landmark

November 30, 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 [1]: ### TODO: Write data loaders for training, validation, and test sets
        ## Specify appropriate transforms, and batch_sizes
        import torchvision
        import torch
        from sklearn.model_selection import train_test_split
        from torch.utils.data.dataset import Subset
        import numpy as np

        batch_size = 128

        mean = np.array([0.485, 0.456, 0.406]) # imagenet standards
        std = np.array([0.229, 0.224, 0.225]) # imagenet standards

        transform = torchvision.transforms.Compose([torchvision.transforms.Resize((224,224)),
                                                     torchvision.transforms.ToTensor(),
                                                     torchvision.transforms.Normalize(mean,std)])
```

```
trainset_before_splitting = torchvision.datasets.ImageFolder('/data/landmark_images/trai
testset = torchvision.datasets.ImageFolder('/data/landmark_images/test', transform=trans
```

```
In [2]: # split train set to training and validation sets
        def train_val_dataset(dataset, validation_split=0.25):
            train_idx, val_idx = train_test_split(list(range(len(dataset))), test_size=validatio
            splitted_dataset = {}
            splitted_dataset['train'] = Subset(dataset, train_idx)
            splitted_dataset['validate'] = Subset(dataset, val_idx)
            return splitted_dataset

        train_validate_datasets = train_val_dataset(trainset_before_splitting)
        trainset = train_validate_datasets['train']
        validateset = train_validate_datasets['validate']
        print("Train set size = ", len(trainset),
              "\nValidate set size = ", len(validateset),
              "\nTest set size = ", len(testset))
```

```
Train set size =  3747
Validate set size =  1249
Test set size =  1250
```

```
In [3]: # dataloaders
        train_dataloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size, shuffle=
        validate_dataloader = torch.utils.data.DataLoader(validateset, batch_size=batch_size, sh
        test_dataloader = torch.utils.data.DataLoader(testset, batch_size=batch_size, shuffle=Tr

        loaders_scratch = {'train': train_dataloader, 'valid': validate_dataloader, 'test': test
```

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: - I used the code "torchvision.transforms.Resize(224,224)" to resize the images to be 224*224 (This size has been chosen based on a similar dataset in here. Moreover, i used imagenet normalization standards. - No i did not augment the dataset, because the size of the dataset is relatively great. However, I may later augment the dataset to enhance the classifier performance.

1.1.2 (IMPLEMENTATION) Visualize a Batch of Training Data

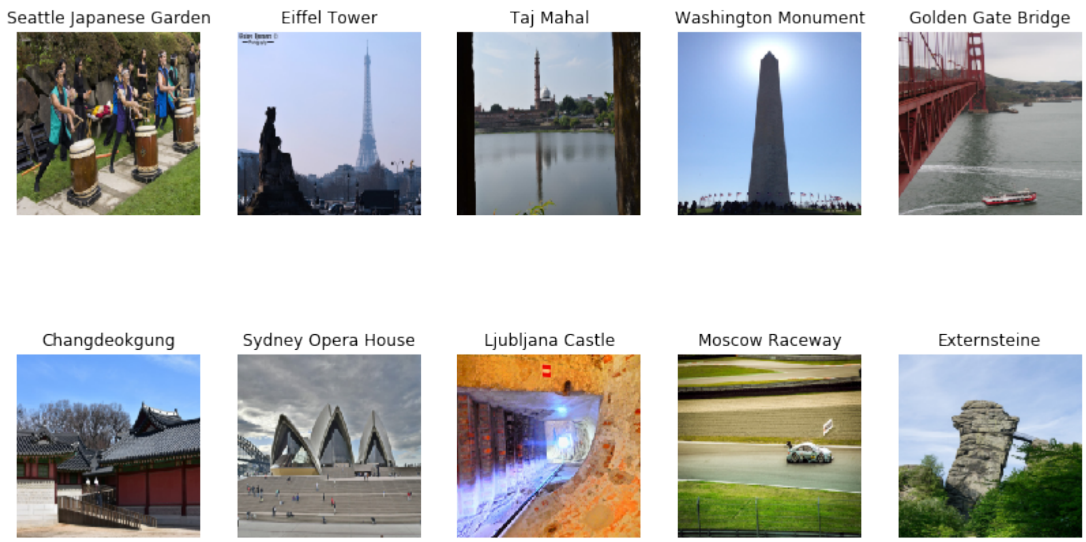
Use the code cell below to retrieve a batch of images from your train data loader, display at least 5 images simultaneously, and label each displayed image with its class name (e.g., "Golden Gate Bridge").

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

```
In [4]: import matplotlib.pyplot as plt
        %matplotlib inline
```

```python
import random

## 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`)

class_names = trainset_before_splitting.classes
number_classes = len(class_names)

# correct output-size of the CNN
param_output_size = len(class_names)

print("number of classes:", number_classes)
print("")
print("class names: \n", class_names)

# In[32]:
# test train loaders to see how it looks like
# get a batch of training datas

def remove_normlization(figure, std, mean):
    return figure * std[:, None, None] + mean[:, None, None]

fig = plt.figure(figsize=(14,8))
for i in range(10):
    ax = fig.add_subplot(2, 5, i+1)
    random_img = random.randint(0, len(trainset))
    # unnormalize the image
    image = remove_normlization(trainset[random_img][0], torch.Tensor(std), torch.Tensor
    # convert it from tensor to image
    plt.imshow(np.transpose(image.numpy(), (1, 2, 0)))
    plt.title(class_names[trainset[random_img][1]][3:].replace("_", " "))
    plt.axis('off')
plt.show()
```

```
number of classes: 50

class names:
 ['00.Haleakala_National_Park', '01.Mount_Rainier_National_Park', '02.Ljubljana_Castle', '03.Dea
```



1.1.3 Initialize use_cuda variable

```
In [5]: # useful variable that tells us whether we should use the GPU
        use_cuda = torch.cuda.is_available()
```

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 [7]: ## TODO: select loss function
        from torch import nn
        import torch.optim as optim

        criterion_scratch = nn.CrossEntropyLoss()

        def get_optimizer_scratch(model):
            ## TODO: select and return an optimizer
            optimizer = optim.Adam(model.parameters(),lr = 0.001)
            return optimizer
```

1.1.5 (IMPLEMENTATION) Model Architecture

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

```
In [19]: # define the CNN architecture
         class Net(nn.Module):
             ## TODO: choose an architecture, and complete the class
```

```python
def __init__(self):
    super(Net, self).__init__()

    # Convolutional layer 1
    self.conv1 = nn.Conv2d(3,16,kernel_size=3,stride=1,padding=1)
    # Convolutional layer 2
    self.conv2 = nn.Conv2d(16,32,kernel_size=3,stride=1,padding=1)
    # Convolutional layer 3
    self.conv3 = nn.Conv2d(32,64,kernel_size=3,stride=1,padding=1)

    # Max pooling
    self.pool = nn.MaxPool2d(2, 2)

    # Fully connected layer 1
    self.fc1 = nn.Linear(64*28*28,512)
    # Fully connected layer 2
    self.fc2 = nn.Linear(512,128)
    # Fully connected layer 3
    self.fc3 = nn.Linear(128,number_classes)
    # Batch normalization
    self.batch_norm = nn.BatchNorm2d(32)

    # Activation function
    self.leaky_relu = nn.LeakyReLU(negative_slope=0.2)

    # Dropout layer
    self.dropout = nn.Dropout(0.3)


def forward(self, x):
    ## Define forward behavior
    x = self.pool(self.leaky_relu(self.conv1(x)))
    x = self.pool(self.leaky_relu(self.conv2(x)))
    x = self.batch_norm(x)
    x = self.pool(self.leaky_relu(self.conv3(x)))

    # Flatten the image
    x = x.view(-1, 64*28*28)

    # Dropout layer
    x = self.dropout(x)

    # Hidden layer
    x = self.leaky_relu(self.fc1(x))
    x = self.leaky_relu(self.fc2(x))

    # Dropout layer
    x = self.dropout(x)
```

```
        # final layer
        x = self.fc3(x)

        return x

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

# instantiate the CNN
model_scratch = Net()

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

In [20]:
```
! pip install torchsummary
```

```
Requirement already satisfied: torchsummary in /opt/conda/lib/python3.6/site-packages (1.5.1)
```

In [21]:
```
from torchsummary import summary

summary(model_scratch, (3, 224, 224))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 16, 224, 224]             448
         LeakyReLU-2         [-1, 16, 224, 224]               0
         MaxPool2d-3         [-1, 16, 112, 112]               0
            Conv2d-4         [-1, 32, 112, 112]           4,640
         LeakyReLU-5         [-1, 32, 112, 112]               0
         MaxPool2d-6           [-1, 32, 56, 56]               0
       BatchNorm2d-7           [-1, 32, 56, 56]              64
            Conv2d-8           [-1, 64, 56, 56]          18,496
         LeakyReLU-9           [-1, 64, 56, 56]               0
        MaxPool2d-10           [-1, 64, 28, 28]               0
          Dropout-11                [-1, 50176]               0
           Linear-12                  [-1, 512]      25,690,624
        LeakyReLU-13                  [-1, 512]               0
           Linear-14                  [-1, 128]          65,664
        LeakyReLU-15                  [-1, 128]               0
          Dropout-16                  [-1, 128]               0
           Linear-17                   [-1, 50]           6,450
================================================================
Total params: 25,786,386
Trainable params: 25,786,386
Non-trainable params: 0
----------------------------------------------------------------
```

```
Input size (MB): 0.57
Forward/backward pass size (MB): 25.28
Params size (MB): 98.37
Estimated Total Size (MB): 124.22
----------------------------------------------------------------
```

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

Answer:
Based on the articles in 1, and 2, I built a simple CNN network that i believe will suit the project. After many trail and error attempts, I've reached this CNN architecture which consists of: - 3 convolutional layers - max pooling layers with size 2*2 after each convolutional layer - 3 fully connected layers - leaky relu activation function - batch normalization - dropout

I've used max pooling after each convolutional layer to focus on the target features. Moreover, to reduce overfitting, I used a 0.3 dropout rate. Additionally, I used batch normalization to speed up the training.

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 [22]: 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
                     optimizer.zero_grad()
                     output = model(data)
                     loss = criterion(output, target)
                     loss.backward()
```

```
            optimizer.step()
            ## record the average training loss, using something like
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data.item() - trai


        ######################
        # 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))




        # 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 ({:.4f} --> {:.4f}), model saved'.format(v

            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 [23]:
```
def custom_weight_init(m):
    ## TODO: implement a weight initialization strategy
    # Ref: https://gist.github.com/jojonki/be1e8af97dfa12c983446391c3640b68
    if isinstance(m, nn.Conv2d):
        n = m.kernel_size[0] * m.kernel_size[1] * m.out_channels
        m.weight.data.normal_(0, np.sqrt(2. / n))
        if m.bias is not None:
            m.bias.data.zero_()
    elif isinstance(m, nn.BatchNorm2d):
        m.weight.data.fill_(1)
        m.bias.data.zero_()
    elif isinstance(m, nn.Linear):
        n = m.in_features
        y = 1.0/np.sqrt(n)
        m.weight.data.normal_(0, y)
        m.bias.data.zero_()


#-#-# Do NOT modify the code below this line. #-#-#
model_scratch.apply(custom_weight_init)
model_scratch = train(20, loaders_scratch, model_scratch, get_optimizer_scratch(model_s
                      criterion_scratch, use_cuda, 'ignore.pt')
```

```
Epoch: 1         Training Loss: 8.322742         Validation Loss: 3.802256
Validation loss decreased (inf --> 3.8023), model saved
Epoch: 2         Training Loss: 3.743800         Validation Loss: 3.563969
Validation loss decreased (3.8023 --> 3.5640), model saved
Epoch: 3         Training Loss: 3.374015         Validation Loss: 3.420589
Validation loss decreased (3.5640 --> 3.4206), model saved
Epoch: 4         Training Loss: 2.990119         Validation Loss: 3.296686
Validation loss decreased (3.4206 --> 3.2967), model saved
Epoch: 5         Training Loss: 2.471693         Validation Loss: 3.405420
Epoch: 6         Training Loss: 1.906232         Validation Loss: 3.374552
Epoch: 7         Training Loss: 1.206116         Validation Loss: 3.609762
Epoch: 8         Training Loss: 0.776571         Validation Loss: 3.828928
Epoch: 9         Training Loss: 0.488964         Validation Loss: 3.902057
Epoch: 10         Training Loss: 0.270912         Validation Loss: 4.211147
Epoch: 11         Training Loss: 0.191489         Validation Loss: 4.218621
Epoch: 12         Training Loss: 0.124388         Validation Loss: 4.540937
Epoch: 13         Training Loss: 0.116799         Validation Loss: 4.555210
Epoch: 14         Training Loss: 0.087392         Validation Loss: 4.619523
Epoch: 15         Training Loss: 0.069931         Validation Loss: 4.560314
Epoch: 16         Training Loss: 0.056170         Validation Loss: 4.666886
Epoch: 17         Training Loss: 0.038629         Validation Loss: 4.875595
Epoch: 18         Training Loss: 0.037546         Validation Loss: 4.867272
Epoch: 19         Training Loss: 0.029856         Validation Loss: 5.159056
Epoch: 20         Training Loss: 0.037907         Validation Loss: 5.150226
```

1.1.8 (IMPLEMENTATION) Train and Validate the Model

Run the next code cell to train your model.

```
In [24]: ## TODO: you may change the number of epochs if you'd like,
         ## but changing it is not required
         num_epochs = 20 # 100

         #-#-# 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: 3.828219         Validation Loss: 3.587366
Validation loss decreased (inf --> 3.5874), model saved
Epoch: 2         Training Loss: 3.336550         Validation Loss: 3.292357
Validation loss decreased (3.5874 --> 3.2924), model saved
Epoch: 3         Training Loss: 2.873586         Validation Loss: 3.110794
Validation loss decreased (3.2924 --> 3.1108), model saved
Epoch: 4         Training Loss: 2.278485         Validation Loss: 3.090255
Validation loss decreased (3.1108 --> 3.0903), model saved
Epoch: 5         Training Loss: 1.493460         Validation Loss: 3.195714
Epoch: 6         Training Loss: 0.842140         Validation Loss: 3.837432
Epoch: 7         Training Loss: 0.465335         Validation Loss: 4.317661
Epoch: 8         Training Loss: 0.246297         Validation Loss: 4.559172
Epoch: 9         Training Loss: 0.158101         Validation Loss: 4.616451
Epoch: 10         Training Loss: 0.127696         Validation Loss: 5.100290
Epoch: 11         Training Loss: 0.128039         Validation Loss: 5.048445
Epoch: 12         Training Loss: 0.080833         Validation Loss: 5.471501
Epoch: 13         Training Loss: 0.063024         Validation Loss: 5.307947
Epoch: 14         Training Loss: 0.061310         Validation Loss: 5.370028
Epoch: 15         Training Loss: 0.047686         Validation Loss: 5.649451
Epoch: 16         Training Loss: 0.033562         Validation Loss: 6.076641
Epoch: 17         Training Loss: 0.037113         Validation Loss: 5.892938
Epoch: 18         Training Loss: 0.039593         Validation Loss: 5.940187
Epoch: 19         Training Loss: 0.029372         Validation Loss: 5.951241
Epoch: 20         Training Loss: 0.026655         Validation Loss: 6.209213
```

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 [25]: 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: 2.916069


Test Accuracy: 28% (353/1250)
```

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 [8]:
```
### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
batch_size = 40
train_dataloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size, shuffle=
validate_dataloader = torch.utils.data.DataLoader(validateset, batch_size=batch_size, sh
test_dataloader = torch.utils.data.DataLoader(testset, batch_size=batch_size, shuffle=Tr
loaders_transfer = {'train': train_dataloader, 'valid': validate_dataloader, 'test': tes
```

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 [9]:
```
## TODO: select loss function
criterion_transfer = nn.CrossEntropyLoss()

def get_optimizer_transfer(model):
    ## TODO: select and return optimizer
    optimizer = optim.Adam(model.parameters(),lr = 0.0001)
    return optimizer
```

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 [10]:
```
## TODO: Specify model architecture
from torchvision import models

model_transfer = models.resnet50(pretrained=True)
model_transfer.fc = nn.Linear(2048, 50)
```

```
    #-#-# 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 used ResNet-50 for transfer learning, because ResNet-50 has been trained with large amount of images (on imagenet dataset), thus ResNet-50 learnt rich features. Moreover, ResNet-50 consists of 50 layers that allow the network to learn deeper features about the input images.

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 [11]: 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
                     optimizer.zero_grad()
                     output = model(data)
                     loss = criterion(output, target)
                     loss.backward()
                     optimizer.step()
                     ## record the average training loss, using something like
                     train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data.item() - trai
```

```
        ######################
        # 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))




        # 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 ({:.4f} --> {:.4f}), model saved'.format(v

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



    return model

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))
```

```
In [12]: # TODO: train the model and save the best model parameters at filepath 'model_transfer.
         train(30, loaders_transfer, model_transfer, get_optimizer_transfer(model_transfer), cri
               use_cuda, 'model_transfer.pt')


         #-#-# 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: 2.255733         Validation Loss: 1.061864
Validation loss decreased (inf --> 1.0619), model saved
Epoch: 2         Training Loss: 0.731235         Validation Loss: 0.800356
Validation loss decreased (1.0619 --> 0.8004), model saved
Epoch: 3         Training Loss: 0.254046         Validation Loss: 0.695375
Validation loss decreased (0.8004 --> 0.6954), model saved
Epoch: 4         Training Loss: 0.084765         Validation Loss: 0.668656
Validation loss decreased (0.6954 --> 0.6687), model saved
Epoch: 5         Training Loss: 0.026962         Validation Loss: 0.646099
Validation loss decreased (0.6687 --> 0.6461), model saved
Epoch: 6         Training Loss: 0.015621         Validation Loss: 0.605803
Validation loss decreased (0.6461 --> 0.6058), model saved
Epoch: 7         Training Loss: 0.008904         Validation Loss: 0.604145
Validation loss decreased (0.6058 --> 0.6041), model saved
Epoch: 8         Training Loss: 0.005847         Validation Loss: 0.586828
Validation loss decreased (0.6041 --> 0.5868), model saved
Epoch: 9         Training Loss: 0.004633         Validation Loss: 0.570815
Validation loss decreased (0.5868 --> 0.5708), model saved
Epoch: 10         Training Loss: 0.003887         Validation Loss: 0.625863
```

```
Epoch: 11       Training Loss: 0.011908         Validation Loss: 0.697986
Epoch: 12       Training Loss: 0.166257         Validation Loss: 1.352336
Epoch: 13       Training Loss: 0.339774         Validation Loss: 1.033824
Epoch: 14       Training Loss: 0.117995         Validation Loss: 0.883715
Epoch: 15       Training Loss: 0.039642         Validation Loss: 0.804033
Epoch: 16       Training Loss: 0.021419         Validation Loss: 0.733000
Epoch: 17       Training Loss: 0.008251         Validation Loss: 0.719835
Epoch: 18       Training Loss: 0.004883         Validation Loss: 0.732427
Epoch: 19       Training Loss: 0.002783         Validation Loss: 0.707583
Epoch: 20       Training Loss: 0.002100         Validation Loss: 0.716145
Epoch: 21       Training Loss: 0.001758         Validation Loss: 0.701463
Epoch: 22       Training Loss: 0.001372         Validation Loss: 0.721168
Epoch: 23       Training Loss: 0.001098         Validation Loss: 0.698059
Epoch: 24       Training Loss: 0.001036         Validation Loss: 0.700530
Epoch: 25       Training Loss: 0.000777         Validation Loss: 0.706165
Epoch: 26       Training Loss: 0.000929         Validation Loss: 0.691126
Epoch: 27       Training Loss: 0.000689         Validation Loss: 0.675701
Epoch: 28       Training Loss: 0.000760         Validation Loss: 0.716700
Epoch: 29       Training Loss: 0.000763         Validation Loss: 0.704825
Epoch: 30       Training Loss: 0.000539         Validation Loss: 0.696166
```

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 [12]: # load the model that got the best validation accuracy
         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

```
In [13]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.548951


Test Accuracy: 86% (1083/1250)
```

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 [24]:
```
model_transfer
```

Out[24]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
  (relu): ReLU(inplace)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
```

```
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
    )
    (3): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
    )
  )
  (layer3): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
      (downsample): Sequential(
```

```
      (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    )
  )
  (1): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
  )
  (2): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
  )
  (3): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
  )
  (4): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
  )
  (5): Bottleneck(
    (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
```

```
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
  )
  (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
  (fc): Linear(in_features=2048, out_features=50, bias=True)
)
```

In [24]:
```
import cv2
from PIL import Image

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

def predict_landmarks(img_path, k):
    ## TODO: return the names of the top k landmarks predicted by the transfer learned
    image = Image.open(img_path).convert('RGB')
```

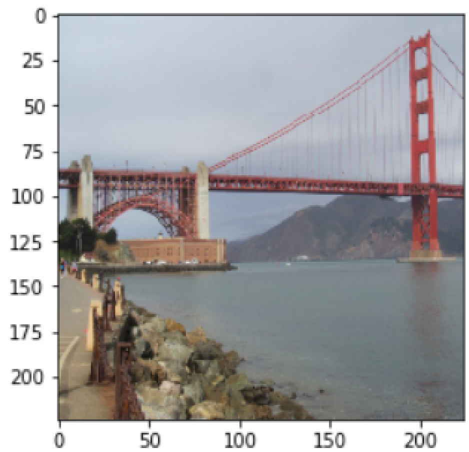
```
    transform = torchvision.transforms.Compose([
        torchvision.transforms.Resize(256),
        torchvision.transforms.CenterCrop(224),
        torchvision.transforms.ToTensor(),
        torchvision.transforms.Normalize(mean, std)])

    image = transform(image)
    image.unsqueeze_(0)

    if use_cuda:
        image = image.cuda()

    model_transfer.eval()

    with torch.no_grad():
        output = model_transfer(image)
        top_values, top_id = output.topk(k)

        top_k_classes = []
        for i in top_id[0].tolist():
            top_k_classes.append(class_names[trainset[i][1]][3:].replace("_", " "))
    return top_k_classes

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

```
Out[24]: ['Monumento a la Revolucion',
          'Dead Sea',
          'Yellowstone National Park',
          'London Olympic Stadium',
          'Central Park']
```

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 [39]:
```
def suggest_locations(img_path):
    # get landmark predictions
    predicted_landmarks = predict_landmarks(img_path, 3)

    ## TODO: display image and display landmark predictions
    image = Image.open(img_path).convert('RGB')
    plt.imshow(image)
    plt.show()
    if len(img_path.split('/')) > 2:
        actual_label = img_path.split('/')[2][3:].replace('_',' ').split('.')[0]
    else:
        actual_label = img_path.split('/')[1][3:].replace('_',' ').split('.')[0]
    print("Actual Label: ", actual_label)
    print("Predicted: Is this picture of the: ", predicted_landmarks[0], ", ",
          predicted_landmarks[1], ", or ", predicted_landmarks[2], "?")

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

```
Actual Label:  Golden Gate Bridge
Predicted: Is this picture of the:  Monumento a la Revolucion ,  Dead Sea , or  Yellowstone Nati
```

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.

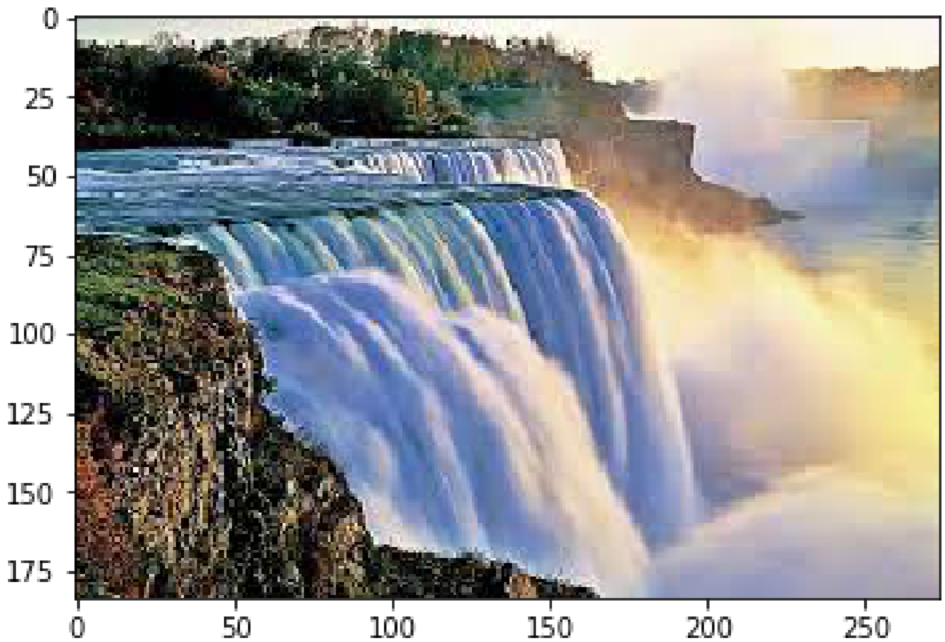
Question 4: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: (Three possible points for improvement)

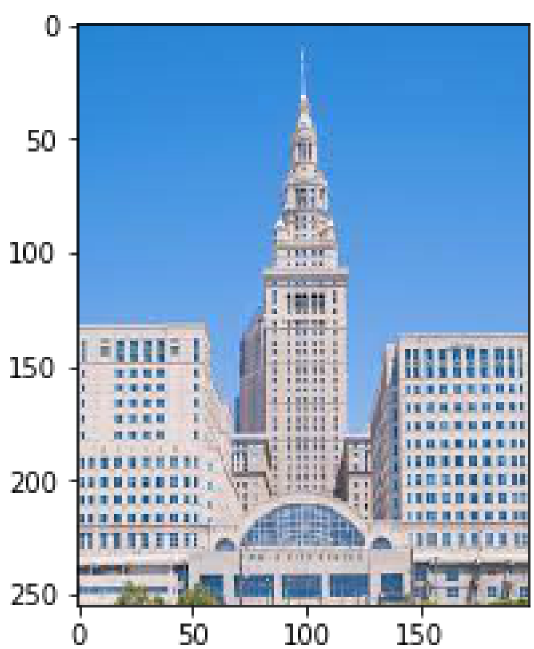
The outputs are not accurate; the model could not identified any test images except one (Taj mahal). However, I can do the follwoing for improvements: 1. Increase the training size by using augmentation techniques either the traditional techniques (rotation, crop, etc) or GAN-based techniques. 2. Work on tuning the model's parameters, learning rate, number of epochs, optimizer, etc. 3. Improve the model architecture and try other classifiers, such as VGG16.

```
In [44]: ## TODO: Execute the `suggest_locations` function on
         ## at least 4 images on your computer.
         ## Feel free to use as many code cells as needed.
         import os
         test_images_path = 'image_from_computer/'

         for img in os.listdir(test_images_path):
             img_path = os.path.join(test_images_path, img)
```

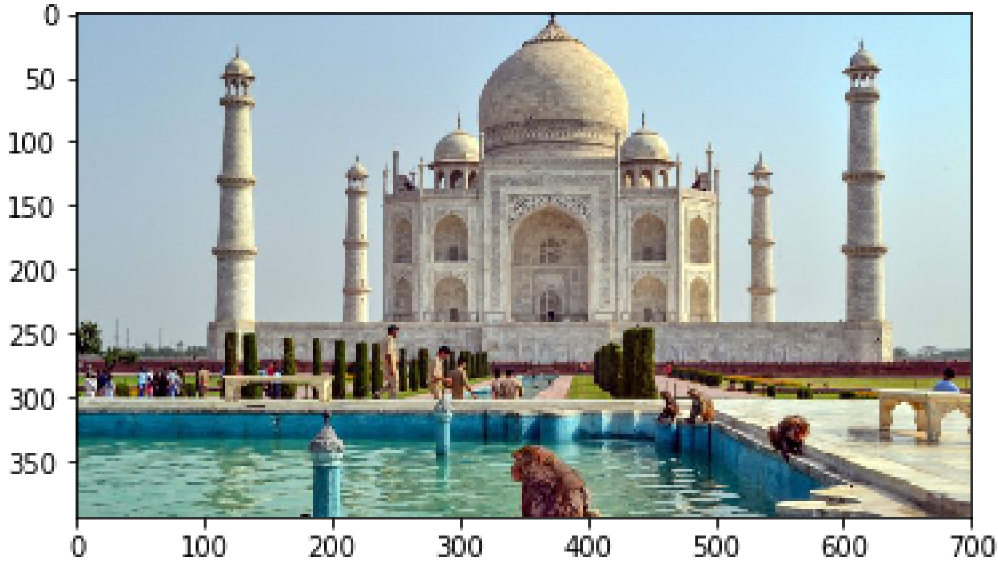
```python
if img_path.lower().endswith(('.png', '.jpg', '.jpeg')):
    suggest_locations(img_path)
```



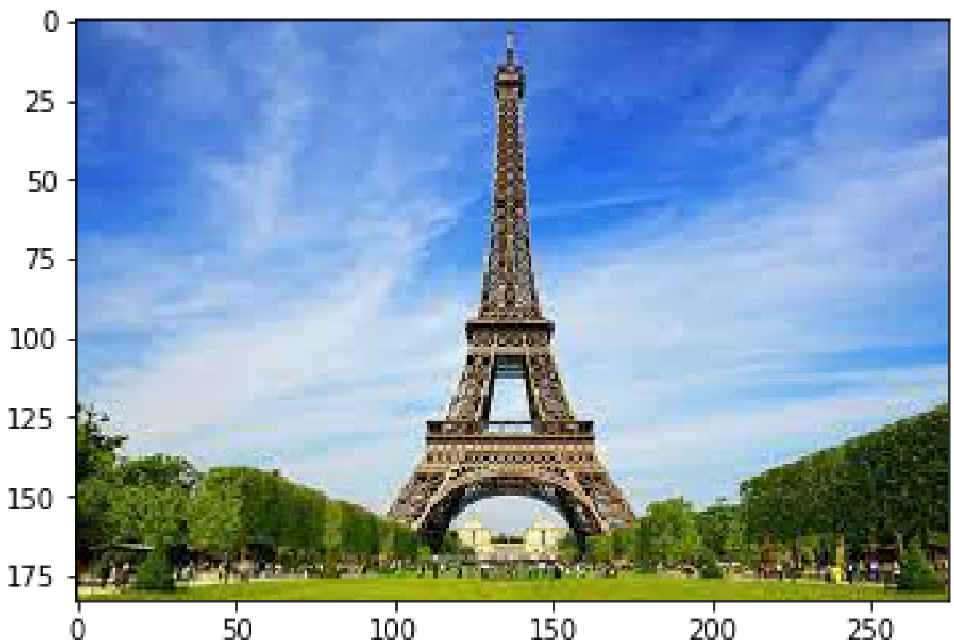
```
Actual Label:  niagara falls
Predicted: Is this picture of the:  Mount Rushmore National Memorial ,  Taj Mahal , or  Haleakal
```



```
Actual Label:  terminal tower
Predicted: Is this picture of the:  Petronas Towers ,  Petronas Towers , or  Changdeokgung ?
```




```
Actual Label:  taj mahal
Predicted: Is this picture of the:  Great Barrier Reef ,  Externsteine , or  Taj Mahal ?
```



```
Actual Label:  effiel tower
Predicted: Is this picture of the:  Dead Sea ,  Petronas Towers , or  London Olympic Stadium ?
```

```
In [ ]:
```