hw2

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1 HW2

Author: Moiz Rasheed

1.1 Part 2: Understanding Data Normalization

The mystery question: If the pixel-value scaling by the piece of code in Slide 28 is on a per-image basis and if the same by the code shown on Slide 26 is on a batch basis, how come the two results are exactly the same?

Looking at part of the source code of `to_tensor`, the function used within `ToTensor.__call__()`, that handles numpy arrays:

```
if isinstance(pic, np.ndarray):
    # handle numpy array
    if pic.ndim == 2:
        pic = pic[:, :, None]

    img = torch.from_numpy(pic.transpose((2, 0, 1))).contiguous()  #(**)
    # backward compatibility
    if isinstance(img, torch.ByteTensor):
        return img.to(dtype=default_float_dtype).div(255)          #(*)
    else:
        return img
```

Line * shows that for numpy arrays of type `numpy.uint8` (which will be converted to tensors of type `ByteTensor` in line **), the tensor is divided by the hardcoded value 255, which was the same max used as the divisor in slide 26.

1.2 Part 3: Programming Tasks

1.2.1 3.1: Setting Up Your Conda Enironment

My `environment.yaml` file is included in the zip. But I prefer making python environments using the built-in python module venv.

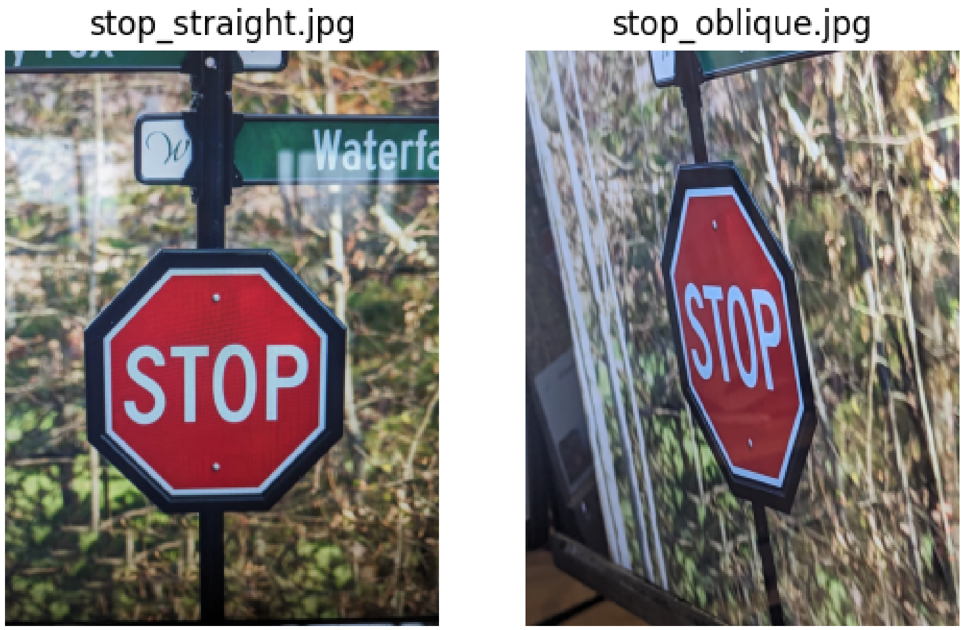
1.2.2 3.2: Becoming Familiar with torchvision.transforms

[63]:
```
from PIL import Image

straight_pic = Image.open('stop_straight.jpg')
oblique_pic = Image.open('stop_oblique.jpg')
```

[64]:
```
import torchvision.transforms.functional as TF
import torchvision.transforms as tvt

totensor = tvt.ToTensor()
topil = tvt.ToPILImage()

straight_img = totensor(straight_pic)
# new_img = TF.affine(straight_img, 0, (0,0), 1, 50)
x0 = 533
y0 = 1430
x1 = 2475
y1 = 3245

px0 = 902
py0 = 814
px1 = 2150
py1 = 3245
w,h = straight_pic.size
new_img = TF.perspective(straight_img, [[x0,y0],[x1,y0],[x1,y1],[x0,y1]],␣
 ↪[[px0,py0],[px1,py0-200],[px1+200,py1+200],[px0,py1]])
new_img = TF.affine(new_img, -10, (0,0), 1, 0)
new_pic = topil(new_img)
new_pic.save('new.jpg')
```

[67]:
```
import matplotlib.pyplot as plt
from matplotlib.image import imread

fig = plt.figure()
list_of_files = ['stop_straight.jpg', 'stop_oblique.jpg']
number_of_files = len(list_of_files)
for i in range(number_of_files):
    a=fig.add_subplot(1,number_of_files,i+1)
    image = imread(list_of_files[i])
    plt.imshow(image)
    plt.axis('off')
    a.set_title(list_of_files[i])

fig2 = plt.figure()
image = imread('new.jpg')
plt.imshow(image)
```

[67]: <matplotlib.image.AxesImage at 0x7ff819c07b80>



In the above images, the two on top are the originals and the one on bottom was generated by transforming `stop_straight.jpg`. I solved this task by making measurements on the `stop_straight.jpg` image and the `stop_oblique.jpg` image to determine the perspective and rotation transformation parameters.

1.2.3 3.3: Creating Your Own Dataset Class

[88]:
```
import os
import torch

class MyDataset(torch.utils.data.Dataset):
    def __init__(self, root):
        super().__init__()
        self.image_files = os.listdir(root)
        self.image_files = [os.path.join(root,file) for file in self.
 ↪image_files]

        self.transform = tvt.Compose([
            tvt.ToTensor(),
            tvt.Resize(200),
            tvt.ColorJitter(brightness=.5, hue=.3),
            tvt.RandomAffine(20, (.3, .3), (.75,2)),
            tvt.RandomPerspective()
        ])

    def __len__(self):
        return len(self.image_files) * 10

    def __getitem__(self, index):
        pic = Image.open(self.image_files[index//10])
        img = self.transform(pic)
        return (img, 0)
```

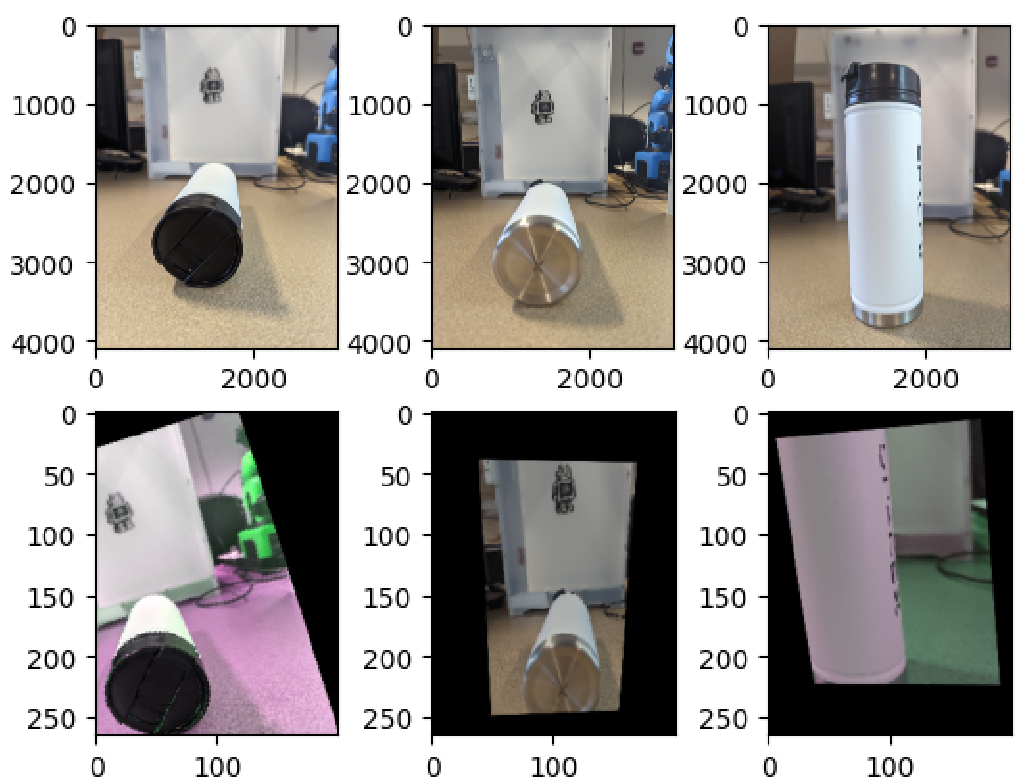
[89]:
```
my_dataset = MyDataset('dataset')
print(len(my_dataset))

index = 10
val = my_dataset[index]
print(val[0].shape, val[1])

index = 50
val = my_dataset[index]
print(val[0].shape, val[1])
```

```
100
torch.Size([3, 265, 200]) 0
```

```
torch.Size([3, 265, 200]) 0
```

[90]:
```python
fig = plt.figure()

fig.add_subplot(2, 3, 1)
plt.imshow(Image.open(my_dataset.image_files[0]))
fig.add_subplot(2, 3, 4)
img, _ = my_dataset[0]
plt.imshow(topil(img))

fig.add_subplot(2, 3, 2)
plt.imshow(Image.open(my_dataset.image_files[1]))
fig.add_subplot(2, 3, 5)
img, _ = my_dataset[10]
plt.imshow(topil(img))

fig.add_subplot(2, 3, 3)
plt.imshow(Image.open(my_dataset.image_files[5]))
fig.add_subplot(2, 3, 6)
img, _ = my_dataset[50]
plt.imshow(topil(img))
```

[90]:
```
<matplotlib.image.AxesImage at 0x7ff8589a8dc0>
```

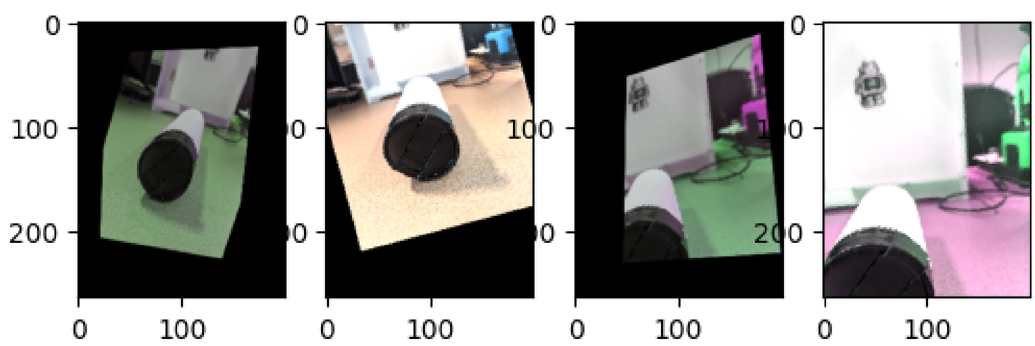


The above row shows the original images and the bottom row shows the transformed versions. I chose to go with a ColorJitter transform because I thought that it could maybe account for different lighting conditions (such as in second column). I went for the RandomAffine and RandomePerspective transform to account for different positions a camera might take a photo in. I also resized my images because they were taking way to long to load.

1.2.4 3.4: Generating Data in Parallel

[91]:
```
my_dataloader = torch.utils.data.DataLoader(my_dataset, batch_size=4,
    num_workers=4)
images, labels = next(iter(my_dataloader))

fig = plt.figure()

fig.add_subplot(1, 4, 1)
plt.imshow(topil(images[0]))
fig.add_subplot(1, 4, 2)
plt.imshow(topil(images[1]))
fig.add_subplot(1, 4, 3)
plt.imshow(topil(images[2]))
fig.add_subplot(1, 4, 4)
plt.imshow(topil(images[3]))
```

[91]:
```
<matplotlib.image.AxesImage at 0x7ff858623c10>
```



[93]:
```
import time

start = time.time()
for i in range(1000):
    my_dataset[i//10]
print("dataset time: " + str(time.time() - start))

start = time.time()
```

```python
for i in range(10):
    for images, labels in my_dataloader:
        pass
print("dataloader time: " + str(time.time() - start))
```

```
dataset time: 118.25628113746643
dataloader time: 67.62583518028259
```

With 4 workers and a batch size of 4, the time difference in loading 1000 images between the dataset and dataloader is shown above.

After some Googling, I found out each worker loads an entire batch and queues it for use it the future. It would be beneficial then to have more workers if the batch size/loading time of a batch is large in comparison to how fast the batch is fed through the network. But if the network takes a while to compute, it is not necessary to have many batches ready in advance.