Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

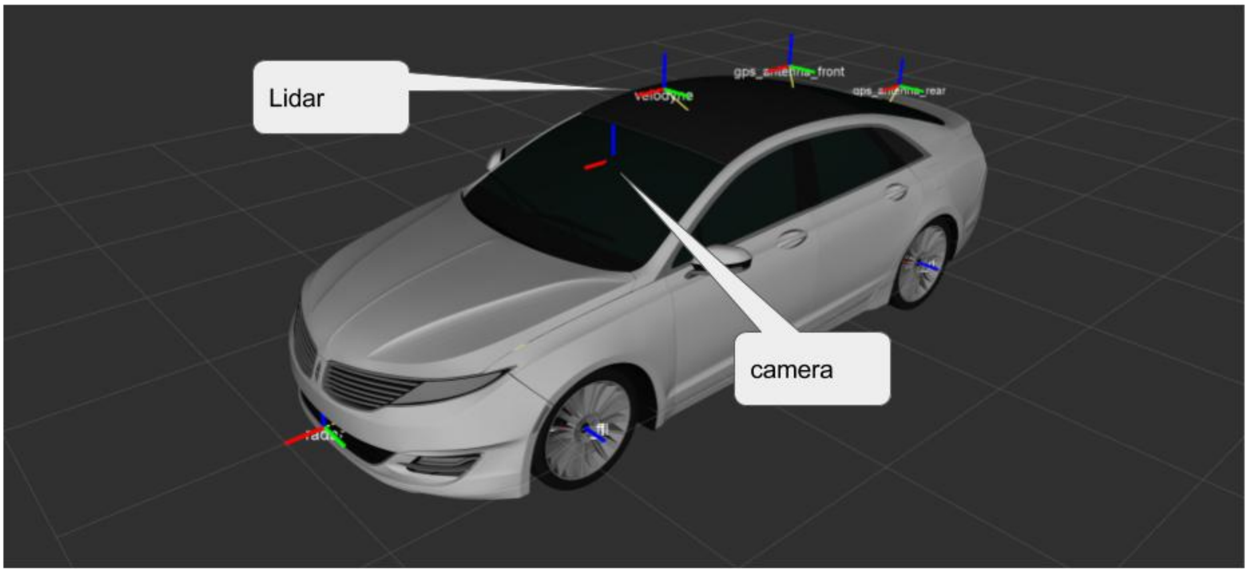
Project Overview

Domain Background

In recent years, the demand for self-driving cars has increased. This requirement is because we believe that the self-driving cars can utilize the safety of society and efforts to improve productivity. For example, many people in Japan need to drive for living even if they are seniors in rural areas. Do not forget the fact that accidents are occurring due to deterioration of the judgment by aging. In such cases, self-driving cars can be utilized to prevent such unfortunate accidents in advance. Of course, this demand is not only Japan but worldwide. Also, for example, it is possible to use automated driving vehicles to reduce the labor load of long distance driving drivers and to suppress the number of public transportation personnel, which can lead to improvement of safety and productivity of society as a whole. Such like that, the needs for self-driving cars exists everywhere. Especially I am interested in the development of automatic driving cars because I can not drive a car with my paper license. When auto-driven cars start to launch, my range of activities increases dramatically, and that degree of freedom also increases. Also, although Japan has entered an aging society, it is necessary to prevent accidents of seniors 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. And its development has been done actively. For example, at this movie, Tesla explains the automatic driving level 3 automatic driving technique. This time, I recognize surrounding objects which are part of this automatic driving system. However, on the other hand, it will be explained in detail later, but if you adopt a method that uses a submillimeter wave sensor like Lidar it will be expensive inevitably. Therefore, in my research, I estimate the position of the car on 3D photographed by Lidar, using only 2D camera images. This is the theme of my research. This initiative also participated in Didi Challenge Competition hosted by DiDi and Udacity and summarized my work.

Datasets and Inputs

The Organizer who is Udacity and Didi provided data set of dataset1, dataset2 for round 1 and dataset for round 2. These datasets are from the actual car with driving. The data contains the image of the forward vision and PointCloud data by Lidar. Besides, including the position on the GPS of the subject vehicle and the surrounding object, but I did not use it in this effort.
The camera and Lidar is installed to the car like below;



reference from here
The camera can capture the image of forward vision, and it is just composed by RGB data, and size is 1400 * 512. On the other hand, Lidar is like this. And Pointcloud data shows the objects captured by Lidar surroundings like this. These data is zipped as a bag file which is based on ROS as known as open source robotic operating system. The relationship of the datasets in this endeavor is that organizer acquired these datasets with the same car with camera and Lidar. In other words, information such as angle of view of the image does not change. I took this advantage in my efforts at this time.
Below, I will post the video prepared as the data. This video captured by an in-vehicle camera and the whole of datasets are about 100Gbyte of such a moving picture.

Also, in my efforts, I used KittiBox[1] and YOLOv2[2] pretrained to detect vehicles and passers-by persons. KittiBox pretrained against cars, YOLOv2 is heard versatile for cars and passersby. I can use these model; it is because our data set assumed that the data set adapted for the general car and there is no significant difference from the object that our data set had. 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.

Problem Statement

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. This trial uses 2D image data to find how cars are 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 quickness, etc.

Metrics

This evaluation will discuss the consistency with the results already prepared for answers. Specifically, the data is made up for testing, and it includes the car position on the 3D map. So 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 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.

reference from here

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.

II. Analysis

Data Exploration

So now I research the data of Datasets. Originally we got the dataset with .bag file, and the bag file contains some topics like below;

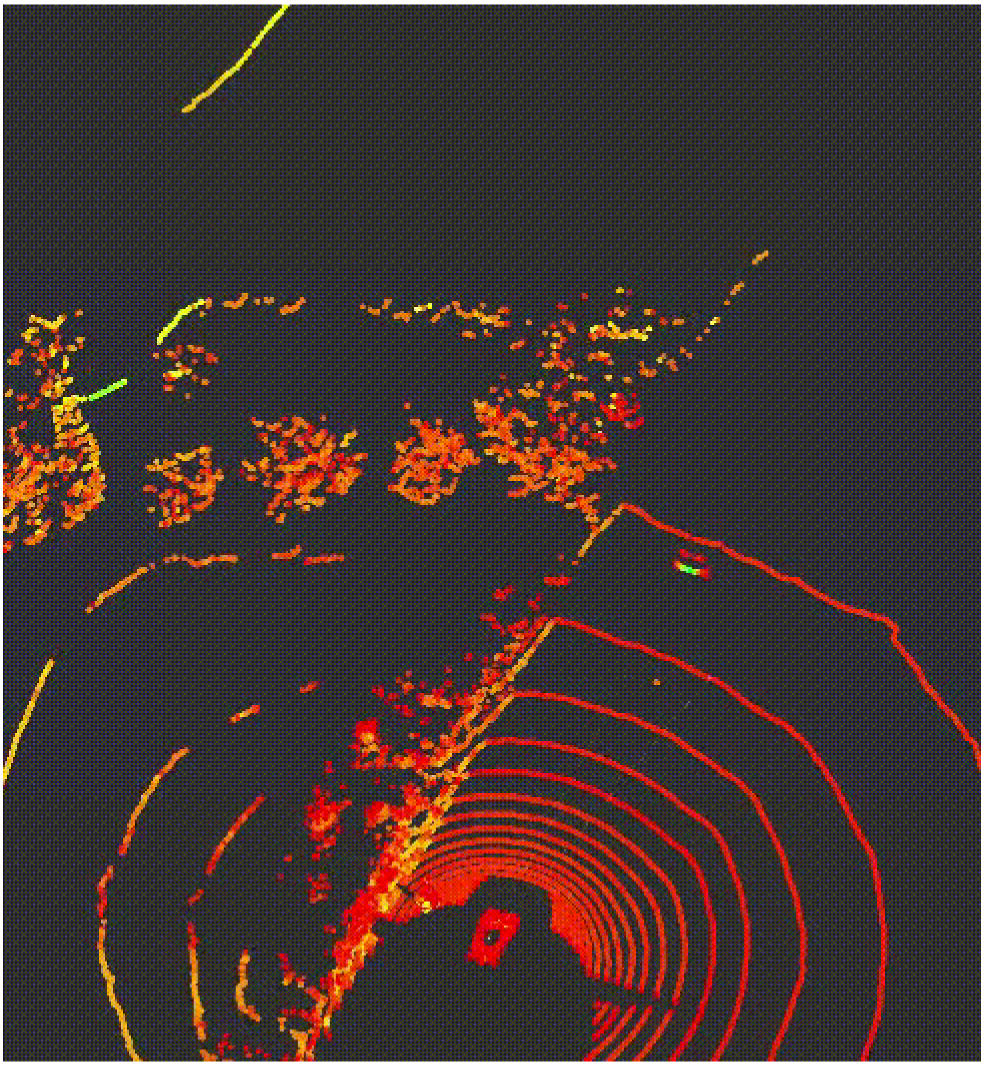
- /cloud_nodelet/parameter_descriptions 1 msg : dynamic_reconfigure/ConfigDescription : Internal data
- /cloud_nodelet/parameter_updates 1 msg : dynamic_reconfigure/Config : Internal data
- /diagnostics 1141 msgs : diagnostic_msgs/DiagnosticArray (3 connections) : Hardware information
- /diagnostics_agg 328 msgs : diagnostic_msgs/DiagnosticArray (2 connections) : Hardware information
- /diagnostics_toplevel_state 328 msgs : diagnostic_msgs/DiagnosticStatus (2 connections) : Hardware information
- /gps/fix 1275 msgs : sensor_msgs/NavSatFix : gps position
- /gps/rtkfix 1639 msgs : nav_msgs/Odometry : gps position
- /gps/time 1559 msgs : sensor_msgs/TimeReference : gps time to harmonize each gpses
- /image_raw 4917 msgs : sensor_msgs/Image : image from the camera
- /obs1/gps/fix 292 msgs : sensor_msgs/NavSatFix : gps position
- /obs1/gps/rtkfix 1634 msgs : nav_msgs/Odometry : gps position
- /obs1/gps/time 1144 msgs : sensor_msgs/TimeReference : gps time to harmonize each gpses
- /radar/points 3277 msgs : sensor_msgs/PointCloud2 : PointCloud data
- /radar/range 3277 msgs : sensor_msgs/Range : PointCloud data
- /radar/tracks 3278 msgs : radar_driver/RadarTracks : PointCloud data
- /rosout 15 msgs : rosgraph_msgs/Log (7 connections) : ROS log
- /tf 16267 msgs : tf2_msgs/TFMessage : Transform
- /velodyne_nodelet_manager/bond 656 msgs : bond/Status (3 connections) : PointCloud data
- /velodyne_packets 1638 msgs : velodyne_msgs/VelodyneScan : PointCloud data
- /velodyne_points 1638 msgs : sensor_msgs/PointCloud2 : PointCloud data These are the ROS data format of topics. These topics are changing in the each frame. In this project, I decided to use only the /image_raw to estimate the position of car, and project it to the 3D Lidar data of velodyne_points.

Exploratory Visualization

Let me show you the visualized data with gif animation, image_raw and pointcloud data.

- camera image view

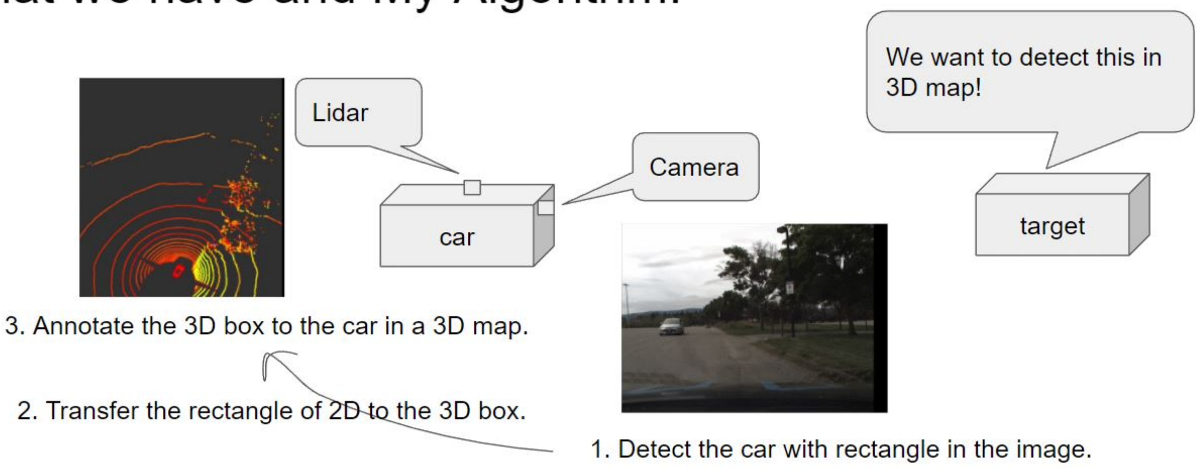
- PointCloud view



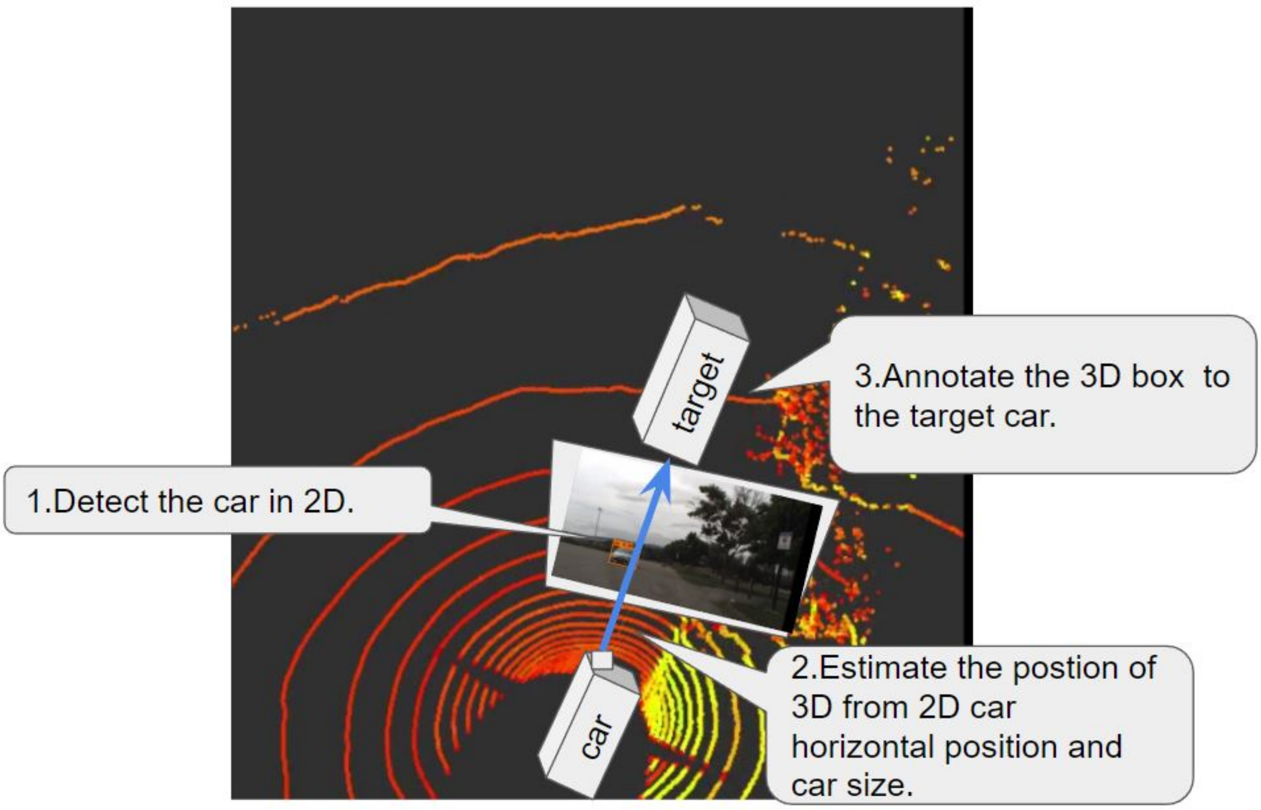
Algorithms and Techniques

Also, in this study, we needed to reproject the position of the car found in 2D to the 3D map. So I thought of an algorithm to estimate these from the car position on the 2D map. To detect cars in the 2D, I use YOLOv2 and KittiBox to compare the prediction of them. In the methodlogical story, 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. These solution will show in the solution report.

What we have and My Algorithm.



How to transfer 2D to 3D.



Benchmark

Here, I will compare the two method of KittiBox and YOLOv2 in the 2D image to evaluate the prediction of the car.

- KittiBox

- YOLOv2

III. Methodology

Implementation

My codes are consist of the files below;

- pipeline.py : main code of processing pipeline

- ImageProcessUtils.py : Utilities of Image processing e.g. Change the image color space, size, apply threshold, and draw boxes.
- generate_tracklet.py : generate result xml file

About pipeline.py

In this file, I implemented the pipeline of the main process of my trial, the abstruct of the pipeline is below;

1. load the image.
2. apply detection to the image, and get rectangle of the object area of car.
3. transfer it to the 3D map.
   Let me show the details.

- About "load the image."

```
images = sorted(glob.glob(os.path.join(path, .jpg)), key=numericalSort)
for fname in images:
        # if using kittibox
        image = mpimg.imread(fname)
        # if using YOLOv2
        image = Image.open(fname)
```

Here is the just only load the image, but the data type of image is not same depends on the library. So, I change how to load the image with matplotlib and PIL.

- About "apply detection to the image, and get rectangle of the object area of car."

```
# if using kittibox
output, bbox = pl.pipeline_kb(image)
# if using YOLOv2
output, bbox = pl.pipeline_yolov2(image)
```

The argment is the image object and return is annotated image as output, and rectangle of the car position as bbox. Additionally each function is below;

```
# Main pipeline process of this project
def pipeline_kb(self, img):
  # convert dtype for uint8 for processing
  img = img.astype(np.uint8)

  # apply kittibox
  out_img, pred_boxes = self.annotate.make_annotate(img, threshold=0.5)

  # stitch windows to centeroid and filter out false positive with heatmap
  heatmap = np.zeros_like(img[:, :, 0])
  heat = self.ipu.add_heat(heatmap, pred_boxes)

  self.ipu.apply_threshold(heat, 100000, 3)
  labels = label(heatmap)
```

```
draw_img = self.ipu.draw_labeled_bboxes(img, labels)

bbox = self.ipu.get_labeled_bboxes(labels)

out_img = draw_img
return out_img, bbox
```

In this kittibox call function, stiich the rectangle to one in the same car using heatmap voted method.

```
# Main pipeline process of this project
def pipeline_yolov2(self, img):

  # apply YOLOv2
  out_img, pred_boxes, pred_classes, pred_scores = self.annotate.make_annotate(img, t


  # get the highest prediction scored rectangle
  max_s = float("-inf")
  bbox = []
  for b, c, s in zip(pred_boxes, pred_classes, pred_scores):
    if c == self.target:
      if s > max_s:
        bbox = [[[b[1], b[0]], [b[3], b[2]]]]
        max_s = s

  return out_img, bbox
```

In this YOLOv2 call function, if there are some rectangle, it neglect the lower scored rectangles, using only highest scored rectangle.

- About "transfer it to the 3D map."

```
def estimate_obstacle_car(bbox):
  bbox = bbox[0]
  # center of the rectangle
  cx = abs((bbox[1][0] + bbox[0][0]) / 2)
  cy = abs((bbox[1][1] + bbox[0][1]) / 2)

  # size of the rectangle
  dx = abs((bbox[1][0] - bbox[0][0]))
  dy = abs((bbox[1][1] - bbox[0][1]))

  # tx, ty and tz are the positions of car in the 3D, x is depth, y is horizontal position and 

  # This equation is from the measurement result of car size and 3D position.
  # tx:dy = 28.7 : 75.9 = 4 : 320
  a = (4 - 28.7) / (320 - 75.9)
  a += -a / 1.5
  b = 28.7 - a * 75.9 - 12 # + is far, - is closer
  tx = a * dy + b
```

```
# This equation is from the measurement result of car size and 3D position.
# ty:cx = 0.2 : 680 = 3.6 : 1293
a = (0.2 - 3.6) / (680. - 1293)
a += a / 3.7
b = 3.6 - a * 680 # + is right, - is left
ty = a * cx + b
ty = -ty + 3.0

# This equation is from the measurement result of car size and 3D position and based o
tz = -0.85
return tx, ty, tz
```

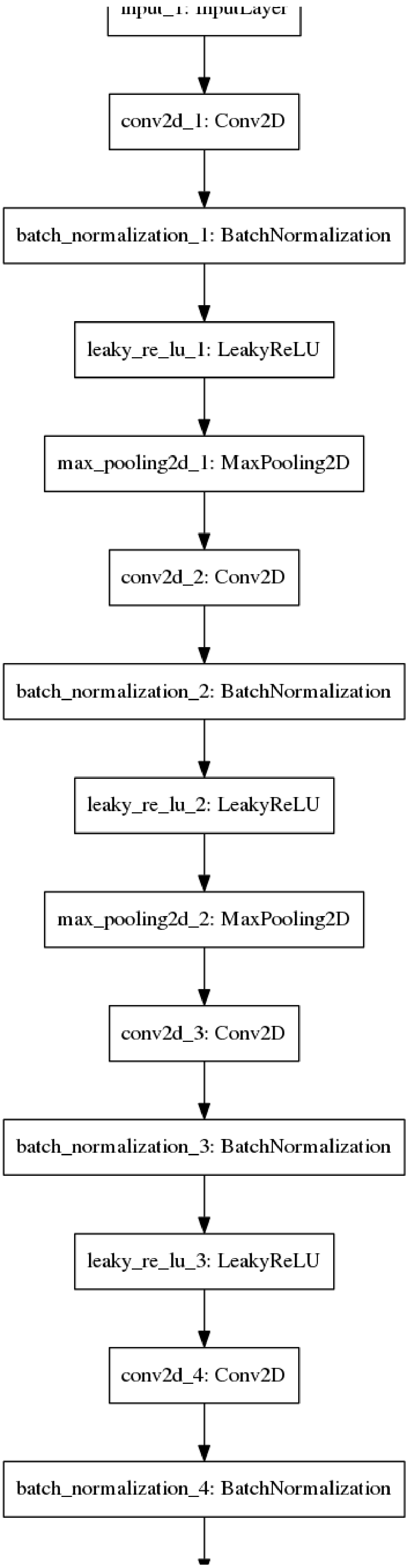
About model

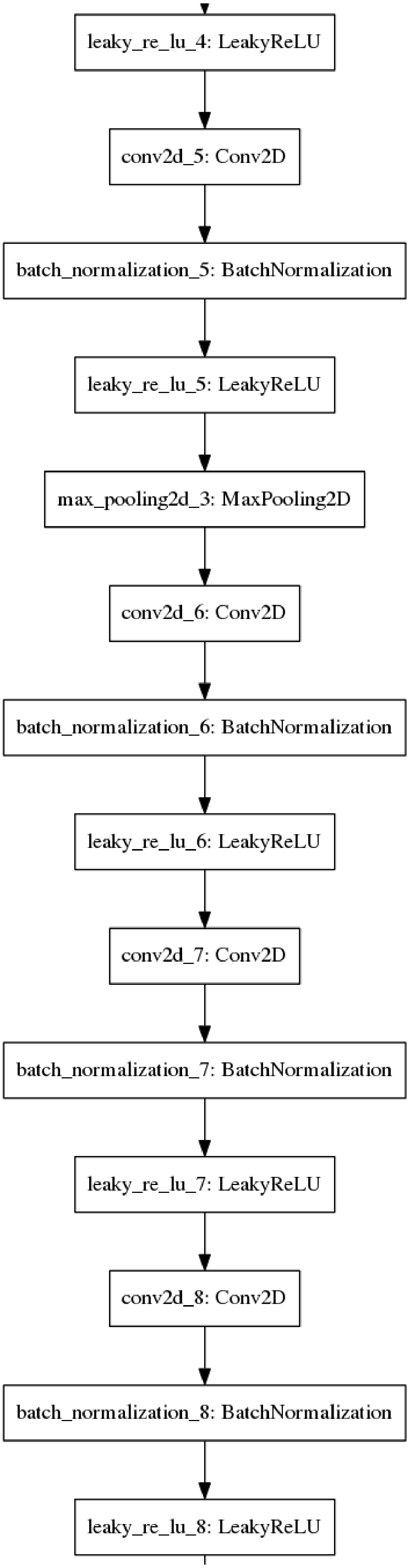
In each library, the DNN is using and the model layer consist of below;

- KittiBox

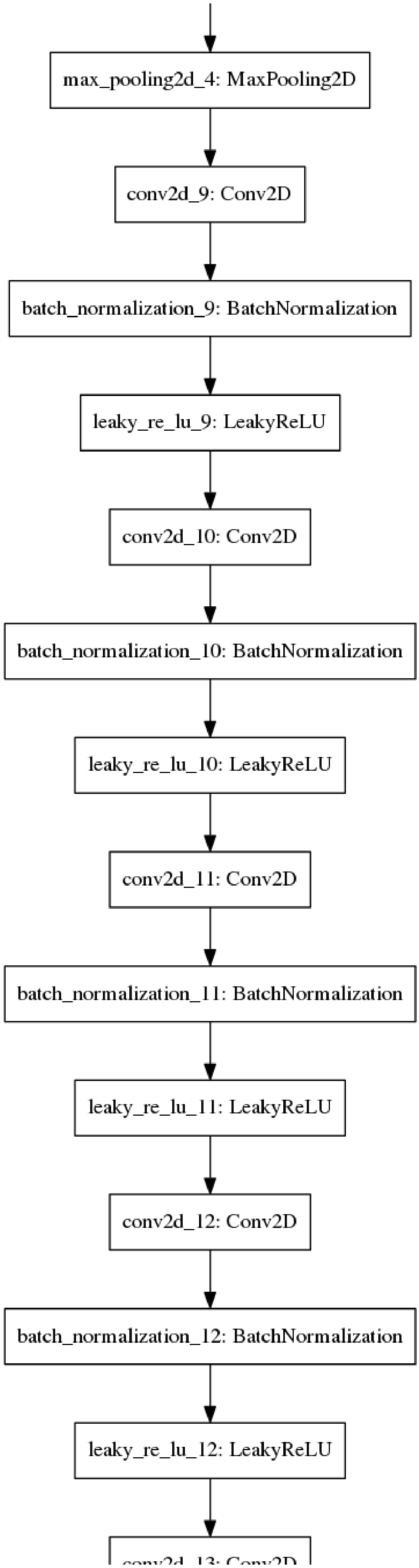
```
Layer name: conv1_1
Layer shape: (3, 3, 3, 64)
Layer name: conv1_2
Layer shape: (3, 3, 64, 64)
Layer name: conv2_1
Layer shape: (3, 3, 64, 128)
Layer name: conv2_2
Layer shape: (3, 3, 128, 128)
Layer name: conv3_1
Layer shape: (3, 3, 128, 256)
Layer name: conv3_2
Layer shape: (3, 3, 256, 256)
Layer name: conv3_3
Layer shape: (3, 3, 256, 256)
Layer name: conv4_1
Layer shape: (3, 3, 256, 512)
Layer name: conv4_2
Layer shape: (3, 3, 512, 512)
Layer name: conv4_3
Layer shape: (3, 3, 512, 512)
Layer name: conv5_1
Layer shape: (3, 3, 512, 512)
Layer name: conv5_2
Layer shape: (3, 3, 512, 512)
Layer name: conv5_3
Layer shape: (3, 3, 512, 512)
Layer name: fc6
Layer shape: [7, 7, 512, 4096]
Layer name: fc7
Layer shape: [1, 1, 4096, 4096]
```

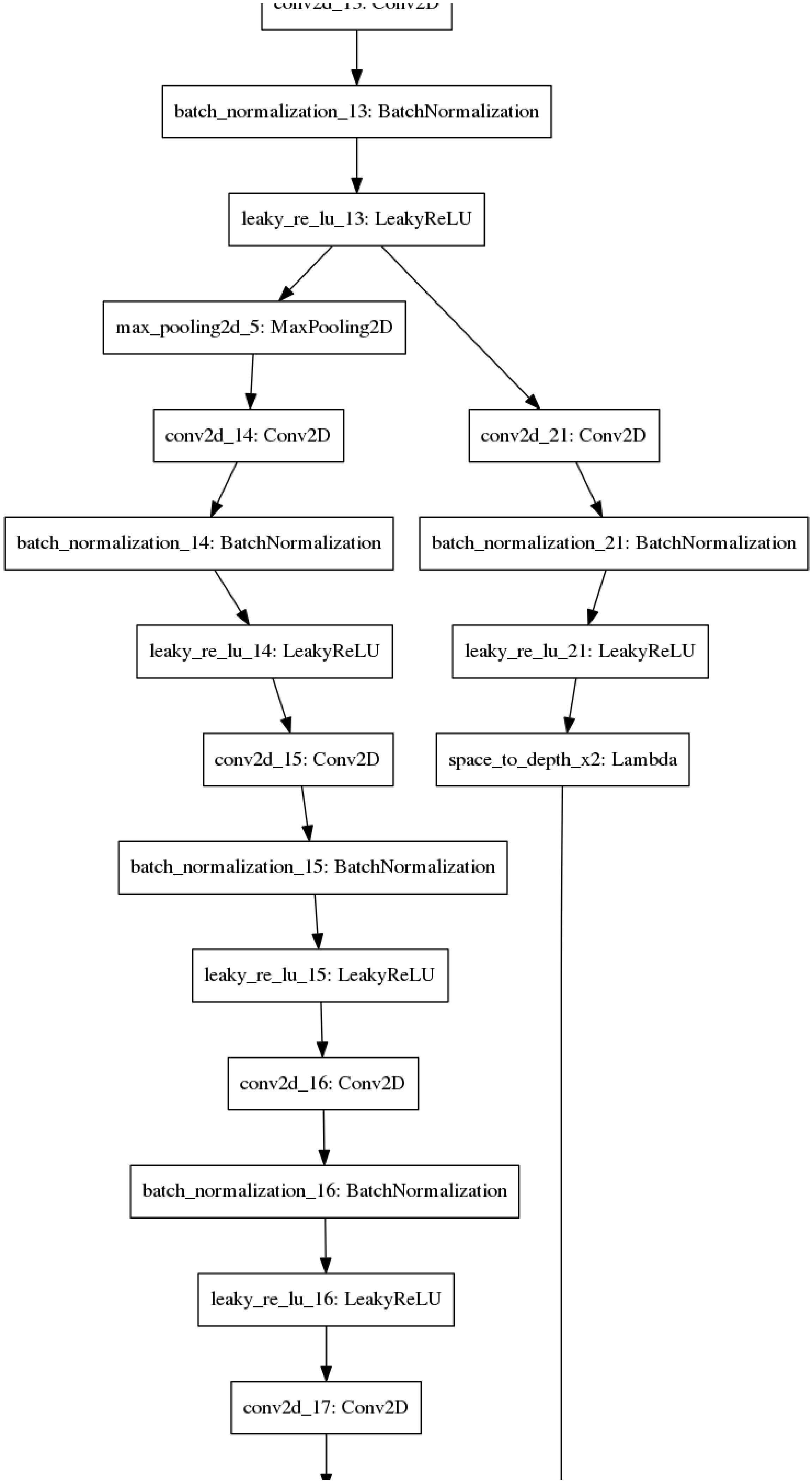
  - YOLOv2

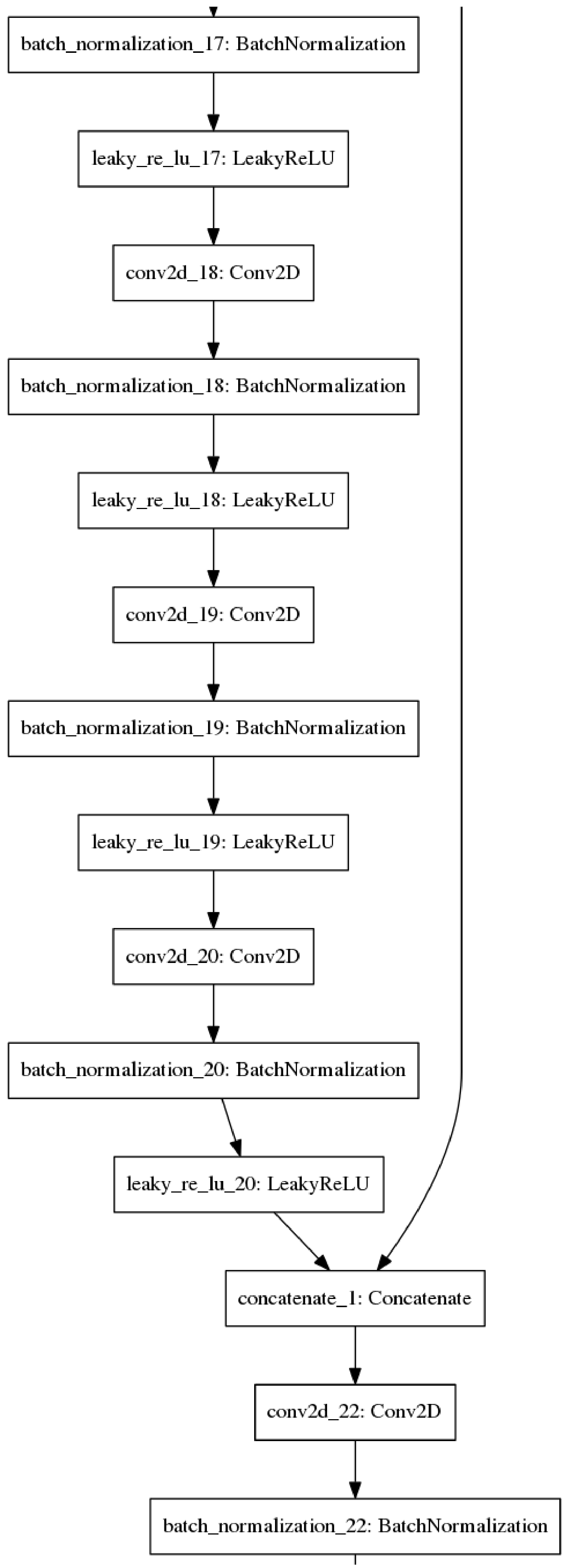

conv2d_1: Conv2D
batch_normalization_1: BatchNormalization
leaky_re_lu_1: LeakyReLU
max_pooling2d_1: MaxPooling2D
conv2d_2: Conv2D
batch_normalization_2: BatchNormalization
leaky_re_lu_2: LeakyReLU
max_pooling2d_2: MaxPooling2D
conv2d_3: Conv2D
batch_normalization_3: BatchNormalization
leaky_re_lu_3: LeakyReLU
conv2d_4: Conv2D
batch_normalization_4: BatchNormalization



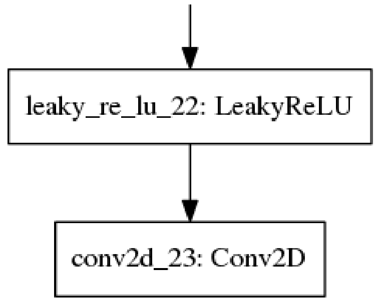
leaky_re_lu_4: LeakyReLU
conv2d_5: Conv2D
batch_normalization_5: BatchNormalization
leaky_re_lu_5: LeakyReLU
max_pooling2d_3: MaxPooling2D
conv2d_6: Conv2D
batch_normalization_6: BatchNormalization
leaky_re_lu_6: LeakyReLU
conv2d_7: Conv2D
batch_normalization_7: BatchNormalization
leaky_re_lu_7: LeakyReLU
conv2d_8: Conv2D
batch_normalization_8: BatchNormalization
leaky_re_lu_8: LeakyReLU


max_pooling2d_4: MaxPooling2D
conv2d_9: Conv2D
batch_normalization_9: BatchNormalization
leaky_re_lu_9: LeakyReLU
conv2d_10: Conv2D
batch_normalization_10: BatchNormalization
leaky_re_lu_10: LeakyReLU
conv2d_11: Conv2D
batch_normalization_11: BatchNormalization
leaky_re_lu_11: LeakyReLU
conv2d_12: Conv2D
batch_normalization_12: BatchNormalization
leaky_re_lu_12: LeakyReLU


conv2d_13: Conv2D
batch_normalization_13: BatchNormalization
leaky_re_lu_13: LeakyReLU
max_pooling2d_5: MaxPooling2D
conv2d_14: Conv2D
conv2d_21: Conv2D
batch_normalization_14: BatchNormalization
batch_normalization_21: BatchNormalization
leaky_re_lu_14: LeakyReLU
leaky_re_lu_21: LeakyReLU
conv2d_15: Conv2D
space_to_depth_x2: Lambda
batch_normalization_15: BatchNormalization
leaky_re_lu_15: LeakyReLU
conv2d_16: Conv2D
batch_normalization_16: BatchNormalization
leaky_re_lu_16: LeakyReLU
conv2d_17: Conv2D



batch_normalization_17: BatchNormalization
leaky_re_lu_17: LeakyReLU
conv2d_18: Conv2D
batch_normalization_18: BatchNormalization
leaky_re_lu_18: LeakyReLU
conv2d_19: Conv2D
batch_normalization_19: BatchNormalization
leaky_re_lu_19: LeakyReLU
conv2d_20: Conv2D
batch_normalization_20: BatchNormalization
leaky_re_lu_20: LeakyReLU
concatenate_1: Concatenate
conv2d_22: Conv2D
batch_normalization_22: BatchNormalization



Refinement

First, I use kittibox, however the accuracy of detection is not good. So, I change the framework to the YOLOv2.

- KittiBox

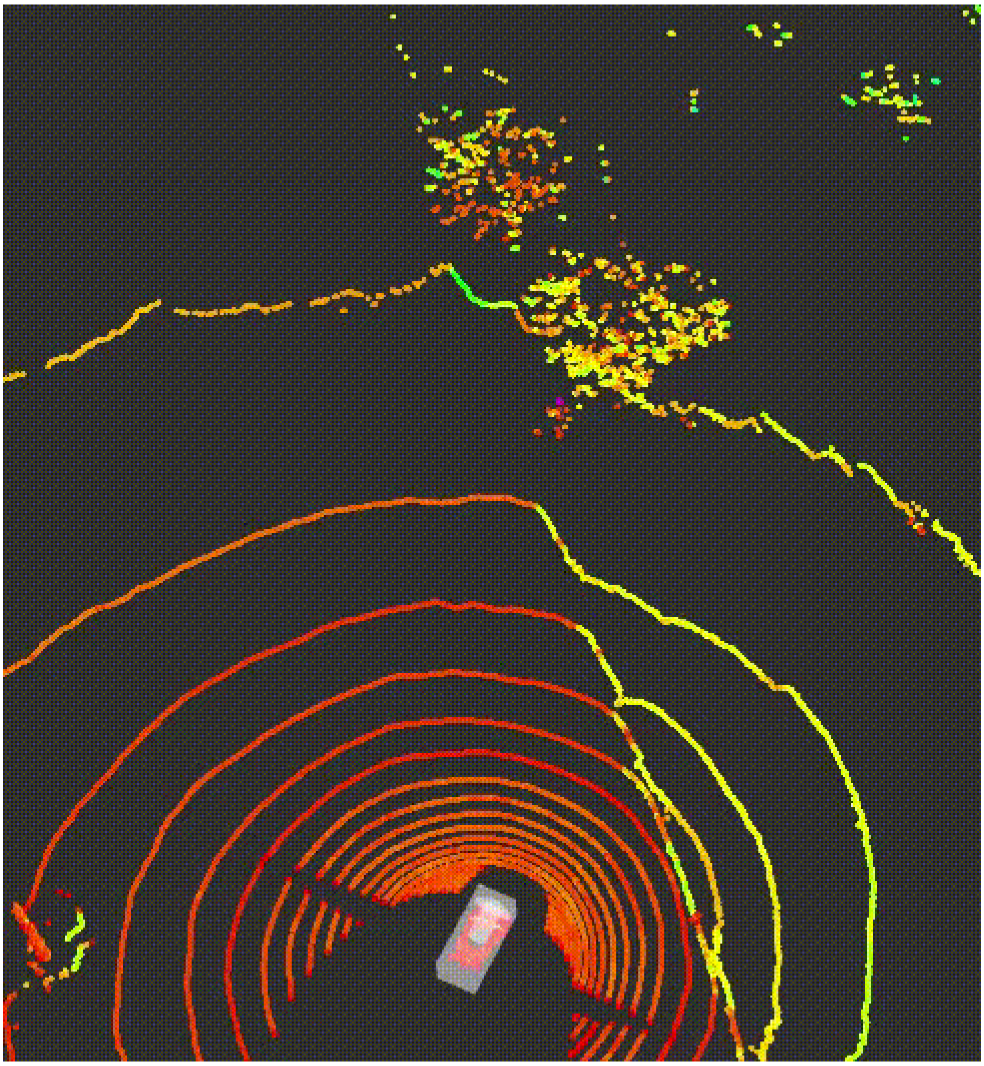
- YOLOv2

IV. Results

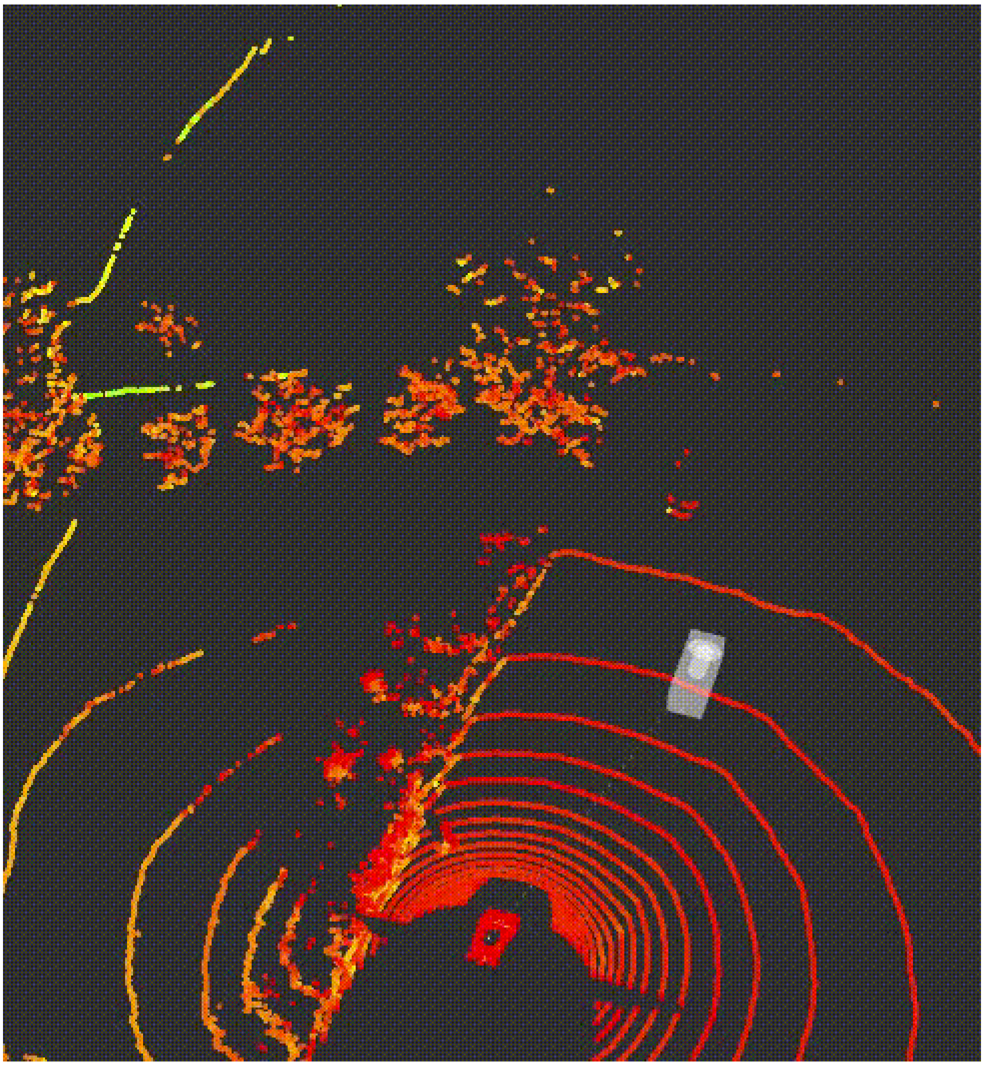
Model Evaluation, Validation and Justification

These are the result of my prediction by YOLOv2, and the box in the 3D is following the car.

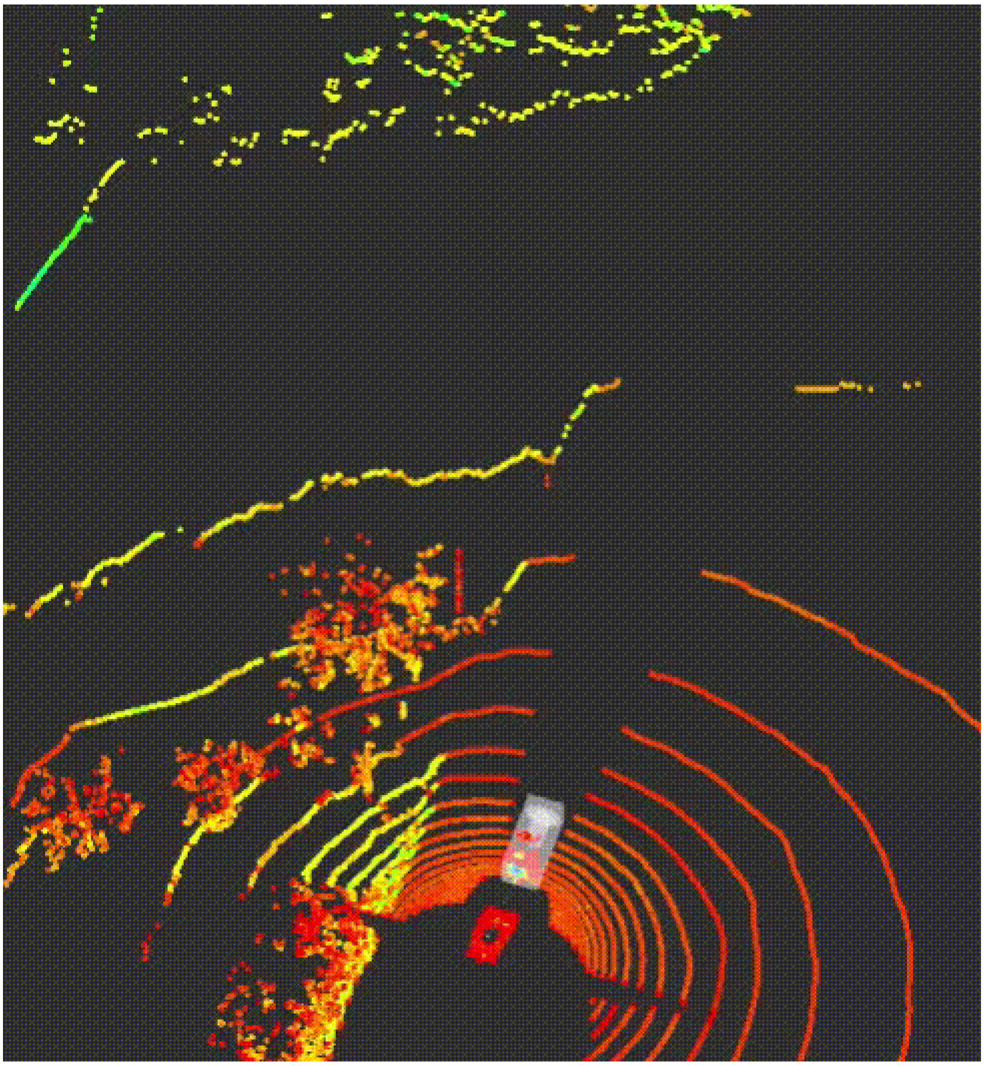
- data : ford01



- data : ford02



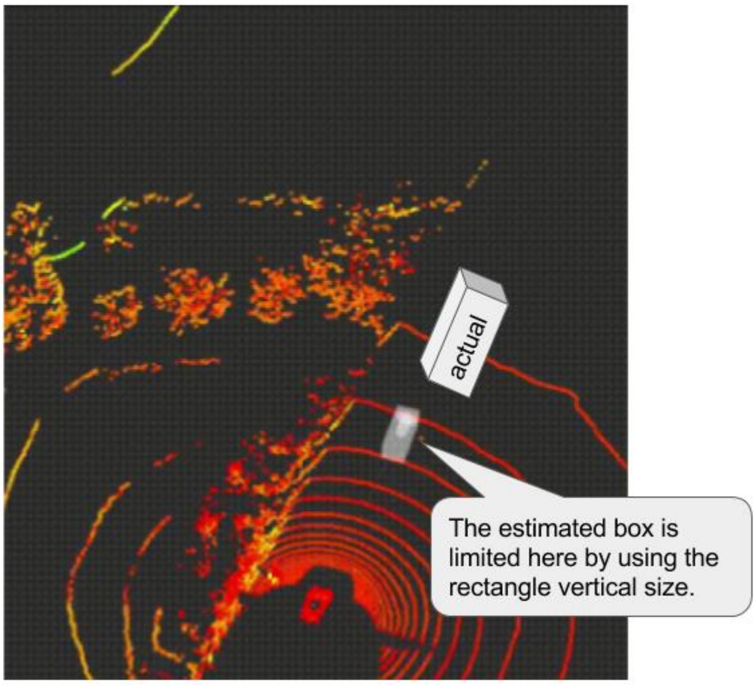
- data : ford03



V. Conclusion

Reflection

In my trial, I use the method of only using 2D picture to estimate the 3D position. This result depends on the prediction of the cars from image so I use the pre-trained model to shortcut. This strategy looks good for me and I can focus on the estimate function from 2D rectangle to 3D box with reasonable precision. About interesting aspects, there are the depth limit of my projection function like below;



I think this is because my estimated model is not good for this problem, but I study a little of optimal theory of perspective it is the fine idea for using the linear equation. So, I think this occurs by using only the image of 2D camera.

Improvement

In the next situation, I will consider below;

- In this trial, I did not consider about image distortion so the result is not well captured in the side of image.
- At a position far from my car the estimater does not clearly detect the object position. This occurs by the limitation of transfer equation is just using the linear function.
- To improve accuracy it should also consider with the PCL data.