

Accelerating and Parallelizing MATLAB Code on HPC Infrastructure



Francesca Perino – Sam Marshalik - Sergio Obando Quintero Application Engineering Team

© 2018 The MathWorks, Inc.



Choose a Parallel Computing Solution

- Do you want to process your data faster?
- Do you want to offload to a cluster?
- Do you want to scale up your big data calculation?



Practical Application of Parallel Computing

- Why parallel computing?
 - Need faster insight on more complex problems with larger datasets
 - Computing infrastructure is broadly available (multicore desktops, GPUs, clusters)
- Why parallel computing with MATLAB
 - Leverage computational power of more hardware
 - Accelerate workflows with minimal to no code changes to your original code
 - Focus on your engineering and research, not the computation



Parallel Computing Paradigm

Multicore Desktops



4



Parallel Computing Paradigm

Clusters







Migrate execution to a cluster environment





Cluster Computing Paradigm

- Prototype on the desktop
- Integrate with existing infrastructure
- Access directly through MATLAB



Parallel Computing Toolbox



Parallel Computing Paradigm NVIDIA GPUs





Steps for writing a MATLAB parallel code

- 1. Best practices in programming
 - Identify bottlenecks (e.g. Profiler, Code analyzer)
 - Vectorization & pre-allocation

2. Better algorithms

- Different algorithmic approach to solve the same problem
- The most recent MATLAB release

3. More processors, cores, and GPUs

- Utilize high level parallel constructs (e.g. parpool, parfor)
- Scale to clusters, grids, and clouds

web(fullfile(docroot, 'matlab/matlab_prog/techniques-for-improving-performance.html'))



Example: Block Processing Images

- Calculate a function at grid points
- Take the mean of larger blocks





Best Practices

- Profile your code
- Minimize file I/O
- Reuse existing graphics components
- Avoid printing to Command Window

Comman	id Window				\odot
	0.6010	0.8987	0.3676	0.4792	0.87^
	0.1969	0.5906	0.0684	0.0408	0.73
	0.7029	0.1359	0.0803	0.1856	0.44
	0.9487	0.1377	0.9798	0.1154	0.89
	0.9230	0.1091	0.6545	0.3363	0.90-
	0.7524	0.1111	0.0034	0.5273	0.07
fx	0.3987	0.1840	0.0568	0.6562	0.24-
•		III			•



Access Multiple Files to Import Specific Columns



8% Import the data	
<pre>data = [xlsread(workbookFile, sheetName, sprintf('A%d:A%d',startRow(1),endB</pre>	Row(1))),
xlsread(workbookFile, sheetName, sprintf('G%d:G%d',startRow(1),endRow(1	L))),
xlsread(workbookFile, sheetName, sprintf('U%d:U%d',startRow(1),endRow(1	L)))];
<pre>for block=2:length(startRow)</pre>	
<pre>tmpDataBlock = [xlsread(workbookFile, sheetName, sprintf('A%d:A%d',star</pre>	tRow(block),endRow(block))),
xlsread(workbookFile, sheetName, sprintf('G%d:G%d',startRow(block),	endRow(block))),
xlsread(workbookFile, sheetName, sprintf('U%d:U%d',startRow(block),	endRow(block)))];
data = [data;tmpDataBlock]; %#ok <agrow></agrow>	
- end	



Access Multiple Files to Import Specific Columns

	8% Method #2:		
	<pre>% we use spreadsheetDatastore </pre>		
spreadsheetDatastore	tic		
Create SpreadsheetDatastore object for collections of spreadsheet data	<pre>dsEngine = spreadsheetDatastore('data','FileExtensions',{'.xls','.xlsm'}); dsEngine.ReadSize = 'file'; %% dsEngine.SelectedVariableNames = {'SPEED','LOAD','BSFC'}; %%</pre>		
Syntax			
<pre>ssds = spreadsheetDatastore(location) ssds = spreadsheetDatastore(location,Name,Value)</pre>			
Description	ii = 1; while hasdata(dsEngine)		
sds = spreadsheetDatastore(location) creates a datastore from the collection of data specified by location of data that are too large to fit in memory. After creating a SpreadsheetDatstore object, you can readvays. See Using SpreadsheetDatastore Objects for more information.	<pre>Engine = read(dsEngine); [val, index] = min(Engine.BSFC);</pre>		
<pre>sds = spreadsheetDatastore(location,Name,Value) specifies additional parameters for ssds using one of or example, spreadsheetDatastore(location, 'FileExtentions', {'.xlsx', '.xls'}) specifies which file epending on the file extensions.</pre>	<pre>EngineMin = Engine(index,:); [~,name] = fileparts(dsEngine.Files{ii}); EngineMin.Name = categorical({name}); % Add the name</pre>		
	AllEngines(ii,:) = EngineMin; ii = ii+1;		
	end		
	toc		



Steps for writing a MATLAB parallel code

- 1. Best practices in programming
 - Identify bottlenecks (e.g. Profiler, Code analyzer)
 - Vectorization & pre-allocation

2. Better algorithms

- Different algorithmic approach to solve the same problem
- The most recent MATLAB release

3. More processors, cores, and GPUs

- Utilize high level parallel constructs (e.g. parpool, parfor)
- Scale to clusters, grids, and clouds

web(fullfile(docroot, 'matlab/matlab_prog/techniques-for-improving-performance.html'))



Exercise: Birthday Paradox

 What is the probability that in a group of 23 randomly selected individual, at least two of them will share the same birthday?





Exercise: Birthday Paradox Implementation

- Profile runBirthdaySum.m
- Edit runBirthdayUnique1.m
 - TODO: without a FOR loop create a list with a random birthday for each member in the group
- Edit runBirthdayVec.m
 - TODO: try a different algorithmic approach based on |sort| to solve the same problem

Add date to the list

Generate a random birth date



Check with dates on the list



Parallel and Distributed Computing with MATLAB



© 2018 The MathWorks, Inc.



Steps for writing a MATLAB parallel code

- 1. Best practices in programming
 - Identify bottlenecks (e.g. Profiler, Code analyzer)
 - Vectorization & pre-allocation

2. Better algorithms

- Different algorithmic approach to solve the same problem
- The most recent MATLAB release

3. More processors, cores, and GPUs

- Utilize high level parallel constructs (e.g. parpool, parfor)
- Scale to clusters, grids, and clouds

web(fullfile(docroot, 'matlab/matlab_prog/techniques-for-improving-performance.html'))



Programming Parallel Applications

- Built-in multithreading
 - Automatically enabled in MATLAB since R2008a
 - Multiple threads in a single MATLAB computation engine
- Parallel-enabled MATLAB Toolboxes
 - Enable parallel computing support by setting a flag or preference

```
..., 'UseParallel', true)
```





Parallel Computing





Parallel-enabled Toolboxes (MATLAB® Product Family)

Enable acceleration by setting a flag or preference

Image Processing

Batch Image Processor, Block Processing, GPU-enabled functions





Original Image of Peppers

Recolored Image of Peppers

Statistics and Machine Learning

GPU-enabled functions, parallel training



Neural Networks

Deep Learning, Neural Network training and simulation



Signal Processing and Communications

GPU-enabled FFT filtering, cross correlation, BER simulations



Computer Vision Bag-of-words workflow



Optimization Estimation of gradients





Programming Parallel Applications

- Built in support
 - -..., 'UseParallel', true)
- Simple programming constructs
 - -parfor, batch





Embarrassingly Parallel: Independent Tasks or Iterations

- No dependencies or communication between tasks
- Examples:
 - Monte Carlo simulations
 - Parameter sweeps
 - Same operation on many files







Mechanics of parfor Loops





Example: Estimate π using the Buffon-Laplace method

	trials	pi_value	diff
1	10	2.5000	0.6416
2	100	3.1250	0.0166
3	1000	3.0541	0.0875
4	10000	3.1401	0.0015
5	100000	3.1572	0.0156
6	1000000	3.1390	0.0025
7	1000000	3.1420	0.0004
8	10000000	3.1417	0.0001

non-dimensional length of grid side, x			
a = 1;			
non-dimensional length of grid side, y			
b = 1;			
non-dimensional length of needle,			
nLength = 0.5;			
number of needles considered			
nNeedles = $10.^{(1:8)}$;			
<pre>for i = 1:length(nNeedles) pi_N(i) = calcPI(nNeedles(i),nLength,a,b); end</pre>			



Factors Governing the Speedup of parfor Loops

- No speedup because computation time too short
- Execution may be slow because of
 - Memory limitations (RAM)
 - File access limitations
- Implicit multithreading
 - MATLAB uses multiple threads for speedup of some operations
 - Use Task Manager or similar on serial code to check on that
- Unbalanced load due to iteration execution times
 - Avoid some iterations taking multiples of the execution time of other iterations.



Programming Parallel Applications

- Built in support
 - -..., 'UseParallel', true)
- Simple programming constructs
 - -parfor, batch
- Full control of parallelization
 - spmd, parfeval





Datatypes for Scaling Data Represent data *not* in "normal" memory

Datatype	Memory Location	Use case
tall	Disks	Pre-processing, statistics, machine learning
distributed	Cluster	Sparse and dense numerics
gpuArray	GPU	GPU computations



Distributed Arrays



Develop applications once, change run environment by changing the profile



Example: Estimate π using the Buffon-Laplace method

- We want to speed up the estimation of π for 10⁹ trials
 - Define a 10^9-by-1 codistributed arrays, distributed by columns with a uniform partition scheme.

```
>x0 = a * rand(nNeedles,1,codistributor);
>y0 = b * rand(nNeedles,1,codistributor);
>phi= 2 * pi * rand(nNeedles,1,codistributor);
```

- Create on x workers

```
spmd
    piN = spmdCalcPI(nNeedles,a,b,nLength);
end
```



Offloading Computations





Offloading Computations



- Send desktop code to cluster resources
 - No parallelism required within code
 - Submit directly from MATLAB
- Leverage supplied infrastructure
 - File transfer / path augmentation
 - Job monitoring
 - Simplified retrieval of results
- Scale offloaded computations



Migrate to Cluster / Cloud

- Use MATLAB Distributed Computing Server
- Change hardware without changing algorithm





Offloading Serial Computations with batch

• Offload the computation to a workstation targets compute-intensive applications





Offload and Scale Computations with batch with a Parallel Pool



batch(..., 'Pool',...)

batch jobs are particularly suitable when you are working on a compute cluster.



Estimate π using the Buffon-Laplace method

Run MATLAB script or function on a worker in the cluster specified by the default cluster profile:

```
c = parcluster()
```

j = batch(c,@batchCalcPI,1,{nNeedles,nLength,a,b},...

```
'Pool',length(nNeedles),...
'AttachedFiles','calcPI.m')
```

Wait for the job to finish. To see your batch job's status or to track its progress, use the Job Monitor, as described in Job Monitor

```
wait(j)
elapsedTime = j.FinishDateTime-j.StartDateTime
```

Get results into a cell array

```
pi_N = fetchOutputs(j);
pi_diff = abs(pi-pi_N{1});
pi_table = table(nNeedles',pi_N{1}',pi_diff','VariableNames',{'trials','pi_value','diff'})
```



Use MATLAB Distributed Computing Server

1. Prototype code





Use MATLAB Distributed Computing Server

- 1. Prototype code
- 2. Get access to an enabled cluster





Use MATLAB Distributed Computing Server

- 1. Prototype code
- 2. Get access to an enabled cluster
- 3. Switch cluster profile to run on cluster resources





Take Advantage of Cluster Hardware

- Offload computation:
 - Free up desktop
 - Access better computers
- Scale speed-up:
 - Use more cores
 - Go from hours to minutes
- Scale memory:
 - Utilize tall arrays and distributed arrays
 - Solve larger problems without re-coding alg





Summary

 Easily develop parallel MATLAB applications without being a parallel programming expert

 Speed up the execution of your MATLAB applications using additional hardware

 Develop parallel applications on your desktop and easily scale to a cluster when needed



Parallel Computing with MATLAB – Beyond PARFOR

Well-known features

- parallel-enabled toolboxes
- parfor/parsim
- gpuArray

Full spectrum of support

- batch submission, jobs and tasks
 batch, createJob, createTask
- asynchronous queue for feval parfeval
- parallel support for big data tall, mapreduce
- distributed arrays ("global arrays")
 distributed, codistributed
- message passing
 labSend, labReceive



Some Other Valuable Resources

- MATLAB Documentation
 - MATLAB \rightarrow Advanced Software Development \rightarrow Performance and Memory
 - Parallel Computing Toolbox
- Parallel and GPU Computing Tutorials
 - <u>https://www.mathworks.com/videos/series/parallel-and-gpu-computing-tutorials-</u> <u>97719.html</u>
- Parallel Computing on the Cloud with MATLAB
 - <u>http://www.mathworks.com/products/parallel-computing/parallel-computing-on-the-cloud/</u>



Monte Carlo Price Simulation I

- 1. Inspect original code in gdpSim.m.
- 2. Vectorize the code performance by eliminating a forloop. Compare timings and results.
- Eliminate the remaining loop.
 Again, compare timings and results.





Monte Carlo Price Simulation III

- 1. Inspect initial code in gdpSimVec.m.
- 2. Accelerate the code performance by parallelizing the **for**-loop.
- 3. Run in parallel pool and compare timings.





Monte Carlo Price Simulation IV

- 1. Inspect initial code in gdpSimPar.m and gdpSimMat.m.
- 2. Combine parallelization and vectorization.
- 3. Compare timings.





Scheduling Jobs and Tasks





Example: Scheduling different solvers on the same ODE system

```
sched = parcluster()
Create job
 job = createJob(sched);
 job.AutoAttachFiles = false;
 myAttachedFiles= {'springDampSolver45.m', 'springDampSolver23.m', ...
                              'springDampSolverAna.m'};
 job.AttachedFiles = myAttachedFiles;
Create tasks in job
 task1 = createTask(job,@springDampSolver45,2,{m,k,b,totalTime});
 task2 = createTask(job,@springDampSolver23,2,{m,k,b,totalTime});
 task3 = createTask(job,@springDampSolverAna,2,{m,k,b,totalTime});
Submit job
 submit(job)
 wait(job)
```





MATLAB and Simulink are registered trademarks of The MathWorks, Inc. See <u>www.mathworks.com/trademarks</u> for a list of additional trademarks. Other product or brand names may be trademarks or registered trademarks of their respective holders. © 2015 The MathWorks, Inc.

© 2018 The MathWorks, Inc.