The Stata Journal (*yyyy*) *vv*, Number *ii*, pp. 1–17

Parallel: Stata module for parallel computing

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Abstract. The `parallel` package allows parallel processing of tasks that are not inter-dependent. This allows all flavors of Stata to take advantage of multiprocessor machines. Even Stata/MP users can benefit as many user-written programs are not automatically parallelized but could be so under our framework.

Keywords: st0001, parallel computing, simulations, high performance computing

1 Parallel computing

Most computers currently have multiple processors. Stata currently uses only one processor except for Stata/MP with certain built-in commands[1]. Many tasks, however, are logically very easy to parallelize. These tasks, called "embarrassingly parallel", are ones where there are no dependencies (or need for communication) between the parallel tasks, for example, reshaping a large dataset, bootstrapping, the jackknife, and Monte Carlo simulations. We provide here the package `parallel`, to parallelize these tasks.[2]

In general, `parallel` works by creating multiple "child" instances of Stata in which each one has its own copy of whatever data it is supposed to work with. By doing this, embarrassingly parallel tasks can be distributed across those instances taking advantage of the user's multiple processors. The primary use case is to invoke `parallel` with a command (or do-file) and distribute the load across N parallel child processes. It proceeds as follows,

1. `parallel` splits the dataset into N pieces.

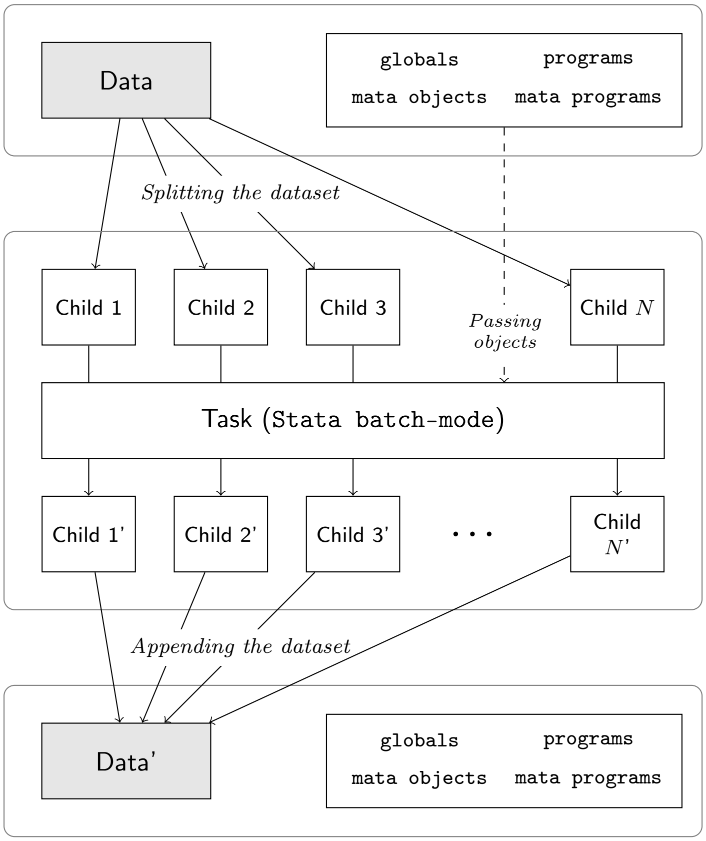
2. `parallel` starts N new instances of Stata. These are referred to as child processes while the original is the parent. In each, one of the pieces of the split dataset is loaded, the command is executed, and the resultant data is saved.

3. `parallel` waits for the child processes to finish and then aggregates the resultant datasets and loads this into memory.

This is diagrammed in figure 1. Notice that this is a setting with "distributed" rather than shared memory between the child processes.

[1] For a list of commands explicitly parallelized see the Stata/MP Performance Report (Stata Press (2016)).

[2] More "fine-grained" parallelism, where tasks need to communicate frequently, could be handled but there is no direct support.



Initial (parent) `Stata` instance loaded with data plus user defined `globals`, `programs`, `mata objects` and `mata programs`

N new `Stata` child instance (batch-mode) started. Programs, globals and mata objects/programs are passed to them.

The same algorithm (task) is simultaneously applied over the child processes.

After every instance stops, the data are aggregated.

Parent `Stata` instance loaded with the new data.

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

Figure 1: How `parallel` works

There are two considerations that limit the parallelization in practice. First, it will never be useful to use more child processes than the number of processors on the machine. Second, processing a task in parallel using `parallel` uses more memory (i.e. RAM). The user is trading memory capacity for processing capacity. Therefore, there is likely to be little benefit if a sequential setup would already utilize close to all of the system memory. If run in parallel, the dataset is split, so the child processes' memory will add up to the same amount of memory used in the parent Stata instance plus the amount of memory that Stata uses while doing its computation. Attempting to use more memroy than is available on the system will cause performance degradations and possibly program errors.

Some existing solution are able to take advantage of multiprocessors systems while implementing a shared memory model. Stata/MP Stata Press (2016) is a flavor of Stata where internal routines are able to take advantage of multiple processors on a machine. `parallel` allows this for generic commands which both expands the set of possible parallelizations and allows this for other flavors of Stata. This module is similar to R's `parallel` package (R Core Team (2018)) and Matlab's parallel toolbox (Sharma and Martin (2009)).

The rest of the paper introduces more details about the usage of the command, and provides examples and benchmarks for the reader to get a better understanding of the potential benefits of using `parallel`.

2 A Stata module for parallel computing

In this section we discuss the syntax of the `parallel` subcommands, technical details of execution, and results returned from the commands.

2.1 Syntax and options

A typical program will use separate `parallel` subcommands for initialization, parallel task execution, cleanup, and possibly diagnostics (for those cases in which the user needs to debug failures reported by `parallel`).

2.1.1 Initialization

To initialize the `parallel` setup use the `initialize` subcommand

parallel initialize [*#*, `force` `statapath(`*path*`)` `includefile(`*filename*`)`]

The main usage of this command is to set the number of child processes to launch when parallelizing later tasks. Options:

- `#` - The number of child processes to use. If omitted the default is to use $\max(\lfloor(\text{num processors})\cdot 0.75\rfloor, 1)$. If there are multiple processors, the default will leave some free for other computer interactions, which should be fine for testing on a personal computer. Note that when using Stata/MP with child tasks that are automatically parallelized by Stata, care should be taken with this option and the `processors()` option for the execution so as not to inadvertently use more processors than are available.

- `force` - To prevent slowdowns due to context switching between tasks there is a soft limit that restricts setting the number of child processes to be more than the number of processors on the system. Use this option to override the limit.

- `statapath(`*stata_path*`)` - By default, `parallel` tries to automatically identify Stata's executable path. In the rare circumstance that this is not correct (e.g. network mapped-drives) this option will override the default and force `parallel` to use a specific path to the executable.

- `includefile(`*filename*`)` - This file will be `include`d in the child processes before the parallelized tasks are executed. This allows one to copy over preferences that `parallel` does not copy automatically (see section 2.3).

Use the following subcommand to determine the number of processors on a system (`c(processors_mach)`returns this on Stata/MP, but it is not available on the other versions).

parallel numprocessors

2.1.2 Parallel task execution

The following are subcommands that execute tasks in parallel.

parallel [`, by(`*varlist*`) force nodata setparallelid(`*pll_ id*`)` *execution_ options*] : *command*

parallel do *dofile* [`, by(`*varlist*`) force nodata setparallelid(`*pll_ id*`)` *execution_ options*]

parallel bs [`, expression(`*exp_ list*`)` *execution_ options bs_ options*] [`:` *command*]

parallel sim [`, expression(`*exp_ list*`)` *execution_ options sim_ options*] [`:` *command*]

parallel append [*file(s)*], do(*command/dofile*) [`in(`*in*`) if(`*if*`) expression(`*expand expression*`)` *execution_ options*]

The : (prefix) notation for `parallel` and the `do` subcommand are the main subcommands while the others are helper utilities. Their usage is shown in sections 3.

`execution_options`:

- `keep` - Keeps auxiliary files generated by `parallel`.
- `keeplast` - Keeps auxiliary files and removes those saved prior to the current execution.
- `noglobal` - Avoids passing current session's global macros to the child processes.
- `programs(`*`namelist`*`)` - A list of programs to be passed to each child processes. This is useful for programs not in the `ADOPATH`. To pass them, `parallel` needs to print the contents of those programs to the output window. If `parallel` is being run from inside an ado file (say `my_cmd.ado`) and will need to access auxiliary local subroutines (other programs defined in the ado), then their names must be passed in as `<main command name.local subrouting name>` (e.g. `my_cmd.aux_prog`) for them to be accessible.
- `mata` - If the algorithm needs to use Mata objects, this option causes each child process to receive every Mata object loaded in the current session (including functions). Note that when Mata objects are loaded into the child processes they will have different locations and therefore pointers may no longer be accurate.

- `randtype(current|datetime|random.org)` - Tells `parallel` whether to use the current random number generator seed (default), the current datetime or random.org API to generate the seeds for each child process.

- `seeds(`*`numlist`*`)` - With this option the user can pass specific random seeds to be used within each child process.

- `processors(`*`integer`*`)` - If running on Stata/MP, sets the number of processors each child process should use. The default value is 0 which means to take no specific change in the child processes.

- `timeout(`*`integer`*`)` - If a child process hasn't started, how much time in seconds does `parallel` wait until it assumes that there was a connection error and thus the child process won't start. The default value is 60.

- `outputopts(`*`namelist`*`)` - Allows generic file-based appending. First, imagine a non-parallel setup where a program generates multiple outputs and the extra outputs are stored in files as in

  ```
  .    my_prog, output1(outputfile1.dta) output2(outputfile2.dta)
  ```

  With `parallel` we add the option `outputopts(output1 output2)` as in

  ```
  .    parallel, outputopts(output1 output2):  my_prog, output1(outputfile1.dta)
  output2(outputfile2.dta)
  ```

  This causes `parallel` to run the parallel tasks with their own pair of temporary files passed in for `output1` and `output2` and then aggregates those to create `outputfile1.dta` and `outputfile2.dta`.

- `deterministicoutput` will eliminate displayed output that would vary depending on the machine (e.g. timers, seeds, and number of parallel child processes) so that log files can be easily compared across runs. Errors are still printed.

- *`dofile`*/`command` - Task to run in parallel. Note that while the prefix notation can handle parameters passed to the user command, `parallel do` can not handle parameters passed to a do file.

Main `parallel` subcommand options:

- `by(`*`varlist`*`)` - Tells the command through which observations the current dataset can be divided, avoiding splitting stories (panels) over two or more child processes. [3]

- `force` - When using `by()`, `parallel` checks whether the dataset is properly sorted. The `force` option skips this check.

[3] The semantics for `by` are not the same as for Stata. When Stata implements `by`, the command that is run will only see a section of the data where the `by`-variables are the same. `parallel`'s semantics are that no observations with the same `by`-values will be in different child processes. It pools together combinations when there are fewer child processes than `by`-var combinations. If Stata-style semantics are needed, the solution is to add `by` in the subcommand. For example,

```
.  parallel, by(byvar):  by byvar:  egen x_max = max(x).
```

- `nodata` - Tells `parallel` not to use loaded data and thus not to try splitting at the beginning or appending anything at the end.
- `setparallelid(`*`pll_id`*`)` - Forces `parallel` to use a specific id.

Bootstrap options

- `expression(`*`exp_list`*`)` - An expression list to be passed to the native `bootstrap` command.
- *`bs_options`* - Further options to be passed to the native `bootstrap` command, including the optional `reps()` parameter.

Simulation options:

- `expression(`*`exp_list`*`)` - An expression list to be passed to the native `simulate` command.
- *`sim_options`* - Further options to be passed to the native `simulate` command, including the required `reps()` parameter.

Append options:

- *`file(s)`* - Explicit list of files to process.
- `expression(`*`expand expression`*`)` - Expression representing file names in the form of `"%fmts, numlist1 [, numlist2 [, ...]]"` . See the Parallel Append example below for more details.
- `in(`*`in`*`)/if(`*`if`*`)` - Opens the file using `if` and `in` accordingly.

2.1.3 Cleanup

Log files from `parallel` execution are saved so that they can be inspected by the user. Use the `clean` subcommand to remove these and any other ancillary files that have been saved:

parallel clean [, `event(`*pll_ id*`)` `all` `force`]

Options:

- `event(`*`pll_id`*`)` - Specifies which executed (and stored) event's (a given invocation of `parallel`) files should be removed.
- `all` - Tells `parallel` to remove every remaining auxiliary files generated by it in the current directory.
- `force` - Forces the command to remove (apparently) in-use auxiliary files. Otherwise these will not get deleted.

If neither an `event` or `all` are specified, `parallel` will use the most recent run's *`pll_id`*.

2.1.4 Diagnostic tools

Additionally there are some diagnostic tools,

parallel version

This command returns the version both to the screen and programmatically.

parallel printlog [#] [, `event(`*pll_id*`)`]

parallel viewlog [#] [, `event(`*pll_id*`)`]

These commands allow users to view logs of the child processes. The initial part of the log file will be from commands generated by `parallel` for setting up the child process (loading data, global macros, settings, etc.). The final part of the log file is where the users task is run. Options:

- # - specifies which child process number of an event to display (default is 1).
- `event(`*`pll_id`*`)` - Specifies which event's log file should be displayed

2.2 Saved Results

The primary result of `parallel` is to return a transformed dataset. In addition `parallel` returns the following values:

Scalars	
`r(pll_n)`	Number of parallel child processes last used.
`r(pll_t_fini)`	Time spent appending and cleaning.
`r(pll_t_calc)`	Time spent completing the parallel job.
`r(pll_t_setu)`	Time spent setting up (before the parallelization) and to finishing the job (after the parallelization).
`r(pll_errs)`	Number of child processes which stopped with an error.
Global Macros	
`LAST_PLL_DIR`	A copy of `r(pll_dir)`.
`LAST_PLL_N`	A copy of `r(pll_n)`.
`LAST_PLL_ID`	A copy of `r(pll_id)`.
`PLL_LASTRNG`	Number of times that `parallel_randomid()` has been executed.
`PLL_STATA_PATH, PLL_CLUSTERS, PLL_CHILDREN, USE_PROCEXEC`	Internal usage. `PLL_CLUSTERS` is deprecated.

`parallel version` saves

Macros	
`r(pll_vers)`	Current version of the module.

`parallel bs` and `parallel sim` save

Scalars

`e(pll)`	Internal usage for `bs` and `sim` subcommands.

2.3 Technical Details

`parallel` does not change the random number generator state upon completion. Subcommands that invoke randomization functions restore the state before finishing.

Log files from the children are stored in `c(tmpdir)` so that they can be inspected by the user. The user will likely want to delete these periodically with `parallel clean, all`.

Given N child processes, within each child process `parallel` creates the macros `pll_id` (equal for all the child processes) and `pll_instance` (ranging 1 up to N, equaling 1 inside the first child process and N inside the last child process), both as global and local macros. This allows the user to set different tasks/actions depending on the child process number. Additionally, the global macro `PLL_CHILDREN` (equal to N) is available within each child process. Note that the locals will be not available inside of programs that are called from `parallel` (in prefix or do-file setup), but will be available inside a script called from `parallel do`.

When launching child Stata processes, several settings are automatically copied over. These include the `PLUS` and `PERSONAL` sysdirs, the global `S_ADO`, the mlib search index, and the `tempname`/`tempvar` state. To start child processes with additional setting changes use the `includefile()` option.

Child processes are managed. If the command is stopped from the parent process then all child processes will be killed directly. The parent process can recover from both errors in the child Stata program and if child Stata processes are killed by the operating system. Child processes are launched using the shell on MacOS and Unix/Linux machines. On Windows machines a compiled plugin launches the child processes using the Win32 API so that it can be used in batch-mode (batch-mode Stata on Windows will not execute shell commands) and so that the child processes do not show a visual window that interrupts the user by flashing on the screen (there is no provided console-only version of Stata on Windows).

Results not explicitly saved in the child processes' datasets will not be available afterward (e.g. matrices, scalars, Mata objects, returns). If the task to be paralellized returns results in this format (e.g. `regression`), then modifications must be used to store (and later use) these results in either the primary dataset or using secondary files (see the *outputopts* options).

Although `parallel` passes through programs, macros and Mata objects, in the current version it is not capable of doing the same with matrices or scalars.

If the number of tasks to be done is less than the number of child processes, `parallel` will temporarily reduce the number of child processes. This is reported in the global macro `LAST_PLL_N`.

Expressions run in the child-processes that contain `_n` or `_N` will be evaluated locally to the child not the parent dataset. These expressions may therefore be different if run in `parallel` than without `parallel`.

2.4 Extending parallel

One of the key features of `parallel` lies in its developer-friendly design. Motivated by ease of code maintenance, `parallel`'s design consists on a rich and thoroughly documented API that facilitates the creation of new routines. Mostly implemented in Mata, `parallel`'s API contains functions for splitting datasets, exporting Mata and Stata routines, writing do-files to be executed by the child processes, launch Stata instances, monitor child processes, and collecting the results generated by the child instances.

To the date, we have knowledge of at least three Stata modules that make use of the API: EVENTSTUDY2, MIPARALLE, and Synth_Runner–the last developed by one of us.

2.5 Installation

The latest stable versions of `parallel` can be installed from a GitHub URL[4],

```
. net install parallel, ///
    from(https://raw.github.com/gvegayon/parallel/stable/)
. mata mata mlib index
```

If one would like the latest development version, use `master` instead of `stable` in the URL. If one is switching the source of the installation materials (e.g. if moving from SSC to GitHub versions), then be sure to uninstall the program explicitly before installing the new version.

```
. ado uninstall parallel
```

An older version of the package is available at the SSC, though it is not kept as up to date, so we recommend the GitHub version.

3 Examples

In this section we discuss basic usage of the commands in some common use cases. The first demonstrates how `parallel` can be initialized, but the latter ones assume this has already been done.

[4] Stata versions before 13 can not install from a GitHub URL, so download a zip file of the repository (https://github.com/gvegayon/parallel/archive/stable.zip), unzip the file, and replace the URL above with the full path to the files.

3.1 Subcommand examples

▷ **Example Prefix**

A minimal example of using `parallel` is

```
. sysuse auto, clear
(1978 Automobile Data)

. parallel initialize 2
N Child processes: 2
Stata dir:  C:\Program Files (x86)\Stata14/StataMP-64.exe

. parallel: gen price2 = price*price
--------------------------------------------------------------------------------
Parallel Computing with Stata
Child processes: 2
pll_id          : <unique ID>
Running at      : <pwd>
Randtype        : datetime
Waiting for the child processes to finish...
child process 0001 has exited without error...
child process 0002 has exited without error...
--------------------------------------------------------------------------------
Enter -parallel printlog #- to checkout logfiles.
--------------------------------------------------------------------------------
. drop price2
```

This example illustrates that many simple tasks can be parallelized. This particular task was not executed faster in parallel since parallel execution has its own overhead and the task was quite easy.

◁

The next example shows the usage of the `do` subcommand.

▷ **Example Do-file**

Suppose that we had the existing do-file

```
//-------------------- make_polynomial.do ----------//
gen price2 = price*price
gen price3 = price2*price
gen price4 = price3*price
```

We can execute it either sequentially or in parallel using

```
. parallel do make_polynomial.do
```

◁

▷ Example Bootstrap

A simple sequential bootstrap would be

```
. sysuse auto, clear
. bs: reg price c.weig##c.weigh foreign rep
```

When parallelized it becomes

```
. parallel bs: reg price c.weig##c.weigh foreign rep
```

◁

▷ Example Simulation

Suppose we have the following simulation program.

```
program define lnsim, rclass
  version 14
  syntax [, obs(integer 1) mu(real 0) sigma(real 1) ]
  drop _all
  set obs ‘obs’
  tempvar z
  gen ‘z’ = exp(rnormal(‘mu’,‘sigma’))
  summarize ‘z’
  return scalar mean = r(mean)
  return scalar Var  = r(Var)
end
```

If we were to run it sequentially we'd use

```
. simulate mean=r(mean) var=r(Var), reps(10000): lnsim, obs(100)
```

To run it in parallel we could instead use a very familiar syntax

```
. parallel sim, expr(mean=r(mean) var=r(Var)) reps(10000): ///
    lnsim, obs(100)
```

◁

▷ Example Append

Imagine we have several dta files named `income.dta` stored in a set of folders ranging from "2008_01" up to "2012_12", that is, a total of 60 files ordered which may look something like this:

```
2008_01/income.dta
2008_02/income.dta
2008_03/income.dta
...more files...
2010_01/income.dta
2010_02/income.dta
2010_03/income.dta
...more files...
2012_10/income.dta
2012_11/income.dta
2012_12/income.dta
```

Now, imagine that for each and every one of those files we would like to execute the following program:

```
program def myprogram
  gen female = (gender == "female")
  collapse (mean) income, by(female) fast
end
```

Instead of writing a `forval`/`foreach` loop (which would be the natural solution for this situation), `parallel append` allows us to smoothly solve this with the following command.

```
. parallel append, do(myprogram) prog(myprogram) ///
        e("%g_%02.0f/income.dta, 2008/2012, 1/12")
```

Where element by element, we are telling `parallel`:

- `do(myprogram)`: execute the command `myprogram`,
- `prog(myprogram)`: `myprogram` is a user written program that needs to passed to child child processes, and
- `e("%g_%02.0f/income.dta, 2008/2012, 1/12")`: this should process files "2008_01/income.dta" up to "2012_12/income.dta".

Besides of the simplicity of its syntax, the advantage of using `parallel append` lies in doing so in a parallel fashion, that is, instead of processing one file at a time, `parallel` manages to process these files in groups of as many files as child processes are set. Step-by-step, what this command does is:

1. Distribute groups of files across child processes
2. Once each child process starts, for each dta file:
    a. Opens the file using `[if]` and `[in]` options.

   b. Executes the command/dofile specified by the user.
   c. Stores the results in a temporary dta file.

3. Finally, once all the files have been processed, append all the resulting files into a single one.

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3.2 Parallelizing a loop

If a user has a loop where the processing in each iteration is independent of the others and the output can be aggregated easily, then it is easily transformed using `parallel`.

Suppose we want to parallelize a general loop

```
forval i=1/‘num_total’{
  //work for i
}
```

We can transform this so that a setup that can be done either in parallel or sequentially.

```
local n_proc = <number set by user>
save currdata.dta, replace
drop _all
set obs ‘num_total’
gen long i = _n
if ‘n_proc’>1 {
  parallel initialize ‘n_proc’
  parallel: parfor_task
}
else {
  parfor_task
}

//——————————————parfor_task.ado——————————————//
program parfor_task
  local num_task = _N
  mkmat i, matrix(tasks_i)
  use currdata.dta, clear
  forval j=1/‘=_N’{
    local i = tasks_i[‘j’,1]
    //work for i
  }
  //put output into main data
end
```

3.3 Consistency

For many tasks we will want to ensure that there is exact consistency between multiple runs of a program. Deterministic programs virtually ensure this. With random functions, a sequential program is usually made consistent by specifying a fixed random seed at the beginning of the program. If one is always using the same number of child processes then the same can be achieved by pre-specifying the seeds with the `seeds` options.

A similar notion of sequential consistency guarantees that results do not differ between sequential and parallel operations. Again, for deterministic programs this is straight-forward to check. If the program has a random component then more care must be taken. To do this, provide the seed for each repetition. Once we do that, we can build upon the previous example about loops (section 3.2) so that the tasks are split to the child processes and show how to collect the output.

▷ Example Sequential consistency

Here we do it with a custom bootstrap implementation

```
set seed 1337
sysuse auto, clear
parallel initialize 2

cap program drop do_work
program do_work
  args main_data
  local num_rep = _N
  tempname tasks pfile
  mkmat n seed, matrix(‘tasks’)
  qui use "‘main_data’", clear
  tempfile estimates
  postfile ‘pfile’ long(n seed) float(b_mpg) using "‘estimates’"
  forval i=1/‘num_rep’{
    local seedi = ‘tasks’[‘i’,2]
    set seed ‘seedi’
    preserve
    bsample
    qui reg price mpg
    post ‘pfile’ (‘=‘tasks’[‘i’,1]’) (‘seedi’) (_b[mpg])
    restore
  }
  postclose ‘pfile’
  use "‘estimates’", clear
end

tempfile maindata
```

```
save "`maindata'"
drop _all
gen long seed = .
qui set obs 99 //number of reps
replace seed = int((-1*`c(minlong)'-1)*runiform())
gen long n=_n
local final_seed = c(seed)
parallel, program(do_work): do_work "`maindata'"
mata: rseed(st_local("final_seed"))
sort n
```

The output will be the same no matter the number of child processes or if `do_work` is run without `parallel`.

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3.4 Parallelizing user commands

A third-party Stata package developer with easily parallelizable tasks can write their packages to take advantage of `parallel` if it is installed. We suggest that `parallel` be a recommended dependendcy rather than a required one as users may be on machines with limited resources. The most common example would be wanting to parallelize an existing loop, so one can follow the examples of the `parallel` for loops or the sequential consistency example. One can put that secondary program in the original ado file (in which case use `myado.ado.subtask` form) or one can make a separate file.

3.5 Debugging

The `parallel` command will issue an error if either it or one of its child processes encounters an error. The first step towards debugging this is to look at the log files (using, e.g., `parallel viewlog`). If this does not show enough information, `trace` can be turned on in the executed task or custom diagnostic information can be printed.

4 Benchmarks

In order to assess the speed-gains obtained when using `parallel`, we present what we think are the two most relevant uses of the module: bootstrapping and simulations. We compared the performance of running each routine in the following fashions on computer with at least four processors[5]: serial, parallel using two child processes, and parallel using four child processes. While the tasks over which we performed the comparisons are rather simple (and not particularly time consuming since all of them took less than a minute to complete), they are useful to illustrate the benefits of using `parallel`.

[5] Tests were run using Stata/IC 12.1 on a Unix machine with an Intel i7-4790 CPU @ 3.60GHz with 8 processors. The code used to perform the benchmarks and generate the figures and tables is available in the project's website.

It is important to keep in mind that, as we will see, the lack of perfectly linear speed-gains is due to the simplicity of the problem with respect to the time that it takes to compute it in a serial fashion. On the other hand, overall, as the problem size (number of simulations, resamplings, etc.) increases, the speed-gains approach linear speed-ups.

4.1 Bootstrapping

In this first benchmark, we use the *auto* dataset shipped with Stata. After expanding each observation 10 times–so the size of the problem increases–we perform a bootstrap of a linear regression model as follows:

```
sysuse auto, clear
expand 10
global size 1000 // 2000, 4000

// Serial fashion
bs, rep($size) nodots: regress mpg weight gear foreign

// Parallel fashion
parallel initialize 2
parallel bs, rep($size) nodots: regress mpg weight gear foreign
parallel initialize 4
parallel bs, rep($size) nodots: regress mpg weight gear foreign
```

For each number of repetitions (1000; 2000; 4000) we ran the problem 1000 times and recorded average computing time. The results are presented in table 4.

Problem size	Serial	2 Clusters	4 Clusters
1000	2.93s	1.62s	1.09s
2000	5.80s	3.13s	2.03s
4000	11.59s	6.27s	3.86s

Table 4: Computing times for each run of a basic bootstrap problem. For each given problem size, each row shows the time in seconds that each method took on average to complete the task.

4.2 Simulations

In the case of simulations, we perform a simple Monte Carlo experiment which consists in two main steps: (1) Generate 1,000 observations as $Y = X\beta + \varepsilon$ where $X \sim N(0,1)$, $\varepsilon \sim N(0,1)$, and $\beta = 2$, and (2) obtain the parameter estimate of β. The code used follows:

```
prog def mysim, rclass
  // Data generating process
  drop _all
  set obs 1000
  gen eps = rnormal()
```

```
    gen X   = rnormal()
    gen Y   = X*2 + eps

    // Estimation
    reg Y X
    mat def ans = e(b)
    return scalar beta = ans[1,1]
  end

  // Serial fashion
  simulate beta=r(beta), reps($size) nodots: mysim

  // Parallel fashion
  parallel initialize 2
  parallel sim, reps($size) expr(beta=r(beta)) nodots: mysim
  parallel initialize 4
  parallel sim, reps($size) expr(beta=r(beta)) nodots: mysim
```

As before, for each number of simulations (1,000; 2,000; 4,000), we ran the problem 1,000 times and recorded average computing time. The results are presented in table 5.

Problem size	Serial	2 Clusters	4 Clusters
1000	2.19s	1.18s	0.73s
2000	4.36s	2.29s	1.33s
4000	8.69s	4.53s	2.55s

Table 5: Computing times for each run of a simple Monte Carlo exercise. For each given problem size, each row shows the time in seconds that each method took on average to complete the task.

5 Discussion

5.1 Development and feedback

Development is done at the https://github.com/gvegayon/parallel/. In case one would like to report a bug or feature request, check first if there is an existing GitHub issue. Please also try the latest development version to see if the problem has been solved already (see section 2.5). If these do not resolve the concern, please submit an issue at the GitHub issue address so that anyone available may help to solve the issue. The issue will prompt for the details such as the steps to reproduce the problem and the output of `creturn list`. The GitHub page also has a wiki with a larger gallery of examples of parallelizing tasks.

5.2 Conclusion

The `parallel` package allows users to take advantage of multiprocessor machines for many generic tasks with a minimum of additional complexity. For tasks where the processor is the limiting factor and that are easily parallelizable, `parallel` may significantly speed up execution. We hope that this package is used not just for ad-hoc processes but can be integrated into other packages as a recommended package.

6 References

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