

# **COMP226: Slides 18**

## **Strategy parameters**

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# Overview

- Recap definition of trading strategy **parameters**
- BBands Overbought/sold strategy: **changing parameters**
- **Enumerating** and **counting** parameter combinations

# Recap

For us trading strategy **parameters** are

- **inputs** (often numerical) required to define the strategy

**For example:**

The parameters of the vanilla **BBands overbought/oversold strategy** we looked are:

- n: the size of the window of a moving average
- sd: the multiple of standard deviations for the Bollinger Bands

# Recall strategy

## *Strategy*

- Long when below lower Bollinger band line
- Short when above upper Bollinger band line

```
bbands <- BBands(prices,n=50,sd=2)
long   <- ifelse(prices<bbands$dn,1,0)
short  <- ifelse(prices>bbands$up,-1,0)
pos    <- lag(long + short)
```

# Effect of changing parameters

- For **fixed**  $n$ , **lower**  $sd$  gives **less stringent** trading condition
- Therefore the condition will likely be met more times so there will be **more active days**
- Let's confirm this **empirically**

# Exploratory code

```
run <- function(prices,n,sd,plotEquity=FALSE) {  
  bbands <- BBands(prices,n=n,sd=sd)  
  long <- ifelse(prices<bbands$dn,1,0)  
  short <- ifelse(prices>bbands$up,-1,0)  
  pos <- long + short  
  pos <- lag(pos)  
  pos[is.na(pos)] <- 0  
  active_days <- sum(abs(pos)) # number of non-flat days  
  equity <- getEquityCurve(getLogReturn(prices),pos)  
  if (plotEquity) print(plot(equity,main="Equity curve"))  
  simple_return <- round(last(as.numeric(equity)),2)  
  return(c(simple_return, active_days))  
}
```

# Varying sd parameter

```
source('../utilities.R')
source('run_bbands.R')
library(quantmod)

prices <- getPrices(readCsvData('../GSPC.csv'))

n <- 10
sd <- seq(0.5,by=0.5,to=2.5)

results <- sapply(sd,function(x) run(prices,n=n,sd=x))
results <- t(results) # transpose
colnames(results) <- c("simple_ret","active_days")
results <- cbind(sd,results)
print(results)
```

# Varying sd parameter

```
> results
      sd simple_ret active_days
[1,] 0.5         1.76         1020
[2,] 1.0         1.21          727
[3,] 1.5         1.15          355
[4,] 2.0         0.35           75
[5,] 2.5        -0.01            6
```

- This confirms that a **lower** sd **results in more trades**
- This is a logical consequence of the strategy definition
- We would find the **same thing for other values of**  $n$



# expand.grid

Now let's consider varying **both** parameters

```
n    <- seq(10 ,by=10 ,to=30)
sd    <- seq(0.5,by=0.5,to=2)

params <- expand.grid(n=n,sd=sd)
```

expand.grid returns a data.frame of **all parameter combinations**

# expand.grid

```
> params
  n  sd
1 10 0.5
2 20 0.5
3 30 0.5
4 10 1.0
5 20 1.0
6 30 1.0
7 10 1.5
8 20 1.5
9 30 1.5
10 10 2.0
11 20 2.0
12 30 2.0
```

# apply

Now we run the strategy with each parameter combination

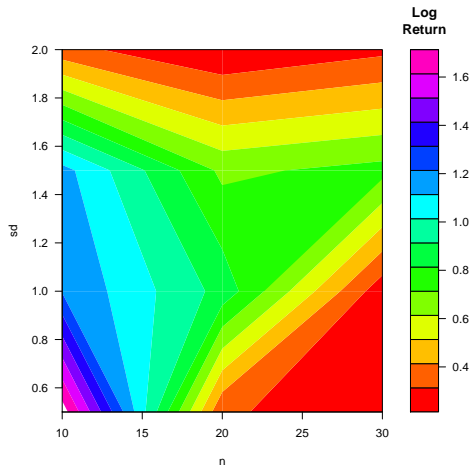
```
res <- apply(params,1,function(x) run(prices,  
                                     n=x['n'],  
                                     sd=x['sd']))  
results <- t(res)  
colnames(results) <- c("simple_ret","active_days")  
results <- cbind(params,results)  
results
```

- apply **applies a function over an array** (here params)
- second argument says: work over the **rows** of params, i.e., execute for each i:  
run(prices,params[i,"n"],params[i,"sd"])

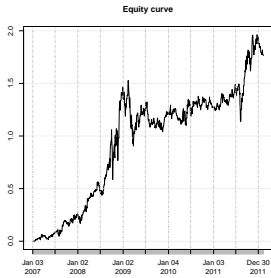
```
> results
      n  sd simple_ret active_days
1   10 0.5         1.76         1020
2   20 0.5         0.32         1033
3   30 0.5         0.28         1008
4   10 1.0         1.21          727
5   20 1.0         0.88          758
6   30 1.0         0.25          752
7   10 1.5         1.15          355
8   20 1.5         0.69          407
9   30 1.5         0.75          423
10  10 2.0         0.35           75
11  20 2.0         0.21          127
12  30 2.0         0.29          138
```

The relationship between active days and n is not so clearcut

# Fitness landscape



# Best result



- **Question:** How **representative** are the best parameters?
- We will return to this issue when we discuss **backtesting**

# Counting parameter combinations

2 parameters:

```
> param1    <- c(10,20,30)
> param2    <- c(0.5,1,1.5,2)
```

The **cardinality** (size) of the two sets

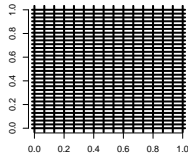
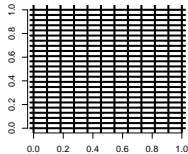
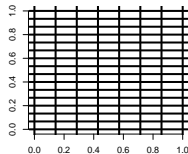
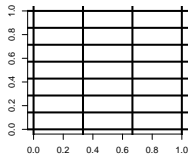
$$|\{10, 20, 30\}| = 3, \quad |\{0.5, 1, 1.5, 2\}| = 4$$

So the total number of **parameter combinations** is:

$$3 \times 4 = 12$$

# The underlying grid

These parameter combinations can be represented on a **2d grid**:





# Counting parameter combinations

```
> param1    <- c(10,20,30,40)
> param2    <- c(5,6,7)
> param3    <- c(0,1,2)
```

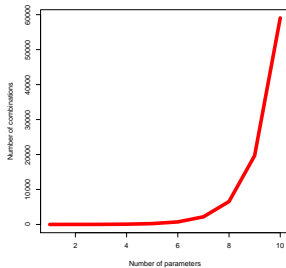
Now we have the product of three **cardinalities**

$$4 \times 3 \times 3 = 36$$

```
> params <- expand.grid(p1=param1,p2=param2,p3=param3)
```

## ***Warning***

The total number of parameter combinations grows **exponentially** with the number of parameters



# Counting parameter combinations

- If there are  $n$  parameters and each can take at least  $k$  different values
- Then there are at least  $k^n$  parameter combinations
- To be precise:

If parameter  $i$ , for  $i=1,\dots,n$ , can take on  $p(i)$  different values, the total number of parameter combinations is

$$\prod_{i=1,\dots,n} p(i)$$

# Selecting parameters

- Trading strategies are typically **parameterized**
- How should one choose **which parameter values to use?**
- Typically **parameter optimization** is used

## ***Parameter optimization***

Pick parameter values that are **likely** to produce good results **in the future**. In the terminology of **machine learning**, we want a model (strategy) that will **generalise** (to the future).

## ***Warning***

Optimization is important but **dangerous**

We will carefully consider how to avoid **over-optimization**  
and how to test the **robustness** of a strategy