Algorithmic Trading

Design your own algorithmic trading strategy in R.

- Number of assets in the strategy: one or more assets
- Type of asset: you select it (stock, commodity, FX, crypto etc)
- Timeframe: you select it
- Coding language: R; you can also use Excel for basic calculations and testing
- Model: regression, ARMA, GARCH, VAR, VEC or any other quantitative model you know. You can combine model with technical analysis indicators (MA, MACD, Bollinger bands etc) as in module 7 examples. You can also use machine learning algorithm (it is not compulsory).

1. Explain the algorithm step by step
2. Provide R code and/or Excel calculations
3. Provide charts
4. Calculate returns, cumulative returns, standard deviation and forecasts
5. Indicate research papers or books on this topic

Trading Strategy

Inspired by Sergey Malchevskiy's Pairs Trading with Cryptocurrencies [1], we will perform statistical arbitrage on a pair of cryptocurrency. The strategy aims to be market neutral where it will take a equal weights of long and short positions on the pair to prevent taking a net long or short position in the market as a whole due to the high unpredictability of the trend in the cryptocurrency market.

The intuition is that a pair of cryptocurrency with highly cointegrated daily return will have their daily returns reverting to 0 spread (difference in their daily returns). The strategy will enter a long/short position when the daily returns spread is high and will exit the positions when the daily returns spread revert to the normal level.

The experiment will determine:

- Pair of cryptocurrency with highly cointegrated daily returns
- z-score to enter into a long/short position
- z-score to exit the long/short position

Timeframe

The timeframe selected to test the model will be the period from early 2018 to late 2018. The period was commonly known to the blockchain community as the "crypto winter" due to falling prices following the plunge in December 2017.

The trend of the market in that timeframe can be seen by the bitcoin price chart below:

R Code

```
library(Quandl)
library(quantmod)
library(timeSeries)
library(corrplot)
library(ggplot2)
library(urca)
library(PerformanceAnalytics)
library(tseries)
```

We will be using cryptocurrency data from Quandl. An API key is needed to retrieve data from Quandl. The analysis will be performed on 6 common pairs of cryptocurrencies that existed back in Jan 2018.

```
Quandl.api_key('')
```

```
pairs = c(
    "ETHBTC",
    "LTCBTC",
    "XRPBTC",
    "XMRBTC",
    "ZECBTC",
```

```
    "DSHBTC"
)
startDate = "2018-01-01"
endDate = "2018-12-01"
```

```
# Create a list of data in the xts format
pairsDataListXts = list()

for(i in 1:length(pairs)){
    pair = pairs[i]
    bifinexPair = paste("BITFINEX/", pair, sep = "")
    pairData = Quandl(bifinexPair, start_date=startDate, end_date=endDate)
    assign(pair, pairData)
    pairDataXts = as.xts(pairData, order.by = pairData$Date, x=pairData$Last)
    pairsDataListXts[[i]] = pairDataXts
}
```

Cointegration Test

Selecting two random cryptocurrencies, we will perform the Johansen test to observe the test statistics and critical value of the test.

```
# Creating a xts object with both time series data of ZEC and DSH
ZECBTCXTS = pairsDataListXts[[5]]
DSHBTCXTS = pairsDataListXts[[6]]
PAIRXTS = merge(ZECBTCXTS, DSHBTCXTS, join = "left")
names(PAIRXTS) = c("ZECBTC", "DSHBTC")
```

```
# Perform Johansen test on the pair
jotest=ca.jo(PAIRXTS, type="trace", K=2, ecdet="none", spec="longrun")
summary(jotest)
```

```
######################
# Johansen-Procedure #
######################

Test type: trace statistic , with linear trend

Eigenvalues (lambda):
[1] 0.040592920 0.009793911

Values of teststatistic and critical values of test:

          test 10pct  5pct  1pct
r <= 1 |  3.20  6.50  8.18 11.65
r = 0  | 16.67 15.66 17.95 23.52

Eigenvectors, normalised to first column:
(These are the cointegration relations)

           ZECBTC.l2 DSHBTC.l2
ZECBTC.l2  1.0000000  1.000000
```

```
DSHBTC.l2 -0.5861501  0.224751

Weights W:
(This is the loading matrix)

            ZECBTC.l2    DSHBTC.l2
ZECBTC.d -0.063673166 -0.006547003
DSHBTC.d  0.008594671 -0.012099956
```

From the test above, we can see that the critical value for (r=0) at 5 pct level is 17.95. We will use the critical value to short list some cryptocurrency pairs before selecting one pair to work with.

```
# Print all pairs that has r = 0 above the critical value of 17.95
R0_CRITICAL = 17.95

# Iterate through the pairs to perform Johansen test on. Print the pairs if they
passes the cointegration test.
for(i1 in 1:length(pairsDataListXts)){
    for(i2 in 1:length(pairsDataListXts)){
        if(i1 != i2){
            PAIRXTS = merge(pairsDataListXts[[i1]], pairsDataListXts[[i2]], join =
"left")
            jotest=ca.jo(PAIRXTS, type="trace", K=2, ecdet="none", spec="longrun")
            if(jotest@teststat[2] >= R0_CRITICAL){
                print(paste(pairs[i1], pairs[i2]))
                print(jotest@teststat)
            }
        }
    }
}
```

```
[1] "ETHBTC XRPBTC"
[1]  2.615824 32.276714
[1] "ETHBTC DSHBTC"
[1]  1.711873 25.922373
[1] "XRPBTC ETHBTC"
[1]  2.615824 32.276714
[1] "XRPBTC ZECBTC"
[1]  4.433185 19.632115
[1] "ZECBTC XRPBTC"
[1]  4.433185 19.632115
[1] "DSHBTC ETHBTC"
[1]  1.711873 25.922373
```

From the test above we can see a few viable cryptocurrency pairs:

- ETH/XRP
- ETH/DSH
- XRP/ZEC

XRP/ZEC will be selected to build the model on.

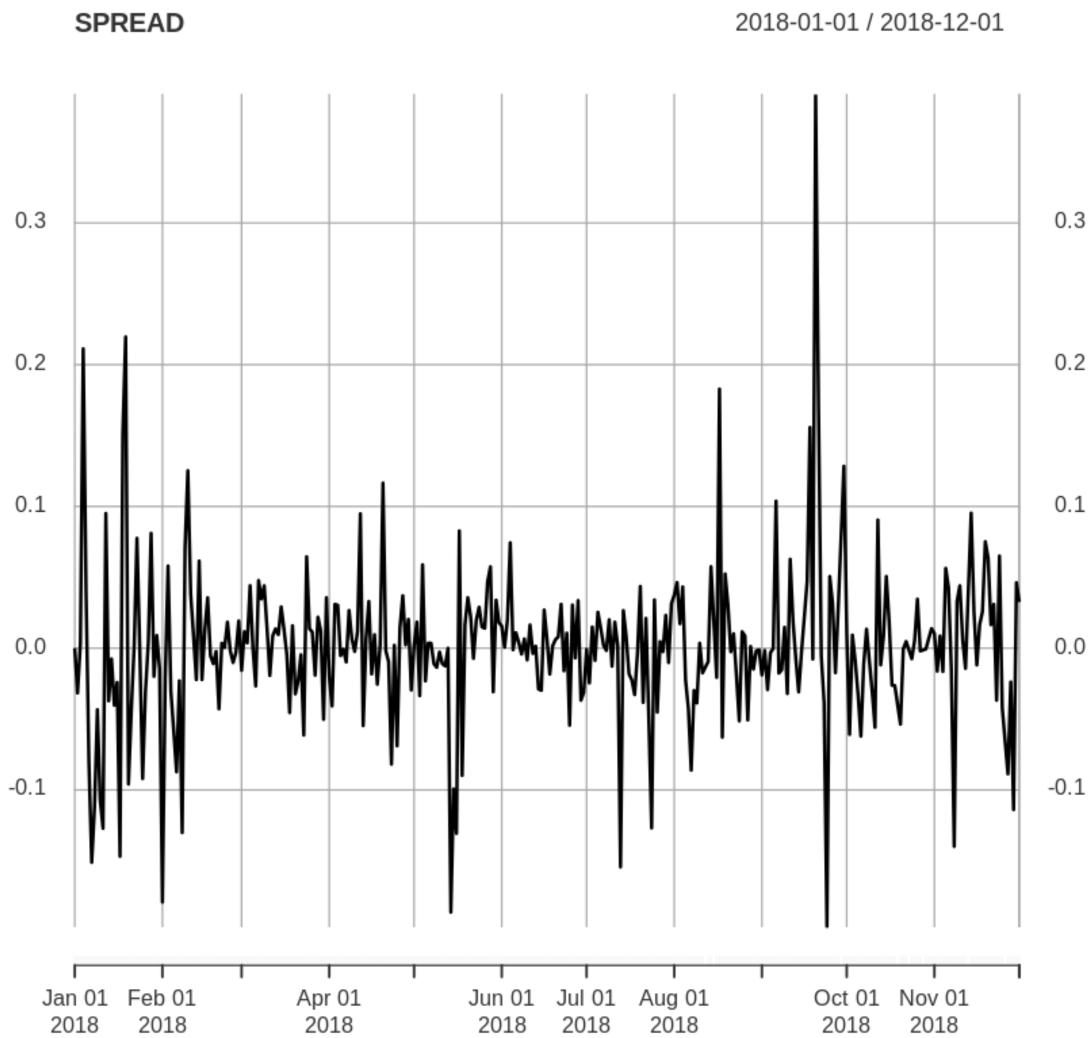
We will plot the price movement of these two cryptocurrencies to observe the data we will be dealing with.

```r
# Plot the nomalised price movement for both XRP and ZEC
XRPBTCXTS = pairsDataListXts[[3]]/pairsDataListXts[[3]][[1]]
ZECBTCXTS = pairsDataListXts[[5]]/pairsDataListXts[[5]][[1]]
PAIRXTS = merge(XRPBTCXTS, ZECBTCXTS, join = "left")
names(PAIRXTS) = c("XRPBTC", "ZECBTC")
plot(PAIRXTS)
```

As we can see above, the pairs do not seem to have high degree of correlation. We will attempt to validate our hypthesis that the daily returns of the pair follows a stationary trend.

The spread for the daily return on the two cryptocurrencies will be plotted first.

```r
# Plotting the spread of XRP/ZEC
XRPXTS_DR = dailyReturn(pairsDataListXts[[3]])
ZECBTS_DR = dailyReturn(pairsDataListXts[[5]])
SPREAD = XRPXTS_DR - ZECBTS_DR
plot(SPREAD)
```



As seen from above, the process for the spread of returns seemed to be stationary, we will confirm this with ADF test.

```
adf.test(SPREAD)
```

```
Warning message in adf.test(SPREAD):
“p-value smaller than printed p-value”



    Augmented Dickey-Fuller Test

data:  SPREAD
Dickey-Fuller = -7.0876, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary
```

The hypothesis that the spread follows a stationary process can be confirmed with the ADF test. This could mean that the trading strategy could work with this cryptocurrency pair.

We will now run the trading strategy with the cryptocurrency pair.

```
# Function to calculate spead based on z-score
Z_SPREAD = function(x){
    return (x * sd(SPREAD) + mean(SPREAD))
}
```

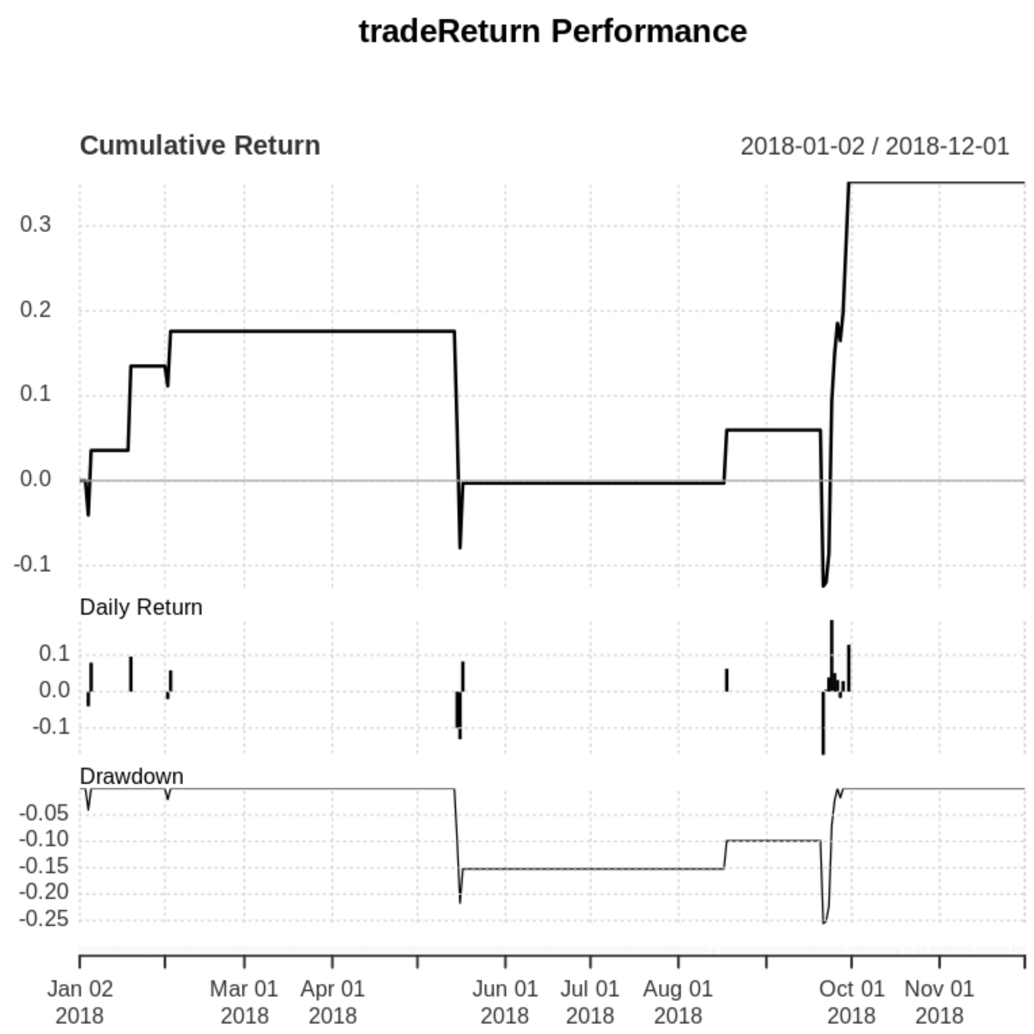
```
# Function to generate signal based on xts dataframe and the critical value to enter
and exit the positions
GENERATE_SIGNAL = function(x, enter, exit){
    # 0 = neutral, 1 = long, -1 = short
    signal = list()
    signal[1] = 0
    for(i in 2:nrow(x)){
        prevPosition = signal[i-1]
        ret = x[[i]]

        if(ret <= (-enter)){
            # Enter long if return <= -ENTER_RET
            signal[i] = 1
        }else if(ret >= enter){
            # Enter short if return >= ENTER_RET
            signal[i] = -1
        }else if(prevPosition == 1 && ret >= exit){
            # Exit long if return >= EXIT_RET
            signal[i] = 0
        }else if(prevPosition == -1 && ret <= (-exit)){
            # Exit short if return <= EXIT_RET
            signal[i] = 0
        }else{
            signal[i] = prevPosition
        }
    }
    signal
}
```

```
# Enter when current return spread is 3 standard deviation away
# and exit when it's 1 standard deviation away
ENTER_RET = Z_SPREAD(3)
EXIT_RET = Z_SPREAD(1)

# Generate signal for long/short position
signal = GENERATE_SIGNAL(SPREAD, ENTER_RET, EXIT_RET)

# Merge signal with the spread in daily returns
RES = merge(SPREAD, signal)

# Calculate the t+1 daily returns based on signal at t
RES$tradeReturn = RES$daily.returns * lag(RES$signal)
```

```r
# Display results
head(RES)
```

```
           daily.returns signal tradeReturn
2018-01-01   0.000000000      0          NA
2018-01-02  -0.031663573      0  0.00000000
2018-01-03   0.003453594      0  0.00000000
2018-01-04   0.211254927     -1  0.00000000
2018-01-05   0.040585192     -1 -0.04058519
2018-01-06  -0.079457605      0  0.07945761
```

```r
# Show performance of the algorithm
charts.PerformanceSummary(na.approx(RES$tradeReturn))
```



From the performace summary above we can observe that the the cumulative return at the end of the year is > 30%. We can also see that the returns are based on few trades across the year. It can also be observed that the strategy is very risky from the huge drop in the returns in the few bad trades as well as the high maximum drawdown of >25%.

To further quantify the strategy, we will calculate the:

- Cumulative return
- Annualised return
- Sharpe ratio
- Annualised Sharpe ratio

```
Return.cumulative(RES$tradeReturn)
Return.annualized(RES$tradeReturn)
maxDrawdown(RES$tradeReturn)
SharpeRatio(RES$tradeReturn, Rf = 0, p=0.95, FUN = "StdDev")
SharpeRatio.annualized(RES$tradeReturn, Rf = 0)
```

	tradeReturn
Cumulative Return	0.352222

	tradeReturn
Annualized Return	0.2627021

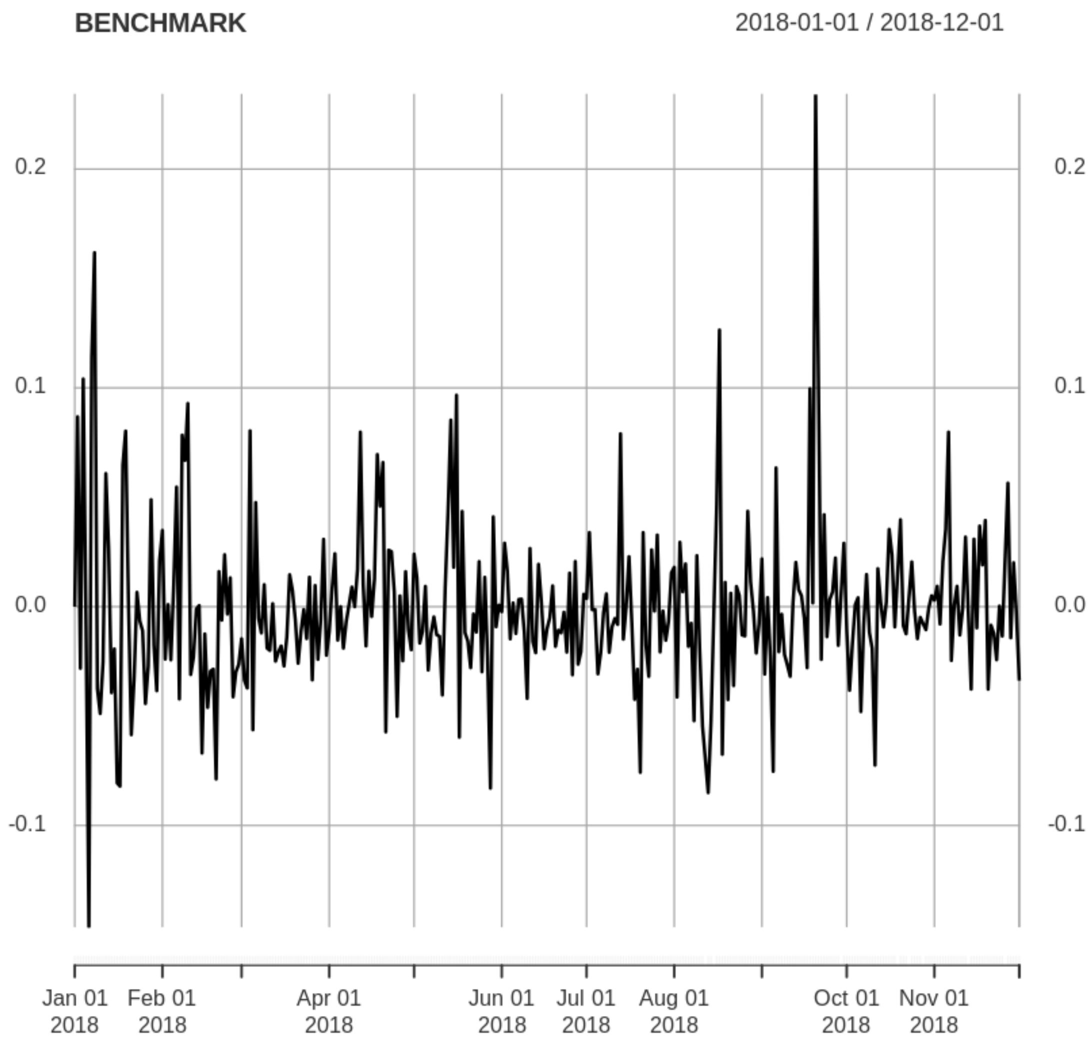
0.255531129087392

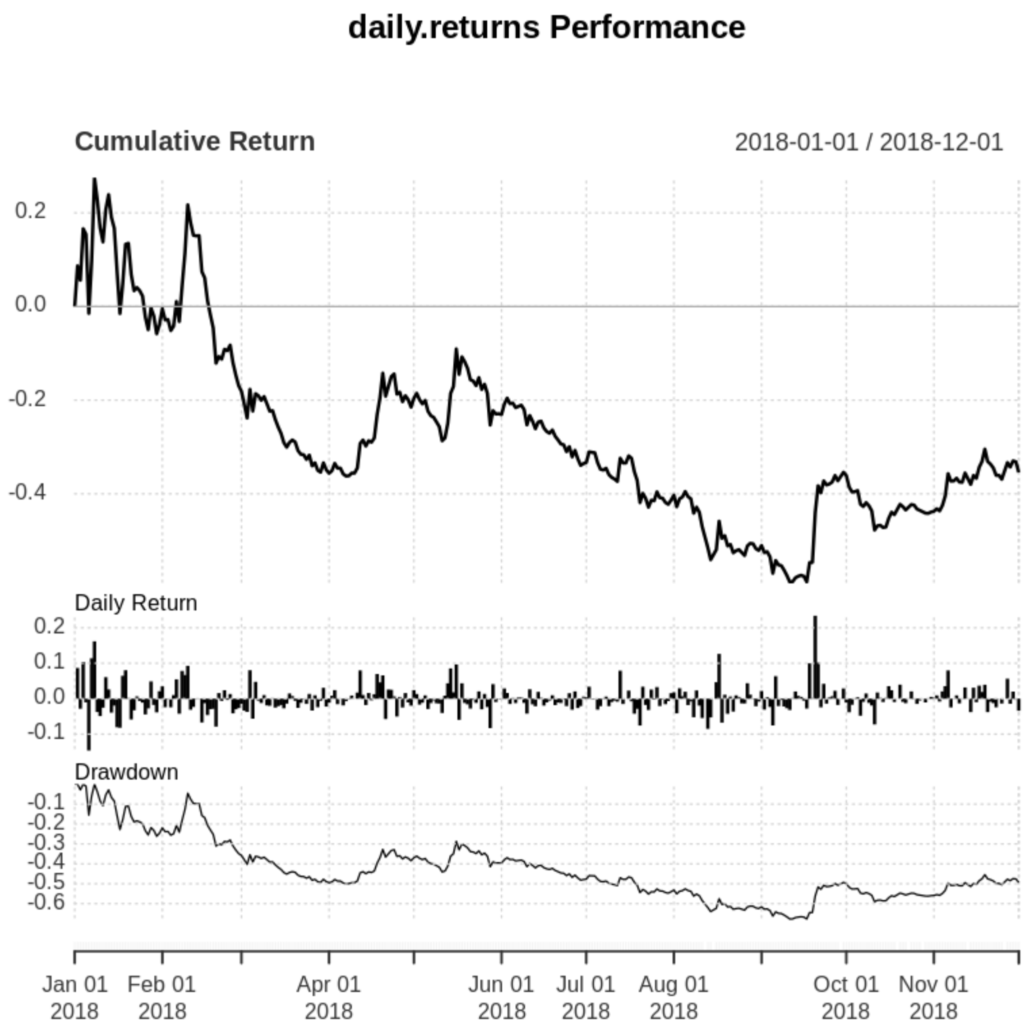
	tradeReturn
StdDev Sharpe (Rf=0%, p=95%):	0.05379146

	tradeReturn
Annualized Sharpe Ratio (Rf=0%)	0.7710583

From the values above, we can see that the model is viable but risky. To have a better understanding of the performance of the model in relation to other models, we will compare it with a benchmark of buy-and-hold strategy which holds both assets in equal weights in the same timeframe.

```
# Create benchmark portfolio
BENCHMARK = (XRPXTS_DR + ZECBTS_DR) / 2

# Plot daily returns of benchmark
plot(BENCHMARK)

# Plot performance of benchmark
charts.PerformanceSummary(na.approx(BENCHMARK))
```


BENCHMARK
2018-01-01 / 2018-12-01
0.2
0.1
0.0
-0.1
Jan 01 2018
Feb 01 2018
Apr 01 2018
Jun 01 2018
Jul 01 2018
Aug 01 2018
Oct 01 2018
Nov 01 2018




```
Return.cumulative(BENCHMARK)
Return.annualized(BENCHMARK)
maxDrawdown(BENCHMARK)
SharpeRatio(BENCHMARK, Rf = 0, p=0.95, FUN = "StdDev")
SharpeRatio.annualized(BENCHMARK, Rf = 0)
```

	daily.returns
Cumulative Return	-0.3542302

	daily.returns
Annualized Return	-0.2860992

0.677199512468512

	daily.returns
StdDev Sharpe (Rf=0%, p=95%):	-0.01609935

	daily.returns
Annualized Sharpe Ratio (Rf=0%)	-0.4688807

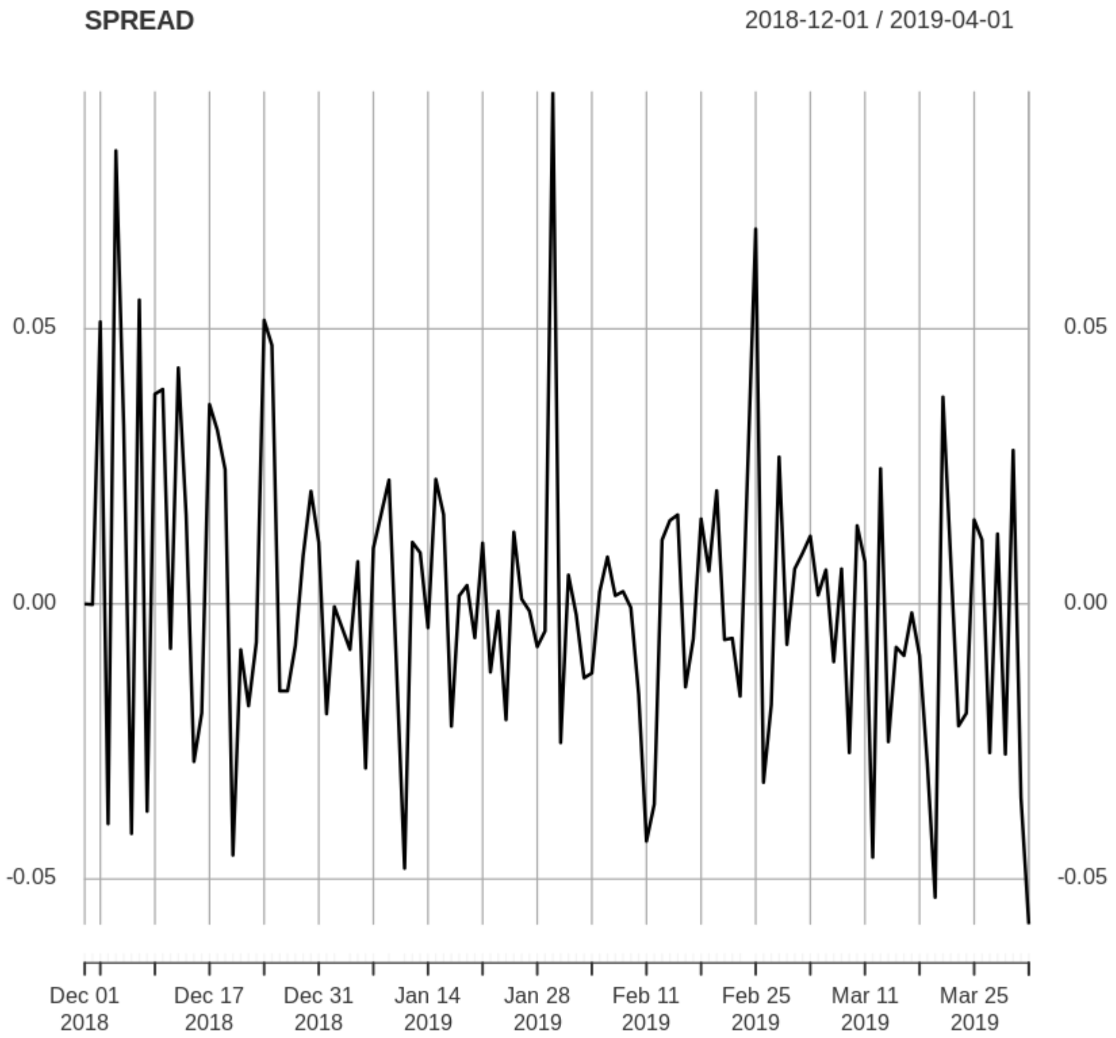
As we can see, the statstical arbitrage model outperforms the buy and hold strategy greatly in the period of market downturn.

Forecast

We will attempt to apply the same model in a different timeframe, up to Apr 2019. The price movement of the market is largly characterised by the sideway movement of the cryptocurrencies as shown by bitcoin's price:


```
# Applying to out-of-sample data
pairs = c(
    "XRPBTC",
    "ZECBTC"
)
startDate = "2018-12-01"
endDate = "2019-04-01"
pairsDataListXts = list()

# Fetch price data
for(i in 1:length(pairs)){
    pair = pairs[i]
    bifinexPair = paste("BITFINEX/", pair, sep = "")
```

```
    pairData = Quandl(bifinexPair, start_date=startDate, end_date=endDate)
    assign(pair, pairData)
    pairDataXts = as.xts(pairData, order.by = pairData$Date, x=pairData$Last)
    pairsDataListXts[[i]] = pairDataXts
}

# Create time series of the spread
XRPXTS_DR = dailyReturn(pairsDataListXts[[1]])
ZECBTS_DR = dailyReturn(pairsDataListXts[[2]])
SPREAD = XRPXTS_DR - ZECBTS_DR
plot(SPREAD)
```

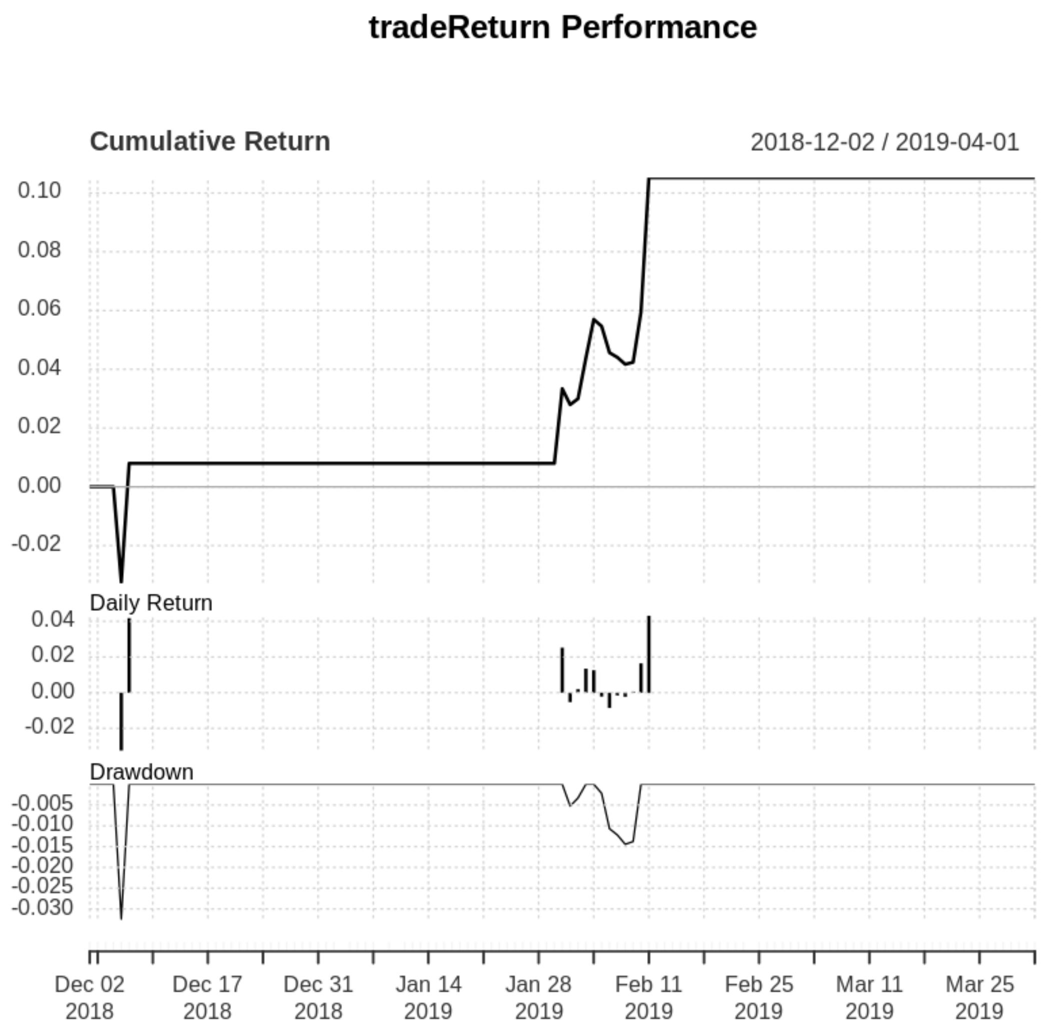



```
# Enter when current return spread is 3 standard deviation away
# and exit when it's 1 standard deviation away
ENTER_RET = Z_SPREAD(3)
EXIT_RET = Z_SPREAD(1)
```

```
signal = GENERATE_SIGNAL(SPREAD, ENTER_RET, EXIT_RET)
RES = merge(SPREAD, signal)
RES$tradeReturn = RES$daily.returns * lag(RES$signal)

# Saving results to be used later
FORECASTED = RES

head(RES)
```

```
           daily.returns signal tradeReturn
2018-12-01  0.0000000000      0          NA
2018-12-02 -0.0001131245      0  0.00000000
2018-12-03  0.0512798584      0  0.00000000
2018-12-04 -0.0399565325      0  0.00000000
2018-12-05  0.0823836816     -1  0.00000000
2018-12-06  0.0324139120     -1 -0.03241391
```

```
charts.PerformanceSummary(na.approx(RES$tradeReturn))
```




```
Return.cumulative(RES$tradeReturn)
Return.annualized(RES$tradeReturn)
maxDrawdown(RES$tradeReturn)
SharpeRatio(RES$tradeReturn, Rf = 0, p=0.95, FUN = "StdDev")
SharpeRatio.annualized(RES$tradeReturn, Rf = 0)
```

	tradeReturn
Cumulative Return	0.1052364

	tradeReturn
Annualized Return	0.2404972

0.0324139119521271

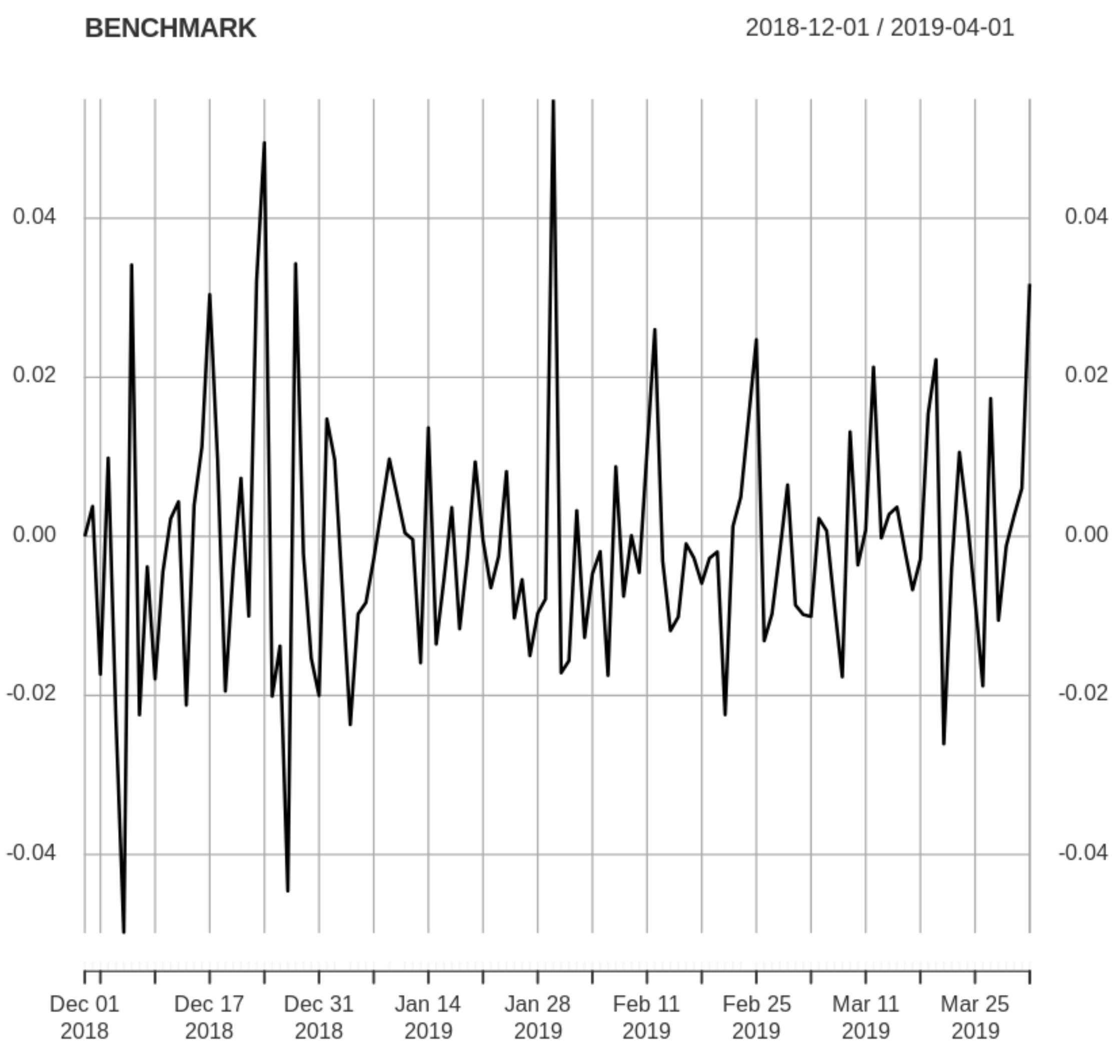
	tradeReturn
StdDev Sharpe (Rf=0%, p=95%):	0.1232066

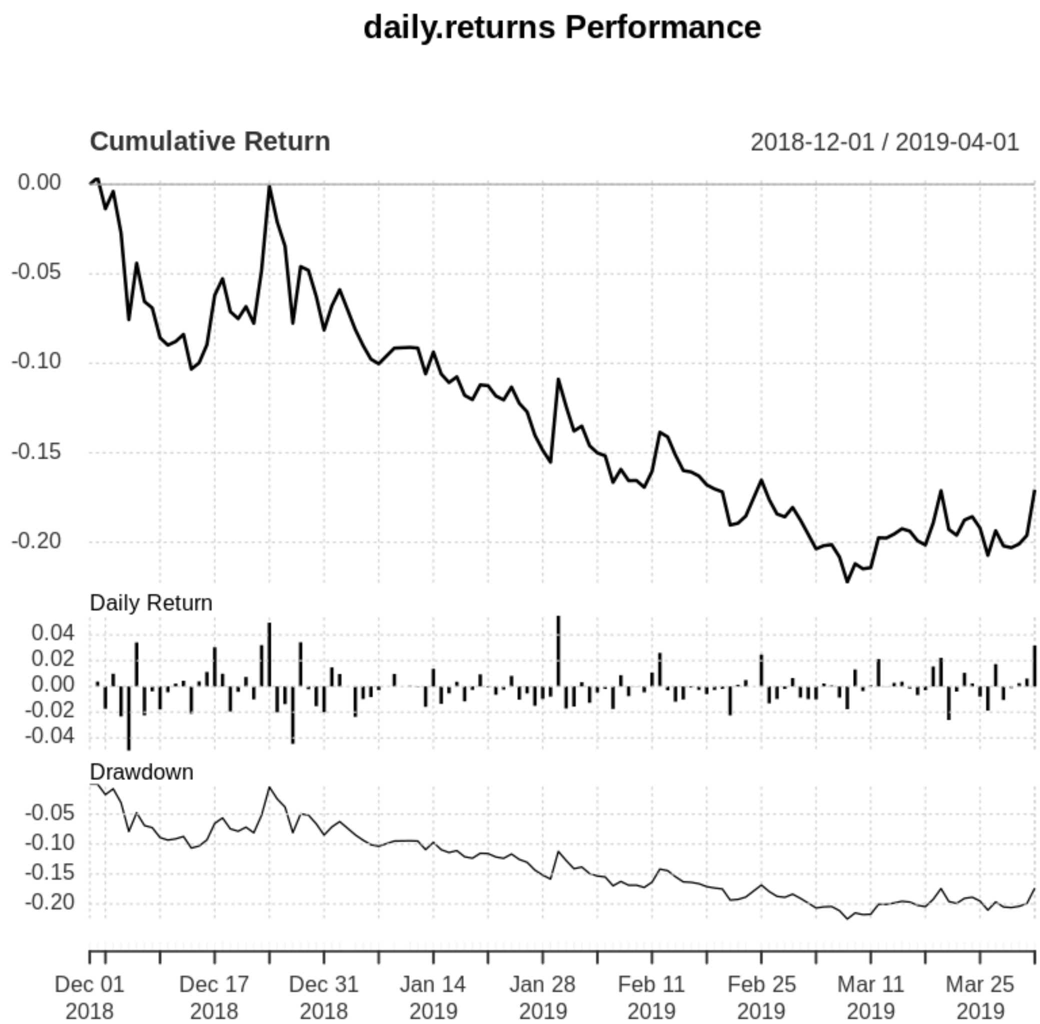
	tradeReturn
Annualized Sharpe Ratio (Rf=0%)	2.119837

From the charts above, we can see that the trading strategy is also applicable in a market with sideway movements. However, we can see that the maximum drawdown is still huge, at >30%.

We can compare the performance with that of a buy-and-hold strategy.

```
# Comparing to benchmarks
BENCHMARK = (XRPXTS_DR + ZECBTS_DR) / 2
plot(BENCHMARK)
charts.PerformanceSummary(na.approx(BENCHMARK))
```





Comparing the performance, we can see that a buy-and-hold strategy greatly underperform compared to the statistical arbitrage model. However, it can also be seen that the maximum drawdown is only at 20%, compared to 30% on the statstical arbitrage model.

Summary

In conclusion, statistical arbitrage on the XRP/ZEC pair is a viable model for automated trading, and outperforms the benchmark. However, we can see that the strategy is very risky, with large drawdowns, but also with high returns.

To determine if the additional rewards is worth the additional risk, we can re-evaluate the model with the Sharpe ratio with a risk-free asset with 2% returns.

```
SharpeRatio(FORECASTED$tradeReturn, Rf = 0.02, p=0.95, FUN = "StdDev")
SharpeRatio.annualized(FORECASTED$tradeReturn, Rf = 0.02)
```

	tradeReturn

StdDev Sharpe (Rf=2%, p=95%):	-2.675277

	tradeReturn
Annualized Sharpe Ratio (Rf=504%)	-8.746845

As seen from the sharpe ratio, the additional returns does not justify the risk as a standalone asset. However, it does not mean that the statistical arbitrage on the pair is not viable to be included in a portfolio. More work can be done to evaluate how this model can be integrated with traditional portfolio to add diversity.

References

[1] https://towardsdatascience.com/pairs-trading-with-cryptocurrencies-e79b4a00b015

Additional Bibliography

- https://analyticsprofile.com/algo-trading/pair-trading-part-1-code-distance-based-pair-trading-strategy-in-r/
- https://timtrice.github.io/backtesting-strategies/index.html
- https://www.econometrics-with-r.org/index.html