CROSS-HPC System Bayesian Optimization with Adaptive Transfer

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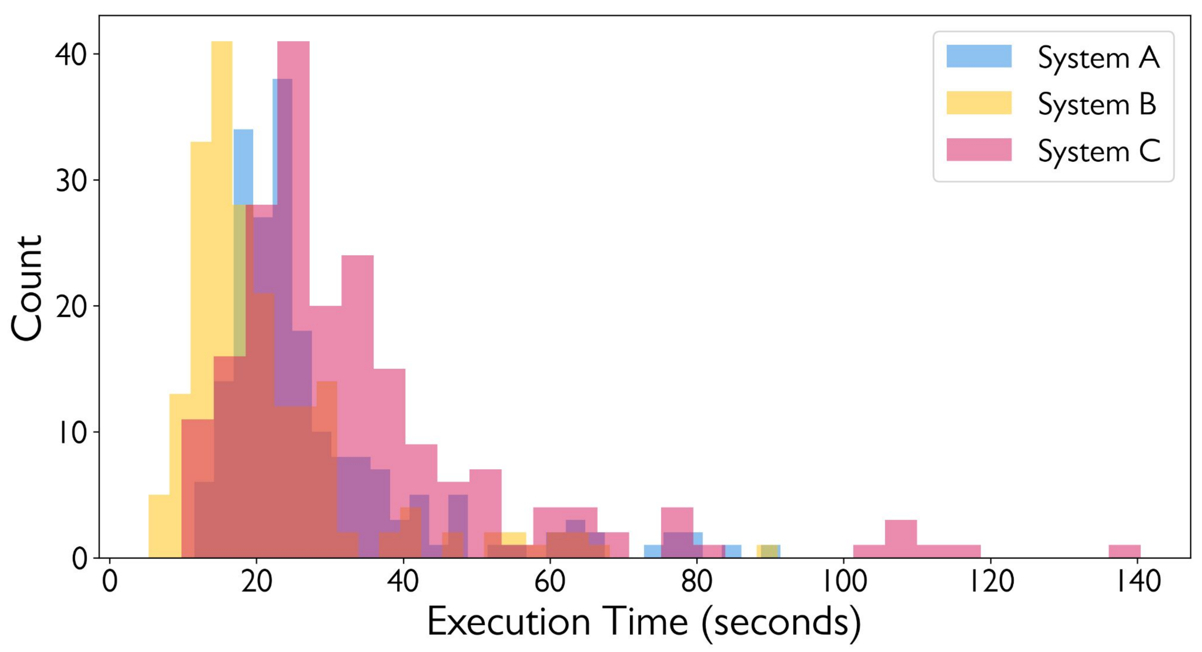
Motivation

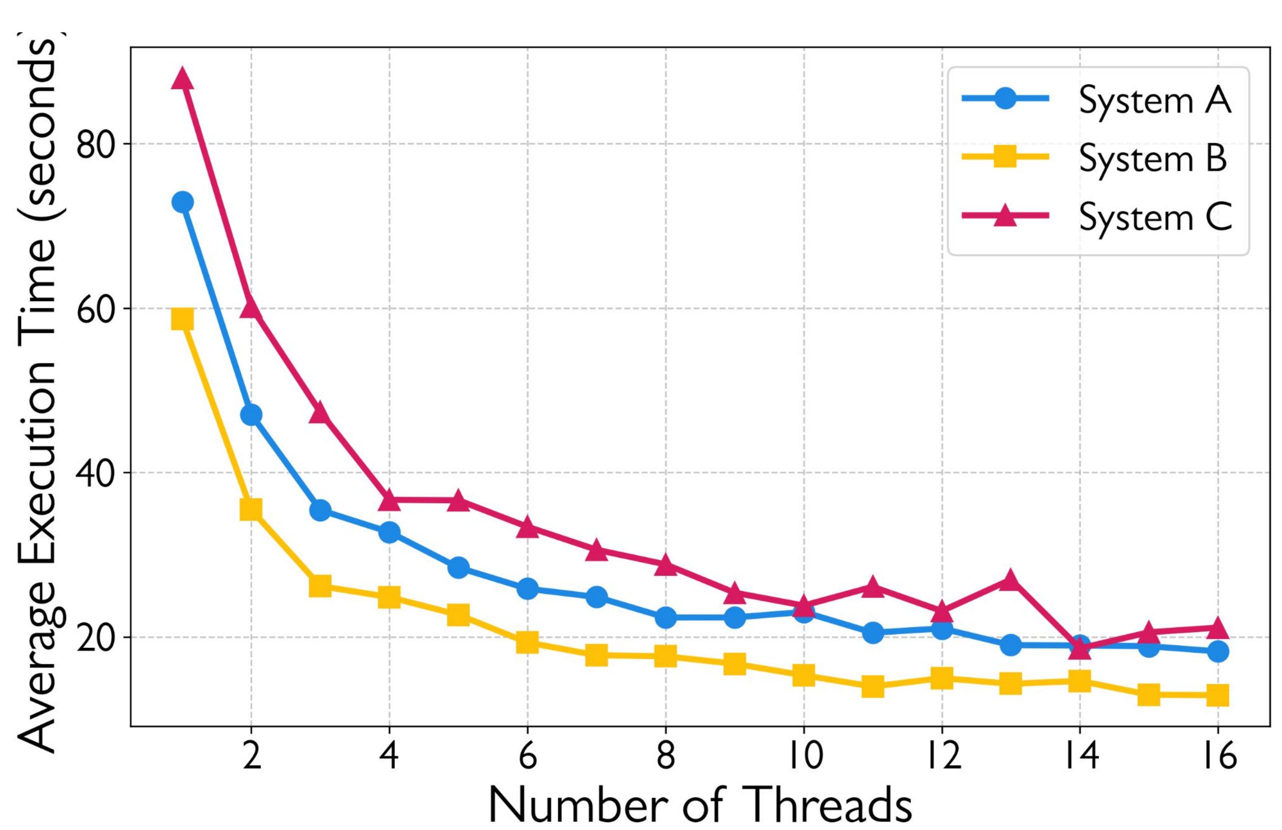
HPC parameter tuning is expensive [1]; each new system requires many costly evaluations. Knowledge from existing systems could accelerate optimization across different architectures.



Execution Time Distribution

Our Contribution

CROSS-BOAT, a novel transfer learning [2] approach for HPC parameter optimization that balances source system knowledge with target system exploration. An adaptive acquisition function that progressively adjusts the influence of source knowledge based on optimization progress and system similarity.



Thread Scaling

CROSS-BOAT

Combines source system insights and target system exploration through dual Gaussian Process models and an adaptive weighting mechanism. Efficiently transfers knowledge while remaining robust to system differences through normalized composite acquisition functions.

Algorithm 1 CROSS-BOAT – CROSS-System Bayesian Optimization with Adaptive Tuning

Require: Source system $\mathcal{S}$, Target system $\mathcal{T}$, Parameter space $\mathcal{X}$, n_s, n_t, T

Ensure: Optimal configuration $\mathbf{x}^*$ for target system

// Source knowledge acquisition

$\mathcal{D}_s \leftarrow \{(\mathbf{x}_i, f_s(\mathbf{x}_i))\}_{i=1}^{n_s}$ where $\mathbf{x}_i \sim \text{LHS}(\mathcal{X})$

$\mu_s, \sigma_s \leftarrow \text{GP}(\mathcal{D}_s)$

// Target initialization

$\mathcal{D}_t \leftarrow \{(\mathbf{x}_j, f_t(\mathbf{x}_j))\}_{j=1}^{n_t}$ where $\mathbf{x}_j \sim \text{LHS}(\mathcal{X})$

for $i = 1$ to T **do**

  $\mu_t, \sigma_t \leftarrow \text{GP}(\mathcal{D}_t)$

  $\mathbf{X}_c \leftarrow$ candidate points from $\mathcal{X}$

  $f_t^* \leftarrow \min_{(\mathbf{x},y)\in\mathcal{D}_t} y$

  // Compute acquisition components

  for $\mathbf{x} \in \mathbf{X}_c$ **do**

    $\text{EI}_t(\mathbf{x}) \leftarrow \mathbb{E}[\max(f_t^* - f_t(\mathbf{x}), 0)]$

    $\text{SK}_t(\mathbf{x}) \leftarrow 1 - \frac{\mu_s(\mathbf{x}) - \min_{\mathbf{x}'} \mu_s(\mathbf{x}')}{\max_{\mathbf{x}'} \mu_s(\mathbf{x}') - \min_{\mathbf{x}'} \mu_s(\mathbf{x}')}$

  end for

  // Normalize and combine

  $w_i \leftarrow \max\{0.5 \cdot (1 - i/T), 0.1\}$

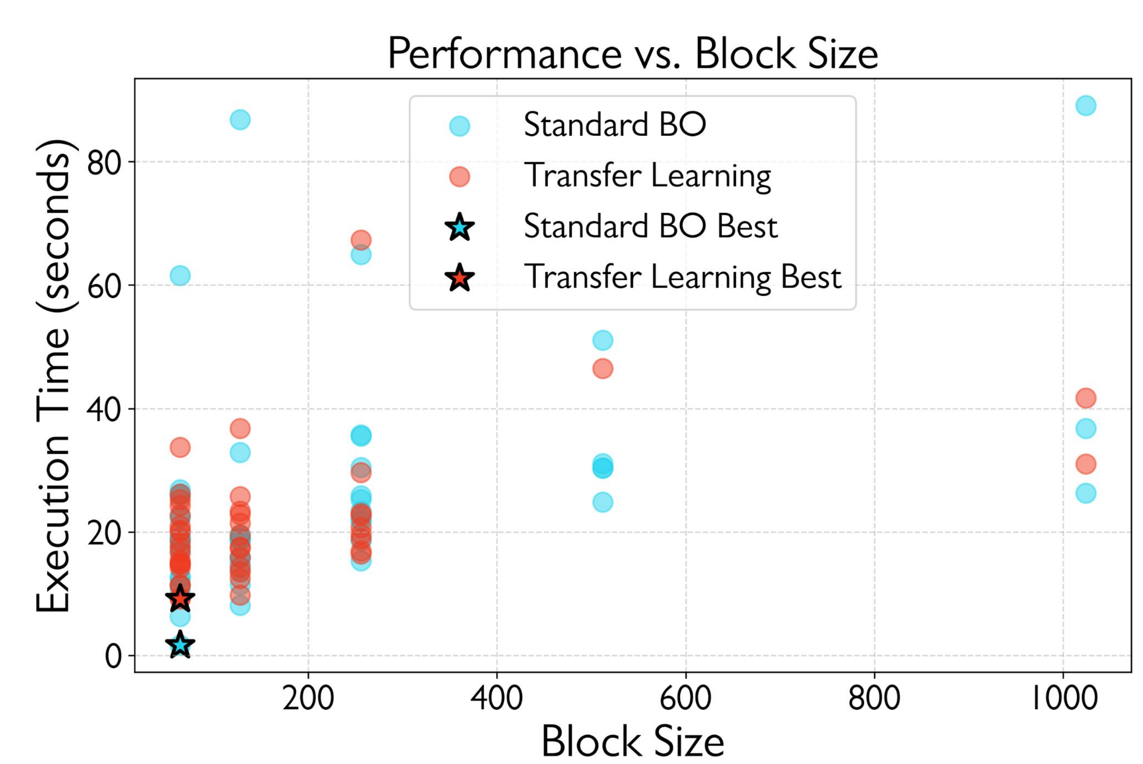
  $\mathbf{x}_{next} \leftarrow \arg\max_{\mathbf{x}\in\mathbf{X}_c} \{(1 - w_i) \cdot \hat{\text{EI}}_t(\mathbf{x}) + w_i \cdot \hat{\text{SK}}_t(\mathbf{x})\}$

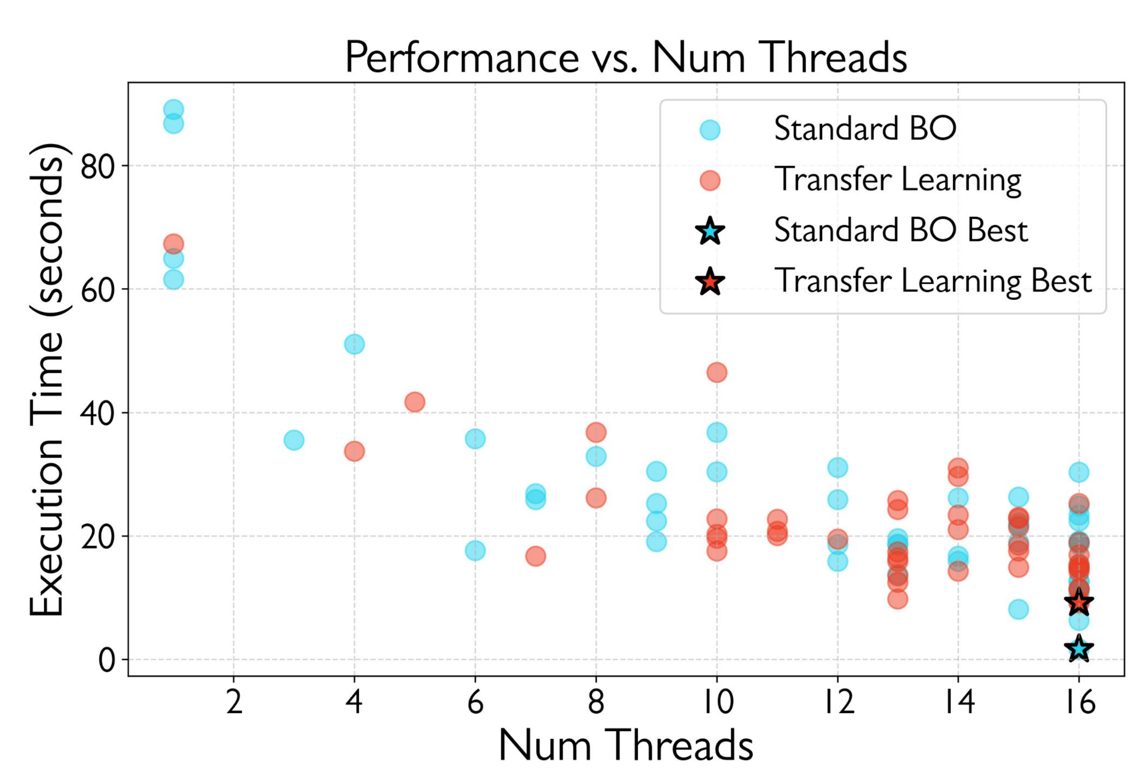
  $\mathcal{D}_t \leftarrow \mathcal{D}_t \cup \{(\mathbf{x}_{next}, f_t(\mathbf{x}_{next}))\}$

end for

return $\arg\min_{(\mathbf{x},y)\in\mathcal{D}_t} y$ =0

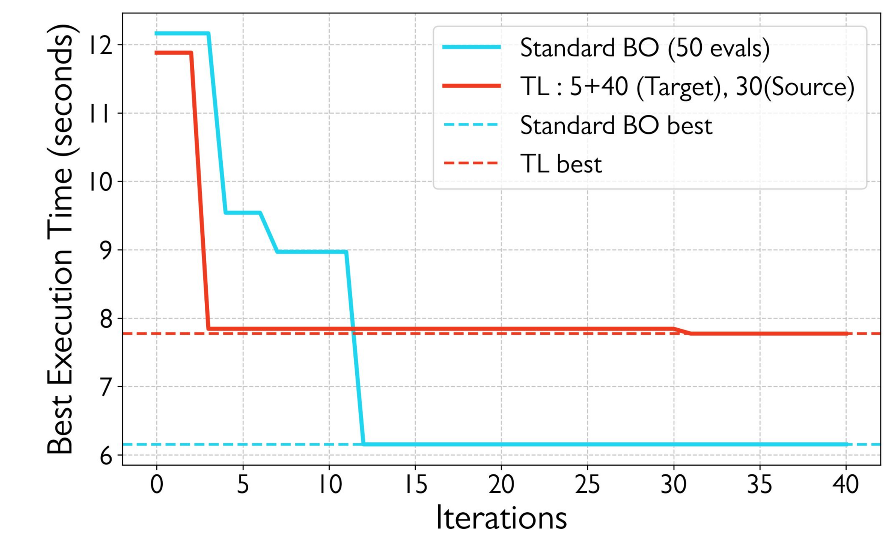
Evaluation



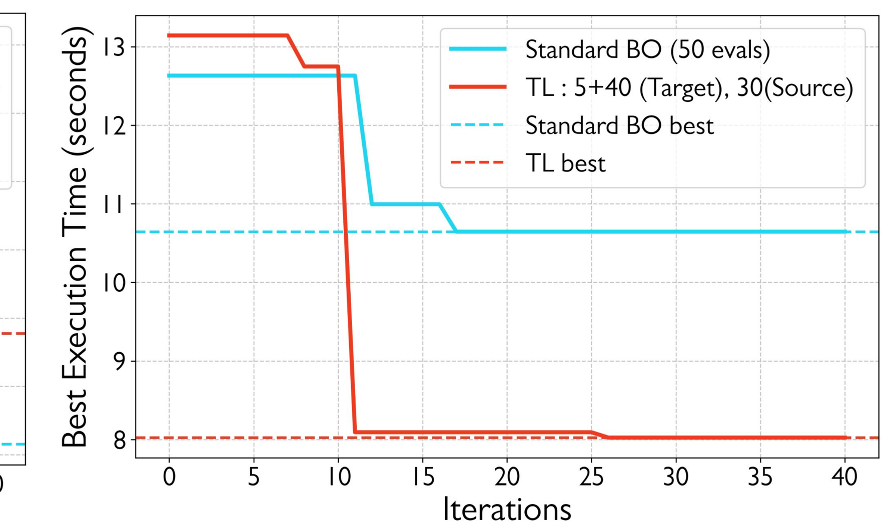


Efficient Exploration by CROSS-BOAT

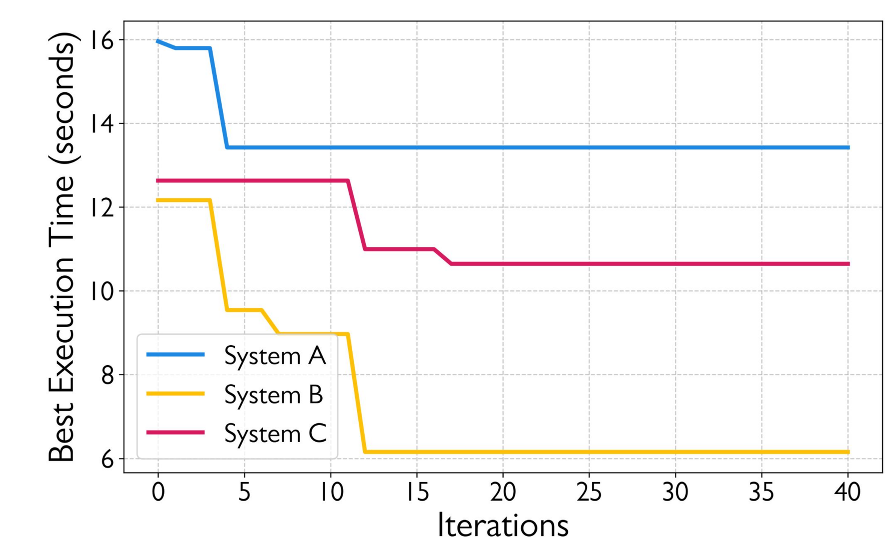
Evaluation



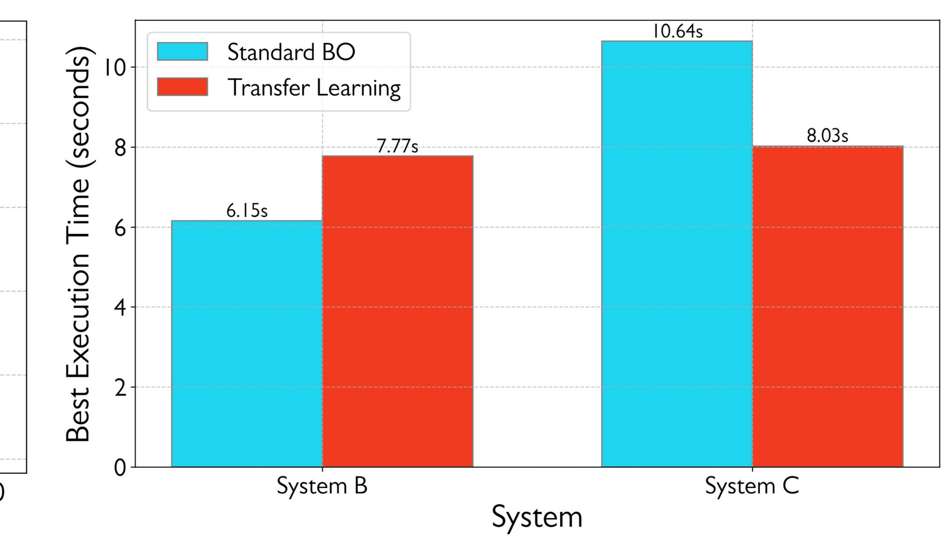
Baseline Convergence for System B



Baseline Convergence for System c



Baseline Convergence



Performance Comparison

Demonstrates 24.5% performance improvement on dissimilar target systems while requiring fewer evaluations than standard Bayesian optimization. Shows intelligent parameter space exploration that quickly identifies optimal configurations across different system architectures.

Conclusion

Transfer learning provides significant benefits for HPC parameter optimization, particularly when target systems differ substantially from source systems. CROSS-BOAT enables more efficient resource utilization during system deployment and upgrades by reducing the optimization overhead.

References

1. Y. Hu, G. Huang, and P. Huang, "Automated reasoning and detection of specious configuration in large systems with symbolic execution," in (OSDI'20).
2. Amit Roy, Prasanna Balaprakash, Paul D Hovland, and Stefan M Wild. 2016. Exploiting performance portability in search algorithms for autotuning. In Parallel and Distributed Processing Symposium Workshops, 2016 IEEE International. IEEE.