

### PARALLELIZING R FUNCTIONS

LIFEWATCH GREECE PROJECT



HCMR, Crete – June 2014 Parallel Functions in R

## The Team

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## □ The Problem



### The Problem

- The R language is
  - single-threaded
  - memory bound
- □ Until recently the largest square matrix was ≈ 46\*10<sup>3</sup> × 46\*10<sup>3</sup>
- The objective is to take advantage of parallel computing solutions to
  - overcome memory barriers (big data segmentation)
  - perform task segmentation (multi-cores, cluster computing)



### The HCMR Cluster

 The HCMR Biocluster comprises two queues
 BigMem: Intel E5-2667 12 cores@2.9 with 385GB RAM

Batch: Intel X5680 96 cores@3.33 with 48GB ram



# The Approach



## The Approach

We use Rstudio and experiment with several R packages, such as
 pbdR, bigmemory
 RMPI, pbdMPI
 Parallel, multicore, snow
 over Linux and OpenMPI paimplementations.

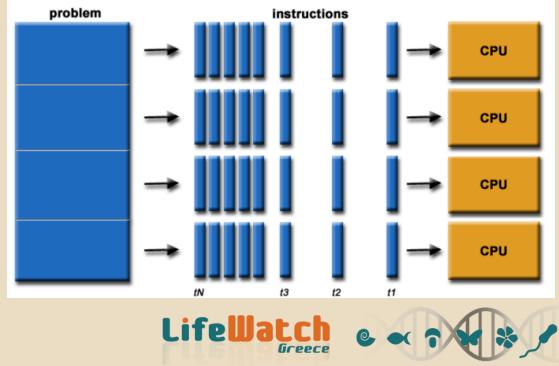
Your code Parallel version of existing functions Parallel R packages Language R OpenMPI Linux



## The Approach

### We focus on the parallelization of functions at two levels of abstraction

- Primitive functions (outer product, matrix multiplication etc)
  problem instructions
- General functions (taxa2dist, taxondive, simper, pca etc.)



### Example 1: Outer product

□ The outer product of vectors is used by many functions

$$[a_1, a_2, \dots, a_N] \otimes [b_1, b_2, \dots, b_N] = \begin{bmatrix} a_1b_1 & a_1b_2 & \dots & a_1b_N \\ a_2b_1 & a_2b_2 & \dots & a_2b_N \\ \vdots & \ddots & \vdots \\ a_Nb_1 & a_Nb_2 & \dots & a_Nb_N \end{bmatrix}$$

If the vectors are big, the matrix does not fit in memory.



### Example 1: Outer product

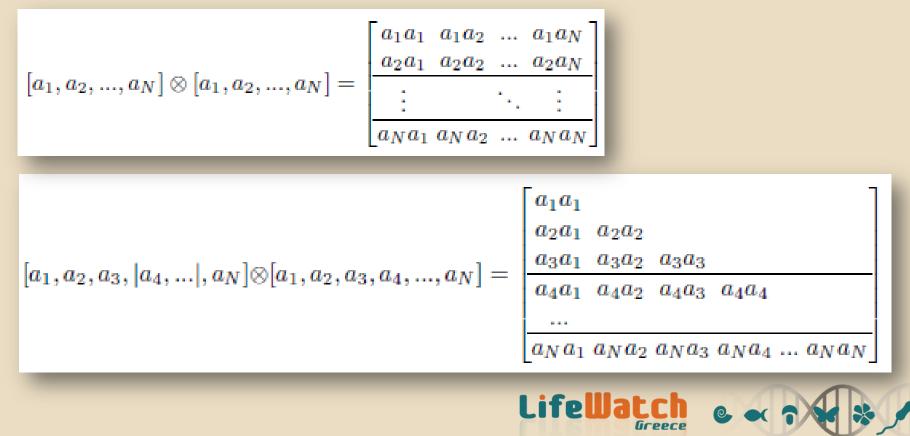
We segment the first vector p parts and each core will calculate m=[N/p] rows

$$[a_1, a_2, |\dots|, a_N] \otimes [b_1, b_2, \dots, b_N] = \begin{bmatrix} a_1b_1 & a_1b_2 & \dots & a_1b_N \\ a_2b_1 & a_2b_2 & \dots & a_2b_N \\ \vdots & \ddots & \vdots \\ \hline a_Nb_1 & a_Nb_2 & \dots & a_Nb_N \end{bmatrix}$$



## Example 1: Outer product

In special cases, we perform optimized allocation reducing the number of computations.



### Low- vs High-level Parallelization

It can be much more efficient to focus on high-level functions, rather than low-level operations.

For instance, we take advantage of the fact that data are already distributed and may need to be reused.



#### □ The Taxondive fuction

del < apply(comm,1, function(x)
 sum(as.dist(outer(x,x))\*dis))</pre>



```
The Taxondive fuction
del <-
    apply(comm,1, function(x)
    sum(as.dist(outer(x,x))*dis))</pre>
```

#### comm is a MxN matrix, where typically M<<N</p>

□ As such, outer (x, x) is a NxN matrix, usually huge.



The Taxondive fuction
del < apply(comm,1, function(x)
 sum(as.dist(outer(x,x))\*dis))</pre>

del, on the other hand, is a vector of length M, usually small.



```
Image: The Taxondive fuction
    del <-
        apply(comm,1, function(x)
            sum(as.dist(outer(x,x))*dis))
    dstar <-
        apply(comm,1, function(x)
            sum(dis*(xx
            <- as.dist(outer(x, x))))/sum(xx))</pre>
```

We need to multiply both from the left and from the right.

LifeWatch

Outer is already distributed

## Experimental valuation



### **Experimental Evaluation**

#### Two different implementations of Taxa2Dist

		Taxa2DistMPI							
	1%			10%			50%		
(cores)	(sec)	(Mb)	(dimensions)	(sec)	(Mb)	(dimensions)	(sec)	(Mb)	dimensions
1	4.861	21.7127	1687 1687	203.793	2177.1769	16893 16893			
2	2.089	10.8628	844 1687	152.567	1088.653	8447 16893			
6	1.63	3.6296	282 1687	72.317	362.9274	2816 16893			
12	1.471	1.8149	141 1687	21.336	181.4638	1409 16893			
24	1.18	0.9139	71 1687	11.721	90.732	704 16893			

#### Taxa2Dist Ddmatrix

		1%			10%		50%
1	4.424	21.7139	-	1218.76	2177.178	-	
2	8.795	10.864	-	1047.17	1088.783	-	
6	11.182	3.633	-	906.015	362.993	-	
12	4.926	1.8214	-				
24	4.834	0.9071	-				



### **Experimental Evaluation**

#### Scalability and performance

		Taxa2DistMPI							
	$\cap$	1%			<b>10</b> %			<b>50%</b>	
(cores)	(sec)	(Mb)	(dimensions)	(sec)	(Mb)	(dimensions)	(sec)	(Mb)	[dimensions
1	4.861	21.7127	1687 1687	203.793	2177.1769	16893 16893			
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							_		
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24	4.834	0.9071	-						





### **Experimental Evaluation**

#### □ The problem here is not time, but data size

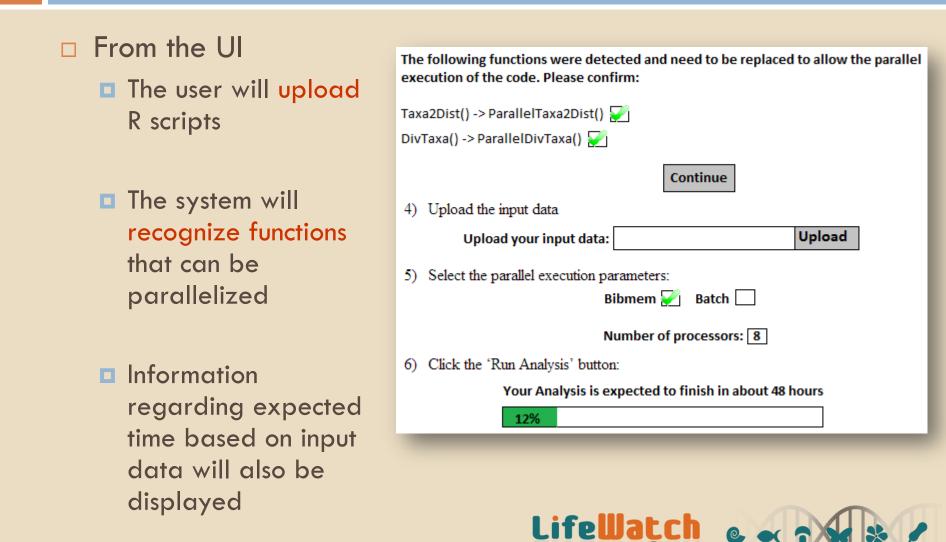
			TaxonDive MPI							
	1%			10%			<b>50</b> %			
1	11.803	22.0245	16871687	978.5	2177.435	16893 16893				
2	5.906	11.0965	844 1687	882.771	1088.846	8447 16893				
6	3.064	3.6296	282 1687	274.484	363.078	2816 16893				
12	2.085	1.9833	141 1687							
24	1.665	0.9139	71 1687							



# Goals and Open Problems



# The R Statistical Processing vLab





 It is not certain that the parallel solution will be more profitable in all cases
 Our evaluation will offer evidence for better resource

management

We need to decide which functions to parallelize (the code for many functions is not always available to us)



# Thank you!

