Landmark Classification & Tagging for Social Media

REVIEW

HISTORY

Requires Changes

4 specifications require changes

Dear Student,

You've done an excellent job at implementing the entire pipeline of the project! 👏

However, there are some changes that you need to make before you can pass the project.
As a reviewer I am required to follow Udacity's guidelines when evaluating projects and hence I had to mark some requirements that need more work from your end.

Please go through the review to see what changes you need to make.
Once you make the desired changes and resubmit the project, you will pass the project and get a step closer to finishing your nanodegree.

Wishing you good luck! 😄

Some general suggestions

Use of assertions and Logging:

- Consider using Python assertions for sanity testing - assertions are great for catching bugs. This is especially true of a dynamically type-checked language like Python where a wrong variable type or shape can cause errors at runtime
- Logging is important for long-running applications. Logging done right produces a report that can be analyzed to debug errors and find crucial information. There could be different levels of logging or logging tags that can be used to filter messages most relevant to someone. Messages can be written to the terminal using print() or saved to file, for example using the Logger module. Sometimes it's worthwhile to catch and log exceptions during a long-running operation so that the operation itself is not aborted.

Debugging:

- Check out this guide on debugging in python

Reproducibility:

- Reproducibility is perhaps the biggest issue in machine learning right now. With so many moving parts present in the code (data, hyperparameters, etc) it is imperative that the instructions and code make it easy for anyone to get exactly the same results (just imagine debugging an ML pipeline where the data changes every time and so you cannot get the same result twice).
- Also consider using random seeds to make your data more reproducible.

Optimization and Profiling:

- Monitoring progress and debugging with Tensorboard: This tool can log detailed information about the model, data, hyperparameters, and more. Tensorboard can be used with Pytorch as well.
- Profiling with Pytorch: Pytorch's profiler can be used to break down profiling information by operations (convolution, pooling, batch norm) and identify performance bottlenecks. The performance traces can be viewed in the browser itself. The profiler is a great tool for quickly comparing GPU vs CPU speedups for example.

Files Submitted

✓

The submission includes the required notebook file and HTML file. When the HTML file is created, all the code cells in the notebook need to have been run so that reviewers can see the final implementation and output.

All files are included in the submission zip
✅ `Jupyter Notebook`
✅ `HTML Report`

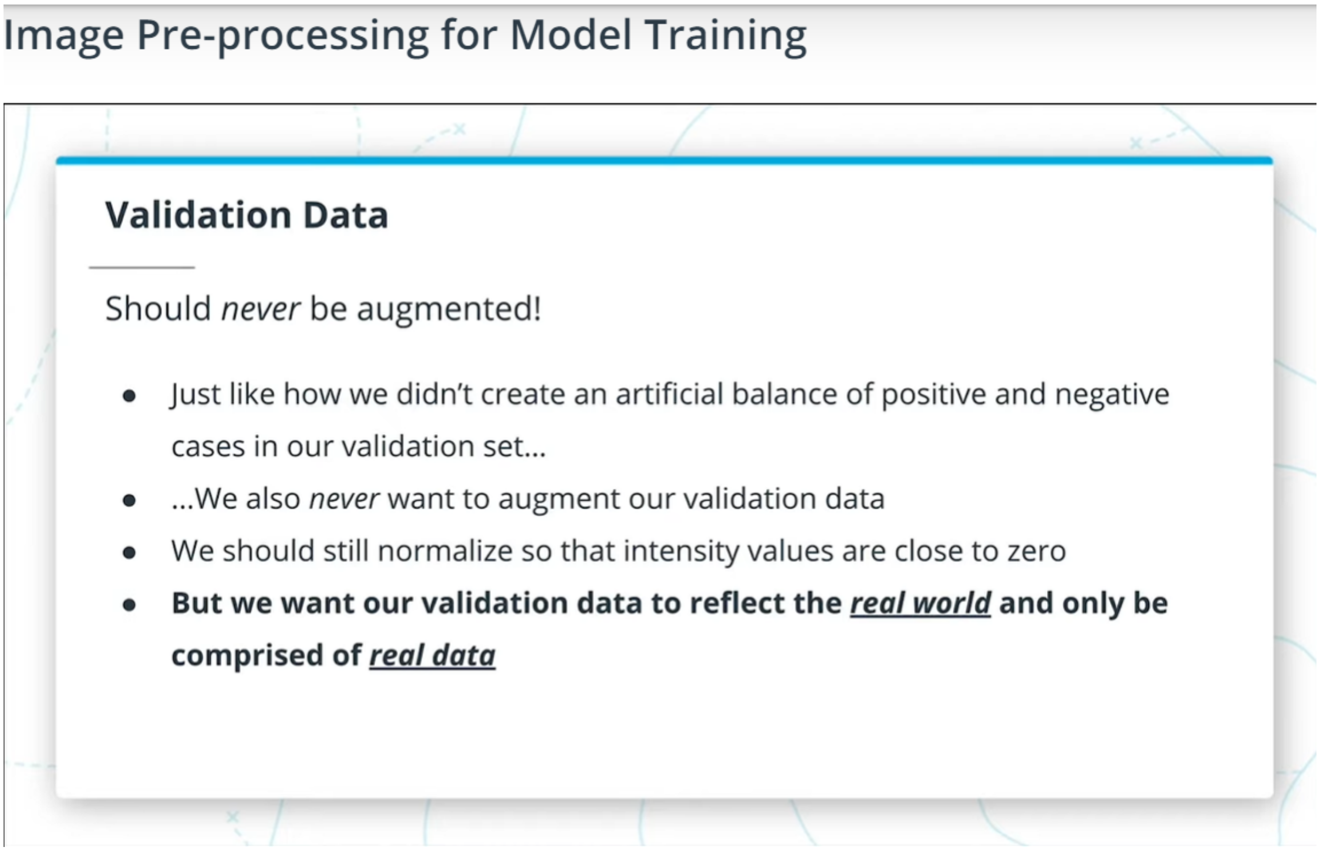
💡 Suggestion:
You can export your conda environment into `environment.yaml` file so that you can recreate your conda environment later while practicing on your own system. Use the following command -

```
conda env export -f environment.yaml
```

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

The submission randomly splits the images at `landmark_images/train` into train and validation sets. The submission then creates a data loader for the created train set, a data loader for the created validation set, and a data loader for the images at `landmark_images/test`.

Kindly note that augmentations are only supposed to be applied to training data. In your current implementation you are subsampling your validation data from the training data, which means that augmentations are also applied to validation data.



To fix this, you should first specify the transforms for the datasets and then apply the sampler. I am sharing a sample code snippet below but you should modify it as per your own needs.

```
train_transform = transforms.Compose([transforms.Resize(224),
                                transforms.CenterCrop(224),
                                transforms.RandomHorizontalFlip(),
                                transforms.ToTensor(),
                                transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

valid_test_transform = transforms.Compose([transforms.Resize(224),
                                transforms.CenterCrop(224),
                                transforms.ToTensor(),
```

```
                                    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

train_data = datasets.ImageFolder('/data/landmark_images/train',transform=train_transfor
m)
valid_data = datasets.ImageFolder('/data/landmark_images/train',transform=valid_test_tra
nsform)
test_data = datasets.ImageFolder('/data/landmark_images/test',transform=valid_test_trans
form)

num_train = len(train_data)
indices = list(range(num_train))
np.random.shuffle(indices)
split = int(np.floor(valid_size *num_train))
train_idx, valid_idx = indices[split:], indices[:split]

train_sampler = SubsetRandomSampler(train_idx)
valid_sampler = SubsetRandomSampler(valid_idx)

train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, sampler=tr
ain_sampler)
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size, sampler=va
lid_sampler)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size)

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

💡 Suggestion: A better way to generate validation data is to use the `splitfolders` module to split the training dataset into training and validation sets.

```
import splitfolders

output = splitfolders.ratio("/data/landmark_images/train", output="output", seed=1337, r
atio=(.8, .2), group_prefix=None)
```

✓

Answer describes each step of the image preprocessing and augmentation. Augmentation (cropping, rotating, etc.) is not a requirement.

- I designed my transforms to be also compatible with the transfer learning task so the images are cropped to be 224 .224 either by random resized crop for the training and validation or by resizing the image to 255.255 which is close enough to the target and the doing a center crop

ignoring the edges of the image.
- I augmented the training and validation data by doing a random horizontal flip because this is common in real world. and I also did a random resize before cropping the image in addition to a random rotation.

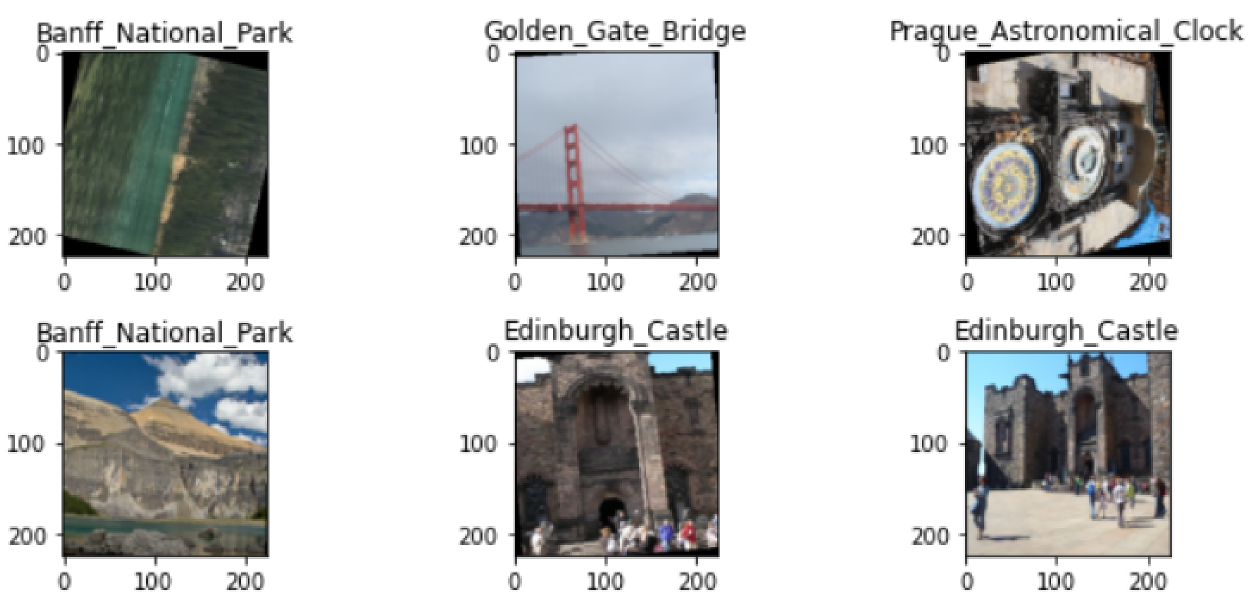
Good description of preprocessing algorithm!

Augmentations help the model generalise better and prevent overfitting on training data. Since landmarks can be present in various orientations in a picture, augmentating the training dataset should dramatically improve model performance.

Suggestion - You can check for class imbalance amongst the class distribution and try implementing something like SMOTE

The submission displays at least 5 images from the train data loader, and labels each image with its class name (e.g., "Golden Gate Bridge").

```
classes=datasets_scratch['train'].classes
images, labels = next(iter(loaders_scratch['train']))

fig,axes = plt.subplots(2,5,figsize=(15, 4))
axes=axes.flatten()

for i,ax in enumerate(axes):
    imshow(images[i],ax)
    ax.set_title(classes[labels[i]][3:])

plt.tight_layout()
```



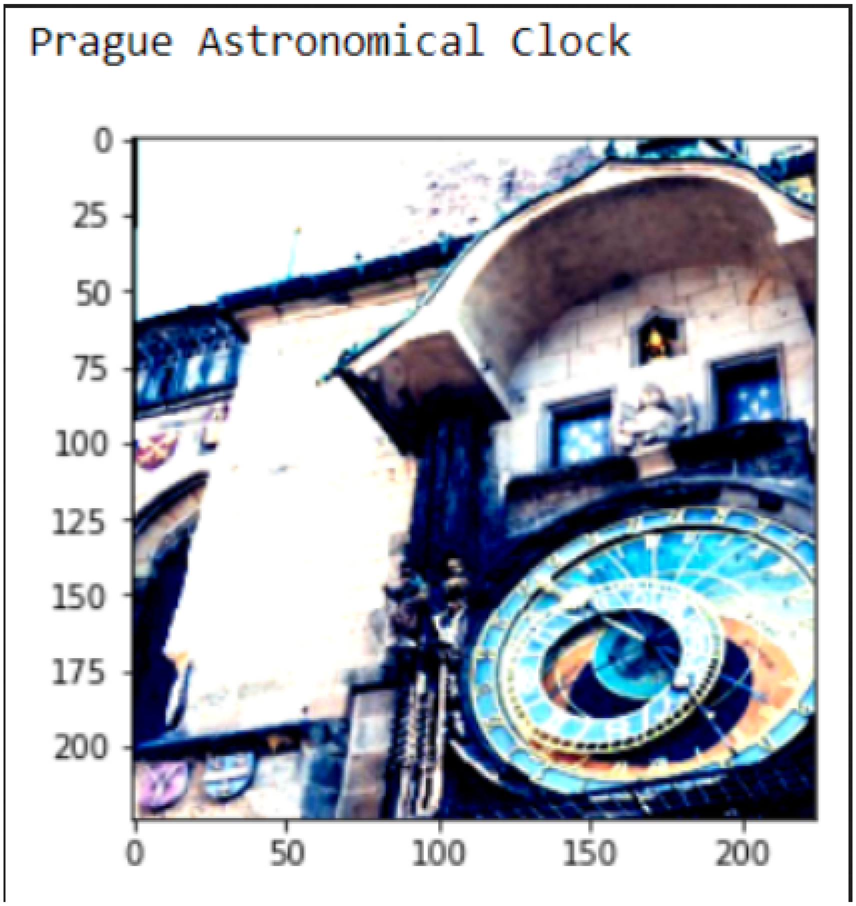
Good job performing Exploratory Visualization to develop a better understanding of the dataset.

This step is more generally referred to as EDA (shot for Exploratory Data Analysis). Performing EDA on the dataset helps us develop a complete understanding of the data especially when working on projects where we are not aware of the characteristics of training data. In case of image classification, it's usually a good idea to visualize atleast a small subset of the images.

💡 You could've processed the class labels and then used them in the plotting functions

```
classes = [item[3:].replace("_", " ") for item in loaders_scratch['train'].dataset.class
es]
```

Then your labels would look as follows:



✓

The submission chooses appropriate loss and optimization functions for this classification task.

Loss function:

- `CrossEntropyLoss`

Optimizer:

- `SGD`

💡 Suggestion: You can also implement a [Learning Rate Scheduler](#) to increase performance and reduce training time.

```
scheduler = optim.lr_scheduler.StepLR(optimizer_scratch, step_size=100, gamma=0.9)
```

You can also check your GPU memory usage during the training sessions as follows

```
print("use_cuda: ",use_cuda," -> ", torch.cuda.get_device_name(0))
print('Memory Usage:')
print('\tAllocated:', round(torch.cuda.memory_allocated(0)/1024**3,1), 'GB')
print('\tCached:   ', round(torch.cuda.memory_reserved(0)/1024**3,1), 'GB')
```

Additional Reading

- Check out this excellent blog post to understand the difference between different loss functions: https://gombru.github.io/2018/05/23/cross_entropy_loss/
- This blog post by Sebastian Ruder on different optimization algorithms is also a good read: https://ruder.io/optimizing-gradient-descent/

The submission specifies a CNN architecture.

```
# 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, kernel_size=9)
        self.conv2_1=nn.Conv2d(16,64,kernel_size=3,padding=1)
        self.conv2_2=nn.Conv2d(64,64,kernel_size=9,stride=3)
        self.conv3_1=nn.Conv2d(64,128,kernel_size=3,padding=1)
        self.conv3_2=nn.Conv2d(128,128,kernel_size=3,stride=2)

        self.pool=nn.MaxPool2d(2,2)

        self.fc1 = nn.Linear(128*8*8, 512)
        self.fc2 = nn.Linear(512, 50)

        self.dropout=nn.Dropout(p=0.2)
```

Your network contains `5` convolution layers and `2` dense layers. Good choice!

The advantage of using a Deep Learning library such as PyTorch is that you only need to define the `forward` function and the `backward` function (i.e. Backpropagation step) is defined automatically by the built-in autograd module. Things would be quite hard if we had to worry about all those gradients and calculus and implement chain rule manually!

💡 Suggestion: You can make use of `nn.Sequential` module to design your architecture more cleanly. This also makes it much easier to keep track of layer sizes as compared to the mental gymnastics required in the traditional approach.

```
class Net(nn.Module):

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

        self.layer1 = nn.Sequential(
            nn.Conv2d(3, 16, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))

        self.layer2 = nn.Sequential(
            nn.Conv2d(16, 32, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))

        self.fc1 = nn.Linear(56*56*32, 50)

    def forward(self, x):

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

        x = x.view(x.size(0), -1)
        x = self.fc1(x)

        return x
```

✓

Answer describes the reasoning behind the selection of layer types.

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

Answer:

- At first, I made a huge network to inccrease the features discovered by the network while reducing dimensionality but it took a lot of time to train so i removed some layers and tried concatinating conv layers before pooling. I achieved good results with a feature vector of size 128.8.8 and the network is so much faster.

Note - When working on a personal project or any other project in corporate scenario, it's a good idea to spend some time thinking about the utilities of using different functions and layers and see if they fit your requirements.

💡 Suggestion - You can use `torchsummary` library to generate a summary of your model architecture as shown below

```
from torchsummary import summary

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

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 16, 224, 224]             448
         MaxPool2d-2         [-1, 16, 112, 112]               0
       BatchNorm2d-3         [-1, 16, 112, 112]              32
            Conv2d-4         [-1, 32, 112, 112]           4,640
         MaxPool2d-5           [-1, 32, 56, 56]               0
       BatchNorm2d-6           [-1, 32, 56, 56]              64
            Conv2d-7           [-1, 64, 56, 56]          18,496
         MaxPool2d-8           [-1, 64, 28, 28]               0
       BatchNorm2d-9           [-1, 64, 28, 28]             128
           Conv2d-10          [-1, 128, 28, 28]          73,856
        MaxPool2d-11          [-1, 128, 14, 14]               0
      BatchNorm2d-12          [-1, 128, 14, 14]             256
           Conv2d-13          [-1, 256, 14, 14]         295,168
        MaxPool2d-14            [-1, 256, 7, 7]               0
      BatchNorm2d-15            [-1, 256, 7, 7]             512
           Linear-16                 [-1, 4096]      51,384,320
          Dropout-17                 [-1, 4096]               0
           Linear-18                 [-1, 1024]       4,195,328
          Dropout-19                 [-1, 1024]               0
           Linear-20                  [-1, 133]         136,325
================================================================
Total params: 56,109,573
Trainable params: 56,109,573
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 17.88
Params size (MB): 214.04
```

```
Estimated Total Size (MB): 232.50
----------------------------------------------------------------
```

The submission implements an algorithm to train a model for a number of epochs and save the "best" result.

The `train()` function only saves checkpoints if the validation loss drops below the previous lowest value ✅

```
        if valid_loss <= valid_loss_min:
            print('Validation loss decreased ... Model saved ...')
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss
```

The submission implements a custom weight initialization function that modifies all the weights of the model. The submission does not cause the training loss or validation loss to explode to `nan`.

```
def custom_weight_init(m):
    ## TODO: implement a weight initialization strategy
    classname = m.__class__.__name__
    # for every Linear layer in a model..
    if classname.find('Linear') != -1:
        # get the number of inputs
        n = m.in_features
        y = (1.0/np.sqrt(n))
        m.weight.data.normal_(0, y)
        m.bias.data.fill_(0)
```

The trained model attains at least 20% accuracy on the test set.

Since model's accuracy relies on its architecture and training methodology, this requirement can only be evaluated once you remove the augmentations in your validation dataset and re-run the training/testing loops.

Please don't worry about it. Once you fix all the issues, the next reviewer will evaluate and pass this requirement.

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

The submission specifies a model architecture that uses part of a pre-trained model.

You chose `resnet50` for transfer learning. That's a good choice!

⚠️ However, please note that since you are reusing dataloaders from previous step you've repeated the augmentation mistake. Augmentations should only be applied to training data.

As an experiment, you could also try some other pre-trained models available in torchvision.models to see which one performs the best (https://pytorch.org/vision/stable/models.html)

✓

The submission details why the chosen architecture is suitable for this classification task.

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.

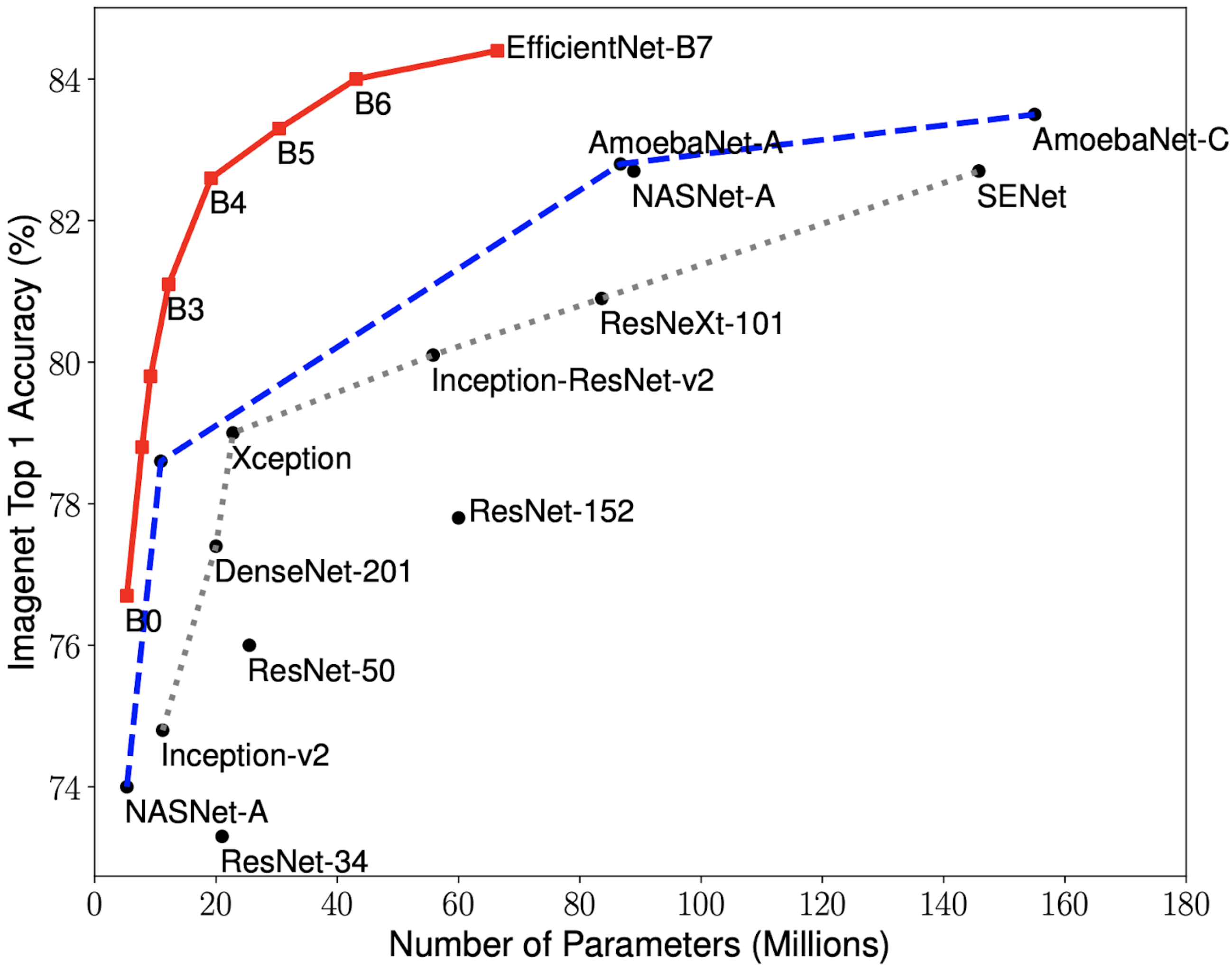
Answer:

- I tried resnet50 as it is a fairly fast model and small model.
- I freezed the model parameters then replaced the classifier with another one that have 50 output classes and used and the relu activation function with dropout to prevent overfitting

You've presented a succinct summary of the transfer learning architecture you implemented. 👏

Models pre-trained on ImageNet database are very good feature extractors already. So, we mostly need to change the dense layers and retrain the network while freezing the convolution layer parameters and only training the fully-connected layers.

Here's a representation of the no. of parameters involved in models vs their ImageNet performance



The submission uses model checkpointing to train the model and saves the model weights with the best validation loss.

Accuracy on the test set is 60% or greater.

Since model's accuracy relies on its architecture and training methodology, this requirement can only be evaluated once you remove the augmentations in your validation dataset and re-run the training/testing loops.

Please don't worry about it. Once you fix all the issues, the next reviewer will evaluate and pass this requirement.

Step 3: Write Your Landmark Prediction Algorithm

The submission implements functionality to use the transfer learned CNN from Step 2 to predict top k landmarks. The returned predictions are the names of the landmarks (e.g., "Golden Gate Bridge").

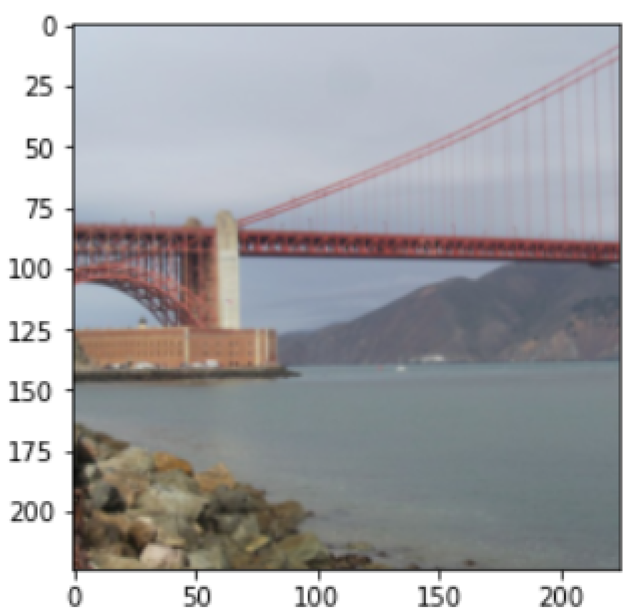
`predict_landmarks` function is defined to take the file path as input and return the class predicted by the CNN.

```
## 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 l
    img = transforms_scratch['test'](Image.open(img_path)).unsqueeze(0)

    model_transfer.load_state_dict(torch.load('model_transfer.pt'))
    model_transfer.eval()
    preds = model_transfer.forward(img.cuda())

    top_classes = preds.topk(k)[1]
    final_preds = [datasets_scratch['train'].classes[i][3:] for i in top_classes
    return final_preds
```

The submission displays a given image and uses the functionality in "Write Your Algorithm, Part 1" to predict the top 3 landmarks.

`suggest_locations()` function is implemented such that it calls the `predict_landmarks()` function defined earlier to fetch the `top-3` predicted class labels and then print them alongside the image.

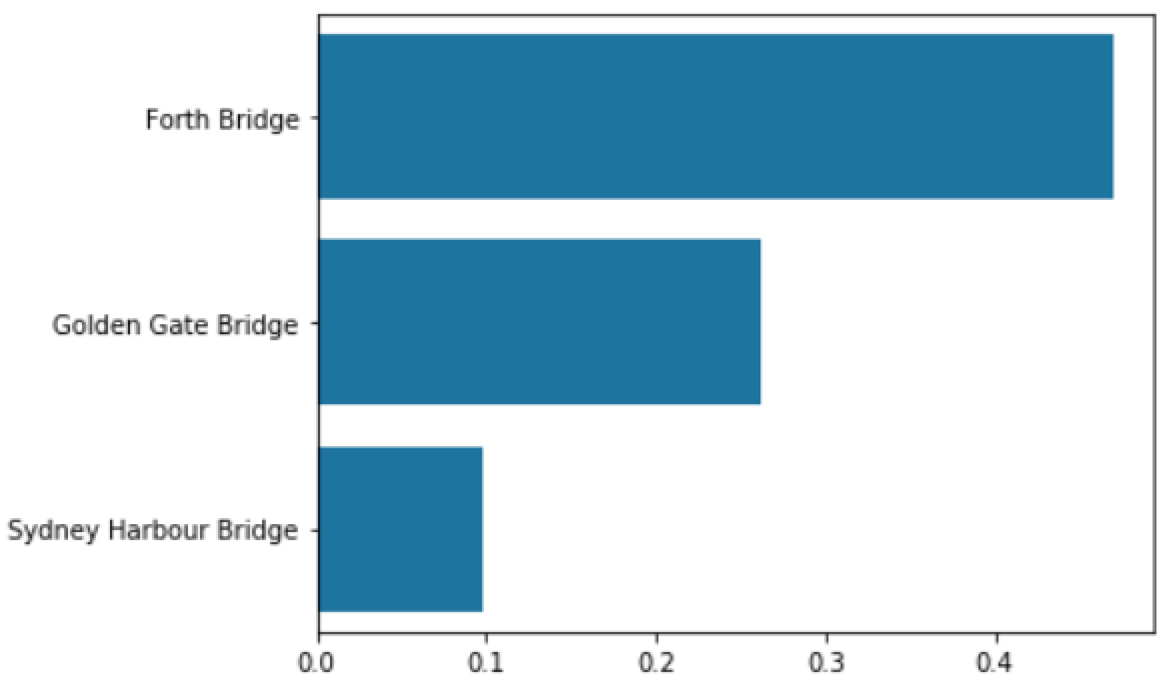
```
Is this picture of the
Golden_Gate_Bridge, Forth_Bridge, Brooklyn_Bridge?
```



💡 Suggestion: You could also display a plot of the predicted topk probabilities as follows

```
def suggest_locations(img_path):

    path = img_path.split('/')
    print(f"Actual Label: {img_path.split('/')[2][3:].replace('_',' ')}")

    # get landmark predictions
    confidence, landmarks  = predict_landmarks(img_path, 3)

    print(f"Predicted Label: {landmarks[0]}")

    img = Image.open(img_path).convert('RGB')

    plt.figure(figsize = (6,10))

    ax = plt.subplot(2,1,1)
    ax.imshow(img)

    plt.subplot(2,1,2)
    sns.barplot(x=confidence, y=landmarks, color=sns.color_palette()[0]);
    plt.show()
```

```
Actual Label: Golden Gate Bridge
Predicted Label: Forth Bridge
```

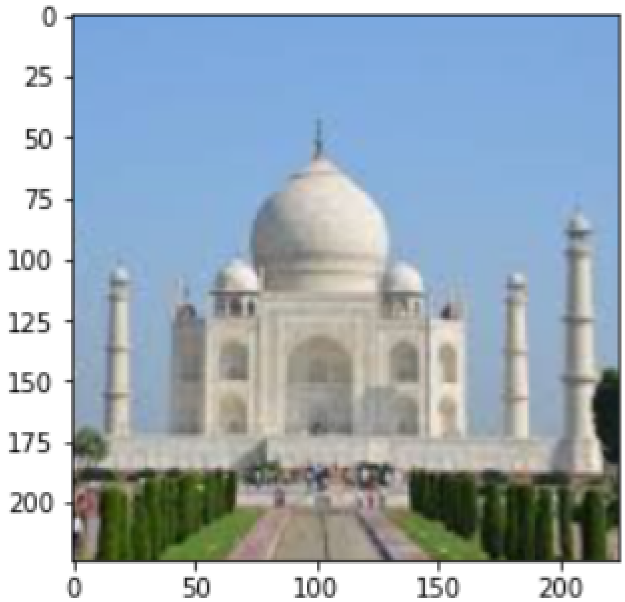


The submission tests at least 4 images.

Model has been successfully tested with external images ✅

```
suggest_locations('./test1.jpg')
```

```
Is this picture of the
Taj_Mahal, Eiffel_Tower, Stockholm_City_Hall?
```



✓

Submission provides at least three possible points of improvement for the classification algorithm.

- It met my expectation but it can achieve better results with some impeovements
- We can train on better data as I think the data have some mistakes and noise that mislead the model for sure.
- We can also experiment different types of augmentation.
- We can train for more epochs and try different optimizers with different learning rates and momentum
- We can also use other pretrained models or more layered resnet. This of course has to improve our results

You've listed a good amalgam of suggestions that can further improve the model's accuracy. 👍

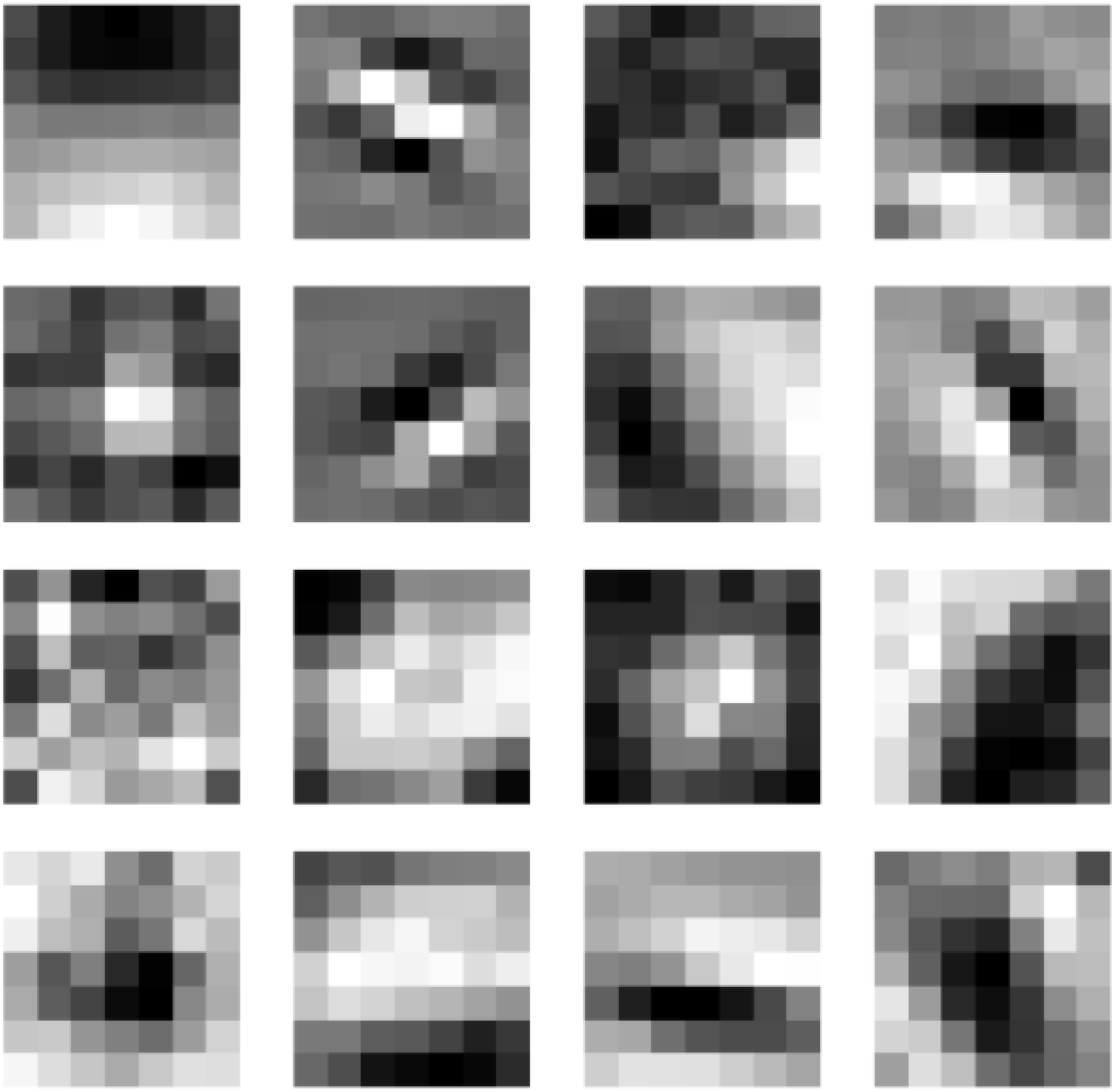
- Adding more layers will help as the depth of convolutions increase, models can learn more features. But, this means training time will also increase considerably.
- Adam is usually a good optimizer for most cases and a standard learning rate of around 0.001 or 0.0005 works well.
- Higher epochs help with learning although at one point the learning would stop as the model becomes really good and starts overfitting.

💡 Suggestion: You can use the extractor library to generate a visualization of the convolutional feature maps as shown below

```
from extractor import Extractor

extractor = Extractor(list(model_transfer.children()))
extractor.activate()
extractor.info()
```

```
# Visualising the filters
import cv2
import torchvision.transforms as transforms

plt.figure(figsize=(25, 25))
for index, filter in enumerate(extractor.CNN_weights[0]):
    if index == 64:
        break
    plt.subplot(8, 8, index + 1)
    plt.imshow(filter[0, :, :].detach(), cmap='gray')
    plt.axis('off')
plt.show()
img = cv2.cvtColor(cv2.imread('./images/Curly-coated_retriever_03896.jpg'), cv2.COLOR_BG
R2GRAY)
plt.imshow(img, cmap='gray')
plt.show()
```

For the image shown above, this is what the feature maps would look like (I am only showing some of the maps due to lack of space):



RESUBMIT

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