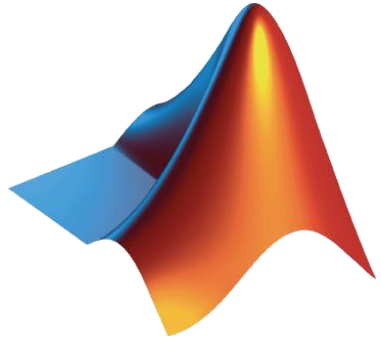
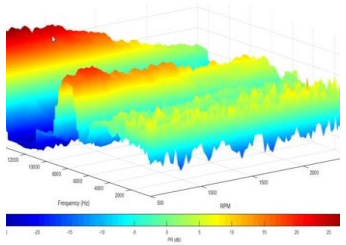
Parallel Computing Hands-On Workshop



Why parallel computing?

- Save time and tackle increasingly complex problems
  - Reduce computation time by using available compute cores and GPUs
- Why parallel computing with MATLAB and Simulink?
  - Accelerate workflows with minimal to no code changes to your original code
  - Scale computations to clusters and clouds
  - Focus on your engineering and research, not the computation

Benefits of Parallel Computing



Automotive Test Analysis
Validation time sped up 2X
Development time reduced 4 months

Discrete-Event Model of Fleet Performance
Simulation time sped up 20X
Simulation time reduced from months to hours

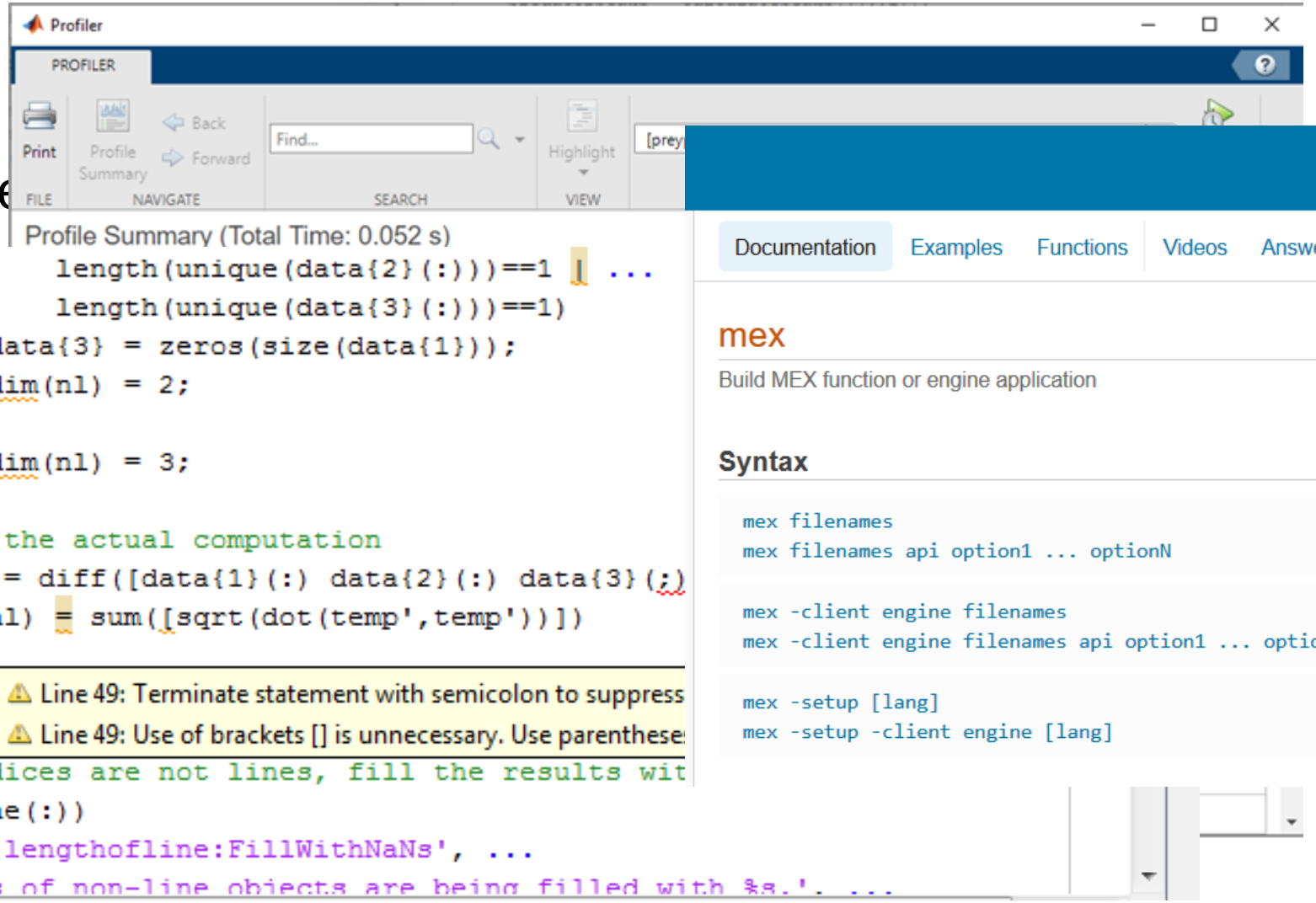
Heart Transplant Study
Process time sped up 6X
4-week process reduced to 5 days

Calculating Derived Market Data
Updates sped up 8X
Updates reduced from weeks to days

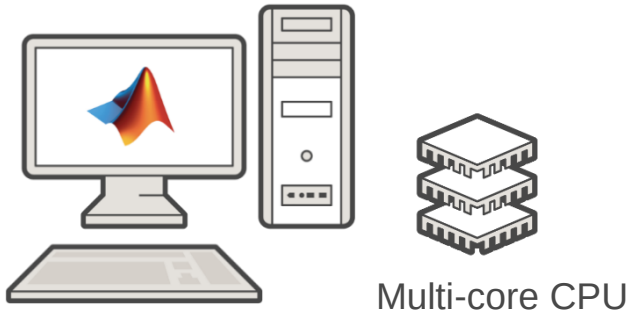
User stories

Optimizing before parallelizing

1. Find bottlenecks
2. Implement effective
3. (Ad



Multicore computing options for MATLAB



Multi-core CPU

MATLAB

MathWorks

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

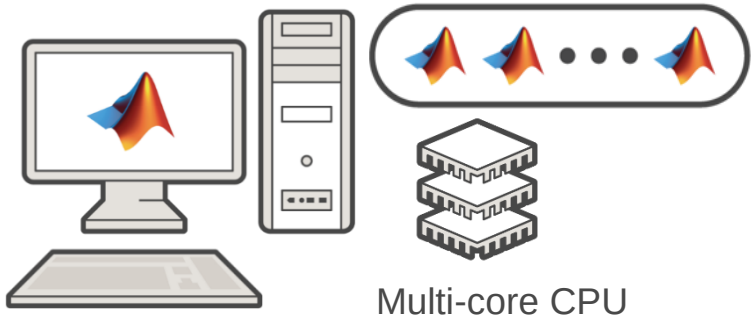
Linear algebra and numerical functions such as `fft`, `\` (`mldivide`), `eig`, `svd`, and `sort` are multithreaded in MATLAB. Multithreaded computations have been on by default in MATLAB since Release 2008a. These functions automatically execute on multiple computational threads in a single MATLAB session, 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

Multicore computing options for MATLAB



MATLAB

Parallel Computing Toolbox

MathWorks

MATLAB Multicore

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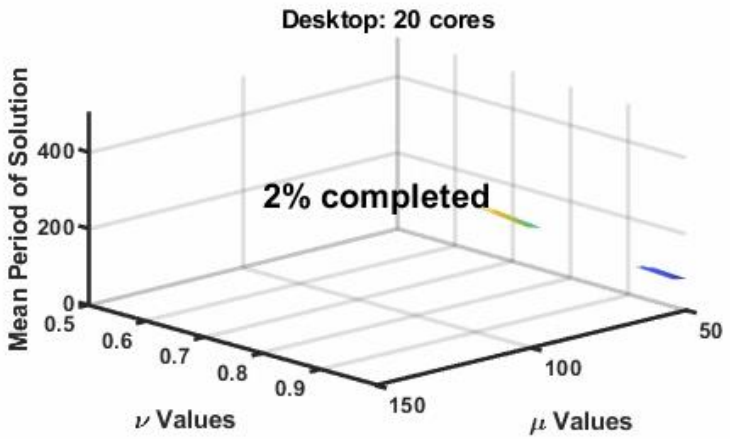
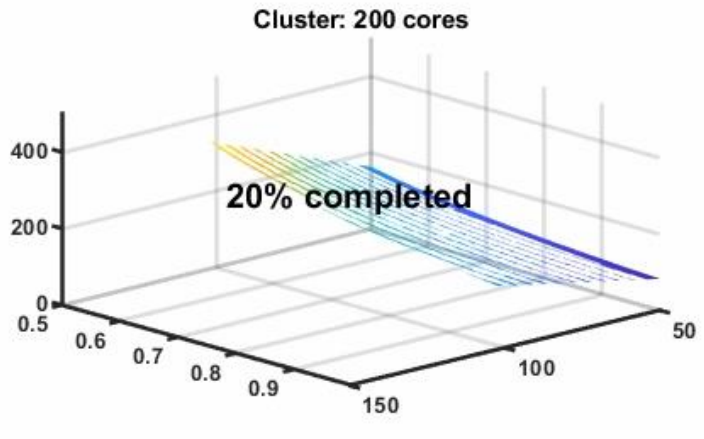
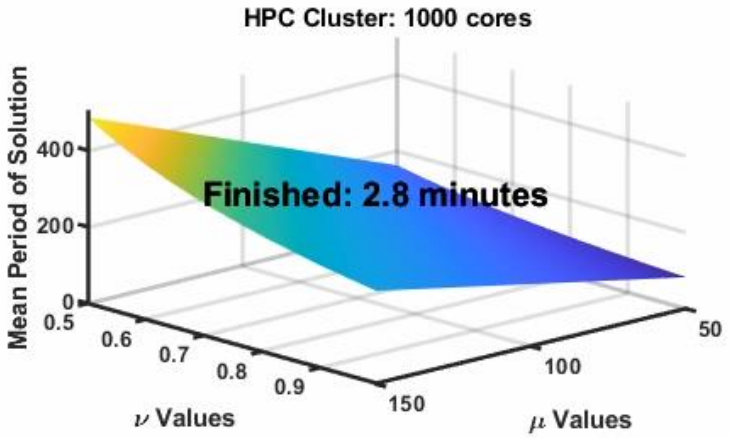
MATLAB multicore

Compute 40,000 iterations

van der Pol Equation study with `parfor`



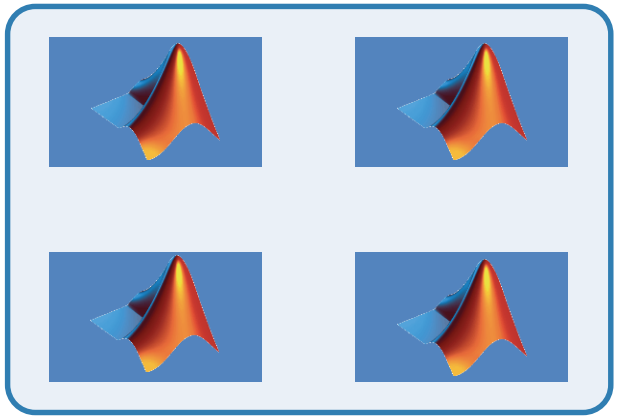




Agenda

- Utilizing multiple cores on a desktop computer
- Accelerating applications with NVIDIA GPUs
- Scaling up to cluster and cloud resources
- Tackling data-intensive problems on desktops and clusters
- Summary and resources

Utilizing multiple CPU cores



MATLAB
Parallel Computing Toolbox

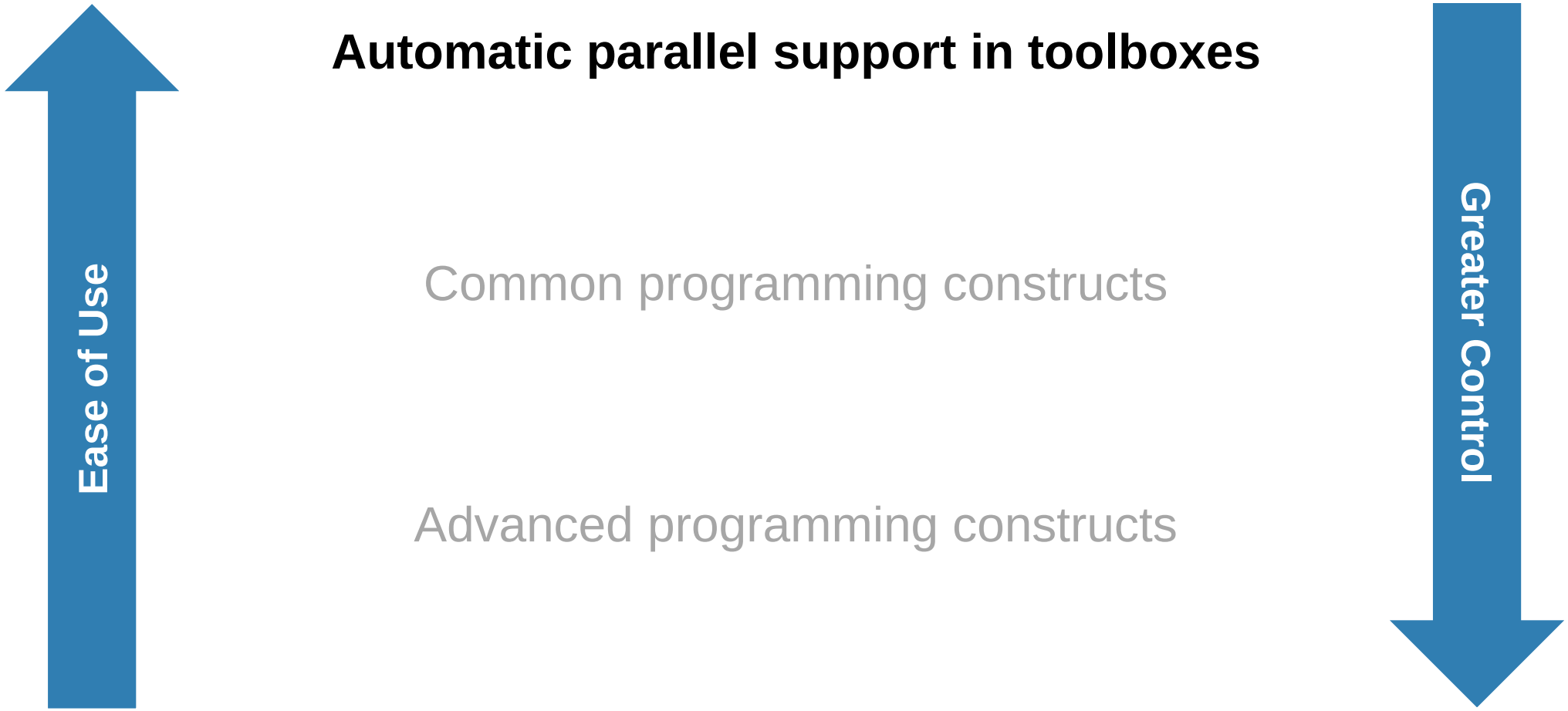
Workers

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

Show fewer details

Parallel pool on local has been running for about 1 min (since 14:12) and will shut down if still idle in 29 minutes. (Reset to 30 minutes) (Shut down now)
Number of workers: 4

Scaling MATLAB applications and Simulink simulations



Automatic parallel support *(MATLAB)*

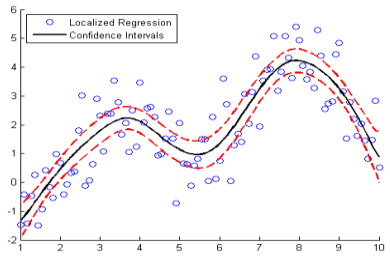
Enable parallel computing support by setting a flag or preference

Image Processing

Batch Image Processor, Block Processing, GPU-enabled functions

Statistics and Machine Learning

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

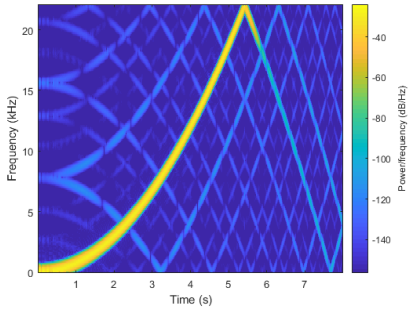


Deep Learning

Deep Learning, Neural Network training and simulation

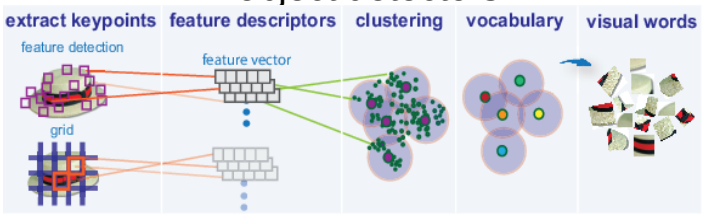
Signal Processing and Communications

GPU-enabled FFT filtering, cross correlation, BER simulations



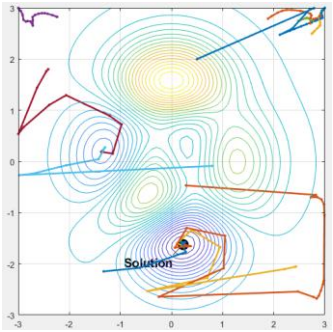
Computer Vision

Bag-of-words workflow, object detectors



Optimization and Global Optimization

Estimation of gradients, parallel search



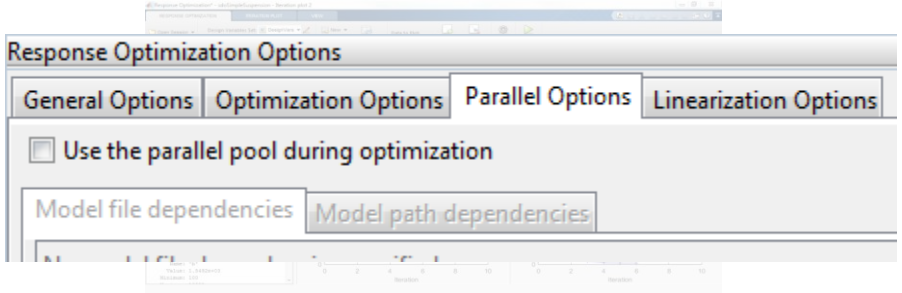
[Other automatic parallel supported toolboxes]

Automatic parallel support *(Simulink)*

Enable parallel computing support by setting a flag or preference

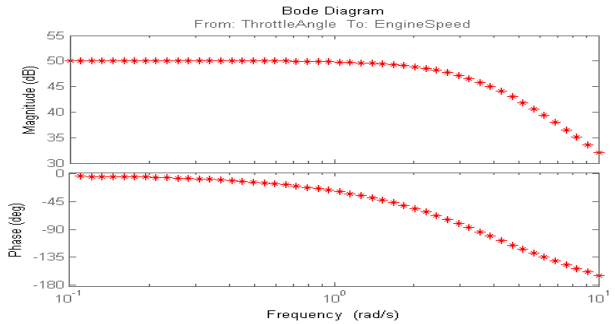
Simulink Design Optimization

Response optimization, sensitivity analysis, parameter estimation



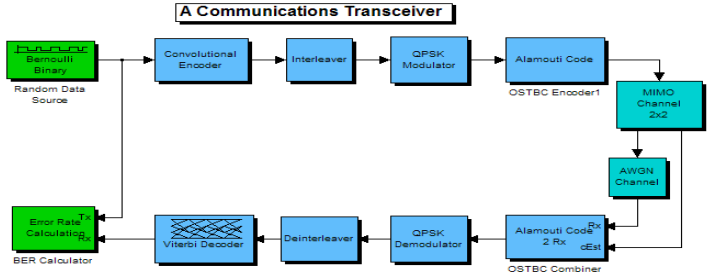
Simulink Control Design

Frequency response estimation



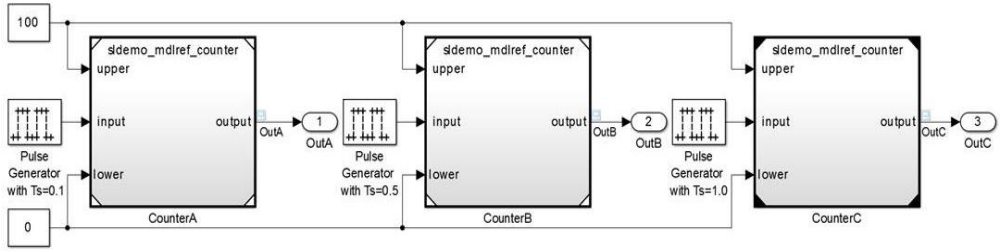
Communication Systems Toolbox

GPU-based System objects for Simulation Acceleration



Simulink/Embedded Coder

Generating and building code



[Other automatic parallel supported toolboxes]

Scaling MATLAB applications and Simulink simulations

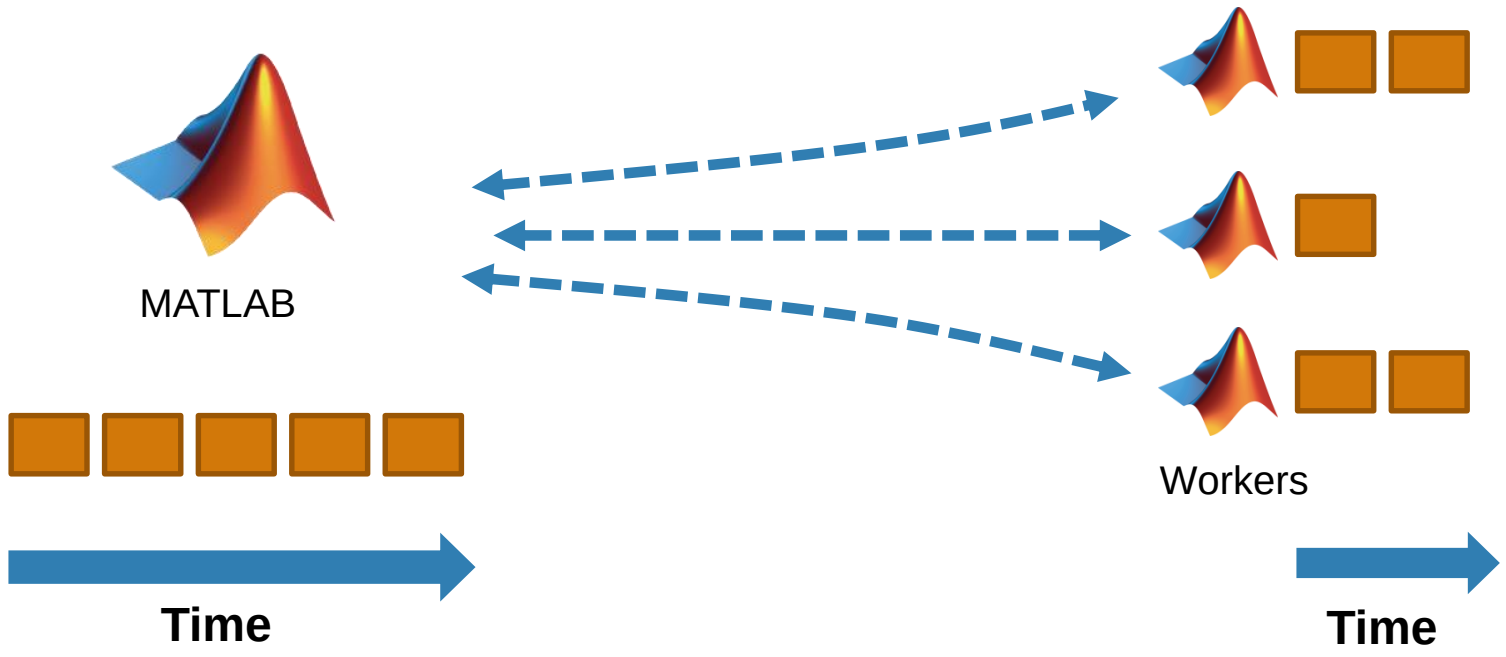
Automatic parallel support in toolboxes

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

Advanced programming constructs

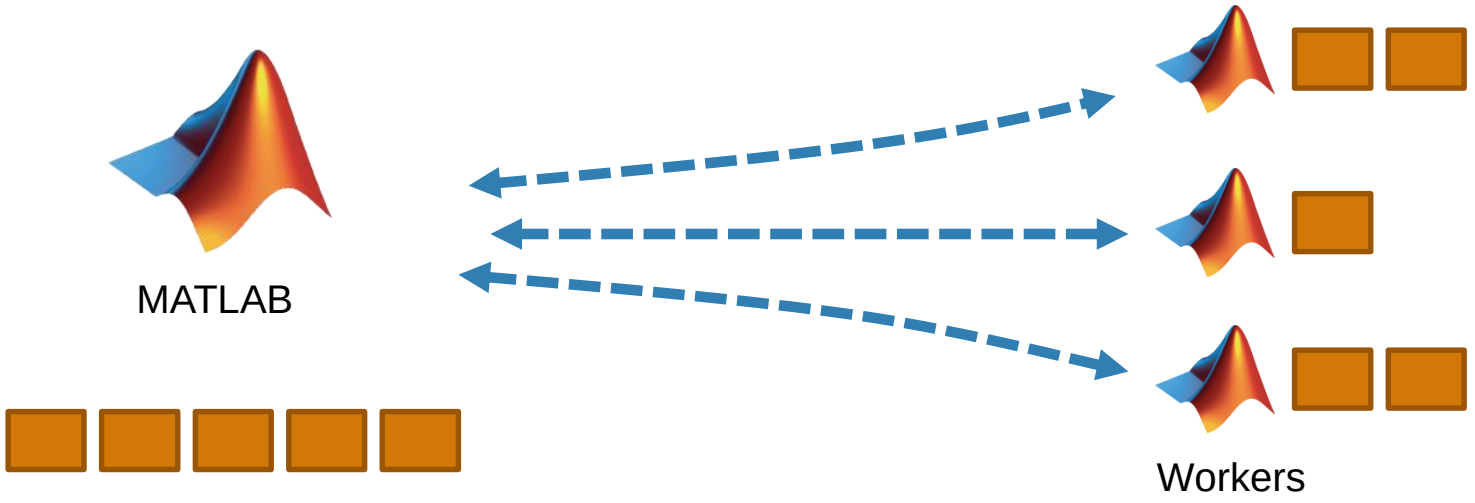
Parallelism using `parfor`

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



Learn more about parfor

Parallelism using `parfor`

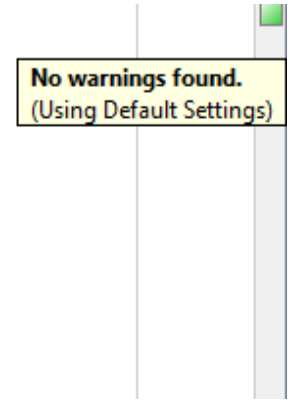



```
a = zeros(5, 1);
b = pi;
for i = 1:5
  a(i) = i + b;
end
disp(a)
```

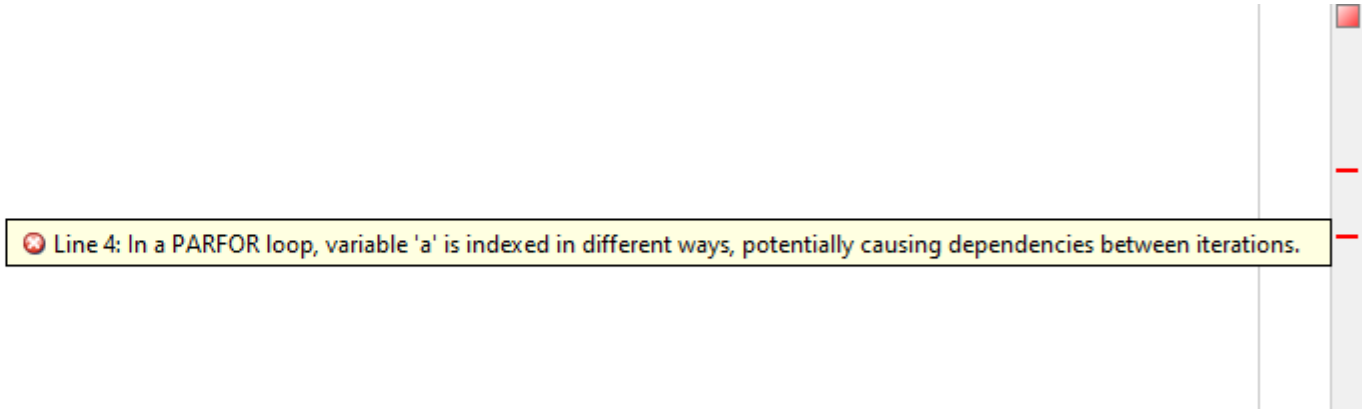
```
a = zeros(5, 1);
b = pi;
parfor i = 1:5
  a(i) = i + b;
end
disp(a)
```

Parallelism using `parfor`

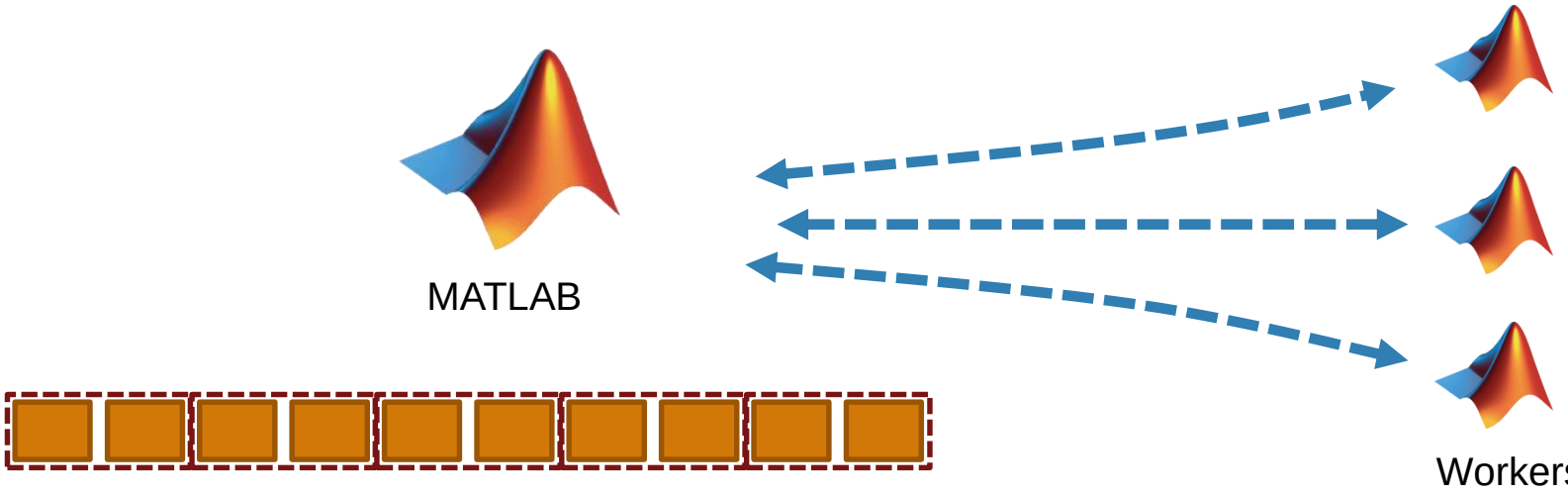
```
1    a = zeros(5, 1);
2    b = pi;
3    parfor i = 1:5
4        a(i) = i + b;
5    end
6    disp(a)
```




```
1    a = zeros(5, 1);
2    b = pi;
3    parfor i = 2:6
4        a(i) = a(i-1) + b;
5    end
6    disp(a)
```

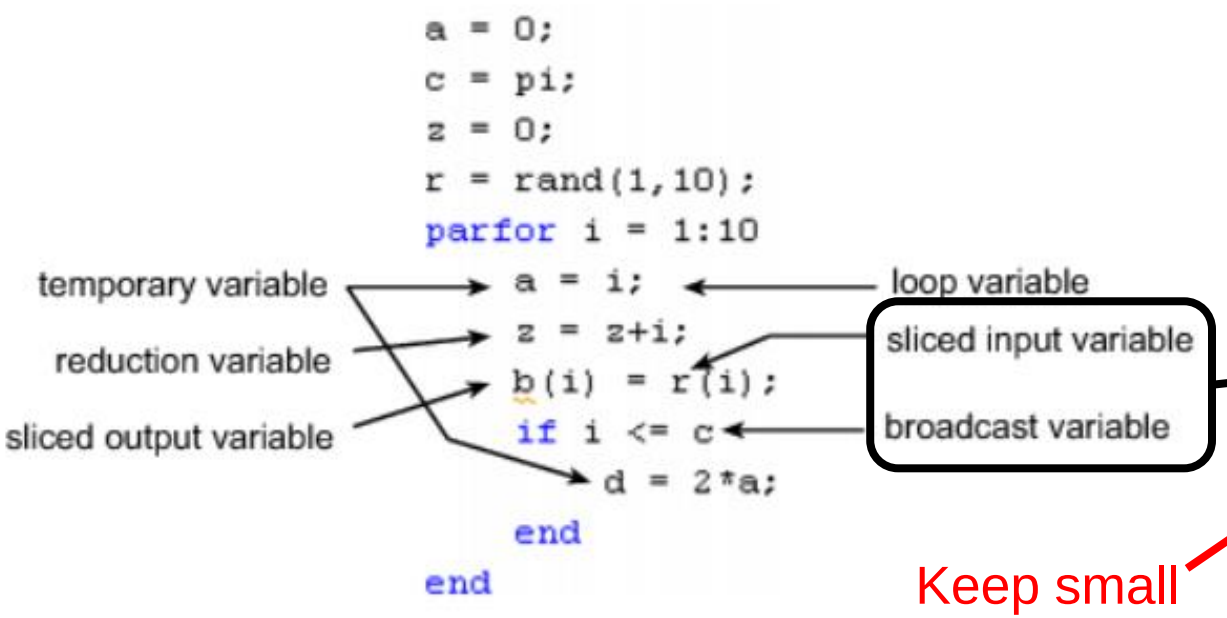


Parallelism using `parfor`




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

Optimizing `parfor`



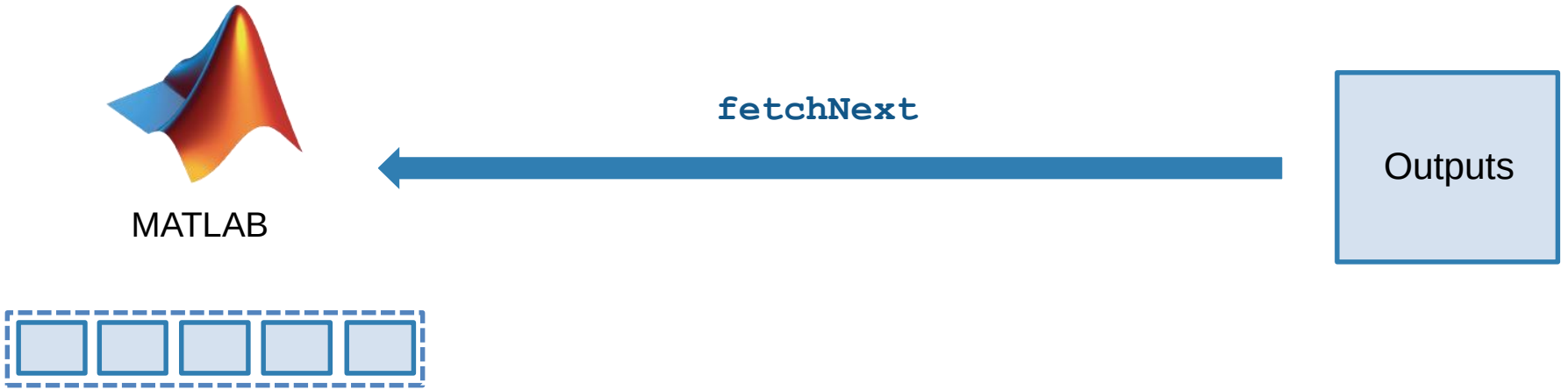
Use more

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]

Parallelism using `parfeval`



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

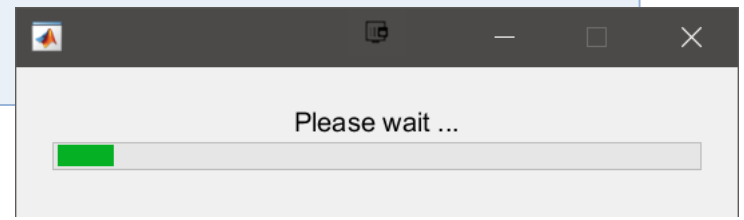
```
for idx = 1:10
   f(idx) = parfeval(@magic,1,idx);
end

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

DataQueue

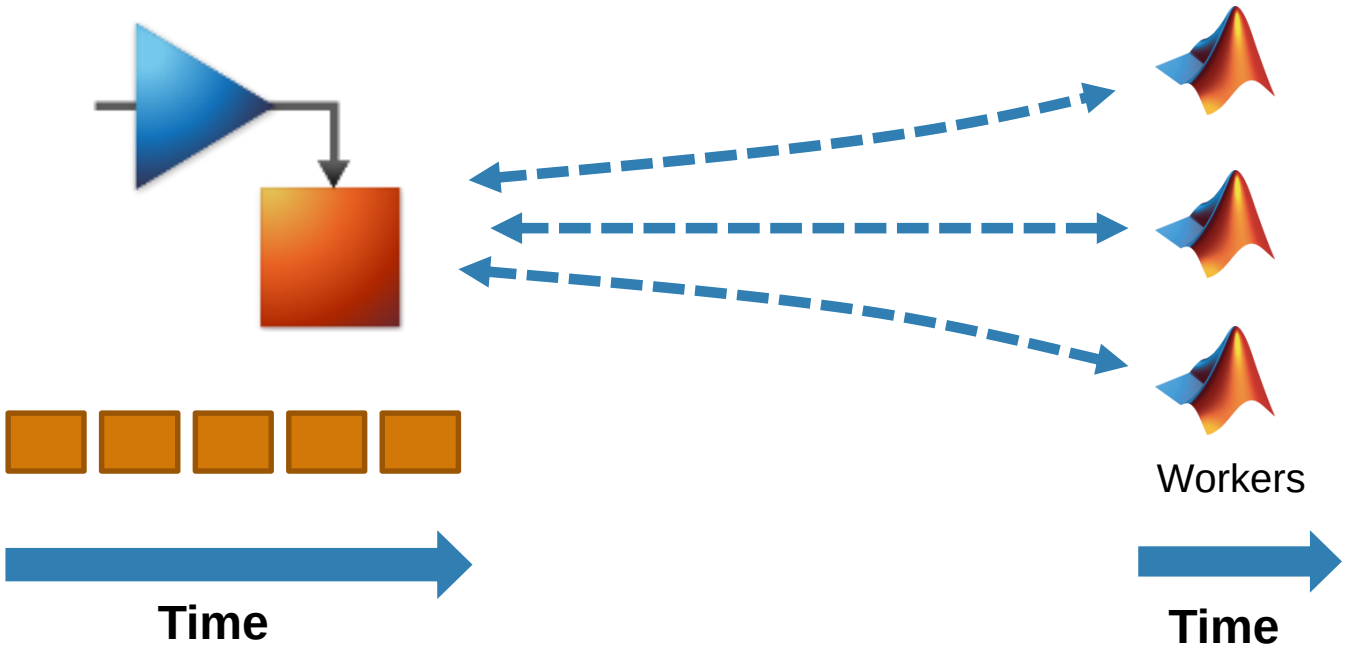
Send data or messages from parallel workers back to the MATLAB client

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
```



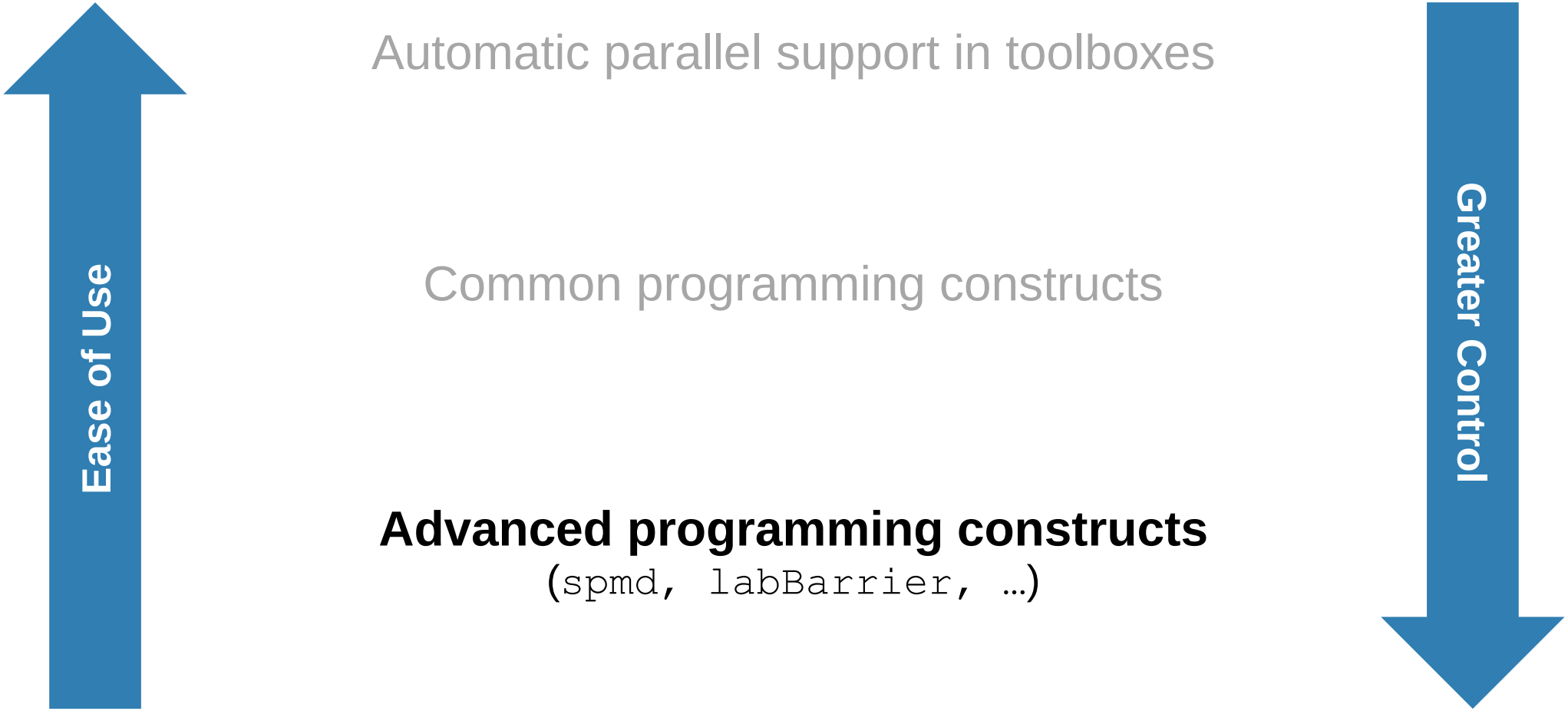
Run multiple simulations in parallel with `parsim`



- 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);
```

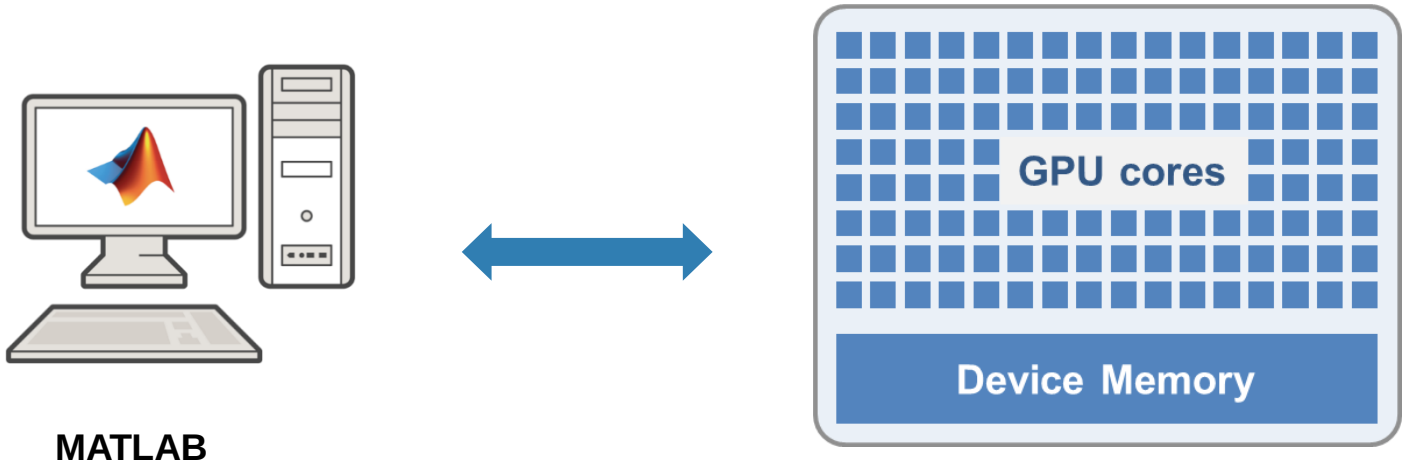
Scaling MATLAB applications and Simulink simulations



Agenda

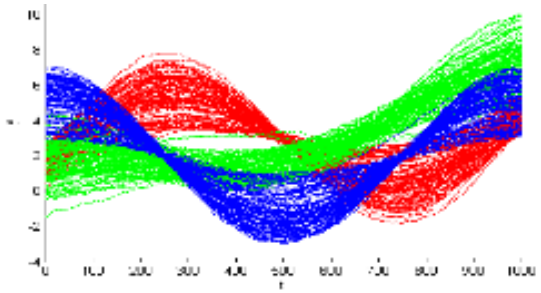
- Utilizing multiple cores on a desktop computer
- Accelerating applications with NVIDIA GPUs
- Scaling up to cluster and cloud resources
- Tackling data-intensive problems on desktops and clusters
- Summary and resources

Utilizing one or multiple GPUs

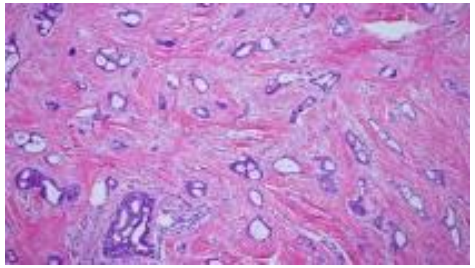


MATLAB
Parallel Computing Toolbox

Accelerating MATLAB applications with GPUs

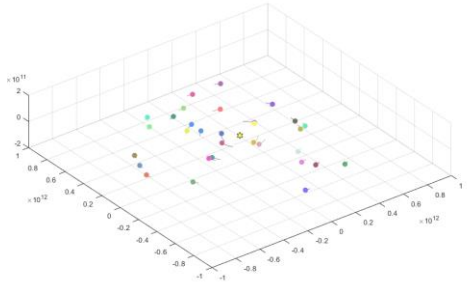


10x speedup
K-means clustering algorithm

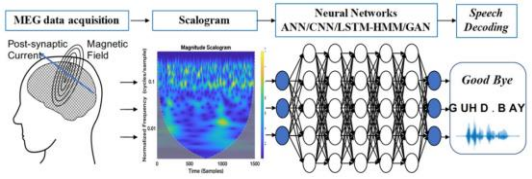


14x speedup
template matching routine

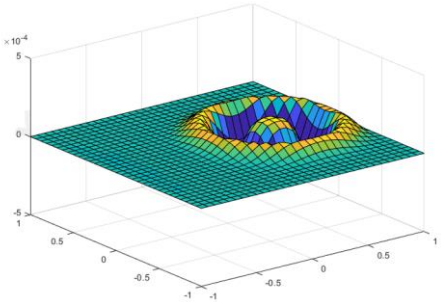
12x speedup
using Black-Scholes model



44x speedup
simulating the movement of celestial objects



10x speedup
deep learning training



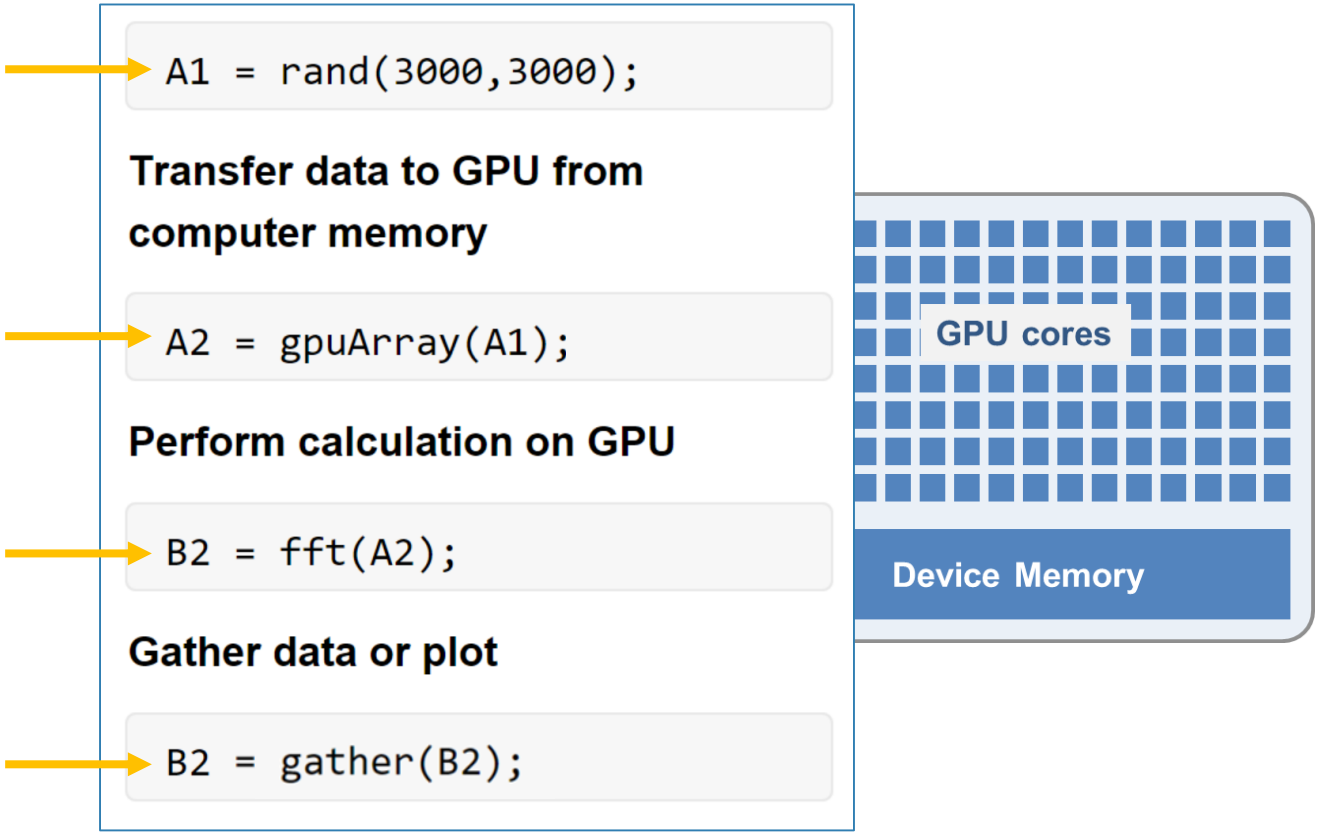
77x speedup
wave equation solving

[More info on running MATLAB functions on a GPU]

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

Speed-up using NVIDIA GPUs

- Ideal Problems
  - massively parallel and/or vectorized operations
  - computationally intensive
- Hundreds of GPU-supported functions
- Use `gpuArray` and `gather` to transfer data between CPU and GPU



MATLAB GPU computing

Agenda

- Utilizing multiple cores on a desktop computer
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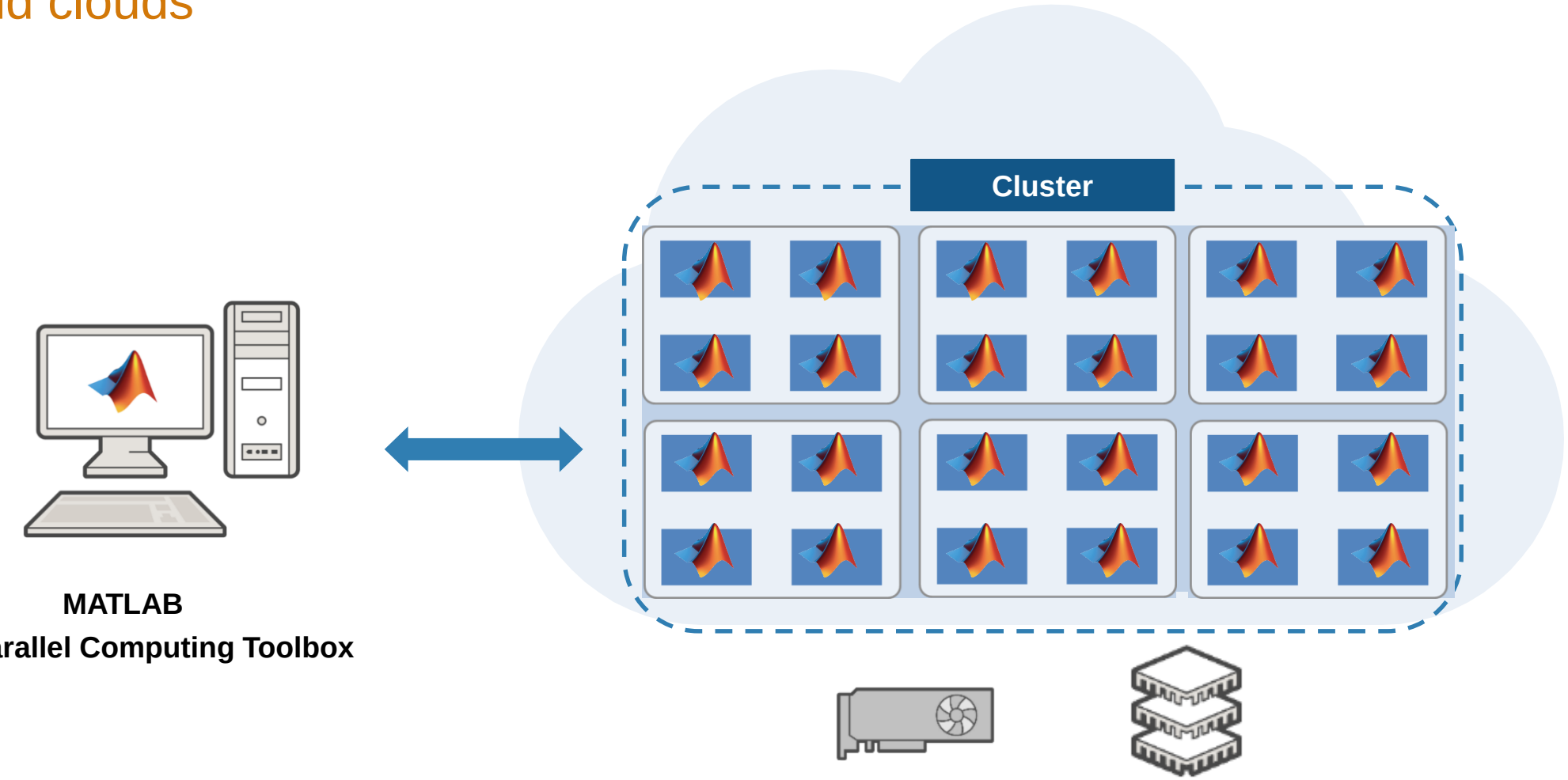
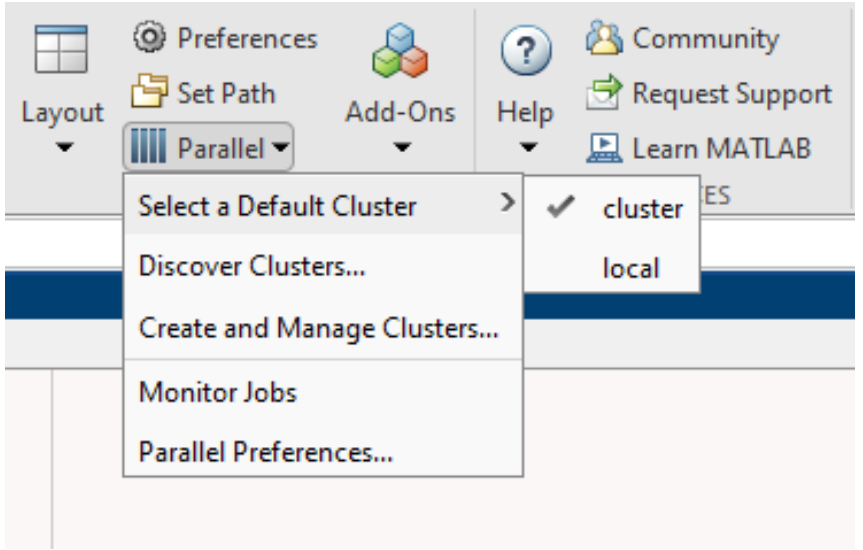
Parallel computing paradigm

Clusters and clouds



Scale to cluster and cloud

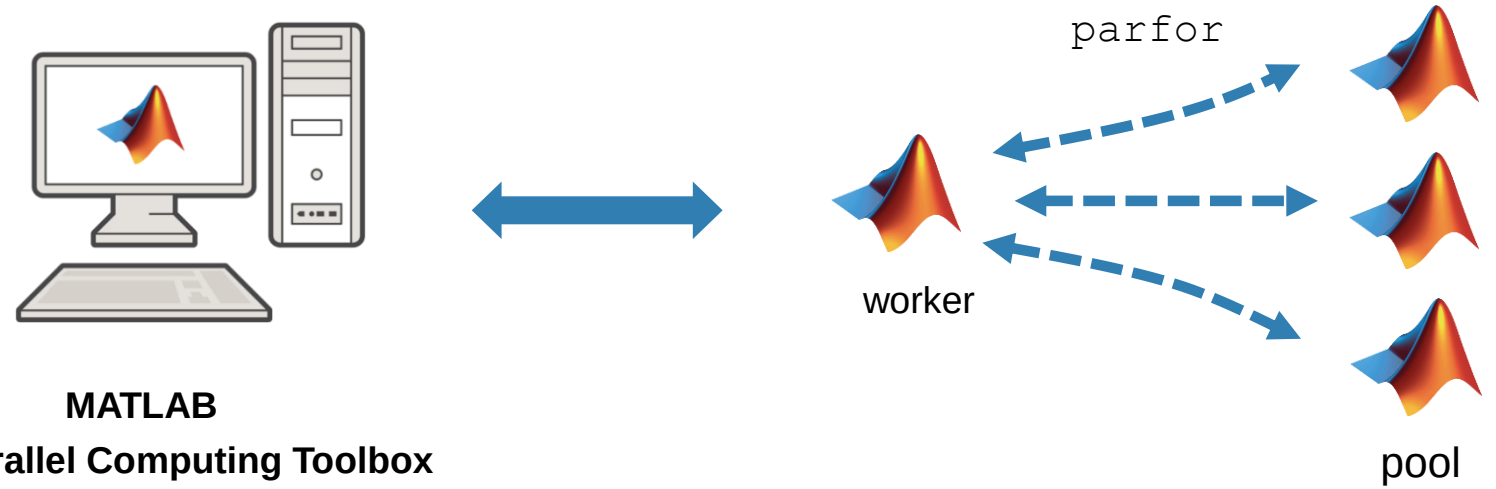
- Use MATLAB Parallel Server
- Change hardware without changing algorithm
- Cross-platform submission



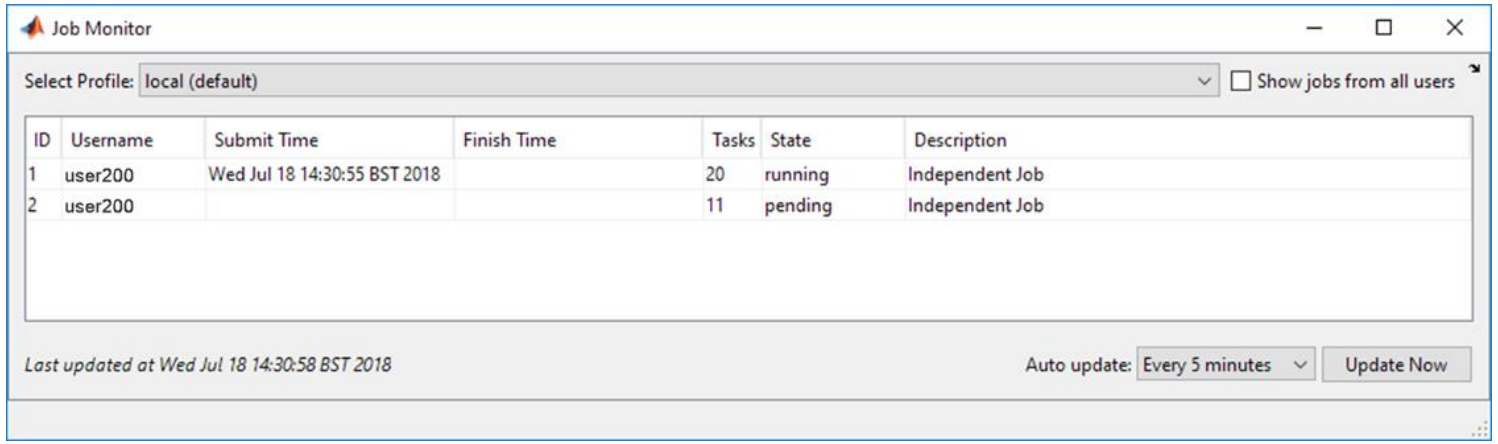
`batch` simplifies offloading computations

Submit jobs to the cluster

```
job = batch('myscript','Pool',3);
```



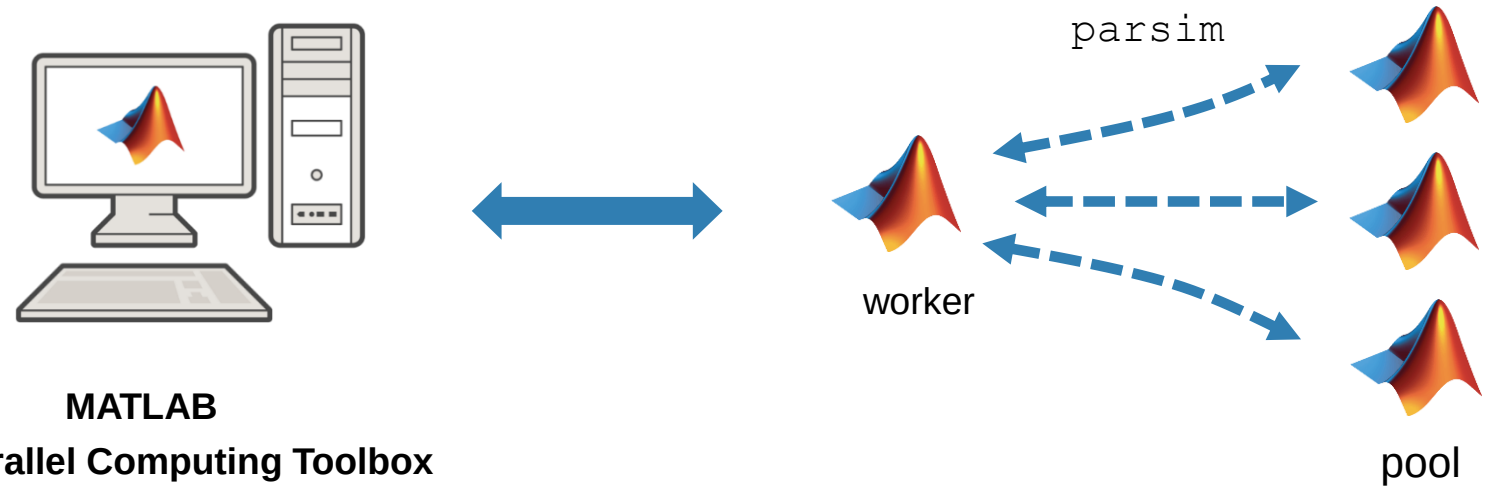

```
>> j.State
ans =
    'running'
>> j.diary
Warning: The diary of this batch job might be incomplete
because the job is still running.
--- Start Diary ---

Analyzed 1 image.
Analyzed 2 images.
Analyzed 3 images.
Analyzed 4 images.

--- End Diary ---
```



`batch` simplifies offloading computations

Submit jobs to the cluster

```
job = batchsim(in,'Pool',3);
```



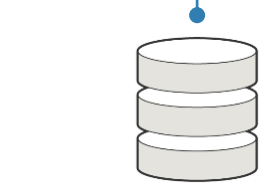
Agenda

- Utilizing multiple cores on a desktop computer
- Accelerating applications with NVIDIA GPUs
- Scaling up to cluster and cloud resources
- Tackling data-intensive problems on desktops and clusters
- Summary and resources

Big data workflows

ACCESS DATA

More data and collections of files than fit in memory

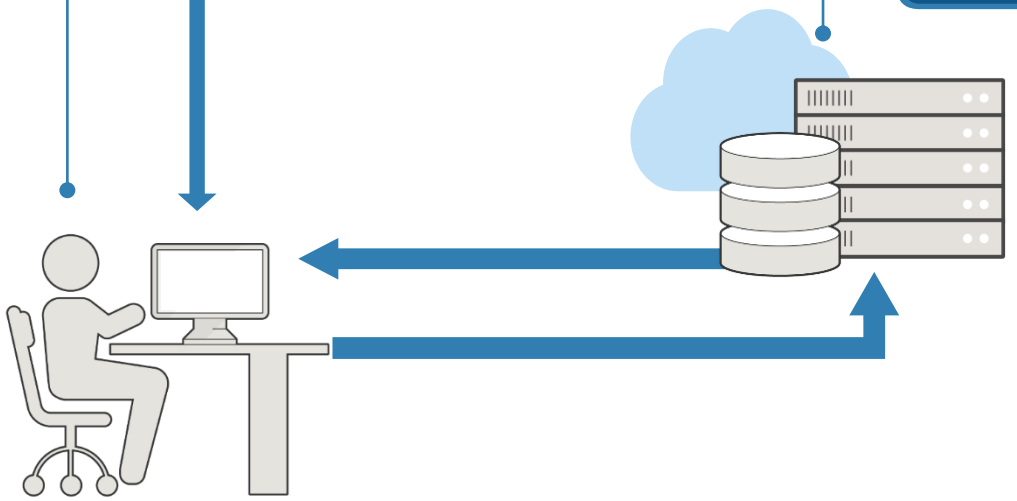


DEVELOP & PROTOTYPE ON THE DESKTOP

Adapt traditional processing tools or learn new tools to work with Big Data

SCALE PROBLEM SIZE

To traditional clusters and Big Data systems like Hadoop



`tall` arrays

- New 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.)

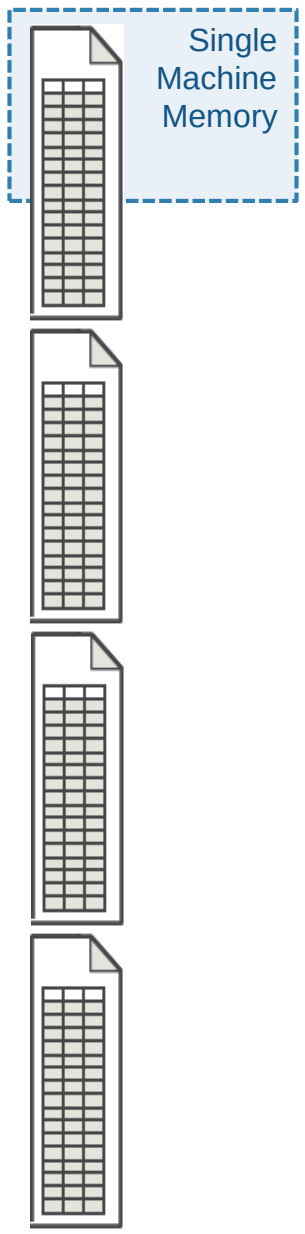
Working with tall arrays

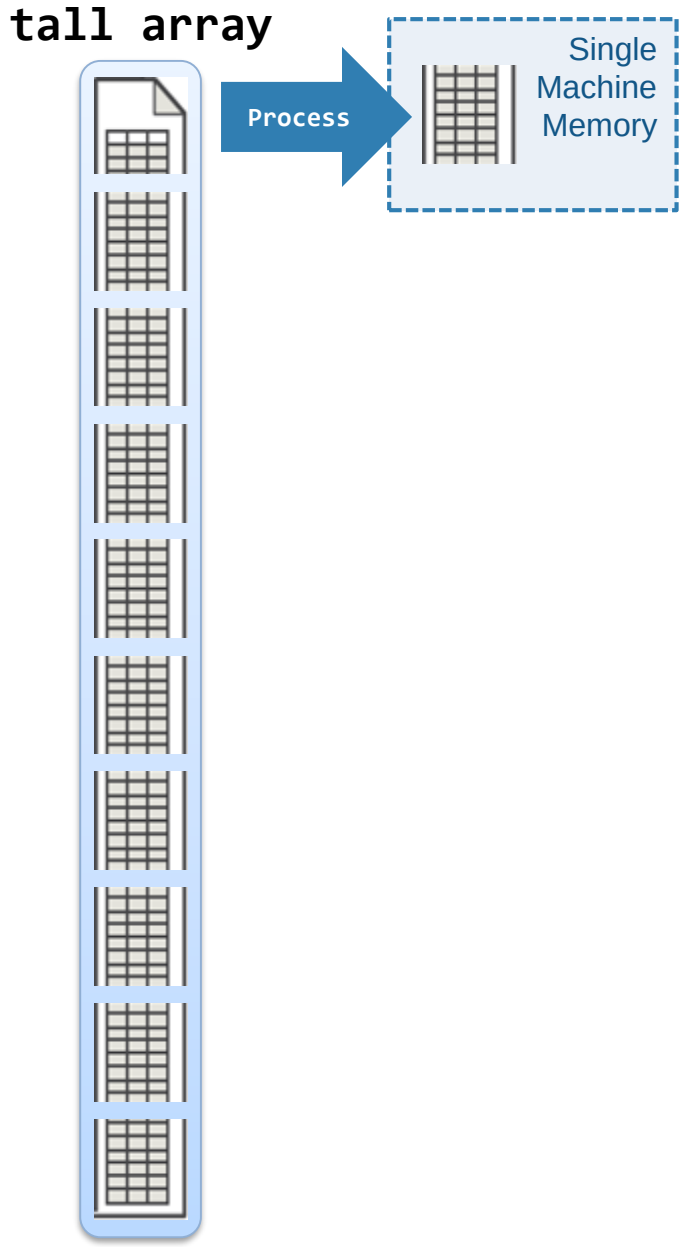
`tall` arrays

- Automatically breaks data up into small “chunks” that fit in memory
- Tall arrays scan through the dataset one “chunk” at a time

```
tt = tall(ds)
mDep = mean(tt.DepDelay,'omitnan')
mDep = gather(mDep)
```

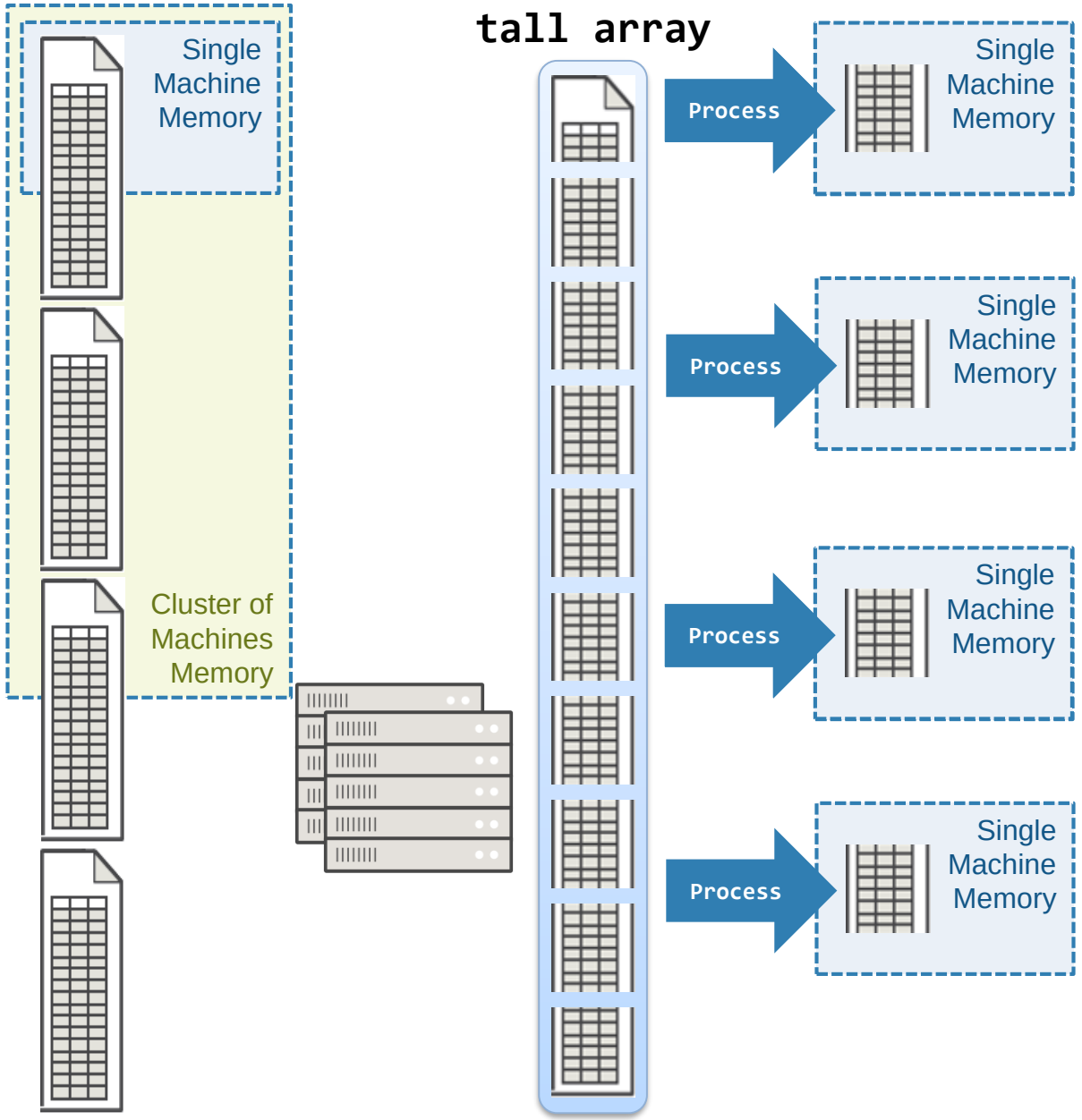
- Processing code for tall arrays is the same as ordinary arrays





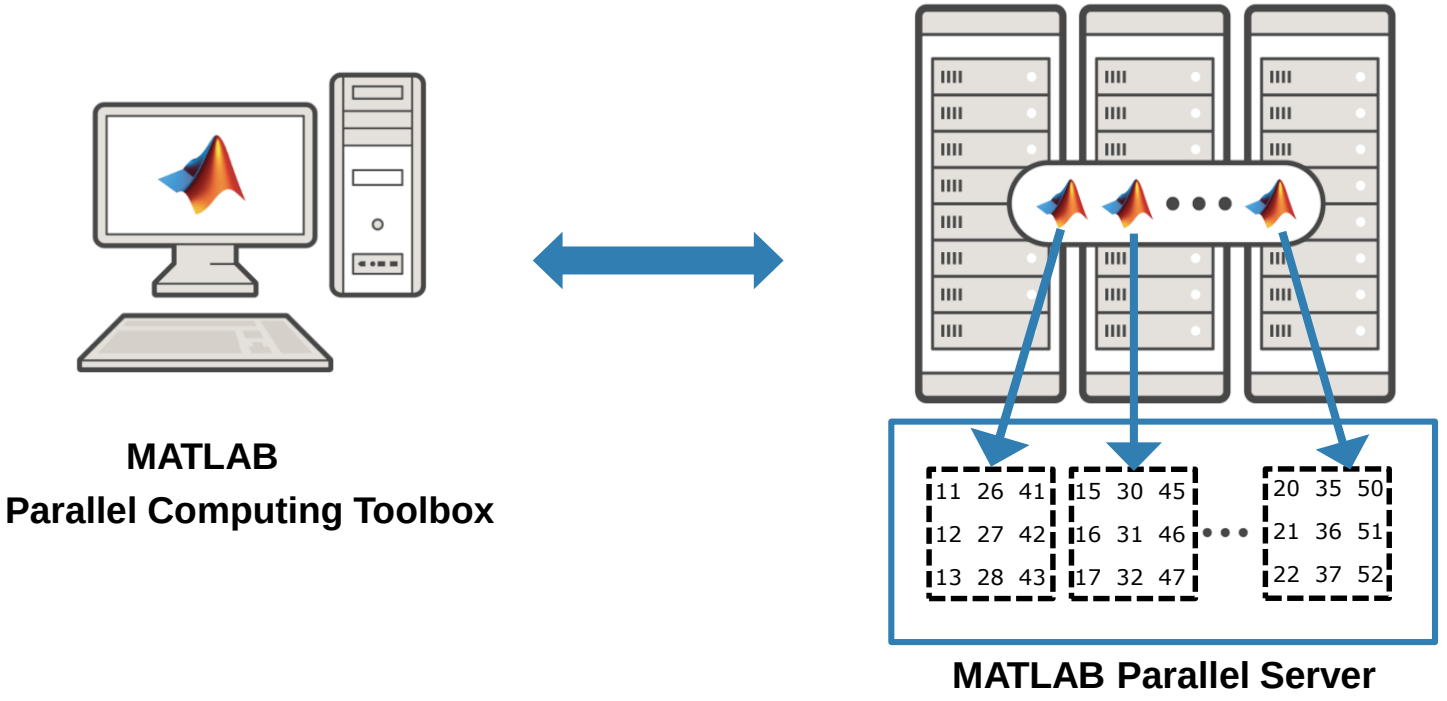
`tall` arrays

- With Parallel Computing Toolbox, process several “chunks” at once
- Can scale up to clusters with MATLAB Parallel Server



`distributed` arrays

- Distribute large matrices across workers running on a cluster
- Support includes matrix manipulation, linear algebra, and signal processing
- Several hundred MATLAB functions overloaded for distributed arrays



distributed arrays

Develop and prototype locally and then scale to the cluster

MATLAB
Parallel Computing Toolbox

```
% prototype with a small data set
parpool('local');

% Read the data - read in part of the data
ds = datastore('colchunk_A_1.csv');

% Send data to workers
dds = distributed(ds);

% Run calculations
A = sparse(dds.i, dds.j, dds.v);
x = A \ distributed.ones(n^2, 1);

% Transfer results to local workspace
xg = gather(x);
```

MATLAB Parallel Server

```
% prototype with a large data set
parpool('cluster');

% Read the data - read the whole dataset
ds = datastore('colchunk_A_*.csv');

% Send data to workers
dds = distributed(ds);

% Run calculations
A = sparse(dds.i, dds.j, dds.v);
x = A \ distributed.ones(n^2, 1);

% Transfer results to local workspace
xg = gather(x);
```

Working with distributed arrays

Agenda

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Summary

- Leverage parallel computing without needing to be parallel expert
- Speed up the execution of MATLAB applications using additional hardware
- Develop parallel applications on the desktop, easily scale to clusters as needed

Some other valuable resources

- Getting started with parallel computing
  - Parallel Computing Toolbox
  - Performance and Memory
  - MATLAB with GPUs

- Scaling to the cluster and cloud
  - MATLAB Parallel Server
  - MATLAB Parallel Server on the cloud
  - Big data with MATLAB