning with PyTorch. Happy coding!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