

```

!git clone https://github.com/ultralytics/yolov5 # clone
%cd yolov5
%pip install -qr requirements.txt # install

import torch
from yolov5 import utils
display = utils.notebook_init() # checks

YOLOv5 🚀 v6.1-11-g63ddb6f torch 1.10.0+cu111 CUDA:0 (Tesla K80, 11441MiB)
Setup complete ✅ (2 CPUs, 12.7 GB RAM, 42.1/78.2 GB disk)

!unzip -q /content/Task_2.zip -d ../

```

▼ 1. Inference

`detect.py` runs YOLOv5 inference on a variety of sources, downloading models automatically from the [latest YOLOv5 release](#), and saving results to `runs/detect`. Example inference sources are:

```

python detect.py --source 0 # webcam
img.jpg # image
vid.mp4 # video
path/ # directory
path/*.jpg # glob
'https://youtu.be/Zgi9g1ksQHc' # YouTube
'rtsp://example.com/media.mp4' # RTSP, RTMP, HTTP stream

```

```

!python detect.py --weights runs/train/exp/weights/best.pt --img 640 --conf 0.7 --source /con
#display.Image(filename='runs/detect/exp/zidane.jpg', width=600)

```



▼ 2. Validate

Validate a model's accuracy on [COCO val](#) or test-dev datasets. Models are downloaded automatically from the [latest YOLOv5 release](#). To show results by class use the `--verbose` flag. Note that `pycocotools` metrics may be ~1% better than the equivalent repo metrics, as is visible below, due to slight differences in mAP computation.

▼ COCO val

Download [COCO val 2017](#) dataset (1GB - 5000 images), and test model accuracy.

```
# Download COCO val
torch.hub.download_url_to_file('https://ultralytics.com/assets/coco2017val.zip', 'tmp.zip')
!unzip -q tmp.zip -d ../datasets && rm tmp.zip
```

```
# Run YOLOv5x on COCO val
!python val.py --weights yolov5x.pt --data coco.yaml --img 640 --iou 0.65 --half
```

```
val: data=/content/yolov5/data/coco.yaml, weights=['yolov5x.pt'], batch_size=32, imgsz=640
YOLOv5 🚀 v6.0-48-g84a8099 torch 1.10.0+cu102 CUDA:0 (Tesla V100-SXM2-16GB, 16160MiB)
```

```
Downloading https://github.com/ultralytics/yolov5/releases/download/v6.0/yolov5x.pt to y
100% 166M/166M [00:03<00:00, 54.1MB/s]
```

```

Fusing layers...
Model Summary: 444 layers, 86705005 parameters, 0 gradients
val: Scanning '../datasets/coco/val2017' images and labels...4952 found, 48 missing, 0 €
val: New cache created: ../datasets/coco/val2017.cache

```

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95:
all	5000	36335	0.729	0.63	0.683	0.496

```

Speed: 0.1ms pre-process, 4.9ms inference, 1.9ms NMS per image at shape (32, 3, 640, 640)

Evaluating pycocotools mAP... saving runs/val/exp/yolov5x_predictions.json...
loading annotations into memory...
Done (t=0.46s)
creating index...
index created!
Loading and preparing results...
DONE (t=5.15s)
creating index...
index created!
Running per image evaluation...
Evaluate annotation type *bbox*
DONE (t=90.39s).
Accumulating evaluation results...
DONE (t=14.54s).
Average Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.507
Average Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.689
Average Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0.552
Average Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.345
Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.559
Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.652
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.381
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.630
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.682
Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.526
Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.732
Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.829
Results saved to runs/val/exp

```

▼ COCO test

Download [COCO test2017](https://cocodataset.org/#download) dataset (7GB - 40,000 images), to test model accuracy on test-dev set (20,000 images, no labels). Results are saved to a *.json file which should be **zipped** and submitted to the evaluation server at <https://competitions.codalab.org/competitions/20794>.

```

# Download COCO test-dev2017
torch.hub.download_url_to_file('https://ultralytics.com/assets/coco2017labels.zip', 'tmp.zip')
!unzip -q tmp.zip -d ../datasets && rm tmp.zip
!f="test2017.zip" && curl http://images.cocodataset.org/zips/$f -o $f && unzip -q $f -d ../da

```

```

# Run YOLOv5x on COCO test
!python val.py --weights yolov5x.pt --data coco.yaml --img 640 --iou 0.65 --half --task test

```

▼ 3. Train




Close the active learning loop by sampling images from your inference conditions with the `roboflow` pip package

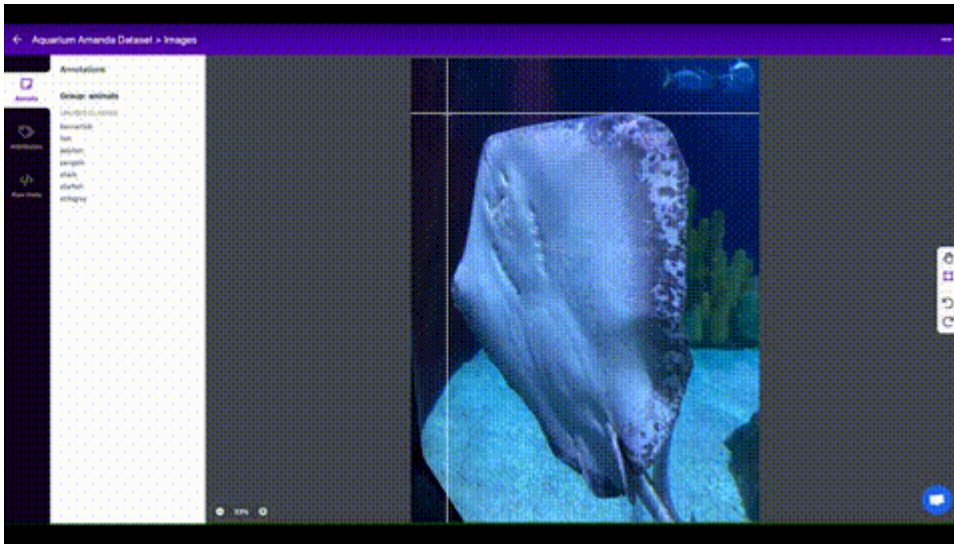
Train a YOLOv5s model on the [COCO128](#) dataset with `--data coco128.yaml`, starting from pretrained `--weights yolov5s.pt`, or from randomly initialized `--weights '' --cfg yolov5s.yaml`.

- **Pretrained Models** are downloaded automatically from the [latest YOLOv5 release](#)
- **Datasets** available for autodownload include: [COCO](#), [COCO128](#), [VOC](#), [Argoverse](#), [VisDrone](#), [GlobalWheat](#), [xView](#), [Objects365](#), [SKU-110K](#).
- **Training Results** are saved to `runs/train/` with incrementing run directories, i.e. `runs/train/exp2`, `runs/train/exp3` etc.

Train on Custom Data with Roboflow 🌟 NEW

[Roboflow](#) enables you to easily **organize, label, and prepare** a high quality dataset with your own custom data. Roboflow also makes it easy to establish an active learning pipeline, collaborate with your team on dataset improvement, and integrate directly into your model building workflow with the `roboflow` pip package.

- Custom Training Example: <https://blog.roboflow.com/how-to-train-yolov5-on-a-custom-dataset/>
- Custom Training Notebook:  [Open in Colab](#)



Label images lightning fast (including with model-assisted labeling)

Tensorboard (optional)

```
%load_ext tensorboard
```

```
%tensorboard --logdir runs/train
```

Weights & Biases (optional)

```
%pip install -q wandb
```

```
import wandb
```

```
wandb.login()
```

Train YOLOv5s on COCO128 for 200 epochs

```
!python train.py --img 640 --batch 5 --epochs 200 --data custom_dataset.yaml.txt --weights yo
```

Downloading <https://ultralytics.com/assets/Arial.ttf> to /root/.config/Ultralytics/Ari
train: weights=yolov5s.pt, cfg=, data=custom_dataset.yaml.txt, hyp=data/hyps/hyp.scr
github: up to date with <https://github.com/ultralytics/yolov5> ✓
 YOLOv5 🚀 v6.1-11-g63ddb6f torch 1.10.0+cu111 CUDA:0 (Tesla K80, 11441MiB)

hyperparameters: lr0=0.01, lrf=0.01, momentum=0.937, weight_decay=0.0005, warmup_epoc

Weights & Biases: run 'pip install wandb' to automatically track and visualize YOLOv5

TensorBoard: Start with 'tensorboard --logdir runs/train', view at <http://localhost:6000>

Downloading <https://github.com/ultralytics/yolov5/releases/download/v6.1/yolov5s.pt> to
 100% 14.1M/14.1M [00:00<00:00, 111MB/s]

Overriding model.yaml nc=80 with nc=7

	from	n	params	module	arguments
0	-1	1	3520	models.common.Conv	[3, 32, 6
1	-1	1	18560	models.common.Conv	[32, 64,
2	-1	1	18816	models.common.C3	[64, 64,
3	-1	1	73984	models.common.Conv	[64, 128,
4	-1	2	115712	models.common.C3	[128, 128
5	-1	1	295424	models.common.Conv	[128, 256
6	-1	3	625152	models.common.C3	[256, 256

```

7          -1  1   1180672  models.common.Conv      [256, 512
8          -1  1   1182720  models.common.C3         [512, 512
9          -1  1    656896  models.common.SPPF       [512, 512
10         -1  1   131584   models.common.Conv       [512, 256
11         -1  1           0  torch.nn.modules.upsampling.Upsample [None, 2,
12        [-1, 6]  1           0  models.common.Concat         [1]
13         -1  1   361984   models.common.C3         [512, 256
14         -1  1    33024   models.common.Conv       [256, 128
15         -1  1           0  torch.nn.modules.upsampling.Upsample [None, 2,
16        [-1, 4]  1           0  models.common.Concat         [1]
17         -1  1    90880   models.common.C3         [256, 128
18         -1  1   147712   models.common.Conv       [128, 128
19        [-1, 14]  1           0  models.common.Concat         [1]
20         -1  1   296448   models.common.C3         [256, 256
21         -1  1   590336   models.common.Conv       [256, 256
22        [-1, 10]  1           0  models.common.Concat         [1]
23         -1  1   1182720  models.common.C3         [512, 512
24        [17, 20, 23]  1    32364  models.yolo.Detect        [7, [[10,
Model Summary: 270 layers, 7038508 parameters, 7038508 gradients, 15.9 GFLOPs

```

Transferred 343/349 items from yolov5s.pt

Scaled weight_decay = 0.0005078125

optimizer: SGD with parameter groups 57 weight (no decay), 60 weight, 60 bias

albumentations: version 1.0.3 required by YOLOv5, but version 0.1.12 is currently installed

train: Scanning '/content/Task_2/labels/Train' images and labels...34 found, 1 missing

train: New cache created: /content/Task_2/labels/Train.cache

train: Caching images (0.0GB ram): 100% 35/35 [00:00<00:00, 439.21it/s]

val: Scanning '/content/Task_2/labels/Val' images and labels...21 found, 0 missing, 0

val: New cache created: /content/Task_2/labels/Val.cache

val: Caching images (0.0GB ram): 100% 21/21 [00:00<00:00, 191.74it/s]

Plotting labels to runs/train/exp/labels.jpg...

AutoAnchor: 1.68 anchors/target, 0.971 Best Possible Recall (BPR). Anchors are a poor

AutoAnchor: Running kmeans for 9 anchors on 34 points...

AutoAnchor: Evolving anchors with Genetic Algorithm: fitness = 0.9455: 100% 1000/1000

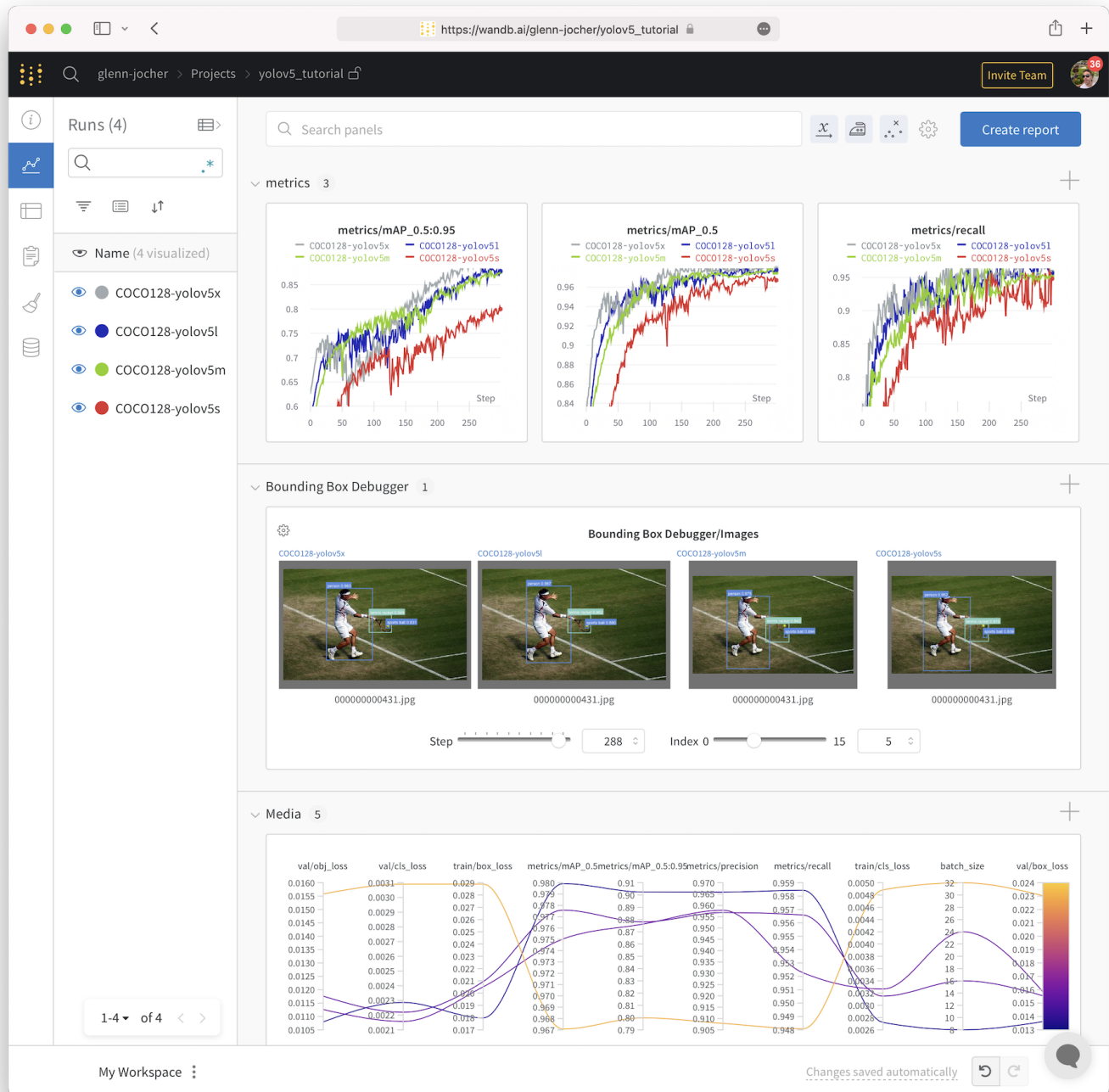
AutoAnchor: the 0.35: 1.0000 best possible recall, 7.53 anchors past the

4. Visualize

Weights & Biases Logging NEW

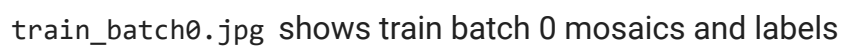
[Weights & Biases](#) (W&B) is now integrated with YOLOv5 for real-time visualization and cloud logging of training runs. This allows for better run comparison and introspection, as well improved visibility and collaboration for teams. To enable W&B `pip install wandb`, and then train normally (you will be guided through setup on first use).

During training you will see live updates at <https://wandb.ai/home>, and you can create and share detailed [Reports](#) of your results. For more information see the [YOLOv5 Weights & Biases Tutorial](#).



Local Logging

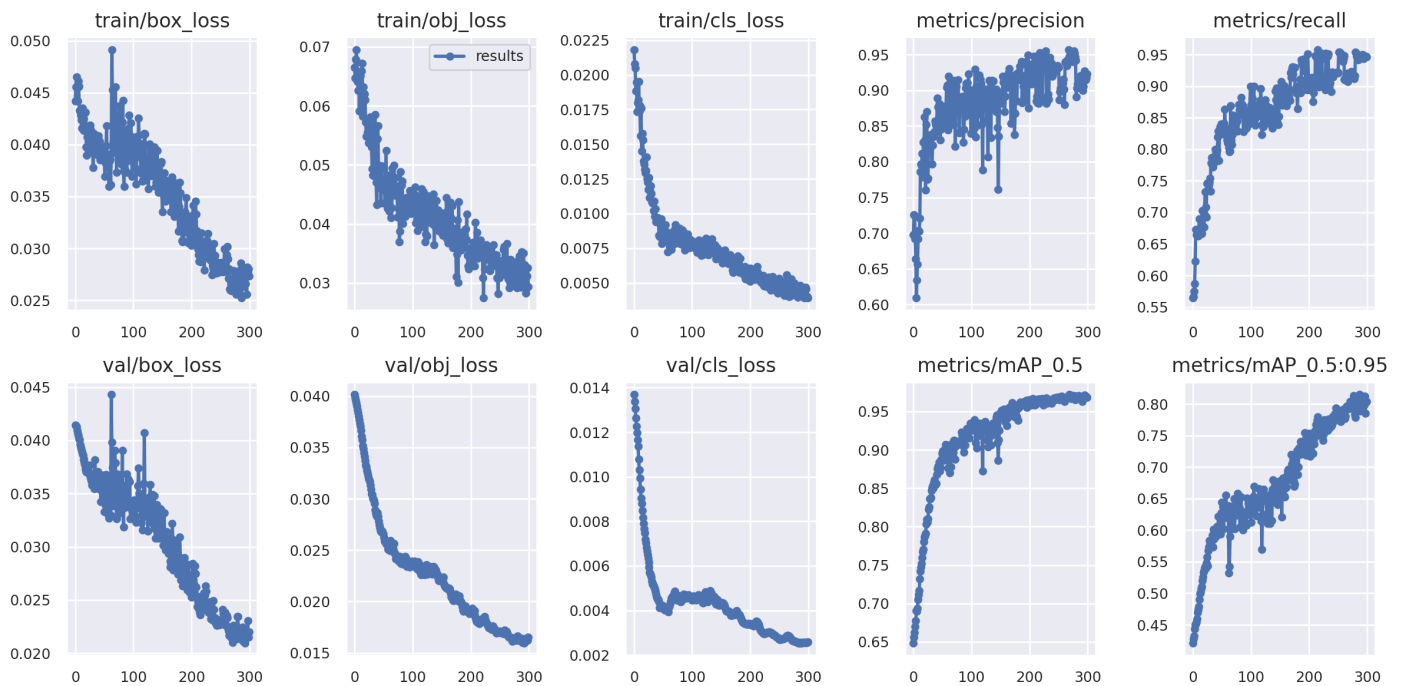
All results are logged by default to `runs/train`, with a new experiment directory created for each new training as `runs/train/exp2`, `runs/train/exp3`, etc. View train and val jpgs to see mosaics, labels, predictions and augmentation effects. Note an Ultralytics **Mosaic Dataloader** is used for training (shown below), which combines 4 images into 1 mosaic during training.





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```
from utils.plots import plot_results
plot_results('path/to/results.csv') # plot 'results.csv' as 'results.png'
```



Environments

YOLOv5 may be run in any of the following up-to-date verified environments (with all dependencies including [CUDA/CUDNN](#), [Python](#) and [PyTorch](#) preinstalled):

- **Google Colab and Kaggle** notebooks with free GPU: [Open in Colab](#) [Open in Kaggle](#)
- **Google Cloud** Deep Learning VM. See [GCP Quickstart Guide](#)
- **Amazon** Deep Learning AML. See [AWS Quickstart Guide](#)
- **Docker Image**. See [Docker Quickstart Guide](#) docker pulls 205k

Status

CI CPU testing **passing**

If this badge is green, all [YOLOv5 GitHub Actions](#) Continuous Integration (CI) tests are currently passing. CI tests verify correct operation of YOLOv5 training ([train.py](#)), testing ([val.py](#)), inference ([detect.py](#)) and export ([export.py](#)) on MacOS, Windows, and Ubuntu every 24 hours and on every commit.

▼ Appendix

Optional extras below. Unit tests validate repo functionality and should be run on any PRs submitted.

```
# Reproduce
for x in 'yolov5n', 'yolov5s', 'yolov5m', 'yolov5l', 'yolov5x':
    !python val.py --weights {x}.pt --data coco.yaml --img 640 --task speed # speed
    !python val.py --weights {x}.pt --data coco.yaml --img 640 --conf 0.001 --iou 0.65 # mAP

# PyTorch Hub
import torch

# Model
model = torch.hub.load('ultralytics/yolov5', 'yolov5s')

# Images
dir = 'https://ultralytics.com/images/'
imgs = [dir + f for f in ('zidane.jpg', 'bus.jpg')] # batch of images

# Inference
results = model(imgs)
results.print() # or .show(), .save()

# CI Checks
%%shell
export PYTHONPATH="$PWD" # to run *.py. files in subdirectories
rm -rf runs # remove runs/
for m in yolov5n; do # models
    python train.py --img 64 --batch 32 --weights $m.pt --epochs 1 --device 0 # train pretrain
    python train.py --img 64 --batch 32 --weights '' --cfg $m.yaml --epochs 1 --device 0 # tra
    for d in 0 cpu; do # devices
        python val.py --weights $m.pt --device $d # val official
        python val.py --weights runs/train/exp/weights/best.pt --device $d # val custom
        python detect.py --weights $m.pt --device $d # detect official
        python detect.py --weights runs/train/exp/weights/best.pt --device $d # detect custom
    done
    python hubconf.py # hub
    python models/yolo.py --cfg $m.yaml # build PyTorch model
    python models/tf.py --weights $m.pt # build TensorFlow model
    python export.py --img 64 --batch 1 --weights $m.pt --include torchscript onnx # export
done

# Profile
from utils.torch_utils import profile
```

```
m1 = lambda x: x * torch.sigmoid(x)
m2 = torch.nn.SiLU()
results = profile(input=torch.randn(16, 3, 640, 640), ops=[m1, m2], n=100)

# Evolve
!python train.py --img 640 --batch 64 --epochs 100 --data coco128.yaml --weights yolov5s.pt -
!d=runs/train/evolve && cp evolve.* $d && zip -r evolve.zip $d && gsutil mv evolve.zip gs://b

# VOC
for b, m in zip([64, 64, 32, 16], ['yolov5s', 'yolov5m', 'yolov5l', 'yolov5x']): # zip(batch
    !python train.py --batch {b} --weights {m}.pt --data VOC.yaml --epochs 50 --cache --img 512

# TensorRT
# https://docs.nvidia.com/deeplearning/tensorrt/install-guide/index.html#installing-pip
!pip install -U nvidia-tensorrt --index-url https://pypi.ngc.nvidia.com # install
!python export.py --weights yolov5s.pt --include engine --imgsz 640 640 --device 0 # export
!python detect.py --weights yolov5s.engine --imgsz 640 640 --device 0 # inference
```

