YOLO

"You Only Look Once" - Object Detection

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What is our project?

Real-Time Object Detection

Locating and identifying:
- Duckiebots
- Ducks
- Stop signs
- Road signs

Real-world application:
- Autonomous driving

DUCKIETOWN

X

YOLO

Object Detection

What is it?

Technique to identify and locate objects in an image or video.

Applications

- Surveillance
- Self-driving cars
- Robotics

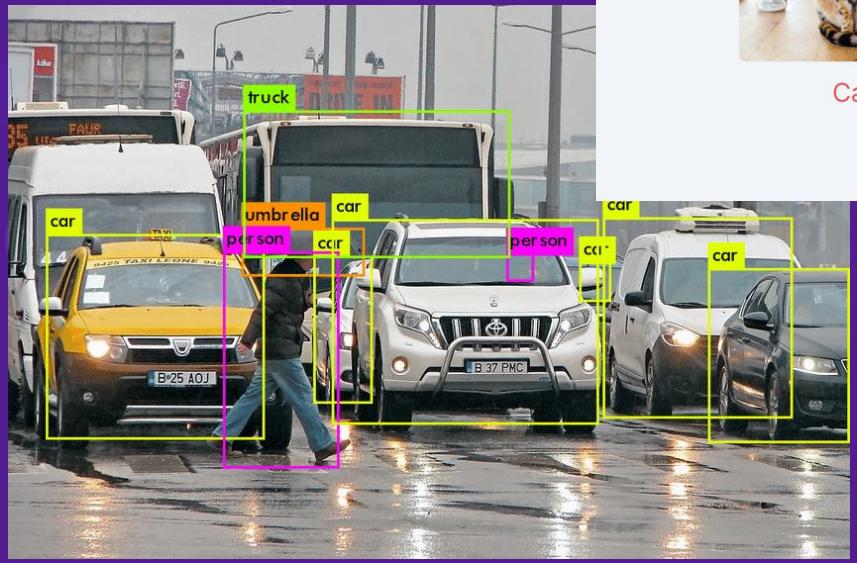
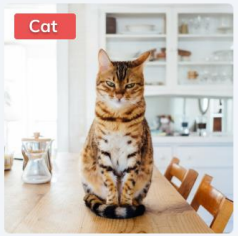


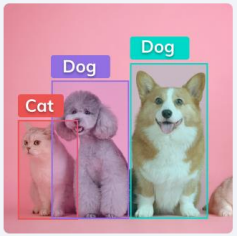
Image Classification vs. Object Detection

Classification



Cat

Detection



Cat, Dog, Dog

V7 Labs

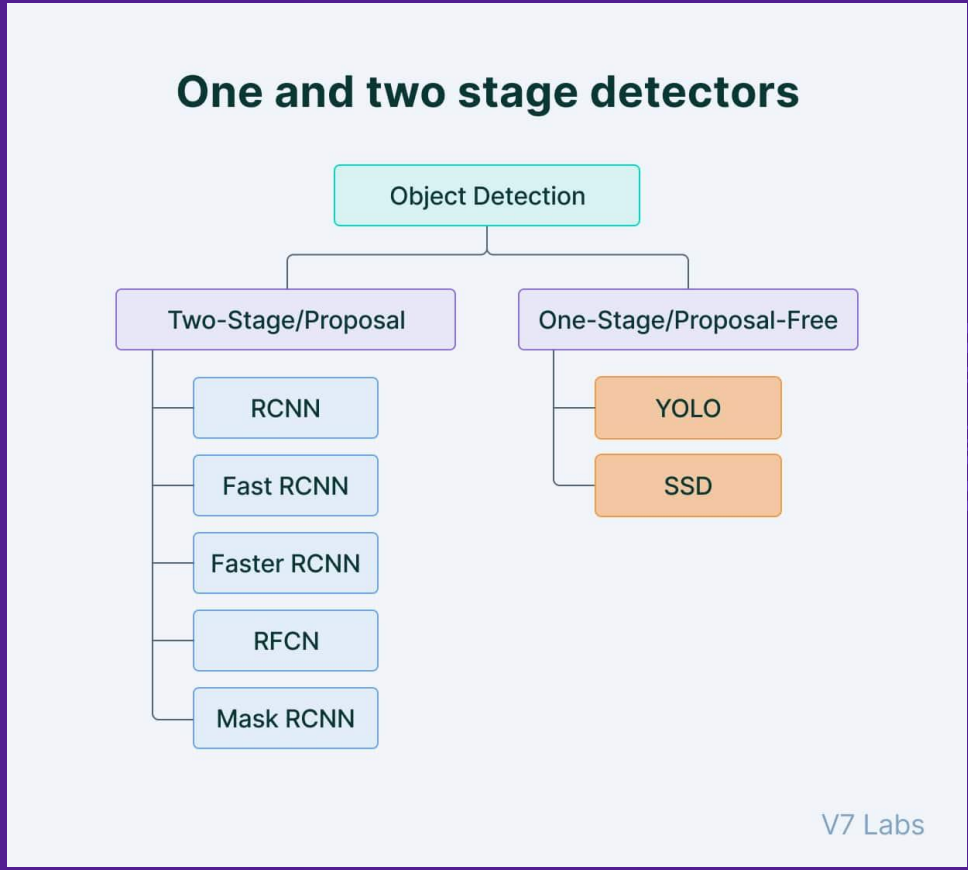
Object Detection

Two-Stage

- Two passes of the input image:
  - 1st: Proposal of set of regions that might contain the object.
  - 2nd: classify and refine regions.
- Computationally expensive.

One-Stage

- One pass of the input image.
- Predicts the bounding step without region proposal.
- Computationally efficient and faster.



(Kundu, 2023)

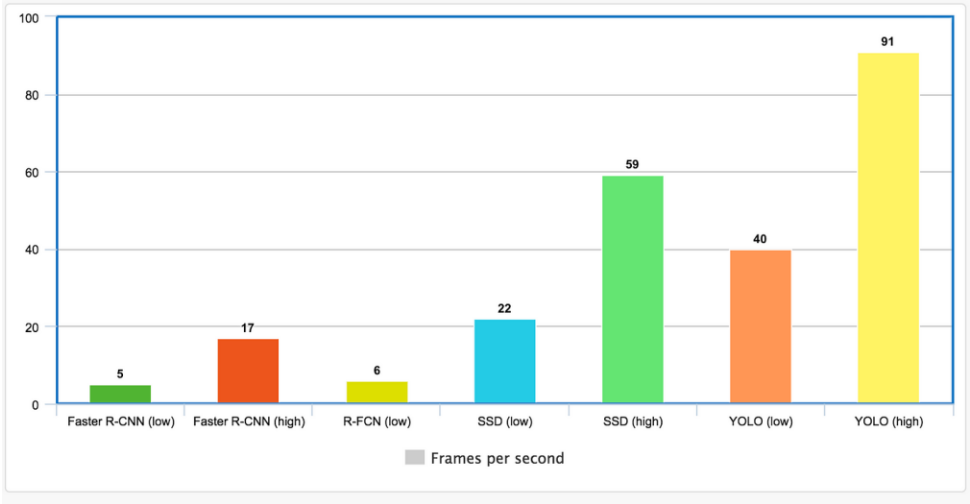
You Only Look Once

- Widely adopted.
- Easy to implement and adapt to new tasks due to its simple architecture.
- Struggles with small objects

Fast

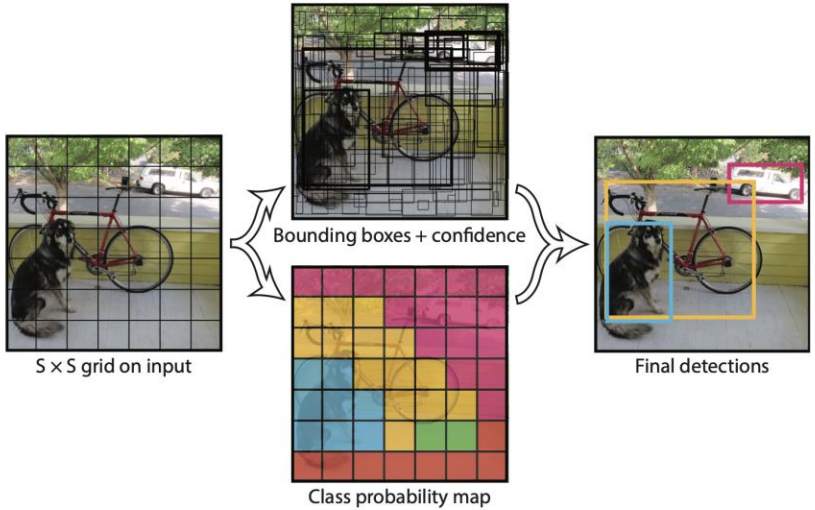
Efficient

Simple



(Hui, 2018)

How does it work?



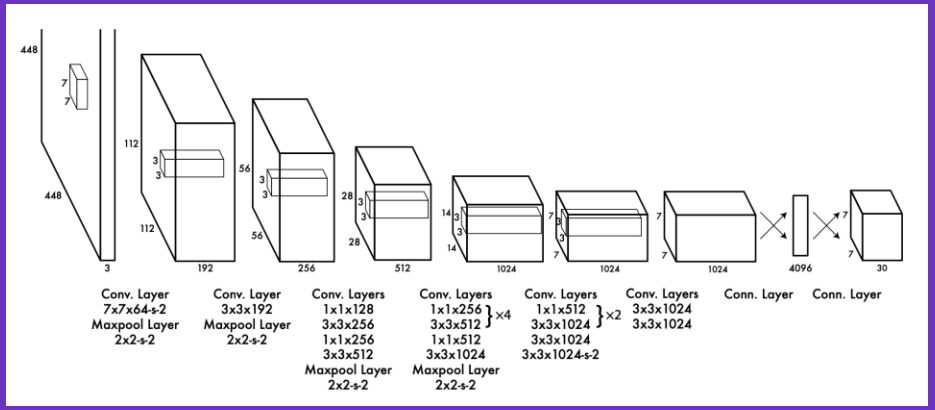
(Redmon et al., 2016)

The Model

- Divide image into an S x S grid.
- Predict B bounding boxes and the confidence for them.
- Predict class probabilities.
- Output final detections.

How does it work?

The Architecture



(Redmon et al., 2016)

Convolutional Layers

Extract features and create features map.

24

Connected Layers

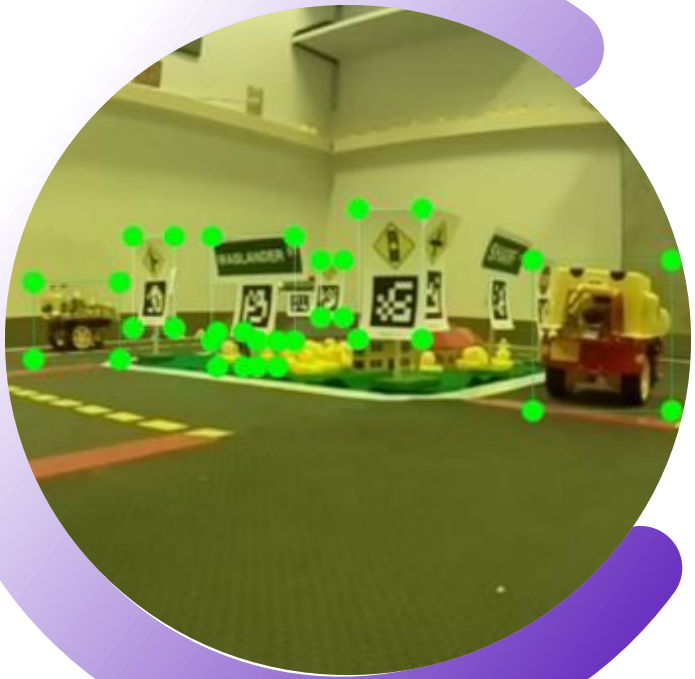
Predict bounding boxes and class probabilities for each cell in the grid.

2

Output

A list of bounding boxes with their respective probabilities.

1



Implementation

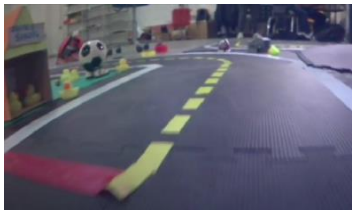
DUCKIETOWN

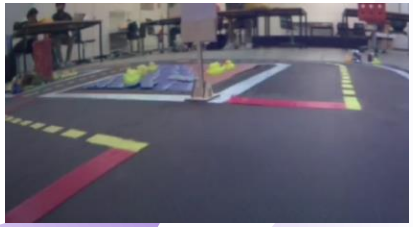
X

YOLO

Implementation

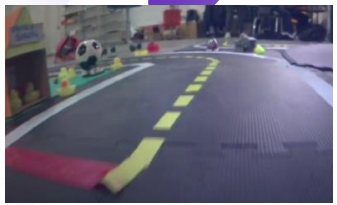
+500 similar images





The Dataset

- 507 compressed images from the duckiebot's camera, capturing the different road signs, duckies and duckiebots during its movement.

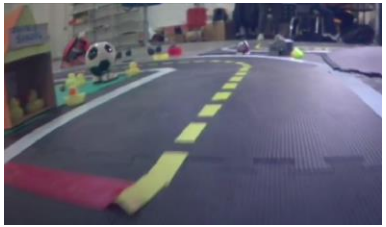


Separation of blurry images from non-blurry ones.

The Dataset

- For optimizing our object detection efficiency, we built a python script to only conserve the non-blurry images, increasing the model training quality, and reducing the training time span.

- With a filtering threshold of 200, the total number of images from the dataset gets reduced from +1500->507



Kept

Removed

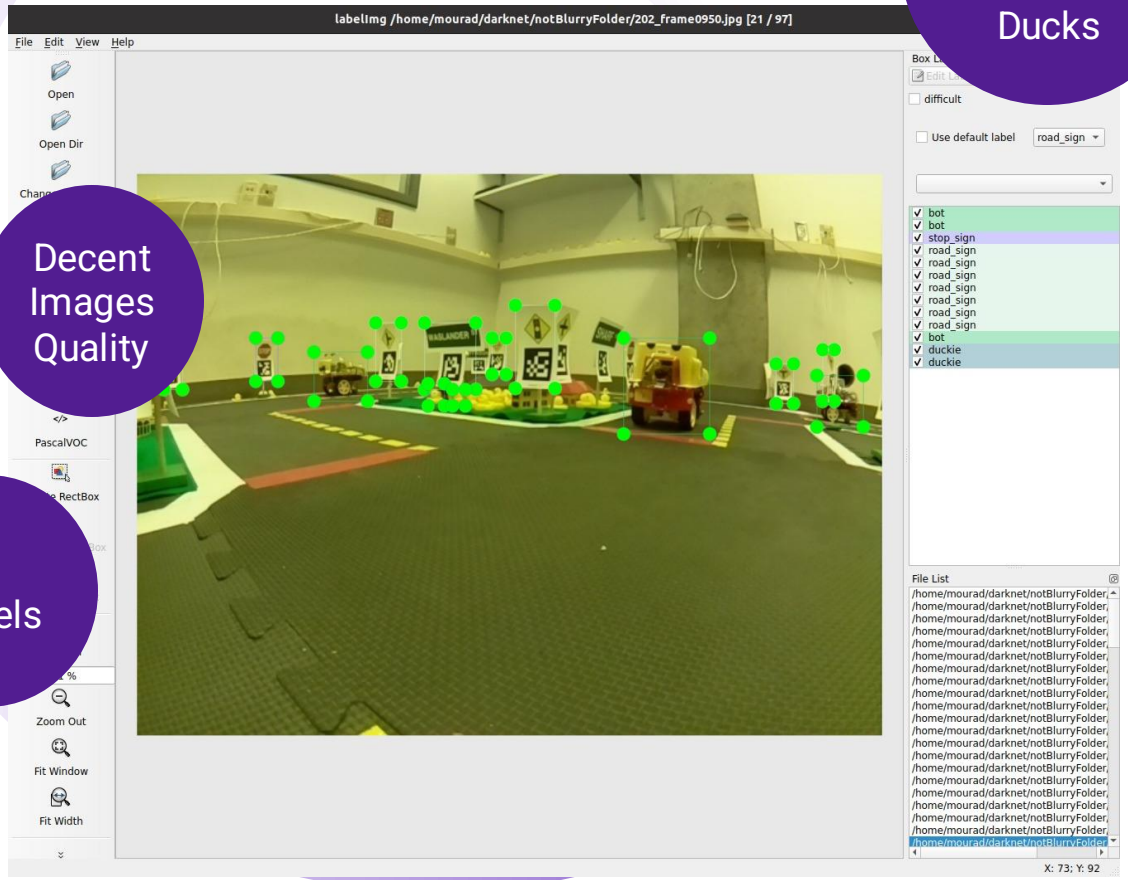
The Laplacian Filter was used for this purpose

detect_blurry_img.py

```python
import argparse
from pathlib import Path
import sys

def main():

    parser = argparse.ArgumentParser(description="Eliminate blurry pictures")
    parser.add_argument("inputFolder", help="Path of folder containing images to classify", type=str)
    parser.add_argument("blurryFolder", help="Path of folder where blurry images will be sent", type=str)
    parser.add_argument("notBlurryFolder", help="Path of folder where non blurry images will be sent", type=str)
    parser.add_argument("--threshold", help="Threshold for blurry detection, default is 200", type=int, default=200)

    args = parser.parse_args()

    data_folder = Path(args.inputFolder)
    blurry_folder = Path(args.blurryFolder)
    good_folder = Path(args.notBlurryFolder)
    threshold = args.threshold

    if not data_folder.is_dir():
        print("{} is not a directory".format(data_folder))
        sys.exit(1)

    if not blurry_folder.is_dir():
        print("{} is not a directory".format(blurry_folder))
        sys.exit(1)

    if not good_folder.is_dir():
        print("{} is not a directory".format(good_folder))
        sys.exit(1)

    # Recognize jpg or jpeg images
    images = list(data_folder.glob('*.jpg'))
    images.extend(list(data_folder.glob('*.jpeg')))

    # Go through all images in data folder
    for imageFile in images:
        print('Processing image {}'.format(imageFile))

        image = cv.imread(str(imageFile))
        gray = cv.cvtColor(image, cv.COLOR_BGR2GRAY)
        fm = cv.Laplacian(gray, cv.CV_64F).var()

        # blurry
        if fm < threshold:
            cv.imwrite(str(blurry_folder.joinpath(imageFile.name)), image)
        # not blurry
        else:
            cv.imwrite(str(good_folder.joinpath(imageFile.name)), image)


if __name__ == "__main__":
    main()
```

Labeling

Stop Signs
Road Signs
Duckiebots
Ducks



Decent
Images
Quality

4
Labels

Training

- Prepare the data for training:
  - Training, Testing, Evaluation sets.
- Prepare config. Files:
  - Classes, model selection, determine classes.
- Fork Darknet repository

Ground Truth Bounding Boxes

```
3 0.19 0.22 0.04 0.13
3 0.23 0.21 0.03 0.13
3 0.62 0.2 0.05 0.11
3 0.7 0.21 0.06 0.15
2 0.96 0.28 0.03 0.12
1 0.34 0.27 0.03 0.04
```

Label

```
datasets/testset/frame_002166_png.rf.a3884e8d84306dec7b86dba2ce4ebca7.jpg
road_sign:Left=319, Top=130, Right=341, Bottom=96

duckie:Left=243, Top=214, Right=283, Bottom=180

road_sign:Left=154, Top=144, Right=172, Bottom=105

road_sign:Left=26, Top=196, Right=84, Bottom=169



datasets/testset/202_frame0806.jpg
stop_sign:Left=86, Top=196, Right=118, Bottom=120

road_sign:Left=115, Top=192, Right=140, Bottom=115

bot:Left=182, Top=208, Right=240, Bottom=156

duckie:Left=419, Top=182, Right=451, Bottom=153

road_sign:Left=371, Top=192, Right=409, Bottom=124

bot:Left=425, Top=244, Right=521, Bottom=148

bot:Left=528, Top=240, Right=598, Bottom=163

duckie:Left=608, Top=216, Right=620, Bottom=196
```

Editing the source code

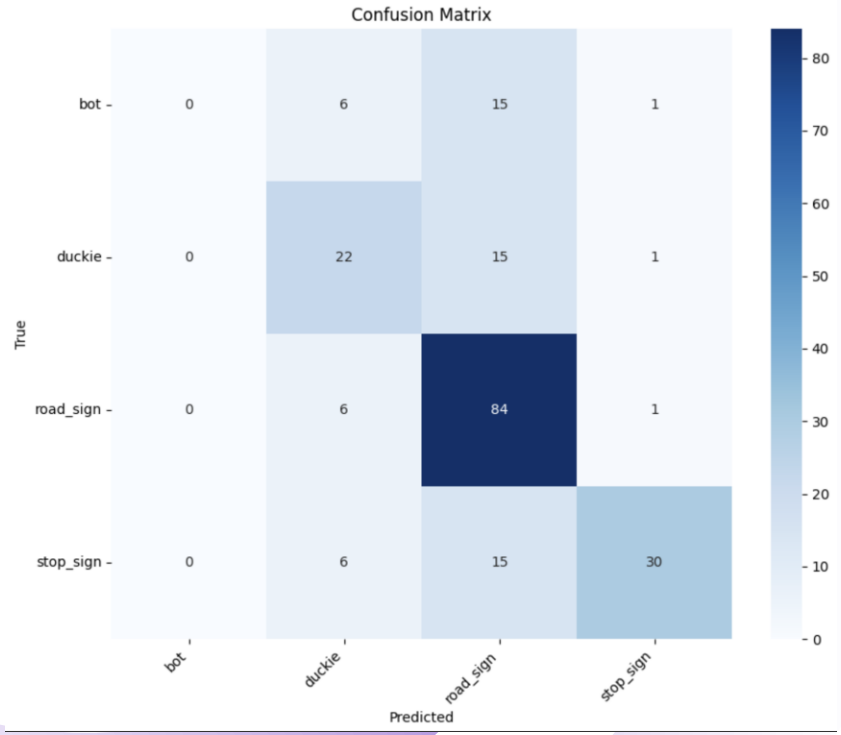
```
layer     filters    size              input                output
    0 conv     32  3 x 3 / 1   416 x 416 x   3   ->   416 x 416 x  32  0.299 BFLOPs
    1 conv     64  3 x 3 / 2   416 x 416 x  32   ->   208 x 208 x  64  1.595 BFLOPs
    .......
  105 conv    255  1 x 1 / 1    52 x  52 x 256   ->    52 x  52 x 255  0.353 BFLOPs
  106 detection
truth_thresh: Using default '1.000000'
Loading weights from yolov3.weights...Done!
data/dog.jpg: Predicted in 0.029329 seconds.
dog: 99%
truck: 93%
bicycle: 99%
```

Before

```
datasets/testset/204_frame0056.jpg: Predicted in 0.179878 seconds.
stop_sign: 88%
Bounding Box: Left=196, Top=112, Right=237, Bottom=190
stop_sign: 70%
Bounding Box: Left=167, Top=148, Right=181, Bottom=175
duckie: 95%
Bounding Box: Left=145, Top=197, Right=166, Bottom=216
duckie: 94%
Bounding Box: Left=89, Top=192, Right=112, Bottom=216
duckie: 87%
Bounding Box: Left=163, Top=196, Right=186, Bottom=219
duckie: 65%
Bounding Box: Left=473, Top=196, Right=491, Bottom=215
bot: 98%
Bounding Box: Left=0, Top=147, Right=69, Bottom=243
```

After

Results



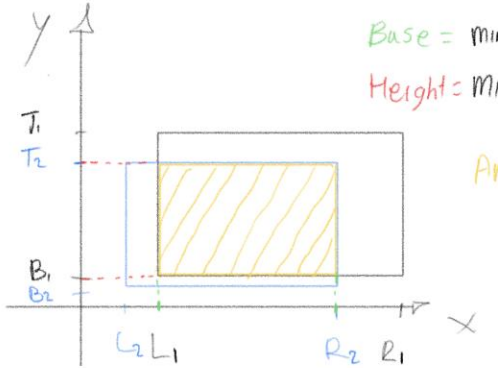
Class: bot
True Positives (TP): 0
True Negatives (TN): 0
False Positives (FP): 0
False Negatives (FN): 44

Class: duckie
True Positives (TP): 22
True Negatives (TN): 0
False Positives (FP): 6
False Negatives (FN): 68

Class: road_sign
True Positives (TP): 84
True Negatives (TN): 0
False Positives (FP): 15
False Negatives (FN): 40

Class: stop_sign
True Positives (TP): 30
True Negatives (TN): 0
False Positives (FP): 1
False Negatives (FN): 13

Intersection



$$Base = \min(R_1, R_2) - \max(L_1, L_2)$$

$$Height = \min(T_1, T_2) - \max(B_1, B_2)$$

$$Area = Base \times Height$$

$$IoU = \frac{Area}{Area}$$

Union:

$$Area = (T_1 - B_1)(R_1 - L_1) + (T_2 - B_2)(R_2 - L_2) - Area$$

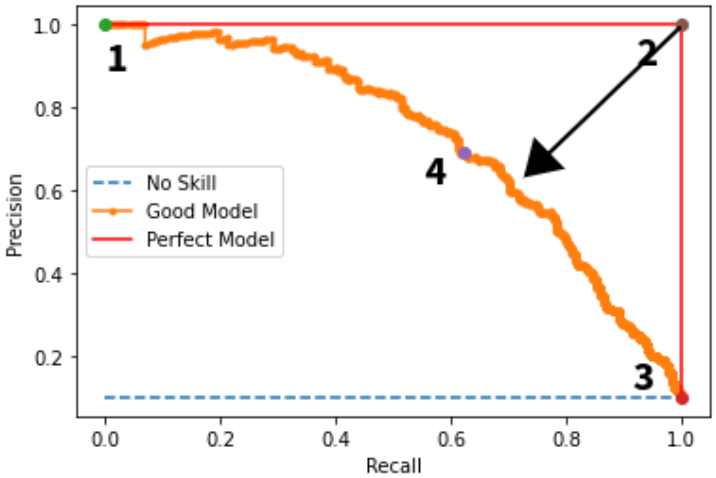
```
intersection_x1 = max(x1, x3)
intersection_y1 = min(y1, y3)
intersection_x2 = min(x2, x4)
intersection_y2 = max(y2, y4)

intersection_area = max(0, intersection_x2 - intersection_x1) * max(0, intersection_y1 - intersection_y2)
#print(f"({intersection_x2}-{intersection_x1})*({intersection_y1}-{intersection_y2})={intersection_area}")

box1_area = abs((x2 - x1) * (y2 - y1))
box2_area = abs((x4 - x3) * (y4 - y3))

union_area = box1_area + box2_area - intersection_area
#print(f"area={box1_area}+{box2_area}={union_area}")

iou = intersection_area / union_area
#print(f"iou={intersection_area}/{union_area}={iou}")
```

Results

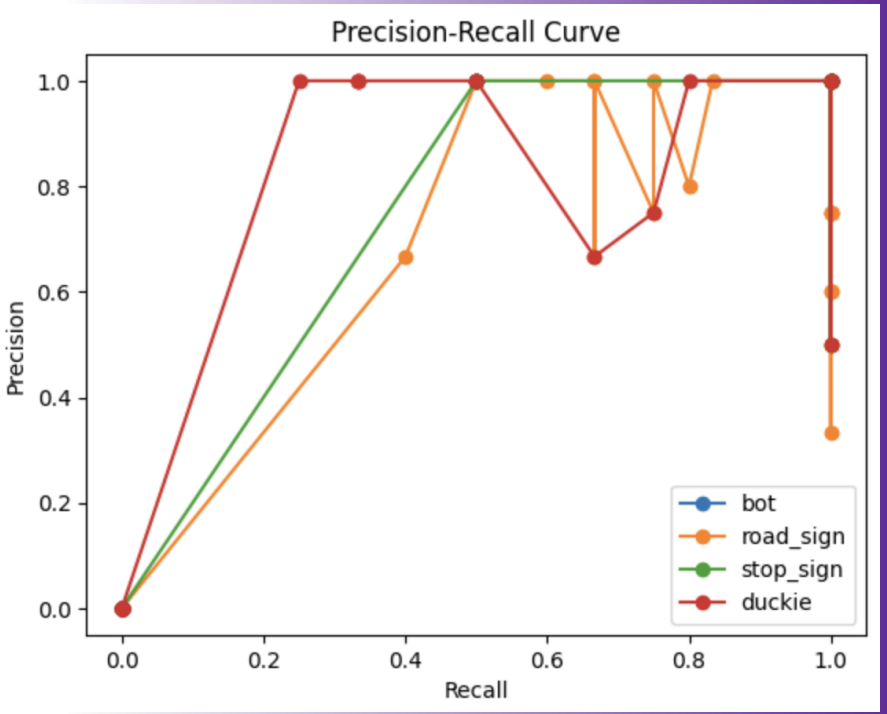
Precision: how often does the model predict correctly?
Precision = TP/(TP+FP)

Recall: has the model predicted every time that it should have predicted?
Recall = TP/(TP+FN)

Average precision: Area under the curve.



Reference



Results

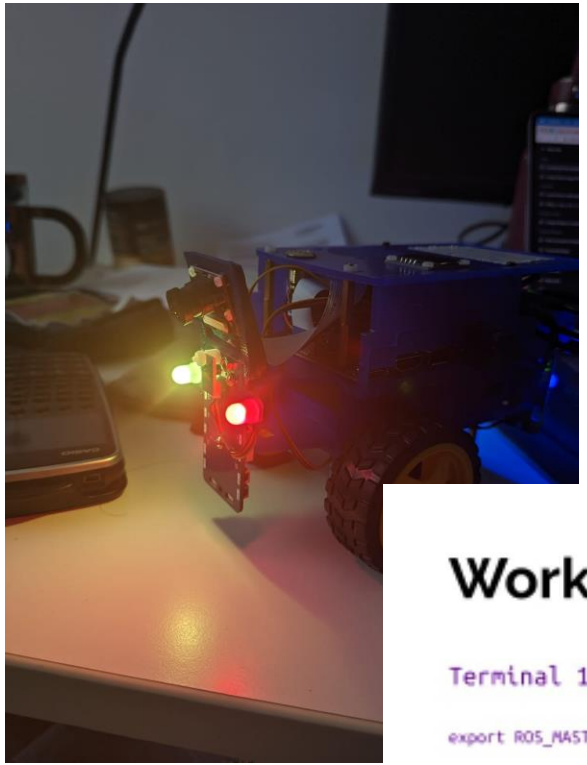
Results

Average precision

Class	Approx. Area Under the Curve (AP)
bot	0.00
duckie	0.77
road_sign	0.65
stop_sign	0.75

Mean Average Precision (mAP) = 0.54

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i$$



Challenges and Recommendations

Assessment Problems

- The "Bot" class only showed False Negatives (FN), and the model failed to detect any instances of this class

Duckiebot

- Wiring problems caused problems turning it on and off.
- Problems with Jetson Nano OS

Work process

Terminal 1

```
export ROS_MASTER_URI=http://[name].local:11311

source ~/svo_ws/devel/setup.bash

rosrun image_transport republish compressed
in:=/[name]/camera_node/image raw
out:=/[name]/camera_node/image/raw
```

darknet_ros node

- Problems accessing the node

THANK YOU

“You only live once - YOLO.”
:)