

▼ Install Dependencies

(Remember to choose GPU in Runtime if not already selected. Runtime --> Change Runtime Type --> Hardware accelerator --> GPU)

```
1 # clone YOLOv5 repository
2 !git clone https://github.com/ultralytics/yolov5 # clone repo
3 %cd yolov5
4 !git reset --hard 886f1c03d839575afecb059accf74296fad395b6
```



```
Cloning into 'yolov5'...
remote: Enumerating objects: 9791, done.
remote: Counting objects: 100% (13/13), done.
remote: Compressing objects: 100% (9/9), done.
remote: Total 9791 (delta 5), reused 9 (delta 4), pack-reused 9778
Receiving objects: 100% (9791/9791), 9.99 MiB | 26.64 MiB/s, done.
Resolving deltas: 100% (6809/6809), done.
/content/yolov5
HEAD is now at 886f1c0 DDP after autoanchor reorder (#2421)
```

```
1 # install dependencies as necessary
2 !pip install -qr requirements.txt # install dependencies (ignore errors)
3 import torch
4
5 from IPython.display import Image, clear_output # to display images
6 from utils.google_utils import gdrive_download # to download models/datasets
7
8 # clear_output()
9 print('Setup complete. Using torch %s %s' % (torch.__version__, torch.cuda.get_
```

```
|████████████████████████████████████████████████████████████████████████████████| 636 kB 5.0 MB/s
Setup complete. Using torch 1.9.0+cu111 _CudaDeviceProperties(name='Tesla P10
```



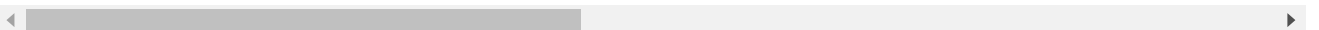
```
1 #follow the link below to get your download code from from Roboflow
2 !pip install -q roboflow
3 from roboflow import Roboflow
4 rf = Roboflow(model_format="yolov5", notebook="roboflow-yolov5")
```

```
|████████████████████████████████████████████████████████████████████████████████| 178 kB 6.3 MB/s
|████████████████████████████████████████████████████████████████████████████████| 1.1 MB 34.4 MB/s
|████████████████████████████████████████████████████████████████████████████████| 138 kB 63.5 MB/s
|████████████████████████████████████████████████████████████████████████████████| 62 kB 1.1 MB/s
```

```
Building wheel for roboflow (setup.py) ... done
```

```
Building wheel for wget (setup.py) ... done
```

```
ERROR: pip's dependency resolver does not currently take into account all the
google-colab 1.0.0 requires requests~=2.23.0, but you have requests 2.26.0 wh
datascience 0.10.6 requires folium==0.2.1, but you have folium 0.8.3 which is
alumentations 0.1.12 requires imgaug<0.2.7,>=0.2.5, but you have imgaug 0.2.
upload and label your dataset, and get an API KEY here: https://app.roboflow.
```



```

1 %cd /content/yolov5
2 #after following the link above, recieve python code with these fields filled in
3 #from roboflow import Roboflow
4 #rf = Roboflow(api_key="YOUR API KEY HERE")
5 #project = rf.workspace().project("YOUR PROJECT")
6 #dataset = project.version("YOUR VERSION").download("yolov5")

```

```

/content/yolov5
loading Roboflow workspace...
loading Roboflow project...
Downloading Dataset Version Zip in American-Mushrooms-1 to yolov5pytorch: 100
Extracting Dataset Version Zip to American-Mushrooms-1 in yolov5pytorch:: 100

```



```

1 # this is the YAML file Roboflow wrote for us that we're loading into this notebook
2 %cat {dataset.location}/data.yaml

```

```

names:
- CoW
- chanterelle
nc: 2
train: American-Mushrooms-1/train/images
val: American-Mushrooms-1/valid/images

```

▼ Define Model Configuration and Architecture

We will write a yaml script that defines the parameters for our model like the number of classes, anchors, and each layer.

You do not need to edit these cells, but you may.

```

1 # define number of classes based on YAML
2 import yaml
3 with open(dataset.location + "/data.yaml", 'r') as stream:
4     num_classes = str(yaml.safe_load(stream)['nc'])

```

```

1 #this is the model configuration we will use for our tutorial
2 %cat /content/yolov5/models/yolov5s.yaml

```

```

# parameters
nc: 80 # number of classes
depth_multiple: 0.33 # model depth multiple
width_multiple: 0.50 # layer channel multiple

# anchors
anchors:
- [10,13, 16,30, 33,23] # P3/8
- [30,61, 62,45, 59,119] # P4/16
- [116,90, 156,198, 373,326] # P5/32

# YOLOv5 backbone
backbone:

```

```
# [from, number, module, args]
[[-1, 1, Focus, [64, 3]], # 0-P1/2
 [-1, 1, Conv, [128, 3, 2]], # 1-P2/4
 [-1, 3, C3, [128]],
 [-1, 1, Conv, [256, 3, 2]], # 3-P3/8
 [-1, 9, C3, [256]],
 [-1, 1, Conv, [512, 3, 2]], # 5-P4/16
 [-1, 9, C3, [512]],
 [-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
 [-1, 1, SPP, [1024, [5, 9, 13]]],
 [-1, 3, C3, [1024, False]], # 9
]
```

```
# YOLOv5 head
```

```
head:
```

```
[[[-1, 1, Conv, [512, 1, 1]],
 [-1, 1, nn.Upsample, [None, 2, 'nearest']],
 [[-1, 6], 1, Concat, [1]], # cat backbone P4
 [-1, 3, C3, [512, False]], # 13

 [-1, 1, Conv, [256, 1, 1]],
 [-1, 1, nn.Upsample, [None, 2, 'nearest']],
 [[-1, 4], 1, Concat, [1]], # cat backbone P3
 [-1, 3, C3, [256, False]], # 17 (P3/8-small)

 [-1, 1, Conv, [256, 3, 2]],
 [[-1, 14], 1, Concat, [1]], # cat head P4
 [-1, 3, C3, [512, False]], # 20 (P4/16-medium)

 [-1, 1, Conv, [512, 3, 2]],
 [[-1, 10], 1, Concat, [1]], # cat head P5
 [-1, 3, C3, [1024, False]], # 23 (P5/32-large)

 [[17, 20, 23], 1, Detect, [nc, anchors]], # Detect(P3, P4, P5)
]
```

```
1 #customize iPython writefile so we can write variables
2 from IPython.core.magic import register_line_cell_magic
3
4 @register_line_cell_magic
5 def writetemplate(line, cell):
6     with open(line, 'w') as f:
7         f.write(cell.format(*globals()))
```

```
1 %%writetemplate /content/yolov5/models/custom_yolov5s.yaml
2
3 # parameters
4 nc: {num_classes} # number of classes
5 depth_multiple: 0.33 # model depth multiple
6 width_multiple: 0.50 # layer channel multiple
7
8 # anchors
9 anchors:
10 - [10,13, 16,30, 33,23] # P3/8
11 - [30,61, 62,45, 59,119] # P4/16
12 - [116,90, 156,198, 373,326] # P5/32
13
```

```

14 # YOLOv5 backbone
15 backbone:
16   # [from, number, module, args]
17   [[-1, 1, Focus, [64, 3]], # 0-P1/2
18    [-1, 1, Conv, [128, 3, 2]], # 1-P2/4
19    [-1, 3, BottleneckCSP, [128]],
20    [-1, 1, Conv, [256, 3, 2]], # 3-P3/8
21    [-1, 9, BottleneckCSP, [256]],
22    [-1, 1, Conv, [512, 3, 2]], # 5-P4/16
23    [-1, 9, BottleneckCSP, [512]],
24    [-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
25    [-1, 1, SPP, [1024, [5, 9, 13]]],
26    [-1, 3, BottleneckCSP, [1024, False]], # 9
27   ]
28
29 # YOLOv5 head
30 head:
31   [[-1, 1, Conv, [512, 1, 1]],
32    [-1, 1, nn.Upsample, [None, 2, 'nearest']],
33    [[-1, 6], 1, Concat, [1]], # cat backbone P4
34    [-1, 3, BottleneckCSP, [512, False]], # 13
35
36    [-1, 1, Conv, [256, 1, 1]],
37    [-1, 1, nn.Upsample, [None, 2, 'nearest']],
38    [[-1, 4], 1, Concat, [1]], # cat backbone P3
39    [-1, 3, BottleneckCSP, [256, False]], # 17 (P3/8-small)
40
41    [-1, 1, Conv, [256, 3, 2]],
42    [[-1, 14], 1, Concat, [1]], # cat head P4
43    [-1, 3, BottleneckCSP, [512, False]], # 20 (P4/16-medium)
44
45    [-1, 1, Conv, [512, 3, 2]],
46    [[-1, 10], 1, Concat, [1]], # cat head P5
47    [-1, 3, BottleneckCSP, [1024, False]], # 23 (P5/32-large)
48
49    [[17, 20, 23], 1, Detect, [nc, anchors]], # Detect(P3, P4, P5)
50   ]

```

▼ Train Custom YOLOv5 Detector

Next, we'll fire off training!

Here, we are able to pass a number of arguments:

- **img:** define input image size
- **batch:** determine batch size
- **epochs:** define the number of training epochs. (Note: often, 3000+ are common here!)
- **data:** set the path to our yaml file
- **cfg:** specify our model configuration

- **weights:** specify a custom path to weights. (Note: you can download weights from the Ultralytics Google Drive [folder](#))
- **name:** result names
- **nosave:** only save the final checkpoint
- **cache:** cache images for faster training

```
1 # train yolov5s on custom data for 100 epochs
2 # time its performance
3 %%time
4 %cd /content/yolov5/
5 !python train.py --img 416 --batch 16 --epochs 100 --data {dataset.location}/da
```

```
/content/yolov5
```

```
github: ⚠ WARNING: code is out of date by 577 commits. Use 'git pull' to up
YOLOv5 v4.0-126-g886f1c0 torch 1.9.0+cu111 CUDA:0 (Tesla P100-PCIE-16GB, 16
```

```
Namespace(adam=False, batch_size=16, bucket='', cache_images=True, cfg='./m
```

```
wandb: Install Weights & Biases for YOLOv5 logging with 'pip install wandb'
Start Tensorboard with "tensorboard --logdir runs/train", view at http://localhost:6006
```

```
hyperparameters: lr0=0.01, lrf=0.2, momentum=0.937, weight_decay=0.0005, wa
```

	from	n	params	module
0	-1	1	3520	models.common.Focus
1	-1	1	18560	models.common.Conv
2	-1	1	19904	models.common.BottleneckCSP
3	-1	1	73984	models.common.Conv
4	-1	1	161152	models.common.BottleneckCSP
5	-1	1	295424	models.common.Conv
6	-1	1	641792	models.common.BottleneckCSP
7	-1	1	1180672	models.common.Conv
8	-1	1	656896	models.common.SPP
9	-1	1	1248768	models.common.BottleneckCSP
10	-1	1	131584	models.common.Conv
11	-1	1	0	torch.nn.modules.upsampling.Upsample
12	[-1, 6]	1	0	models.common.Concat
13	-1	1	378624	models.common.BottleneckCSP
14	-1	1	33024	models.common.Conv
15	-1	1	0	torch.nn.modules.upsampling.Upsample
16	[-1, 4]	1	0	models.common.Concat
17	-1	1	95104	models.common.BottleneckCSP
18	-1	1	147712	models.common.Conv
19	[-1, 14]	1	0	models.common.Concat
20	-1	1	313088	models.common.BottleneckCSP
21	-1	1	590336	models.common.Conv
22	[-1, 10]	1	0	models.common.Concat
23	-1	1	1248768	models.common.BottleneckCSP
24	[17, 20, 23]	1	18879	models.yolo.Detect

```
/usr/local/lib/python3.7/dist-packages/torch/nn/functional.py:718: UserWarn
return torch.max_pool2d(input, kernel_size, stride, padding, dilation, ce
Model Summary: 283 layers, 7257791 parameters, 7257791 gradients, 16.8 GFL0
```

```
Scaled weight_decay = 0.0005
```

```
Optimizer groups: 62 .bias, 70 conv.weight, 59 other
```

```
train: Scanning 'American-Mushrooms-1/train/labels' for images and labels..
```

```
train: New cache created: American-Mushrooms-1/train/labels.cache
```

```
train: Caching images (0.1GB): 100% 123/123 [00:00<00:00, 511.60it/s]
```

```
val: Scanning 'American-Mushrooms-1/valid/labels' for images and labels... !
```

```

val: New cache created: American-Mushrooms-1/valid/labels.cache
val: Caching images (0.0GB): 100% 5/5 [00:00<00:00, 321.12it/s]
[W pthreadpool-cpp.cc:90] Warning: Leaking Caffe2 thread-pool after fork. (
[W pthreadpool-cpp.cc:90] Warning: Leaking Caffe2 thread-pool after fork. (
Plotting labels...

autoanchor: Analyzing anchors... anchors/target = 3.48, Best Possible Recall
Image sizes 416 train, 416 test
Using 2 dataloader workers
Logging results to runs/train/yolov5s_results
Starting training for 100 epochs...

```

▼ Evaluate Custom YOLOv5 Detector Performance

Training losses and performance metrics are saved to Tensorboard and also to a logfile defined above with the **--name** flag when we train. In our case, we named this `yolov5s_results`. (If given no name, it defaults to `results.txt`.) The results file is plotted as a png after training completes.

Note from Glenn: Partially completed `results.txt` files can be plotted with `from utils.utils import plot_results; plot_results()`.

```

1 # Start tensorboard
2 # Launch after you have started training
3 # logs save in the folder "runs"
4 %load_ext tensorboard
5 %tensorboard --logdir runs

```

TensorBoard

SCALARS

INACTIVE

- ☐ Show data download links
- ☐ Ignore outliers in chart scaling

Tooltip sorting method: **default** ▼

Smoothing



0.6

Horizontal Axis

STEP

RELATIVE

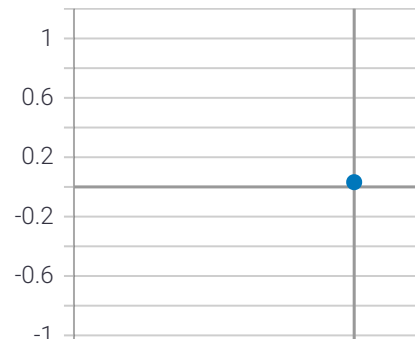
Filter tags (regular expressions ...)

metrics

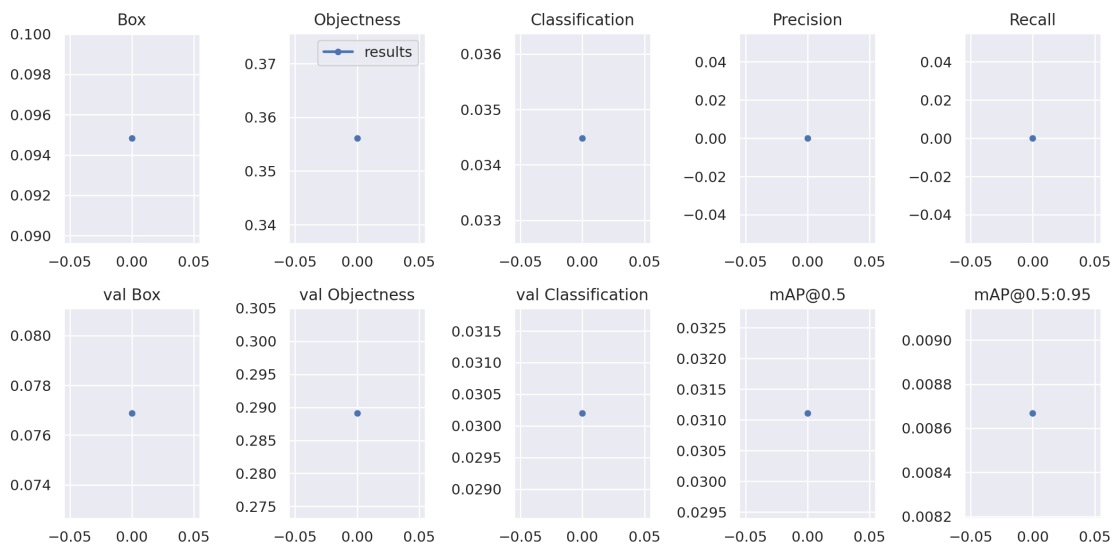
4 ^

mAP_0.5

tag: metrics/mAP_0.5



```
1 # we can also output some older school graphs if the tensor board isn't working
2 from utils.plots import plot_results # plot results.txt as results.png
3 Image(filename='/content/yolov5/runs/train/yolov5s_results/results.png', width=
```



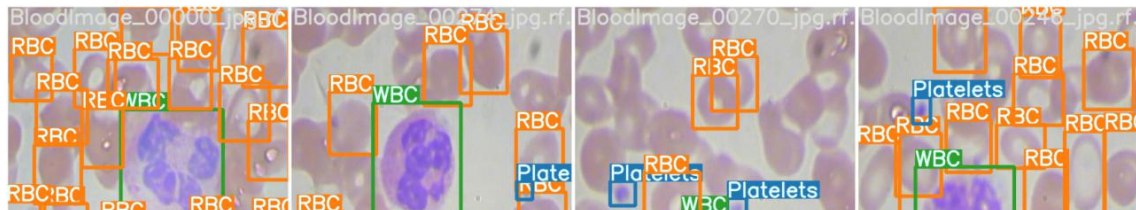
▼ Curious? Visualize Our Training Data with Labels

After training starts, view `train*.jpg` images to see training images, labels and augmentation effects.

Note a mosaic dataloader is used for training (shown below), a new dataloading concept developed by Glenn Jocher and first featured in [YOLOv4](#).

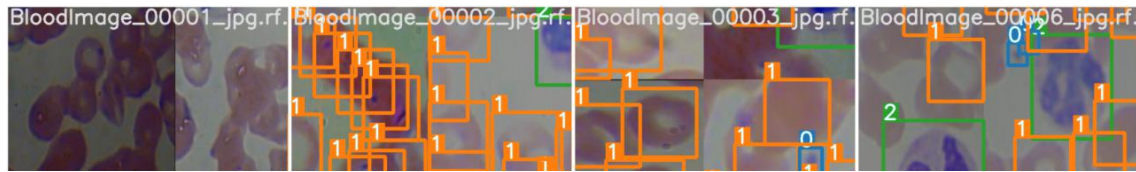
```
1 # first, display our ground truth data
2 print("GROUND TRUTH TRAINING DATA:")
3 Image(filename='/content/yolov5/runs/train/yolov5s_results/test_batch0_labels.jp
```


GROUND TRUTH TRAINING DATA:



```
1 # print out an augmented training example
2 print("GROUND TRUTH AUGMENTED TRAINING DATA:")
3 Image(filename='/content/yolov5/runs/train/yolov5s_results/train_batch0.jpg', w:
```

GROUND TRUTH AUGMENTED TRAINING DATA:



▼ Run Inference With Trained Weights

Run inference with a pretrained checkpoint on contents of `test/images` folder downloaded from Roboflow.



```
1 # trained weights are saved by default in our weights folder
2 %ls runs/
```

```
train/
```



```
1 %ls runs/train/yolov5s_results/weights
```

```
best.pt  last.pt
```



```
1 # when we ran this, we saw .007 second inference time. That is 140 FPS on a TESL
2 # use the best weights!
3 %cd /content/yolov5/
4 !python detect.py --weights runs/train/yolov5s_results/weights/best.pt --img 410
```

```
/content/yolov5
```

```
Namespace(agnostic_nms=False, augment=False, classes=None, conf_thres=0.4, de
Using torch 1.7.1+cu101 CPU
```

```
Fusing layers...
```

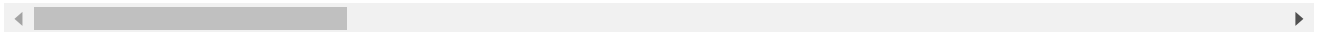
```
Model Summary: 232 layers, 7251912 parameters, 0 gradients
```

```
image 1/36 /content/test/images/BloodImage_00038_jpg.rf.ffa23e4b5b55b523367f3
image 2/36 /content/test/images/BloodImage_00044_jpg.rf.e7760375eba4bc20c5746
image 3/36 /content/test/images/BloodImage_00062_jpg.rf.1belca0ecdf783798fc10
image 4/36 /content/test/images/BloodImage_00090_jpg.rf.cdbf8f6ed3b93fa902a0b
image 5/36 /content/test/images/BloodImage_00099_jpg.rf.e3c42cd68359527494a53
image 6/36 /content/test/images/BloodImage_00112_jpg.rf.978cec39235980055c2ad
image 7/36 /content/test/images/BloodImage_00113_jpg.rf.a17463f1ddc2e7729f935
image 8/36 /content/test/images/BloodImage_00120_jpg.rf.6725d54bf5615683448eb
image 9/36 /content/test/images/BloodImage_00133_jpg.rf.39ee4e4a097a7b40defa5
image 10/36 /content/test/images/BloodImage_00134_jpg.rf.0d9da503b62e0034a281
image 11/36 /content/test/images/BloodImage_00154_jpg.rf.e5b45569e9cbdeled36
image 12/36 /content/test/images/BloodImage_00160_jpg.rf.894e8c8c7179ec9958a4
image 13/36 /content/test/images/BloodImage_00190_jpg.rf.3e0bf272a5f8ea902775
image 14/36 /content/test/images/BloodImage_00191_jpg.rf.313648dd345edbdd0058
image 15/36 /content/test/images/BloodImage_00204_jpg.rf.04ba9998769a12d374e6
image 16/36 /content/test/images/BloodImage_00227_jpg.rf.d1790b0cdc042312d1e0
image 17/36 /content/test/images/BloodImage_00235_jpg.rf.283fff79a1188b82f5a5
image 18/36 /content/test/images/BloodImage_00241_jpg.rf.757020b43fe3414a0f66
image 19/36 /content/test/images/BloodImage_00254_jpg.rf.e95bc889425924cc7a35
image 20/36 /content/test/images/BloodImage_00265_jpg.rf.7d102d5f38caddb90a46
image 21/36 /content/test/images/BloodImage_00266_jpg.rf.2521623f1047a9502b27
image 22/36 /content/test/images/BloodImage_00275_jpg.rf.585f5abcf10f926c74ac
```

```

image 23/36 /content/test/images/BloodImage_00278_jpg.rf.cfe491c301184766df6a
image 24/36 /content/test/images/BloodImage_00284_jpg.rf.63402cee4454cb6d7655
image 25/36 /content/test/images/BloodImage_00289_jpg.rf.72f51d668e5ebc31700b
image 26/36 /content/test/images/BloodImage_00301_jpg.rf.885ee9fbea0573ba35b9
image 27/36 /content/test/images/BloodImage_00302_jpg.rf.911302bb5caaf9467e10
image 28/36 /content/test/images/BloodImage_00325_jpg.rf.c8ab9fc71ad718a95901
image 29/36 /content/test/images/BloodImage_00334_jpg.rf.8b2c2a9c5a39e78eb74a
image 30/36 /content/test/images/BloodImage_00336_jpg.rf.8d3e710e8696c10bcbb1
image 31/36 /content/test/images/BloodImage_00337_jpg.rf.b6cb228440b9158cafec
image 32/36 /content/test/images/BloodImage_00350_jpg.rf.e2c472c90de4ce51fe4f
image 33/36 /content/test/images/BloodImage_00359_jpg.rf.03331bc3903822adbe98
image 34/36 /content/test/images/BloodImage_00369_jpg.rf.c3818de705d661536ed7
image 35/36 /content/test/images/BloodImage_00385_jpg.rf.865551dd16b189945cbb
image 36/36 /content/test/images/BloodImage_00386_jpg.rf.c708422b2d9c642f200a
Results saved to runs/detect/exp2
Done. (6.319s)

```



```

1 #display inference on ALL test images
2 #this looks much better with longer training above
3
4 import glob
5 from IPython.display import Image, display
6
7 for imageName in glob.glob('/content/yolov5/runs/detect/exp/*.jpg'): #assuming .
8     display(Image(filename=imageName))
9     print("\n")

```

▼ Export Trained Weights for Future Inference

Now that you have trained your custom detector, you can export the trained weights you have made here for inference on your device elsewhere

```

1 from google.colab import drive
2 drive.mount('/content/gdrive')

```

Mounted at /content/gdrive

```

1 %cp /content/yolov5/runs/train/yolov5s_results/weights/best.pt /content/gdrive/I

```

Congrats!

Hope you enjoyed this!

--Team [Roboflow](#)

