

Design and Implementation of Knowledge Base for Runtime Management of Software Defined Hardware

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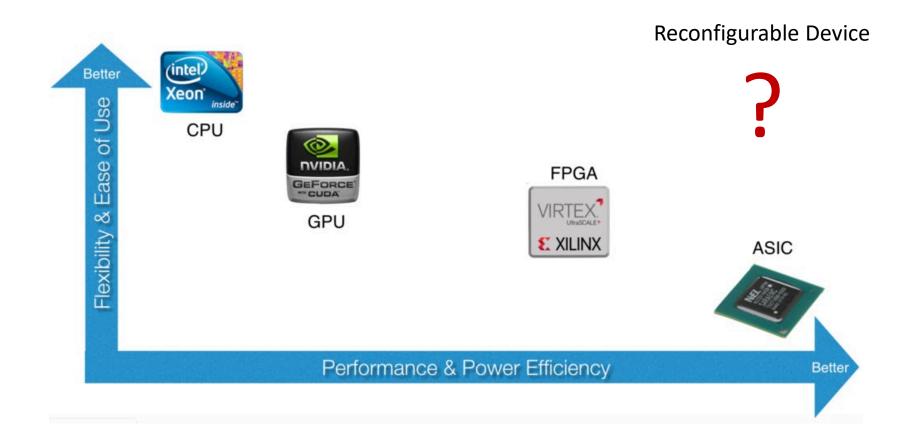
- Motivation and Background
- The Knowledge Base
 - Tripartite Representation
 - Creation
 - Interaction with Other Components
- Performance of the Knowledge Base
- Conclusion



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Motivation





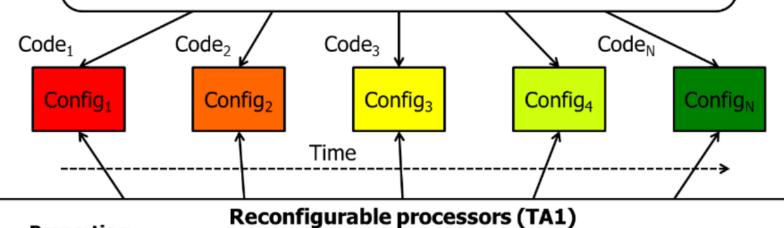
Background: SDH Program



High-level program

Dynamic HW/SW compilers for high-level languages (TA2)

- 1. Generate optimal configuration based on static analysis code
- 2. Generates optimal code
- 3. Re-optimize machine code and processor configuration based on runtime data



Properties:

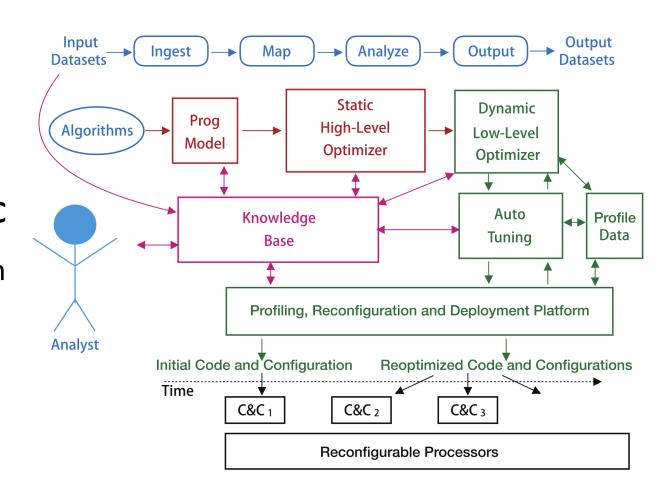
- 1. Reconfiguration times: 300 1,000 ns
- 2. Re-allocatable compute resources i.e. ALUs for address computation or math
- 3. Re-allocatable memory resources i.e. cache/register configuration to match data
- 4. Malleable external memory access i.e. reconfigurable memory controller



Background: DDARING Project



Aim to accelerate data-intensive workflows to achieve near-ASIC performance with high-level programming

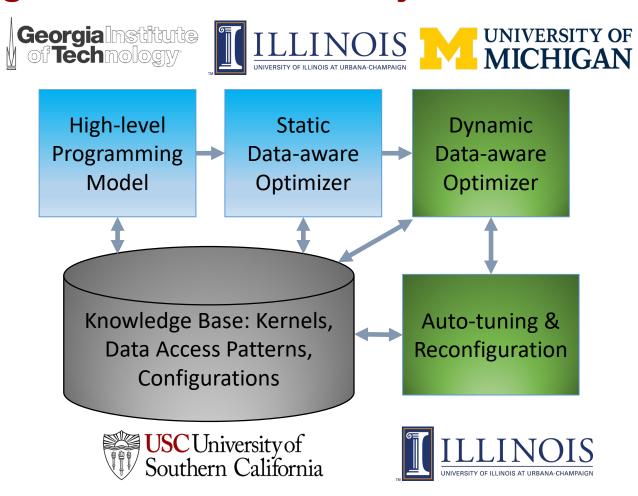




language

Background: DDARING Project





The knowledge base, a center component in the DDARING Project





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The Knowledge Base



- Challenge:
 - To store program metadata and status on previous executions
 - To analyze the gathered information
 - To answer queries from other component rapidly
- ➤ Our approach: the knowledge base
 - ✓ Dynamic and expendable
 - ✓ Continuously gather knowledge during execution of workflow
 - ✓ Identify optimal implementations of workflows on optimal hardware configurations
 - ✓ Answer to compile- and run-time queries in real time

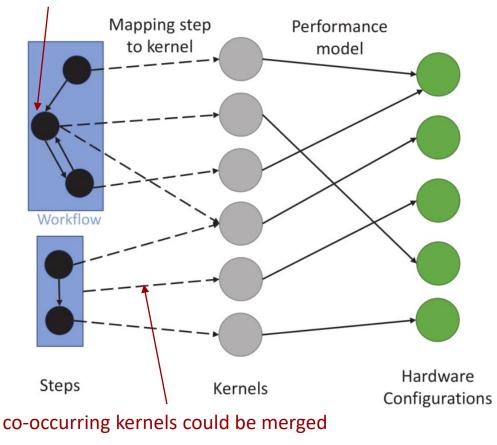


The Knowledge Base: Tripartite Representation



- Rich tripartite graph representation $G(V_1, V_2, V_3, E)$
 - V₁: Domain Specific Language Level steps
 - V_2 : Bare bone tasks or kernels
 - V_3 : Hardware configurations
 - $E(V_1, V_2)$: Mapping of steps to kernels, captures the algorithmic realizations of steps
 - $E(V_2, V_3)$: Mapping of kernels to hardware configurations, captures the performance models

one step (or kernels) could have multiple mappings



The Knowledge Base: Tripartite Representation **BFS Tree** 16 cores Node Tree Interconnections Classification 3840 Sampling **CUDA** cores Loss Calculation Accelerators with Coherent Memory Forward Prop. **FPGA** Gradient 1451k logic cells Backward Prop. dashed line edges in black means less show optimal Inferencing precision mapping needed, hence Hardware mapped to FPGA

> Example of the knowledge base capturing the node classification workflow (demonstrated on heterogeneous architecture)

Kernels



Steps

Configurations

The Knowledge Base: Creation

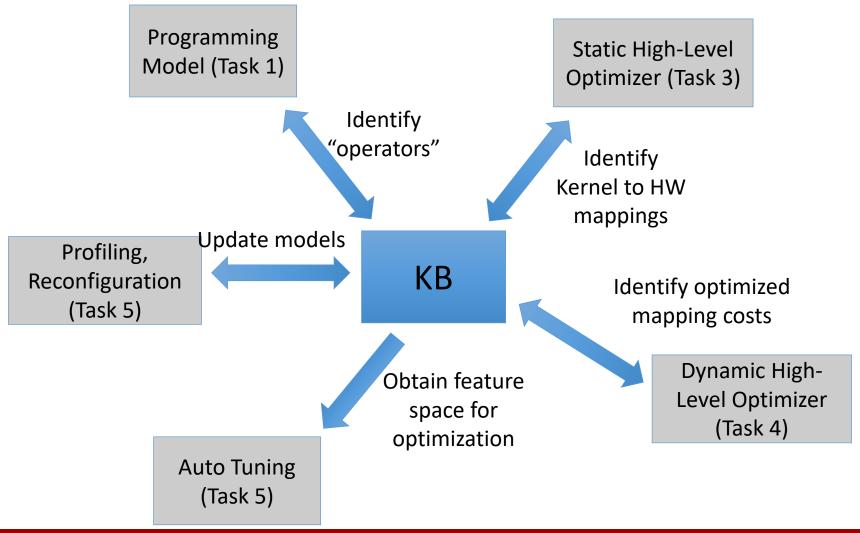


- The knowledge base is created by offline discovery and dynamic updates.
 - ➤ Offline discovery:
 - Choose some typical workflows
 - Manually profile the selected workflows
 - Decompose the workflows into steps and kernels
 - Construct the performance model
 - ➤ Dynamic Updates:
 - Get updates from the profiling and reconfiguration component
 - Modify the tripartite graph accordingly



The Knowledge Base: Interaction with Other Components









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Performance of the Knowledge Base



- The knowledge base implementation:
 - Object oriented, with each node or edge as a class
 - Adjacency list graph in the C++ Boost Library
 - Single thread

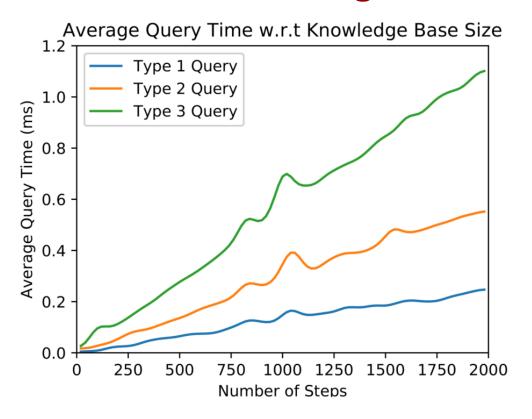
Query types:

- Type 1 query: For a given step in the knowledge base, return all kernels linked with that step.
- Type 2 query: For a given kernel and a given hardware configuration in the knowledge base, return the performance model for executing the kernel on the hardware configuration.
- Type 3 query: For a given kernel in the knowledge base, return the performance models for executing the kernels on all hardware configurations.



Performance of the Knowledge Base





Number of kernels = 1.5 times than number of steps Number of hardware configurations = 10

The feature of the nodes and edges are filled with random content

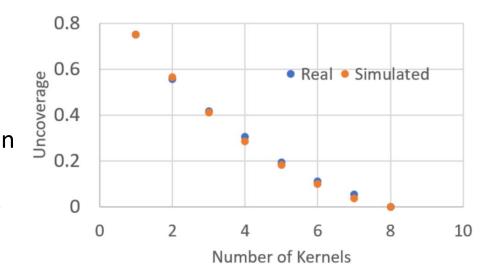


Kernel Coverage



- However, we do not need a large knowledge base!
- Kernel coverage: percentage of stored kernels included a collection of workflows
- We model the coverage by setting the possibility that a kernel is included in one workflow follows preferential attachment rule with a fixed parameter λ

Cumulative uncovered workflows vs number of kernels



 $\lambda = 2.5$ with real kernel coverage

Only 8 kernels needed to cover 60+ workflows!





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Conclusion



- ➤ We proposed a expendable and dynamic rich labeled tripartite network representation of the knowledge base.
- The knowledge base gathers the knowledge of optimized implementations of key algorithmic steps and kernels on various parameterized hardware.
- The knowledge base is implemented using the C++ Boost Library and is capable of answering different types of queries rapidly.
- On going work: Portable lightweight deep learning models for kernel performance [submitted]



Thank You!

