Just tired of endless loops!

or `parallel`: Stata module for parallel computing

George G. Vega[1]   Brian Quistorff[2]

[1]University of Southern California
g.vegayon@gmail.com

[2]Microsoft AI and Research
Brian.Quistorff@microsoft.com

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Agenda

Motivation

- Both computation speeds and size of data are ever increasing
- Often our work is easily broken down into independent chunks
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- Often our work is easily broken down into independent chunks
- But, implementing parallel computing even for these "embarrassingly parallel" problems is not easy, most of this due to lack of (user-friendly) statistical computing tools.
- `parallel` aims to make a contribution to these issues.

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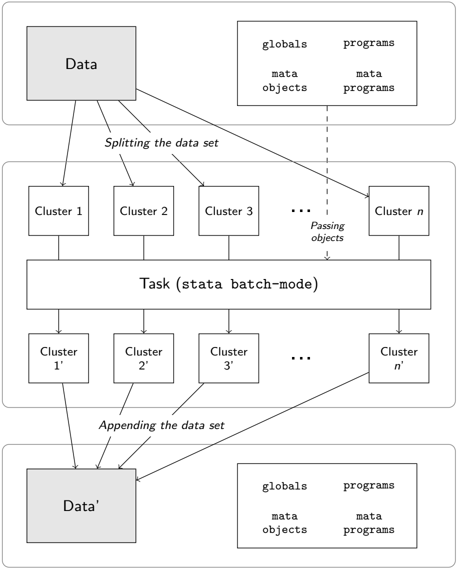
- Thus having a quad-core computer can lead to a 400% speedup.

What is and how does it work

How does it work?



Starting (current) `stata` instance loaded with data plus user defined `globals`, `programs`, `mata objects` and `mata programs`

A new `stata` instance (batch-mode) for every data-clusters. Programs, globals and mata objects/programs are passed to them.

The same algorithm (task) is simultaneously applied over the data-clusters.

After every instance stops, the data-clusters are appended into one.

Ending (resulting) `stata` instance loaded with the new data.

User defined `globals`, `programs`, `mata objects` and `mata programs` remind unchanged.

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  3. Child process reads its list of tasks, loads the real dataset, and does it's own looping over tasks
- If the list of tasks is not initially definable then the "nodata" alternative mechanism allows for more flexibility.

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parallel: gen n = _N
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Parallel's backend

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```
  cap clear all
  cd ~
1 set seed 34815
  set memory 16777216b
  cap set maxvar 5000
  cap set matsize 400
2 local pll_instance 1
  local pll_id efcql2tspr
  capture {
  noisily {
3 use __pllefcql2tsprdataset if _efcql2tsprcut == 1
  gen n = _N
  }
  }
4 save __pllefcql2tsprdta1, replace
  local result = _rc
  cd ~
5 mata: write_diagnosis(st_local("result"),
  >"__pllefcql2tsprfinito1")
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```
  cap clear all
  cd ~
1 set seed 98327
  set memory 16777216b
  cap set maxvar 5000
  cap set matsize 400
2 local pll_instance 2
  local pll_id efcql2tspr
  capture {
  noisily {
3 use __pllefcql2tsprdataset if _efcql2tsprcut == 2
  gen n = _N
  }
  }
4 save __pllefcql2tsprdta2, replace
  local result = _rc
  cd ~
5 mata: write_diagnosis(st_local("result"),
  >"__pllefcql2tsprfinito2")
```

Benchmarks

Simple example: Serial replace

Serial fashion

```
do mydofile.do
```

Parallel fashion

```
parallel do mydofile.do
```

Figure: mydofile.do

```
local size = _N
forval i=1/`size' {
        qui replace x = ///
            1/sqrt(2*`c(pi)')*exp(-(x^2/2)) in `i'
}
```

Table: Serial replacing using a loop on a Linux Server (16 clusters)

	100,000	1,000,000	10,000,000
CPU	1.43	16.94	144.68
Total	0.34	3.20	12.49
Setup	0.00	0.00	0.00
Compute	0.32	3.07	11.54
Finish	0.02	0.12	0.95
Ratio (compute)	4.50	5.51	12.53
Ratio (total)	4.22 (26%)	5.30 (30%)	11.58 (72%)

Tested on a Intel Xeon X470 (hexadeca-core) machine

Benchmarks

Monte Carlo simulation (Windows Machine)

Serial fashion

```
do myexperiment.do
```

Parallel fashion

```
parallel do myexperiment.do, nodata
```

Figure: myexperiment.do

```
local num_of_intervals = 50
if length("`pll_id'") == 0 {
    local start = 1
    local end = `num_of_intervals'
}
else {
    local ntot = floor(`num_of_intervals'/$PLL_CLUSTERS)
    local start = (`pll_instance' - 1)*`ntot' + 1
    local end = (`pll_instance')*`ntot'
    if `pll_instance' == $PLL_CLUSTERS local end = 10
}
local reps 10000
forval i=`start'/`end' {
    qui use census2, clear
    gen true_y = age
    gen z_factor = region
    sum z_factor, meanonly
    scalar zmu = r(mean)
    qui {
        gen y1 = .
        gen y2 = .
        local c = `i'
        set seed `c'
        simulate c=r(c) mu1=r(mu1) se_mu1 = r(se_mu1) ///
                mu2=r(mu2) se_mu2 = r(se_mu2), ///
                saving(cc`i', replace) nodots reps(`reps'): ///
                mcsimul1, c(`c')
    }
}
```

Table: Monte Carlo Experiment on a Windows Machine (4 clusters)

	2	4
CPU	111.49	114.13
Total	58.02	37.48
Setup	0.00	0.00
Compute	58.02	37.48
Finish	0.00	0.00
Ratio (compute)	1.92	3.04
Ratio (total)	1.92 (96%)	3.04 (76%)

Tested on a Intel i3 2120 (dual-core) machine

Benchmarks

Monte Carlo simulation (Unix Machine)

Serial fashion

```
do myexperiment.do
```

Parallel fashion

```
parallel do myexperiment.do, nodata
```

Table: Monte Carlo Experiment on a Linux Server (16 clusters)

	2	4	8	16
CPU	164.79	164.04	162.84	163.89
Total	69.85	34.28	19.00	10.78
Setup	0.00	0.00	0.00	0.00
Compute	69.85	34.28	19.00	10.78
Finish	0.00	0.00	0.00	0.00
Ratio (compute)	2.36	4.78	8.57	15.21
Ratio (total)	2.36 (118%)	4.78 (120%)	8.57 (107%)	15.21 (95%)

Tested on a Intel Xeon X470 (hexadeca-core) machine

Serial fashion

```
reshape wide tipsolic rutemp opta derecho ngiros, ///
        i(id) j(time)
```

Parallel fashion

```
parallel, by(id) :reshape wide tipsolic rutemp opta derecho ngiros, ///
        i(id) j(time)
```

Table: Reshaping wide a large database on a Linux Server (8 clusters)

	100,000	1,000,000	5,000,000
CPU	5.51	72.70	392.97
Total	2.33	17.46	86.44
Setup	0.00	0.00	0.00
Compute	1.83	12.42	57.93
Finish	0.50	5.04	28.51
Ratio (compute)	3.01	5.85	6.78
Ratio (total)	2.37 (29%)	4.16 (52%)	4.55 (57%)

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Syntax and Usage

Setup

parallel setclusters `# [, force]`

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parallel `[, by(`*varlist*`) programs mata seeds(`*string*`) randtype(`*random.org|datetime*`)`
`processors(`*integer*`) nodata]:` *stata_cmd*

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parallel setclusters # [, force]

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processors(*integer*) nodata]: *stata_cmd*

Do syntax

parallel do *filename*
[, by(*varlist*) programs mata seeds(*string*) randtype(*random.org*|*datetime*)
processors(*integer*) nodata]

Syntax and Usage

Recommendations on its usage

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- Whatever StataMP does better.
- (Currently) Tasks that already take up all of RAM.

Concluding Remarks

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