```
%matplotlib inline
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Transfer Learning for Computer Vision Tutorial

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In this tutorial, you will learn how to train a convolutional neural network for image classification using transfer learning. You can read more about the transfer learning at `cs231n notes <https://cs231n.github.io/transfer-learning/>`__

Quoting these notes,

```
In practice, very few people train an entire Convolutional Network
from scratch (with random initialization), because it is relatively
rare to have a dataset of sufficient size. Instead, it is common to
pretrain a ConvNet on a very large dataset (e.g. ImageNet, which
contains 1.2 million images with 1000 categories), and then use the
ConvNet either as an initialization or a fixed feature extractor for
the task of interest.
```

These two major transfer learning scenarios look as follows:

- **Finetuning the convnet**: Instead of random initialization, we initialize the network with a pretrained network, like the one that is trained on imagenet 1000 dataset. Rest of the training looks as usual.
- **ConvNet as fixed feature extractor**: Here, we will freeze the weights for all of the network except that of the final fully connected layer. This last fully connected layer is replaced with a new one with random weights and only this layer is trained.

```
# License: BSD
# Author: Sasank Chilamkurthy

from __future__ import print_function, division

import torch
import torch.nn as nn
import torch.optim as optim
```

```
from torch.optim import lr_scheduler
import numpy as np
import torchvision
from torchvision import datasets, models, transforms
import matplotlib.pyplot as plt
import time
import os
import copy

plt.ion()   # interactive mode
```

Load Data

We will use torchvision and torch.utils.data packages for loading the data.

The problem we're going to solve today is to train a model to classify **ants** and **bees**. We have about 120 training images each for ants and bees. There are 75 validation images for each class. Usually, this is a very small dataset to generalize upon, if trained from scratch. Since we are using transfer learning, we should be able to generalize reasonably well.

This dataset is a very small subset of imagenet.

.. Note :: Download the data from `here <https://download.pytorch.org/tutorial/hymenoptera_data.zip>`_ and extract it to the current directory.

```
# 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 = '/content/drive/MyDrive/Colab Notebooks/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,
```

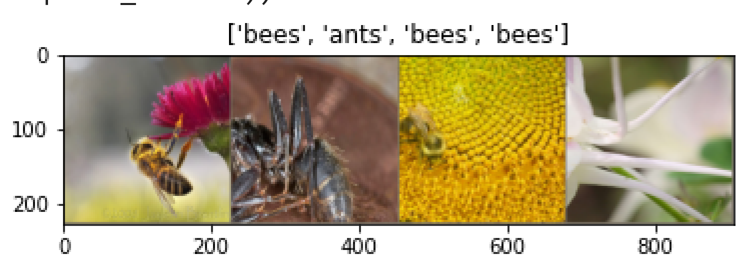
```
                                              shuffle=True, num_workers=4)
              for x in ['train', 'val']}
dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'val']}
class_names = image_datasets['train'].classes

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

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning:
  cpuset_checked))
```

Visualize a few images ^^^^^^^^^^^^^^^^^^^^^ Let's visualize a few training images so as to understand the data augmentations.

```
def imshow(inp, title=None):
    """Imshow 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


# 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])
```

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning:
  cpuset_checked))
```



Training the model

Now, let's write a general function to train a model. Here, we will illustrate:

- Scheduling the learning rate
- Saving the best model

In the following, parameter `scheduler` is an LR scheduler object from `torch.optim.lr_scheduler`.

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

    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    for epoch in range(num_epochs):
        print('Epoch {}/{}'.format(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('{} Loss: {:.4f} Acc: {:.4f}'.format(
                phase, epoch_loss, epoch_acc))

            # deep copy the model
            if phase == 'val' and epoch_acc > best_acc:
                best_acc = epoch_acc
                best_model_wts = copy.deepcopy(model.state_dict())

        print()

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

    # load best model weights
    model.load_state_dict(best_model_wts)
    return model
```

Visualizing the model predictions ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

Generic function to display predictions for a few images

```
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('predicted: {}'.format(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)
```

Finetuning the convnet

Load a pretrained model and reset final fully connected layer.

```
model_ft = models.resnet18(pretrained=True)
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)
```

```
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache
100%                                        44.7M/44.7M [00:03<00:00, 14.0MB/s]
```

Train and evaluate ^^^^^^^^^^^^^^^^^^

It should take around 15-25 min on CPU. On GPU though, it takes less than a minute.

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

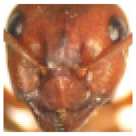
```
----------
train Loss: 0.3379 Acc: 0.8484
val Loss: 0.1615 Acc: 0.9412

Epoch 15/24
----------
train Loss: 0.3266 Acc: 0.8648
val Loss: 0.1596 Acc: 0.9412

Epoch 16/24
----------
train Loss: 0.2432 Acc: 0.8852
val Loss: 0.1879 Acc: 0.9412
```

```
Epoch 17/24
----------
train Loss: 0.2228 Acc: 0.8975
val Loss: 0.1509 Acc: 0.9412

Epoch 18/24
----------
train Loss: 0.2878 Acc: 0.8770
val Loss: 0.1723 Acc: 0.9412

Epoch 19/24
----------
train Loss: 0.2862 Acc: 0.8648
val Loss: 0.1632 Acc: 0.9346

Epoch 20/24
----------
train Loss: 0.2559 Acc: 0.9016
val Loss: 0.1497 Acc: 0.9346

Epoch 21/24
----------
train Loss: 0.2771 Acc: 0.9057
val Loss: 0.1913 Acc: 0.9477

Epoch 22/24
----------
train Loss: 0.3208 Acc: 0.8566
val Loss: 0.1834 Acc: 0.9477

Epoch 23/24
----------
train Loss: 0.3733 Acc: 0.8361
val Loss: 0.1716 Acc: 0.9477

Epoch 24/24
----------
train Loss: 0.2421 Acc: 0.8893
val Loss: 0.1521 Acc: 0.9412

Training complete in 2m 55s
Best val Acc: 0.954248
```

```
visualize_model(model_ft)
```

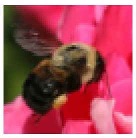
```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning:
  cpuset_checked))
```

predicted: ants



predicted: ants

predicted: bees



predicted: bees

predicted: bees

ConvNet as fixed feature extractor

Here, we need to freeze all the network except the final layer. We need to set requires_grad == False to freeze the parameters so that the gradients are not computed in backward().

You can read more about this in the documentation here <https://pytorch.org/docs/notes/autograd.html#excluding-subgraphs-from-backward>__.

```
model_conv = torchvision.models.resnet18(pretrained=True)
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)
```

Train and evaluate ^^^^^^^^^^^^^^^^^^

On CPU this will take about half the time compared to previous scenario. This is expected as gradients don't need to be computed for most of the network. However, forward does need to be computed.

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

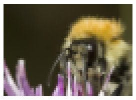
```
Epoch 0/24
----------
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarni
  cpuset_checked))
train Loss: 0.5580 Acc: 0.6844
val Loss: 0.2909 Acc: 0.8824

Epoch 1/24
----------
train Loss: 0.4961 Acc: 0.7746
val Loss: 0.1842 Acc: 0.9281

Epoch 2/24
----------
train Loss: 0.4373 Acc: 0.7951
val Loss: 0.1909 Acc: 0.9412

Epoch 3/24
----------
train Loss: 0.3328 Acc: 0.8770
val Loss: 0.1981 Acc: 0.9412

Epoch 4/24
----------
train Loss: 0.4518 Acc: 0.8115
val Loss: 0.2081 Acc: 0.9542

Epoch 5/24
----------
train Loss: 0.6585 Acc: 0.7172
val Loss: 0.2739 Acc: 0.9085

Epoch 6/24
----------
train Loss: 0.5140 Acc: 0.7746
val Loss: 0.2659 Acc: 0.9085

Epoch 7/24
```

```
----------
train Loss: 0.4688 Acc: 0.8074
val Loss: 0.2292 Acc: 0.9281

Epoch 8/24
----------
train Loss: 0.4157 Acc: 0.8156
val Loss: 0.1915 Acc: 0.9542

Epoch 9/24
----------
train Loss: 0.3267 Acc: 0.8689
val Loss: 0.2294 Acc: 0.9346

Epoch 10/24
----------
train Loss: 0.3703 Acc: 0.8402
val Loss: 0.1949 Acc: 0.9542
```

```
visualize_model(model_conv)

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

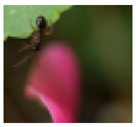
```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:481: UserWarning:
  cpuset_checked))
```

predicted: bees



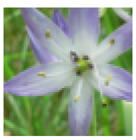
Further Learning

If you would like to learn more about the applications of transfer learning, checkout our `Quantized Transfer Learning for Computer Vision Tutorial <https://pytorch.org/tutorials/intermediate/quantized_transfer_learning_tutorial.html>`_.



predicted: ants

predicted: ants



predicted: ants

✓ 0s completed at 9:39 PM