

Convex Allocations under I/O Constraints

New Challenges in Scheduling Theory, Aussois

Raphaël Bleuse, Giorgio Lucarelli, Denis Trystram



March 31, 2016

Outline

1 Context

- Supercomputer' architecture
- Jobs characteristics
- Convexity

2 Problem Formalization

3 Preliminary Results

- Complexity
- Approximation Algorithm

4 Conclusion

Bluewaters' Architecture

System Summary

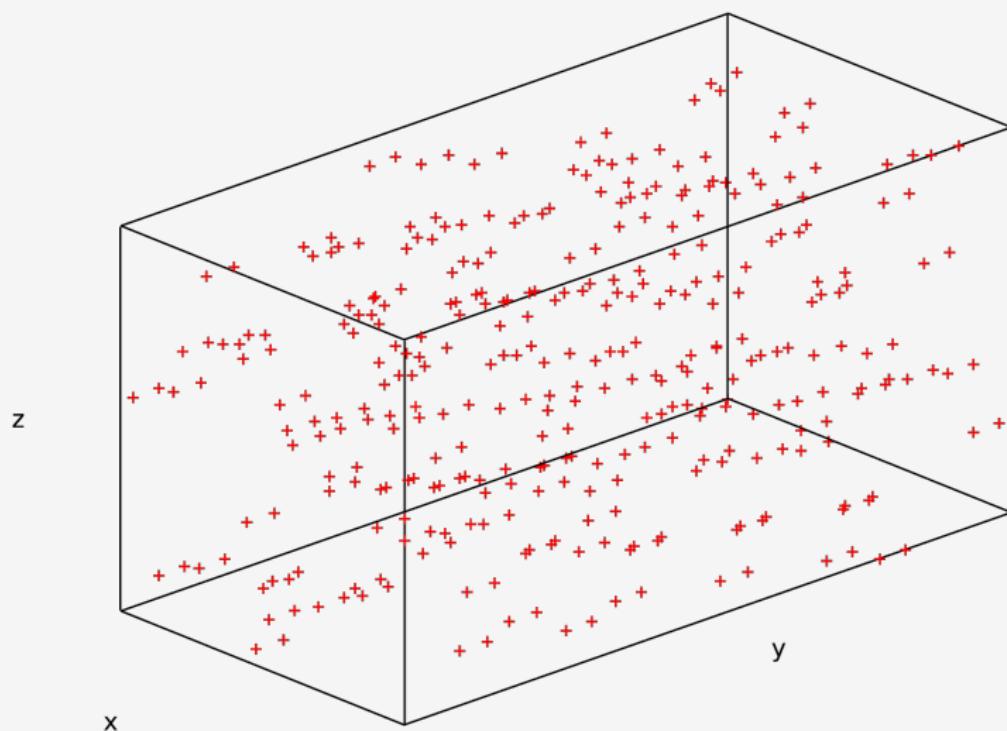
- 288 cabinets
- 26,868 compute nodes / 396,032 cores
- 672 I/O nodes

Network Topology

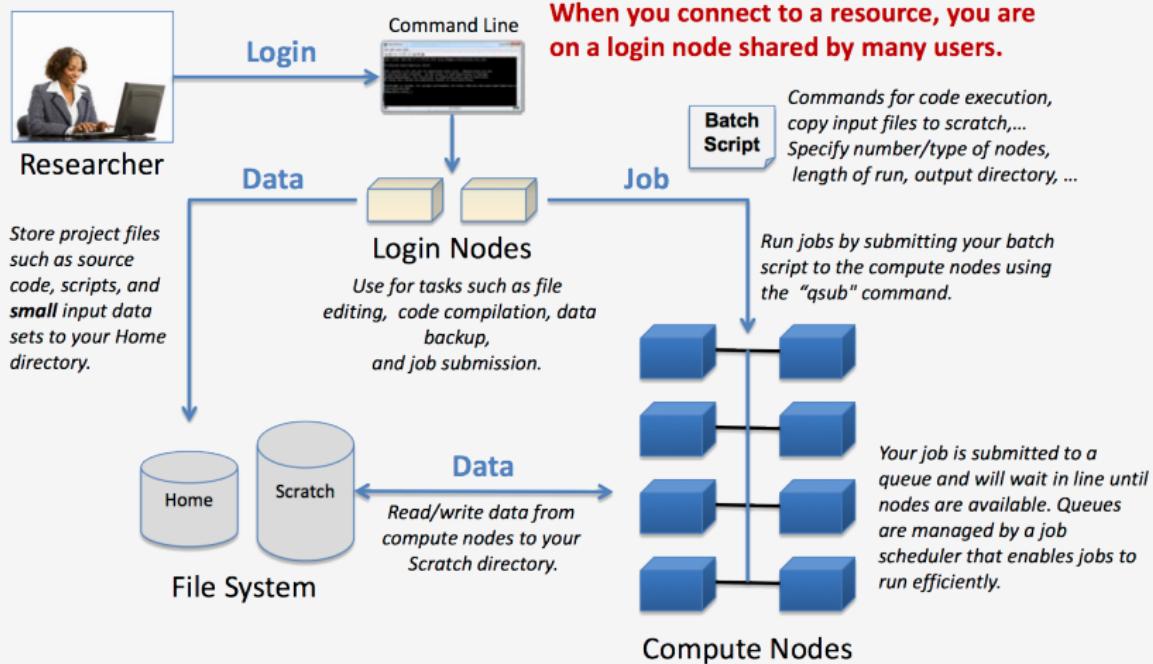
- 3D Torus: $24 \times 24 \times 24$
- single, multi-purpose network
- 2 nodes per interconnection
- static routing (x , then y , then z)

Bluewaters' Architecture

I/O nodes

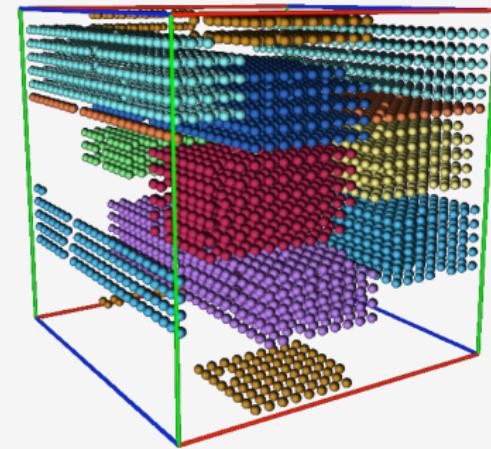
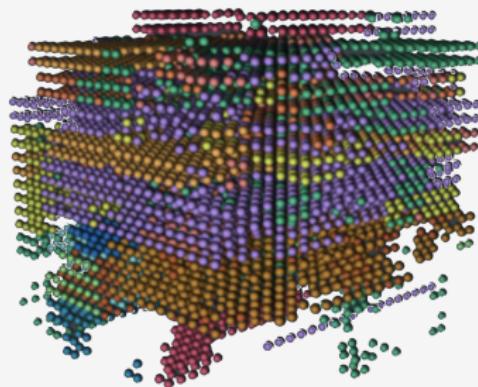


User Interaction



Allocation example

snapshot of the 10 biggest jobs



[Enos et al., 2014]

- fragmentation hinders performances
- convexity improves overall performances
- convexity helps reducing variability in run time

1 Context

- Supercomputer' architecture
- Jobs characteristics
- Convexity

2 Problem Formalization

3 Preliminary Results

- Complexity
- Approximation Algorithm

4 Conclusion

Properties recap.

- unique & multi-purpose interconnection network
- heterogeneous nodes (compute & others)
- convexity (w.r.t. topology) to reduce interferences

Formalization of ConvexIO

- machine
- interconnection topology
 - 2 independent sets of nodes: \mathcal{S}_C & $\mathcal{S}_{I/O}$
 - distribution: mapping of the nodes on the topology

- tasks
- independent
 - p_j : processing time
 - q_j : number of requested nodes in \mathcal{S}_C
 - κ_j : requested nodes in $\mathcal{S}_{I/O}$

objective minimizing C_{\max}

constraints convex allocations

Further insight on κ_j

κ_j : number of requested nodes in $\mathcal{S}_{I/O}$

User/System do not care which nodes are allocated:

- spare nodes
- in-situ analysis nodes

κ_j : subset of $\mathcal{S}_{I/O}$

User/System do care about allocated nodes:

- I/O placement (data)

1 Context

- Supercomputer' architecture
- Jobs characteristics
- Convexity

2 Problem Formalization

3 Preliminary Results

- Complexity
- Approximation Algorithm

4 Conclusion

\mathcal{NP} -completeness

Theorem

ConvexIO is \mathcal{NP} -complete.

Proof.

by reduction to **2-Part**

2-Part Given $\{\alpha_j\}_j$ such that $\sum \alpha_j = A$.

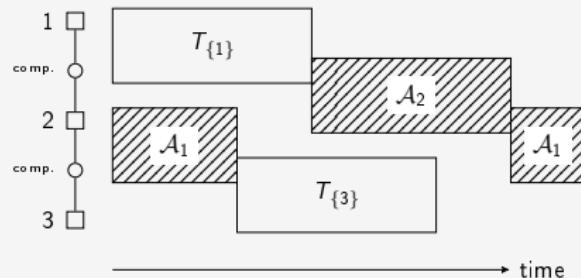
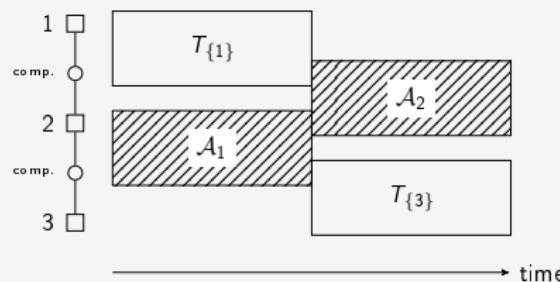
Find $\mathcal{A}_1, \mathcal{A}_2$ such that $\sum_{\alpha_j \in \mathcal{A}_1} \alpha_j = \sum_{\alpha_j \in \mathcal{A}_2} \alpha_j = \frac{A}{2}$.

ConvexIO

- 2 compute nodes + 3 I/O nodes.
- $\alpha_j \mapsto T_j : q_j = 1, \kappa_j = \{2\}, p_j = \alpha_j$.
- for $\text{io} \in \{1, 3\}$, add $T_{\{\text{io}\}} : q_j = 1, \kappa_j = \{\text{io}\}, p_j = \frac{A}{2}$.



\mathcal{NP} -completeness (bis)

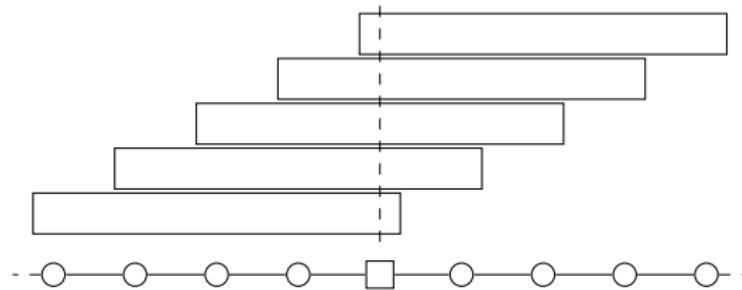


Approximation Algorithm on 1D topology

Setup

- 1D line/toric topology.
- Relates to $P|fix_j|C_{\max}$ and $P|set_j|C_{\max}$.

Eligible allocations of a task



Approximation Algorithm on 1D topology

- 1 determine an allocation of nodes minimizing the overall load
- 2 derive a feasible schedule using Gergov's DSA algorithm [Gergov, 1999]

Approximation Algorithm on 1D topology

Allocation step: linear program

$$\min \mathcal{L}$$

$$\text{s.t. } \mathcal{L} \geq L_i \quad \forall i$$

$$L_i \geq \sum_j x_{j,s} \mathbf{1}_{i \in [s, s+q_j]} p_j \quad \forall i$$

$$\sum_s x_{j,s} = 1 \quad \forall j$$

$$x_{j,s} \quad \forall j, s$$

+ I/O pinning constraints

Approximation Algorithm on 1D topology

Allocation step: linear program

$$\min \mathcal{L}$$

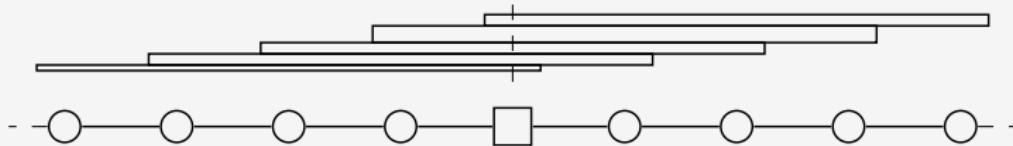
$$\text{s.t. } \mathcal{L} \geq L_i \quad \forall i$$

$$L_i \geq \sum_j x_{j,s} \mathbf{1}_{i \in [s, s+q_j]} p_j \quad \forall i$$

$$\sum_s x_{j,s} = 1 \quad \forall j$$

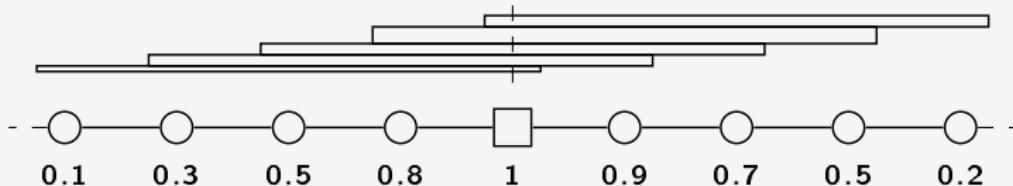
$$x_{j,s} \quad \forall j, s$$

+ I/O pinning constraints



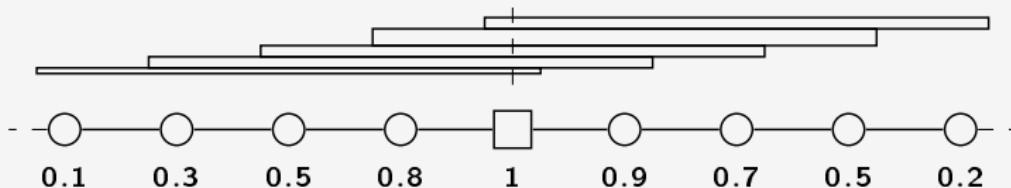
Approximation Algorithm on 1D topology

Allocation step: rounding



Approximation Algorithm on 1D topology

Allocation step: rounding



Contributions

- model for HPC infrastructure
- approximation algorithm for **ConvexIO** on 1D topology

Directions

- improve approximation ratio
- formulation without linear programming
- extend topology dimension

Questions?

References |

-  Enos, J., Bauer, G., Brunner, R., Islam, S., Steed, M., Jackson, D., and Fiedler, R. (2014).
Topology-Aware Job Scheduling Strategies for Torus Networks.
Cray User Group.
-  Gergov, J. (1999).
Algorithms for Compile-time Memory Optimization.
In *Proceedings of the Tenth Annual ACM-SIAM Symposium on Discrete Algorithms*, SODA '99, pages 907–908, Philadelphia, PA, USA. Society for Industrial and Applied Mathematics.