

OBJECT DETECTION WITH TENSORFLOW API

18th MAY, 10AM – 2.30PM SHERLY CENDANA

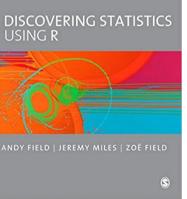
Connect with me! ©

Email: sherlyck2013@gmail.com

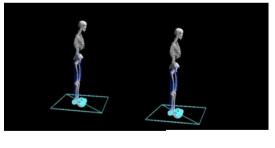
LinkedIn: www.linkedin.com/in/sherlyck

"When it's fun, you enjoy it. When you're afraid of it, it becomes stress."











Tag #WWCodeSingapore on Instagram

Take a picture or upload pictures of

- 1. Something green
- 2. Someone cool
- 3. Your favourite item

AGENDA

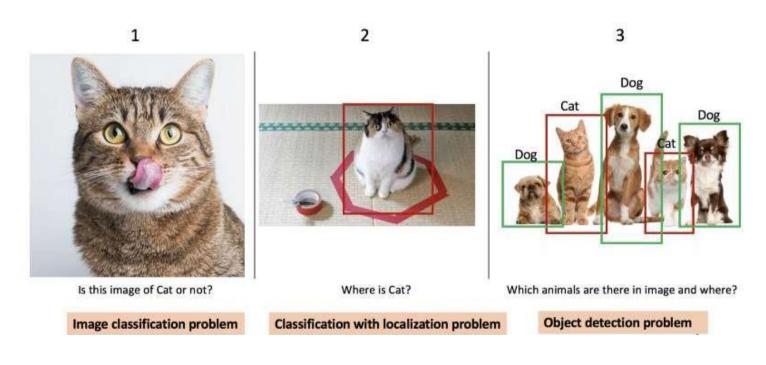
- 1. Introduction
- 2. What is Object Detection
- 3. State of Object Detection
- Tensorflow Object Detection API
 - Preparing Data Crawling data from Instagram #hashtags
 - Selecting the model
 - Training & Evaluating (Optional)
 - Using the model Visualizing
- 5. References

USE CASES



WHAT IS OBJECT DETECTION?

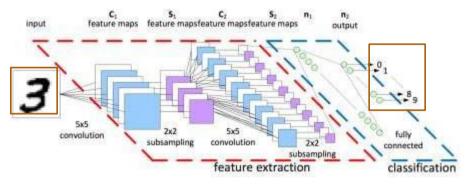
Object detection = Object Classification + Object Localization



OUTPUT OF OBJECT DETECTION

Object detection = Object Classification + Object Localization

Object classification: Output is the one number (index) of a class



Object Localization: Output is the four numbers - coordinates of bounding box





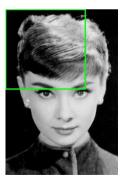
OBJECT DETECTION FRAMEWORK

Object detection = Object Classification + Object Localization

1 Region Proposal

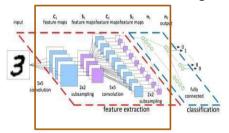
Generate regions of interest

- Selective search
 Clustering approach to group pixels
- Sliding window approach Bounding boxes used as ROI

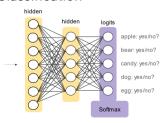


Object Classification

1. Feature extraction & learning

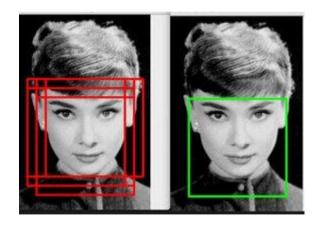


2. Classification



3 Non maximum suppression (NMS)

Post-processing step where overlapping boxes are combined into a single bounding



STATE OF OBJECT DETECTION

APPROACH



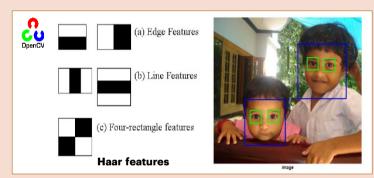






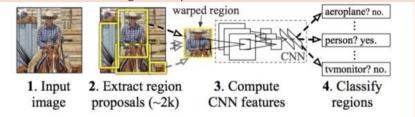
First Object Detection Framework:

Haar feature-based cascade classifiers

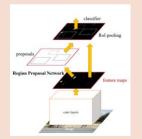


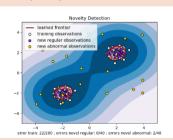
Deep learning approach:

 R-CNN Selective Search Region Proposal - Convolutional Neural Network



 Faster R-CNN Region Proposal Network (RPN) – Convolutional Neural network

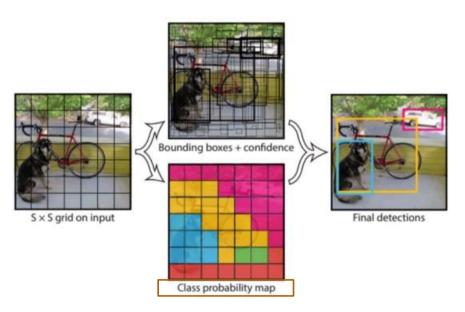


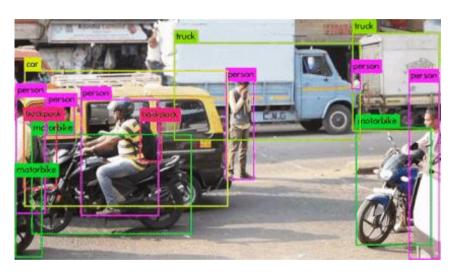


- YOLO (You Look Only Once)
- SSD (Single Shot MultiBox Detector)

DEEP LEARNING APPROACH

YOLO (You Look Only Once)





Class probability map: how confident the model is that the box contains an object and also how accurate it thinks the box is that it predicts

TENSORFLOW OBJECT DETECTION API

Open Source trainable models which makes it easy to construct, train and deploy object detection models

INSTALLATION - 1

- Install Anaconda
 Go to https://www.anaconda.com/download/
- 2. Create new virtual environment and activate the environment

conda create -n tfdev pip python=3.6 conda activate tfdev

3. Install tensorflow & pre-requisites

pip install --ignore-installed --upgrade tensorflow==1.9 pip install pillow==5.41 lxml==4.3.1 jupyter notebook matplotlib==3.02 opencv-python pip install -r requirements.txt

TENSORFLOW OBJECT DETECTION API

Open Source trainable models which makes it easy to construct, train and deploy object detection models

INSTALLATION -2

4. Download tensorflow models repo Go to https://github.com/tensorflow/models, git-clone or download zip file.

Create a new folder under a path of your choice and name it TensorFlow. (C:\Users\XX\tensorflow). From your Anaconda/Command Prompt cd into the TensorFlow directory. Extract content inside the TensorFlow folder. Rename the extracted folder models-master to models

5. Install Protobuf

Load the Google Protobuf folder in C:\Program Files (Windows) add 'C:\Program Files\Google Protobuf\bin' into your environtment variable

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

TENSORFLOW OBJECT DETECTION API

Open Source trainable models which makes it easy to construct, train and deploy object detection models

INSTALLATION -3

6. Add necessary environment variables

```
(Windows) Add into Environment Variables > System Variables > PATH 'C:\Users\XX\tensorflow\models\research\object_detection', 'C:\Users\XX \tensorflow\models\research' 'C:\Users\XX \tensorflow\models\research\slim'
```

(Linux)
export PYTHONPATH=\$PYTHONPATH:<PATH_TO_TF>/TensorFlow/models/research/object_detection
export PYTHONPATH=\$PYTHONPATH:<PATH_TO_TF>/TensorFlow/models/research:<PATH_TO_TF>/TensorFlow/models/research/slim

cd tensorflow/models/research python setup.py build python setup.py install

7. Test installation and run object_detection_tutorial.ipynb

cd tensorflow/models/research/object_detection jupyter notebook

CREATE DATASET

Getting Images

1. INTERNET CRAWL

- 1. Download from Instagram
 - ^ what we are doing today!
- Scrap images from Google using <u>Faktun Bulk Image Downloader</u>

2. CREATE IMAGE DATASET

Image Annotation Tools

- 1. Coco Annotator
- 2. VGG Annotator (VIA)
- 3. <u>LabelImg</u>
- 4. FIAT (Fast Image Data Annotation Tool)



CRAWLING DATA FROM INSTAGRAM #HASHTAGS

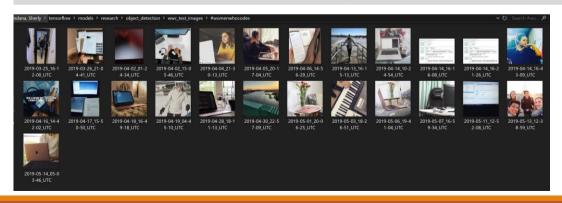
INSTALLATION

1. Install InstaLoader

pip install instaloader

2. Create a folder 'wwc_test_images' in /tensorflow/models/research/object_detection

instaloader --no-videos --no-metadata-json --no-captions "#womenwhocodes" instaloader --no-videos --no-metadata-json --no-captions "#womenwhocodesg"

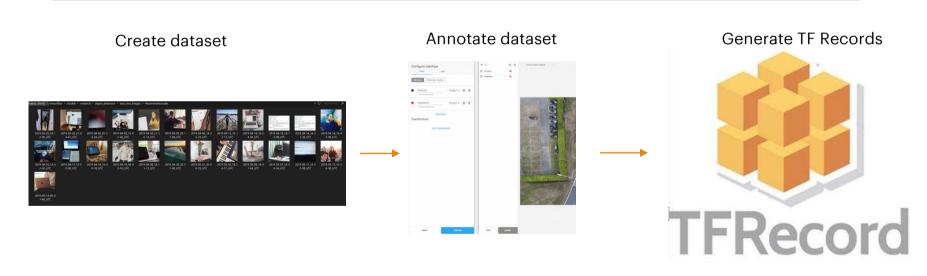




CREATE DATASET - TF RECORDS

- 1. Tensorflow Object Detection API uses the TFRecord file format
- 2. Crawl Images > Annotation Tool > Generate tf records

python generate_tfrecord.py --csv_input=data/train_labels.csv --output_path=train.record



MODEL SELECTION

- Tensorflow Object Detection API contains detection models pre-trained on the <u>COCO dataset</u>, the <u>Kitti dataset</u>, and the <u>Open Images dataset</u>.
- 2. Go to: Model Collection

Item	Description
Model Name	Config file that was used to train this model
Speed (ms)	running time in ms per 600x600 image
COCO mAP[^1]	Mean Average Precision of how well the model performed on the COCO dataset (0 to 100, higher the better)
Outputs	Type of output: Boxes, and Masks if applicable

COCO-trained models

Model name	Speed (ms)	COCO mAP[^1]	Outputs
ssd_mobilenet_v1_coco	30	21	Boxes
ssd_mobilenet_v1_0.75_depth_coco ☆	26	18	Boxes
ssd_mobilenet_v1_quantized_coco ☆	29	18	Boxes
ssd_mobilenet_v1_0.75_depth_quantized_coco ☆	29	16	Boxes
ssd_mobilenet_v1_ppn_coco ☆	26	20	Boxes
ssd_mobilenet_v1_fpn_coco ☆	56	32	Boxes
ssd_resnet_50_fpn_coco ☆	76	35	Boxes
ssd_mobilenet_v2_coco	31	22	Boxes
ssd_mobilenet_v2_quantized_coco	29	22	Boxes
ssdlite_mobilenet_v2_coco	27	22	Boxes
ssd_inception_v2_coco	42	24	Boxes
faster_rcnn_inception_v2_coco	58	28	Boxes

DEEP LEARNING APPROACH

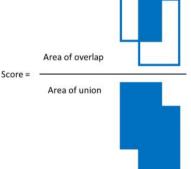
Model & Frozen weights used: ssd_mobilenet_v1_coco_2017_11_17

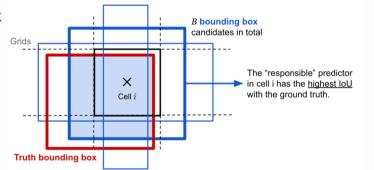
SSD: SINGLE SHOT MULTIBOX DETECTOR

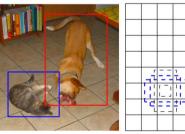
Each bounding box will have a score associated (likelihood of the box containing an object).

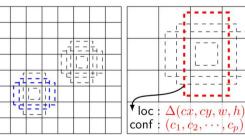
Detection is a true positive if it has an 'intersection over union' (IoU or overlap)











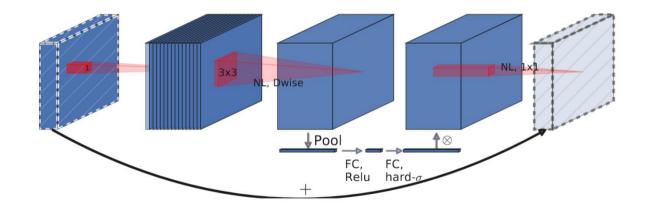
DEEP LEARNING APPROACH

Model & Frozen weights used: ssd_mobilenet_v1_coco_2017_11_17

MOBILENET

Table 1. MobileNet Body Architecture

Table 1. MobileNet Body Architecture			
Type / Stride	Filter Shape	Input Size	
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$	
Conv dw / s1	$3 \times 3 \times 32 \text{ dw}$	$112 \times 112 \times 32$	
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$	
Conv dw / s2	$3 \times 3 \times 64 \text{ dw}$	$112 \times 112 \times 64$	
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$	
Conv dw / s1	$3 \times 3 \times 128 \text{ dw}$	$56 \times 56 \times 128$	
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$	
Conv dw / s2	$3 \times 3 \times 128 \mathrm{dw}$	$56 \times 56 \times 128$	
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$	
Conv dw / s1	$3 \times 3 \times 256 \text{ dw}$	$28 \times 28 \times 256$	
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$	
Conv dw / s2	$3 \times 3 \times 256 \text{ dw}$	$28 \times 28 \times 256$	
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$	
5× Conv dw / s1	$3 \times 3 \times 512 \text{ dw}$	$14 \times 14 \times 512$	
Conv / s1	$1\times1\times512\times512$	$14 \times 14 \times 512$	
Conv dw / s2	$3 \times 3 \times 512 \text{ dw}$	$14 \times 14 \times 512$	
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$	
Conv dw / s2	$3 \times 3 \times 1024 \text{ dw}$	$7 \times 7 \times 1024$	
Conv / s1	$1\times1\times1024\times1024$	$7 \times 7 \times 1024$	
Avg Pool / s1	Pool 7 × 7	$7 \times 7 \times 1024$	
FC/s1	1024×1000	$1 \times 1 \times 1024$	
Softmax / s1	Classifier	$1 \times 1 \times 1000$	





CONFIGURE PIPELINE

- 1. Tensorflow Object Detection API uses protobuf files to configure the training and evaluation process
- 2. Go to: Configuration Pipeline
- 3. Refer to pipeline.config in the folder

Item	Description
model	Type of model
train_config	Model parameters ie. SGD parameters, input preprocessing and feature extractor initialization values
eval_config	Evaluation metrics
train_input_config	Training dataset
eval_input_config	Evaluation dataset

```
train config:
model {
                                                                           eval config: {
                                         batch size: 1
 faster rcnn {
                                                                            metrics set: "coco detection metrics"
                                         optimizer {
                                                                            num examples: 100
    num classes: 1
                                          momentum optimizer: {
                                                                             num visualizations: 15
    image resizer
                                            learning rate: {
                                                                            max num boxes to visualize: 1000
                                              manual step learning rate {
      keep aspect ratio resizer {
                                                                            visualization export dir: "/sherly/tfdevtest/output/viz"
                                               initial learning rate: 0.0003
                                                                            keep image id for visualization export: true
        min dimension: 300
                                               schedule {
                                                                            eval interval secs: 60
        max dimension: 1024
                                                 step: 900000
                                                 learning rate: .00003
                                               schedule {
    feature extractor {
                                                step: 1200000
                                                 learning rate: .000003
      type: 'faster rcnn resnet101'
   train input reader: {
      tf record input reader {
         input path: "/sherly.cendana/tfdevtest/output/train holdout.record"
      label map path: "/data/tfdevtest/output/labelmap.pbtxt"
    eval input reader: {
       tf record input reader {
         input path: "/sherly.cendana/tfdevtest/output/test holdout.record"
       label map path: "/data/tfdevtest/output/labelmap.pbtxt"
       shuffle: false
       num readers: 1
```



TRAINING AND EVALUATING

1. Training the model

```
cd tensorflow/models/research

python object_detection/train.py
--logtostderr
--pipeline_config_path=/tensorflow/models/object_detection/samples/configs/ssd_mobilenet_v1_p ets.config
--train_dir=${PATH_TO_ROOT_TRAIN_FOLDER}
```

2. Evaluating the model

```
cd tensorflow/models/research

python object_detection/eval.py \
--logtostderr \
--pipeline_config_path=${PATH_TO_YOUR_PIPELINE_CONFIG} \
--checkpoint_dir=${PATH_TO_TRAIN_DIR} \
--eval_dir=${PATH_TO_EVAL_DIR}
```

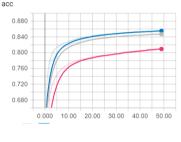
3. Visualise the training and evaluation results using tensorboard

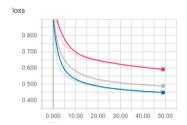
```
cd tensorflow/models/research tensorboard --logdir <directory>/train_logs --port 6004
```

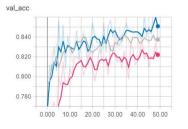
TENSORBOARD - TENSORFLOW'S VISUALIZATION TOOLKIT

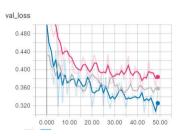
- 1. Tensorboard aids understanding, help in debug, and optimize TensorFlow programs
- 2. Go to: Tensorboard











MODEL USAGE (1/2)

Using the photos we have crawled from Instagram, apply the object detection model on the images.
 Ensure that dataset is present in the folder:



Load jupyter notebook 'wwc_object_detection_tutorial.ipynb'



cd tensorflow/models/research

Ensure that your tensorflow version is later than 1.12

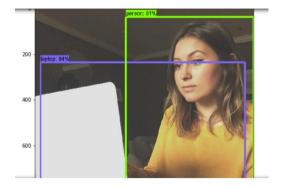
MODEL USAGE (2/2)

3. Load the path to your images

```
PATH_TO_TEST_IMAGES_DIR ='wwc_test_images/#womenwhocodes'
TEST_IMAGE_PATHS =[]
for file in os.listdir(PATH_TO_TEST_IMAGES_DIR):
    if file.endswith(".jpg"):
        print(os.path.join(PATH_TO_TEST_IMAGES_DIR, file))
        TEST_IMAGE_PATHS.append(os.path.join(PATH_TO_TEST_IMAGES_DIR, file))
```

4. Run the notebook and you should see the following output:







THANK YOU!

Go to: www.menti.com and use the code 20 40 96

REFERENCES

- https://towardsdatascience.com/how-to-train-your-own-object-detector-with-tensorflows-object-detector-api-bec72ecfe1d9
- https://www.kdnuggets.com/2017/10/deep-learning-object-detection-comprehensive-review.html
- http://www.machinelearninguru.com/deep_learning/tensorflow/basics/tfrecord/tfrecord/tfrecord.html
- https://www.coursera.org/learn/convolutional-neural-networks
- https://www.tensorflow.org/guide/summaries_and_tensorboard
- https://lilianweng.github.io/lil-log/2018/12/27/object-detection-part-4.html
- https://arxiv.org/pdf/1512.02325.pdf