# Parallel Computing with MATLAB Hands-On Workshop

**Steve Schäfer**
*MathWorks Academia Group*
steves@mathworks.com

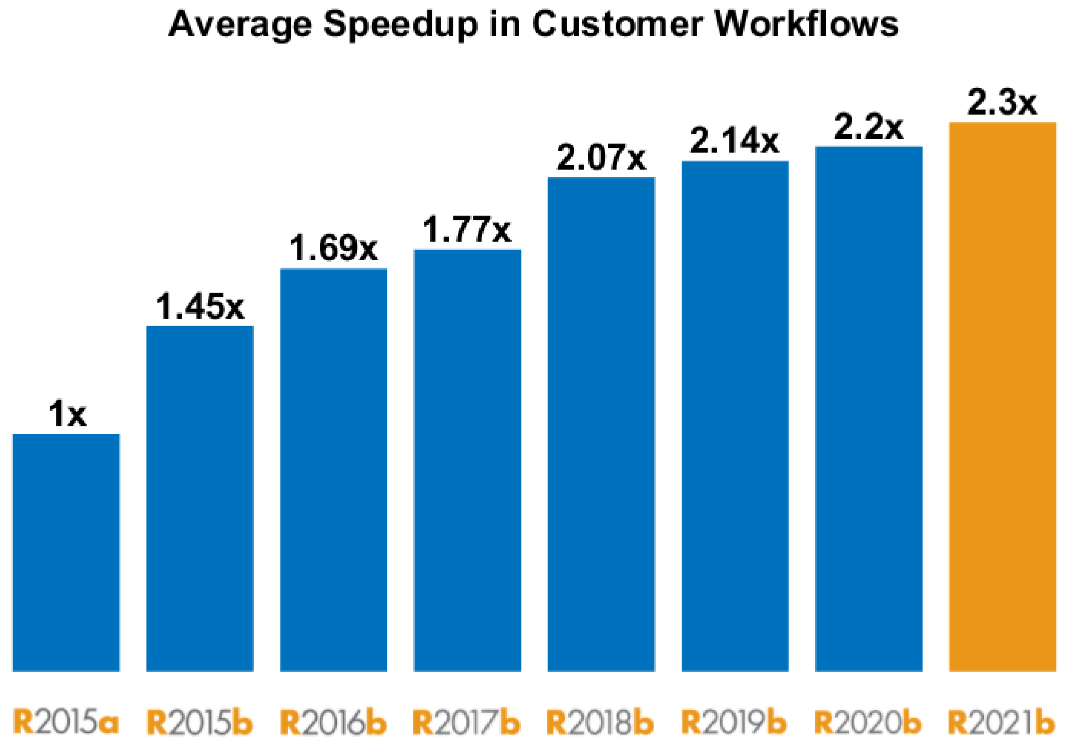
# Agenda

- Accelerating Serial MATLAB Code
- Introduction to Parallel Computing with MATLAB
- Speeding up computation with the **`Parallel Computing Toolbox`**
- Using GPUs with MATLAB
- Scaling up to a Cluster using **`MATLAB Parallel Server`**
- Overview of Big Data Capabilities in MATLAB (Optional)

# Accelerating Serial MATLAB Code

# Run MATLAB code faster by …

- installing the latest release R2021b
  - Incremental improvements each release
  - Examples: Faster differential equation solvers and reading of images, render plots using less memory
  - Increased speed of MATLAB startup
- using built-in functions and data-types:
  - Regular performance improvements
  - These are extensively documented and tested with each other; constantly updated.



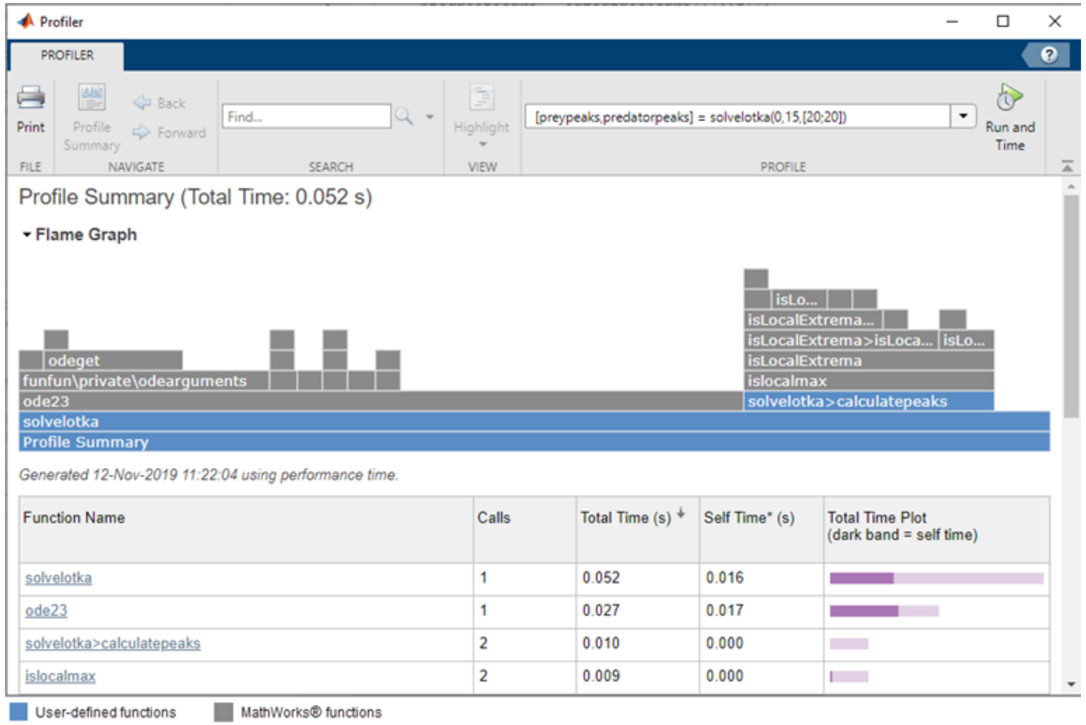
# Optimize your code before parallelizing for best performance

- Try using functions instead of scripts. Functions are generally faster.
- Instead of resizing arrays dynamically, **pre-allocate** memory.
- Create a new variable rather than assigning data of a different type to an existing variable.
- **Vectorize** — Use matrix and vector operations instead of for-loops.
- Avoid printing too much data on the screen, reuse existing graphics handles.
- Avoid programmatic use of `cd`, `addpath`, and `rmpath` when possible.

# Optimize your code before parallelizing for best performance

- Use **`tic`** & **`toc`** to
  - time your code executions

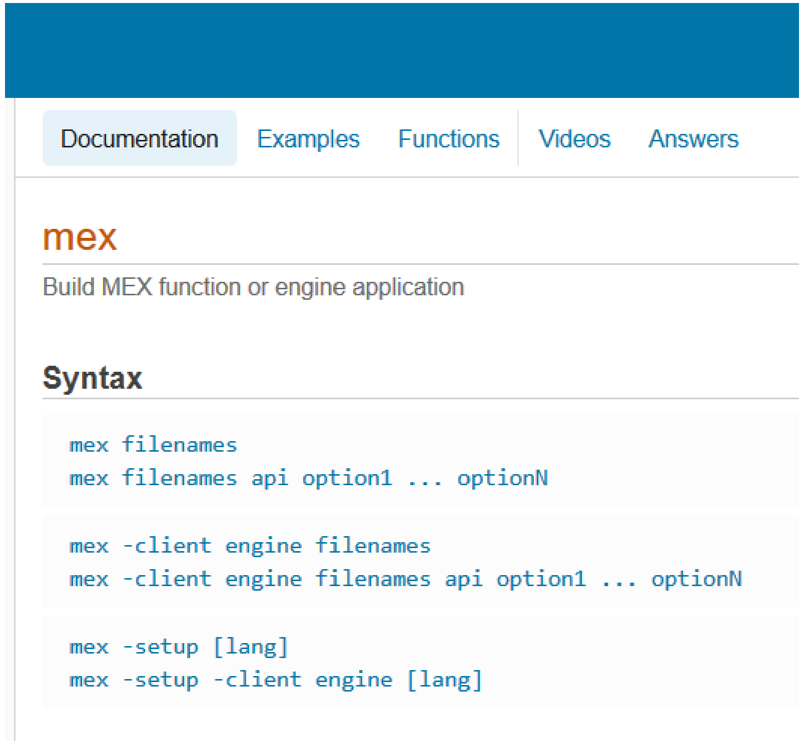
- Use [MATLAB Profiler]() to
  - analyse the execution time
  - Identify bottlenecks.




[Techniques for accelerating MATLAB algorithms and applications]()

# Optimize your code before parallelizing for best performance

- Replace code with MEX functions (Advanced)
  - Generate MATLAB Executable (MEX) C/C++ or CUDA code from a function.
  - Use MATLAB Coder & GPU Coder Apps to generate code more easily.
  - Lots of supported functions
  - Massive speed-up for certain applications



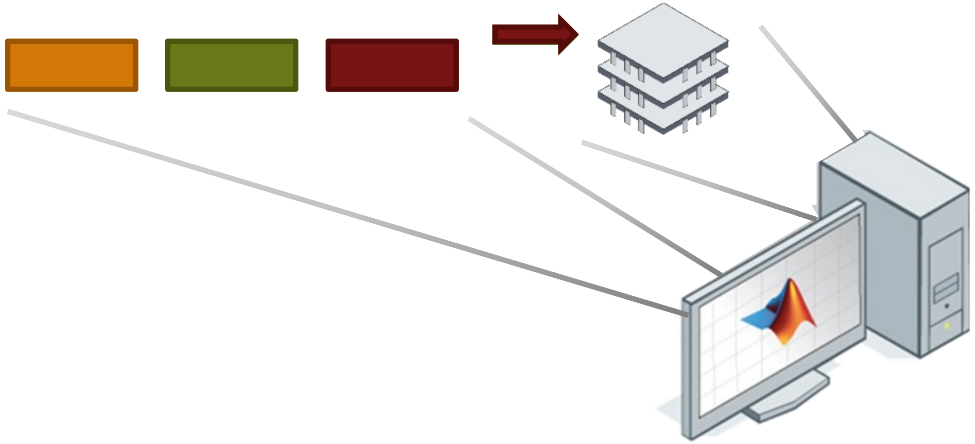

Techniques for accelerating MATLAB algorithms and applications

# Now for something different:

- So far we've mostly talked about using only one core of your computer
  – But your CPU probably has many cores (2-16+), which you can utilise.
  – You may also have access to a GPU, which has hundreds of cores.
  – Or a powerful workstation or HPC Cluster or an AWS EC2 instance with multiple cores.
- Now we'll look at how to utilise these.
  – We are using the `Parallel Computing Toolbox` on your local machine
  – and `MATLAB Parallel Server` for (remote) cluster or cloud computing

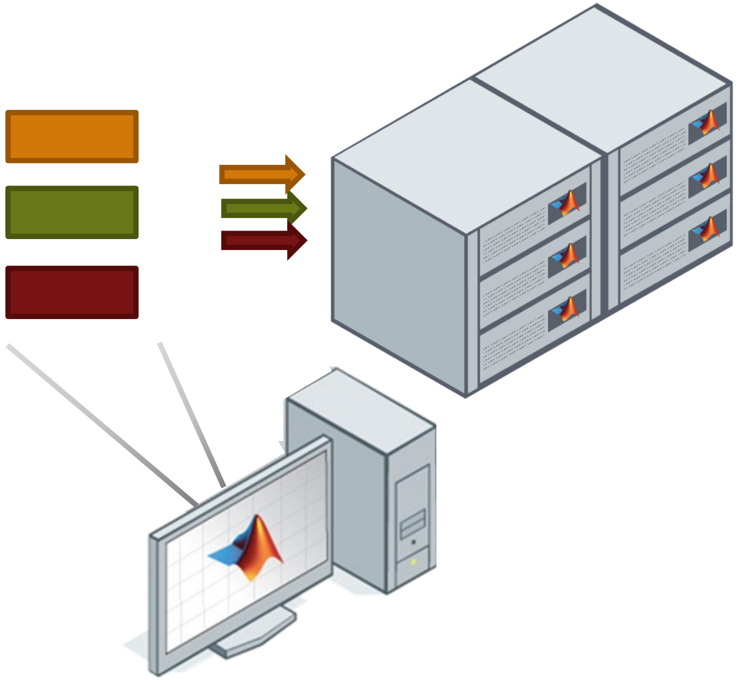
# What is Parallel Computing?

## Serial



Code executes in sequence

## Parallel

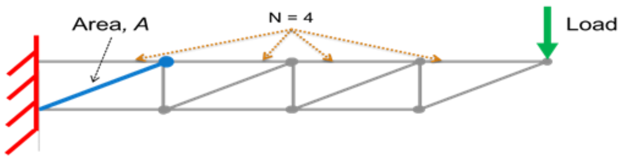


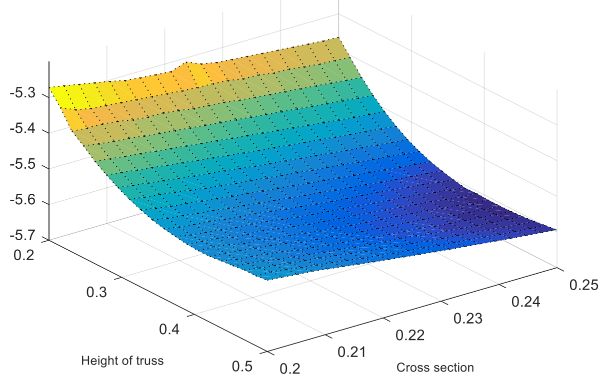
Code executes in parallel

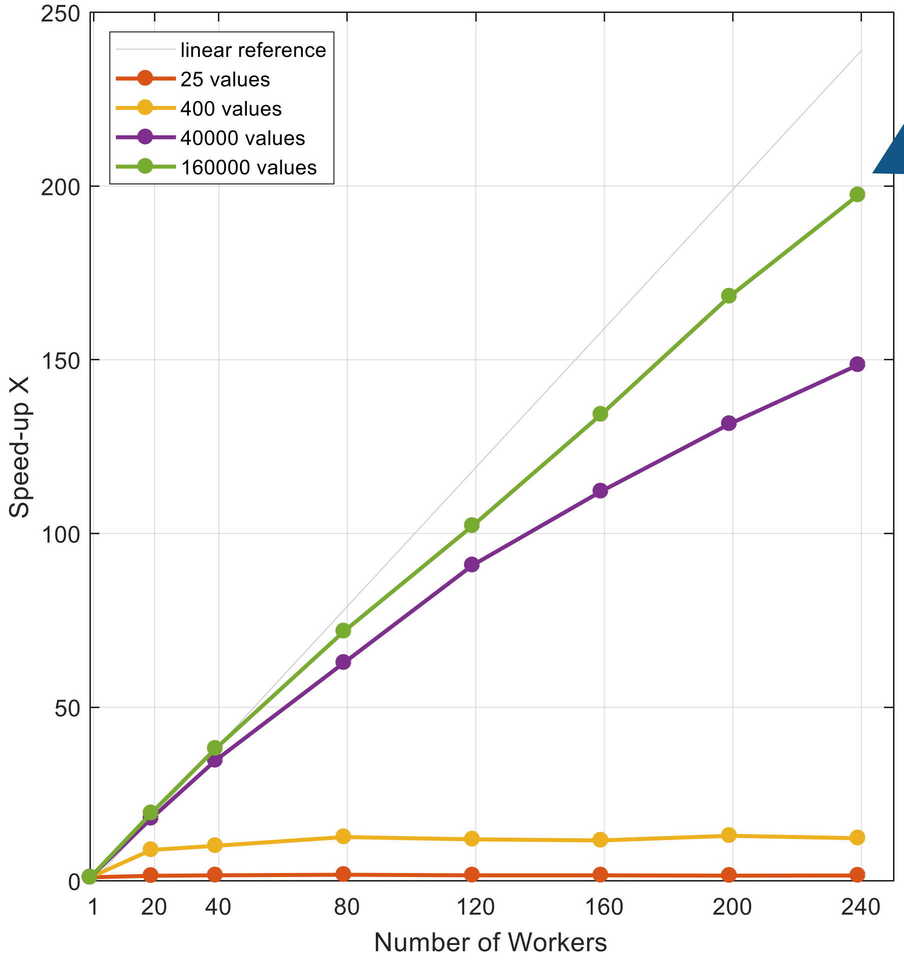
# Why is Parallel Computing useful?

## Great potential for accelerating certain types of applications

$$M\ddot{x} + C\dot{x} + Kx = F$$




200x faster!

| Workers in pool | Compute time (minutes) | | | |
|---|---|---|---|---|
| | 160e3 values | 40e3 values | 400 values | 25 values |
| **1** | 70 | 17 | 0.19 | 0.02 |
| **20** | 3.6 | 0.9 | 0.02 | 0.01 |
| **40** | 1.8 | 0.5 | 0.02 | 0.01 |
| **80** | 1.0 | 0.3 | 0.02 | 0.01 |
| **160** | 0.5 | 0.2 | 0.02 | 0.01 |
| **240** | 0.4 | 0.1 | 0.02 | 0.01 |

Processor: Intel Xeon E5-class v2
16 physical cores per node
MATLAB R2017a

# What types of problems can Parallel Computing be used for?

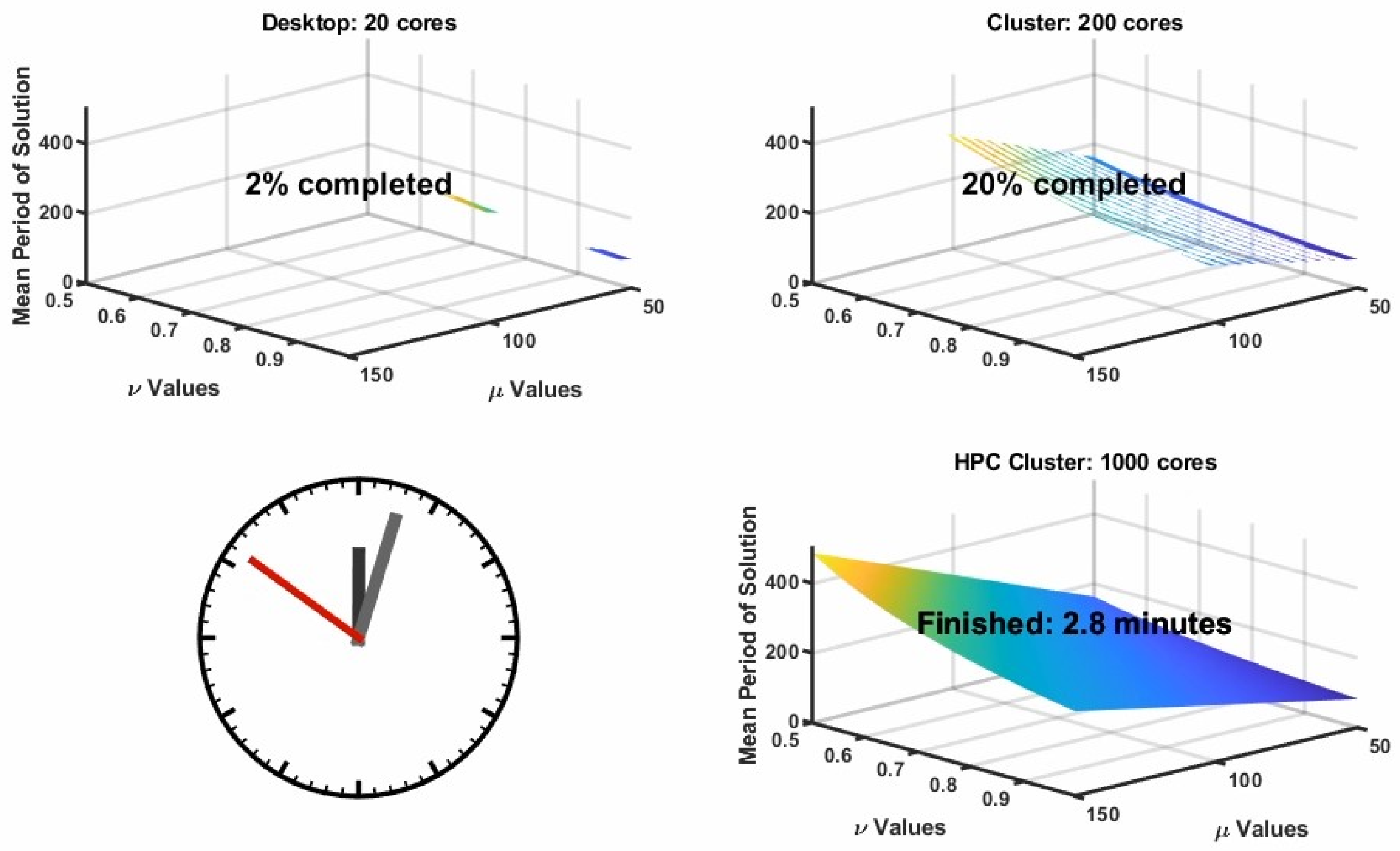
- Large problems that can be easily broken down into lots of smaller ones, which are then solved at the same time
- “Embarrassingly Parallel”
  - Term originally coined by Cleve Moler, who created the first version of MATLAB in 1984

Some Examples:

- Mesh-based solutions for Partial Differential Equations (PDEs)
- Independent Simulations with different parameters
- Discrete Fourier Transforms, with each harmonic calculated independently

# Parameter Sweep for a van der Pol Oscillator (a common ODE):

## Speeding up the same code in three different environments



# When to use Parallel Computing?

## Some questions to consider

- Do you need to solve larger problems faster?
- Have you already optimized your serial code?
- Can your problem be solved in parallel?

- If so, do you have access to:
  - A multi-core or multi-processor computer?
  - A graphics processing unit (GPU)?
  - Access to an HPC Cluster or AWS?

# NASA Langley Accelerates Acoustic Data Analysis with GPU Computing

## Challenge

Accelerate the analysis of sound recordings from wind tunnel tests of aircraft components

## Solution

- Use Parallel Computing Toolbox to process acoustic data
- Cut processing time by running computationally intensive operations on a GPU

## Results

- GPU computations completed 40 times faster
- Algorithm GPU-enabled in 30 minutes
- Processing of test data accelerated

**Wind tunnel test setup featuring the Hybrid Wing Body model (inverted), with 97-microphone phased array (top) and microphone tower (left).**

*“Our **legacy code took up to 40 minutes** to analyze a single wind tunnel test. The addition of GPU computing with Parallel Computing Toolbox **cut it to under a minute**. It took 30 minutes to get our MATLAB algorithm working on the GPU—no low-level CUDA programming was needed.”*

*- Christopher Bahr, research aerospace engineer at NASA*

[Link to user story]

# Virgin Orbit Simulates LauncherOne Stage Separation Events

## Challenge

Simulate separation events for LauncherOne spacecraft

## Solution

- Use MATLAB, Simulink, and Simscape Multibody to model components and automate Monte Carlo simulations
- Used Parallel Computing Toolbox to run simulations in parallel on multicore processors

## Results

- Simulations completed 10 times faster
- Simulation set up times cut by up to 90%
- Hardware designs informed by simulation results


**Virgin Orbit's LauncherOne vehicle assembled (top), with exploded view showing the fairing, payload, and first and second stages (bottom).**

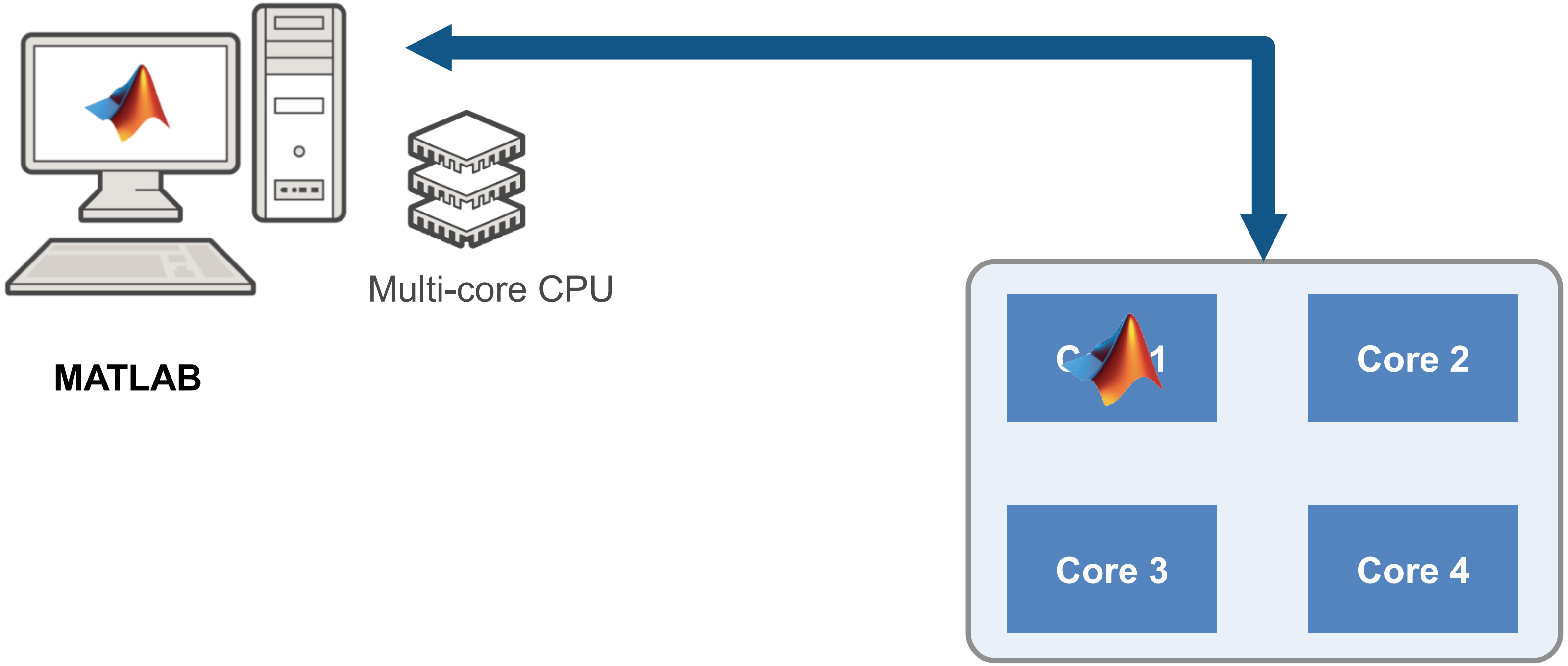
*"With Simulink, we can employ simplifying assumptions and parallel processing to reduce simulation times from days to hours…Just as important, we can automate the simulations so they run in the background or overnight, and have the results waiting for us in the morning."*

*- Patrick Harvey, Associate Engineer at Virgin Orbit*

Link to user story

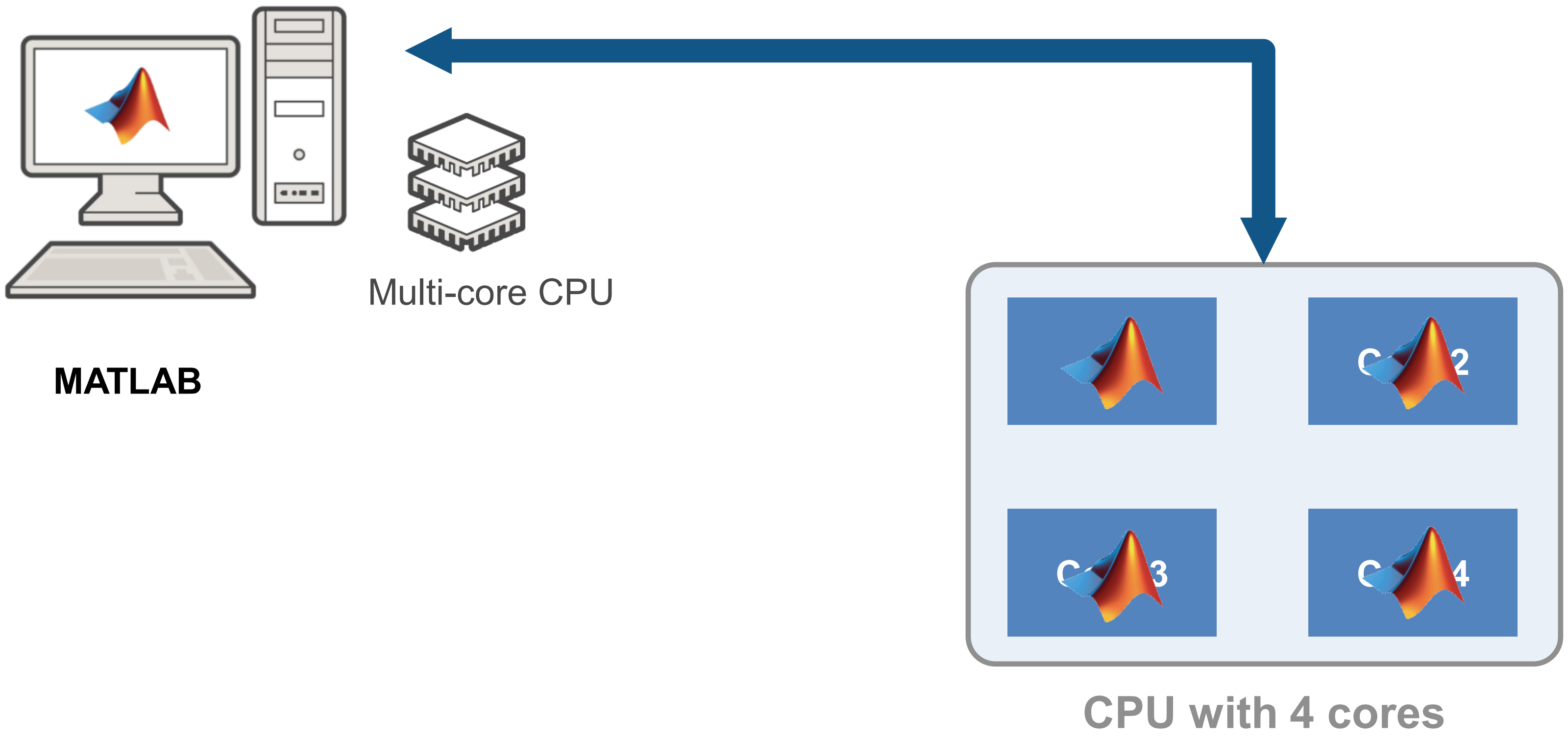
# Introduction to Parallel Computing with MATLAB

# Most of your MATLAB code runs on one core




CPU with 4 cores

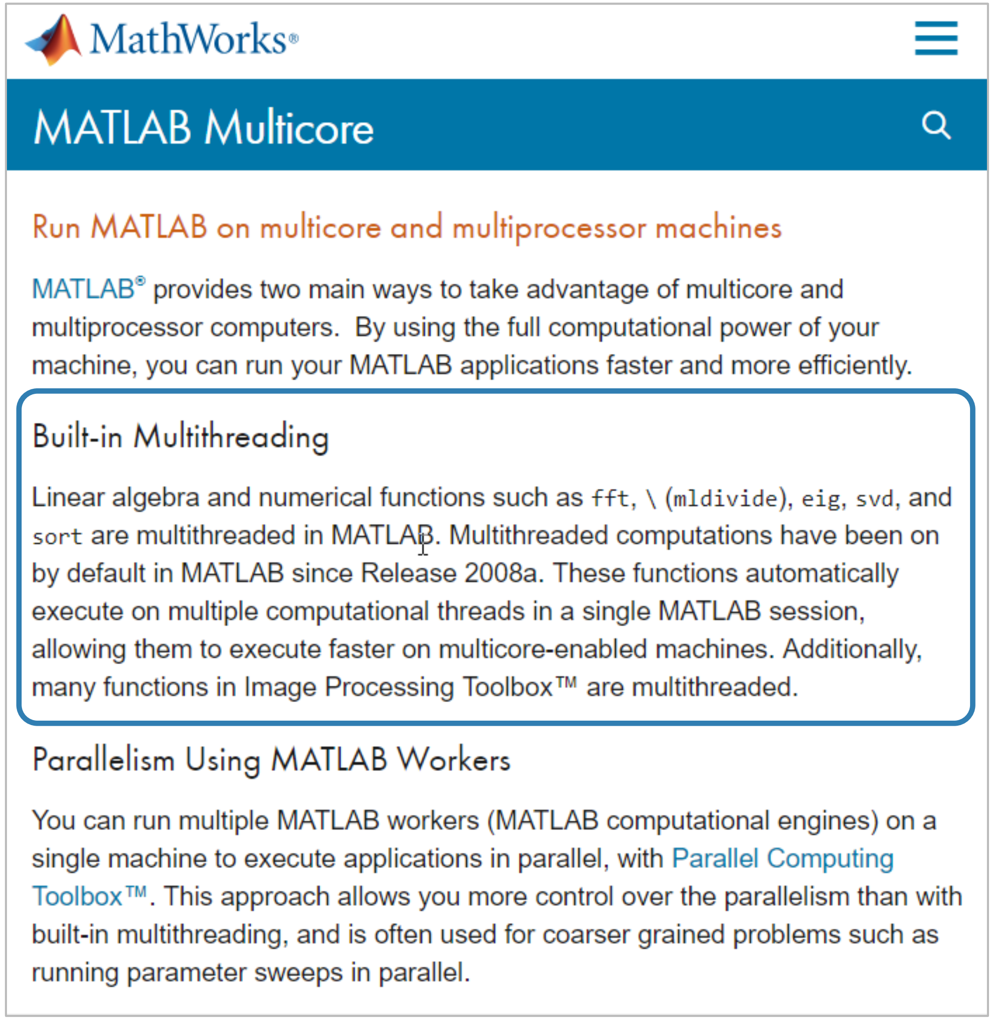
# Run multiple iterations by utilizing multiple CPU cores



# MATLAB has built-in multithreading

Multi-core CPU

**MATLAB**



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## MATLAB Multicore

### Run MATLAB on multicore and multiprocessor machines

MATLAB® provides two main ways to take advantage of multicore and multiprocessor computers. By using the full computational power of your machine, you can run your MATLAB applications faster and more efficiently.

### Built-in Multithreading

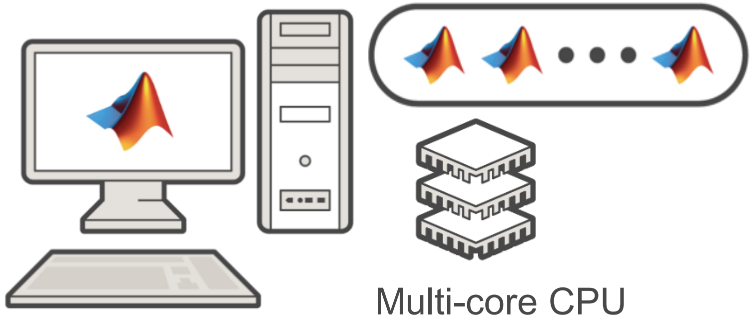
Linear algebra and numerical functions such as `fft`, `\` (`mldivide`), `eig`, `svd`, and `sort` are multithreaded in MATLAB. Multithreaded computations have been on by default in MATLAB since Release 2008a. These functions automatically execute on multiple computational threads in a single MATLAB session, allowing them to execute faster on multicore-enabled machines. Additionally, many functions in Image Processing Toolbox™ are multithreaded.

### Parallelism Using MATLAB Workers

You can run multiple MATLAB workers (MATLAB computational engines) on a single machine to execute applications in parallel, with Parallel Computing Toolbox™. This approach allows you more control over the parallelism than with built-in multithreading, and is often used for coarser grained problems such as running parameter sweeps in parallel.

[MATLAB multicore](MATLAB multicore)

# MATLAB workers execute applications in parallel




**MATLAB**
**Parallel Computing Toolbox**

MathWorks®

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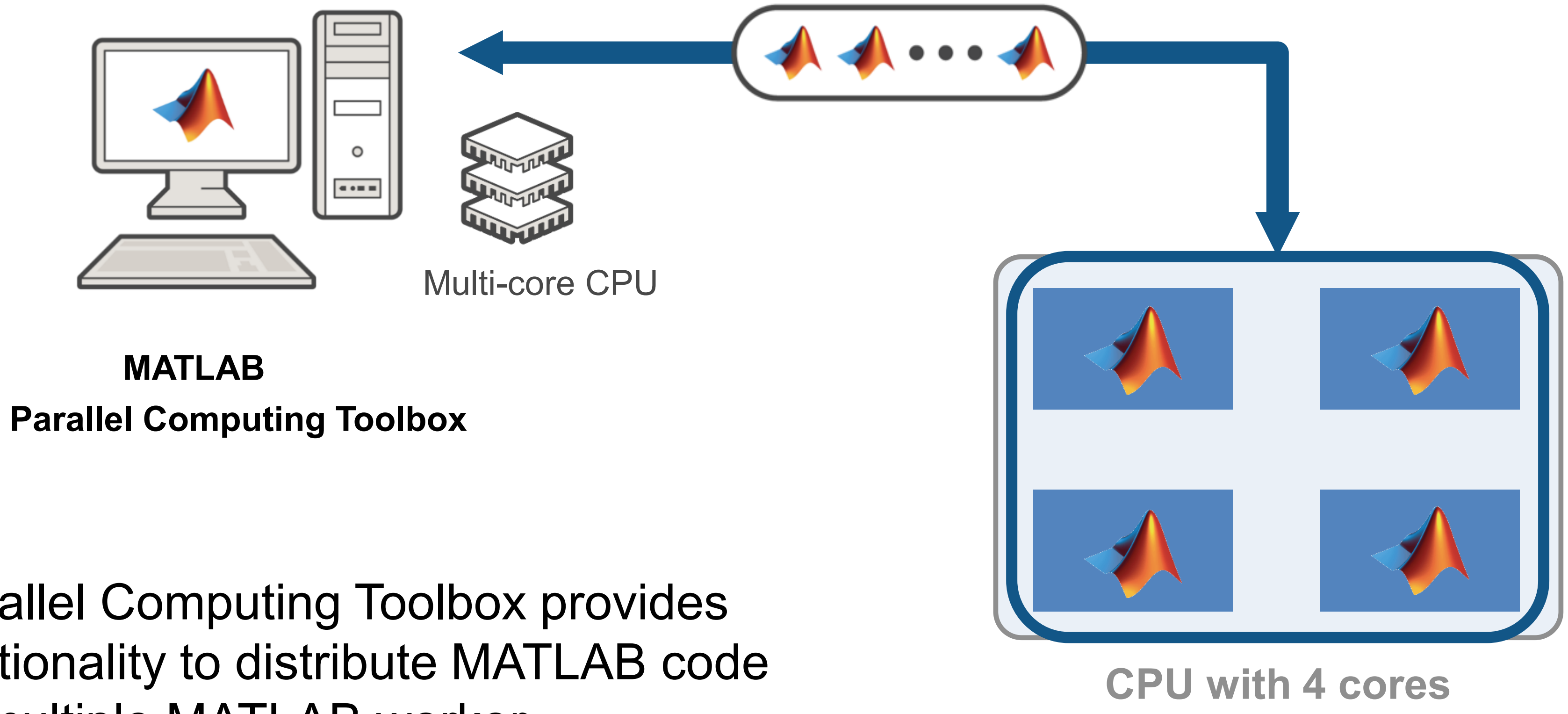
MATLAB multicore

# MATLAB + Parallel Computing Toolbox

## Leverage multiple cores on your machine with explicit parallel techniques

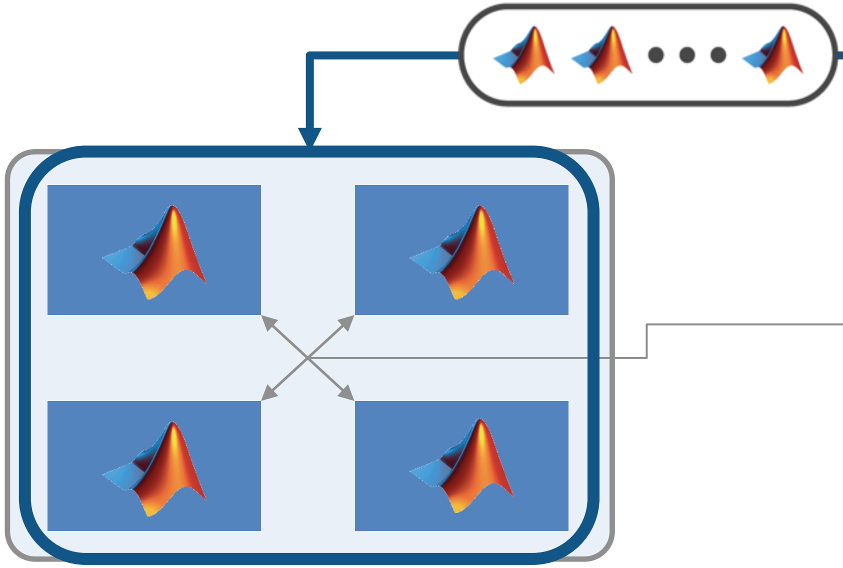



- The Parallel Computing Toolbox provides the functionality to distribute MATLAB code across multiple MATLAB worker.

# MATLAB + Parallel Computing Toolbox

## Terminology

- **MATLAB client**:
  – the MATLAB session you interact with.
  – The client instructs the workers with parallel language functions.



CPU with 4 cores

- **Parallel pool**:
  – a set of MATLAB workers.
- **MATLAB workers**:
  – MATLAB computational engines that run in the background without a graphical desktop.

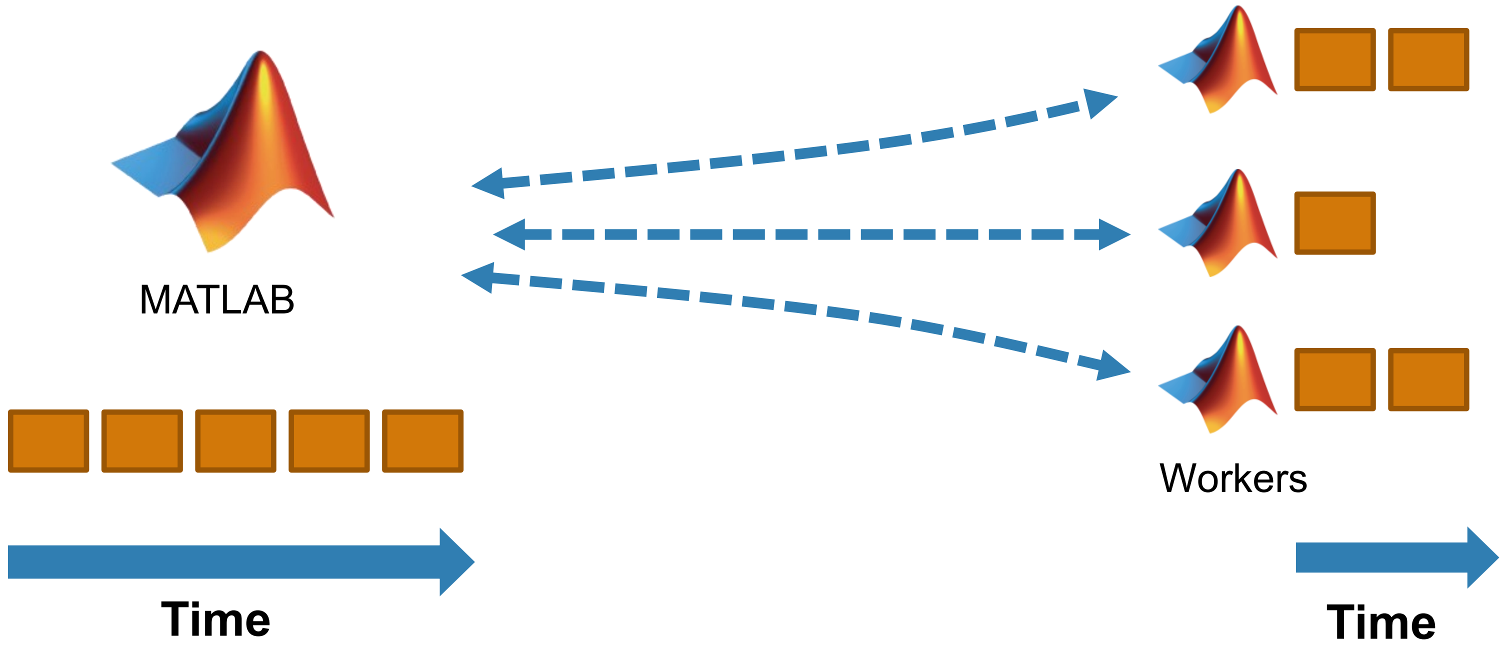
# MATLAB + Parallel Computing Toolbox

## Only simple modifications to your code required

Three good commands to know:

| | | |
|---|---|---|
| `for` → `parfor` | | (parallel for-loop) |
| `feval` → `parfeval` | | (parallel function evaluations) |
| `sim` → `parsim` | | (parallel Simulink runs) |

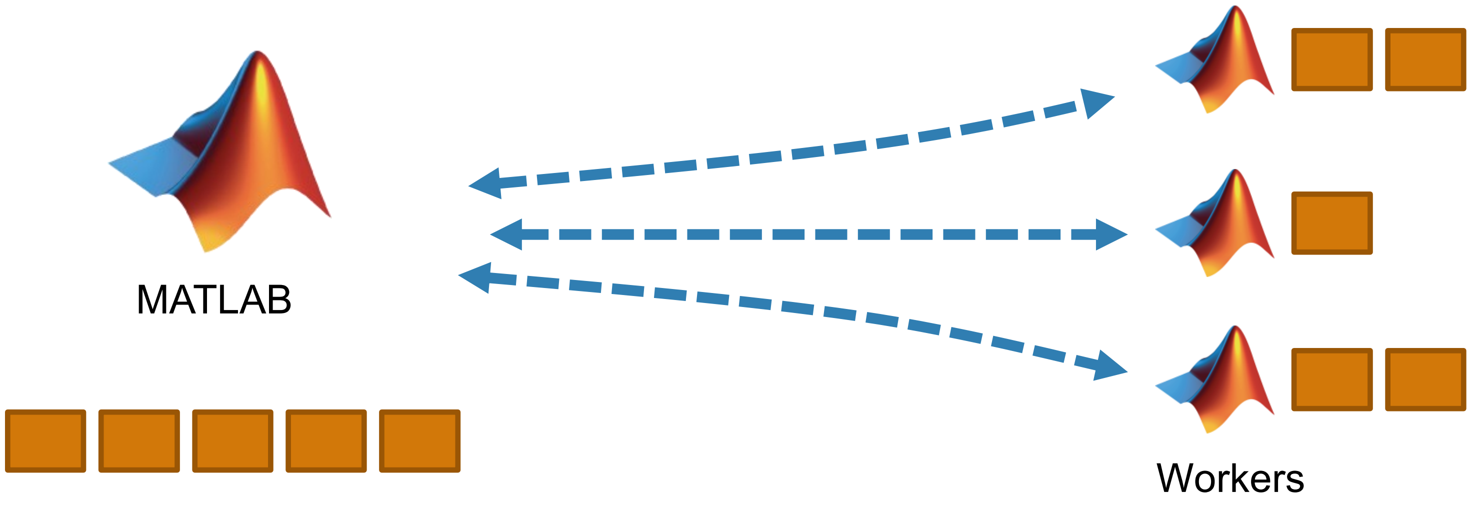
# Explicit parallelism with `parfor`




- Run iterations in parallel
- Examples: parameter sweeps, Monte Carlo simulations

[Learn more about parfor]

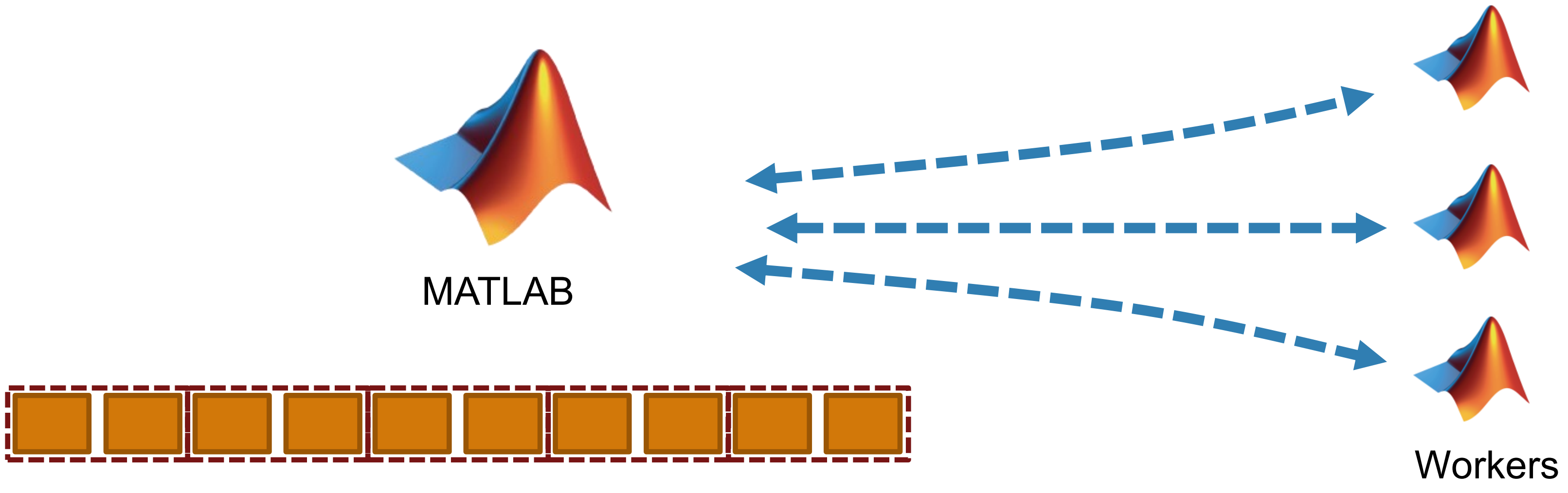
# Explicit parallelism with `parfor`




```
a = zeros(5, 1);
b = pi;
for i = 1:5
  a(i) = i + b;
end
disp(a)
```

```
a = zeros(5, 1);
b = pi;
parfor i = 1:5
  a(i) = i + b;
end
disp(a)
```

# Explicit parallelism with `parfor`




```
a = zeros(10, 1);
b = pi;
parfor i = 1:10
  a(i) = i + b;
end
disp(a)
```

# Speed up a parameter sweep using `parfor`

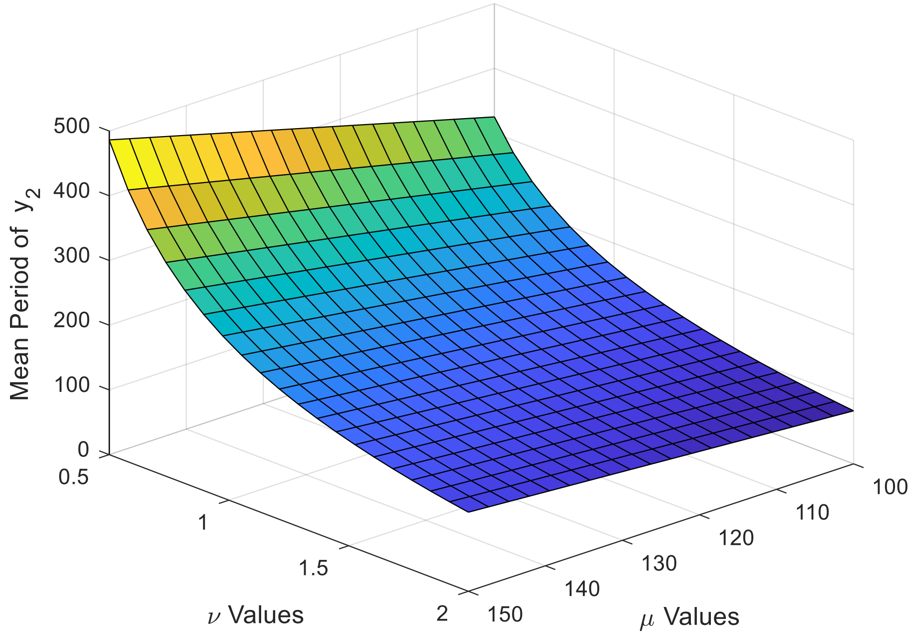
## Demo: Parameter sweep for van der Pol oscillator

- System of ODEs

$$\dot{y}_1 = \nu y_2$$
$$\dot{y}_2 = \mu(1 - y_1^2)y_2 - y_1$$

- Compute mean period of y

- Use **`parfor`**, study impact of $\nu, \mu$



# Hands-On Exercise:
# Introduction to `parfor`

# Factors that govern speedup of `parfor` loops

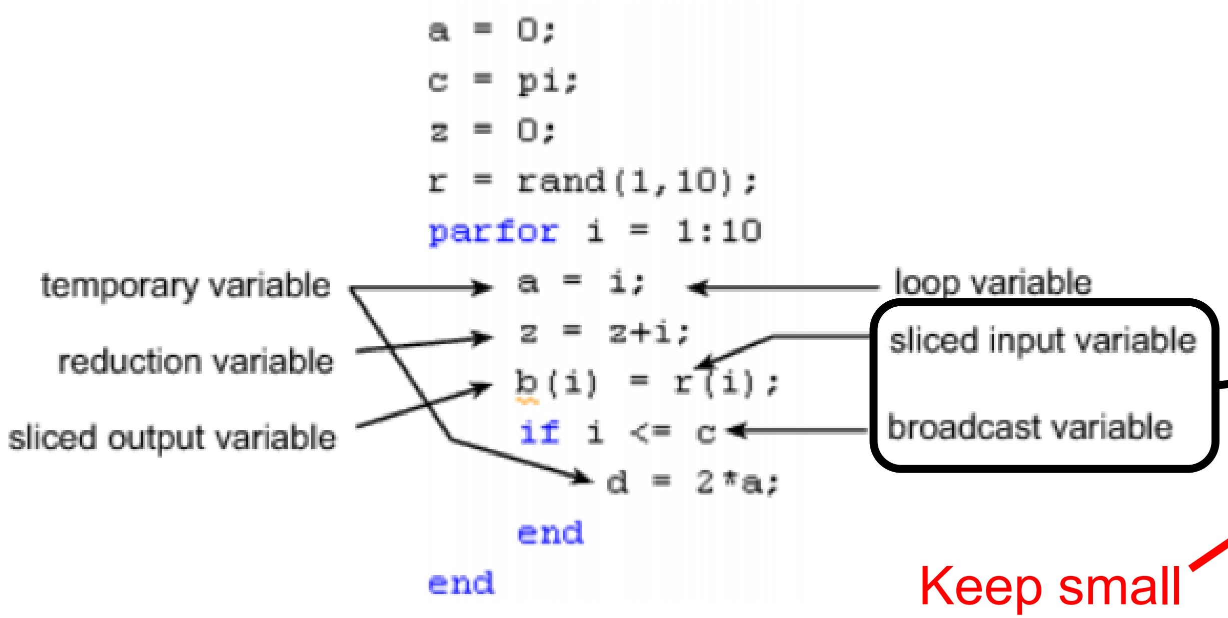
- May not be much speedup when computation time is too short

- Execution may be slow because of:
  - Memory limitations (RAM)
  - File access limitations

- Implicit multithreading
  - MATLAB uses multiple threads for speedup of some operations
  - Use Resource Monitor 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

# Optimizing `parfor`




Use more

Keep small

| Type | Category |
|---|---|
| sliced input | input |
| broadcast | input |
| reduction | output |
| sliced output | output |
| loop | only exist on worker |
| temporary | only exist on worker |

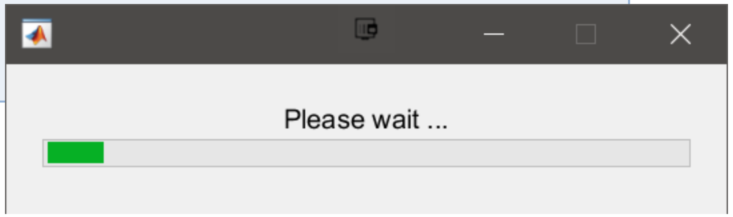
[Troubleshooting variables in parfor-loops]

# Execute additional code as iterations complete

- Send data or messages from parallel workers back to the MATLAB client

- Retrieve intermediate values and track computation progress

```
function a = parforWaitbar

D = parallel.pool.DataQueue;
h = waitbar(0, 'Please wait ...');
afterEach(D, @nUpdateWaitbar)

N = 200;
p = 1;

parfor i = 1:N
    a(i) = max(abs(eig(rand(400))));
    send(D, i)
end

    function nUpdateWaitbar(~)
        waitbar(p/N, h)
        p = p + 1;
    end
end
```



# Execute functions in parallel asynchronously using `parfeval`


- Asynchronous execution on parallel workers
- Useful for “needle in a haystack” problems

```
for idx = 1:10
   f(idx) = parfeval(@magic,1,idx);
end

for idx = 1:10
   [completedIdx,value] = fetchNext(f);
   magicResults{completedIdx} = value;
end
```

# Hands-On Exercise:
# Introduction to `parfeval`

# Automatic parallel support *(MATLAB)*

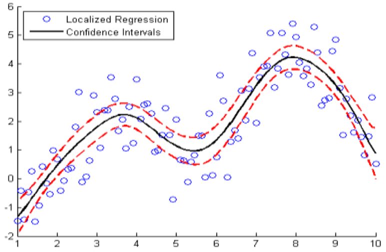
## Enable parallel computing support by setting a flag or preference

### Image Processing

Batch Image Processor, Block Processing, GPU-enabled functions


### Statistics and Machine Learning

Resampling Methods, k-Means clustering, GPU-enabled functions

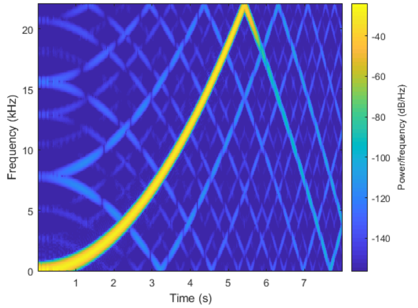



### Deep Learning

Deep Learning, Neural Network training and simulation

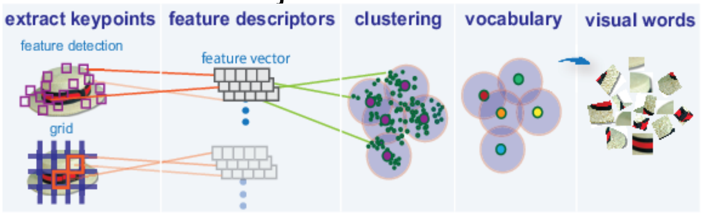
### Signal Processing and Communications

GPU-enabled FFT filtering, cross correlation, BER simulations



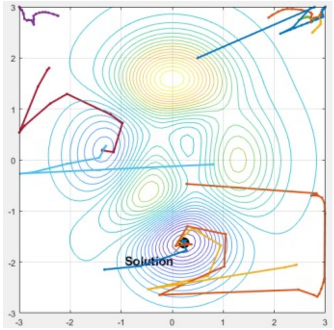

### Computer Vision

Bag-of-words workflow, object detectors




### Optimization and Global Optimization

Estimation of gradients, parallel search



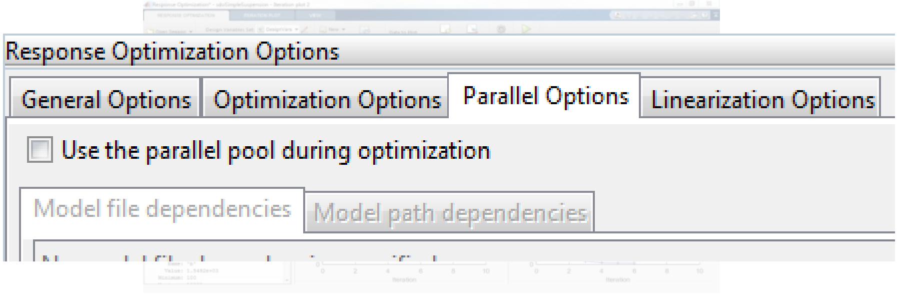

www.mathworks.com/products/parallel-computing/parallel-support

# Automatic parallel support *(Simulink)*

## Enable parallel computing support by setting a flag or preference

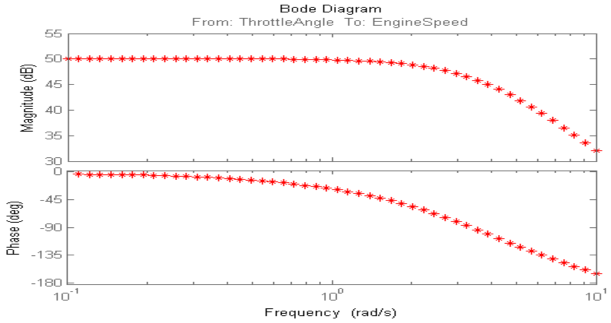
### Simulink Design Optimization

Response optimization, sensitivity analysis, parameter estimation



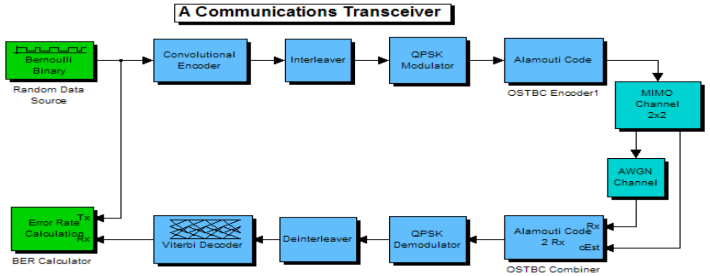

### Simulink Control Design

Frequency response estimation



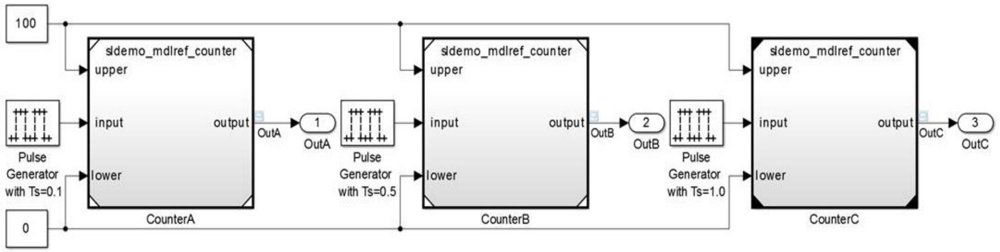

### Communication Systems Toolbox

GPU-based System objects for Simulation Acceleration



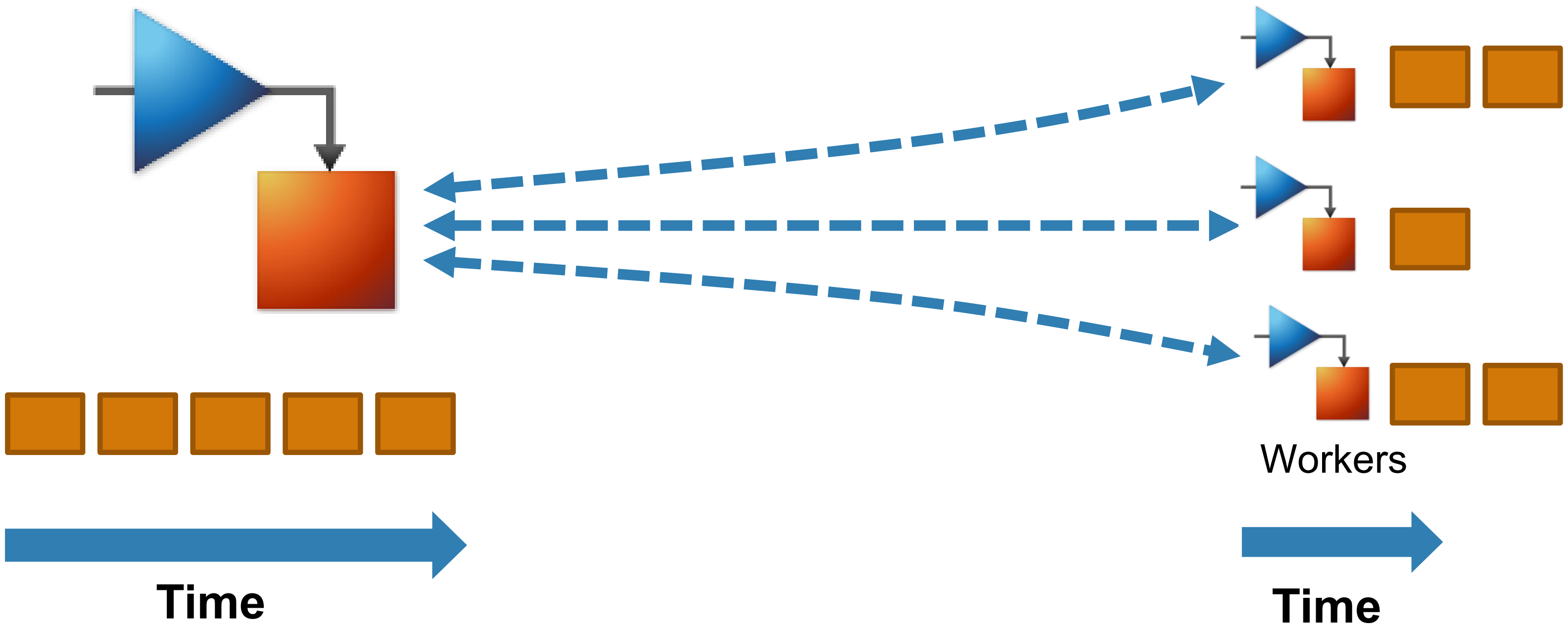

### Simulink/Embedded Coder

Generating and building code




[Additional automatic parallel support]

# Run multiple Simulink simulations in parallel with `parsim`

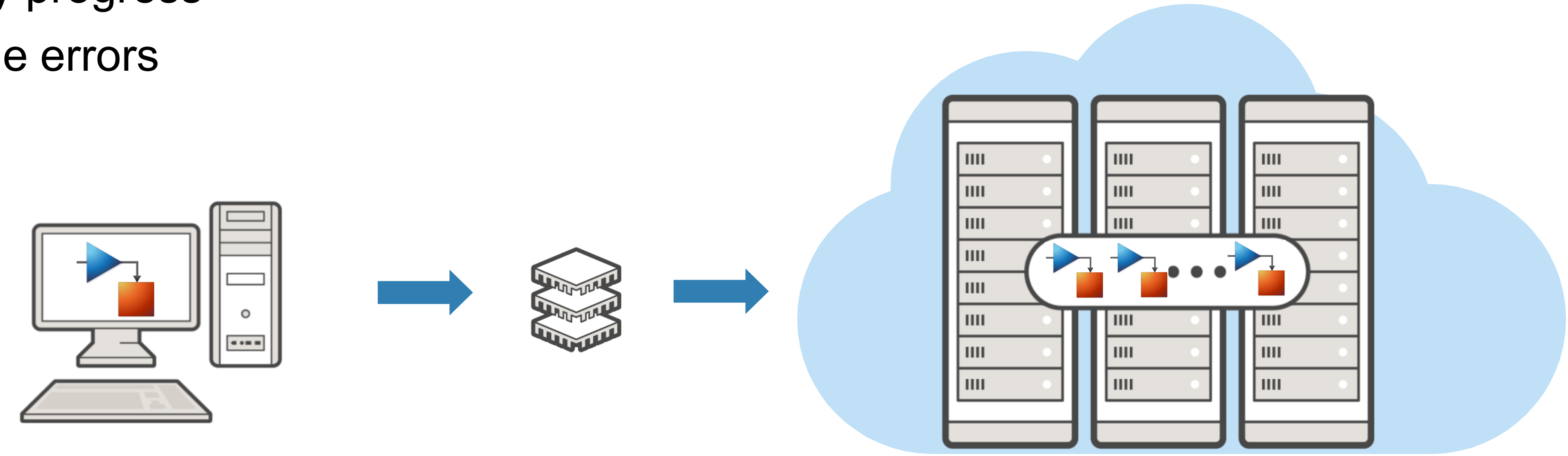



- Run independent Simulink simulations in parallel using the **`parsim`** function

```
for i = 10000:-1:1
    in(i) = Simulink.SimulationInput(my_model);
    in(i) = in(i).setVariable(my_var, i);
end
out = parsim(in);
```

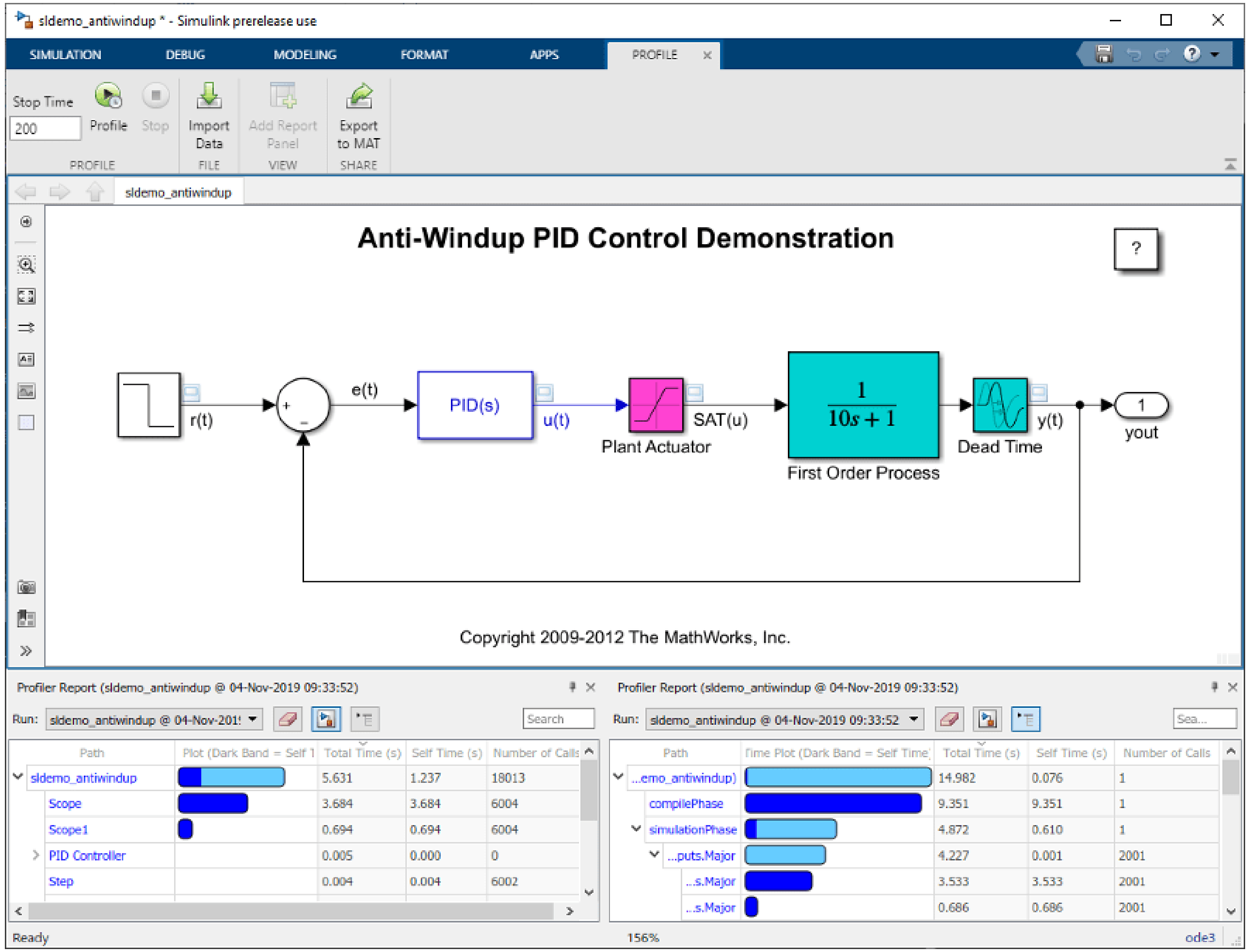
# Benefits of using `parsim`

- Run multiple simulations on your machine or clouds and clusters
- Transfer base workspace variables to workers
- Automatically transfer all files to workers
- Automatically return file logging data
- Automatically manage build folders
- Display progress
- Manage errors



Desktop Multicore Cluster

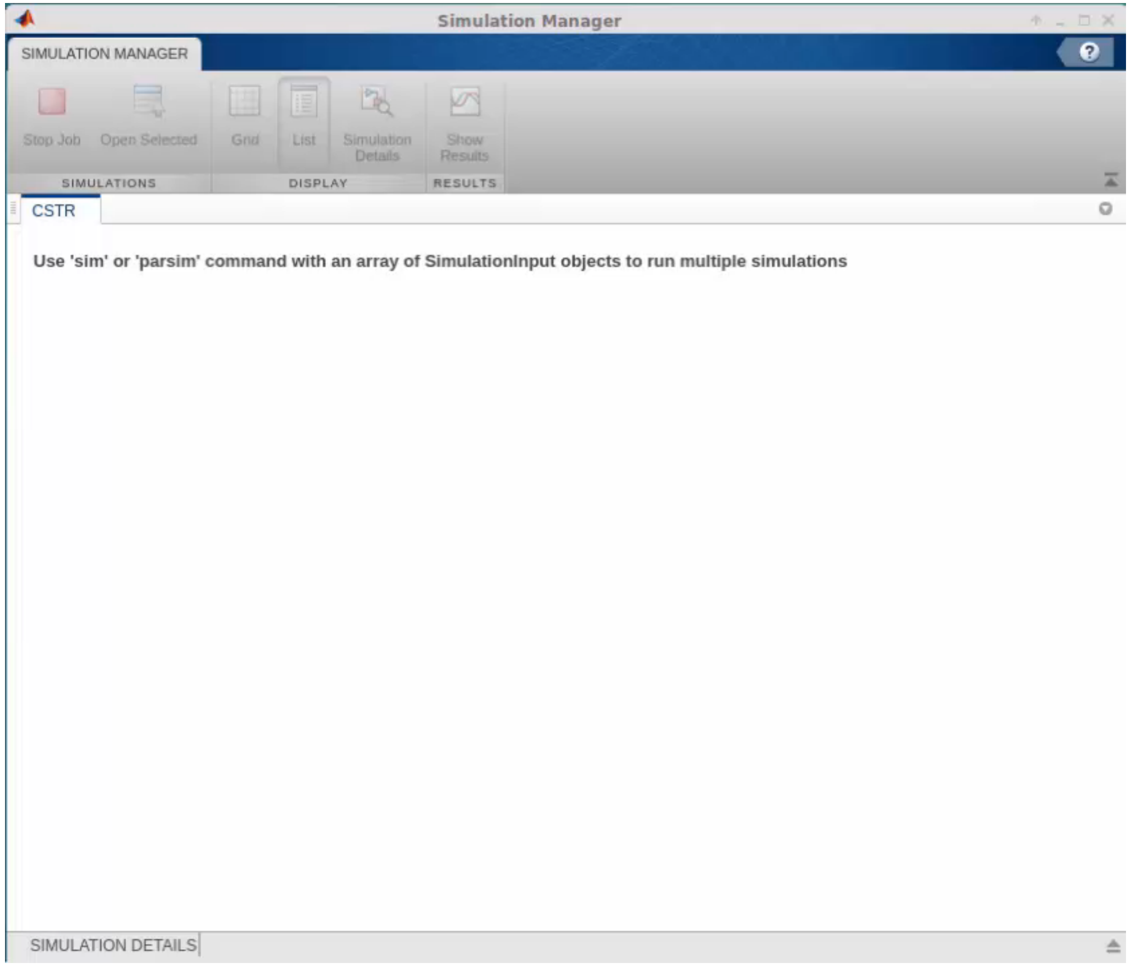
# Profile Simulink performance




How Profiler Captures Performance Data

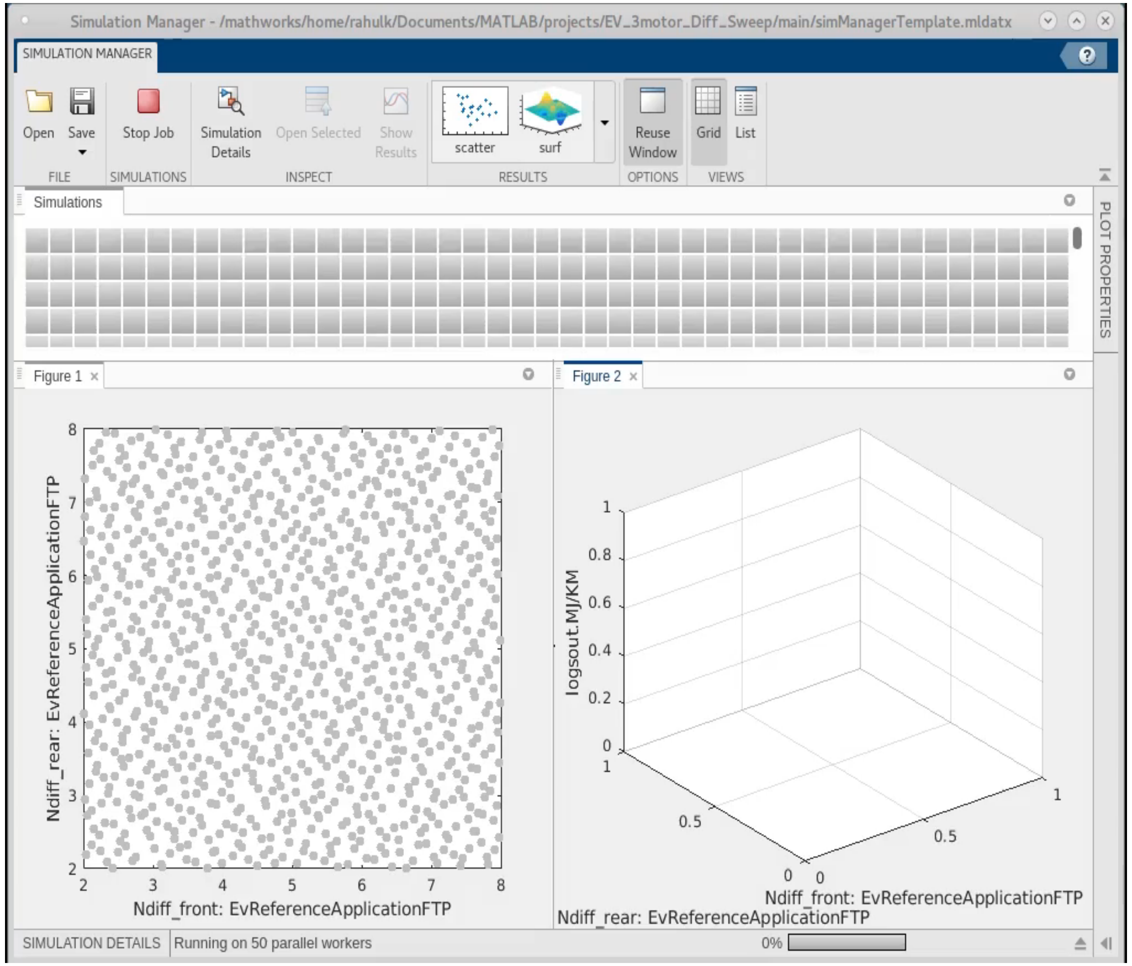
# Monitor multiple simulations at once with Simulation Manager

- View the progress of the simulations
- Examine simulation settings and diagnostics
- View simulation results in the Simulation Data Inspector



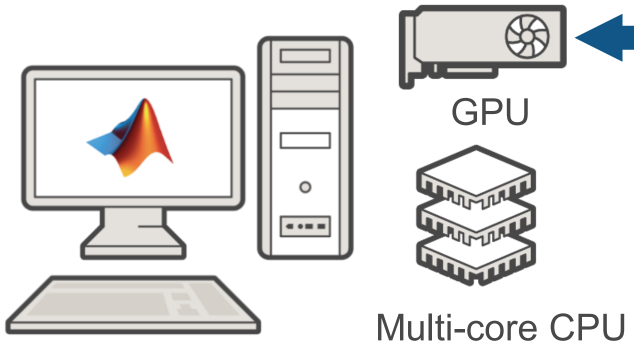
# Simulation Manager can also be used to inspect the variation in outputs with parameters

- Visualize simulation results as the simulations are running

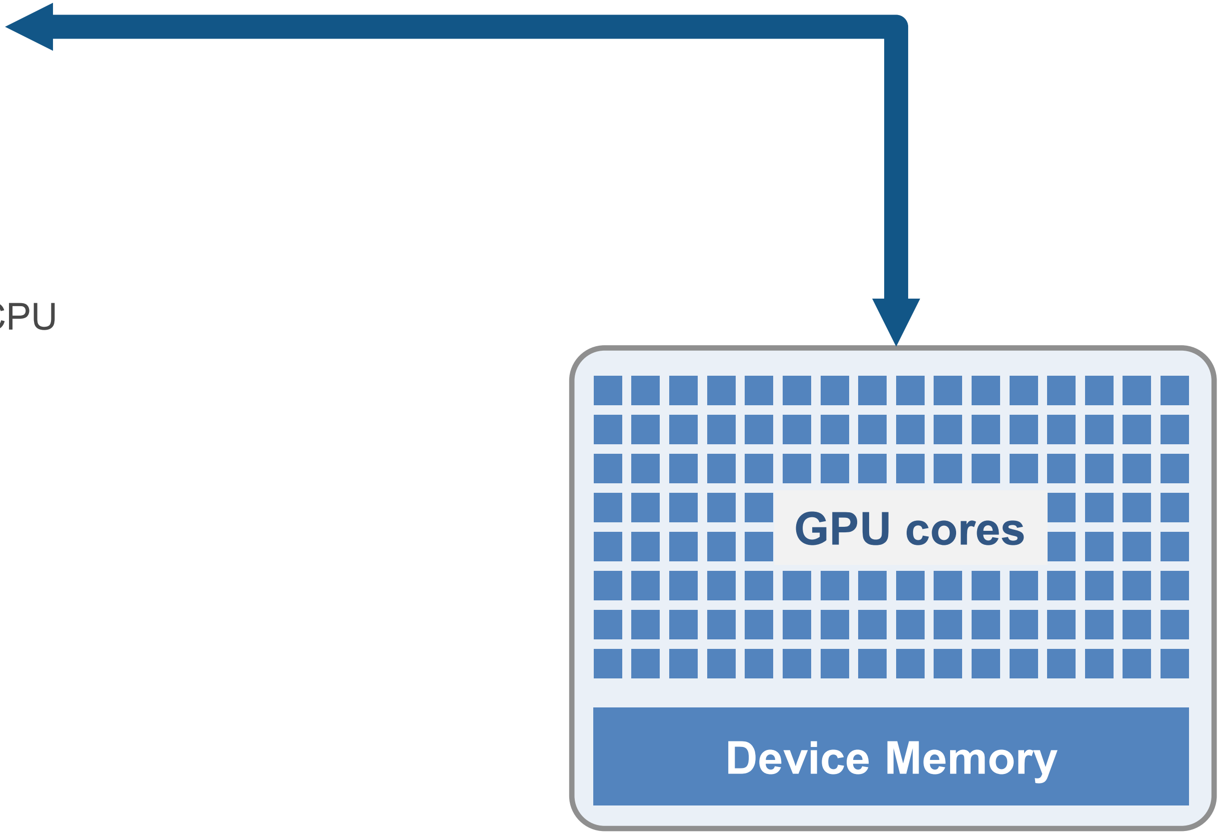


# Accelerate applications with NVIDIA GPUs

# Using NVIDIA GPUs with the Parallel Computing Toolbox




**MATLAB**
**Parallel Computing Toolbox**



# Leverage your GPU to accelerate your MATLAB code

- Ideal Problems
  - massively parallel and/or vectorized operations
  - computationally intensive
- 999+ GPU-supported functions (documentation)
- Use **`gpuArray`** and **`gather`** to transfer data between CPU & GPU

```
A1 = rand(3000,3000);
```

**Transfer data to GPU from computer memory**

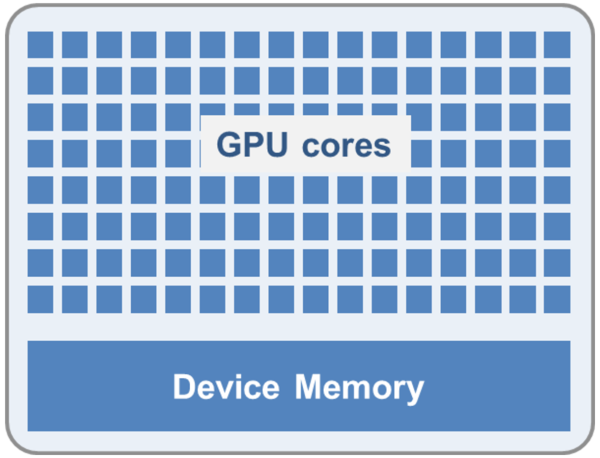
```
A2 = gpuArray(A1);
```

**Perform calculation on GPU**

```
B2 = fft(A2);
```

**Gather data or plot**

```
B2 = gather(B2);
```




MATLAB GPU computing

# How do I know if I have a supported GPU?

- In MATLAB, type:

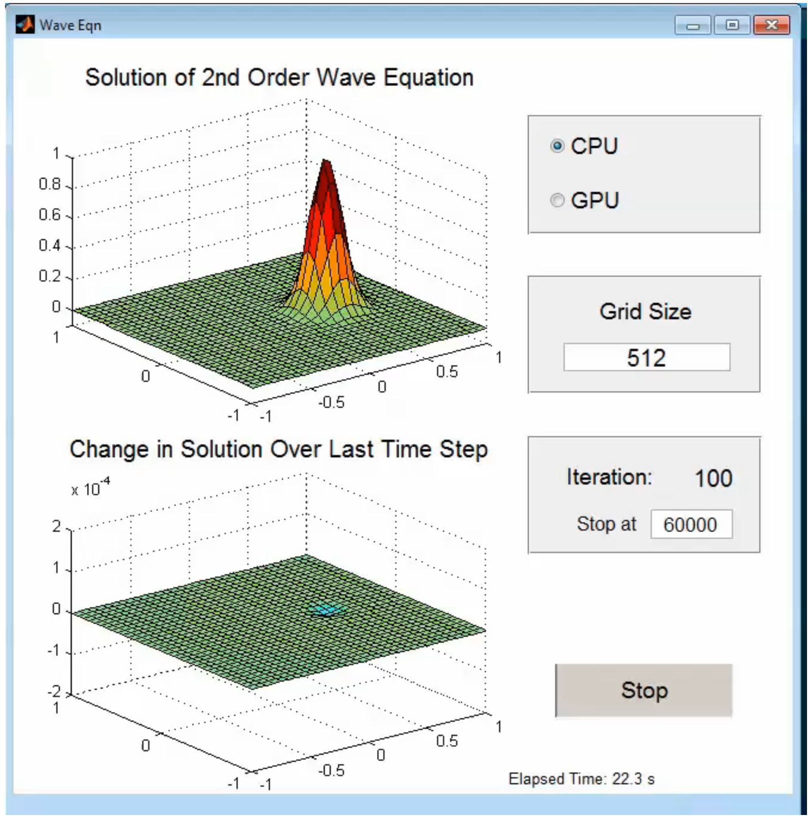
**>> gpuDevice**

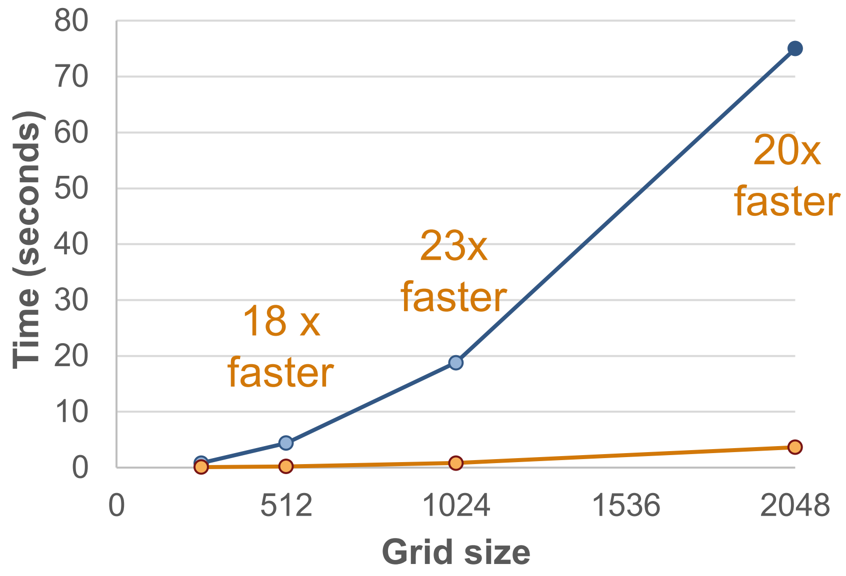
- If you see a CUDA Device, you are good to go.
  - The key number to note is the 'ComputeCapability'
  - See [Support for NVIDIA GPU architecture by MATLAB release]()

```
>> gpuDevice

ans =

  CUDADevice with properties:

                      Name: 'Tesla V100-DGXS-16GB'
                     Index: 1
         ComputeCapability: '7.0'
            SupportsDouble: 1
             DriverVersion: 10
            ToolkitVersion: 10
        MaxThreadsPerBlock: 1024
          MaxShmemPerBlock: 49152
        MaxThreadBlockSize: [1024 1024 64]
               MaxGridSize: [2.1475e+09 65535 65535]
                 SIMDWidth: 32
               TotalMemory: 1.6908e+10
           AvailableMemory: 1.6130e+10
       MultiprocessorCount: 80
              ClockRateKHz: 1530000
               ComputeMode: 'Default'
      GPUOverlapsTransfers: 1
    KernelExecutionTimeout: 1
          CanMapHostMemory: 1
           DeviceSupported: 1
            DeviceSelected: 1

>> gpuDeviceCount

ans =

     4
```

# Run Same Code on CPU and GPU

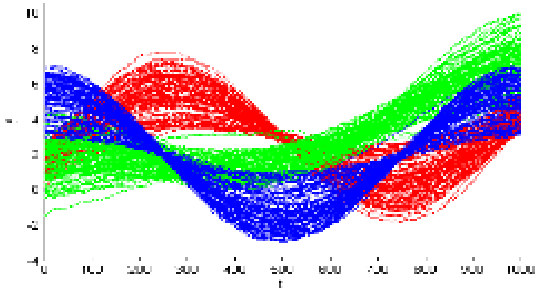
## Demo: Solving 2nd Order Wave Equation



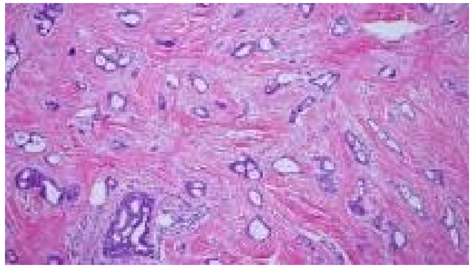




| CPU | GPU |
|---|---|
| Intel(R) Xeon(R)<br>W3550 3.06GHz<br>4 cores<br>memory bandwidth 25.6 Gb/s | NVIDIA Tesla K20c<br>706MHz<br>2496 cores<br>memory bandwith 208 Gb/s |

# Speeding up MATLAB Applications with GPUs

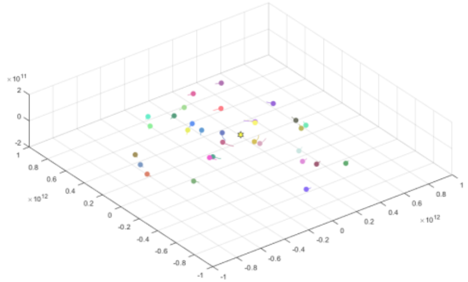


**10x speedup**
*K-means clustering algorithm*

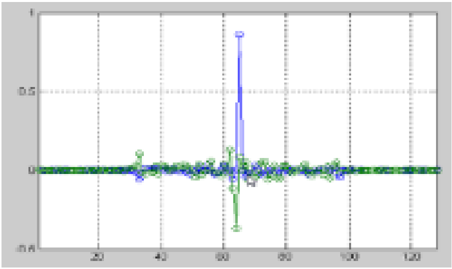


**14x speedup**
*template matching routine*

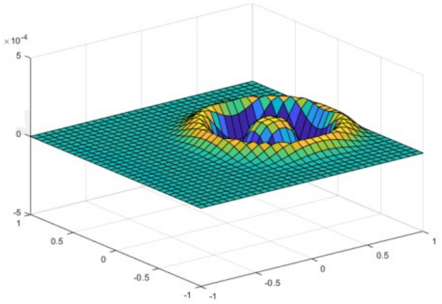
**12x speedup**
*using Black-Scholes model*



**44x speedup**
*simulating the movement of celestial objects*



**4x speedup**
*adaptive filtering routine*

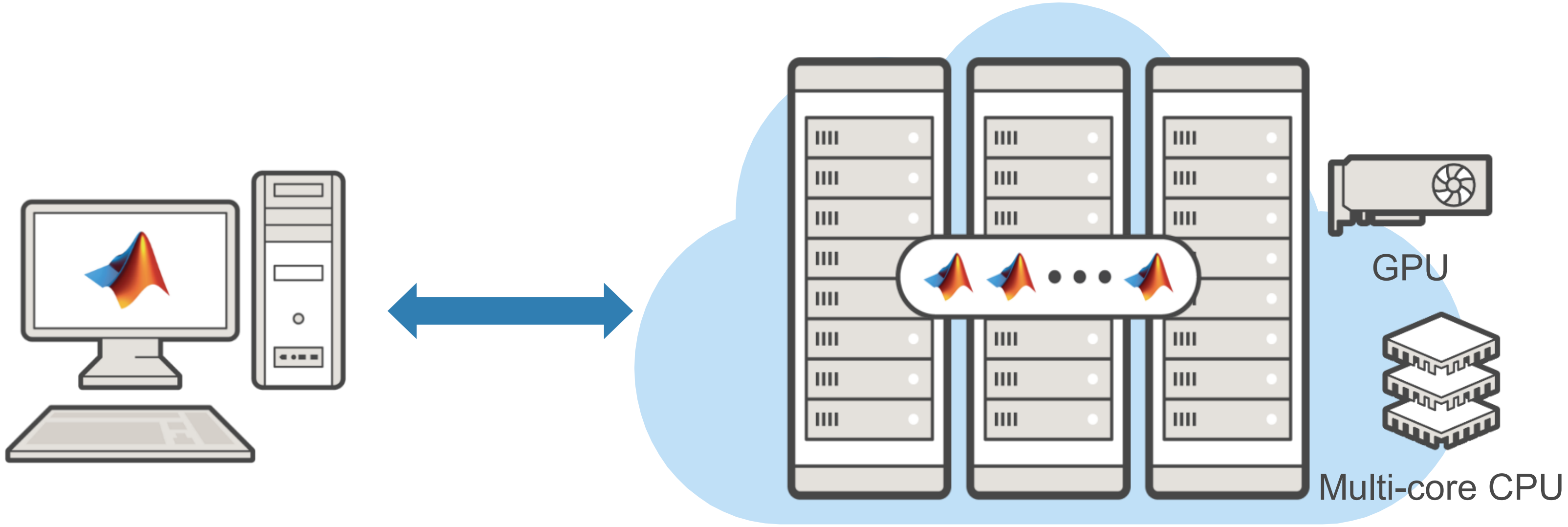


**77x speedup**
*wave equation solving*

*NVIDIA Titan V GPU, Intel® Core™ i7-8700T Processor (12MB Cache, 2.40GHz)*

# Scaling to Cluster with MATLAB Parallel Server (Outlook)

# Parallel computing on your desktop, clusters, and clouds




**MATLAB**
**Parallel Computing Toolbox**

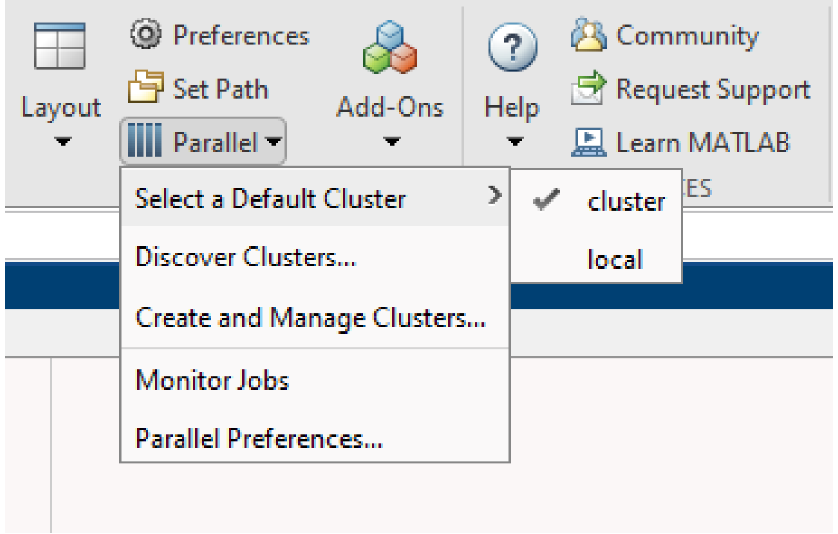
**MATLAB Parallel Server**

- Prototype and develop on the desktop
- Integrate with your infrastructure
- Access directly through MATLAB

# Scale to clusters and clouds

With MATLAB Parallel Server, you can…

- Use more hardware with minimal code change
- Submit to on-premise or cloud clusters
- Support cross-platform submission
  - Windows client to Linux cluster



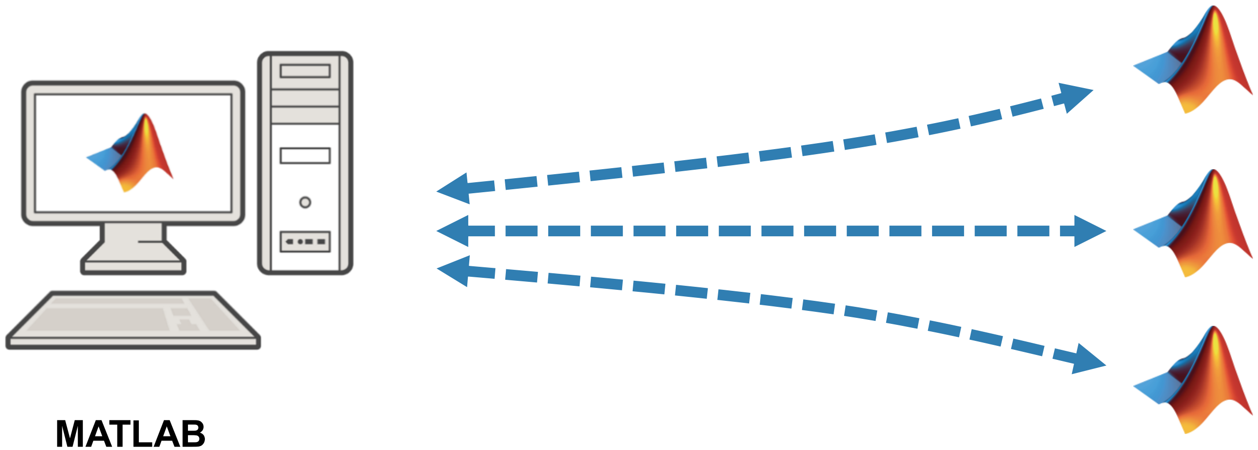
# Interactive parallel computing

## Leverage cluster resources in MATLAB

```
>> parpool(myCluster,3)
>> myScript
```

myScript.m:

```
a = zeros(5, 1);
b = pi;
parfor i = 1:5
   a(i) = i + b;
end
```



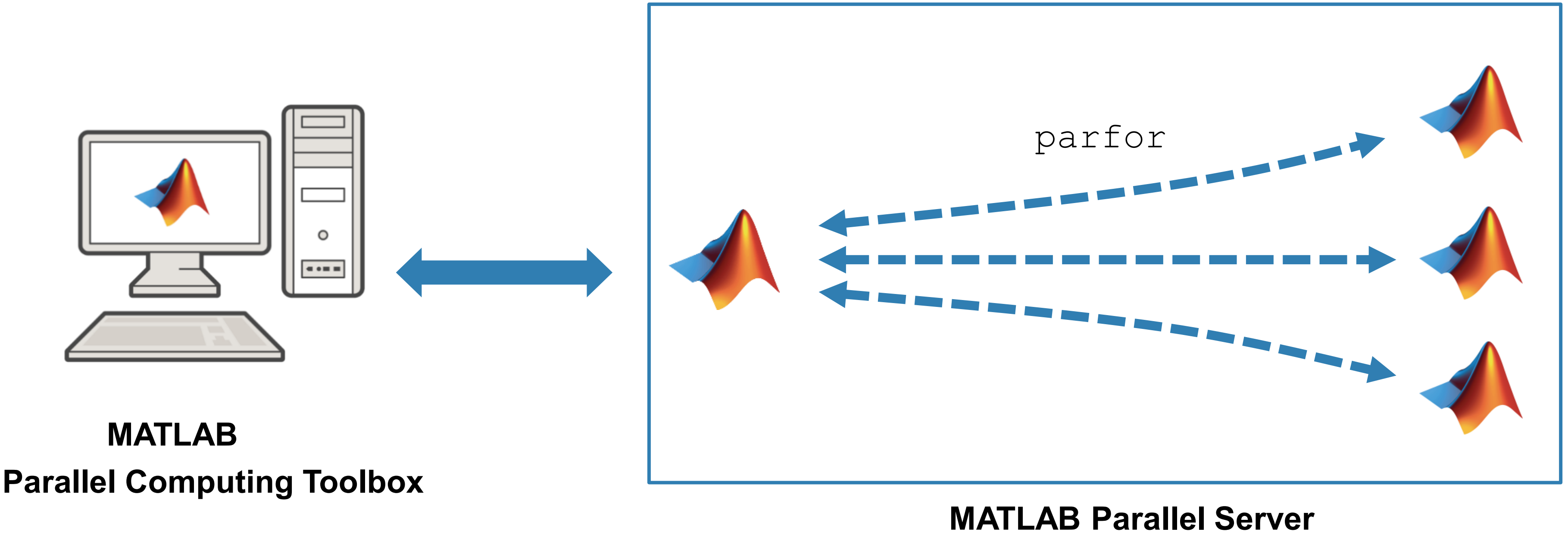
**MATLAB**
**Parallel Computing Toolbox**

**MATLAB Parallel Server**

# `batch` simplifies offloading computations

## Submit MATLAB jobs to the cluster

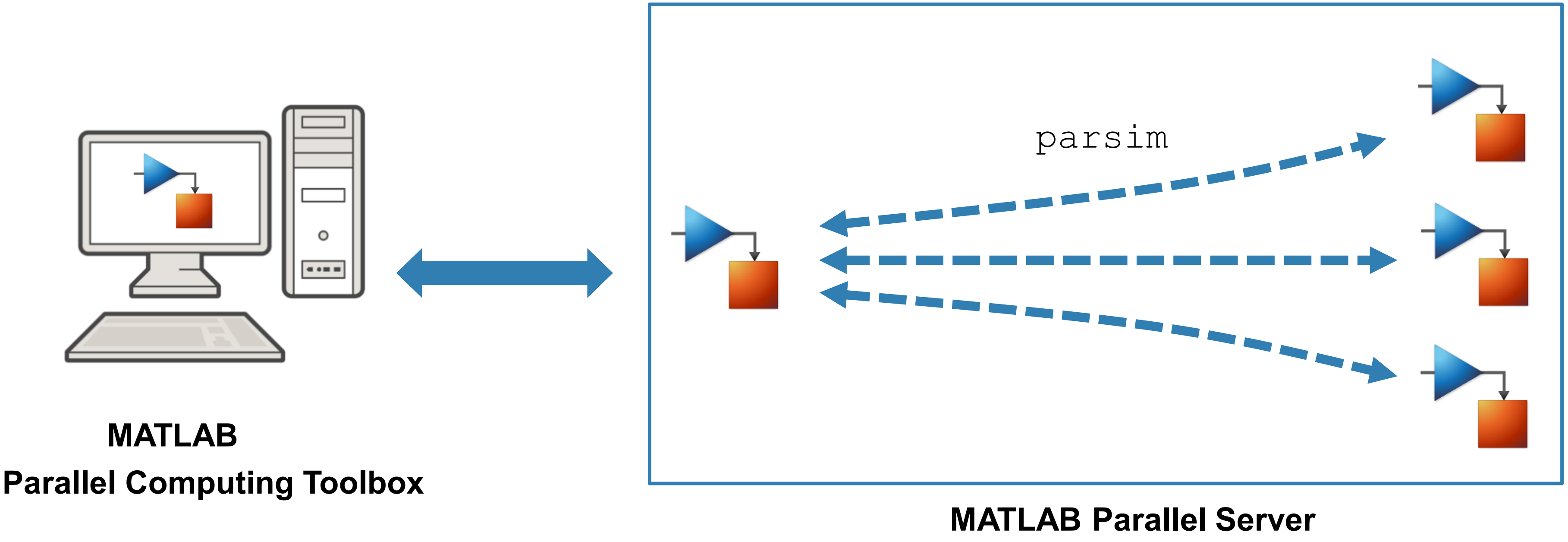
```
>> job = batch(myCluster,'myScript','Pool',3)
```



# `batch` simplifies offloading simulations

## Submit Simulink jobs to the cluster

```
>> job = batchsim(myCluster,in,'Pool',3)
```



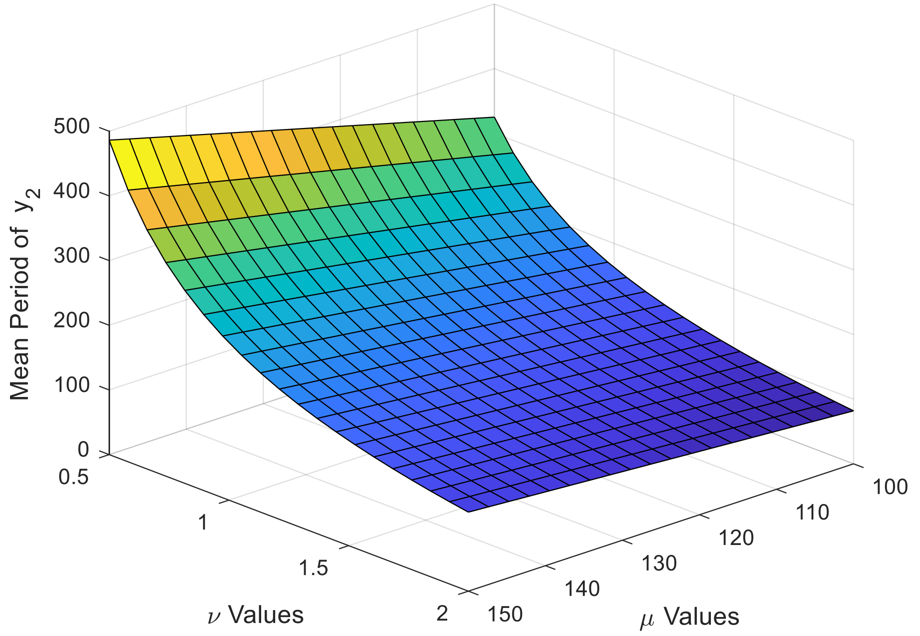
# Speed up a parameter sweep using `parfor` on a cluster with MATLAB Parallel Server

## Demo: Parameter sweep for van der Pol oscillator

- System of ODEs

$$\dot{y}_1 = \nu y_2$$
$$\dot{y}_2 = \mu(1 - y_1^2)y_2 - y_1$$

- Compute mean period of $y$
- Use **`parfor`**, study impact of $\nu, \mu$



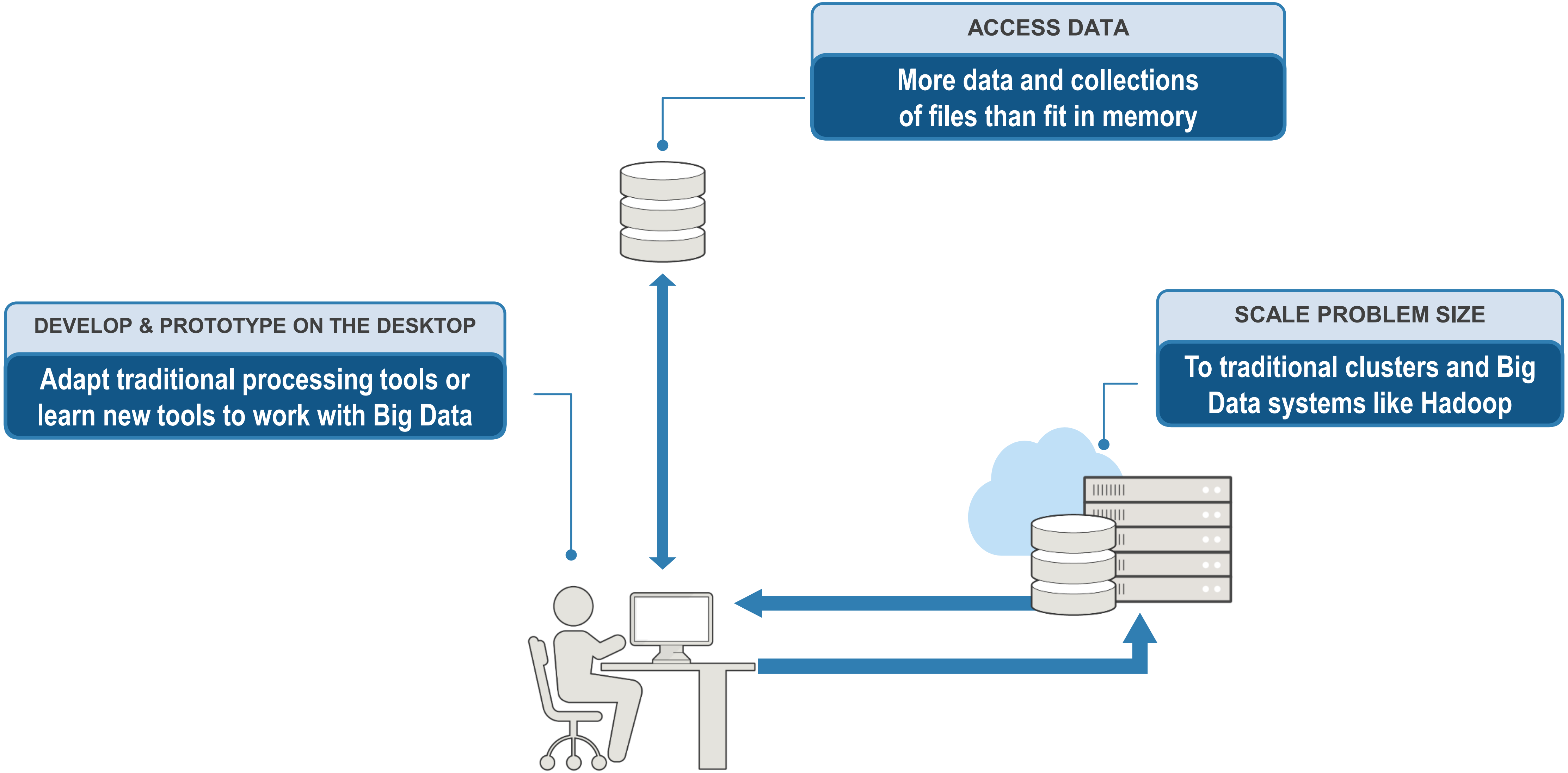
# Working with Big Data
# (Optional)

# Big Data capabilities in MATLAB

Wouldn’t it be nice if we could:

- Easily access data however it is stored?
- Prototype algorithms quickly using small data sets?
- And then scale up to big data sets running on large clusters?
- **All using the same intuitive MATLAB syntax we are used to?**

# Big data workflow



# Access data with `datastore`

- **For:**
  – Handling collections of files or large files
- **Provides:**
  – Preview and configure I/O properties
  – Read data into memory *(all at once, or incrementally)*
  – Transform data one file at a time for data engineering workflows
  – Combine with tall arrays to analyze the entire out-of-memory dataset with few code changes

```
ds = datastore("data_flat\*.csv")

                    Files: {
                           'C:\Marketing\WhatsNew\datastores\data_f
                           'C:\Marketing\WhatsNew\datastores\data_f
                           'C:\Marketing\WhatsNew\datastores\data_f
                            ... and 86 more
                           }
             FileEncoding: 'UTF-8'
 AlternateFileSystemRoots: {}
    PreserveVariableNames: false
        ReadVariableNames: true
            VariableNames: {'TimeStamp', 'TimeZone', 'Name' ... and
           DatetimeLocale: en_US

 Text Format Properties:
           NumHeaderLines: 0
                Delimiter: ','
             RowDelimiter: '\r\n'
           TreatAsMissing: ''
             MissingValue: NaN

 Advanced Text Format Properties:
          TextscanFormats: {'%{MM/dd/uuuu HH:mm:ss}D', '%q', '%q'
```

# Use datastores for reading collections of files into memory

**Access**


`*datastore`

*** = ACCESS FROM**
*(file, source)*
*Choose data types*

```
tabularTextDatastore
spreadsheetDatastore
fileDatastore
…
```

**Explore and Discover**

```
readall(ds)
```

`*write`

*** = TO**
*(file, source)*

`write*`

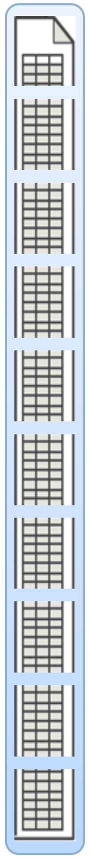
*** = OUT OF**
*(data type, format)*

**Share**


[Select Datastore for File Format or Application](#)

# `tall` arrays

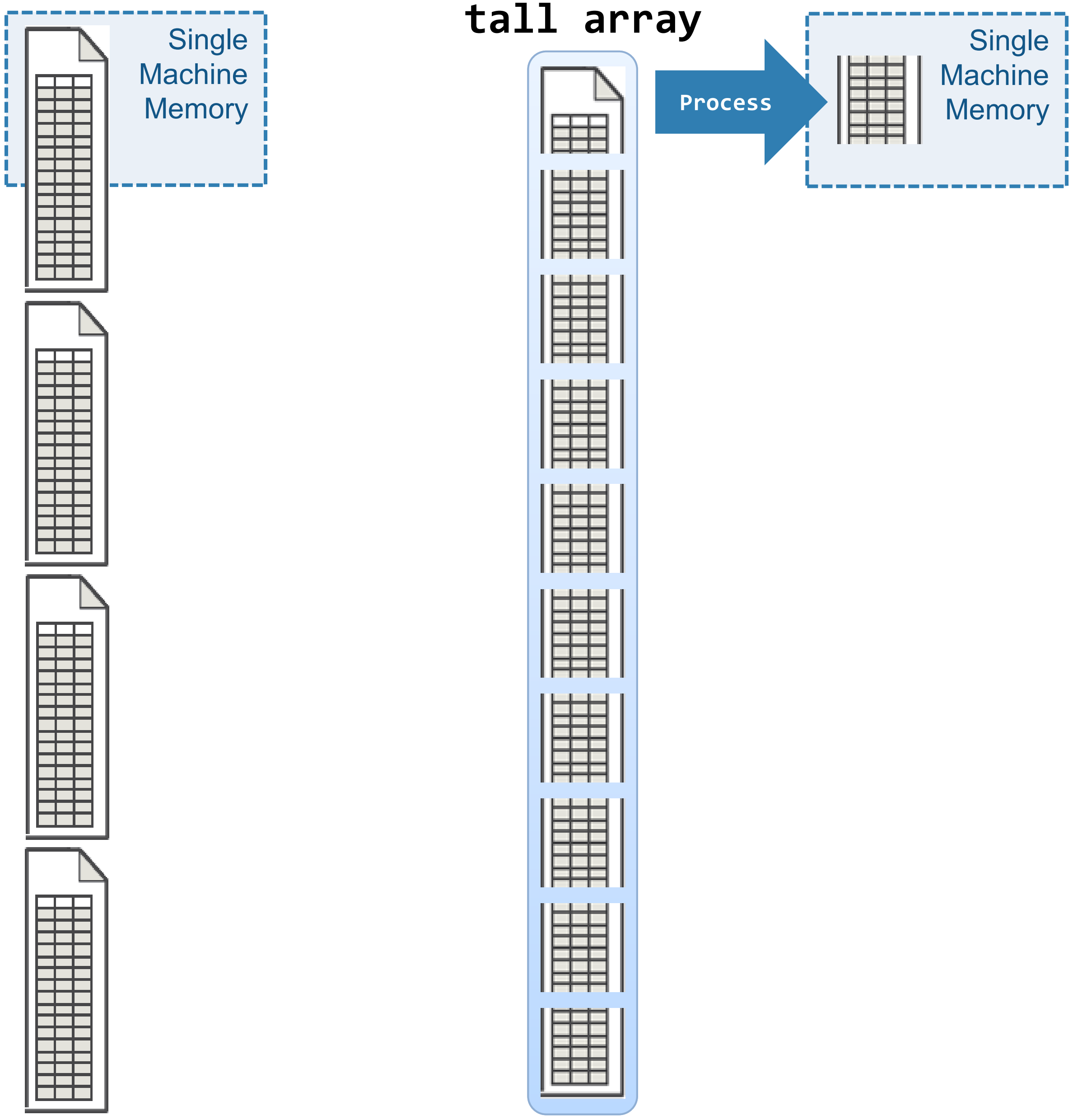
- Data type designed for data that doesn’t fit into memory
- Lots of observations (hence “tall”)
- Looks like a normal MATLAB array
  - Supports numeric types, tables, datetimes, strings, etc.
  - Supports several hundred functions for basic math, stats, indexing, etc.
  - Statistics and Machine Learning Toolbox support (clustering, classification, etc.)



[Working with tall arrays]

# `tall` arrays

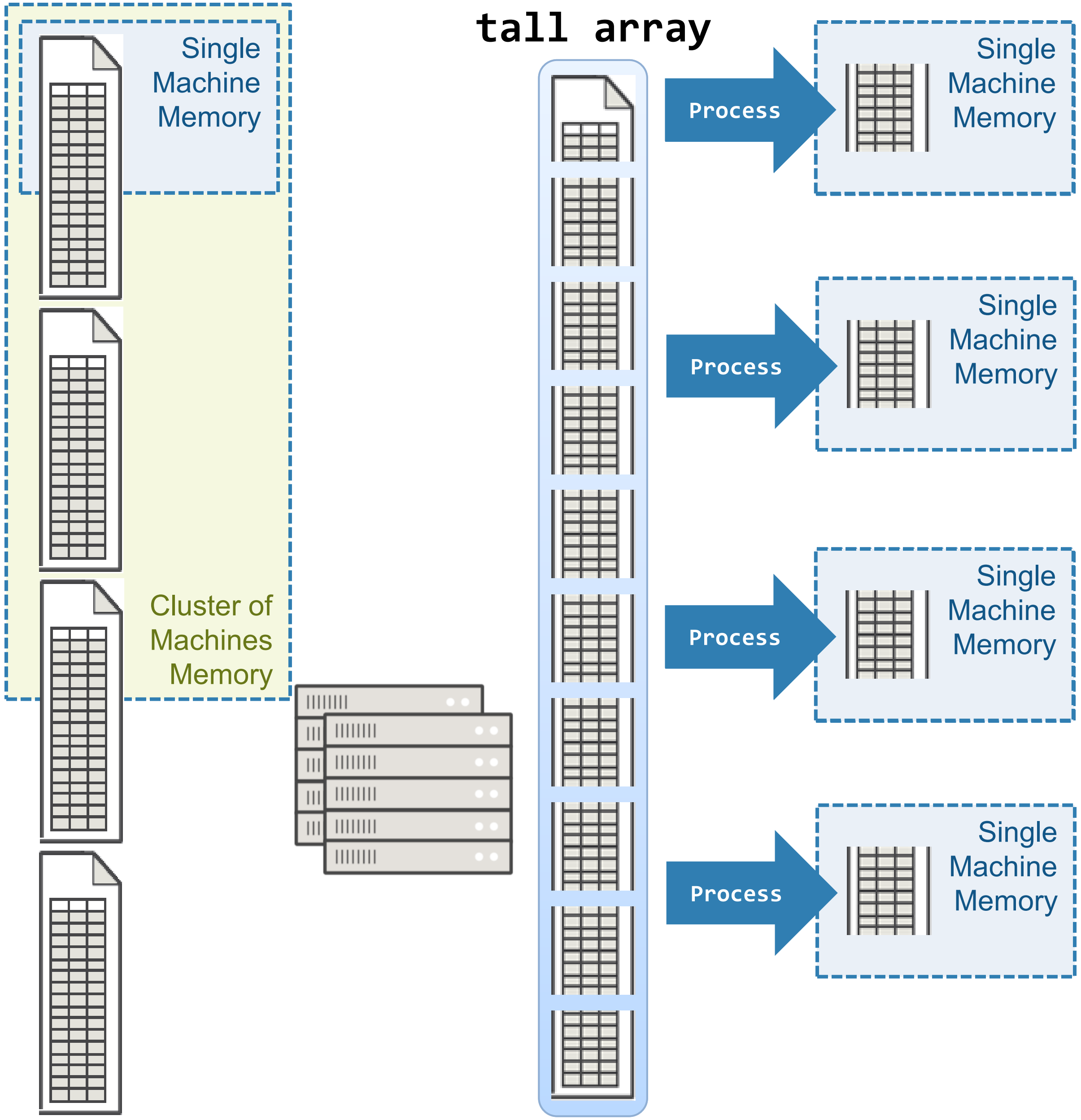
- Automatically breaks data up into small "chunks" that fit in memory
- Tall arrays scan through the dataset one "chunk" at a time
- Processing code for tall arrays is the same as ordinary arrays



# `tall` arrays

- With Parallel Computing Toolbox, process several “chunks” at once

- Can scale up to clusters with MATLAB Parallel Server



# Big Data Without Big Changes

## One file

### Access Data

```
measured = readtable('PumpData.csv');
measured = table2timetable(measured);
```

### Preprocess Data

**Select data of interest**

```
measured = measured(timerange(seconds(1),seconds(2)),'Speed')
```

**Work with missing data**

```
measured = fillmissing(measured,'linear');
```

**Calculate statistics**

```
m = mean(measured.Speed);
s = std(measured.Speed);
```

## One hundred files

### Access Data

```
measured = datastore('PumpData*.csv');
measured = tall(measured);
measured = table2timetable(measured);
```

### Preprocess Data

**Select data of interest**

```
measured = measured(timerange(seconds(1),seconds(2)),'Speed')
```

**Work with missing data**

```
measured = fillmissing(measured,'linear');
```

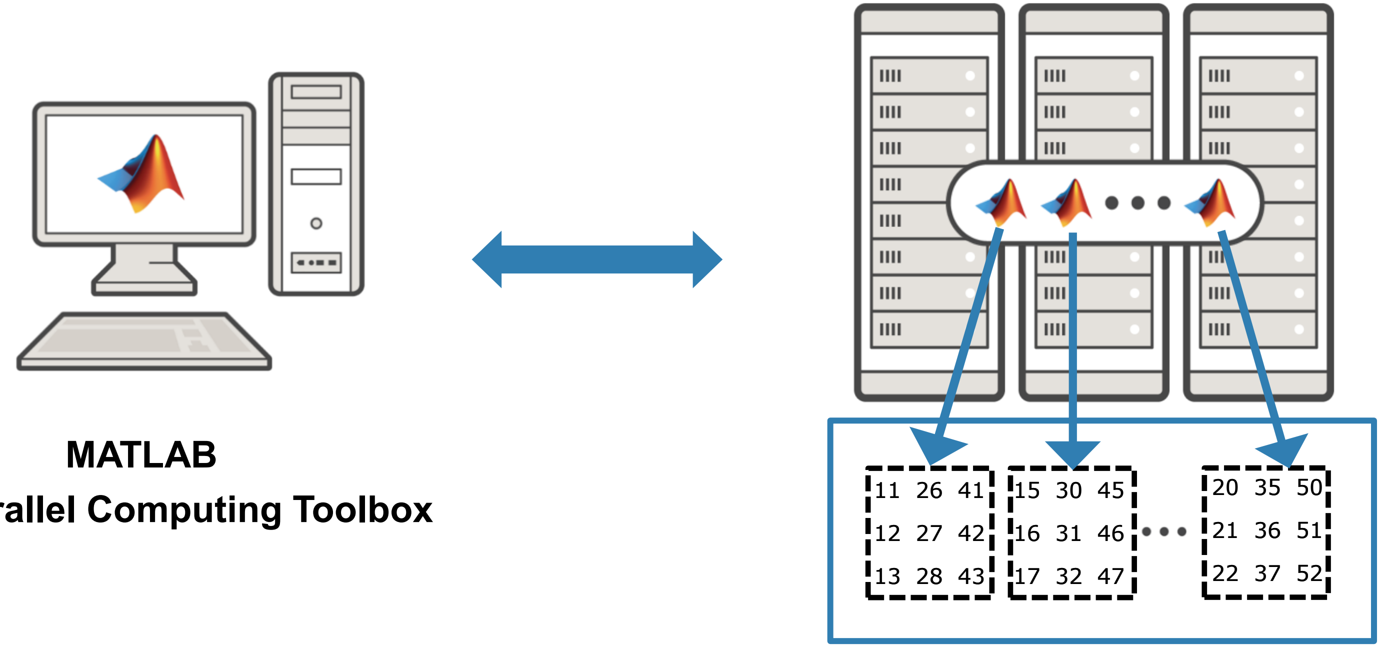
**Calculate statistics**

```
m = mean(measured.Speed);
s = std(measured.Speed);
```

```
[m,s] = gather(m,s);
```

# distributed arrays

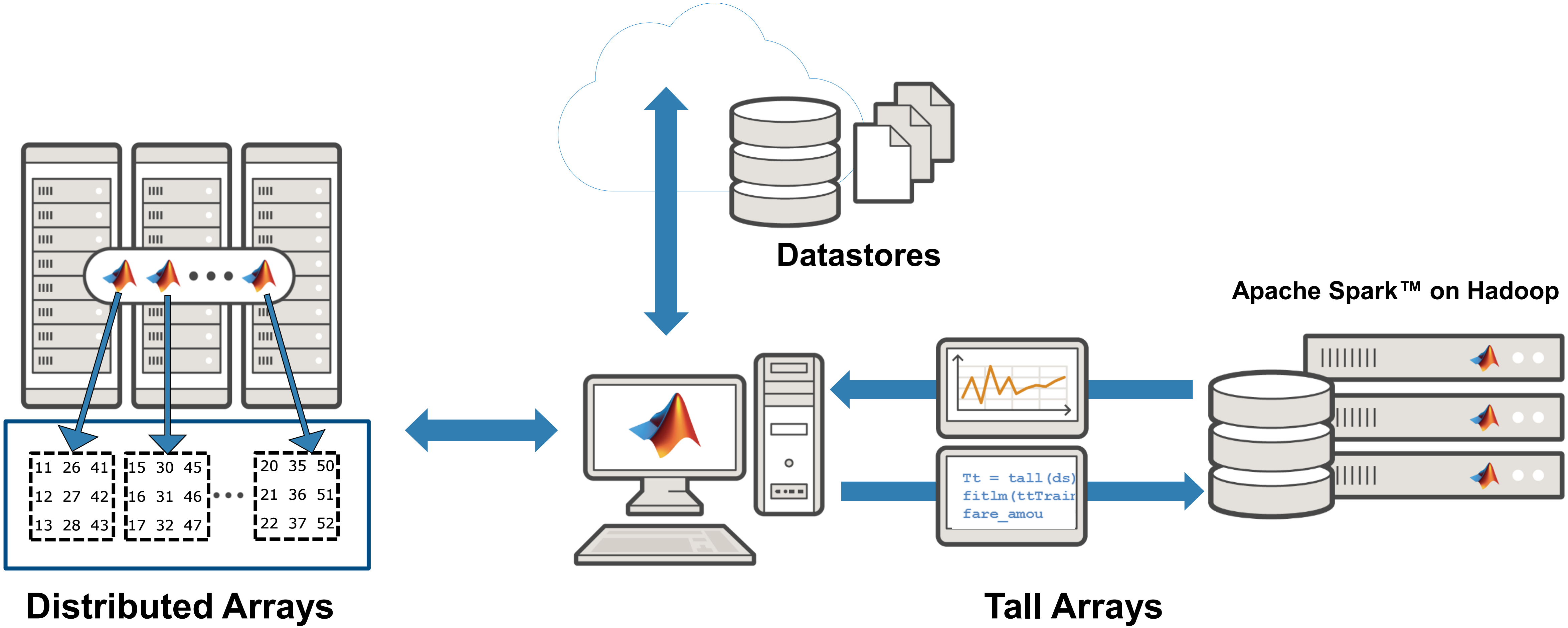
- Keep large datasets in-memory, split among workers running on a cluster
- Common Actions: Matrix Manipulation & Linear Algebra and Signal Processing
- Several hundred MATLAB functions overloaded for distributed arrays




**MATLAB**
**Parallel Computing Toolbox**

**MATLAB Parallel Server**

# Big Data Capabilities in MATLAB with Parallel Computing

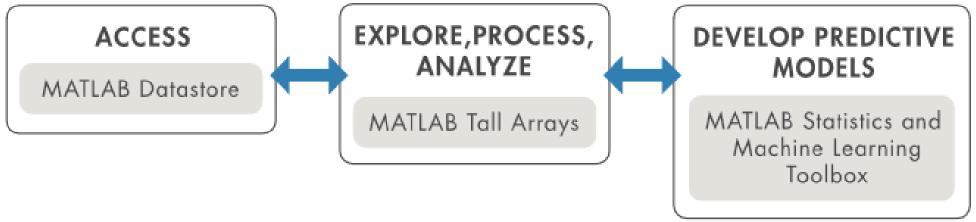


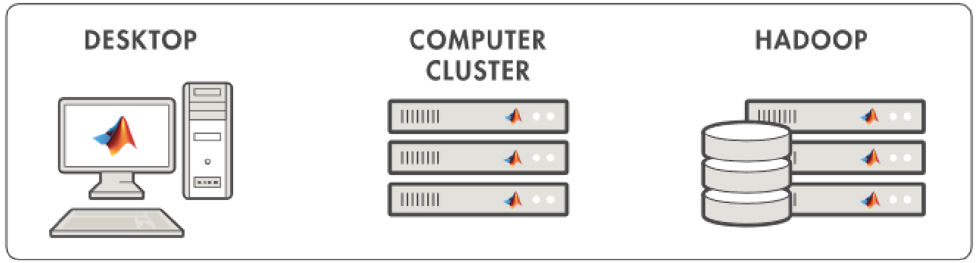
# Summary – Working with Big Data in MATLAB

- Use **`datastores`** to manage data processing from large collections of files.
- Use **`Tall Arrays`** to process files too big to fit in memory.
- Use **`Distributed Arrays`** and **`GPU Arrays`** to parallelize problems for solving on multiple workers at once.
- Use **`Parallel Computing Toolbox`** (on Desktop) or **`MATLAB Parallel Server`** (on clusters) to scale-up solutions.

# Learn More on Big Data

- Strategies for Efficient Use of Memory
- Resolving "Out of Memory" Errors
- Big Data with MATLAB
- MATLAB Tall Arrays in Action



# Summary

# Run MATLAB on Multicore Machines

- Built-in multithreading (implicit)
  - Automatically enabled in MATLAB
  - Multiple computational threads in a single MATLAB session
  - Functions such as `fft`, `eig`, `svd`, and `sort` are multithreaded in MATLAB
  - Additionally, many image processing functions are multithreaded

- Parallel computing using explicit techniques
  - Multiple computation engines (workers) controlled by a single session
  - High-level constructs to let you parallelize MATLAB applications
  - Perform MATLAB computations on GPUs
  - Scale parallel applications beyond a single machine to clusters and clouds

# Scaling MATLAB applications and Simulink simulations

Ease of Use

**Automatic parallel support in toolboxes**

(…,`'UseParallel',true`)

Common programming constructs

Advanced programming constructs

Greater Control

# Scaling MATLAB applications and Simulink simulations

Ease of Use

Automatic parallel support in toolboxes

**Common programming constructs**
(`parfor, parfeval, parsim, …`)

Advanced programming constructs

Greater Control

# Scaling MATLAB applications and Simulink simulations

Ease of Use

Automatic parallel support in toolboxes

Common programming constructs

**Advanced programming constructs**

(`spmd`, `parfevalOnAll`, …)

Greater Control

# Summary

- Use **`Parallel Computing Toolbox`** on the Desktop to speed up your computationally intensive applications using multiple CPU cores or GPUs.
- Scale up to Clusters or Cloud using **`MATLAB Parallel Server`**
- Use Big Data capabilities such as Tall and Distributed Arrays, Datastores to further scale up solutions.


**Steve Schäfer**
*MathWorks Academia Group*
steves@mathworks.com