Parallel processing

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Parallel processing

- One way of making your code faster is to make use of parallel processing
- Here, parallel processing = when several simulation runs are computed simultaneously
- This is not always easy, and may not be worth doing unless you're running into serious efficiency issues...

A bit of history

- My first computer (mid-90s) had a 66 MHz processor
- My current office computer runs at 4.5 GHz almost 70 times the frequency 1
- Engineering problem/reality: the faster you make a processor run, the hotter it gets
- Engineering advance: smaller and smaller "lithographies" for processor manufacturing, meaning you can fit more transistors in a given surface area (Moore's Law)
- Put these two together and you have the idea of a multi-core processor

Parallel processing

- But now you have a **software challenge**: how do I make all processor cores work in parallel, if my code is a linear sequence of operations?
- In ABM, you often need to repeat a simulation many times.
 - Excellent use case for multi-core processors: each core can run an independent simulation in parallel
 - After every core has finished, we just collect the results

¹It should be noted that processor frequency is *not* the only thing affecting the overall speed of a computer. There have also been improvements in memory speed, memory bus speed, the speed of storage media, and so on. These all play a role.

Distributed.jl

- In Julia, the *Distributed.jl* package makes this easy
- If your processor has, say, 4 cores and you want to engage them all, write:

```
using BenchmarkTools
using Distributed
addprocs(4)
```

• This makes Julia run in 4 parallel processes, each process being sent to an individual processor core

Example

• Let's simulate a population of 1000 SimpleVLs over 100,000 time steps:

```
@everywhere include("../jl/VL.jl")
@everywhere using .VL

@everywhere function simulation()
  pop = [SimpleVL(0.1, 0.01, 0.4, 0.1) for i in 1:1000]
    [interact!(rand(pop), rand(pop)) for t in 1:1_000_000]
end

simulation()
```

```
1000000-element Vector{Float64}:
0.099
0.099
0.099
0.099
0.099
0.099
0.099
0.099
0.099
0.099
0.099
0.099
0.099
0.099
```

```
0.7756139769533772
```

- 0.7165702959436901
- 0.7283948757303422
- 0.6614666780354128
- 0.7214256766831326
- 0.6796228748435917
- 0.7444645825482015
- 0.6440435681838119
- 0.7210202889379991
- 0.7387954982496935
- 0.6210025622875553
- 0.5896568573415677
 - What if we want to repeat this 10 times?
 - We can do it in series:

```
for rep in 1:10
    simulation()
end
```

• Or we can parallelize:

```
@distributed for rep in 1:10
    simulation()
end
```

- Here, each repetition gets assigned to a process/core. Once the process finishes, it becomes available for another repetition.
- The function definition additionally has to be prepended by the @everywhere macro, which makes the function available to

How much speed-up do we obtain?

```
@benchmark for rep in 1:10
    simulation()
end
```

```
BenchmarkTools.Trial: 2 samples with 1 evaluation.
```

Range (min ... max): 3.517 s ... 3.913 s GC (min ... max): 11.54% ... 20.68%

Time (median): 3.715 s GC (median): 16.35%

```
Time (mean ± ): 3.715 s ± 279.864 ms GC (mean ± ): 16.35% ± 6.46%

3.52 s Histogram: frequency by time 3.91 s <

Memory estimate: 4.99 GiB, allocs estimate: 90010030.

#@benchmark @distributed for rep in 1:10
# simulation()
#end
```

Thinking about the speed gain

- We've called upon 4 cores
- Why is the code not 4 times faster?
- Complex reasons, but, for example: the cores still share the same bus to memory, so there is an inevitable bottleneck

Collecting the results

- The output of every simulation is a vector of numbers, namely, the **p** field of a randomly chosen speaker
- We can collect these into a matrix, so that each vector becomes one of the columns of the matrix. This is accomplished with hcat ("horizontal catenate"):

```
#result = @distributed (hcat) for rep in 1:10
# simulation()
#end
```

Amdahl's Law