Machine Learning Engineer Nanodegree

Capstone Proposal

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Proposal

Domain Background

Development of automated driving vehicles has been actively carried out in recent years. For example, in this movie, Tesla explains the automatic driving technique of automatic driving Level 3. In my efforts this time, we will recognize surrounding objects that are part of this automatic driving system.
Also, this initiative is a result of participating in Didi challenge competition that I organized by DiDi and Udacity and summarizing the results we worked.

Problem Statement

The challenge this time is to understand and detect the objects around the vehicle. The sensor uses camera and Lidar. The goal is to identify the location of nearby cars and pedestrians on the 3D map from this information. The detected objects are scored based on the following idea.

IOU Per Object Type

This is a volume based intersection over union metric. The intersection is the overlapping volume of prediction bounding boxes with ground truth bounding boxes. The union is the combined volume of predicted and ground truth boxes. The IOU is equivalent to TP/(TP + FP + FN) where

- True positives = correctly predicted volume that overlaps ground truth
- False positives = incorrectly predicted volume that does not overlap ground truth
- False negatives = ground truth volume not overlapped by any predictions

For this implementation, all of the intersection and union volumes are added up across all frames for each object type and then the ratio is calculated on the summed volumes. For the 'All' field, the scores across all relevant object types are averaged.

It should be noted that predictions are matched with ground truth boxes of the same object type based on the largest overlap and then neither are matched again in that frame. Unmatched predictions overlapping a ground truth box that's already been matched will be considered false positives. Unmatched ground truth volumes that overlap with predictions better matched with another ground truth will be considered false negatives.

The reason why this indicator is correct is that by accurately grasping the position of the target object on the 3D map with something like a 3D box, it is possible to know the relationship between the vehicle and the surroundings, It is because you can handle the steering wheel after understanding the situation properly. Doing so prevents unfortunate accidents involving conflicts.
Especially I am interested in the development of automatic driving cars because I can not drive a car with paper drivers. When auto-driven cars are sold, my range of actions increases dramatically, and that degree of freedom also increases. Also, although Japan has entered an aging society, it is necessary to prevent accidents of elderly people in advance, and in anticipation of an increase in the demand for transportation methods accompanying such social changes, self-driving vehicles are revolutionary We believe we can demonstrate the effect. And, if I can contribute to the development of that technology, I do not think there is any more honor.

Datasets and Inputs

The organizer provided this dataset was. These data sets are obtained from the data of the actual driving of the car. The data contains the image of the forward vision, PointCloud data by Lidar. Besides, the position on the GPS of the subject vehicle and the surrounding object is included, but it was not used in this effort.
The relationship with the problem of the data set this time is that it is acquired by the same car and camera, Lidar for own vehicle. In other words, information such as angle of view of the image does not change. I took advantage of this in my efforts this time.
Below, I will post the video prepared as the data of this time. This was taken with an in-vehicle camera, and about 100 G of such a moving picture was prepared.

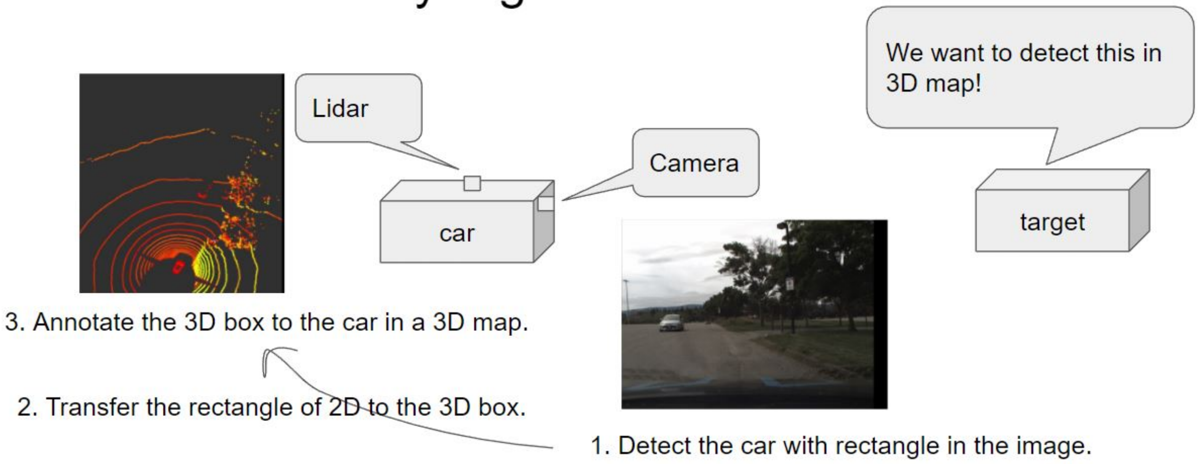
Also, in my efforts this time, I used KittiBox[1] and YOLOv2[2] which I have already learned to detect vehicles and passers-by persons. KittiBox is learned against cars, YOLOv 2 is heard versatile for cars and passersby. It is assumed that the data set adopted for the current test was acquired by a general car and there is no significant difference from the object that can be detected by the learned model, which is a prerequisite I will. We applied these learned models to the movie as above and identified the position of the car.

[1] MultiNet: Real-time Joint Semantic Reasoning for Autonomous Driving; Marvin Teichmann et al.
[2] YOLO9000: Better, Faster, Stronger; Joseph Redmon et al.

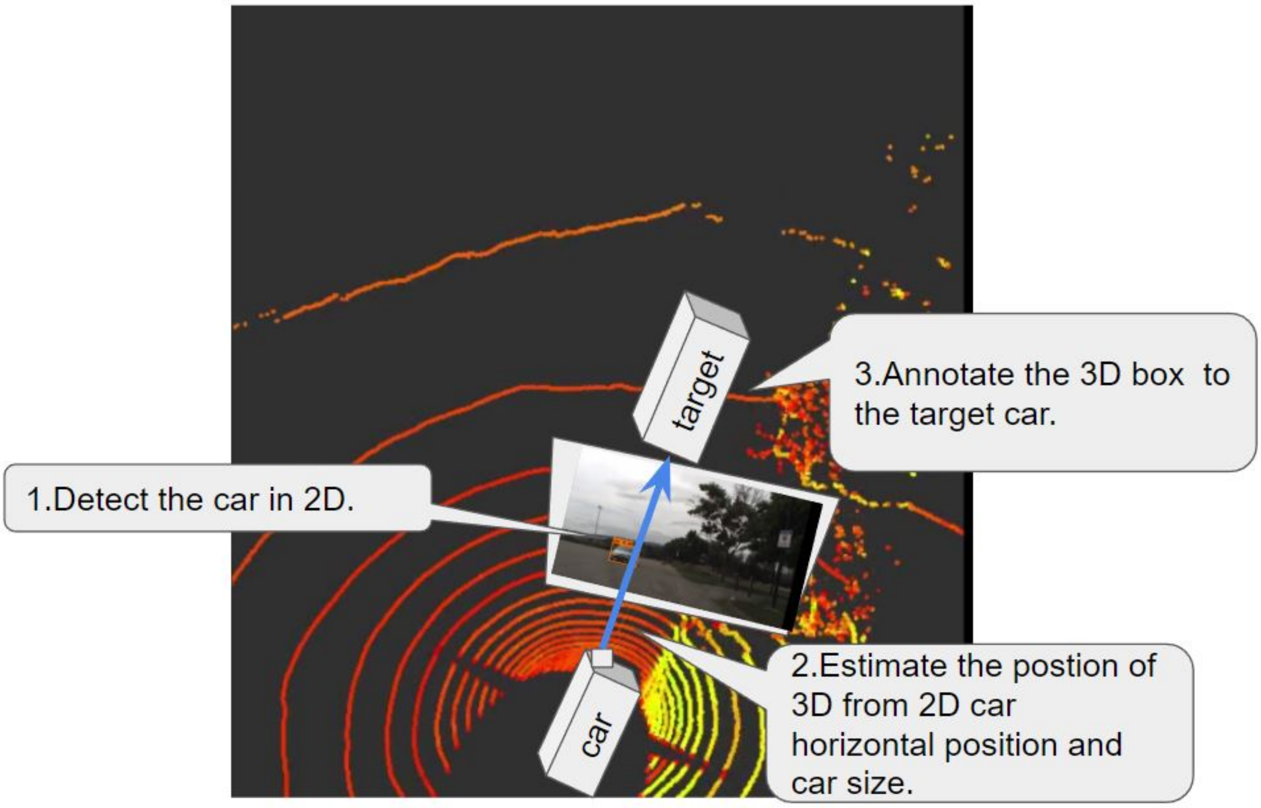
Solution Statement

Also, in this study, we needed to project the position of the car found in 2D to the position of the car on the 3D map. So I thought of an algorithm to estimate these from the car position on the 2D map. Specifically, the lateral direction uses the parallel orientation of the center position of the detected car region, and the depth direction uses the length of the area in the height direction of the detected vehicle region.

What we have and My Algorithm.



How to transfer 2D to 3D.



Benchmark Model

In this study, we compare Kittibox and YOLOv 2 first. The benchmark model is Kittibox, and compare the results of YOLOv 2 with that. Then, based on the result, decide an appropriate model and describe the effect when reflecting those models on the 3D map. Also, the composition of DNN of each model is not described here because the purpose is different. Please check each thesis.

Evaluation Metrics

This evaluation will discuss the consistency with the results already prepared for answers. Specifically, it is made for testing as a data set, and by using data whose answers are known on the 3D map, it is possible to determine to what degree of correct answer rate in each model for the position information I will confirm and evaluate it. The evaluation index is as described in the Problem Statement above.

Project Design

As a rough flow, we will first compare Kittibox and YOLOv 2 to the same image data and compare the differences. This uses 2D image data to find how much cars are being detected. However, since there is no correct answer data, this may be a little qualitative evaluation, but I will make it possible to explain as quickly as possible using animation, etc. Next, we project them onto PointCloud data on 3D map and compare them. Since quantitative data of score should be able to be calculated here, we will examine it also by using movies, etc. while utilizing it. I will discuss regarding how much they correspond to the actual 3D position, and how much support is available for blurred data in 3D. Also, I will not discuss too much about the model difference, but in general it is a prospect that YOLOv 2 will be better. Since it comes from precision and real-time pre-confirmation information, we will keep it to the extent that it is confirmed by experiments just in case of this examination. The theme of this study is how to project 3D information only with 2D information, for example, Lidar is very expensive as equipment and thinks that the risk of failure is high because it is a complicated mechanism. So, if we can estimate the 3D position only from the camera image, we think that it is useful both economically and maintenance. Even if it is impossible to detect the surrounding objects from the camera image alone perfectly, if it is possible to recognize to some extent, the performance of the Lidar will be degraded, or in the event of a failure it will be possible to perform automatic operation with only the camera, such as fail-safe I think that we can also help. So, we believe that if this technology is established the possibility of more automatic operation will increase. In that sense, in this project, I would like to confirm that I can only use 2D camera images and how far I can go.