Basic Image Recognition in PyTorch

In [1]:

```
%pylab inline
!date; hostname; whoami; pwd; curl https://ipinfo.io/hostname; nvidia-smi -L
from imp import reload
from torch import nn, optim
from torch.nn import functional as F
from torchmore import layers, flex
import torch
from torchvision import datasets, transforms
from torchvision.datasets import imagenet
import os.path
from torch.utils import data as torchdata
import helpers
```

```
Populating the interactive namespace from numpy and matplotlib
Mon Dec  9 23:12:28 PST 2019
sedna
tmb
/home/tmb/exp/bigdata19
c-67-170-103-104.hsd1.wa.comcast.net
GPU 0: GeForce GTX 1080 Ti (UUID: GPU-2d5cf167-db75-89ec-c6f7-5639237768ce)
```

Steps

- load training data from disk
- shuffle the training data
- create batches
- create a model
- create a trainer
- update the weights for each batch

File Based Datasets

Standard storage format for ImageNet under PyTorch consists of:

- a meta file
- individual image files

In [6]:

```
for p in "/home/tmb/data/imagenet-raw:/data19/imagenet-raw:/mdata/imagenet-raw".split(":"):
    p += "/ILSVRC2012_devkit_t12"
    if os.path.exists(p):
        devkit_root12 = p
        break
print(devkit_root12)
print(os.popen(f"ls -l {devkit_root12}").read())
```

```
/mdata/imagenet-raw/ILSVRC2012_devkit_t12
total 24
-r--r--r-- 1 tmb  tmb  1246 Jun 14  2012 COPYING
dr-xr-xr-x 2 tmb  tmb  4096 Jun 14  2012 data
dr-xr-xr-x 2 tmb  tmb  4096 Jun 14  2012 evaluation
-r--r--r-- 1 tmb  tmb  8479 Jun 14  2012 readme.txt
lrwxrwxrwx 1 root root    8 Dec  9 23:13 train -> ../train
lrwxrwxrwx 1 root root    6 Dec  9 23:13 val -> ../val
```

Augmentation

We usually have some kind of augmentation or conversion function.

In [3]:

```
augmentation_function = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
])
```

Dataset Class

Many datasets have predefined classes that understand the directory layout and metadata format.

In [4]:

```
training_ds = datasets.ImageNet(devkit_root12, transform=augmentation_function)
```

Random Access

Until PyTorch 1.2, all datasets behaved like arrays; at runtime, the image file name is looked up in the metadata and the corresponding image is read.

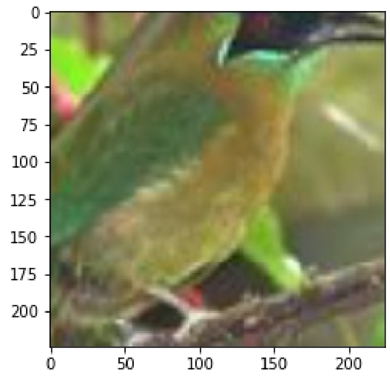
In [5]:

```
image, cls = training_ds[123456]
print(image.shape, image.dtype, image.min(), image.max(), cls)
imshow(image.permute(1, 2, 0).numpy())
```

```
torch.Size([3, 224, 224]) torch.float32 tensor(0.0039) tensor(1.) 95
```

Out[5]:

```
<matplotlib.image.AxesImage at 0x7fe680794610>
```



Data Loader

Datasets are wrapped in `DataLoader` instances; these:

- shuffle the training samples
- create batches out of the training data
- handle multicore preprocessing

In [6]:

```
training_dl = torchdata.DataLoader(training_ds, batch_size=32, shuffle=True, num_workers=8)
```

Data Loaders as Iterators

`DataLoader` instances create iterators over batches composed of random samples.

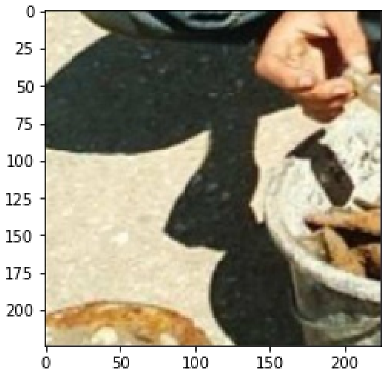
In [7]:

```
image_batch, cls_batch = next(iter(training_dl))
print(image_batch.shape, image_batch.dtype, image_batch.min(), image_batch.max(), cls_batch.min(), cls_batch.max(
))
imshow(image_batch[0].permute(1, 2, 0).numpy())
```

```
torch.Size([32, 3, 224, 224]) torch.float32 tensor(0.) tensor(1.) tensor(64) tensor(943)
```

Out[7]:

<matplotlib.image.AxesImage at 0x7fe67c43dd10>



Model Construction

- PyTorch by default uses direct computation
- models can perform computation directly or be composed of modules
- the `torchmore` library provides useful layers like `layers.Input`

In [8]:

```
from torchvision import models
def make_model():
    return nn.Sequential(
        layers.Input("BDHW", range=(0, 1), sizes=[(2, 9999), 3, 224, 224]),
        models.resnet18()
    )
model = make_model()
model.cuda();
```

Trainers

We usually abstract training into a `Trainer` class: keeps track of model, optimizer, parameters, loss function, history; displays progress.

```
class Trainer(object):
    def __init__(self, model): ...
    def train_batch(self, inputs, targets): ...
    def train_for(self, nsamples, dataloader): ...
    def evaluate(self, dataloader): ...
    def set_lr(self, lr): ...
```

In [9]:

```
trainer = helpers.Trainer(model)
trainer.set_lr(1e-3)
```

Training a Single Batch

This are the main training steps in PyTorch:

- clear gradients
- perform forward step
- compute loss
- propagate gradients backwards
- update the weights (`optimizer.step`)

Training a Single Batch

In [9]:

```
!sed '/def train_batch/,/return/!d;/#/d;/set_last/d' helpers.py
```

```
    def train_batch(self, images, targets):
        self.optimizer.zero_grad()
        outputs = self.model.forward(images.cuda())
        loss = self.criterion(outputs, targets.cuda())
        loss.backward()
        self.optimizer.step()
        return float(loss)
```

Training Loop

Batch training is usually wrapped into a training loop that takes a `DataLoader` instance as an argument.

In [5]:

```
!sed '/def train_for/,/pass/!d;/display_time/,+2d;/last =/,+1d;/total =/s/=.*/= 0/' helpers.py
```

```
    def train_for(self, nsamples, loader, quiet=False):
        total = 0
        while total < nsamples:
            src = iter(loader)
            try:
                while total < nsamples:
                    with self.timers.loading:
                        images, classes = next(src)
                    with self.timers.training:
                        l = self.train_batch(images, classes)
                    total += images.size(0)
                    self.losses.append((total, l))
            except StopIteration:
                pass
```

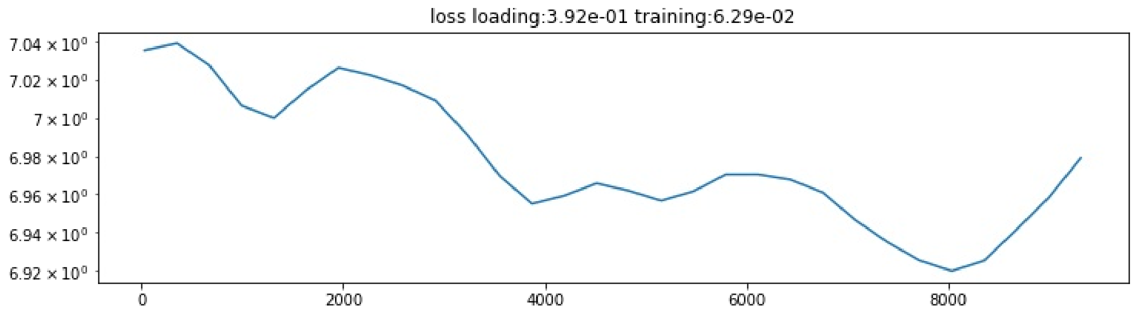
Training

This is the usual training output:

- a plot of the loss
- loading and training times
- NB: loading is much slower than training here, a result of file I/O

In [12]:

```
trainer.train_for(10000, training_dl)
clf()
```




```
<Figure size 864x216 with 0 Axes>
```