

Project: Car detection on KITTI dataset

Muhammad Haris Ibrahim

muhammad.ibrahim@student.uni-luebeck.de

Abstract

Detecting cars on the road is a critical task for autonomous driving. This must be done with high precision and in real-time. In this paper, we develop a 2D car detector by fine tuning the YOLO-v3 object detector to detect cars on a scaled down version of KITTI dataset. We achieved 50 percent mean Average Precision after finetuning YOLO-v3 model previously trained on MS COCO dataset. Improvements to the training process are required to achieve better results.

1. Introduction

Object detection is a critical task for autonomous driving. An autonomous vehicle must be able to detect and keep track of objects of interest in its environment. The classification of objects is not enough, their position and orientation in the environment must also be predicted. Another challenge is that these detections must be performed at high precision and recall but also in real-time on edge devices. The objects of interest can be lane line markings, traffic signs, vehicles, pedestrians and more.

In this project, we focus only on detecting cars. Car detection is specially important in autonomous driving to avoid collisions and plan safe trajectories even at low levels of autonomy.

There are many deep learning based approaches for object detection. We adapt YOLO-v3 [11], a general purpose 2D object detector based on a Convolutional Neural Network (CNN) architecture. For training and evaluating our car detector, we will use a simplified version of KITTI dataset containing cars with 2D bounding box labels [3].

YOLO-v3 is an improved version of YOLO [10] which achieves higher mean Average Precision (mAP) on 2D object detection datasets like MS-COCO [8] while still being real-time. YOLO-v3 is an end to end CNN and performs predictions in only 1 pass.

Transfer learning is then used to finetune it for car detection on our version of KITTI dataset. We obtained 50 percent mean Average Precision (mAP) on a validation set.

Image 30



Figure 1. Detections of the model developed in this project on a sample image from the test set.

2. Related Work

Since the success of Convolutional Neural Network (CNN) based approaches like Alexnet [5] on image classification tasks, many similar approaches have been designed for object detection. Region Proposal CNNs (RCNN) [12] and its various variants use handcrafted algorithms to generate proposals for regions of interest. These proposals are then passed to a CNN which produces class and confidence predictions. The predictions are then fed back into the region proposal algorithm. This means that multiple passes are required to perform good predictions. This makes these networks slow at inference time. These multi-stage detectors are, therefore, not realtime.

YOLO architecture and Single Shot Detector [9] solved this problem by performing the object detection in only one evaluation of the network. These are end to end CNNs. Out of these two, YOLO is the fastest.

YOLO architecture frames the object detection problem as a regression problem. It divides the image into a $S \times S$ grid, where S is the grid size. For each of these grid cells, there are three bounding box predictors in the output layer. A bounding box prediction consists of 4 coordinates of the bounding box. Each grid cell also includes a class prediction.

YOLO-v3 also divides the images into $S \times S$ cell, but it

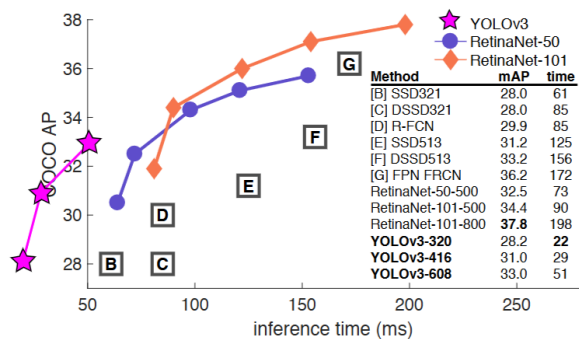


Figure 2. speed (ms) vs accuracy (AP) on MS COCO test set. YOLOv3 outperforms many multistage and single stage object detectors in AP while being faster than all of them. This image is adapted from [11] which is itself a version of image from [7]

produces class probabilities for each bounding box not just for each grid cell. Predictions are also made at three different scales. Prediction of the bounding box coordinates are also as offsets of bounding box priors (anchor boxes). These anchor boxes are based on shapes of bounding boxes common for the problem. The network outputs a large number of predictions. Bounding box and class predictions are made at 3 scales, SxS grid cells per scale, and 3 per grid cells. Non Maximum Suppression (NMS) is applied to keep only the best predictions. YOLO-v3 has already been applied to many object detection problems like face detection [6], pedestrian detection [14] and much more.

A brief comparison of the performance of many object detection frameworks is shown in Figure 2.

There are more recent and improved versions of YOLO such as [13] that are not developed by the original authors. Recent works like Detection Transformer [1] use a CNN backbone with a transformer encoder and decode blocks. These approaches achieve higher mAP precision. They also remove the need for anchor boxes and NMS. Because of the limits of the dataset, limited time and GPU compute, we use the YOLOv3 architecture and not the newer ones.

3. Method

In this section, we provide a summary of the YOLO-v3 architecture.

3.1. Bounding Boxes

YOLO-v3 like many other object detectors does not predict the absolute coordinates of the bounding box. The bounding box centre coordinates are predicted as offsets to position of the top left corner of the grid cell. The width and height of the box are predicted as offset of the width and height of anchor boxes. These anchor boxes are pre-defined based on the likely shapes of anchor boxes for the

problem at hand. The bounding box offsets are t_x, t_y, t_w, t_h . If the position of the top left of grid cell relative to the top left of the image is given by (c_x, c_y) and the bounding box has width and height p_w, p_h , then the bounding box coordinates are calculated by:

$$b_x = \sigma(t_x) + c_x$$

$$b_y = \sigma(t_y) + c_y$$

$$b_w = p_w e^{t_w}$$

$$b_h = p_h e^{t_h}$$

The ground truth values will be the left side of the above equations. We rearrange the equations to find the ground truth offsets.

The authors used clustering analysis to find the anchor box dimensions which have the most overlap with ground truth boxes on MS COCO dataset. We did not do such analysis on our dataset and used the anchor box dimensions reported in the original paper.

There are 09 anchors boxes—03 at each scale. Each grid cells within a scale, predicts three bounding boxes as offsets of these anchors boxes. The anchor boxes are in sets of three where the size of each set is according to the prediction scale.

3.2. Objectness score

Along with 04 coordinates of the bounding box, the network also predicts a objectness score for the bounding box. At test time, this is the confidence of the model in predicting that an object exists in the box and how well the box fits the object. At training time, this score should be the intersection over union between the predicted box and the ground truth box. The loss function forces this behaviour.

3.3. Class predictions

The network predicts a class probability for each bounding box. At training time, we use Cross entropy loss for classification prediction of the box. This is probability that there exists an object of class i given that there is an object in the box, $\Pr(\text{Class}_i | \text{Object})$. We can multiply this by objectness score to get the classification confidence.

3.4. Features extraction backbone

The backbone of the network is a 53 layer CNN named as Darknet 53. The overall summary of the layers is shown in Table 1. The authors did not explain any further details about the backbone. After spending sometime with the source code, our understanding is that each CNN block in the Table consists of a CNN layer, followed by leaky ReLU activation layer, and lastly a Batch Normalization layer. The filter sizes are mentioned in the Table. The 1x, 2x and such

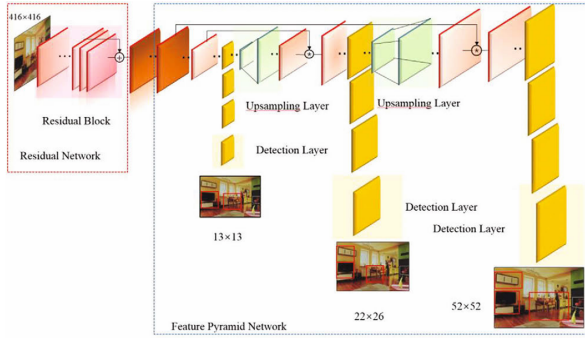


Figure 3. speed (ms) vs accuracy (AP) on MS. COCO test set. YOLOv3 outperforms many multistage and single stage object detectors in AP while being faster than all of them. This image is adapted from [11] which is itself a version of image from [7]

labels in the Table show the number of repeats. So, 2x means that such a block is repeated 2 times. It should be noted that the architecture includes skip connections like Resnets [4]. The authors trained this backbone for image classification on ImageNet dataset [2]. Further details about the training process is were not provided. We assume a strategy similar to the YOLO-v1 was used.

3.5. Three Scale Predictions

The extracted features of the backbone are then passed to the detection heads at three different scales. The size of the outputs are decided by dividing the image into $S \times S$ grid. There are three different grid sizes for three different scales. The idea is to use a coarser grid to help detect large object, then a medium size grid and then finally a smaller grid size. At each scale, the network has $S \times S$ predictors. Each grid cell has three predictors. Each predictor then predicts 4 bounding box coordinates (as offsets to three anchors), 1 objectness score and C class probabilities for C classes. So the total predictions at each scale are $S \times S \times [3 \times (4 + 1 + C)]$. After the output of the feature extract backbone, several convolutional layers are added. The overall structure can be seen in Figure 3 The detection head for the first scale then adds two more Convolutional blocks. The outputs of this blocks is a $S \times S \times [3 \times (4 + 1 + C)]$ tensor. For the second scale prediction, we take the output of the network just where the first detection head is attached and then upscale it by 2x. We then concatenate this feature map with a feature map a couple of blocks before. The idea is to use earlier feature maps along with upscaled current feature maps to make predictions on a higher resolution. This helps with detecting medium and small objects. The second detection head is then attached here which then adds two more CNN blocks to make predictions. The process is repeated to get predictions for the third scale.

The network makes predictions at three different scales

	Type	Filters	Size	Output
1x	Convolutional	32	3×3	256×256
	Convolutional	64	$3 \times 3 / 2$	128×128
	Convolutional	32	1×1	128×128
	Residual	64	3×3	
2x	Convolutional	128	$3 \times 3 / 2$	64×64
	Convolutional	64	1×1	64×64
	Convolutional	128	3×3	
	Residual			64×64
8x	Convolutional	256	$3 \times 3 / 2$	32×32
	Convolutional	128	1×1	32×32
	Convolutional	256	3×3	
	Residual			32×32
8x	Convolutional	512	$3 \times 3 / 2$	16×16
	Convolutional	256	1×1	16×16
	Convolutional	512	3×3	
	Residual			16×16
4x	Convolutional	1024	$3 \times 3 / 2$	8×8
	Convolutional	512	1×1	8×8
	Convolutional	1024	3×3	
	Residual			8×8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Table 1. Darknet-53.

inspired by feature pyramid networksstage of the network

YOLO-v3 predicts 04 bounding box coordinates. These are the x and y coordinates for the centre of the box and width and height of the bounding box. The centre is predicted relative to the bounds of the grid cell edge. The equation for the bounding box look like:

On the left side are the absolute

They acheived this by dividing the image into a $S \times S$ grid of "predictors". Each predictor is responsible for generating predictions for an object, if the centre of the object bounding box lies in within the grid cell. The predictor generates a class probabilities, objectness confidence, and 4 bounding box coordinates.

Also, formulas often help to make the mathematical background clearer. How to insert them is given here:

$$a + b + a = 2 \cdot a + b.$$

It is essential that the reader is able to understand your method according to this section.

4. Evaluation

4.1. Experimental Setup

Here, you should describe the data you used for training, the hyper parameter settings, how you split the data into a training and a test set, etc.. Additionally, you should explain how you adapted your method to work well on your problem setup.

Method	Frobnability
Theirs	Frumpy
Ours	Makes one's heart Frob

Table 2. Results. Ours is better.

4.2. Discussion

In the discussion, you present and discuss the results your method achieved in the provided setups, why which set up works better, The numbers (accuracy of your TEST set) should be given in a table, as e.g. Table 2. You should also show exemplary images for which you achieved good results and examples, where the algorithm did not work as expected. Give possible explanations for both cases, e.g. “what could be the reason for missing a Pedestrian?” “.

5. Conclusion and Future Work

Finally, you shortly summarize what you achieved in your work and point out what could be done in the future to get even better results.

References

- [1] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In *European conference on computer vision*, pages 213–229. Springer, 2020.
- [2] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pages 248–255, 2009.
- [3] A Geiger, P Lenz, C Stiller, and R Urtasun. Vision meets robotics: The kitti dataset. *The International Journal of Robotics Research*, 32(11):1231–1237, 2013.
- [4] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.
- [5] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C.J. Burges, L. Bottou, and K.Q. Weinberger, editors, *Advances in Neural Information Processing Systems*, volume 25. Curran Associates, Inc., 2012.
- [6] Lin, Li Zheng-Chun, Jiang Dian, Wang Yun-Zhi, Chao Jing, and Zhang. Yolov3: Face detection in complex environments. In *International Journal of Computational Intelligence System*, pages 1153–1160. Press, 2020.
- [7] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision*, pages 2980–2988, 2017.
- [8] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer vision–ECCV 2014: 13th European conference, zurich, Switzerland, September 6–12, 2014, proceedings, part v 13*, pages 740–755. Springer, 2014.
- [9] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C Berg. Ssd: Single shot multibox detector. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14*, pages 21–37. Springer, 2016.
- [10] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 779–788, 2016.
- [11] Joseph Redmon and Ali Farhadi. Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*, 2018.
- [12] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*, pages 91–99, 2015.
- [13] Chien-Yao Wang, Alexey Bochkovskiy, and Hong-Yuan Mark Liao. Yolov7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 7464–7475, 2023.
- [14] Yulin Yang, Baolong Guo, Cheng Li, and Yunpeng Zhi. Microsoft coco: Common objects in context. In *An Improved YOLOv3 Algorithm for Pedestrian Detection on UAV Imagery*, pages 253–261. Springer Singapore, 2020.