IoT attack detection

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Contents

Introduction

The **detection_of_IoT_botnet_attacks_N_BaIoT** data set[1] contains a traffic data from 9 commercial IoT (*Internet of Things*) devices authentically infected by Mirai and BASHLITE (Gafgyt).

The data set has 115 attributes (parameters), below is the description of their headers:

1. It has 5 time-frames: L5 (1 min), L3 (10 sec), L1 (1.5 sec), L0.1 (500 ms) and L0.01 (100 ms)[2].
2. The statistics extracted from each traffic stream for each time-frame:
    - *weight*: the weight of the stream (can be viewed as the number of items observed in recent history)
    - *mean*
    - *std (variance)*
    - *radius*: the root squared sum of the two streams' variances
    - *magnitude*: the root squared sum of the two streams' means
    - *covariance*: an approximated covariance between two streams

[1] https://archive.ics.uci.edu/ml/datasets/detection_of_IoT_botnet_attacks_N_BaIoT
[2] https://arxiv.org/pdf/1805.03409.pdf, p.3

- *pcc*: an approximated correlation coefficient between two streams

3. It has following stream aggregations:
    - *MI*: ("Source MAC-IP" in N-BaIoT paper) Stats summarizing the recent traffic from this packet's host (IP + MAC)
    - *H*: ("Source IP" in N-BaIoT paper) Stats summarizing the recent traffic from this packet's host (IP)
    - *HH*: ("Channel" in N-BaIoT paper) Stats summarizing the recent traffic going from this packet's host (IP) to the packet's destination host.
    - *HH_jit*: ("Channel jitter" in N-BaIoT paper) Stats summarizing the jitter of the traffic going from this packet's host (IP) to the packet's destination host.
    - *HpHp*: ("Socket" in N-BaIoT paper) Stats summarizing the recent traffic going from this packet's host+port (IP) to the packet's destination host+port. Example 192.168.4.2:1242 -> 192.168.4.12:80

Thus, the column *'MI_dir_L5_weight'* in the data set shows the weight of the recent traffic from the packet's host for L5 time-frame.

I've added extra *'botnet'* column, where I keep information about attacks from the different botnets and benign traffic. I've used "ga_" prefix for Gafgyt attacks, and "ma_" prefix for Mirai attacks. List of attacks executed and tested can be found in "N-BaIoT: Network-based Detectionof IoT Botnet Attacks Using Deep Autoencoders"[3] article.

Data set structure can be found in **"Appendix. Data set structure"**.

The team that collected this data set used 2/3 of their benign traffic (their train set) to train their *deep autoencoder*. Then they used remaining 1/3 of benign traffic and all the malicious data (their test set) to detect anomalies with *deep autoencoder*. The detection of the cyber attacks launched from each of the above IoT devices concluded with 100% TPR.

In HarvardX PH125.9x Data Science course we learned several algorithms that can be used for classification, such as **KNN**, **rpart** or **randomForest**.

My aim in this project is to check how well these algorithms can detect anomalies (classify benign traffic or attack) in the data set, how accurate can they perform classification. I have no intention to compare algorithms between each other.

The source data set consists of *.csv and *.rar files, each representing the benign traffic or attack, that are divided into folders with device names[4]. Because R has no package that can unpack *.rar files on its own, so all *.rar archives have to be manually unpacked with command line or third-party applications, depending on the OS. Therefore, I had to prepare the data set for this project that can be easily downloaded.

The size of the whole data set was more that 1TB. Nowadays it's not a problem to find a hosting to share this large data set, but I thought that anyone who will check this project won't be happy to download it. Because the team that collected this data set trained and tested their *deep autoencoder* for each device separately, I decided that I can use the data only from one device for my project. I've used the data only from *Danmini doorbell* device, but the data for other devices can be downloaded from the source and prepared for classification using provided *download-data.R* script.

The data set for *Danmini doorbell* has the size of 970MB in *data.csv* file and only 200MB in *data.zip* archive. I used the third-party file hosting to share it, because the archive file size exceeds GitHub limits of file size that can be stored on it.

The archive file is downloading during the first time when using project's script and saving as *data.csv* file in a local project data folder. For next time, saved *data.csv* file is used.

[3] https://arxiv.org/pdf/1805.03409.pdf, p.5

[4] https://archive.ics.uci.edu/ml/machine-learning-databases/00442

Dataset analisys

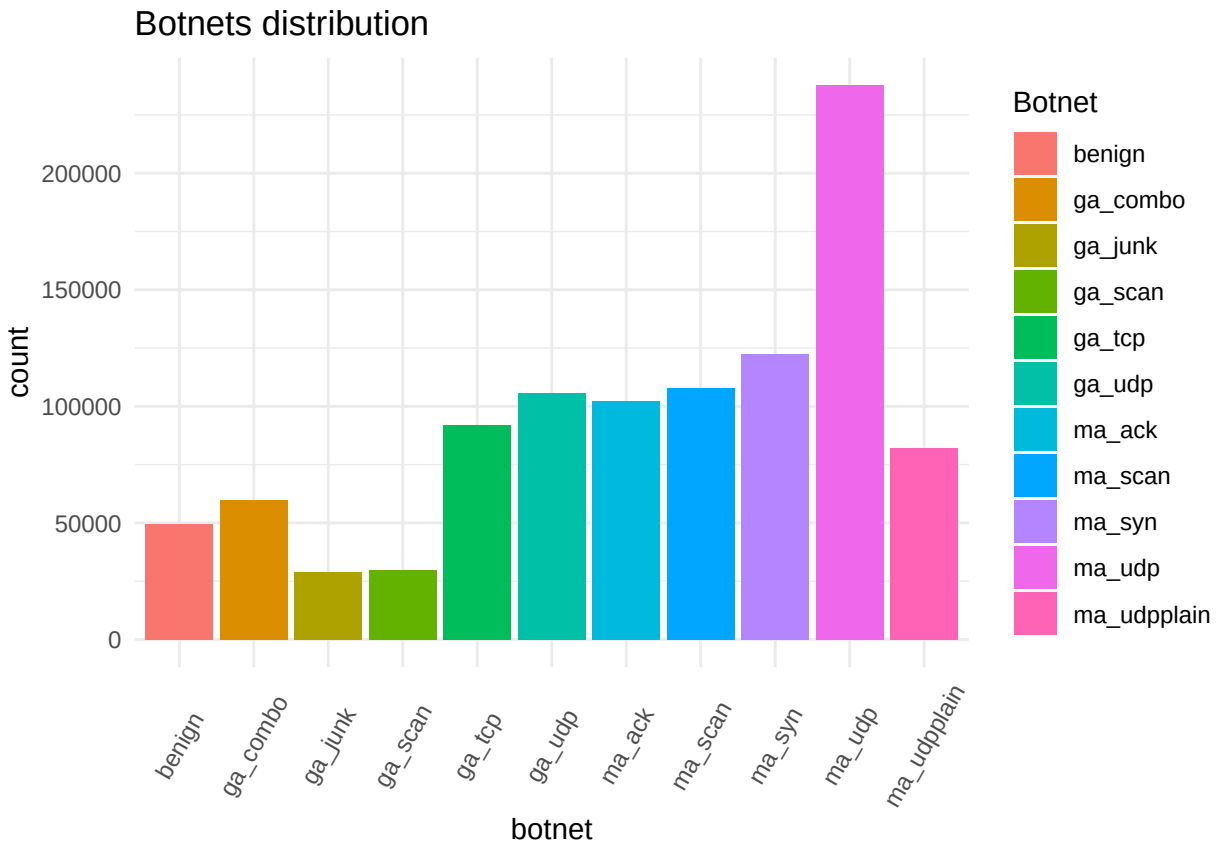
```
# Data frame dimensions
dim( df )
```

```
## [1] 1018298     116
```

The data set for *Danmini doorbell* device consists of more than 1 million rows. It has 115 attributes, and the 'botnet' column (116^{th}) contains the outcome for the classification.

```
## # A tibble: 11 x 3
##    botnet           n   prop
##    <fct>        <int>  <dbl>
##  1 ma_udp      237665 0.233
##  2 ma_syn      122573 0.120
##  3 ma_scan     107685 0.106
##  4 ga_udp      105874 0.104
##  5 ma_ack      102195 0.100
##  6 ga_tcp       92141 0.0905
##  7 ma_udpplain  81982 0.0805
##  8 ga_combo     59718 0.0586
##  9 benign       49548 0.0487
## 10 ga_scan      29849 0.0293
## 11 ga_junk      29068 0.0285
```

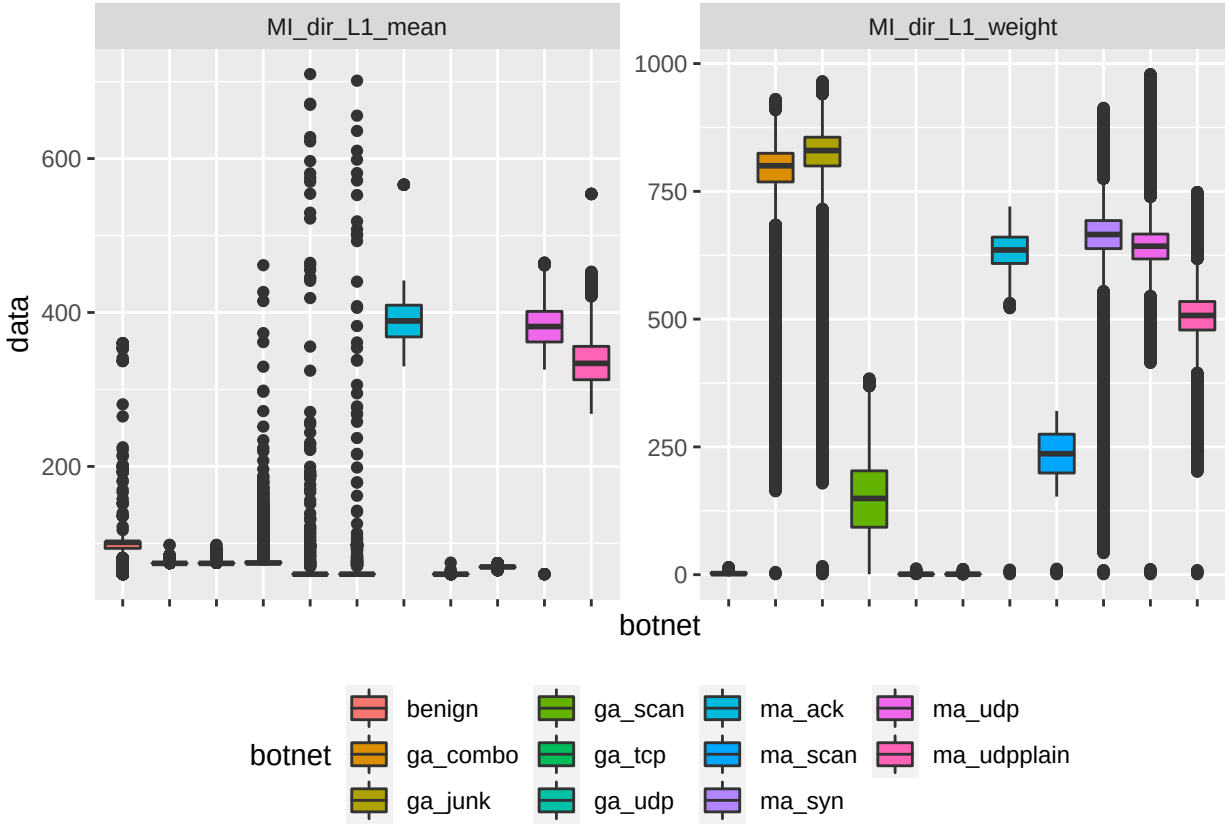
There are 11 botnets in the data set: 10 attacks plus benign traffic. Benign traffic is only 4.87% of all traffic.



The full data exploration will take a lot of pages, as the whole data set has 115 attributes, I created *data_exploration.pdf* with full data exploration. The *data_exploration.R* script and *data_exploration.Rmd* Rmarkdown files can also be found on GitHub.

Here I will mention my conclusions from this exploration.

My research has shown that I can use *weight*, *mean* and *covariance* columns for classification if I need to reduce the data set dimensions. This is clearly visible on small time frames such as L1.



The plot above for *MI_dir_L1_weight* column shows that almost all types of attacks, excluding *ga_tcp* and *ga_udp*, can be separated from benign traffic, as their IQR and medians have higher values than benign traffic. *ga_tcp* and *ga_udp* attacks camouflage very well as benign traffic on this plot.

However, the plot for *MI_dir_L1_mean* column shows that IQR and median is higher for benign traffic compared with these parameters for *ga_tcp* and *ga_udp* attacks. Thus, this column data will help to separate *ga_tcp* and *ga_udp* attacks from the benign traffic.

Therefore, as I wrote above, *weight* and *mean* columns can be used for attack classification. As all the attacks have outliers, the information these columns contain is not enough, so *covariance* column can also be used for classification.

Once again, the full data exploration can be found on GitHub:

- *data_exploration.pdf*
- *data_exploration.R* script
- *data_exploration.Rmd* Rmarkdown

Methods

We have learned several methods for the data classification in HarvardX PH125.9x Data Science course, such as **KNN**, **rpart** and **randomForest**.

rpart and **randomForest** are easy to use algorithms because all you need to do is to separate the data frame into two parts (train and test set) and allow functions to do their work. That's why I decided to check how well **KNN** method can perform the attack classification. I used two approaches for **KNN** algorithm: PCA and *train()* function from *caret* package.

The team that collected this data frame used 2/3 of the benign traffic to train *deep autoencoder*. I can't use this approach, because all learned algorithms in the course need to know all possible outcomes after training. Thus, I will simply divide the data set into two equal parts (train and test sets), as my aim is only to check how accurate these algorithms are in classification.

I have

```
## [1] '4.0.2'
```

R version, and it has

```
## [1] 8060
```

MB memory limit.

When I tried to perform some algorithms on the whole original data set, I got memory allocation error. I decided to use only a part of the original data set for these algorithms.

KNN

KNN (with PCA)

I will use 60% of the original data set and select only columns that contain *weight* parameter. Then I will separate data set into train and test sets, make them equal dimensions and convert them into matrices. After that I will perform PCA with train set.

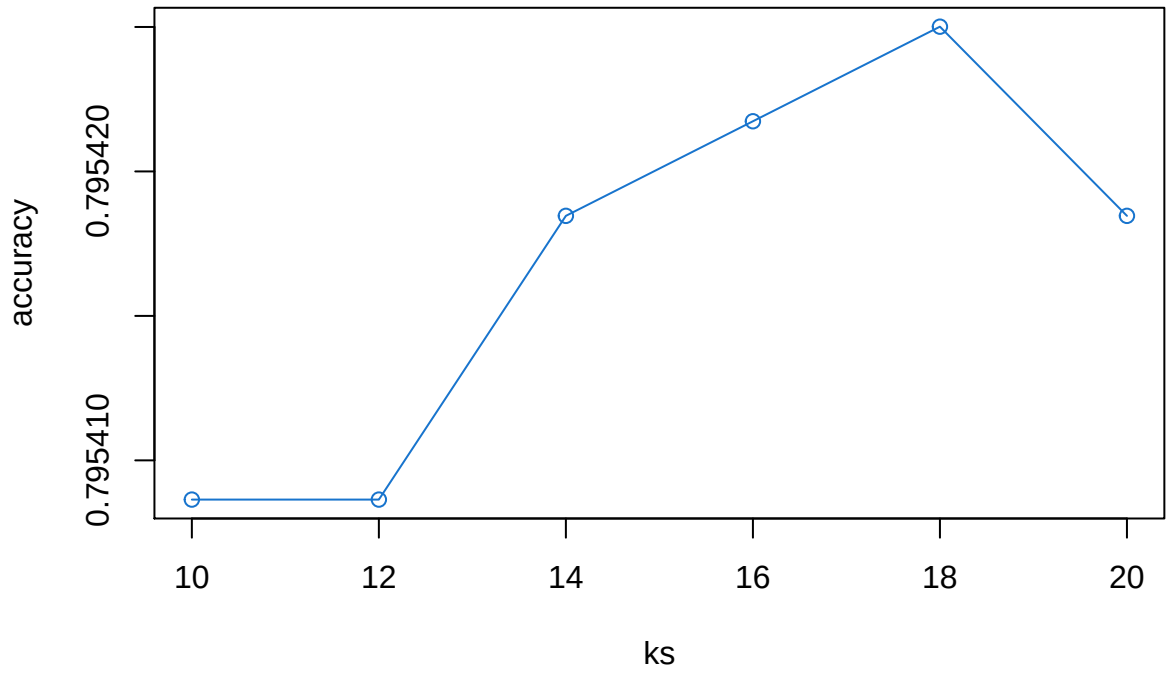
```
setSeed()

# 1. Check only columns with 'weight' attribute
pattern <- "(weight)"

# Select only columns that match the pattern. In this case - only 'weight' column
tmp <- df %>% select( botnet, grep( pattern = pattern, ignore.case = TRUE, x = colnames ) )

# As I have memory limit, I use only 60% of the data set
prop <- 0.6
test_index <- createDataPartition( y = tmp$botnet, times = 1, p = prop, list = FALSE)
tmp <- tmp[ test_index, ]

# Create train and test sets
test_index <- createDataPartition( y = tmp$botnet, times = 1, p = 0.5, list = FALSE)
train_set <- tmp[ -test_index, ]
test_set <- tmp[ test_index, ]
```

```
# Number of rows in the train set
n_train <- nrow( train_set )

# Number of rows in the test set
n_test <- nrow( test_set )

# Make both sets equal dimensions (with equal number of rows)
if( n_test > n_train ) {
  test_set <- test_set[ 1:n_train, ]
} else {
  train_set <- train_set[ 1:n_test, ]
}

# Convert train set as matrix
train_set <- train_set %>% data.matrix()

# Create levels for attacks classification
levels <- as.factor( train_set[ ,1 ] )

# Now remove 1st column, that represents 'botnet' column
train_set <- train_set[ ,-1 ]

# Convert test set as matrix
test_set <- test_set %>% data.matrix()

# Botnets outcome for the test set
bots <- as.factor( test_set[ ,1 ] )

# Now remove 1st column, that represents 'botnet' column
test_set <- test_set[ ,-1 ]

# Perform PCA
pca <- prcomp( train_set )
```

Next, I will perform cross-validation to check how many principal components give maximum accuracy in attack detection (classification). My previous research have shown that I can use from 10 to 20 principal components with step = 2 for cross-validation.

```
# Please, pay attention that this algorithm is slow.

# Make cross-validation and calculate classification accuracy
ks <- seq( 10, 20, 2 )

# Prepare test set: remove all column means
col_means <- colMeans( test_set )
x_test <- sweep( test_set, 2, col_means ) %*% pca$rotation

# Please, take a note that this takes a time
accuracy <- sapply( ks, function( k ) {
  # Prepare train set
  x_train <- pca$x[ , 1:k ]

  # Train the algorithm
```

```
  fit <- knn3( x_train, levels, use.all = FALSE )

  # Prepare test set
  x_test_k <- x_test[ , 1:k ]

  # Predict
  y_hat <- predict( fit, x_test_k, type = "class" )
  cm <- confusionMatrix( y_hat, bots )
  return( cm$overall[ "Accuracy" ] )
})

# Plot k ~ accuracy
plot( ks, accuracy, type = "o", col = "dodgerblue3" )
```




```
## [1] "K =  18"
```

```
## [1] "Max accuracy =  0.795425009902222"
```

This method doesn't give significant result as its classification accuracy is only 79.54%. On the other hand, I used only one *weight* column for classification.

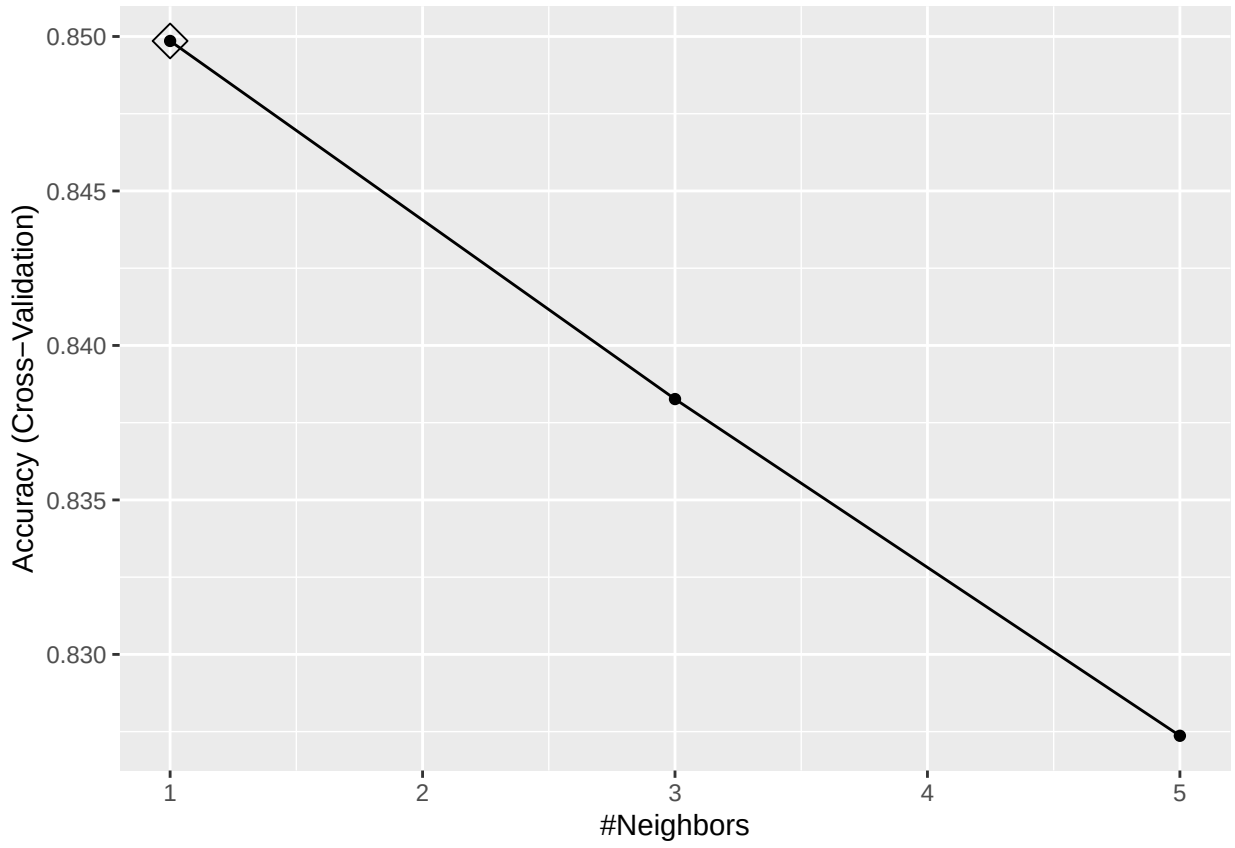
I decided not to perform classification using *weight*, *mean* and *covariance* columns with this algorithm, as even with only *weight* column, it works really slow (about 3hrs with my memory limit).

After that, I decided to use *train()* function from *caret* package to check its **KNN** method.

KNN (with caret package)

I will use all 115 columns for classification and 2% of the original data set, because of the memory limit. I will perform 10-fold cross-validation to find better parameters for the algorithm.

```
# 2. Using train() function from caret package with "knn" method
setSeed()

prop <- 0.02
test_index <- createDataPartition( y = df$botnet, times = 1, p = prop, list = FALSE )
tmp <- df[ test_index, ]

# Create train and test sets
test_index <- createDataPartition( y = tmp$botnet, times = 1, p = 0.5, list = FALSE)
train_set <- tmp[ -test_index, ]
test_set <- tmp[ test_index, ]

# Use 10-fold cross-validation
control <- trainControl( method = "cv", number = 10, p = 0.9 )
fit_knn <- train( botnet ~ ., data = train_set, method = "knn",
                  tuneGrid = data.frame( k = seq( 1, 5, 2 ) ),
                  trControl = control )

ggplot( fit_knn, highlight = TRUE )
```



Its classification accuracy is:

```
y_hat <- predict( fit_knn, test_set, type = "raw" )
cm <- confusionMatrix( y_hat, test_set$botnet )
cm$overall[ "Accuracy" ]
```

```
##  Accuracy
## 0.8578581
```

Sensitivity is the quantity, referred to as the true positive rate (TPR), while *specificity* is also called the true negative rate (TNR). Both of them show how accurate the classification was made for each attack or benign traffic.

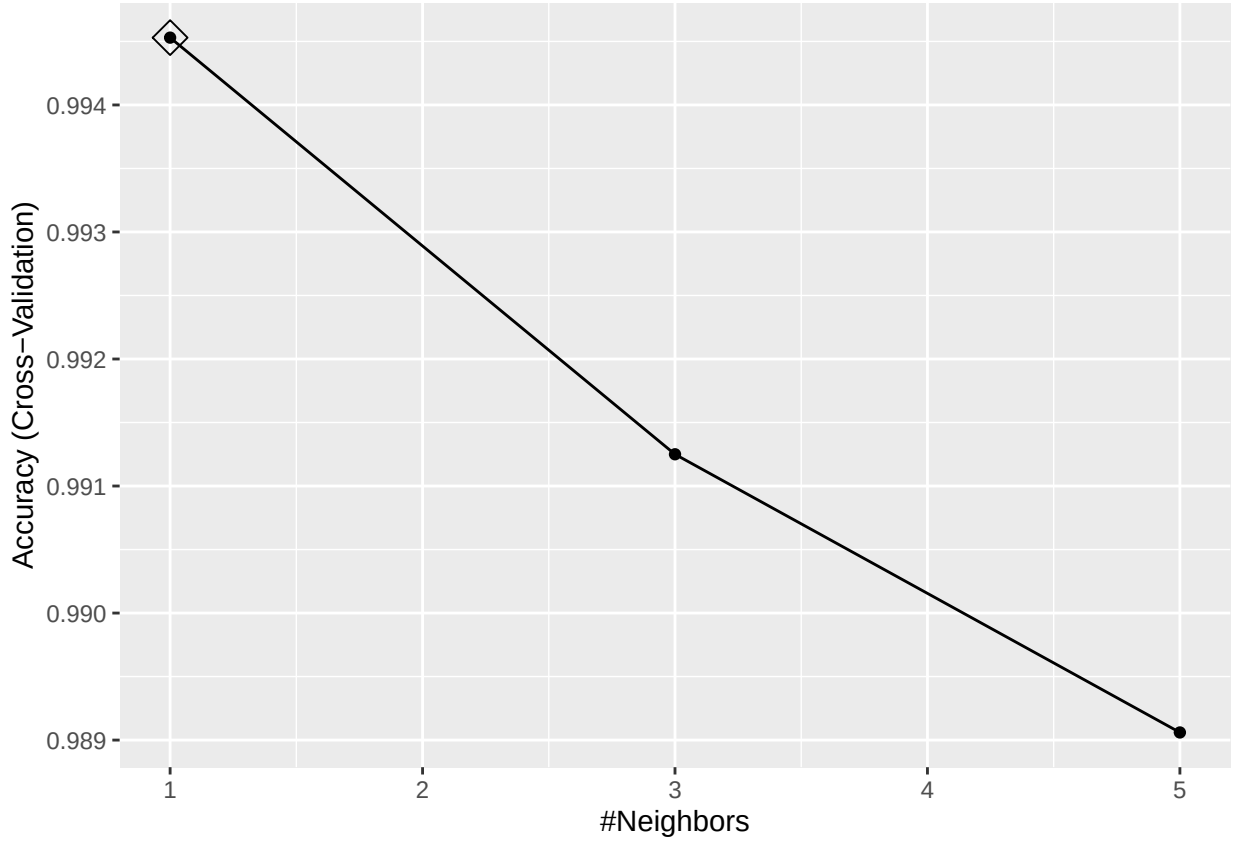
```
##                     Sensitivity Specificity
## Class: benign         0.9697581   0.9981426
## Class: ga_combo       0.9431438   0.9970800
## Class: ga_junk        0.9037801   0.9971706
## Class: ga_scan        0.9832776   0.9996966
## Class: ga_tcp         0.9989154   1.0000000
## Class: ga_udp         1.0000000   0.9998904
## Class: ma_ack         0.6369863   0.9567921
## Class: ma_scan        1.0000000   0.9998902
## Class: ma_syn         0.6843393   0.9587100
## Class: ma_udp         0.8081615   0.9427657
## Class: ma_udpplain    0.8158537   0.9833458
```

We have learned in the course, that k=1 may lead to over-training, because each row in the data set is used to predict itself. In this particular case, it's reasonable, in my opinion, because the team that collected the data set used a similar approach. They used only *benign traffic* to train their *deep autoencoder*, this is pretty close to use of k=1 in **KNN** method. Furthermore, data exploration has shown that some attribute combinations (such as *weight*, *mean* and *covariance*) can help to clearly separate *benign traffic* from the attacks, and thus, even with k=1 it becomes possible to make great classification.

My next step is to reduce the original data set dimensions, keeping only *weight*, *mean* and *covariance* columns for L1 and L0.01 time frames. This step will allow me to use 20% of the original data set with my memory limit.

```
# 3. Let's reduce the data set dimensions and increase its size
# 20% of data (because of memory limit), 24 attributes
setSeed()

prop <- 0.2
test_index <- createDataPartition( y = df$botnet, times = 1, p = prop, list = FALSE )
tmp <- df[ test_index, ]

pattern <- "L(0.0)?1_(weight|mean|covariance)"
tmp <- tmp %>% select( botnet, grep( pattern = pattern, ignore.case = TRUE, x = colnames ) )

# Create train and test sets
test_index <- createDataPartition( y = tmp$botnet, times = 1, p = 0.5, list = FALSE)
train_set <- tmp[ -test_index, ]
test_set <- tmp[ test_index, ]

# Use 10-fold cross-validation
control <- trainControl( method = "cv", number = 10, p = 0.9 )
```

```
fit_knn2 <- train( botnet ~ ., data = train_set, method = "knn",
                   tuneGrid = data.frame( k = seq(1, 5, 2 ) ),
                   trControl = control )

ggplot( fit_knn2, highlight = TRUE )
```




```
y_hat <- predict( fit_knn2, test_set, type = "raw" )
cm <- confusionMatrix( y_hat, test_set$botnet )
cm$overall[ "Accuracy" ]
```

```
##  Accuracy
## 0.9948446
```

The result shows that using only *weight*, *mean* and *covariance* columns for L1 and L0.01 time frames gives the accuracy of the classification (attack detection) about 99.48%!

Sensitivity and *specificity* show how accurate the classification was made for each attack or benign traffic:

```
##                     Sensitivity Specificity
## Class: benign         0.9917255   0.9993187
## Class: ga_combo       0.9783992   0.9987691
## Class: ga_junk        0.9580323   0.9988780
## Class: ga_scan        0.9845896   0.9996055
## Class: ga_tcp         0.9992404   0.9998596
```

```
## Class: ga_udp        0.9991500   0.9998794
## Class: ma_ack        0.9936399   0.9991814
## Class: ma_scan       0.9988857   0.9998243
## Class: ma_syn        0.9992658   0.9999107
## Class: ma_udp        0.9967181   0.9991418
## Class: ma_udpplain   0.9991462   0.9999893
```

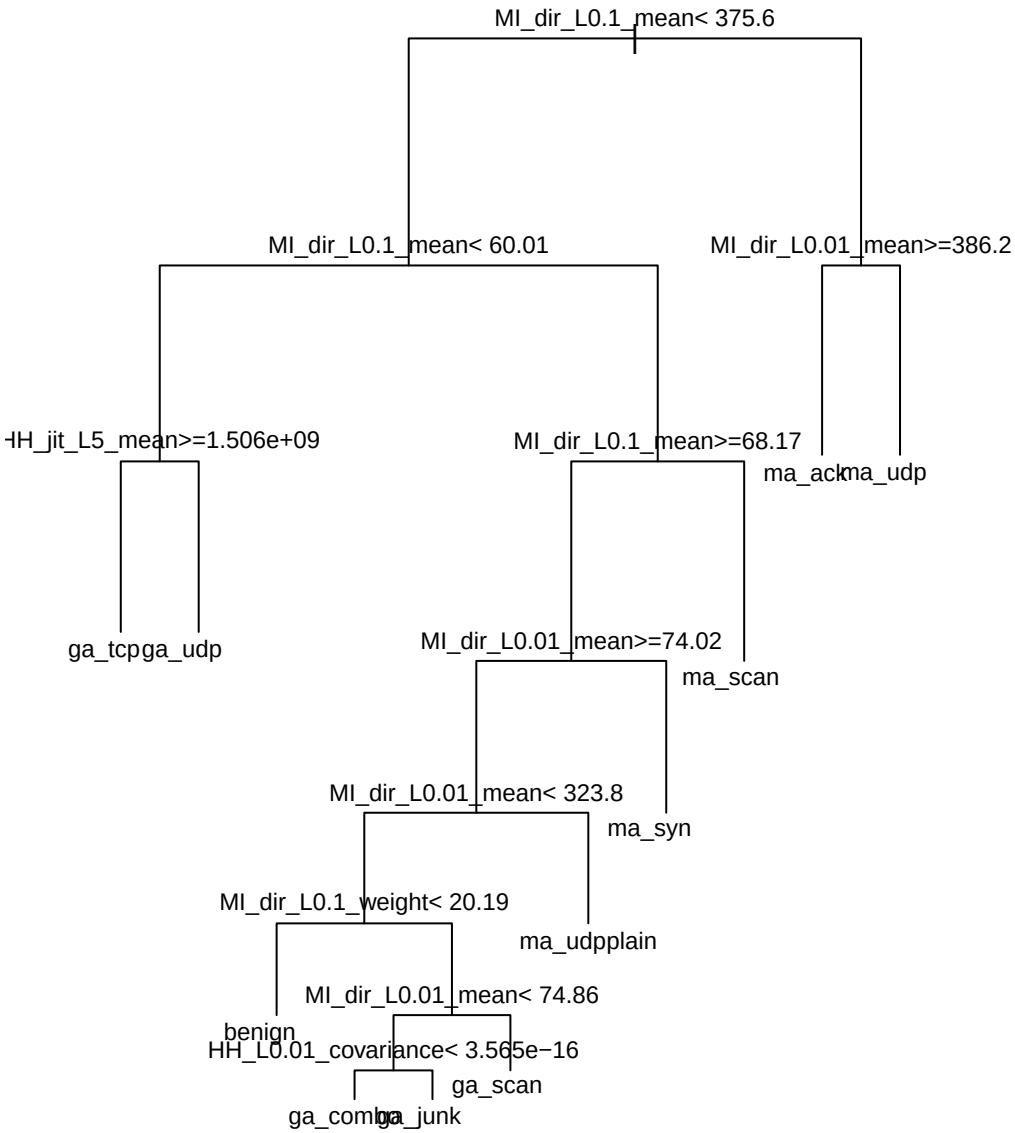
rpart

This method allows the use all 115 attributes and whole original data set even with my memory limit.

```
setSeed()

# Use whole data set with all attributes
tmp <- df

# Create train and test sets
test_index <- createDataPartition( y = tmp$botnet, times = 1, p = 0.5, list = FALSE)
train_set <- tmp[ -test_index, ]
test_set <- tmp[ test_index, ]

fit_rpart <- rpart( botnet ~ ., data = train_set )
```

Visualize the decision tree:

rpart decision tree



According to the decision tree above, **rpart** mostly uses *mean* column and sometimes makes its decisions using *weight* and *covariance* columns. The data exploration also has shown that using only *weight*, *mean* and *covariance* columns will be enough to detect attacks (make their classification).

```
y_hat <- predict( fit_rpart, test_set, type = "class" )
cm <- confusionMatrix( y_hat, as.factor(test_set$botnet ) )
cm$overall[ "Accuracy" ]
```

```
##  Accuracy
## 0.9865639
```

The accuracy of the attack detection (classification) using **rpart** method is not as high and is about 98.66%.

Check *sensitivity* and *specificity* for each attack or benign traffic:

```
##                     Sensitivity Specificity
## Class: benign         0.9996771   0.9998926
## Class: ga_combo       0.9978566   0.9861337
## Class: ga_junk        0.5419017   0.9998767
## Class: ga_scan        0.9997990   0.9998685
## Class: ga_tcp         0.9988713   0.9999935
## Class: ga_udp         0.9990744   0.9999912
## Class: ma_ack         1.0000000   0.9999935
## Class: ma_scan        0.9999814   1.0000000
## Class: ma_syn         1.0000000   1.0000000
## Class: ma_udp         0.9999748   0.9999923
## Class: ma_udpplain    0.9999268   0.9999915
```

randomForest

The method builds a lot of trees for each forest, so the computation time will be considerable. I will use only 10% of the original data set, because of the memory limit.

```
setSeed()
prop <- 0.1
test_index <- createDataPartition( y = df$botnet, times = 1, p = prop, list = FALSE )
tmp <- df[ test_index, ]

# Create train and test sets
test_index <- createDataPartition( y = tmp$botnet, times = 1, p = 0.5, list = FALSE )
train_set <- tmp[ -test_index, ]
test_set <- tmp[ test_index, ]

fit_rm <- randomForest( botnet ~ . , data = train_set )
y_hat <- predict( fit_rm, test_set, type = "class")
cm <- confusionMatrix( y_hat, test_set$botnet )
cm$overall[ "Accuracy" ]
```

```
## Accuracy
## 0.999784
```

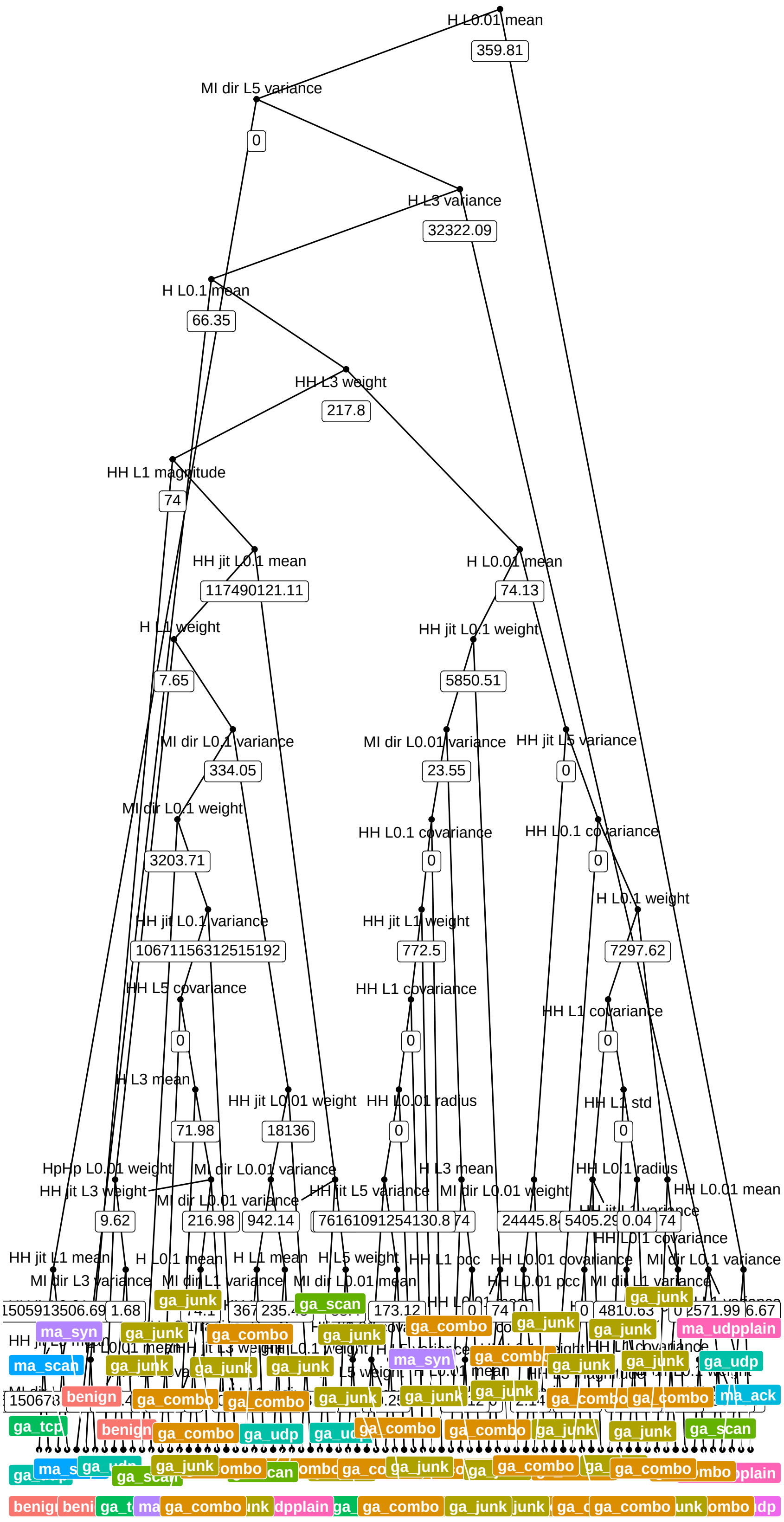
The accuracy of the classification (attack detection) is 99.98%! It really is a significant result!

```
##                     Sensitivity Specificity
## Class: benign         1.0000000   0.9999174
## Class: ga_combo       1.0000000   0.9999374
## Class: ga_junk        0.9972490   1.0000000
## Class: ga_scan        1.0000000   1.0000000
## Class: ga_tcp         0.9995660   1.0000000
## Class: ga_udp         0.9994333   0.9999781
## Class: ma_ack         1.0000000   1.0000000
## Class: ma_scan        0.9998143   0.9999780
## Class: ma_syn         1.0000000   0.9999777
## Class: ma_udp         0.9999159   1.0000000
## Class: ma_udpplain    1.0000000   0.9999786
```

Sensitivity shows that the method has 100% TPR in some attack detection or close to 100% for other attacks. This result correlates with the result that was obtained by the team that collected the original data set!

It will be interesting to visualize at least one decision tree from the 'forest'. **randomForest** package has no tool for visualization, however, the decision tree can be visualized using method described in *"Plotting trees from Random Forest models with ggraph"*[5] article.

[5]https://shiring.github.io/machine_learning/2017/03/16/rf_plot_ggraph


H L0.01 mean
359.81
MI dir L5 variance
0
H L3 variance
32322.09
H L0.1 mean
66.35
HH L3 weight
217.8
HH L1 magnitude
74
HH jit L0.1 mean
117490121.11
H L0.01 mean
74.13
H L1 weight
7.65
HH jit L0.1 weight
5850.51
MI dir L0.1 variance
334.05
MI dir L0.01 variance
23.55
HH jit L5 variance
0
MI dir L0.1 weight
3203.71
HH L0.1 covariance
0
HH L0.1 covariance
0
H L0.1 weight
HH jit L0.1 variance
10671156312515192
HH jit L1 weight
772.5
7297.62
HH L5 covariance
0
HH L1 covariance
0
HH L1 covariance
0
H L3 mean
71.98
HH jit L0.01 weight
18136
HH L0.01 radius
0
HH L1 std
0

Result

I've checked how accurate **KNN**, **rpart** and **randomForest** methods are in detecting the cyber attacks. Here is the final result:

```
## # A tibble: 5 x 5
##   Method                     Predictors    Data_proportion Parameters Accuracy
##   <chr>                      <chr>                  <dbl> <chr>         <dbl>
## 1 KNN (with PCA)             25, (weight)             0.6  "k = 18"      0.795
## 2 KNN (with caret package)   115                      0.02 "k = 1"       0.858
## 3 KNN (caret, reduced data) 24,(L1,L0.01)             0.2  "k = 1"       0.995
## 4 rpart                      115                      1    ""            0.987
## 5 randomForest               115                      0.1  ""            1.00
```

As seen from the result table, **randomForest** method gives 100% accuracy in classification. It also gives 100% TPR in detecting either *benign traffic* or some attacks. But for other attacks, it gives TPR ~ 99.7%. Unfortunately, this means it can detect some attacks as *benign traffic*. For security reason it's not as good. I found that the result highly correlates with the result that the team that collected the data set got.

rpart method uses all 115 attributes and whole data set to make its decision tree, works fast, but its classification accuracy is 98.7%.

KNN method on *reduced* data set gives the classification accuracy of about 99.5%.

Conclusion

The methods we learned in HarvardX PH125.9x Data Science course give great accuracy in the attack detection with some memory or time limits. **randomForest** method gives 100% accuracy in attack classification and 100% TPR in *benign traffic* detection. The team that collected the original data set got 100% TPR in detecting cyber attacks.

I divided the data set into two parts: train and test sets, because the methods we learned in the course have to know all possible outcomes after training. The team used *benign traffic* to train their deep autodecoder.

I have memory limit of 8GB on my laptop with 4.0.2 R version. This limit allowed me to use 10% of the original data set to check the classification accuracy for **randomForest** method. I also checked this method on a computer with 4.0.4 R version and 32GB of memory limit. This memory limit allowed to use 60% of the original data set.

The aim that I set for my project, namely, to check how accurate the methods we learned in the course in detecting attacks, has been achieved.

However, if I were to further engage in the cyber attack detection, then I would choose **randomForest** method and would explore at least two ways:

1. **randomForest** classifies some attack with TPR less than 100%. This means, that it may consider some attacks as *benign traffic* and may pass them. That's inappropriate for the security reasons.

Knowing that it detects *benign traffic* with 100% TPR, I may consider other traffic as attacks and reject it. Perhaps, I need to reshape the data set, only keeping *benign traffic* or *attack* values in *botnet* column, i.e. having only two possible outcomes. In this case **randomForest** may clearly separate *benign traffic* from the attacks, I suppose.

2. Perform following steps to increase the data set size to use with **randomForest** method:

- Use higher spec PC to increase memory
- Arrange attributes by their importance for the method
- Reduce the data set by removing less important attributes

Steps above will allow me to use all the rows of the original data set and check if this increases *sensitivity* in the attack detection and keeps the accuracy high.

Another task that smoothly follows from my project is to compare the methods between each other. To do this, I need to find the minimum data set on which all methods can work. Then I can compare their execution speed and classification accuracy.

Apendix

Data set structure

```
# Data frame structure
str( df )
```

```
## 'data.frame':    1018298 obs. of  116 variables:
##  $ botnet                : Factor w/ 11 levels "benign","ga_combo",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ MI_dir_L5_weight      : num  1 1 1.86 1 1.68 ...
##  $ MI_dir_L5_mean        : num  60 354 360 337 172 ...
##  $ MI_dir_L5_variance    : num  0 0 35.8 0 18487.4 ...
##  $ MI_dir_L3_weight      : num  1 1 1.91 1 1.79 ...
##  $ MI_dir_L3_mean        : num  60 354 360 337 183 ...
##  $ MI_dir_L3_variance    : num  0 0 35.9 0 18928.2 ...
##  $ MI_dir_L1_weight      : num  1 1 1.97 1 1.93 ...
##  $ MI_dir_L1_mean        : num  60 354 360 337 193 ...
##  $ MI_dir_L1_variance    : num  0 0 36 0 19154 ...
##  $ MI_dir_L0.1_weight    : num  1 1 2 1 1.99 ...
##  $ MI_dir_L0.1_mean      : num  60 354 360 337 198 ...
##  $ MI_dir_L0.1_variance  : num  0 0 36 0 19182 ...
##  $ MI_dir_L0.01_weight   : num  1 1 2 1 2 ...
##  $ MI_dir_L0.01_mean     : num  60 354 360 337 198 ...
##  $ MI_dir_L0.01_variance: num  0 0 36 0 19182 ...
##  $ H_L5_weight           : num  1 1 1.86 1 1.68 ...
##  $ H_L5_mean             : num  60 354 360 337 172 ...
##  $ H_L5_variance         : num  0.00 4.59e-06 3.58e+01 0.00 1.85e+04 ...
##  $ H_L3_weight           : num  1 1 1.91 1 1.79 ...
##  $ H_L3_mean             : num  60 354 360 337 183 ...
##  $ H_L3_variance         : num  0.00 4.58e-03 3.59e+01 0.00 1.89e+04 ...
##  $ H_L1_weight           : num  1 1.03 2 1 1.93 ...
##  $ H_L1_mean             : num  60 354 360 337 193 ...
##  $ H_L1_variance         : num  0 4.3 40.4 0 19153.8 ...
##  $ H_L0.1_weight         : num  1 2.6 3.59 1 1.99 ...
##  $ H_L0.1_mean           : num  60 347 352 337 198 ...
##  $ H_L0.1_variance       : num  0 34.1 100.1 0 19182 ...
##  $ H_L0.01_weight        : num  1 5.32 6.32 1 2 ...
##  $ H_L0.01_mean          : num  60 344 348 337 198 ...
##  $ H_L0.01_variance      : num  0 22.2 81.6 0 19182.2 ...
##  $ HH_L5_weight          : num  1 1 1.86 1 1 ...
```

```
##  $ HH_L5_mean           : num  60 354 360 337 60 ...
##  $ HH_L5_std            : num  0 0.00214 5.98242 0 0 ...
##  $ HH_L5_magnitude      : num  60 354 360 337 524 ...
##  $ HH_L5_radius         : num  0.00 4.59e-06 3.58e+01 0.00 3.18e+04 ...
##  $ HH_L5_covariance     : num  0 0 0 0 0 ...
##  $ HH_L5_pcc            : num  0 0 0 0 0 ...
##  $ HH_L3_weight         : num  1 1 1.91 1 1 ...
##  $ HH_L3_mean           : num  60 354 360 337 60 ...
##  $ HH_L3_std            : num  0 0.0676 5.994 0 0 ...
##  $ HH_L3_magnitude      : num  60 354 360 337 483 ...
##  $ HH_L3_radius         : num  0.00 4.58e-03 3.59e+01 0.00 4.64e+04 ...
##  $ HH_L3_covariance     : num  0 0 0 0 0 ...
##  $ HH_L3_pcc            : num  0 0 0 0 0 ...
##  $ HH_L1_weight         : num  1 1.03 2 1 1 ...
##  $ HH_L1_mean           : num  60 354 360 337 60 ...
##  $ HH_L1_std            : num  0 2.07 6.36 0 0 ...
##  $ HH_L1_magnitude      : num  60 354 360 337 438 ...
##  $ HH_L1_radius         : num  0 4.3 40.4 0 58393.6 ...
##  $ HH_L1_covariance     : num  0 0 0 0 0 ...
##  $ HH_L1_pcc            : num  0 0 0 0 0 ...
##  $ HH_L0.1_weight       : num  1 2.6 3.59 1 1 ...
##  $ HH_L0.1_mean         : num  60 347 352 337 60 ...
##  $ HH_L0.1_std          : num  0 5.84 10 0 0 ...
##  $ HH_L0.1_magnitude    : num  60 347 352 337 420 ...
##  $ HH_L0.1_radius       : num  0 34.1 100.1 0 62080.6 ...
##  $ HH_L0.1_covariance   : num  0 0 0 0 0 ...
##  $ HH_L0.1_pcc          : num  0 0 0 0 0 ...
##  $ HH_L0.01_weight      : num  1 5.32 6.32 1 1 ...
##  $ HH_L0.01_mean        : num  60 344 348 337 60 ...
##  $ HH_L0.01_std         : num  0 4.71 9.03 0 0 ...
##  $ HH_L0.01_magnitude   : num  60 344 348 337 418 ...
##  $ HH_L0.01_radius      : num  0 22.2 81.6 0 62388.6 ...
##  $ HH_L0.01_covariance  : num  0 0 0 0 0 ...
##  $ HH_L0.01_pcc         : num  0 0 0 0 0 ...
##  $ HH_jit_L5_weight     : num  1 1 1.86 1 1 ...
##  $ HH_jit_L5_mean       : num  1.51e+09 4.98 2.32 1.51e+09 1.51e+09 ...
##  $ HH_jit_L5_variance   : num  0.00 4.23e-07 6.06 0.00 0.00 ...
##  $ HH_jit_L3_weight     : num  1 1 1.91 1 1 ...
##  $ HH_jit_L3_mean       : num  1.51e+09 4.98 2.40 1.51e+09 1.51e+09 ...
##  $ HH_jit_L3_variance   : num  0 0.000422 6.079503 0 0 ...
##  $ HH_jit_L1_weight     : num  1 1.03 2 1 1 ...
##  $ HH_jit_L1_mean       : num  1.51e+09 5.09 2.57 1.51e+09 1.51e+09 ...
##  $ HH_jit_L1_variance   : num  0 0.418 6.581 0 0 ...
##  $ HH_jit_L0.1_weight   : num  1 2.6 3.59 1 1 ...
##  $ HH_jit_L0.1_mean     : num  1.51e+09 3.12e+01 2.26e+01 1.51e+09 1.51e+09 ...
##  $ HH_jit_L0.1_variance : num  0 6976 5228 0 0 ...
##  $ HH_jit_L0.01_weight  : num  1 5.32 6.32 1 1 ...
##  $ HH_jit_L0.01_mean    : num  1.51e+09 5.80e+01 4.88e+01 1.51e+09 1.51e+09 ...
##  $ HH_jit_L0.01_variance: num  0 12741 11172 0 0 ...
##  $ HpHp_L5_weight       : num  1 1 1.86 1 1 ...
##  $ HpHp_L5_mean         : num  60 354 360 337 60 ...
##  $ HpHp_L5_std          : num  0 0.00214 5.98242 0 0 ...
##  $ HpHp_L5_magnitude    : num  60 354 360 337 60 ...
##  $ HpHp_L5_radius       : num  0.00 4.59e-06 3.58e+01 0.00 0.00 ...
```

```
##  $ HpHp_L5_covariance   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ HpHp_L5_pcc          : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ HpHp_L3_weight       : num  1 1 1.91 1 1 ...
##  $ HpHp_L3_mean         : num  60 354 360 337 60 ...
##  $ HpHp_L3_std          : num  0 0.0676 5.994 0 0 ...
##  $ HpHp_L3_magnitude    : num  60 354 360 337 60 ...
##  $ HpHp_L3_radius       : num  0 0.00458 35.92849 0 0 ...
##  $ HpHp_L3_covariance   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ HpHp_L3_pcc          : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ HpHp_L1_weight       : num  1 1.03 2 1 1 ...
##  $ HpHp_L1_mean         : num  60 354 360 337 60 ...
##  $ HpHp_L1_std          : num  0 2.07 6.36 0 0 ...
##  $ HpHp_L1_magnitude    : num  60 354 360 337 60 ...
##   [list output truncated]
```