landmark

March 6, 2022

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]: import os
        import numpy as np
        from torchvision import transforms, datasets
        from torch.utils.data.sampler import SubsetRandomSampler
        from torch.utils.data import DataLoader
        import workspace_utils

        ### TODO: Write data loaders for training, validation, and test sets
        ## Specify appropriate transforms, and batch_sizes

        # For image loading later
        batch_size = 20
        num_workers = 0
        valid_set_size = 0.2

        # Creates the directories for test and training data
        data_dir = '/data/landmark_images'
```

```
train_dir = os.path.join(data_dir, 'train/')
test_dir = os.path.join(data_dir, 'test/')

# Create the transformations for the images
transform = transforms.Compose([
    transforms.RandomResizedCrop(512),
    transforms.ToTensor(), # Turn to tensor object
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)) # Normalize in all image dime
])

# Loads in the test and training data
train_data = datasets.ImageFolder(train_dir, transform=transform)
test_data = datasets.ImageFolder(test_dir, transform=transform)

# Create a random split for training and validation sets
np.random.seed(42)
length = len(train_data)
indicies = list(range(length))
np.random.shuffle(indicies)
split = int(np.floor(length * valid_set_size))
valid_idx, train_idx = indicies[:split], indicies[split:]

# Establsih samples for traing and validation sets
train_sampler = SubsetRandomSampler(train_idx)
valid_sampler = SubsetRandomSampler(valid_idx)

# Establish dataloader's for training, validation, and testing sets
train_loader = DataLoader(train_data, batch_size=batch_size, sampler=train_sampler, num_
valid_loader = DataLoader(train_data, batch_size=batch_size, sampler=valid_sampler, num_
test_loader = DataLoader(test_data, batch_size=batch_size, num_workers=num_workers)

loaders_scratch = {'train': train_loader, 'valid': valid_loader, 'test': test_loader}
```

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 resizes the images by cropping random portions of the images to a size of 512x512 forming a square image. I choose to have the input tensor's be 512x512 because I looked at the images and saw that most pictures were around 800x600 so I wanted to resize to something smaller than those dimensions and have the final images be square.
- I did not augment the data set because my thought process is the data is already very varied as far as locations, angles, and perspectives so changing the data further seems like it will add very little information for the network to pick up on later and make it more difficult to detech locations.

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 [2]:
```python
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`)

# Create a list of the different classes of locations
classes = []
for entry in train_data.classes:
    idx, loc_name = entry.split('.') # Grabs the name of a location
    classes.append(loc_name)

dataiter = iter(train_loader)
images, labels = dataiter.next()
images = images.numpy()

# Figure to plot the images on
fig = plt.figure(figsize=(25, 4))

# Plot a single batch of images
for idx in range(batch_size):
    # Create a subplot to plot the image
    ax = fig.add_subplot(2, batch_size/2, idx+1, xticks=[], yticks=[])

    # Unnormalize the image
    img = images[idx]
    img = img/2 + 0.5

    # Plot the image
    plt.imshow(np.transpose(img, (1, 2, 0)))
    ax.set_title(classes[labels[idx]])
```

1.1.3 Initialize use_cuda variable

```
In [3]: import torch
        # 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 [4]: import torch.nn as nn
        import torch.optim as optim
        ## TODO: select loss function
        criterion_scratch = nn.CrossEntropyLoss()

        def get_optimizer_scratch(model):
            ## TODO: select and return an optimizer
            optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)
            return optimizer
```

```
In [5]: len(classes)
```

```
Out[5]: 50
```

1.1.5 (IMPLEMENTATION) Model Architecture

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

```
In [6]: 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.conv1 = nn.Conv2d(3, 16, 3, padding=1)
                self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
                self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
                self.conv4 = nn.Conv2d(64, 128, 3, padding=1)
                self.pool = nn.MaxPool2d(4, 4)
                self.dropout = nn.Dropout(0.25)
```

```
        self.fc1 = nn.Linear(128 * 8 * 8, 500)
        self.fc2 = nn.Linear(500, 50)

    def forward(self, x):
        ## Define forward behavior
        # (3 -> 16 feature maps) & (512x512 -> 128x128)
        x = self.pool(F.relu(self.conv1(x)))
        # (16 -> 32 feature maps) & (128x128 -> 32x32)
        x = self.pool(F.relu(self.conv2(x)))
        # (32 -> 64 feature maps) & (32x32 -> 8x8 )
        x = self.pool(F.relu(self.conv3(x)))
        # (64 -> 128 feature maps) & (8x8 -> 8x8)
        x = F.relu(self.conv4(x))

        # print(x.shape)
        # Transform to a vector
        x = x.view(-1, 128 * 8 * 8)

        # Fully connected layers
        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()

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

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

Answer: I made network convolutonal layers with pooling/relu opertions applied after each convolutional pass and 2 fully connected layers with dropout. The reason I kept the network this size is because it seemed like increasing size would require too much memory and more computational power to train the network in what I consider to be a reasonalble amount of time. I added dropout to decrease overtraining and make the network more robust.

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 [7]: 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() - tr
                    # Set optimizer gradient to zero
                    optimizer.zero_grad()
                    # Pass the data to the model get the output
                    output = model(data)
                    # Calculation the loss
                    loss = criterion(output, target)
                    # Calculate the gradient
                    loss.backward()
                    # Update the weights
                    optimizer.step()
                    # Update the training loss
                    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
```

```
                # Get the model predictions/logits
                output = model(data)
                # Calculate the loss
                loss = criterion(output, target)
                # Calculate the validation loss
                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 st
            if valid_loss <= valid_loss_min:
                print('Validation loss decreased ({:.6f} -> {:.6f}). Saving model...'.format
                    valid_loss_min,
                    valid_loss))
                torch.save(model.state_dict(), save_path)
                valid_loss_min = valid_loss



        return model
```

In [8]:
```
model_scratch.conv1.weight.shape
```

Out[8]:
```
torch.Size([16, 3, 3, 3])
```

In [9]:
```
model_scratch.conv1.weight.shape
```

Out[9]:
```
torch.Size([16, 3, 3, 3])
```

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 [24]:
```
from workspace_utils import active_session

def custom_weight_init(m):
    ## TODO: implement a weight initialization strategy
    if isinstance(m, nn.Linear):
        y = m.in_features
        std = 1/np.sqrt(y)
```

```
            m.weight.data.normal_(0, std)
            m.bias.data.fill_(0)
        if isinstance(m, nn.Conv2d):
            y = 1
            for dim in range(1, len(m.weight.shape)):
                y *= m.weight.shape[dim]
            nn.init.normal_(m.weight, mean=0, std=1/np.sqrt(y))
```

```
with active_session():
    #-#-# 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(mod
                          criterion_scratch, use_cuda, 'ignore.pt')
```

```
Epoch: 1         Training Loss: 3.903833         Validation Loss: 3.878267
Validation loss decreased (inf -> 3.878267). Saving model...
Epoch: 2         Training Loss: 3.845885         Validation Loss: 3.794670
Validation loss decreased (3.878267 -> 3.794670). Saving model...
Epoch: 3         Training Loss: 3.755822         Validation Loss: 3.701164
Validation loss decreased (3.794670 -> 3.701164). Saving model...
Epoch: 4         Training Loss: 3.665021         Validation Loss: 3.678234
Validation loss decreased (3.701164 -> 3.678234). Saving model...
Epoch: 5         Training Loss: 3.606801         Validation Loss: 3.599449
Validation loss decreased (3.678234 -> 3.599449). Saving model...
Epoch: 6         Training Loss: 3.532845         Validation Loss: 3.560143
Validation loss decreased (3.599449 -> 3.560143). Saving model...
Epoch: 7         Training Loss: 3.486892         Validation Loss: 3.487685
Validation loss decreased (3.560143 -> 3.487685). Saving model...
Epoch: 8         Training Loss: 3.426312         Validation Loss: 3.433023
Validation loss decreased (3.487685 -> 3.433023). Saving model...
Epoch: 9         Training Loss: 3.358826         Validation Loss: 3.394131
Validation loss decreased (3.433023 -> 3.394131). Saving model...
Epoch: 10         Training Loss: 3.301398         Validation Loss: 3.337939
Validation loss decreased (3.394131 -> 3.337939). Saving model...
Epoch: 11         Training Loss: 3.238332         Validation Loss: 3.267975
Validation loss decreased (3.337939 -> 3.267975). Saving model...
Epoch: 12         Training Loss: 3.202713         Validation Loss: 3.224211
Validation loss decreased (3.267975 -> 3.224211). Saving model...
Epoch: 13         Training Loss: 3.179730         Validation Loss: 3.208624
Validation loss decreased (3.224211 -> 3.208624). Saving model...
Epoch: 14         Training Loss: 3.084310         Validation Loss: 3.157845
Validation loss decreased (3.208624 -> 3.157845). Saving model...
Epoch: 15         Training Loss: 3.048072         Validation Loss: 3.135768
Validation loss decreased (3.157845 -> 3.135768). Saving model...
```

```
Epoch: 16        Training Loss: 3.003725        Validation Loss: 3.158186
Epoch: 17        Training Loss: 2.976902        Validation Loss: 3.086858
Validation loss decreased (3.135768 -> 3.086858). Saving model...
Epoch: 18        Training Loss: 2.882773        Validation Loss: 3.055384
Validation loss decreased (3.086858 -> 3.055384). Saving model...
Epoch: 19        Training Loss: 2.869254        Validation Loss: 3.021903
Validation loss decreased (3.055384 -> 3.021903). Saving model...
Epoch: 20        Training Loss: 2.823795        Validation Loss: 2.991128
Validation loss decreased (3.021903 -> 2.991128). Saving model...
```

1.1.8 (IMPLEMENTATION) Train and Validate the Model

Run the next code cell to train your model.

In [27]:
```
## TODO: you may change the number of epochs if you'd like,
## but changing it is not required
num_epochs = 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)

with active_session():
    # train the model
    model_scratch = train(num_epochs, loaders_scratch, model_scratch, get_optimizer_scr
                          criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1        Training Loss: 3.912220        Validation Loss: 3.912008
Validation loss decreased (inf -> 3.912008). Saving model...
Epoch: 2        Training Loss: 3.911065        Validation Loss: 3.911368
Validation loss decreased (3.912008 -> 3.911368). Saving model...
Epoch: 3        Training Loss: 3.909739        Validation Loss: 3.910686
Validation loss decreased (3.911368 -> 3.910686). Saving model...
Epoch: 4        Training Loss: 3.907062        Validation Loss: 3.908185
Validation loss decreased (3.910686 -> 3.908185). Saving model...
Epoch: 5        Training Loss: 3.900087        Validation Loss: 3.900007
Validation loss decreased (3.908185 -> 3.900007). Saving model...
Epoch: 6        Training Loss: 3.879420        Validation Loss: 3.861965
Validation loss decreased (3.900007 -> 3.861965). Saving model...
Epoch: 7        Training Loss: 3.822483        Validation Loss: 3.803667
```

```
Validation loss decreased (3.861965 -> 3.803667). Saving model...
Epoch: 8        Training Loss: 3.780161         Validation Loss: 3.807475
Epoch: 9        Training Loss: 3.756594         Validation Loss: 3.768713
Validation loss decreased (3.803667 -> 3.768713). Saving model...
Epoch: 10       Training Loss: 3.730341         Validation Loss: 3.743523
Validation loss decreased (3.768713 -> 3.743523). Saving model...
Epoch: 11       Training Loss: 3.718146         Validation Loss: 3.738452
Validation loss decreased (3.743523 -> 3.738452). Saving model...
Epoch: 12       Training Loss: 3.687807         Validation Loss: 3.730287
Validation loss decreased (3.738452 -> 3.730287). Saving model...
Epoch: 13       Training Loss: 3.658962         Validation Loss: 3.703213
Validation loss decreased (3.730287 -> 3.703213). Saving model...
Epoch: 14       Training Loss: 3.652757         Validation Loss: 3.678224
Validation loss decreased (3.703213 -> 3.678224). Saving model...
Epoch: 15       Training Loss: 3.628696         Validation Loss: 3.655939
Validation loss decreased (3.678224 -> 3.655939). Saving model...
Epoch: 16       Training Loss: 3.608001         Validation Loss: 3.647971
Validation loss decreased (3.655939 -> 3.647971). Saving model...
Epoch: 17       Training Loss: 3.567295         Validation Loss: 3.614173
Validation loss decreased (3.647971 -> 3.614173). Saving model...
Epoch: 18       Training Loss: 3.520055         Validation Loss: 3.529809
Validation loss decreased (3.614173 -> 3.529809). Saving model...
Epoch: 19       Training Loss: 3.486685         Validation Loss: 3.507316
Validation loss decreased (3.529809 -> 3.507316). Saving model...
Epoch: 20       Training Loss: 3.437333         Validation Loss: 3.486139
Validation loss decreased (3.507316 -> 3.486139). Saving model...
Epoch: 21       Training Loss: 3.398168         Validation Loss: 3.456382
Validation loss decreased (3.486139 -> 3.456382). Saving model...
Epoch: 22       Training Loss: 3.374065         Validation Loss: 3.405373
Validation loss decreased (3.456382 -> 3.405373). Saving model...
Epoch: 23       Training Loss: 3.345085         Validation Loss: 3.445684
Epoch: 24       Training Loss: 3.313020         Validation Loss: 3.392197
Validation loss decreased (3.405373 -> 3.392197). Saving model...
Epoch: 25       Training Loss: 3.266623         Validation Loss: 3.348276
Validation loss decreased (3.392197 -> 3.348276). Saving model...
Epoch: 26       Training Loss: 3.266106         Validation Loss: 3.360063
Epoch: 27       Training Loss: 3.213054         Validation Loss: 3.329116
Validation loss decreased (3.348276 -> 3.329116). Saving model...
Epoch: 28       Training Loss: 3.165282         Validation Loss: 3.309636
Validation loss decreased (3.329116 -> 3.309636). Saving model...
Epoch: 29       Training Loss: 3.145217         Validation Loss: 3.301576
Validation loss decreased (3.309636 -> 3.301576). Saving model...
Epoch: 30       Training Loss: 3.103912         Validation Loss: 3.213808
Validation loss decreased (3.301576 -> 3.213808). Saving model...
Epoch: 31       Training Loss: 3.082132         Validation Loss: 3.164955
Validation loss decreased (3.213808 -> 3.164955). Saving model...
Epoch: 32       Training Loss: 3.037023         Validation Loss: 3.289268
Epoch: 33       Training Loss: 3.031725         Validation Loss: 3.154785
```

```
Validation loss decreased (3.164955 -> 3.154785). Saving model...
Epoch: 34        Training Loss: 2.963592        Validation Loss: 3.158855
Epoch: 35        Training Loss: 2.940414        Validation Loss: 3.126459
Validation loss decreased (3.154785 -> 3.126459). Saving model...
Epoch: 36        Training Loss: 2.918165        Validation Loss: 3.067498
Validation loss decreased (3.126459 -> 3.067498). Saving model...
Epoch: 37        Training Loss: 2.846321        Validation Loss: 3.029877
Validation loss decreased (3.067498 -> 3.029877). Saving model...
Epoch: 38        Training Loss: 2.839702        Validation Loss: 3.055947
Epoch: 39        Training Loss: 2.791566        Validation Loss: 3.129979
Epoch: 40        Training Loss: 2.797694        Validation Loss: 2.990691
Validation loss decreased (3.029877 -> 2.990691). Saving model...
Epoch: 41        Training Loss: 2.704203        Validation Loss: 3.108203
Epoch: 42        Training Loss: 2.661948        Validation Loss: 2.975880
Validation loss decreased (2.990691 -> 2.975880). Saving model...
Epoch: 43        Training Loss: 2.634888        Validation Loss: 3.046082
Epoch: 44        Training Loss: 2.633228        Validation Loss: 2.937806
Validation loss decreased (2.975880 -> 2.937806). Saving model...
Epoch: 45        Training Loss: 2.563595        Validation Loss: 2.929991
Validation loss decreased (2.937806 -> 2.929991). Saving model...
Epoch: 46        Training Loss: 2.560954        Validation Loss: 2.892004
Validation loss decreased (2.929991 -> 2.892004). Saving model...
Epoch: 47        Training Loss: 2.536725        Validation Loss: 2.880273
Validation loss decreased (2.892004 -> 2.880273). Saving model...
Epoch: 48        Training Loss: 2.528930        Validation Loss: 2.932040
Epoch: 49        Training Loss: 2.503833        Validation Loss: 2.996176
Epoch: 50        Training Loss: 2.480724        Validation Loss: 2.968123
Epoch: 51        Training Loss: 2.421576        Validation Loss: 2.886661
Epoch: 52        Training Loss: 2.383040        Validation Loss: 2.863658
Validation loss decreased (2.880273 -> 2.863658). Saving model...
Epoch: 53        Training Loss: 2.342077        Validation Loss: 2.818968
Validation loss decreased (2.863658 -> 2.818968). Saving model...
Epoch: 54        Training Loss: 2.326854        Validation Loss: 2.850520
Epoch: 55        Training Loss: 2.322403        Validation Loss: 2.811921
Validation loss decreased (2.818968 -> 2.811921). Saving model...
Epoch: 56        Training Loss: 2.272488        Validation Loss: 2.827979
Epoch: 57        Training Loss: 2.262736        Validation Loss: 2.773678
Validation loss decreased (2.811921 -> 2.773678). Saving model...
Epoch: 58        Training Loss: 2.227270        Validation Loss: 2.812337
Epoch: 59        Training Loss: 2.194669        Validation Loss: 2.834338
Epoch: 60        Training Loss: 2.199898        Validation Loss: 2.888571
Epoch: 61        Training Loss: 2.131942        Validation Loss: 2.746343
Validation loss decreased (2.773678 -> 2.746343). Saving model...
Epoch: 62        Training Loss: 2.134201        Validation Loss: 2.851724
Epoch: 63        Training Loss: 2.080947        Validation Loss: 2.904340
Epoch: 64        Training Loss: 2.084511        Validation Loss: 2.755855
Epoch: 65        Training Loss: 2.016590        Validation Loss: 2.827489
Epoch: 66        Training Loss: 2.015391        Validation Loss: 2.766136
```

```
Epoch: 67         Training Loss: 1.992612         Validation Loss: 2.722081
Validation loss decreased (2.746343 -> 2.722081). Saving model...
Epoch: 68         Training Loss: 1.969365         Validation Loss: 2.766178
Epoch: 69         Training Loss: 1.929400         Validation Loss: 2.793447
Epoch: 70         Training Loss: 1.917043         Validation Loss: 2.770155
Epoch: 71         Training Loss: 1.908032         Validation Loss: 2.796311
Epoch: 72         Training Loss: 1.857837         Validation Loss: 2.804325
Epoch: 73         Training Loss: 1.885052         Validation Loss: 2.780686
Epoch: 74         Training Loss: 1.837474         Validation Loss: 2.767279
Epoch: 75         Training Loss: 1.821439         Validation Loss: 2.779665
Epoch: 76         Training Loss: 1.788216         Validation Loss: 2.830009
Epoch: 77         Training Loss: 1.762388         Validation Loss: 2.811820
Epoch: 78         Training Loss: 1.743783         Validation Loss: 2.760809
Epoch: 79         Training Loss: 1.707009         Validation Loss: 2.823418
Epoch: 80         Training Loss: 1.717643         Validation Loss: 2.862113
Epoch: 81         Training Loss: 1.722814         Validation Loss: 2.800407
Epoch: 82         Training Loss: 1.743371         Validation Loss: 2.789273
Epoch: 83         Training Loss: 1.647129         Validation Loss: 2.886743
Epoch: 84         Training Loss: 1.574194         Validation Loss: 2.824427
Epoch: 85         Training Loss: 1.617427         Validation Loss: 2.813213
Epoch: 86         Training Loss: 1.617625         Validation Loss: 2.961021
Epoch: 87         Training Loss: 1.567892         Validation Loss: 2.899850
Epoch: 88         Training Loss: 1.567965         Validation Loss: 2.746227
Epoch: 89         Training Loss: 1.566285         Validation Loss: 2.807855
Epoch: 90         Training Loss: 1.531520         Validation Loss: 2.758199
Epoch: 91         Training Loss: 1.537148         Validation Loss: 2.786772
Epoch: 92         Training Loss: 1.472860         Validation Loss: 2.885344
Epoch: 93         Training Loss: 1.518817         Validation Loss: 2.700497
Validation loss decreased (2.722081 -> 2.700497). Saving model...
Epoch: 94         Training Loss: 1.495972         Validation Loss: 2.834321
Epoch: 95         Training Loss: 1.458828         Validation Loss: 2.781152
Epoch: 96         Training Loss: 1.423566         Validation Loss: 2.776850
Epoch: 97         Training Loss: 1.420817         Validation Loss: 2.697124
Validation loss decreased (2.700497 -> 2.697124). Saving model...
Epoch: 98         Training Loss: 1.388591         Validation Loss: 2.779982
Epoch: 99         Training Loss: 1.393741         Validation Loss: 2.742143
Epoch: 100         Training Loss: 1.404948         Validation Loss: 2.779643
```

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 [10]: 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: 2.648871


Test Accuracy: 38% (484/1250)
```

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 [11]:
```
import os
import numpy as np
from torchvision import transforms, datasets
from torch.utils.data import DataLoader
from torch.utils.data.sampler import SubsetRandomSampler

### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes

# Data Directory locations
loc_dir = '/data/landmark_images/'
data_dir = os.path.join(loc_dir, 'train/')
test_dir = os.path.join(loc_dir, 'test/')

# Dataloader arguments
batch_size = 20
num_workers = 0
valid_set_size = 0.2


# Create the transformations
transform = transforms.Compose([
    transforms.RandomResizedCrop(512),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

# Load data into files
train_data = datasets.ImageFolder(data_dir, transform=transform)
test_data = datasets.ImageFolder(test_dir, transform=transform)

# Create indicies for testing and validation sets
np.random.seed(42)
length = len(train_data)
indicies = list(range(length))
np.random.shuffle(indicies)
split = int(np.floor(length * valid_set_size))
valid_idx, train_idx = indicies[:split], indicies[split:]
```

```
# Create samplers for testing and validation sets
train_sampler = SubsetRandomSampler(train_idx)
valid_sampler = SubsetRandomSampler(valid_idx)

# Create dataloaders
train_loader = DataLoader(train_data, batch_size=batch_size, num_workers=num_workers, s
valid_loader = DataLoader(train_data, batch_size=batch_size, num_workers=num_workers, s
test_loader = DataLoader(test_data, batch_size=batch_size, num_workers=num_workers)

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 [12]: import torch.nn as nn
         import torch.optim as optim

         ## TODO: select loss function
         criterion_transfer = nn.CrossEntropyLoss()


         def get_optimizer_transfer(model):
             ## TODO: select and return optimizer
             optimzer = optim.SGD(model.classifier.parameters(), lr=0.001, momentum=0.9)
             return optimzer
```

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

         model_transfer = models.vgg16(pretrained=True)

         # Freeze the gradient for the layers in the features section
         for param in model_transfer.features.parameters():
             param.requires_grad = False

         # Replace the first fully connected classifier layer
         n_outputs = model_transfer.classifier[0].out_features
         model_transfer.classifier[0] = nn.Linear(131072, n_outputs)
```

```
        # Replace the final output layer with a new layer with appropirate outputs
        n_inputs = model_transfer.classifier[6].in_features
        model_transfer.classifier[6] = nn.Linear(n_inputs, len(classes))


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

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

In [10]:
```
print(model_transfer)
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
```

```
    (1): ReLU(inplace)
    (2): Dropout(p=0.5)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace)
    (5): Dropout(p=0.5)
    (6): Linear(in_features=4096, out_features=50, bias=True)
  )
)
```

```
In [14]: model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

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: The only two layers I felt I needed to change were the first and last layers of the classifier portion of the neural network of vgg16. I used vgg16 since I was familiar with it from the video examples and know it makes a great classification network composed of layers I learned about in this nanodegree program. I changed the first layer of the classifier because the original input gets flattened to something different than what the network expects. Next, I changed the last layer to have 50 outputs corresponding to the 50 locations we are trying to classify instead of the 1000 outputs of the original vgg16 network.

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 [2]: from workspace_utils import active_session

        # TODO: train the model and save the best model parameters at filepath 'model_transfer.p

        num_epochs = 10
        with active_session():
            # train the model
            model_transfer = train(num_epochs, loaders_transfer, model_transfer, get_optimizer_t
                                   criterion_transfer, 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'))
```

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 [15]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)

Test Loss: 1.135507


Test Accuracy: 69% (867/1250)
```

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 [72]: 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

             # Lod the image and perform the apprpriate transformations to the data
             img = Image.open(img_path)
             img = transform(img)
             img = torch.unsqueeze(img, 0).cuda()

             # Pass the image data to the network to get the predictions
             model_transfer.eval()
             output = model_transfer(img)

             # Get the top k values and the corresponding indexes
             top_preds, ind_pred = output.data.topk(k)

             # Get the class predictions
             class_predictions = []
             for ind in ind_pred[0]:
```

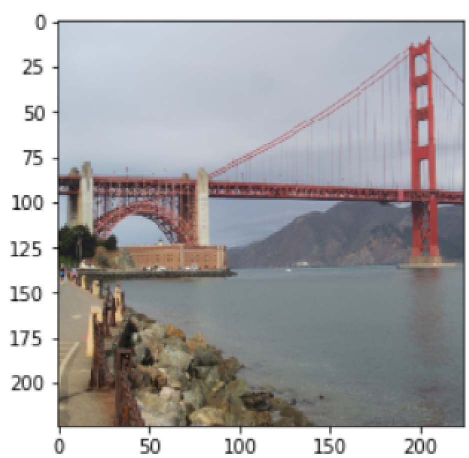
```
        class_predictions.append(classes[ind])

    # Return the class predictions
    return class_predictions


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

```
Out[72]: ['Golden_Gate_Bridge',
 'Brooklyn_Bridge',
 'Dead_Sea',
 'Forth_Bridge',
 'Sydney_Harbour_Bridge']
```

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

    ## TODO: display image and display landmark predictions
    # Load the image data
    img = Image.open(img_path)

    # Plot the image data and display the output
```

```
    plt.clf()
    plt.imshow(img)
    plt.show()

    # Create the the text output and print it
    text = "Is this a picture of the\n{}, {}, or {}?".format(predicted_landmarks[0],
                                                            predicted_landmarks[1],
                                                            predicted_landmarks[2])
    print(text)
```

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


```
Is this a picture of the
Golden_Gate_Bridge, Brooklyn_Bridge, or Forth_Bridge?
```

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.

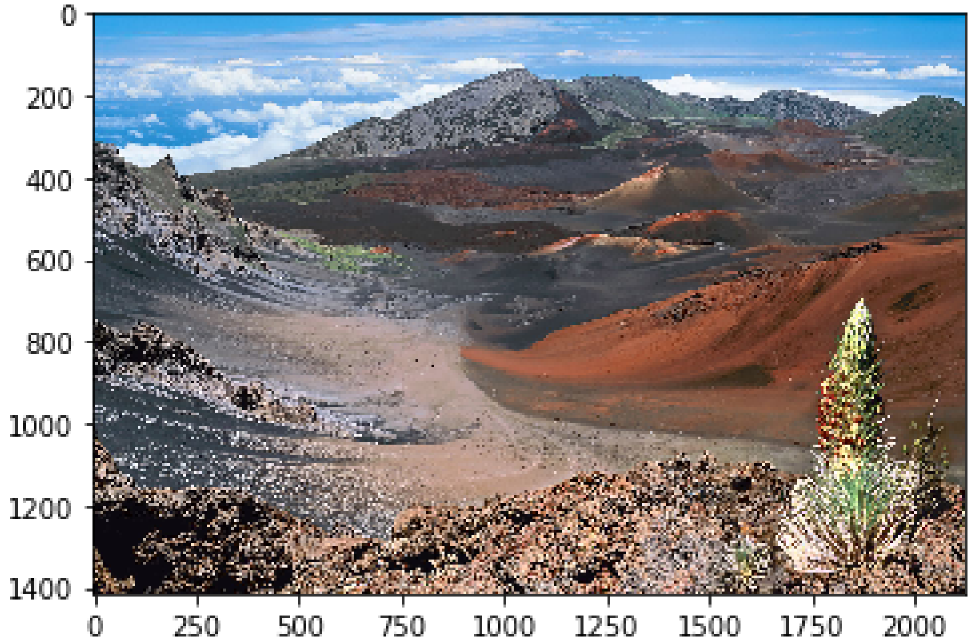
The output is better than I expected. Three things I could do better is let the network train for longer since I only let it run for 11 epochs and wanted it to run longer but the process got interrupted. I could also tweak the data and apply rotations to possibly make the network more robust. A third thing I could do would be to get more photos of the locations so the network could train in more data.

Answer: (Three possible points for improvement)

```
In [82]: ## TODO: Execute the `suggest_locations` function on
         ## at least 4 images on your computer.
         ## Feel free to use as many code cells as needed.

         # Load images to look at
         my_four_images = datasets.ImageFolder('my_images/', transform=transform)
```

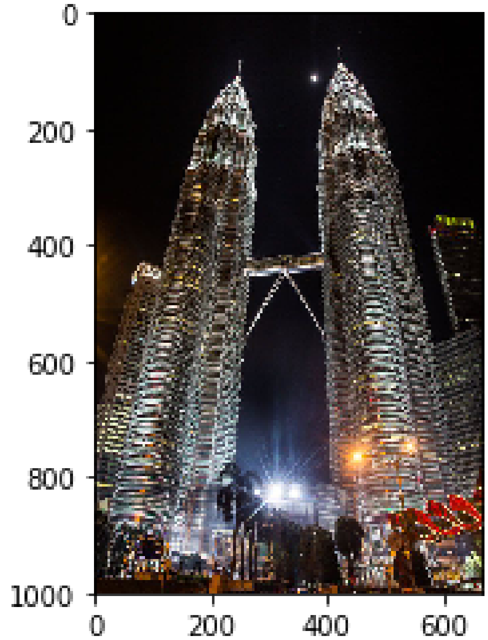
```
In [92]: for img, idx in iter(my_four_images):
             print(img.size(), idx)

         # Image locations in the current working directory
         img_locs = ['my_images/Haleakala_National_Park/Haleakala_National_Park.jpg',
                     'my_images/Kantaji-Temple/Kantaji-Temple.png',
                     'my_images/Petronas_Towers/Petronas_Towers.jpg',
                     'my_images/Trevi_Fountain/Trevi_Fountain.png']

         # Apply the suggested_locations function to my images that I downloaded off of google
         for img in img_locs:
             suggest_locations(img)
```

```
torch.Size([3, 512, 512]) 1
torch.Size([3, 512, 512]) 2
torch.Size([3, 512, 512]) 3
torch.Size([3, 512, 512]) 4
```

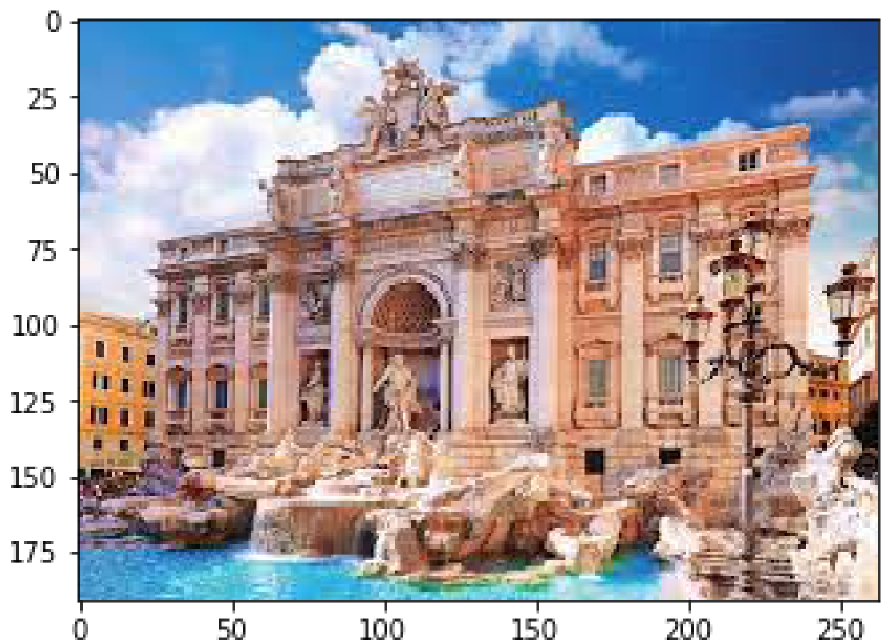


Is this a picture of the
Death_Valley_National_Park, Haleakala_National_Park, or Banff_National_Park?

```
Is this a picture of the
Kantanagar_Temple, Gateway_of_India, or Taj_Mahal?
```




```
Is this a picture of the
Petronas_Towers, Brooklyn_Bridge, or Terminal_Tower?
```



```
Is this a picture of the
Trevi_Fountain, Kantanagar_Temple, or Temple_of_Olympian_Zeus?
```