TensorFlow setup Documentation

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# CONTENTS:

## 1 Installation

1.1 General Remarks ................................................. 3  
1.2 Install Anaconda Python 3.7 (Optional) .......................... 3  
1.3 TensorFlow Installation ........................................ 4  
  1.3.1 TensorFlow CPU ........................................... 4  
   1.3.1.1 Create a new Conda virtual environment (Optional) ........... 4  
   1.3.1.2 Install TensorFlow CPU for Python ........................ 5  
   1.3.1.3 Test your Installation .................................. 5  
  1.3.2 TensorFlow GPU ........................................... 5  
   1.3.2.1 Install CUDA Toolkit .................................. 6  
   1.3.2.2 Install CUDNN .......................................... 6  
   1.3.2.3 Environment Setup ...................................... 6  
   1.3.2.4 Update your GPU drivers (Optional) ........................ 7  
   1.3.2.5 Create a new Conda virtual environment .................. 7  
   1.3.2.6 Install TensorFlow GPU for Python ....................... 8  
   1.3.2.7 Test your Installation .................................. 8  
  1.4 TensorFlow Models Installation .................................. 9  
   1.4.1 Install Prerequisites ...................................... 9  
   1.4.2 Downloading the TensorFlow Models ........................ 10  
   1.4.3 Protobuf Installation/Compilation ......................... 10  
   1.4.4 Adding necessary Environment Variables ................... 11  
   1.4.5 COCO API installation (Optional) .......................... 12  
   1.4.6 Test your Installation .................................... 12  
  1.5 LabelImg Installation ......................................... 15  
   1.5.1 Get from PyPI (Recommended) .............................. 15  
   1.5.2 Use precompiled binaries (Easy) ........................... 15  
   1.5.3 Build from source (Hard) .................................. 16  

## 2 Detect Objects Using Your Webcam .......................... 17  

## 3 Training Custom Object Detector ......................... 21  

3.1 Preparing workspace ............................................ 21  
3.2 Annotating images .............................................. 22  
3.3 Partitioning the images ........................................ 23  
3.4 Creating Label Map ............................................. 26  
3.5 Creating TensorFlow Records ................................. 26  
  3.5.1 Converting *.xml to *.csv ................................. 27  
  3.5.2 Converting from *.csv to *.record ........................ 29  
3.6 Configuring a Training Pipeline .............................. 32  
3.7 Training the Model .............................................. 36
3.8 Evaluating the Model (Optional) ................................................................. 38
3.9 Monitor Training Job Progress using TensorFlow ....................................... 39
3.10 Exporting a Trained Inference Graph ......................................................... 40

4 Common issues 41
4.1 Python crashes - TensorFlow GPU .............................................................. 41
4.2 Cleaning up Nvidia containers (TensorFlow GPU) ....................................... 41
4.3 labelImg saves annotation files with .xml extension .................................... 42
4.4 “WARNING:tensorflow:Entity <bound method X of <Y>> could not be transformed…” 42

5 Indices and tables 43
Important:  This tutorial is intended for TensorFlow 1.14, which (at the time of writing this tutorial) is the latest stable version before TensorFlow 2.x.

Tensorflow 1.15 has also been released, but seems to be exhibiting instability issues.

A version for Tensorflow 1.9 can be found here.

A version for Tensorflow 2.x is in the making and a link will be added here when ready.

This is a step-by-step tutorial/guide to setting up and using TensorFlow’s Object Detection API to perform, namely, object detection in images/video.

The software tools which we shall use throughout this tutorial are listed in the table below:

<table>
<thead>
<tr>
<th>Target Software versions</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>OS</td>
<td>Windows, Linux</td>
</tr>
<tr>
<td>Python</td>
<td>3.7</td>
</tr>
<tr>
<td>TensorFlow</td>
<td>1.14</td>
</tr>
<tr>
<td>CUDA Toolkit</td>
<td>10.0</td>
</tr>
<tr>
<td>CuDNN</td>
<td>7.6.5</td>
</tr>
<tr>
<td>Anaconda</td>
<td>Python 3.7 (Optional)</td>
</tr>
</tbody>
</table>
1.1 General Remarks

• There are two different variations of TensorFlow that you might wish to install, depending on whether you would like TensorFlow to run on your CPU or GPU, namely TensorFlow CPU and TensorFlow GPU. I will proceed to document both and you can choose which one you wish to install.

• If you wish to install both TensorFlow variants on your machine, ideally you should install each variant under a different (virtual) environment. If you attempt to install both TensorFlow CPU and TensorFlow GPU, without making use of virtual environments, you will either end up failing, or when we later start running code there will always be an uncertainty as to which variant is being used to execute your code.

• To ensure that we have no package conflicts and/or that we can install several different versions/variants of TensorFlow (e.g. CPU and GPU), it is generally recommended to use a virtual environment of some sort. For the purposes of this tutorial we will be creating and managing our virtual environments using Anaconda, but you are welcome to use the virtual environment manager of your choice (e.g. virtualenv).

1.2 Install Anaconda Python 3.7 (Optional)

Although having Anaconda is not a requirement in order to install and use TensorFlow, I suggest doing so, due to it’s intuitive way of managing packages and setting up new virtual environments. Anaconda is a pretty useful tool, not only for working with TensorFlow, but in general for anyone working in Python, so if you haven’t had a chance to work with it, now is a good chance.

Windows

• Go to https://www.anaconda.com/download/
• Download Anaconda Python 3.7 version for Windows
• Run the downloaded executable (.exe) file to begin the installation. See here for more details.
• (Optional) In the next step, check the box “Add Anaconda to my PATH environment variable”. This will make Anaconda your default Python distribution, which should ensure that you have the same default Python distribution across all editors.

Linux

• Go to https://www.anaconda.com/download/
• Download Anaconda Python 3.7 version for Linux
• Run the downloaded bash script (.sh) file to begin the installation. See here for more details.
• When prompted with the question “Do you wish the installer to prepend the Anaconda<2 or 3> install location to PATH in your /home/<user>/.bashrc ?”, answer “Yes”. If you enter “No”, you must manually add the path to Anaconda or conda will not work.

1.3 TensorFlow Installation

As mentioned in the Remarks section, there exist two generic variants of TensorFlow, which utilise different hardware on your computer to run their computationally heavy Machine Learning algorithms.

1. The simplest to install, but also in most cases the slowest in terms of performance, is TensorFlow CPU, which runs directly on the CPU of your machine.

2. Alternatively, if you own a (compatible) Nvidia graphics card, you can take advantage of the available CUDA cores to speed up the computations performed by TensorFlow, in which case you should follow the guidelines for installing TensorFlow GPU.

1.3.1 TensorFlow CPU

Getting setup with an installation of TensorFlow CPU can be done in 3 simple steps.

**Important:** The term *Terminal* will be used to refer to the Terminal of your choice (e.g. Command Prompt, Power-shell, etc.)

1.3.1.1 Create a new Conda virtual environment (Optional)

• Open a new *Terminal* window

• Type the following command:

```
conda create -n tensorflow_cpu pip python=3.7
```

• The above will create a new virtual environment with name tensorflow_cpu

• Now lets activate the newly created virtual environment by running the following in the *Terminal* window:

```
activate tensorflow_cpu
```

Once you have activated your virtual environment, the name of the environment should be displayed within brackets at the beggining of your cmd path specifier, e.g.:

```
(tensorflow_cpu) C:\Users\sglvladi>
```
1.3.1.2 Install TensorFlow CPU for Python

* Open a new Terminal window and activate the `tensorflow_cpu` environment (if you have not done so already)
* Once open, type the following on the command line:

```
$ pip install --ignore-installed --upgrade tensorflow==1.14
```
* Wait for the installation to finish

1.3.1.3 Test your Installation

* Open a new Terminal window and activate the `tensorflow_cpu` environment (if you have not done so already)
* Start a new Python interpreter session by running:

```
$ python
```
* Once the interpreter opens up, type:

```
>>> import tensorflow as tf
```
* If the above code shows an error, then check to make sure you have activated the `tensorflow_cpu` environment and that `tensorflow_cpu` was successfully installed within it in the previous step.
* Then run the following:

```
>>> hello = tf.constant('Hello, TensorFlow!')
>>> sess = tf.Session()
```
* Once the above is run, if you see a print-out similar (or identical) to the one below, it means that you could benefit from installing TensorFlow by building the sources that correspond to your specific CPU. Everything should still run as normal, but potentially slower than if you had built TensorFlow from source.

```
2019-02-28 11:59:25.810663: I T:\src\github\tensorflow\tensorflow\core\-->platform\cpu_feature_guard.cc:141] Your CPU supports instructions that this TensorFlow binary was not compiled to use: AVX2
```
* Finally, run the following:

```
>>> print(sess.run(hello))
b'Hello, TensorFlow!'
```

1.3.2 TensorFlow GPU

The installation of TensorFlow GPU is slightly more involved than that of TensorFlow CPU, mainly due to the need of installing the relevant Graphics and CUDA drivers. There’s a nice Youtube tutorial (see here), explaining how to install TensorFlow GPU. Although it describes different versions of the relevant components (including TensorFlow itself), the installation steps are generally the same with this tutorial.

Before proceeding to install TensorFlow GPU, you need to make sure that your system can satisfy the following requirements:
Prerequisites

<table>
<thead>
<tr>
<th>Nvidia GPU (GTX 650 or newer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CUDA Toolkit v10.0</td>
</tr>
<tr>
<td>CuDNN 7.6.5</td>
</tr>
<tr>
<td>Anaconda with Python 3.7 (Optional)</td>
</tr>
</tbody>
</table>

1.3.2.1 Install CUDA Toolkit

Windows

Follow this link to download and install CUDA Toolkit 10.0.

Linux

Follow this link to download and install CUDA Toolkit 10.0 for your Linux distribution.

1.3.2.2 Install CuDNN

Windows

- Go to https://developer.nvidia.com/rdp/cudnn-download
- Create a user profile if needed and log in
- Select cuDNN v7.6.5 (Nov 5, 2019), for CUDA 10.0
- Download cuDNN v7.6.5 Library for Windows 10
- Extract the contents of the zip file (i.e. the folder named cuda) inside <INSTALL_PATH>\NVIDIA GPU Computing Toolkit\CUDA\v10.0\, where <INSTALL_PATH> points to the installation directory specified during the installation of the CUDA Toolkit. By default <INSTALL_PATH> = C:\Program Files.

Linux

- Go to https://developer.nvidia.com/rdp/cudnn-download
- Create a user profile if needed and log in
- Select cuDNN v7.6.5 (Nov 5, 2019), for CUDA 10.0
- Download cuDNN v7.6.5 Library for Linux
- Follow the instructions under Section 2.3.1 of the CuDNN Installation Guide to install CuDNN.

1.3.2.3 Environment Setup

Windows

- Go to Start and Search “environment variables”
- Click “Edit the system environment variables”. This should open the “System Properties” window
- In the opened window, click the “Environment Variables…” button to open the “Environment Variables” window.
- Under “System variables”, search for and click on the Path system variable, then click “Edit…”
- Add the following paths, then click “OK” to save the changes:
  - <INSTALL_PATH>\NVIDIA GPU Computing Toolkit\CUDA\v10.0\bin
1.3.2.4 Update your GPU drivers (Optional)

If during the installation of the CUDA Toolkit (see Install CUDA Toolkit) you selected the Express Installation option, then your GPU drivers will have been overwritten by those that come bundled with the CUDA toolkit. These drivers are typically NOT the latest drivers and, thus, you may wish to update your drivers.

- Select your GPU version to download
- Install the driver for your chosen OS

1.3.2.5 Create a new Conda virtual environment

- Open a new Terminal window
- Type the following command:

  ```
  conda create -n tensorflow_gpu pip python=3.7
  ```

- The above will create a new virtual environment with name `tensorflow_gpu`
- Now let's activate the newly created virtual environment by running the following in the Anaconda Prompt window:

  ```
  activate tensorflow_gpu
  ```

Once you have activated your virtual environment, the name of the environment should be displayed within brackets at the beginning of your cmd path specifier, e.g.:

```
(tensorflow_gpu) C:\Users\sgvladi>
```
1.3.2.6 Install TensorFlow GPU for Python

- Open a new Terminal window and activate the tensorflow_gpu environment (if you have not done so already)
- Once open, type the following on the command line:

```
pip install --upgrade tensorflow-gpu==1.14
```
- Wait for the installation to finish

1.3.2.7 Test your Installation

- Open a new Terminal window and activate the tensorflow_gpu environment (if you have not done so already)
- Start a new Python interpreter session by running:

```
python
```
- Once the interpreter opens up, type:

```
>>> import tensorflow as tf
```
- If the above code shows an error, then check to make sure you have activated the tensorflow_gpu environment and that tensorflow_gpu was successfully installed within it in the previous step.
- Then run the following:

```
>>> hello = tf.constant('Hello, TensorFlow!')
>>> sess = tf.Session()
```
- Once the above is run, you should see a print-out similar (but not identical) to the one bellow:

```
2019-11-25 07:20:32.449116: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1618] Found device 0 with properties:
name: GeForce GTX 1070 Ti major: 6 minor: 1 memoryClockRate(GHz): 1.683
pciBusID: 0000:01:00.0
2019-11-25 07:20:32.460799: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1746] Found device 0 with properties:
name: GeForce GTX 1070 Ti major: 6 minor: 1 memoryClockRate(GHz): 1.683
pciBusID: 0000:01:00.0
(continues on next page)
Finally, run the following:

```python
>>> print(sess.run(hello))
b'Hello, TensorFlow!'```

## 1.4 TensorFlow Models Installation

Now that you have installed TensorFlow, it is time to install the models used by TensorFlow to do its magic.

### 1.4.1 Install Prerequisites

Building on the assumption that you have just created your new virtual environment (whether that’s `tensorflow_cpu`, `tensorflow_gpu` or whatever other name you might have used), there are some packages which need to be installed before installing the models.

<table>
<thead>
<tr>
<th>Prerequisite packages</th>
<th>Tutorial version-build</th>
</tr>
</thead>
<tbody>
<tr>
<td>pillow</td>
<td>6.2.1-py37hdc69c19_0</td>
</tr>
<tr>
<td>lxml</td>
<td>4.4.1-py37h1350720_0</td>
</tr>
<tr>
<td>jupyter</td>
<td>1.0.0-py37_7</td>
</tr>
<tr>
<td>matplotlib</td>
<td>3.1.1-py37hc8f65d3_0</td>
</tr>
<tr>
<td>opencv</td>
<td>3.4.2-py37hc319ecb_0</td>
</tr>
<tr>
<td>pathlib</td>
<td>1.0.1-cp37</td>
</tr>
</tbody>
</table>

The packages can be installed using `conda` by running:

```bash
conda install <package_name>(=<version>) <package_name>(=<version>) ... <package_name>(=<version>)
```

where `<package_name>` can be replaced with the name of the package, and optionally the package version can be specified by adding the optional specifier `=<version>` after `<package_name>`. For example, to simply install all packages at their latest versions you can run:

```bash
conda install pillow lxml jupyter matplotlib opencv cython
```

Alternatively, if you don’t want to use Anaconda you can install the packages using `pip`:

```bash
pip install <package_name>(==<version>) <package_name>(==<version>) ... <package_name>(==<version>)
```

but you will need to install `opencv-python` instead of `opencv`. 

### 1.4.2 Install TensorFlow Models

Once the prerequisites are installed, TensorFlow models can be installed by running:

```bash
pip install tensorflow_models
```

After installation, you can import the models and use them as follows:

```python
from tensorflow_models import model

model.run()  # Run the model
```
1.4.2 Downloading the TensorFlow Models

**Note:** To ensure compatibility with the chosen version of Tensorflow (i.e. 1.14.0), it is generally recommended to use one of the TensorFlow Models releases, as they are most likely to be stable. Release v1.13.0 is the last unofficial release before v2.0 and therefore is the one used here.

- Create a new folder under a path of your choice and name it `TensorFlow` (e.g. `C:\Users\sgvladi\Documents\TensorFlow`).
- From your `Terminal` `cd` into the `TensorFlow` directory.
- To download the models you can either use Git to clone the TensorFlow Models v.1.13.0 release inside the TensorFlow folder, or you can simply download it as a ZIP and extract it’s contents inside the TensorFlow folder. To keep things consistent, in the latter case you will have to rename the extracted folder `models-r1.13.0` to `models`.
- You should now have a single folder named `models` under your `TensorFlow` folder, which contains another 4 folders as such:

```
TensorFlow
|-- models
   |-- official
   |-- research
   |-- samples
   |-- tutorials
```

1.4.3 Protobuf Installation/Compilation

The Tensorflow Object Detection API uses Protobufs to configure model and training parameters. Before the framework can be used, the Protobuf libraries must be downloaded and compiled.

This should be done as follows:

- Head to the [protoc releases page](#)
- Download the latest `protoc-*.zip` release (e.g. `protoc-3.11.0-win64.zip` for 64-bit Windows)
- Extract the contents of the downloaded `protoc-*.zip` in a directory `<PATH_TO_PB>` of your choice (e.g. `C:\Program Files\Google Protobuf`)
- Extract the contents of the downloaded `protoc-*.zip`, inside `C:\Program Files\Google Protobuf`
- Add `<PATH_TO_PB>` to your `Path` environment variable (see [Environment Setup](#))
- In a new `Terminal`, `cd` into `TensorFlow/models/research/` directory and run the following command:

```
# From within TensorFlow/models/research/
protoc object_detection/protos/*.proto --python_out=. 
```

**Important:** If you are on Windows and using Protobuf 3.5 or later, the multi-file selection wildcard (i.e `*.proto`) may not work but you can do one of the following:

Windows Powershell

```
NOTE: You MUST open a new `Terminal` for the changes in the environment variables to take effect.
```
# From within TensorFlow/models/research/
Get-ChildItem object_detection/protos/*.proto | foreach {protoc "object_detection/protos/$($_.Name)" --python_out=.}

Command Prompt

# From within TensorFlow/models/research/
for /f %i in ('dir /b object_detection\protos\*.proto') do protoc object_detection\protos\%i --python_out=.

1.4.4 Adding necessary Environment Variables

1. Install the TensorFlow/models/research/object_detection package by running the following from TensorFlow/models/research:

   # From within TensorFlow/models/research/
ip install .

2. Add research/slim to your PYTHONPATH:

   Windows
   
   • Go to Start and Search “environment variables”
   • Click “Edit the system environment variables”. This should open the “System Properties” window
   • In the opened window, click the “Environment Variables...” button to open the “Environment Variables” window.
   • Under “System variables”, search for and click on the PYTHONPATH system variable,
     – If it exists then click “Edit...” and add <PATH_TO_TF>/TensorFlow/models/research/slim to the list
     – If it doesn’t already exist, then click “New...”, under “Variable name” type PYTHONPATH and under “Variable value” enter <PATH_TO_TF>/TensorFlow/models/research/slim
   • Then click “OK” to save the changes:

   Linux
   
   The Installation docs suggest that you either run, or add to ~/.bashrc file, the following command, which adds these packages to your PYTHONPATH:

   # From within tensorflow/models/research/
   export PYTHONPATH=$PYTHONPATH:<PATH_TO_TF>/TensorFlow/models/research/slim

   where, in both cases, <PATH_TO_TF> replaces the absolute path to your TensorFlow folder. (e.g. <PATH_TO_TF> = C:\Users\sglvladi\Documents if TensorFlow resides within your Documents folder)
1.4.5 COCO API installation (Optional)

The `pycocotools` package should be installed if you are interested in using COCO evaluation metrics, as discussed in *Evaluating the Model (Optional)*.

**Windows**

Run the following command to install `pycocotools` with Windows support:

```bash
pip install git+https://github.com/philferriere/cocoapi.git#subdirectory=PythonAPI
```

Note that, according to the package’s instructions, Visual C++ 2015 build tools must be installed and on your path. If they are not, make sure to install them from here.

**Linux**

Download cocoapi to a directory of your choice, then make and copy the pycocotools subfolder to the TensorFlow/ models/research directory, as such:

```bash
git clone https://github.com/cocodataset/cocoapi.git
cd cocoapi/PythonAPI
make
cp -r pycocotools <PATH_TO_TF>/TensorFlow/models/research/
```

**Note:** The default metrics are based on those used in Pascal VOC evaluation.

- To use the COCO object detection metrics add `metrics_set: "coco_detection_metrics"` to the `eval_config` message in the config file.
- To use the COCO instance segmentation metrics add `metrics_set: "coco_mask_metrics"` to the `eval_config` message in the config file.

1.4.6 Test your Installation

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

  ```bash
  # From within TensorFlow/models/research/object_detection
  jupyter notebook
  ```

- This should start a new *jupyter notebook* server on your machine and you should be redirected to a new tab of your default browser.
- Once there, simply follow *sentdex's Youtube video* to ensure that everything is running smoothly.
- When done, your notebook should look similar to the image bellow:
Important:

1. If no errors appear, but also no images are shown in the notebook, try adding `%matplotlib inline` at the start of the last cell, as shown by the highlighted text in the image below:
2. If Python crashes when running the last cell, have a look at the Terminal window you used to run jupyter notebook and check for an error similar (maybe identical) to the one below:

```
2018-03-22 03:07:54.623130: E C:\tf_jenkins\workspace\rel-win\M\windows-gpu\PY\36\tensorflow\stream_executor\cuda\cuda_dnn.cc:378] Loaded runtime CuDNN library: 7101 (compatibility version 7100) but source was compiled with 7003 (compatibility version 7000). If using a binary, install, upgrade your CuDNN library to match. If building from sources, make sure the library loaded at runtime matches a compatible version specified during compile configuration.
```

- If the above line is present in the printed debugging, it means that you have not installed the correct version of the cuDNN libraries. In this case make sure you re-do the Install CUDNN step, making sure you instal cuDNN v7.6.5.
1.5 LabelImg Installation

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

1.5.1 Get from PyPI (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:

   ```bash
   pip install labelImg
   ```
3. labelImg can then be run as follows:

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

1.5.2 Use precompiled binaries (Easy)

Precompiled binaries for both Windows and Linux can be found here. Installation is done in three simple steps:

1. Inside your 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:

   ```bash
   TensorFlow
   ├── addons
   │   └── labelImg
   │       └── models
   │           ├── official
   │           │   └── research
   │           └── samples
   │                   └── tutorials
   │
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   ```

4. labelImg can then be run as follows:

   ```bash
   # From within Tensorflow/addons/labelImg
   labelImg
   # or
   labelImg [IMAGE_PATH] [PRE-DEFINED CLASS FILE]
   ```
1.5.3 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.²
   - 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
    |   | official
    |   | research
    |   | samples
    |   | tutorials
```

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

Linux
sudo apt-get install pyqt5-dev-tools
sudo pip install -r requirements/requirements-linux-python3.txt
make qt5py3
```

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]
```

² The latest repo commit when writing this tutorial is 8d1bd68.
Hereby you can find an example which allows you to use your camera to generate a video stream, based on which you can perform object_detection.

To run the example, simply create a new file under `<PATH_TO_TF>/TensorFlow/models/research/object_detection` and paste the code below.

```python
import numpy as np
import os
import six.moves.urllib as urllib
import sys
import tarfile
import tensorflow as tf
import zipfile
from collections import defaultdict
from io import StringIO
from matplotlib import pyplot as plt
from PIL import Image
from object_detection.utils import label_map_util
from object_detection.utils import visualization_utils as vis_util

# Define the video stream
cap = cv2.VideoCapture(0)  # Change only if you have more than one webcams

# What model to download.
# Models can be found here: https://github.com/tensorflow/models/blob/master/research/object_detection/g3doc/detection_model_zoo.md
MODEL_NAME = 'ssd_inception_v2_coco_2017_11_17'
MODEL_FILE = MODEL_NAME + '.tar.gz'
DOWNLOAD_BASE = 'http://download.tensorflow.org/models/object_detection/

# Path to frozen detection graph. This is the actual model that is used for the object detection.
PATH_TO_CKPT = MODEL_NAME + '/frozen_inference_graph.pb'

# List of the strings that is used to add correct label for each box.
PATH_TO_LABELS = os.path.join('data', 'mscoco_label_map.pbtxt')

# Number of classes to detect
NUM_CLASSES = 90

# Download Model
if not os.path.exists(os.path.join(os.getcwd(), MODEL_FILE)):
    (continues on next page)
print("Downloading model")
open = urllib.request.URLopener()
open.retrieve(DOWNLOAD_BASE + MODEL_FILE, MODEL_FILE)
tar_file = tarfile.open(MODEL_FILE)
for file in tar_file.getmembers():
    file_name = os.path.basename(file.name)
    if 'frozen_inference_graph.pb' in file_name:
        tar_file.extract(file, os.getcwd())

# Load a (frozen) Tensorflow model into memory.
detection_graph = tf.Graph()
with detection_graph.as_default():
    od_graph_def = tf.compat.v1.GraphDef()
    with tf.io.gfile.GFile(PATH_TO_CKPT, 'rb') as fid:
        serialized_graph = fid.read()
        od_graph_def.ParseFromString(serialized_graph)
        tf.import_graph_def(od_graph_def, name='')

# Loading label map
# Label maps map indices to category names, so that when our convolution network
# predicts '5', we know that this corresponds to 'airplane'. Here we use internal
# utility functions, but anything that returns a dictionary mapping integers to
# appropriate string labels would be fine
label_map = label_map_util.load_labelmap(PATH_TO_LABELS)
categories = label_map_util.convert_label_map_to_categories(
    label_map, max_num_classes=NUM_CLASSES, use_display_name=True)
category_index = label_map_util.create_category_index(categories)

# Helper code
def load_image_into_numpy_array(image):
    (im_width, im_height) = image.size
    return np.array(image.getdata()).reshape((im_height, im_width, 3)).astype(np.uint8)

# Detection
with detection_graph.as_default():
    with tf.compat.v1.Session(graph=detection_graph) as sess:
        while True:
            # Read frame from camera
            ret, image_np = cap.read()
            # Expand dimensions since the model expects images to have shape: [1, \n            None, None, 3]
            image_np_expanded = np.expand_dims(image_np, axis=0)
            # Extract image tensor
            image_tensor = detection_graph.get_tensor_by_name('image_tensor:0')
            # Extract detection boxes
            boxes = detection_graph.get_tensor_by_name('detection_boxes:0')
            # Extract detection scores
            scores = detection_graph.get_tensor_by_name('detection_scores:0')
            # Extract detection classes
            classes = detection_graph.get_tensor_by_name('detection_classes:0')
            # Extract number of detections
            num_detections = detection_graph.get_tensor_by_name('detection_boxes:0')
'num_detections:0')

# Actual detection.
(boxes, scores, classes, num_detections) = sess.run(
    [boxes, scores, classes, num_detections],
    feed_dict={image_tensor: image_np_expanded})

# Visualization of the results of a detection.
vis_util.visualize_boxes_and_labels_on_image_array(
    image_np,
    np.squeeze(boxes),
    np.squeeze(classes).astype(np.int32),
    np.squeeze(scores),
    category_index,
    use_normalized_coordinates=True,
    line_thickness=8)

# Display output
cv2.imshow('object detection', cv2.resize(image_np, (800, 600)))

if cv2.waitKey(25) & 0xFF == ord('q'):
    cv2.destroyAllWindows()
    break
CHAPTER THREE

TRAINING CUSTOM OBJECT DETECTOR

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

- Installed TensorFlow, either CPU or GPU (See TensorFlow Installation)
- Installed TensorFlow Models (See TensorFlow Models Installation)
- Installed labelImg (See LabellImg 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 its progress
6. How to export the resulting model and use it to detect objects.

3.1 Preparing 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\sgvladi\Documents), with the following directory tree:

   TensorFlow
   ├── addons
   │    └── labelImg
   ├── models
   │    ├── official
   │    │    ├── research
   │    │    └── samples
   │    └── tutorials

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
   │    └── labelImg
   ├── models

(continues on next page)
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 a different model. The typical structure for training folders is shown below.

```
training_demo
  ├── annotations
  │    └── test
  │        └── train
  ├── images
  │    └── pre-trained-model
  │    └── training
  └── README.md
```

Here’s an explanation for each of the folders/files 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.

- **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.

- **pre-trained-model**: This folder will contain the pre-trained model of our choice, which shall be used as a starting checkpoint for our training job.

- **training**: This folder will contain the training pipeline configuration file *.config, as well as a *.pbtxt label map file and all files generated during the training of our model.

- **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.

### 3.2 Annotating images

To annotate images we will be using the **labelImg** package. If you haven’t installed the package yet, then have a look at [LabelImg Installation](#).

- 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 **Anaconda/Command Prompt** window and **cd** into **Tensorflow\addons\labelImg**.
• If (as suggested in *Labellmg Installation*) you created a separate Conda environment for `labelImg` then go ahead and activate it by running:

```bash
activate labelImg
```

• Next go ahead and start `labelImg`, pointing it to your `training_demo\images` folder.

```bash
python labelImg.py ..\.\workspace\training_demo\images
```

• A File Explorer Dialog window 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:

![LabelImg window](image)

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.

### 3.3 Partitioning the images

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 90%/10%, i.e. 90% of the images are used for training and the rest 10% is maintained for testing, but you can choose 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:
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
import shutil
from PIL import Image
from shutil import copyfile
import argparse
import glob
import math
import random
import xml.etree.ElementTree as ET

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-_\.\-\(\):])+(.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))

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()

To use the script, simply copy and paste the code above in a script named partition_dataset.py. Then, assuming you have all your images and *.xml files inside training_demo\images, just run the following
Once the script has finished, there should exist two new folders 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.

3.4 Creating 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 I show an example label map (e.g label_map.pbtxt), assuming that our dataset contains 2 labels, dogs and cats:

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

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

Label map files have the extension .pbtxt and should be placed inside the training_demo\annotations folder.

3.5 Creating 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.

There are two steps in doing so:

- Converting the individual *.xml files to a unified *.csv file for each dataset.
- Converting the *.csv files of each dataset to *.record files (TFRecord format).

Before we proceed to describe the above steps, let’s create a directory where we can store some scripts. 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 our TensorFlow directory tree structure, up to now:

```plaintext
TensorFlow
  ├── addons
  │     └── labelImg
  │     └── models
  │         └── official
  │         └── research
  └── official
```
3.5.1 Converting *.xml to *.csv

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 *.csv for each of the two.

Here is an example script that allows us to do just that:

```python
"""
Usage:
# Create train data:
python xml_to_csv.py -i [PATH_TO_IMAGES_FOLDER]/train -o [PATH_TO_ANNOTATIONS_FOLDER]/ →train_labels.csv

# Create test data:
python xml_to_csv.py -i [PATH_TO_IMAGES_FOLDER]/test -o [PATH_TO_ANNOTATIONS_FOLDER]/ →test_labels.csv
"""

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

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

    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'):
        try:
            tree = ET.parse(xml_file)
            root = tree.getroot()
            for member in root.findall('object'):
                value = (root.find('filename').text,
                         int(root.find('size')[0].text),
                         int(root.find('size')[1].text),
                         member[0].text,
                         )
            xml_list.append(value)

    column_name = ['filename', 'width', 'height', 'class', 'name']
    xml_df = pd.DataFrame(xml_list, columns=column_name)

    return xml_df

if __name__ == '__main__':
    parser = argparse.ArgumentParser()
    parser.add_argument('-i', '--input', help='Directory with all .xml files
                        generated by labelImg')
    parser.add_argument('-o', '--output', help='Directory with .csv files
                        generated by script')
    args = parser.parse_args()

    xml_df = xml_to_csv(args.input)
    xml_df.to_csv(args.output, index=None, header=True)
```
int(member[4][0].text),
int(member[4][1].text),
int(member[4][2].text),
int(member[4][3].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 main():
    # Initiate argument parser
    parser = argparse.ArgumentParser(
        description="Sample TensorFlow XML-to-CSV converter")
    parser.add_argument("-i",
                        "--inputDir",
                        help="Path to the folder where the input .xml files are stored",
                        type=str)
    parser.add_argument("-o",
                        "--outputFile",
                        help="Name of output .csv file (including path)", type=str)
    args = parser.parse_args()
    if(args.inputDir is None):
        args.inputDir = os.getcwd()
    if(args.outputFile is None):
        args.outputFile = args.inputDir + "/labels.csv"
    assert(os.path.isdir(args.inputDir))
    xml_df = xml_to_csv(args.inputDir)
    xml_df.to_csv(args.outputFile, index=None)
    print('Successfully converted xml to csv.')
    if __name__ == '__main__':
        main()

- Create a new file with name xml_to_csv.py under TensorFlow\scripts\preprocessing, open it, paste the above code inside it and save.

- 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 xml_to_csv.py -i [PATH_TO_IMAGES_FOLDER]/train -o [PATH_TO_ 
  ANNOTATIONS_FOLDER]/train_labels.csv
Once the above is done, there should be 2 new files under the training_demo\annotations folder, named test_labels.csv and train_labels.csv, respectively.

### 3.5.2 Converting from *.csv to *.record

Now that we have obtained our *.csv annotation files, we will need to convert them into TFRecords. Below is an example script that allows us to do just that:

```python
# Create train data:
python generate_tfrecord.py --label=<LABEL> --csv_input=<PATH_TO_ANNOTATIONS_FOLDER>/train_labels.csv --output_path=<PATH_TO_ANNOTATIONS_FOLDER>/train.record

# Create test data:
python generate_tfrecord.py --label=<LABEL> --csv_input=<PATH_TO_ANNOTATIONS_FOLDER>/test_labels.csv --output_path=<PATH_TO_ANNOTATIONS_FOLDER>/test.record
```

```python
from __future__ import division
from __future__ import print_function
from __future__ import absolute_import

import os
import io
import pandas as pd
import tensorflow as tf
import sys

sys.path.append("../../models/research")

from PIL import Image
from object_detection.utils import dataset_util
from collections import namedtuple, OrderedDict

flags = tf.app.flags
flags.DEFINE_string('csv_input', '', 'Path to the CSV input')
flags.DEFINE_string('output_path', '', 'Path to output TFRecord')
flags.DEFINE_string('label', '', 'Name of class label')
# if your image has more labels input them as
# flags.DEFINE_string('label0', '', 'Name of class[0] label')
# flags.DEFINE_string('label1', '', 'Name of class[1] label')
# and so on.
```
flags.DEFINE_string('img_path', '', 'Path to images')
FLAGS = flags.FLAGS

# TO-DO replace this with label map
# for multiple labels add more else if statements

def class_text_to_int(row_label):
    if row_label == FLAGS.label:  # 'ship':
        return 1
    # comment upper if statement and uncomment these statements for multiple labelling
    # if row_label == FLAGS.label0:
    #    return 1
    # elif row_label == FLAGS.label1:
    #    return 0
    else:
        None

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'
    # check if the image format is matching with your images.
    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),
    })

    return tf_example
'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(FLAGS.output_path)
    path = os.path.join(os.getcwd(), FLAGS.img_path)
    examples = pd.read_csv(FLAGS.csv_input)
    grouped = split(examples, 'filename')
    for group in grouped:
        tf_example = create_tf_example(group, path)
        writer.write(tf_example.SerializeToString())
    writer.close()
    output_path = os.path.join(os.getcwd(), FLAGS.output_path)
    print('Successfully created the TFRecords: {}'.format(output_path))

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

• Create a new file with name generate_tfrecord.py under TensorFlow\scripts\preprocessing, open it, paste the above code inside it and save.

• Once this is done, cd into TensorFlow\scripts\preprocessing and run:

    # Create train data:
    python generate_tfrecord.py --label=<LABEL> --csv_input=<PATH_TO_  
    ANNOTATIONS_FOLDER>/train_labels.csv --img_path=<PATH_TO_IMAGES_FOLDER>/train --output_path=<PATH_TO_  
    ANNOTATIONS_FOLDER>/train.record

    # Create test data:
    python generate_tfrecord.py --label=<LABEL> --csv_input=<PATH_TO_  
    ANNOTATIONS_FOLDER>/test_labels.csv --img_path=<PATH_TO_IMAGES_FOLDER>/test --output_path=<PATH_TO_ANNOTATIONS_FOLDER>/test.record

    # For example
    # python generate_tfrecord.py --label=ship --csv_input=C:\Users\sgvladi\  
    Documents\TensorFlow\workspace\training_demo\annotations\train_labels.csv --output_path=C:\Users\sgvladi\Documents\TensorFlow\workspace\training_demo\images\train

Once the above is done, there should be 2 new files under the training_demo\annotations folder, named

3.5. Creating TensorFlow Records 31
3.6 Configuring a Training Pipeline

For the purposes of this tutorial we will not be creating a training job from the scratch, but rather we will go through how to 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_inception_v2_coco model, since it provides a relatively good trade-off between performance and speed, however there are a number of other models you can use, all of which are listed in TensorFlow’s detection model zoo. More information about the detection performance, as well as reference times of execution, for each of the available pre-trained models can be found here.

First of all, we need to get ourselves the sample pipeline configuration file for the specific model we wish to retrain. You can find the specific file for the model of your choice here. In our case, since we shall be using the ssd_inception_v2_coco model, we shall be downloading the corresponding ssd_inception_v2_coco.config file.

Apart from the configuration file, we also need to download the latest pre-trained NN for the model we wish to use. This can be done by simply clicking on the name of the desired model in the tables found in TensorFlow’s 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 folder that you see when the compressed folder is opened (typically it will have the same name as the compressed folder, without the *.tar.gz extension), and extract its contents inside the folder training_demo\pre-trained-model.

Now that we have downloaded and extracted our pre-trained model, let’s have a look at the changes that we shall need to apply to the downloaded *.config file (highlighted in yellow):

```python
# SSD with Inception v2 configuration for MSCOCO Dataset.
# Users should configure the fine_tune_checkpoint field in the train config as
# well as the label_map_path and input_path fields in the train_input_reader and
# eval_input_reader. Search for "PATH_TO_BE_CONFIGURED" to find the fields that
# should be configured.

model {
  ssd {
    num_classes: 1 # Set this to the number of different label classes
    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
      }
    }
    similarity_calculator {
      (continues on next page)
```
iou_similarity {
}

anchor_generator {
  ssd_anchor_generator {
    num_layers: 6
    min_scale: 0.2
    max_scale: 0.95
    aspect_ratios: 1.0
    aspect_ratios: 2.0
    aspect_ratios: 0.5
    aspect_ratios: 3.0
    aspect_ratios: 0.3333
    reduce_boxes_in_lowest_layer: true
  }
}

image_resizer {
  fixed_shape_resizer {
    height: 300
    width: 300
  }
}

box_predictor {
  convolutional_box_predictor {
    min_depth: 0
    max_depth: 0
    num_layers_before_predictor: 0
    use_dropout: false
    dropout_keep_probability: 0.8
    kernel_size: 3
    box_code_size: 4
    apply_sigmoid_to_scores: false
    conv_hyperparams {
      activation: RELU_6,
      regularizer {
        l2_regularizer {
          weight: 0.00004
        }
      }
      initializer {
        truncated_normal_initializer {
          stddev: 0.03
          mean: 0.0
        }
      }
    }
  }
}

feature_extractor {
  type: 'ssd_inception_v2' # Set to the name of your chosen pre-trained model
  min_depth: 16
  depth_multiplier: 1.0
  conv_hyperparams {
    activation: RELU_6,
    regularizer {
      l2_regularizer {
        (continues on next page)
weight: 0.00004
}

initializer {
  truncated_normal_initializer {
    stddev: 0.03
    mean: 0.0
  }
}

batch_norm {
  train: true,
  scale: true,
  center: true,
  decay: 0.9997,
  epsilon: 0.001,
}

override_base_feature_extractor_hyperparams: true

loss {
  classification_loss {
    weighted_sigmoid {
    }
  }

  localization_loss {
    weighted_smooth_l1 {
    }
  }

  hard_example_miner {
    num_hard_examples: 3000
    iou_threshold: 0.99
    loss_type: CLASSIFICATION
    max_negatives_per_positive: 3
    min_negatives_per_image: 0
  }

  classification_weight: 1.0
  localization_weight: 1.0
}

normalize_loss_by_num_matches: true

post_processing {
  batch_non_max_suppression {
    score_threshold: 1e-8
    iou_threshold: 0.6
    max_detections_per_class: 100
    max_total_detections: 100
  }

  score_converter: SIGMOID
}

train_config: {
  batch_size: 12 # Increase/Decrease this value depending on the available memory.
  optimizer {
    rms_prop_optimizer: {
      learning_rate:
    }
  }
}
```

exponential_decay_learning_rate {
  initial_learning_rate: 0.004
  decay_steps: 800720
  decay_factor: 0.95
}
}
momentum_optimizer_value: 0.9
decay: 0.9
epsilon: 1.0
}
}

fine_tune_checkpoint: "pre-trained-model/model.ckpt" # Path to extracted files of pre-trained model
from_detection_checkpoint: true

# Note: The below line limits the training process to 200K steps, which we empirically found to be sufficient enough to train the pets dataset. This effectively bypasses the learning rate schedule (the learning rate will never decay). Remove the below line to train indefinitely.
num_steps: 200000
data_augmentation_options {
  random_horizontal_flip {
  }
}
data_augmentation_options {
  ssd_random_crop {
  }
}

train_input_reader: {
  tf_record_input_reader {
    input_path: "annotations/train.record" # Path to training TFRecord file
  }
  label_map_path: "annotations/label_map.pbtxt" # Path to label map file
}

eval_config: {
  # (Optional): Uncomment the line below if you installed the Coco evaluation tools and you want to also run evaluation
  # metrics_set: "coco_detection_metrics"
  # (Optional): Set this to the number of images in your <PATH_TO_IMAGES_FOLDER>/train
  # if you want to also run evaluation
  num_examples: 8000
  # Note: The below line limits the evaluation process to 10 evaluations.
  # Remove the below line to evaluate indefinitely.
  max_evals: 10
}

eval_input_reader: {
  tf_record_input_reader {
    input_path: "annotations/test.record" # Path to testing TFRecord file
  }
  label_map_path: "annotations/label_map.pbtxt" # Path to label map file
  shuffle: false
  num_readers: 1
}
```

3.6. Configuring a Training Pipeline
It is worth noting here that the changes to lines 178 and 181 above are optional. These should only be used if you installed the COCO evaluation tools, as outlined in the COCO API installation (Optional) 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 under training_demo/training.

### 3.7 Training the Model

#### Standard

**Note:** This tab describes the training process using Tensorflow's new model training script, namely model_main.py, as suggested by the Tensorflow Object Detection docs. The advantage of using this script is that it interleaves training and evaluation, essentially combining the train.py and eval.py Legacy scripts.

If instead you would like to use the legacy train.py script, switch to the Legacy tab.

Before we begin training our model, let's go and copy the TensorFlow/models/research/object_detection/model_main.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, cd inside the training_demo folder and type the following:

```bash
python model_main.py --alsologtostderr --model_dir=training/ --pipeline_config_path=training/ssd_inception_v2_coco.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):

```text
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:Restoring parameters from ssd_inception_v2_coco_2017_11_17/model.ckpt
INFO:tensorflow:Running local_init_op.
INFO:tensorflow:Done running local_init_op.
INFO:tensorflow:Saving checkpoints for 0 into training\model.ckpt.
INFO:tensorflow:loss = 16.100115, step = 0
...
```

**Important:** The output will normally look like it has “frozen” after the loss for step 0 has been logged, 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.

#### Legacy

Before we begin training our model, let's go and copy the TensorFlow/models/research/object_detection/legacy/train.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, cd inside the training_demo folder and type the following:

```bash
python train.py --logtostderr --train_dir=training/ --pipeline_config_path=training/ ssd_inception_v2_coco.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):

```plaintext
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:depth of additional conv before box predictor: 0
INFO:tensorflow:Restoring parameters from ssd_inception_v2_coco_2017_11_17/model.ckpt
INFO:tensorflow:Running local_init_op.
INFO:tensorflow:Done running local_init_op.
INFO:tensorflow:Starting Session.
INFO:tensorflow:Saving checkpoint to path training\model.ckpt
INFO:tensorflow:Starting Queues.
INFO:tensorflow:global_step/sec: 0
INFO:tensorflow:global step 2: loss = 16.2202 (0.937 sec/step)
INFO:tensorflow:global step 3: loss = 13.7876 (0.904 sec/step)
INFO:tensorflow:global step 4: loss = 12.9230 (0.894 sec/step)
INFO:tensorflow:global step 5: loss = 12.7497 (0.922 sec/step)
INFO:tensorflow:global step 6: loss = 11.7563 (0.936 sec/step)
INFO:tensorflow:global step 7: loss = 11.7245 (0.910 sec/step)
INFO:tensorflow:global step 8: loss = 10.7993 (0.916 sec/step)
INFO:tensorflow:global step 9: loss = 9.1277 (0.890 sec/step)
INFO:tensorflow:global step 10: loss = 9.3972 (0.919 sec/step)
INFO:tensorflow:global step 11: loss = 9.9487 (0.897 sec/step)
INFO:tensorflow:global step 12: loss = 8.7954 (0.884 sec/step)
INFO:tensorflow:global step 13: loss = 7.4329 (0.906 sec/step)
INFO:tensorflow:global step 14: loss = 7.8270 (0.897 sec/step)
INFO:tensorflow:global step 15: loss = 6.4877 (0.894 sec/step)
...
```

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 your 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 your 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 an 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.

- How big the dataset is: The higher the number of images in your dataset, the longer it will take for the model to reach satisfactory levels of detection performance.
- 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…

### 3.8 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 and the script used for training (i.e. `model_main.py` (Standard) or `train.py` (Legacy)).

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 _image_partitioning_ sec 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 (Optional).
2. Secondly, we must modify the configuration pipeline (`*.config` script).
   - See lines 178 and 181 of the script in Configuring a Training Pipeline.
3. The third step depends on what method (script) was used when running the training in Training the Model. See below for details:
   - **Standard**
     - The `model_main.py` script interleaves training and evaluation. Therefore, assuming that the following two steps were followed correctly, nothing else needs to be done.
   - **Legacy**
     - When using the Legacy scripts, evaluation is run using the `eval.py` script. This is done as follows:
       - Copy the TensorFlow/models/research/object_detection/legacy/eval.py script and paste it inside the `training_demo` folder.
• Now, to initiate an evaluation job, `cd` inside the `training_demo` folder and type the following:

```
python eval.py --logtostderr --pipeline_config_path=training/ssd_inception_v2_coco.config --checkpoint_dir=training/ --eval_dir=training/eval_0
```

While the evaluation process is running, it will periodically (every 300 sec by default) check and use the latest `training/model.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 `training/eval_0`. These files can then be used to monitor the computed metrics, using the process described by the next section.

### 3.9 Monitor Training Job Progress using TensorBoard

A very nice feature of TensorFlow, is that it allows you to continuously 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=training/\n```

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 1.6.0 at http://YOUR-PC:6006 (Press CTRL+C to quit)
```

Once this is done, go to your browser and type `http://YOUR-PC: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):
3.10 Exporting a Trained Inference Graph

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:

- Open a new Anaconda/Command Prompt
- Activate your TensorFlow conda environment (if you have one), e.g.:
  ```
  activate tensorflow_gpu
  ```
- Copy the TensorFlow/models/research/object_detection/export_inference_graph.py script and paste it straight into your training_demo folder.
- Check inside your training_demo/training folder for the model.ckpt-* checkpoint file with the highest number following the name of the dash e.g. model.ckpt-34350. This number represents the training step index at which the file was created.
- Alternatively, simply sort all the files inside training_demo/training by descending time and pick the model.ckpt-* file that comes first in the list.
- Make a note of the file’s name, as it will be passed as an argument when we call the export_inference_graph.py script.
- Now, cd inside your training_demo folder, and run the following command:
  ```
  python export_inference_graph.py --input_type image_tensor --pipeline_config_path training/ssd_inception_v2_coco.config --trained_checkpoint_prefix training/model.ckpt-13302 --output_directory trained-inference-graphs/output_inference_graph_v1.pb
  ```
Below is a list of common issues encountered while using TensorFlow for objects detection.

4.1 Python crashes - TensorFlow GPU

If you are using TensorFlow GPU and when you try to run some Python object detection script (e.g. Test your Installation), after a few seconds, Windows reports that Python has crashed then have a look at the Anaconda/Command Prompt window you used to run the script and check for a line similar (maybe identical) to the one below:

```
2018-03-22 03:07:54.623130: E C:\tf_jenkins\workspace\rel-win\M\windows-gpu\PY\36\tensorflow\stream_executor\cuda\cuda_dnn.cc:378] Loaded runtime
→CuDNN library: 7101 (compatibility version 7100) but source was compiled
→with 7003 (compatibility version 7000). If using a binary install,
→upgrade your CuDNN library to match. If building from sources, make sure
→the library loaded at runtime matches a compatible version specified
→during compile configuration.
```

If the above line is present in the printed debugging, it means that you have not installed the correct version of the cuDNN libraries. In this case make sure you re-do the Install CUDNN step, making sure you instal cuDNN v7.0.5.

4.2 Cleaning up Nvidia containers (TensorFlow GPU)

Sometimes, when terminating a TensorFlow training process, the Nvidia containers associated to the process are not cleanly terminated. This can lead to bogus errors when we try to run a new TensorFlow process.

Some known issues caused by the above are presented below:

- Failure to restart training of a model. Look for the following errors in the debugging:

```
2018-03-23 03:03:10.326902: E C:\tf_jenkins\workspace\rel-win\M\windows-gpu\PY\36\tensorflow\stream_executor\cuda\cuda_dnn.cc:385] could not
→create cudnn handle: CUDNN_STATUS_ALLOC_FAILED
2018-03-23 03:03:10.330475: E C:\tf_jenkins\workspace\rel-win\M\windows-gpu\PY\36\tensorflow\stream_executor\cuda\cuda_dnn.cc:352] could not
→destroy cudnn handle: CUDNN_STATUS_BAD_PARAM
2018-03-23 03:03:10.333797: W C:\tf_jenkins\workspace\rel-win\M\windows-gpu\PY\36\tensorflow\stream_executor\stream.h:1983] attempting to
→perform DNN operation using StreamExecutor without DNN support
```

(continues on next page)
To solve such issues in Windows, open a Task Manager windows, look for Tasks with name NVIDIA Container and kill them by selecting them and clicking the End Task button at the bottom left corner of the window.

If the issue persists, then you’re probably running out of memory. Try closing down anything else that might be eating up your GPU memory (e.g. Youtube videos, webpages etc.)

4.3 labellImg saves annotation files with .xml extension

At the time of writing up this document, I haven’t managed to identify why this might be happening. I have joined a GitHub issue, at which you can refer in case there are any updates.

One way I managed to fix the issue was by clicking on the “Change Save Dir” button and selecting the directory where the annotations files should be stores. By doing so, you should not longer get a pop-up dialog when you click “Save” (or Ctrl+s), but you can always check if the file was saved by looking at the bottom left corner of labellImg.

4.4 “WARNING:tensorflow:Entity <bound method X of <Y>> could not be transformed …”

In some versions of Tensorflow, you may see errors that look similar to the ones below:

```
WARNING:tensorflow:Entity <bound method Conv.call of <tensorflow.python.layers.convolutional.Conv2D object at 0x000001E92103EDD8>> could not be transformed and will be executed as-is. Please report this to the AutgoGraph team. When filing the bug, set the verbosity to 10 (on Linux, `export AUTOGRAPH_VERBOSITY=10`) and attach the full output. Cause: converting <bound method Conv.call of <tensorflow.python.layers.convolutional.Conv2D object at 0x000001E92103EDD8>>: AssertionError: Bad argument number for Name: 3, expecting 4
```

These warnings appear to be harmless form my experience, however they can saturate the console with unnecessary messages, which makes it hard to scroll through the output of the training/evaluation process.

As reported here, this issue seems to be caused by a mismatched version of gast. Simply downgrading gast to version 0.2.2 seems to remove the warnings. This can be done by running:

```
pip install gast==0.2.2
```
CHAPTER
FIVE

INDICES AND TABLES

• genindex
• modindex
• search