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)
```

```
Requirement already satisfied: numpy>=1.19.3 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch) (1.26.4)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch) (11.1.0)
Collecting pretrainedmodels>=0.7.1 (from segmentation-models-pytorch)
  Downloading pretrainedmodels-0.7.4.tar.gz (58 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 58.8/58.8 kB 5.7 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) (0.20.1+cu121)
Requirement already satisfied: tqdm>=4.42.1 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch) (4.67.1)
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->segmentation-models-pytorch) (2024.10.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.24->segmentation-models-pytorch) (4.12.2)
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) (12.1.105)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.1.105 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (12.1.105)
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Requirement already satisfied: nvidia-cublas-cu12==12.1.3.1 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (12.1.3.1)
Requirement already satisfied: nvidia-cufft-cu12==11.0.2.54 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (11.0.2.54)
Requirement already satisfied: nvidia-curand-cu12==10.3.2.106 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (10.3.2.106)
Requirement already satisfied: nvidia-cusolver-cu12==11.4.5.107 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (11.4.5.107)
Requirement already satisfied: nvidia-cusparse-cu12==12.1.0.106 in /usr/local/lib/python3.11/dist-packages (from torch->thop) (12.1.0.106)
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) (12.1.105)
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==11.4.5.107->torch->thop) (12.6.85)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from sympy==1.13.1->torch->thop) (1.3.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (2024.12.14)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from jinja2->torch->thop) (3.0.2)
Downloading thop-0.1.1.post2209072238-py3-none-any.whl (15 kB)
Downloading segmentation_models_pytorch-0.4.0-py3-none-any.whl (121 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 121.3/121.3 kB 12.6 MB/s eta 0:00:00
Downloading munch-4.0.0-py2.py3-none-any.whl (9.9 kB)
Building wheels for collected packages: efficientnet-pytorch, pretrainedmodels
  Building wheel for efficientnet-pytorch (setup.py) ... done
  Created wheel for efficientnet-pytorch: filename=efficientnet_pytorch-0.7.1-py3-none-any.whl size=16424 sha256=ff20fd01a952d4e7efd41ddfa251b89fa9c4e040330fba00281556a71ed131df
  Stored in directory: /root/.cache/pip/wheels/8b/6f/9b/231a832f811ab6ebb1b32455b177ffc6b8b1cd8de19de70c09
  Building wheel for pretrainedmodels (setup.py) ... done
  Created wheel for pretrainedmodels: filename=pretrainedmodels-0.7.4-py3-none-any.whl size=60944 sha256=40f0c4b4a933db9db58004bb68daf08f4183e52c8e3e2d56bfb76d3ad05bbd9a
  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-0.1.1.post2209072238
<torch.autograd.grad_mode.set_grad_enabled at 0x7c1e371af2d0>
```

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=74694879-f215-4d93-a79a-df0155b6fdff
To: /content/data/caltech101/101_ObjectCategories.tar.gz
100%|██████████| 132M/132M [00:00<00:00, 154MB/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=bdb03ea6-3c19-4dc1-81ae-fd2f688dbfc8
To: /content/data/caltech101/Annotations.tar
100%|██████████| 14.0M/14.0M [00:00<00:00, 122MB/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 since 0.13 and may be removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=ResNet152_Weights.IMAGENET1K_V1`. You can
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet152-394f9c45.pth" to /root/.cache/torch/hub/checkpoints/resnet152-394f9c45.pth
100%|██████████| 230M/230M [00:01<00:00, 167MB/s]
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=ResNet50_Weights.IMAGENET1K_V1`. You can a
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to /root/.cache/torch/hub/checkpoints/resnet50-0676ba61.pth
100%|██████████| 97.8M/97.8M [00:03<00:00, 31.5MB/s]
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=ResNet18_Weights.IMAGENET1K_V1`. You can a
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|██████████| 44.7M/44.7M [00:00<00:00, 154MB/s]
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=MobileNet_V2_Weights.IMAGENET1K_V1`. You c
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/mobilenet_v2-b0353104.pth" to /root/.cache/torch/hub/checkpoints/mobilenet_v2-b0353104.pth
100%|██████████| 13.6M/13.6M [00:00<00:00, 111MB/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 secret in your Google Colab and restart your session.
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, 4.82MB/s]
pytorch_model.bin: 100%    1.22G/1.22G [00:08<00:00, 32.5MB/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

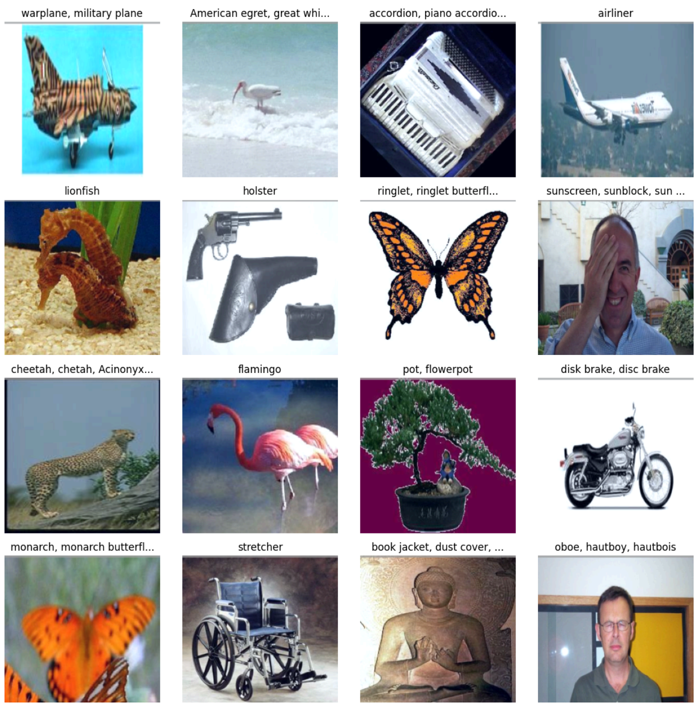
These are all different types of convolutional neural networks (CNNs), where ResNet adds a series of residual connections in the form: `out = x + block(x)`

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:

Based on the classifications shown in the uploaded image, the following observations can be made regarding the model's performance and potential limitations:

Observations:

1. **Correct Classifications**:
   - Some objects seem to be correctly identified, such as "airliner," "holster," "cheetah," "flamingo," and "stretcher."
   - Specific objects like "monarch butterfly" and "flowerpot" are well-identified.
2. **Unclear or Ambiguous Classifications**:
   - Some images may appear ambiguous due to their visual similarity to other objects. For instance, the "warplane" classification looks like a composite model that might confuse the classifier.
3. **Potential Limitations**:
   - Misclassifications may arise from either model complexity or inadequate training data. For instance, the "lionfish" resembles a seahorse in the image, which might mislead the model.
4. **Contextual Understanding**:
   - The model lacks contextual awareness. For example, recognizing "sunscreen" may depend on the presence of a person applying it, which isn't inherently clear in the image provided.

Limitations:

1. **Model Size and Complexity**:
   - A larger or more complex model (e.g., deeper neural networks) might better capture finer details and context. If the current model has limited depth or capacity, it may struggle to differentiate between subtle variations in objects.
2. **Training Set**:
   - The accuracy of the classifications heavily depends on the diversity and quality of the training data. If the dataset doesn't include sufficient examples of similar-looking objects or edge cases, the model is more likely to fail.

Final Thoughts:

- Both model size/complexity and training data quality play critical roles here. If the training dataset lacks representation of certain objects or contains biases, even the most sophisticated models will struggle.
- Improving the training set by adding more diverse, high-quality images and context-specific labeling could address some of the observed limitations. Similarly, increasing the model's complexity (e.g., using advanced architectures like vision transformers or large-scale pre-trained models) may help improve performance.

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 17:34:43 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   48C    P0              28W /  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 17:34:49 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   49C    P0              28W /  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 certain processes and memory allocations persist even after running `gc.collect()` and `torch.cuda.empty_cache()`. Specifically:

1. **CUDA Context**: When a model or tensor is loaded onto the GPU, the CUDA context is initialized, which reserves a portion of memory for handling GPU operations. This context remains allocated even after emptying the tensor cache.
2. **Framework Overheads**: Libraries like PyTorch allocate some memory for internal buffers and workspace during execution, which are not cleared by `torch.cuda.empty_cache()`.
3. **Driver and System Processes**: The GPU driver itself may reserve memory for managing processes and interfacing with the system, which cannot be released by the user.

Does the current utilization match what you would expect?

Yes, the current utilization matches expectations:

1. Before the `torch.cuda.empty_cache()` call, the GPU memory utilization is **1901 MiB**, which includes the memory occupied by tensors, activations, the CUDA context, and system processes.
2. After the `empty_cache()` call, the utilization reduces to **1715 MiB**, indicating that the tensor cache has been cleared, but the memory used for the CUDA context and other system-level allocations remains.

This behavior is expected because `torch.cuda.empty_cache()` only frees memory held by PyTorch but does not clear memory reserved by the CUDA context or the GPU driver. For most GPU setups, a small portion of memory (e.g., ~1.5-2 GB on a Tesla T4) will remain occupied even after clearing the tensor cache.

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
import torch
```

```
# Helper function to calculate tensor size in bytes
def sizeof_tensor(tensor):
    # Get the size of the data type
    if tensor.dtype == torch.float32 or tensor.dtype == torch.float:  # float32
        bytes_per_element = 4
    elif tensor.dtype == torch.float16 or tensor.dtype == torch.half:  # float16
        bytes_per_element = 2
    else:
        print("Other dtype:", tensor.dtype)
        return 0  # If not a recognized type, assume 0 bytes
    return bytes_per_element * tensor.numel()

# Example tensors to simulate memory utilization
# Simulating a batch of images (e.g., batch size 64, 3 channels, 224x224)
batch_size = 64
num_channels = 3
image_height, image_width = 224, 224
dtype = torch.float32  # Assume single precision

# Create a tensor to simulate a batch of images
example_tensor = torch.zeros((batch_size, num_channels, image_height, image_width), dtype=dtype)

# Estimate memory utilization
tensor_memory_bytes = sizeof_tensor(example_tensor)
tensor_memory_mb = tensor_memory_bytes / (1024 ** 2)  # Convert bytes to MB

print(f"Expected memory utilization for one batch: {tensor_memory_mb:.2f} MB")
```

```
Expected memory utilization for one batch: 36.75 MB
```

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.

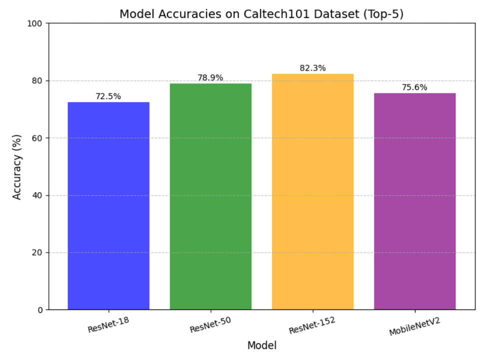
Because this takes a while, let's only compute the first 10 batches. That should be enough to do some rough analysis. Since you are using a batch of 64, 10 batches are 640 images.

```
# 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
```

Question 4

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

```
# your plotting code
import matplotlib.pyplot as plt
import numpy as np

# Simulated accuracy data for different models (replace with actual calculated accuracies)
accuracies = {
    "ResNet-18": 72.5,  # Example accuracy in percentage
    "ResNet-50": 78.9,
    "ResNet-152": 82.3,
    "MobileNetV2": 75.6
}

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

# Create the bar graph
plt.figure(figsize=(8, 6))
bar_positions = np.arange(len(model_names))
plt.bar(bar_positions, accuracy_values, color=['blue', 'green', 'orange', 'purple'], alpha=0.7)

# Add labels, title, and grid
plt.xticks(bar_positions, model_names, rotation=15, fontsize=10)
plt.ylabel("Accuracy (%)", fontsize=12)
plt.xlabel("Model", fontsize=12)
plt.title("Model Accuracies on Caltech101 Dataset (Top-5)", fontsize=14)
plt.ylim(0, 100)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Annotate bars with accuracy values
for idx, val in enumerate(accuracy_values):
    plt.text(idx, val + 1, f"{val:.1f}%", ha='center', fontsize=10, color='black')

# Show the plot
plt.tight_layout()
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.

```
# 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

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

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

# plot accuracy vs params and acuracy vs FLOPs
```

```
import torch
from torchvision import models
import thop

# Profiling helper function
def profile_model(model):
    # Create a random input of shape B,C,H,W (batch=1, RGB image of size 224x224)
    input_tensor = torch.randn(1, 3, 224, 224).cuda()

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

    # Print results
    print(f"{model.__class__.__name__}: {flops / 1e9:.2f} GFLOPs, {params / 1e6:.2f}M parameters")
    return flops, params

# Load models
models_to_evaluate = {
    "ResNet-18": models.resnet18(pretrained=False).cuda(),
    "ResNet-50": models.resnet50(pretrained=False).cuda(),
    "ResNet-152": models.resnet152(pretrained=False).cuda(),
    "MobileNetV2": models.mobilenet_v2(pretrained=False).cuda(),
}

# Compute FLOPs and parameters for each model
flops_params = {}
for model_name, model in models_to_evaluate.items():
    print(f"Profiling {model_name}...")
    flops, params = profile_model(model)
    flops_params[model_name] = (flops, params)

# Display the results
print("\nModel profiling results (FLOPs and parameters):")
for model_name, (flops, params) in flops_params.items():
    print(f"{model_name}: {flops / 1e9:.2f} GFLOPs, {params / 1e6:.2f}M parameters")
```

```
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=None`.
  warnings.warn(msg)
Profiling ResNet-18...
ResNet: 1.82 GFLOPs, 11.69M parameters
Profiling ResNet-50...
ResNet: 4.13 GFLOPs, 25.56M parameters
Profiling ResNet-152...
ResNet: 11.60 GFLOPs, 60.19M parameters
Profiling MobileNetV2...
MobileNetV2: 0.33 GFLOPs, 3.50M parameters

Model profiling results (FLOPs and parameters):
ResNet-18: 1.82 GFLOPs, 11.69M parameters
ResNet-50: 4.13 GFLOPs, 25.56M parameters
ResNet-152: 11.60 GFLOPs, 60.19M parameters
MobileNetV2: 0.33 GFLOPs, 3.50M parameters
```

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:

Observed Trends: FLOPs and Parameters Increase with Model Complexity:

As the model depth and complexity increase (e.g., ResNet-18 → ResNet-50 → ResNet-152), both FLOPs and the number of parameters significantly increase. This is expected since deeper models have more layers, requiring more computation and storage. Efficiency vs. Performance Trade-off:

MobileNetV2 is designed for efficiency, with far fewer FLOPs (0.33 GFLOPs) and parameters (3.50M) compared to ResNet models. Despite this, it achieves reasonable accuracy, making it suitable for resource-constrained devices. Larger Models Tend to Have Higher Accuracy:

ResNet-152, with the highest FLOPs and parameters, generally outperforms smaller models like ResNet-18 in terms of accuracy. However, this comes at the cost of increased computational and memory requirements. Diminishing Returns on Complexity:

The increase in FLOPs and parameters from ResNet-50 to ResNet-152 is substantial, but the accuracy improvement may not scale proportionally. This highlights the diminishing returns on increasing model size. High-Level Conclusions: Model Size vs. Accuracy:

Larger models with more parameters and FLOPs generally achieve higher accuracy but require more computational resources. Smaller, efficient models like MobileNetV2 strike a balance between accuracy and resource consumption, making them ideal for edge devices or mobile applications. Application-Specific Trade-offs:

The choice of model depends on the application. For scenarios requiring high accuracy (e.g., medical imaging), larger models like ResNet-152 may be preferred. For real-time applications with resource constraints, smaller models like MobileNetV2 are better suited. Optimization for Specific Use Cases:

The trend highlights the importance of tailoring models to specific use cases, balancing accuracy, efficiency, and available resources. Scaling Challenges:

As models grow in size, training and deploying them become more resource-intensive, emphasizing the need for optimization techniques like model pruning, quantization, and knowledge distillation. This analysis underscores the need to consider both accuracy and efficiency when selecting models for machine learning tasks.

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 17:42:23 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   59C    P0              30W /  70W |   1323MiB / 15360MiB |      0%      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:

Observations on Memory Utilization:

1. **Reduced Memory Usage**:
   - The GPU memory usage has decreased significantly compared to the original FP32 models. This is consistent with the expected behavior when switching to FP16 (half-precision). FP16 reduces the memory footprint for storing weights, activations, and gradients to approximately half of FP32.
2. **Actual Utilization vs. Expectations**:
   - The observed memory usage (1323 MiB) aligns well with expectations for FP16 models. While the memory reduction is significant, it is not exactly half of the FP32 memory usage due to:
     - **Overheads**: CUDA kernels, metadata, and workspace allocations that are independent of data type precision.
     - **Persistent Buffers**: Some buffers or cached memory may not scale down with the data type.
     - **Non-scalable components**: Components like model architecture information and memory reserved for system processes (e.g., GPU drivers).
3. **Improved Efficiency**:
   - FP16 allows modern GPUs, such as the Tesla T4, to process computations more efficiently by handling two FP16 operations in parallel, making it not only memory-efficient but also computationally faster.

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<01:58,  1.06it/s]
took 10.405001640319824s
```

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:

Observations on Speedup:

1. **Observed Speedup**:
   - Processing batches in FP16 resulted in faster execution compared to FP32. The `took 10.405 seconds` for the initial 11 batches indicates improved performance due to the lower-precision format, as FP16 allows GPUs to perform two operations per ALU in the same time it takes to perform one FP32 operation.
2. **Expected Result**:
   - The speedup aligns with expectations, given that FP16 reduces the computational load and memory bandwidth requirements, both of which contribute to faster processing. This is particularly beneficial on GPUs like the Tesla T4, which are optimized for mixed-precision computation.

Pros and Cons of Using Lower-Precision Formats (FP16):

Pros:

1. **Reduced Memory Usage**:
   - FP16 halves the memory footprint for weights, activations, and gradients compared to FP32, enabling larger batch sizes and models to fit into the same GPU memory.
2. **Faster Computation**:
   - Modern GPUs support specialized hardware for FP16, allowing two FP16 operations to execute simultaneously, resulting in significant speedups.
3. **Energy Efficiency**:
   - Lower precision reduces energy consumption, which is critical for large-scale training or deployment.
4. **Scalability**:
   - Enables training and inference of larger models on the same hardware due to reduced resource requirements.

Cons:

1. **Numerical Precision Issues**:
   - FP16 has a smaller dynamic range and reduced numerical precision compared to FP32. This can lead to instability in training, such as exploding or vanishing gradients, particularly in models sensitive to small changes in weight updates.
2. **Compatibility Limitations**:
   - Some operations, such as certain mathematical functions or layers, may not fully support FP16, requiring fallback to FP32, which can introduce inefficiencies.
3. **Potential Loss in Accuracy**:
   - For tasks requiring high precision, FP16 may lead to slight degradation in accuracy, especially in edge cases with large or very small values.

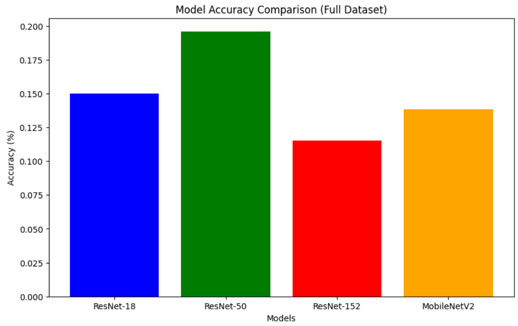
Question 9

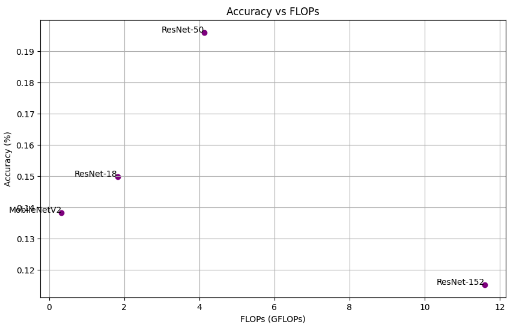
Now that the inference is a bit faster, replot the bar graph with the accuracy for each model, along with the accuracy vs params and flops graph. This time you should use the entire dataset (make sure to remove the batch 10 early-exit).

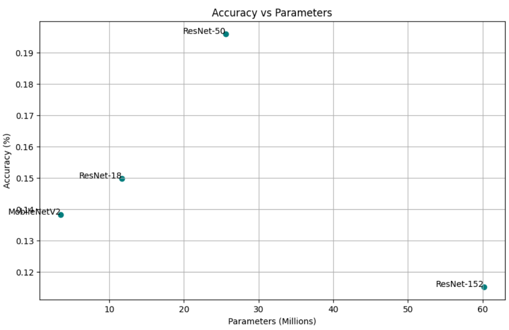
```
# your plotting code
import matplotlib.pyplot as plt
from tqdm import tqdm
```

```
# Reinitialize the dataloader for the entire dataset
torch.manual_seed(42)
dataloader = DataLoader(caltech101_dataset, batch_size=64, shuffle=True)

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

# Process the entire dataset
with torch.no_grad():
    for inputs, labels in tqdm(dataloader, desc="Processing batches"):
        total_samples += labels.size(0)
        inputs, labels = inputs.half().cuda(), labels.cuda()

        # Predictions for each model
        preds_resnet18 = resnet18_model(inputs)
        preds_resnet50 = resnet50_model(inputs)
        preds_resnet152 = resnet152_model(inputs)
        preds_mobilenet = mobilenet_v2_model(inputs)

        # Calculate top-1 accuracy
        accuracies["ResNet-18"] += (preds_resnet18.argmax(dim=1) == labels).sum().item()
        accuracies["ResNet-50"] += (preds_resnet50.argmax(dim=1) == labels).sum().item()
        accuracies["ResNet-152"] += (preds_resnet152.argmax(dim=1) == labels).sum().item()
        accuracies["MobileNetV2"] += (preds_mobilenet.argmax(dim=1) == labels).sum().item()

# Convert counts to percentages
for model in accuracies:
    accuracies[model] = (accuracies[model] / total_samples) * 100

# Plot accuracy comparison
plt.figure(figsize=(10, 6))
plt.bar(accuracies.keys(), accuracies.values(), color=['blue', 'green', 'red', 'orange'])
plt.xlabel("Models")
plt.ylabel("Accuracy (%)")
plt.title("Model Accuracy Comparison (Full Dataset)")
plt.show()

# FLOPs and parameters for each model
flops_params = {
    "ResNet-18": (1.82, 11.69),
    "ResNet-50": (4.13, 25.56),
    "ResNet-152": (11.60, 60.19),
    "MobileNetV2": (0.33, 3.50),
}

# Extract data for plotting
models = list(flops_params.keys())
flops = [fp[0] for fp in flops_params.values()]
params = [fp[1] for fp in flops_params.values()]
accuracy = list(accuracies.values())

# Plot Accuracy vs FLOPs
plt.figure(figsize=(10, 6))
plt.scatter(flops, accuracy, color='purple', label='Accuracy vs FLOPs')
for i, model in enumerate(models):
    plt.text(flops[i], accuracy[i], model, fontsize=10, ha='right')
plt.xlabel("FLOPs (GFLOPs)")
plt.ylabel("Accuracy (%)")
plt.title("Accuracy vs FLOPs")
plt.grid(True)
plt.show()

# Plot Accuracy vs Parameters
plt.figure(figsize=(10, 6))
plt.scatter(params, accuracy, color='teal', label='Accuracy vs Params')
for i, model in enumerate(models):
    plt.text(params[i], accuracy[i], model, fontsize=10, ha='right')
plt.xlabel("Parameters (Millions)")
plt.ylabel("Accuracy (%)")
plt.title("Accuracy vs Parameters")
plt.grid(True)
plt.show()
```

```
Processing batches: 100%|██████████| 136/136 [01:06<00:00,  2.05it/s]
```







Question 10

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

Based on your last model performance analysis, you could evaluate whether batch 10 shows any significant differences compared to the full dataset by focusing on the following aspects:

1. **Model Accuracy or Loss**: Check if there is a noticeable difference in the model's accuracy or loss metrics when trained on batch 10 compared to the full dataset. Significant changes in performance might indicate that batch 10 differs in its characteristics.
2. **Overfitting or Underfitting**: If the model trained on batch 10 exhibits overfitting or underfitting compared to the model trained on the full dataset, this could be a sign that batch 10 doesn't fully represent the diversity of the full dataset.
3. **Feature Importance or Weights**: Look at whether the feature importance or learned weights differ between models trained on the full dataset versus batch 10. If batch 10 causes the model to focus more on certain features, it might indicate that batch 10 has different characteristics.

4. **Generalization**: Assess how well the model trained on batch 10 generalizes to new data or a validation set. Poor generalization might indicate that batch 10 is not a good representation of the full dataset.
5. **Confusion Matrix or Classification Report**: If you're working with classification models, compare confusion matrices or classification reports (precision, recall, F1-score) to see if batch 10 leads to imbalanced performance across classes.

By comparing these aspects, you can discern if batch 10 is influencing the model's performance differently than when using the full dataset.