Managing Computational Resources with Machine Learning Policies

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MLSysOps

Introduction

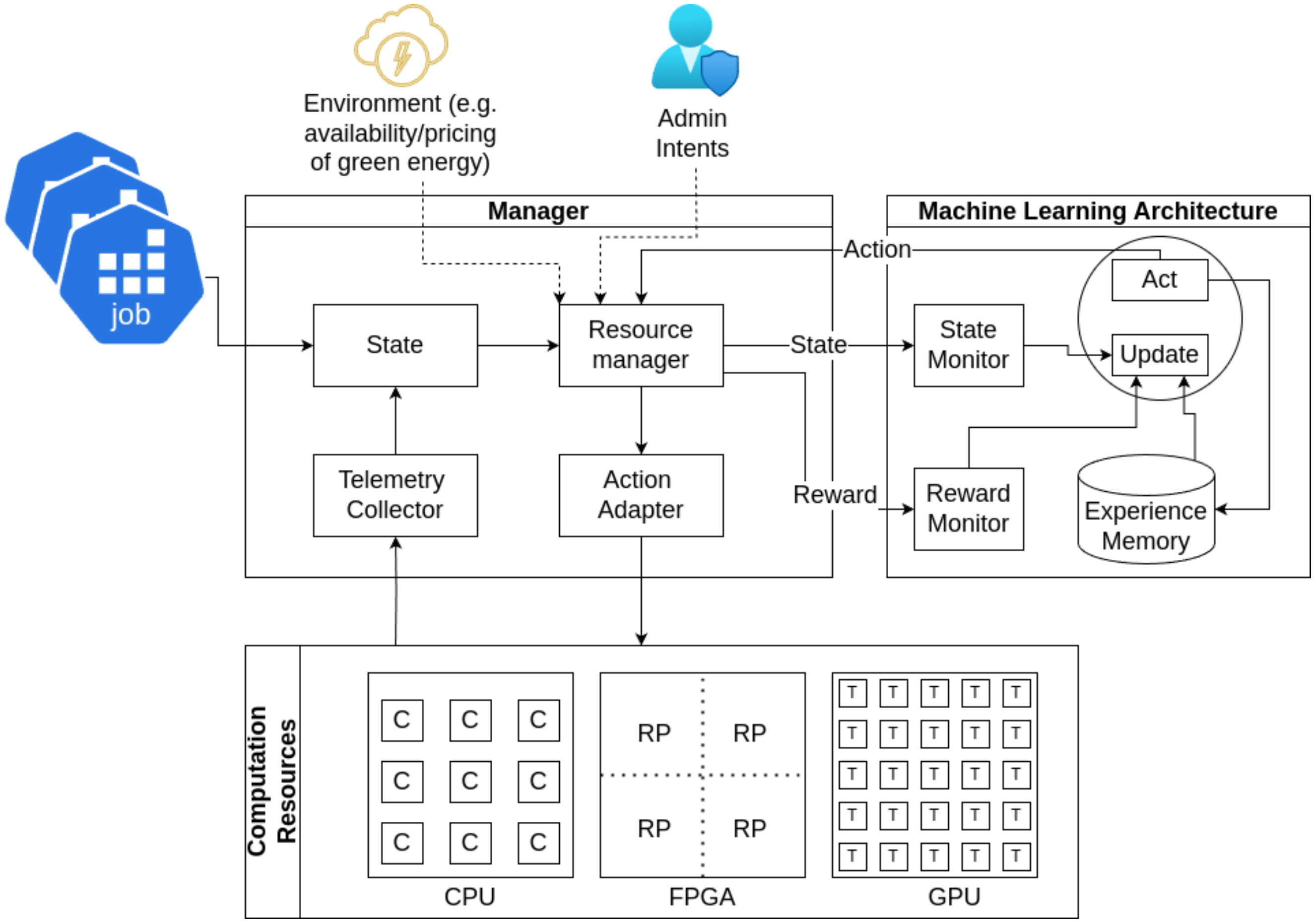
- **Challenge**
  - Efficient Resource Allocation in Edge - Cloud Environments
- **Problem**
  - How to dynamically balance performance requirements, energy efficiency, and system constraints
  - Heterogeneous computing devices (CPUs, GPUs, FPGAs), workload diversity, multiple configuration options
  - Our Focus is on ML workloads
- **Approach**
  - Adaptive Reinforcement Learning (RL)-based congiruation engine in multicore CPUs in cloud nodes.

System Architecture

Key components

- A **system manager** that constantly monitors the system and accepts new job requests.
- An **RL architecture** to guide resource allocation and configuration decisions based on the State of the system
- **Telemetry** collectors to capture HW metrics and **Action** adapters to apply any needed configuration.
- **Heterogeneous** node architecture comprising CPUs, GPUs, FPGA

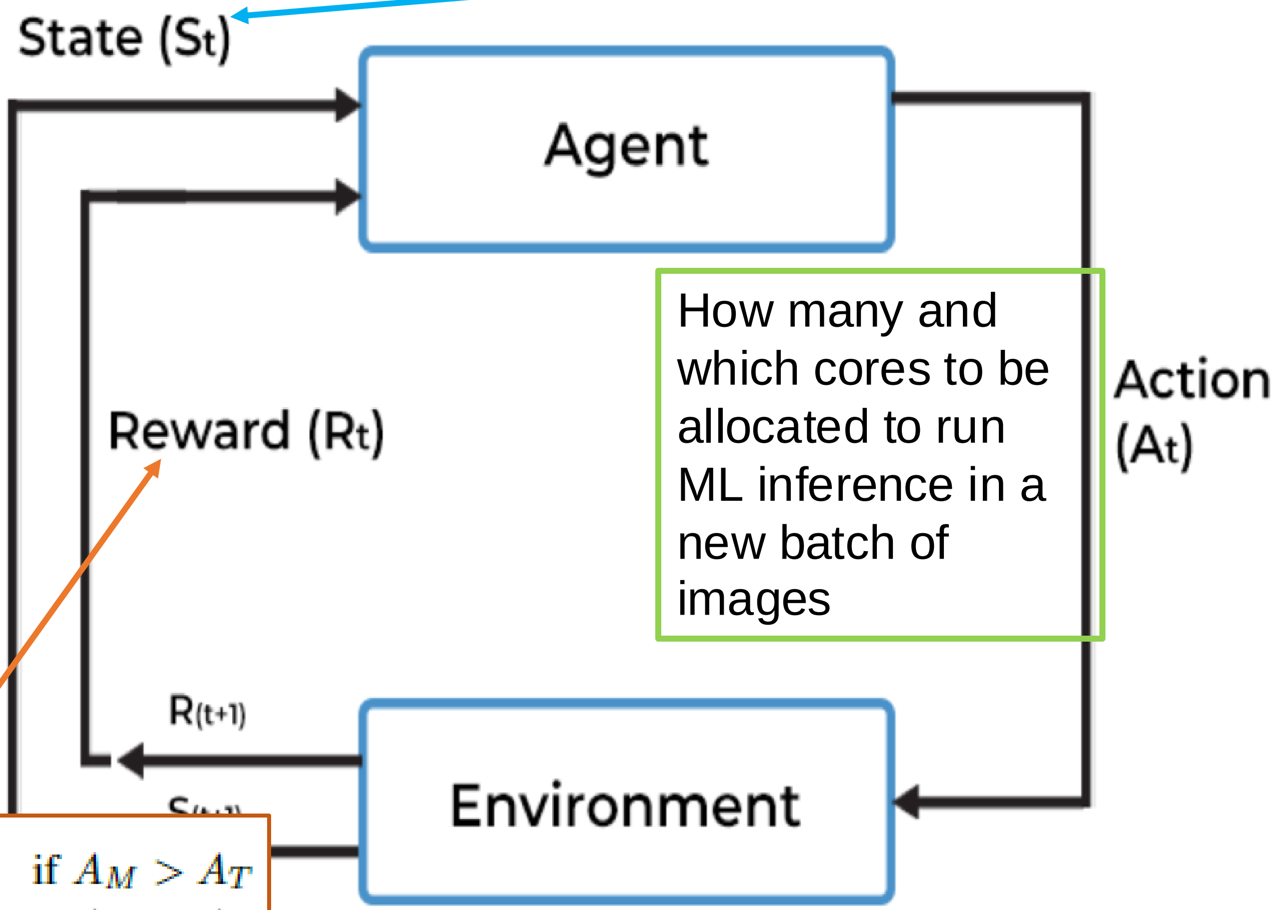
  Note: Only multicore CPUs in this work



Reinforcement Learning Agent

- RL is a type of ML algorithm where an **Agent** learns how to take **Actions** by interacting with the **Environment** to maximize a cumulative **Reward**.
- Our **objective** is to reduce power dissipation without exceeding a user-defined execution latency.
- **Reward** function penalizes Actions that result in high latency (1st criterion) and high power (2nd criterion)

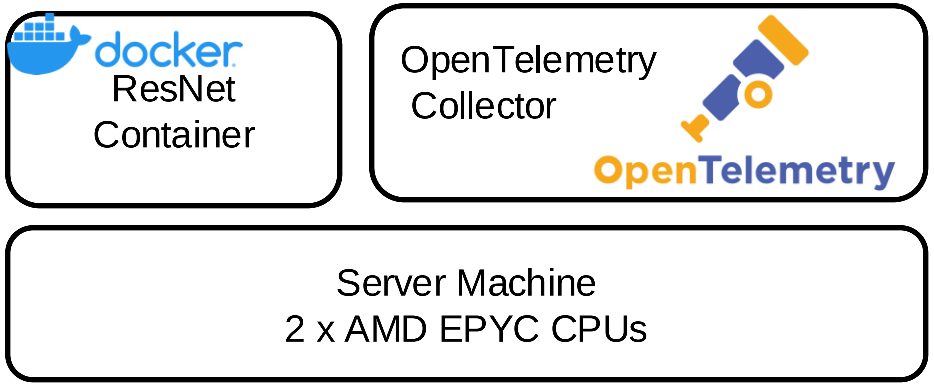
1. Average CPU utilization per core
2. Power Dissipation per Core
3. ML inference latency



$$reward = \begin{cases} -100 & \text{if } A_M > A_T \\ -\sqrt{Power_C} & \text{if } A_M \leq A_T \end{cases}$$

Experimental Set up

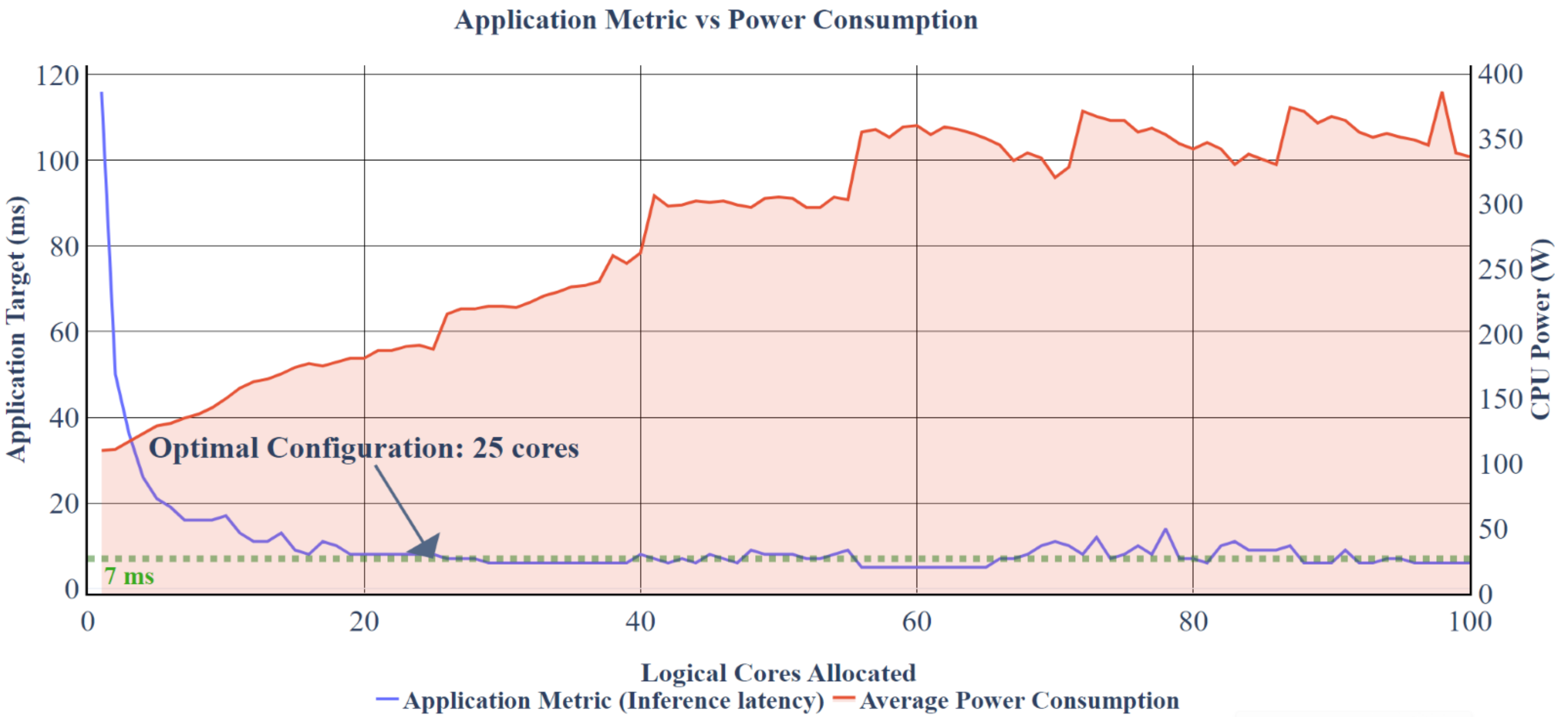
- Datacenter-grade node consisting of a dual-socket AMD EPYC, 64 physical (128 logical) cores
- 1-100 Logical cores actually used
- Metrics recorded using Open Telemetry tools
- Containerized ResNet used as workload
- Trained the RL agents using 200,000 timesteps & offline.



Experimental Evaluation (I)

Set Application Latency Target A_T for batch inference to 7ms

- optimal configuration when 25 logical cores are allocated to run ResNet in parallel
- beyond that, performance stagnates while power (obviously) increases



Experimental Evaluation (II)

Experiments for various Application Latency Targets A_T

RL agent achieves allocations which are very close to the optimal allocations

Application Latency Target (ms)	Predicted Configuration (Cores to allocate)	Handpicked configuration (Cores to allocate)
5	57	61
7	25	25
10	35	34
15	10	11

Conclusion and Future Work

- RL models achieve near-optimal core allocation for performance-constrained ML inference having power dissipation as optimization criterion
- The node-level manager is part of a larger mechanism that implements the MAPE model (Monitor, Analyze, Plan, Execute) at the Cloud-Edge continuum
- Future Work (node-level)
  - Use on Hardware accelerators (GPUs, FPGAs)
  - Thread affinity, voltage/frequency scaling
  - Different versions of the ML workload spanning performance vs accuracy
  - Carbon intensity as additional optimization criterion
  - Data collection

Thank you!