

Final Report

-By Team 04

OUTLINE

1. Final choice of submitted strategy	3
1.1 Introduction of integrated trading system	3
1.1.1 Trading Strategy	3
1.1.2 Position sizing (Wager Strategy)	7
1.1.3 Risk Management	9
1.2 Strategies of different parts working together	11
1.3 Optimizing and checking the robustness of strategy	14
2. Justification of submitted strategy	18
2.1 The process led to this particular strategy	18
2.2 Justifying the choice of position sizing, and other key elements of strategy.	24
2.3 Considering the strategy compare with alternatives.	30
2.4 Managing risk in the strategy	31
3. Evaluation and analysis of performance on part 3	36
3.1 The strategy performs relative to expectations	36
3.1.1 Dataset Breakdown	36
3.1.2 Series Breakdown	40
3.1.3 Trading Breakdown	41
3.2 The mistakes at the technical level, planning and teamwork	42
3.2.1 Strategy mistakes	42
3.2.2 Coding mistakes	43
3.2.3 Planning and teamwork mistakes	43
3.3 What have we learnt and how would we do things differently	44
3.3.1 Strategy and Coding Improvement	44
3.3.2 Planning and Teamwork Improvement	45
4. Breakdown of team work	47

1. Final choice of submitted strategy

1.1 Introduction of integrated trading system

Our final submitted strategy is a simple trading system consisting of 4 main trading strategies deciding which series we should buy or sell, 2 wager strategies to decide how much we should invest in each series and 5 risk management strategies to prevent extreme risk happening.

We try to harness profit from 4 perspectives; thus 4 individual trading sub-strategies are considered in our final submitted strategy, which are BBands Trend-following Strategy, BBands Mean-reversion Strategy, Triple Moving Average Strategy and Lawrence Macmillan Volatility Trading System. Instructions of which series we should buy or sell are given by them.

1.1.1 Trading Strategy

BBands Trend-following Strategy

In this trend strategy, it is believed that there are small likelihood prices exceed a reasonable range according to statistical ground truth and when it really happens, the herd effect will be followed, thus we should invest in it.

In the code, we long series when price breakthroughs its daily upper bound and short series when price breakthroughs its daily lower bound. We hold when we already have positions and daily prices are still in the trend. Otherwise, we exit.

```
1 getOrders.bbtbf <- function(store, newRowList, currentPos, info, params){
2
3   # init today's enter positions on each series
4   pos <- allzero
5
6   # default exit yesterday's overall positions
7   marketOrders <- -currentPos
8
9   # we need to wait until Lookback to get the bbands signal
10  if (store$iter >= params$lookback){
11    for (i in params$series){
12
13      # Calculate everyday bbands upper/lower bounds
14      up <- last(BBands(store$cl[1:store$iter,i], sd=params$BBTF_up_sdParam)[,3])
15      dn <- last(BBands(store$cl[1:store$iter,i], sd=params$BBTF_dn_sdParam)[,1])
16
17      # enter conditions
18
19      # Long enter when cross the upper bound
20      if(store$cl[store$iter, i] > up){
21        pos[i] <- params$posSizes[i]
22      }
23      # short enter when cross the lower bound
24      else if(store$cl[store$iter, i] < dn){
25        pos[i] <- -params$posSizes[i]
26      }
27
28      # hold conditions
```

```
29
30      if(currentPos[i] > 0){ # when in Long position
31        # hold when still in the long trend
32        if (store$cl[store$iter, i] > store$cl[store$iter-1, i]){
33          pos[i] <- currentPos[i]
34        }
35      }
36      else if (currentPos[i] < 0){ # when in short position
37        # hold when still in the short trend
38        if (store$cl[store$iter, i] < store$cl[store$iter-1, i]){
39          pos[i] <- currentPos[i]
40        }
41      }
42
43      # exit conditions
44
45      if(currentPos[i] != 0 & pos[i] == 0){
46        pos[i] <- 0
47      }
48    }
49  }
50
51  marketOrders <- marketOrders + pos
52
53  return(list(store=store,marketOrders=marketOrders,
54            limitOrders1=allzero,limitPrices1=allzero,
55            limitOrders2=allzero,limitPrices2=allzero))
56 }
```

BBands Mean-reversion Strategy

The basic trading philosophy of this strategy is similar to ***BBands Trend-following Strategy*** but the price will return to 'normal' range is expected in Mean-reversion strategy.

As can be seen from the code, we short series when price breakthroughs its daily upper bound and long series when price breakthroughs its daily lower bound. We hold when we already have positions and daily prices do not reach the Moving Average target. Otherwise, we exit.

```
1  getOrders.bbmr <- function(store, newRowList, currentPos, info, params){
2    # init today's enter positions on each series
3    pos <- allzero
4
5    # default exit yesterday's overall positions
6    marketOrders <- -currentPos
7
8    # we need to wait until Lookback to get the bbands signal
9    if (store$iter > params$lookback){
10     for (i in params$series){
11
12       # calculate everyday bbands upper/lower bounds
13       up <- last(BBands(store$cl[1:store$iter,i], sd=params$BBMR_up_sdParam)[,3])
14       dn <- last(BBands(store$cl[1:store$iter,i], sd=params$BBMR_dn_sdParam)[,1])
15
16       # everyday re-calculate today's ma30
17       sma <- last(SMA(store$op[1:store$iter,i], params$BBMR_SMA))
18
19       # enter conditions
20
21       # short enter when cross the upper bound
22       if(store$cl[store$iter, i] > up){
23         pos[i] <- -params$posSizes[i]
24       }
25       # Long enter when cross the Lower bound
26       else if(store$cl[store$iter, i] < dn){
27         pos[i] <- params$posSizes[i]
28       }
29
30       # hold conditions
31
32       if(currentPos[i] > 0){ # when in Long position
33         # Long hold when not reach MA
34         if (store$cl[store$iter, i] > sma){
35           pos[i] <- currentPos[i]
36         }
37       }
38       else if (currentPos[i] < 0){ # when in short position
39         # short hold when not reach MA
40         if (store$cl[store$iter, i] < sma){
41           pos[i] <- currentPos[i]
42         }
43       }
44     }
45
46     # exit conditions
47
48     if(currentPos[i] != 0 & pos[i] == 0){
49       pos[i] <- 0
50     }
51   }
52 }
53 marketOrders <- marketOrders + pos
54 return(list(store=store,marketOrders=marketOrders,
55           limitOrders1=allzero,limitPrices1=allzero,
56           limitOrders2=allzero,limitPrices2=allzero))
57 }
```

Triple Moving Average Strategy

This trend strategy aims to invest money in clear trends such as the short-term average prices dropping quicker than long-term average prices.

As is shown below, we long series when short-term MA > mid-term MA > long-term MA and short series when short-term MA < mid-term MA < long-term MA. We hold when we already have positions and daily prices do not reach the Moving Average target. Otherwise, we exit.

```
1 getOrders.tma<- function(store, newRowList, currentPos, info, params){
2   # init today's enter positions on each series
3   pos <- allzero
4
5   # default exit yesterday's overall positions
6   marketOrders <- -currentPos
7
8   # we need to wait until day 101 so that we have ma100 signal
9   if(store$iter > params$lookback){
10    for(i in params$series){
11
12      # everyday re-calculate today's
13      # short term ma e.g. MA5
14      # mid term ma e.g. MA30
15      # long term ma e.g. MA100
16      sma1 <- last(SMA(store$op[1:store$iter,i], params$TMA_MA1))
17      sma2 <- last(SMA(store$op[1:store$iter,i], params$TMA_MA2))
18      sma3 <- last(SMA(store$op[1:store$iter,i], params$TMA_MA3))
19
20      # enter conditions
21
22      # Long enter when ma5 > ma30 > ma100
23      if((sma1 > sma2) & (sma2 > sma3)){
24        # pos[i] <- params$posSizes[i] * 1000000 / store$cl[store$iter,i]
25        pos[i] <- params$posSizes[i]
26        # short enter when ma5 < ma30 < ma100
27      }
28      else if((sma1 < sma2) & (sma2 < sma3)){
29        pos[i] <- -params$posSizes[i]
30      }
31
32      # hold conditions
33
34      # long hold when still in the long trend
35      if(currentPos[i] > 0 & store$cl[store$iter, i] > sma1){
36        pos[i] <- currentPos[i]
37      }
38      # short hold when still in the short trend
39      else if (currentPos[i] < 0 & store$cl[store$iter, i] < sma1){
40        pos[i] <- currentPos[i]
41      }
42
43      # exit conditions
44
45      if(currentPos[i] != 0 & pos[i] == 0){
46        pos[i] <- 0
47      }
48    }
49  }
50  marketOrders <- marketOrders + pos
51  return(list(store=store,marketOrders=marketOrders,
52            limitOrders1=allzero,limitPrices1=allzero,
53            limitOrders2=allzero,limitPrices2=allzero))
54 }
```

Lawrence Macmillan Volatility Trading System

Volatility is the rate at which stock prices change and can be calculated using the standard deviation formula and by comparing historical volatility over different lengths of time, such as 10, 20 and 50 days, and 100 days. Systematic buying mechanics rules are followed in this strategy:

1. historical volatility is short aligned, i.e., the range of volatility is getting narrower, suggesting the calm before the storm.
2. calculate historical volatility at 5, 10, 20, 30 and 100 days and find its standard deviation.

As demonstrated, we long series when $\text{std1} < 0$ and $\text{std1} < \text{std2} < \text{std3} < \text{std4} < \text{std5}$ (std1 - std5 stands for different lengths of time, from short to long). We hold when we already have positions and daily prices do not reach the Moving Average target. Otherwise, we exit.

```
1 getOrders.lmv<- function(store, newRowList, currentPos, info, params){
2   # init today's enter positions on each series
3   pos <- allzero
4
5   # default exit yesterday's overall positions
6   marketOrders <- -currentPos
7
8   # we need to wait until day 101 so that we have ema100 signal
9   if(store$iter > params$lookback){
10    for(i in params$series){
11
12      # everyday re-calculate today's ema at diff. terms
13      # e.g. ema5/ema10/ema20/ema30/ema100
14      ema1 <- last(EMA(store$c1[1:store$iter,i],params$LMV_EMA1))
15      ema2 <- last(EMA(store$c1[1:store$iter,i],params$LMV_EMA2))
16      ema3 <- last(EMA(store$c1[1:store$iter,i],params$LMV_EMA3))
17      ema4 <- last(EMA(store$c1[1:store$iter,i],params$LMV_EMA4))
18      ema5 <- last(EMA(store$c1[1:store$iter,i],params$LMV_EMA5))
19
20      # everyday re-calculate today's std5/std10/std20/std30/std100
21      std1 <- store$c1[store$iter,i] - ema1
22      std2 <- store$c1[store$iter,i] - ema2
23      std3 <- store$c1[store$iter,i] - ema3
24      std4 <- store$c1[store$iter,i] - ema4
25      std5 <- store$c1[store$iter,i] - ema5
26
27      # enter conditions
28
29      # Long enter when the volatility is getting smaller and in the down trend
30      if(std1<std2 &
31         std2<std3 &
32         std3<std4 &
33         std4<std5 &
34         std1 < 0){
35        pos[i] <- params$posSizes[i]
36      }
37
38      # hold conditions
39
40      if(pos[i] != 0 | std1 < 0){
41        pos[i] <- currentPos[i]
42      }
43
44      # exit conditions
45
46      if(currentPos[i] != 0 & pos[i] == 0){
47        pos[i] <- 0
48      }
49    }
50  }
51  marketOrders <- marketOrders + pos
52  return(list(store=store,marketOrders=marketOrders,
53            limitOrders1=allzero,limitPrices1=allzero,
54            limitOrders2=allzero,limitPrices2=allzero))
55 }
```

1.1.2 Position sizing (Wager Strategy)

Position sizing, what is also called wager strategy in this report, determine how much we should invest in each series each bet. Therefore, two approaches: Kelly formula and Martingale Strategy are introduced on behalf of long-term and short-term information.

Kelly formula

$$f^* = \frac{bp - q}{b} = \frac{p(b + 1) - 1}{b},$$

where:

- f^* is the percentage of available funds that should be used for the next bet.
- b is the odds available for the bet (excluding the principal).
- p is the winning rate.
- q is the losing rate, i.e., $1 - p$.

As a long-term optimal wager strategy, the Kelly formula is implemented as shown above to calculate how much we should invest in each series in each bet by using our trading system in the long run.

The performance of the final strategy is derived by using the test set (1000 days part1 data + 500 days part2 data) and the following function, and then get the long-term optimal betting ratio as our initial wagers for part 3 data for each of the 10 series in the final submitted strategy.

```

1 # *****
2 # performance measurement
3 perfCalc <- function(test, pfolioPnl){
4
5   lastProfit <- vector(mode="numeric",length=10)
6   winTimes <- vector(mode="numeric",length=10)
7   WinBalance <- vector(mode="numeric",length=10)
8   loseTimes <- vector(mode="numeric",length=10)
9   loseBalance <- vector(mode="numeric",length=10)
10  tradeTimes <- vector(mode="numeric",length=10)
11  gambitRate <- vector(mode="numeric",length=10)
12  kelly <- vector(mode="numeric",length=10)
13  winRate <- vector(mode="numeric",length=10)
14  lossRate <- vector(mode="numeric",length=10)
15
16  pnl <- as.double(pfolioPnl[["pfoliosPnl"]][nrow(pfolioPnl[["pfoliosPnl"]]),2])
17  PDratio <- pfolioPnl[["fitAgg"]]
18  activeness <- as.double(test[["k"]])
19
20  for (d in 2:1500){
21    for (i in 1:10){
22      # store money spend for establish position
23      if (flagStore[d-1,i] == 1 |
24          flagStore[d-1,i] == 2){
25        lastProfit[i] <- -moneySpendStore[d, i]
26      }
27      # when clear position, calculate this trade whether lose or win,
28      # when losing, lastProfit = 1 , else 0
29      else if(flagStore[d-1,i] == 5){
30        if (lastProfit[i] - moneySpendStore[d, i] > 0){
31          winTimes[i] <- winTimes[i] + 1
32          WinBalance[i] <- WinBalance[i] + (lastProfit[i] - moneySpendStore[d,
33        ])
34        }else if (lastProfit[i] - moneySpendStore[d, i] < 0){
35          loseTimes[i] <- loseTimes[i] + 1
36          loseBalance[i] <- loseBalance[i] + (lastProfit[i] - moneySpendStore[d,
37        ])
38        }
39      }
40    }
41
42    for (i in 1:10){
43      winRate[i] <- winTimes[i]/tradeTimes[i]
44      lossRate[i] <- 1-winRate[i]
45      gambitRate[i] <- (winTimes[i]/WinBalance[i]) / (loseTimes[i]/loseBalance[i])
46      kelly[i] <- ((gambitRate[i]+1)*winRate[i] - 1) / gambitRate[i]
47    }
48
49    avg_winRate <- mean(winRate, na.rm = TRUE)
50    avg_lossRate <- mean(lossRate, na.rm = TRUE)
51    avg_winTimes <- mean(winTimes, na.rm = TRUE)
52    avg_loseTimes <- mean(loseTimes, na.rm = TRUE)
53    avg_tradeTimes <- mean(tradeTimes, na.rm = TRUE)
54    sum_winTimes <- sum(winTimes, na.rm = TRUE)
55    sum_loseTimes <- sum(loseTimes, na.rm = TRUE)
56    sum_tradeTimes <- sum(tradeTimes, na.rm = TRUE)
57    sum_kelly <- sum(kelly, na.rm = TRUE)
58    expected_profit <- pnl / sum_tradeTimes
59
60    res <- list('pnl'=pnl,
61              'PDratio'=PDratio,
62              'activeness'=activeness,
63              'winTimes'=winTimes,
64              'loseTimes'=loseTimes,
65              'tradeTimes'=tradeTimes,
66              'WinBalance'=WinBalance,
67              'loseBalance'=loseBalance,
68              'winRate'=winRate,
69              'lossRate'=lossRate,
70              'gambitRate'=gambitRate,
71              'kelly'=kelly,
72              'avg_winRate'=avg_winRate,
73              'avg_lossRate'=avg_lossRate,
74              'avg_winTimes'=avg_winTimes,
75              'avg_loseTimes'=avg_loseTimes,
76              'avg_tradeTimes'=avg_tradeTimes,
77              'sum_winTimes'=sum_winTimes,
78              'sum_loseTimes'=sum_loseTimes,
79              'sum_tradeTimes'=sum_tradeTimes,
80              'sum_kelly'=sum_kelly,
81              'expected_profit'=expected_profit
82            )
83    return(res)
84  }

```

Martingale Strategy

Martingale Strategy has been proven profitable at trend trading in short-term. From preliminary analysis, we know that except series 1,6,10 are highly volatile and have no obvious trend in part 1 data, the other series are obviously desirable for trend strategy. Therefore, we double our wager at one series after losing until winning as the code shows.

```

1 # *****
2 # Martingale Wager strategy
3
4 Martingale <- function(params, store){
5   for (i in params$series){
6     # store money spend for establish position
7     if (flagStore[store$iter,i] == 1 |
8         flagStore[store$iter,i] == 2){
9       Martingale_lastProfit[i] <- -moneySpendStore[store$iter+1, i]
10    }
11    # when clear position, calculate this trade whether lose or win,
12    # when losing, lastProfit = 1 , else 0
13    else if(flagStore[store$iter,i] == 5){
14      if (Martingale_lastProfit[i] - moneySpendStore[store$iter+1, i] < 0){
15        Martingale_lastProfit[i] <- 1
16      }else{
17        Martingale_lastProfit[i] <- 0
18      }
19    }
20    # when clear position and lose, double the wager for the next time
21    if (flagStore[store$iter,i] == 5 & Martingale_lastProfit[i] == 1){
22      Martingale_multiplier[i] <- Martingale_multiplier[i] * params$Martingale
23    }
24    # if win, just reset the wager to the initial amount
25    else if (flagStore[store$iter,i] == 5 & Martingale_lastProfit[i] == 0){
26      Martingale_multiplier[i] <- 1
27    }
28  }
29 }

```


1.1.3 Risk Management

Risk management is vital to prevent extreme cases happening like anomaly data. Hence, 5 risk management strategies including Stop-gain, Stop-loss and Strategy-exit mechanisms are applied.

Drawdown Stopgain

Drawdown Stopgain is used by comparing the daily drawdown of price and our target to decide whether we should exit our position in one series.

```
1 # *****
2 # Drawdown Stop-gain method
3
4 # The Drawdown Stop-gain method is a strategy that does not involve
5 # any Stop-gain strategy in a bull market,
6 # and then redeems when there is a relatively Large short-term Drawdown
7
8 Drawdown_Stopgain <- function(params, store, currentPos, Orders){
9   for (i in params$series){
10     # store money spend at position establish moment
11     if (flagStore[store$iter,i] == 1 |
12         flagStore[store$iter,i] == 2){
13       Drawdown_lastProfit[i] <- moneySpendStore[store$iter+1, i]
14     }
15
16     else if (flagStore[store$iter,i] == 3
```

```
17       & store$cl[store$iter, i] > Drawdown_lastProfit[i]/currentPos[i]){
18       if ((store$cl[store$iter, i] - store$cl[store$iter-1, i]) /
19           store$cl[store$iter-1, i] < params$Stopgain_long_param){
20         Orders[i] = -currentPos[i]
21       }
22     }
23     else if(flagStore[store$iter,i] == 4
24             & Drawdown_lastProfit[i]/currentPos[i] > store$cl[store$iter, i]){
25       if ((store$cl[store$iter, i] - store$cl[store$iter-1, i]) /
26           store$cl[store$iter-1, i] > params$Stopgain_short_param){
27         Orders[i] = -currentPos[i]
28       }
29     }
30   }
31   return(Orders)
32 }
```

Time Stops

Time stops method is utilized to check if we have been in trade too long in one series by counting days in trade after entering a position.

```
1 # *****
2 # Time stops
3
4 ## check if we have been in trade too long
5 #
6 ## we maintain that pos[i] is an integer
7 ## if pos[i] == 0 we were flat last period
8 ## if pos[i] > 0 we have been long for count[i] periods
9 ## if pos[i] < 0 we have been short for count[i] periods
10 #
11 time_Stops <- function(params, store, currentPos, Orders){
12   for (i in params$series){
13
14     # Long holding period calculation
15
16     if (flagStore[store$iter, i] == 1) { # in long position today
17       timeStops_count[i] <- 1
18     }
19     else if (timeStops_count[i] > 0 & Orders[i] == 0){
20       timeStops_count[i] <- timeStops_count[i] + 1
```

```
21   }
22
23   # short holding period calculation
24
25   if (flagStore[store$iter, i] == 2) { # in short position today
26     timeStops_count[i] <- -1
27   }
28   else if (timeStops_count[i] < 0 & Orders[i] == 0){
29     timeStops_count[i] <- timeStops_count[i] - 1
30   }
31
32   if(timeStops_count[i] == params$long_holdPeriod |
33       timeStops_count[i] == -params$short_holdPeriod){ # reached holding period
34     Orders[i] <- -currentPos[i] # don't stay short
35     timeStops_count[i] <- 0 # reset count to 0
36   }
37 }
38
39 return(Orders)
40 }
```

Trailing Stops

This strategy evaluates if the daily prices decrease over 8% compared with its highest price over holding period, and if we are in a long position, then exit all positions in one series. If the daily prices increased over 8% compared with its lowest price over holding period, and if we are in a short position, then exit all positions in one series.

```

1 # *****
2 # Trailing Stops
3
4 # if daily close price decrease over 8% compared with
5 # Highest Close over holding period,
6 # and we are in long position, then exit
7
8 trailing_Stops <- function(params, store, currentPos, Orders){
9   for (i in params$series){
10     # store num of days in trade each time
11     if (flagStore[store$iter,i] == 1 |
12         flagStore[store$iter,i] == 2){
13       trailStops_count[i] <- 1
14     }
15
16     else if(flagStore[store$iter,i] == 3 |
17             flagStore[store$iter,i] == 4){
18       if (store$cl[store$iter,i] <
19           max(store$cl[(store$iter-trailStops_count[i]):(store$iter-1)], i)) *
20           (1-params$trailingStops_long_param) & currentPos[i] > 0){
21         Orders[i] <- -currentPos[i] # don't stay Long
22       }
23       else if (store$cl[store$iter,i] >
24               min(store$cl[(store$iter-trailStops_count[i]):(store$iter-1),
25                   i]) *
26                   (1+params$trailingStops_short_param) & currentPos[i] < 0){
27         Orders[i] <- -currentPos[i] # don't stay short
28       }
29       trailStops_count[i] <- trailStops_count[i] + 1
30     }
31   }
32   return(Orders)
33 }

```

VaR and ES

The VaR and ES approach to evaluate extreme risk will be tested in Part 3 data each day. If a pre-defined huge loss happened, we exit all positions in one series.

```

1 # *****
2 # VaR and ES risk control
3
4 # to prevent extreme cases happen
5 VaR_ES_Stops <- function(params, store, currentPos, Orders){
6   for (i in params$series){
7     # Calculate returns
8     RETS<- diff(log(store$cl[1:store$iter,i]))
9
10    if(VaR(RETS, p=params$VaR_p, method = "gaussian") < params$VaR_ret){
11      Orders[i] <- -currentPos[i]
12    }
13    else if(ES(RETS, p=params$ES_p, method = "gaussian") < params$ES_ret){
14      Orders[i] <- -currentPos[i]
15    }
16  }
17  return(Orders)
18 }

```

Strategy Exit Mechanism

This strategy aims to stop losses when our trading system permanently fails by setting a continuous fail times limit and accumulating money loss target for each series. If one of these two conditions triggered, a series will stop trading forever.

```

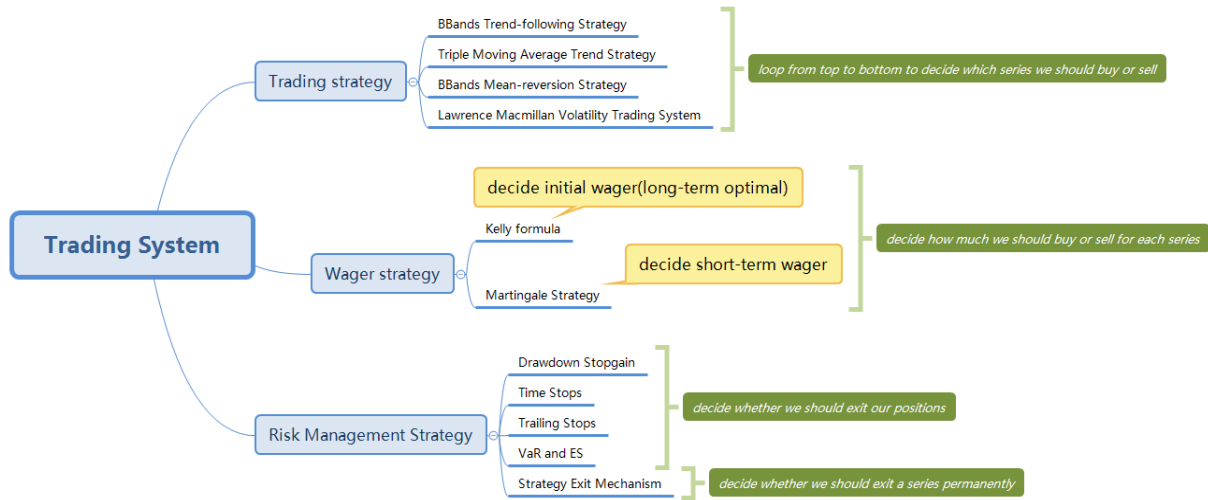
1 # *****
2 # Strategy Exit Mechanism
3
4 Strategy_Exit <- function(params, store){
5   for (i in params$series){
6     # if strategyExit on series i already triggered then just pass
7     if (strategyExit_multiplier[i] == 0){
8       next
9     }
10
11     # store money spend when enter
12     if (flagStore[store$iter,i] == 1 |
13         flagStore[store$iter,i] == 2){
14       SE_lastProfit[i] <- -moneySpendStore[store$iter+1, i]
15     }
16     # when clear position, calculate this trade whether lose or win,
17     # when losing, SE_lastProfit = 1 , else 0
18     else if(flagStore[store$iter,i] == 5){
19       cum_pnl[i] <- cum_pnl[i] + (SE_lastProfit[i] - moneySpendStore[store$iter+
20       1, i])
21       if (SE_lastProfit[i] - moneySpendStore[store$iter+1, i] < 0){
22         SE_lastProfit[i] <- 1
23       }else{
24         SE_lastProfit[i] <- 0
25       }
26     }
27
28     if (flagStore[store$iter,i] == 5 & SE_lastProfit[i] == 1){
29       lossTimes[i] <- lossTimes[i] + 1
30     }
31     # if win, just reset the lossTimes to the initial 0
32     else if (flagStore[store$iter,i] == 5 & SE_lastProfit[i] == 0){
33       lossTimes[i] <- 0
34     }
35
36     # stop trading particular series
37     # if strategy bet wrong params$strategyExit_params times
38     if (lossTimes[i] >= params$strategyExit_params){
39       strategyExit_multiplier[i] <- 0
40     }
41
42     # stop trading particular series
43     # if strategy cumulatively loses more than £50k
44     if (cum_pnl[i] < -50000){
45       strategyExit_multiplier[i] <- 0
46     }
47   }
48 }

```

1.2 Strategies of different parts working together

Generally, our trading system top-down design is as Graph 1 shows:

Graph 1. Trading System Mechanics



```

1 # Combined Strategy -----
2
3 getOrders <- function(store, newRowList, currentPos, info, params){
4
5   # init store
6
7   if (is.null(store)) { #init store in the first day
8     store <- initStore(newRowList,params$series)}
9   else{
10    store <- updateStore(store, newRowList, params$series) #after day 1, update
everyday data to store
11  }
12
13  # init market Orders & Limit Orders12 & Limit Prices12
14
15  marketOrders <- allzero
16  limitOrders1 <- allzero;limitPrices1 <- allzero
17  limitOrders2 <- allzero;limitPrices2 <- allzero
18
19  if (store$iter >= params$lookback){
20
21    # A kind Reminder
22    # *****
23    # store$iter day 0 = moneySpendStore Day 1
24    # *****
25
26    # calculate Today's real money spend on each series
27    moneySpendCalc(params, store)
28
29    # market condition filter(tbc)
30    # 1. if trigger anomaly(e.g. extreme Low volume...) then we stop trading for
at least 30 days(tbd)
31    # 2. ...
32
33    bbtf <- getOrders.bbtf(store, newRowList, currentPos, info, params)
34    tma <- getOrders.tma(store, newRowList, currentPos, info, params)
35    bbmr <- getOrders.bbmr(store, newRowList, currentPos, info, params)
36    lmv <- getOrders.lmv(store, newRowList, currentPos, info, params)
37
38
39    # decide which strategy should dominate
40
41    for(i in params$series){ # looping series
42
43      # main Logic
44
45      if(currentPos[i] == 0 & flagStore[store$iter,i] == 6){
46        order_index <- 1
47        # Looping orders order by Priority
48        for(s in orders_4){
49          # if orders[s] decides to long or short any shares of stock using marke

```

```

t/Limit orders
52   # then stop and output orders to combined strategy orders
53   if(s$marketOrders[i] != 0){
54     marketOrders[i] <- s$marketOrders[i]
55
56     # store which strategy is dominated which series everyday, store in c
odes
57     # 1:5 stands for (mm, bbtf, tma, bbmr, lmv) separately
58     SOCStore[store$iter+1,i] <- order_index
59     break
60   }
61   order_index <- order_index + 1
62 }
63 }
64
65 else if(currentPos[i] != 0){ # if someone is on charge
66   # continue using decisions made by the same strategy
67   SOCStore[store$iter+1,i] <- SOCStore[store$iter,i]
68   marketOrders[i] <- orders_4[[SOCStore[store$iter+1,i]]]$marketOrders[i]
69 }
70 }
71
72 # Wager Strategy
73
74 Martingale(params,store)
75 # reversed_Martingale(params,store)
76
77 # Risk Control Strategy
78
79 # Stop-gain Strategy
80 marketOrders <- Drawdown_Stopgain(params, store, currentPos, marketOrders)
81
82 # Stop-Loss Strategy
83 # Time Stops
84 marketOrders <- time_Stops(params, store, currentPos, marketOrders)
85 # Trailing Stops
86 marketOrders <- trailing_Stops(params, store, currentPos, marketOrders)
87 # VaR and ES Stops
88 marketOrders <- VaR_ES_Stops(params, store, currentPos, marketOrders)
89
90 # Strategy Exit Strategy
91 Strategy_Exit(params, store)
92 }
93
94 # Log everyday on trade signals
95 SignalLog(params, store, currentPos, marketOrders, limitOrders1, limitOrder2)
96
97 # update market/Limit orders everyday
98 marketOrderStore[store$iter+1,] <- marketOrders # stores market Orders of str
ategy on each series everyday
99
100 return(list(store=store,marketOrders=marketOrders,
101            limitOrders1=limitOrders1,limitPrices1=limitPrices1,
102            limitOrders2=limitOrders2,limitPrices2=limitPrices2))
103 }

```

Like Graph 1 and the Combined Strategy code shows, every day our trading system runs 4 trading strategies, 5 risk management strategies and 2 wager strategies in

sequence. Throughout this daily procedure, the trading decision is derived from daily OHLCV information and trading signals.

The daily OHLCV information is passed by the Backtester every day, updated and stored in sets of intermediate variables. Most trading signals, like Moving Average on our trading strategies, are pre-processed every day using the OHLCV stored in these variables.

```

1 # *****
2 # Store OHLCV for feeding backtester
3
4 # Store close price
5 initClStore <- function(newRowList,series) {
6   clStore <- matrix(0,nrow=maxRows,ncol=length(series))
7   return(clStore)
8 }
9 updateClStore <- function(clStore, newRowList, series, iter) {
10  for (i in 1:length(series))
11    clStore[iter,i] <- as.numeric(newRowList[[series[i]]]$Close)
12  return(clStore)
13 }
14
15 # store open price
16 initOpStore<- function(newRowList,series){
17  opStore<- matrix(0,nrow=maxRows,ncol=length(series))
18  return(opStore)
19 }
20 updateOpStore<- function(opStore,newRowList,series,iter){
21  for(i in 1:length(series))
22    opStore[iter,i]<- as.numeric(newRowList[[series[i]]]$Open)
23  return(opStore)
24 }
25
26 # store high price
27 initHiStore<- function(newRowList,series){
28  hiStore<- matrix(0,nrow=maxRows,ncol=length(series))
29  return(hiStore)
30 }
31 updateHiStore<- function(hiStore,newRowList,series,iter){
32  for(i in 1:length(series))
33    hiStore[iter,i]<- as.numeric(newRowList[[series[i]]]$High)
34  return(hiStore)
35 }
36
37 # store low price
38 initLoStore<- function(newRowList,series){
39  loStore<- matrix(0,nrow=maxRows,ncol=length(series))
40  return(loStore)
41 }
42
43 updateLoStore<- function(loStore,newRowList,series,iter){
44  for(i in 1:length(series))
45    loStore[iter,i]<- as.numeric(newRowList[[series[i]]]$Low)
46  return(loStore)
47 }
48
49 # store volume
50 initVolStore<- function(newRowList,series){
51  volStore<- matrix(0,nrow=maxRows,ncol=length(series))
52  return(volStore)
53 }
54
55 updateVolStore<- function(volStore,newRowList,series,iter){
56  for(i in 1:length(series))
57    volStore[iter,i]<- as.numeric(newRowList[[series[i]]]$Volume)
58  return(volStore)
59 }
60
61 # store full list
62 initFullStore<- function(newRowList,series){
63  fullStore<- vector(mode="list", length=length(series))
64  fullStore<- lapply(fullStore, function(x) x=xts(data.frame(Open=0,High=0,Low=0,
65    Close=0,Volume=0), as.Date(0))[-1,])
66  return(fullStore)
67 }
68
69 updateFullStore<- function(fullStore,newRowList, series, iter){
70  for(i in 1:length(series)){
71    NEW<- xts(matrix(as.numeric(newRowList[[series[i]]]),nrow=1),as.Date(index(newRowList[[series[i]]])))
72    fullStore[[i]]<- rbind(fullStore[[i]], NEW)
73  }
74  return(fullStore)
75 }
76
77 # TOTAL DATA STORED IN STORE VARIABLE
78 initStore <- function(newRowList.series) {
79   return(list(iter=0,
80     cl=initClStore(newRowList,series),
81     op=initOpStore(newRowList,series),
82     hi=initHiStore(newRowList,series),
83     lo=initLoStore(newRowList,series),
84     vol=initVolStore(newRowList,series),
85     full= initFullStore(newRowList,series)
86   )
87 )
88
89 updateStore <- function(store, newRowList, series) {
90   store$iter <- store$iter + 1
91   store$cl <- updateClStore(store$cl,newRowList,series,store$iter)
92   store$op <- updateOpStore(store$op,newRowList,series,store$iter)
93   store$hi <- updateHiStore(store$hi,newRowList,series,store$iter)
94   store$lo <- updateLoStore(store$lo,newRowList,series,store$iter)
95   store$vol <- updateVolStore(store$vol,newRowList,series,store$iter)
96   store$full<- updateFullStore(store$full,newRowList,series,store$iter)
97   return(store)
98 }

```

Trading signals including strategy controlling signals, position signals and real money spent signals.

Strategy controlling signals log which trading strategy is dominating one series at a period of time and daily trading status of one series. These two signals are denoted as SOCStore and flagStore separately in the following code.

```

1 # # stores strategy decisions on each series everyday
2 # 1:Long enter, 2:short enter, 3:Long hold,
3 # 4:short hold, 5:clear position, 6:nothing happen
4 flagStore <- matrix(0,nrow=3100,ncol=10)
5 # stores strategy on charge on each series, 1:4 for 4 strategies
6 SOCStore <- matrix(0,nrow=3100,ncol=10)

```

Take SOCStore for instance, on day 221, if only BBands Mean-reversion Strategy triggers and decides to buy 100 shares of series 1, and it exits on day 223. Then values of SOCStore (221, 1), (222,1) and (223,1) would be the sequence encoding of BBands Mean-reversion Strategy, which is 2 showing that from day 221 to 223, BBands Mean-reversion Strategy controls series 1. Therefore, in this period of time, all trading decisions should be made by this strategy in case other strategies increase positions on series 1 or trade on different directions.

Their encoding conditions are shown in the code below:

```

1 # *****
2 # Log Trade Signal
3 # record combined strategy trade signals
4
5 SignalLog <- function(params, store, currentPos, marketOrders, limitOrders1, limitOrders2){
6
7   for(i in params$series){
8
9     # enter conditions
10
11     # currentpos is empty
12     if(currentPos[i] == 0){
13       if(marketOrders[i] > 0){ # if today marketOrder or limitOrder > 0
14         flagStore[store$iter+1,i] <- 1 # Long enter flag
15       }
16       else if(marketOrders[i] < 0){ # if today marketOrder < 0
17         flagStore[store$iter+1,i] <- 2 # short enter flag
18       }
19     }
20
21     # hold conditions
22
23     # when in Long position
24     if (marketOrders[i] == 0){
25       if(currentPos[i] > 0){
26         flagStore[store$iter+1,i] <- 3 # Long hold flag
27       }
28       # when in short position
29       else if (currentPos[i] < 0){
30         flagStore[store$iter+1,i] <- 4 # short hold flag
31       }
32     }
33
34     # exit conditions
35
36     if (currentPos[i] != 0 & marketOrders[i] != 0){
37       flagStore[store$iter+1,i] <- 5 # exit flag
38     }
39
40     # no trading condition
41
42     if (currentPos[i] == 0 & marketOrders[i] == 0){
43       flagStore[store$iter+1,i] <- 6 # no trading flag
44       SOCStore[store$iter+1,i] <- 0
45     }
46   }
47 }

```

Similar to Strategy controlling signals, the position signals and real money spent signals, denoted as marketOrderStore and moneySpendStore respectively in the code, are used to store daily market orders and real money spent on market orders on each series. Because we only used market orders to trade in this trading system, these two signals can be considered as the daily orders and money logs of our trading system, which can be utilized to calculate a number of matrixes like Win Rate, Loss Rate, Continuous Loss Times, Win/Loss amount for a single trade. These matrices play an important role in our Wager Strategy and Risk Management Strategy.

```

1 # Helper global variables-----
2
3 # for init vector
4
5 allzero <- rep(0,10) # used for initializing vectors
6 maxRows <- 3100 # set maxRows as the number of rows in data
7
8 # # stores strategy decisions on each series everyday
9 # 1:Long enter, 2:short enter, 3:Long hold,
10 # 4:short hold, 5:clear position, 6:nothing happen
11 flagStore <- matrix(0,nrow=3100,ncol=10)
12 # stores strategy on charge on each series, 1:4 for 4 strategies
13 SOCStore <- matrix(0,nrow=3100,ncol=10)
14
15 # store everyday orders and real money spent for each series
16
17 moneySpendStore <- matrix(0,nrow=3100,ncol=10) # stores real money spent of strategy on each series everyday
18 marketOrderStore <- matrix(0,nrow=3100,ncol=10) # stores market orders on each series everyday
19
20 # some global variables for wager strategy and risk strategies
21
22 Martingale_multiplier <- rep(1,10) # Martingale multiplier
23 Martingale_lastProfit <- vector(mode="numeric",length=10) # stores profit in the last trade for each series over time
24 revMartingale_lastProfit <- vector(mode="numeric",length=10) # stores profit in the last trade for each series over time
25 timeStops_count <- rep(0,10) # for Time Stops holding period counting
26 trailStops_count <- vector(mode="numeric",length=10) # stores number of days in trade
27 SE_lastProfit <- vector(mode="numeric",length=10) # stores profit in the last trade for each series over time for Strategy Exit
28 lastProfit <- vector(mode="numeric",length=10) # stores profit in the last trade for each series over time
29 lossTimes <- vector(mode="numeric",length=10) # stores loss times
30 strategyExit_multiplier <- rep(1,10) # Strategy Exit multiplier
31 Drawdown_lastProfit <- vector(mode="numeric",length=10) # stores profit in the last trade for each series over time for Drawdown Stop Gain
32 cum_pnl <- vector(mode="numeric",length=10) # stores cumulative pnl

```

Take Drawdown Stop-gain method code as an example to demonstrate how these signals contribute to Risk Management Strategy.

Like the following code indicates, we store total money spent on series 'i' when entering a position as 'Enter Cost' where flagStore is 1 or 2(stands for long/short enter) with our variable 'moneySpendStore' at day 'store\$iter+1' on 'Drawdown_lastProfit[i]'. When trading strategy decides to hold our positions on series i(flagStore = 3 or 4, which stands for long/short hold), this risk strategy needs to calculate the rolling gain drawdown to decide if we should exit instantly.

```

1 # *****
2 # Drawdown Stop-gain method
3
4 # The Drawdown Stop-gain method is a strategy that does not
5 # involve any Stop-gain strategy in a bull market,
6 # and then redeems when there is a relatively Large short-term Drawdown
7
8 Drawdown_Stopgain <- function(params, store, currentPos, Orders){
9   for (i in params$series){
10     # store money spend when enter position
11     if (flagStore[store$iter,i] == 1 |
12         flagStore[store$iter,i] == 2){
13       Drawdown_lastProfit[i] <- moneySpendStore[store$iter+1, i]
14     }
15
16     else if (flagStore[store$iter,i] == 3
17              & store$cl[store$iter, i] > Drawdown_lastProfit[i]/currentPos[i]){
18       if ((store$cl[store$iter, i] - store$cl[store$iter-1, i]) /
19           store$cl[store$iter-1, i] < params$Stopgain_long_param){
20         Orders[i] = -currentPos[i]
21       }
22     }
23
24     else if(flagStore[store$iter,i] == 4
25             & Drawdown_lastProfit[i]/currentPos[i] > store$cl[store$iter, i]){
26       if ((store$cl[store$iter, i] - store$cl[store$iter-1, i]) /
27           store$cl[store$iter-1, i] > params$Stopgain_short_param){
28         Orders[i] = -currentPos[i]
29       }
30     }
31   }
32   return(Orders)
33 }

```

1.3 Optimizing and checking the robustness of strategy

Except for the 'lookback' and 'series' in the last parameter set we define directly as '100' and '1:10', because of the longest-term MA signal limit in the LMV strategy. If 'lookback' is below 100 days, we cannot get MA100, thus we do not make any transactions in the first 100 days. In addition, 4 trading strategies for 10 series in the training set and test set data have different performance, and if the series are filtered based on different winning strategies, it will lead to high development costs, so we do not put any restrictions on 'series'.

Regarding optimization method, genetic algorithm and 'Multi-mcga' R package are implemented by randomly generating 35 parameters in pre-defined times of 'evolution' and finally selecting the best-K performance parameter sets as the code below indicates.

```

1 epoch <- 0
2
3
4 evalFunc <- function(x) {
5   s=Sys.time() #timer
6   source('D:/preloading.R');
7
8   epoch <- epoch + 1
9
10  params.opt <- list(lookback=100, # watch window, default 100, means no trade a
    t the first 100 days
11                    series=1:10, # contol which series we want to trade, defaul
    t 1:10
12                    posSizes=c(x[1],x[2],x[3],x[4],x[5],x[6],x[7],x[8],x[9],x[1
    0]), # control series viable to TMA
13                    long_holdPeriod=x[11], # control maximum long holding perio
    d
14                    short_holdPeriod=x[12], # control maximum short holding per
    iod
15                    TMA_MA1=x[13], TMA_MA2=x[14], TMA_MA3=x[15], # control shor
    t/Mid/Long term signals for TMA
16                    LMV_EMA1=x[16], LMV_EMA2=x[17], LMV_EMA3=x[18], LMV_EMA4=x[1
    9], LMV_EMA5=x[20], # control short/Mid/Long term signals for TMA
17                    BBMR_SMA=x[21], # control exit SMA for BBMR
18                    BBMR_up_sdParam=x[22], BBMR_dn_sdParam=x[23], # control Upp
    er/Lower bounds for BBMR
19                    BBTF_up_sdParam=x[24], BBTF_dn_sdParam=x[25], # control Upp
    er/Lower bounds for BBTF
20                    srategyExit_params=x[26], # controls maximum acceptable fai
    ling times for combined strategy
21                    VaR_p=x[27], VaR_ret=x[28], # control extreme risk measurem
    ent for VaR
22                    ES_p=x[29], ES_ret=x[30], # control extreme risk measuremen
    t for ES
23                    trailingStops_long_param=x[31], # control trailing history
    bound when Long Hold
24                    trailingStops_short_param=x[32], # control trailing history
    bound when Short Hold
25                    Stopgain_long_param=x[33], # control short-term Drawdown Le
    vel when Long Hold
26                    Stopgain_short_param=x[34], # control short-term Drawdown l
    evel when Short Hold
27                    Martingale=x[35]) # control martingale multiplier
28
29  test.opt <- backtest(dataList, getOrder, params.opt, sMult=0.2)
30  pfolioPnl.opt <- plotResults(dataList, test.opt, plotType='ggplot2',
31                             titleString=paste('Strategy Performance, Epoch:',ep
    och))
32
33  final_perf <- perfCalc(test=test.opt, pfolioPnl=pfolioPnl.opt)
34
35  result <- numeric(4)

```

```

36  result[1] <- -final_perf$pn1
37  result[2] <- -final_perf$PDratio
38  result[3] <- -final_perf$activeness
39  result[4] <- -final_perf$expected_profit
40
41  cat('*****')
42  cat('\n')
43  cat('epoch:',epoch)
44  cat('\n')
45  e=Sys.time()
46  cat('runtime: ', e-s)
47  cat('\n\n')
48  cat('params:')
49  print(params.opt)
50  cat('pn1:', -result[1])
51  cat('\n')
52  cat('PDRatio:', -result[2])
53  cat('\n')
54  cat('avtiveness:', -result[3])
55  cat('\n')
56  cat('expected_profit:', -result[4])
57  cat('\n')
58  cat('*****')
59  cat('\n')
60
61  return(result)
62 }
63
64 # constrainFunc <- function(x) {
65 #   x[11] >= 1
66 #   x[11] <= 3
67 #   x[12] <= 8
68 #   x[12] >= 1
69 # }
70
71 res <- nsga2(fn = evalFunc, idim = 35, odim = 4, cdim=0, # constraints=constrai
    nFunc
72             popsize = 100, generations=3,
73             lower.bounds=c(0,0,0,0,0,0,0,0,0,0, # posSizes
74                           1,1,2,20,50,2,10,30,60,80, # params 11-20
75                           2,1,1,1,4,0.8,-0.2,0.8,-0.2, # params 21-30
76                           0.01,0.01,-0.2,0.01,1.1), # params 31-34
77             upper.bounds=c(4000,200,100000,2000,1000,18000,1000,1200,1200,240,
78                           10,10,10,50,100,10,30,60,80,100,
79                           50,5,5,5,12,0.999,-0.01,0.999,-0.01,
80                           0.2,0.2,-0.01,0.2, 3))
81
82 #
83 # Result <- cbind(res[['par']],res[['value']])
84 # Result <- cbind(Result, res[['pareto.optimal']])
85 # write.csv(Result, "D:/result.xls")
86
87 # X <- unlist(Result[1,1:40])

```

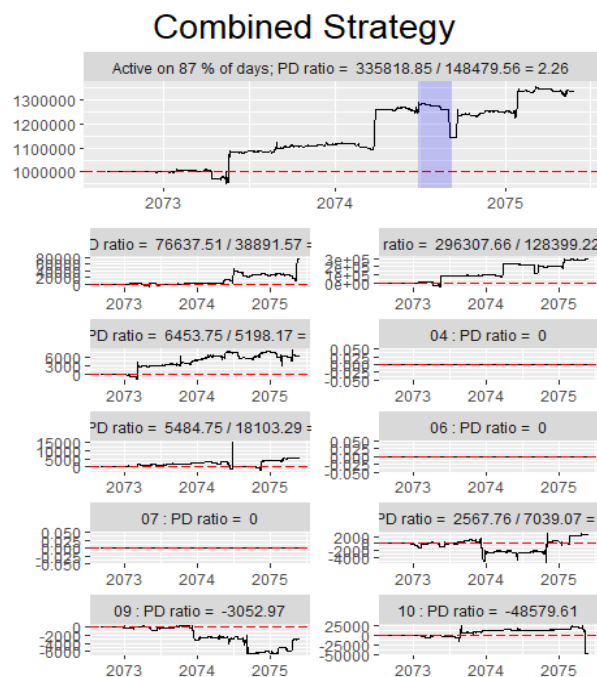
In this process, the most important thing is to define the objective function. At first, we defined the objective function as maximizing PNL and PD ratio, and among the final 100 sets of parameters produced after 100 iterations, we found that these parameter combinations all clearly overfitting, for example, most of them having significantly high profits in the training set (part 1 data), but the profits and positions as well as the number of trades were concentrated in minor series. What's worse, most of the parameter portfolios are inactive and stop trading after making some money. Not surprisingly, in the test set (part 2 data) performance, the 100 final results all showed completely different and relatively large drawdowns and losses, and were very volatile over the trading period. Next, we adjusted the objective function and added two new indicators, Activeness and Expect Profit into the objective function, in order to make our parameter combinations trade more frequently, rather than relying on minor times of trading to make money and then stop trading afterwards to ensure that the final parameter combinations are robust enough, rather than random luck. By bringing in Expect Profit, the maximization of expected profit in each trade can also guarantee our long-term performance is robust. In the meantime, we adjusted the train set to 1000

days data of part 1 plus 500 days data of part 2 and the population sizes of Genetic Algorithm to 100 per generation and 100 generations in total to ensure there are enough mutations of parameters and the information of 10 series during part 2 data.

Table 1. Final Top-100 Performance Parameter Sets after Genetic Algorithm optimization

Like Table 1. Shows, after adjustments, we got the 100 sets of top performance parameters. By observation, we found that some parameters regressed around certain enumerated values, so we directly take their plural for these parameters as our final parameters. For those parameters with more dispersed enumeration values, we took the average value of them as our final choice. Finally, as Graph 2 demonstrated, we achieved a robust profit in the test set (last 500 days part 2 data) which had a relatively low drawdown and relatively stable profit over time.

Graph 2. Performance of Combined Strategy with optimized parameter set on Part 2 data



2. Justification of submitted strategy

2.1 The process led to this particular strategy

In part 2 of the project, from data analysis, 6 strategies are developed that might be suitable for trading 10 series. However, as can be seen from Graph 3, in the test set (1000 days part1 data + 500 days part2 data), we found that The Jump Trading Strategy did not trigger at all no matter what parameters we chose, so we just discarded it.

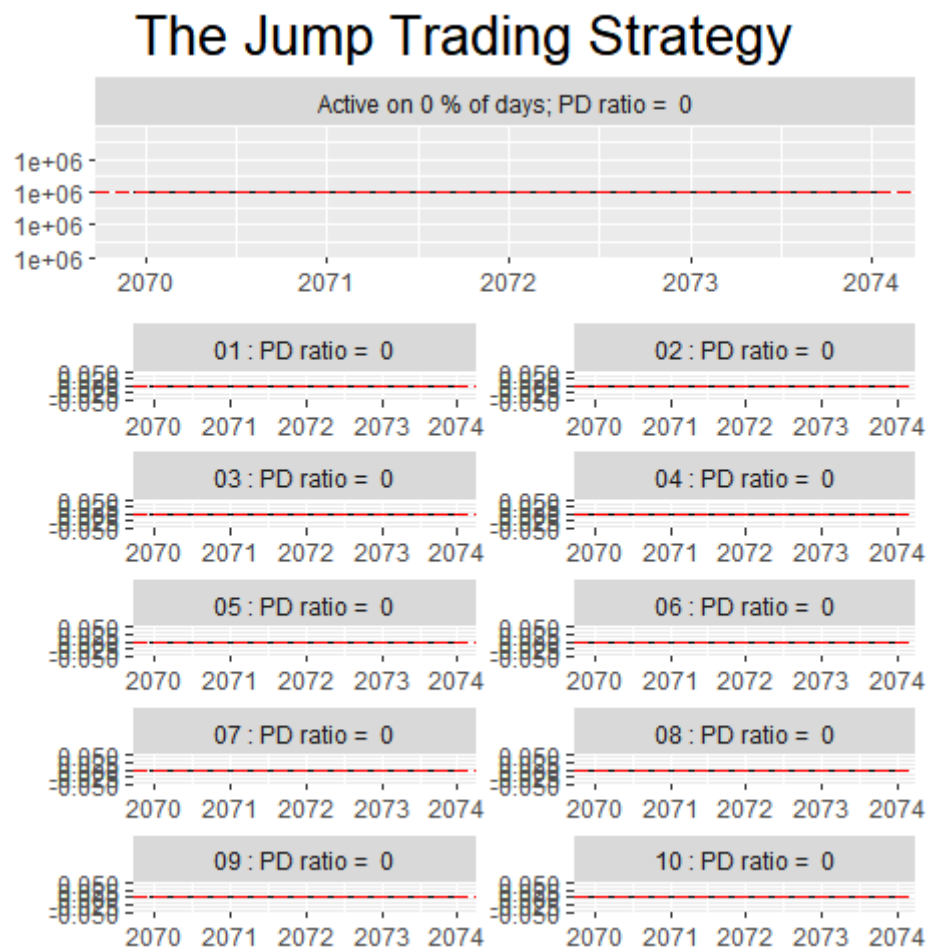
```
1 # 4. The Jump Trading Strategy -----
2 # (abandoned)
3 #
4 # The Jump Trading System is a psychological trading system that
5 # measures sudden price changes due primarily to excessive emotional reactions.
6 # Its basic movement is in a downtrend where prices fluctuate
7 # around the lower range of the box range for 5 to 10 days,
8 # then open price sharply lower below the trend line with extreme selling sentiment,
9 # and if it then rebounds to yesterday's lows, it indicates a reversal of market
10 # energy
11 # and another bullish upward move is ready to take place. Systematic buying mechanical rules.
12 # 1. close price 4% below the five-day MA to ensure the signal occurs on a downtrend.
13 # 2. and open price is 1% below yesterday's low price.
14 # 3. Closing rally above yesterday's low price.
15 # init params
16 params.jt <- list(lookback=5, series=1:10, posSizes=rep(1,10), holdPeriod=6) # tb
17 d
18 # main strategy
19 getOrders.jt<- function(store, newRowList, currentPos, info, params){
20   # used for initializing vectors
21   allzero <- rep(0,length(newRowList))
22
23   # init store
24   if (is.null(store)) {
25     store <- initStore(newRowList,params$series)}else{
26     store <- updateStore(store, newRowList, params$series)
27   }
28
29   # init today's enter positions on each series
30   pos <- allzero
31
32   # default exit yesterday's overall positions
33   marketOrders <- -currentPos
34
35   # we need to wait until day 101 so that we have ema100 signal
36   if(store$iter > params$lookback){
```

```

37   for(i in params$series){
38     # everyday re-calculate today's ema5
39     ema5 <- last(EMA(store$cl[1:store$iter,i],5))
40
41     # Long enter
42     if(((store$cl[store$iter,i] - ema5) / ema5 <= -0.04) &
43        ((store$op[store$iter,i] - store$lo[store$iter-1,i]) / store$lo[store$iter-1,i] <= -0.01) &
44        (store$cl[store$iter,i] > store$lo[store$iter-1,i])){
45       # pos[i] <- params$posSizes[i]*1000000 / store$cl[store$iter,i]
46       pos[i] <- params$posSizes[i]
47
48       # exit when direction turned again
49     }else if(((currentPos[i] != 0) &
50              (store$cl[store$iter,i] < store$cl[store$iter-1,i]))){
51       pos[i] <- 0
52
53       # hold when still in the trend
54     }else if(((currentPos[i] != 0) &
55              (store$cl[store$iter,i] >= store$cl[store$iter-1,i]))){
56       pos[i] <- currentPos[i]
57     }
58     #
59     # # check if we have been in trade too Long
60     #
61     # # we maintain that pos[i] is an integer
62     # # if pos[i] == 0 we were flat last period
63     # # if pos[i] > 0 we have been long for store$count[i] periods
64     # # if pos[i] < 0 we have been short for store$count[i] periods
65     #
66     # if (pos[params$series[i]] > 0) {# Long signal today
67     #   if (store$count[i] < 0) # last time we were short
68     #     store$count[i] == 1
69     #   else if (store$count[i] == params$holdPeriod) { # reached holding period
70     #     pos[params$series[i]] <- 0 # don't stay Long
71     #     store$count[i] <- 0 # reset count to 0
72     #   }
73     #   else # 0 <= store$count[i] != (should be <) params$holdPeriod
74     #     store$count[i] <- store$count[i] + 1
75     #   }
76     #   #
77     #   # else if (pos[params$series[i]] < 0) {# short signal today
78     #   #   if (store$count[i] > 0) # last time we were Long
79     #   #     store$count[i] == -1
80     #   #   else if (store$count[i] == -params$holdPeriod) { # reached holding period
81     #   #     pos[params$series[i]] <- 0 # don't stay short
82     #   #     store$count[i] <- 0 # reset count to 0
83     #   #   }
84     #   #   else # 0 >= store$count[i] != (should be >) -params$holdPeriod
85     #   #     store$count[i] <- store$count[i] - 1
86     #   #   }
87     #   # else{
88     #   #   store$count[i] <- 0 # reset count to 0
89     #   # }
90   }
91 }
92 marketOrders <- marketOrders + pos
93 return(list(store=store,marketOrders=marketOrders,
94            limitOrders1=allzero,limitPrices1=allzero,
95            limitOrders2=allzero,limitPrices2=allzero))
96 }
97
98 test.jt<- backtest(dataList, getOrders.jt, params.jt, sMult=0.2)
99 pfolioPnL.jt <- plotResults(dataList, test.jt, plotType='ggplot2',
100                             titleString='The Jump Trading Strategy')

```

Graph 3. Performance of The Jump Trading Strategy with default parameters on training set
(1000 days part 1 + 500 days part 2)



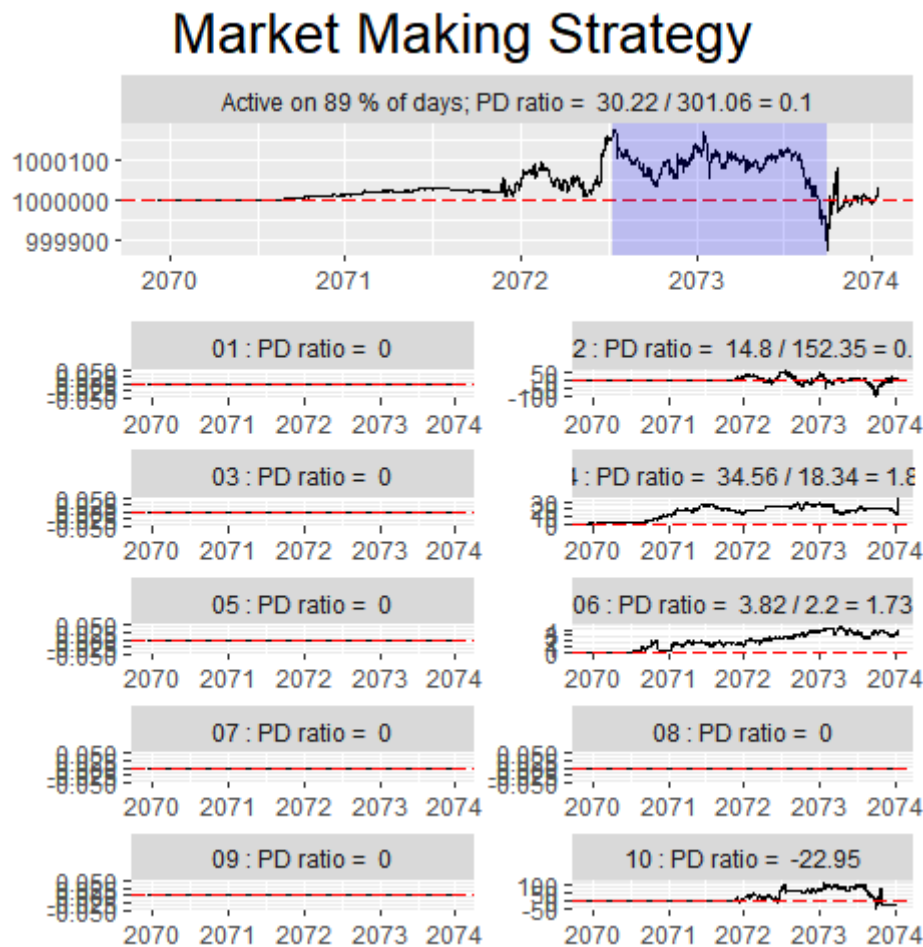
The Market Making Strategy performed well in both part 1 and part 2 data like Graph 3 displayed, but due to the immaturity of our system design for trading signal logging mechanism before development, we mistakenly used the Market Orders information sent back to the Backtester framework for each day to record trade information. To make it worse, our initial code was developed with BBands Mean-reversion Market Orders, which led to a redesign of the entire signal system if we tried to use Limit Orders later on, so we finally had to abandon the Market Making Strategy and Limit Orders.

```

1 # 3. Market Making Strategy -----
2 # One of the most important types of high-frequency trading strategies is
3 # Market Making, i.e., making profits by earning bid-ask spreads
4 # But in our case, we want to exploit the market by setting a proper
5 # spread range so that we can betting on both sides by Limit orders
6 # Buy Low and sell high to make profit
7
8 # init params
9 params.mm <- list(lookback=0, series=1:10,
10                  posSizes=rep(1,10), spread=0.08, holdPeriod=6) # tbd
11
12 # main strategy
13 getOrders.mm<- function(store, newRowList, currentPos, info, params){
14   # used for initializing vectors
15   allzero <- rep(0,length(newRowList))
16
17   # if our positions reach 2 times betting level then exit yesterday's overall po
18   sitions
19   marketOrders<- ifelse(abs(currentPos)>2*params$posSizes, -currentPos, 0)
20
21   # init store
22   if (is.null(store)) {
23     store <- initStore(newRowList,params$series)}else{
24     store <- updateStore(store, newRowList, params$series)
25   }
26
27   # init today's enter positions on each series
28   pos <- allzero
29
30   # init LimitPrices1/LimitPrices2/LimitOrders1/LimitOrders2
31   limitPrices1<- allzero; limitOrders1<- allzero
32   limitPrices2<- allzero; limitOrders2<- allzero
33
34   if(store$iter > params$lookback){
35     for(i in params$series){
36       # market making - betting on both sides
37       # limitOrders1[i]<- params$posSizes[i]*1000000/store$cl[store$iter,i]
38       limitOrders1[i]<- params$posSizes[i]
39       limitPrices1[i]<- (store$hl[store$iter,i]+store$lo[store$iter,i])/2+params
40       $spread*store$cl[store$iter,i]
41       limitOrders2[i]<- -params$posSizes[i]
42       limitPrices2[i]<- (store$hl[store$iter,i]+store$lo[store$iter,i])/2+params
43       $spread*store$cl[store$iter,i]
44     }
45     # # check if we have been in trade too Long
46     # # we maintain that pos[i] is an integer
47     # # if pos[i] == 0 we were flat last period
48     # # if pos[i] > 0 we have been Long for store$count[i] periods
49     # # if pos[i] < 0 we have been short for store$count[i] periods
50     #
51     # if (pos[params$series[i]] > 0) {# Long signal today
52     #   if (store$count[i] < 0) # Last time we were short
53     #     store$count[i] == 1
54     #   else if (store$count[i] == params$holdPeriod) { # reached holding perio
55     d
56     #     pos[params$series[i]] <- -currentPos[i] # don't stay Long
57     #     store$count[i] <- 0 # reset count to 0
58     #   }
59     #   else # 0 <= store$count[i] != (should be <) params$holdPeriod
60     #     store$count[i] <- store$count[i] + 1
61     #   }
62     # }
63     # else if (pos[params$series[i]] < 0) {# short signal today
64     #   if (store$count[i] > 0) # Last time we were Long
65     #     store$count[i] == -1
66     #   else if (store$count[i] == -params$holdPeriod) { # reached holding peri
67     od
68     #     pos[params$series[i]] <- -currentPos[i] # don't stay short
69     #     store$count[i] <- 0 # reset count to 0
70     #   }
71     #   else # 0 >= store$count[i] != (should be >) -params$holdPeriod
72     #     store$count[i] <- store$count[i] - 1
73     #   }
74     # }
75     # else{
76     #   store$count[i] <- 0 # reset count to 0
77     # }
78   }
79   }
80
81   marketOrders <- marketOrders + pos
82   return(list(store=store,marketOrders=marketOrders,
83              limitOrders1=limitOrders1,limitPrices1=limitPrices1,
84              limitOrders2=limitOrders2,limitPrices2=limitPrices2))
85 }
86
87 test.mm<- backtest(dataList, getOrders.mm, params.mm, sMult=0.2)
88 pfolioPnL.mm <- plotResults(dataList, test.mm, plotType='ggplot2',
89                             titleString='Market Making Strategy')

```

Graph 4. Performance of Market Making Strategy with default parameters on training set
(1000 days part 1 + 500 days part 2)



Regarding the selection of trading strategies and series, we found that with the initial parameter settings, the remaining 4 trading strategies were able to obtain different profit on different series. But each strategy itself triggered not much, only being active 10-20% of period. So, it was natural to come out with the idea to involve them in the decision making together. However, when we noticed a problem that if all strategies make decisions together, multiple strategies may be triggered on the same series at the same time, and the positions placed by different strategies may lead to additional positions or cancel each other out. Therefore, we decided to set priorities according to the performance of the four strategies in the test set, so that the strategy with the higher priority makes the first decision. If the strategy with the higher priority does not place any order, then the strategy with the lower priority continues to make judgments until all four strategies complete their decisions. Finally, we execute the highest priority non-empty trade order.

```

1 # part of code from Combined Strategy code
2
3 # market condition filter(tbc)
4 # 1. if trigger anomaly(e.g. extreme low volume...) then we stop trading for
   at least 30 days(tbd)
5 # 2. ...
6
7 bbtF <- getOrders.bbtF(store, newRowList, currentPos, info, params)
8 tma <- getOrders.tma(store, newRowList, currentPos, info, params)
9 bbmr <- getOrders.bbmr(store, newRowList, currentPos, info, params)
10 lmv <- getOrders.lmv(store, newRowList, currentPos, info, params)
11
12 # order by Priority (derived from individual Strategy Performance)
13 orders_4 <- list(bbtF, tma, bbmr, lmv)
14
15 # decide which strategy should dominate
16
17 for(i in params$series){ # Looping series
18
19   # main logic
20
21   if(currentPos[i] == 0 & flagStore[store$iter,i] == 6){
22     order_index <- 1
23     # Looping orders order by Priority
24     for(s in orders_4){
25       # if orders[s] decides to long or short any shares of stock using marke
t/limit orders
26       # then stop and output orders to combined strategy orders
27       if(s$marketOrders[i] != 0){
28         marketOrders[i] <- s$marketOrders[i]
29
30         # store which strategy is dominated which series everyday, store in c
odes
31         # 1:5 stands for (mm, bbtF, tma, bbmr, lmv) separately
32         SOCStore[store$iter+1,i] <- order_index
33         break
34       }
35       order_index <- order_index + 1
36     }
37   }
38
39   else if(currentPos[i] != 0){ # if someone is on charge
40     # continue using decisions made by the same strategy
41     SOCStore[store$iter+1,i] <- SOCStore[store$iter,i]
42     marketOrders[i] <- orders_4[[SOCStore[store$iter+1,i]]]$marketOrders[i]
43   }
44 }

```

In relation to the selection of series, the Kelly Formula is utilized based on the performance of the 10 series on the test set to get the long-term optimal wager, which ensures optimal long-term profitability with minimal risk of bankruptcy.

2.2 Justifying the choice of position sizing, and other key elements of strategy.

As mentioned in the Part 1 report, there are three main components in our position sizing strategy: Wager strategy, Capital Utilization and Leverage.

According to the Wager Strategy, we tried the Kelly formula with mathematically strict long-term optimal betting ratios, the Martingale Strategy and the Reverse Martingale strategy respectively, using the BBands Mean-reversion Strategy with default parameter settings. For comparison, we used fixed wager strategy and performance-based fixed wager strategy as comparison groups as benchmark, and we also split the training and test sets to observe the performance of these 3 strategies over time to ensure our results are robust.

```
1 # *****
2 # Martingale Wager strategy
3
4 Martingale <- function(params, store){
5   for (i in params$series){
6     # store money spend for establish position
7     if (flagStore[store$iter,i] == 1 |
8         flagStore[store$iter,i] == 2){
9       Martingale_lastProfit[i] <- -moneySpendStore[store$iter+1, i]
10    }
11    # when clear position, calculate this trade whether lose or win,
12    # when losing, LastProfit = 1 , else 0
13    else if(flagStore[store$iter,i] == 5){
14      if (Martingale_lastProfit[i] - moneySpendStore[store$iter+1, i] < 0){
15        Martingale_lastProfit[i] <- 1
16      }else{
17        Martingale_lastProfit[i] <- 0
18      }
19    }
20    # when clear position and Lose, double the wager for the next time
21    if (flagStore[store$iter,i] == 5 & Martingale_lastProfit[i] == 1){
22      Martingale_multiplier[i] <- Martingale_multiplier[i] * params$Martingale
23    }
24    # if win, just reset the wager to the initial amount
25    else if (flagStore[store$iter,i] == 5 & Martingale_lastProfit[i] == 0){
26      Martingale_multiplier[i] <- 1
27    }
28  }
29 }
30
31
32 # *****
33 # Reversed Martingale Wager strategy
34
35 reversed_Martingale <- function(params, store){
36   for (i in params$series){
37     # store money spend for establish position
38     if (flagStore[store$iter,i] == 1 |
39         flagStore[store$iter,i] == 2){
40       revMartingale_lastProfit[i] <- -moneySpendStore[store$iter+1, i]
41    }
```



```

42 # when clear position, calculate pnl
43 # when winning, LastProfit = 1 , else 0
44 else if(flagStore[store$iter,i] == 5){
45   if (revMartingale_lastProfit[i] - moneySpendStore[store$iter+1, i] > 0){
46     revMartingale_lastProfit[i] <- 1
47   }else{
48     revMartingale_lastProfit[i] <- 0
49   }
50 }
51
52 # when clear position and win, double the wager for the next time
53 if (flagStore[store$iter,i] == 5 & revMartingale_lastProfit[i] == 1){
54   Martingale_multiplier[i] <- Martingale_multiplier[i] * params$Martingale
55 }
56 # if win, just reset the wager to the initial amount
57 else if (flagStore[store$iter,i] == 5 & revMartingale_lastProfit[i] == 0){
58   Martingale_multiplier[i] <- 1
59 }
60 }
61 }
62
63 # the Kelly best ratio for each series can only derive from final performance
64 # using the following function
65
66 # *****
67 # performance measurement
68 perfCalc <- function(test, pfolioPnL){
69
70   lastProfit <- vector(mode="numeric",length=10)
71   winTimes <- vector(mode="numeric",length=10)
72   WinBalance <- vector(mode="numeric",length=10)
73   loseTimes <- vector(mode="numeric",length=10)
74   loseBalance <- vector(mode="numeric",length=10)
75   tradeTimes <- vector(mode="numeric",length=10)
76   gambitRate <- vector(mode="numeric",length=10)
77   kelly <- vector(mode="numeric",length=10)
78   winRate <- vector(mode="numeric",length=10)
79   lossRate <- vector(mode="numeric",length=10)
80
81   pnl <- as.double(pfolioPnL[["pfoliosPnL"]][nrow(pfolioPnL[["pfoliosPnL"]]),2])
82   PDratio <- pfolioPnL[["fitAgg"]]
83   activeness <- as.double(test[["k"]])
84
85   for (d in 2:1000){
86     for (i in 1:10){
87       # store money spend for establish position
88       if (flagStore[d-1,i] == 1 |
89         flagStore[d-1,i] == 2){
90         lastProfit[i] <- -moneySpendStore[d, i]
91       }
92       # when clear position, calculate this trade whether Lose or win,
93       # when losing, LastProfit = 1 , else 0
94       else if(flagStore[d-1,i] == 5){
95         if (lastProfit[i] - moneySpendStore[d, i] > 0){
96           winTimes[i] <- winTimes[i] + 1
97           WinBalance[i] <- WinBalance[i] + (lastProfit[i] - moneySpendStore[d,
98 i))
99         }else if (lastProfit[i] - moneySpendStore[d, i] < 0){
100           loseTimes[i] <- loseTimes[i] + 1
101           loseBalance[i] <- loseBalance[i] + (lastProfit[i] - moneySpendStore[d,
102 i))
103         }
104         tradeTimes[i] <- tradeTimes[i] + 1
105       }
106     }
107   }
108   for (i in 1:10){
109     winRate[i] <- winTimes[i]/tradeTimes[i]
110     lossRate[i] <- 1-winRate[i]
111     gambitRate[i] <- (winTimes[i]/WinBalance[i]) / (loseTimes[i]/loseBalance[i])
112     kelly[i] <- ((gambitRate[i]+1)*winRate[i] - 1) / gambitRate[i]
113   }
114
115   avg_winRate <- mean(winRate, na.rm = TRUE)
116   avg_lossRate <- mean(lossRate, na.rm = TRUE)
117   avg_winTimes <- mean(winTimes, na.rm = TRUE)
118   avg_loseTimes <- mean(loseTimes, na.rm = TRUE)
119   avg_tradeTimes <- mean(tradeTimes, na.rm = TRUE)
120   sum_winTimes <- sum(winTimes, na.rm = TRUE)
121   sum_loseTimes <- sum(loseTimes, na.rm = TRUE)
122   sum_tradeTimes <- sum(tradeTimes, na.rm = TRUE)

```

```

122 sum_kelly <- sum(kelly, na.rm = TRUE)
123 expected_profit <- pnl / sum_tradeTimes
124
125 res <- list('pnl'=pnl,
126            'PDratio'=PDratio,
127            'activeness'=activeness,
128            'winTimes'=winTimes,
129            'loseTimes'=loseTimes,
130            'tradeTimes'=tradeTimes,
131            'WinBalance'=WinBalance,
132            'loseBalance'=loseBalance,
133            'winRate'=winRate,
134            'lossRate'=lossRate,
135            'gambitRate'=gambitRate,
136            'kelly'=kelly,
137            'avg_winRate'=avg_winRate,
138            'avg_lossRate'=avg_lossRate,
139            'avg_winTimes'=avg_winTimes,
140            'avg_loseTimes'=avg_loseTimes,
141            'avg_tradeTimes'=avg_tradeTimes,
142            'sum_winTimes'=sum_winTimes,
143            'sum_loseTimes'=sum_loseTimes,
144            'sum_tradeTimes'=sum_tradeTimes,
145            'sum_kelly'=sum_kelly,
146            'expected_profit'=expected_profit
147          )
148 return(res)
149 }

```

Like the codes above show, the Kelly best ratio for each series can only derive from calculating the win rate, loss rate, expected gain for each trade using final performance. At this point, we are left with 1 question, how exactly should we apply Kelly formula? Our first idea was to calculate the Kelly best wager ratio separately for different strategies and different series, thus obtaining 40(4*10) wagers. But we found that when there are more parameters, the easier it is to over-fit. In addition, we find it too expensive to develop separate statistics on the performance of each sub-trading strategy in our final Combined strategy. Thus, this idea is abandoned. Finally, we considered the whole trading system as a whole and then used the Kelly formula only for the series, and found that the over-fit was not so serious.

*Table 2. Combined Strategy Performance in Training Set (1000 days part 1 + 500 days part 2)
with different Wager Strategy*

Wager Strategy(initial wager)	PD ratio	PnL	Trigger Times	Invested No. Of Series	Win times	Lose times	Expected Profit per time	Win Rate	Loss Rate
<i>fixed wager (\$50,000 worth shares for each series)</i>	-443048.5	-443048.5	293	10	129	163	-1512.11	40.65%	59.35%
<i>fixed wager (\$100,000 worth shares for each series)</i>	-260402.3	-260402.3	175	10	82	93	-1488.01	46.75%	53.25%
<i>performance-based fixed wager (based on \$50,000 fixed wager PnL, bad series deducted)</i>	-153846.63	-153846.63	164	5	78	86	-938.09	46.60%	53.40%
<i>performance-based fixed wager(based on \$100,000 fixed wager PnL, bad series deducted)</i>	2.07	118957.77	29	3	12	17	4101.99	41.11%	58.89%
<i>Fixed Kelly optimal ratio wager</i>	1.05	58645.8	301	7	130	171	194.84	44.23%	55.77%

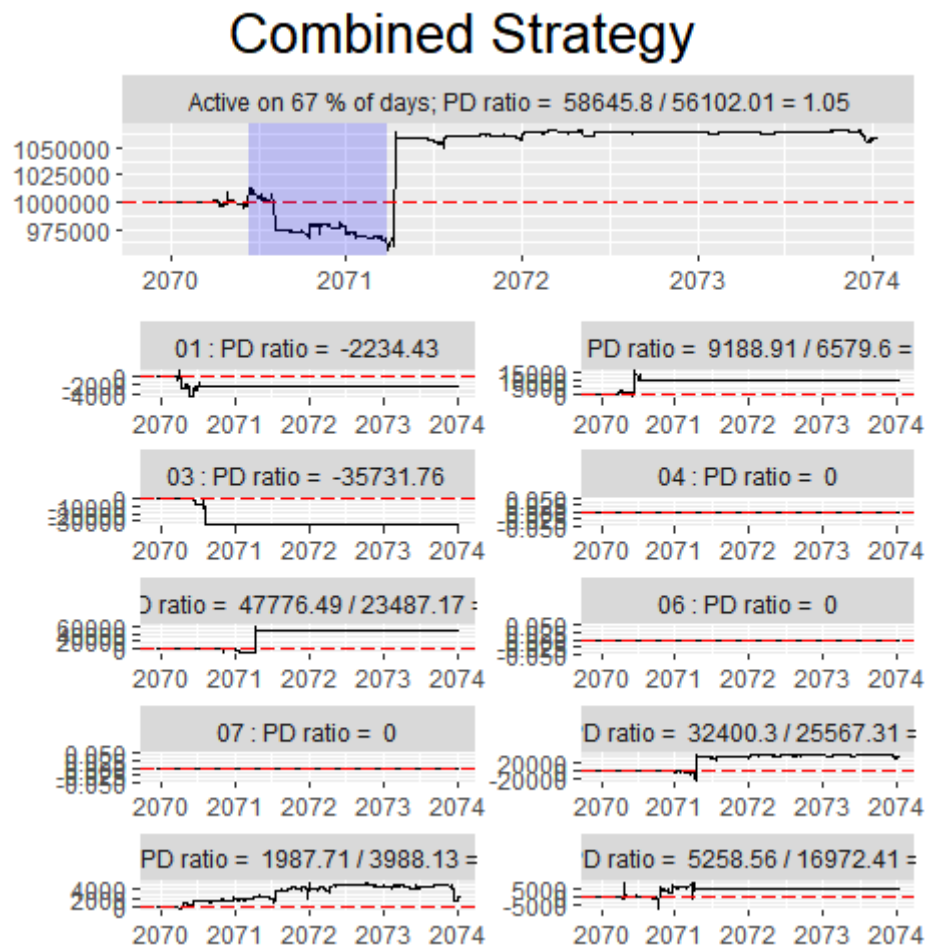
From observing the Table 2 data, it is shown that although the performance-based fixed wager strategy (based on \$100,000 fixed wager PnL, bad series deducted) can get 2.07 PD Ratio. However, it is mainly concentrated on only 3 series and the number of trading is very small, which does not meet the requirement of trading frequency at all, and this is also in the case of using the prior knowledge of known performance of fixed wager strategy on the same data set. On the contrary, as can be seen about Kelly's performance, in the first 200 days, it only slightly decreased, with no large drawbacks over time. In the following periods, it gained a relatively good profit. What's more, the number of invested series and trading frequency are in line with the requirements.

The next step is to consider which wager strategy should be selected at series level, Martingale Strategy or Reverse Martingale Strategy. The biggest difference between these two strategies is that one doubles the bet after winning in a series and the other doubles the bet after losing. Just as we test the Kelly formula for viability, the same AB test is launched for these 2 strategies.

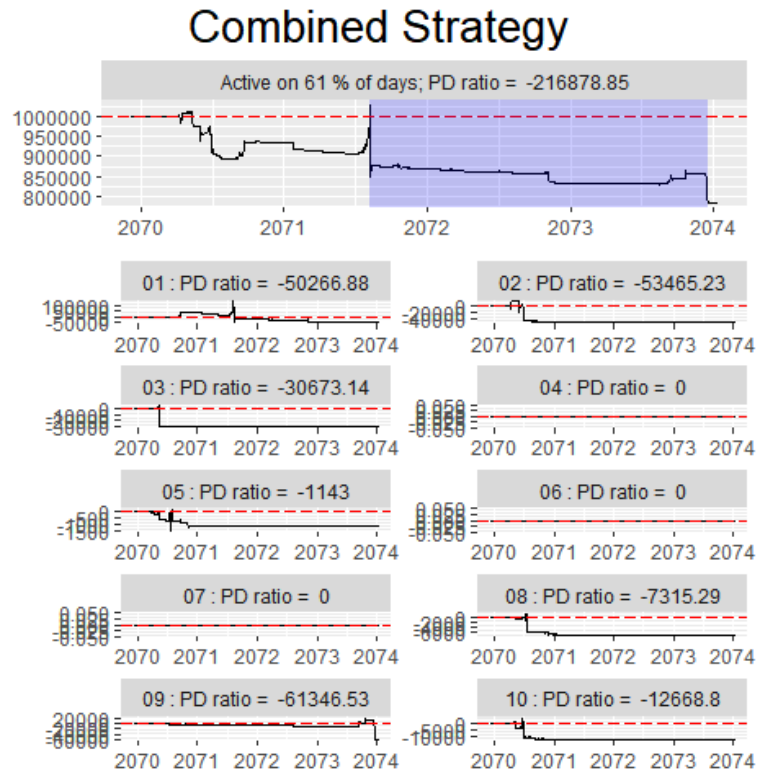
*Table 3. Combined Strategy Performance in Training Set (1000 days part 1 + 500 days part2)
with Martingale Strategy and Reverse Martingale Strategy*

Wager Strategy(technical level)	PD ratio	PnL	Trigger Times	Win times	Lose times	Expected Profit per time	Win Rate	Loss Rate
<i>Martingale</i>	1.05	58645.8	301	130	171	194.84	44.23%	55.77%
<i>Reverse Martingale</i>	-216878.85	-216878.85	297	134	163	-730.23	45.29%	54.71%
<i>Control Group(without these 2 strategies)</i>	-41472.99	-41472.99	476	212	264	-87.13	41.40%	58.60%

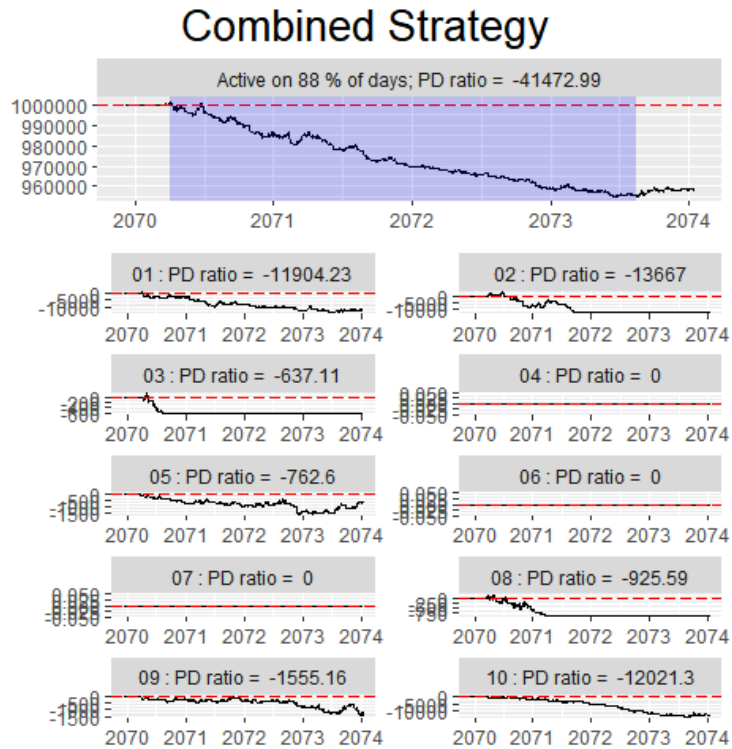
Graph 5. Performance of Combined Strategy with optimized parameters and Martingale in Training Set (1000 days part 1 + 500 days part2)



Graph 6. Performance of Combined Strategy with optimized parameters and Reverse Martingale in Training Set (1000 days part 1 + 500 days part2)



Graph 7. Performance of Combined Strategy with optimized parameters and without wager strategy in Training Set (1000 days part 1 + 500 days part2)



According to Table 3, the Martingale Strategy obviously outperforms the other 2 strategies, except that win rate for Martingale is about 1% lower than the Reverse Martingale strategy and 175 fewer Trigger Times than the control group. In addition, the Reverse Martingale Strategy and the control group were consistently losing money on any series during the experimental period.

Regarding the exploration of capital utilization and leverage, our initial idea was to get many performance matrices, such as total capital utilization, average capital utilization and leverage, by increasing or decreasing positions proportionally by 10 series. Then by using these indicators, we can get the relationship between profit and loss indicators and capital utilization and leverage, so as to find the optimal capital utilization and leverage. However, we gave up the development of this idea because of the code complexity and lack of time.

Apart from position sizing, like what mentioned in Section 1, the division of the data set is also very important. As suggested in the course, the dataset can be divided into part 1 data as training set and part 2 as test set. But the problem is that the transaction data is discrete time series data and highly path dependent, but the features may be completely inconsistent at relatively long-time intervals. Therefore, it is very difficult to find a reasonable length of the segmented data set. We have tried to train our parameters by defining the training set as 1000, 1200, 1500, 1800 days, but finally found that only the split of 1500/500 days works best for 10 series. If the training set takes too short, underfitting may occur, resulting in strategy that ends up performing poorly. If the training set takes too long, it is easy to over-fit the training data to get good performance only in the training set and poor performance in the test or validation set. We decided to use 1500 days/500 days splitting method to split the part 1 and part 2 data sets by observing the performance using different strategies and parameters, which were very stable over time.

2.3 Considering the strategy compare with alternatives.

Because even if an effective strategy can be found based on the historical data, there is no way to find out how long that strategy will continue to be effective in the future, and how reliable it can be. Thus, integrated learning is a more reliable system because a strategy is certainly easier to fail and more fragile than an integrated trading system.

Inspired by the concept of integration learning in the field of machine learning, at the beginning 3 natural ideas about trading system design came up to us.

Boosting, we ask the opinions of the four strategies daily based on their performance

on training set, from the best-performing strategy to the worst-performing strategy, and then take the opinion of the better performed strategy that was the first to decide to place an order.

Bagging, each day we poll 4 strategies, and then we get their judgment on each series, and finally take the plurality of the judgment execution.

Stacking, we allocate different amounts of money to each of the four strategies based on their performance on training set, and then sum the number of orders placed every day in the following. Due to the high development cost, we cannot develop all 3 systems and then launch AB experiments to find the optimal system. There is a famous saying in machine learning: No free lunch, which means that no matter what model or strategy is used, the theoretical result should be the same under the same scenario and the same batch of data. In addition, we developed the Boosting system first, therefore we ended up using this trading system directly instead of trying the other 2.

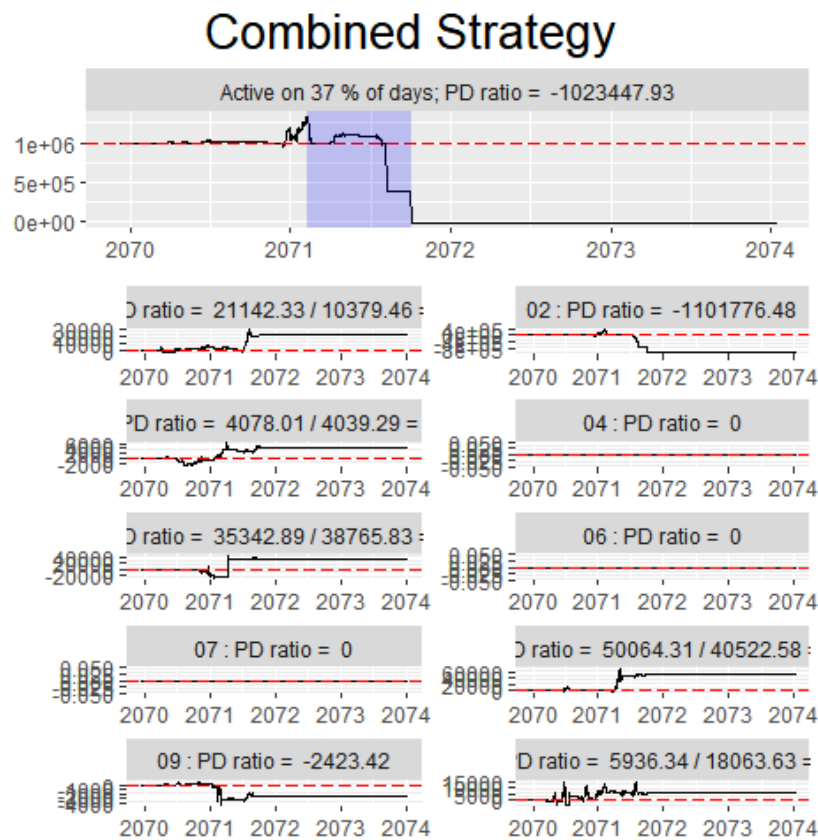
2.4 Managing risk in the strategy

As explained in Section 1, there are 5 risk strategies: 1 take-profit strategy, 3 stop-loss strategies and 1 strategy exit mechanism. To explore whether these risk strategies are effective and how these risk management strategies affect our trading system, similarly, a series of AB experiments was launched.

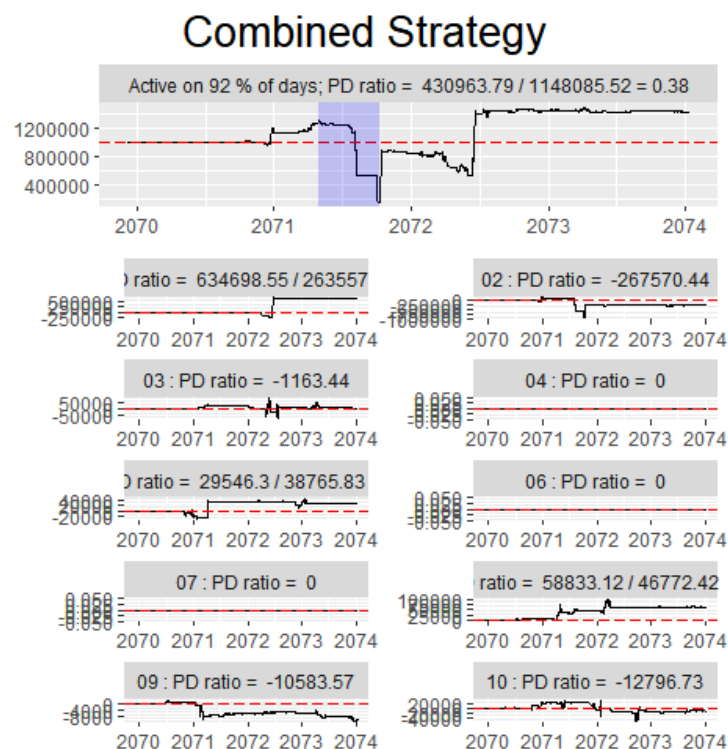
Table 4. Combined Strategy Performance in Training Set (1000 days part 1 + 500 days part2) with different Risk Management Strategy

Risk Management Strategy	PD ratio	PnL	Trigger Times	Win times	Lose times	Expected Profit per time	Win Rate	Loss Rate
<i>Control Group(no risk strategy)</i>	-1023447.93	-1023447.93	146	48	98	-6764.63	33.19%	66.81%
<i>Drawdown Stopgain</i>	0.38	430963.79	332	139	193	1298.08	41.15%	58.85%
<i>Drawdown Stop-gain + Time Stops</i>	-1317377.46	-1317377.46	478	219	259	-1324.42	45.79%	54.21%
<i>Drawdown Stop-gain + Time Stops + Trailing Stops</i>	-1071837.34	-1071837.34	395	185	210	-1795.94	46.69%	53.31%
<i>Drawdown Stop-gain + Time Stops + Trailing Stops + VaR_ES_Stops</i>	-1071837.34	-1071837.34	395	185	210	-1795.94	46.69%	53.31%
<i>Drawdown Stop-gain + Time Stops + Trailing Stops + VaR_ES Stops + Strategy Exit</i>	1.05	58645.8	301	130	171	194.84	44.23%	55.77%

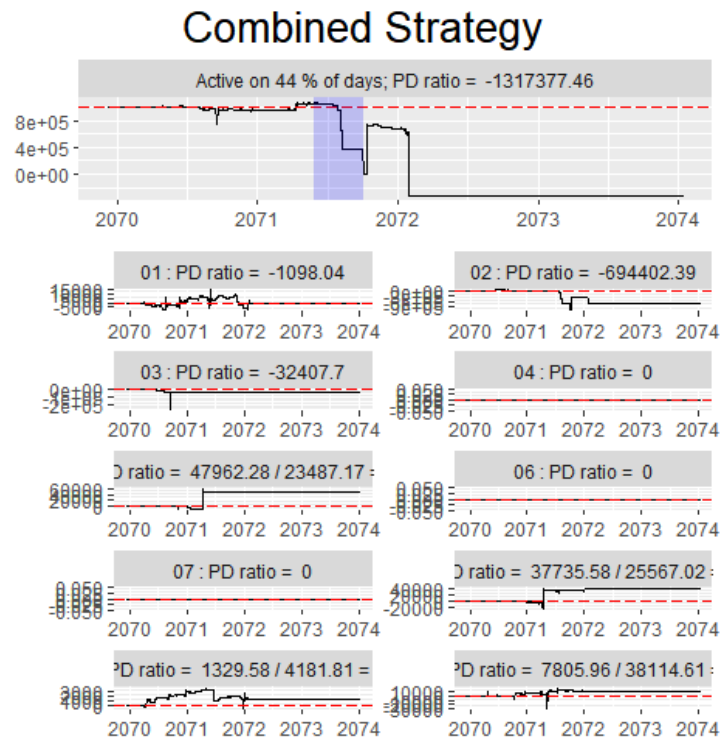
Graph 8. Performance of Combined Strategy with optimized parameters and without risk management in Training Set (1000 days part 1 + 500 days part2)



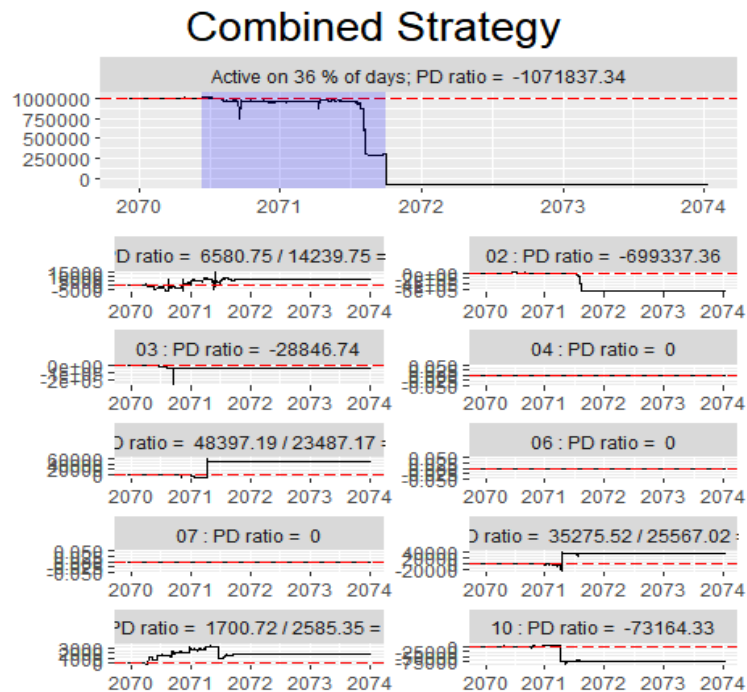
Graph 9. Performance of Combined Strategy with final parameters and with Drawdown Stop-gain in Training Set (1000 days part 1 + 500 days part2)



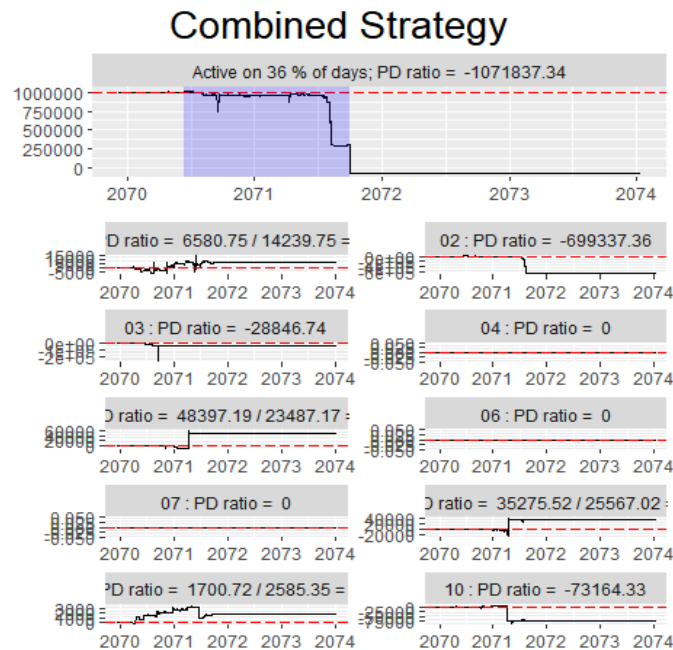
Graph 10. Performance of Combined Strategy with final parameters and with Drawdown
Stop-gain + Time Stops in Training Set (1000 days part 1 + 500 days part2)



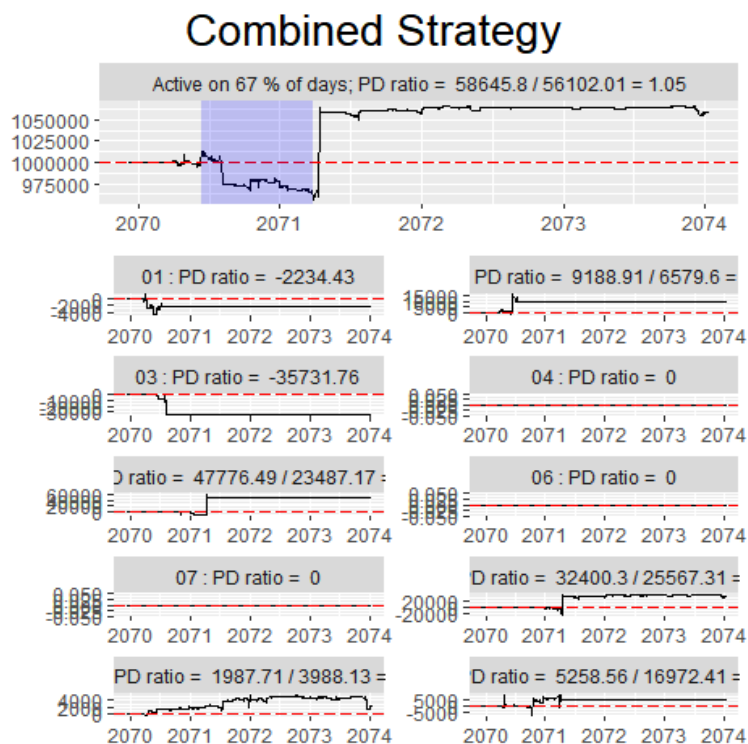
Graph 11. Performance of Combined Strategy with final parameters and with Drawdown Stop-gain + Time Stops + Trailing Stops in Training Set (1000 days part 1 + 500 days part2)



Graph 12. Performance of Combined Strategy with final parameters and with Drawdown Stop-gain + Time Stops + Trailing Stops + VaR_ES_Stops in Training Set (1000 days part 1 + 500 days part2)



Graph 13. Performance of Combined Strategy with final parameters and with Drawdown Stop-gain + Time Stops + Trailing Stops + VaR_ES Stops + Strategy Exit in Training Set (1000 days part 1 + 500 days part2)



As you can see from the table and graphs above, the biggest impact on our trading system is on Drawdown Stopgain and Strategy Exit. Comparing the data of Control Group and Drawdown Stopgain, as can be observed that all indicators of performance have a very strong positive impact by Stopgain method. After adding 3 stop-loss strategies, although the total number of Trigger Times and Win Rate increased, the losses were huge on a few series, leading to the system going bankrupt eventually. This shows that although our stop-loss strategies were able to prevent the loss from expanding on some series, on a few series it led to reopening the position quickly due to the unreasonable setting of the time interval between trades especially making the loss bigger when combined with the Martingale strategy. And more frequent large amount of entering led us to suffer more slippage. In some series, such as series 1, due to unreasonable parameter settings in the risk strategy, premature exit of positions led to a minor loss directly from a large profit. This phenomenon was improved after the strategy exit mechanism was finally added.

3.Evaluation and analysis of performance on part 3

3.1 The strategy performs relative to expectations

3.1.1 Dataset Breakdown

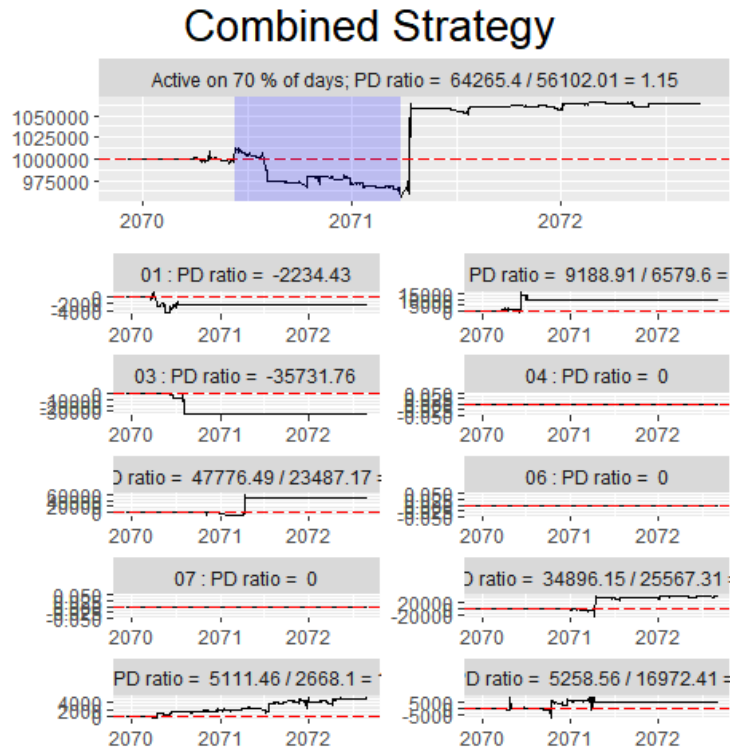
From Table 5, we can see that the Activeness in part 3 compared with part 1 decreased by 40%, and the number of Trigger Times decreased by 26%, while all other matrix largely increased, indicating that our trading system are quite stable in part 1 and part 3, and our trading system has learned the pattern of data in part 1 quite well. However, the trading signal parameters in the trading strategy seem over-fit, which leads to a lower Trigger Times. The trading signal parameters can be adjusted subsequently to increase the Trigger Times.

In addition, by comparing the data of part 2 and part 3, we can learn that except for the win rate of part 3, which is 2% higher than part 2, all other indicators have dropped significantly, which shows that our trading system obviously over-fit on the part 2 data, but this is within expectations. Because our training set includes the first 500 days of data of part 2, which is future information that is not supposed to be known. Therefore, the performance on the part 2 data is not confident.

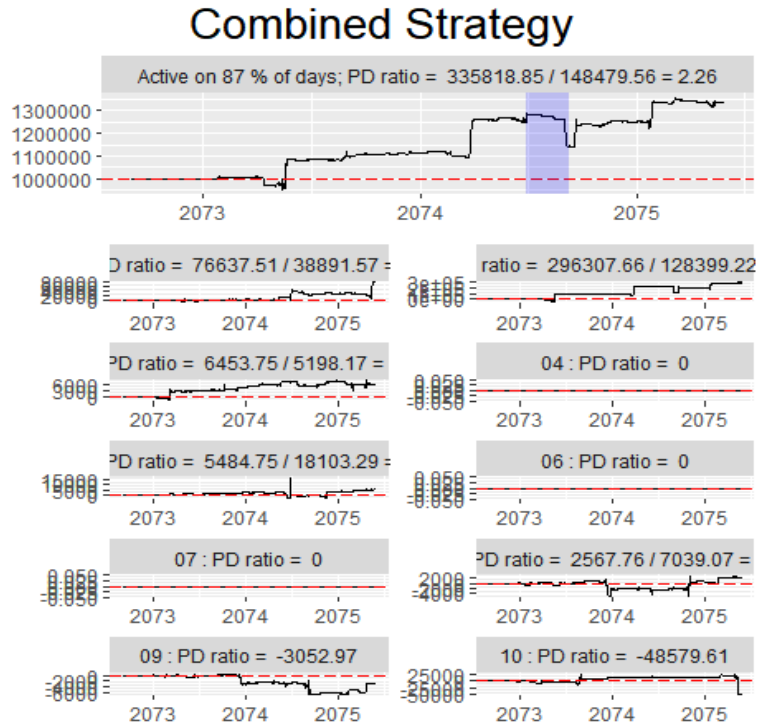
Table 5. Performance of final submitted Strategy in 3 datasets

Dataset	PD ratio	PnL	Max Drawdown	Activeness	Trigger Times	Win times	Lose times	Expected Profit per time	Win Rate	Loss Rate
<i>Part 1</i>	1.15	64265.4	56102.01	70%	301	129	172	213.51	44.08%	55.92%
<i>Part 1 vs. Part 3</i>	3.48%	32.05%	26.99%	-40.00%	-26.58%	-10.85%	-38.37%	79.85%	13.97%	-11.02%
<i>Part 2</i>	2.26	335818.85	148479.56	87.00%	650	321	328	516.64	49.18%	50.82%
<i>Part 2 vs. Part 3</i>	-47.35%	-74.73%	-52.02%	-51.72%	-66.00%	-64.17%	-67.68%	-25.68%	2.16%	-2.09%
<i>Part 3</i>	1.19	84860.68	71241.39	42%	221	115	106	383.99	50.24%	49.76%

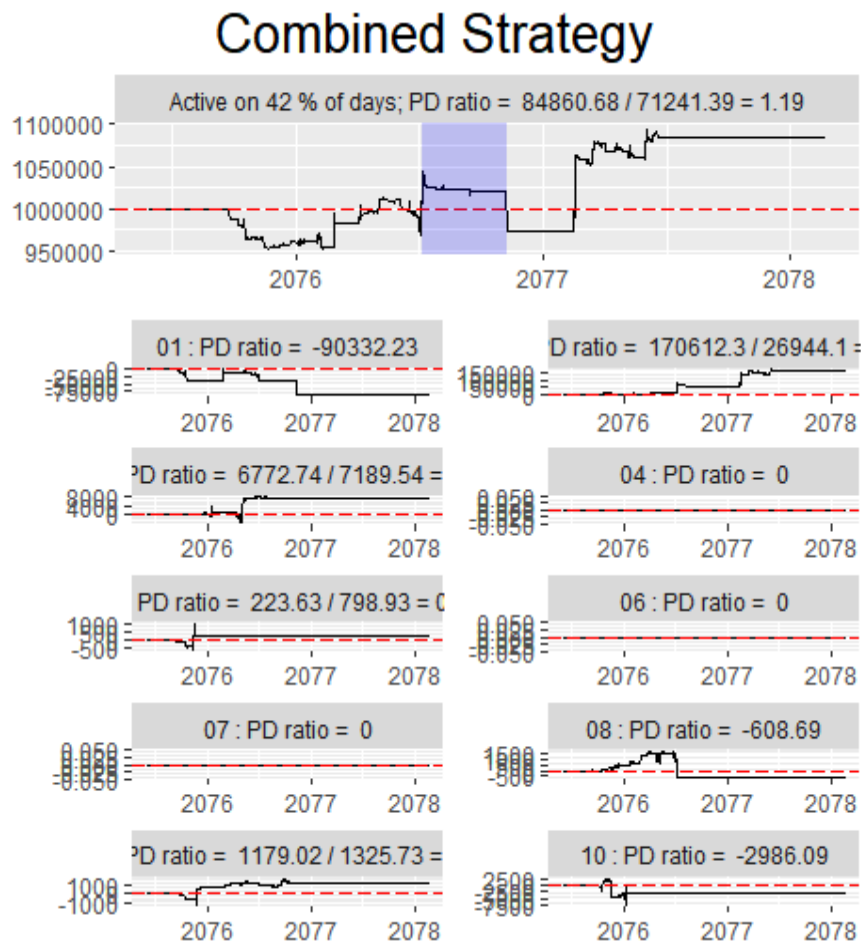
Graph 14. Performance of final submitted Strategy in Part 1



Graph 15. Performance of final submitted Strategy in Part 2



Graph 16. Performance of final submitted Strategy in Part 3

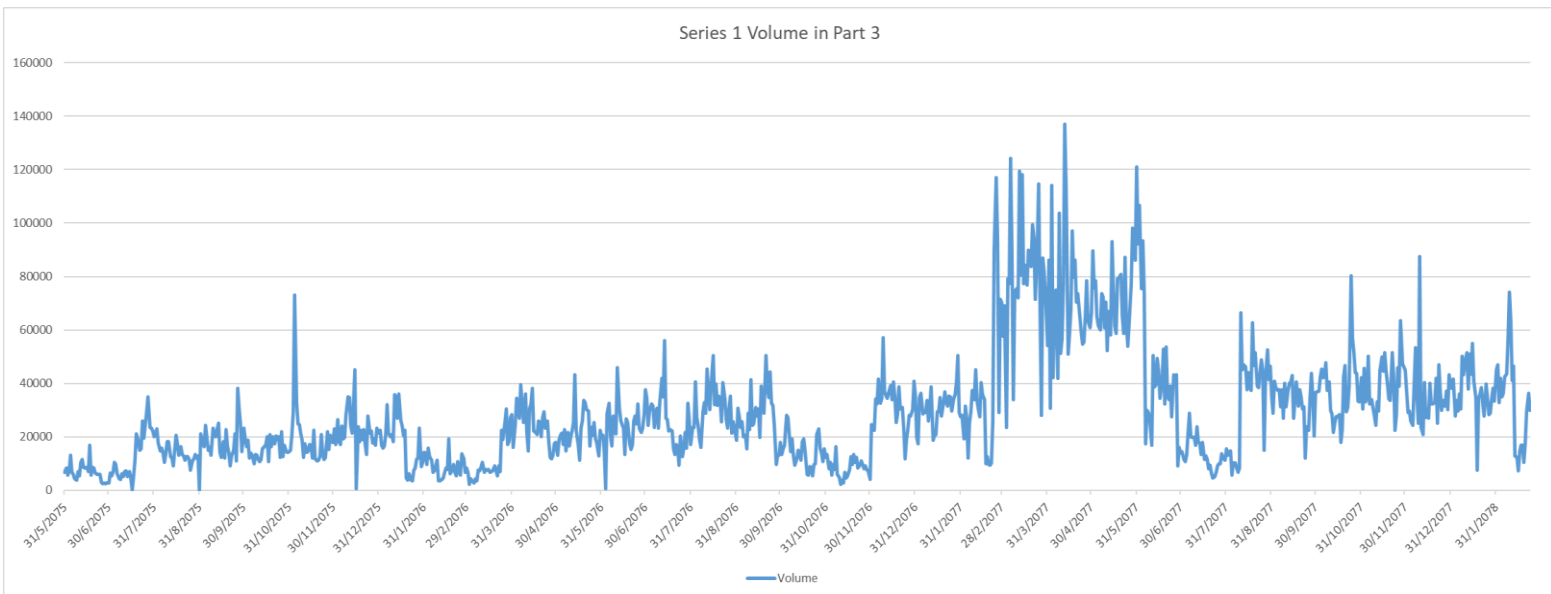


Comparing part 1 and part 3 data, we can see that series 1 is the greatest loss series in terms of overall trading system losses, and the losses on series 1 had two major great drawbacks, which occurred near June and October 2076. According to Graph 17, we can see that OHLC has been in a steady upward trend around June and October 2076, and no significant abnormal data fluctuations have observed. Based on Graph 18, as can be seen, Volume in series 1 is in a fluctuating upward trend in June and a fluctuating downward trend in October 2076, respectively.

Graph 17. Series 1 OHLC price in Part 3



Graph 18. Series 1 Volume in Part 3



After ruling out the data anomalies, we are basically sure that the loss on series 1 in part 3 data is due to our trading system itself.

3.1.2 Series Breakdown

According to Table 6, we can see that in part 1, our strategy performs poorly on series 3, 5, 8, 9. Win Rate on series 3, 5, 8 are less than 40%, while the odds-on series 3 and 9 are the lowest, at -35.11 and -3.84 respectively. But as marked in Table 7, the performance of our trading system on different series in part 3 has completely changed, with the performance on series 1, 2, 10 being the worst. Also, as can be noted, the Kelly's optimal bet ratio on all 7 series has changed greatly.

Table 6. Series Breakdown Performance of final submitted Strategy in Part 1

Series	Win Balance	Loss Balance	Gambit Rate	Kelly	Trigger Times	Win times	Lose times	Win Rate	Loss Rate
<u>1</u>	5839.61	-7144.13	-1.43	0.86	13	7	6	53.85%	46.15%
<u>2</u>	193508.55	-118431.11	-1.10	0.97	14	9	5	64.28%	35.71%
<u>3</u>	342.50	-36074.26	-35.11	0.27	12	3	9	25%	75%
<u>4</u>	0	0	0	0	0	0	0	0	0
<u>5</u>	84221.38	-10379.86	-0.06	12.58	32	10	22	31.25%	68.75%
<u>6</u>	0	0	0	0	0	0	0	0	0
<u>7</u>	0	0	0	0	0	0	0	0	0
<u>8</u>	62356.47	-38829.28	-0.41	1.88	96	38	58	39.58%	60.42%
<u>9</u>	10289.88	-49143.22	-3.84	0.59	92	41	51	44.57%	55.43%
<u>10</u>	76028.21	-41036.17	-0.54	1.43	42	21	21	50%	50%

Table 7. Series Breakdown Performance of final submitted Strategy in Part 3

Series	Win Balance	Loss Balance	Gambit Rate	Kelly	Trigger Times	Win times	Lose times	Win Rate	Loss Rate
<u>1</u>	31434.62	-121766.85	-2.26	0.65	19	7	12	36.8%	63.2%
<u>2</u>	315370.41	-1059259.31	-3.14	0.65	60	29	31	48.33%	51.67%
<u>3</u>	94530.02	-48315.12	-0.51	1.48	36	18	18	50%	50%
<u>4</u>	0	0	0	0	0	0	0	0	0
<u>5</u>	95159.95	-454.37	-0.01	67.89	7	4	3	57.14%	42.86%
<u>6</u>	0	0	0	0	0	0	0	0	0
<u>7</u>	0	0	0	0	0	0	0	0	0
<u>8</u>	582451.01	-427564.72	-0.90	1.05	40	22	18	55%	45%
<u>9</u>	275057.77	-1178.12	-0.01	21.39	39	29	10	74.36%	25.64%
<u>10</u>	442807.33	-1179066.94	-1.14	0.91	20	6	14	30%	70%

3.1.3 Trading Breakdown

As is shown in Table 8 and Table 9, we found that Sum Long Enter Times + Sum Short Enter Times is not equal to Sum Exit Times, which means there is a bug in our trading signal recording system. For instance, in Table 8 Series 1, Long Enter Times + Sum Short Enter Times is greater than Sum Exit Times, which means that the number of exit times is more than the number of enter times, which is obviously not in line with reality. Secondly, according to the Trigger Times of 4 trading strategies on the 10 series, we can find that most trades are mainly concentrated in the TMA Strategy, the top priority BBTF strategy only triggered a few times, while the last 2 strategies did not trigger at all. This may be due to the bug in the signal system, or the trading signal limits for BBTF, BBMR and LMV strategies are too strict, or the trading signal limits for TMA strategy are far too loose, which squeezes the trigger opportunities of the other strategies.

Table 8. Trading Breakdown Performance of final submitted Strategy in Part 1

Series	Sum Long Enter Times	Sum Short Enter Times	Sum Long Hold Times	Sum Short Hold Times	Sum Exit Times	BBTF Trigger Times	TMA Trigger Times	BBMR Trigger Times	LMV Trigger Times
<u>1</u>	6	6	23	25	13	3	70	0	0
<u>2</u>	5	5	15	23	14	9	53	0	0
<u>3</u>	5	11	0	36	12	2	62	0	0
<u>4</u>	0	0	0	0	0	0	0	0	0
<u>5</u>	43	8	85	21	32	18	171	0	0
<u>6</u>	0	0	0	0	0	0	0	0	0
<u>7</u>	0	0	0	0	0	0	0	0	0
<u>8</u>	69	44	199	151	96	24	535	0	0
<u>9</u>	46	42	243	147	92	16	554	0	0
<u>10</u>	8	24	21	112	42	9	198	0	0

Table 9. Trading Breakdown Performance of final submitted Strategy in Part 3

Series	Sum Long Enter Times	Sum Short Enter Times	Sum Long Hold Times	Sum Short Hold Times	Sum Exit Times	BBTF Trigger Times	TMA Trigger Times	BBMR Trigger Times	LMV Trigger Times
<u>1</u>	106	11	33	31	19	14	186	0	0
<u>2</u>	50	14	158	7	60	17	272	0	0
<u>3</u>	18	17	67	48	36	2	184	0	0
<u>4</u>	0	0	0	0	0	0	0	0	0
<u>5</u>	1	3	3	12	7	0	26	0	0
<u>6</u>	0	0	0	0	0	0	0	0	0
<u>7</u>	0	0	0	0	0	0	0	0	0
<u>8</u>	11	10	46	83	40	3	187	0	0
<u>9</u>	15	22	51	86	39	4	209	0	0
<u>10</u>	11	1	41	2	20	2	73	0	0

3.2 The mistakes at the technical level, planning and teamwork

3.2.1 Strategy mistakes

1. Lack of market filter

In the part 1 data analysis we found a large number of data anomalies in the series, such as sudden spikes or sudden drops in trading volume, but we did not make good use of this information in the final submitted trading system.

2. Bad feature engineering

Four strategies are basically single-trading factor strategies, which do not exploit factor characteristics, interactions between factors, and timing characteristics well.

3. Fixed Kelly Optimal Ratio

Due to the code complexity limitation, Kelly optimal position ratio is set to fixed, but by comparing the performance of the final submitted trading system on part 1 and part 3 data, we can know that the 10 series are changing over time, and the win rate, loss rate and odds change dramatically, resulting in the initial optimal position ratio is no longer applicable.

4. The strategy exit mechanism did not consider the sub-strategy dimension, but treats the whole trading system as one.

5. Limit order and Market Making Strategy are not utilized

Due to the code complexity limitation of the trading signal recording system, the limit order and market making strategy are not utilized. While the limit order can significantly reduce our slippage error, and the MM strategy is known to perform quite well on both part 1 and part 2 data.

6. The lack of position-adding strategy

Assume that the trading system or strategy in a few series perform continuous good in the short period of time, and there is no a judgment to add positions to expand the profitability.

7. Strategy Exit Mechanism is too simple

The trading system exits all positions when triggers risk management strategy or exit conditions in 4 trading strategies, without a mechanism to gradually reduce positions, resulting in the possibility of frequent trading in the short-term relatively high volatile market.

8. There may be bugs or bad design in the trading signaling system

From previous analysis, we know that in part 3, the trading is mainly concentrated in the TMA strategy, while the other 3 strategies have basically not been triggered. The trading system may have a mechanism design problem or coding bug. For example, the TMA condition is too easy to trigger. This problem should be tested in the part 2 design stage.

3.2.2 Coding mistakes

1. Instead of using intermediate variables to reduce computation, global variables are used frequently, which leads to low fault tolerance, and is not conducive to subsequent iterations.

2. Trading signal recording system design problems

Trading signaling system used "today's position + today's market order" instead of each series of the daily position changes to get, resulting in the signaling logic of the limit order signal being too complex by using money spent calculation module, and finally gave up the attempt. What's worse, the trading signal recording system may have a bug.

3.2.3 Planning and teamwork mistakes

1. Insufficient communication between team members.

During the implementation phase, because each person was responsible for a difficult part of the code, a lot of time was spent on developing the code, which reduced the time for communication, and the communication between group members was sometimes not clear to their own group members due to some over-extensive knowledge.

2. Inefficient learning.

In the first phase we came up with a lot of ideas and presented them in our presentation, but in the development phase we underestimated the development time of the part of the code we were responsible for, which resulted in not fully implementing each of the ideas.

3. No team leader.

As we all became more familiar with the project this year, we did not have a team leader, but it turned out that the importance of the team leader was not only to divide the work among the team members, but also to lead the team to follow the planned schedule.

3.3 What have we learnt and how would we do things differently

3.3.1 Strategy and Coding Improvement

First of all, a market filter should be added, such as making corresponding operational strategies according to the quantitative determination of whether the data (OHLCV, trading indicators) is abnormal according to the 3-sigma principle, and the performance of each strategy during the period of abnormal data on the training set. We can stop trading particular series if a series is judged to be abnormal. In addition, the market filter should quantitatively define the bull and bear markets, and then the performance of each of the four strategies in the bull and bear markets can be derived on the training set, so that different trading strategies can be activated in the corresponding market conditions to obtain better performance.

In addition, we should strengthen the feature engineering. For example, we can activate different system designs (boosting, bagging, stacking) in different periods after the failure of particular system, mix multiple signals or use multiple factors at the same time to filter noise, combine multiple factors together.

Periodically, the initial position for each trade for each series should be adjusted according to the Kelly optimal position. For instance, every 100 days recalculate the performance of the trading system in 10 series over the last 100 days, and if the overall Kelly changes more than 10% than before, the initial position will be readjusted to the new Kelly value.

The strategy exit mechanism should calculate the number of continuous loss times of each trading strategy on each series, and if a strategy reaches the customized

parameters on a certain series, then exit this strategy for all subsequent trades on this series instead of prohibiting this series from all trading strategies.

The trading signaling system should be redesigned based on daily position changes instead of "today's position + today's market order", and include limit order and MM strategies.

A position adding/decrease strategy to gradually increase or decrease positions according to data analysis. Say if a strategy has a win rate above 70% in the last 50 days on a series, and we already held certain positions in this series and the enter signal is triggered again, then we can increase our position in this series again.

3.3.2 Planning and Teamwork Improvement

1. More precise division of work for team members.

For example, those who are good at coding can do more code development, those who are good at writing can do more report writing, and those who are good at leading and coordinating information within the team can become team leader.

2. Improve the ability of team members to execute learning and learn effectively.

In this project, we searched for a lot of ideas in the design phase, but in the second phase, some of the ideas were not developed because of the lack of ability to learn new knowledge, which is a great pity. In addition, the actual time taken to develop the genetic algorithm was much longer than we had initially anticipated. With regard to learning effectiveness, the lack of sufficient discernment when searching for relevant information led to a lot of time being wasted on sifting through invalid resources during subsequent discussions

3. Improving communication skills between team members.

The team's efficiency is greatly enhanced by good understanding and communication, especially when communicating with team members about the code they are responsible for developing.

4. Improve team members' thinking skills.

Trying to grasp the essence of a problem and solving large and complex problems often requires structured thinking skills - breaking down a vague problem into

something that can be analyzed in detail is the first step in thinking and solving problems.

4. Breakdown of team work

Chia-Wei Liu

Assignment 2:

1. Co-designing and developing trading system
2. Searching for information about the implementation of Martingale
3. Working with team members to integrate all information
4. Completing the development of the trading strategy
5. Developing code of Martingale
6. Integrating trading strategies
7. Developing code for risk control section

Assignment 3:

1. Reviewing with team members the shortcomings of the strategy, such as over-fitting and insufficient optimal robustness tests.
2. Reviewing with the team members the possible new ideas that can be developed if we continue to deepen the process, such as market condition filtering.
3. Writing section 1 Final choice of submitted strategy

Shuying Zhai

Assignment 2:

1. Co-designing and developing trading system.
2. Accessing information on the implementation of Kelly formula.
3. Working with team members to integrate all information.
4. Completing the development of the trading strategy.
5. Developing code of Kelly formula section.
6. Adding robustness checks following feedback.

Assignment 3:

1. Reviewing with team members the shortcomings of the strategy, such as over-fitting and less than optimal robustness tests.
2. Reviewing with the team members the possible new ideas that can be developed if we continue to deepen the process, such as market condition filtering.
3. Writing section 2 Justification of submitted strategy.

Yushan Zhang

Assignment 2:

1. Co-designing and developing trading system.
2. Accessing relevant information on the implementation of genetic algorithms.
3. Working with team members to integrate all information.
4. Developing of code related to genetic algorithms section.
5. Completing parameter optimization.
6. Adjusting trading signals based on parameter optimization results.

Assignment 3:

1. Reviewing with team members the shortcomings of the strategy, such as over-fitting and less than optimal robustness tests.
2. Reviewing with the team members the possible new ideas that can be developed if we continue to deepen the process, such as market condition filtering.
3. Writing section 3 Evaluation and analysis of performance in part 3.