50.039 Theory and Practice of Deep Learning
Coding Homework 5

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March 3, 2019

1 Custom dataset class

We write a custom dataset class with the ability to load image and label paths, and implement a static method `train_val_test_split()` to automatically split the dataset into the training, validation, and test sets.

Constructor

The class constructor takes the directory path containing the images, a file containing all the image paths, a `.npy` file containing all the labels, and loads a Pandas `DataFrame` with keys as image paths and values as their corresponding labels.

```
class FlowerDataset(Dataset):
  def __init__(self, image_dir, image_paths,
    label_file, transform=None):
    self.image_dir = image_dir
    self.labels = np.load(label_file)
    self.image_label_pairs = self._load_paths(
    image_paths)
    self.transform = transform
```

Subclass implementations

We need to necessarily implement `__len__()` and `__getitem__()` since we are subclassing `torch.utils.data.Dataset`. To be more efficient, we only load images when the item is accessed via `dataset[index]`.

```
  def __len__(self):
    return len(self.image_label_pairs)

  def __getitem__(self, idx):
    # apply transforms
    image_path = self.image_label_pairs.index[
    idx]
    image = self._load_image(image_path)
    if self.transform is not None:
      image = self.transform(image)
    label = self.labels[idx]
    return {'image': image,
        'label': label}
```

Loading data

Two private methods here for data loading. The first method `_load_paths()` constructs a Pandas `DataFrame` object containing the image paths and their corresponding labels. The second method `_load_image()` loads an image from the given path as a `PIL.Image`. Single-channel (grayscale) images are stacked into 3-channel images here using `numpy.repeat()`.

```
  def _load_paths(self, file_path):
    """
    params:  file_path, a path pointing to
    where the image paths are stored.
    returns: dictionary with keys '
    full_image_path', and values 'label'
    """
    split_set = {}
    with open(file_path) as f:
      lines = f.readlines()
      num_lines = len(lines)
      assert(num_lines == len(self.labels))
      for line_num in range(num_lines):
        full_image_path = os.path.join(self.
    image_dir, lines[line_num].strip('\n'))
        split_set[full_image_path] = self.
    labels[line_num]
    return pd.DataFrame.from_dict(split_set,
    orient='index')

  def _load_image(self, image_path):
    img = Image.open(image_path)
    img.load()
    img = np.array(img)
    if len(img.shape) == 2:
      img = np.expand_dims(img, 2)
      img = np.repeat(img, 3, 2)
    return Image.fromarray(img)
```

Implementing splits

In the final class method, we implement a method to split the dataset into training, validation and test sets. This returns three splits with type `torch.utils.data.Subset`, which can be directly fed into the `torch.utils.data.DataLoader` class.

```
  def train_val_test_split(self, train_ratio,
    val_ratio):
```

```
dataset_length = len(self.
image_label_pairs)
train_length = int(train_ratio *
dataset_length)
val_length = int(val_ratio *
dataset_length)
test_length = len(self) - train_length -
val_length
splits = [train_length, val_length,
test_length]
return random_split(self, splits)
```

2 Data loading

Data augmentation and split ratio

We apply only a center crop of size 200. A training, validation, test split of $0.7, 0.1, 0.2$ is carried out using our split function above:

```
transform = transforms.Compose([transforms.
    CenterCrop(200), transforms.ToTensor()])
dataset = FlowerDataset('data', 'image_paths.
    txt', 'labels.npy', transform=transform)
train_set, val_set, test_set = dataset.
    train_val_test_split(0.7, 0.1)
```

Batch size

We then construct three loaders for each of the sets with a `batch_size` of 32.

```
train_loader = DataLoader(train_set,
    batch_size=32, shuffle=True, num_workers
    =4)
val_loader = DataLoader(val_set, batch_size
    =32, shuffle=True, num_workers=4)
test_loader = DataLoader(test_set, batch_size
    =32, shuffle=True, num_workers=4)
```

3 Loss function

We choose `CrossEntropyLoss` for our 102-class dataset. Categorical cross entropy loss is the natural choice for multi-class classification.

4 Hyperparameters and optimizer

After validating over a small number of epochs, we choose a learning rate of 10^{-3} and a batch size of 32. We use SGD with momentum.

```
batch_size = 32
num_epochs = 50
learning_rate = 1e-3
```

```
optimizer = optim.SGD(model.parameters(), lr=
    learning_rate, momentum=0.9)
CE = nn.CrossEntropyLoss()
```

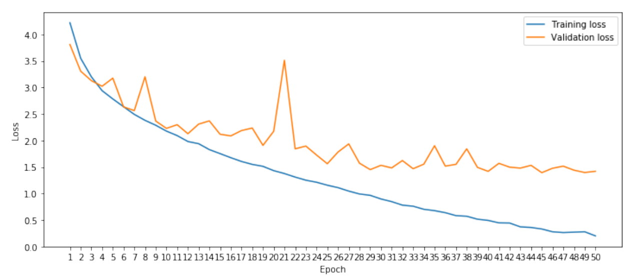
5 Task I: Training all layers of ResNet18

Initializing the model

We can initialize an untrained model with a custom number of classes using the `num_classes` argument. Examining the PyTorch source code, this passes the number of classes into the `ResNet` constructor, which builds a FC layer with that number of classes.

```
model = models.resnet18(num_classes=102).to(
    device)
```

Training and validation results



We observe the training loss decreasing and the validation loss decreasing but not converging. The best epoch's results:

```
Epoch: 45
Training set: Average loss: 0.3338
Validation set: Average loss: 1.3952, Accuracy
    : 540/818 (66%)
Saving model (epoch 45) with lowest validation
     loss: 1.395247207238124
```

Test accuracy: 62%

This model (epoch 45) fairs decently on the test set:

```
Test set: Accuracy: 1011/1639 (62%)
```

6 Task II: Training over pretrained ResNet18

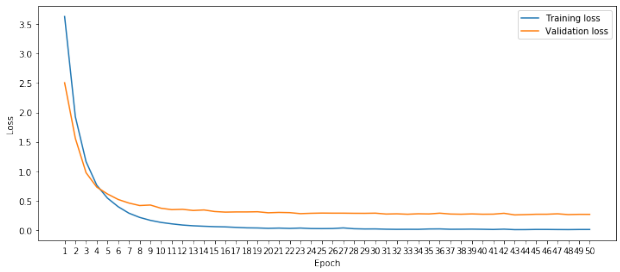
Initializing the model

We can initialize an pretrained model with a custom number of classes using the `pretrained=True` argument.

However, we cannot specify the number of classes using the same method in Task I. Instead, we have to explicitly reset the FC layer:

```
model = models.resnet18(pretrained=True)
model.fc = nn.Linear(512, 102)
model.to(device)
```

Training and validation results



We observe the both training loss and the validation loss decreasing and converging. The best epoch's results:

```
Epoch: 43
Training set: Average loss: 0.0107
Validation set: Average loss: 0.2609, Accuracy
    : 770/818 (94%)
Saving model (epoch 43) with lowest validation
     loss: 0.26094281100309813
```

Test accuracy: 93%

This model (epoch 43) fairs well on the test set:

```
Test set: Accuracy: 1522/1639 (93%)
```

7 Task III: Training 2 pre-final layers of ResNet18

Initializing the model

In ResNet18, the forward pass is:

```
def forward(self, x):
  x = self.conv1(x)
  x = self.bn1(x)
  x = self.relu(x)
  x = self.maxpool(x)

  x = self.layer1(x)
  x = self.layer2(x)
  x = self.layer3(x)
  x = self.layer4(x)

  x = self.avgpool(x)
  x = x.view(x.size(0), -1)
  x = self.fc(x)
```

We can train only the 2 pre-final layers (`layer3`, `layer4`) by loading the pre-trained model, then setting the `requires_grad` attribute of the parameters outside these two layers to `False`. The `relu`, `maxpool`, and `avgpool` layers do not contain any parameters, so they are not frozen. We write a function `freeze()` to freeze the gradient in the parameters in the layer.

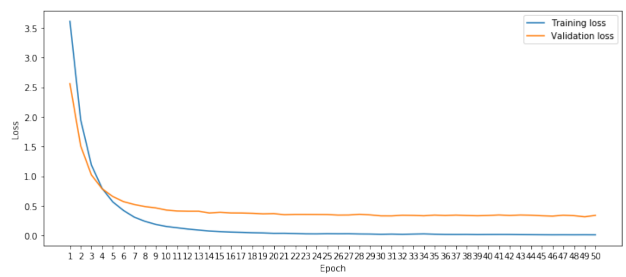
```
def freeze(layer):
    for param in layer.parameters():
        param.requires_grad = False

model = models.resnet18(pretrained=True)

# freeze all layers before layer3
freeze(model.conv1)
freeze(model.bn1)
freeze(model.layer1)
freeze(model.layer2)
model.fc = nn.Linear(512, 102)

model.to(device)
```

Training and validation results



We observe the both training loss and the validation loss decreasing and converging. The best epoch's results:

```
Epoch: 49
Training set: Average loss: 0.0114
Validation set: Average loss: 0.3148, Accuracy
    : 756/818 (92%)
Saving model (epoch 49) with lowest validation
     loss: 0.31477418828469056
```

Test accuracy: 92%

This model (epoch 49) fairs well on the test set:

```
Test set: Accuracy: 1503/1639 (92%)
```