pytator Documentation

CVision AI

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Contents:

OpenEM is a library that provides advanced video analytics for fisheries electronic monitoring (EM) data. It currently supports detection, classification, counting and measurement of fish during landing or discard. This functionality is available via a deployment library with pretrained models available in our example data (see tutorial). The base library is written in C++, with bindings available for both Python and C#. Examples are included for all three languages.

The current release also includes a training library for the all OpenEM functionality. The library is distributed as a native Windows library and as a Docker image.

Watch the video below to see a video of OpenEM in action:

CHAPTER 1

Quick Start

This document is a quick start guide in how to use the OpenEM package. The instructions in this guide still work for newer versions, but usage of the python inference library is encouraged.

1.1 Example data

This tutorial requires the OpenEM example data which can be downloaded via BitTorrent here.

1.2 Installation

1.2.1 Docker

- Make sure you have installed nvidia-docker 2 as described here.
- Pull the docker image from Docker Hub:

```
docker pull cvisionai/openem_lite:latest
```

- Start a bash session in the image with the volume containing the example data mounted. The default train.ini file assumes a directory structure as follows:

```
working-dir
|- openem_example_data
|- openem_work
|- openem_model
```

The openem_work and openem_model directories may be empty, and openem_example_data is the example data downloaded at the beginning of this tutorial. The following command will start the bash shell within the container with working-dir mounted to /data. The openem library is located at /openem.

```
nvidia-docker run --name openem --rm -ti -v <Path to working-dir>:/data cvisionai/
↪openem_lite bash
```

If using any X11 code, it is important to also enable X11 connections within the docker image:

```
nvidia-docker run --name openem --rm -ti -v <Path to working-dir>:/data -v"$HOME/.
↪Xauthority:/root/.Xauthority:rw" --env=DISPLAY --net=host cvisionai/openem_lite bash
```

Note: Instead of `$HOME/.Xauthority` one should use the authority file listed from executing: `xauth info`

1.2.2 Launching additional shell into a running container

If the container was launched with `--name openem`, then the following command launches another bash process in the running container:

`docker exec --env=DISPLAY -it openem bash`

Substitute `openem` for what ever you named your container. If you didn't name your container, then you need to find your running container via `docker ps` and use:

`docker exec --env=DISPLAY -it <hash_of_container> bash`

1.3 Running the deployment library (0.1.3 and later)

In version 0.1.3 the deployment library has changed from a C++ library with variable language bindings, to a single python library.

In versions 0.1.3 and later there is a unit test for each inference module that runs against the example data provided above. To run the test suite; launch the openem-lite image with the example data mounted and the `deploy_dir` environment variable set appropriately.

The included `Makefile` in config facilitates this by forwarding the host's `work_dir` environment variable to the container's `deploy_dir` variable. In the config directory with `work_dir` set to `/path/to/the/openem_example_data` run `make inference_bash`.

The `inference_bash` target launches the nvidia container with recommended settings on device 0; forwarding port 10001 for potential tensorboard usage.

1.3.1 Running the tests in the container

The unit tests can be used to verify the underlying computing envioronment for inference and serve as a regression test against modifications to optomize image preprocessing or result post processing. The unit tests are also an example usage of the python deployment API.

- Whilst in the container navigate to `/deploy_python`
- Type:

```
python -m unittest test
```

- The results of the tests will print out.
- On machines with limited memory resources, it may be required to run each unit test individually, this can be done by replacing `test` with `test.CountTest` or `test.DetectionTest`

1.4 Training library

To train a model from the example data you will need to modify the configuration file included with the distribution at train/train.ini. This file is included as an example so you will need to modify some paths in it to get it working. Start by making a copy of this file and modify the paths section as follows:

```
[Paths]
# Path to directory that contains training data.
TrainDir=<Path to OpenEM example data>/train
# Path to directory for storing intermediate outputs.
WorkDir=<Path where you want to store working files>
# Path to directory for storing final model outputs.
ModelDir=<Path where you want to store models>
# Path to directory that contains test data.
TestDir=<Path to OpenEM example data>/test
```

1.4.1 Extracting imagery

TrainDir is the path to the example training data. WorkDir is where temporary files are stored during training. ModelDir contains model outputs that can be used directly by the deployment library. Once you have modified your copy of train.ini to use the right paths on your system, you can do the following:

```
python train.py train.ini extract_images
```

Where train.ini is your modified copy. This command will go through the videos and annotations and start dumping images into the working directory. It will take a few hours to complete. Images are dumped in:

```
<WorkDir>/train_imgs
```

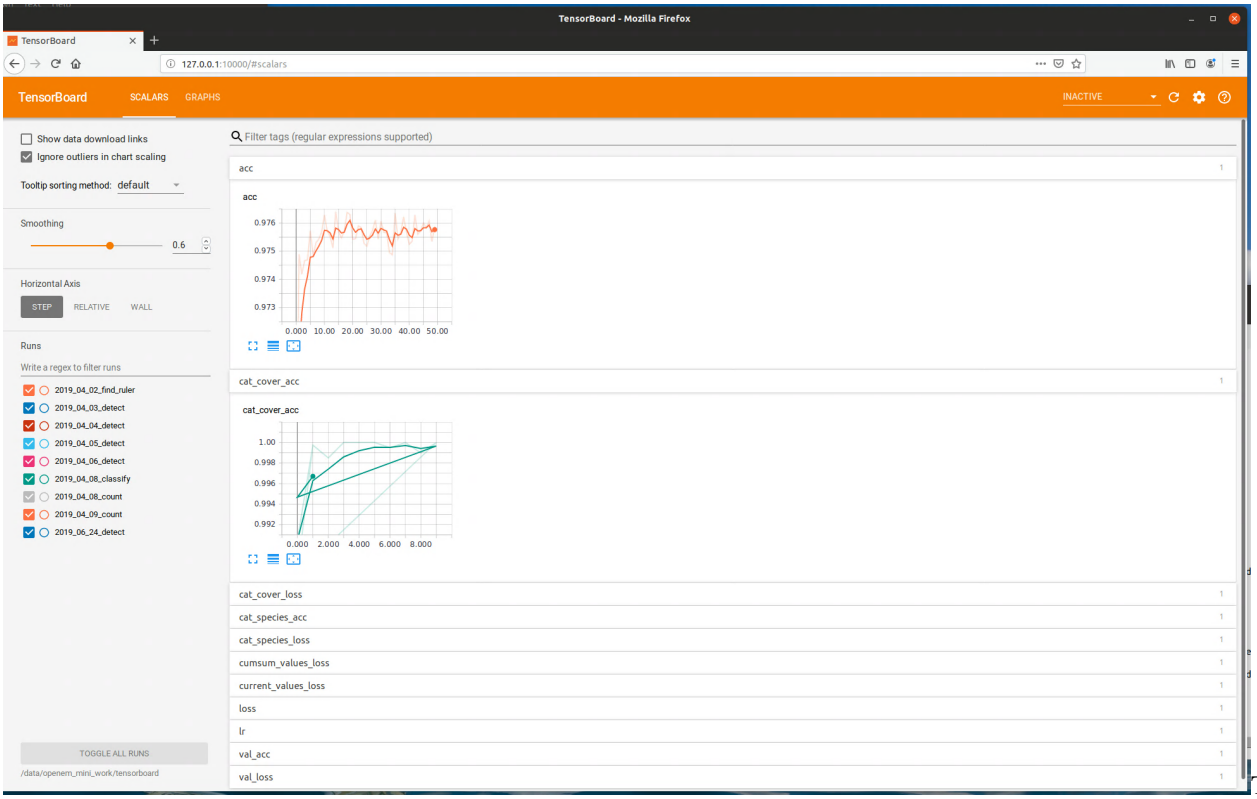
1.4.2 Ruler Training

Next, you can do some training. To train the find ruler model you can do the following command:

```
python train.py train.ini find_ruler_train
```

This will start training the find ruler model. This will take a while. If you want to monitor the training outside of the command line, you can use Tensorboard. This is a program that serves a webpage for monitoring losses during training runs. Use the following command:

```
tensorboard --logdir <path to WorkDir>/tensorboard --port 10000
```



Tensorboard example

Then you can open a web browser on the same machine and go to 127.0.0.1:10000. This will display a live view of the training results. You can also use a different machine on the same network and modify the IP address accordingly. All training steps output tensorboard files, so you can monitor training of any of the openem models using this utility.

Once training completes, a new model will be converted to protobuf format and saved at:

```
<ModelDir>/deploy/find_ruler/find_ruler.pb
```

This file is the same format used in the example data for the deployment library.

Running Inference on train/val data

Now that we have a model for finding rulers, we can run the algorithm on all of our extracted images. Run the following command:

```
python train.py train.ini find_ruler_predict
```

This will use the model that we just trained to find the ruler endpoints. The outputs of this are stored at:

```
<WorkDir>/inference/find_ruler.csv
```

This file has a simple format, which is just a csv containing the video ID and (x, y) location in pixels of the ruler endpoints. Note that this makes the assumption that the ruler is not moving within a particular video. If it is, you will need to split up your videos into segments in which the ruler is stationary (only for training purposes).

It is possible to train only particular models in openem. Suppose we always know the position of the ruler in our videos and do not need the find ruler algorithm. In this case, we can manually create our own find ruler inference file that contains the same information and store it in the path above. So for example, if we know the ruler is always horizontal spanning the entire video frame, we would use the same (x, y) coordinates for every video in the csv.

1.4.3 Extract ROIs for Detection Training

The next step is extracting the regions of interest for the videos as determined in the previous step. Run the following:

```
python train.py train.ini extract_rois
```

This will dump the ROI image corresponding to each extracted image into:

```
<WorkDir>/train_rois
```

1.4.4 Training Detector

OpenEM supports two detector models. One is the Single Shot Detector the other is RetinaNet. Both models can be trained using the `train.py` tool within OpenEM. The underlying RetinaNet implementation is a forked version of keras_retinanet.

Train RetinaNet Detector

To properly train the retinanet model, additional steps are required to generate intermediate artifacts for the underlying retinanet train scripts. These intermediate artifacts are stored in `<work_dir>/retinanet`. In `train.ini`, additional parameters are supported for retinanet specifically:

```
# Random seed for validation split
ValRandomSeed=200
# Validation poulation (0 to 1.0)
ValPopulation=0.2
# Backbone for retinanet implementation
Backbone=resnet152
```

`ValPopulation` is used by the `retinanet_split` to generate a validation population from the overall training population.

Generate required retinanet artifacts

```
# Generate a csv file compatible with retinanet representing the entire training␣
↪population (incl. species.csv)
python3 train.py /path/to/train.ini retinanet_prep

# Split population based on ValPopulation and ValRandomSeed
python3 train.py /path/to/train.ini retinanet_split
```

At this point the split script will print out useful analytics to verify the feasibility of your training set. Some considerations for building a succesful training set:

- If multi-class detection is used, it is important to be coignizant of population count of each class.
- If footage varies by camera, time, a blend across the scenarios is a good idea to be representatitive of operational conditions.
- If a training set is determined to be insufficient it can always be augmented.

Initiate retinanet training

```
python3 train.py /path/to/train.ini retinanet_train
```

At this point you will see retinanet training output including losses and current epoch. Tensorboard can be run from `<openem_work>/retinanet/train_log` and model files are stored in `<openem_work>/retinanet/train_snapshots`.

Converting keras-style model to static protobuf format

The keras training script results in a series of h5 files, one for each training epoch. To convert a given epoch to the protobuf format, utilize the `/scripts/convertToPb.py` script within the openem-lite container.

An example invocation is:

```
# Create detection model folder
mkdir -p /data/openem_model/deploy/detect/

# Output epoch 17 to the model area
python3 /scripts/convertToPb.py --resnet /data/openem_work/retinanet/train_snapshots/
↪resnet152_csv_17.h5 /data/openem_model/deploy/detect/detect_retinanet.pb
```

Running inference with the protobuf graph output

Similar to the SSD procedure `train.py` can be used to generate detection results on the training population (training + validation).

```
# Generate a detect.csv from retinanet detections
python3 train.py /path/to/train.ini retinanet_predict
```

Note: If training both SSD and RetinaNet, care should be taken not to overwrite the respective `detect.csv` files.

Executing in production environment

The `scripts/infer.py` file can be used as an example or starting point for production runs of inference. The inputs of the inference script support both openem flavor CSV and retinanet inputs. This can be used to generate detection results on just validation imagery or batches of test imagery.

Extracting Retinanet Detection Images

The procedure to extract the detection images for retinanet is identical to the *SSD procedure*.

Train Single Shot Detector

Once all ROIs are extracted, run the following:

```
python train.py train.ini detect_train
```

This training will likely take a couple days. As before you can monitor progress using tensorboard.

By default, the model weights saved to protobuf format are those that correspond to the epoch that yielded the lowest validation loss during training. For various reasons we may wish to choose a different epoch. In this tutorial, we will choose a different epoch for the detect model so that it will be more likely to work on fish when they are covered by a hand. To do this use the following command:

```
python select_epoch.py train.ini detect 8
```

This will save over the previously saved detection model in protobuf format, using the model weights from epoch 8. This epoch was selected for this tutorial after some experimentation. You can use the select_epoch.py script to select the epoch of any of the four openem models.

Besides using it for selecting an earlier epoch, select_epoch.py can also be used when you wish to terminate a training run early. For example, you may find that a training run has converged (losses are no longer decreasing) after 20 epochs even though you have set the number of epochs to 50. If you stop the training run, the script will not get to the point where it writes the best model to disk in protobuf format. This script will allow you to write the latest epoch to protobuf format manually.

Now we can do detection on all of the ROI images:

```
python train.py train.ini detect_predict
```

This will create a new inference output at:

```
<WorkDir>/inference/detect.csv
```

1.4.5 Extracting detection imagery

As with the find ruler output, if you have a situation where you do not need detection (you always know where the fish is) then you can create this file manually and continue with the next steps.

Next we can extract the detection images:

```
python train.py train.ini extract_dets
```

This will dump all of the detection outputs into:

```
<WorkDir>/train_dets
```

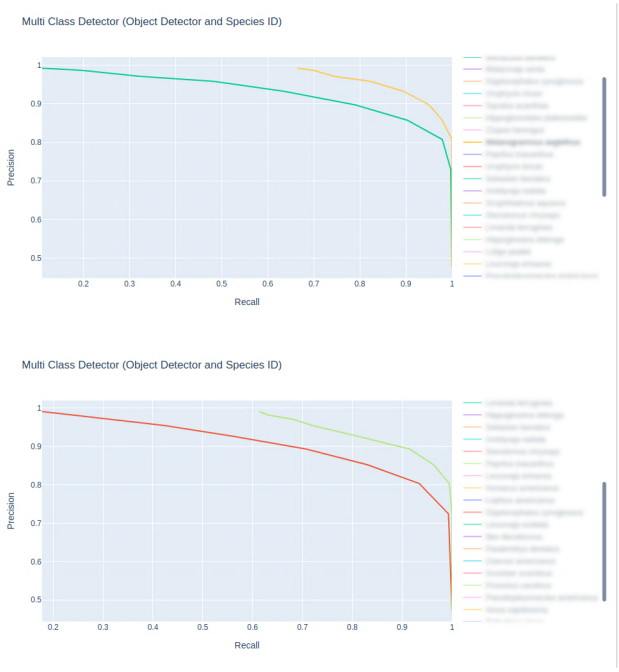
1.4.6 Evaluating detection performance

Traditional graphs using mAP metrics can be generated using `scripts/detection_metrics.py` and `scripts/make_pr_graph.py`. Example invocation:

```
# openem_val.csv is the truth data for the validation set
# results.csv is the detection results from the inference results from the validation␣
↪set
python3 scripts/detection_metrics.py --truth /data/openem_val.csv --output-matrix pr-
↪curve.npy results.csv

# Outputs the PR curve to pr.png
python3 scripts/make_pr_graph.py --output pr.png pr-curve.npy
```

Advanced usage of detection_metrics.py includes changing sweep parameters of keep threshold, and changing the iou threshold for determining a true positive. `detection_metrics.py --help` can be utilized to explore this use-cases.



blurred_species

The notebook file in `scripts/jupyter/species_graph.ipynb` can be used as a foundation to generate interative precision-recall graphs.

1.4.7 Training the rest of the algorithm pipeline

And finally we can repeat the train/predict cycle for the classifier and counting algorithms:

```
python train.py train.ini classify_train
python train.py train.ini classify_predict
python train.py train.ini count_train
```

As with other training steps, these will take a while and can be monitored with TensorBoard. We should now have protobuf models in our designated model directory for all four models.

1.4.8 Testing complete algorithm chain

To test our newly trained models, we can use the test videos included with the openem example data. Run the following command:

```
python train.py train.ini test_predict
```

This will run the algorithm models end to end on all videos in the TestDir as specified in train.ini. The outputs will be in:

```
<WorkDir>/test
```

One csv will be output for each test video, and will contain the keyframe and species of each fish found. We can compare these outputs to the truth data contained in the example data with the following command:

```
python train.py train.ini test_eval
```

CHAPTER 2

Building Datasets

Now that you have done training using the example data, you can try doing the same with your own data. Follow the *data collection* and *annotation* guidelines to build your own training set. Once you have a dataset, you can modify the train.ini file's Data section to include new species to match your data, then repeat the same training process you went through with the example data.

CHAPTER 3

Data Collection Guidelines

3.1 Region of interest

The region of interest (ROI) is the part of the video frame that may contain fish. Although the ROI may be the entire video frame, typically the ROI is only part of it. Some algorithms in OpenEM, such as detection, will perform better if the input images are cropped to the ROI. Therefore, many of the data collection guidelines are driven by recommendations for the ROI, not the entire video frame.

3.2 Environment

The example data is all taken during the daytime. Algorithms in OpenEM can work under other conditions, such as with artificial lighting at night or at dawn/dusk for users who wish to train models on their own data. Keep in mind, however, that generally speaking lower variability in appearance will lead to better algorithm performance.

3.3 Camera characteristics

Video data is expected to have three channels of color (RGB). Camera resolution is driven by the resolution of the region of interest. The resolution of the ROI should be near 720 x 360 pixels, but lower resolution may still yield acceptable results.

3.4 Camera placement

Video should be taken from the overhead perspective, perpendicular to the broadside of any fish in the field of view. We recommend that the camera be aligned with perpendicular within 20 degrees. If possible, the region of interest should be located near the center of the camera field of view to minimize lens distortion.

3.5 Use of rulers

OpenEM has functionality that allows for automatic determination of the region of interest. This functionality requires the use of a ruler that will span the region of interest whenever a fish may require detection. See figure 1 for examples of a region of interest spanned by a ruler.

3.6 Fish movement

Each fish that is to be detected, counted, classified, or measured should be moved through the ROI in the following way:

- The fish is oriented head to tail horizontally within the ROI. The ROI itself may be rotated within the video frame, but fish within the ROI should be oriented along one of its primary axes.
- The fish should pass through the ROI along a linear path.
- At some point while passing through the ROI, the camera should have an unobstructed view of the fish (no hands or other objects in front of it).

CHAPTER 4

Annotation Guidelines

This document describes the data layout for building your own models with OpenEM. Training routines in OpenEM expect the following directory layout:

```
your-top-level-directory
├── test
│   ├── truth
│   │   ├── test_video_0.csv
│   │   ├── test_video_1.csv
│   │   └── test_video_2.csv
│   └── videos
│       ├── test_video_0.mp4
│       ├── test_video_1.mp4
│       └── test_video_2.mp4
└── train
    ├── length.csv
    ├── cover.csv
    ├── masks
    │   ├── images
    │   │   ├── 00000.jpg
    │   │   ├── 00001.jpg
    │   │   └── 00002.jpg
    │   └── masks
    │       ├── 00000.png
    │       ├── 00001.png
    │       └── 00002.png
    └── videos
        ├── train_video_0.mp4
        ├── train_video_1.mp4
        └── train_video_2.mp4
```

Many of the annotations require video frame numbers. It is important to point out that most video players do not have frame level accuracy, so attempting to convert timestamps in a typical video player to frame numbers will likely be inaccurate. Therefore we recommend using a frame accurate video annotator such as Tator, or converting your video to a series of images before annotating.

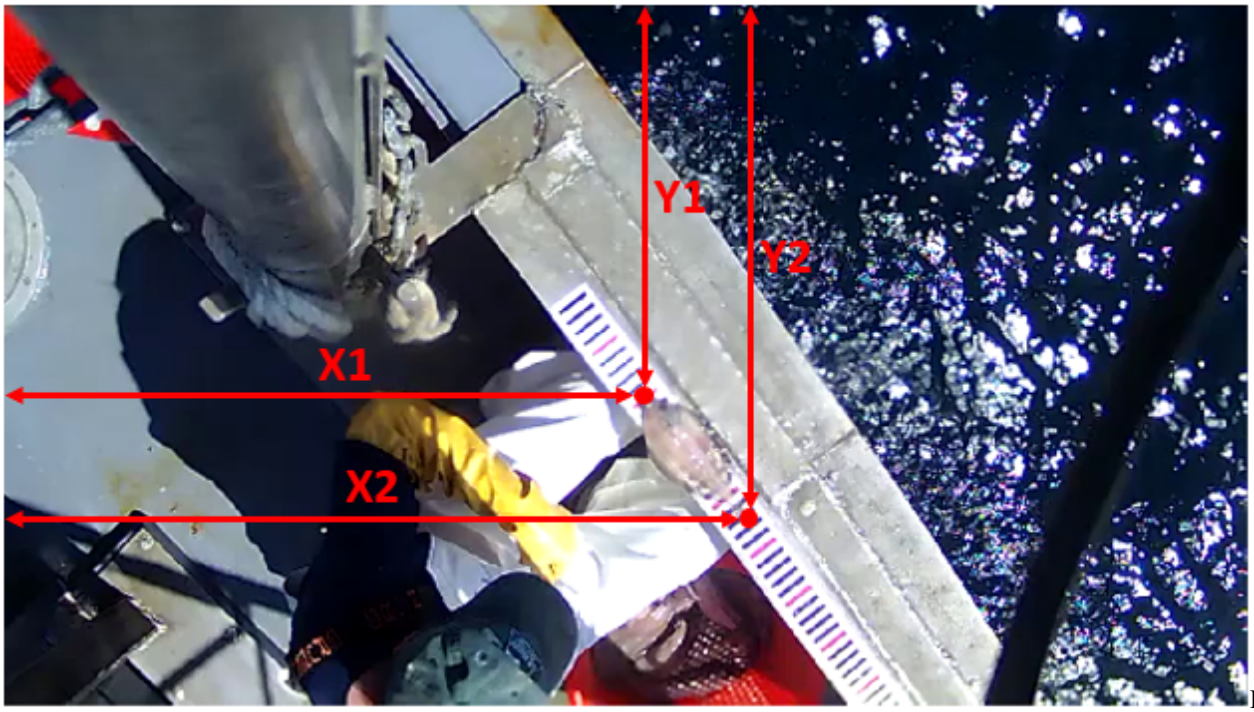
4.1 Train directory

videos contains video files in mp4 format. The content of these videos should follow the *data collection guidelines*. We refer to the basename of each video file as the *video ID*, a unique identifier for each video. In the directory layout above, the video ID for the videos are train_video_0, train_video_1, and train_video_2.

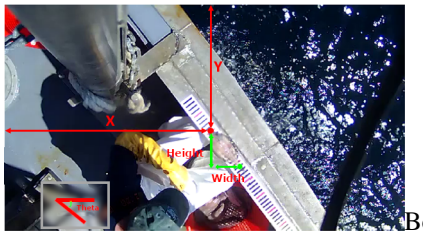
masks/images contains single frames from the videos. Each image in this directory has a corresponding binary mask image in **masks/masks**. The high values (RGB value of [255, 255, 255]) in the mask correspond to the ruler, and it is zeros elsewhere.

length.csv contains length annotations of fish in the videos. Each row corresponds to an individual fish, specifically the video frame containing the clearest view of each fish. This file is also used to train the counting algorithm, so exactly one frame should be annotated per individual fish. The columns of this file are:

- *video_id*: The basename of the video.
- *frame*: The zero-based frame number in the video.
- Choose one of the following annotation styles:
  - *x1, y1, x2, y2*: xy-coordinates of the tip and tail of the fish in pixels.
  - *x,y,width,height,theta*: xy-coordinates of box surrounding the fish in pixels.
- *species_id*: The one-based index of the species as listed in the ini file, as described in the *tutorial*. If this value is zero, it indicates that no fish are present. While length.csv can be used to include no fish example frames, it is encouraged to instead include them in cover.csv. Both are used when training the detection model, but only cover.csv is used when training the classification model.



Length



coordinates of a clearly visible fish. Box coordinates of a clearly visible fish.

cover.csv contains examples of frames that contain no fish, fish covered by a hand or other obstruction, and fish that can be clearly viewed. The columns of this file are:

- *video_id*: The basename of the video.
- *frame*: The zero-based frame number in the video.
- *cover*: 0 for no fish, 1 for covered fish, 2 for clear view of fish.

Example of image with no fish.

Example of image with covered fish.

Example of image with clear fish.

4.2 Test directory

videos contains videos that are different from the videos in the train directory but collected in a similar way.

truth contains a csv corresponding to each video. Each row corresponds to a fish in the video. The columns in this

file are:

- *frame*: The keyframe for each fish.
- *species*: Species of each fish.
- *length*: Length of each fish in pixels.

4.3 Skipping training steps

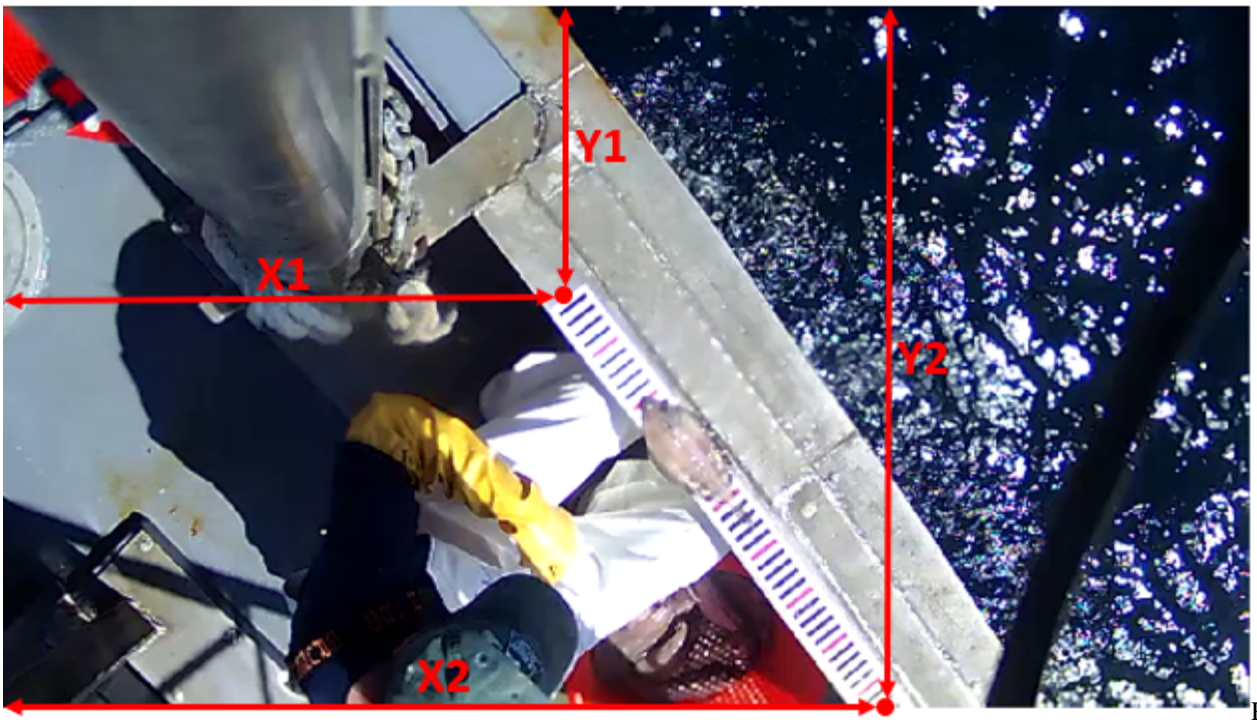
It is possible to train only some models in openem. For example, you may wish to only train the detect model or only the classify model. During training, there are steps in which model outputs are predicted for use in the next model in the pipeline. In each of these cases, the outputs are written to one of:

```
<WorkDir>/inference/find_ruler.csv
<WorkDir>/inference/detect.csv
<WorkDir>/inference/classify.csv
```

The name of the file corresponds to the model that generated it. If you would like to skip training one of these models but a model you wish to train depends on one of these files, you will need to generate the missing file manually as if it were part of the training set annotations. Below is a description of each file:

find_ruler.csv contains the ruler position in each video. The columns of this file are:

- *video_id*: The basename of the video.
- *x1, y1, x2, y2*: xy-coordinates of the ends of the ruler in pixels.



Ruler coordinates for a video.

detect.csv contains the bounding box around fish in the video frames. The columns of this file are:

- *video_id*: The basename of the video.
- *frame*: The zero-based frame number in the video.

- *x, y, w, h*: The top, left, width, and height of the bounding box in pixels. The origin is at the top left of the video frame.
- *det_conf*: Detection confidence, between 0 and 1. This should be 1 for manually annotation.
- *det_species*: The one-based index of the species as listed in the ini file.

classify.csv contains the cover and species for the highest confidence detection in each frame. It has the following columns:

- *video_id*: The basename of the video.
- *frame*: The zero-based frame number in the video.
- *no_fish, covered, clear*: Cover category. One of these should be set to 1.0, others should be zero.
- *speces__, species_**: Species category. The species__ corresponds to background (not a fish). One of these should be set to 1.0, others should be zero.

CHAPTER 5

Build and Test Instructions

Choose your distribution:

- Windows library
- *Docker image*

CHAPTER 6

Using OpenEM with Docker

6.1 OpenEM Lite image

The OpenEM docker image in version 0.1.3 and upwards has been retooled to be a slimmer image based on NVIDIA's GPU cloud offerings. The `openem_lite` image can be used for both training and inference of OpenEM models.

6.1.1 Installing the image

The docker image is provided from dockerhub, and can be installed with:

```
docker pull cvisionai/openem_lite:latest
```

6.1.2 Building the image

- Follow instructions here to install nvidia-docker.
- From the openem config directory run the following command:

```
make openem_lite
```

6.1.3 Running outside of docker

Versions 0.1.3 and later of OpenEM do not have a hard requirement of using the supplied docker image. It is possible to install the openem deployment library outside of docker.

```
$> cd deploy_python
$> pip3 install .
$> python3
%python3> import openem
```

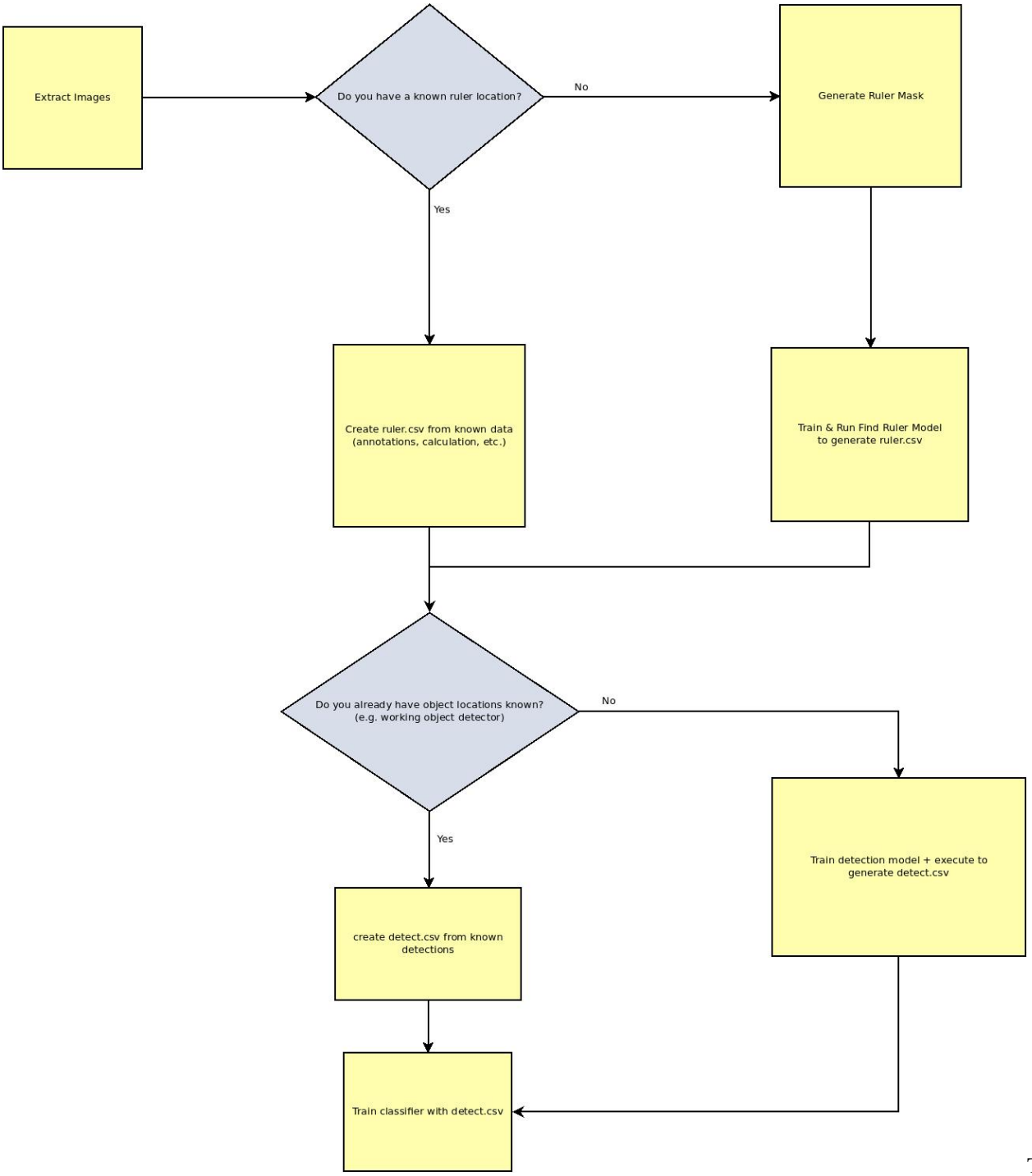
CHAPTER 7

Frequently Asked Questions

From time to time, various questions on how to use OpenEM are asked by the community of users. This document attempts to consolidate the most asked questions to assist new users of the library.

7.1 Training & Data curation

OpenEM allows for flexibly deploying parts of the pipeline relevant for a given problem set. With this complexity comes complication in understanding what is required for a given training run. The following flowchart shows the decision tree required for setting up training data.



Training data flowchart

7.2 Docker-related

7.2.1 What is Docker?

Docker is a container management system. It allows us to package OpenEM as a unit effectively equivilant to a light weight Virtual Machine. All system dependencies are taken care of such that OpenEM can work with minimal administriva.

Key terms to understand in our usage of Docker.

- Image : A Docker *image* is the entity downloaded with a `docker pull` command. It is the filesystem contents of a given container. + To see images you have on your system, use `docker images`
- Container: A Docker *container* is the running instance of the "Light weight VM". + To see running containers you have on your system, use `docker ps`

7.2.2 How do I get files to/from a docker container?

It is preferred to get a file from a docker container while it is still running. The commands provided in the `tutorial.md` file use bind mounts to expose a directory on the host to running container.

In the following example, the folder `/mnt/md0` on the host is mounted as `/data` to the perspective of the docker container.

```
docker run --rm -ti -v /mnt/md0:/data ubuntu bash
```

7.2.3 I got an error like "Gtk-WARNING **: 11:14:47.519: cannot open display: ".

Because the docker container is running as an isolated environment it doesn't have access to the windowing environment of the host (X11). For trusted images the easiest way to facilitate this is to use the same syntax as some of the commands in `tutorial.md` to allow the container instance to use the host X11 network.

Specifically that entails adding `-v"$HOME/.Xauthority:/root/.Xauthority:rw" --env=DISPLAY --net=host` to the docker invocation.

The following command creates a vanilla ubuntu X11-enabled container: `docker run --rm -ti -v"$HOME/.Xauthority:/root/.Xauthority:rw" --env=DISPLAY --net=host ubuntu bash`

Important: When using `--net host` the container isn't as isolated from the hosts network interface.

Important: The prompt of the container using the `--net host` will look similar the host prompt. Care should be taken to avoid mistakes.

7.2.4 I wanted to launch tensorboard, but I can't access the shell in the running

7.2.5 container any longer.

If the container was launched with `--name openem`, then the following command launches another bash process in the running container:

```
docker exec --env=DISPLAY -it openem bash
```

Substitute `openem` for what ever you named your container. If you didn't name your container, then you need to find your running container via `docker ps` and use:

```
docker exec --env=DISPLAY -it <hash_of_container> bash
```

CHAPTER 8

Deployment API

As of version 0.1.3, the deployment library is a python module. The documentation of the module can be found below.

8.1 Installing

In the *deploy_python* folder, *pip3 install .* can be used to install the package.

8.2 Package openem

OpenEM Inference Deployment Package

8.2.1 Base objects

Define base classes for openem models

class openem.models.**ImageModel**(*model_path*, *image_dims=None*, *gpu_fraction=1.0*, *input_name='input_1:0'*, *output_name='output_node0:0'*, *optimize=True*, *optimizer_args=None*, *batch_size=1*, *cpu_only=False*)

Bases: object

Base class for serving image-related models from tensorflow

Initialize an image model object model_path : str or path-like object

Path to the frozen protobuf of the tensorflow graph

image_dims [tuple] Tuple for image dims: (<height>, <width>, <channels>) If None, is inferred from the graph.

gpu_fraction [float] Fraction of GPU allowed to be used by this object.

input_name [str] Name of the tensor that serves as the image input

output_name [str or list of str] Name(s) of the the tensor that serves as the output of the network. If a singular tensor is given; then the process function will return that singular tensor. Else the process function returns each tensor output in the order specified in this function as a list.

batch_size [int] Maximum number of images to process as a batch

cpu_only: bool If true will only use CPU for inference

inputShape()
Returns the shape of the input image for this network

process(*batch_size=None*)
Process the current batch of image(s).

Returns None if there are no images.

8.2.2 Find Ruler

Module for finding ruler masks in raw images

class openem.FindRuler.**RulerMaskFinder**(*model_path*, *image_dims=None*)
Bases: *openem.models.ImageModel*

Class for finding ruler masks from raw images

addImage(*image*)

Add an image to process in the underlying ImageModel after running preprocessing on it specific to this model.

image: np.ndarray the underlying image (not pre-processed) to add to the model's current batch

process(*postprocess=True*)

Runs the base ImageModel and does a high-pass filter only allowing matches greater than 127 to make it into the resultant mask

Returns the mask of the ruler in the size of the network image, the user must resize to input image if different.

openem.FindRuler.**findRoi**(*image_mask*, *h_margin*)
Returns the roi of a given mask; with additional padding added both horizontally and vertically based off of h_margin and the underlying aspect ratio. image_mask: array

Represents image mask

h_margin: int Number of pixels to use

openem.FindRuler.**rectify**(*image*, *endpoints*)
Rectifies an image such that the ruler(in endpoints) is flat image: array

Represents an image or image mask

endpoints: array Represents 2 pair of endpoints for a ruler

openem.FindRuler.**rulerEndpoints**(*image_mask*)
Find the ruler end points given an image mask image_mask: 8-bit single channel image_mask

openem.FindRuler.**rulerPresent**(*image_mask*)
Returns true if a ruler is present in the frame

8.2.3 Detection

Detection Results

class openem.Detect.**Detection**(*location*, *confidence*, *species*, *frame*, *video_id*)

Create new instance of Detection(location, confidence, species, frame, video_id)

confidence
Alias for field number 1

frame
Alias for field number 3

location
Alias for field number 0

species
Alias for field number 2

video_id
Alias for field number 4

Single Shot Detector

class openem.Detect.SSD.**SSDDetector**(*model_path*, *image_dims=None*, *gpu_fraction=1.0*, *input_name='input_1:0'*, *output_name='output_node0:0'*, *optimize=True*, *optimizer_args=None*, *batch_size=1*, *cpu_only=False*)

Bases: *openem.models.ImageModel*

Initialize an image model object model_path : str or path-like object

Path to the frozen protobuf of the tensorflow graph

image_dims [tuple] Tuple for image dims: (<height>, <width>, <channels>) If None, is inferred from the graph.

gpu_fraction [float] Fraction of GPU allowed to be used by this object.

input_name [str] Name of the tensor that serves as the image input

output_name [str or list of str] Name(s) of the the tensor that serves as the output of the network. If a singular tensor is given; then the process function will return that singular tensor. Else the process function returns each tensor output in the order specified in this function as a list.

batch_size [int] Maximum number of images to process as a batch

cpu_only: bool If true will only use CPU for inference

addImage(*image*, *cookie=None*)

Add an image to process in the underlying ImageModel after running preprocessing on it specific to this model.

image: np.array of the underlying image (not pre-processed) to add to the model's current batch.

process()

Runs network to find fish in batched images by performing object detection with a Single Shot Detector (SSD).

Returns a list of Detection (or None if batch is empty)

openem.Detect.SSD.**decodeBoxes**(*loc*, *anchors*, *variances*, *img_size*)
Decodes bounding box from network output

loc: Bounding box parameters one box per element anchors: Anchors box parameters, one box per element variances: Variances per box

Returns a Nx4 matrix of bounding boxes

Retinanet Detector

RetinaNet Object Detector for OpenEM

class openem.Detect.RetinaNet.**RetinaNetDetector**(*modelPath*, *meanImage=None*, *gpuFraction=1.0*, *imageShape=(360*, *720)*, ***kwargs*)
Bases: *openem.models.ImageModel*

Initialize the RetinaNet Detector model modelPath: str

path-like object to frozen pb graph

meanImage: np.array Mean image subtracted from image prior to network insertion. Can be None.

image_shape: tuple (height, width) of the image to feed into the detector network.

class openem.Detect.RetinaNet.**RetinaNetPreprocessor**(*meanImage=None*)
Bases: object

Perform preprocessinig for RetinaNet inputs Meets the callable interface of openem.Detect.Preprocessor

8.2.4 Classification

Module for performing classification of a detection

class openem.Classify.**Classification**(*species*, *cover*, *frame*, *video_id*)
Bases: tuple

Create new instance of Classification(species, cover, frame, video_id)

cover
Alias for field number 1

frame
Alias for field number 2

species
Alias for field number 0

video_id
Alias for field number 3

class openem.Classify.**Classifier**(*model_path*, *gpu_fraction=1.0*, ***kwargs*)
Bases: *openem.models.ImageModel*

Initialize an image model object model_path : str or path-like object

Path to the frozen protobuf of the tensorflow graph

gpu_fraction [float] Fraction of GPU allowed to be used by this object.

addImage(*image*, *cookie=None*)

Add an image to process in the underlying ImageModel after running preprocessing on it specific to this model.

image: np.ndarray the underlying image (not pre-processed) to add to the model's current batch

process()
Process the current batch of image(s).

Returns None if there are no images.

8.2.5 Count

Module for finding keyframes

class openem.Count.**KeyframeFinder**(*model_path*, *img_width*, *img_height*, *gpu_fraction=1.0*)
Bases: object

Model to find keyframes of a given species

Initialize a keyframe finder model. Gives a list of keyframes for each species. Caveats of this model:

- Assumes tracking 1 classification/detection per frame

model_path [str or path-like object] Path to the frozen protobuf of the tensorflow graph

img_width: Width of the image input to detector (pixels) img_height: Height of image input to decttor (pixels) gpu_fraction : float

Fraction of GPU allowed to be used by this object.

process(*classifications*, *detections*)
Process the list of classifications and detections, which must be the same length.

The outer dimension in each parameter is a frame; and the inner a list of detection or classification in a given frame

classifications: list of list of openem.Classify.Classfication detections: list of list of openem.Detect.Detection

sequenceSize()
Returns the effective number of frames one can process in an individual sequence

CHAPTER 9

OpenEM and Tator Pipelines

Tator is a web-based media management and curation project. Part of the media management is executing algorithms or *workflows* on a set of media. OpenEM is able to be run within the confines of a Tator workflow. Currently Retinanet-based Detection is supported for inference within a workflow.

9.1 Using the Reference Detection Workflow

The reference workflow can be used by modifying the *scripts/tator/detection_workflow.yaml* to match those of the given project.

9.1.1 Generating a data image

The reference workflow at run-time pulls a docker image containing network coefficients and weights. To generate a weights image, one can use the *scripts/make_pipeline_image.py* in a manner similar to below:

```
python3 make_pipeline_image.py --graph-pb <trained.pb> --train-ini <path_to_train.ini>
↪ --publish <docker_hub_user>/<image_name>
```

Note the values of <docker_hub_user> and <image_name> for use in the next section.

The referenced train.ini can be a subset of full *train.ini*; a minimal configuration such as the following is acceptable for the requirements of *uploadToTator.py*:

```
[Data]
# Names of species, separated by commas.
Species=Fish
```

9.1.2 Using the reference workflow definition

A reference workflow yaml is in the repository which can be modified to indicate project-specific requirements. *img_max_side*, *img_min_side*, *batch_size*, and *keep_threshold* map to the arguments in *infer.py* directly.

This workflow is for executing retinanet-based detections on a video dataset using tensor-rt enabled hardware.

Nominally the only parameters required to change is the strategy definition.

```
apiVersion: argoproj.io/v1alpha1
kind: Workflow
metadata:
  generateName: openem-workflow-
spec:
  entrypoint: pipeline
  ttlSecondsAfterFinished: 3600
  volumes:
  - name: dockersock
    hostPath:
      path: /var/run/docker.sock
  templates:
  - name: pipeline
    steps:
    - - name: worker
        template: worker
  - name: worker
    inputs:
      artifacts:
      - name: strategy
        path: /data/strategy.yaml
        raw:
          data: |
            img-size: [<max>,<min>]
            keep-threshold: <keep>
            batch-size: <batch>
            date_image: <docker_image>
            version_id: <version_id>
            box_type_id: <localization_id>
    container:
      image: cvisionai/openem_lite:latest
      volumeMounts:
        - name: dockersock
          mountPath: /var/run/docker.sock
      resources:
        limits:
          nvidia.com/gpu: 1
      env:
      - name: TATOR_MEDIA_IDS
        value: "{{workflow.parameters.media_ids}}"
      - name: TATOR_API_SERVICE
        value: "{{workflow.parameters.rest_url}}"
      - name: TATOR_AUTH_TOKEN
        value: "{{workflow.parameters.rest_token}}"
      - name: TATOR_PROJECT_ID
        value: "{{workflow.parameters.project_id}}"
      - name: TATOR_WORK_DIR
        value: "/work"
      volumeMounts:
      - name: workdir
        mountPath: /work
      command: [python3]
      args: ["/scripts/tator/detection_entry.py"]
```

9.2 Detailed Mechanics

This section walks through the mechanics of the reference workflow so that users could build more elaborate workflows on OpenEM technology.

A Tator Workflow is specified no differently than a regular Argo workflow, other than there is an expectation the Tator REST API is used to access media files and supply results to a project.

A canonical Tator workflow has three parts: setup, execution, and teardown. More advanced workflows can replace the execution stage with multiple stages using the directed acyclic graph capabilities of argo.

9.2.1 Project setup

A project for using this workflow has a media type (either a video type or an image type) represented by a `<media_type_id>`. The project also has a localization box type represented by `<box_type_id>`. The `<media_type_id>>` has the following required attributes:

Object Detector Processed A string attribute type that is set to the date time when the object detector finishes processing the media file.

The `<box_type_id>` requires the following attributes:

Species A string representing the name for an object class. If 'Species' is not an appropriate name for class, this can be customized via the `species_attr_name` key in the pipeline argument object to the teardown stage. It defaults to 'Species' if not specified.

Confidence A float attribute representing the score of the detection. If 'Confidence' is not a desired name, it can be customized via the `confidence_attr_name` key in the pipeline argument object to the teardown stage. It defaults to 'Confidence' if not specified.

9.2.2 Acquiring media

The example *setup.py* provides a canonical way to download media for a given workflow.

9.2.3 Executing Work

The heart of the reference workflow is *infer.py* from the openem_lite docker image. However, it is useful to have a layer of scripting above that CLI utility to translate workflow definitions to the underlying utility.

9.2.4 Submitting results

infer.py generates a csv with inference results, so another utility must interpret these results and submit to the underlying Tator web service. A script called *uploadToTator.py* is located in scripts, but similar to *infer.py*; inserting a layer between the raw script can be helpful to manage the environment.

CHAPTER 10

Tracking

Tracking is the concept of associating a detection from a frame or image to a detection in another frame or image. A "Track" is a series of detections each representing multiple looks at the same underlying real-world object.

10.1 Tracking methodology considerations

The tracks are generated by joining detections into tracklets, or an associated group of detections. Iterations are performed to then join tracklets into larger tracklets until confidence is reached that all tracklets are now well-formed tracks. The amount of loops is discussed under "Data Considerations". For the purposes of implementation symetry, the first iteration casts detections to each be a tracklet containing 1 detection.

Each stage of the loop executes a graph-based algorithm that solves which tracklets to join based on the weights associated with each edge in the graph. More than 2 edges can be joined in 1 iteration of the graph edge contraction. There are an infinite number of ways to calculate weights of each edge. OpenEM supports edge weight methods using ML/AI or traditional computational methods.

An example tracker using Tator as a data store for both detections and tracks is located in *scripts/tator_tracker.py*.

10.1.1 Recursive graph solving overview

10.1.2 Simple IoU

A tracker starts with a list of detections. In some video, specifically higher frame-rate low-occlusion video, the IoU of one detection to another can be highly indicatative the object is the same across frames. The IoU weighting mechanism can start to have errors on long overlapping tracks. As an example picture looking across a two-way street, assuming a well-trained object detector it is probable almost all frames could capture two oncoming cars passing each other. However, an IoU tracker can misjudge truth by looking only at overlap of detections, resulting in 'track swappage'. In this case rather than have 2 cars, one traveling left, one traveling right, the tracker may track 2 cars each driving towards the middle and turning around.

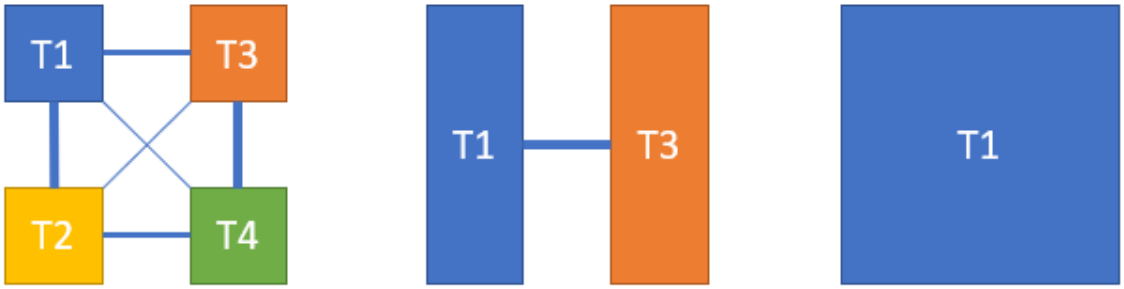


Fig. 1: The graph edge contraction above shows the contraction of four tracks into one via iterative contraction. The weights of the graph are qualatatively shown as the width of the line connecting each graph edge.

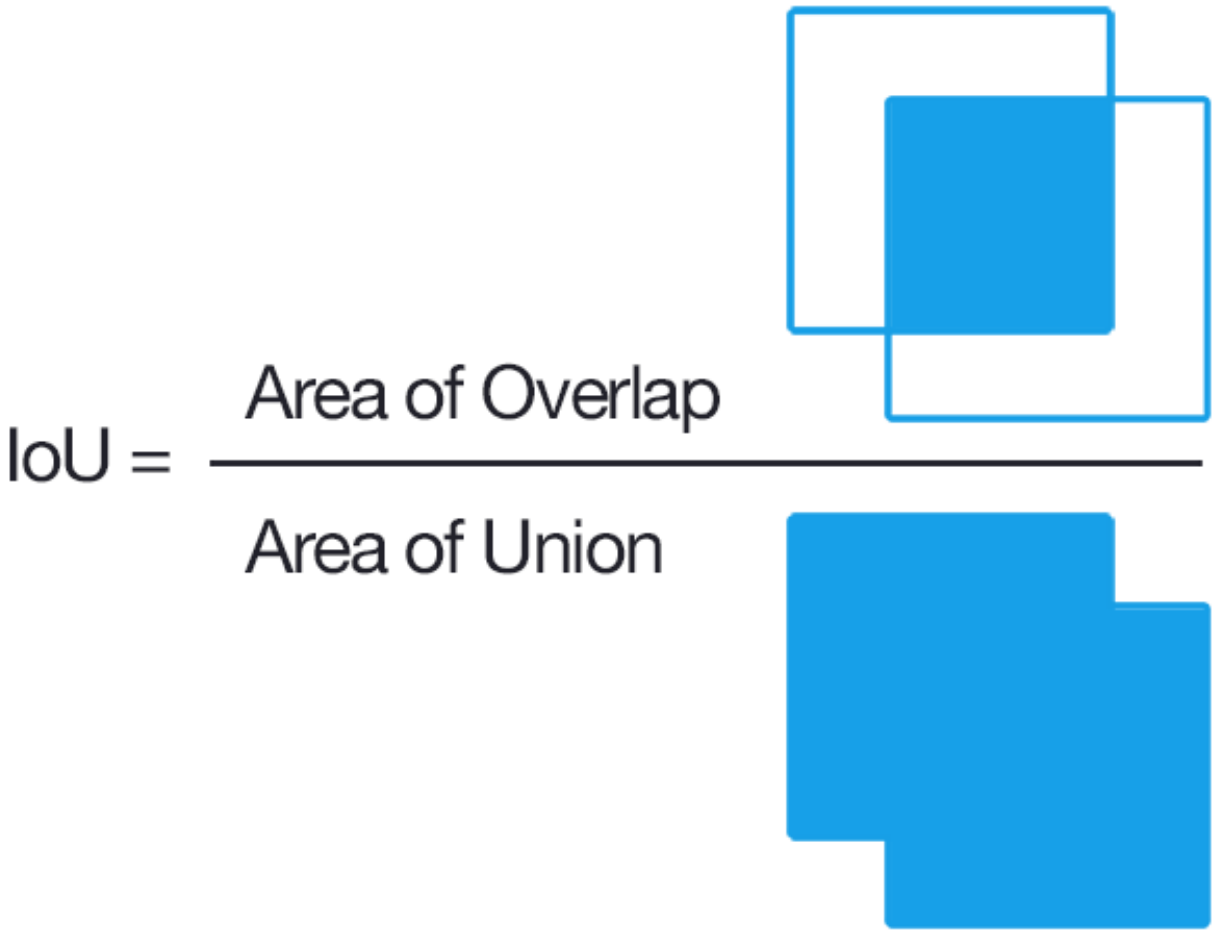


Fig. 2: Graphical depiction of intersection over union (IoU). Adrian Rosebrock / CC BY-SA (https://creativecommons.org/licenses/by-sa/4.0)

10.1.3 Directional

Directional tracking generates edge weight based on the similarity of velocity between two tracks. In the example car example above, a the IoU strategy may be limited to only create track lengths up to N frames. Given N frames, each IoU-based track can have a calculated velocity and edge weights are valued based on the simularity of velocity between two tracks. The directional model can add fidelity to an IoU tracker if objects have defined motion patterns to bias association based on the physical characteristics of the object being tracked.

Directional tracking can be difficult for objects that move erradically or ultimately become occluded for long periods of time. Directional tracking also does not help identify tracks that leave and return the field of view within a recording.

10.1.4 Siamese CNN

This method compares two tracklets that each have no more than 1 detection. The appearance features of each detection or series of detections are extracted and compared. The simularity of each detection is used as an edge in the graph. This method of edge weight determination can help recognize if detections are the same even if no motion or overlap is present between multiple looks at the object. Using the car example above, the appearance features of a red car would match it to a similar look at the same red car. This method can run into issues for objects that change or transform their appearance. Using the car example above, an exposed weakness to this approach would be if one car was a convertible in the process of folding in the roof.

This method requires a trained model.

10.1.5 Multiple stage approach

Each one of these stages can be used in conjunction with another. The reference tracker shows the concept of using different methods based on the current iteration of the network. This fusion approach can be useful to

10.2 Training considerations

Of the currently supported reference methods, the Siamese CNN is the only method requiring training. <TODO: insert link to how to train siamese data>.

Bootstraping the tracker can be useful in the generation of training data. Utilizing the IoU or Directional tracker methods can generate data to be reviewed by annotators. After this review, data can be used to train the Siamese CNN. This can result in more training data for associating detections faster, than having annotators start by manually associating detections.

10.3 Tracker strategy

The `--strategy-config` argument to `tator_tracker.py` expects a yaml file that allows for the configuration of the tracker. The options above are exposed via the yaml syntax. An example with commentary is provided below:

```
method: iou #One of 'hybrid', 'iou', or 'iou-motion'
args: #keyword arguments to the underlying strategy initializer (tracking/weights.py)
   threshold: 0.20 # Sets the IoU threshold for linkage
extension: # Optional
   method: linear-motion #linear-motion (TODO: add additional methods, like KCF, etc.)
frame-diffs: [1,16,32,128] # List of what frames to run the graph solver on
class-method: # optional external module used to classify tracks
```

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```
   pip: git+https://github.com/cvisionai/tracker_classification # Name or pip package or URL
   function: tracker_rules.angle.classify_track #Function to use to classify tracks
   args: # keyword arguments specific to classify method
      minimum_length: 50
      label: Direction
      names:
         Entering: [285, 360]
         Entering: [0,75]
         Exiting: [105,265]
         Unknown: [0,360]
```

10.3.1 Classification plugins

An example classification plugin project can be found here on github. The example aligns with the sample strategy above. `media_id` is a dictionary representing a media element *proposed_track_element* is a list of detection objects.

Full definition of the dictionary and detection object is implementation specific, for tator-backed deployments the definitions apply for Media and detections. At a minimum the media dictionary must supply a width and height of the media. Each detection must have at a minimum an x,y,height,width each in relative coordinates (0.0 to 1.0). Additional properties for each detection may be present in a given detection `attributes` object.

```
def classify_track(media_id,
                   proposed_track_element,
                   minimum_length=2,
                   label='Label',
                   names={}):
```

10.3.2 Example Tator Workflow

In its entirety a reference tator workflow is supplied.

```
apiVersion: argoproj.io/v1alpha1
kind: Workflow
metadata:
  generateName: tracker-example
spec:
  entrypoint: pipeline
  ttlStrategy:
    SecondsAfterSuccess: 600
    SecondsAfterFailure: 86400
  volumeClaimTemplates:
  - metadata:
      name: workdir
    spec:
      storageClassName: aws-efs
      accessModes: [ "ReadWriteOnce" ]
      resources:
        requests:
          storage: 50Mi
  volumes:
  - name: dockersock
    hostPath:
```

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```
      path: /var/run/docker.sock
  templates:
  - name: pipeline
    steps:
    - - name: worker
        template: worker
  - name: worker
    inputs:
      artifacts:
      - name: strategy
        path: /work/strategy.yaml
        raw:
          data: |
            method: iou-motion
            extension:
              method: linear-motion
            frame-diffs: [1,16,32,128]
            class-method:
              pip: git+https://github.com/cvisionai/tracker_classification
              function: tracker_rules.angle.classify_track
              args:
                minimum_length: 50
                label: Direction
                names:
                   Entering: [285, 360]
                   Entering: [0,75]
                   Exiting: [105,265]
                   Unknown: [0,360]
    container:
      image: cvisionai/openem_lite:experimental
      imagePullPolicy: Always
      resources:
        requests:
          cpu: 4000m
      env:
      - name: TATOR_MEDIA_IDS
        value: "{{workflow.parameters.media_ids}}"
      - name: TATOR_API_SERVICE
        value: "{{workflow.parameters.rest_url}}"
      - name: TATOR_AUTH_TOKEN
        value: "{{workflow.parameters.rest_token}}"
      - name: TATOR_PROJECT_ID
        value: "{{workflow.parameters.project_id}}"
      - name: TATOR_PIPELINE_ARGS
        value: "{\"detection_type_id\": 65, \"tracklet_type_id\": 30, \"version_id\":␣
↪53, \"mode\": \"nonvisual\"}"
      volumeMounts:
      - name: workdir
        mountPath: /work
      command: [python3]
      args: ["/scripts/tator/tracker_entry.py"]
```

CHAPTER 11

Classification

Tator is a web-based media management and curation project. Part of the media management is executing algorithms or *workflows* on a set of media. OpenEM is able to be run within the confines of a Tator workflow. Currently Retinanet-based Detection is supported for inference within a workflow.

11.1 Using the Reference Classification Workflow

The reference workflow can be used by modifying the *scripts/tator/classification_workflow.yaml* to match those of the given project.

11.1.1 Generating a data image

The reference workflow at run-time pulls a docker image containing network coefficients and weights. To generate a weights image, one can use the *scripts/make_classification_image.py* in a manner similar to below:

```
python3 make_classification_image.py [-h] [--publish] [--image-tag IMAGE_TAG] models␣
↪[models ...]

positional arguments:
   models                One or more models to incorporate into image.

optional arguments:
   -h, --help            show this help message and exit
   --publish             If supplied pushes to image repo
   --image-tag IMAGE_TAG
                         Name of image to build/publish
```

11.1.2 Using the reference workflow definition

A reference workflow yaml is in the repository which can be modified to indicate project-specific requirements. Arguments in the `tator` section refer to tator-level semantics such as the `track_type_id` to acquire thumbnails from

and the attribute name to use, to output predictions `label_attribute`.

Options in the `ensemble_config` section map to the arguments and defaults used to initialize `openem2.Classifier.thumbnail_classifier.EnsembleClassifier`

Options to `track_params` section map to the arguments and defaults to the `process_track_results` function of the instantiated `EnsembleClassifier`.

```
apiVersion: argoproj.io/v1alpha1
kind: Workflow
metadata:
  generateName: classifier-example
spec:
  entrypoint: pipeline
  ttlStrategy:
    SecondsAfterSuccess: 600
    SecondsAfterFailure: 86400
  volumes:
  - name: dockersock
    hostPath:
      path: /var/run/docker.sock
  templates:
  - name: pipeline
    steps:
    - - name: worker
        template: worker
  - name: worker
    inputs:
      artifacts:
      - name: strategy
        path: /work/strategy.yaml
        raw:
          data: |
            tator:
              track_type_id: 30
              label_attribute: Predicted
            ensemble_config:
              classNames:
                - Commercial
                - Recreational
              batchSize: 16
            track_params:
              high_entropy_name: Unknown
              entropy_cutoff: 0.40
            data_image: cvisionai/odfw_class_weights
    container:
      image: cvisionai/openem_lite2:experimental
      imagePullPolicy: Always
      resources:
        requests:
          cpu: 4000m
        limits:
          nvidia.com/gpu: 1
      env:
      - name: TATOR_MEDIA_IDS
        value: "{{workflow.parameters.media_ids}}"
      - name: TATOR_API_SERVICE
        value: "{{workflow.parameters.rest_url}}"
      - name: TATOR_AUTH_TOKEN
```

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```
        value: "{{workflow.parameters.rest_token}}"
      - name: TATOR_PROJECT_ID
        value: "{{workflow.parameters.project_id}}"
      volumeMounts:
      - name: dockersock
        mountPath: /var/run/docker.sock
      command: [python3]
      args: ["-m", "openem2.classification.tator", "--strategy", "/data/strategy.yaml
↪"]
```

11.1.3 Project setup

A project for using this workflow has a video type represented by a <media_type_id>. The project also has a localization box type represented by <box_type_id>. The project has a <track_type_id> that associates multiple localizations as the same physical object.

The <media_type_id>> has the following required attributes:

Track Classification Processed A string attribute type that is set to the date time when the object detector finishes processing the media file.

The <track_type_id> requires the following attributes:

<label_attribute> A string representing the name for an object class. If 'Label' is not an appropriate name for class, this can be customized via the label_attribute key in the strategy definition.

Entropy This float attribute represents the uncertainty of the classification algorithm in its determination.

CHAPTER 12

Quick Start

This document is a quick start guide in how to use the legacy 0.1.2 OpenEM package. The instructions in this guide still work for newer versions, but usage of the python inference library is encouraged.

12.1 Example data

This tutorial requires the OpenEM example data which can be downloaded via BitTorrent here.

12.2 Installation

OpenEM is distributed as a native Windows library or as a Docker image. See below for your selected option.

```
Warning: The windows binary releases have been deprecated as of
version 0.1.3.

Refer to the python deployment library.
```

12.2.1 Windows

- Download the library from our releases page.
- Follow the instructions to set up a Python environment.
- Open an Anaconda command prompt.
- Navigate to where you downloaded OpenEM.

12.2.2 Docker

- Make sure you have installed nvidia-docker 2 as described here.
- Pull the docker image from Docker Hub:

```
docker pull cvisionai/openem:latest
```

- Start a bash session in the image with the volume containing the example data mounted. The default train.ini file assumes a directory structure as follows:

```
working-dir
|- openem_example_data
|- openem_work
|- openem_model
```

The openem_work and openem_model directories may be empty, and openem_example_data is the example data downloaded at the beginning of this tutorial. The following command will start the bash shell within the container with working-dir mounted to /data. The openem library is located at /openem.

```
nvidia-docker run --name openem --rm -ti -v <Path to working-dir>:/data cvisionai/
↪openem bash
```

If using any X11 code, it is important to also enable X11 connections within the docker image:

```
nvidia-docker run --name openem --rm -ti -v <Path to working-dir>:/data -v"$HOME/.
↪Xauthority:/root/.Xauthority:rw" --env=DISPLAY --net=host cvisionai/openem bash
```

Note: Instead of `$HOME/.Xauthority` one should use the authority file listed from executing: `xauth info`

12.2.3 Launching additional shell into a running container

If the container was launched with `--name openem`, then the following command launches another bash process in the running container:

```
docker exec --env=DISPLAY -it openem bash
```

Substitute `openem` for what ever you named your container. If you didn't name your container, then you need to find your running container via `docker ps` and use:

```
docker exec --env=DISPLAY -it <hash_of_container> bash
```

12.3 Running the deployment library demo (0.1.2 and earlier)

- Navigate to examples/deploy/python.
- Type:

```
python video.py -h
```

- This will show you the command line arguments to process a series of videos end to end. The command will look something like:

```
python video.py \
    <path to openem_example_data>/find_ruler/find_ruler.pb \
    <path to openem_example_data>/detect/detect.pb \
    <path to openem_example_data>/classify/classify.pb \
    <path to openem_example_data>/count/count.pb \
    <path to video 1> <path to video 2> <path to video 3>
```

- The output will be a csv file with the same base name and location as each video.

12.3.1 Running with Docker

- If you do not want to enter a docker bash shell and instead want to process a video directly, you can use the following command:

```
nvidia-docker run --rm -ti -v \
    <path to openem_example_data>/deploy:/openem_models \
    -e find_ruler_model=/openem_models/find_ruler/find_ruler.pb \
    -e detect_model=/openem_models/detect/detect.pb \
    -e classify_model=/openem_models/classify/classify.pb \
    -e count_model=/openem_models/count/count.pb \
    -e video_paths="<path to video 1> <path to video 2> <path to video 3>" \
    -e CUDA_VISIBLE_DEVICES=0 cvisionai/openem
```

12.4 Deployment library (0.1.2 and earlier)

Navigate to examples/deploy. This directory contains the examples for the main library in the cc directory, plus python and csharp if you built the bindings to the main library. Source files for these examples are located here for your inspection. In addition, there is a script that will run all of the examples for you if you point it to the location of the example data. This script is called run_all.py.

Now invoke the run_all.py script to see how to run it:

```
python run_all.py -h
```

This will show you the command line options for this script, and give you an explanation of each of the available examples to run. The simplest way to invoke the script is as follows:

```
python run_all.py <path to OpenEM example data>
```

Doing so will run all available examples in all languages for which you built the software.

Once you are able to run the examples, you are encouraged to inspect the source code for the language that you plan to use for your application.

12.5 Training library

To train a model from the example data you will need to modify the configuration file included with the distribution at train/train.ini. This file is included as an example so you will need to modify some paths in it to get it working. Start by making a copy of this file and modify the paths section as follows:

```
[Paths]
# Path to directory that contains training data.
TrainDir=<Path to OpenEM example data>/train
# Path to directory for storing intermediate outputs.
WorkDir=<Path where you want to store working files>
# Path to directory for storing final model outputs.
ModelDir=<Path where you want to store models>
# Path to directory that contains test data.
TestDir=<Path to OpenEM example data>/test
```

12.5.1 Extracting imagery

TrainDir is the path to the example training data. WorkDir is where temporary files are stored during training. ModelDir contains model outputs that can be used directly by the deployment library. Once you have modified your copy of train.ini to use the right paths on your system, you can do the following:

```
python train.py train.ini extract_images
```

Where train.ini is your modified copy. This command will go through the videos and annotations and start dumping images into the working directory. It will take a few hours to complete. Images are dumped in:

```
<WorkDir>/train_imgs
```

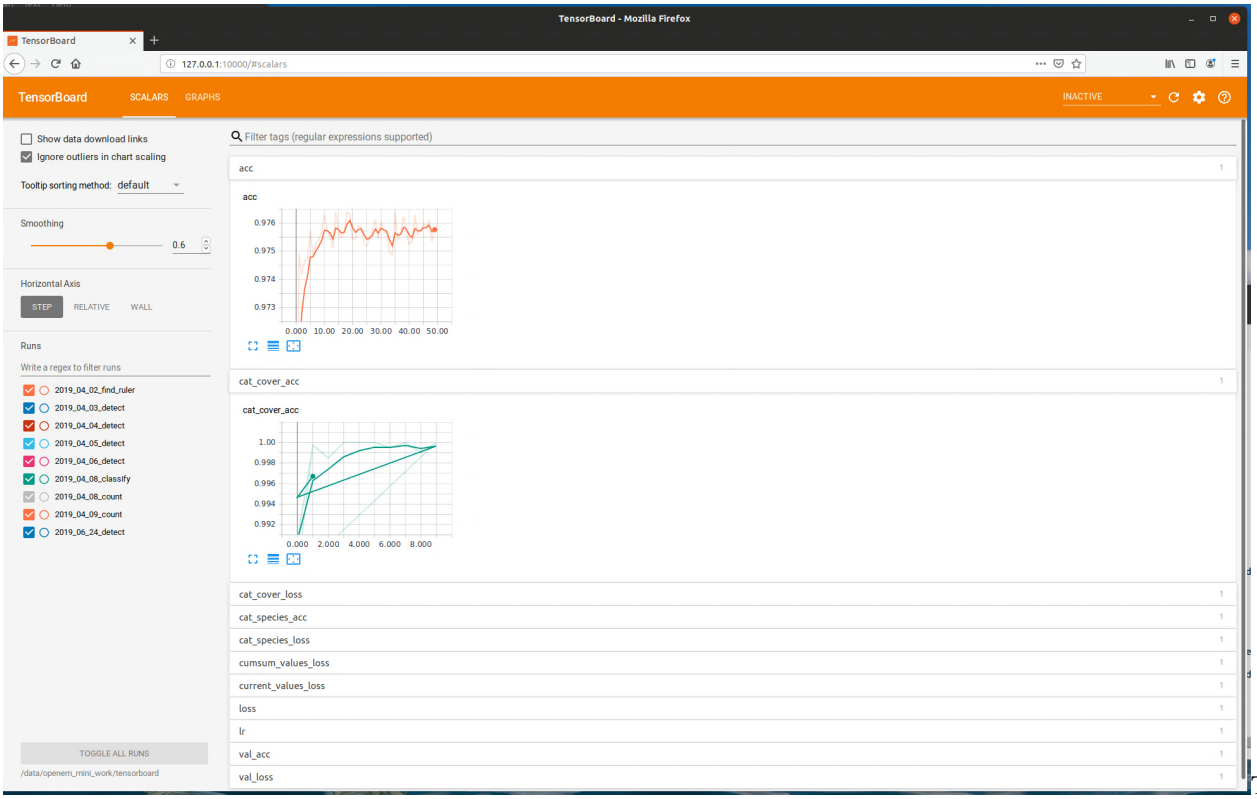
12.5.2 Ruler Training

Next, you can do some training. To train the find ruler model you can do the following command:

```
python train.py train.ini find_ruler_train
```

This will start training the find ruler model. This will take a while. If you want to monitor the training outside of the command line, you can use Tensorboard. This is a program that serves a webpage for monitoring losses during training runs. Use the following command:

```
tensorboard --logdir <path to WorkDir>/tensorboard --port 10000
```



Tensorboard example

Then you can open a web browser on the same machine and go to 127.0.0.1:10000. This will display a live view of the training results. You can also use a different machine on the same network and modify the IP address accordingly. All training steps output tensorboard files, so you can monitor training of any of the openem models using this utility.

Once training completes, a new model will be converted to protobuf format and saved at:

```
<ModelDir>/deploy/find_ruler/find_ruler.pb
```

This file is the same format used in the example data for the deployment library.

Running Inference on train/val data

Now that we have a model for finding rulers, we can run the algorithm on all of our extracted images. Run the following command:

```
python train.py train.ini find_ruler_predict
```

This will use the model that we just trained to find the ruler endpoints. The outputs of this are stored at:

```
<WorkDir>/inference/find_ruler.csv
```

This file has a simple format, which is just a csv containing the video ID and (x, y) location in pixels of the ruler endpoints. Note that this makes the assumption that the ruler is not moving within a particular video. If it is, you will need to split up your videos into segments in which the ruler is stationary (only for training purposes).

It is possible to train only particular models in openem. Suppose we always know the position of the ruler in our videos and do not need the find ruler algorithm. In this case, we can manually create our own find ruler inference file that contains the same information and store it in the path above. So for example, if we know the ruler is always horizontal spanning the entire video frame, we would use the same (x, y) coordinates for every video in the csv.

12.5.3 Extract ROIs for Detection Training

The next step is extracting the regions of interest for the videos as determined in the previous step. Run the following:

```
python train.py train.ini extract_rois
```

This will dump the ROI image corresponding to each extracted image into:

```
<WorkDir>/train_rois
```

CHAPTER 13

Using OpenEM with Docker

13.1 Legacy Image (with C++ inference library)

The docker image has only been built on Ubuntu 18.04 LTS. If you simply want to use the docker image you can get the latest release with:

```
docker pull cvisionai/openem:latest
```

13.1.1 Building the image

- Follow instructions here to install nvidia-docker.
- From the openem config directory run the following command:

```
make openem_image
```

This will generate the dockerfile from the template and execute the build. If not initialized, it will setup any submodules required for the project.

The resulting image will have the OpenEM binary distribution in /openem.

CHAPTER 14

Change Log

Version	Date	Description of changes
0.1.4	XXX-2020	• Add support and scripts for Tator support • Make image models multi-process capable • Documentation improvements
0.1.3	Jan-2020	• Add RetinaNet based detector • Add pure python inference library • Deprecate C++ library • Alpha support for Xavier-based platforms
0.1.2	June-2019	• Docker image cleanups • Add Improved documentation
0.1.1	Feb-2019	• Fix training in Docker
0.1.0	Jan-2019	• First stable release • Training/Inference examples

CHAPTER 15

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