



Methods and Experiences for Developing Abstractions for Data-intensive, Scientific Applications

Andre Luckow¹ and Shantenu Jha^{2,3}

¹Ludwig-Maximilian University, Munich, Germany ²RADICAL, ECE, Rutgers University, Piscataway, NJ 08854, USA ³Brookhaven National Laboratory, Upton, NY, USA





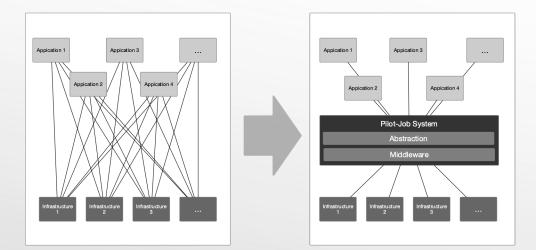
Large number of scientific applications require high performance compute and data capabilities. Many challenges related to infrastructure and management exist:

- Heterogeneous infrastructure increases complexity: instruments, edge, fog, HPC, cloud, serverless, accelerators need to be integrated.
- Elasticity: dynamic, externally induced changes to resource demands
- Scheduling and provisioning of resources in a complex and dynamic environment: right amount of resources at right time
- Different application components require different programming models: HPC (MPI, OpenMP, CUDA/GPUs), Big Data (MapReduce, Streaming), Serverless
- Limited interoperability between infrastructures: Resource management of tied to specific API of system (e.g. HPC schedulers or cloud API)
- **Distributed Compute and Data:** Data sources distributed across different environments (IoT, cloud, HPC, serverless)

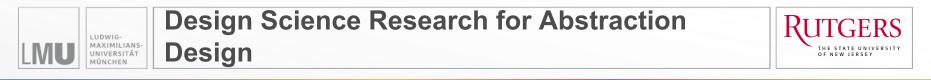


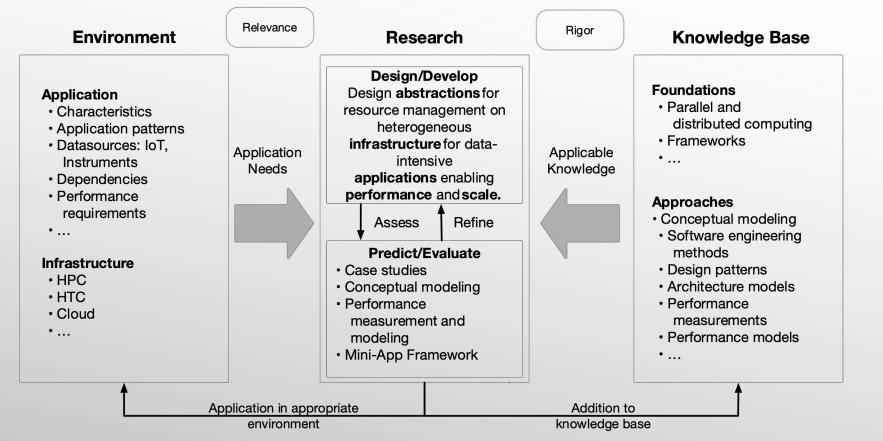


Multiple distinct applications with complex characteristics and infrastructure requirements. The complexity of infrastructure and applications prevents critical scalability and make scientific progress. **Objective: Abstractions that can support multiple applications across different scales and heterogeneity.**



Challenge: Designing useful abstraction is challenging. Hiding complexity does not automatically lead to simple interfaces. Effective methods for developing and evaluation abstractions required!







Problem Statement: Application Characteristics and Requirements



Work	Method	Scope	Description Conceptual framework for analyzing and understanding distributed data-intensive applications scenarios	
Scientific Applications: Introducing distributed dynamic data-intensive (D3) science: Understanding applications and infrastructure [1].	Survey, Workshop, Literature Review	13 applications, 9 questions		
Big Data Ogres: Towards an understanding of facets and exemplars of big data applications [2, 3, 4]	Workshops, Literature Review	51 NIST Use Cases using 4 views and 40+ facets	Conceptual framework for characterizing commonalities and patterns in Big Data applications	
Streaming computational science: Applications, technology and re- source management for HPC [5,6]	Workshops, Literature Review	12 applications, 4 applications categories	Characterization of streaming applications	

[1] Shantenu Jha, Daniel S. Katz, Andre Luckow, Neil Chue Hong, Omer Rana, and Yogesh Simmhan. Introducing distributed dynamic data- intensive (d3) science: Understanding applications and infrastructure. Concurrency and Computation: Practice and Experience, 29(8), 2017.

[2] Shantenu Jha, Judy Qiu, Andre Luckow, Pradeep Kumar Mantha, and Geoffrey Charles Fox. A tale of two data-intensive paradigms: Applications, abstractions, and architectures. Proceedings of 3rd IEEE Internation Congress of Big Data, abs/1403.1528, 2014.

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[6] Geoffrey C. Fox, Devarshi Ghoshal, Shantenu Jha, Andre Luckow, and Lavanya Ramakrishnan. Streaming computational science: Applications, technology and resource management for hpc. http://dsc.soic. indiana.edu/publications/streaming-nysds-abstract.pdf, 2017.



Problem Statement: Definition of 5 Application Scenarios Based on Analysis of >70 Applications



	Task-Parallel	Data-Parallel	Dataflow	Iterative	Streaming
Description	Focus on functional de- composition into tasks and control flow	Decomposition of a problem into a diverse set of dependent and parallel tasks	Multiple processing stages modeled with a directed acyclic graph	Multiple generations of tasks with sharing of data between the generations	Processing of unbounded data feeds in near- realtime
Characteristics	Decomposition of a problem into a diverse set of de- pendent and parallel tasks	Embarrassingly parallel, loosely-coupled with minimal communication.	Multiple stages, loosely- coupled parallelism, global communication for shuffle operation	Loosely coupled par- allelism with global communication for up- dating machine learning model parameters	Data is processed in small batches often using data- parallel algorithms.
Examples	Molecular Dynamics [1], Ensemble-Kalman Filter [2], Scientific Gateways and Workflows [3]	Map-Only analytics [4], Molecular Data analysis Hausdorff Distance [5]	MapReduce for sequence alignment [6], Molecular Data analysis leaflet finder and RMSD [7]	Machine learning algorithms, K-Means [7]	Streaming for light source data [8]

[1] Andre Luckow, Shantenu Jha, Joohyun Kim, Andre Merzky, and Bettina Schnor. Adaptive Replica-Exchange Simulations. Royal Society Philosophical Transactions A, 2009. [2] Yaakoub El-Khamra and Shantenu Jha. Developing autonomic dis- tributed scientific applications: A case study from history matching using ensemble kalman-filters. In Proceedings of the 6th International Con- ference Industry Session on Grids Meets Autonomic Computing, GMAC '09, pages 19–28, New York, NY, USA, 2009. ACM.

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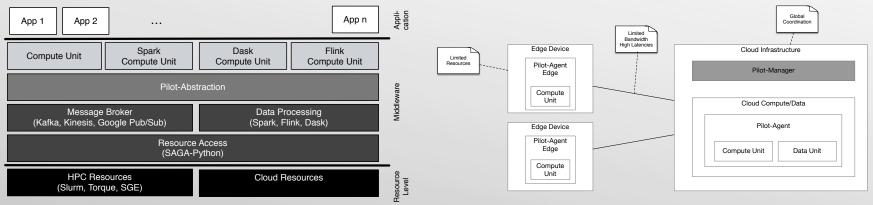
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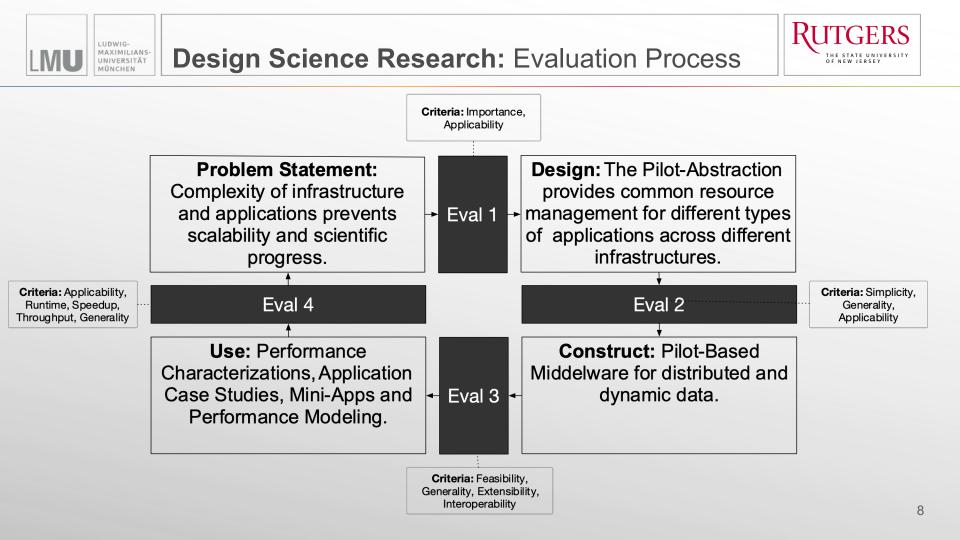




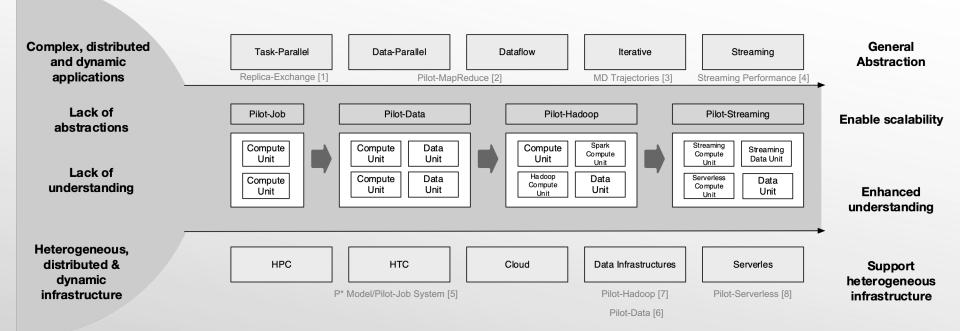
Pilot-Job System: A system that generalizes a placeholder job to provide multi-level scheduling to allow application-level control over the system scheduler via a scheduling overlay.

The **Pilot-Abstraction** generalizes the concept of resource and task execution management across different applications (HPC, MapReduce, streaming) and infrastructures (edge, cloud, HPC, serverless).









[1] Andre Luckow, Shantenu Jha, Joohyun Kim, Andre Merzky, and Bettina Schnor. Adaptive Replica-Exchange Simulations. Royal Society Philosophical Transactions A, 2009.

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