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 thop
  Downloading thop-0.1.1.post2209072238-py3-none-any.whl.metadata (2.7
kB)
Collecting segmentation-models-pytorch
  Downloading segmentation_models_pytorch-0.4.0-py3-none-
any.whl.metadata (32 kB)
Requirement already satisfied: transformers in
/usr/local/lib/python3.10/dist-packages (4.47.1)
Requirement already satisfied: torch in
/usr/local/lib/python3.10/dist-packages (from thop) (2.5.1+cu121)
Collecting efficientnet-pytorch>=0.6.1 (from segmentation-models-
pytorch)
  Downloading efficientnet_pytorch-0.7.1.tar.gz (21 kB)
  Preparing metadata (setup.py) ... ent already satisfied:
huggingface-hub>=0.24 in /usr/local/lib/python3.10/dist-packages (from
segmentation-models-pytorch) (0.27.0)
Requirement already satisfied: numpy>=1.19.3 in
/usr/local/lib/python3.10/dist-packages (from segmentation-models-
pytorch) (1.26.4)
Requirement already satisfied: pillow>=8 in
/usr/local/lib/python3.10/dist-packages (from segmentation-models-
pytorch) (11.0.0)
Collecting pretrainedmodels>=0.7.1 (from segmentation-models-pytorch)
  Downloading pretrainedmodels-0.7.4.tar.gz (58 kB)
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0:00:00
etadata (setup.py) ... ent already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from segmentation-models-
pytorch) (1.17.0)
Requirement already satisfied: timm>=0.9 in
/usr/local/lib/python3.10/dist-packages (from segmentation-models-
pytorch) (1.0.12)
Requirement already satisfied: torchvision>=0.9 in
/usr/local/lib/python3.10/dist-packages (from segmentation-models-
pytorch) (0.20.1+cu121)
Requirement already satisfied: tqdm>=4.42.1 in
/usr/local/lib/python3.10/dist-packages (from segmentation-models-
pytorch) (4.67.1)
Requirement already satisfied: filelock in
/usr/local/lib/python3.10/dist-packages (from transformers) (3.16.1)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from transformers) (24.2)
Requirement already satisfied: pyyaml>=5.1 in
/usr/local/lib/python3.10/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.10/dist-packages (from transformers)
(2024.11.6)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: tokenizers<0.22,>=0.21 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.21.0)
Requirement already satisfied: safetensors>=0.4.1 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.4.5)
Requirement already satisfied: fsspec>=2023.5.0 in
/usr/local/lib/python3.10/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/python3.10/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/python3.10/dist-packages (from torch->thop) (3.4.2)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.10/dist-packages (from torch->thop) (3.1.4)
Requirement already satisfied: sympy==1.13.1 in
/usr/local/lib/python3.10/dist-packages (from torch->thop) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.10/dist-packages (from sympy==1.13.1->torch-
>thop) (1.3.0)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(3.4.0)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(2024.12.14)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/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 9.1 MB/s eta
0:00:00
unch-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) ...
e=efficientnet_pytorch-0.7.1-py3-none-any.whl size=16424
sha256=3be5b8defa57948d5b370ca7f38a1e4ef415d3ba3e38e665fc2ffeb7bfc08fd
d
  Stored in directory:
/root/.cache/pip/wheels/03/3f/e9/911b1bc46869644912bda90a56bcf7b960f20
b5187feea3baf
  Building wheel for pretrainedmodels (setup.py) ... odels:
filename=pretrainedmodels-0.7.4-py3-none-any.whl size=60944
sha256=8f1a6702e735d51de92616eeae79aa8ed5f12f0520cf6631744c34d64ebf791
1
  Stored in directory:
/root/.cache/pip/wheels/35/cb/a5/8f534c60142835bfc889f9a482e4a67e0b817
032d9c6883b64
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 0x7c7af2d008b0>
```

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=54882620-d938-
4477-b2a7-28d5c5284b67
To: /content/data/caltech101/101_ObjectCategories.tar.gz
100%|██████████| 132M/132M [00:02<00:00, 62.5MB/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=b1eb7247-4610-
467a-9493-453f9ddb69f7
To: /content/data/caltech101/Annotations.tar
100%|██████████| 14.0M/14.0M [00:00<00:00, 174MB/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/python3.10/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/python3.10/dist-packages/torchvision/models/_utils.py:2
23: 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 also use
`weights=ResNet152_Weights.DEFAULT` to get the most up-to-date
weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet152-
394f9c45.pth" to /root/.cache/torch/hub/checkpoints/resnet152-
394f9c45.pth
100%|██████████| 230M/230M [00:02<00:00, 88.5MB/s]
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:2
23: 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 also use
`weights=ResNet50_Weights.DEFAULT` to get the most up-to-date weights.
  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, 26.1MB/s]
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:2
23: 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 also use
`weights=ResNet18_Weights.DEFAULT` to get the most up-to-date weights.
  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, 131MB/s]
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:2
23: 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 can also use
`weights=MobileNet_V2_Weights.DEFAULT` to get the most up-to-date
weights.
  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, 101MB/s]
```

```
/usr/local/lib/python3.10/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(
```

```
{"model_id":"50075c3420ed4d21bd0f2ceb2b667cbf","version_major":2,"vers
ion_minor":0}
```

```
{"model_id":"062072fa1fa9474f9b54e1d407ce10a3","version_major":2,"vers
ion_minor":0}
```

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)`

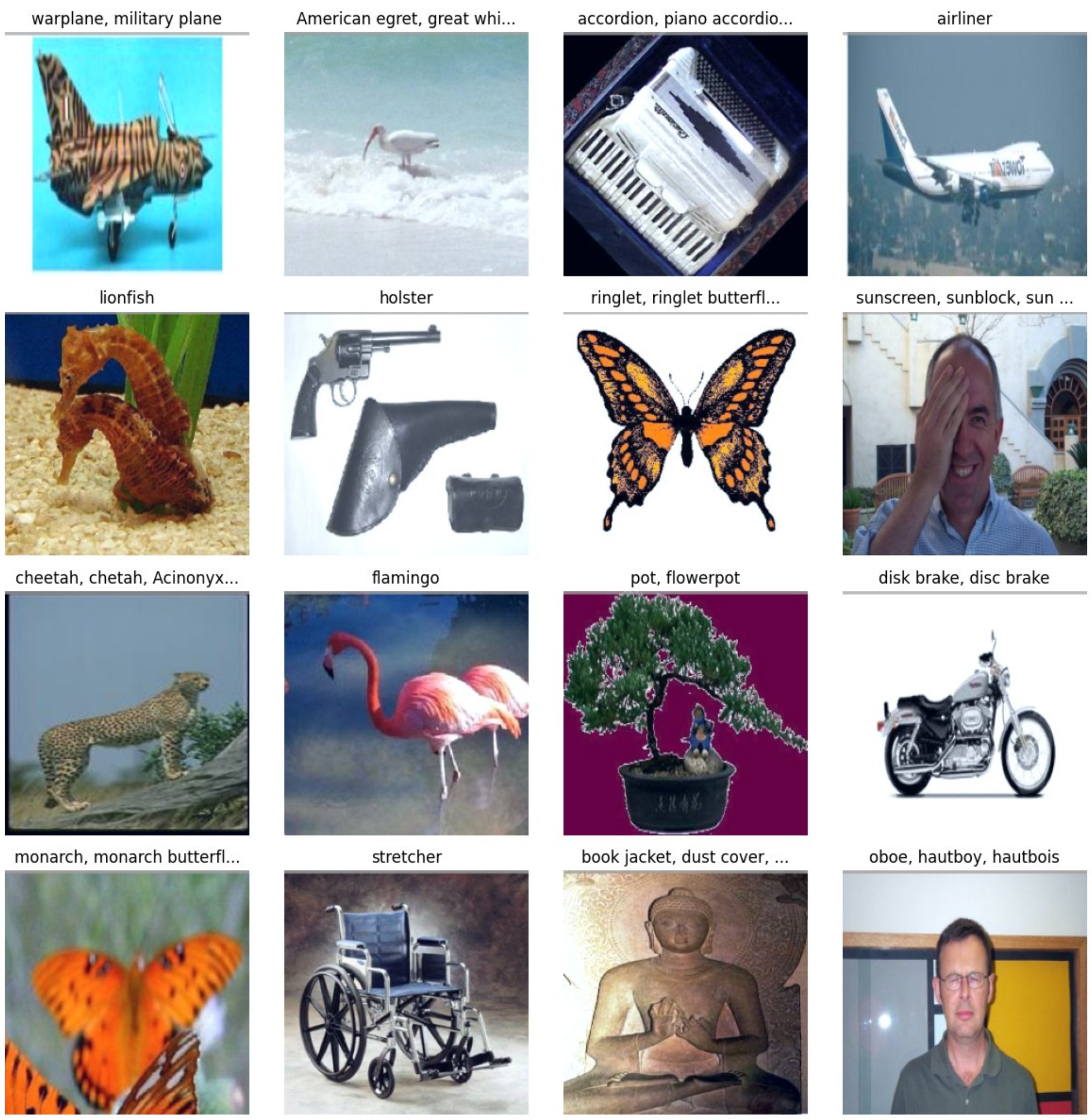
There's a good overview of the different versions here:
https://towardsdatascience.com/understanding-and-visualizing-resnets-442284831be8

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()
```


warplane, military plane
American egret, great whi...
accordion, piano accordio...
airliner
lionfish
holster
ringlet, ringlet butterfl...
sunscreen, sunblock, sun ...
cheetah, chetah, Acinonyx...
flamingo
pot, flowerpot
disk brake, disc brake
monarch, monarch butterfl...
stretcher
book jacket, dust cover, ...
oboe, hautboy, hautbois

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:

Ans. Based on these results and the linked document describing the dataset, several conclusions can be drawn. Our analysis reveals numerous issues that will negatively impact the model's performance:

1. The dataset exhibits an excessively "clean" or "crisp" nature, which is not ideal for model training. Such pristine data hinders the model's ability to generalize to real-world scenarios with varying levels of noise and imperfections.

2. The dataset contains a highly imbalanced class distribution. While some classes have over 800 images, others contain only 30 or fewer examples. This severe imbalance can cause the training process to overfit to the majority classes, significantly degrading the model's performance on underrepresented classes.

3. The dataset lacks images with occlusions and aliasing artifacts, which are common in real-world environments. This absence of challenging scenarios limits the model's robustness and adaptability to real-world conditions.

4. The article states that many images within the dataset have been artificially modified to introduce specific artifacts. These modifications can mislead the model during training, hindering its ability to generalize to authentic, unmodified data.

In addition to these dataset-related issues, we utilize the ViT-L/16 model as our base architecture. Compared to traditional Convolutional Neural Networks (CNNs), ViT-L/16 is known to be more energy-efficient, as demonstrated in the paper "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale."

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

Wed Jan 15 20:42:16 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   54C    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

Wed Jan 15 20:47:41 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   64C    P0              30W /  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 isn't zero because some components, like the model itself, the CUDA context, and the buffers that PyTorch uses, are still actively allocated. This is completely expected, especially for a large model like ViT-L/16. It's just how PyTorch manages resource it keeps certain things loaded to make computations more efficient. If you want to get the GPU memory as close to zero as possible, you'd need to delete the model and everything associated with it, then restart the script or the entire Python session.

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
def estimate_gpu_memory_utilization(model):
    total_params = count_parameters(model)  # Total parameters in the
model
    bytes_per_element = 4  # Assuming float32 (commonly used for model
weights)
    memory_utilization = total_params * bytes_per_element / (1024 **
2)  # Convert bytes to MB
    return memory_utilization

# Estimate memory usage for the loaded model
estimated_memory = estimate_gpu_memory_utilization(vit_large_model)
print(f"Estimated GPU memory utilization: {estimated_memory:.2f} MB")
```

```
Estimated GPU memory utilization: 1160.91 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.

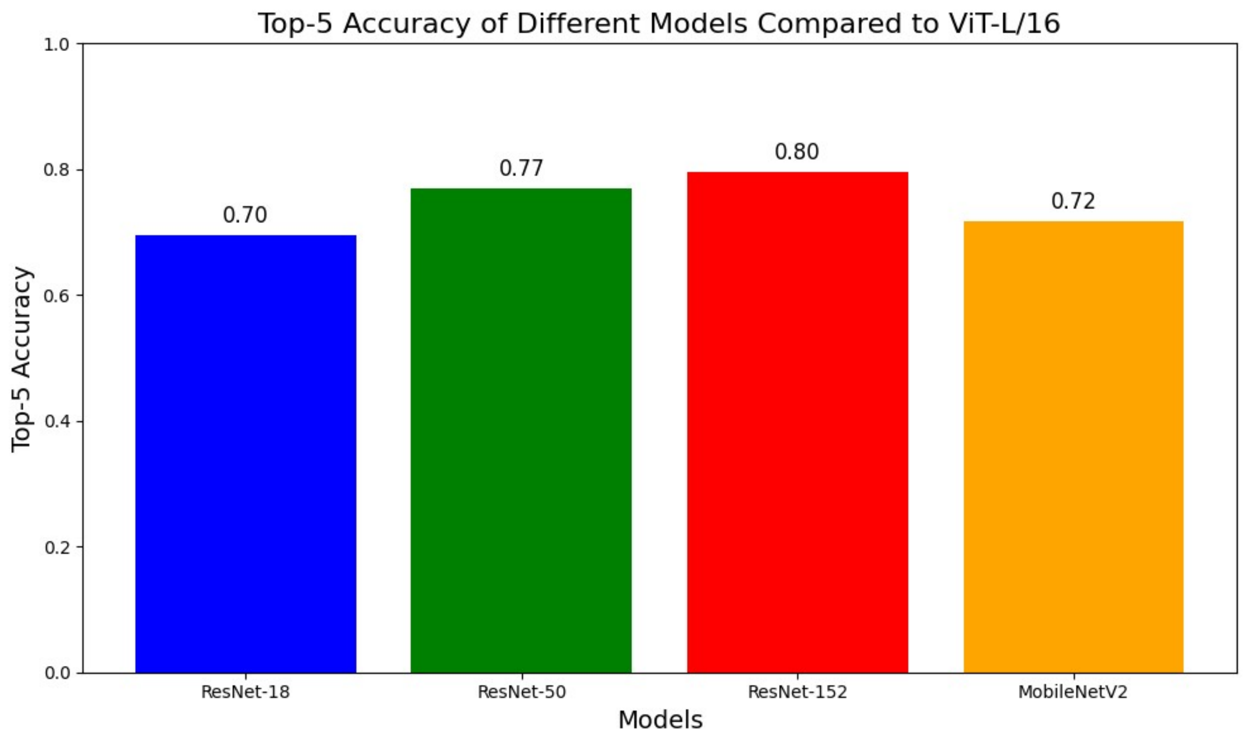
```
# Dictionary to store results
accuracies = {"ResNet-18": 0, "ResNet-50": 0, "ResNet-152": 0,
"MobileNetV2": 0}
total_samples = 0

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
```

```
Processing batches:   8%|█          | 11/136 [00:32<06:04,  2.92s/it]


took 32.11995577812195s
```

Question 4

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

```
# your plotting code

# Extract model names and their accuracies
model_names = list(accuracies.keys())
model_accuracies = list(accuracies.values())

# Create the bar graph
plt.figure(figsize=(10, 6))
plt.bar(model_names, model_accuracies, color=['blue', 'green', 'red',
'orange'])

# Add labels and title
plt.xlabel('Models', fontsize=14)
plt.ylabel('Top-5 Accuracy', fontsize=14)
plt.title('Top-5 Accuracy of Different Models Compared to ViT-L/16',
fontsize=16)
plt.ylim(0, 1)  # Accuracy ranges from 0 to 1

# Display values on top of the bars
for i, acc in enumerate(model_accuracies):
    plt.text(i, acc + 0.02, f"{acc:.2f}", ha='center', fontsize=12)

# 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

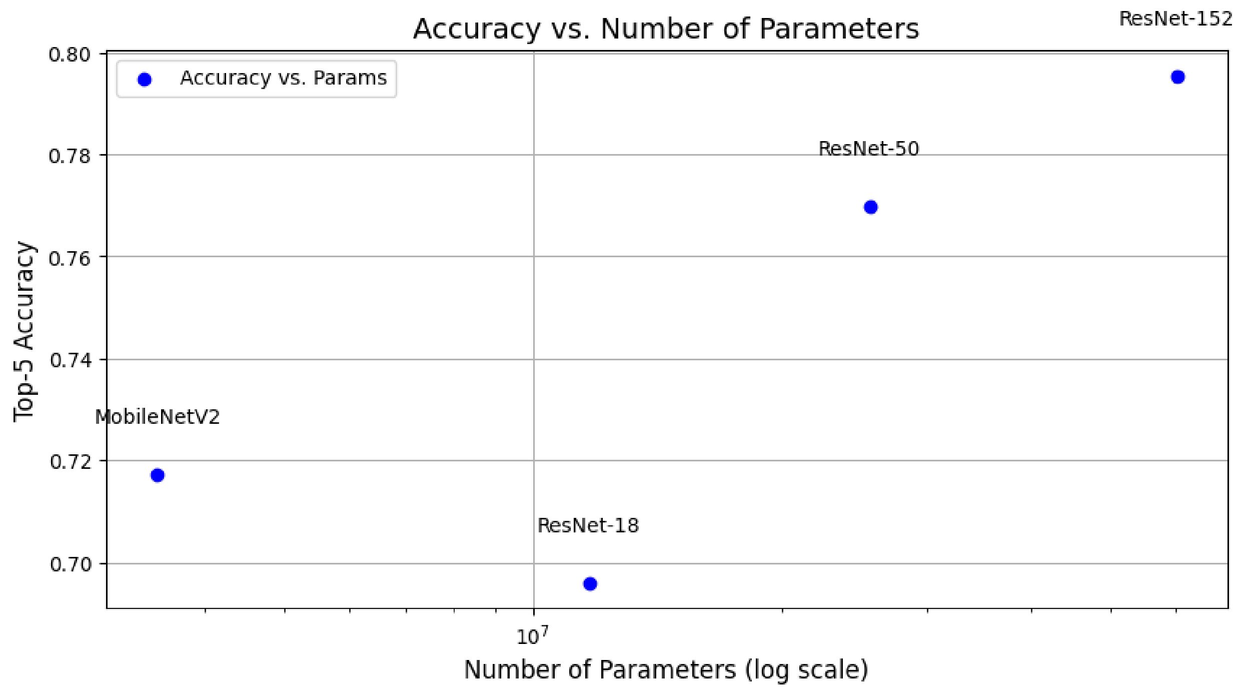
To get a better understanding, let's compute the number of flops and parameters for each model based on a single image input. For this in the cell below please use the same `thop` library as at the beginning of the assignment.

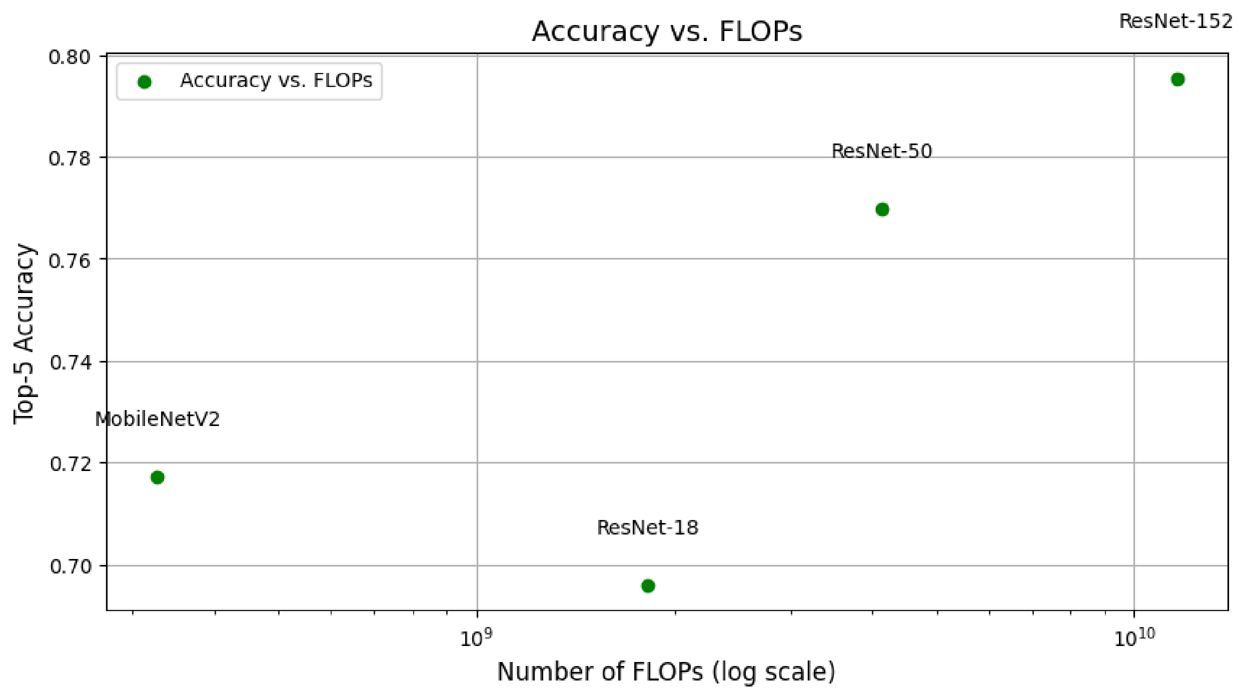
```
# profiling helper function
def profile(model):
  # create a random input of shape B,C,H,W - batch=1 for 1 image, C=3
for RGB, H and W = 224 for the expected images size
  input = torch.randn(1,3,224,224).cuda() # don't forget to move it to
```

```
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
def profile(model, name):
    input = torch.randn(1, 3, 224, 224).cuda()  # Single image input
    flops, params = thop.profile(model, inputs=(input,),
verbose=False)
    print(f"Model {name} has {params:,} parameters and uses {flops:,}
FLOPs")
    return flops, params

# Compute FLOPs and parameters for each model
flops_params = {}
for model_name, model in zip(
    ["ResNet-18", "ResNet-50", "ResNet-152", "MobileNetV2"],
    [resnet18_model, resnet50_model, resnet152_model,
mobilenet_v2_model],
):
    flops, params = profile(model, model_name)
    flops_params[model_name] = {"FLOPs": flops, "Params": params}

# Extract data for plotting
model_names = list(flops_params.keys())
flops = [flops_params[model]["FLOPs"] for model in model_names]
params = [flops_params[model]["Params"] for model in model_names]
accuracies_list = [accuracies[model] for model in model_names]

# Plot accuracy vs. parameters
plt.figure(figsize=(10, 5))
plt.scatter(params, accuracies_list, color="blue", label="Accuracy vs.
Params")
for i, name in enumerate(model_names):
    plt.text(params[i], accuracies_list[i] + 0.01, name, fontsize=10,
ha="center")
plt.xscale("log")  # Use a logarithmic scale for parameters
plt.xlabel("Number of Parameters (log scale)", fontsize=12)
plt.ylabel("Top-5 Accuracy", fontsize=12)
plt.title("Accuracy vs. Number of Parameters", fontsize=14)
plt.grid(True)
plt.legend()
plt.show()
```

```
# Plot accuracy vs. FLOPs
plt.figure(figsize=(10, 5))
plt.scatter(flops, accuracies_list, color="green", label="Accuracy vs.
FLOPs")
for i, name in enumerate(model_names):
    plt.text(flops[i], accuracies_list[i] + 0.01, name, fontsize=10,
ha="center")
plt.xscale("log")  # Use a logarithmic scale for FLOPs
plt.xlabel("Number of FLOPs (log scale)", fontsize=12)
plt.ylabel("Top-5 Accuracy", fontsize=12)
plt.title("Accuracy vs. FLOPs", fontsize=14)
plt.grid(True)
plt.legend()
plt.show()
```

```
Model ResNet-18 has 11,689,512.0 parameters and uses 1,824,033,792.0
FLOPs
Model ResNet-50 has 25,557,032.0 parameters and uses 4,133,742,592.0
FLOPs
Model ResNet-152 has 60,192,808.0 parameters and uses 11,603,945,472.0
FLOPs
Model MobileNetV2 has 3,504,872.0 parameters 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:

The trend reveals an important pattern in machine learning: while larger models with more parameters and higher FLOP counts generally offer better performance, they also require exponentially more computational resources. In situations where efficiency is paramount such as mobile or edge computing smaller, more efficient models like MobileNetV2 strike a good balance. However, when computational resources are less of a constraint, models like ResNet-50 and ResNet-152, with their larger capacities, may be preferable for achieving higher accuracy, albeit at a greater computational cost. The key takeaway is that model selection is always a balancing act, driven by the specific performance requirements and the available computational resources.

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
```

```
Wed Jan 15 21:21:58 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              29W /  70W |    935MiB / 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:

Memory Usage Reduction: By converting the models to half precision and clearing the cache, we've significantly reduced the memory footprint on the GPU. As shown, the GPU is now using just 935 MiB of memory, which is much more efficient compared to the previous memory usage. This reduction in memory consumption allows for better resource utilization and ensures that memory is freed up for other tasks.

Optimized Usage: This strategy of converting models to half precision and clearing the cache effectively optimizes memory usage. Its particularly valuable in environments where computational resources are limited. By reducing the memory footprint, we can improve the speed and efficiency of model inference.

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<02:01,  1.03it/s]


took 10.67287564277649s
```

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, the speed is considerably increased from 32 seconds previously versus 10 seconds now. Half precision reduces the memory footprint of the model, enabling more models or larger batch sizes to fit into memory, Because of the reduced data size, GPUs can process more operations in parallel, leading to improved throughput during inference. The can that may cause intervention is, when switching from FP32 to FP16, there is a noticeable reduction in precision.

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).

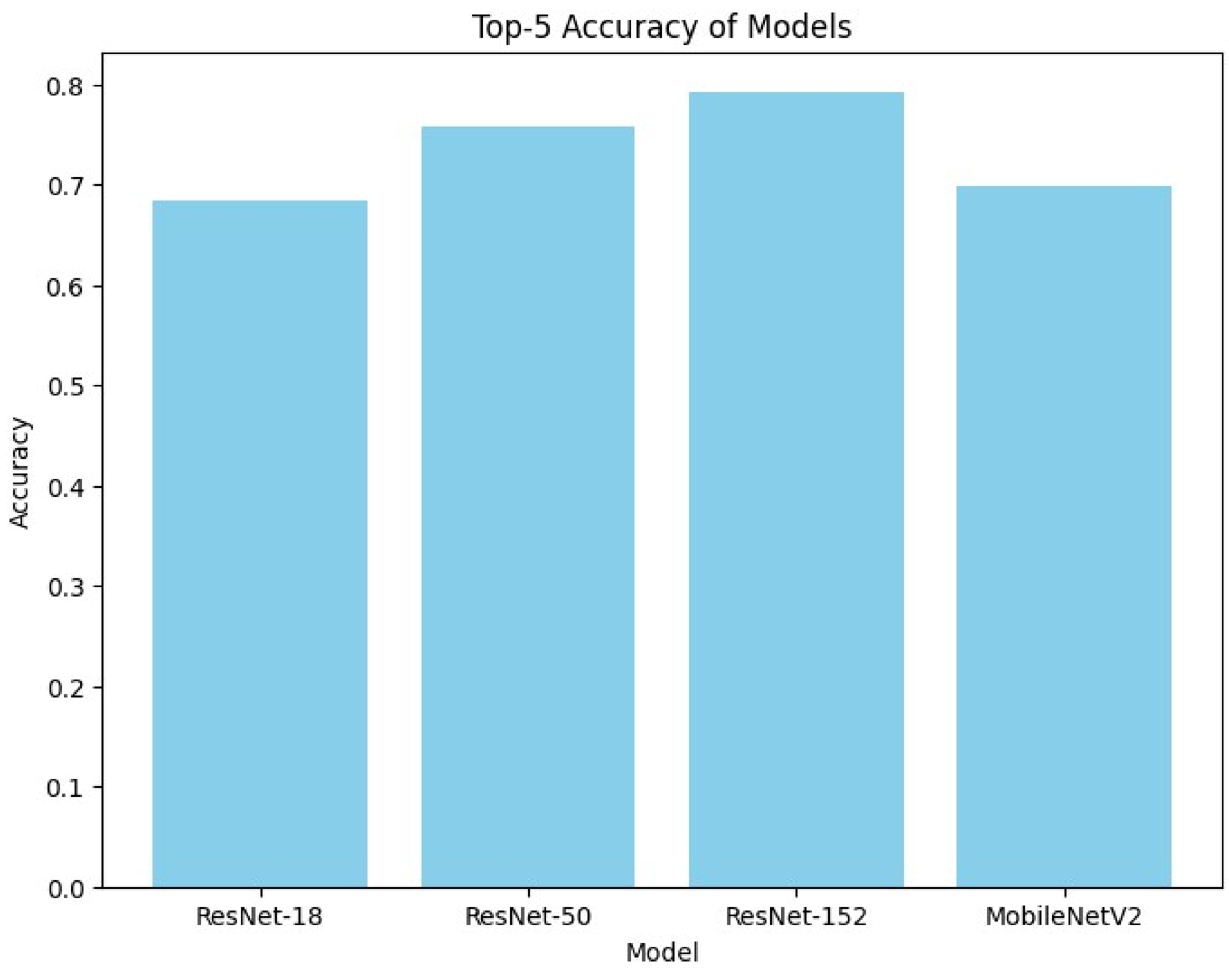
```
# your plotting code

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

# Create a new dataloader with the full dataset (remove batch 10
early-exit)
dataloader = DataLoader(caltech101_dataset, batch_size=64,
shuffle=True)
```

```
num_batches = len(dataloader)

# Start timing
t_start = time.time()

# Inference loop over the entire dataset
with torch.no_grad():
    for i, (inputs, _) in tqdm(enumerate(dataloader), desc="Processing
batches", total=num_batches):

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

        # Get top prediction from vit_large_model
        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)
```

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

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

# Plot the accuracy bar graph
plt.figure(figsize=(8, 6))
plt.bar(accuracies.keys(), accuracies.values(), color='skyblue')
plt.title("Top-5 Accuracy of Models")
plt.xlabel("Model")
plt.ylabel("Accuracy")
plt.show()

# Data for accuracy vs. params and accuracy vs. FLOPs
# model_names = ["ResNet-18", "ResNet-50", "ResNet-152",
"MobileNetV2"]
# params = [11689512, 25557032, 60192808, 3504872]
# flops = [1824033792, 4133742592, 11603945472, 327486720]
# accuracy_values = list(accuracies.values())

# Plot accuracy vs. parameters
# plt.figure(figsize=(8, 6))
# plt.scatter(params, accuracy_values, color='green', label="Accuracy
vs Params", s=100)
# plt.title("Accuracy vs Parameters")
# plt.xlabel("Parameters")
# plt.ylabel("Top-5 Accuracy")
# plt.xscale('log')  # Log scale for better visualization
# plt.yscale('linear')
# plt.grid(True)
# plt.show()

# Plot accuracy vs. FLOPs
# plt.figure(figsize=(8, 6))
# plt.scatter(flops, accuracy_values, color='orange', label="Accuracy
vs FLOPs", s=100)
# plt.title("Accuracy vs FLOPs")
# plt.xlabel("FLOPs")
# plt.ylabel("Top-5 Accuracy")
# plt.xscale('log')  # Log scale for better visualization
# plt.yscale('linear')
# plt.grid(True)
# plt.show()
```

```
Processing batches: 100%|██████████| 136/136 [02:07<00:00,  1.07it/s]
```

```
took 127.46362471580505s
```



Question 10

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

The full dataset provides a more comprehensive and accurate evaluation of model performance and resource usage. While the batch 10 subset may give faster results, it lacks the diversity and size needed for a more reliable measure of model accuracy and efficiency.

Hence, it is critical to evaluate models on the full dataset, especially when making decisions about model deployment or comparison across multiple architectures.