13.03.2021 (dd.mm.yyyy) Onurcan Köken

official TRANSFER LEARNING FOR COMPUTER VISION TUTORIAL by PyTorch

finetuning - initialize the network weights instead of random initialization

freeze the network except the fully connected layers

classify ants and bees

120 training images each for ants and bees

75 validation images for each class

very small dataset to generalize upon, if trained from scratch

transfer learning makes the model to generalize reasonably well

DATA: https://download.pytorch.org/tutorial/hymenoptera_data.zip

train ant - 123 bee - 121

validation ant - 70 bee - 83

```
%matplotlib inline
```

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 initializaion, 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.

```
# load the data
import requests, zipfile, io
r = requests.get("https://download.pytorch.org/tutorial/hymenoptera_data.zip")
z = zipfile.ZipFile(io.BytesIO(r.content))
z.extractall("data/")
```

```
# 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])
```

```
        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")
```

```
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```

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])
```

```
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```

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/resnet18-5c106cde.pth" to /root/.c
```

100% 44.7M/44.7M [00:00<00:00, 73.1MB/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)
```

```
Epoch 12/24
----------
train Loss: 0.2603 Acc: 0.8770
val Loss: 0.1787 Acc: 0.9608

Epoch 13/24
----------
train Loss: 0.2706 Acc: 0.8975
val Loss: 0.2016 Acc: 0.9346

Epoch 14/24
----------
```

```
train Loss: 0.2710 Acc: 0.8852
val Loss: 0.1833 Acc: 0.9542

Epoch 15/24
----------
train Loss: 0.2652 Acc: 0.8893
val Loss: 0.2300 Acc: 0.9085

Epoch 16/24
----------
train Loss: 0.2265 Acc: 0.8852
val Loss: 0.2350 Acc: 0.8954

Epoch 17/24
----------
train Loss: 0.3100 Acc: 0.8648
val Loss: 0.2139 Acc: 0.9216

Epoch 18/24
----------
train Loss: 0.2745 Acc: 0.8811
val Loss: 0.1946 Acc: 0.9542

Epoch 19/24
----------
train Loss: 0.2589 Acc: 0.8852
val Loss: 0.1948 Acc: 0.9412

Epoch 20/24
----------
train Loss: 0.2910 Acc: 0.8607
val Loss: 0.1853 Acc: 0.9542

Epoch 21/24
----------
train Loss: 0.2248 Acc: 0.9303
val Loss: 0.1975 Acc: 0.9346

Epoch 22/24
----------
train Loss: 0.1873 Acc: 0.9385
val Loss: 0.2127 Acc: 0.9281

Epoch 23/24
----------
train Loss: 0.3130 Acc: 0.8770
```

```
visualize_model(model_ft)
```

```
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  cpuset_checked))
```

predicted: bees

predicted: bees

predicted: ants

predicted: ants

predicted: ants

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)
```

```
val Loss: 0.1606 Acc: 0.9673

Epoch 12/24
----------
train Loss: 0.3386 Acc: 0.8484
val Loss: 0.1634 Acc: 0.9477

Epoch 13/24
----------
train Loss: 0.5044 Acc: 0.7541
val Loss: 0.2044 Acc: 0.9281

Epoch 14/24
----------
train Loss: 0.3930 Acc: 0.8279
val Loss: 0.1645 Acc: 0.9542

Epoch 15/24
----------
train Loss: 0.3336 Acc: 0.8566
val Loss: 0.1724 Acc: 0.9477

Epoch 16/24
----------
train Loss: 0.3622 Acc: 0.8197
val Loss: 0.1596 Acc: 0.9542

Epoch 17/24
----------
train Loss: 0.3258 Acc: 0.8525
val Loss: 0.1570 Acc: 0.9542

Epoch 18/24
----------
train Loss: 0.3376 Acc: 0.8648
val Loss: 0.1772 Acc: 0.9542

Epoch 19/24
----------
train Loss: 0.2922 Acc: 0.8689
val Loss: 0.1694 Acc: 0.9412

Epoch 20/24
----------
train Loss: 0.3149 Acc: 0.8402
val Loss: 0.1563 Acc: 0.9673

Epoch 21/24
----------
train Loss: 0.3138 Acc: 0.8730
val Loss: 0.1613 Acc: 0.9608
```

```
Epoch 22/24
----------
train Loss: 0.3149 Acc: 0.8566
val Loss: 0.1856 Acc: 0.9281

Epoch 23/24
----------
```

```
visualize_model(model_conv)

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

```
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  cpuset_checked))
```
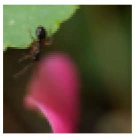

predicted: ants



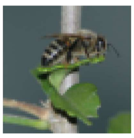
predicted: bees

predicted: ants

predicted: bees

predicted: bees

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
>_.