

# R with future

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# Parallel computation in general

Computing in parallel: “Separate” computations are performed on different threads/cores

- ▶ Parallel without communication
- ▶ Parallel with communication
- ▶ in R: opens new instances of R (forked, socket cluster, MPI, via SLURM jobs)

Other specifics:

- ▶ Parallelisation over CPUs vs. over GPUs (latter not covered today)
- ▶ Multithreading: Parallelisation with shared memory, typically working on the same (big) task



# Parallelisation without communication

- ▶ No communication needed (only collection of results)
  - ▶ Running script on different data sets
  - ▶ Simulations (distribute replications and/or parameters sets)

## Main issues when computing in parallel

- ▶ Load balancing
- ▶ Copying of objects between R instances
- ▶ (Nested parallelisms)
- ▶ Setting seeds
- ▶ (Overhead of parallelisation approach)

# Working on bwUniCluster

To run the code on bwUniCluster, open an interactive session

```
salloc -t 120 -p single -n 2  
module load math/R/4.1.2
```

Part 1 and part 2 of this course should also run on most local computers ( if  $> 1$  CPU).



# Prerequisites

Install the following R packages on bwUniCluster (we use R 4.1.2)

```
install.packages(c("future", "parallelly",  
                  "future.apply", "doFuture",  
                  "future.batchtools",  
                  "tictoc")) #tictoc for very easy timing
```

futureverse project leader: Henrik Bengtsson (Department of Epidemiology & Biostatistics at UCSF)

[Homepage](#), latest releases on CRAN.

Main package: [future](#)



# R libraries needed today

```
library("future")  
library("parallelly")  
library("future.apply")  
library("doFuture")
```

## Loading required package: foreach

```
library("future.batchtools")  
library("tictoc")
```



# The idea behind R future

- ▶ R usually allocates and computes in one step
- ▶ future wraps the assignment up in a new object - which can then be computed/resolved on any R process
  - ▶ (and NOT NECESSARILY IN THE ONE IT WAS DEFINED IN).

```
library(future)
```

```
x <- 1
```

```
mode(x)
```

```
## [1] "numeric"
```

```
future_x <- future(1, lazy = TRUE)
```

```
mode(future_x)
```

```
## [1] "environment"
```

```
mode(value(future_x))
```

```
## [1] "numeric"
```



# General scheme of future

- ▶ Any `future(...)` you run can be run in serial or parallel (forked, socket cluster, ..., via SLURM)
- ▶ You simply specify how any futures are run by `plan(...)`. This is called the parallel resp. serial backend
- ▶ Seeds can be set in such a way that results stay reproducible regardless of backend ( via l'Ecuyer RNG)

⇒ Code stays the same when you switch the backend, essentially you only change `plan(...)`





## Some interesting plans on a single node

- ▶ `plan(strategy=sequential)`: Serial execution of futures within the main R session
- ▶ `plan(strategy=multicore,workers=n)`: Forks `n` workers from main R (not on Windows, not in GUIs as Rstudio)
- ▶ `plan(multisession,workers=n)`: `n` separate (background) R processes as workers
- ▶ The main R waits for all futures to be distributed across workers - main R only blocked after this if `# workers < # futures`
- ▶ Change the `plan` by simply invoking a different `plan`

# Details on future

```
str(future)
```

- ▶ lazy: Should `future(...)` be evaluated asap or only when queried for value?
- ▶ seed (default=FALSE): Should seeds be set (via L'Ecruyer RNG, reproducible regardless of backend used)
- ▶ globals: control over R objects that future needs from the global environment (auto-identified by default)
- ▶ packages: specific packages needed to evaluate the future

# The difference between futures and assign (aka <-)

```
#availableCores(); availableWorkers()
plan(strategy=multisession,workers=4)
testf1 <- function(){Sys.sleep(6);return(Sys.getpid())}
s1 <- replicate(3,future(testf1()))
sapply(s1,resolved)
```

```
## [1] FALSE FALSE FALSE
```

```
sapply(s1,value)
```

```
## [1] 24236 24237 24235
```

```
replicate(3,value(future(testf1())))
```

```
## [1] 24236 24236 24236
```

Exercise: Does this behave differently if workers=2?



# The difference between futures and assign (aka <-)

```
#availableCores(); availableWorkers()
plan(strategy=multisession,workers=4)
testf1 <- function(){Sys.sleep(6);return(Sys.getpid())}
s1 <- replicate(3,future(testf1()))
sapply(s1,resolved)
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## [1] FALSE FALSE FALSE
```

```
sapply(s1,value)
```

```
## [1] 24236 24237 24235
```

```
replicate(3,value(future(testf1())))
```

```
## [1] 24236 24236 24236
```

Exercise: Does this behave differently if workers=2? Check package 'promises' for non-blocking futures



## Futures make any loop or vectorization parallel

```
set.seed(44)
testf1 <- function(){Sys.sleep(sample(6))
                        return(Sys.getpid())}
res1 <- vector("list",10)
for (i in 1:10){
  res1[[i]] <- future(testf1(),seed=TRUE)
}
str(res1[[1]])
```

```
## Classes 'MultisessionFuture', 'ClusterFuture', 'Multiproc'
```

```
res2 <- sapply(res1,value)
table(res2)
```

```
## res2
## 24234 24235 24236 24237
##      3      3      2      2
```

“Exercise”: Use vectorization (\*apply) instead of the loop



# Timing via R package tictoc

```
tic()  
Sys.sleep(3) #Any code  
toc()
```

```
## 3.004 sec elapsed
```

```
tic()  
Sys.sleep(3)  
toc()
```

```
## 3.006 sec elapsed
```



## A test function and some R objects

```
test_node <- function(i,exportsth=NULL){  
  str(exportsth) #Do sth. cheap w. object  
  p1 <- date() #get date  
  sleep_t <- sample(10,1) #random sleep time  
  Sys.sleep(sleep_t) #sleep in R  
  x <- Sys.info() #System info, including host name  
  return(c(run=i,time_start=p1,time_end=date(),  
          pid=Sys.getpid(),host=x["nodename"],  
          sleep_time=sleep_t))}  
  
small_thing <- "cookies"  
big_thing <- matrix(rnorm(1e6),nrow=1000)
```

## Exercise: Compare future's plans

Test the behaviour of plans `multisession` and `multicore` with 3 workers

- ▶ Use the test function `test_node` and “force” it to import a big or small object
- ▶ Use some method to run several (4) instances of this test (which then get distributed via `plan`)
- ▶ Time the executions
- ▶ Are there differences? How is the load balancing?





## Hints: general structure

```
library(...), ...
```

```
#For each plan to test
```

```
tic()
```

```
set.seed(...)
```

```
plan(...)
```

```
LOOP i 1:4 start
```

```
... <- future(...(i), seed=TRUE)
```

```
LOOP end
```

```
LOOP start
```

```
value(future i)
```

```
LOOP end
```

```
toc()
```

