landmark

April 7, 2022

1 Landmark Classification and Tagging using CNN

1.1 Project Requirements

1.2 Dataset

Dataset can be downloaded from here

```
In [ ]: # custom lib
        HAS_GPU = 0

        if HAS_GPU:
            !pip install mxnet-cu80
        else:
            !pip install mxnet
```

```
In [2]: # imports

        ## stdlib
        from datetime import datetime
        from os import mkdir
        from os.path import exists

        ## numerical lib
        import numpy as np

        ## deep learing lib
        import mxnet as mx
        from mxnet import nd, gluon, autograd, init
        from mxnet.gluon import nn
        from mxnet.gluon.data.vision import datasets, transforms

        ## plotting lib
        import matplotlib.pyplot as plt
```

```
In [3]: # setup context
        gpu_count = mx.context.num_gpus()
        ctx = mx.gpu(0) if (gpu_count > 0) else mx.cpu()
        print("using context: ", ctx)
```

```
using context:  cpu(0)
```

1.3 Load Data and Setup Data Iterators

```
In [4]: # global constants
        DATASET_FOLDER = "landmark_images"
        TRAIN_FOLDER   = f"{DATASET_FOLDER}/train"
        TEST_FOLDER    = f"{DATASET_FOLDER}/test"

        INPUT_IMAGE_W_H   = (256, 256)
        N_OUTPUT_CLASSES  = 50
```

```
In [5]: # transformations that should be used for Batch Augmentation
        BATCH_AUGMENTATION_TRANSFORMATIONS = [transforms.RandomResizedCrop(INPUT_IMAGE_W_H, scal
                                              transforms.RandomFlipTopBottom(),
                                              transforms.RandomFlipLeftRight(),
                                              transforms.RandomResizedCrop(INPUT_IMAGE_W_H, scal

        # transformations that should be used for augmenting data during loading
        DATA_AUGMENTATION_TRANSFORMATIONS  = [transforms.RandomFlipLeftRight(),
                                              transforms.RandomResizedCrop(INPUT_IMAGE_W_H, scal

        # transformations that should be used regardless of the above two
        INITIAL_TRANSFORMATIONS = [transforms.Resize(INPUT_IMAGE_W_H),
                                   transforms.ToTensor()]
```

```
In [6]: # helper dataset functions
        # split train set into training and validation set
        def train_valid_split(dataset, valid_frac:float)->(np.ndarray, np.ndarray):
            '''
            TODO: Fill this
            '''
            train = None
            valid = None

            def update_indices(start, end, train_indices, valid_indices):
                data_len = end - start
                if data_len == 0:
                    return train_indices, valid_indices

                train_data_len = int(data_len*(1.0 - valid_frac))
                valid_data_len = data_len - train_data_len

                if train_indices is not None:
                    train_indices = np.hstack((train_indices, np.arange(start, start+train_data_
                    valid_indices = np.hstack((valid_indices, np.arange(start+train_data_len, en
                else:
```

```
            train_indices = np.arange(start, start+train_data_len)
            valid_indices = np.arange(start+train_data_len, end+1)
        return train_indices, valid_indices

    # store label start and end indices
    ref_label, label_start, label_end = 0, 0, 0

    # split each label and store their indices
    for i, (_, label) in enumerate(dataset.items):
        if (label == ref_label):
            label_end = i
        else:
            # finalize last label
            train, valid = update_indices(label_start, label_end, train, valid)

            # reset counters
            ref_label, label_start, label_end = label, i, i

    # last class
    train, valid = update_indices(label_start, label_end, train, valid)

    return train, valid

# custom data sample for Gluon DataLoader
class RandomIndicesSampler(gluon.data.Sampler):
    '''
    TODO: Fill this
    '''
    def __init__(self, indices):
        self.length_ = len(indices)
        self.indices_ = indices

    def __iter__(self):
        np.random.shuffle(self.indices_)
        return iter(self.indices_)

    def __len__(self):
        return self.length_

def generate_datasets(train_folder:str, test_folder:str, config:dict):
    if 'batch_size' not in config:
        raise KeyError
    if 'last_batch' not in config:
        raise KeyError
    if 'valid_frac' not in config:
        raise KeyError
    if 'batch_aug' not in config:
        raise KeyError
```

```
dataloader_params = dict(batch_size=config['batch_size'],
                         last_batch=config['last_batch'])

train_dataset_transforms = INITIAL_TRANSFORMATIONS
if not config['batch_aug']:
    train_dataset_transforms = DATA_AUGMENTATION_TRANSFORMATIONS
    train_dataset_transforms.extend(INITIAL_TRANSFORMATIONS)

train_dataset_transforms = transforms.Compose(train_dataset_transforms)
test_dataset_transforms  = transforms.Compose(INITIAL_TRANSFORMATIONS)

# create train dataset
train_dataset = datasets.ImageFolderDataset(train_folder, 1)

# create test dataset
test_dataset  = datasets.ImageFolderDataset(test_folder, 1)

# create data generators
train_indices, valid_indices = train_valid_split(train_dataset, config['valid_frac']

train_datagen = gluon.data.DataLoader(train_dataset.transform_first(train_dataset_tr
                                      sampler=RandomIndicesSampler(indices=train_ind
                                      **dataloader_params)

valid_datagen = gluon.data.DataLoader(train_dataset.transform_first(train_dataset_tr
                                      sampler=RandomIndicesSampler(indices=valid_ind
                                      **dataloader_params)

test_datagen  = gluon.data.DataLoader(test_dataset.transform_first(test_dataset_tran
                                      **dataloader_params)

return train_datagen, valid_datagen, test_datagen
```

Question 1: Describe your chosen procedure for preprocessing the data.
- How does your code resize the images (by cropping, stretching, etc)? What size did you pick for the input tensor, and why?
Answer: The code resizes images to (256 x 256) size. The reason for this specific size is that, picking smaller size is only making some useful features getting compressed and the quality is lost. Picking bigger size requires more layers or bigger kernel size for the starting layers to downsample. So, image size of (256 x 256) with tuned kernel size extracted features properly.

- Did you decide to augment the dataset? If so, how(through translations, flips, rotations, etc)? If not, why not?
Answer: Yes, I decided to augment the dataset. I selected 2 different transformations to augment, randomResizedCrop of count 2 with different parameters, randomFlipTopBottom, randomFlipLeftRight.

1.4 Model Architecture Setup

```
In [7]: landmark_cnn = nn.HybridSequential()

        # add convolutional layers
        landmark_cnn.add(

            # Feature extraction layers
                         nn.Conv2D(channels=16, kernel_size=(4,4), strides=(1,1)),
                         nn.BatchNorm(),
                         nn.Activation('relu'),

                         nn.Conv2D(channels=32, kernel_size=(4,4), strides=(2,2)),
                         nn.BatchNorm(),
                         nn.Activation('relu'),
                         nn.AvgPool2D(pool_size=(2,2), strides=(2,2)),

                         nn.Conv2D(channels=64, kernel_size=(4,4), strides=(1,1)),
                         nn.BatchNorm(),
                         nn.Activation('relu'),
                         nn.MaxPool2D(pool_size=(2,2), strides=(2,2)),

                         nn.Conv2D(channels=128, kernel_size=(3,3), strides=(1,1)),
                         nn.BatchNorm(),
                         nn.Activation('relu'),
                         nn.MaxPool2D(pool_size=(2,2), strides=(2,2)),

                         nn.Conv2D(channels=256, kernel_size=(3,3), strides=(1,1)),
                         nn.BatchNorm(),
                         nn.Activation('relu'),
                         nn.MaxPool2D(pool_size=(2,2), strides=(2,2)),

            # classification layers
                         nn.Flatten(),

                         nn.Dense(units=200),
                         nn.BatchNorm(),
                         nn.Activation('relu'),
                         nn.Dropout(rate=0.2),

                         nn.Dense(units=100),
                         nn.BatchNorm(),
                         nn.Activation('relu'),
                         nn.Dropout(rate=0.2),

                         nn.Dense(units=N_OUTPUT_CLASSES, activation='relu')
                         )
```

```python
# finalize model by passing in a dummy input
dummy_input = nd.ones(shape= (64, 3, ) + INPUT_IMAGE_W_H, dtype='float32', ctx=ctx)
landmark_cnn.initialize(force_reinit=True, init=init.Xavier(), ctx=ctx)
landmark_cnn.summary(dummy_input)

########## LOAD ALREADY TRAINED PARAMETERS ############################################
landmark_cnn.load_parameters("model_ckpts/model_ckpt_03-26-2022_16-50-16.params", ctx=ct

# create computational tree
landmark_cnn.hybridize()
```

```
--------------------------------------------------------------------------------
        Layer (type)                                Output Shape         Param #
================================================================================
               Input                            (64, 3, 256, 256)               0
            Conv2D-1                           (64, 16, 253, 253)             784
         BatchNorm-2                           (64, 16, 253, 253)              64
        Activation-3                           (64, 16, 253, 253)               0
            Conv2D-4                           (64, 32, 125, 125)            8224
         BatchNorm-5                           (64, 32, 125, 125)             128
        Activation-6                           (64, 32, 125, 125)               0
         AvgPool2D-7                             (64, 32, 62, 62)               0
            Conv2D-8                             (64, 64, 59, 59)           32832
         BatchNorm-9                             (64, 64, 59, 59)             256
       Activation-10                             (64, 64, 59, 59)               0
        MaxPool2D-11                             (64, 64, 29, 29)               0
           Conv2D-12                            (64, 128, 27, 27)           73856
        BatchNorm-13                            (64, 128, 27, 27)             512
       Activation-14                            (64, 128, 27, 27)               0
        MaxPool2D-15                            (64, 128, 13, 13)               0
           Conv2D-16                            (64, 256, 11, 11)          295168
        BatchNorm-17                            (64, 256, 11, 11)            1024
       Activation-18                            (64, 256, 11, 11)               0
        MaxPool2D-19                              (64, 256, 5, 5)               0
          Flatten-20                                   (64, 6400)               0
            Dense-21                                    (64, 200)         1280200
        BatchNorm-22                                    (64, 200)             800
       Activation-23                                    (64, 200)               0
          Dropout-24                                    (64, 200)               0
            Dense-25                                    (64, 100)           20100
        BatchNorm-26                                    (64, 100)             400
       Activation-27                                    (64, 100)               0
          Dropout-28                                    (64, 100)               0
       Activation-29                   <Symbol dense2_relu_fwd>               0
       Activation-30                                     (64, 50)               0
            Dense-31                                     (64, 50)            5050
================================================================================
Parameters in forward computation graph, duplicate included
```

```
   Total params: 1719398
   Trainable params: 1717806
   Non-trainable params: 1592
Shared params in forward computation graph: 0
Unique parameters in model: 1719398
--------------------------------------------------------------------------------
```

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

Answer: I wanted to see if I can create a bottlenecks in the model by keeping parameter count small so the network will try to only extract useful features and discard noise. So, first I created a model with 300K ish parameters. Then I realized the output features from CNN layers are quite bad and nothing useful can be classified from them. From here on, I increased by each layer, trained the model for 5 epochs, analyzed outputs of each layer to make sure the outputs from the layer are anything meaningful. I also played with different stride sizes and selected the final one in such a way that the final image from those layers are useful and downsampling is not resulting in distored features.

Addition of Batch Normalization First I played without Batch Normalization. Without batch normalization, I noticed some weights in some layers are bigger than the rest leading to these weights over-contributing. Hence I added batch normalization which improved accuracy and speeded up the training.
Batch Normalization

Addition of Batch Augmentation Even with Batch Normalization and dropout, the model was still overfitting. To improve generalization I have done some research and found out that using batch augmentation the model generalization can be improved significantly. This can be seem clearly in the training log output where train and valid accuracy are moving in the same fashion.
Batch Augmentation

1.5 Helper Training Loops, Model Checkpointing and Batch Augmentation

```
In [8]: def batch_augmentation(x_batch, y_batch, transformations):
            '''
            TODO: Fill this
            '''
            transforms_len = len(transformations)
            x_batch_aug     = nd.empty((BATCH_SIZE*transforms_len, 3, ) + INPUT_IMAGE_W_H)

            for i in range(transforms_len):
                for k, j in enumerate(range(i*BATCH_SIZE, (i+1)*BATCH_SIZE)):
                    x_batch_aug[j, :, :, :] = transformations[i].forward(x_batch[k, :, :, :].tra
            y_batch_aug = nd.tile(y_batch, reps=transforms_len)
            return x_batch_aug, y_batch_aug

        def train_loop_one_epoch(model, config:dict)->(float, str):
            cumulative_train_loss = 0.0
```

```
trainer_step_size = config['batch_size']
if config['batch_aug']:
    trainer_step_size *= len(BATCH_AUGMENTATION_TRANSFORMATIONS)

n_steps = len(config['train_datagen'])
for i, (x_batch, y_batch) in enumerate(config['train_datagen']):

    # augment batch
    if config['batch_aug']:
        x_batch_aug, y_batch_aug = batch_augmentation(x_batch,
                                                      y_batch,
                                                      BATCH_AUGMENTATION_TRANSFORMAT
    else:
        x_batch_aug = x_batch
        y_batch_aug = y_batch

    # split the dataset into sub-batches to run on devices
    x_data_list = gluon.utils.split_and_load(x_batch_aug, config['devices'])
    y_data_list = gluon.utils.split_and_load(y_batch_aug, config['devices'])

    # forward + backward
    with autograd.record():
        y_predicts = [model(x) for x in x_data_list]
        losses     = [config['loss_fcn'](y_predict, y)
                      for y_predict, y in zip(y_predicts, y_data_list)]
    for loss in losses:
        loss.backward()

    # update network parameters
    config['trainer'].step(trainer_step_size)

    # calculate loss over multiple devices
    step_loss = 0.0
    for loss in losses:
        step_loss += (loss.mean()).asscalar()
    cumulative_train_loss *= 0.5
    cumulative_train_loss += (0.5*step_loss)

    log_str = f"loss: {cumulative_train_loss:0.5f}"

    # calculate metrics
    for metric in config['metrics']:
        metric_name = ''
        metric_val  = 0.0
        for y_predict, y_true in zip(y_predicts, y_data_list):
            y_predict_sftmx = nd.SoftmaxActivation(y_predict)
            metric.update(preds=y_predict_sftmx, labels=y_true)
            metric_name, val = metric.get()
```

```python
                metric_val += val

            log_str = f"{log_str}, {metric_name}: {metric_val:0.5f}"

        print("train | (%d/%d): %s"%(i, n_steps, log_str), end='\r')
    print('')

    # reset metrics so they can be calculated from a clean state
    for metric in config['metrics']:
        metric.reset()

    return cumulative_train_loss, log_str

def validation_loop_one_epoch(model, config:dict)->(float, str):
    cumulative_val_loss = 0.0

    for i, (x_batch, y_batch) in enumerate(config['valid_datagen']):

        # split the dataset into sub-batches to run on devices
        x_data_list = gluon.utils.split_and_load(x_batch, config['devices'])
        y_data_list = gluon.utils.split_and_load(y_batch, config['devices'])

        # perform forward pass on a batch of inputs
        for x, y in zip(x_data_list, y_data_list):
            y_predict = model(x)
            loss = config['loss_fcn'](y_predict, y)

            # update loss and metrics
            cumulative_val_loss += loss.mean().asscalar()
            for metric in config['metrics']:
                y_predict_sftmx = nd.SoftmaxActivation(y_predict)
                metric.update(preds=y_predict_sftmx, labels=y)

    cumulative_val_loss /= len(config['valid_datagen'])

    # logging
    log_str = f"valid | loss: {cumulative_val_loss:0.5f}"
    for metric in config['metrics']:
        name, val = metric.get()
        metric.reset()
        log_str = f"{log_str}, {name}: {val:0.5f}"

    print(log_str)
    return cumulative_val_loss, log_str

def model_ckpt(model):
    '''
    TODO: define this
```

```
    '''
    if not exists("model_ckpts"):
        mkdir("model_ckpts")

    time_str = datetime.now().strftime("%m-%d-%Y_%H-%M-%S")
    file_name = f"model_ckpts/model_ckpt_{time_str}_architecture.json"

    # save model
    sym_json = model(mx.sym.var('data')).tojson()
    with open(file_name, 'w') as out_file:
        out_file.write(sym_json)

    # write metadata to metadata file
    with open("model_ckpt_metadata.txt", "a") as out_file:
        out_file.write(f"##################################\n")
        out_file.write(f"{file_name}\n")

def params_ckpt(model, epoch:int,
                train_loss:float, train_log:str,
                valid_loss:float, valid_log)->None:
    '''
    TODO: define this
    '''
    if not exists("model_ckpts"):
        mkdir("model_ckpts")

    time_str = datetime.now().strftime("%m-%d-%Y_%H-%M-%S")
    file_name = f"model_ckpts/model_ckpt_{time_str}.params"

    # checkpoint model
    model.save_parameters(file_name)

    # write metadata to metadata file
    with open("model_ckpt_metadata.txt", "a") as out_file:
        out_file.write(f"{train_log}\n")
        out_file.write(f"{valid_log}\n")
        out_file.write(f"{file_name}\n")
        out_file.write(f"-------------------\n")

    print("model ckpt: ", file_name)
```

1.6 Training Setup

In [9]:
```
model_ckpt(landmark_cnn)

# define loss and metrics for the training loop
train_config = {}
train_config['optimizer'] = mx.optimizer.Adam(learning_rate=1e-3, wd=0.000001) # weight
```

```
train_config['metrics']    = [mx.metric.Accuracy(), mx.metric.TopKAccuracy(top_k=3)]
train_config['loss_fcn']   = gluon.loss.SoftmaxCrossEntropyLoss(from_logits=False, sparse
train_config['trainer']    = gluon.Trainer(landmark_cnn.collect_params(), optimizer=train
train_config['devices']    = [ctx]
train_config['model_ckpt_freq'] = 1 # for every n epochs ckpt model

train_config['batch_size'] = 64
train_config['batch_aug']  = True
train_config['valid_frac'] = 0.2
train_config['last_batch'] = 'rollover'

train_datagen, valid_datagen, test_datagen = generate_datasets(TRAIN_FOLDER,
                                                               TEST_FOLDER,
                                                               train_config)
train_config['train_datagen'] = train_datagen
train_config['valid_datagen'] = valid_datagen
train_config['test_datagen']  = test_datagen
```

1.7 Training

In [ ]:
```
for epoch in range(1):
    print(f"Epoch {epoch}")

    train_loss, train_log = train_loop_one_epoch(landmark_cnn, train_config)
    valid_loss, valid_log = validation_loop_one_epoch(landmark_cnn, train_config)

    if (( (epoch+1) % train_config['model_ckpt_freq']) == 0):
        params_ckpt(landmark_cnn, epoch, train_loss, train_log, valid_loss, valid_log)
```

Model Training Log for the above architecture

```
model_ckpts/model_ckpt_03-26-2022_15-54-16_architecture.json

loss: 3.54252, accuracy: 0.07686, top_k_accuracy_3: 0.16702
valid | loss: 3.22635, accuracy: 0.15430, top_k_accuracy_3: 0.27246
model_ckpts/model_ckpt_03-26-2022_15-56-36.params
-------------------
loss: 3.35044, accuracy: 0.13779, top_k_accuracy_3: 0.27111
valid | loss: 3.37275, accuracy: 0.20221, top_k_accuracy_3: 0.38879
model_ckpts/model_ckpt_03-26-2022_15-58-53.params
-------------------
loss: 3.30736, accuracy: 0.19013, top_k_accuracy_3: 0.34426
valid | loss: 3.09646, accuracy: 0.18262, top_k_accuracy_3: 0.34570
model_ckpts/model_ckpt_03-26-2022_16-01-09.params
-------------------
loss: 3.10783, accuracy: 0.21346, top_k_accuracy_3: 0.37739
valid | loss: 3.21768, accuracy: 0.22978, top_k_accuracy_3: 0.39062
model_ckpts/model_ckpt_03-26-2022_16-03-26.params
```

```
-------------------
loss: 2.98798, accuracy: 0.25076, top_k_accuracy_3: 0.42358
valid | loss: 2.83091, accuracy: 0.28711, top_k_accuracy_3: 0.48047
model_ckpts/model_ckpt_03-26-2022_16-06-03.params
-------------------
loss: 2.98827, accuracy: 0.27273, top_k_accuracy_3: 0.44915
valid | loss: 2.68636, accuracy: 0.28027, top_k_accuracy_3: 0.47070
model_ckpts/model_ckpt_03-26-2022_16-08-17.params
-------------------
loss: 2.85646, accuracy: 0.29751, top_k_accuracy_3: 0.47543
valid | loss: 2.89119, accuracy: 0.31158, top_k_accuracy_3: 0.51838
model_ckpts/model_ckpt_03-26-2022_16-10-40.params
-------------------
loss: 2.73997, accuracy: 0.32220, top_k_accuracy_3: 0.50838
valid | loss: 2.40487, accuracy: 0.35156, top_k_accuracy_3: 0.53320
model_ckpts/model_ckpt_03-26-2022_16-12-57.params
-------------------
loss: 2.55314, accuracy: 0.33446, top_k_accuracy_3: 0.52651
valid | loss: 2.92921, accuracy: 0.29779, top_k_accuracy_3: 0.48805
model_ckpts/model_ckpt_03-26-2022_16-15-34.params
-------------------
loss: 2.46018, accuracy: 0.35597, top_k_accuracy_3: 0.54057
valid | loss: 2.52907, accuracy: 0.35254, top_k_accuracy_3: 0.54395
model_ckpts/model_ckpt_03-26-2022_16-17-51.params
-------------------
loss: 2.22234, accuracy: 0.41060, top_k_accuracy_3: 0.60200
valid | loss: 2.10641, accuracy: 0.43262, top_k_accuracy_3: 0.62109
model_ckpts/model_ckpt_03-26-2022_16-22-06.params
-------------------
loss: 2.31832, accuracy: 0.42956, top_k_accuracy_3: 0.62506
valid | loss: 2.35482, accuracy: 0.44210, top_k_accuracy_3: 0.62776
model_ckpts/model_ckpt_03-26-2022_16-24-22.params
-------------------
loss: 2.12482, accuracy: 0.43838, top_k_accuracy_3: 0.62847
valid | loss: 2.07038, accuracy: 0.44434, top_k_accuracy_3: 0.63672
model_ckpts/model_ckpt_03-26-2022_16-26-55.params
-------------------
loss: 2.16807, accuracy: 0.45048, top_k_accuracy_3: 0.63672
valid | loss: 2.32213, accuracy: 0.45772, top_k_accuracy_3: 0.63879
model_ckpts/model_ckpt_03-26-2022_16-29-13.params
-------------------
loss: 2.07938, accuracy: 0.45389, top_k_accuracy_3: 0.64120
valid | loss: 2.17284, accuracy: 0.45312, top_k_accuracy_3: 0.63965
model_ckpts/model_ckpt_03-26-2022_16-31-38.params
-------------------
loss: 2.17414, accuracy: 0.45376, top_k_accuracy_3: 0.64182
valid | loss: 2.03556, accuracy: 0.45996, top_k_accuracy_3: 0.63867
model_ckpts/model_ckpt_03-26-2022_16-33-55.params
```

```
-------------------
loss: 2.07557, accuracy: 0.45472, top_k_accuracy_3: 0.64835
valid | loss: 2.17024, accuracy: 0.44922, top_k_accuracy_3: 0.63672
model_ckpts/model_ckpt_03-26-2022_16-39-05.params
-------------------
loss: 2.06082, accuracy: 0.45409, top_k_accuracy_3: 0.64600
valid | loss: 2.04519, accuracy: 0.45996, top_k_accuracy_3: 0.63770
model_ckpts/model_ckpt_03-26-2022_16-41-34.params
-------------------
loss: 2.09399, accuracy: 0.45911, top_k_accuracy_3: 0.65045
valid | loss: 2.30844, accuracy: 0.45404, top_k_accuracy_3: 0.63603
model_ckpts/model_ckpt_03-26-2022_16-43-52.params
-------------------
loss: 2.15045, accuracy: 0.45602, top_k_accuracy_3: 0.64340
valid | loss: 2.14090, accuracy: 0.46191, top_k_accuracy_3: 0.64746
model_ckpts/model_ckpt_03-26-2022_16-47-59.params
-------------------
loss: 2.19072, accuracy: 0.46075, top_k_accuracy_3: 0.64825
valid | loss: 2.06220, accuracy: 0.44531, top_k_accuracy_3: 0.63086
model_ckpts/model_ckpt_03-26-2022_16-50-16.params                          ------------> Best Fit
```

After this the model is not able to improve. Tried many different architectures, increased parameter count to 4.7ish Million but the model is only overfitting.
One problem that was observed is that, some of the images in the dataset are bad and/or not making sense.

1.8 Helper Functions for Model Evaluation

```
In [10]: def xtab(list1, list2, dim=None, include_zero=False):
             '''
             TODO: Fill this
             '''
             if isinstance(list1, list):
                 list1 = np.array(list1)
             if isinstance(list2, list):
                 list2 = np.array(list2)

             if len(list1) != len(list2):
                 raise ValueError("list1 and list2 should be of same size")

             max_dim = dim if dim else max(np.max(list1), np.max(list2))
             max_dim = max_dim+1 if include_zero else max_dim

             out = np.zeros(shape=(max_dim, max_dim), dtype=np.int32)

             for l1, l2 in zip(list1, list2):
                 out[l1, l2] += 1
```

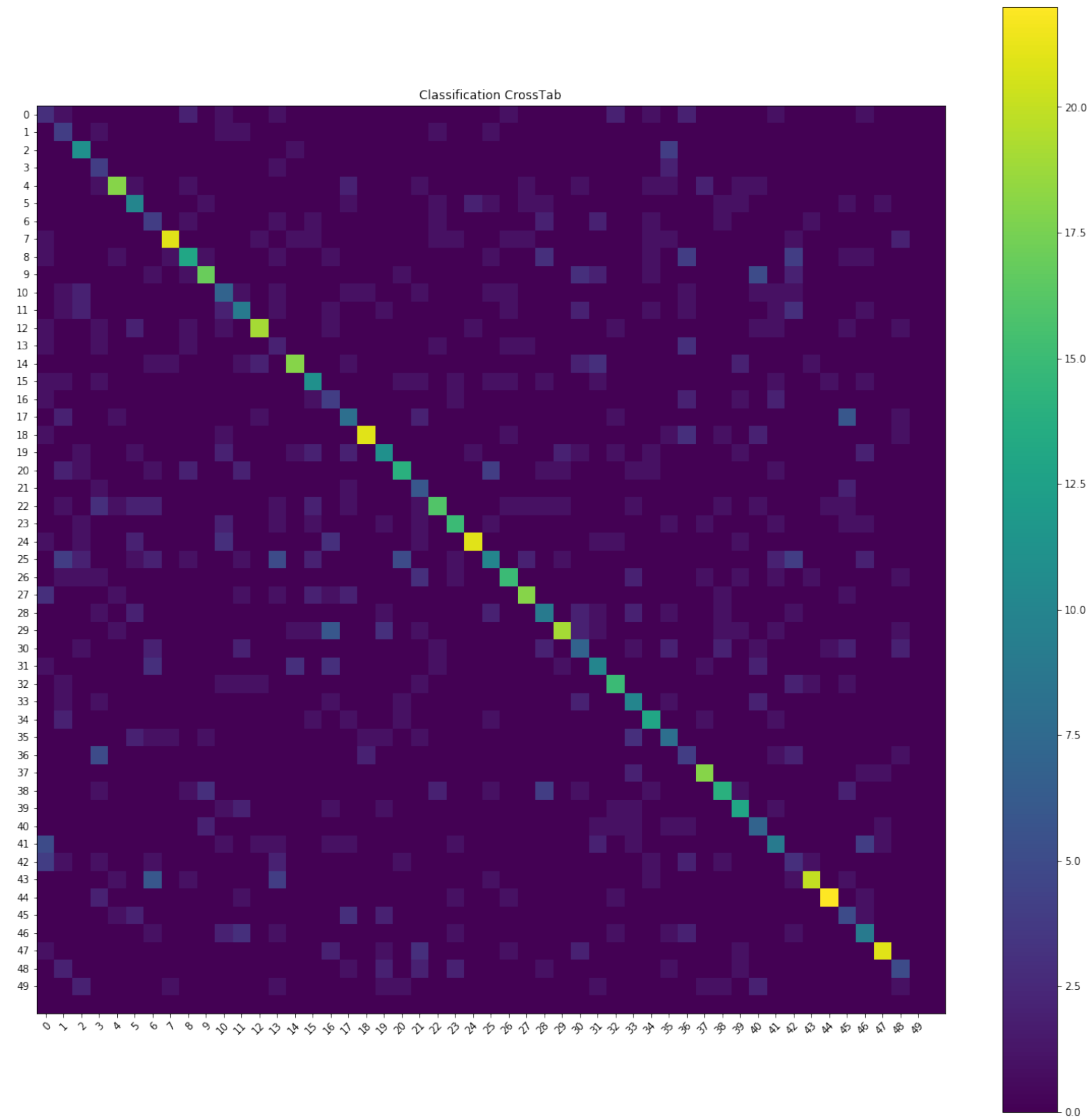
```python
        return out

    def evaluate(model, config:dict):
        '''
        TODO: Fill this
        '''
        cumulative_loss = 0.0
        crosstab = np.zeros(shape=(N_OUTPUT_CLASSES+1, N_OUTPUT_CLASSES+1), dtype=np.int32)

        for i, (x_batch, y_batch) in enumerate(config['test_datagen']):

            # split the dataset into sub-batches to run on devices
            x_data_list = gluon.utils.split_and_load(x_batch, config['devices'])
            y_data_list = gluon.utils.split_and_load(y_batch, config['devices'])

            # perform forward pass on a batch of inputs
            step_loss = 0.0
            for x, y in zip(x_data_list, y_data_list):
                y_predict = model(x)
                loss = config['loss_fcn'](y_predict, y)

                # update loss and metrics
                cumulative_loss += loss.mean().asscalar()
                y_predict_sftmx = nd.SoftmaxActivation(y_predict)

                for metric in config['metrics']:
                    metric.update(preds=y_predict_sftmx, labels=y)

                # calculate crosstab
                y_predict_classes = np.argmax(y_predict_sftmx.asnumpy(), axis=1)
                crosstab += xtab(y_predict_classes, y.asnumpy(), dim=N_OUTPUT_CLASSES, incl

        cumulative_loss /= len(config['test_datagen'])
        return cumulative_loss, {metric.get()[0]: metric.get()[1] for metric in config['met
```

1.9 Model Evaluation

In [11]:
```python
# evaluate
test_config = {}
test_config['test_datagen'] = train_config['test_datagen']
test_config['metrics']      = train_config['metrics']
test_config['devices']      = train_config['devices']
test_config['loss_fcn']     = train_config['loss_fcn']

for metric in test_config['metrics']:
    metric.reset()
test_loss, test_accuracies, cross_tab = evaluate(landmark_cnn, test_config)
```

```python
# show results
print(f"Test\n Loss: {test_loss}\n{test_accuracies}")

plt.figure(figsize=(20, 20))

axis_labels = [f"{i}" for i in range(N_OUTPUT_CLASSES)]#[s for s in test_dataset.synset
ax = plt.gca()
im = ax.imshow(cross_tab)
cbar = ax.figure.colorbar(im, ax=ax)

ax.set_xticks(range(0, N_OUTPUT_CLASSES))
ax.set_yticks(range(0, N_OUTPUT_CLASSES))
ax.set_xticklabels(axis_labels)
ax.set_yticklabels(axis_labels)

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

plt.title("Classification CrossTab", fontsize=12)
plt.show()
```

```
Test
 Loss: 2.0726248741149904
{'accuracy': 0.46957236842105265, 'top_k_accuracy_3': 0.6587171052631579}
```



1.10 Weight Initialization Test

In [ ]:
```
init_new = init.Normal(sigma=0.2)
landmark_cnn_new = landmark_cnn[:]
landmark_cnn_new.initialize(init=init_new, force_reinit=True, ctx=ctx)
landmark_cnn_new.hybridize()
landmark_cnn_new
```

1.10.1 Train with new initialization

In [ ]:
```
# setup
train_config_new = train_config
```

```
    train_config_new['trainer'] = gluon.Trainer(landmark_cnn_new.collect_params(),
                                                optimizer=train_config_new['optimizer'])
```

```
In [ ]: for epoch in range(2):
            print(f"Epoch {epoch}")

            train_loss, train_log = train_loop_one_epoch(landmark_cnn_new, train_config_new)
            valid_loss, valid_log = validation_loop_one_epoch(landmark_cnn_new, train_config_new
```

Training Log output

```
Epoch 0
train | (60/61): loss: 3.87712, accuracy: 0.08282, top_k_accuracy_3: 0.16005
valid | loss: 3.66212, accuracy: 0.11426, top_k_accuracy_3: 0.23633
Epoch 1
train | (61/62): loss: 3.64604, accuracy: 0.11700, top_k_accuracy_3: 0.22341
valid | loss: 3.25397, accuracy: 0.19141, top_k_accuracy_3: 0.31738
Epoch 2
train | (61/62): loss: 3.48943, accuracy: 0.14737, top_k_accuracy_3: 0.27262
valid | loss: 3.55357, accuracy: 0.21415, top_k_accuracy_3: 0.36305
Epoch 3
train | (60/61): loss: 3.48995, accuracy: 0.17841, top_k_accuracy_3: 0.31058
valid | loss: 3.23983, accuracy: 0.24121, top_k_accuracy_3: 0.37402
Epoch 4
train | (61/62): loss: 3.34187, accuracy: 0.20161, top_k_accuracy_3: 0.34621
valid | loss: 2.93397, accuracy: 0.25195, top_k_accuracy_3: 0.40820
Epoch 5
train | (61/62): loss: 3.33749, accuracy: 0.22455, top_k_accuracy_3: 0.37714
valid | loss: 3.28899, accuracy: 0.26103, top_k_accuracy_3: 0.40533
Epoch 6
train | (60/61): loss: 3.13213, accuracy: 0.24328, top_k_accuracy_3: 0.39581
valid | loss: 2.78515, accuracy: 0.29785, top_k_accuracy_3: 0.45605
```

1.11 Transfer Learning

Out of all pre-trained models, I chose MobileNetV2 as the parameter count is much closer to the model I designed but the architecture is quite different. Hence, I am curious to see how well it will be able to handle current problem.

- Pre-trained Model References
- Mxnet-ModelZoo
- Depthwise Separable Convolutions-1
- Depthwise Separable Convolutions-2
- MobileNetV2 details
- Residual, BottleNeck, Inverted Residual, Linear BottleNeck

```
In [11]: from mxnet.gluon.model_zoo import vision
```

In [12]:
```
#setup pretrained model
mobilenetv2 = vision.mobilenet_v2_1_0(pretrained=True, ctx=ctx)

# add top layer
mobilenetv2.output.add(nn.Dense(units=500), nn.BatchNorm())
mobilenetv2.output[-2:].initialize(init=init.Xavier(), ctx=ctx)

mobilenetv2.output.add(nn.Activation('relu'), nn.Dropout(0.2))

mobilenetv2.output.add(nn.Dense(units=50))
mobilenetv2.output[-1].initialize(init=init.Xavier(), ctx=ctx)


########## LOAD ALREADY TRAINED PARAMETERS ############################################
mobilenetv2.load_parameters('model_ckpts/model_ckpt_04-06-2022_22-02-28.params', ctx=ct

# collect trainable parameters
mobilenetv2_trainable_params = mobilenetv2.collect_params()

# summarize network
mobilenetv2.summary(dummy_input)
mobilenetv2.hybridize()
```

```
Downloading /root/.mxnet/models/mobilenetv2_1.0-36da4ff1.zipf07d8590-52bf-42be-8acd-54ed3b7f4f3f
--------------------------------------------------------------------------------
        Layer (type)                                Output Shape         Param #
================================================================================
               Input                            (64, 3, 256, 256)               0
            Conv2D-1                          (64, 32, 128, 128)             864
         BatchNorm-2                          (64, 32, 128, 128)             128
             RELU6-3                          (64, 32, 128, 128)               0
            Conv2D-4                          (64, 32, 128, 128)            1024
         BatchNorm-5                          (64, 32, 128, 128)             128
             RELU6-6                          (64, 32, 128, 128)               0
            Conv2D-7                          (64, 32, 128, 128)             288
         BatchNorm-8                          (64, 32, 128, 128)             128
             RELU6-9                          (64, 32, 128, 128)               0
           Conv2D-10                          (64, 16, 128, 128)             512
        BatchNorm-11                          (64, 16, 128, 128)              64
 LinearBottleneck-12                          (64, 16, 128, 128)               0
           Conv2D-13                          (64, 96, 128, 128)            1536
        BatchNorm-14                          (64, 96, 128, 128)             384
            RELU6-15                          (64, 96, 128, 128)               0
           Conv2D-16                            (64, 96, 64, 64)             864
        BatchNorm-17                            (64, 96, 64, 64)             384
            RELU6-18                            (64, 96, 64, 64)               0
           Conv2D-19                            (64, 24, 64, 64)            2304
        BatchNorm-20                            (64, 24, 64, 64)              96
```

LinearBottleneck-21	(64, 24, 64, 64)	0
Conv2D-22	(64, 144, 64, 64)	3456
BatchNorm-23	(64, 144, 64, 64)	576
RELU6-24	(64, 144, 64, 64)	0
Conv2D-25	(64, 144, 64, 64)	1296
BatchNorm-26	(64, 144, 64, 64)	576
RELU6-27	(64, 144, 64, 64)	0
Conv2D-28	(64, 24, 64, 64)	3456
BatchNorm-29	(64, 24, 64, 64)	96
LinearBottleneck-30	(64, 24, 64, 64)	0
Conv2D-31	(64, 144, 64, 64)	3456
BatchNorm-32	(64, 144, 64, 64)	576
RELU6-33	(64, 144, 64, 64)	0
Conv2D-34	(64, 144, 32, 32)	1296
BatchNorm-35	(64, 144, 32, 32)	576
RELU6-36	(64, 144, 32, 32)	0
Conv2D-37	(64, 32, 32, 32)	4608
BatchNorm-38	(64, 32, 32, 32)	128
LinearBottleneck-39	(64, 32, 32, 32)	0
Conv2D-40	(64, 192, 32, 32)	6144
BatchNorm-41	(64, 192, 32, 32)	768
RELU6-42	(64, 192, 32, 32)	0
Conv2D-43	(64, 192, 32, 32)	1728
BatchNorm-44	(64, 192, 32, 32)	768
RELU6-45	(64, 192, 32, 32)	0
Conv2D-46	(64, 32, 32, 32)	6144
BatchNorm-47	(64, 32, 32, 32)	128
LinearBottleneck-48	(64, 32, 32, 32)	0
Conv2D-49	(64, 192, 32, 32)	6144
BatchNorm-50	(64, 192, 32, 32)	768
RELU6-51	(64, 192, 32, 32)	0
Conv2D-52	(64, 192, 32, 32)	1728
BatchNorm-53	(64, 192, 32, 32)	768
RELU6-54	(64, 192, 32, 32)	0
Conv2D-55	(64, 32, 32, 32)	6144
BatchNorm-56	(64, 32, 32, 32)	128
LinearBottleneck-57	(64, 32, 32, 32)	0
Conv2D-58	(64, 192, 32, 32)	6144
BatchNorm-59	(64, 192, 32, 32)	768
RELU6-60	(64, 192, 32, 32)	0
Conv2D-61	(64, 192, 16, 16)	1728
BatchNorm-62	(64, 192, 16, 16)	768
RELU6-63	(64, 192, 16, 16)	0
Conv2D-64	(64, 64, 16, 16)	12288
BatchNorm-65	(64, 64, 16, 16)	256
LinearBottleneck-66	(64, 64, 16, 16)	0
Conv2D-67	(64, 384, 16, 16)	24576
BatchNorm-68	(64, 384, 16, 16)	1536

RELU6-69	(64, 384, 16, 16)	0
Conv2D-70	(64, 384, 16, 16)	3456
BatchNorm-71	(64, 384, 16, 16)	1536
RELU6-72	(64, 384, 16, 16)	0
Conv2D-73	(64, 64, 16, 16)	24576
BatchNorm-74	(64, 64, 16, 16)	256
LinearBottleneck-75	(64, 64, 16, 16)	0
Conv2D-76	(64, 384, 16, 16)	24576
BatchNorm-77	(64, 384, 16, 16)	1536
RELU6-78	(64, 384, 16, 16)	0
Conv2D-79	(64, 384, 16, 16)	3456
BatchNorm-80	(64, 384, 16, 16)	1536
RELU6-81	(64, 384, 16, 16)	0
Conv2D-82	(64, 64, 16, 16)	24576
BatchNorm-83	(64, 64, 16, 16)	256
LinearBottleneck-84	(64, 64, 16, 16)	0
Conv2D-85	(64, 384, 16, 16)	24576
BatchNorm-86	(64, 384, 16, 16)	1536
RELU6-87	(64, 384, 16, 16)	0
Conv2D-88	(64, 384, 16, 16)	3456
BatchNorm-89	(64, 384, 16, 16)	1536
RELU6-90	(64, 384, 16, 16)	0
Conv2D-91	(64, 64, 16, 16)	24576
BatchNorm-92	(64, 64, 16, 16)	256
LinearBottleneck-93	(64, 64, 16, 16)	0
Conv2D-94	(64, 384, 16, 16)	24576
BatchNorm-95	(64, 384, 16, 16)	1536
RELU6-96	(64, 384, 16, 16)	0
Conv2D-97	(64, 384, 16, 16)	3456
BatchNorm-98	(64, 384, 16, 16)	1536
RELU6-99	(64, 384, 16, 16)	0
Conv2D-100	(64, 96, 16, 16)	36864
BatchNorm-101	(64, 96, 16, 16)	384
LinearBottleneck-102	(64, 96, 16, 16)	0
Conv2D-103	(64, 576, 16, 16)	55296
BatchNorm-104	(64, 576, 16, 16)	2304
RELU6-105	(64, 576, 16, 16)	0
Conv2D-106	(64, 576, 16, 16)	5184
BatchNorm-107	(64, 576, 16, 16)	2304
RELU6-108	(64, 576, 16, 16)	0
Conv2D-109	(64, 96, 16, 16)	55296
BatchNorm-110	(64, 96, 16, 16)	384
LinearBottleneck-111	(64, 96, 16, 16)	0
Conv2D-112	(64, 576, 16, 16)	55296
BatchNorm-113	(64, 576, 16, 16)	2304
RELU6-114	(64, 576, 16, 16)	0
Conv2D-115	(64, 576, 16, 16)	5184
BatchNorm-116	(64, 576, 16, 16)	2304

RELU6-117	(64, 576, 16, 16)	0
Conv2D-118	(64, 96, 16, 16)	55296
BatchNorm-119	(64, 96, 16, 16)	384
LinearBottleneck-120	(64, 96, 16, 16)	0
Conv2D-121	(64, 576, 16, 16)	55296
BatchNorm-122	(64, 576, 16, 16)	2304
RELU6-123	(64, 576, 16, 16)	0
Conv2D-124	(64, 576, 8, 8)	5184
BatchNorm-125	(64, 576, 8, 8)	2304
RELU6-126	(64, 576, 8, 8)	0
Conv2D-127	(64, 160, 8, 8)	92160
BatchNorm-128	(64, 160, 8, 8)	640
LinearBottleneck-129	(64, 160, 8, 8)	0
Conv2D-130	(64, 960, 8, 8)	153600
BatchNorm-131	(64, 960, 8, 8)	3840
RELU6-132	(64, 960, 8, 8)	0
Conv2D-133	(64, 960, 8, 8)	8640
BatchNorm-134	(64, 960, 8, 8)	3840
RELU6-135	(64, 960, 8, 8)	0
Conv2D-136	(64, 160, 8, 8)	153600
BatchNorm-137	(64, 160, 8, 8)	640
LinearBottleneck-138	(64, 160, 8, 8)	0
Conv2D-139	(64, 960, 8, 8)	153600
BatchNorm-140	(64, 960, 8, 8)	3840
RELU6-141	(64, 960, 8, 8)	0
Conv2D-142	(64, 960, 8, 8)	8640
BatchNorm-143	(64, 960, 8, 8)	3840
RELU6-144	(64, 960, 8, 8)	0
Conv2D-145	(64, 160, 8, 8)	153600
BatchNorm-146	(64, 160, 8, 8)	640
LinearBottleneck-147	(64, 160, 8, 8)	0
Conv2D-148	(64, 960, 8, 8)	153600
BatchNorm-149	(64, 960, 8, 8)	3840
RELU6-150	(64, 960, 8, 8)	0
Conv2D-151	(64, 960, 8, 8)	8640
BatchNorm-152	(64, 960, 8, 8)	3840
RELU6-153	(64, 960, 8, 8)	0
Conv2D-154	(64, 320, 8, 8)	307200
BatchNorm-155	(64, 320, 8, 8)	1280
LinearBottleneck-156	(64, 320, 8, 8)	0
Conv2D-157	(64, 1280, 8, 8)	409600
BatchNorm-158	(64, 1280, 8, 8)	5120
RELU6-159	(64, 1280, 8, 8)	0
GlobalAvgPool2D-160	(64, 1280, 1, 1)	0
Conv2D-161	(64, 1000, 1, 1)	1280000
Flatten-162	(64, 1000)	0
Dense-163	(64, 500)	500500
BatchNorm-164	(64, 500)	2000

```
      Activation-165                                   (64, 500)               0
         Dropout-166                                   (64, 500)               0
           Dense-167                                    (64, 50)           25050
     MobileNetV2-168                                    (64, 50)               0
================================================================================
Parameters in forward computation graph, duplicate included
   Total params: 4066686
   Trainable params: 4031510
   Non-trainable params: 35176
Shared params in forward computation graph: 0
Unique parameters in model: 4066686
--------------------------------------------------------------------------------
```

```
In [13]: # setup trainer
         model_ckpt(mobilenetv2)

         # define loss and metrics for the training loop
         mobilenet_train_config = {}
         mobilenet_train_config['optimizer'] = mx.optimizer.Adam(learning_rate=1e-3, wd=0.000001
         mobilenet_train_config['metrics']   = [mx.metric.Accuracy(), mx.metric.TopKAccuracy(top
         mobilenet_train_config['loss_fcn']  = gluon.loss.SoftmaxCrossEntropyLoss(from_logits=Fa
         mobilenet_train_config['trainer']   = gluon.Trainer(mobilenetv2_trainable_params, optim
         mobilenet_train_config['devices']   = [ctx]
         mobilenet_train_config['model_ckpt_freq'] = 1 # for every n epochs ckpt model

         mobilenet_train_config['batch_size'] = 64
         mobilenet_train_config['batch_aug']  = False
         mobilenet_train_config['valid_frac'] = 0.2
         mobilenet_train_config['last_batch'] = 'rollover'

         train_datagen, valid_datagen, test_datagen = generate_datasets(TRAIN_FOLDER,
                                                                       TEST_FOLDER,
                                                                       mobilenet_train_config)
         mobilenet_train_config['train_datagen'] = train_datagen
         mobilenet_train_config['valid_datagen'] = valid_datagen
         mobilenet_train_config['test_datagen']  = test_datagen
```

```
In [ ]: # perform training
        for epoch in range(1):
            print(f"Epoch {epoch}")

            train_loss, train_log = train_loop_one_epoch(mobilenetv2, mobilenet_train_config)
            valid_loss, valid_log = validation_loop_one_epoch(mobilenetv2, mobilenet_train_confi

            if (( (epoch+1) % mobilenet_train_config['model_ckpt_freq']) == 0):
                params_ckpt(mobilenetv2, epoch, train_loss, train_log, valid_loss, valid_log)
```

Transfer Learning Training Log

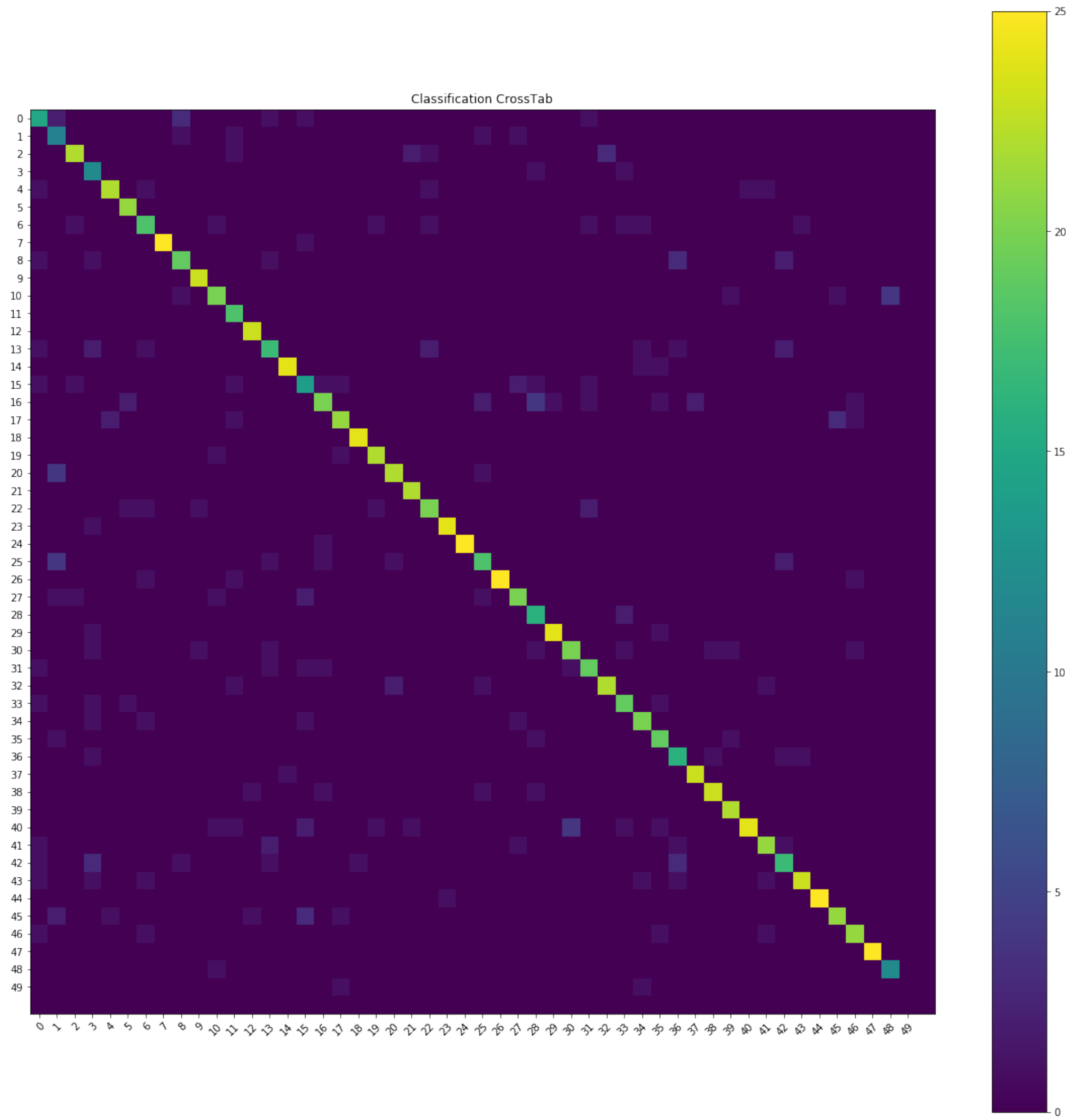
```
loss: 1.77507, accuracy: 0.42008, top_k_accuracy_3: 0.58171 --------> Freezed Conv Layers, Train
valid | loss: 1.56214, accuracy: 0.60352, top_k_accuracy_3: 0.75684
model_ckpts/model_ckpt_04-06-2022_21-33-27.params
-------------------
loss: 1.18948, accuracy: 0.62878, top_k_accuracy_3: 0.78881 --------> Freezed Conv Layers, Train
valid | loss: 1.32506, accuracy: 0.63672, top_k_accuracy_3: 0.77344
model_ckpts/model_ckpt_04-06-2022_21-35-19.params
-------------------
loss: 1.16967, accuracy: 0.68221, top_k_accuracy_3: 0.82686 --------> Freezed Conv Layers, Train
valid | loss: 1.30251, accuracy: 0.68474, top_k_accuracy_3: 0.81342
model_ckpts/model_ckpt_04-06-2022_21-37-04.params
-------------------
loss: 1.13735, accuracy: 0.71183, top_k_accuracy_3: 0.85297 --------> Freezed Conv Layers, Train
valid | loss: 1.19720, accuracy: 0.68750, top_k_accuracy_3: 0.82129
model_ckpts/model_ckpt_04-06-2022_21-39-07.params
-------------------
loss: 1.02352, accuracy: 0.74849, top_k_accuracy_3: 0.87147 --------> Freezed Conv Layers, Train
valid | loss: 1.08014, accuracy: 0.68848, top_k_accuracy_3: 0.82617
model_ckpts/model_ckpt_04-06-2022_21-41-10.params
-------------------
loss: 1.67483, accuracy: 0.50026, top_k_accuracy_3: 0.68494 --------> Train Conv Layers, Train F
valid | loss: 1.80864, accuracy: 0.54395, top_k_accuracy_3: 0.70605
model_ckpts/model_ckpt_04-06-2022_21-47-07.params
-------------------
loss: 1.35442, accuracy: 0.60081, top_k_accuracy_3: 0.76764 --------> Train Conv Layers, Train F
valid | loss: 1.57531, accuracy: 0.56055, top_k_accuracy_3: 0.73242
model_ckpts/model_ckpt_04-06-2022_21-49-05.params
-------------------
loss: 1.10537, accuracy: 0.64667, top_k_accuracy_3: 0.80670 --------> Train Conv Layers, Train F
valid | loss: 1.58002, accuracy: 0.60662, top_k_accuracy_3: 0.78493
model_ckpts/model_ckpt_04-06-2022_21-50-43.params
-------------------
loss: 1.10785, accuracy: 0.68058, top_k_accuracy_3: 0.83478 --------> Train Conv Layers, Train F
valid | loss: 1.42574, accuracy: 0.63574, top_k_accuracy_3: 0.79590
model_ckpts/model_ckpt_04-06-2022_21-52-20.params
-------------------
loss: 1.12698, accuracy: 0.69556, top_k_accuracy_3: 0.83518 --------> Train Conv Layers, Train F
valid | loss: 1.41816, accuracy: 0.63477, top_k_accuracy_3: 0.77344
model_ckpts/model_ckpt_04-06-2022_21-54-03.params
-------------------
loss: 0.69484, accuracy: 0.77394, top_k_accuracy_3: 0.89768 --------> Train Conv Layers, Train F
valid | loss: 1.14930, accuracy: 0.70772, top_k_accuracy_3: 0.84651
model_ckpts/model_ckpt_04-06-2022_21-55-50.params
-------------------
loss: 0.53942, accuracy: 0.82659, top_k_accuracy_3: 0.92264 --------> Train Conv Layers, Train F
valid | loss: 0.97534, accuracy: 0.71875, top_k_accuracy_3: 0.84863
model_ckpts/model_ckpt_04-06-2022_21-58-41.params
-------------------
```

```
loss: 0.54136, accuracy: 0.84199, top_k_accuracy_3: 0.92792 --------> Train Conv Layers, Train F
valid | loss: 1.05582, accuracy: 0.74081, top_k_accuracy_3: 0.85846
model_ckpts/model_ckpt_04-06-2022_22-00-28.params
-------------------
loss: 0.37884, accuracy: 0.85030, top_k_accuracy_3: 0.93700 --------> Train Conv Layers, Train F
valid | loss: 0.97149, accuracy: 0.74707, top_k_accuracy_3: 0.86816
model_ckpts/model_ckpt_04-06-2022_22-02-28.params          --------> Select this as a Best Fit
-------------------
```

1.12 Evaluation

In [15]:
```python
# evaluate
test_config = {}
test_config['test_datagen'] = mobilenet_train_config['test_datagen']
test_config['metrics']      = mobilenet_train_config['metrics']
test_config['devices']      = mobilenet_train_config['devices']
test_config['loss_fcn']     = mobilenet_train_config['loss_fcn']

for metric in test_config['metrics']:
    metric.reset()
test_loss, test_accuracies, cross_tab = evaluate(mobilenetv2, test_config)

# show results
print(f"Test\n Loss: {test_loss}\n{test_accuracies}")

plt.figure(figsize=(20, 20))

axis_labels = [f"{i}" for i in range(N_OUTPUT_CLASSES)]#[s for s in test_dataset.synset
ax = plt.gca()
im = ax.imshow(cross_tab)
cbar = ax.figure.colorbar(im, ax=ax)

ax.set_xticks(range(0, N_OUTPUT_CLASSES))
ax.set_yticks(range(0, N_OUTPUT_CLASSES))
ax.set_xticklabels(axis_labels)
ax.set_yticklabels(axis_labels)

# Rotate the tick labels and set their alignment.
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")

plt.title("Classification CrossTab", fontsize=12)
plt.show()
```

```
Test
 Loss: 0.6526021227240563
{'accuracy': 0.821546052631579, 'top_k_accuracy_3': 0.9194078947368421}
```



1.13 Step 3: Write Your Landmark Prediction Algorithm

Great job creating your CNN models! Now that you have put in all the hard work of creating accurate classifiers, let's define some functions to make it easy for others to use your classifiers.

1.13.1 (IMPLEMENTATION) Write Your Algorithm, Part 1

Implement the function `predict_landmarks`, which accepts a file path to an image and an integer k, and then predicts the **top k most likely landmarks**. You are **required** to use your transfer learned CNN from Step 2 to predict the landmarks.

An example of the expected behavior of `predict_landmarks`: