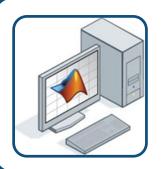


Accelerating MATLAB algorithms

By Dr Jasmina Lazić Application Engineer MathWorks



Agenda



Accelerating MATLAB code with parallel computing



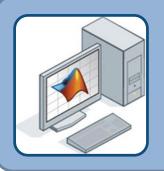
Scaling up: accessing more/better hardware



Big data with MATLAB: an overview



Agenda



Accelerating MATLAB code with parallel computing



Scaling up: accessing more/better hardware



Big data with MATLAB: an overview

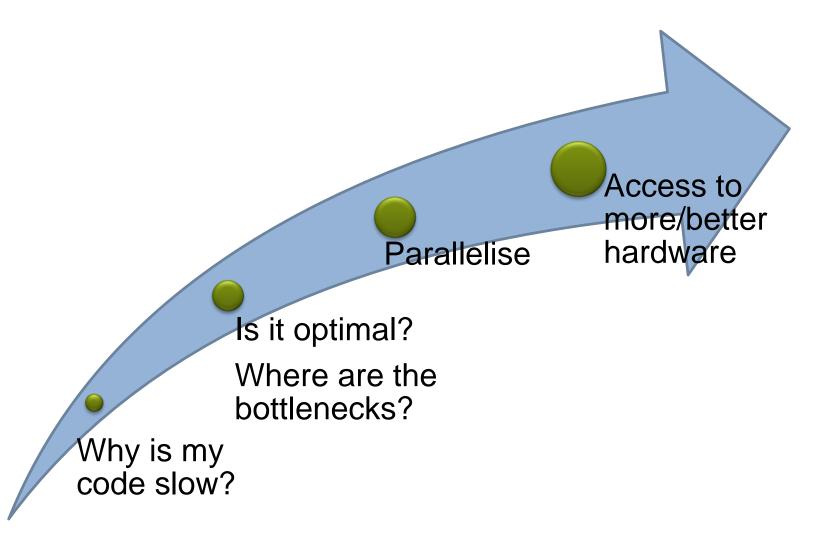


Accelerating MATLAB code

- Profile and optimise your code
- Introduction to parallel computing tools
- Solving big technical problems in MATLAB
 - Programming task parallel applications
 - Programming data parallel applications



Who wants faster code?





Using More Hardware

Built-in multithreading

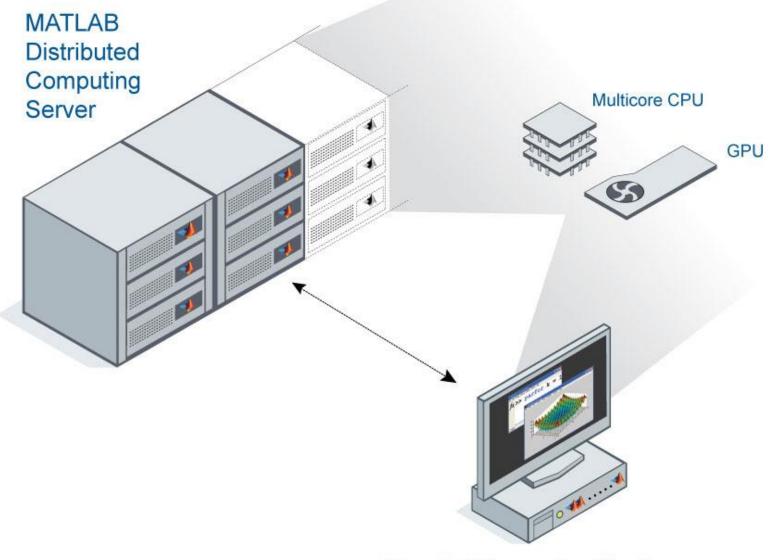
- Automatically enabled in MATLAB since R2008a
- Multiple threads in a single MATLAB computation engine <u>www.mathworks.com/discovery/multicore-matlab.html</u>

Parallel computing using explicit techniques

- Multiple computation engines controlled by a single session
- High-level constructs to let you parallelise MATLAB applications
- Perform MATLAB computations on GPUs



Parallel Computing Products



Parallel Computing Toolbox



Solving Big Technical Problems

Challenges You could... Solutions Long running Larger Compute Pool Wait (e.g. More Processors) Computationally intensive Reduce size Larger Memory Pool Large data set of problem (e.g. More Machines)

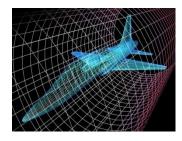




Optimizing JIT Steel Manufacturing Schedule

Cut simulation time from 1 hour to 5 minutes

Heart Transplant Studies
3-4 weeks reduced to 5 days



Flight Test Data Analysis

16x Faster

Mobile Communications Technology

Simulation time reduced from weeks to hours, 5x more scenarios





Hedge Fund Portfolio Management

Simulation time reduced from 6 hours to 1.2 hours



Programming Parallel Applications (CPU)

Ease of Use

Parallel enabled functionality in toolboxes

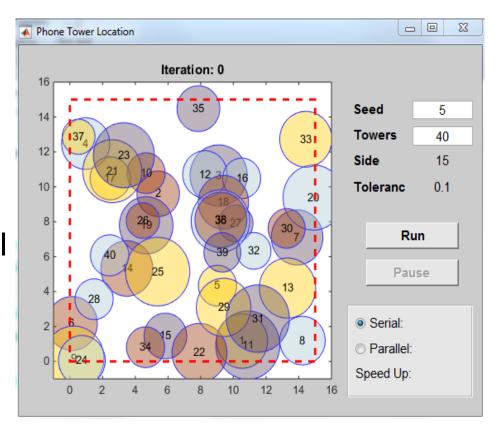




Example: Optimizing Cell Tower Position

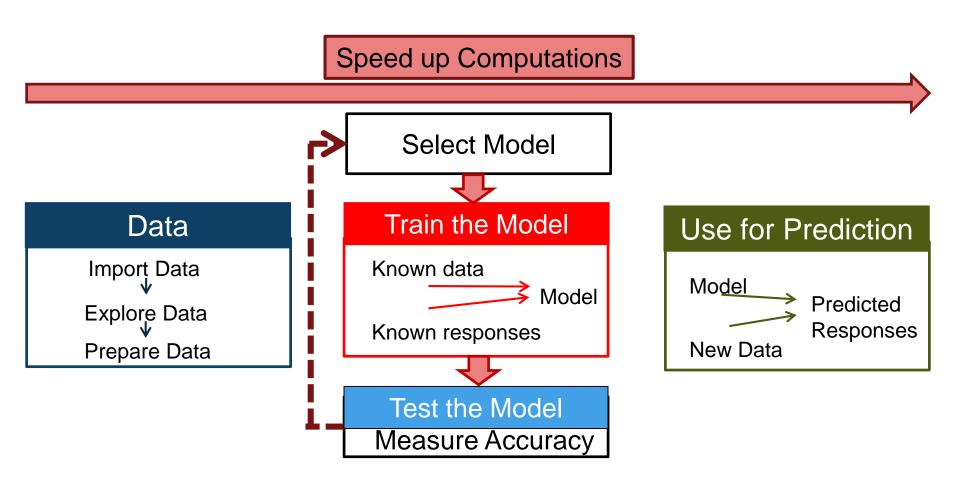
Parallel enabled functionality

- With Parallel Computing Toolbox use parallel enabled algorithms in Optimization Toolbox
- Run optimization in parallel
- Use pool of MATLAB workers





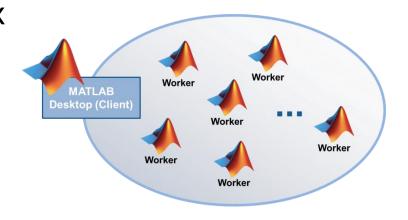
Supervised Learning - Workflow





Tools Providing Parallel Computing Support

- Optimization Toolbox
- Global Optimization Toolbox
- Statistics Toolbox and MachineLearning Toolbox
- Signal Processing Toolbox
- Neural Network Toolbox
- Image Processing Toolbox



'UseParallel', true options = optimset('UseParallel', true);

Directly leverage functions in Parallel Computing Toolbox

www.mathworks.com/builtin-parallel-support

Programming Parallel Applications (CPU)

Ease of Use

Parallel enabled functionality in toolboxes

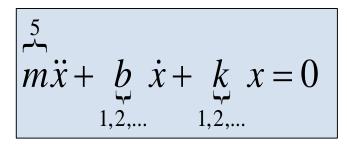
Simple programming constructs:
 parfor, batch, distributed

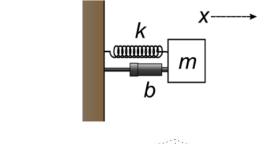


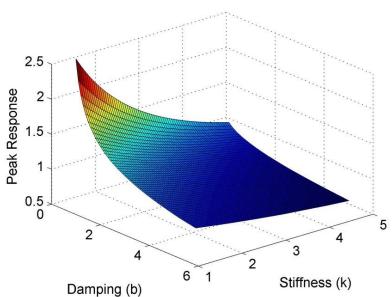
Example: Parameter Sweep of ODEs

Parallel for-loops

- Parameter sweep of ODE system
 - Damped spring oscillator
 - Sweep through different values of damping and stiffness
 - Record peak value for each simulation
- Convert for to parfor
- Use pool of MATLAB workers

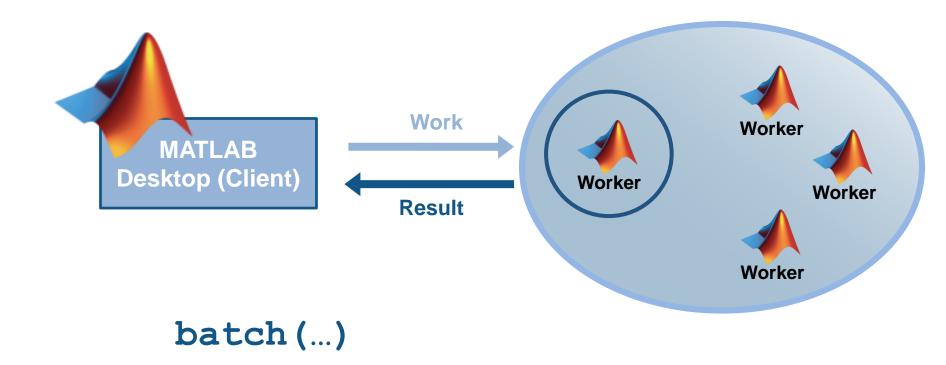






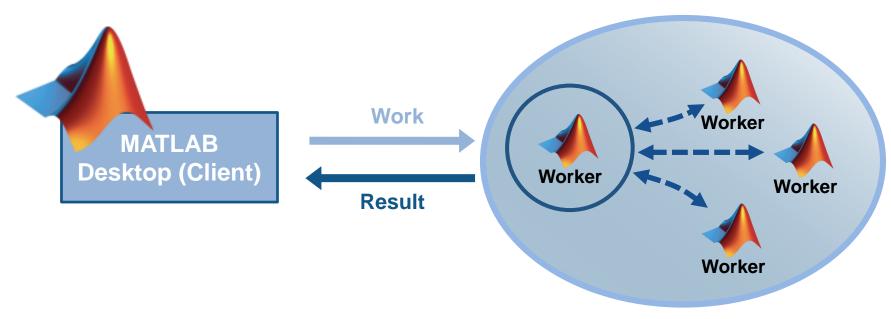


Offload Computations with batch





Offload and Scale Computations with batch & pool



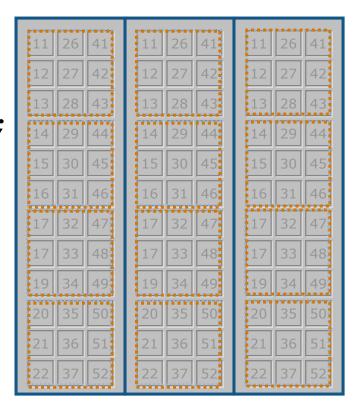
batch (..., 'Pool',...)



distributed

Split data over multiple cores

```
parpool('local')
A = distributed.randn(1000);
[V,D] = eig((A+A')/2);
D = gather(D);
```



Programming Parallel Applications (CPU)

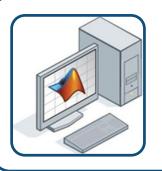
Ease of Use

Parallel enabled functionality in toolboxes

- Simple programming constructs:
 parfor, batch, distributed
- Advanced programming constructs: createJob, spmd, labSend/labReceive



Agenda



Accelerating MATLAB code with parallel computing



Scaling up: accessing more/better hardware



Big data with MATLAB: an overview



Using more hardware: why and when?



We have seen that with PCT we get some speed up locally and we have access to a powerful server or cluster with MDCS



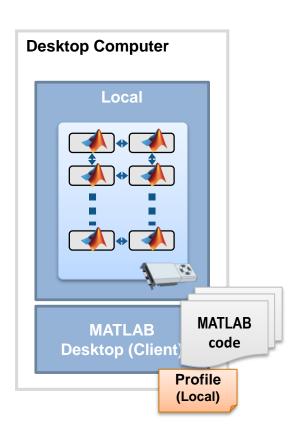
Our data is too large to fit in the desktop memory



We have access to GPUs



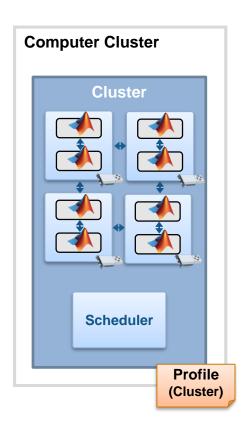
Use MATLAB Distributed Computing Server



1. Prototype code



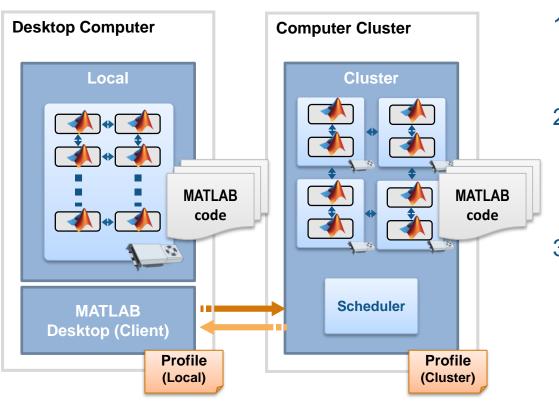
Use MATLAB Distributed Computing Server



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



Use MATLAB Distributed Computing Server

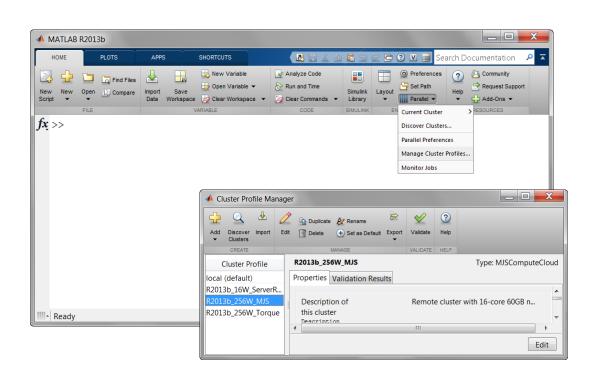


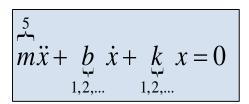
- 1. Prototype code
- Get access to an enabled cluster
- Switch cluster profile to run on cluster resources

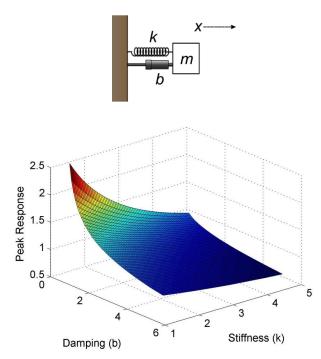


Example: Migrate from Desktop to Cluster

 Change hardware without changing algorithmic code

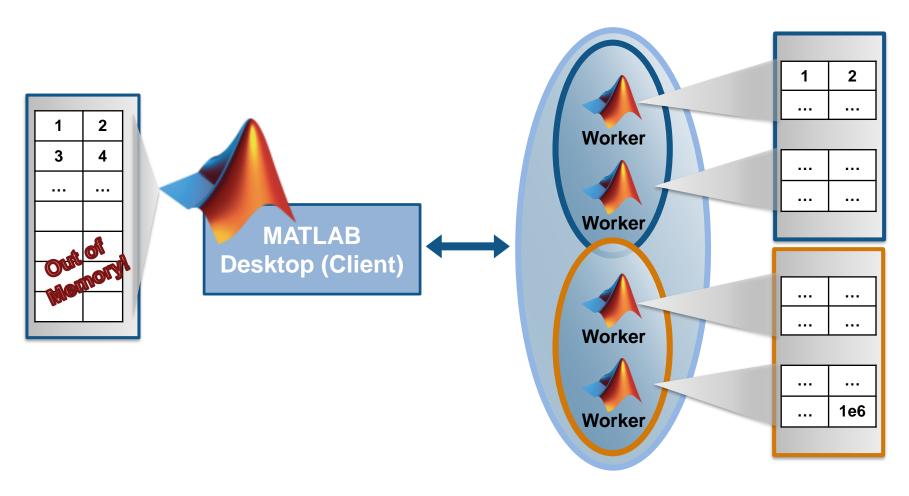








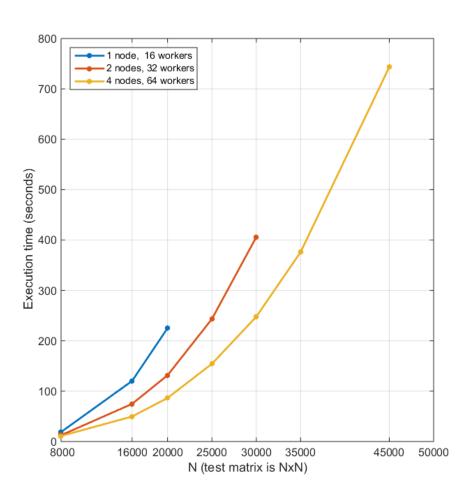
Overcoming Desktop Memory Limitations





Distributed Memory Calculations

Multiplication of 2 NxN matrices



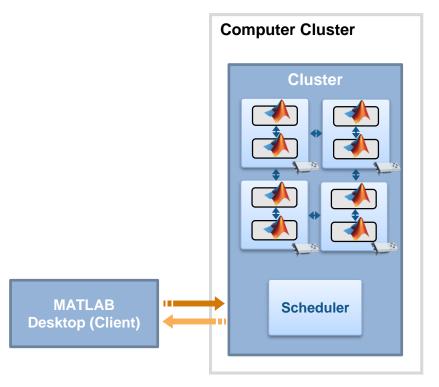
	Execu	ition time (sec	onds)
N	1 node, 16 workers	2 nodes, 32 workers	4 nodes, 64 workers
8000	19	13	11
16000	120	75	50
20000	225	132	86
25000	-	243	154
30000	-	406	248
35000	-	-	376
45000	-	-	743
50000	-	-	-

Processor: Intel Xeon E5-class v2 16 cores, 60 GB RAM per compute node, 10 Gb Ethernet



Take Advantage of Cluster Hardware

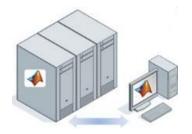
- Offload computation:
 - Free up desktop
 - Access better computers
- Scale speed-up:
 - Use more cores
 - Go from hours to minutes
- Scale memory:
 - Utilize distributed arrays
 - Solve larger problems without re-coding algorithms
- Leverage supplied infrastructure
 - File transfer / path augmentation
 - Job monitoring





Further Scaling Big Data Capacity

MATLAB supports a number of programming constructs for use with clusters



- General compute clusters
 - Parallel for loops embarrassingly parallel algorithms
 - SPMD distributed processing
- Hadoop clusters
 - MapReduce analyze data stored in the Hadoop Distributed File System



What is a Graphics Processing Unit (GPU)

- Originally for graphics acceleration, now also used for scientific calculations
- Massively parallel array of integer and floating point processors
 - Typically hundreds of processors per card
 - GPU cores complement CPU cores
- Dedicated high-speed memory



^{*} Parallel Computing Toolbox requires NVIDIA GPUs with Compute Capability 1.3 or higher, including NVIDIA Tesla 20-series products. See a complete listing at www.nvidia.com/object/cuda_gpus.html

Programming Parallel Applications (GPU)

Ease of Use

Built-in support with Toolboxes

- Simple programming constructs:
 gpuArray, gather
- Advanced programming constructs:
 arrayfun, bsxfun, spmd
- Interface for experts:CUDAKernel, MEX support



Accessing GPUs (Graphics Processing Units)

```
>> A = someArray(200, 10000);
>> G = gpuArray(A); % Push to GPU memory
>> F = cov(G);
>> B = gather(F) % Bring back into MATLAB
```





CPU/GPU comparison

```
%% CPU
Acpu = rand(2000);

tic
Bcpu = cov(Acpu);
toc

Elapsed time is 0.264531
```

Elapsed time is 0.264531 seconds.

```
%% GPU
Agpu = gpuArray.rand(2000);
tic
Bgpu = cov(Agpu);
wait(gpuDevice);
toc
B = gather(Bgpu);
Elapsed time is 0.041266 seconds.
```

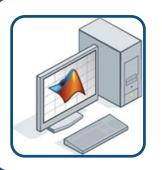


Summary

- Develop parallel MATLAB applications without being a parallel programming expert
- Speed up the execution of your MATLAB applications using additional hardware
- Prototype on your desktop and easily scale to a cluster



Agenda



Accelerating MATLAB code with parallel computing



Scaling up: accessing more/better hardware



Big data with MATLAB: an overview



Big Data

"Any collection of data sets so large and complex that it becomes difficult to process using... traditional data processing applications."

(Wikipedia)

FINANCE Market Risk, Regulatory



AUTO Fleet Data Analysis



Medical
Devices
Patient Outcomes



ENERGY

Asset Optimization



- Access to Data
- Rapid data exploration
- Development of scalable algorithms
- Ease of deployment



Considerations: large data analytics Data Characteristics

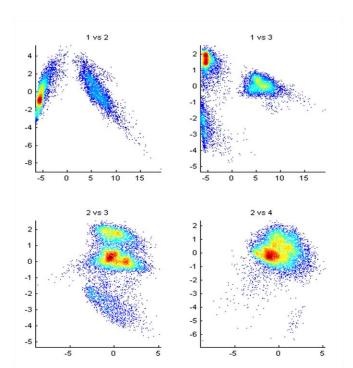
- 1. Size & type of data?
- 2. Where is your data?
- 3. What hardware do you have access to?
- 4. Analysis Characteristics
 - Embarrassingly Parallel
 - Analyse sub-segments of data and aggregate results
 - Operate on entire dataset



Big Data Capabilities in MATLAB

Memory and Data Access

- 64-bit processors
- Memory Mapped Variables
- Disk Variables
- Databases
- Datastores



Programming Constructs

- Streaming
- Block Processing
- Parallel-for loops
- GPU Arrays
- SPMD and Distributed Arrays
- MapReduce

Platforms

- Desktop (Multicore, GPU)
- Clusters
- Cloud Computing (MDCS on EC2)
- Hadoop



Big Data on the Desktop

MATLAB

datastore

Access files or collections of files that do not fit into memory

- Preview data structure and format
- Import data using column names
- Incremental access to data

	Desktop		Name	Date modified	Туре	Size
	Downlo		¶ 1987.csv	8/13/2014 3:37 PM	WinZip File	12,356 KB
	■ Google		¶ 1988.csv	8/13/2014 3:45 PM	WinZip File	48,339 KB
	Mathworks Recent Places	893	1989.csv	8/13/2014 3:44 PM	WinZip File	48,050 KB
		riaces	1990.csv	8/13/2014 3:45 PM	WinZip File	50,822 KB
		¶ 1991.csv	8/13/2014 3:43 PM	WinZip File	48,709 KB	
>> preview(ds)				/inZip File	48,869 KB	
-	(42)				/inZip File	48,938 KB
ans =					/inZip File	49,926 KB
Year	Month	h DayofMon		DayOfWeek	/inZip File	73,127 KB
					/inZip File	74,110 KB
1987	10	21		3	/inZip File	74,908 KB
				_	/inZip File	74,887 KB
1987	10	26		1		
1987	10	23		5		

```
airdata = datastore('*.csv');
airdata.SelectedVariables = {'Distance', 'ArrDelay'};
data = read(airdata);
```

mapreduce

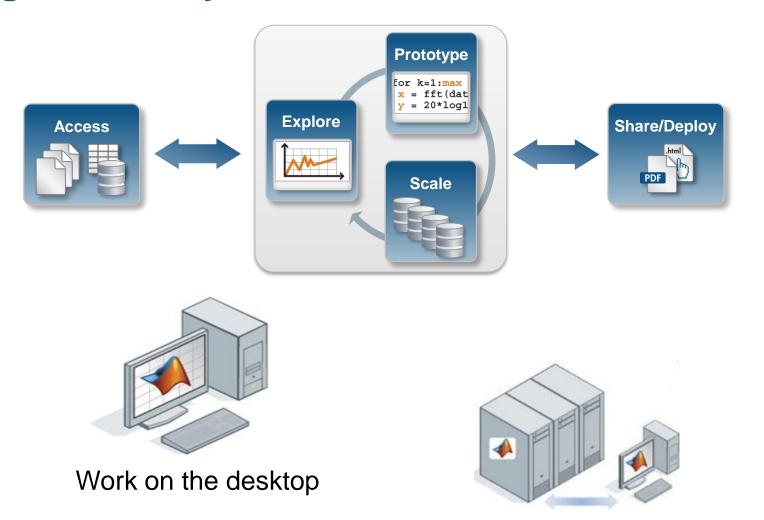
Programming technique for analyzing data sets that do not fit into memory

- Tabular text files or big database tables
- Increase compute capacity with parallel processing
- Access HDFS to develop algorithms for use on Hadoop

```
Map 0%
              Reduce 0%
Map 20%
              Reduce 0%
Map 40%
              Reduce 0%
Map 60%
              Reduce 0%
Map 80%
              Reduce 0%
Map 100%
              Reduce 25%
Map 100%
              Reduce 50%
Map 100%
              Reduce 75%
Map 100%
              Reduce 100%
```



Big Data Analytics with MATLAB



Scale capacity as needed