RUNNING SLATE USING THE PARSEC RUNTIME SYSTEM

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SLATE AND PARSEC

Slate:

- Parallel implementation of LAPACK, ScaLAPACK and BLAS routines
- C++ API
- Capable of exploiting multicore CPUs and GPU devices
- MPI, OpenMP and CUDA

SLATE AND PARSEC

Slate:

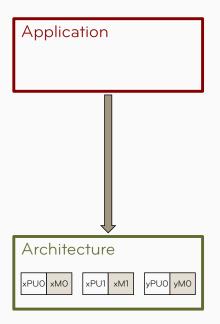
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- Capable of exploiting multicore CPUs and GPU devices
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Parsec:

- General purpose runtime system
- Supports various domain specific language such as DTD, JDF and TTG
- Asynchronous distributed-memory communication engine
- GPU driver currently supporting NVIDIA GPUs
- Capable of managing data consistency across various memory nodes

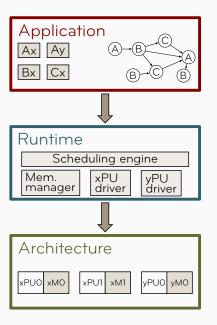
Objective: Integrate the PaRSEC runtime system into the Slate library as an alternative to the standard MPI+OpenMP+CUDA model.

RUNTIME SYSTEMS



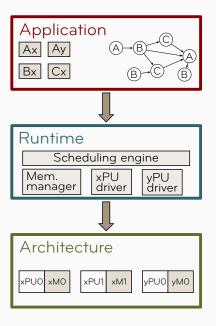
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 - o requires a big programming effort.
 - o is difficult to maintain and update.
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 - o Data management
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- The workload is expressed as a DAG (Directed Acyclic Graph) of tasks.

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- Ability to exploit of fine-grain parallelism.
- Let the runtime system handle memory transfers and data coherency.
- Maximize computation-communication overlapping while benefiting from collective communications.
- Enable task pipelining between sequence of routine calls.

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Make this integration as transparent as possible for the Slate developers:

- High-level algorithm description.
 - ▼ Issue with hard-coded OpenMP directive at the higher level.
- Data-distribution: 2D block-cyclic.
- GPU task mapping.

RUNTIME SYSTEMS AND PROGRAMMING MODELS

This approach has been assessed in the domain of dense linear algebra and sparse algorithms.

- Programming models: Sequential Task Flow (STF), Parametrized Tasks Graph (PTG)
- Runtime systems: PaRSEC, StarPU, QUARK, IntelTBB
- Scientific libraries: (D)PLASMA, Chameleon, SyLVER, qr_mumps, PasTiX

Slate algorithms relies on control flow dependencies and nested parallelism

```
for (p = 0; p < nc; ++p) {
   Factor(p);

  for (u = p+1; u < nc; ++u) {
      Update(p, u) ;
   }
}</pre>
```

 At the higher level Slate expresses dependencies using a 1D block partitioning

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for (p = 0; p < nc; ++p) {
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for (p = 0; p < nc; ++p) {
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- Factor(p) and Update(p, u) are executed asynchronously
- Dependencies between panel factorization and trailing submatrix update are expressed explicitly to the runtime system
- Tasks are not associated with real data (factors) but symbolic ones: data transfer must be done explicitly i.e send if the tile is local, receive otherwise

Nested parallel within Factor and Update

```
Factor(p) {
    Potrf(tile(p,p));

    for (r = p+1; r < nr; ++r) {
        Trsm(tile(p,p), tile(r,p));
    }
}</pre>
```

Numerical operations execute on underlying 2D data partitioning

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- Execution of independent tasks is done asynchronously using OpenMP

```
Factor(p) {
#omp task
    Potrf(tile(p,p));
    wait_for_all();

    for (r = p+1; r < nr; ++r) {
#omp task
        Trsm(tile(p,p), tile(r,p));
    }
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- 2) Tasks are associated with data (manipulated within computational kernels) along with access mode (Read, Write, Read-Write) and shape (dimensions, stride, type, etc) information
- ⇒ Task dependencies are inferred to ensure the sequential consistency of the parallel code
- ⇒ Data transfers can be automatically issued by the runtime system

Using STF model within Slate

```
Factor(p) {
    insert(Potrf, tile(p,p) );
    wait_for_all();
    send(tile(p,p)); or recieve(tile(p,p));
    wait_for_all();
    for (r = p+1; r < nr; ++r) {
        insert(Trsm, tile(p,p) , tile(r,p) );
    }
    wait_for_all();
}</pre>
```

• Use Parsec to asynchronously execute the task on tiles

```
Factor(p) {
    insert(Potrf, tile(p,p):RW);
    wait_for_all();
    send(tile(p,p)); or recieve(tile(p,p));
    wait_for_all();
    for (r = p+1; r < nr; ++r) {
        insert(Trsm, tile(p,p):R, tile(r,p):RW);
    }
    wait_for_all();
}</pre>
```

- Use Parsec to asynchronously execute the task on tiles
- Add data access and shape information to the runtime system

```
Factor(p) {
    insert(Potrf, tile(p,p):RW);
    send(tile(p,p)); or recieve(tile(p,p));
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    for (r = p+1; r < nr; ++r) {
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- Use Parsec to asynchronously execute the task on tiles
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- Use Parsec to asynchronously execute the task on tiles
- Add data access and shape information to the runtime system
- Remove explicit synchronization barrier
- Remove explicit data transfer routines

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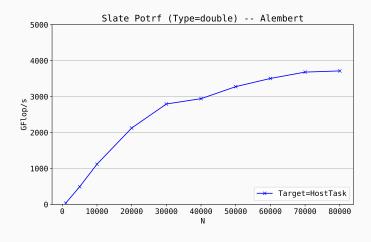
- The DAG is represented using a compact format which is problem size independent.
- The dataflow is explicitly encoded i.e. task dependencies are explicitly given to the runtime system.
- The runtime handles the communications implicitly using the dataflow representation.

NUMERICAL EXPERIMENTS: ALEMBERT

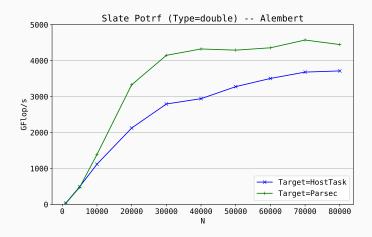
System Alembert (Saturn):

- Haswell E5-2650 v3 @ 2.30GHz, 2 × 10 cores
- 64GB RAM (NUMA)
- 9 nodes
- Infiniband EDR 100G
- Compiler GCC 7.3
- BLAS and LAPACK libraries from Intel MKL 19.3
- Open MPI 3.0

Numerical experiments: Alembert

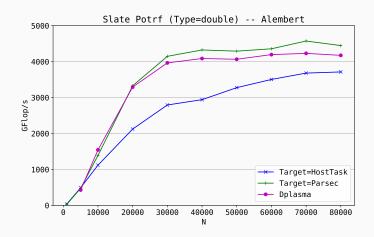


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The Parsec target compares favourably to Slate implementation

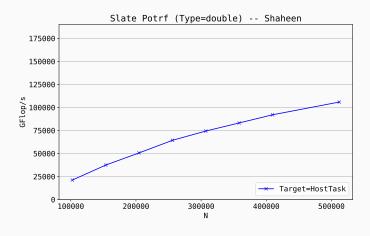
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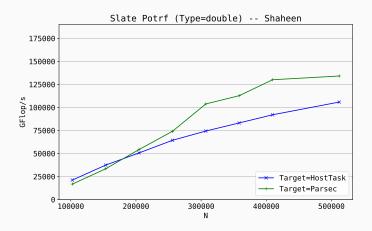


- The Parsec target compares favourably to Slate implementation
- It outperforms DPlasma

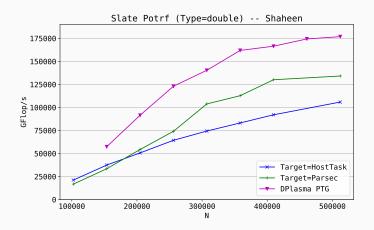
System Shaheen (Kaust):

- Intel Haswell @ 2.30GHz, 2 × 16 cores
- 128GB RAM (NUMA)
- 256 nodes (8192 cores)
- Cray Aries interconnect with Dragonfly topology
- Intel C++ compiler
- BLAS and LAPACK libraries from Intel MKL 19.3
- Cray MPI (MPICH3)





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- Performs poorly compared to DPlasma

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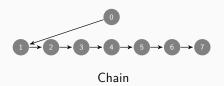
Use of collective communication patterns that better fits the network topology e.g. Broadcast



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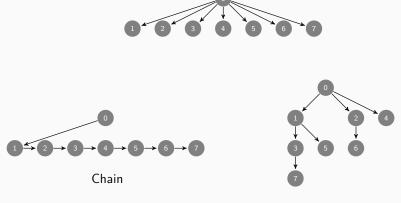
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Binomial tree

SLATE-PARSEC POTRF

Using STF model within Slate and integrating collective communications

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 Integrate the communication information in the task flow by inserting a task in the DAG

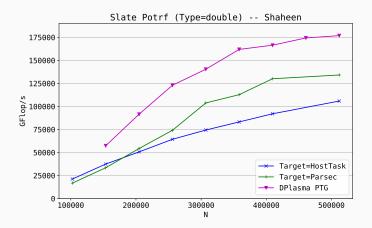
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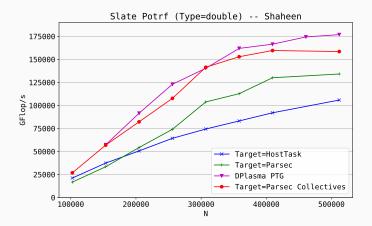
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- Integrate the communication information in the task flow by inserting a task in the DAG
- Communication in non-blocking but data access information guarantee sequential consistency



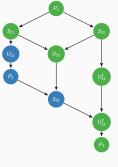
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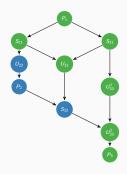
- The Parsec target compares favourably to Slate (main branch) implementation
- The Parsec target performance is dramatically improved by using collective communication patterns

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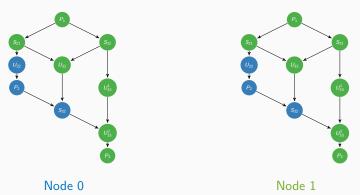


Node 0



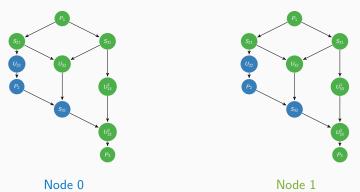
Node 1

In a distributed memory context, one limitation of the DTD interface lies in the fact that the whole DAG is unrolled on every nodes.



• The number of local tasks in the factorization only represent a fraction $(\frac{1}{np})$ of the total tasks $O((\frac{n}{nb})^3)$

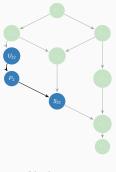
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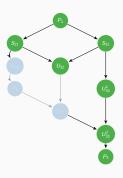
- The number of local tasks in the factorization only represent a fraction $(\frac{1}{np})$ of the total tasks $O((\frac{n}{nb})^3)$
- The cost for the task creation and submission is not negligible for large matrix size and when increasing the number of processes

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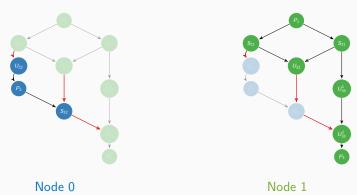


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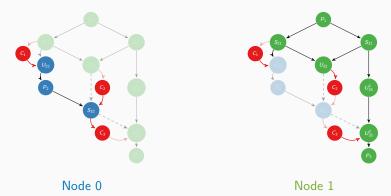
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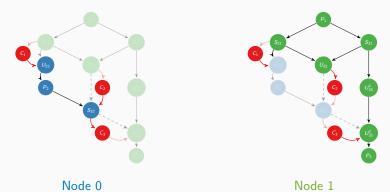
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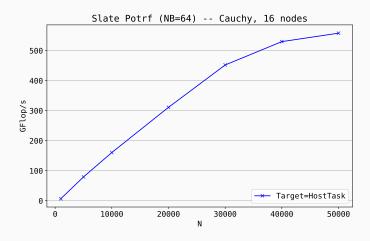
- Problem: Only partial information available locally, matching message tags becomes difficult
- Locally insert remote tasks responsible for communications on every nodes: globally consistent message identification
- Slate provide this information to the runtime system

NUMERICAL EXPERIMENTS: CAUCHY

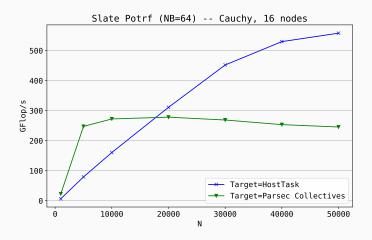
System Cauchy (Saturn):

- Westmere-EP E5606 @2.13GHz, 2×4 cores
- 24GB RAM (NUMA)
- 16 nodes
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- Compiler GCC 7.3
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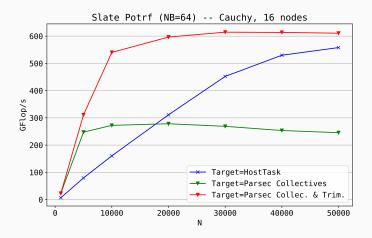


Numerical experiments: Cauchy



 Using a relatively small tile size, the time spent for the task creation and submission becomes greater than the execution of local tasks

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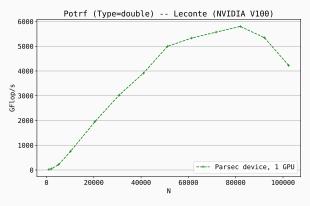
- Using a relatively small tile size, the time spent for the task creation and submission becomes greater than the execution of local tasks
- Trimming the DAG allows us to alleviate this issue thus improving the scalability of the factorization

Numerical experiments: Leconte

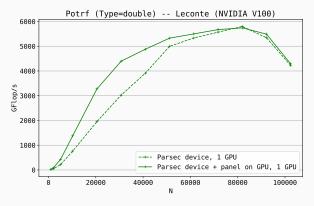
System Leconte (Saturn):

- Broadwell Intel CPU E5-2698 v4 @ 2.20GHz, 2 × 20 cores
- 500GB RAM (NUMA)
- 8 NVIDIA V100 GPUs
- Compiler GCC 8.4
- BLAS and LAPACK libraries from Intel MKL 20.0
- NVIDIA CUDA 10.2

- Panel factorization and update on GPU
- Using one GPU

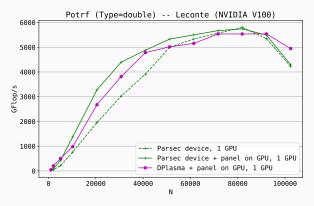


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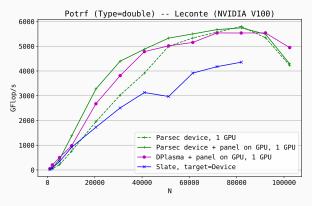
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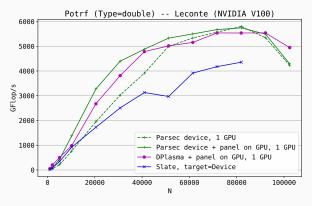
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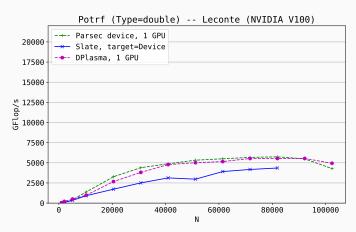
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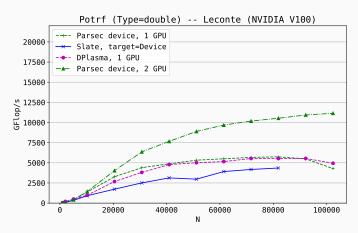


- Scalability improved by executing panel on GPU
- The Parsec target Compares favourably to current DPlasma code
- Slate-Parsec is about 20% faster than the original Slate
- Slate can no longer perform the factorization if the matrix does not fit in the GPU memory

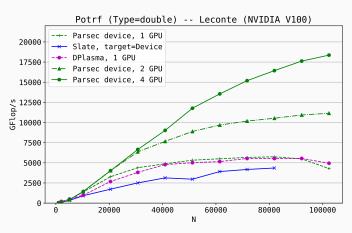
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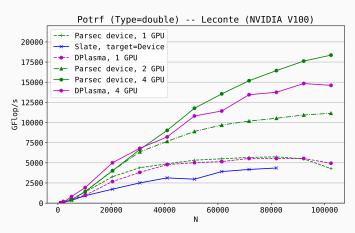
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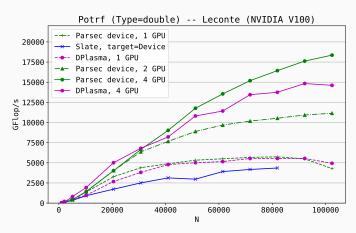
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CONCLUSIONS AND FUTURE WORK

Conclusions:

- Parsec helps to efficiently run Slate algorithms by exploiting fine-grained parallelism and maximizing computation-communication overlap
- Parsec ease data management on heterogeneous architectures

Future work:

- Experiment on GPU-based distributed memory systems (e.g. Summit)
- Add support for AMD GPU architectures in Parsec