Data Structure and a Naive Model

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0. Quantitative question

- Can we design a self-driving car?
- Can we predict the appropriate acceleration and steering angle based on data collected by the camera and GPS, such as speed, acceleration, steering angle and camera images?

1. Data Structure

45 GB compressed, 80 GB uncompressed (unzip it in Windows 10, not Mac OS)

```
list.files(file.path("comma-dataset"), recursive = T)
```

```
##  [1] "camera/2016-01-30--11-24-51.h5" "camera/2016-01-30--13-46-00.h5"
##  [3] "camera/2016-01-31--19-19-25.h5" "camera/2016-02-02--10-16-58.h5"
##  [5] "camera/2016-02-08--14-56-28.h5" "camera/2016-02-11--21-32-47.h5"
##  [7] "camera/2016-03-29--10-50-20.h5" "camera/2016-04-21--14-48-08.h5"
##  [9] "camera/2016-05-12--22-20-00.h5" "camera/2016-06-02--21-39-29.h5"
## [11] "camera/2016-06-08--11-46-01.h5" "LICENSE"
## [13] "log/2016-01-30--11-24-51.h5"    "log/2016-01-30--13-46-00.h5"
## [15] "log/2016-01-31--19-19-25.h5"    "log/2016-02-02--10-16-58.h5"
## [17] "log/2016-02-08--14-56-28.h5"    "log/2016-02-11--21-32-47.h5"
## [19] "log/2016-03-29--10-50-20.h5"    "log/2016-04-21--14-48-08.h5"
## [21] "log/2016-05-12--22-20-00.h5"    "log/2016-06-02--21-39-29.h5"
## [23] "log/2016-06-08--11-46-01.h5"
```

We will need 'h5' package to extract data from *.h5 files.

```
library("h5")
log <- H5File(file.path("comma-dataset", "log", "2016-06-08--11-46-01.h5"))
```

```
## Warning in H5File(file.path("comma-dataset", "log",
## "2016-06-08--11-46-01.h5")): This function is deprecated, use h5file
## instead
```

```
image <- H5File(file.path("comma-dataset", "camera", "2016-06-08--11-46-01.h5"))
```

```
## Warning in H5File(file.path("comma-dataset", "camera",
## "2016-06-08--11-46-01.h5")): This function is deprecated, use h5file
## instead
```

```
log_names <- list.datasets(log, recursive = TRUE)
image_names <- list.datasets(image, recursive = TRUE)
```

So the function insists that I am deprecating it. Well.

1.1 Image Data

The image part are pixel images, 20 pic per sec, 320*160 pixels per pic, with RGB format.

```r
image[image_names]  #check the image we loaded
```

```
## DataSet 'X' (18177 x 3 x 160 x 320)
## type: integer
## chunksize: 1024 x 3 x 160 x 320
## maxdim: 18177 x 3 x 160 x 320
```

So the dimension is **Frames * RGB * Columns * Rows**.

Image data are basically **4 d arrays**.

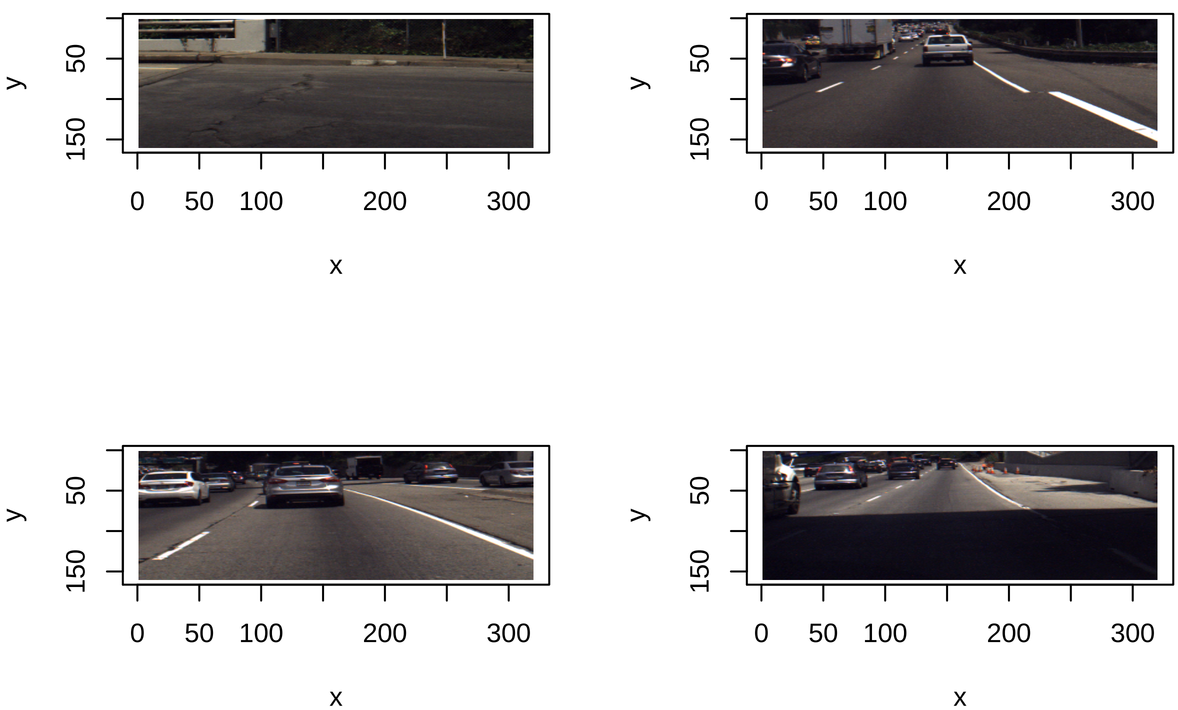
```r
range(image[image_names][1,,,])
```

```
## [1]  20 255
```

The values coincide with RGB format.

Actually why don't we check some of the images:

```r
library(imager)
par(mfrow = c(2, 2))
plot(as.cimg(aperm(image[image_names][10001,,,], c(4,3,1,2))))  #the start of training set
plot(as.cimg(aperm(image[image_names][13001,,,], c(4,3,1,2))))  #the end of training set
plot(as.cimg(aperm(image[image_names][14002,,,], c(4,3,1,2))))  #the start of test set
plot(as.cimg(aperm(image[image_names][15002,,,], c(4,3,1,2))))  #the end of test set
```



```
par(mfrow = c(1, 1))
```

Difficulties to overcome:

Sometimes the roads are with lines while sometimes they don't;

It could be a truck but it also could be the shadow (cars in the same direction do stay longer though).

1.2 Log Data

reference: link to comma.ai github

The log files are with the same names, but under the "./comma-dataset/log/" folder.

Let's check the first hierachy of the log:

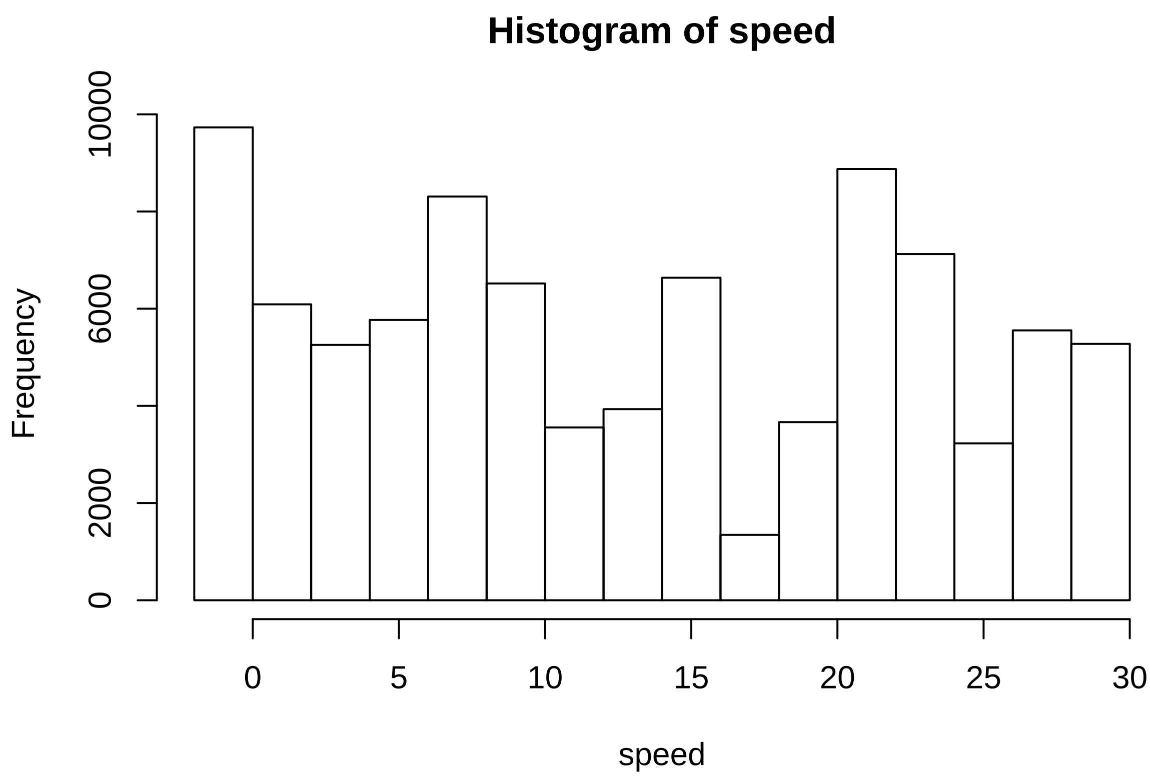
```
log_names
```

```
##  [1] "/UN_D_cam1_ptr"     "/UN_D_lidar_ptr"    "/UN_D_radar_msg"
##  [4] "/UN_D_rawgps"       "/UN_T_cam1_ptr"     "/UN_T_lidar_ptr"
##  [7] "/UN_T_radar_msg"    "/UN_T_rawgps"       "/blinker"
## [10] "/brake"             "/brake_computer"    "/brake_user"
## [13] "/cam1_ptr"          "/car_accel"         "/fiber_accel"
## [16] "/fiber_compass"     "/fiber_compass_x"   "/fiber_compass_y"
## [19] "/fiber_compass_z"   "/fiber_gyro"        "/fiber_temperature"
## [22] "/gas"               "/gear_choice"       "/idx"
## [25] "/rpm"               "/rpm_post_torque"   "/selfdrive"
## [28] "/speed"             "/speed_abs"         "/speed_fl"
## [31] "/speed_fr"          "/speed_rl"          "/speed_rr"
## [34] "/standstill"        "/steering_angle"    "/steering_torque"
## [37] "/times"             "/velodyne_gps"      "/velodyne_heading"
## [40] "/velodyne_imu"
```

There are speed[28], acceleration[14], steering angle[35], steering torque[36].

Check the speed first:

```
temp <- log[log_names[28]]@dim
speed <- log[log_names[28]][1:temp]
rm(temp)
hist(speed)
```

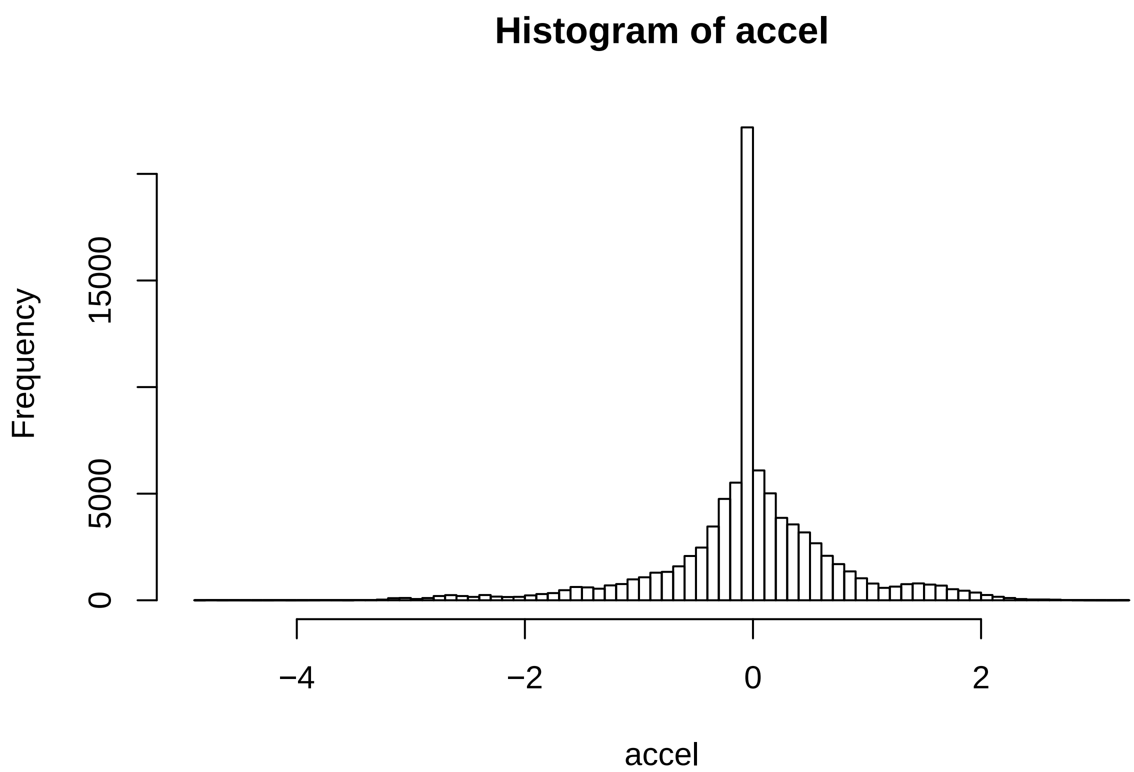


Acceleration:

```
temp <- log[log_names[14]]@dim
accel <- log[log_names[14]][1:temp]
rm(temp)
range(accel)
```

```
## [1] -4.844243  3.290349
```

```
hist(accel, breaks = 100)
```



Most of the time, the car keeps its speed;

```r
sum(accel > 0.8)
```

```
## [1] 9393
```

```r
sum(accel < -0.8)
```

```
## [1] 9919
```

```r
length(accel)
```

```
## [1] 90870
```

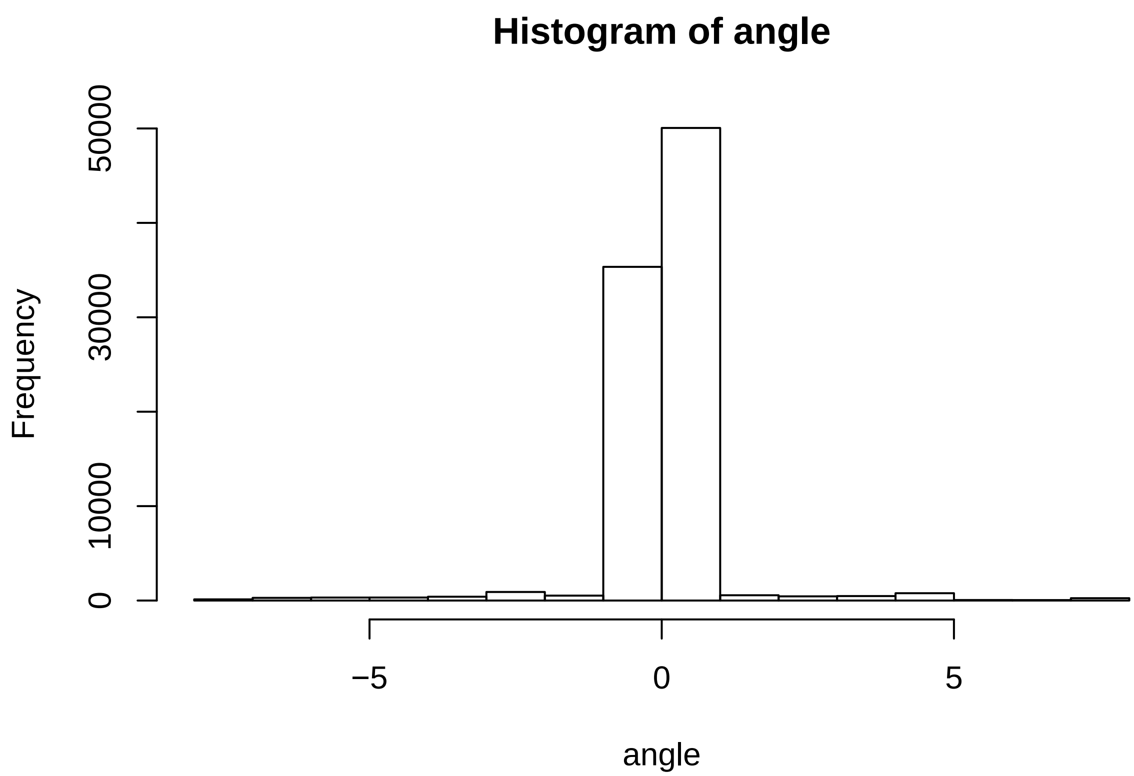
```r
accel_tri <- 1 * (accel > 0.8) - 1 * (accel < - 0.8)  #this is the "answer" for supervised learning
```

It would be great if we can first of all predict accelerating/slowing down/keeping speed status.

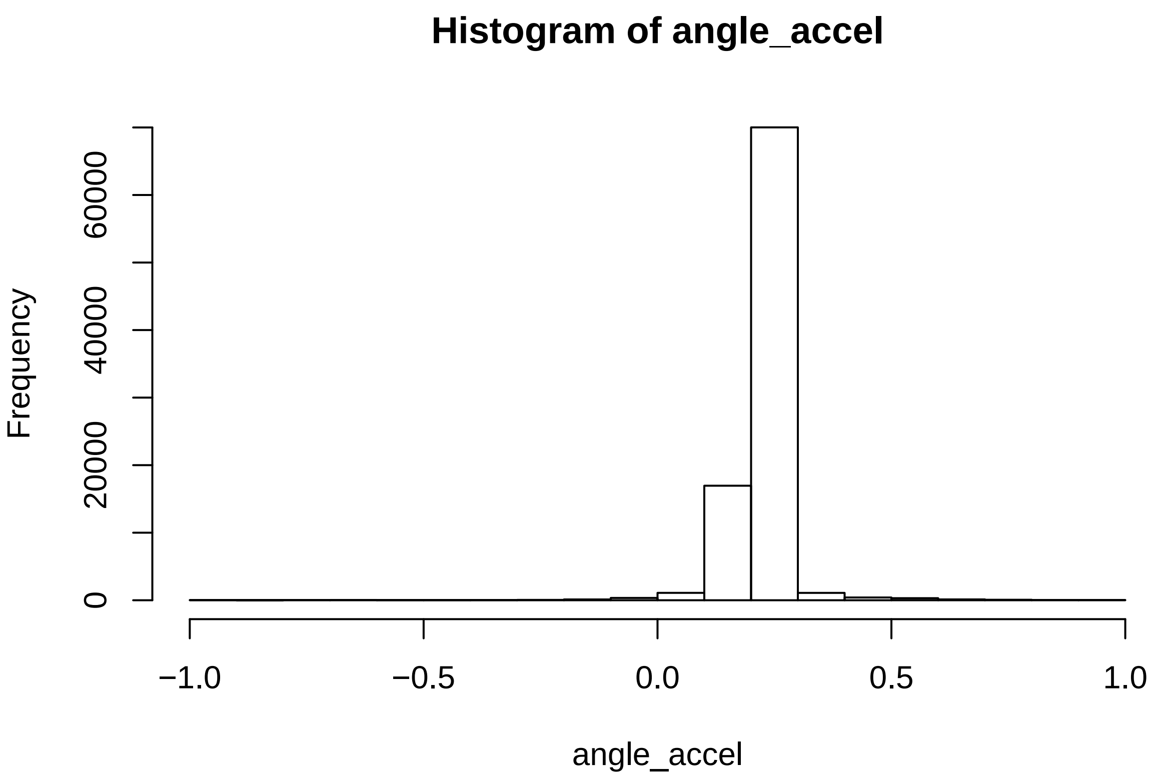
Steering:

```r
library(scales)

temp <- log[log_names[35]]@dim
angle <- log[log_names[35]][1:temp]
rm(temp)
angle <- scale(angle)
```

```r
temp <- log[log_names[36]]@dim
angle_accel <- log[log_names[36]][1:temp]
rm(temp)
angle_accel <- rescale(angle_accel, to = c(-1, 1))

hist(angle)
```




```r
hist(angle_accel)
```



It would help the training that we scale the variables.

1.3 Timeline

The "/cam1_ptr" in log file records the timeline.

```
temp <- log[log_names[13]]@dim
timeline_image <- log[log_names[13]][1:temp]
rm(temp)
length(timeline_image)
```

```
## [1] 90870
```

```
range(timeline_image)
```

```
## [1]     0 18176
```

Simple calculation:

There are 90870 time points in log, 18176 time points in image;

100Hz for log; 20Hz for image;

$90870/100 = 18176/20 = 908.8$ sec $= 15.1$ min;

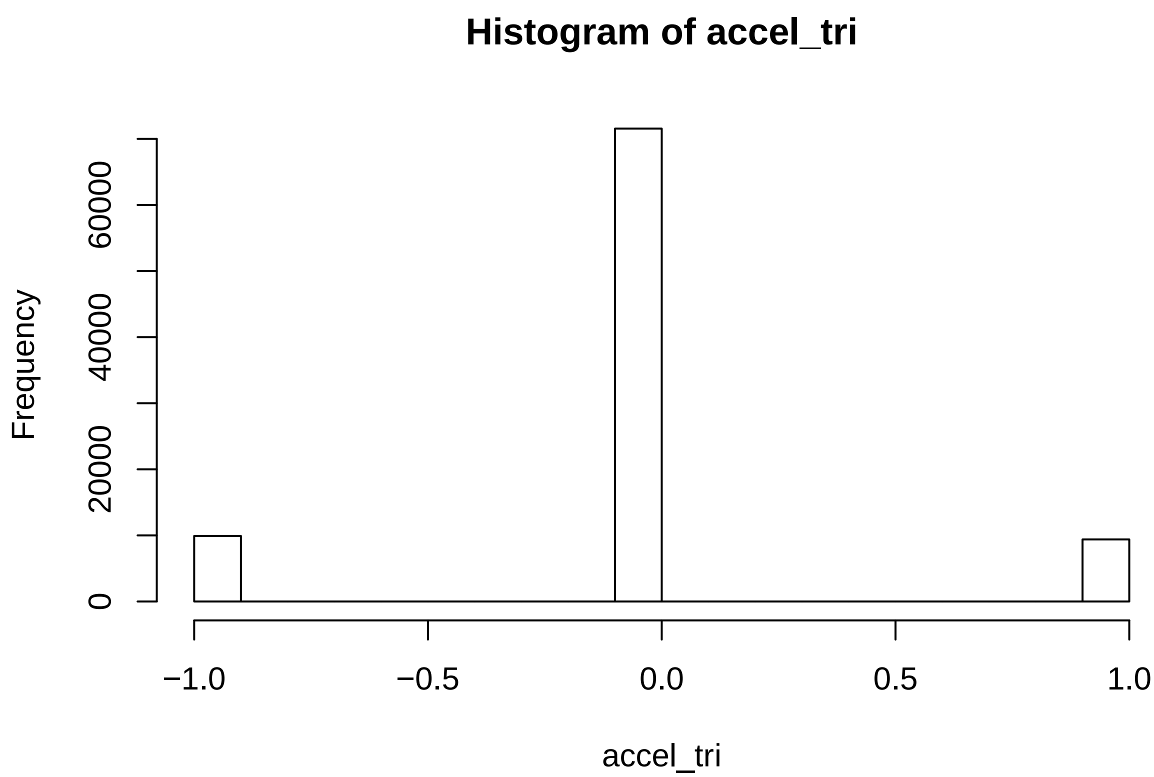
It is the shortest driving set.

2. A Naive Model

We will predict acceleration status, but we won't use image for now.

So it is a helpful warmup for convolutional network training.

```
hist(accel_tri)
```



The naive model:

Acceleration status ~ 10sec **speed** + 10sec **steering angle** + 10sec **angle acceleration**

2.1 Training, Validation and Testing set

```
set.seed(160920)
index_train <- sample(50001:65000, size = 10000)
index_validation <- setdiff(50001:65000, index_train)
index_test <- 70001:75000

set_train <- matrix(0, 10000, 31)
set_train[,1] <- as.matrix(accel_tri[index_train])
for (i in 1:10) {
    set_train[,i + 1] <- speed[index_train-i*100]
    set_train[,i + 11] <- angle[index_train-i*100]
    set_train[,i + 21] <- angle_accel[index_train-i*100]
}
```

```r
set_validation <- matrix(0, 5000, 31)
set_validation[,1] <- as.matrix(accel_tri[index_validation])
for (i in 1:10) {
    set_validation[,i + 1] <- speed[index_validation-i*100]
    set_validation[,i + 11] <- angle[index_validation-i*100]
    set_validation[,i + 21] <- angle_accel[index_validation-i*100]
}

set_test <- matrix(0, 5000, 31)
set_test[,1] <- as.matrix(accel_tri[index_test])
for (i in 1:10) {
    set_test[,i + 1] <- speed[index_test-i*100]
    set_test[,i + 11] <- angle[index_test-i*100]
    set_test[,i + 21] <- angle_accel[index_test-i*100]
}
```

2.2 Fitting with random forests

```r
library(randomForest)
model_naive <- randomForest(set_train[,2:31], as.factor(set_train[,1]))

sum(predict(model_naive, set_validation[,2:31]) == set_validation[,1])/5000  #validation
```

```
## [1] 0.9926
```

```r
sum(predict(model_naive, set_test[,2:31]) == set_test[,1])/5000  #test
```

```
## [1] 0.6182
```

The validation set is contaminated.

```r
sum(predict(model_naive, set_test[set_test[,1] == 0 ,2:31]) == set_test[set_test[,1] == 0 ,1])/sum(set_t
```

```
## [1] 0.8944928
```

```r
sum(predict(model_naive, set_test[set_test[,1] == 1 ,2:31]) == set_test[set_test[,1] == 1 ,1])/sum(set_t
```

```
## [1] 0.006711409
```

```r
sum(predict(model_naive, set_test[set_test[,1] == -1 ,2:31]) == set_test[set_test[,1] == -1 ,1])/sum(set
```

```
## [1] 0
```

So we can see that the image data is needed.

3. Plan this week

The project is difficult in two meanings:

```
- We need to deal with image data;
- Convolutional learning is always difficult.
```

In addition, we will need to predict acceleration and steering angle in the end.

Tasks:

- Example codes for angle prediction; visualizing the results
- Simple ideas for image data: stamping out by grid regions; outlier detection
- Papers regarding convolutional learning
- A slightly improved model with images involved