FuPerMod: a Framework for Optimal Data Partitioning for Parallel Scientific Applications on Dedicated Heterogeneous HPC Platforms

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Introduction

- Modern HPC platform = system of heterogeneous devices and links
- How to execute data-parallel applications efficiently?
  - balance the load between processors
  - optimize communications
- **Data partitioning** = load balancing for data-parallel applications
  - performance models of processors

Introduction

- Modern HPC platform = system of heterogeneous devices and links
- How to execute data-parallel applications efficiently?
  - balance the load between processors
  - optimize communications
- **Data partitioning** = load balancing for data-parallel applications
  - performance models of processors
- **Data-parallel scientific applications:** sparse matrices and meshes
  - sparse matrices and meshes can be represented as graphs
  - graph partitioning = optimization of comm. & load balancing
- **Graph partitioning software**
  - ParMETIS, SCOTCH, JOSTLE
    minimize the communication cost with account for heterogeneity
  - Zoltan, PaGrid
    minimize the execution time using a cost function

Introduction

- **Computational heterogeneity in graph partitioning software**
  weights = constants representing the relative speeds of processors
  - must be provided as input - how to find them?
  - const speed is not accurate, especially for dynamic partitioning, self-adaptive applications, hybrid platforms

Introduction

- **Computational heterogeneity in graph partitioning software**
  weights = constants representing the relative speeds of processors
  - must be provided as input - how to find them?
  - const speed is not accurate, especially for dynamic partitioning, self-adaptive applications, hybrid platforms
- **Solution:** a general-purpose framework for data partitioning based on accurate and efficient performance modeling

  benchmarks $\rightarrow$ *models* $\rightarrow$ *partitioning algorithm* $\rightarrow$ *partitioning (weights)*
- **Main challenges**
  - performance modeling of interconnected devices and optimized kernels
  - complexity of model-based data partitioning algorithms

Introduction

FuPerMod framework

- Support of wide range of platforms and applications
- Static data partitioning

  exhaustive benchmarks $\rightarrow$ *detailed models* $\rightarrow$ *static algorithm* $\rightarrow$ *partitioning*
- Dynamic data partitioning and load balancing

  $\{$*benchmark* $\rightarrow$ *approx. models* $\rightarrow$ *dynamic algorithm* $\rightarrow$ *partitioning*$\}+$

In this talk

- Use case scenarios
  - Static data partitioning on a hybrid node
  - Dynamic load balancing on a heterogeneous cluster
- FuPerMod programming interface

Outline

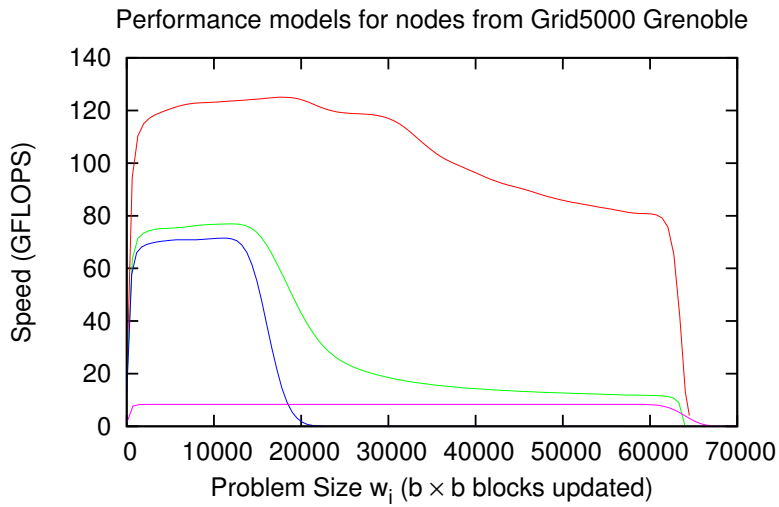
Data partitioning on heterogeneous platforms

Traditionally, performance is defined by Constant Performance Model (CPM):

- Computed from clock speed or by performing a benchmark
- Computations partitioned proportionally to the speed of processors
- Efficient but simplistic: algorithms may fail to balance the load [1]

Functional Performance Model (FPM):

- Speed as a function of problem size [2]: $s(x) = x/t(x)$
- Realistic performance of hardware and application
- Complex data partitioning algorithms (geometrical, numerical) [3]



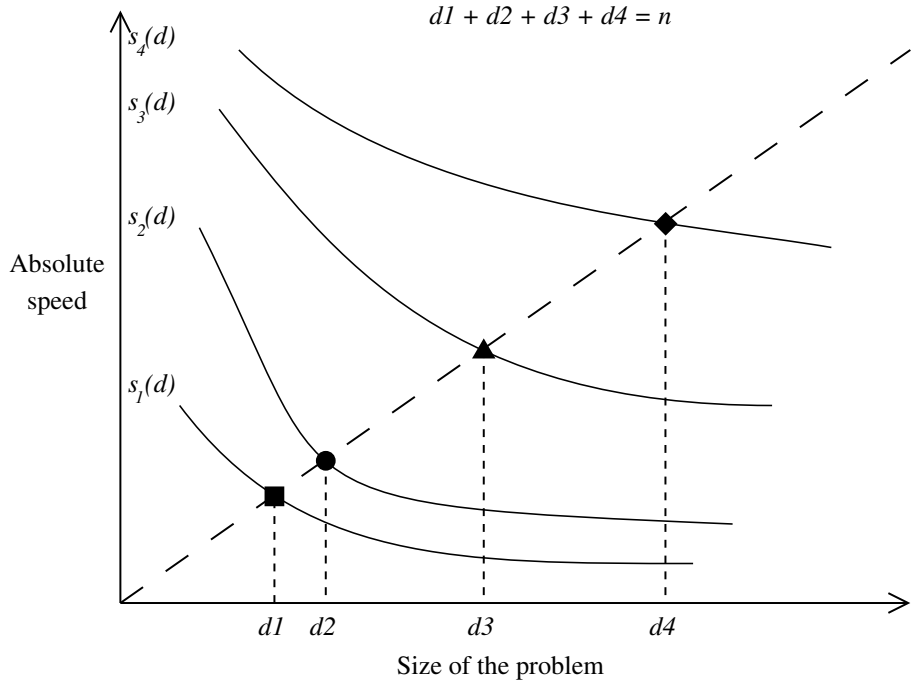
[1] D. Clarke et al: Dynamic load balancing of parallel iterative routines on platforms with memory heterogeneity (2010)
[2] A. Lastovetsky et al: Data partitioning with a functional performance model of heterogeneous processors (2007)
[3] V. Rychkov et al: Using multidimensional solvers for optimal data partitioning on dedicated heterogeneous platforms (2011)

Data partitioning with functional performance models

Load is balanced when:

all processors complete work within the same time:

$$\begin{cases} t_1(d_1) \approx t_2(d_2) \approx \ldots \approx t_p(d_p) \\ d_1 + d_2 + \ldots + d_p = N \end{cases}$$



solution lies on a line passing through the origin:

$$d_i / s_i(d_i) = const$$

- Originally designed for heterogeneous uniprocessor clusters
- Used for static and dynamic data partitioning
- Extended for hybrid multicore multi-GPU nodes [1] and clusters [2]

[1] Z. Zhong et al: Data Partitioning on Heterogeneous Multicore and Multi-GPU Systems Using Functional Performance Models of Data-Parallel Applications (2012)
[2] D. Clarke et al: Hierarchical Partitioning Algorithm for Scientific Computing on Highly Heterogeneous CPU + GPU Clusters (2012)

Outline

Static data partitioning on a hybrid node

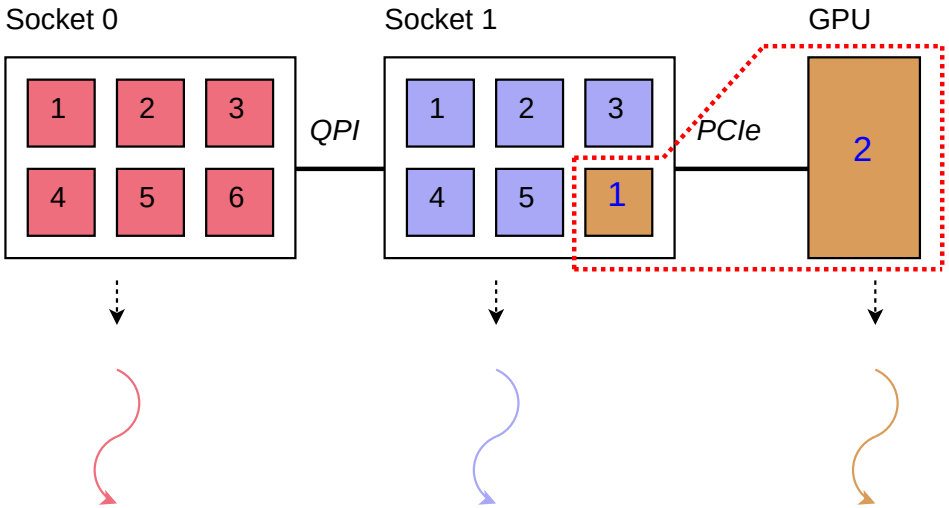
Hardware	CPU (AMD)	GPUs (NVIDIA)	
Architecture	Opteron 8439SE	GF GTX680	Tesla C870
Core Clock	2.8 GHz	1006 MHz	600 MHz
Number of Cores	4×6 cores	1536 cores	128 cores
Memory Size	4×16 GB	2048 MB	1536 MB
Memory Bandwidth	NUMA	192.3 GB/s	76.8 GB/s
Software	multi-threaded	CUDA + out-of-core	
Processes	1 per socket		1 per device

exhaustive benchmarks $\rightarrow$ *detailed models* $\rightarrow$ *static algorithm* $\rightarrow$ *partitioning*

Configuration of data-parallel application

- No idle compute devices
  - may not be the optimal configuration (out of scope of this study)
- Even load of identical compute devices
  - no evidence that uneven load will improve performance
- One-to-one mapping of processes/threads to compute devices
  - no evidence that many-to-one will improve performance
- Same one-to-one mapping for all runs of the program
  - mapping is not delegated to the operating environment

Configuration of data-parallel application

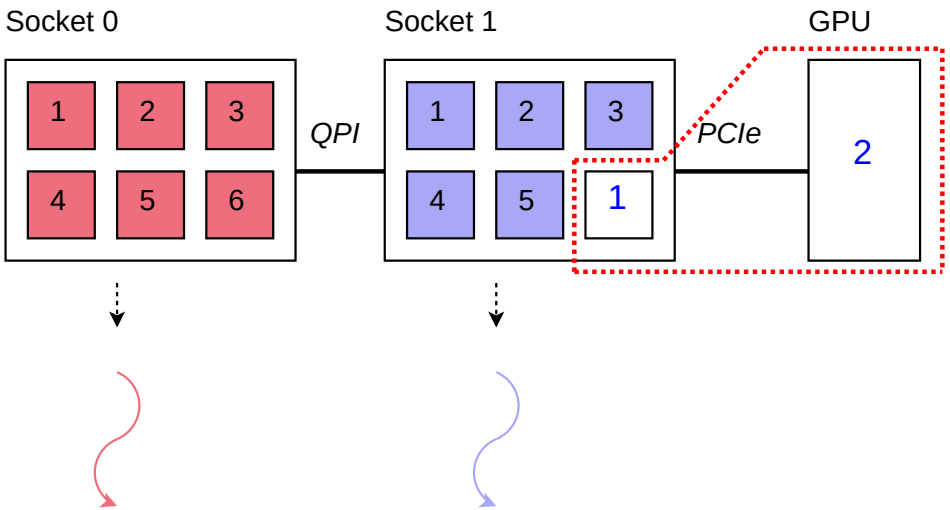


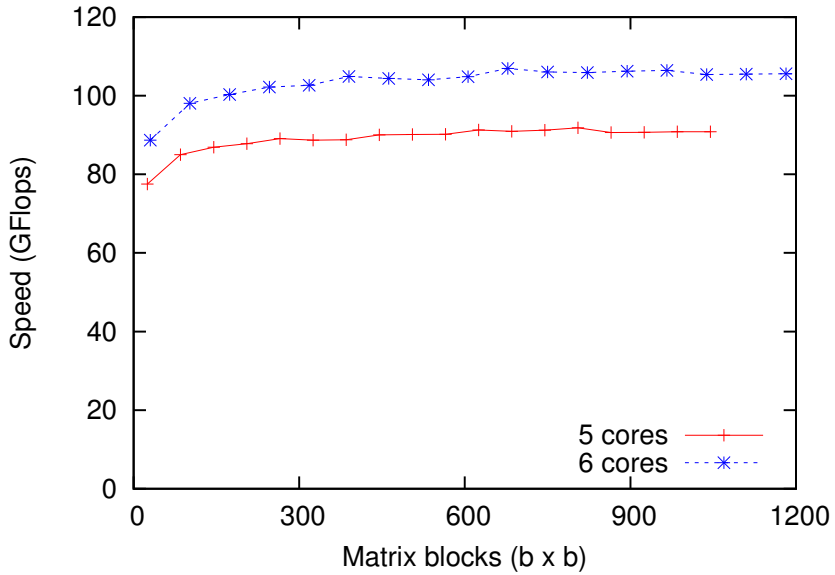
Relatively independent groups of devices: : 6 cores, 5 cores, 1 core + GPU
each group = abstract processor (uni- or multi-processor)

- Cores in a group interfere with each other due to resource contention
- All cores in a group execute the same amount of workload in parallel
- GPU kernel computation time and data transfer time are both included
- Host core for GPU is chosen to maximize data throughput between GPU and NUMA memory

Computation performance models of multicore

$S_c(x)$: speed of c cores that execute a multi-threaded kernel and share system resources, x units distributed between cores

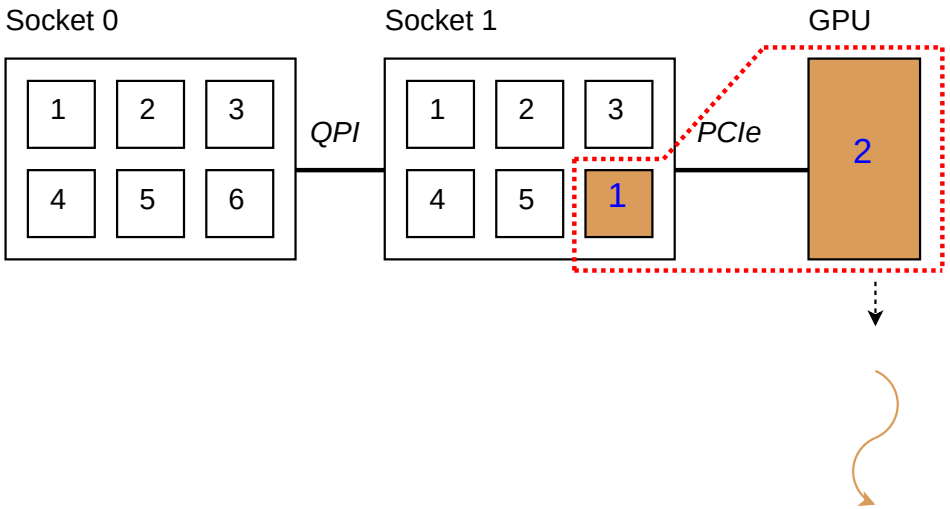


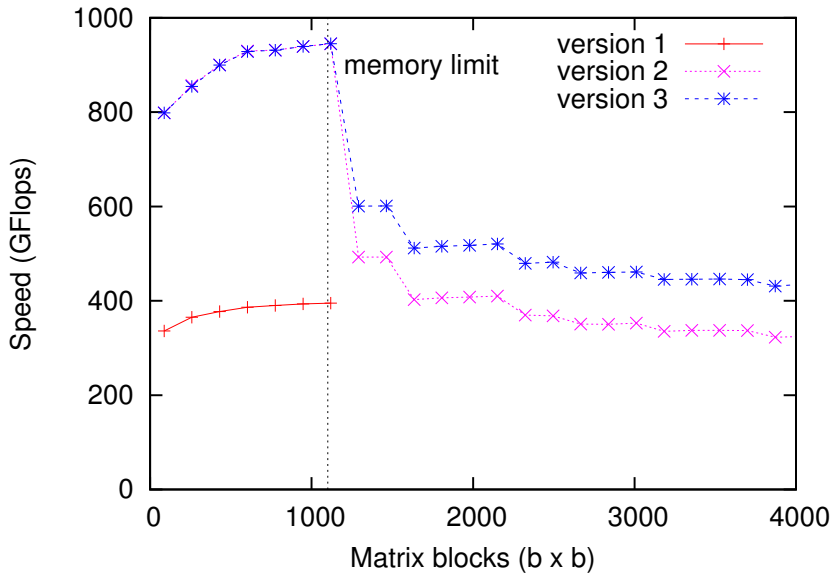


- $S_5(x)$: 5-threaded kernel on a socket, 1 core idle
- $S_6(x)$: 6-threaded kernel on a socket

Computation performance models of GPU

$g(x)$: combined speed of a GPU and its dedicated core, including data transfers



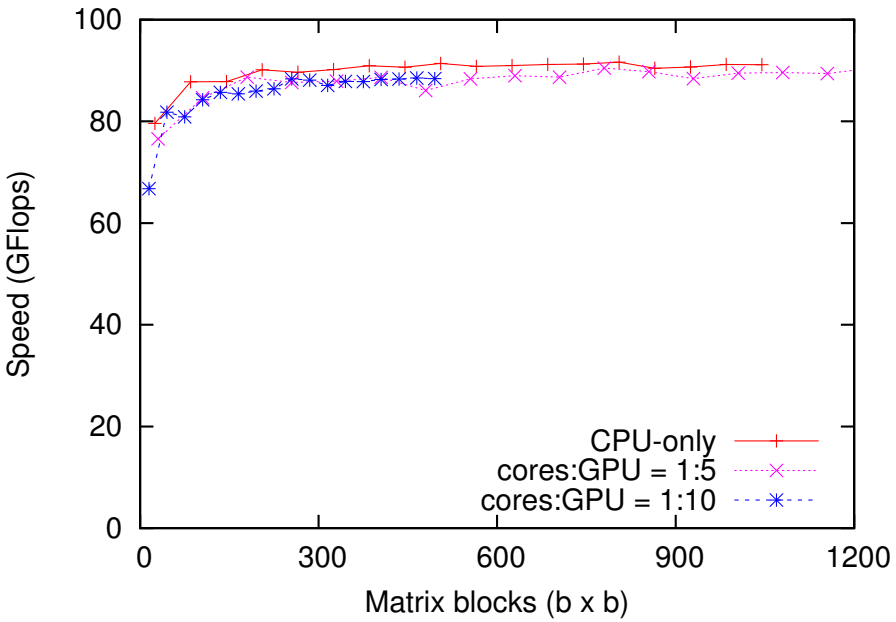


- $g(x)$ (version 1): native CUDA kernel
- $g(x)$ (version 2): accumulate intermediate results + out-of-core
- $g(x)$ (version 3): version 2 + overlap data transfers and kernel executions

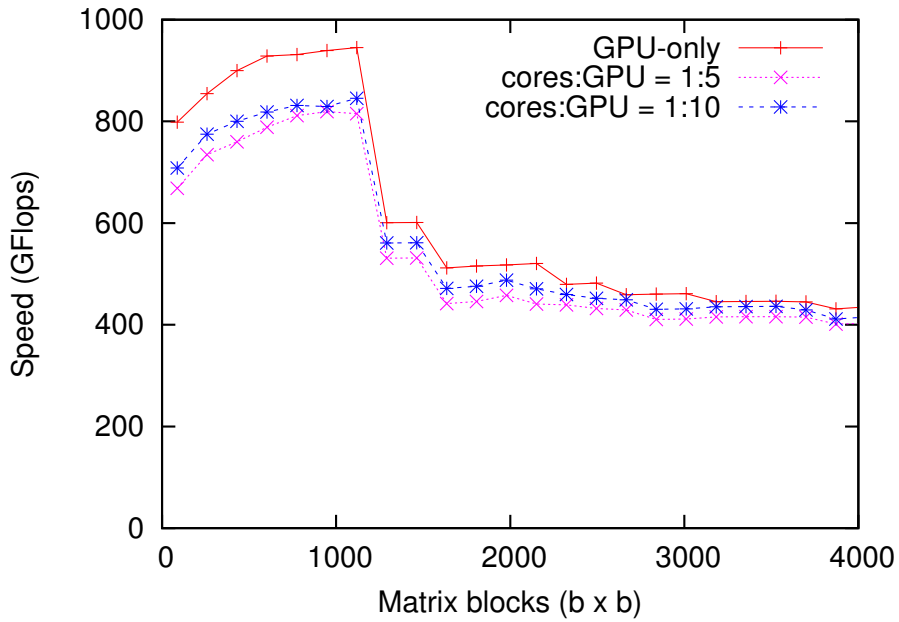
Impact of Resource Contention to Performance Modeling

- CPU and GPU kernel benchmarking simultaneously in a socket
- FPM of multiple cores $S_5(x)$ is barely affected
- FPM of GPU $g(x)$ gets 85% accuracy (speed drops by 7 - 15%)

$s_5(x)$, speed of multiple cores



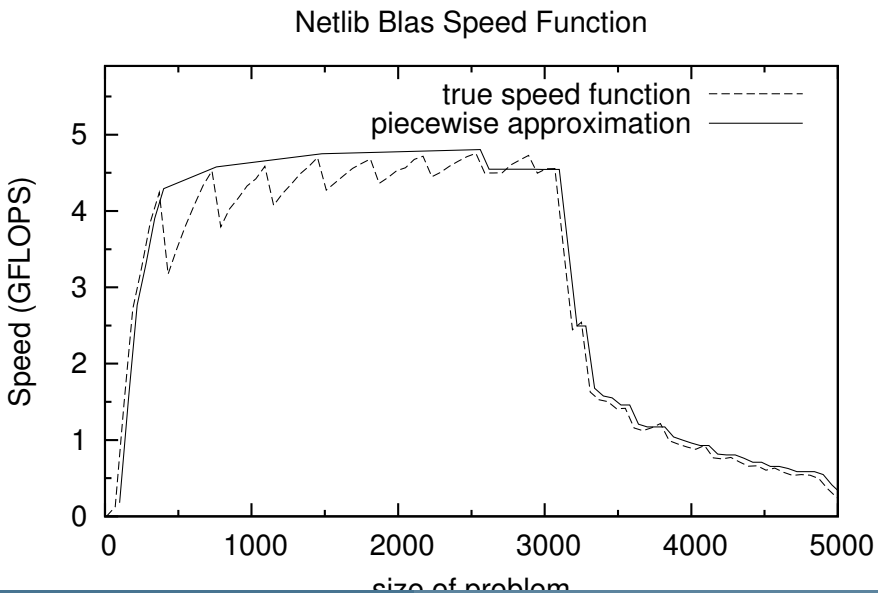
$g(x)$, speed of a GPU

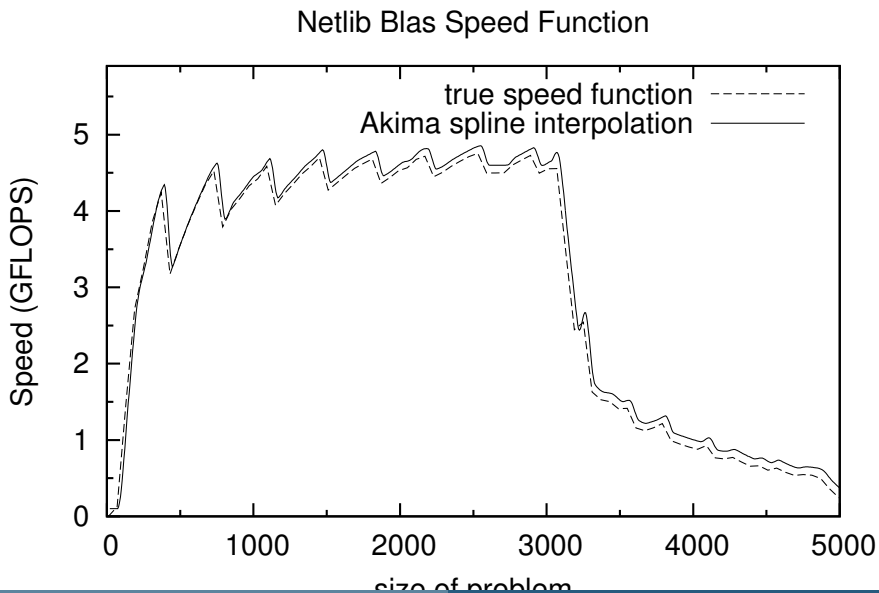


FuPerMod: implemented models

- FPM based on the piecewise linear interpolation of the time function
- FPM based on the Akima spline interpolation of the time function
- CPM (requires only one experimental point)

```
// X = piecewise, interp, constant
fupermod_model* model =
  fupermod_model_X_alloc(int count, fupermod_point* points);
int d = 1000;
double t =  model->t(model, d);
double s = d / model->t(model, d);
```





API for computation performance modeling

Computation performance model

```
struct fupermod_model {
  int count;                // number of data points
  fupermod_point* points; // data points
  // approximation of the time function
  double (*t)(fupermod_model* model, double x);
  // add a point and update the approximation
  int (*update)(fupermod_model* model, fupermod_point point);
};
```

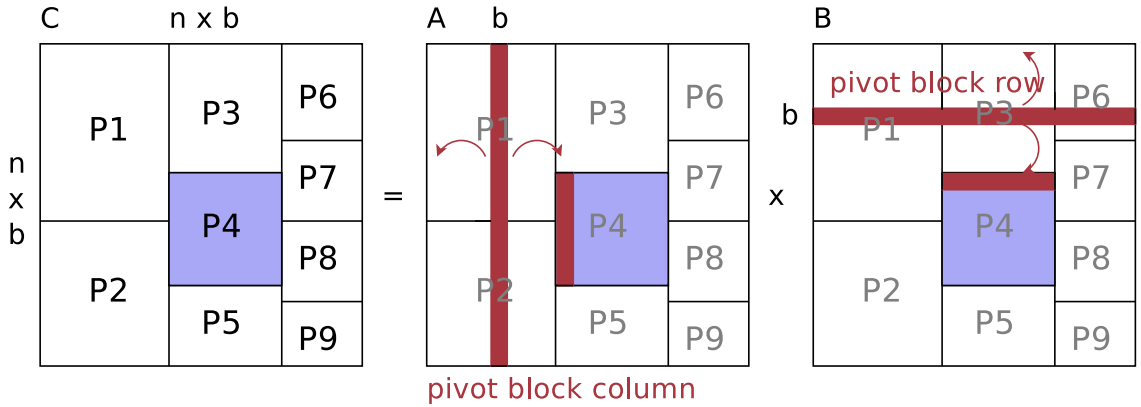
Data point

```
struct fupermod_point {
  int d;     // problem size
  double t; // execution time
  int reps; // actual repetitions
  double ci;// confidence interval
};
```

How to obtain data points? $\longrightarrow$ profiling, benchmarking

Computation performance measurement

- Parallel matrix multiply: heterogeneous algorithm with minimized volume of communications*
  based on SUMMA



* O. Beaumont et al: Matrix Multiplication on Heterogeneous Platforms (2001)

Computation performance measurement

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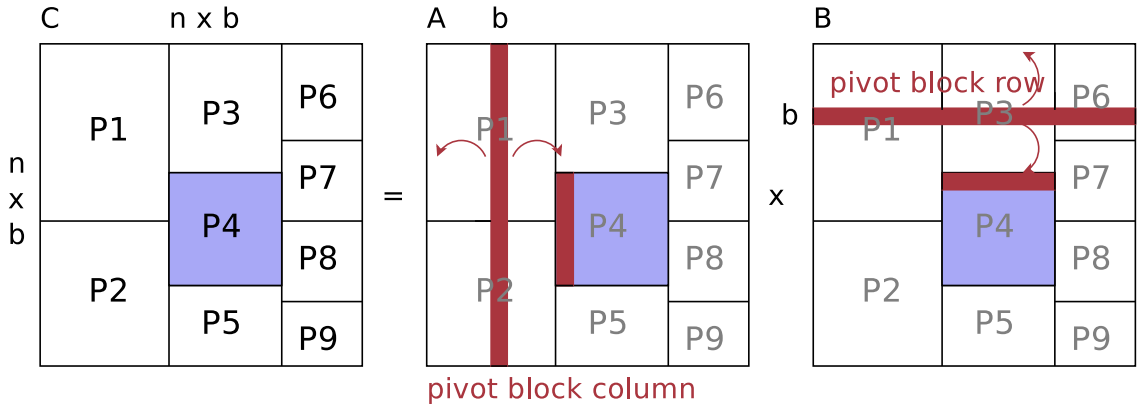
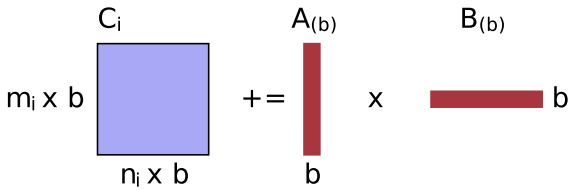
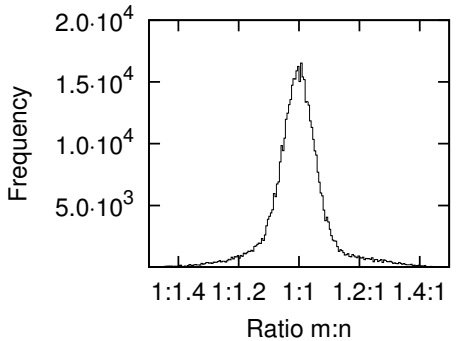
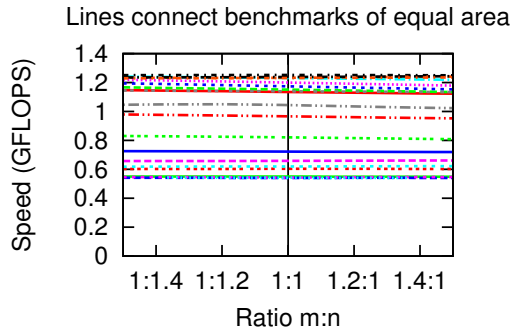


- Computation kernel: panel update
  representative for the entire application



- Speed: function of area
  can be measured for square matrices





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Computation kernel

```
// allocate blocks of matrix, pivot row and column
int initialize(int d, void* params) {
  int m = n = sqrt(d);
  int b = params->b;
  params->C  = malloc(m * b * n * b);
  params->WA = malloc(m * b * b);
  params->WB = malloc(n * b * b);
}

// characteristic computation
// dgemm = optimized implementation from ACML (AMD) or CUBLAS (NVIDIA)
int execute(pthread_mutex_t* mutex, void* params) {
  dgemm(params->WA, params->WB, params->C);
}

// deallocate data
int finalize(void* params) {
  free(params->C);
  free(params->WA);
  free(params->WB);
}
```

API for computation performance measurement

Computation kernel

```
// data allocation/deallocation excluded from measurement
// params - application-specific parameters
// mutex - to terminate benchmarking if it takes too long
struct fupermod_kernel {
  int (*initialize)(int d, void* params);
  int (*execute)(pthread_mutex_t* mutex, void* params);
  int (*finalize)(void* params);
};
```

Benchmark for computation kernel

```
int fupermod_benchmark(
  // kernel and problem size
  fupermod_kernel* kernel, int d,
  // statistical parameters
  fupermod_precision precision,
  // to sync some procs if needed
  MPI_Comm comm_sync,
  // returns a data point
  fupermod_point* point
);
```

$\{benchmark(kernel, problem\ size) \rightarrow point\}+ \rightarrow model$

FuPerMod: implemented static partitioning algorithms

- geometrical algorithm based on the piecewise-linear FPMs
- numerical algorithm based on the Akima-spline FPMs
- basic algorithm based on CPMs

```
// X = geometric, multiroot, basic
int fupermod_partition_X(
  int size, fupermod_model** models, fupermod_dist* dist);
```

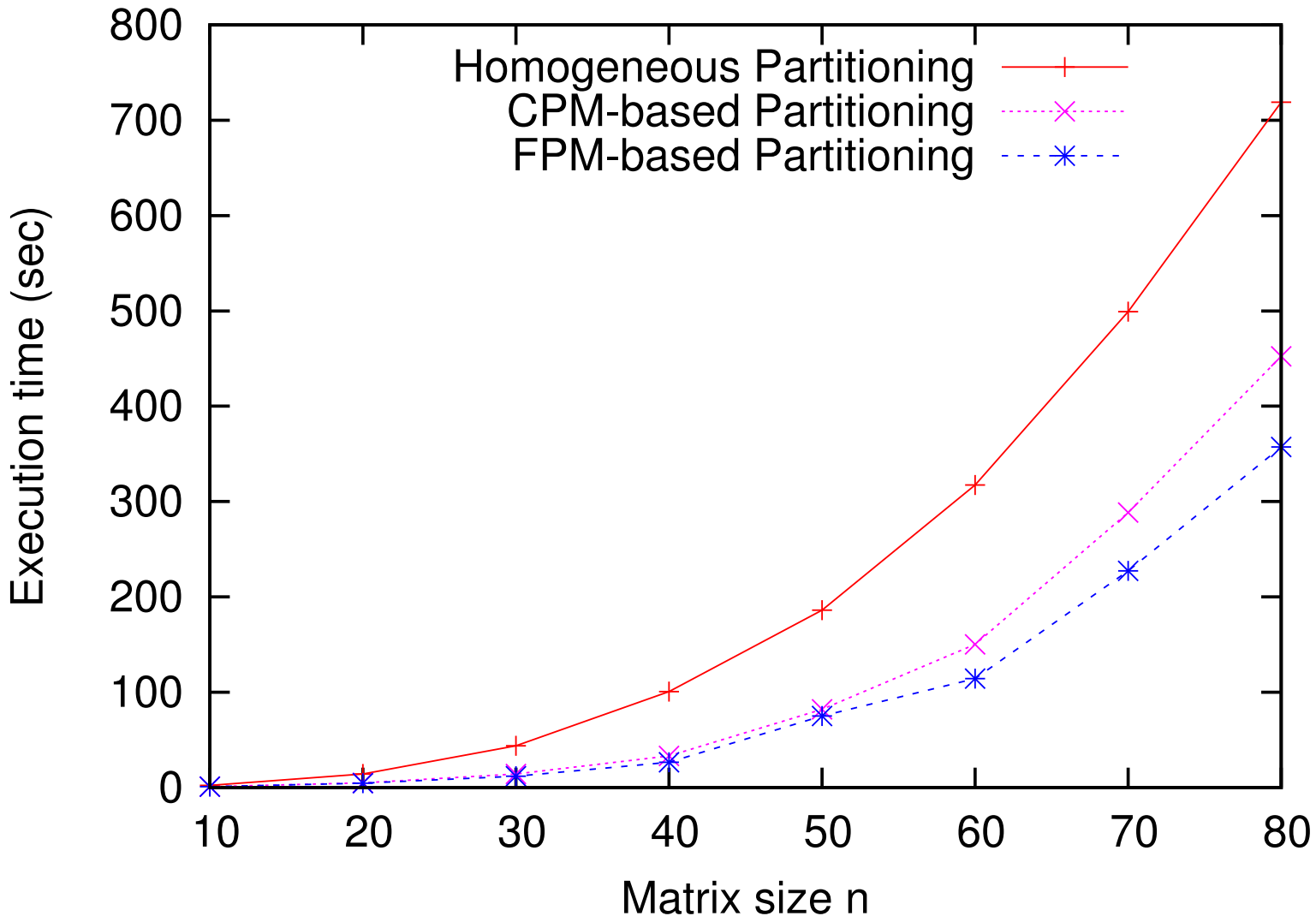
Partitioning

```
struct fupermod_dist {
  int D;     // total problem size
  int size; // number of procs
  fupermod_part* parts;
};
```

```
struct fupermod_part {
  int d;     // data chunk
  double t; // execution time
};
```

exhaustive benchmarks $\rightarrow$ *detailed models* $\rightarrow$ *static algorithm* $\rightarrow$ *partitioning*

Static data partitioning: experiments



Outline

Dynamic load balancing on a heterogeneous cluster

Iterative routine (Jacobi method): $x^{k+1} = f(x^k),\ k = 0, 1, \ldots$

```
MPI_Comm comm;
// Jacobi data: partitioned matrix/vectors
double *A = ..., *b = ..., *x = ...;
// main loop
while (error > eps) {
  // iteration of Jacobi method
  jacobi_iterate(comm, A, b, x, &error);
}
```

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while (error > eps) {
  // redistribution of Jacobi data
  jacobi_redistribute(comm, A, b, x, end - start);
  // iteration of Jacobi method
  gettimeofday(&start);
  jacobi_iterate(comm, A, b, x, &error);
  gettimeofday(&end);
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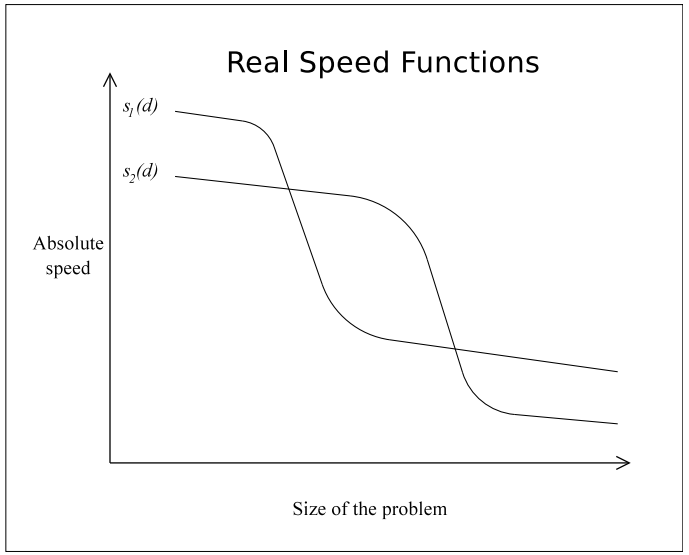
$\{benchmark \rightarrow approx.\ models \rightarrow dynamic\ algorithm \rightarrow partitioning\}+$

Dynamic FPM-based data partitioning

Functional performance models can be built:

- exhaustively in advance
- dynamically at run time



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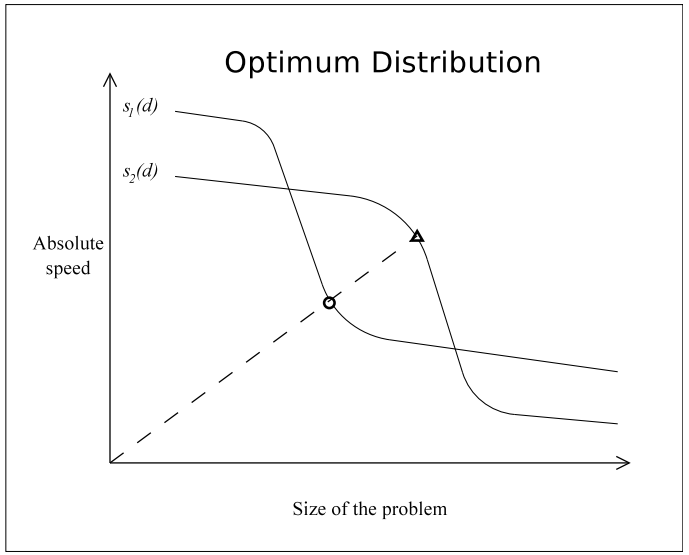

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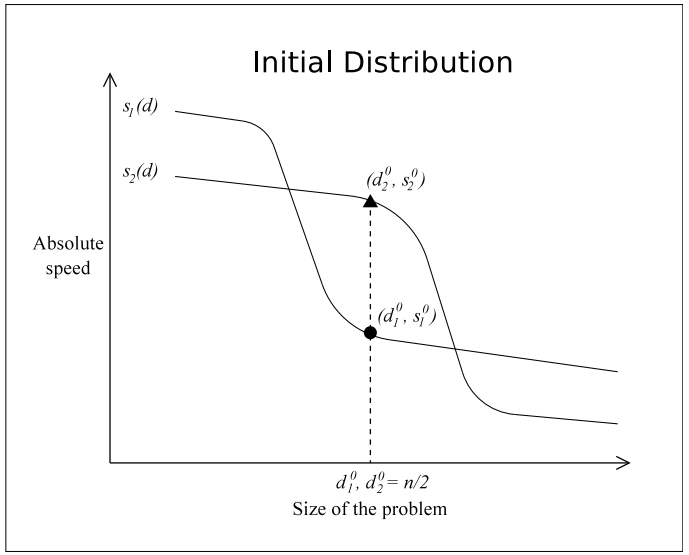
Initial: point $(n/p, s_i^0)$ with speed $s_i^0 = \dfrac{n/p}{t_i(n/p)}$

first function approximation $s_i'(x) \equiv s_i^0$



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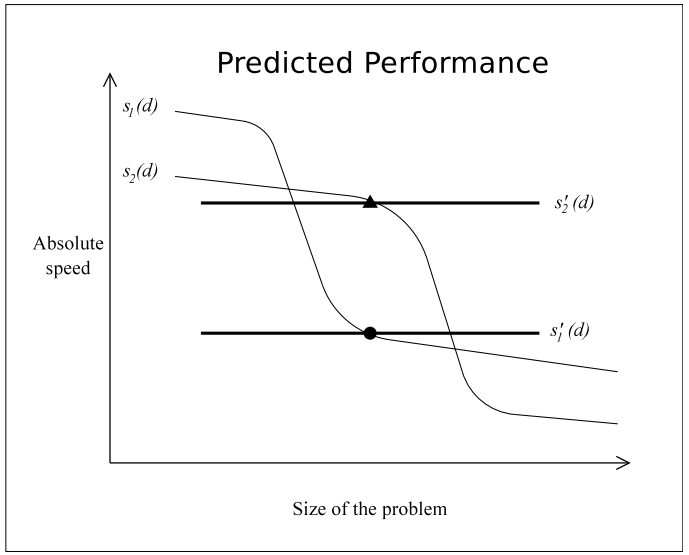

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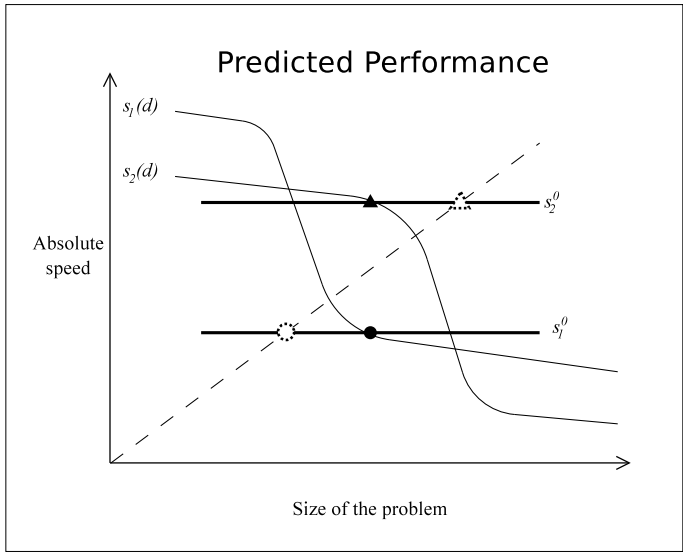

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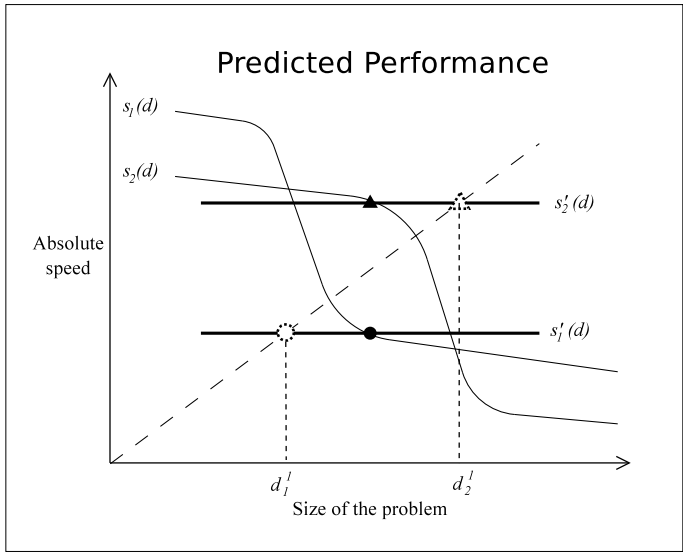

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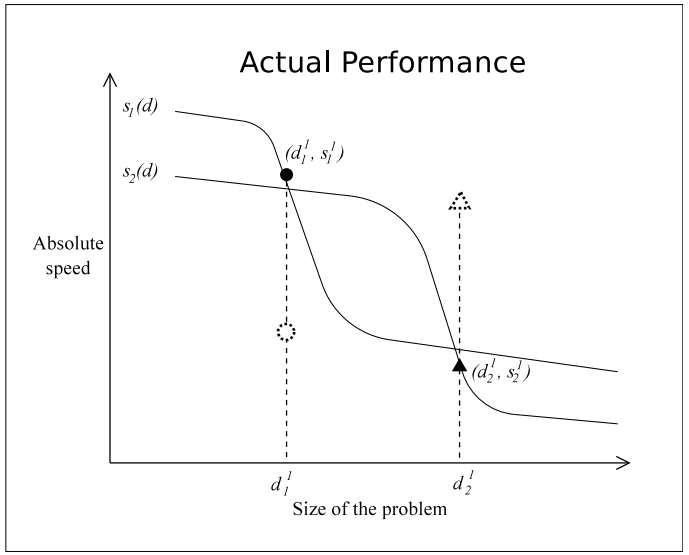

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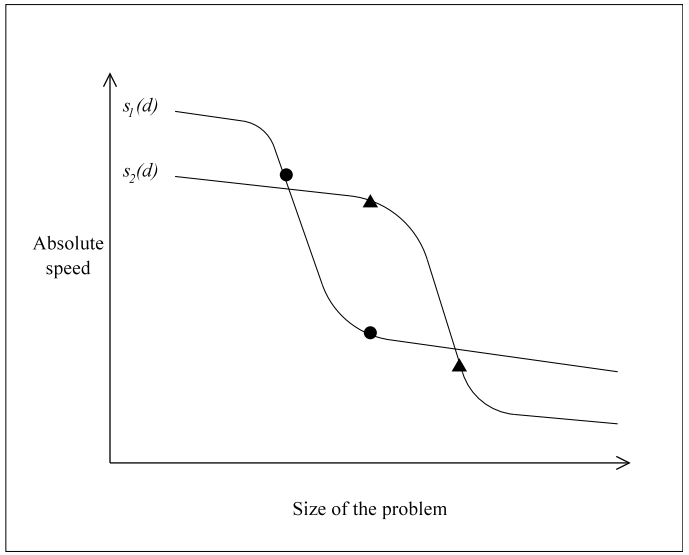

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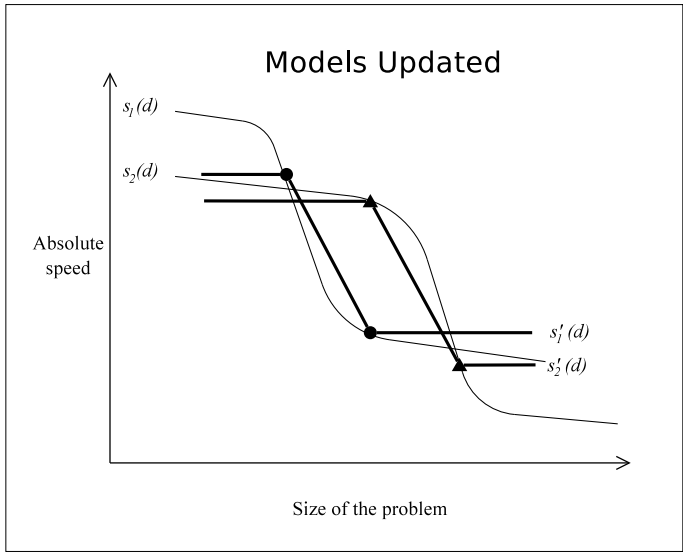

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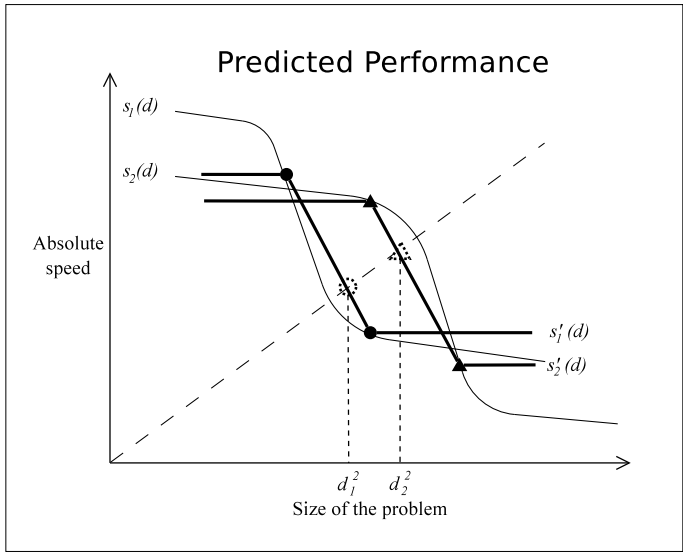

Dynamic FPM-based data partitioning

Functional performance models can be built:

- exhaustively in advance
- dynamically at run time

Initial: point $(n/p, s_i^0)$ with speed $s_i^0 = \dfrac{n/p}{t_i(n/p)}$

first function approximation $s_i'(x) \equiv s_i^0$

Iterations: point (d_i^k, s_i^k) with speed $s_i^k = \dfrac{d_i^k}{t_i(d_i^k)}$

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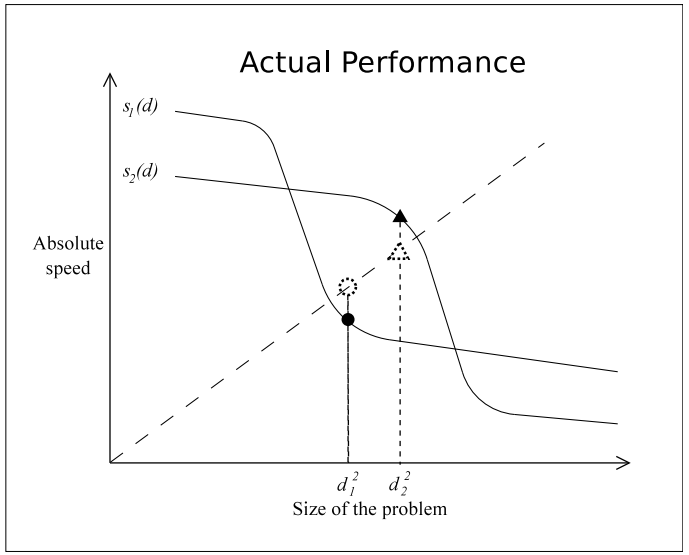

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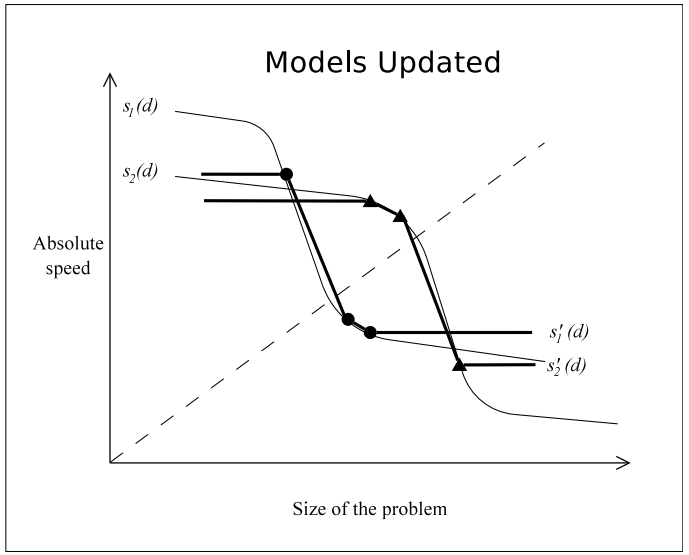

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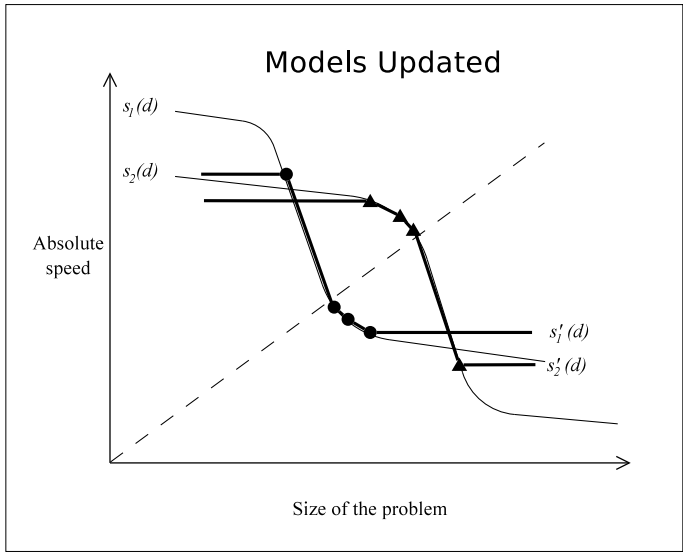


Dynamic load balancing: Jacobi method

```
MPI_Comm_size(comm, &size);
// piecewise linear FPMs
fupermod_model** models = malloc(sizeof(fupermod_model*) * size);
for (i = 0; i < size; i++)
  models[i] = fupermod_model_piecewise_alloc();
// current distribution, initially even
fupermod_dist* dist = fupermod_dist_alloc(D, size);
// context for dynamic load balancing
fupermod_dynamic balancer = { fupermod_partition_geometric,
  size, models, fupermod_dist_alloc(D, size) };
// Jacobi data: dist->parts[i].d rows/els allocated for matrix/vectors
double *A = ..., *b = ..., *x = ...;
// main loop
while (error > eps) {
  // redistribution of Jacobi data: dist --> balancer.dist
  jacobi_redistribute(comm, dist, A, b, x, balancer.dist);
  // store the current distribution
  fupermod_dist_copy(dist, balancer.dist);
  // iteration of Jacobi method
  gettimeofday(&start);
  jacobi_iterate(comm, dist, A, b, x, &error);
  // add new points (now-start) and balance the load
  fupermod_balance_iterate(&balancer, comm, start);
}
```

API for dynamic partitioning and load balancing

Context of the dynamic algorithms

```
struct fupermod_dynamic {
  fupermod_partition partition; // partitioning algorithm
  int size;                     // number of procs
  fupermod_model** models;      // current approximations
  fupermod_dist* dist;          // current partitioning
}
```

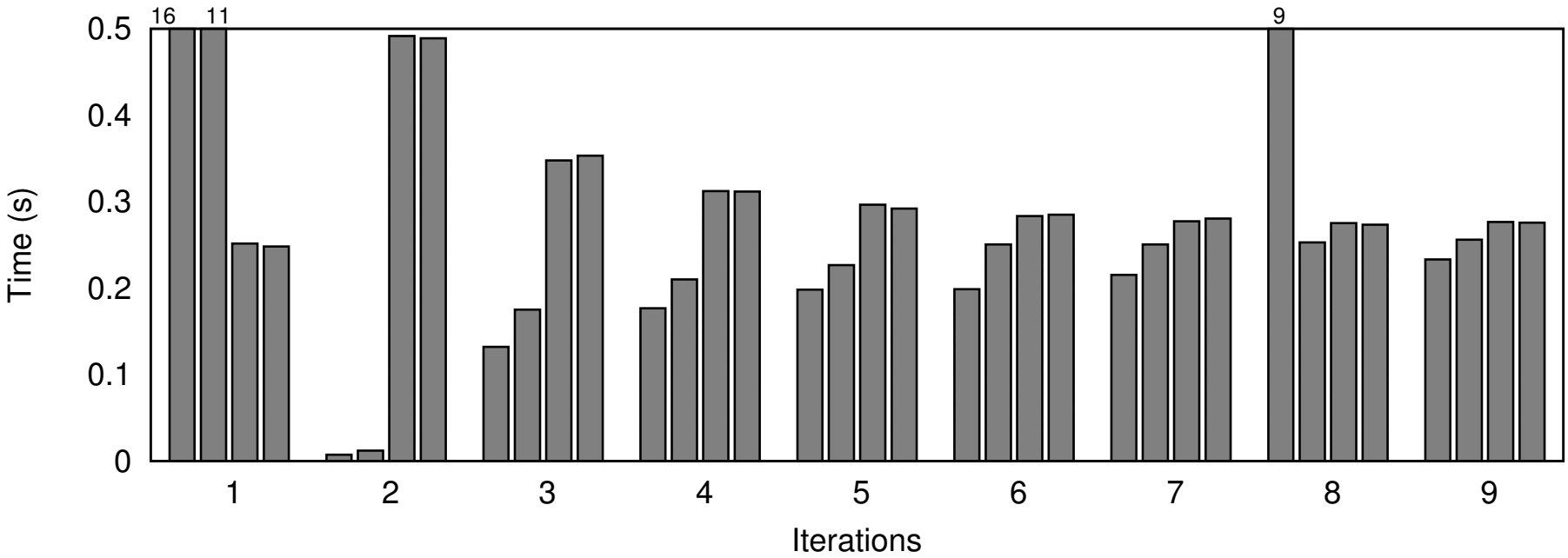
Dynamic data partitioning

```
// performs a benchmark
int fupermod_partition_iterate(fupermod_dynamic*, MPI_Comm comm,
  fupermod_precision precision, fupermod_benchmark* benchmark,
  double eps);
```

Dynamic load balancing

```
// requires the start time as input
int fupermod_balance_iterate(fupermod_dynamic*, MPI_Comm comm,
  struct timespec start);
```

Dynamic load balancing on a heterogeneous cluster



Conclusion

FuPerMod: general-purpose data partitioning framework

- accurate and cost-effective performance measurement
- construction of computation performance models, using different methods of interpolation of time and speed
- invocation of model-based data partitioning algorithms for static and dynamic load balancing

`http://hcl.ucd.ie/project/fupermod`

Thank You!

University College Dublin

Heterogeneous Computing Laboratory

Science Foundation Ireland

China Scholarship Council

Instituto de Engenharia de Sistemas e Computadores

Instituto Superior Tecnico Universidade de Lisboa

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