Training Custom Object Detector

So, up to now you should have done the following:

- Installed TensorFlow (See TensorFlow Installation)
- Installed TensorFlow Object Detection API (See TensorFlow Object Detection API Installation)

Now that we have done all the above, we can start doing some cool stuff. Here we will see how you can train your own object detector, and since it is not as simple as it sounds, we will have a look at:

1. How to organise your workspace/training files
2. How to prepare/annotate image datasets
3. How to generate tf records from such datasets
4. How to configure a simple training pipeline
5. How to train a model and monitor it's progress
6. How to export the resulting model and use it to detect objects.

Preparing the Workspace

1. If you have followed the tutorial, you should by now have a folder `Tensorflow`, placed under `<PATH_TO_TF>` (e.g. `C:/Users/sglvladi/Documents`), with the following directory tree:

```
TensorFlow/
├─ addons/ (Optional)
│  └─ labelImg/
└─ models/
   ├─ community/
   ├─ official/
   ├─ orbit/
   ├─ research/
   └─ ...
```

2. Now create a new folder under `TensorFlow` and call it `workspace`. It is within the `workspace` that we will store all our training set-ups. Now let's go under workspace and create another folder named `training_demo`. Now our directory structure should be as so:

```
TensorFlow/
├─ addons/ (Optional)
│  └─ labelImg/
├─ models/
│  ├─ community/
│  ├─ official/
│  ├─ orbit/
│  ├─ research/
│  └─ ...
└─ workspace/
   └─ training_demo/
```

3. The `training_demo` folder shall be our *training folder*, which will contain all files related to our model training. It is advisable to create a separate training folder each time we wish to train on a different dataset. The typical structure for training folders is shown below.

```
training_demo/
├─ annotations/
├─ exported-models/
├─ images/
│  ├─ test/
│  └─ train/
├─ models/
├─ pre-trained-models/
└─ README.md
```

Here's an explanation for each of the folders/filer shown in the above tree:

- `annotations`: This folder will be used to store all `*.csv` files and the respective TensorFlow `*.record` files, which contain the list of annotations for our dataset images.
- `exported-models`: This folder will be used to store exported versions of our trained model(s).
- `images`: This folder contains a copy of all the images in our dataset, as well as the respective `*.xml` files produced for each one, once `labelImg` is used to annotate objects.
    - `images/train`: This folder contains a copy of all images, and the respective `*.xml` files, which will be used to train our model.
    - `images/test`: This folder contains a copy of all images, and the respective `*.xml` files, which will be used to test our model.

- `models`: This folder will contain a sub-folder for each of training job. Each subfolder will contain the training pipeline configuration file `*.config`, as well as all files generated during the training and evaluation of our model.
- `pre-trained-models`: This folder will contain the downloaded pre-trained models, which shall be used as a starting checkpoint for our training jobs.

- `README.md` : This is an optional file which provides some general information regarding the training conditions of our model. It is not used by TensorFlow in any way, but it generally helps when you have a few training folders and/or you are revisiting a trained model after some time.

If you do not understand most of the things mentioned above, no need to worry, as we'll see how all the files are generated further down.

Preparing the Dataset

Annotate the Dataset

Install LabelImg

There exist several ways to install `labelImg` . Below are 3 of the most common.

Using PIP (Recommended)

1. Open a new *Terminal* window and activate the *tensorflow_gpu* environment (if you have not done so already)
2. Run the following command to install `labelImg` :

```
pip install labelImg
```

3. `labelImg` can then be run as follows:

```
labelImg
# or
labelImg [IMAGE_PATH] [PRE-DEFINED CLASS FILE]
```

Use precompiled binaries (Easy)

Precompiled binaries for both Windows and Linux can be found here .

Installation is the done in three simple steps:

1. Inside you `TensorFlow` folder, create a new directory, name it `addons` and then `cd` into it.
2. Download the latest binary for your OS from here. and extract its contents under `Tensorflow/addons/labelImg` .
3. You should now have a single folder named `addons/labelImg` under your `TensorFlow` folder, which contains another 4 folders as such:

```
TensorFlow/
├─ addons/
│  └─ labelImg/
└─ models/
   ├─ community/
   ├─ official/
   ├─ orbit/
   ├─ research/
   └─ ...
```

4. `labelImg` can then be run as follows:

```
# From within Tensorflow/addons/labelImg
labelImg
# or
labelImg [IMAGE_PATH] [PRE-DEFINED CLASS FILE]
```

Build from source (Hard)

The steps for installing from source follow below.

1. Download labelImg

- Inside you `TensorFlow` folder, create a new directory, name it `addons` and then `cd` into it.
- To download the package you can either use Git to clone the labelImg repo inside the `TensorFlow\addons` folder, or you can simply download it as a ZIP and extract it's contents inside the `TensorFlow\addons` folder. To keep things consistent, in the latter case you will have to rename the extracted folder `labelImg-master` to `labelImg`. [1]
- You should now have a single folder named `addons\labelImg` under your `TensorFlow` folder, which contains another 4 folders as such:

```
TensorFlow/
├─ addons
│  └─ labelImg/
└─ models/
   ├─ community/
   ├─ official/
   ├─ orbit/
   ├─ research/
   └─ ...
```

1

The latest repo commit when writing this tutorial is 8d1bd68.

2. Install dependencies and compiling package

- Open a new *Terminal* window and activate the *tensorflow_gpu* environment (if you have not done so already)
- `cd` into `TensorFlow/addons/labelImg` and run the following commands:

Windows | Linux

```
conda install pyqt=5
pyrcc5 -o libs/resources.py resources.qrc
```

3. Test your installation

- Open a new *Terminal* window and activate the *tensorflow_gpu* environment (if you have not done so already)
- `cd` into `TensorFlow/addons/labelImg` and run the following command:

```
# From within Tensorflow/addons/labelImg
python labelImg.py
# or
python labelImg.py [IMAGE_PATH] [PRE-DEFINED CLASS FILE]
```

Annotate Images

- Once you have collected all the images to be used to test your model (ideally more than 100 per class), place them inside the folder `training_demo/images`.
- Open a new *Terminal* window.
- Next go ahead and start `labelImg`, pointing it to your `training_demo/images` folder.
  - If you installed `labelImg` Using PIP (Recommended):

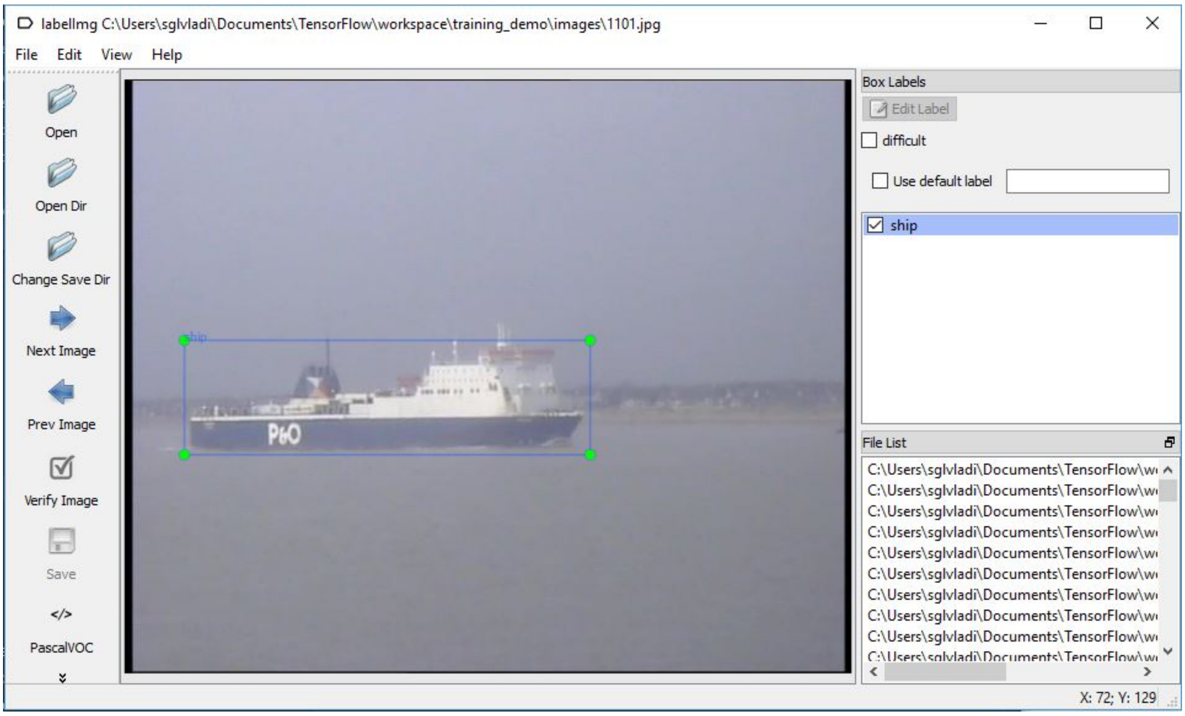
    ```
    labelImg <PATH_TO_TF>/TensorFlow/workspace/training_demo/images
    ```

  - Othewise, `cd` into `Tensorflow/addons/labelImg` and run:

    ```
    # From within Tensorflow/addons/labelImg
    python labelImg.py ../../workspace/training_demo/images
    ```

- A File Explorer Dialog windows should open, which points to the `training_demo/images` folder.
- Press the “Select Folder” button, to start annotating your images.

Once open, you should see a window similar to the one below:



I won't be covering a tutorial on how to use `labelImg`, but you can have a look at labelImg's repo for more details. A nice Youtube video demonstrating how to use `labelImg` is also available here. What is important is that once you annotate all your images, a set of new `*.xml` files, one for each image, should be generated inside your `training_demo/images` folder.

Partition the Dataset

Once you have finished annotating your image dataset, it is a general convention to use only part of it for training, and the rest is used for evaluation purposes (e.g. as discussed in Evaluating the Model (Optional)).

Typically, the ratio is 9:1, i.e. 90% of the images are used for training and the rest 10% is maintained for testing, but you can chose whatever ratio suits your needs.

Once you have decided how you will be splitting your dataset, copy all training images, together with their corresponding `*.xml` files, and place them inside the `training_demo/images/train` folder. Similarly, copy all testing images, with their `*.xml` files, and paste them inside `training_demo/images/test`.

For lazy people like myself, who cannot be bothered to do the above, I have put together a simple script that automates the above process:

```python
""" usage: partition_dataset.py [-h] [-i IMAGEDIR] [-o OUTPUTDIR] [-r RATIO] [-x]

Partition dataset of images into training and testing sets

optional arguments:
  -h, --help            show this help message and exit
  -i IMAGEDIR, --imageDir IMAGEDIR
                        Path to the folder where the image dataset is stored. If not specified,
the CWD will be used.
  -o OUTPUTDIR, --outputDir OUTPUTDIR
                        Path to the output folder where the train and test dirs should be
created. Defaults to the same directory as IMAGEDIR.
  -r RATIO, --ratio RATIO
                        The ratio of the number of test images over the total number of images.
The default is 0.1.
  -x, --xml             Set this flag if you want the xml annotation files to be processed and
copied over.
"""
import os
import re
from shutil import copyfile
import argparse
import math
import random


def iterate_dir(source, dest, ratio, copy_xml):
    source = source.replace('\\', '/')
    dest = dest.replace('\\', '/')
    train_dir = os.path.join(dest, 'train')
    test_dir = os.path.join(dest, 'test')

    if not os.path.exists(train_dir):
        os.makedirs(train_dir)
    if not os.path.exists(test_dir):
        os.makedirs(test_dir)

    images = [f for f in os.listdir(source)
              if re.search(r'([a-zA-Z0-9\s_\\.\-\(\):])+(?i)(.jpg|.jpeg|.png)$', f)]

    num_images = len(images)
    num_test_images = math.ceil(ratio*num_images)

    for i in range(num_test_images):
        idx = random.randint(0, len(images)-1)
        filename = images[idx]
        copyfile(os.path.join(source, filename),
                 os.path.join(test_dir, filename))
        if copy_xml:
            xml_filename = os.path.splitext(filename)[0]+'.xml'
            copyfile(os.path.join(source, xml_filename),
                     os.path.join(test_dir,xml_filename))
        images.remove(images[idx])

    for filename in images:
        copyfile(os.path.join(source, filename),
                 os.path.join(train_dir, filename))
        if copy_xml:
            xml_filename = os.path.splitext(filename)[0]+'.xml'
            copyfile(os.path.join(source, xml_filename),
                     os.path.join(train_dir, xml_filename))
```

```python
def main():

    # Initiate argument parser
    parser = argparse.ArgumentParser(description="Partition dataset of images into training and
testing sets",
                                     formatter_class=argparse.RawTextHelpFormatter)
    parser.add_argument(
        '-i', '--imageDir',
        help='Path to the folder where the image dataset is stored. If not specified, the CWD
will be used.',
        type=str,
        default=os.getcwd()
    )
    parser.add_argument(
        '-o', '--outputDir',
        help='Path to the output folder where the train and test dirs should be created. '
             'Defaults to the same directory as IMAGEDIR.',
        type=str,
        default=None
    )
    parser.add_argument(
        '-r', '--ratio',
        help='The ratio of the number of test images over the total number of images. The
default is 0.1.',
        default=0.1,
        type=float)
    parser.add_argument(
        '-x', '--xml',
        help='Set this flag if you want the xml annotation files to be processed and copied
over.',
        action='store_true'
    )
    args = parser.parse_args()

    if args.outputDir is None:
        args.outputDir = args.imageDir

    # Now we are ready to start the iteration
    iterate_dir(args.imageDir, args.outputDir, args.ratio, args.xml)


if __name__ == '__main__':
    main()
```

- Under the `TensorFlow` folder, create a new folder `TensorFlow/scripts`, which we can use to store some useful scripts.
- To make things even tidier, let's create a new folder `TensorFlow/scripts/preprocessing`, where we shall store scripts that we can use to preprocess our training inputs. Below is out `TensorFlow` directory tree structure, up to now:

```
TensorFlow/
├─ addons/ (Optional)
│  └─ labelImg/
├─ models/
│  ├─ community/
│  ├─ official/
│  ├─ orbit/
│  ├─ research/
│  └─ ...
├─ scripts/
│  └─ preprocessing/
└─ workspace/
   └─ training_demo/
```

- Click here to download the above script and save it inside `TensorFlow/scripts/preprocessing`.
- Then, `cd` into `TensorFlow/scripts/preprocessing` and run:

```
python partition_dataset.py -x -i [PATH_TO_IMAGES_FOLDER] -r 0.1

# For example
# python partition_dataset.py -x -i
C:/Users/sglvladi/Documents/Tensorflow/workspace/training_demo/images -r 0.1
```

Once the script has finished, two new folders should have been created under `training_demo/images`, namely `training_demo/images/train` and `training_demo/images/test`, containing 90% and 10% of the images (and `*.xml` files), respectively. To avoid loss of any files, the script will not delete the images under `training_demo/images`. Once you have checked that your images have been safely copied over, you can delete the images under `training_demo/images` manually.

Create Label Map

TensorFlow requires a label map, which namely maps each of the used labels to an integer values. This label map is used both by the training and detection processes.

Below we show an example label map (e.g `label_map.pbtxt`), assuming that our dataset containes 2 labels, `dogs` and `cats`:

```
item {
    id: 1
    name: 'cat'
}

item {
    id: 2
    name: 'dog'
}
```

Label map files have the extention `.pbtxt` and should be placed inside the `training_demo/annotations` folder.

Create TensorFlow Records

Now that we have generated our annotations and split our dataset into the desired training and testing subsets, it is time to convert our annotations into the so called `TFRecord` format.

Convert `*.xml` to `*.record`

To do this we can write a simple script that iterates through all `*.xml` files in the `training_demo/images/train` and `training_demo/images/test` folders, and generates a `*.record` file for each of the two. Here is an example script that allows us to do just that:

```
""" Sample TensorFlow XML-to-TFRecord converter

usage: generate_tfrecord.py [-h] [-x XML_DIR] [-l LABELS_PATH] [-o OUTPUT_PATH] [-i IMAGE_DIR]
[-c CSV_PATH]

optional arguments:
  -h, --help            show this help message and exit
  -x XML_DIR, --xml_dir XML_DIR
                        Path to the folder where the input .xml files are stored.
  -l LABELS_PATH, --labels_path LABELS_PATH
                        Path to the labels (.pbtxt) file.
  -o OUTPUT_PATH, --output_path OUTPUT_PATH
                        Path of output TFRecord (.record) file.
  -i IMAGE_DIR, --image_dir IMAGE_DIR
                        Path to the folder where the input image files are stored. Defaults to
the same directory as XML_DIR.
  -c CSV_PATH, --csv_path CSV_PATH
                        Path of output .csv file. If none provided, then no file will be
written.
"""

import os
import glob
import pandas as pd
import io
import xml.etree.ElementTree as ET
import argparse

os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'    # Suppress TensorFlow logging (1)
import tensorflow.compat.v1 as tf
from PIL import Image
from object_detection.utils import dataset_util, label_map_util
from collections import namedtuple

# Initiate argument parser
parser = argparse.ArgumentParser(
    description="Sample TensorFlow XML-to-TFRecord converter")
parser.add_argument("-x",
                    "--xml_dir",
                    help="Path to the folder where the input .xml files are stored.",
                    type=str)
parser.add_argument("-l",
                    "--labels_path",
                    help="Path to the labels (.pbtxt) file.", type=str)
parser.add_argument("-o",
                    "--output_path",
                    help="Path of output TFRecord (.record) file.", type=str)
parser.add_argument("-i",
                    "--image_dir",
                    help="Path to the folder where the input image files are stored. "
                         "Defaults to the same directory as XML_DIR.",
                    type=str, default=None)
parser.add_argument("-c",
                    "--csv_path",
                    help="Path of output .csv file. If none provided, then no file will be "
                         "written.",
                    type=str, default=None)

args = parser.parse_args()

if args.image_dir is None:
    args.image_dir = args.xml_dir
```

```
label_map = label_map_util.load_labelmap(args.labels_path)
label_map_dict = label_map_util.get_label_map_dict(label_map)


def xml_to_csv(path):
    """Iterates through all .xml files (generated by labelImg) in a given directory and
combines
    them in a single Pandas dataframe.

    Parameters:
    ----------
    path : str
        The path containing the .xml files
    Returns
    -------
    Pandas DataFrame
        The produced dataframe
    """

    xml_list = []
    for xml_file in glob.glob(path + '/*.xml'):
        tree = ET.parse(xml_file)
        root = tree.getroot()
        filename = root.find('filename').text
        width = int(root.find('size').find('width').text)
        height = int(root.find('size').find('height').text)
        for member in root.findall('object'):
            bndbox = member.find('bndbox')
            value = (filename,
                     width,
                     height,
                     member.find('name').text,
                     int(bndbox.find('xmin').text),
                     int(bndbox.find('ymin').text),
                     int(bndbox.find('xmax').text),
                     int(bndbox.find('ymax').text),
                     )
            xml_list.append(value)
    column_name = ['filename', 'width', 'height',
                   'class', 'xmin', 'ymin', 'xmax', 'ymax']
    xml_df = pd.DataFrame(xml_list, columns=column_name)
    return xml_df


def class_text_to_int(row_label):
    return label_map_dict[row_label]


def split(df, group):
    data = namedtuple('data', ['filename', 'object'])
    gb = df.groupby(group)
    return [data(filename, gb.get_group(x)) for filename, x in zip(gb.groups.keys(),
gb.groups)]


def create_tf_example(group, path):
    with tf.gfile.GFile(os.path.join(path, '{}'.format(group.filename)), 'rb') as fid:
        encoded_jpg = fid.read()
    encoded_jpg_io = io.BytesIO(encoded_jpg)
    image = Image.open(encoded_jpg_io)
    width, height = image.size

    filename = group.filename.encode('utf8')
    image_format = b'jpg'
```

```
    xmins = []
    xmaxs = []
    ymins = []
    ymaxs = []
    classes_text = []
    classes = []

    for index, row in group.object.iterrows():
        xmins.append(row['xmin'] / width)
        xmaxs.append(row['xmax'] / width)
        ymins.append(row['ymin'] / height)
        ymaxs.append(row['ymax'] / height)
        classes_text.append(row['class'].encode('utf8'))
        classes.append(class_text_to_int(row['class']))

    tf_example = tf.train.Example(features=tf.train.Features(feature={
        'image/height': dataset_util.int64_feature(height),
        'image/width': dataset_util.int64_feature(width),
        'image/filename': dataset_util.bytes_feature(filename),
        'image/source_id': dataset_util.bytes_feature(filename),
        'image/encoded': dataset_util.bytes_feature(encoded_jpg),
        'image/format': dataset_util.bytes_feature(image_format),
        'image/object/bbox/xmin': dataset_util.float_list_feature(xmins),
        'image/object/bbox/xmax': dataset_util.float_list_feature(xmaxs),
        'image/object/bbox/ymin': dataset_util.float_list_feature(ymins),
        'image/object/bbox/ymax': dataset_util.float_list_feature(ymaxs),
        'image/object/class/text': dataset_util.bytes_list_feature(classes_text),
        'image/object/class/label': dataset_util.int64_list_feature(classes),
    }))
    return tf_example


def main(_):

    writer = tf.python_io.TFRecordWriter(args.output_path)
    path = os.path.join(args.image_dir)
    examples = xml_to_csv(args.xml_dir)
    grouped = split(examples, 'filename')
    for group in grouped:
        tf_example = create_tf_example(group, path)
        writer.write(tf_example.SerializeToString())
    writer.close()
    print('Successfully created the TFRecord file: {}'.format(args.output_path))
    if args.csv_path is not None:
        examples.to_csv(args.csv_path, index=None)
        print('Successfully created the CSV file: {}'.format(args.csv_path))


if __name__ == '__main__':
    tf.app.run()
```

- Click here to download the above script and save it inside `TensorFlow/scripts/preprocessing`.
- Install the `pandas` package:

```
conda install pandas # Anaconda
                     # or
pip install pandas   # pip
```

- Finally, `cd` into `TensorFlow/scripts/preprocessing` and run:

```
# Create train data:
python generate_tfrecord.py -x [PATH_TO_IMAGES_FOLDER]/train -l
[PATH_TO_ANNOTATIONS_FOLDER]/label_map.pbtxt -o
[PATH_TO_ANNOTATIONS_FOLDER]/train.record

# Create test data:
python generate_tfrecord.py -x [PATH_TO_IMAGES_FOLDER]/test -l
[PATH_TO_ANNOTATIONS_FOLDER]/label_map.pbtxt -o
[PATH_TO_ANNOTATIONS_FOLDER]/test.record

# For example
# python generate_tfrecord.py -x
C:/Users/sglvladi/Documents/Tensorflow/workspace/training_demo/images/train -l
C:/Users/sglvladi/Documents/Tensorflow/workspace/training_demo/annotations/label_map.pbtxt
 -o
C:/Users/sglvladi/Documents/Tensorflow/workspace/training_demo/annotations/train.record
# python generate_tfrecord.py -x
C:/Users/sglvladi/Documents/Tensorflow/workspace/training_demo/images/test -l
C:/Users/sglvladi/Documents/Tensorflow2/workspace/training_demo/annotations/label_map.pbtx
 -o
C:/Users/sglvladi/Documents/Tensorflow/workspace/training_demo/annotations/test.record
```

Once the above is done, there should be 2 new files under the `training_demo/annotations` folder, named `test.record` and `train.record`, respectively.

Configuring a Training Job

For the purposes of this tutorial we will not be creating a training job from scratch, but rather we will reuse one of the pre-trained models provided by TensorFlow. If you would like to train an entirely new model, you can have a look at TensorFlow's tutorial.

The model we shall be using in our examples is the SSD ResNet50 V1 FPN 640x640 model, since it provides a relatively good trade-off between performance and speed. However, there exist a number of other models you can use, all of which are listed in TensorFlow 2 Detection Model Zoo.

Download Pre-Trained Model

To begin with, we need to download the latest pre-trained network for the model we wish to use. This can be done by simply clicking on the name of the desired model in the table found in TensorFlow 2 Detection Model Zoo. Clicking on the name of your model should initiate a download for a `*.tar.gz` file.

Once the `*.tar.gz` file has been downloaded, open it using a decompression program of your choice (e.g. 7zip, WinZIP, etc.). Next, open the `*.tar` folder that you see when the compressed folder is opened, and extract its contents inside the folder `training_demo/pre-trained-models`. Since we downloaded the SSD ResNet50 V1 FPN 640x640 model, our `training_demo` directory should now look as follows:

```
training_demo/
├─ ...
├─ pre-trained-models/
│  └─ ssd_resnet50_v1_fpn_640x640_coco17_tpu-8/
│     ├─ checkpoint/
│     ├─ saved_model/
│     └─ pipeline.config
└─ ...
```

Note that the above process can be repeated for all other pre-trained models you wish to experiment with. For example, if you wanted to also configure a training job for the EfficientDet D1 640x640 model, you can download the model and after extracting its context the demo directory will be:

```
training_demo/
├─ ...
├─ pre-trained-models/
│  ├─ efficientdet_d1_coco17_tpu-32/
│  │  ├─ checkpoint/
│  │  ├─ saved_model/
│  │  └─ pipeline.config
│  └─ ssd_resnet50_v1_fpn_640x640_coco17_tpu-8/
│     ├─ checkpoint/
│     ├─ saved_model/
│     └─ pipeline.config
└─ ...
```

Configure the Training Pipeline

Now that we have downloaded and extracted our pre-trained model, let's create a directory for our training job. Under the `training_demo/models` create a new directory named `my_ssd_resnet50_v1_fpn` and copy the `training_demo/pre-trained-models/ssd_resnet50_v1_fpn_640x640_coco17_tpu-8/pipeline.config` file inside the newly created directory. Our `training_demo/models` directory should now look like this:

```
training_demo/
├─ ...
├─ models/
│  └─ my_ssd_resnet50_v1_fpn/
│     └─ pipeline.config
└─ ...
```

Now, let's have a look at the changes that we shall need to apply to the `pipeline.config` file (highlighted in yellow):

```
model {
  ssd {
    num_classes: 1 # Set this to the number of different label classes
    image_resizer {
      fixed_shape_resizer {
        height: 640
        width: 640
      }
    }
    feature_extractor {
      type: "ssd_resnet50_v1_fpn_keras"
      depth_multiplier: 1.0
      min_depth: 16
      conv_hyperparams {
        regularizer {
          l2_regularizer {
            weight: 0.00039999998989515007
          }
        }
        initializer {
          truncated_normal_initializer {
            mean: 0.0
            stddev: 0.029999999329447746
          }
        }
        activation: RELU_6
        batch_norm {
          decay: 0.996999979019165
          scale: true
          epsilon: 0.0010000000474974513
        }
      }
      override_base_feature_extractor_hyperparams: true
      fpn {
        min_level: 3
        max_level: 7
      }
    }
    box_coder {
      faster_rcnn_box_coder {
        y_scale: 10.0
        x_scale: 10.0
        height_scale: 5.0
        width_scale: 5.0
      }
    }
    matcher {
      argmax_matcher {
        matched_threshold: 0.5
        unmatched_threshold: 0.5
        ignore_thresholds: false
        negatives_lower_than_unmatched: true
        force_match_for_each_row: true
        use_matmul_gather: true
      }
    }
    similarity_calculator {
      iou_similarity {
      }
    }
    box_predictor {
      weight_shared_convolutional_box_predictor {
        conv_hyperparams {
```

```
          regularizer {
            l2_regularizer {
              weight: 0.00039999998989515007
            }
          }
          initializer {
            random_normal_initializer {
              mean: 0.0
              stddev: 0.009999999776482582
            }
          }
          activation: RELU_6
          batch_norm {
            decay: 0.996999979019165
            scale: true
            epsilon: 0.0010000000474974513
          }
        }
        depth: 256
        num_layers_before_predictor: 4
        kernel_size: 3
        class_prediction_bias_init: -4.599999904632568
      }
    }
    anchor_generator {
      multiscale_anchor_generator {
        min_level: 3
        max_level: 7
        anchor_scale: 4.0
        aspect_ratios: 1.0
        aspect_ratios: 2.0
        aspect_ratios: 0.5
        scales_per_octave: 2
      }
    }
    post_processing {
      batch_non_max_suppression {
        score_threshold: 9.99999993922529e-09
        iou_threshold: 0.6000000238418579
        max_detections_per_class: 100
        max_total_detections: 100
        use_static_shapes: false
      }
      score_converter: SIGMOID
    }
    normalize_loss_by_num_matches: true
    loss {
      localization_loss {
        weighted_smooth_l1 {
        }
      }
      classification_loss {
        weighted_sigmoid_focal {
          gamma: 2.0
          alpha: 0.25
        }
      }
      classification_weight: 1.0
      localization_weight: 1.0
    }
    encode_background_as_zeros: true
    normalize_loc_loss_by_codesize: true
    inplace_batchnorm_update: true
    freeze_batchnorm: false
```

```
  }
}
train_config {
  batch_size: 8 # Increase/Decrease this value depending on the available memory (Higher values require more memory and vice-versa)
  data_augmentation_options {
    random_horizontal_flip {
    }
  }
  data_augmentation_options {
    random_crop_image {
      min_object_covered: 0.0
      min_aspect_ratio: 0.75
      max_aspect_ratio: 3.0
      min_area: 0.75
      max_area: 1.0
      overlap_thresh: 0.0
    }
  }
  sync_replicas: true
  optimizer {
    momentum_optimizer {
      learning_rate {
        cosine_decay_learning_rate {
          learning_rate_base: 0.03999999910593033
          total_steps: 25000
          warmup_learning_rate: 0.013333000242710114
          warmup_steps: 2000
        }
      }
      momentum_optimizer_value: 0.8999999761581421
    }
    use_moving_average: false
  }
  fine_tune_checkpoint: "pre-trained-models/ssd_resnet50_v1_fpn_640x640_coco17_tpu-8/checkpoint/ckpt-0" # Path to checkpoint of pre-trained model
  num_steps: 25000
  startup_delay_steps: 0.0
  replicas_to_aggregate: 8
  max_number_of_boxes: 100
  unpad_groundtruth_tensors: false
  fine_tune_checkpoint_type: "detection" # Set this to "detection" since we want to be training the full detection model
  use_bfloat16: false # Set this to false if you are not training on a TPU
  fine_tune_checkpoint_version: V2
}
train_input_reader {
  label_map_path: "annotations/label_map.pbtxt" # Path to label map file
  tf_record_input_reader {
    input_path: "annotations/train.record" # Path to training TFRecord file
  }
}
eval_config {
  metrics_set: "coco_detection_metrics"
  use_moving_averages: false
}
eval_input_reader {
  label_map_path: "annotations/label_map.pbtxt" # Path to label map file
  shuffle: false
  num_epochs: 1
  tf_record_input_reader {
    input_path: "annotations/test.record" # Path to testing TFRecord
  }
}
```

It is worth noting here that the changes to lines `178` to `179` above are optional. These should only be used if you installed the COCO evaluation tools, as outlined in the COCO API installation section, and you intend to run evaluation (see Evaluating the Model (Optional)).

Once the above changes have been applied to our config file, go ahead and save it.

Training the Model

Before we begin training our model, let's go and copy the `TensorFlow/models/research/object_detection/model_main_tf2.py` script and paste it straight into our `training_demo` folder. We will need this script in order to train our model.

Now, to initiate a new training job, open a new *Terminal*, `cd` inside the `training_demo` folder and run the following command:

```
python model_main_tf2.py --model_dir=models/my_ssd_resnet50_v1_fpn --
pipeline_config_path=models/my_ssd_resnet50_v1_fpn/pipeline.config
```

Once the training process has been initiated, you should see a series of print outs similar to the one below (plus/minus some warnings):

```
...
WARNING:tensorflow:Unresolved object in checkpoint:
(root).model._box_predictor._base_tower_layers_for_heads.class_predictions_with_background.4.10.g

W0716 05:24:19.105542  1364 util.py:143] Unresolved object in checkpoint:
(root).model._box_predictor._base_tower_layers_for_heads.class_predictions_with_background.4.10.g

WARNING:tensorflow:Unresolved object in checkpoint:
(root).model._box_predictor._base_tower_layers_for_heads.class_predictions_with_background.4.10.b

W0716 05:24:19.106541  1364 util.py:143] Unresolved object in checkpoint:
(root).model._box_predictor._base_tower_layers_for_heads.class_predictions_with_background.4.10.b

WARNING:tensorflow:Unresolved object in checkpoint:
(root).model._box_predictor._base_tower_layers_for_heads.class_predictions_with_background.4.10.m

W0716 05:24:19.107540  1364 util.py:143] Unresolved object in checkpoint:
(root).model._box_predictor._base_tower_layers_for_heads.class_predictions_with_background.4.10.m

WARNING:tensorflow:Unresolved object in checkpoint:
(root).model._box_predictor._base_tower_layers_for_heads.class_predictions_with_background.4.10.m

W0716 05:24:19.108539  1364 util.py:143] Unresolved object in checkpoint:
(root).model._box_predictor._base_tower_layers_for_heads.class_predictions_with_background.4.10.m

WARNING:tensorflow:A checkpoint was restored (e.g. tf.train.Checkpoint.restore or
tf.keras.Model.load_weights) but not all checkpointed values were used. See above for specific
issues. Use expect_partial() on the load status object, e.g.
tf.train.Checkpoint.restore(...).expect_partial(), to silence these warnings, or use
assert_consumed() to make the check explicit. See
https://www.tensorflow.org/guide/checkpoint#loading_mechanics for details.
W0716 05:24:19.108539  1364 util.py:151] A checkpoint was restored (e.g.
tf.train.Checkpoint.restore or tf.keras.Model.load_weights) but not all checkpointed values
were used. See above for specific issues. Use expect_partial() on the load status object, e.g.
tf.train.Checkpoint.restore(...).expect_partial(), to silence these warnings, or use
assert_consumed() to make the check explicit. See
https://www.tensorflow.org/guide/checkpoint#loading_mechanics for details.
WARNING:tensorflow:num_readers has been reduced to 1 to match input file shards.
INFO:tensorflow:Step 100 per-step time 1.153s loss=0.761
I0716 05:26:55.879558  1364 model_lib_v2.py:632] Step 100 per-step time 1.153s loss=0.761
...
```

Important

The output will normally look like it has “frozen”, but DO NOT rush to cancel the process. The training outputs logs only every 100 steps by default, therefore if you wait for a while, you should see a log for the loss at step 100.

The time you should wait can vary greatly, depending on whether you are using a GPU and the chosen value for `batch_size` in the config file, so be patient.

If you ARE observing a similar output to the above, then CONGRATULATIONS, you have successfully started your first training job. Now you may very well treat yourself to a cold beer, as waiting on the training to finish is likely to take a while. Following what people have said online, it seems that it is advisable to allow you model to reach a `TotalLoss` of at least 2 (ideally 1 and lower) if you want to achieve "fair" detection results. Obviously, lower `TotalLoss` is better, however very low `TotalLoss` should be avoided, as the model may end up overfitting the dataset, meaning that it will perform poorly when applied to images outside the dataset. To monitor `TotalLoss`, as well as a number of other metrics, while your model is training, have a look at Monitor Training Job Progress using TensorBoard.

If you ARE NOT seeing a print-out similar to that shown above, and/or the training job crashes after a few seconds, then have a look at the issues and proposed solutions, under the Common issues section, to see if you can find a solution. Alternatively, you can try the issues section of the official Tensorflow Models repo.

> **Note**
>
> Training times can be affected by a number of factors such as:
>
> - The computational power of you hardware (either CPU or GPU): Obviously, the more powerful your PC is, the faster the training process.
> - Whether you are using the TensorFlow CPU or GPU variant: In general, even when compared to the best CPUs, almost any GPU graphics card will yield much faster training and detection speeds. As a matter of fact, when I first started I was running TensorFlow on my *Intel i7-5930k* (6/12 cores @ 4GHz, 32GB RAM) and was getting step times of around *12 sec/step*, after which I installed TensorFlow GPU and training the very same model -using the same dataset and config files- on a *EVGA GTX-770* (1536 CUDA-cores @ 1GHz, 2GB VRAM) I was down to *0.9 sec/step*!!! A 12-fold increase in speed, using a "low/mid-end" graphics card, when compared to a "mid/high-end" CPU.
> - The complexity of the objects you are trying to detect: Obviously, if your objective is to track a black ball over a white background, the model will converge to satisfactory levels of detection pretty quickly. If on the other hand, for example, you wish to detect ships in ports, using Pan-Tilt-Zoom cameras, then training will be a much more challenging and time-consuming process, due to the high variability of the shape and size of ships, combined with a highly dynamic background.
> - And many, many, many, more....

Evaluating the Model (Optional)

By default, the training process logs some basic measures of training performance. These seem to change depending on the installed version of Tensorflow.

As you will have seen in various parts of this tutorial, we have mentioned a few times the optional utilisation of the COCO evaluation metrics. Also, under section Partition the Dataset we partitioned our dataset in two parts, where one was to be used for training and the other for evaluation. In this section we will look at how we can use these metrics, along with the test images, to get a sense of the performance achieved by our model as it is being trained.

Firstly, let's start with a brief explanation of what the evaluation process does. While the training process runs, it will occasionally create checkpoint files inside the `training_demo/training` folder, which correspond to snapshots of the model at given steps. When a set of such new checkpoint files is generated, the evaluation process uses these files and evaluates how well the model performs in detecting objects in the test dataset. The results of this evaluation are summarised in the form of some metrics, which can be examined over time.

The steps to run the evaluation are outlined below:

1. Firstly we need to download and install the metrics we want to use.
    - For a description of the supported object detection evaluation metrics, see here.
    - The process of installing the COCO evaluation metrics is described in COCO API installation.
2. Secondly, we must modify the configuration pipeline (`*.config` script).
    - See lines 178-179 of the script in Configure the Training Pipeline.
3. The third step is to actually run the evaluation. To do so, open a new *Terminal*, `cd` inside the `training_demo` folder and run the following command:

```
python model_main_tf2.py --model_dir=models/my_ssd_resnet50_v1_fpn --
pipeline_config_path=models/my_ssd_resnet50_v1_fpn/pipeline.config --
checkpoint_dir=models/my_ssd_resnet50_v1_fpn
```

Once the above is run, you should see a checkpoint similar to the one below (plus/minus some warnings):

```
...
WARNING:tensorflow:From C:\Users\sglvladi\Anaconda3\envs\tf2\lib\site-
packages\object_detection\inputs.py:79: sparse_to_dense (from
tensorflow.python.ops.sparse_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Create a `tf.sparse.SparseTensor` and use `tf.sparse.to_dense` instead.
W0716 05:44:10.059399 17144 deprecation.py:317] From
C:\Users\sglvladi\Anaconda3\envs\tf2\lib\site-packages\object_detection\inputs.py:79:
sparse_to_dense (from tensorflow.python.ops.sparse_ops) is deprecated and will be
removed in a future version.
Instructions for updating:
Create a `tf.sparse.SparseTensor` and use `tf.sparse.to_dense` instead.
WARNING:tensorflow:From C:\Users\sglvladi\Anaconda3\envs\tf2\lib\site-
packages\object_detection\inputs.py:259: to_float (from tensorflow.python.ops.math_ops)
is deprecated and will be removed in a future version.
Instructions for updating:
Use `tf.cast` instead.
W0716 05:44:12.383937 17144 deprecation.py:317] From
C:\Users\sglvladi\Anaconda3\envs\tf2\lib\site-packages\object_detection\inputs.py:259:
to_float (from tensorflow.python.ops.math_ops) is deprecated and will be removed in a
future version.
Instructions for updating:
Use `tf.cast` instead.
INFO:tensorflow:Waiting for new checkpoint at models/my_ssd_resnet50_v1_fpn
I0716 05:44:22.779590 17144 checkpoint_utils.py:125] Waiting for new checkpoint at
models/my_ssd_resnet50_v1_fpn
INFO:tensorflow:Found new checkpoint at models/my_ssd_resnet50_v1_fpn\ckpt-2
I0716 05:44:22.882485 17144 checkpoint_utils.py:134] Found new checkpoint at
models/my_ssd_resnet50_v1_fpn\ckpt-2
```

While the evaluation process is running, it will periodically check (every 300 sec by default) and use the latest `models/my_ssd_resnet50_v1_fpn/ckpt-*` checkpoint files to evaluate the performance of the model. The results are stored in the form of tf event files (`events.out.tfevents.*`) inside `models/my_ssd_resnet50_v1_fpn/eval_0`. These files can then be used to monitor the computed metrics, using the process described by the next section.

Monitor Training Job Progress using TensorBoard

A very nice feature of TensorFlow, is that it allows you to coninuously monitor and visualise a number of different training/evaluation metrics, while your model is being trained. The specific tool that allows us to do all that is Tensorboard.

To start a new TensorBoard server, we follow the following steps:

- Open a new *Anaconda/Command Prompt*
- Activate your TensorFlow conda environment (if you have one), e.g.:

```
activate tensorflow_gpu
```

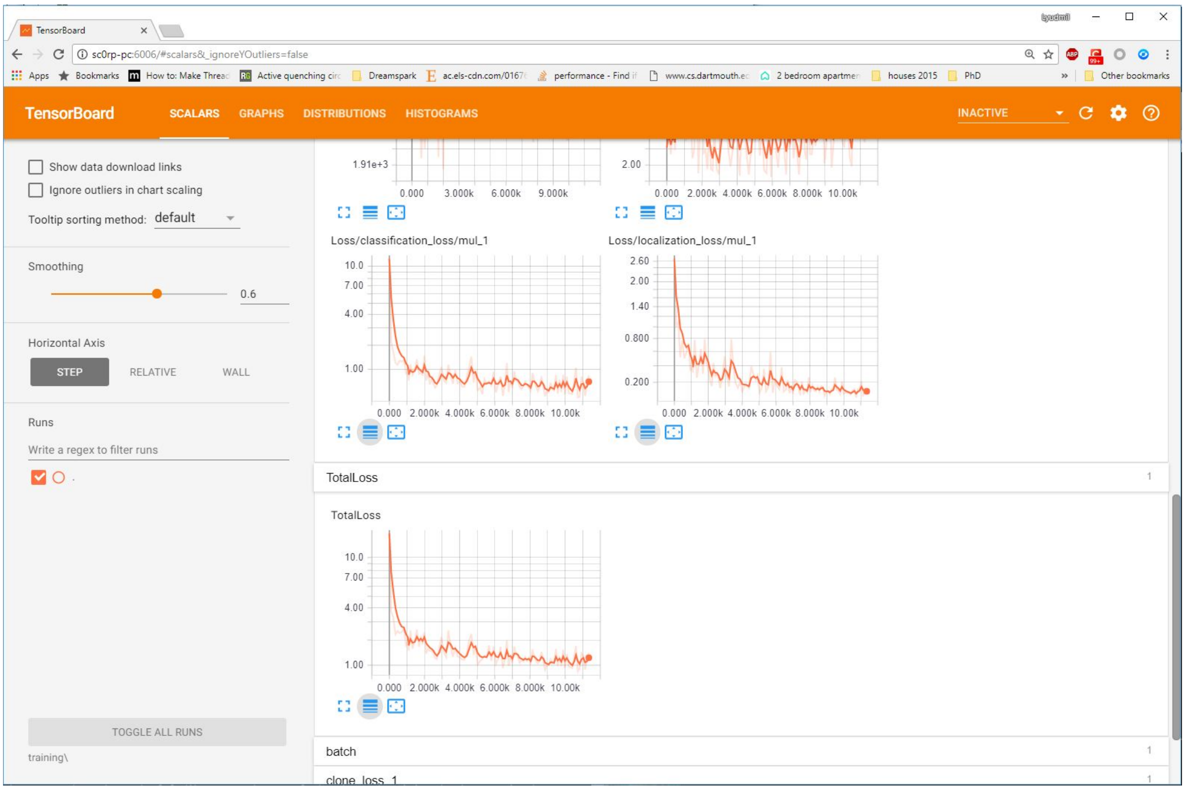
- `cd` into the `training_demo` folder.
- Run the following command:

```
tensorboard --logdir=models/my_ssd_resnet50_v1_fpn
```

The above command will start a new TensorBoard server, which (by default) listens to port 6006 of your machine. Assuming that everything went well, you should see a print-out similar to the one below (plus/minus some warnings):

```
...
TensorBoard 2.2.2 at http://localhost:6006/ (Press CTRL+C to quit)
```

Once this is done, go to your browser and type `http://localhost:6006/` in your address bar, following which you should be presented with a dashboard similar to the one shown below (maybe less populated if your model has just started training):



Exporting a Trained Model

Once your training job is complete, you need to extract the newly trained inference graph, which will be later used to perform the object detection. This can be done as follows:

- Copy the `TensorFlow/models/research/object_detection/exporter_main_v2.py` script and paste it straight into your `training_demo` folder.
- Now, open a *Terminal*, `cd` inside your `training_demo` folder, and run the following command:

```
python .\exporter_main_v2.py --input_type image_tensor --pipeline_config_path
.\models\my_ssd_resnet50_v1_fpn\pipeline.config --trained_checkpoint_dir
.\models\my_ssd_resnet50_v1_fpn\ --output_directory .\exported-models\my_model
```

After the above process has completed, you should find a new folder `my_model` under the `training_demo/exported-models`, that has the following structure:

```
training_demo/
├─ ...
├─ exported-models/
│  └─ my_model/
│     ├─ checkpoint/
│     ├─ saved_model/
│     └─ pipeline.config
└─ ...
```

This model can then be used to perform inference.

Note

You may get the following error when trying to export your model:

```
Traceback (most recent call last):
  File ".\exporter_main_v2.py", line 126, in <module>
    app.run(main)
  File "C:\Users\sglvladi\Anaconda3\envs\tf2\lib\site-packages\absl\app.py", line 299, in
run
    _run_main(main, args)
  ...
  File "C:\Users\sglvladi\Anaconda3\envs\tf2\lib\site-
packages\tensorflow\python\keras\engine\base_layer.py", line 1627, in get_losses_for
    reachable = tf_utils.get_reachable_from_inputs(inputs, losses)
  File "C:\Users\sglvladi\Anaconda3\envs\tf2\lib\site-
packages\tensorflow\python\keras\utils\tf_utils.py", line 140, in get_reachable_from_inputs
    raise TypeError('Expected Operation, Variable, or Tensor, got ' + str(x))
TypeError: Expected Operation, Variable, or Tensor, got level_5
```

If this happens, have a look at the “TypeError: Expected Operation, Variable, or Tensor, got level_5” issue section for a potential solution.