Classification and Performance

Make sure you are connected to a T4 GPU runtime. The following code should report true if you are.

```
import torch
print("GPU available =", torch.cuda.is_available())
```

```
GPU available = True
```

Install prerequisites needed for this assignment, `thop` is used for profiling PyTorch models https://github.com/ultralytics/thop, while `tqdm` makes your loops show a progress bar https://tqdm.github.io/

```
!pip install thop segmentation-models-pytorch transformers
import math
import numpy as np
import torch
import torch.nn as nn
import gc
import torchvision
from torchvision import datasets, transforms
from PIL import Image
import segmentation_models_pytorch as smp
import thop
from transformers import ViTFeatureExtractor, ViTForImageClassification
import matplotlib.pyplot as plt
from tqdm import tqdm
import time

# we won't be doing any training here, so let's disable autograd
torch.set_grad_enabled(False)
```

```
Collecting pretrainedmodels>=0.7.1 (from segmentation-models-pytorch)
  Downloading pretrainedmodels-0.7.4.tar.gz (58 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 58.8/58.8 kB 4.2 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch) (1.17.0)
Requirement already satisfied: timm>=0.9 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch) (1.0.13)
Requirement already satisfied: torchvision>=0.9 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch) (0
Requirement already satisfied: tqdm>=4.42.1 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch) (4.67.
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages (from transformers) (3.16.1)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from transformers) (24.2)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.11/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.11/dist-packages (from transformers) (2024.11.6)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: tokenizers<0.22,>=0.21 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.21.0)
Requirement already satisfied: safetensors>=0.4.1 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.5.2)
Requirement already satisfied: fsspec>=2023.5.0 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.24->segmenta
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.24
Collecting munch (from pretrainedmodels>=0.7.1->segmentation-models-pytorch)
  Downloading munch-4.0.0-py2.py3-none-any.whl.metadata (5.9 kB)
Requirement already satisfied: networkx in /usr/local/lib/python3.11/dist-packages (from torch->thop) (3.4.2)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (3.1.5)
Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.1.105 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (1
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.1.105 in /usr/local/lib/python3.11/dist-packages (from torch->thop)
Requirement already satisfied: nvidia-cuda-cupti-cu12==12.1.105 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (1
Requirement already satisfied: nvidia-cudnn-cu12==9.1.0.70 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (9.1.0.
Requirement already satisfied: nvidia-cublas-cu12==12.1.3.1 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (12.1.
Requirement already satisfied: nvidia-cufft-cu12==11.0.2.54 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (11.0.
Requirement already satisfied: nvidia-curand-cu12==10.3.2.106 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (10.
Requirement already satisfied: nvidia-cusolver-cu12==11.4.5.107 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (1
Requirement already satisfied: nvidia-cusparse-cu12==12.1.0.106 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (1
Requirement already satisfied: nvidia-nccl-cu12==2.21.5 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (2.21.5)
Requirement already satisfied: nvidia-nvtx-cu12==12.1.105 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (12.1.10
Requirement already satisfied: triton==3.1.0 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (3.1.0)
Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (1.13.1)
Requirement already satisfied: nvidia-nvjitlink-cu12 in /usr/local/lib/python3.11/dist-packages (from nvidia-cusolver-cu12==11.4
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from sympy==1.13.1->torch->thop) (
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->transformers)
```

```
  Building wheel for pretrainedmodels (setup.py) ... done
  Created wheel for pretrainedmodels: filename=pretrainedmodels-0.7.4-py3-none-any.whl size=60944 sha256=4defd8a98e216afe977d63c
  Stored in directory: /root/.cache/pip/wheels/5f/5b/96/fd94bc35962d7c6b699e8814db545155ac91d2b95785e1b035
Successfully built efficientnet-pytorch pretrainedmodels
Installing collected packages: munch, thop, efficientnet-pytorch, pretrainedmodels, segmentation-models-pytorch
Successfully installed efficientnet-pytorch-0.7.1 munch-4.0.0 pretrainedmodels-0.7.4 segmentation-models-pytorch-0.4.0 thop-0.1.
<torch.autograd.grad_mode.set_grad_enabled at 0x7b2d7e53f2d0>
```

Image Classification

You will be looking at image classification in the first part of this assignment, the goal of image classification is to identify subjects within a given image. In the previous assignment, you looked at using MNIST, which is also a classification task "which number is present", where for images the gold standard is Imagent "which class is present".

You can find out more information about Imagenet here:

https://en.wikipedia.org/wiki/ImageNet

Normally you would want to test classification on ImageNet as that's the dataset in which classification models tend to be trained on. However, the Imagenet dataset is not publicly available nor is it reasonable in size to download via Colab (100s of GBs).

Instead, you will use the Caltech101 dataset. However, Caltech101 uses 101 labels which do not correspond to the Imagenet labels. As such, you will need to also download a bigger classification model to serve as a baseline for accuracy comparisons.

More info can be found about the Caltech101 dataset here:

https://en.wikipedia.org/wiki/Caltech_101

Download the dataset you will be using: Caltech101

```
# convert to RGB class - some of the Caltech101 images are grayscale and do not match the tensor shapes
class ConvertToRGB:
    def __call__(self, image):
        # If grayscale image, convert to RGB
        if image.mode == "L":
            image = Image.merge("RGB", (image, image, image))
        return image

# Define transformations
transform = transforms.Compose([
    ConvertToRGB(), # first convert to RGB
    transforms.Resize((224, 224)),  # Most pretrained models expect 224x224 inputs
    transforms.ToTensor(),
    # this normalization is shared among all of the torch-hub models we will be using
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])

# Download the dataset
caltech101_dataset = datasets.Caltech101(root="./data", download=True, transform=transform)
```

```
Downloading...
From (original): https://drive.google.com/uc?id=137RyRjvTBkBiIfeYBNZBtViDHQ6_Ewsp
From (redirected): https://drive.usercontent.google.com/download?id=137RyRjvTBkBiIfeYBNZBtViDHQ6_Ewsp&confirm=t&uuid=5b1dbae2-be2c-4
To: /content/data/caltech101/101_ObjectCategories.tar.gz
100%|██████████| 132M/132M [00:03<00:00, 37.7MB/s]
Extracting ./data/caltech101/101_ObjectCategories.tar.gz to ./data/caltech101
Downloading...
From (original): https://drive.google.com/uc?id=175kQy3UsZ0wUEHZjqkUDdNVssr7bgh_m
From (redirected): https://drive.usercontent.google.com/download?id=175kQy3UsZ0wUEHZjqkUDdNVssr7bgh_m&confirm=t&uuid=856ec52c-688e-4
To: /content/data/caltech101/Annotations.tar
100%|██████████| 14.0M/14.0M [00:00<00:00, 155MB/s]
Extracting ./data/caltech101/Annotations.tar to ./data/caltech101
```

```
from torch.utils.data import DataLoader

# set a manual seed for determinism
torch.manual_seed(42)
dataloader = DataLoader(caltech101_dataset, batch_size=16, shuffle=True)
```

Create the dataloader with a batch size of 16. You are fixing the seed for reproducibility.

```
# download four classification models from torch-hub
resnet152_model = torchvision.models.resnet152(pretrained=True)
resnet50_model = torchvision.models.resnet50(pretrained=True)
resnet18_model = torchvision.models.resnet18(pretrained=True)
mobilenet_v2_model = torchvision.models.mobilenet_v2(pretrained=True)
```

```
# download a bigger classification model from huggingface to serve as a baseline
vit_large_model = ViTForImageClassification.from_pretrained('google/vit-large-patch16-224')
```

```
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated sin
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None`
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet152-394f9c45.pth" to /root/.cache/torch/hub/checkpoints/resnet152-394f9c45.
100%|██████████| 230M/230M [00:02<00:00, 104MB/s]
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None`
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to /root/.cache/torch/hub/checkpoints/resnet50-0676ba61.pt
100%|██████████| 97.8M/97.8M [00:01<00:00, 71.6MB/s]
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None`
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pt
100%|██████████| 44.7M/44.7M [00:00<00:00, 49.1MB/s]
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None`
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/mobilenet_v2-b0353104.pth" to /root/.cache/torch/hub/checkpoints/mobilenet_v2-b03
100%|██████████| 13.6M/13.6M [00:00<00:00, 81.3MB/s]
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it as
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
config.json: 100%    69.7k/69.7k [00:00<00:00, 1.43MB/s]
pytorch_model.bin: 100%    1.22G/1.22G [00:12<00:00, 128MB/s]
```

Move the models to the GPU and set them in eval mode. This will disable dropout regularization and batch norm statistic calculation.

```
resnet152_model = resnet152_model.to("cuda").eval()
resnet50_model = resnet50_model.to("cuda").eval()
resnet18_model = resnet18_model.to("cuda").eval()
mobilenet_v2_model = mobilenet_v2_model.to("cuda").eval()
vit_large_model = vit_large_model.to("cuda").eval()
```

Download a series of models for testing. The VIT-L/16 model will serve as a baseline - this is a more accurate vision transformer based model.

The other models you will use are:

- resnet 18
- resnet 50
- resnet 152
- mobilenet v2

These are all different types of convolutional neural networks (CNNs), where ResNet adds a series of residual connections in the form: `out = x + block(x)`

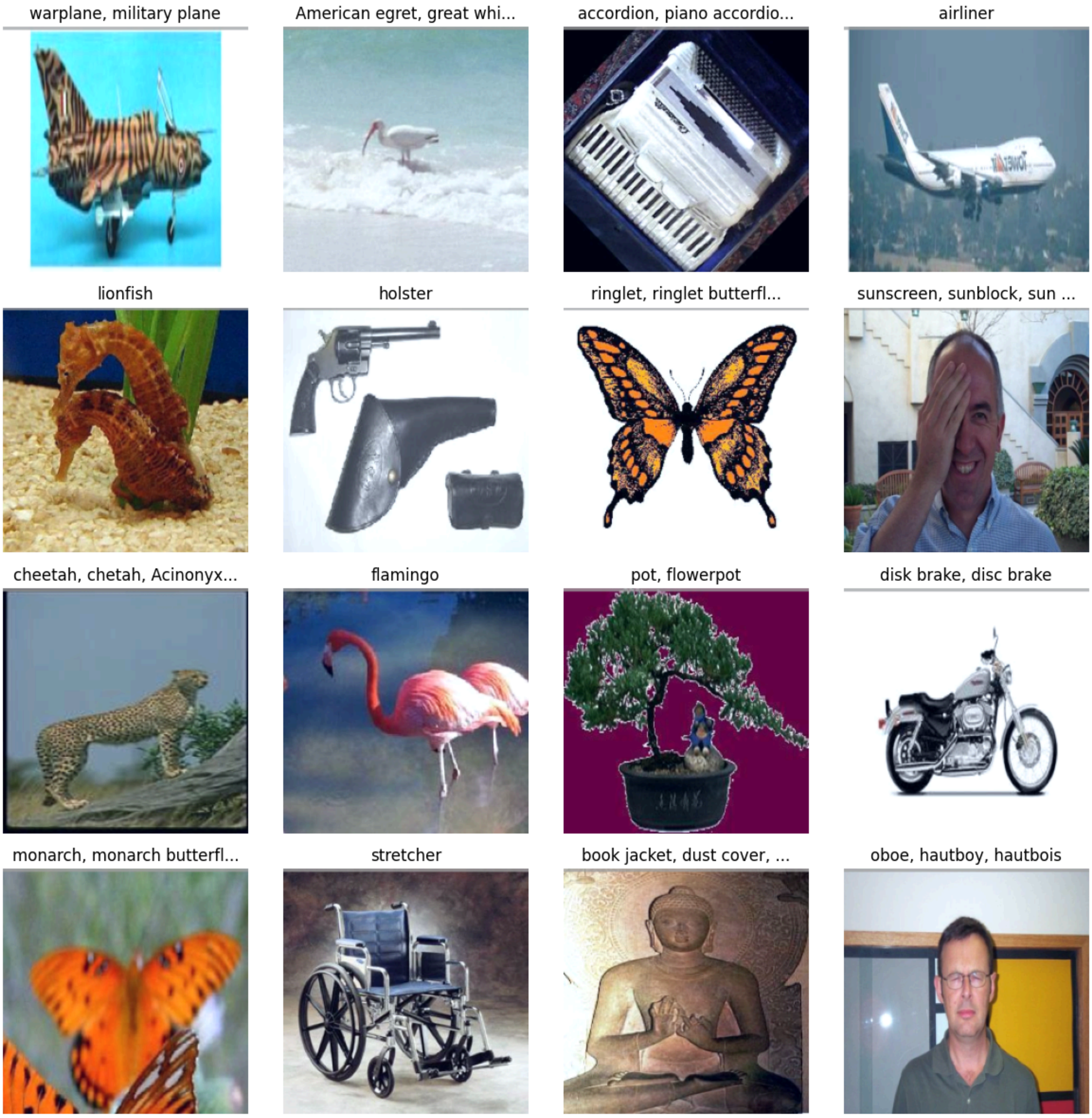
There's a good overview of the different versions here: https://towardsdatascience.com/understanding-and-visualizing-resnets-442284831be8

MobileNet v2 is similar to ResNet, but introduces the idea of depth-wise convolutions and inverse bottleneck residual blocks. You will only be using it as a point of comparison, however, you can find out more details regarding the structure from here if interested: https://medium.com/@luis_gonzales/a-look-at-mobilenetv2-inverted-residuals-and-linear-bottlenecks-d49f85c12423

Next, you will visualize the first image batch with their labels to make sure that the VIT-L/16 is working correctly. Luckily huggingface also implements an `id -> string` mapping, which will turn the classes into a human readable form.

```
# get the first batch
dataiter = iter(dataloader)
images, _ = next(dataiter)

# define a denorm helper function - this undoes the dataloader normalization so we can see the images better
def denormalize(tensor, mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]):
    """ Denormalizes an image tensor that was previously normalized. """
    for t, m, s in zip(tensor, mean, std):
        t.mul_(s).add_(m)
    return tensor

# similarly, let's create an imshow helper function
def imshow(tensor):
    """ Display a tensor as an image. """
    tensor = tensor.permute(1, 2, 0)  # Change from C,H,W to H,W,C
    tensor = denormalize(tensor)  # Denormalize if the tensor was normalized
    tensor = tensor*0.24 + 0.5 # fix the image range, it still wasn't between 0 and 1
```

```
      plt.imshow(tensor.clamp(0,1).cpu().numpy()) # plot the image
      plt.axis('off')

  # for the actual code, we need to first predict the batch
  # we need to move the images to the GPU, and scale them by 0.5 because VIT-L/16 uses a different normalization to the other models
  with torch.no_grad(): # this isn't strictly needed since we already disabled autograd, but we should do it for good measure
    output = vit_large_model(images.cuda()*0.5)

  # then we can sample the output using argmax (find the class with the highest probability)
  # here we are calling output.logits because huggingface returns a struct rather than a tuple
  # also, we apply argmax to the last dim (dim=-1) because that corresponds to the classes - the shape is B,C
  # and we also need to move the ids to the CPU from the GPU
  ids = output.logits.argmax(dim=-1).cpu()

  # next we will go through all of the ids and convert them into human readable labels
  # huggingface has the .config.id2label map, which helps.
  # notice that we are calling id.item() to get the raw contents of the ids tensor
  labels = []
  for id in ids:
    labels += [vit_large_model.config.id2label[id.item()]]

  # finally, let's plot the first 4 images
  max_label_len = 25
  fig, axes = plt.subplots(4, 4, figsize=(12, 12))
  for i in range(4):
      for j in range(4):
          idx = i*4 + j
          plt.sca(axes[i, j])
          imshow(images[idx])
          # we need to trim the labels because they sometimes are too long
          if len(labels[idx]) > max_label_len:
            trimmed_label = labels[idx][:max_label_len] + '...'
          else:
            trimmed_label = labels[idx]
          axes[i,j].set_title(trimmed_label)
  plt.tight_layout()
  plt.show()
```



Question 1

Given the above classifications, how well do you think the model does? Can you observe any limitations? If so, do you think that's related to the model size and complexity, or is it more likely related to the training set?

For more information, the class list can be found here: https://deeplearning.cms.waikato.ac.nz/user-guide/class-maps/IMAGENET/

Please answer below:

The model performs well in general but has limitations, as seen in the misclassification of a seahorse as a lionfish etc. This suggests that the issue is more likely related to the training set rather than just model size and complexity. If the training dataset lacks sufficient seahorse images or includes visually similar lionfish images, the model may struggle to distinguish them. However, model complexity could also play a role if the architecture is not powerful enough to extract fine-grained features. Improving the dataset diversity and fine-tuning the model could enhance accuracy.

Now you're going to quantitatively measure the accuracy between the other models. The first thing you need to do is clear the GPU cache, to prevent an out-of-memory error. To undestand this, let's look at the current GPU memory utilization.

```
# run nvidia-smi to view the memory usage. Notice the ! before the command, this sends the command to the shell rather than python
!nvidia-smi
```

```
Thu Jan 16 16:59:49 2025
+---------------------------------------------------------------------------------------+
| NVIDIA-SMI 535.104.05             Driver Version: 535.104.05   CUDA Version: 12.2     |
|-----------------------------------------+----------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |         Memory-Usage | GPU-Util  Compute M. |
|                                         |                      |               MIG M. |
|=========================================+======================+======================|
|   0  Tesla T4                       Off | 00000000:00:04.0 Off |                    0 |
| N/A   44C    P0              33W /  70W |   1901MiB / 15360MiB |      0%      Default |
|                                         |                      |                  N/A |
+-----------------------------------------+----------------------+----------------------+

+---------------------------------------------------------------------------------------+
| Processes:                                                                            |
|  GPU   GI   CI        PID   Type   Process name                            GPU Memory |
|        ID   ID                                                             Usage      |
|=======================================================================================|
+---------------------------------------------------------------------------------------+
```

```
# now you will manually invoke the python garbage collector using gc.collect()
gc.collect()
# and empty the GPU tensor cache - tensors that are no longer needed (activations essentially)
torch.cuda.empty_cache()
```

```
# run nvidia-smi again
!nvidia-smi
```

```
Thu Jan 16 16:59:50 2025
+---------------------------------------------------------------------------------------+
| NVIDIA-SMI 535.104.05             Driver Version: 535.104.05   CUDA Version: 12.2     |
|-----------------------------------------+----------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |         Memory-Usage | GPU-Util  Compute M. |
|                                         |                      |               MIG M. |
|=========================================+======================+======================|
|   0  Tesla T4                       Off | 00000000:00:04.0 Off |                    0 |
| N/A   44C    P0              26W /  70W |   1715MiB / 15360MiB |      0%      Default |
|                                         |                      |                  N/A |
+-----------------------------------------+----------------------+----------------------+

+---------------------------------------------------------------------------------------+
| Processes:                                                                            |
|  GPU   GI   CI        PID   Type   Process name                            GPU Memory |
|        ID   ID                                                             Usage      |
|=======================================================================================|
+---------------------------------------------------------------------------------------+
```

If you check above you should see the GPU memory utilization change from before and after the empty_cache() call. Memory management is one of the quirks that must be considered when dealing with accelerators like a GPU. Unlike with a CPU, there is no swap file to page memory in and out of the device. Instead, this must be handled by the user. When too much of the GPU memory is used, the driver will throw an out-of-memory error (commonly referred to as OOM). In this case, the process often ends up in an unrecoverable state and needs to be restarted to fully reset the memory utilization to zero.

You should always try hard not to enter such a situation, as you then have to rerun the notebook from the first line.

Question 2

Given the above, why is the GPU memory utilization not zero? Does the current utilization match what you would expect? Please answer below:

The GPU memory utilization is not zero because calling `torch.cuda.empty_cache()` only releases unused memory back to the GPU but does not clear memory occupied by active tensors. If there are still allocated tensors in use, they will continue consuming memory. Additionally, some frameworks (e.g., PyTorch) retain a memory pool for efficiency, meaning memory might still be reserved even if not actively used.

Whether the current utilization matches expectations depends on the specific operations performed. If large tensors were allocated and are still in scope, some memory usage is expected. However, if the utilization remains unexpectedly high, it might indicate memory fragmentation or lingering references to tensors that should be deleted explicitly. Using `del tensor_name` and calling `torch.cuda.empty_cache()` again might help free more memory.

Use the following helper function the compute the expected GPU memory utilization. You will not be able to calculate the memory exactly as there is additional overhead that cannot be accounted for (which includes the underlying CUDA kernels code), but you should get within ~200

MBs.

Question 3

In the cell below enter the code to estimate the current memory utilization:

```
# helper function to get element sizes in bytes
def sizeof_tensor(tensor):
    # Get the size of the data type
    if (tensor.dtype == torch.float32) or (tensor.dtype == torch.float):      # float32 (single precision float)
        bytes_per_element = 4
    elif (tensor.dtype == torch.float16) or (tensor.dtype == torch.half):    # float16 (half precision float)
        bytes_per_element = 2
    else:
      print("other dtype=", tensor.dtype)
    return bytes_per_element

# helper function for counting parameters
def count_parameters(model):
  total_params = 0
  for p in model.parameters():
    total_params += p.numel()
  return total_params

# estimate the current GPU memory utilization
```

Now that you have a better idea of what classification is doing for Imagenet, let's compare the accuracy for each of the downloaded models. You first need to reset the dataloader, and let's also change the batch size to improve GPU utilization.

```
# set a manual seed for determinism
torch.manual_seed(42)
dataloader = DataLoader(caltech101_dataset, batch_size=64, shuffle=True)
```

Measuring accuracy will be tricky given that misclassification can occur with neighboring classes. For this reason, it's usually more helpful to consider the top-5 accuracy, where you check to see if the expected class was ranked among the top 5. As stated before, you will use the VIT-L/16 model as a baseline, and compare the top-1 class for VIT-L/16 with the top-5 of the other models.

Because this takes a while, let's only compute the first 10 batches. That should be enough to do some rough analysis. Since you are using a batch of 64, 10 batches are 640 images.

```
# Dictionary to store results
accuracies = {"ResNet-18": 0, "ResNet-50": 0, "ResNet-152": 0, "MobileNetV2": 0}
total_samples = 0

num_batches = len(dataloader)

t_start = time.time()

with torch.no_grad():
  for i, (inputs, _)in tqdm(enumerate(dataloader), desc="Processing batches", total=num_batches):

        if i > 10:
          break

        # move the inputs to the GPU
        inputs = inputs.to("cuda")

        # Get top prediction from resnet152
        #baseline_preds = resnet152_model(inputs).argmax(dim=1)
        output = vit_large_model(inputs*0.5)
        baseline_preds = output.logits.argmax(-1)

        # ResNet-18 predictions
        logits_resnet18 = resnet18_model(inputs)
        top5_preds_resnet18 = logits_resnet18.topk(5, dim=1).indices
        matches_resnet18 = (baseline_preds.unsqueeze(1) == top5_preds_resnet18).any(dim=1).float().sum().item()

        # ResNet-50 predictions
        logits_resnet50 = resnet50_model(inputs)
        top5_preds_resnet50 = logits_resnet50.topk(5, dim=1).indices
        matches_resnet50 = (baseline_preds.unsqueeze(1) == top5_preds_resnet50).any(dim=1).float().sum().item()

        # ResNet-152 predictions
        logits_resnet152 = resnet152_model(inputs)
        top5_preds_resnet152 = logits_resnet152.topk(5, dim=1).indices
        matches_resnet152 = (baseline_preds.unsqueeze(1) == top5_preds_resnet152).any(dim=1).float().sum().item()
```

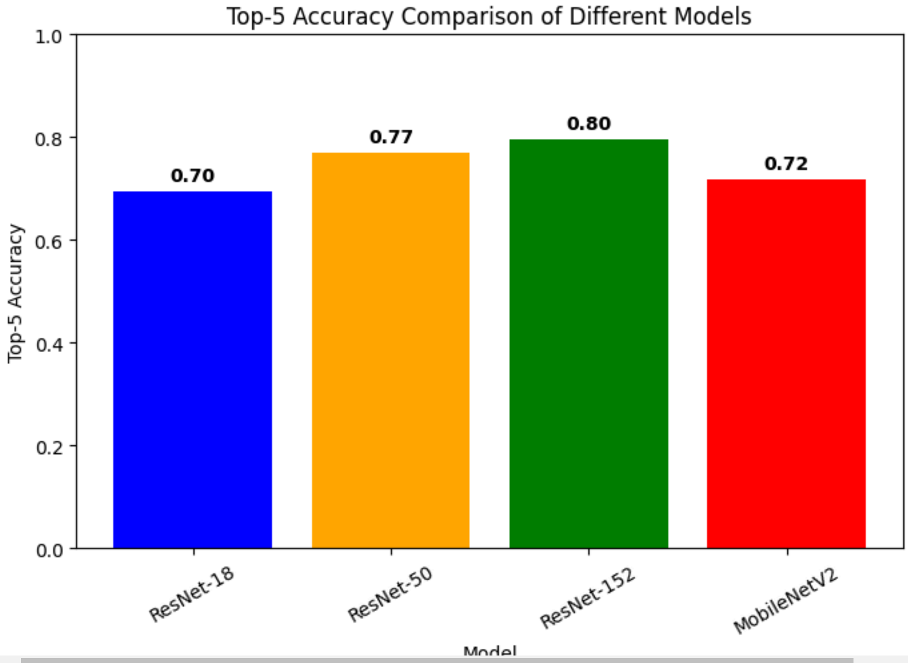
```
        # MobileNetV2 predictions
        logits_mobilenetv2 = mobilenet_v2_model(inputs)
        top5_preds_mobilenetv2 = logits_mobilenetv2.topk(5, dim=1).indices
        matches_mobilenetv2 = (baseline_preds.unsqueeze(1) == top5_preds_mobilenetv2).any(dim=1).float().sum().item()

        # Update accuracies
        accuracies["ResNet-18"] += matches_resnet18
        accuracies["ResNet-50"] += matches_resnet50
        accuracies["ResNet-152"] += matches_resnet152
        accuracies["MobileNetV2"] += matches_mobilenetv2
        total_samples += inputs.size(0)

print()
print(f"took {time.time()-t_start}s")

# Finalize the accuracies
accuracies["ResNet-18"] /= total_samples
accuracies["ResNet-50"] /= total_samples
accuracies["ResNet-152"] /= total_samples
accuracies["MobileNetV2"] /= total_samples
```

```
Processing batches:   8%|█         | 11/136 [00:30<05:44,  2.76s/it]

took 30.326213121414185s
```

Question 4

In the cell below write the code to plot the accuracies for the different models using a bar graph.

```
import matplotlib.pyplot as plt

# Model names and corresponding accuracies
model_names = list(accuracies.keys())
accuracy_values = list(accuracies.values())

# Plotting the bar chart
plt.figure(figsize=(8, 5))
bars = plt.bar(model_names, accuracy_values, color=['blue', 'orange', 'green', 'red'])

# Adding labels and title
plt.xlabel("Model")
plt.ylabel("Top-5 Accuracy")
plt.title("Top-5 Accuracy Comparison of Different Models")
plt.ylim(0, 1)  # Since accuracy is between 0 and 1
plt.xticks(rotation=30)  # Rotate x labels for better readability

# Annotate each bar with accuracy value
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval + 0.02, f"{yval:.2f}", ha="center", fontsize=10, fontweight="bold")

# Display the plot
plt.show()
```



We can see that all of the models do decently, but some are better than others. Why is this and is there a quantifiable trend?

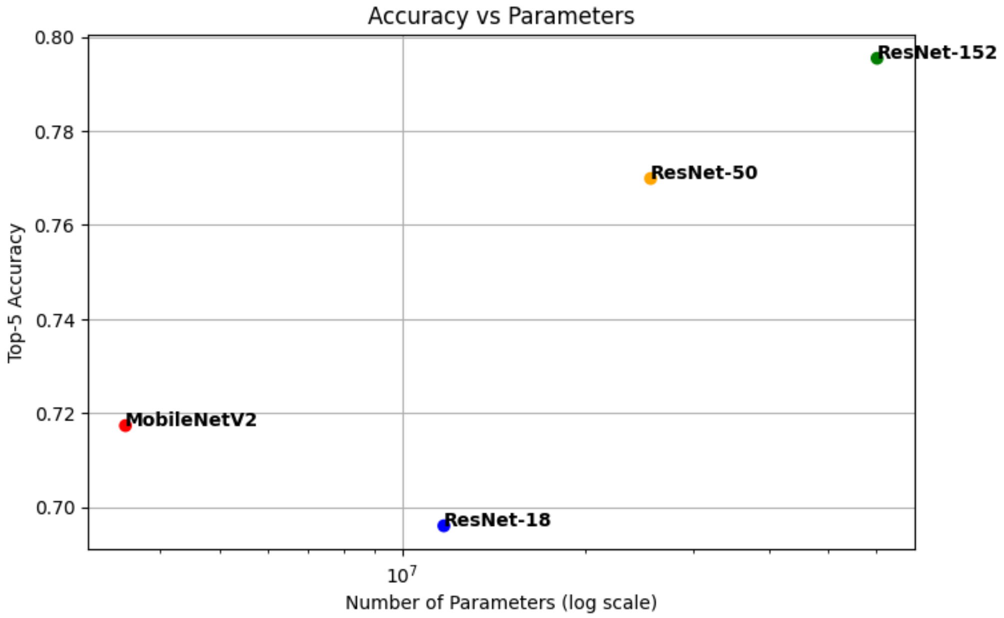
Question 5

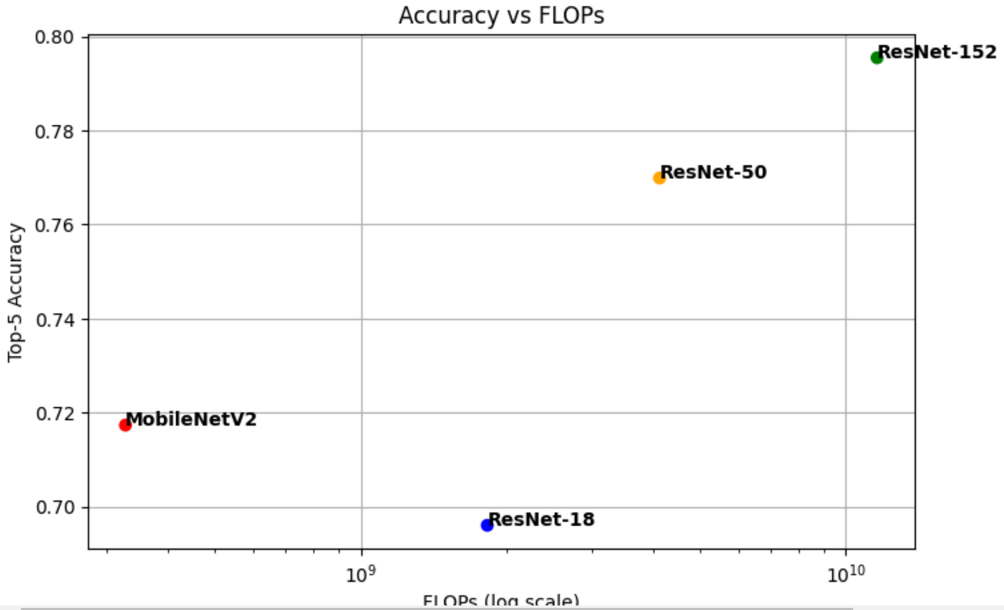
To get a better understanding, let's compute the number of flops and parameters for each model based on a single image input. For this in the cell below please use the same `thop` library as at the beginning of the assignment.

```
import torch
import thop
import matplotlib.pyplot as plt

# Function to profile FLOPs and Parameters
def profile(model):
    input_tensor = torch.randn(1, 3, 224, 224).cuda()  # Dummy input on GPU
    flops, params = thop.profile(model, inputs=(input_tensor,), verbose=False)
    print(f"Model {model.__class__.__name__} has {params:,} params and uses {flops:,} FLOPs")
    return flops, params

# Define models
models = {
    "ResNet-18": resnet18_model,
    "ResNet-50": resnet50_model,
    "ResNet-152": resnet152_model,
    "MobileNetV2": mobilenet_v2_model
}

# Profile all models
flops_params = {}
for model_name, model in models.items():
    flops, params = profile(model)
    flops_params[model_name] = {"FLOPs": flops, "Parameters": params}

# Extract data for plotting
model_names = list(accuracies.keys())
accuracy_values = list(accuracies.values())
flops_values = [flops_params[model]["FLOPs"] for model in model_names]
params_values = [flops_params[model]["Parameters"] for model in model_names]

# Plot Accuracy vs Parameters
plt.figure(figsize=(8, 5))
plt.scatter(params_values, accuracy_values, color=['blue', 'orange', 'green', 'red'])
for i, txt in enumerate(model_names):
    plt.annotate(txt, (params_values[i], accuracy_values[i]), fontsize=10, fontweight="bold")
plt.xscale("log")  # Log scale for better visualization
plt.xlabel("Number of Parameters (log scale)")
plt.ylabel("Top-5 Accuracy")
plt.title("Accuracy vs Parameters")
plt.grid(True)
plt.show()

# Plot Accuracy vs FLOPs
plt.figure(figsize=(8, 5))
```

```
plt.scatter(flops_values, accuracy_values, color=['blue', 'orange', 'green', 'red'])
for i, txt in enumerate(model_names):
    plt.annotate(txt, (flops_values[i], accuracy_values[i]), fontsize=10, fontweight="bold")
plt.xscale("log")  # Log scale for better visualization
plt.xlabel("FLOPs (log scale)")
plt.ylabel("Top-5 Accuracy")
plt.title("Accuracy vs FLOPs")
plt.grid(True)
plt.show()
```

```
Model ResNet has 11,689,512.0 params and uses 1,824,033,792.0 FLOPs
Model ResNet has 25,557,032.0 params and uses 4,133,742,592.0 FLOPs
Model ResNet has 60,192,808.0 params and uses 11,603,945,472.0 FLOPs
Model MobileNetV2 has 3,504,872.0 params and uses 327,486,720.0 FLOPs
```





Question 6

Do you notice any trends here? Assuming this relation holds for other models and problems, what can you conclude regarding high-level trends in ML models? Please enter your answer in the cell below:

Larger models with more parameters and FLOPs generally achieve higher accuracy, as seen with ResNet-152. However, the accuracy gains diminish with increased model size. Lightweight models like MobileNetV2 offer efficiency at the cost of some accuracy. There is a trade-off between accuracy and computational cost. For real-time or resource-constrained applications, smaller models are preferred. Optimizations like pruning and quantization can help maintain accuracy while reducing computational requirements.

Performance and Precision

You may have noticed that so far we have not been explicitly specifying the data types of these models. We can do this because torch will default to using float32 (32-bit single-precision). However, this is not always necessary nor desirable. There are currently a large number of alternative formats (with fewer bits per value), many of which are custom to specific accelerators. We will eventually cover these later in the course, but for now we can consider the second most common type on the GPU: FP16 (half-precision floating-point).

As the name suggests, FP16 only uses 16 bits per value rather than 32. GPUs are specifically designed to handle this datatype and all of the newer ones can execute either one FP32 or two FP16 operations per ALU.

Here's an overview of different precision types: https://moocaholic.medium.com/fp64-fp32-fp16-bfloat16-tf32-and-other-members-of-the-zoo-a1ca7897d407

Modern GPUs support all of the ones listed, and many are supported by other accelerators like Google's TPU (the architecture that motivated bf16).

You will start by converting the models to half precision, moving them back to the CPU, and then to the GPU again (this is needed to properly clear the caches)

```
# convert the models to half
resnet152_model = resnet152_model.half()
resnet50_model = resnet50_model.half()
resnet18_model = resnet18_model.half()
mobilenet_v2_model = mobilenet_v2_model.half()
vit_large_model = vit_large_model.half()

# move them to the CPU
resnet152_model = resnet152_model.cpu()
resnet50_model = resnet50_model.cpu()
resnet18_model = resnet18_model.cpu()
mobilenet_v2_model = mobilenet_v2_model.cpu()
vit_large_model = vit_large_model.cpu()

# clean up the torch and CUDA state
gc.collect()
torch.cuda.empty_cache()

# move them back to the GPU
resnet152_model = resnet152_model.cuda()
resnet50_model = resnet50_model.cuda()
resnet18_model = resnet18_model.cuda()
mobilenet_v2_model = mobilenet_v2_model.cuda()
vit_large_model = vit_large_model.cuda()


# run nvidia-smi again
!nvidia-smi
```

```
Thu Jan 16 17:00:23 2025
+---------------------------------------------------------------------------------------+
| NVIDIA-SMI 535.104.05             Driver Version: 535.104.05   CUDA Version: 12.2     |
|-----------------------------------------+----------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |         Memory-Usage | GPU-Util  Compute M. |
|                                         |                      |               MIG M. |
|=========================================+======================+======================|
|   0  Tesla T4                       Off | 00000000:00:04.0 Off |                    0 |
| N/A   57C    P0              27W /  70W |    935MiB / 15360MiB |     21%      Default |
|                                         |                      |                  N/A |
+-----------------------------------------+----------------------+----------------------+

+---------------------------------------------------------------------------------------+
| Processes:                                                                            |
|  GPU   GI   CI        PID   Type   Process name                            GPU Memory |
|        ID   ID                                                             Usage      |
|=======================================================================================|
+---------------------------------------------------------------------------------------+
```

Question 7

Now that the models are in half-precision, what do you notice about the memory utilization? Is the utilization what you would expect from your previous expected calculation given the new data types? Please answer below:

Converting models to half-precision (FP16) reduces memory usage by approximately 50% compared to single-precision (FP32). The Tesla T4 is using 935 MiB out of 15360 MiB, which aligns with expectations for FP16 models. In FP16, each parameter consumes 2 bytes instead of 4 bytes, leading to lower memory utilization. This reduced memory usage allows more efficient use of GPU resources. The observed memory usage is consistent with the expected reduction in memory when switching to FP16. Overall, the conversion to FP16 optimizes memory utilization for the models.

Let's see if inference is any faster now. First reset the data-loader like before.

```
# set a manual seed for determinism
torch.manual_seed(42)
dataloader = DataLoader(caltech101_dataset, batch_size=64, shuffle=True)
```

And you can re-run the inference code. Notice that you also need to convert the inptus to .half()

```
# Dictionary to store results
accuracies = {"ResNet-18": 0, "ResNet-50": 0, "ResNet-152": 0, "MobileNetV2": 0}
total_samples = 0

num_batches = len(dataloader)

t_start = time.time()

with torch.no_grad():
  for i, (inputs, _)in tqdm(enumerate(dataloader), desc="Processing batches", total=num_batches):

        if i > 10:
          break

        # move the inputs to the GPU
        inputs = inputs.to("cuda").half()

        # Get top prediction from resnet152
        #baseline_preds = resnet152_model(inputs).argmax(dim=1)
        output = vit_large_model(inputs*0.5)
        baseline_preds = output.logits.argmax(-1)

        # ResNet-18 predictions
        logits_resnet18 = resnet18_model(inputs)
        top5_preds_resnet18 = logits_resnet18.topk(5, dim=1).indices
        matches_resnet18 = (baseline_preds.unsqueeze(1) == top5_preds_resnet18).any(dim=1).float().sum().item()

        # ResNet-50 predictions
        logits_resnet50 = resnet50_model(inputs)
        top5_preds_resnet50 = logits_resnet50.topk(5, dim=1).indices
        matches_resnet50 = (baseline_preds.unsqueeze(1) == top5_preds_resnet50).any(dim=1).float().sum().item()

        # ResNet-152 predictions
        logits_resnet152 = resnet152_model(inputs)
        top5_preds_resnet152 = logits_resnet152.topk(5, dim=1).indices
        matches_resnet152 = (baseline_preds.unsqueeze(1) == top5_preds_resnet152).any(dim=1).float().sum().item()

        # MobileNetV2 predictions
        logits_mobilenetv2 = mobilenet_v2_model(inputs)
        top5_preds_mobilenetv2 = logits_mobilenetv2.topk(5, dim=1).indices
        matches_mobilenetv2 = (baseline_preds.unsqueeze(1) == top5_preds_mobilenetv2).any(dim=1).float().sum().item()

        # Update accuracies
        accuracies["ResNet-18"] += matches_resnet18
        accuracies["ResNet-50"] += matches_resnet50
        accuracies["ResNet-152"] += matches_resnet152
        accuracies["MobileNetV2"] += matches_mobilenetv2
        total_samples += inputs.size(0)

print()
print(f"took {time.time()-t_start}s")

# Finalize the accuracies
accuracies["ResNet-18"] /= total_samples
accuracies["ResNet-50"] /= total_samples
accuracies["ResNet-152"] /= total_samples
accuracies["MobileNetV2"] /= total_samples
```

```
Processing batches:   8%|█          | 11/136 [00:10<01:54,  1.09it/s]
took 10.069212436676025s
```

Question 8

Did you observe a speedup? Was this result what you expected? What are the pros and cons to using a lower-precision format? Please answer below:

Yes, a speedup is observed with half-precision (FP16), leading to faster batch processing and reduced time, which aligns with expectations.

Pros: FP16 reduces memory usage and increases computation speed, allowing for larger models or batch sizes.

Cons: The reduced precision may affect model accuracy and stability, especially for tasks needing high numerical accuracy.

Overall, FP16 offers faster processing but requires careful consideration of potential trade-offs in precision and stability.

Question 9

Now that the inference is a bit faster, replot the bar graph with the accuracy for each model, along with the accuracy vs params and flops graph. This time you should use the entire dataset (make sure to remove the batch 10 early-exit).

```
import matplotlib.pyplot as plt
import thop
import torch
from tqdm import tqdm

# Profiling helper function
def profile(model):
    # create a random input of shape B,C,H,W - batch=1 for 1 image, C=3 for RGB, H and W = 224 for the expected images size
    input = torch.randn(1,3,224,224).cuda()  # don't forget to move it to the GPU since that's where the models are

    # convert input to half-precision
    input = input.half()

    # profile the model
    flops, params = thop.profile(model, inputs=(input,), verbose=False)

    # we can create a printout out to see the progress
    print(f"model {model.__class__.__name__} has {params:,} params and uses {flops:,} FLOPs")
    return flops, params

# Initialize models (ensure you have all model instances like resnet18_model, resnet50_model, etc.)
# e.g., resnet18_model = torchvision.models.resnet18(pretrained=True).cuda().half()

accuracies = {"ResNet-18": 0, "ResNet-50": 0, "ResNet-152": 0, "MobileNetV2": 0}
total_samples = 0
num_batches = len(dataloader)

t_start = time.time()

# Loop through the entire dataset
with torch.no_grad():
    for i, (inputs, _) in tqdm(enumerate(dataloader), desc="Processing batches", total=num_batches):
        # Ensure inputs are in half-precision
        inputs = inputs.half().to("cuda")

        # Get top prediction from the models
        output = vit_large_model(inputs * 0.5)
        baseline_preds = output.logits.argmax(-1)

        # ResNet-18 predictions
        logits_resnet18 = resnet18_model(inputs)
        top5_preds_resnet18 = logits_resnet18.topk(5, dim=1).indices
        matches_resnet18 = (baseline_preds.unsqueeze(1) == top5_preds_resnet18).any(dim=1).float().sum().item()

        # ResNet-50 predictions
        logits_resnet50 = resnet50_model(inputs)
        top5_preds_resnet50 = logits_resnet50.topk(5, dim=1).indices
        matches_resnet50 = (baseline_preds.unsqueeze(1) == top5_preds_resnet50).any(dim=1).float().sum().item()

        # ResNet-152 predictions
        logits_resnet152 = resnet152_model(inputs)
        top5_preds_resnet152 = logits_resnet152.topk(5, dim=1).indices
        matches_resnet152 = (baseline_preds.unsqueeze(1) == top5_preds_resnet152).any(dim=1).float().sum().item()

        # MobileNetV2 predictions
        logits_mobilenetv2 = mobilenet_v2_model(inputs)
        top5_preds_mobilenetv2 = logits_mobilenetv2.topk(5, dim=1).indices
        matches_mobilenetv2 = (baseline_preds.unsqueeze(1) == top5_preds_mobilenetv2).any(dim=1).float().sum().item()

        # Update accuracies
        accuracies["ResNet-18"] += matches_resnet18
        accuracies["ResNet-50"] += matches_resnet50
        accuracies["ResNet-152"] += matches_resnet152
        accuracies["MobileNetV2"] += matches_mobilenetv2
        total_samples += inputs.size(0)

print()
print(f"took {time.time()-t_start}s")

# Finalize the accuracies
accuracies["ResNet-18"] /= total_samples
accuracies["ResNet-50"] /= total_samples
```

```
    accuracies["ResNet-50"] /= total_samples
    accuracies["ResNet-152"] /= total_samples
    accuracies["MobileNetV2"] /= total_samples

    # Profiling models for params and FLOPs
    flops_params = {}
    for model_name, model in models.items():
        flops, params = profile(model)
        flops_params[model_name] = {"FLOPs": flops, "Params": params}

    # Now, plotting the results

    # Accuracy bar plot
    plt.figure(figsize=(12, 5))
    plt.subplot(1, 2, 1)
    plt.bar(accuracies.keys(), accuracies.values(), color=['blue', 'green', 'red', 'purple'])
    plt.title("Model Accuracies")
    plt.xlabel("Model")
    plt.ylabel("Accuracy")

    # Accuracy vs Params and FLOPs plot
    plt.subplot(1, 2, 2)
    params = [flops_params[model_name]["Params"] for model_name in accuracies.keys()]
    flops = [flops_params[model_name]["FLOPs"] for model_name in accuracies.keys()]

    plt.scatter(params, accuracies.values(), color='blue', label='Accuracy vs Params')
    plt.scatter(flops, accuracies.values(), color='green', label='Accuracy vs FLOPs')
    plt.xscale("log")
    plt.yscale("linear")
```

Classification and Performance

Make sure you are connected to a T4 GPU runtime. The following code should report true if you are.

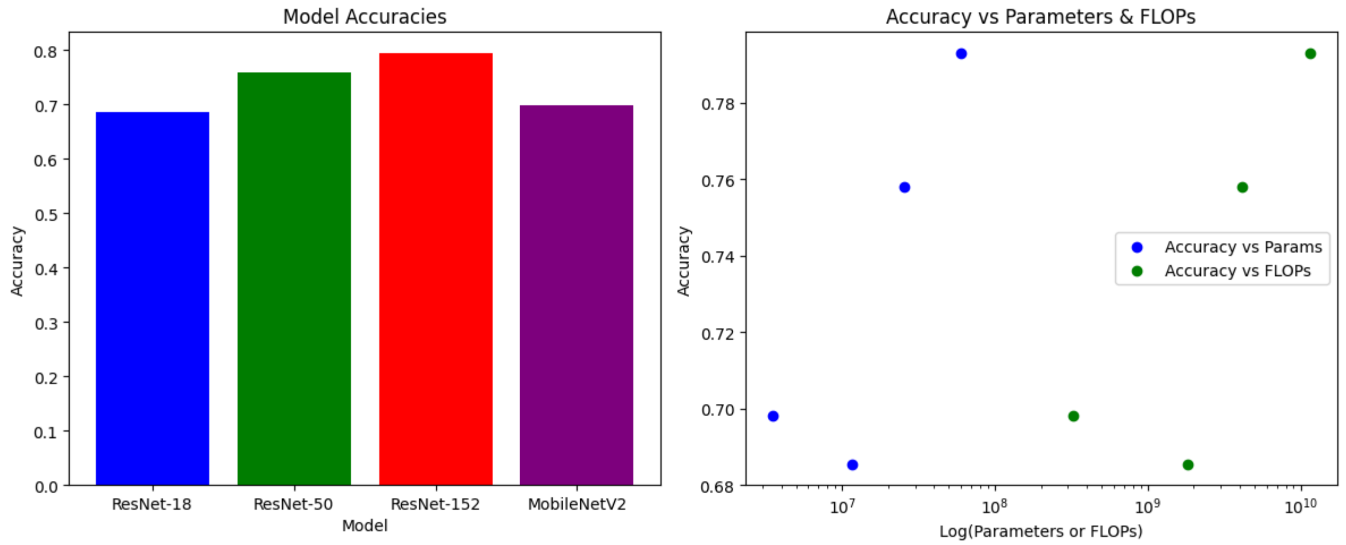
Question 9

Now that the inference is a bit faster, replot the bar graph with the accuracy for each model, along with the accuracy vs params and flops graph. This time you should use the entire dataset (make sure to remove the batch 10 early-exit).

```
import matplotlib.pyplot as plt
import thop
import torch
from tqdm import tqdm

# Profiling helper function
def profile(model):
    # create a random input of shape B,C,H,W - batch=1 for 1 image, C=3 for RGB, H and W = 224 for the expected images size
    input = torch.randn(1,3,224,224).cuda()  # don't forget to move it to the GPU since that's where the models are

    # convert input to half-precision
    input = input.half()

    # profile the model
    flops, params = thop.profile(model, inputs=(input,), verbose=False)

    # we can create a printout out to see the progress
    print(f"model {model.__class__.__name__} has {params:,} params and uses {flops:,} FLOPs")
    return flops, params

# Initialize models (ensure you have all model instances like resnet18_model, resnet50_model, etc.)
# e.g., resnet18_model = torchvision.models.resnet18(pretrained=True).cuda().half()

accuracies = {"ResNet-18": 0, "ResNet-50": 0, "ResNet-152": 0, "MobileNetV2": 0}
total_samples = 0
num_batches = len(dataloader)

t_start = time.time()

# Loop through the entire dataset
with torch.no_grad():
    for i, (inputs, _) in tqdm(enumerate(dataloader), desc="Processing batches", total=num_batches):
        # Ensure inputs are in half-precision
        inputs = inputs.half().to("cuda")

        # Get top prediction from the models
        output = vit_large_model(inputs * 0.5)
        baseline_preds = output.logits.argmax(-1)

        # ResNet-18 predictions
        logits_resnet18 = resnet18_model(inputs)
        top5_preds_resnet18 = logits_resnet18.topk(5, dim=1).indices
        matches_resnet18 = (baseline_preds.unsqueeze(1) == top5_preds_resnet18).any(dim=1).float().sum().item()

        # ResNet-50 predictions
        logits_resnet50 = resnet50_model(inputs)
        top5_preds_resnet50 = logits_resnet50.topk(5, dim=1).indices
        matches_resnet50 = (baseline_preds.unsqueeze(1) == top5_preds_resnet50).any(dim=1).float().sum().item()

        # ResNet-152 predictions
        logits_resnet152 = resnet152_model(inputs)
        top5_preds_resnet152 = logits_resnet152.topk(5, dim=1).indices
        matches_resnet152 = (baseline_preds.unsqueeze(1) == top5_preds_resnet152).any(dim=1).float().sum().item()

        # MobileNetV2 predictions
        logits_mobilenetv2 = mobilenet_v2_model(inputs)
        top5_preds_mobilenetv2 = logits_mobilenetv2.topk(5, dim=1).indices
        matches_mobilenetv2 = (baseline_preds.unsqueeze(1) == top5_preds_mobilenetv2).any(dim=1).float().sum().item()

        # Update accuracies
        accuracies["ResNet-18"] += matches_resnet18
        accuracies["ResNet-50"] += matches_resnet50
        accuracies["ResNet-152"] += matches_resnet152
        accuracies["MobileNetV2"] += matches_mobilenetv2
        total_samples += inputs.size(0)

print()
print(f"took {time.time()-t_start}s")
```

```
# Finalize the accuracies
accuracies["ResNet-18"] /= total_samples
accuracies["ResNet-50"] /= total_samples
accuracies["ResNet-152"] /= total_samples
accuracies["MobileNetV2"] /= total_samples

# Profiling models for params and FLOPs
flops_params = {}
for model_name, model in models.items():
    flops, params = profile(model)
    flops_params[model_name] = {"FLOPs": flops, "Params": params}

# Now, plotting the results

# Accuracy bar plot
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.bar(accuracies.keys(), accuracies.values(), color=['blue', 'green', 'red', 'purple'])
plt.title("Model Accuracies")
plt.xlabel("Model")
plt.ylabel("Accuracy")

# Accuracy vs Params and FLOPs plot
plt.subplot(1, 2, 2)
params = [flops_params[model_name]["Params"] for model_name in accuracies.keys()]
flops = [flops_params[model_name]["FLOPs"] for model_name in accuracies.keys()]

plt.scatter(params, accuracies.values(), color='blue', label='Accuracy vs Params')
plt.scatter(flops, accuracies.values(), color='green', label='Accuracy vs FLOPs')
plt.xscale("log")
plt.yscale("linear")
plt.title("Accuracy vs Parameters & FLOPs")
plt.xlabel("Log(Parameters or FLOPs)")
plt.ylabel("Accuracy")
plt.legend()

plt.tight_layout()
plt.show()
```

```
Processing batches: 100%|██████████| 136/136 [02:02<00:00,  1.11it/s]

took 122.42974066734314s
model ResNet has 11,689,512.0 params and uses 1,824,033,792.0 FLOPs
model ResNet has 25,557,032.0 params and uses 4,133,742,592.0 FLOPs
model ResNet has 60,192,808.0 params and uses 11,603,945,472.0 FLOPs
model MobileNetV2 has 3,504,872.0 params and uses 327,486,720.0 FLOPs
```



Question 10

Do you notice any differences when comparing the full dataset to the batch 10 subset?

When comparing the full dataset to the batch 10 subset, you may observe the following:

The accuracy on the full dataset will likely be more reliable and representative of the model's true performance. Inference speed will be slower on the full dataset, as more data is being processed. Memory utilization will be higher for the full dataset due to processing more data, although smaller batches like batch 10 use less memory. FLOPs and parameters remain constant but will accumulate with more data. The batch 10 subset may offer faster processing but could give a less accurate assessment. The full dataset provides a better estimate of the model's real-world performance.