

# HPC & PARALLEL PROGRAMMING IN R

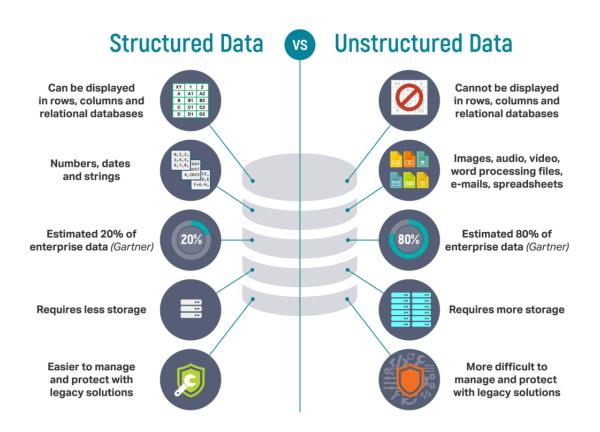
New cloud computing possibilities for researchers & students

Kristoffer Gulmark Poulsen & Lars Nondal CBS



### **About You?**

- 1. What **type and size** of data do you work with?
- 2. What programming languages do you work in (e.g. R, Python..)?
- 3. Are you familiar with parallel programming?
- 4. Are you familiar with high performance computing
- 5. In particular UCloud?



### **Program Today**

- Introduction to UCloud platform (if needed)
- Basic theory of parallel programming
- Parallel programming basics within R.
- Parallelization of a ML models within the Tidymodels framework.
- https://cbs-hpc.github.io/



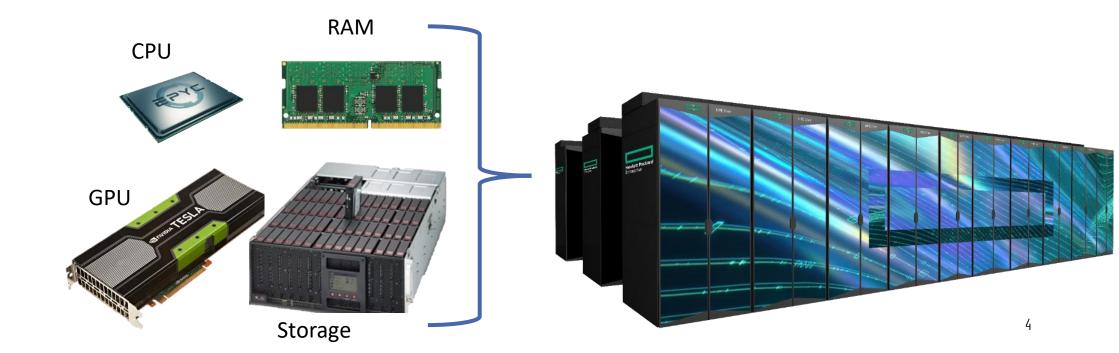
### What is High Performance Computing (supercomputer)?

### Network of processors, hard drives & other hardware

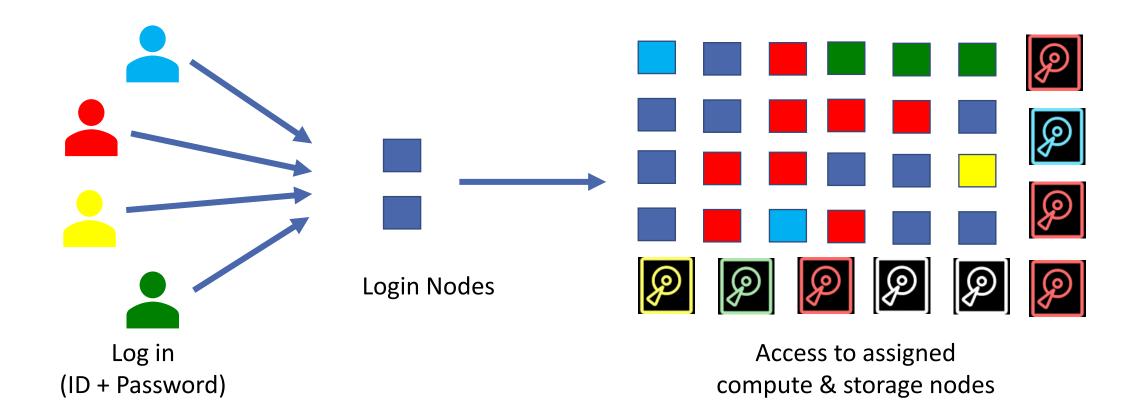
#### Hardware

CBS i

- **Core**: Processing unit on a single machine.
- Node: A single machine.
- Cluster: Network of multiple nodes.



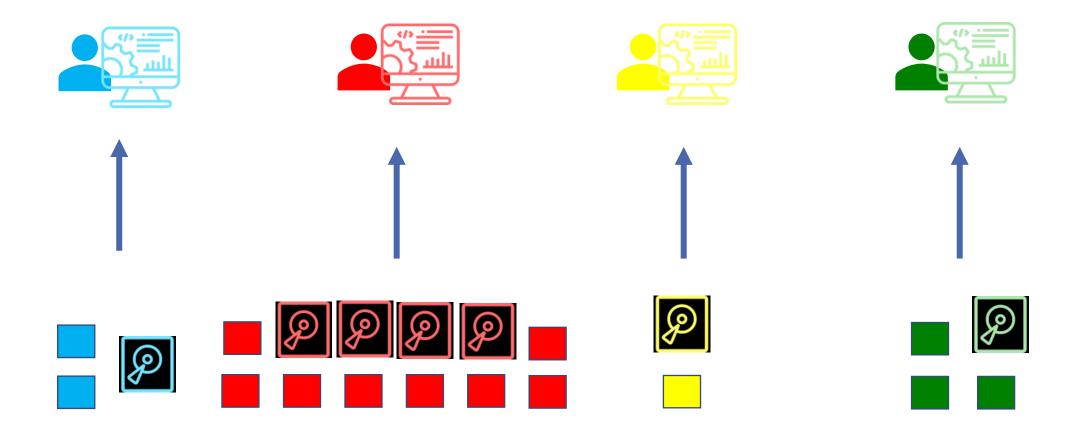
### Accessing an HPC...





### Accessing an HPC...

• Your assigned resources (HW + SW) can be used from your PC



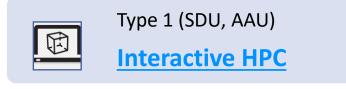
### When HPC might be for you

- Applying ML/AI
- Running simulation and resampling techniques
- Working with large datasets
- My laptop runs out of memory
- My workflow is running very slow



### **National HPC facilities**

• Collaboration between Universities and DeiC (Danish e-Infrastructure Cooperation)





Type 2 (AU,KU & DTU)
Throughput HPC



arge Memory HPC



Type 5 (EuroHPC Consortium)
<u>LUMI Capability HPC</u>

https://www.deic.dk/en/supercomputing/national-hpc-facilities



### Type 1: Interactive HPC

Cloud-based (HPC) systems (e.g. similar to google colab, amazon aws)

User friendly with Graphical User Interface (GUI).

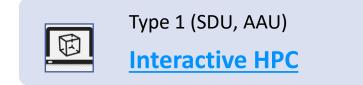
Lots of preinstalled software (R, Python, Stata & Matlab)

Collaborative projects – work & share files with others

**GDPR-Compliant** 

Access with university credentials from <u>https://cloud.sdu.dk</u>

- <u>xxx@student.cbs.dk</u>
- <u>xxx@cbs.dk</u>
- 1000 DKK Free credit.







### Type 1: SDU

• CPU resources

Type 1 (SDU, AAU)Interactive HPC

- GUI based
- Wide range of applications
- Slurm and Spark Cluster

Name	vCPU	Memory (GB)	GPU	Price
	De	eiC Interactive HPC (SDU)	: u1-standard ——	
😣 u1-standard-1	1 (Intel Xeon Gold 6130)	6	None	0,07 DKK/hour
😣 u1-standard-2	2 (Intel Xeon Gold 6130)	12	None	0,16 DKK/hour
😣 u1-standard-4	4 (Intel Xeon Gold 6130)	24	None	0,33 DKK/hour
😣 u1-standard-8	8 (Intel Xeon Gold 6130)	48	None	0,67 DKK/hour
🙉 u1-standard-16	16 (Intel Xeon Gold 6130)	96	None	1,36 DKK/hour
😣 u1-standard-32	32 (Intel Xeon Gold 6130)	192	None	2,74 DKK/hour
😣 u1-standard-64	64 (Intel Xeon Gold 6130)	384	None	5,49 DKK/hour

### Support at CBS

Local CBS support

- Lars Nondal & <u>Kristoffer Gulmark Poulsen</u>
- Contact: <u>rdm@cbs.dk</u> or directly to Kristoffer (<u>kgp.lib@cbs.dk</u>)

**User support:** Advising and granting resources, technical problems.

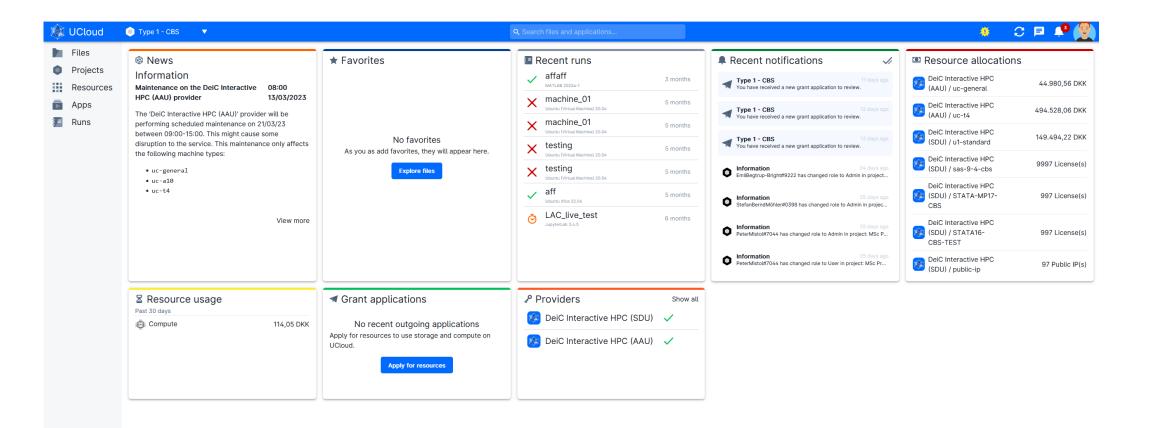
**Consultation:** Code development etc.

**Teaching:** "<u>High Performance Computing</u>", "<u>HPC & Parallel Programming in R</u> and <u>Python</u>" and "<u>Train your ML/AI Model</u> <u>on GPUs</u>".

Documentation and Tutorials: <u>https://cbs-hpc.github.io/</u>



### **UCloud Dashboard**



https://cloud.sdu.dk/app/dashboard



Type 1/Type 1 - CBS
 KristofferGulmarkP...
 UCloud Docs
 SDU Data Protection

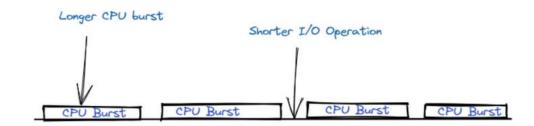
### Why is it taking so long?

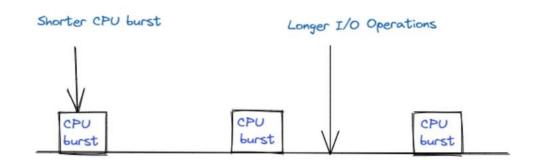
### Computation can be slow for one of three reasons:

**CPU bound** when computational time is restricted by processor.

**I/O bound** when reading **from** and **to disk/database** is limiting factor.

**Memory bound** when limited by the memory required to hold the working data.

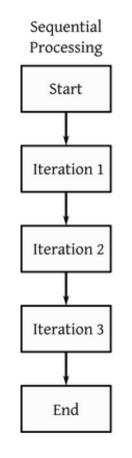






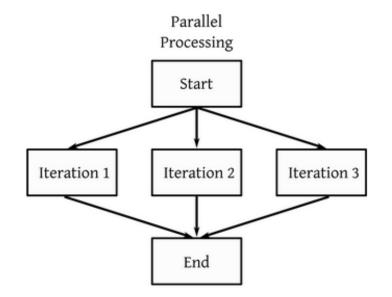
### **Sequential Computing**

- Single core processor
- Multiple tasks which runs overlapping but **not** at same time
- Synchronous tasks



#### **Parallel Computing**

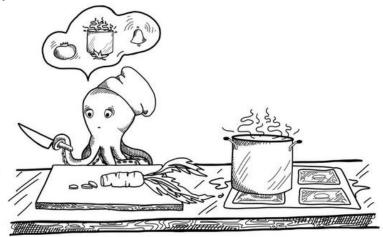
- Multi-core processor
- Multiple tasks which runs overlapping.
- Synchronous/Asynchronous

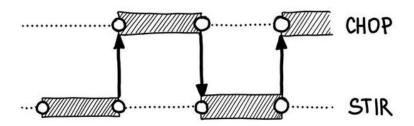




### **Sequential Computing**

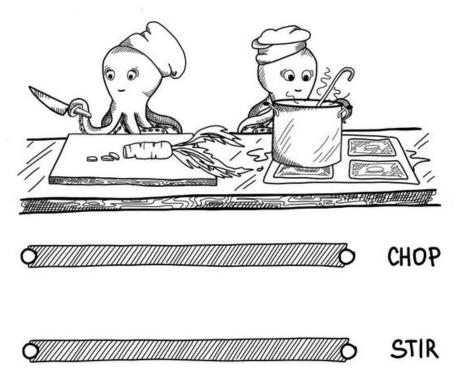
- Single core processor
- Multiple tasks which runs overlapping but **not** at same time.
- Synchronous tasks





#### **Parallel Computing**

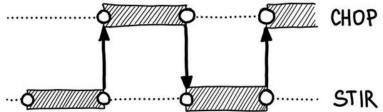
- Multi-core processor
- Multiple tasks which runs overlapping.
- Synchronous/Asynchronous



#### Concurrency

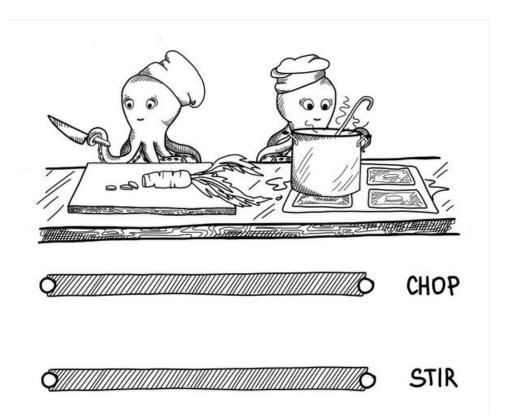
• Executing multiple tasks at the same time but not necessarily simultaneously.



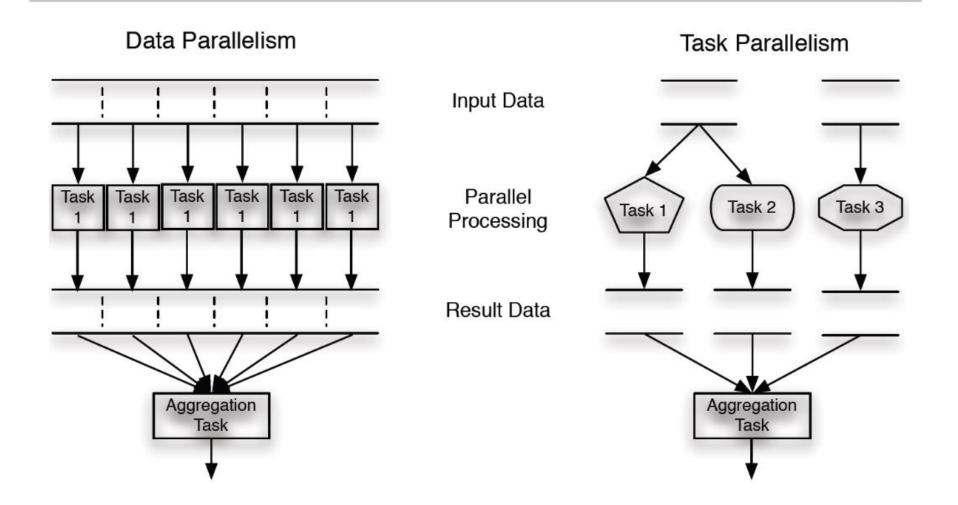


#### Parallelism

- One task is split into subtasks and run in parallel at the exact same time.
- Run multiple tasks in in parallel on multiple CPUs at the exact same time









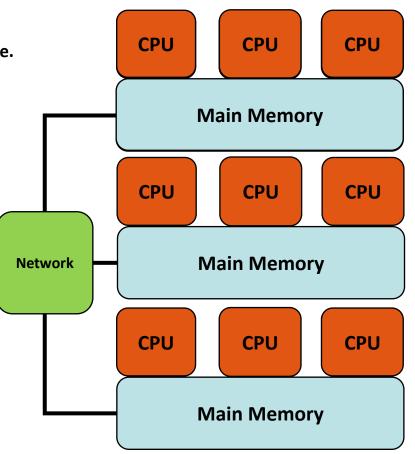
## **Models for Parallel Programming**

Shared Memory Parallelism (SMP) work is divided between multiple cores running on a single machine.

Distributed Memory Parallelism (Distributed Computing) work is divided between multiple machines.

Implicit/Hidden Parallelism - is implemented automatically by the Compiler, Interpreter or Library.

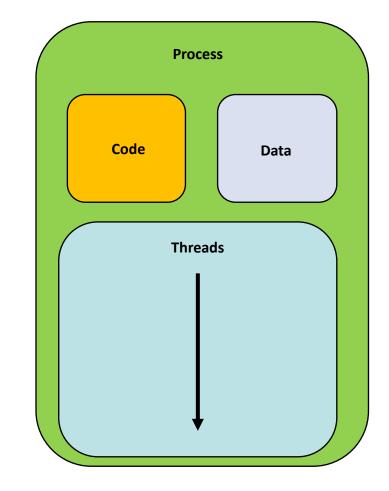
Explicit Parallelism - is written into the source code by the Programmer.





### Terminology

- Embarrassing/ Perfectly Parallel the tasks can be run independently, and they don't need to communicate.
- **Process**: Execution of a program . A given executable (e.g., Python or R) may start up multiple processes.
- **Thread**: Path of execution within a single process.
- Interpreted High-level code converted to machine code and executed <u>line by line</u>. (Python & R)
- Compiled All code is converted to machine code and then program is executed. (C & Fortran)





## SIMD & Multi-Threading

### Single Instruction, Multiple Data (SIMD)

- single thread/processor where each processing unit (PU) performs the same instruction on different data.
- Vectorization.

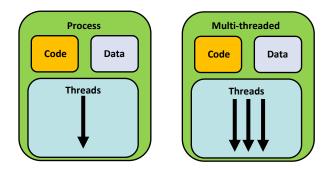
### **Multi-Threading**

- Threads are multiple paths of execution within a single process.
- Appears as a single process.

#### Single instruction, multiple threads (SIMT)

Python and R are examples of single-threaded programming languages.

SIMD Instruction pool



top - 15:12:02 up 2 days, 54 min, 0 users, load average: 6.42, 6.45, 6.45 Tasks: 10 total, 1 running, 9 sleeping, 0 stopped, 0 zombie %Cpu(s): 11.0 us, 0.3 sy, 0.0 ni, 88.7 id, 0.0 wa, 0.0 hi, 0.0 si, 0.0 st MiB Mem : 385583.7 total, 193583.0 free, 102124.0 used, 89876.6 buff/cache MiB Swap: 8192.0 total, 4461.5 free, 3730.5 used. 280235.0 avail Mem

PID	USER	PR	NI	VIRT	RES	SHR		%CPU	MEM	TIME+	COMMAND
243	ucloud	20	0	3970780	962704	74288		278.1	0.2	0:44.50	rsession
202	rstudio+	20	0	182200	18268	14724		0.7	0.0	0:01.00	rserver
1	ucloud	20	0	6896	3428	3196	S	0.0	0.0	0:00.05	start-rstu+
7	root	20	0	10420	4920	4376	S	0.0	0.0	0:00.00	sudo
8	root	20	0	200	4	0	S	0.0	0.0	0:00.01	s6-svscan
37	root	20	0	200	4	0	S	0.0	0.0	0:00.00	s6-supervi+
198	root	20	0	200	4	0	S	0.0	0.0	0:00.00	s6-supervi+
265	ucloud	20	0	2492	580	512	S	0.0	0.0	0:00.01	sh
271	ucloud	20	0	8168	4904	3408	S	0.0	0.0	0:00.01	bash
273	ucloud	20	0	10032	3824	3316	R	0.0	0.0	0:00.12	top



### SIMD & Multi-Threading in Python and R

**SIMT** is achieved in several ways:

#### **Through external libraries**

- Written in other languages (e.g. C, C++, Fortran) that run multi-threaded.
- Linear algebra routines (BLAS & LAPACK) implemented in libraries such as MKL, OpenBLAS or BLIS.
- NumPy, SciPy and Pandas
- built-in R functions

#### "Static Compilers"

- OpenMP/GCC (GNU Compiler Collection)
- Rcpp
- Cython

#### **Dynamic/JIT Compilers:**

- Numba
- JITR

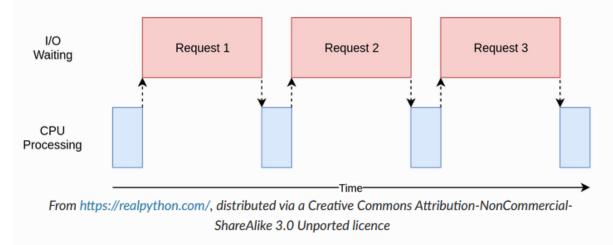
File       Edit       Code       View       Plots       Session       Build       Debug         Image: Session in the session	MiB Mem : 385583	, 1 , 0. .7 to	l run <b>3</b> sy otal,	ning, /, <b>0.0</b> r <b>193583</b> .	9 sleep ni, 88.7 .0 free,	oing, 0 / id, 0. 102124	) stopped .0 wa, ( .0 used,	i, 0 0.0 hi 89870	zombie , 0.0 si, 0.0 st
( R 4.2.1 . /work/ ≈)	PID USER	PR	NI	VIRT	RES	SHR	%CPU	MEM	TIME+ COMMAND
> n <- 4*1024	243 ucloud	20				74288	278.1	0.2	0:44.50 rsession
A <- matrix( rnorm(n*n), ncol=n, nrow=n ) B <- matrix( rnorm(n*n), ncol=n, nrow=n )	202 rstudio+	20	0	182200	18268	14724	0.3		0:01.00 rserver
C <- A %*% B	1 ucloud	20	0	6896	3428	3196 9	6 0.0	0.0	0:00.05 start-rstu
	7 root	20	0	10420	4920	4376 \$	6 0.0	0.0	0:00.00 sudo
	8 root	20	0	200	4	0 9	S 0.0	0.0	0:00.01 s6-svscan
	37 root	20	Θ	200	4	0 5	6 0.0	0.0	0:00.00 s6-supervi
	198 root	20	Θ	200	4	0 9	6.0	0.0	0:00.00 s6-supervi
	265 ucloud	20	0	2492	580	512 \$	S 0.0	0.0	0:00.01 sh
	271 ucloud	20	0	8168	4904	3408 \$	6 0.0	0.0	0:00.01 bash

3316 R 0.0 0.0 0:00.12 top

10032

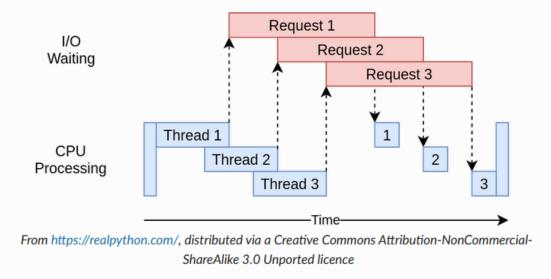
273 ucloud

20 Θ 3824



This is how an I/O-bound application might look:

The speedup gained from multithreading I/O bound problems can be understood from the following image.





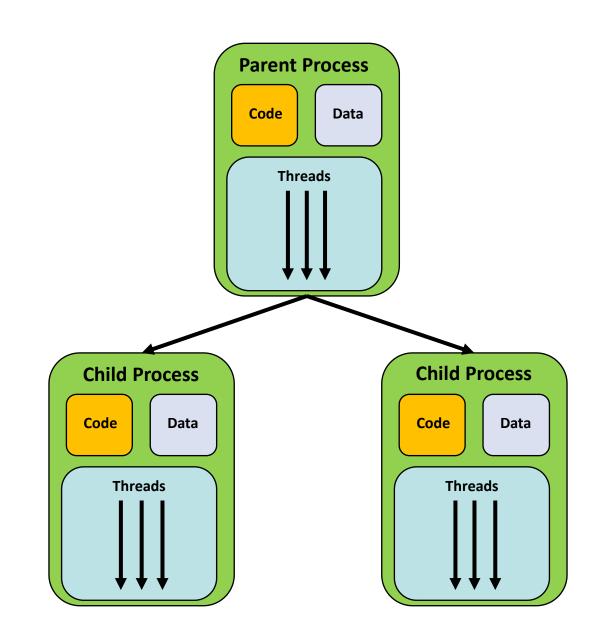
### **Multi-Processing**

#### Fork

- Only available on UNIX machines (Linux, Mac, and the likes).
- The child process is an identical "cloned" of the parent process.
- Single machine

### Spawn/Socket (PSOCK)

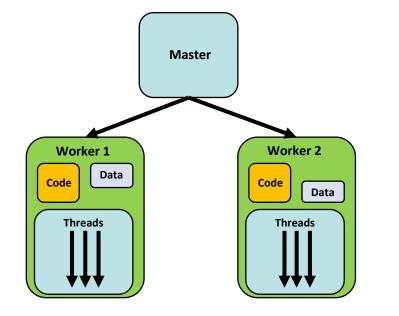
- Available on Unix and Windows.
- The parent process starts a fresh/empty process.
- Code & data needs to copied onto the new child process
- Can be scaled to multiple machines/cluster.





## Multi-Processing - Splitting Data

#### Passing only data "chucks" to each worker



Big chunks are generally better than little chunks

for (i in 1:10) { for (j in 1:1000000) { # Execution of code



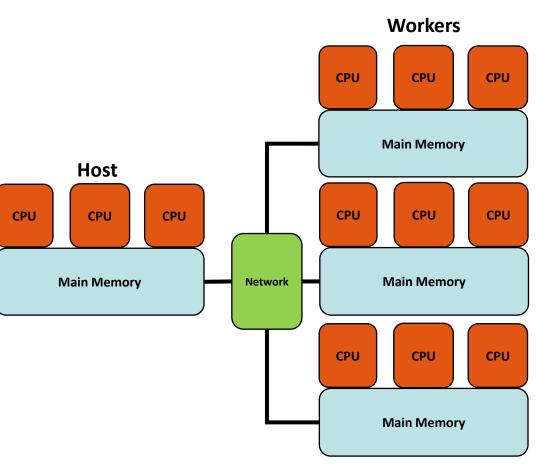
## **Distributed Computing on HPC**

#### **Distributed Memory Parallelism** (Distributed Computing)

- Multiple machines with its own private memory.
- Message Passing Interface (MPI)
- Host schedules the work across the workers

#### **HPC Job Schedulers:**

- Portable Batch System (PBS)
- Simple Linux Utility for Resource Management (SLURM)
- IBM Spectrum LSF
- Sun Grid Engine (SGE)







# PARALLEL PROGRAMMING IN R

Kristoffer Gulmark Poulsen & Lars Nondal CBS



## **R Packages - Overview**

#### **Compilers (Not covered)**

- Rcpp
- *JIT*

#### parallel package

- multicore
- Snow

#### foreach loop adaptation of parallel

• doParallel, doSnow, doMC & doMPI...

#### Tidymodels framework

• Examples of parallel computing

#### Scalable Frameworks(Not covered)

- future
- SparkR

https://cran.r-project.org/web/views/HighPerformanceComputing.html



### Iterations

### There are two styles of iterations

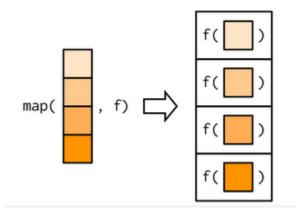
for (i in 1:3) print(sqrt(i))

#### for and while loops

- It is often the most intuitive way to begin.
- Imperative programming .

#### functional programming

- Readability & code redundancy
- Functionals are a functions that takes a function as an input and returns a vector as output.
- E.g. apply() or map()





### R Packages- *Parallel*

- *multicore*: Multi-processing on single machine through forking (Not Covered Today).
- Snow (Simple Network of Workstations): Can fork/spawning on multiple machines/clusters.
- *paralellel* serve as "*parallel backend*" to many/most packages, so worth understanding.
- It is all based on *apply* form of R iteration:

Base R	snow			
lapply	parLapply			
sapply	parSapply			
vapply	-			
apply(rowwise)	parRapply, parApply(,1)			
apply(columnwise)	parCapply, parApply(,2)			



### R Packages- *Parallel /snow*

Snow (Simple Network of Workstations): Can fork/spawning on multiple machines/clusters.

#### Functions:

- cl<- makeCluster(n,type ="PSOCK") (Default)</li>
- cl<- makeCluster(n,type ="FORK")</li>
- *stopCluster(cl)* stops clusters
- clusterExport(cl,data) Copies data to processes
- clusterApply(cl,data,func) Runs analysis in parallel
- clusterApplyLB() dynamic load balancing
- clusterEvalQ(cl, expr) Evaluating an expression
- clusterSplit(cl,data) data splitting

#### ClusterApply

cl <- makeCluster(4)
system.time(clusterExport(cl, "jan2010"))</pre>

user system elapsed 0.128 0.027 0.574

system.time(cares <- clusterApply(cl, rep(5,4), do.n.kmeans))</pre>

user system elapsed 0.357 0.039 11.064

### R Packages- *foreach* loop adaptation of *parallel*

Parallelization using the "for loop" iteration through the *foreach* package.

for (i in 1:3) print(sqrt(i))

library(foreach)
foreach (i=1:3) %do% sqrt(i)

library(doParallel)
registerDoParallel(3) # use multicore-style forking
foreach (i=1:3) %dopar% sqrt(i)

cl <- makePSOCKcluster(3)
registerDoParallel(cl) # use the just-made PSOCK cluster
foreach (i=1:3) %dopar% sqrt(i)</pre>

CBS 📉

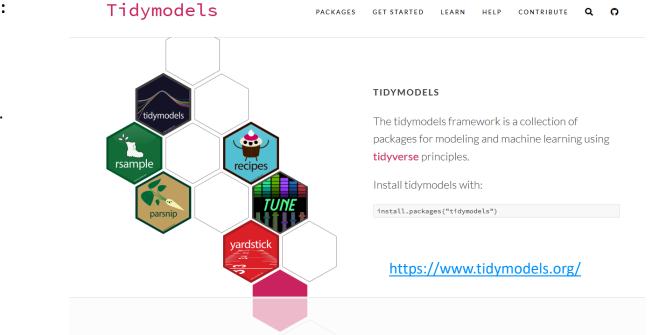
Many different backends:

- doParallel <u>https://cran.r-project.org/web/packages/doParallel/index.html</u>
- doSnow <u>https://cran.r-project.org/web/packages/doSNOW/index.html</u>
- doMC <u>https://cran.r-project.org/web/packages/doMC/index.html</u>
- doMPI <u>https://cran.r-project.org/web/packages/doMPI/index.html</u>

Tidymodels

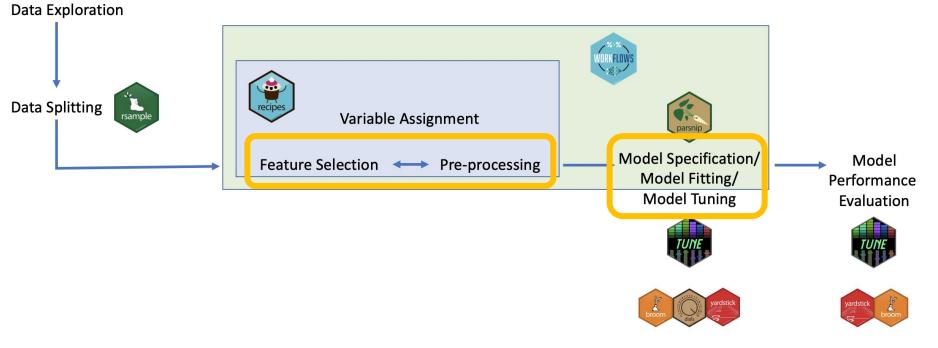
#### Tidyverse/Tidymodels

- The tidyverse is a language for solving data science challenges with R code.
- Both tidymodels is built on the tidyverse principles:
  - Should be intuitive
  - Consistence syntax: function naming, arguments.





### *Tidymodels* - Workflow

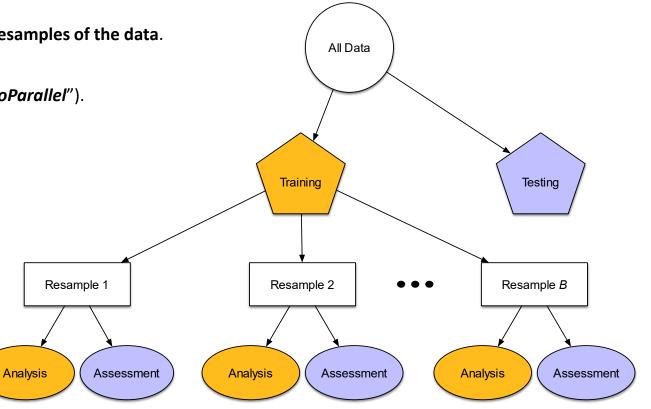


https://jhudatascience.org/tidyversecourse/model.html

### **Tidymodels** - Model Fitting and Tuning

Model performance and optimization is based on resampling methods which are just embarrassing parallel!!

- fit\_resamples() computes a set of performance metrics across one or more resamples.
- tune\_grid() of performance for tuning parameters across one or more resamples of the data.
- *foreach* package is used in combination with a backend package (e.g. "*doParallel*").
- Many ML/AI packages within Tidymodels have built-in parallelisation.





### **Tidymodels** - Model Fitting and Tuning

nnet\_tune <nnet\_workflow %>%
tune\_grid(hotel\_validation,
 grid = nGrid,
 control = control\_grid(save\_pred = TRUE,parallel\_over = "everything"),
 metrics = metric\_set(roc\_auc))

#### "resamples"

- then tuning will be performed in parallel over resamples alone.
- Within each resample, the preprocessor (i.e. recipe or formula) is reused across all models.

#### "everything"

- An outer parallel loop will iterate over resamples.
- An inner parallel loop will iterate over all **unique combinations of preprocessor** and **model tuning parameters** for that specific resample.
- This will result in the preprocessor being re-processed multiple times
- Pre-processing depended.



### *Tidymodels* - Case

- Hotel bookings data from Antonio, Almeida, and Nunes (2019)
- Aim: to predict which hotels are preferred by families with children.
- Data frame: 50.000 entries and 23 variables

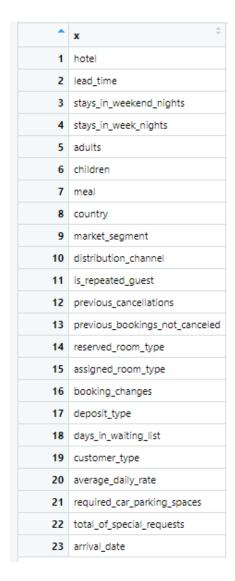
#### **Data Splitting**

set.seed(123)

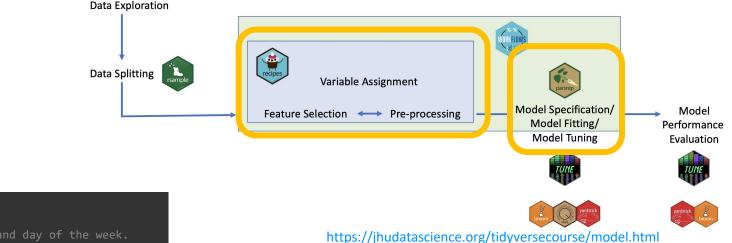
```
# Split into Training and Testing set
splits <- initial_split(hotels, strata = children)
hotel_train <- training(splits)
hotel_test <- testing(splits)</pre>
```

#### Methodology used: Classification

- Random Forrest ranger::ranger()
- Neural Network *nnet::nnet()*



### *Tidymodels* - Model Tuning



#### **Pre-processing with recipes**

rf\_recipe < recipe(children ~ ., data = hotel\_train) %>%
 step\_date(arrival\_date) %>% # creates predictors for the year, month, and day of the week.
 step\_holiday(arrival\_date) %>% # generates a set of indicator variables for specific holidays.
 step\_rm(arrival\_date) #removes variables;

#### Model Specifications

### Cores = parallel::detectCores() set.seed(345)

# Define Model
rf\_model <rand\_forest(mtry = tune(), min n = tune(), trees = 1000) %>%
set\_engine("ranger", num.threads = Cores) %>%
set\_mode("classification")

Random Forrest - *ranger::ranger()* 

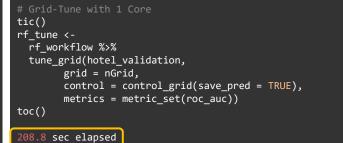
#### # Define Workflow

rf\_workflow <workflow() %>%
add\_model(rf\_model) %>%
add\_recipe(rf\_recipe)

#### **Grid Tuning – In Parallel**

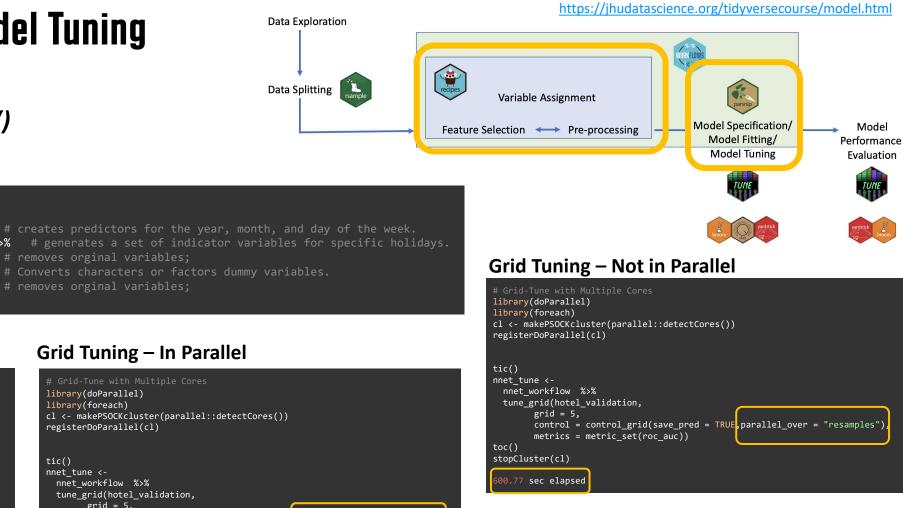
<pre># Grid-Tune with 8(4) Cores tic() rf_tune &lt;-     rf_workflow %&gt;%     tune_grid(hotel_validation,         grid = nGrid,         control = control_grid(save_pred = TRUE),         metrics = metric_set(roc_auc))</pre>	# Gri tic() rf_tu rf_ tun
toc()	toc()
47.3 sec elapsed	208.8

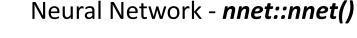
#### Grid Tuning – Not in Parallel





### *Tidymodels* - Model Tuning





#### **Pre-processing with recipes**

recipe(children ~ ., data = hotel train) %>% step date(arrival date) %>% step rm(arrival date) %>% step dummy(all nominal predictors()) %>% step zv(all predictors()) %>% step normalize(all predictors())

step holiday(arrival date, holidays = holidays) %>% # generates a set of indicator variables for specific holidays. # removes orginal variables;

# removes orginal variables;

**293.41** sec elapsed

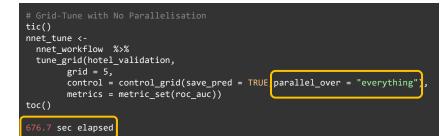
#### **Model Specifications**

# Define Model nnet model <mlp(hidden units = tune(), penalty = tune(), epochs = tune()) %>% set engine("nnet", trace = 0,MaxNWts = 10000) %>% set mode("classification")

# Define Workflow nnet workflow <workflow() %>% add model(nnet model) %>% add recipe(nnet recipe)



cl <- n	(Toreach) akePSOCKcluster(parallel::detectCores()) DoParallel(cl)
<pre>tic()</pre>	
nnet_ti	ne <-
nnet_	workflow %>%
tune_	grid(hotel_validation,
	grid = 5,
	<pre>control = control_grid(save_pred = TRUE parallel_over = "everything</pre>
	<pre>metrics = metric_set(roc_auc))</pre>
toc()	
stopClu	ster(cl)





# **QUESTIONS?**

Kristoffer Gulmark Poulsen & Lars Nondal CBS

