Notebook

November 14, 2024

0.0.1 Assignment 03

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1. Manual Dense Network with Backpropagation for CIFAR-10

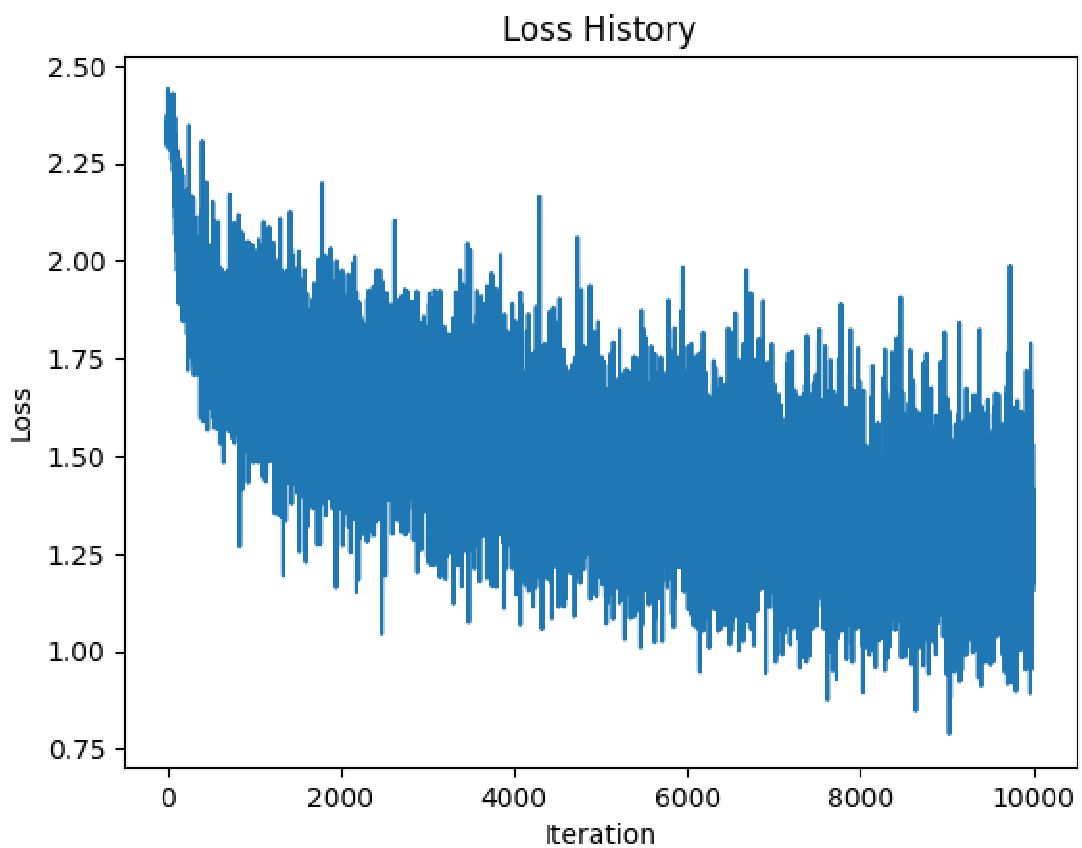
[27]:
```
import torch
import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np
import torch.nn as nn

# 1. Dataloading
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

batch_size = 50

trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size,
                                          shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                       download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size,
                                         shuffle=False, num_workers=2)

classes = ('plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck')

# 2. Define Network Parameters
Din = 3 * 32 * 32  # Input size (flattened CIFAR-10 image size)
H = 100  # Hidden layer size
K = 10  # Output size (number of classes in CIFAR-10)
```

```python
std = 1e-5

# Initialize weights and biases
w1 = torch.randn(Din, H) * std
b1 = torch.zeros(H)
w2 = torch.randn(H, K) * std
b2 = torch.zeros(K)

# Hyperparameters
epochs = 10
lr = 0.005  # Learning rate
loss_history = []

# sigmoid function
def sigmoid(x):
    return 1 / (1 + torch.exp(-x))

# CrossEntropy Loss
def CrossEntropyLoss(y_pred, y_true):
    smooth = 1e-9
    loss = -torch.sum(y_true * torch.log(y_pred + smooth)) / y_true.shape[0]
    return loss

# 3. Training Loop
# 3. Training Loop
for epoch in range(epochs):
    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # Get inputs and labels
        inputs, labels = data
        Ntr = inputs.shape[0]  # Batch size
        x_train = inputs.view(Ntr, -1)  # Flatten input to (Ntr, Din)
        y_train_onehot = nn.functional.one_hot(labels, K).float()  # Convert labels to one-hot encoding

        # Forward pass with middle layer
        hidden = sigmoid(x_train.mm(w1) + b1)  # Middle layer with sigmoid activation
        y_pred = torch.softmax(hidden.mm(w2) + b2, dim=1) # Output layer activation

        # Loss calculation (CrossEntropy loss)
        loss = CrossEntropyLoss(y_pred, y_train_onehot)  # Cross-entropy loss
        loss_history.append(loss.item())
        running_loss += loss.item()

        # Backpropagation
```

```
        dy_pred = (y_pred - y_train_onehot) # Loss derivative
        dw2 = hidden.t().mm(dy_pred)
        db2 = dy_pred.sum(dim=0)

        # Backpropagation to hidden layer
        dhidden = dy_pred.mm(w2.t()) * (hidden * (1 - hidden))  # Derivative of sigmoid
        dw1 = x_train.t().mm(dhidden)
        db1 = dhidden.sum(dim=0)

        # Parameter update
        w1 -= lr * dw1
        b1 -= lr * db1
        w2 -= lr * dw2
        b2 -= lr * db2

    print(f"Epoch {epoch + 1}/{epochs}, Loss: {running_loss / len(trainloader):.4f}")

# 4. Plotting the Loss History
plt.plot(loss_history)
plt.title("Loss History")
plt.xlabel("Iteration")
plt.ylabel("Loss")
plt.show()

# 5. Calculate Accuracy
def calculate_accuracy(loader, w1, b1, w2, b2):
    correct = 0
    total = 0
    with torch.no_grad():
        for data in loader:
            inputs, labels = data
            N = inputs.shape[0]
            x = inputs.view(N, -1)

            # Forward pass
            z1 = x.mm(w1) + b1
            a1 = torch.sigmoid(z1)
            z2 = a1.mm(w2) + b2
            y_pred = torch.argmax(z2, dim=1)

            total += labels.size(0)
            correct += (y_pred == labels).sum().item()
    return 100 * correct / total

train_acc = calculate_accuracy(trainloader, w1, b1, w2, b2)
```

```
test_acc = calculate_accuracy(testloader, w1, b1, w2, b2)

print(f"Training Accuracy: {train_acc:.2f}%")
print(f"Test Accuracy: {test_acc:.2f}%")
```

```
Files already downloaded and verified
Files already downloaded and verified
Epoch 1/10, Loss: 1.9065
Epoch 2/10, Loss: 1.6863
Epoch 3/10, Loss: 1.5995
Epoch 4/10, Loss: 1.5337
Epoch 5/10, Loss: 1.4796
Epoch 6/10, Loss: 1.4279
Epoch 7/10, Loss: 1.3841
Epoch 8/10, Loss: 1.3450
Epoch 9/10, Loss: 1.3100
Epoch 10/10, Loss: 1.2768
```




```
Training Accuracy: 57.25%
Test Accuracy: 46.91%
```

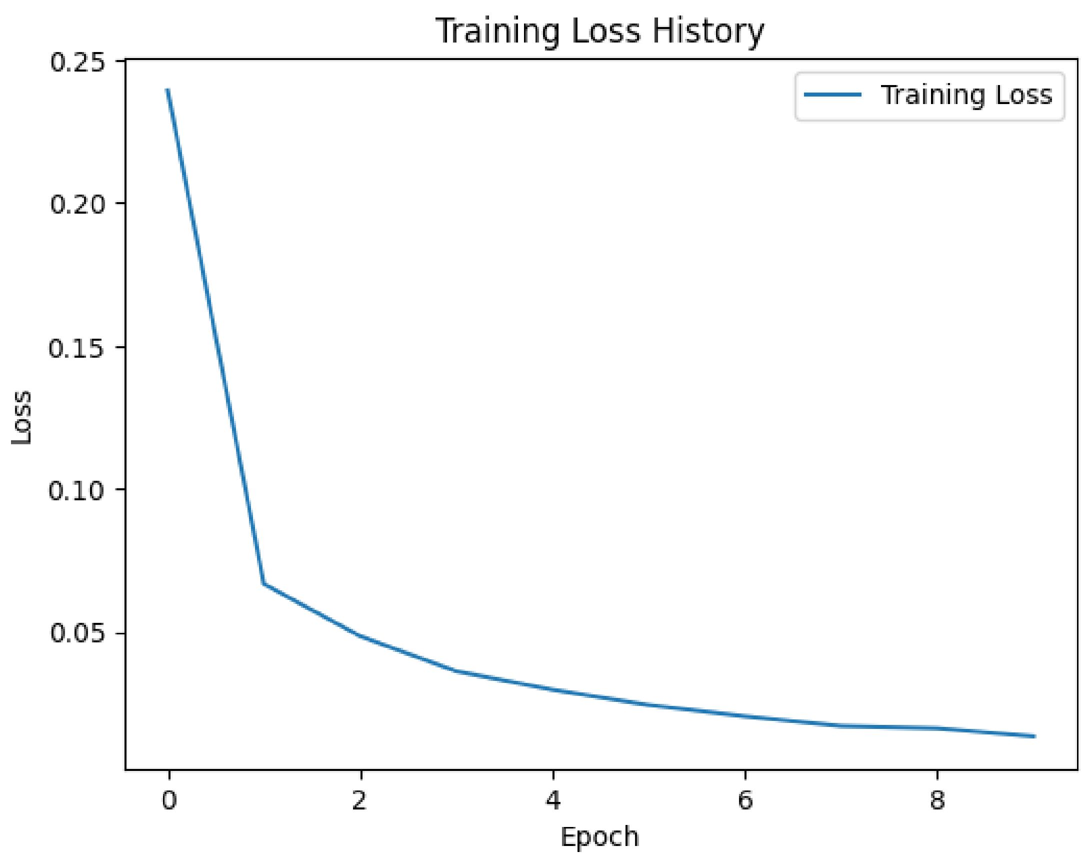
2. LeNet-5 network for MNIST using Pytorch

[11]:
```python
import torch
import torchvision.datasets as datasets
import torch.nn.functional as F
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import torch.nn as nn
import torch.optim as optim
import numpy as np

# Data preparation
transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
 ↪5,), (0.5,))])
trainset = datasets.MNIST('./data', train=True, download=True,␣
 ↪transform=transform)
testset = datasets.MNIST('./data', train=False, download=True,␣
 ↪transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=64, shuffle=True)
testloader = torch.utils.data.DataLoader(testset, batch_size=64, shuffle=False)

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Define LeNet-5
class LeNet5(nn.Module):

    # network structure
    def __init__(self):
        super(LeNet5, self).__init__()
        self.conv1 = nn.Conv2d(1, 6, 5, padding=2)
        self.conv2 = nn.Conv2d(6, 16, 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):
        '''
        One forward pass through the network.

        Args:
            x: input
        '''
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv2(x)), (2, 2))
        x = x.view(-1, self.num_flat_features(x))
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
```

```
        return x

    def num_flat_features(self, x):
        '''
        Get the number of features in a batch of tensors `x`.
        '''
        size = x.size()[1:]
        return np.prod(size)

model = LeNet5().to(device)

# Training and evaluation
criterion = nn.CrossEntropyLoss().to(device)
optimizer = optim.Adam(model.parameters(), lr=0.001)

epochs = 10
train_losses = []

# Training loop
for epoch in range(epochs):
    running_loss = 0.0
    for inputs, labels in trainloader:
        inputs, labels = inputs.to(device), labels.to(device)

        optimizer.zero_grad()
        loss = criterion(model(inputs), labels)
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    # Record average loss for this epoch
    train_losses.append(running_loss / len(trainloader))
    print(f"Epoch {epoch + 1}/{epochs}, Loss: {train_losses[-1]:.4f}")

# Plot training loss
plt.plot(train_losses, label='Training Loss')
plt.title("Training Loss History")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.show()

# Calculate training accuracy
model.eval()
correct_train = sum((torch.max(model(inputs.to(device)), 1)[1] == labels.
 ↪to(device)).sum().item()
```

```
                    for inputs, labels in trainloader)
train_accuracy = 100 * correct_train / len(trainloader.dataset)
print(f"Training accuracy: {train_accuracy:.2f}%")

# Calculate test accuracy
correct_test = sum((torch.max(model(inputs.to(device)), 1)[1] == labels.
 ↪to(device)).sum().item()
                    for inputs, labels in testloader)
test_accuracy = 100 * correct_test / len(testloader.dataset)
print(f"Test accuracy: {test_accuracy:.2f}%")
```

```
Epoch 1/10, Loss: 0.2393
Epoch 2/10, Loss: 0.0667
Epoch 3/10, Loss: 0.0485
Epoch 4/10, Loss: 0.0362
Epoch 5/10, Loss: 0.0298
Epoch 6/10, Loss: 0.0244
Epoch 7/10, Loss: 0.0205
Epoch 8/10, Loss: 0.0171
Epoch 9/10, Loss: 0.0163
Epoch 10/10, Loss: 0.0135
```



Training accuracy: 99.75%
Test accuracy: 98.99%

3. Transfer Learning ResNet-18

[20]:
```python
import os
import urllib.request
import zipfile

# Define the paths
dataset_url = "https://download.pytorch.org/tutorial/hymenoptera_data.zip"
dataset_dir = "data/"
zip_path = os.path.join(dataset_dir, "hymenoptera_data.zip")

# Create the directory if it doesn't exist
os.makedirs(dataset_dir, exist_ok=True)

# Download the dataset
print("Downloading Hymenoptera dataset...")
urllib.request.urlretrieve(dataset_url, zip_path)
print("Download complete!")

# Extract the dataset
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(dataset_dir)
print("Dataset extracted!")

# Clean up the zip file
os.remove(zip_path)
print("Hymenoptera dataset is ready at:", dataset_dir)
```

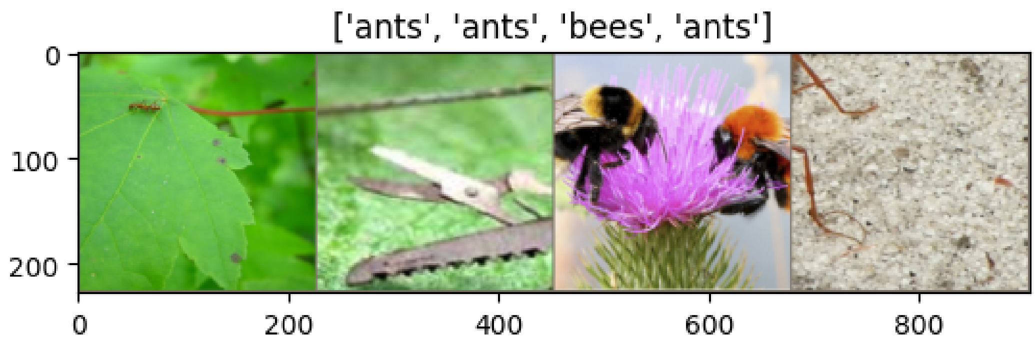
```
Downloading Hymenoptera dataset…
Download complete!
Dataset extracted!
Hymenoptera dataset is ready at: data/
```

[21]:
```python
#transfer learning on a pre-trained ResNet-18 model

import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
import torch.backends.cudnn as cudnn
import numpy as np
import torchvision
from torchvision import datasets, models, transforms
import matplotlib.pyplot as plt
```

```
import time
import os
from PIL import Image
from tempfile import TemporaryDirectory

cudnn.benchmark = True
plt.ion()

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

data_dir = 'data/hymenoptera_data'
image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x),
 ↪data_transforms[x]) for x in ['train', 'val']}
dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=4,
 ↪shuffle=True, num_workers=4) for x in ['train', 'val']}
dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'val']}
class_names = image_datasets['train'].classes

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

[22]:
```
def imshow(inp, title=None):
    """Display image for Tensor."""
    inp = inp.numpy().transpose((1, 2, 0))
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    inp = std * inp + mean
    inp = np.clip(inp, 0, 1)
    plt.imshow(inp)
    if title is not None:
        plt.title(title)
    plt.pause(0.001)  # pause a bit so that plots are updated
```

```python
# Get a batch of training data
inputs, classes = next(iter(dataloaders['train']))

# Make a grid from batch
out = torchvision.utils.make_grid(inputs)

imshow(out, title=[class_names[x] for x in classes])
```



[23]:
```python
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()

    # Create a temporary directory to save training checkpoints
    with TemporaryDirectory() as tempdir:
        best_model_params_path = os.path.join(tempdir, 'best_model_params.pt')

        torch.save(model.state_dict(), best_model_params_path)
        best_acc = 0.0

        for epoch in range(num_epochs):
            print(f'Epoch {epoch}/{num_epochs - 1}')
            print('-' * 10)

            # Each epoch has a training and validation phase
            for phase in ['train', 'val']:
                if phase == 'train':
                    model.train()  # Set model to training mode
                else:
                    model.eval()   # Set model to evaluate mode

                running_loss = 0.0
                running_corrects = 0
```

```
                # Iterate over data.
                for inputs, labels in dataloaders[phase]:
                    inputs = inputs.to(device)
                    labels = labels.to(device)

                    # zero the parameter gradients
                    optimizer.zero_grad()

                    # forward
                    # track history if only in train
                    with torch.set_grad_enabled(phase == 'train'):
                        outputs = model(inputs)
                        _, preds = torch.max(outputs, 1)
                        loss = criterion(outputs, labels)

                        # backward + optimize only if in training phase
                        if phase == 'train':
                            loss.backward()
                            optimizer.step()

                    # statistics
                    running_loss += loss.item() * inputs.size(0)
                    running_corrects += torch.sum(preds == labels.data)
                if phase == 'train':
                    scheduler.step()

                epoch_loss = running_loss / dataset_sizes[phase]
                epoch_acc = running_corrects.double() / dataset_sizes[phase]

                print(f'{phase} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

                # deep copy the model
                if phase == 'val' and epoch_acc > best_acc:
                    best_acc = epoch_acc
                    torch.save(model.state_dict(), best_model_params_path)

            print()

        time_elapsed = time.time() - since
        print(f'Training complete in {time_elapsed // 60:.0f}m {time_elapsed % 60:.0f}s')
        print(f'Best val Acc: {best_acc:4f}')

        # load best model weights
        model.load_state_dict(torch.load(best_model_params_path, weights_only=True))
    return model
```

[37]:

```
def visualize_model(model, num_images=6):
    was_training = model.training
    model.eval()
    images_so_far = 0
    fig = plt.figure()

    with torch.no_grad():
        for i, (inputs, labels) in enumerate(dataloaders['val']):
            inputs = inputs.to(device)
            labels = labels.to(device)

            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)

            for j in range(inputs.size()[0]):
                images_so_far += 1
                ax = plt.subplot(num_images//2, 2, images_so_far)
                ax.axis('off')
                ax.set_title(f'predicted: {class_names[preds[j]]}')
                imshow(inputs.cpu().data[j])

                if images_so_far == num_images:
                    model.train(mode=was_training)
                    return
        model.train(mode=was_training)
```

(a) Fine tuning the model

[25]:

```
model_ft = models.resnet18(weights='IMAGENET1K_V1')
num_ftrs = model_ft.fc.in_features
# Here the size of each output sample is set to 2.
# Alternatively, it can be generalized to ``nn.Linear(num_ftrs,␣
↪len(class_names))``.
model_ft.fc = nn.Linear(num_ftrs, 2)

model_ft = model_ft.to(device)

criterion = nn.CrossEntropyLoss()

# Observe that all parameters are being optimized
optimizer_ft = optim.SGD(model_ft.parameters(), lr=0.001, momentum=0.9)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)
```

[26]:

```
model_ft = train_model(model_ft, criterion, optimizer_ft, exp_lr_scheduler,
                       num_epochs=25)
```

```
Epoch 0/24
----------
train Loss: 0.6254 Acc: 0.6721
val Loss: 0.7416 Acc: 0.6928

Epoch 1/24
----------
train Loss: 0.9047 Acc: 0.7008
val Loss: 0.4710 Acc: 0.7908

Epoch 2/24
----------
train Loss: 0.6499 Acc: 0.7500
val Loss: 0.5068 Acc: 0.7843

Epoch 3/24
----------
train Loss: 0.5456 Acc: 0.7664
val Loss: 0.6359 Acc: 0.8235

Epoch 4/24
----------
train Loss: 0.8030 Acc: 0.7623
val Loss: 0.9245 Acc: 0.6732

Epoch 5/24
----------
train Loss: 0.5848 Acc: 0.7828
val Loss: 0.5252 Acc: 0.8301

Epoch 6/24
----------
train Loss: 0.7505 Acc: 0.7213
val Loss: 0.3388 Acc: 0.8562

Epoch 7/24
----------
train Loss: 0.2870 Acc: 0.8525
val Loss: 0.2648 Acc: 0.8954

Epoch 8/24
----------
train Loss: 0.3687 Acc: 0.8443
val Loss: 0.2479 Acc: 0.8824

Epoch 9/24
----------
train Loss: 0.3819 Acc: 0.8115
```

```
val Loss: 0.2391 Acc: 0.8889

Epoch 10/24
----------
train Loss: 0.3647 Acc: 0.8443
val Loss: 0.2139 Acc: 0.8954

Epoch 11/24
----------
train Loss: 0.3786 Acc: 0.8238
val Loss: 0.2430 Acc: 0.8954

Epoch 12/24
----------
train Loss: 0.2399 Acc: 0.8852
val Loss: 0.2134 Acc: 0.8954

Epoch 13/24
----------
train Loss: 0.2695 Acc: 0.8770
val Loss: 0.2293 Acc: 0.9085

Epoch 14/24
----------
train Loss: 0.2947 Acc: 0.8648
val Loss: 0.2078 Acc: 0.8954

Epoch 15/24
----------
train Loss: 0.3202 Acc: 0.8607
val Loss: 0.2955 Acc: 0.8954

Epoch 16/24
----------
train Loss: 0.3070 Acc: 0.8770
val Loss: 0.2118 Acc: 0.9020

Epoch 17/24
----------
train Loss: 0.2856 Acc: 0.8566
val Loss: 0.2179 Acc: 0.9085

Epoch 18/24
----------
train Loss: 0.3494 Acc: 0.8361
val Loss: 0.2765 Acc: 0.9020

Epoch 19/24
```

```
----------
train Loss: 0.3034 Acc: 0.8770
val Loss: 0.2298 Acc: 0.9020

Epoch 20/24
----------
train Loss: 0.3141 Acc: 0.8648
val Loss: 0.2470 Acc: 0.9085

Epoch 21/24
----------
train Loss: 0.3212 Acc: 0.8607
val Loss: 0.2294 Acc: 0.8889

Epoch 22/24
----------
train Loss: 0.2924 Acc: 0.8852
val Loss: 0.2393 Acc: 0.8954

Epoch 23/24
----------
train Loss: 0.2239 Acc: 0.9221
val Loss: 0.2923 Acc: 0.8889

Epoch 24/24
----------
train Loss: 0.4148 Acc: 0.8197
val Loss: 0.2201 Acc: 0.9085

Training complete in 4m 56s
Best val Acc: 0.908497
```

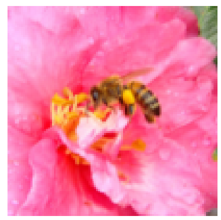
[38]:

```
visualize_model(model_ft)
```

predicted: ants

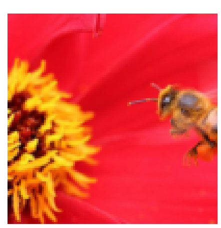
predicted: ants

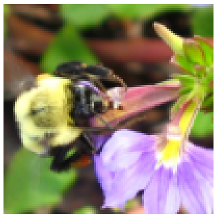
predicted: bees



predicted: ants

predicted: bees





(b) Using model as feature extractor

- Since the requires_grad = False for resnet18 model back bone, parameters are not learnable. It works as a feature extractor.

[30]:
```
model_conv = torchvision.models.resnet18(weights='IMAGENET1K_V1')
for param in model_conv.parameters():
    param.requires_grad = False

# Parameters of newly constructed modules have requires_grad=True by default
num_ftrs = model_conv.fc.in_features
model_conv.fc = nn.Linear(num_ftrs, 2)

model_conv = model_conv.to(device)

criterion = nn.CrossEntropyLoss()

# Observe that only parameters of final layer are being optimized as
# opposed to before.
optimizer_conv = optim.SGD(model_conv.fc.parameters(), lr=0.001, momentum=0.9)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_conv, step_size=7, gamma=0.1)

model_conv = train_model(model_conv, criterion, optimizer_conv,␣
 ↪exp_lr_scheduler, num_epochs=25)
```

```
Epoch 0/24
----------
train Loss: 0.8673 Acc: 0.5820
val Loss: 0.3036 Acc: 0.8627

Epoch 1/24
----------
train Loss: 0.4794 Acc: 0.7910
val Loss: 0.3874 Acc: 0.8301
```

```
Epoch 2/24
----------
train Loss: 0.5695 Acc: 0.7541
val Loss: 0.1773 Acc: 0.9412

Epoch 3/24
----------
train Loss: 0.4277 Acc: 0.8156
val Loss: 0.2050 Acc: 0.9216

Epoch 4/24
----------
train Loss: 0.5197 Acc: 0.8115
val Loss: 0.1782 Acc: 0.9346

Epoch 5/24
----------
train Loss: 0.4769 Acc: 0.8115
val Loss: 0.1701 Acc: 0.9346

Epoch 6/24
----------
train Loss: 0.6592 Acc: 0.7336
val Loss: 0.2651 Acc: 0.9216

Epoch 7/24
----------
train Loss: 0.4874 Acc: 0.7746
val Loss: 0.1631 Acc: 0.9477

Epoch 8/24
----------
train Loss: 0.3222 Acc: 0.8689
val Loss: 0.1594 Acc: 0.9412

Epoch 9/24
----------
train Loss: 0.3284 Acc: 0.8566
val Loss: 0.1742 Acc: 0.9412

Epoch 10/24
----------
train Loss: 0.2488 Acc: 0.8934
val Loss: 0.1610 Acc: 0.9412

Epoch 11/24
----------
train Loss: 0.3282 Acc: 0.8730
```

```
val Loss: 0.1690 Acc: 0.9346

Epoch 12/24
----------
train Loss: 0.4046 Acc: 0.8238
val Loss: 0.1561 Acc: 0.9412

Epoch 13/24
----------
train Loss: 0.3408 Acc: 0.8566
val Loss: 0.2095 Acc: 0.9346

Epoch 14/24
----------
train Loss: 0.3345 Acc: 0.8525
val Loss: 0.1939 Acc: 0.9346

Epoch 15/24
----------
train Loss: 0.3681 Acc: 0.8443
val Loss: 0.1512 Acc: 0.9542

Epoch 16/24
----------
train Loss: 0.3577 Acc: 0.8566
val Loss: 0.1985 Acc: 0.9412

Epoch 17/24
----------
train Loss: 0.3899 Acc: 0.8279
val Loss: 0.1692 Acc: 0.9412

Epoch 18/24
----------
train Loss: 0.3803 Acc: 0.8115
val Loss: 0.1678 Acc: 0.9346

Epoch 19/24
----------
train Loss: 0.3976 Acc: 0.8156
val Loss: 0.1544 Acc: 0.9477

Epoch 20/24
----------
train Loss: 0.2497 Acc: 0.8893
val Loss: 0.1834 Acc: 0.9346

Epoch 21/24
```

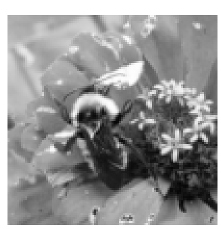
```
----------
train Loss: 0.2886 Acc: 0.8566
val Loss: 0.1437 Acc: 0.9412

Epoch 22/24
----------
train Loss: 0.3038 Acc: 0.8648
val Loss: 0.1548 Acc: 0.9346

Epoch 23/24
----------
train Loss: 0.2939 Acc: 0.8852
val Loss: 0.1746 Acc: 0.9346

Epoch 24/24
----------
train Loss: 0.2756 Acc: 0.8730
val Loss: 0.1582 Acc: 0.9412

Training complete in 4m 33s
Best val Acc: 0.954248
```

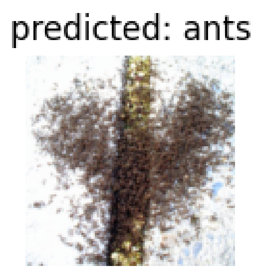
[39]:

```
visualize_model(model_conv)

plt.ioff()
plt.show()
```

predicted: bees

predicted: bees





This notebook was converted with convert.ploomber.io