

Resource-Conditioned Reinforcement Learning for Physics Instrument Design

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Designing advanced particle-physics instruments requires navigating a high-dimensional space of discrete and continuous choices while satisfying strict constraints on material, cost, and geometry. In practice, these constraints evolve throughout an experiment's lifetime, making it insufficient to optimize a single "best" detector configuration. We present a resource-conditioned reinforcement learning (RL) framework for detector design that produces families of optimized configurations matched to different constraint levels. Building on prior RL-based instrument design workflows (arXiv:2412.10237), we train agents that condition their policy on available resources and other problem parameters, enabling a single training run to generate multiple designs spanning a spectrum of feasible budgets and geometries.

We demonstrate the approach on longitudinal calorimeter design, where the agent learns to adapt sensor placement and layer thickness patterns in a non-linear way as resources change, yielding a set of optimized architectures that directly expose performance–cost trade-offs (e.g., energy resolution versus material usage). We discuss practical aspects of constraint handling and feasibility enforcement, and we outline how the same conditional formulation can be extended to additional design degrees of freedom—such as total detector size, spatial envelopes, or task-specific operating points—supporting interactive studies for decision-makers. This work reframes detector optimization from producing a single configuration to learning a controllable design policy that can respond to shifting requirements during experiment design.

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