Task-Based *H*-Matrix Arithmetics

Part I: Algorithm Design

Ronald Kriemann MPI MIS

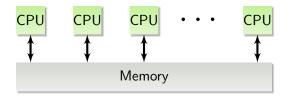
Winterschool on *H*-Matrices

2014



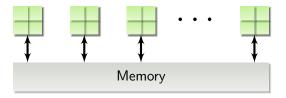
Introduction

We consider *shared-memory* systems, i.e. computers with several CPUs all accessing the same memory.



Having a single address space for all processors, simplifies parallel programming because inter-process *communication is free*.

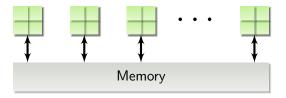
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Nowadays, each CPU consists of several compute *cores*. *Multi-core* CPUs have 8-16 cores, e.g. Intel Xeon or AMD Opteron CPUs, whereas *many-core* CPUs have 64 or more cores, e.g. Intel XeonPhi.

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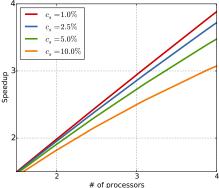
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The main problem on such systems is to keep all cores busy.

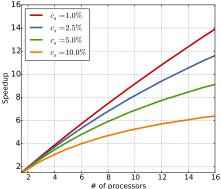
If cores are idle during the execution of an algorithm, the *parallel speedup* will deteriorate very rapidly.

The reason is *Amdahl's Law*: the influence of the sequential part on the speedup:



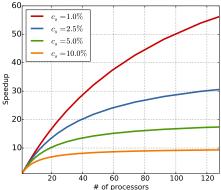
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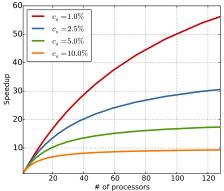
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Sources of idleness: sequential code, overhead, inefficiencies.

An algorithm typically consists of many individual operations, e.g. each update of y_i in the dense matrix-vector multiplication

for
$$i = 0, \dots, n-1$$
 do
for $j = 0, \dots, n-1$ do
 $y_i = y_i + A_{ij}x_j;$

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In a parallel algorithm, an *atomic* set of operations, which is executed by a *single* processor is called a *task*.

Designing algorithms by concentrating on tasks can help to reduce idle times on many-core systems.

An algorithm can be implemented with a different task granularity:

for
$$i = 0, ..., n - 1$$
 do
for $j = 0, ..., n - 1$ do
task // One task per matrix entry
 $y_i = y_i + A_{ij}x_j$;
for $i = 0, ..., n - 1$ do
task // One task per row
for $j = 0, ..., n - 1$ do
 $y_i = y_i + A_{ij}x_j$;

If a task is too small, too much overhead due to task management may occur.

If task granularity is too large, too few tasks may result, leaving processors idle.

Often, between different tasks *dependencies* exists, e.g. the result of one task is the input of another task:

```
procedure DOTPRODUCT(x, y, i, j)

if i = j then

task

return x_i \cdot y_i;

else

task

d_0 := \text{DOTPRODUCT}(x, y, i, (i + j)/2 - 1);

d_1 := \text{DOTPRODUCT}(x, y, (i + j)/2, j);

return d_0 + d_1;
```

Here, the computation of the sub intervals has to finish *before* computing the final result.

To achieve an optimal parallel speedup, the task granularity and the *execution order* of all tasks need to be optimal for a specific computer system.

Various factors are to consider for an optimal granularity and execution order: costs of tasks, number of processors, processor layout, memory hierarchy, etc..

Often, some of these factors are *unknown* or very *specific* to a computer system.

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Often, some of these factors are *unknown* or very *specific* to a computer system.

Fortunately, there is software available, which may be used to

- simplify task definition and
- optimise execution order.

However, for this, algorithm design has to be changed to be *task-based*

Let I be an index set, T(I) a (binary) \mathcal{H} -tree over I and $T = T(I \times I)$ a \mathcal{H}_{\times} -tree over T(I) with $\mathcal{L}(T)$ being the set of leaves of T.

The basic algorithm for \mathcal{H} -matrix construction is

```
procedure MATRIXCONSTRUCT(T)
for all b \in \mathcal{L}(T) do
```

if b is admissible then
 build low-rank matrix;
else
 build dense matrix;

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The construction of *each* leaf in T defines a new task.

The main properties of

```
procedure MATRIXCONSTRUCT(T)
for all b \in \mathcal{L}(T) do
task
build dense/low-rank matrix for b;
```

are

- much more tasks $(\#\mathcal{L}(T))$ than processors and
- construction of a block does not depend on other blocks.

The main properties of

procedure MATRIXCONSTRUCT(T) #pragma omp parallel for // loop-parallelisation in OpenMP for all $b \in \mathcal{L}(T)$ do // each b on a different p

build dense/low-rank matrix for b;

are

- much more tasks $(\#\mathcal{L}(T))$ than processors and
- construction of a block does not depend on other blocks.

With this, a simple *loop-parallelisation* will result in an optimal parallel speedup.

When *coarsening* is added to matrix construction, the algorithm is implemented via recursion, creating *dependencies* between tasks:

```
procedure MATRIXCONSTRUCT(b \in T)

if b \in \mathcal{L}(T) then

build dense/low-rank matrix for b;

else

for all b' \in \mathcal{S}(b) do

MATRIXCONSTRUCT(b');

coarsen matrix for b;
```

The coarsening may be performed only after all sub blocks have been created!

$\mathcal H\text{-}\mathsf{Matrix}$ Construction with Coarsening

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Properties:

- still much more tasks (#T) than processors and
- tasks are not independent (dependency follows hierarchy).

$\mathcal H\text{-}\mathsf{Matrix}$ Construction with Coarsening

A parallel version of MATRIXCONSTRUCT with simple loop-parallelisation:

```
procedure MATRIXCONSTRUCT(b \in T)

if b \in \mathcal{L}(T) then

build dense/low-rank matrix for b;

else

#pragma omp parallel for

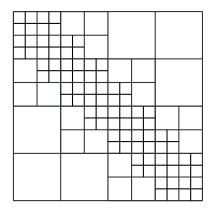
for all b' \in S(b) do

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```

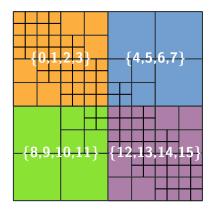
coarsen matrix for b;

Here, blocks of the \mathcal{H}_{\times} -tree are mapped to processors in a *top-down* way.

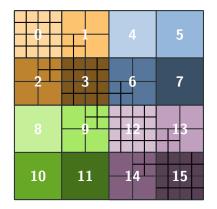
Top-down mapping during matrix construction for $\mathcal{P} = \{0, \dots, 15\}$:



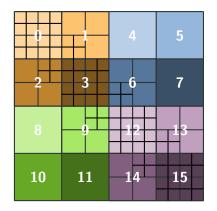
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Problem: costs for matrix construction *differ* depending on position in matrix leading to load imbalance and hence, idle processors.

$\mathcal H\text{-}\mathsf{Matrix}$ Construction with Coarsening

As an alternative, only the tasks and their dependencies are defined, without processor mapping (bottom-up approach):

```
procedure MATRIXCONSTRUCT(b \in T)

if b \in \mathcal{L}(T) then

task

build leaf matrix;

else

task

for all b' \in \mathcal{S}(b) do // define task dependencies

sub task: MATRIXCONSTRUCT(b');

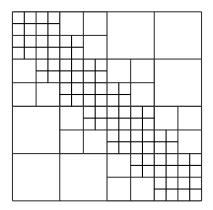
coarsen matrix for b;
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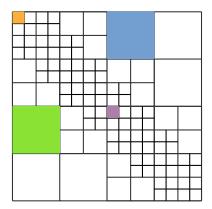
This creates a task dependency tree equal to the \mathcal{H}_{\times} -tree.

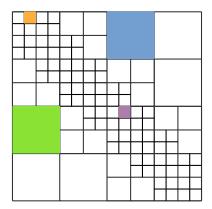
Since tasks appear early in the hierarchy, hierarchy traversal is distributed to all processors.

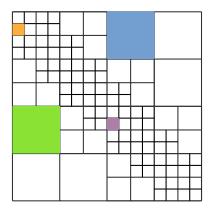
As long as there are ready tasks, no processor idles.

$\mathcal H\text{-}\mathsf{Matrix}$ Construction with Coarsening

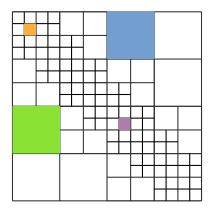


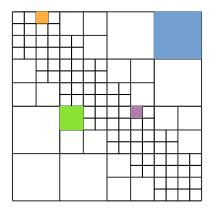




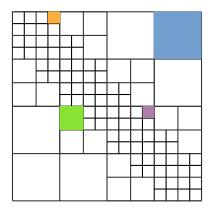


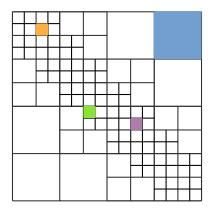
$\mathcal H\text{-}\mathsf{Matrix}$ Construction with Coarsening



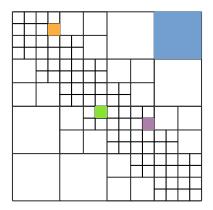


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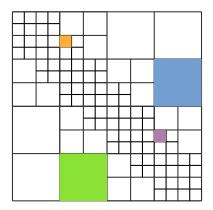




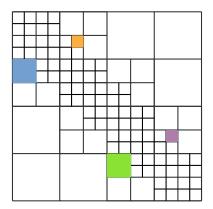
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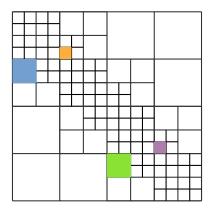
\mathcal{H} -Matrix Construction with Coarsening



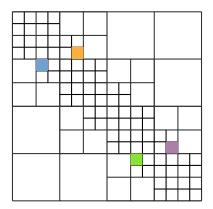
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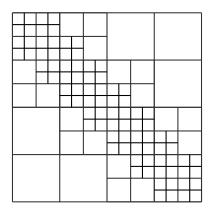


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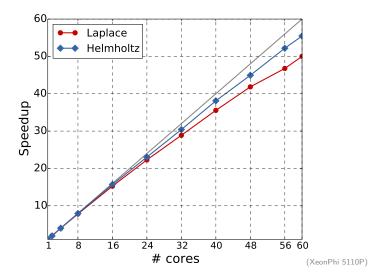
\mathcal{H} -Matrix Construction with Coarsening

Mapping of matrix blocks to processors when using tasks:



Idling may still happen, e.g. if a very costly task is scheduled at the end of the computation (but very unlikely in a typical \mathcal{H} -matrix).

 \mathcal{H} -matrix construction for Laplace-/Helmholtz-SLP on unit sphere:



H-Matrix Multiplication

\mathcal{H} -Matrix Multiplication

We consider the general update form $A := \alpha B \cdot C + A$, which results in the following recursion:

```
procedure MUL(\alpha, A, B, C)

if A, B, C are block matrices then

for i \in 0, 1 do

for j \in 0, 1 do

for \ell \in 0, 1 do

mul(\alpha, A_{ij}, B_{i\ell}, C_{\ell j});

else
```

 $A := A + \alpha BC;$

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else

task

A := A + \alpha BC;
```

The work is performed if one of the matrices is a leaf matrix. Hence, this forms a task.

Critical Sections

During matrix multiplication, different tasks update the same matrix block, which therefore forms a *critical section*, i.e. at most one processor may write to the same matrix block at a time.

```
procedure MUL(\alpha, A, B, C)

if A, B, C are block matrices then

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for i, j, l \in 0, 1 do

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else

task

lock A

A := A + \alpha BC;

unlock A
```

A *mutex* ensures, that only one processor may enter a critical section while all other processors will wait for the mutex to be unlocked.

Critical Sections

To avoid processor idling while waiting for a locked mutex, the update may be split into computing the update matrix and applying the update:

```
procedure MUL(\alpha, A, B, C)

if A, B, C are block matrices then

for i, j, l \in 0, 1 do

mul(\alpha, A_{ij}, B_{i\ell}, C_{\ell j});

else

task // compute update

T := \alpha BC;

task // apply update

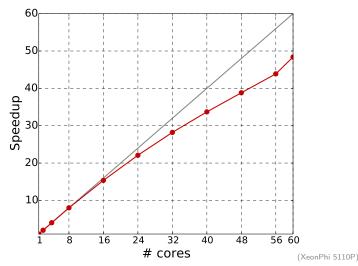
lock A

A := A + T;

unlock A
```

Computing T is *independent* from all other tasks.

 $\mathcal H\text{-matrix}$ multiplication for (unsymmetric) Laplace-SLP matrix on unit sphere:



Kriemann, »Task-Based H-Matrix Arithmetics«

$\mathcal H\text{-}\mathsf{LU}$ Factorisation

$\mathcal{H}\text{-}\mathsf{LU}$ Factorisation

For an $\mathcal H\text{-Matrix}\;A$ over T, the LU factorisation A=LU is defined by the block structure of A,L and U

$$\begin{pmatrix} A_{00} & A_{01} \\ A_{10} & A_{11} \end{pmatrix} = \begin{pmatrix} L_{00} & \\ L_{10} & L_{11} \end{pmatrix} \cdot \begin{pmatrix} U_{00} & U_{01} \\ & U_{11} \end{pmatrix},$$

which leads to the following equations:

$$\begin{aligned} A_{00} &= L_{00} U_{00} & (\text{Recursion}) \\ A_{01} &= L_{00} U_{01} & (\text{Matrix Solve}) \\ A_{10} &= L_{10} U_{00} & (\text{Matrix Solve}) \\ A_{11} &= L_{10} U_{01} + L_{11} U_{11} & (\text{Update and Recursion}) \end{aligned}$$

Classical \mathcal{H} -LU Algorithm

The above equations directly translate into an algorithm for the $\mathcal{H}\text{-}\text{LU}$ factorisation:

```
procedure LU(A, L, U)

LU(A_{00}, L_{00}, U_{00});

SOLVELOWER(A_{01}, L_{00}, U_{01});

SOLVEUPPER(A_{10}, L_{10}, U_{00});

MULTIPLY(-1, L_{10}, U_{01}, A_{11});

LU(A_{11}, L_{11}, U_{11});
```

Classical \mathcal{H} -LU Algorithm

The above equations directly translate into an algorithm for the \mathcal{H} -LU factorisation and matrix solves:

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MULTIPLY(-1, L_{10}, U_{01}, A_{11});

LU(A_{11}, L_{11}, U_{11});
```

procedure SOLVELOWER(A, L, B)SOLVELOWER (A_{00}, L_{00}, B_{00}) ; SOLVELOWER (A_{01}, L_{00}, B_{01}) ; MULTIPLY $(-1, L_{10}, B_{00}, A_{11})$; MULTIPLY $(-1, L_{10}, B_{01}, A_{11})$; SOLVELOWER (A_{10}, L_{11}, B_{10}) ; SOLVELOWER (A_{11}, L_{11}, B_{11}) ;

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Both procedures only consist of *recursion* and *matrix multiplication*.

Only at the level of leaves, specialised algorithms are needed, e.g. factorise dense matrix or solve low-rank matrix.

Parallelisation

The algorithm is by itself inherently *sequential*.

Only the matrix solves may be performed in parallel:

```
procedure LU(A, L, U)

LU(A_{00}, L_{00}, U_{00});

{ SOLVELOWER(A_{01}, L_{00}, U_{01}) SOLVEUPPER(A_{10}, L_{10}, U_{00}); }

MULTIPLY(-1, L_{10}, U_{01}, A_{11});

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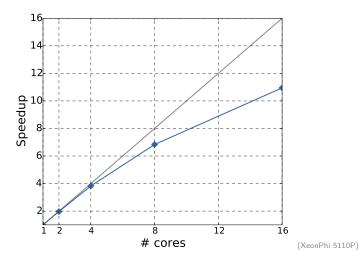
MULTIPLY(-1, L_{10}, U_{01}, A_{11});

LU(A_{11}, L_{11}, U_{11});
```

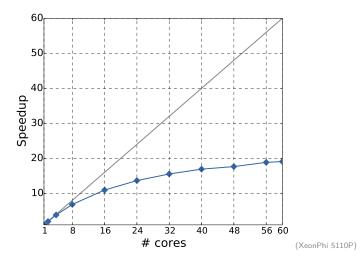
Matrix solve algorithm can be parallelised only slightly better:

procedure SOLVELOWER(A, L, B){ SOLVELOWER (A_{00}, L_{00}, B_{00}) ; SOLVELOWER (A_{01}, L_{00}, B_{01}) ; } { MULTIPLY $(-1, L_{10}, B_{00}, A_{10})$; MULTIPLY $(-1, L_{10}, B_{01}, A_{11})$; } { SOLVELOWER (A_{10}, L_{11}, B_{10}) ; SOLVELOWER (A_{11}, L_{11}, B_{11}) ; }

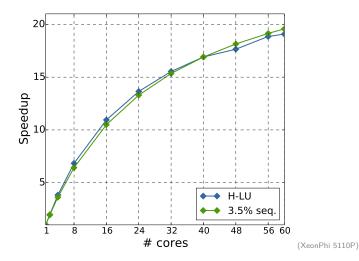
Parallel speedup for the \mathcal{H} -LU factorisation of the \mathcal{H} -matrix defined by the Laplace SLP on the unit sphere:



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Function trace of \mathcal{H} -LU factorisation:

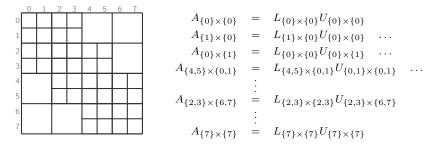


(Xeon E5-2640)

Task-based \mathcal{H} -LU Factorisation

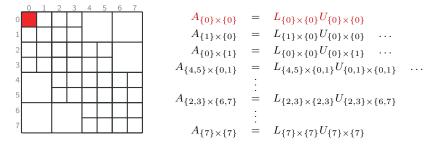
The equations

 $A_{00} = L_{00}U_{00} \qquad A_{11} = L_{10}U_{01} + L_{11}U_{11}$ $A_{01} = L_{00}U_{01} \qquad A_{10} = L_{10}U_{00}$



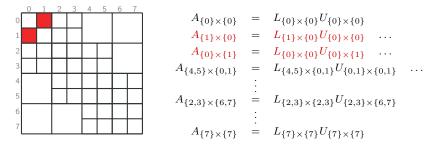
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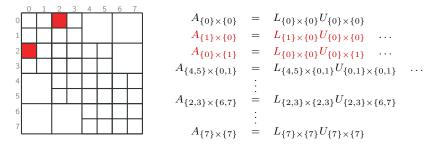
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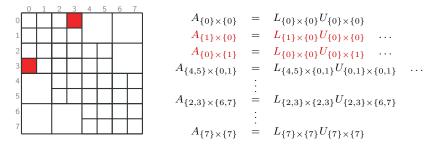
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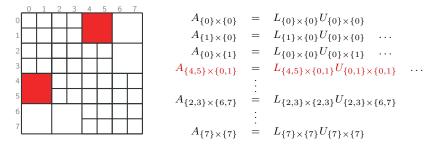
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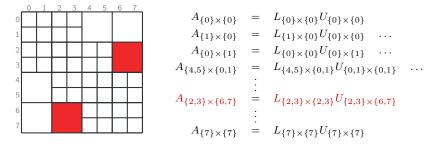
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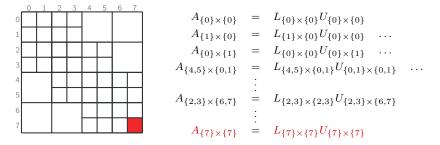
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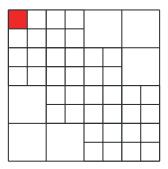
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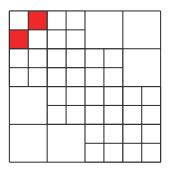
Task Execution Order

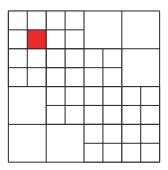
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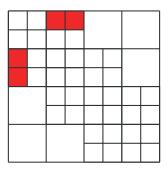


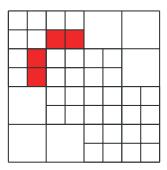
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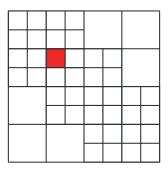
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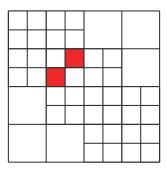


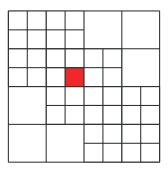


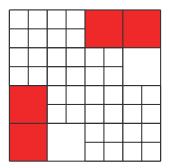


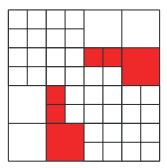


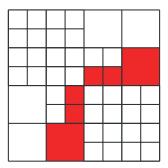


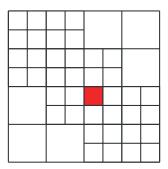


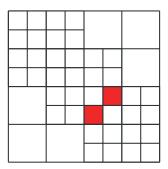


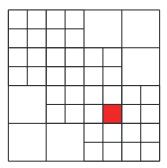


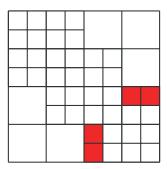


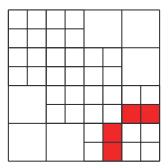


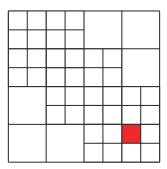


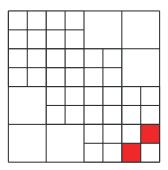




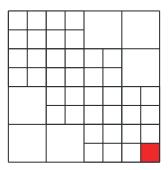




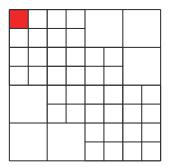


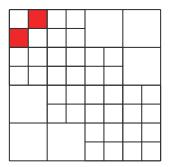


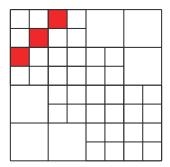
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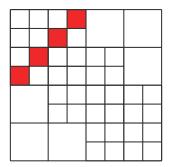


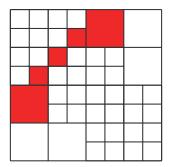
To handle all tasks, 19 steps are needed.

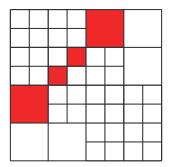


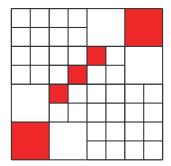


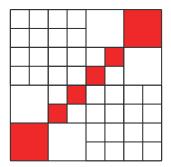


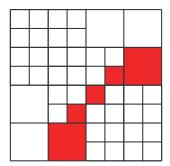


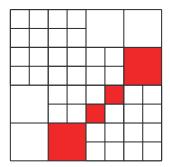


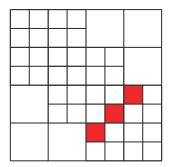


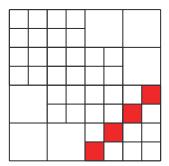


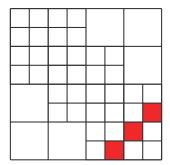


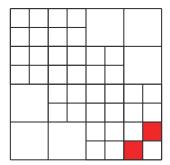




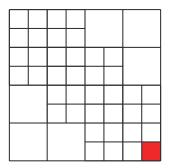






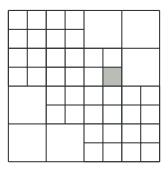


An optimal execution order only needs *15* steps and diagonal tasks can be executed *simultaneously* with off-diagonal tasks:



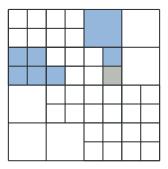
For the 46 tasks in the example, the parallel speedup is increased from $\frac{46}{19}\approx 2.42$ to $\frac{46}{15}\approx 3.07$ (not counting update tasks).

The equations of the \mathcal{H} -LU factorisation also define *data dependencies* between matrix blocks



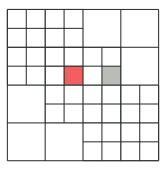
The equations of the \mathcal{H} -LU factorisation also define *data dependencies* between matrix blocks, e.g.

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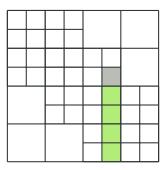
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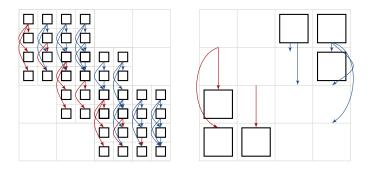
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- factorise or solve matrix blocks after applying all updates,
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- perform matrix updates after matrix solves.



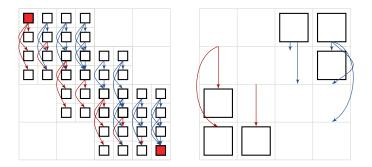
Task Dependencies

The tasks and their dependencies can also be represented in the form of a *directed acyclic graph* (*DAG*) with tasks as nodes and dependencies as edges:



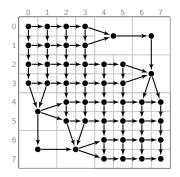
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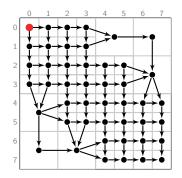


The *start node* of this DAG is the upper left matrix block, while the *end node* is the lower left matrix block.

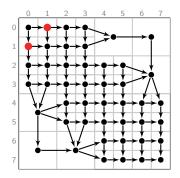
As with implicit task dependencies, nodes in a DAG are scheduled for execution, when all dependencies are met, i.e. predecessor tasks have finished.



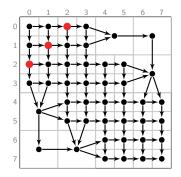
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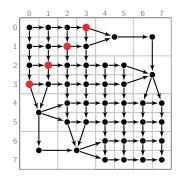
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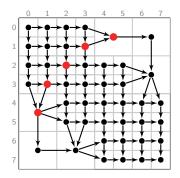
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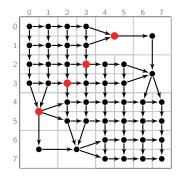
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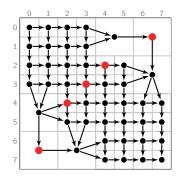
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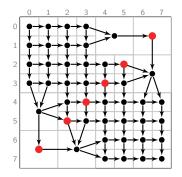
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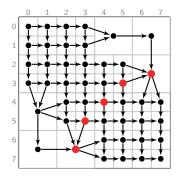
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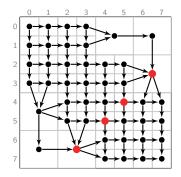
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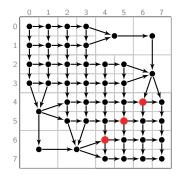
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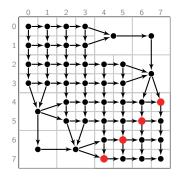
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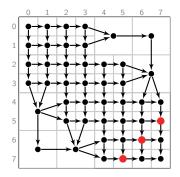
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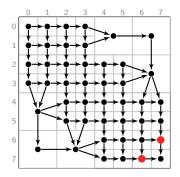
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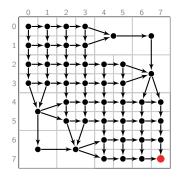
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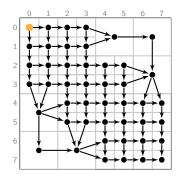
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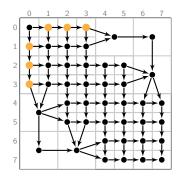
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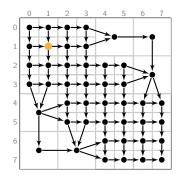
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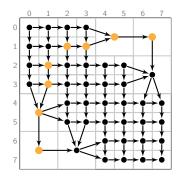
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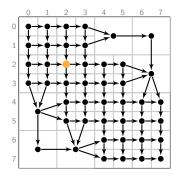
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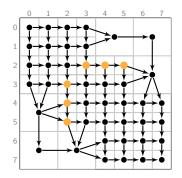
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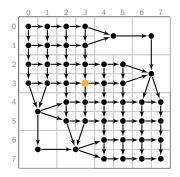
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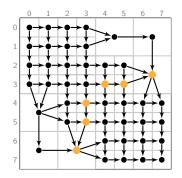
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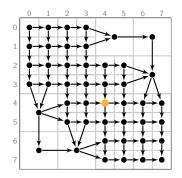
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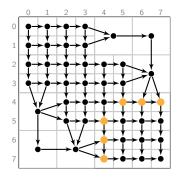
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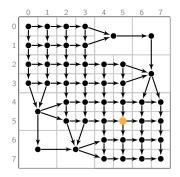
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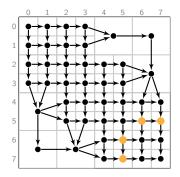
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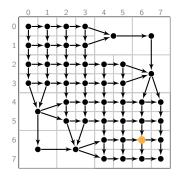
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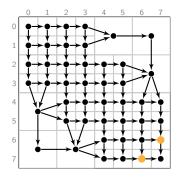
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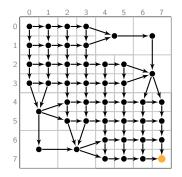
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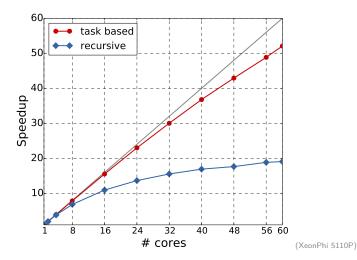
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Again, the \mathcal{H} -LU factorisation of the Laplace SLP operator is computed. The speedup of the task based algorithm is:



Function trace of \mathcal{H} -LU factorisation:



(Xeon E5-2640)

Function trace of \mathcal{H} -LU factorisation:

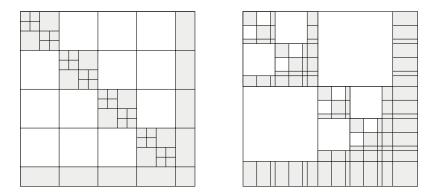


(Xeon E5-2640)

Domain-Decomposition

Domain-Decomposition

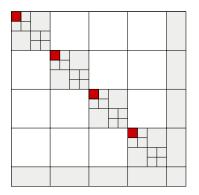
If domain decomposition or nested dissection is applied, $\mathcal H\text{-matrices}$ have large, zero, off-diagonal blocks:

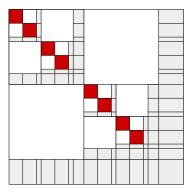


During LU factorisation, these blocks will remain zero, resulting in a higher level of parallelism.

Domain-Decomposition

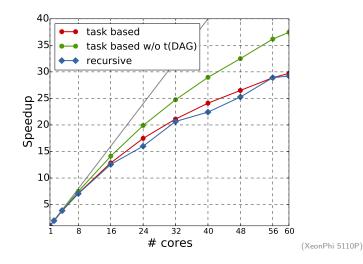
The task-based \mathcal{H} -LU factorisation algorithm *automatically* exploits this parallelism by using *several* start nodes in the DAG:



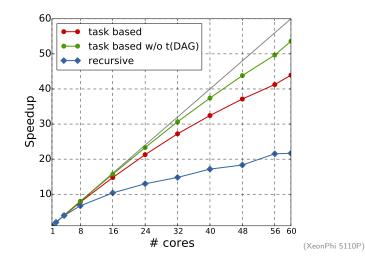


The parallel speedup of the recursive \mathcal{H} -LU algorithm is limited by the size of the interface.

 \mathcal{H} -LU factorisation for convection-diffusion equation in \mathbb{R}^2 :



 \mathcal{H} -LU factorisation for convection-diffusion equation in \mathbb{R}^3 :



Literature

Literature

🔋 R. Kriemann,

H-LU Factorization on Many-Core Systems, MIS Preprint, 5/2014.

🔋 R. Kriemann,

Parallel H-Matrix Arithmetics on Shared Memory Systems, Computing, 74:273–297, 2005.