

# **Composition of Algorithmic Building Blocks in Template Task Graphs**

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PAW/ATM'22, held in conjunction with SC'22

## Task Graphs and their Composition

Composition is essential for scalable software development



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Do we know how to compose task graphs?

# Why Task Graph Composition

 Assume N consecutive functions implemented using the same task programming model

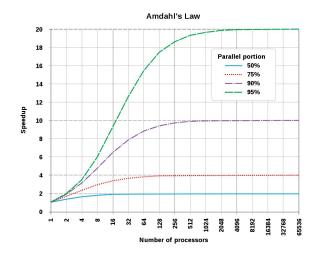
N forks and joins without composition

Write-back to data structures instead of direct flow

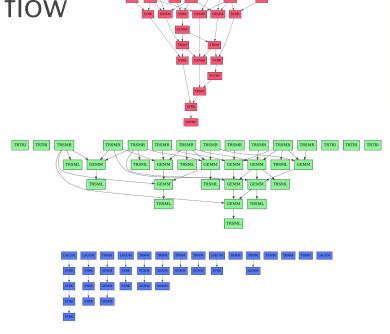
Gene Amdahl says that's bad



https://upload.wikimedia.org/wikipedia/commons/1/1a/Gene\_Amdahl\_o n a classic grey Ferguson tractor at Amdahl.JPG



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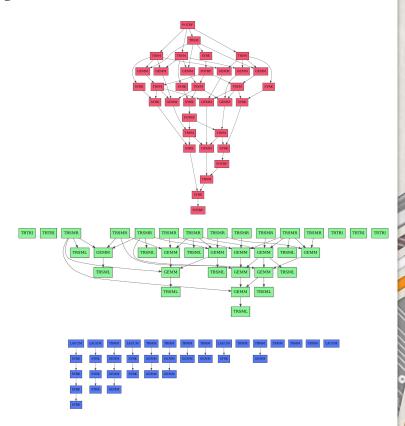




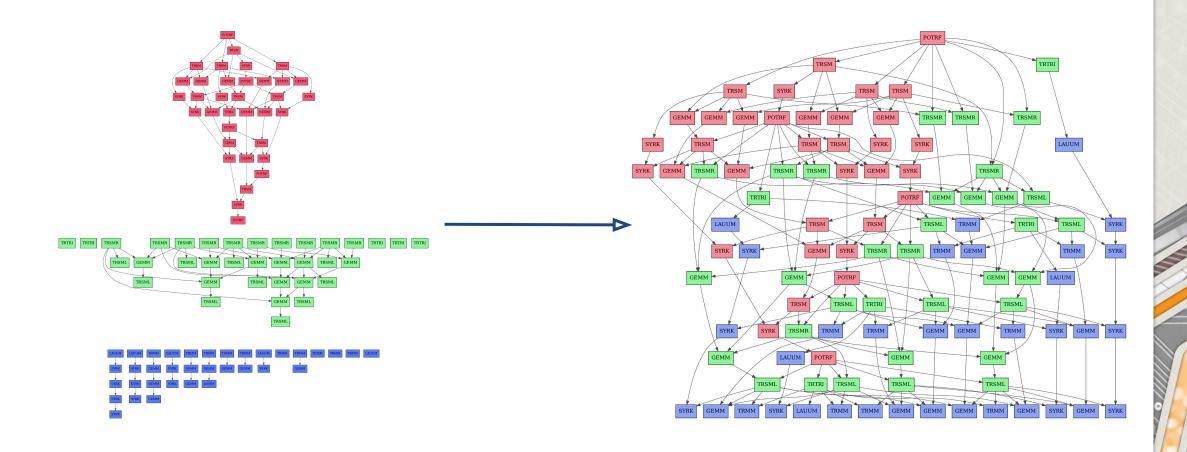


# **Example: Cholesky Matrix Inversion**

- Cholesky Factorization (POTRF) followed by matrix inversion
  - Given A, compute A<sup>-1</sup>
  - A: Hermitian positive-definite matrix
- Inversion: Given L from POTRF
  - Compute L<sup>-1</sup> from L (TRTRI)
  - Compute  $A^{-1} = (L^{-1})^T L^{-1}$  (LAUUM)
  - POTRI = TRTRI ⊕ LAUUM
- POINV = POTRF ⊕ POTRI = POTRF ⊕ TRTRI ⊕ LAUUM



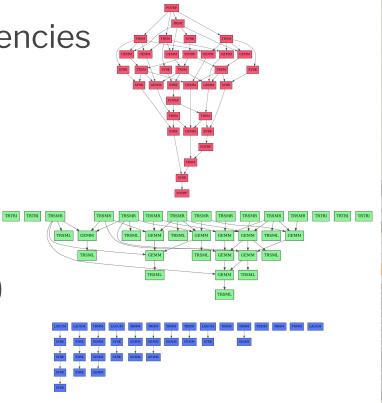
#### Task Graph Composition at Work





#### **Existing Approaches to Task Graph Composition**

- **Dependency**-based approaches
  - o OpenMP, OmpSs, StarPU, PaRSEC DTD, ...
  - Sequential discovery of tasks and their dependencies
  - Limited discovery windows
  - Limited scalability
- Handle-based approaches (HPX)
  - Composition through future passing
  - One future per element
  - Significant efforts for LA required
- Parameterized Task Graphs (PaRSEC PTG)
  - Flow within a graph
  - Operates exclusively on data collections
  - Missing: external interfaces

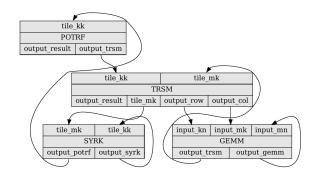


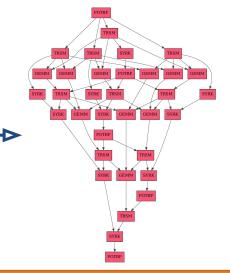




## Introducing: Template Task Graphs

- Algorithms expressed as abstract graphs
  - All possible edges in task graph declared a priori
  - Template Tasks (TT) with input and output terminals
  - Tasks are instances of TTs identified by IDs
  - Edges represent sets of values flowing between tasks
  - Data movement through the graph handled by TTG
- Template Task Graph unrolled during execution
  - Fully distributed graph discovery



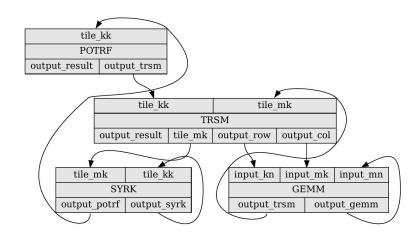






#### Edges in Template Task Graphs

- Edges connect template tasks through terminals
- Tasks decide on which output terminal(s) to send data
- Edges connect
  - A single output terminal (its input)
  - Multiple input terminals (its output)



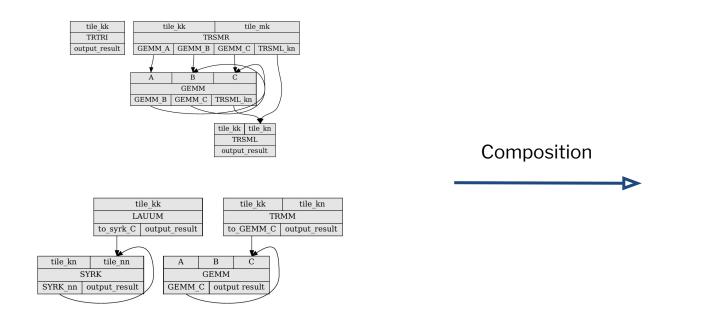
Can we use Edges to connect Task Graphs?\*

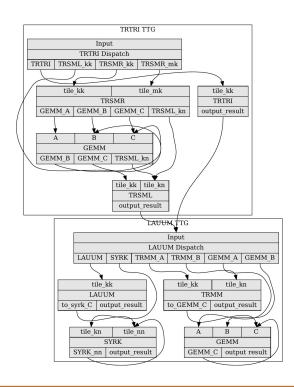




#### Connecting Graphs: Edges as Composition Devices

- Introduce Dispatch Tasks to Task Graphs
  - Dispatch incoming data to internal tasks
  - Internal edges and tasks not visible to outside
  - Single output edge, to connect to successors



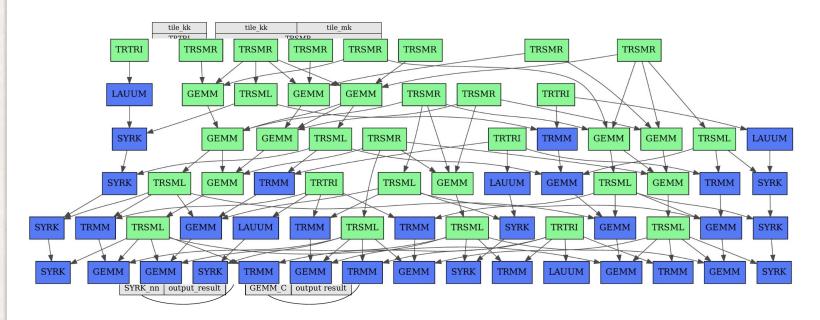


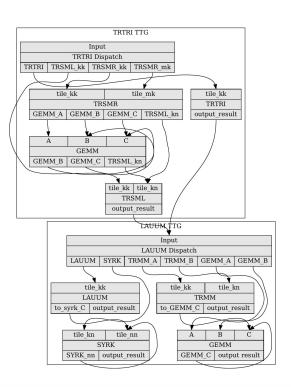




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#### Task Graphs as Black Box Functions

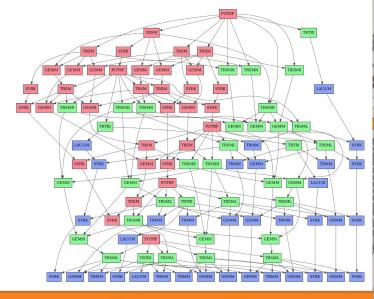
- Edges: well-defined interface between graphs
- Internal structure of a task-graph irrelevant to caller
- Composing TRTRI & LAUUM into POTRI

```
using namespace std;
                                                                    Input Edge
    auto make_potri_ttg(ttg::Edge<Key2, MatrixTile>&input,
                        ttg::Edge<Key2, MatrixTile>&output)
                                                                    Output Edge
     ttq::Edge<Key2, MatrixTile>
                        trtri_to_lauum("trtri_to_lauum"); 
                                                                    Internal Edge
      auto ttg trtri = make trtri ttg(input, trtri to lauum);
                                                                    Internal
      auto ttg_lauum = make_lauum_ttg(trtri_to_lauum, output);
                                                                    Subgraphs
      auto ins = make_tuple(ttg_trtri->template in<0>());
      auto outs = make tuple(ttg lauum->template out<0>());
     vector<unique_ptr<ttq::TTBase>> ops(2);
     ops[0] = std::move(ttg trtri);
                                                                    New
      ops[1] = std::move(ttq_lauum);
                                                                    Template
                                                                    Task Graph
     return ttg::make_ttg(std::move(ops),
18
                           ins, outs, "POTRI TTG");
```



## Benefits of Task Graph Composition

- Minimized serial application parts
- Application-level depth-first execution (memory reuse)
  - Cache reuse
  - Device data transfer minimization (for out-of-core computation)
- Flexibility: reusing intermediate results becomes trivial
  - Example: tiles of a Cholesky factorized matrix
    - As input for POTRI
    - Used together with POTRI results
  - TTG will manage tile copies



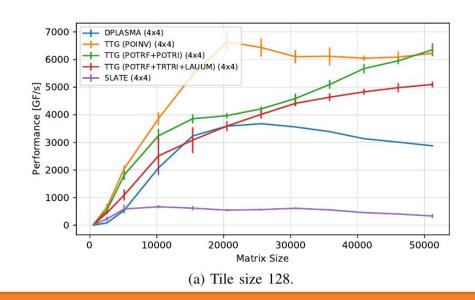


## **Experimental Evaluation: Test System Setup**

- All experiments executed on Hawk
  - Installed at HLRS in Stuttgart, Germany
  - 2x64core AMD EPYC nodes, 2.2 GHz
  - Mellanox ConnectX-6
- Open MPI 4.1.0
- GCC 10.2.0

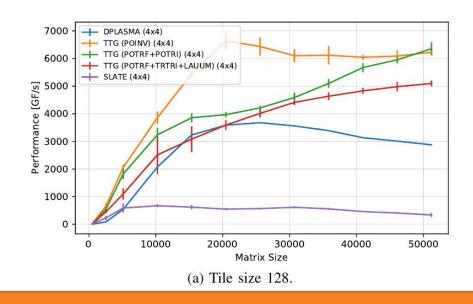


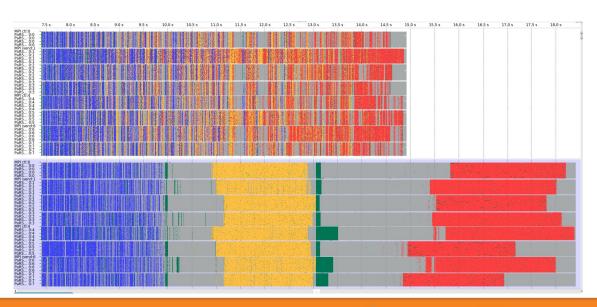
- 16 nodes on Hawk, 64 threads each
- Full composition beneficial for small tile sizes
  - Fine-grain composition helps hide communication latency
  - Beats both DPLASMA (based on PaRSEC PTG) and SLATE





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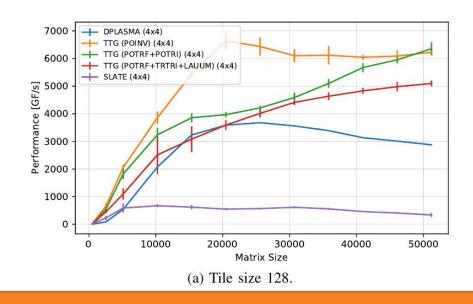


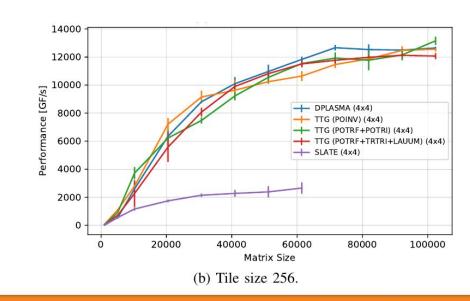






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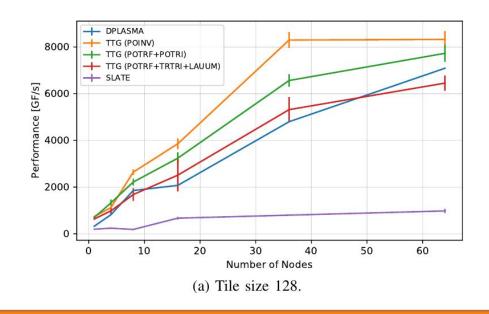


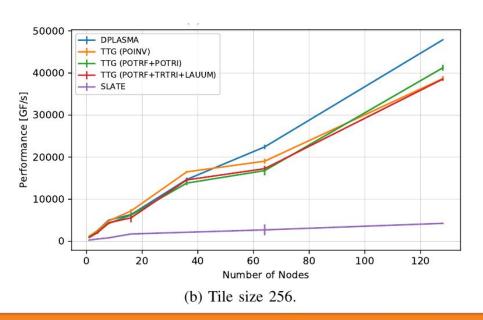






- Scaling from 1-64 nodes on Hawk
  - Full composition beneficial for smaller tasks



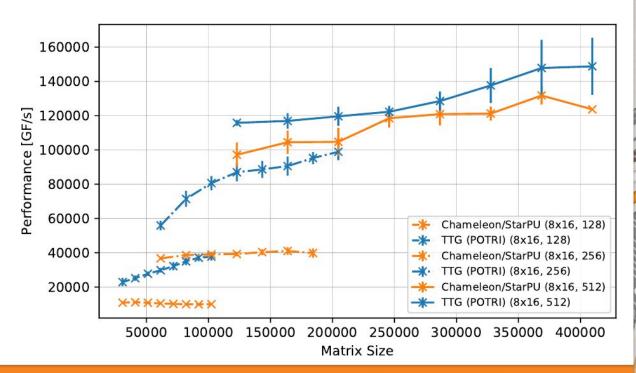






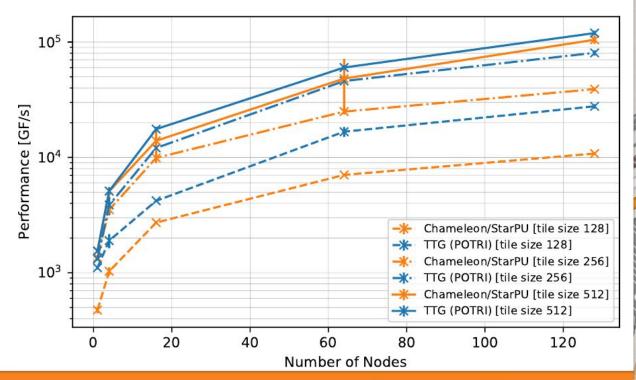
#### POTRI: Comparison with Chameleon

- 128 nodes on Hawk
- Chameleon (v1.1.0, using StarPU 1.3.9)
- POTRI: TRTRI ⊕ LAUUM
- TTG performance benefits
  - Depth-first execution
  - Parallel distributed task discovery



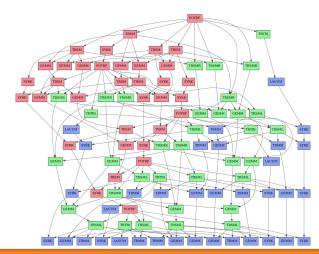
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#### Conclusions

- Task graph composition helps hide communication latencies
- Edges represent sets of future values
  - Distribute values to multiple subscribers (input terminals)
  - Provide a clean interface to encapsulate black-box functionality
  - Coupling of graphs through single input, single output Edge
- Full-scale application composition without breaking abstraction barriers



#### **Future Work**

- GPU support (beyond Unified Memory, 2023)
- Inverse data flow: pulling data from the bottom of the task graph
- Coupling of different task-based programming models
  - Example: TiledArray & TTG

#### Questions?

Check us out on Github:

github.com/TESSEorg/ttg/



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This research was supported partly by NSF awards #1931347 and #1931384, and by the Exascale Computing Project (17-SC-20-SC), a collaborative effort of the U.S. Department of Energy Office of Science and the National Nuclear Security Administration. We gratefully acknowledge the provision of computational resources by the High-Performance Computing Center (HLRS) at the University of Stuttgart, Germany.

