CS 498: Assignment 5: 3D Multi Object Tracking

Priyam Mazumdar, priyamm2

April 17, 2022

Submission

You will be submitting two files, "kalman_filter.py" and "matching.py". Please put together a single PDF with your answers and figures for each problem, and submit it to Gradescope (Course Code: JBXJVZ). We recommend you add your answers to the latex template files we provided. More details on what to report are in the provided code.

Reminder: please put your name and netid in your pdf.

Provided Files

Files you will modify:

- kalman_filter.py:
  - define_model (define dynamics)
  - update (observation model)
  - predict (state propagation)
- matching.py (greedy matching algorithm)
- main.py (for visualization and debugging)

Files you will not (need to) modify:

- evaluate.py: run this after running main.py to do evaluation, i.e. "python evaluate.py"
- kitti_calib/oxts.py: these are used for something called ego-motion-compensation, explained in code
- matching_utils.py: contains the function iou(box_a, box_b) which you will need to compute similarity when doing matching
- utils.py: some utils used by main.py, you should look at Box3D
- vis.py: some code for visualizing the data. You only really need vis_obj, which is described more clearly in main.py

File structure

```
data
├── calib
│   └── training
│       └── [seq_name].txt
├── detection
│   └── [seq_name].txt
├── label
│   └── [seq_name].txt
├── oxts
│   └── training
│       └── [seq_name].txt
├── image_02
│   └── training
│       └── [seq_name]
│           └── [frame_num].png
└── results
    ├── eval (files in here will be created automatically)
    └── img_vis (files in here will be created automatically)
```

Multi Object Tracking (MOT)

In this assignment, you will implement a multi object tracker for 3D objects. In other words, given a sequence of frames taken from the perspective of a car, track the other cars in the images. In this project we will develop our tracking algorithm on KITTI dataset(`http://www.cvlibs.net/datasets/kitti/`).

The idea is as follows: we can use a good pre-trained object detector to find objects in each frame (we've already done that for you, check `https://github.com/sshaoshuai/PointRCNN` if you want to know more). Now, simply identifying objects is not good enough, so we want to track them across frames for consistency. You will implement two main methods which together will do this quite well.

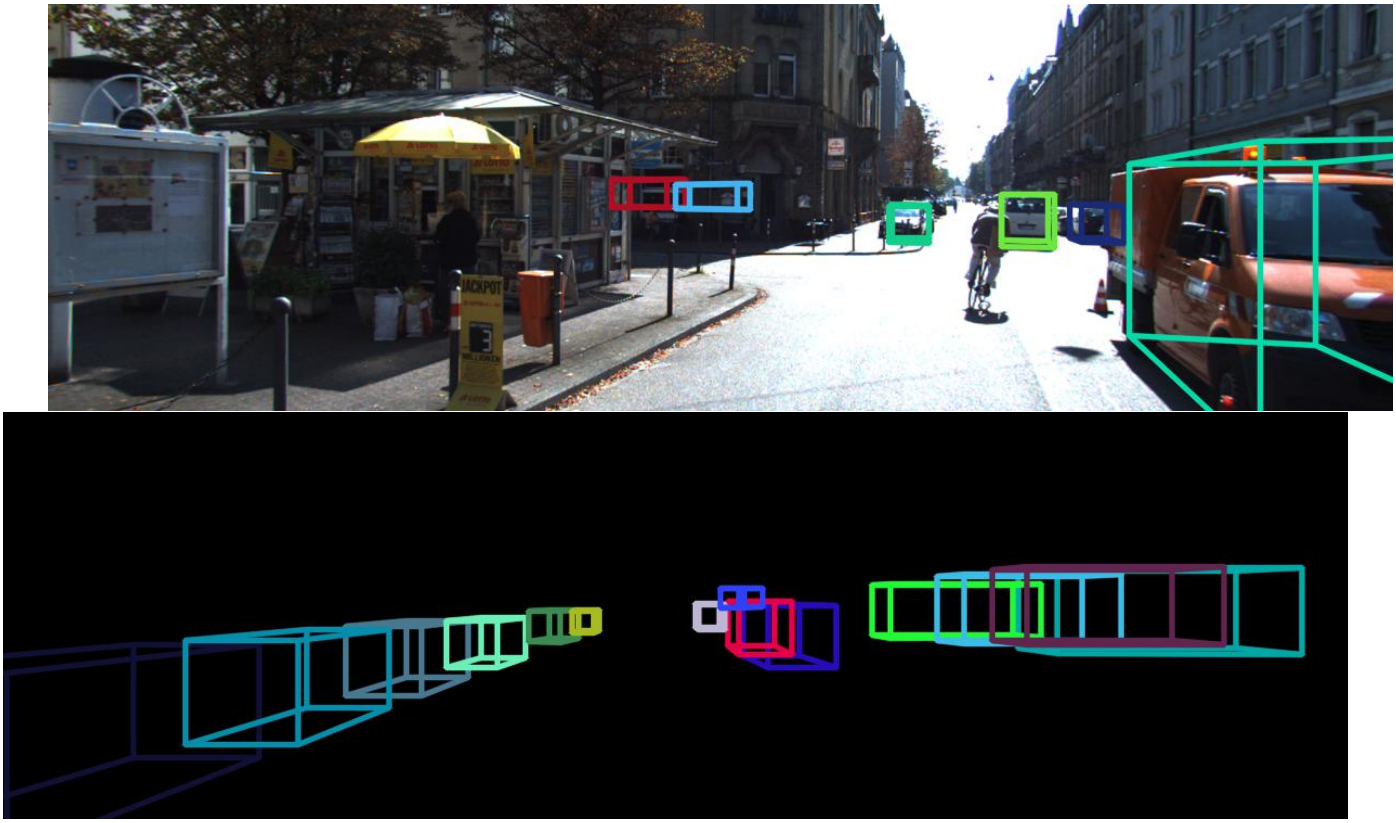
The first is a matching algorithm: given a list of 3D bounding boxes for objects detected by the object detector in the current frame, match them to objects you are already tracking from the previous frame.

The second is a Kalman Filter. Just matching current detections to past trackers is not great since cars can move and therefore the previous and current bounding boxes will not overlap perfectly (this is especially problematic if an object becomes occluded for a few frames). To deal with this issue you will implement a Kalman Filter for forward propagating each object. Moreover, you will now use each object detection to "update" the state of your tracked object, as an observation to the filter.

Question 0 (Inspect the Data)[1 pt]: Before you begin the actual assignment, read the code we've provided. Namely read through "main.py" so you understand the basic structure of the algorithm and the functionality of each component. You will need to modify main.py, but only for debugging/visualization purposes.

For this question, please visualize the detections for frame 100 of the first and second sequences, i.e. sequence 0000 and sequence 0001. Each detection should be a different color. You should work off the code we provided in the Visualization section of main.py.

Please download the images for the first sequence (0000), and put them in the right place in the directory structure above. Use your illinois address to access the drive link: `https://drive.google.com/file/d/15lWATvV4p9UCShnnPa2SEL8BTh2twIm4/view?usp=sharing`



Question 1 (Greedy Matching)[3 pt]: For this question you will be modifying "matching.py". You should implement a greedy matching approach, whereby you match pairs of detections and tracked objects in order of similarity. First match the detection and tracker that are most similar, then remove them from the set, and continue, until you have no trackers or no detections. Also, if the similarity for a match is more than the provided threshold, do not consider the pair a match.

Notice we provide you with "iou(box_a, box_b)" to compute similarity between 3D detected regions.

Question 2 (Trivial Update) [1 pt]: You'll notice that even though you've implemented matching, the trackers themselves don't update location. For this question you will implement a trivial update to each tracker in kalman_filter.py. Given a matched detection z, simply set the associated tracker to have the same bounding box z. In other words, we simply trust the observation 100% when updating the state, neglecting any motion or noise models.

In your pdf please show your code for this part, it should be very simple. Report your evaluation MOTA for this setting (meaning matching=greedy, predict() is unimplemented, and the update is trivial).

Question 2 Answer: My results with trivial updates was a MOTA of 0.8419 on only trial 0000 and 0.7690 across all 21 trials. Below is the simple code of trivial updates:

```
if trivial:
    self.x[:7] = z
```

Question 3 (Kalman Linear Dynamics) [3 pt]: For this part you will fill in define_model() in the class Kalman. The state **x** should consist three dimensional box center, raw angle, three dimensional box size, and finally three dimensional linear velocity (total 10D). The motion model is a constant linear

velocity model in 3D. Your model should be linear, meaning x' = x + dx = Ax. In addition you should define the measurement model and measurement uncertainty, meaning H and Sigma and Q. In your pdf please report A, H, Sigma, Q, and R. Explain why each is set the way it is.

Question 3 Answer: The following are the matrices that I used for running my Kalman Filter

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$Q = \begin{bmatrix} 10 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.01 \end{bmatrix}$$

$$Sigma = \begin{bmatrix} 200 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 200 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 200 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 200 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 200 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 200 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 200 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$R = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Although there was a lot of trial and error to select these matrices, I want to offer some intuition for these choices. From left to right of the matricies, each number indicates some property of x, y, z, theta, l, w, h, dx, dy, dz. First, the setup for matrix A was from lecture 12. We can see that it is an identity matrix, and then the weights corresponding to the dx, dy, and dz for their respective x, y, and z rows are the change in time which I assumed as intervals of 1. Matrix Sigma represents the initial uncertainty of the model, which would be very high at the start. We would not have a good idea of the parameters x, y, z, theta, l, w, and h when initially tracking, but notice that I also set lower values for dx, dy, dz. This is because although we are not fully sure about x, y and z, we have assumed a linear model and the change in x, y and z is more predictable. Similarly for matrix Q, we are adding on additional uncertainty to these values, with less to our dx, dy, and dz. I attempted tuning the R matrix but I got the highest performance from leaving it as an identity. Lastly our H matrix indicates all the variables outside of our change in x, y and z and is used in the update step of X.

Question 4 (Kalman Update) [3 pt]: Now implement a proper Kalman Filter Update step, where you use a matched object detection as a noisy observation for updating the state. See lecture 10-12 for more details.

In your pdf please describe the Kalman Filter linear update mathematically and report your evaluation MOTA under this setting (matching=greedy, predict() unimplemented, update implemented).

Question 4 Answer: The Kalman update step is to update a kalman filter based on an incoming observation. This is done by the following series of steps as described in lecture 12.

$$\mu_{z_{t+1}} = H\mu_{t+1|t} \text{ Update mu for time t+1}$$

$$S_{t+1} = H\Sigma_{t+1|t}H^T + R \text{ Sigma at time t + 1}$$

$$K_{t+1} = \Sigma_{t+1|t}H^T S_{t+1}^{-1} \text{ Update K for time t+1}$$

$$\mu_{t+1|t+1} = \mu t + 1|t + K_{t+1}(z_{t+1} - \mu_{z_{t+1}}) \text{ Full update for state (self.x)}$$

$$\Sigma_{t+1|t+1} = \Sigma t + 1|t - K_{t+1}H\Sigma_{t+1|t} \text{ Full update for Sigma (self.Sigma)}$$

Once the update step was implemented, we saw that our MOTA for 0000.txt for 0.0558 and then 0.0270 across all 21 trials. The reason for this significant fall in performance is that we are updating our model with incoming inputs but we are not actually predicting the new location of our bounding boxes given this information.

Question 5 (Kalman Predict) [2 pt]: Up until now, each frame the detections were compared to each tracker, and then matched trackers were updated. But our matching is poor because the detections and trackers do not overlap (they are one frame apart). In this question you will implement the Kalman Filter Predict step, where you forward propagate the state according to the dynamics model you defined earlier.

In your pdf please describe the predict step, and report your evaluation MOTA under this setting (matching=greedy, predict and update both implemented).

Question 5 Answer: The predict step takes our updated model and then predicts the new location of our bounding boxes. This is done by the following steps:

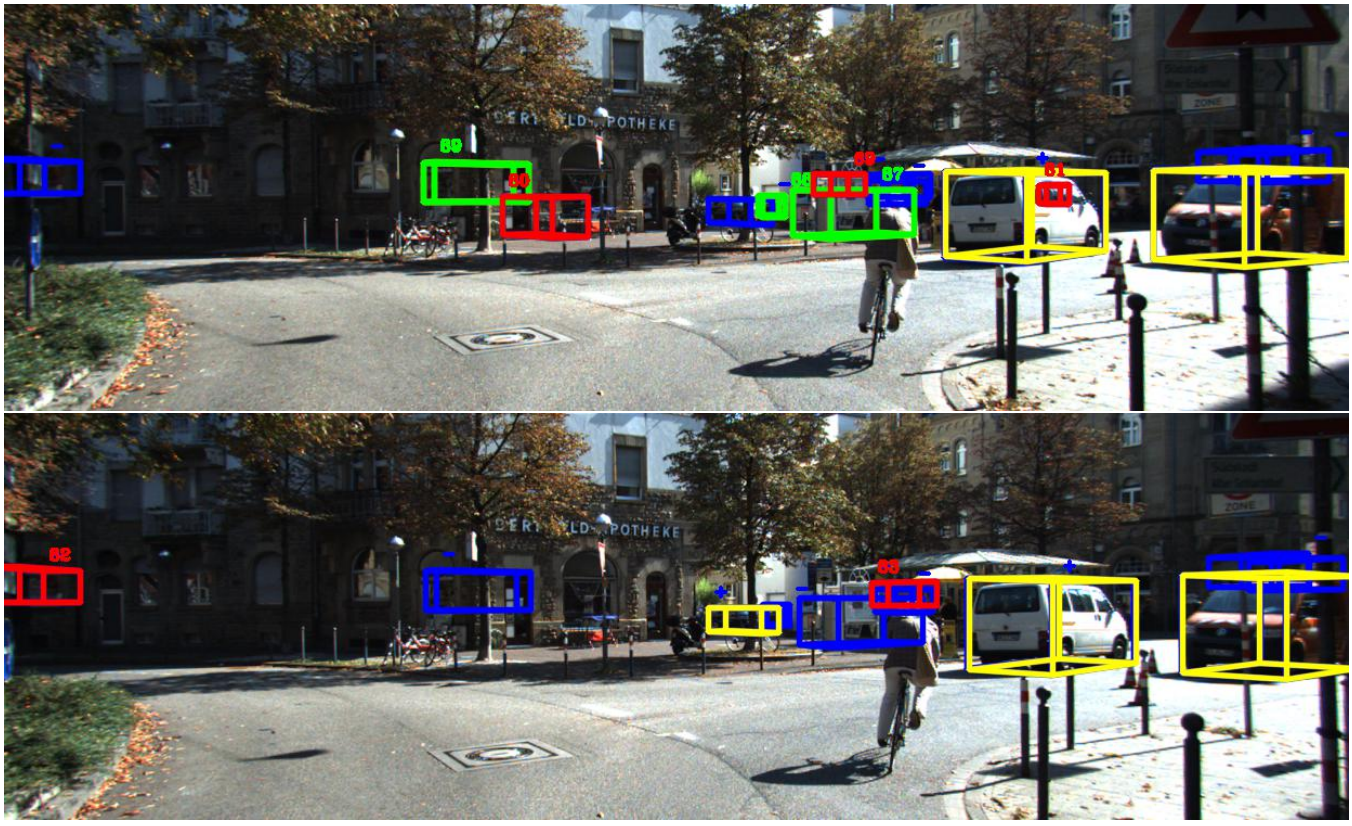
$$\mu_{t+1|t} = A\mu_{t|t} + B\mu_t$$
$$\Sigma_{t+1|t} = A\Sigma_{t|t}A^T + Q$$

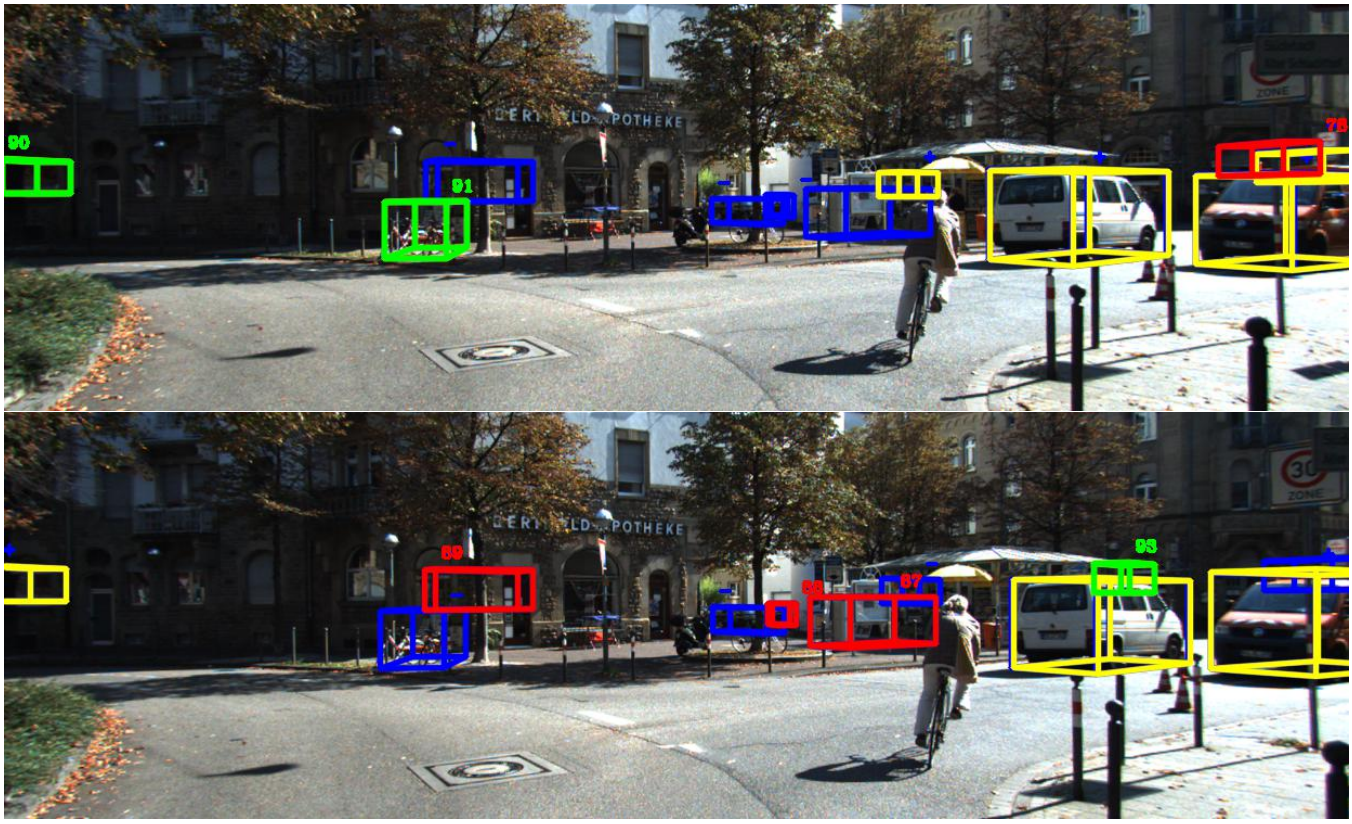
What this is doing is taking the updated matrices from our update step based on the new incoming observation, and then uses that to predict the location of the new bounding box.

The performance of this on 0000.txt was a MOTA of 0.8465 and 0.7759 across all 21 samples. Therefore we see a slight improvement from using only trivial update!

Question 6 (Final Visualization) [1 pt]: Please visualize some results from your final code. Pick at least 4 consecutive frames from sequence 0000. For each frame visualize all in one image:

- Show birthed trackers in green
- Show dead trackers in red
- For the rest of the trackers (these were matched), show each before predict and after update. Show their corresponding detections. Color the trackers in blue and detections in yellow. Add text above each tracker with its ID and the text "-" for before predict or "+" for after update.

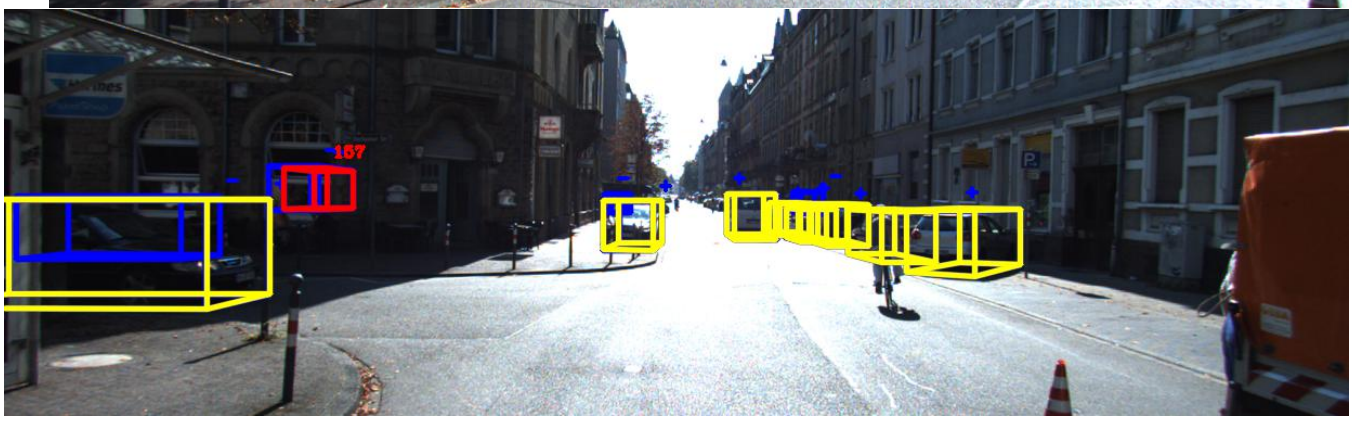




We can see that tracking is happening correctly on our moving white van as well as the parked car on the right. We also see that box 89 in green that is an incorrectly placed tracker also dies in the 4th image as there was no updates to it.

Question 7 (Analysis) [1 pt]: Please run the run `python evaluate.py` and report your MOTA, TPs, ID switches, FRAGs and FPs at the best threshold. Please also visualize at least two failure cases and explain the reason. Please discuss what can be done to avoid these failures.

Question 7 Answer: Final evaluation of our model:
MOTA: 0.7897
TP: 3057
ID Switches: 0
FRAG: 17
FP: 514



We can see that we have two cases of failure here with incorrectly predicted boxes. There are two ways we can improve this: - First we have to double check the accuracy of our detectors. We could potentially find some ways to filter our poor detectors which would immediately solve our problem. - If the first is not possible, then we can reduce the time till the death of a tracker. This way any misplaced trackers will exist for shorter periods of time and improve the overall accuracy.