landmark

July 8, 2021

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for Landmark Classification

In this notebook, some template code has already been provided for you, and you will need to implement additional functionality to successfully complete this project. You will not need to modify the included code beyond what is requested. Sections that begin with **'(IMPLEMENTATION)'** in the header indicate that the following block of code will require additional functionality which you must provide. Instructions will be provided for each section, and the specifics of the implementation are marked in the code block with a 'TODO' statement. Please be sure to read the instructions carefully!

> **Note**: Once you have completed all the code implementations, you need to finalize your work by exporting the Jupyter Notebook as an HTML document. Before exporting the notebook to HTML, all the code cells need to have been run so that reviewers can see the final implementation and output. You can then export the notebook by using the menu above and navigating to **File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. Markdown cells can be edited by double-clicking the cell to enter edit mode.

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.
## Step 0: Download Datasets and Install Python Modules

Note: if you are using the Udacity workspace, *YOU CAN SKIP THIS STEP*. The dataset can be found in the `/data` folder and all required Python modules have been installed in the workspace.

Download the landmark dataset. Unzip the folder and place it in this project's home directory, at the location `/landmark_images`.

Install the following Python modules: * cv2 * matplotlib * numpy * PIL * torch * torchvision

## Step 1: Create a CNN to Classify Landmarks (from Scratch)

In this step, you will create a CNN that classifies landmarks. You must create your CNN *from scratch* (so, you can't use transfer learning *yet*!), and you must attain a test accuracy of at least 20%.

Although 20% may seem low at first glance, it seems more reasonable after realizing how difficult of a problem this is. Many times, an image that is taken at a landmark captures a fairly mundane image of an animal or plant, like in the following picture.

Just by looking at that image alone, would you have been able to guess that it was taken at the Haleakal National Park in Hawaii?

An accuracy of 20% is significantly better than random guessing, which would provide an accuracy of just 2%. In Step 2 of this notebook, you will have the opportunity to greatly improve accuracy by using transfer learning to create a CNN.

Remember that practice is far ahead of theory in deep learning. Experiment with many different architectures, and trust your intuition. And, of course, have fun!

1.1.1 (IMPLEMENTATION) Specify Data Loaders for the Landmark Dataset

Use the code cell below to create three separate data loaders: one for training data, one for validation data, and one for test data. Randomly split the images located at `landmark_images/train` to create the train and validation data loaders, and use the images located at `landmark_images/test` to create the test data loader.

Note: Remember that the dataset can be found at `/data/landmark_images/` in the workspace.

All three of your data loaders should be accessible via a dictionary named `loaders_scratch`. Your train data loader should be at `loaders_scratch['train']`, your validation data loader should be at `loaders_scratch['valid']`, and your test data loader should be at `loaders_scratch['test']`.

You may find this documentation on custom datasets to be a useful resource. If you are interested in augmenting your training and/or validation data, check out the wide variety of transforms!

```
In [8]: ### TODO: Write data loaders for training, validation, and test sets
        ## Specify appropriate transforms, and batch_sizes
        import torch
        import numpy as np
        from torchvision import datasets,models
        import torchvision.transforms as transforms
        from torch.utils.data.sampler import SubsetRandomSampler

        #
        num_workers = 0
        batch_size = 32
        valid_size = 0.2
        #transformations 64*64
        transform = transforms.Compose([
            transforms.Resize((64,64)),
            transforms.ToTensor(),
            transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
```

```
    ])

#datasets
train_data = datasets.ImageFolder('/data/landmark_images/train',transform=transform)
test_data  = datasets.ImageFolder('/data/landmark_images/test',transform=transform)

# train/val split
num_train = len(train_data)
indices = list(range(num_train))
np.random.shuffle(indices)
split = int(np.floor(valid_size * num_train))
train_idx, valid_idx = indices[split:], indices[:split]
train_sampler = SubsetRandomSampler(train_idx)
valid_sampler = SubsetRandomSampler(valid_idx)

#dataloaders
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,sampler=tra
valid_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, sampler=va
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size, num_workers=

# specify the image classes
classes = test_data.classes
print(classes)
loaders_scratch = {'train': train_loader, 'valid': valid_loader, 'test': test_loader}
```

```
['00.Haleakala_National_Park', '01.Mount_Rainier_National_Park', '02.Ljubljana_Castle', '03.Dead
```

Question 1: Describe your chosen procedure for preprocessing the data. - How does your code resize the images (by cropping, stretching, etc)? What size did you pick for the input tensor, and why? - Did you decide to augment the dataset? If so, how (through translations, flips, rotations, etc)? If not, why not?

Answer: my code resize the images for two reasons. first the images as provided are of varied sizes and need to be of one size for the input tensor. Second the code resizes the images to a much smaller size of 64*64 for quicker computation while still keeping enough image featuresalso i went with power of 2 for my sizing. initially I went with 128 but through experimentation found that 128 takes too much time to traning, 32 losses the image feature and 64 was good middle ground for feature preserving and training speed

as for transformation I went only with the necessary resize, to tensor and normalization as advised by session instructor as adding more augmentation will make the problem harder and slows training. some augmentation like center-crop can be added with no big impact on the code speed and model accuracy but is opt-out of doing so.

1.1.2 (IMPLEMENTATION) Visualize a Batch of Training Data

Use the code cell below to retrieve a batch of images from your train data loader, display at least 5 images simultaneously, and label each displayed image with its class name (e.g., "Golden Gate Bridge").

Visualizing the output of your data loader is a great way to ensure that your data loading and preprocessing are working as expected.

```
In [9]: import matplotlib.pyplot as plt
        %matplotlib inline

        ## TODO: visualize a batch of the train data loader

        ## the class names can be accessed at the `classes` attribute
        ## of your dataset object (e.g., `train_dataset.classes`)

        '''this code is really the same as the one in the course videos since I do not know how
        def imshow(img):
            img = img / 2 + 0.5  # unnormalize
            plt.imshow(np.transpose(img, (1, 2, 0)))

        dataiter = iter(train_loader)
        images, labels = dataiter.next()
        images = images.numpy()
        fig = plt.figure(figsize=(25, 4))
        for idx in np.arange(20):
            ax = fig.add_subplot(2, 20/2, idx+1, xticks=[], yticks=[])
            imshow(images[idx])
            ax.set_title(classes[labels[idx]][3:])
```

1.1.3 Initialize use_cuda variable

```
In [10]: # useful variable that tells us whether we should use the GPU
         use_cuda = torch.cuda.is_available()
         print(use_cuda)
```

```
True
```

1.1.4 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_scratch`, and fill in the function `get_optimizer_scratch` below.

```
In [11]: ## TODO: select loss function
         import torch.nn as nn
         import torch.optim as optim

         criterion_scratch = nn.CrossEntropyLoss()

         def get_optimizer_scratch(model):
             ## TODO: select and return an optimizer
             '''lr between 0.1 to 0.15 is good range'''
             return optim.SGD(model.parameters(), lr=0.15)
```

1.1.5 (IMPLEMENTATION) Model Architecture

Create a CNN to classify images of landmarks. Use the template in the code cell below.

```
In [12]: import torch.nn as nn
         import torch.nn.functional as F
         # define the CNN architecture
         class Net(nn.Module):
             ## TODO: choose an architecture, and complete the class
             def __init__(self):
                 super(Net, self).__init__()
                 ## Define layers of a CNN
                 self.conv0 = nn.Conv2d(3, 16, 3, padding=1)
                 self.conv1 = nn.Conv2d(16, 32, 3, padding=1)
                 self.conv2 = nn.Conv2d(32, 64, 3, padding=1)
                 self.conv3 = nn.Conv2d(64, 128, 3, padding=1)
                 self.pool = nn.MaxPool2d(2, 2)
                 # linear layers
                 self.fc1 = nn.Linear(128 * 4 * 4, 1024)
                 self.fc2 = nn.Linear(1024, 50)
                 self.dropout = nn.Dropout(0.50)

             def forward(self, x):
                 ## Define forward behavior
                 x = self.pool(F.relu(self.conv0(x)))
                 x = self.pool(F.relu(self.conv1(x)))
                 x = self.pool(F.relu(self.conv2(x)))
                 x = self.pool(F.relu(self.conv3(x)))
                 x = x.view(-1, 128 * 4 * 4)
                 x = self.dropout(x)
                 x = F.relu(self.fc1(x))
                 x = self.dropout(x)
                 x = self.fc2(x)
                 return x
```

```
        #-#-# Do NOT modify the code below this line. #-#-#

        # instantiate the CNN
        model_scratch = Net()
        print(model_scratch)

        # move tensors to GPU if CUDA is available
        if use_cuda:
            model_scratch.cuda()
```

```
Net(
  (conv0): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv1): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=2048, out_features=1024, bias=True)
  (fc2): Linear(in_features=1024, out_features=50, bias=True)
  (dropout): Dropout(p=0.5)
)
```

Question 2: Outline the steps you took to get to your final CNN architecture and your reasoning at each step.

Answer: the main thing i considered when making the CNN is training speed since I started the project on my pc so i did not want a lot of layers in the CNN and my session instructor also said that one does not need a big CNN to get good results. so in the start i went with 3 conv2d from 3 to 64 filter but added one more to get total 128 filter in the end. as for the linear layer i went with 2 since having just one 2048 -> 50 seems ineffective in my point if view and more than 2 layers according to my instructor is enough for such small CNN. while this answer is the boiled down version of what i did a lot of trial and error was undertaken to get the final CNN

1.1.6 (IMPLEMENTATION) Implement the Training Algorithm

Implement your training algorithm in the code cell below. Save the final model parameters at the filepath stored in the variable `save_path`.

```
In [13]: def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
             """returns trained model"""
             # initialize tracker for minimum validation loss
             valid_loss_min = np.Inf

             for epoch in range(1, n_epochs+1):
                 # initialize variables to monitor training and validation loss
                 train_loss = 0.0
                 valid_loss = 0.0

                 ###################
                 # train the model #
```

```
    ###################
    # set the module to training mode
    model.train()
    for batch_idx, (data, target) in enumerate(loaders['train']):
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()

        ## TODO: find the loss and update the model parameters accordingly
        ## record the average training loss, using something like
        ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data.item() - t
        optimizer.zero_grad()
        output = model(data)
        loss = criterion(output, target)
        loss.backward()
        optimizer.step()
        train_loss += ((1 / (batch_idx + 1)) * (loss.data.item() - train_loss))


    ######################
    # validate the model #
    ######################
    # set the model to evaluation mode
    model.eval()
    for batch_idx, (data, target) in enumerate(loaders['valid']):
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()

        ## TODO: update average validation loss
        output = model(data)
        loss = criterion(output, target)
        valid_loss += ((1 / (batch_idx + 1)) * (loss.data.item() - valid_loss))

    #average out the losses
    train_loss = train_loss/len(train_loader.sampler)
    valid_loss = valid_loss/len(valid_loader.sampler)

    # print training/validation statistics
    print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
        epoch,
        train_loss,
        valid_loss
        ))

    ## TODO: if the validation loss has decreased, save the model at the filepath s
    if valid_loss <= valid_loss_min:
        print('Validation loss decreased.Saving model')
```

```
                torch.save(model.state_dict(),save_path)
                valid_loss_min = valid_loss

        return model
```

1.1.7 (IMPLEMENTATION) Experiment with the Weight Initialization

Use the code cell below to define a custom weight initialization, and then train with your weight initialization for a few epochs. Make sure that neither the training loss nor validation loss is `nan`.

Later on, you will be able to see how this compares to training with PyTorch's default weight initialization.

```
In [7]: const = 0 #set to false/0 for rand uniform or true/1 for constant
        w = 10 # constant weight / uni-dis range
        def custom_weight_init(m):
            ## TODO: implement a weight initialization strategy
            classname = m.__class__.__name__
            if const:
                if classname.find('Linear') != -1:
                    m.weight.data.fill_(const_w)
                    m.bias.data.fill_(const_w)
                if classname.find('Conv2d') != -1:
                    m.weight.data.fill_(const_w)
            else:
                if classname.find('Linear') != -1:
                    m.weight.data.uniform_(-w,w)
                    m.bias.data.uniform_(-w,w)
                if classname.find('Conv2d') != -1:
                    m.weight.data.uniform_(-w,w)

        #-#-# Do NOT modify the code below this line. #-#-#
        model_scratch.apply(custom_weight_init)
        # print pramameter loop
        #for param in model_scratch.parameters(): print(param.data)
        model_scratch = train(20, loaders_scratch, model_scratch, get_optimizer_scratch(model_sc
```

```
Epoch: 1         Training Loss: 2133171.388149        Validation Loss: 0.009196
Validation loss decreased.Saving model
Epoch: 2         Training Loss: 0.002134        Validation Loss: 0.008225
Validation loss decreased.Saving model
Epoch: 3         Training Loss: 0.001934        Validation Loss: 0.007631
Validation loss decreased.Saving model
Epoch: 4         Training Loss: 0.001770        Validation Loss: 0.006950
Validation loss decreased.Saving model
Epoch: 5         Training Loss: 0.001632        Validation Loss: 0.006436
Validation loss decreased.Saving model
Epoch: 6         Training Loss: 0.001518        Validation Loss: 0.006038
Validation loss decreased.Saving model
```

```
Epoch: 7         Training Loss: 0.001426        Validation Loss: 0.005698
Validation loss decreased.Saving model
Epoch: 8         Training Loss: 0.001352        Validation Loss: 0.005448
Validation loss decreased.Saving model
Epoch: 9         Training Loss: 0.001291        Validation Loss: 0.005176
Validation loss decreased.Saving model
Epoch: 10         Training Loss: 0.001240        Validation Loss: 0.004968
Validation loss decreased.Saving model
Epoch: 11         Training Loss: 0.001199        Validation Loss: 0.004824
Validation loss decreased.Saving model
Epoch: 12         Training Loss: 0.001165        Validation Loss: 0.004692
Validation loss decreased.Saving model
Epoch: 13         Training Loss: 0.001136        Validation Loss: 0.004554
Validation loss decreased.Saving model
Epoch: 14         Training Loss: 0.001111        Validation Loss: 0.004487
Validation loss decreased.Saving model
Epoch: 15         Training Loss: 0.001090        Validation Loss: 0.004388
Validation loss decreased.Saving model
Epoch: 16         Training Loss: 0.001071        Validation Loss: 0.004306
Validation loss decreased.Saving model
Epoch: 17         Training Loss: 0.001055        Validation Loss: 0.004245
Validation loss decreased.Saving model
Epoch: 18         Training Loss: 0.001040        Validation Loss: 0.004183
Validation loss decreased.Saving model
Epoch: 19         Training Loss: 0.001028        Validation Loss: 0.004122
Validation loss decreased.Saving model
Epoch: 20         Training Loss: 0.001017        Validation Loss: 0.004080
Validation loss decreased.Saving model
```

1.1.8 (IMPLEMENTATION) Train and Validate the Model

Run the next code cell to train your model.

```
In [8]: ## TODO: you may change the number of epochs if you'd like,
        ## but changing it is not required
        num_epochs = 20 #100 epochs is way too much, 20 to 10 is far more suitable

        #-#-# Do NOT modify the code below this line. #-#-#

        # function to re-initialize a model with pytorch's default weight initialization
        def default_weight_init(m):
            reset_parameters = getattr(m, 'reset_parameters', None)
            if callable(reset_parameters):
                m.reset_parameters()

        # reset the model parameters
        model_scratch.apply(default_weight_init)
```

```
# train the model
model_scratch = train(num_epochs, loaders_scratch, model_scratch, get_optimizer_scratch(
                      criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1        Training Loss: 0.000979        Validation Loss: 0.003919
Validation loss decreased.Saving model
Epoch: 2        Training Loss: 0.000976        Validation Loss: 0.003852
Validation loss decreased.Saving model
Epoch: 3        Training Loss: 0.000952        Validation Loss: 0.003730
Validation loss decreased.Saving model
Epoch: 4        Training Loss: 0.000935        Validation Loss: 0.003674
Validation loss decreased.Saving model
Epoch: 5        Training Loss: 0.000919        Validation Loss: 0.003632
Validation loss decreased.Saving model
Epoch: 6        Training Loss: 0.000896        Validation Loss: 0.003412
Validation loss decreased.Saving model
Epoch: 7        Training Loss: 0.000882        Validation Loss: 0.003385
Validation loss decreased.Saving model
Epoch: 8        Training Loss: 0.000846        Validation Loss: 0.003342
Validation loss decreased.Saving model
Epoch: 9        Training Loss: 0.000820        Validation Loss: 0.003265
Validation loss decreased.Saving model
Epoch: 10        Training Loss: 0.000792        Validation Loss: 0.003104
Validation loss decreased.Saving model
Epoch: 11        Training Loss: 0.000761        Validation Loss: 0.003006
Validation loss decreased.Saving model
Epoch: 12        Training Loss: 0.000733        Validation Loss: 0.002984
Validation loss decreased.Saving model
Epoch: 13        Training Loss: 0.000698        Validation Loss: 0.002994
Epoch: 14        Training Loss: 0.000669        Validation Loss: 0.002802
Validation loss decreased.Saving model
Epoch: 15        Training Loss: 0.000634        Validation Loss: 0.002746
Validation loss decreased.Saving model
Epoch: 16        Training Loss: 0.000603        Validation Loss: 0.002848
Epoch: 17        Training Loss: 0.000563        Validation Loss: 0.002737
Validation loss decreased.Saving model
Epoch: 18        Training Loss: 0.000534        Validation Loss: 0.002730
Validation loss decreased.Saving model
Epoch: 19        Training Loss: 0.000496        Validation Loss: 0.002765
Epoch: 20        Training Loss: 0.000478        Validation Loss: 0.002793
```

1.1.9 (IMPLEMENTATION) Test the Model

Run the code cell below to try out your model on the test dataset of landmark images. Run the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 20%.

```
In [14]: def test(loaders, model, criterion, use_cuda):

             # monitor test loss and accuracy
             test_loss = 0.
             correct = 0.
             total = 0.

             # set the module to evaluation mode
             model.eval()

             for batch_idx, (data, target) in enumerate(loaders['test']):
                 # move to GPU
                 if use_cuda:
                     data, target = data.cuda(), target.cuda()
                 # forward pass: compute predicted outputs by passing inputs to the model
                 output = model(data)
                 # calculate the loss
                 loss = criterion(output, target)
                 # update average test loss
                 test_loss = test_loss + ((1 / (batch_idx + 1)) * (loss.data.item() - test_loss)
                 # convert output probabilities to predicted class
                 pred = output.data.max(1, keepdim=True)[1]
                 # compare predictions to true label
                 correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
                 total += data.size(0)

             print('Test Loss: {:.6f}\n'.format(test_loss))

             print('\nTest Accuracy: %2d%% (%2d/%2d)' % (
                 100. * correct / total, correct, total))

         # load the model that got the best validation accuracy
         model_scratch.load_state_dict(torch.load('model_scratch.pt'))
         test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 2.712013


Test Accuracy: 32% (404/1250)
```

## Step 2: Create a CNN to Classify Landmarks (using Transfer Learning)

You will now use transfer learning to create a CNN that can identify landmarks from images. Your CNN must attain at least 60% accuracy on the test set.

1.1.10 (IMPLEMENTATION) Specify Data Loaders for the Landmark Dataset

Use the code cell below to create three separate data loaders: one for training data, one for validation data, and one for test data. Randomly split the images located at `landmark_images/train` to create the train and validation data loaders, and use the images located at `landmark_images/test` to create the test data loader.

All three of your data loaders should be accessible via a dictionary named `loaders_transfer`. Your train data loader should be at `loaders_transfer['train']`, your validation data loader should be at `loaders_transfer['valid']`, and your test data loader should be at `loaders_transfer['test']`.

If you like, **you are welcome to use the same data loaders from the previous step**, when you created a CNN from scratch.

```
In [15]: ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes

         #assuming that the imports were done in past cells
         '''import torch
         import numpy as np
         from torchvision import datasets,models
         import torchvision.transforms as transforms
         from torch.utils.data.sampler import SubsetRandomSampler'''

         #the following code is written similar as the course videos and provided notebooks
         num_workers = 0
         batch_size = 32
         valid_size = 0.2
         '''transformations change size to 224*224 for vgg16'''
         transform = transforms.Compose([
             transforms.Resize((224,224)),
             transforms.ToTensor(),
             transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
             ])

         #datasets
         train_data = datasets.ImageFolder('/data/landmark_images/train',transform=transform)
         test_data  = datasets.ImageFolder('/data/landmark_images/test',transform=transform)

         # train/val split
         num_train = len(train_data)
         indices = list(range(num_train))
         np.random.shuffle(indices)
         split = int(np.floor(valid_size * num_train))
         train_idx, valid_idx = indices[split:], indices[:split]
         train_sampler = SubsetRandomSampler(train_idx)
         valid_sampler = SubsetRandomSampler(valid_idx)

         #dataloaders
```

```
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,sampler=tr
valid_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, sampler=v
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size, num_workers

classes = train_data.classes
#print(classes)
loaders_transfer = {'train': train_loader, 'valid': valid_loader, 'test': test_loader}
```

1.1.11 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_transfer`, and fill in the function `get_optimizer_transfer` below.

```
In [16]: ## TODO: select loss function
         criterion_transfer = nn.CrossEntropyLoss()

         def get_optimizer_transfer(model):
             ## TODO: select and return optimizer
             #need very low lr since vgg16 layer are mostly trained and just need to train the l
             return optim.SGD(model.classifier[6].parameters(), lr=0.001)
```

1.1.12 (IMPLEMENTATION) Model Architecture

Use transfer learning to create a CNN to classify images of landmarks. Use the code cell below, and save your initialized model as the variable `model_transfer`.

```
In [17]: ## TODO: Specify model architecture

         model_transfer = models.vgg16(pretrained=True)
         #freeze the conv/feature layers
         for param in model_transfer.features.parameters():
             param.requires_grad = False
         model_transfer.classifier[6] = nn.Linear(model_transfer.classifier[6].in_features, 50)
         #print(model_transfer)

         #-#-# Do NOT modify the code below this line. #-#-#

         if use_cuda:
             model_transfer = model_transfer.cuda()
```

Question 3: Outline the steps you took to get to your final CNN architecture and your reasoning at each step. Describe why you think the architecture is suitable for the current problem.

Answer: I went with VGG CNNs after a discussion with my session instructor we found that VGG is has sufficiently similar dataset. since VGG was similar and the dataset was larger than ours I used EndCoV method and went with VGG16 since it was small enough to not take huge time training and would still give good results.

As for how I modified it I simply kept all put the last classifier layer and froze the weights of the conv layers also i replaced the last classifier layer out channel with the number of the landmarks dataset classes.

1.1.13 (IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. Save the final model parameters at filepath `'model_transfer.pt'`.

```
In [13]: # TODO: train the model and save the best model parameters at filepath 'model_transfer.
         #very much the same code as the from scratch except it is with moded vgg16
         num_epochs = 20
         train(num_epochs, loaders_transfer, model_transfer, get_optimizer_transfer(model_transf

         #-#-# Do NOT modify the code below this line. #-#-#
         # load the model that got the best validation accuracy
         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

```
Epoch: 1         Training Loss: 0.000948         Validation Loss: 0.003512
Validation loss decreased.Saving model
Epoch: 2         Training Loss: 0.000836         Validation Loss: 0.003148
Validation loss decreased.Saving model
Epoch: 3         Training Loss: 0.000749         Validation Loss: 0.002864
Validation loss decreased.Saving model
Epoch: 4         Training Loss: 0.000683         Validation Loss: 0.002661
Validation loss decreased.Saving model
Epoch: 5         Training Loss: 0.000633         Validation Loss: 0.002471
Validation loss decreased.Saving model
Epoch: 6         Training Loss: 0.000592         Validation Loss: 0.002336
Validation loss decreased.Saving model
Epoch: 7         Training Loss: 0.000558         Validation Loss: 0.002213
Validation loss decreased.Saving model
Epoch: 8         Training Loss: 0.000531         Validation Loss: 0.002131
Validation loss decreased.Saving model
Epoch: 9         Training Loss: 0.000507         Validation Loss: 0.002052
Validation loss decreased.Saving model
Epoch: 10         Training Loss: 0.000486         Validation Loss: 0.001982
Validation loss decreased.Saving model
Epoch: 11         Training Loss: 0.000470         Validation Loss: 0.001921
Validation loss decreased.Saving model
Epoch: 12         Training Loss: 0.000454         Validation Loss: 0.001868
Validation loss decreased.Saving model
Epoch: 13         Training Loss: 0.000441         Validation Loss: 0.001801
Validation loss decreased.Saving model
Epoch: 14         Training Loss: 0.000431         Validation Loss: 0.001780
Validation loss decreased.Saving model
Epoch: 15         Training Loss: 0.000418         Validation Loss: 0.001729
Validation loss decreased.Saving model
Epoch: 16         Training Loss: 0.000408         Validation Loss: 0.001709
Validation loss decreased.Saving model
Epoch: 17         Training Loss: 0.000398         Validation Loss: 0.001674
Validation loss decreased.Saving model
Epoch: 18         Training Loss: 0.000391         Validation Loss: 0.001633
```

```
Validation loss decreased.Saving model
Epoch: 19        Training Loss: 0.000383        Validation Loss: 0.001638
Epoch: 20        Training Loss: 0.000377        Validation Loss: 0.001598
Validation loss decreased.Saving model
```

1.1.14 (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of landmark images. Use the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 60%.

```
In [18]: model_transfer.load_state_dict(torch.load('model_transfer.pt'))
         test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 1.494581


Test Accuracy: 69% (869/1250)
```

## Step 3: Write Your Landmark Prediction Algorithm
Great job creating your CNN models! Now that you have put in all the hard work of creating accurate classifiers, let's define some functions to make it easy for others to use your classifiers.

1.1.15 (IMPLEMENTATION) Write Your Algorithm, Part 1

Implement the function `predict_landmarks`, which accepts a file path to an image and an integer k, and then predicts the **top k most likely landmarks**. You are **required** to use your transfer learned CNN from Step 2 to predict the landmarks.

An example of the expected behavior of `predict_landmarks`:

```
>>> predicted_landmarks = predict_landmarks('example_image.jpg', 3)
>>> print(predicted_landmarks)
['Golden Gate Bridge', 'Brooklyn Bridge', 'Sydney Harbour Bridge']
```

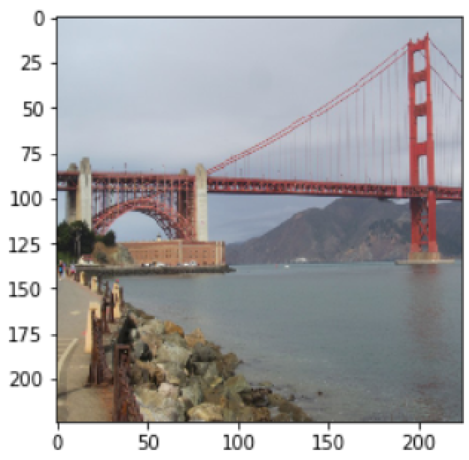
```
In [19]: import cv2
         from PIL import Image
         from torch.autograd import Variable as var

         ## the class names can be accessed at the `classes` attribute
         ## of your dataset object (e.g., `train_dataset.classes`)

         '''I am assuming that cuda is used'''
         #standard transformation and resize to 224*224 for vgg standard
         trans = transforms.Compose([
             transforms.Resize((224,224)),
             transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])

#the following function img_load was
def img_load(img_path):
    img = Image.open(img_path)
    img = var(trans(img).float(), requires_grad=True)
    img = img.unsqueeze(0) # through my search this is needed for vgg cnns
    return img.cuda()

def predict_landmarks(img_path, k):
    ## TODO: return the names of the top k landmarks predicted by the transfer learned
    data=img_load(img_path)
    model_transfer.eval()
    output = model_transfer(data).cpu().detach().numpy() # need .cpu().detach().numpy()
    indexes = np.argpartition(output[0],k)[:k] #get indexes for top k landmarks
    places = []
    for ind in indexes:
        places.append(classes[ind][3:].replace('_'," "))
    return places

# test on a sample image
predict_landmarks('images/test/09.Golden_Gate_Bridge/190f3bae17c32c37.jpg', 5)
```

```
Out[19]: ['Wroclaws Dwarves',
          'Stonehenge',
          'Great Barrier Reef',
          'Seattle Japanese Garden',
          'Trevi Fountain']
```

1.1.16 (IMPLEMENTATION) Write Your Algorithm, Part 2

In the code cell below, implement the function `suggest_locations`, which accepts a file path to an image as input, and then displays the image and the **top 3 most likely landmarks** as predicted by `predict_landmarks`.

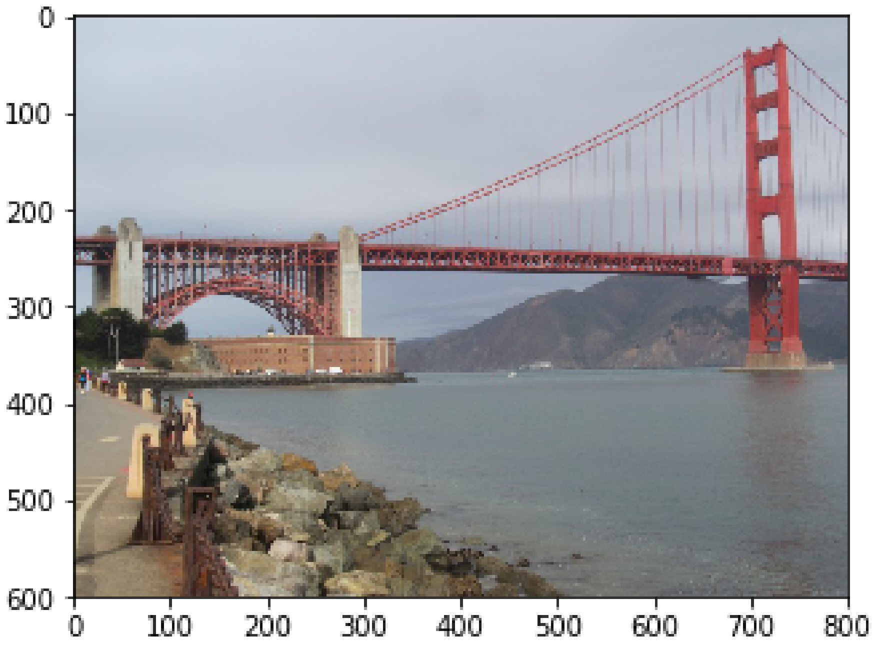
Some sample output for `suggest_locations` is provided below, but feel free to design your own user experience!



```
Is this picture of the
Golden Gate Bridge, Brooklyn Bridge, or Sydney Harbour Bridge?
```

```
In [20]: import matplotlib.pyplot as plt
         import matplotlib.image as plt_img
         def suggest_locations(img_path):
             # get landmark predictions
             predicted_landmarks = predict_landmarks(img_path, 3)
             ## TODO: display image and display landmark predictions
             img = plt_img.imread(img_path)
             img = plt.imshow(img)
             # I am to tired to add text to the pic itself
             print("Is this the Picture of:")
             for i in range(len(predicted_landmarks)):
                 print (str((i+1))+"-"+str(predicted_landmarks[i]))

         # test on a sample image
         suggest_locations('images/test/09.Golden_Gate_Bridge/190f3bae17c32c37.jpg')
```

```
Is this the Picture of:
1-Wroclaws Dwarves
2-Stonehenge
3-Great Barrier Reef
```



1.1.17 (IMPLEMENTATION) Test Your Algorithm

Test your algorithm by running the `suggest_locations` function on at least four images on your computer. Feel free to use any images you like.

Question 4: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: (Three possible points for improvement)

The output on test seemed promising with 70+% but when doing the Algorithm it did not classify any of the 5 images correctly. I expected the such results to be honest

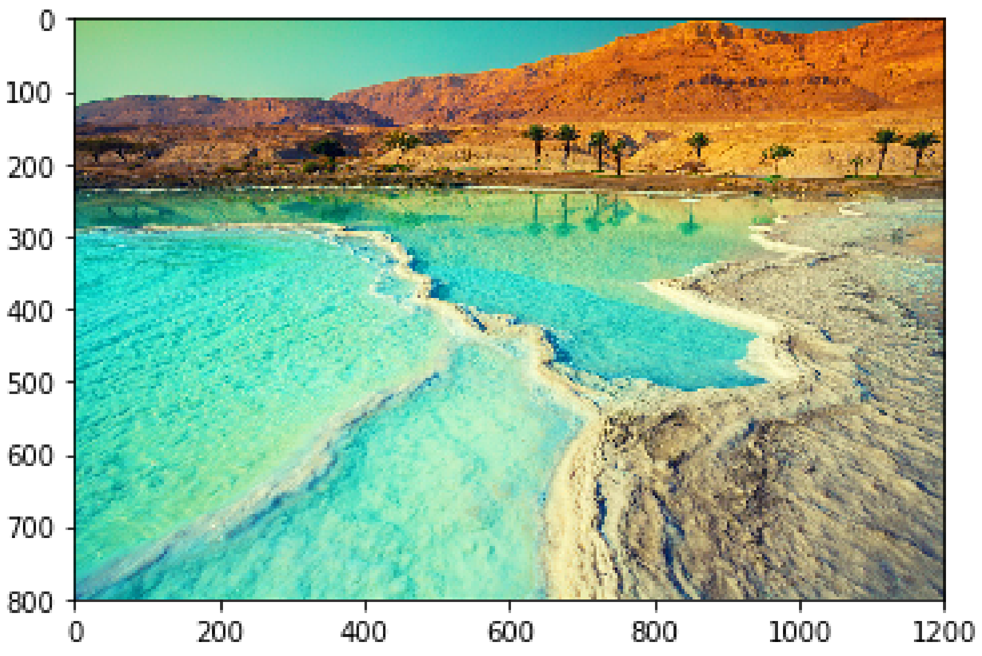
there is 2 main point of improvement that can be done:

1- add more landmark class the dataset is really small with 50 class 2- the sample per class are really low need way more images per class to get better result since the task is difficult and the images of landmark can be rather unclear of the landmark it self

the last point is simple 3- deeper/bigger CNN architecture with a lot more training will do better but due to the time needed for training it will take long time to train and test

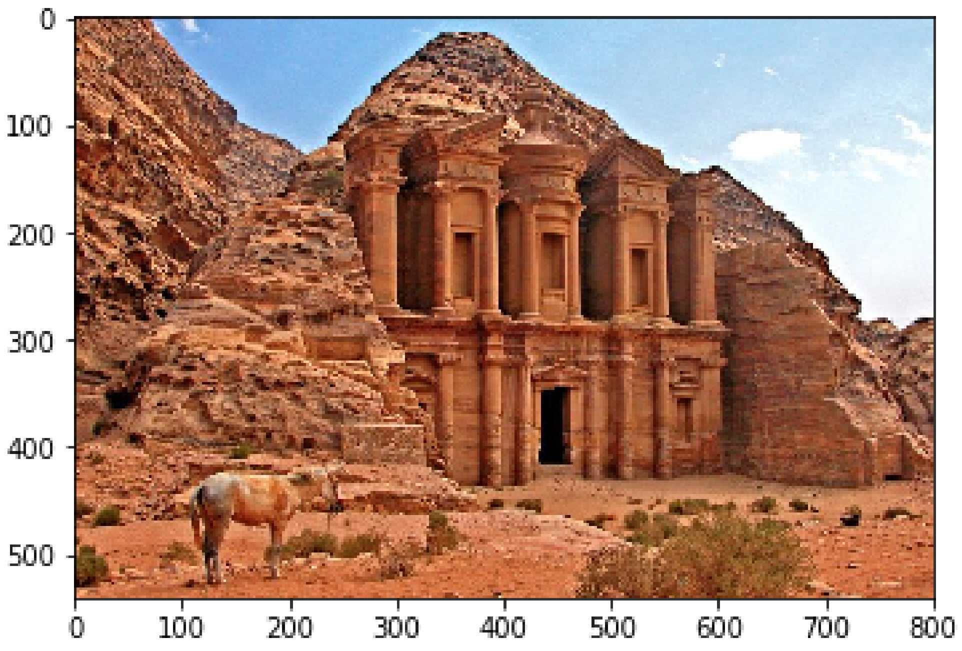
```
In [21]: ## TODO: Execute the `suggest_locations` function on
         ## at least 4 images on your computer.
         ## Feel free to use as many code cells as needed.
         suggest_locations('Dead-sea.jpg')
```

```
Is this the Picture of:
1-Prague Astronomical Clock
2-Vienna City Hall
3-Gateway of India
```

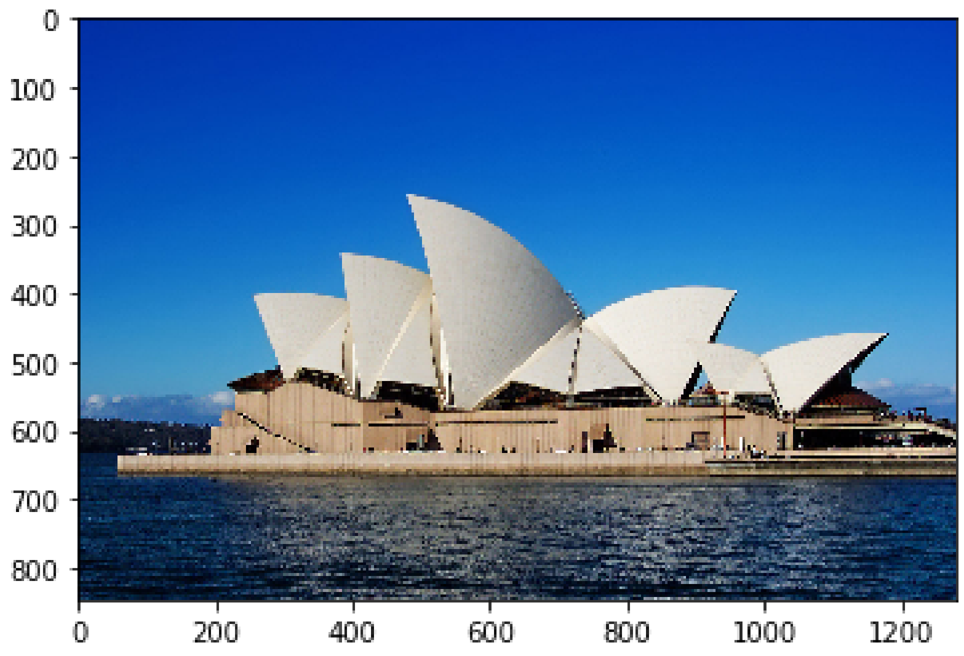


```
In [22]: suggest_locations('Petra.jpg')
```

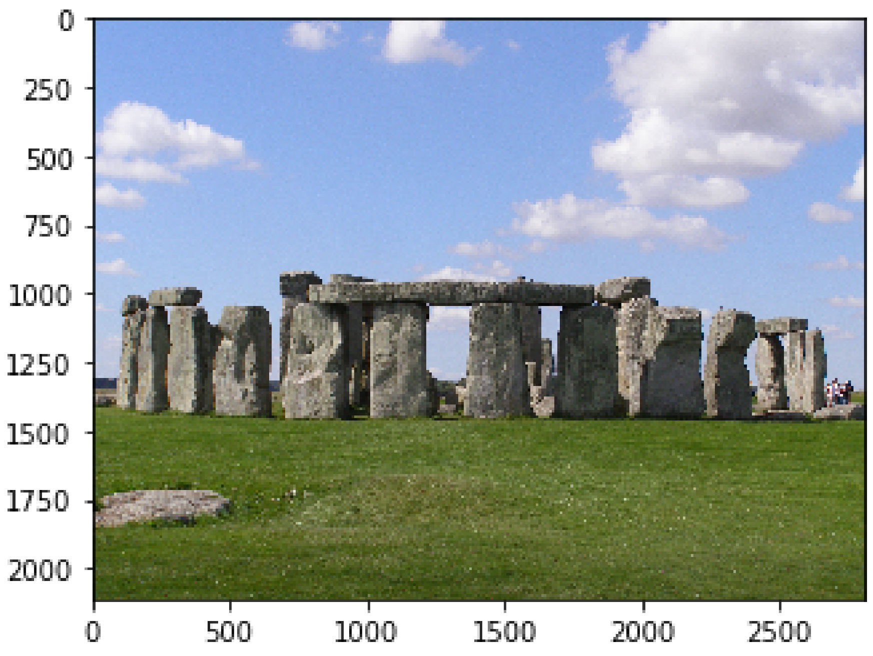
```
Is this the Picture of:
1-Great Barrier Reef
2-Moscow Raceway
3-Washington Monument
```



```
In [23]: suggest_locations('Sydney_Opera_House.jpg')

Is this the Picture of:
1-Soreq Cave
2-Gullfoss Falls
3-Externsteine
```

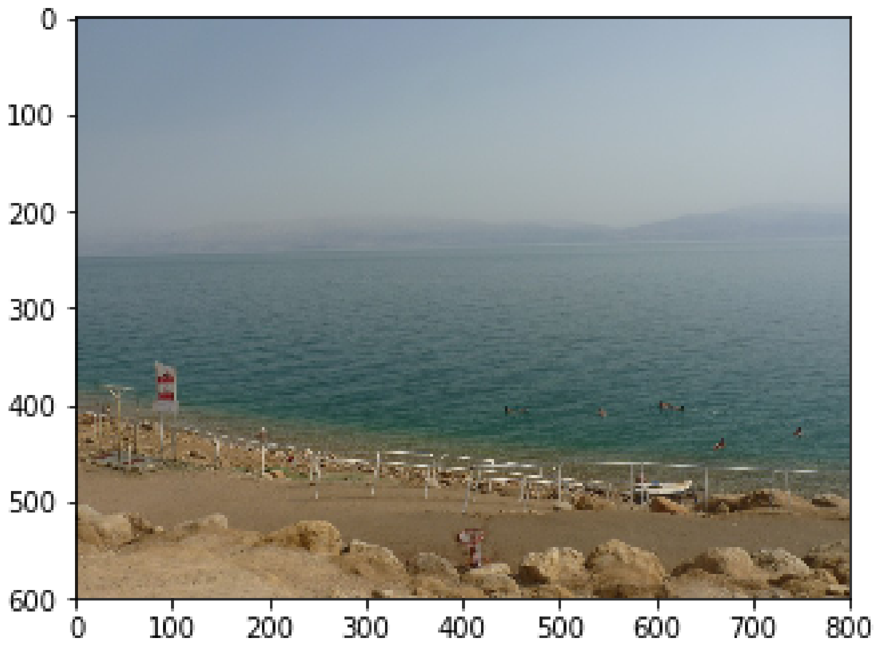


```
In [24]: suggest_locations('Stonehenge.jpg')

Is this the Picture of:
1-Terminal Tower
2-Moscow Raceway
3-London Olympic Stadium
```



```
In [25]: suggest_locations('/data/landmark_images/train/03.Dead_Sea/0a14dfa30efe67ab.jpg')
```

```
Is this the Picture of:
1-Wroclaws Dwarves
2-Kantanagar Temple
3-Prague Astronomical Clock
```



```
In [ ]:
```

```
In [ ]:
```