LlamaTune: Sample-Efficient DBMS Configuration Tuning

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DBMS Configuration Tuning

Tuning DBMS knob values is *essential* for achieving high-performance

default values are sub-optimal; often chosen for compatibility rather than performance

```
...
bgwriter_lru_maxpages: 100
commit_delay: 0
deadlock_timeout: 1000ms
default_statistics_target: 100
effective_cache_size: 4GB
random_page_cost: 1.0
wal_sync_method: fdatasync
work_mem: 4MB
...
```

Default Configuration

PostgreSQL

Tuning Process →

```
...
bgwriter_lru_maxpages: 20
commit_delay: 150
deadlock_timeout: 4500ms
default_statistics_target: 30
effective_cache_size: 16GB
random_page_cost: 1.25
wal_sync_method: open_fdatasync
work_mem: 16MB
...
```

Tuned Configuration

PostgreSQL

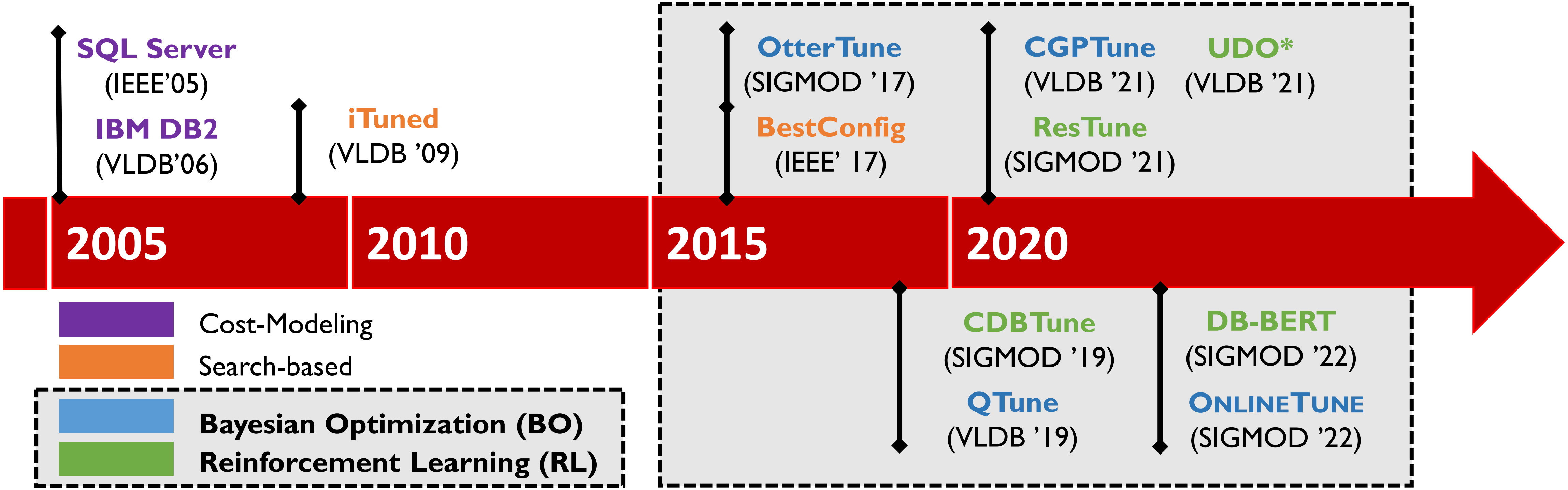
Properly tuned database systems can achieve 3-6x *higher* throughput [1]

[1] Dana Van Aken et. al. *Automatic Database Management System Tuning Through Large-scale Machine Learning*. (SIGMOD ’17)

Automated DBMS Configuration Tuning

DBMSs increasing *complexity* made this task harder for DBAs

- Hundreds of configuration knobs
- Knob heterogeneity (discrete, continuous, categorical)
- Unknown interactions among different knobs (and their values…)



Motivation

Sample-efficiency is a *crucial* requirement to use tuners on *diverse* workloads

Even state-of-the-art optimizers need **~100** samples (>10 hours) to converge to optimal config, when tuning new workloads *without* any prior knowledge

Recent DBMS configuration tuning experimental study / comparison [2]

#1: SMAC the best overall (BO-based \w Random Forest model)

#2: DDPG performed good when tuning ~20 knobs (RL-based, CDBTune)

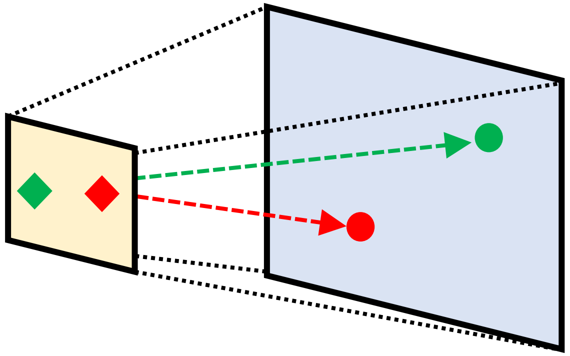
High-dimensional configuration search space is a *major* contributing factor

Can we leverage DBMS-specific *insights* to improve tuning performance?

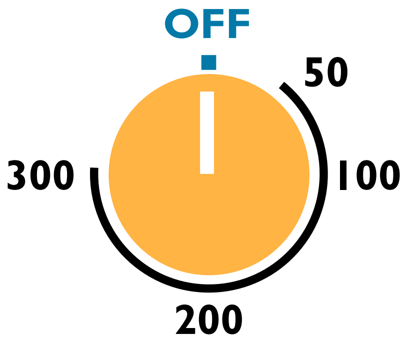
[2] Zhang et. al. Facilitating Database Tuning with Hyper-Parameter Optimization: A Comprehensive Experimental Evaluation (VLDB '22)

LlamaTune Overview

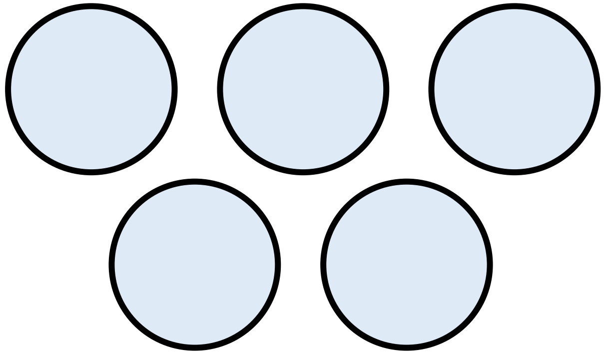
Tuner design that leverages *domain knowledge* to improve the sample efficiency of the underlying configuration optimizers



Low-Dimensional Search Space Tuning



Special Knob Values Handling



Knob Values Bucketization

Reduces configuration *evaluations* by up to **11x** ; up to **21%** higher *throughput*

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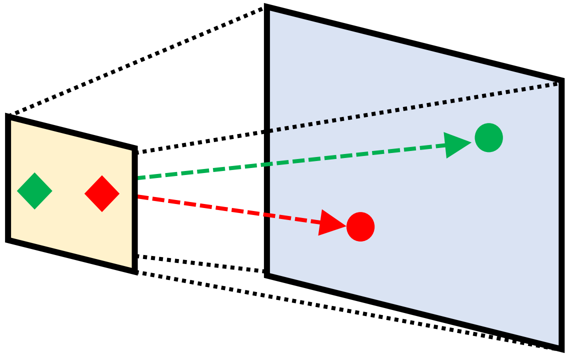

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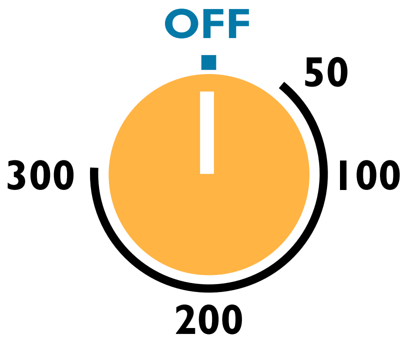

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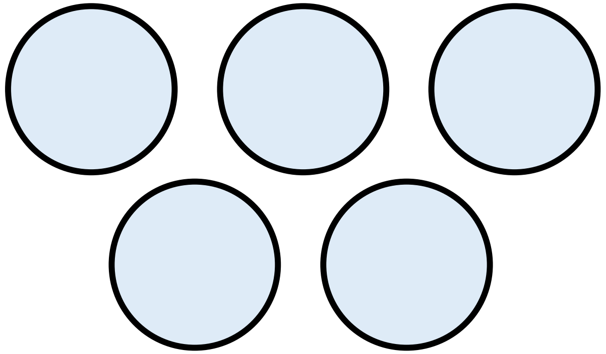

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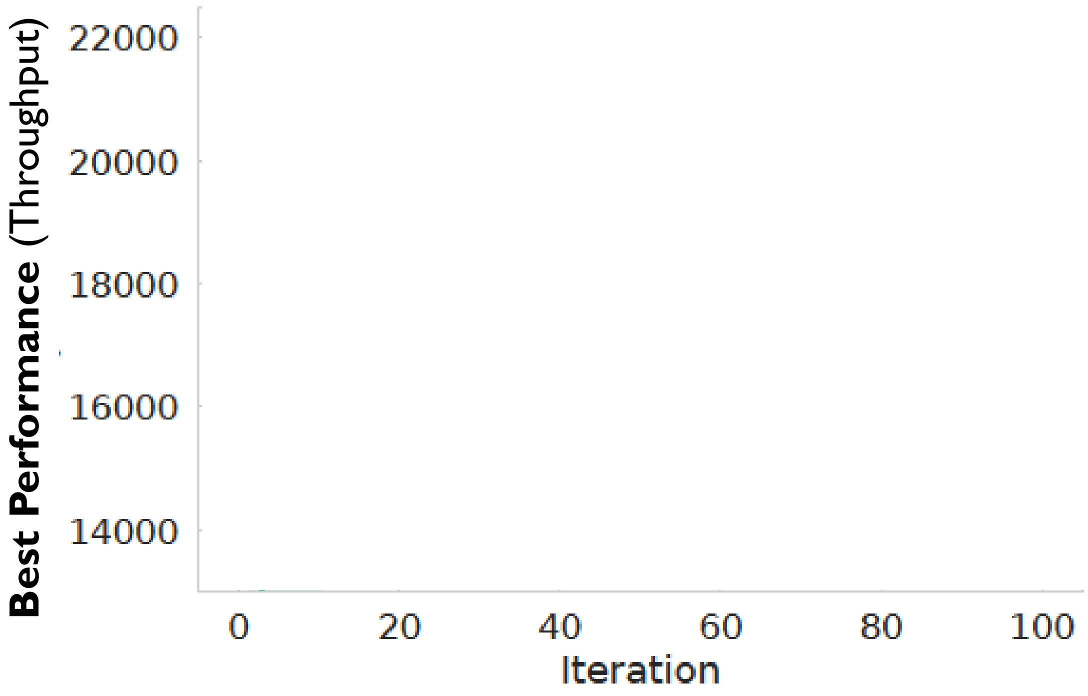
Low-Dimensional Tuning – Important Knobs

Tuning few important knobs can yield optimal DBMS performance

PostgreSQL, 90 knobs, YCSB-A (50%/50% read/write), SF=20, SMAC, average of 5 runs



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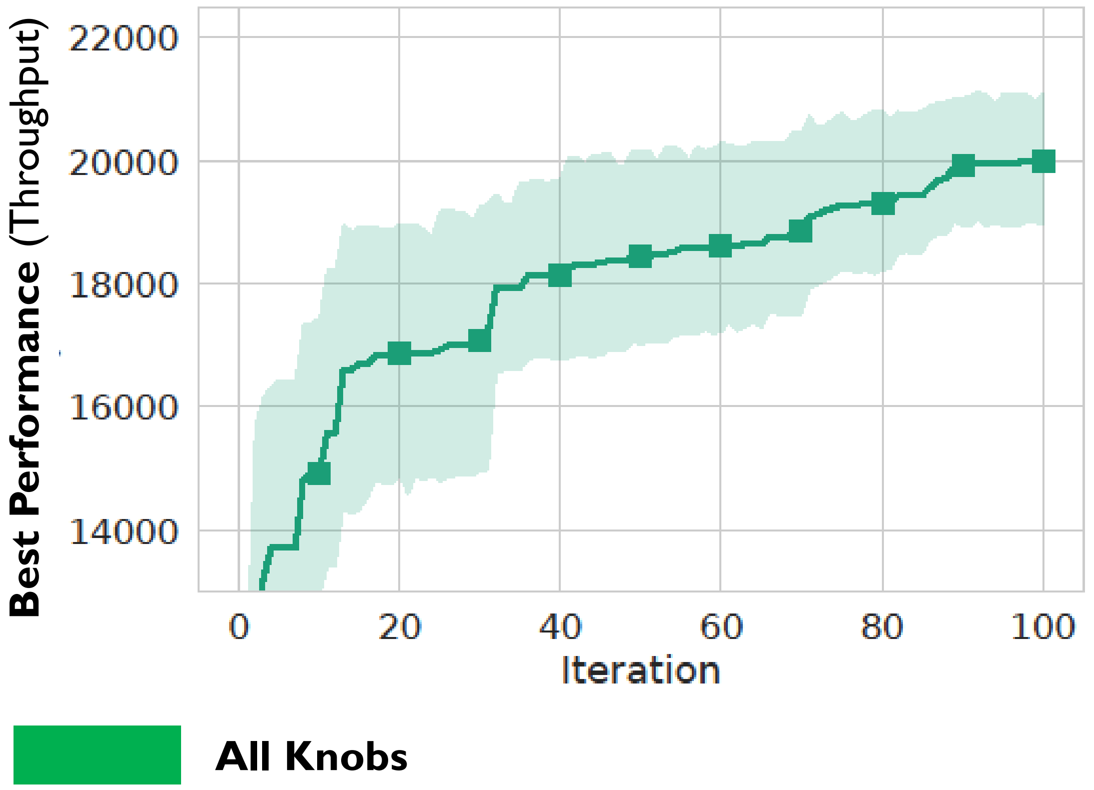

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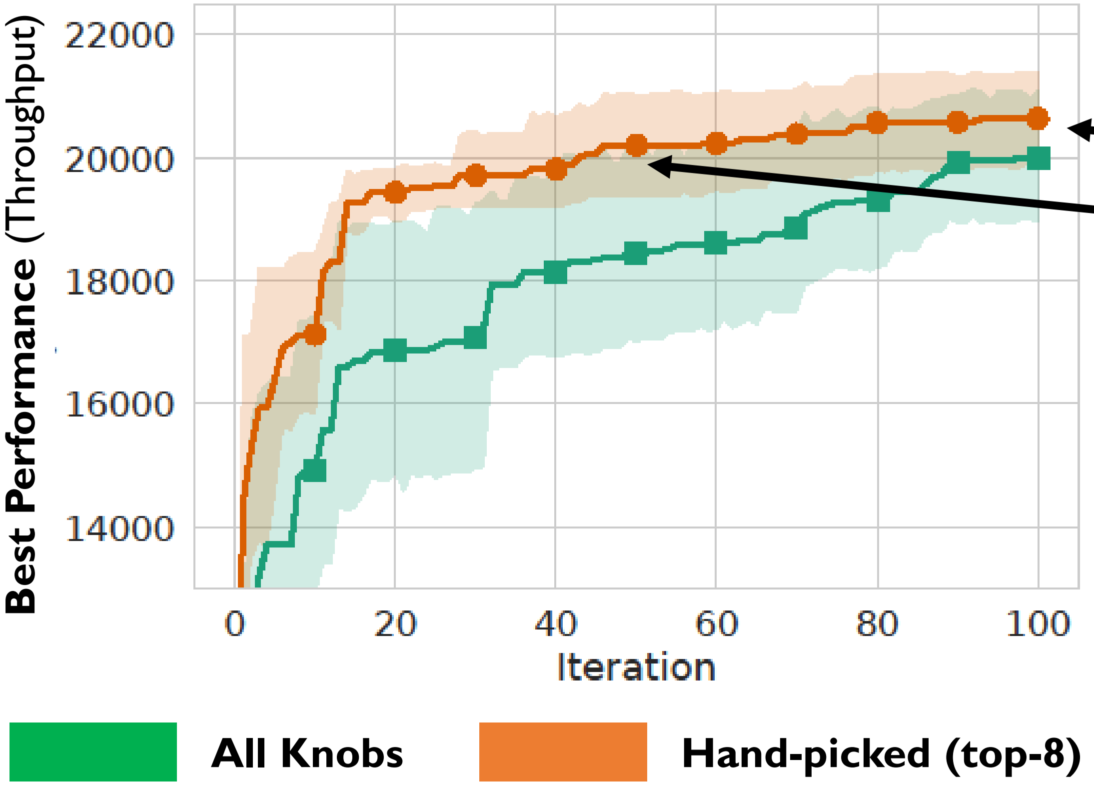

Higher Final Throughput

Faster Convergence to the optimal config. (evaluate fewer configurations to reach baseline optimal performance)

Tuning *smaller* search space (8 vs 90 knobs) can realize gains!

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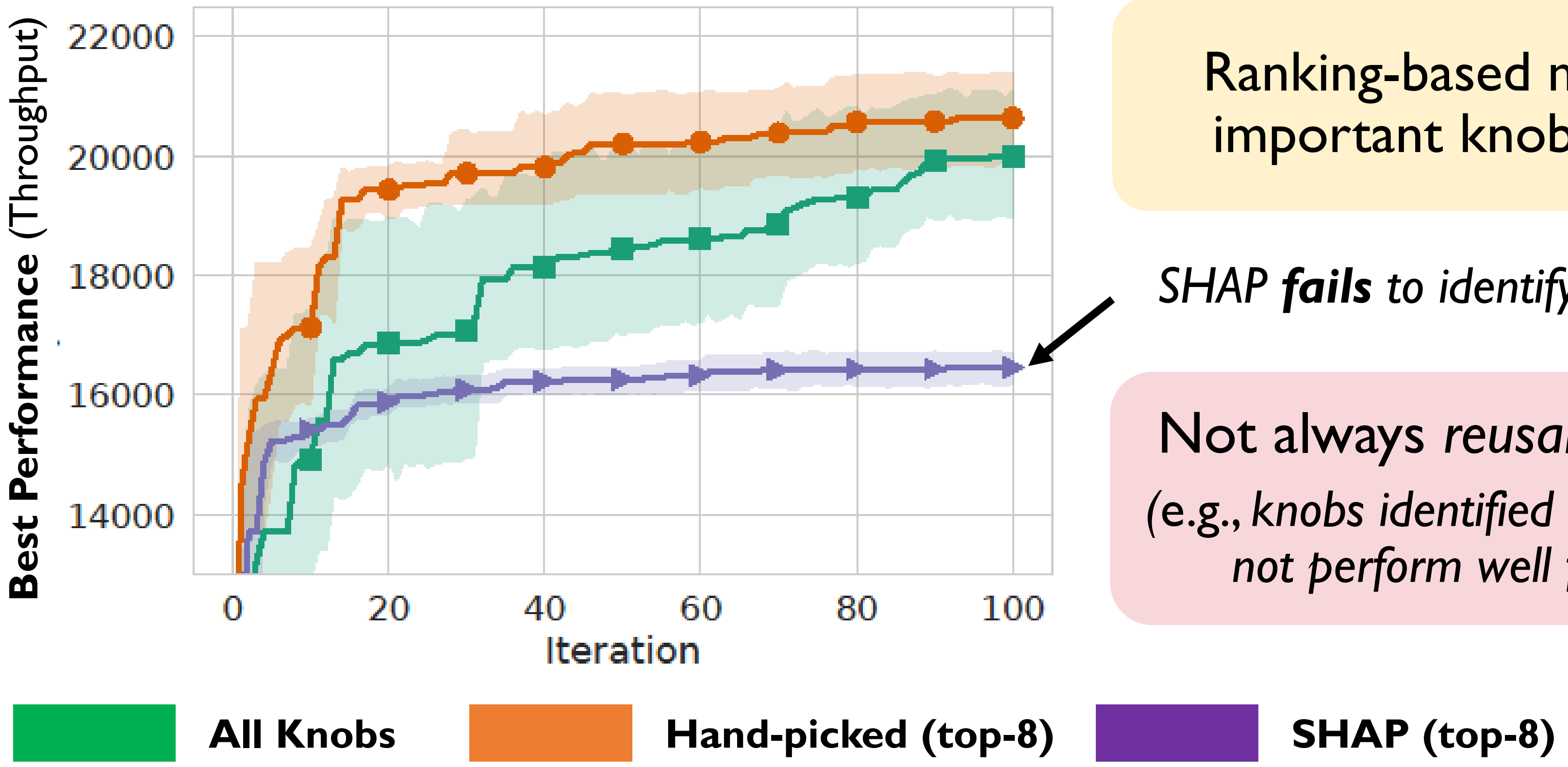


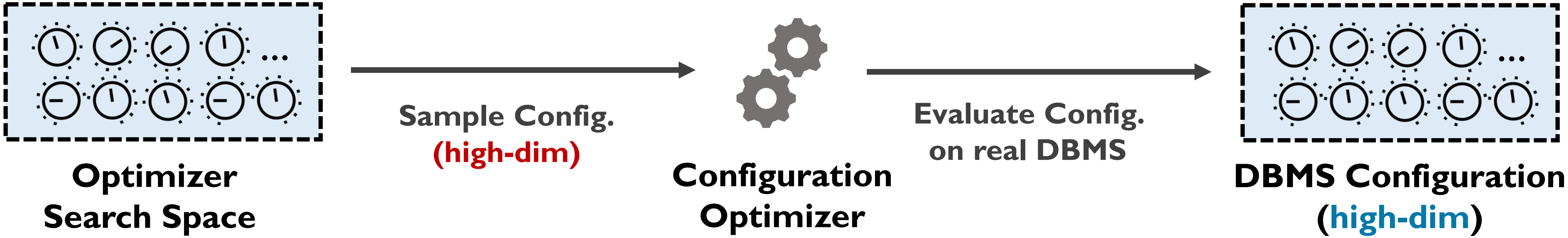
Ranking-based methods that identify important knobs are *slow*, *inaccurate*

*SHAP **fails** to identify <u>all</u> important knobs*

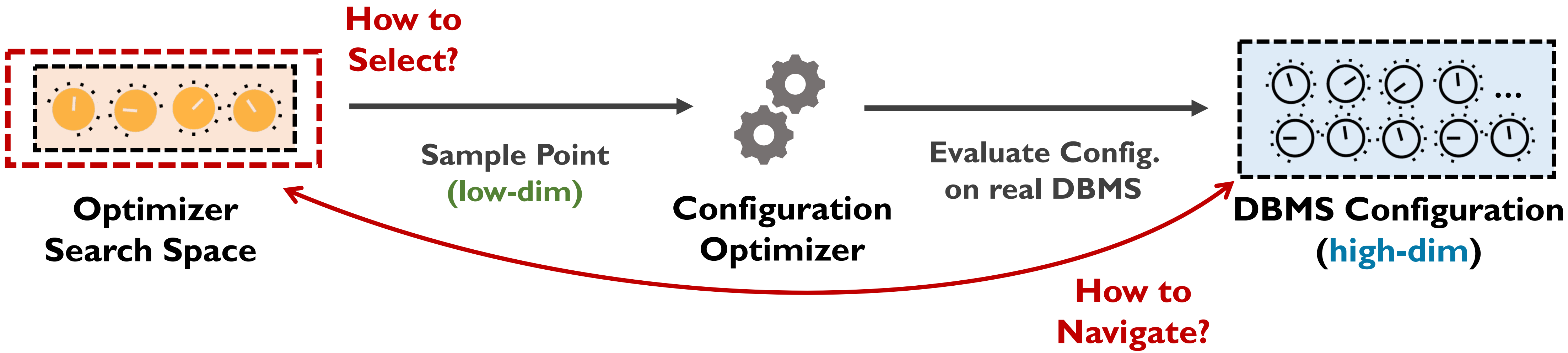
Not always *reusable* across workloads!

(e.g., knobs identified as important for YCSB-A do not perform well for TPC-C, when tuned)

Low-Dimensional Tuning



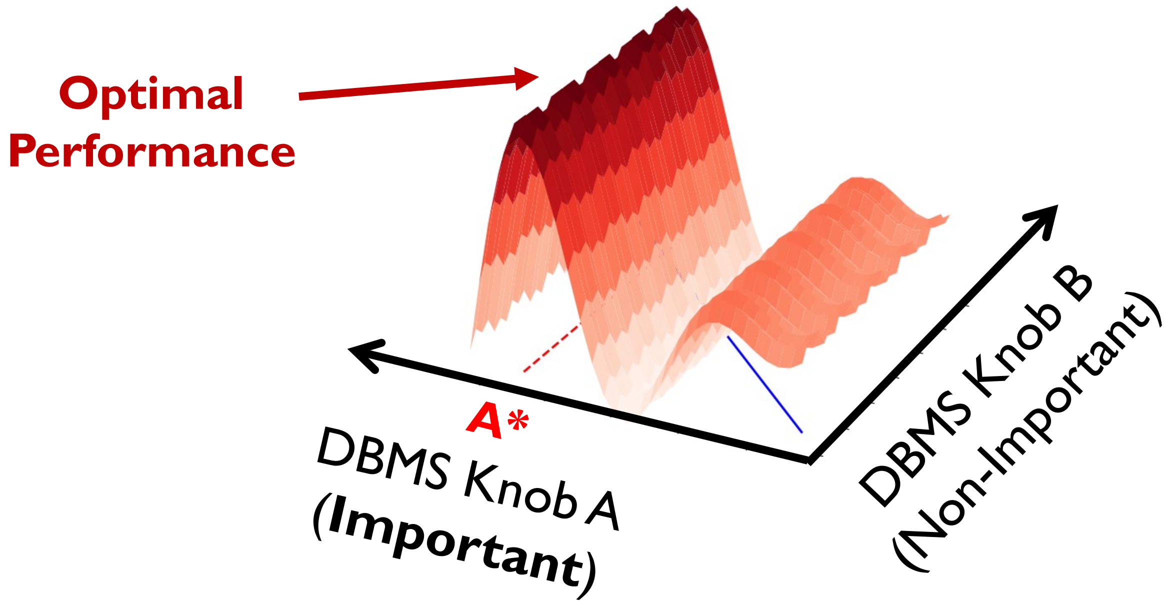
Use fewer knobs (dimensions) to *model* the DBMS performance behavior

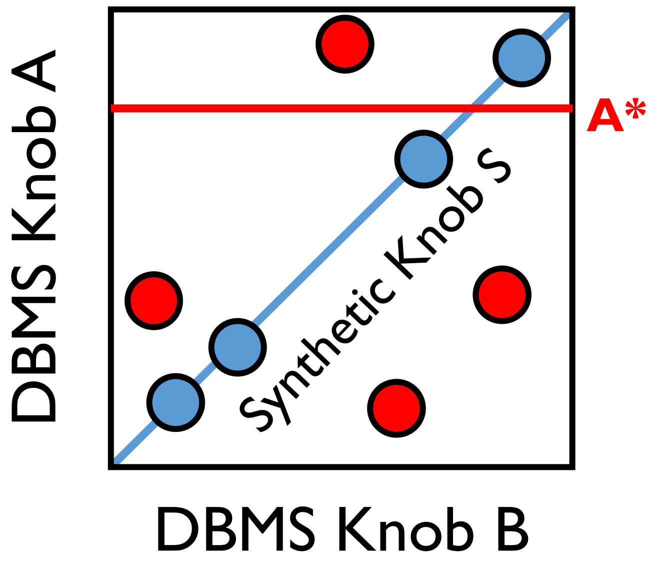


Synthetic Low-Dimensional Search Space

Combine multiple <u>physical</u> DBMS knobs to create few *synthetic* knobs

- No actual meaning themselves – their values determine the **real** DBMS knob values
- Optimizer now tunes these synthetic knobs (i.e., low-dimensional search space)





How to construct this *mapping* from low-dim space to high-dim one?

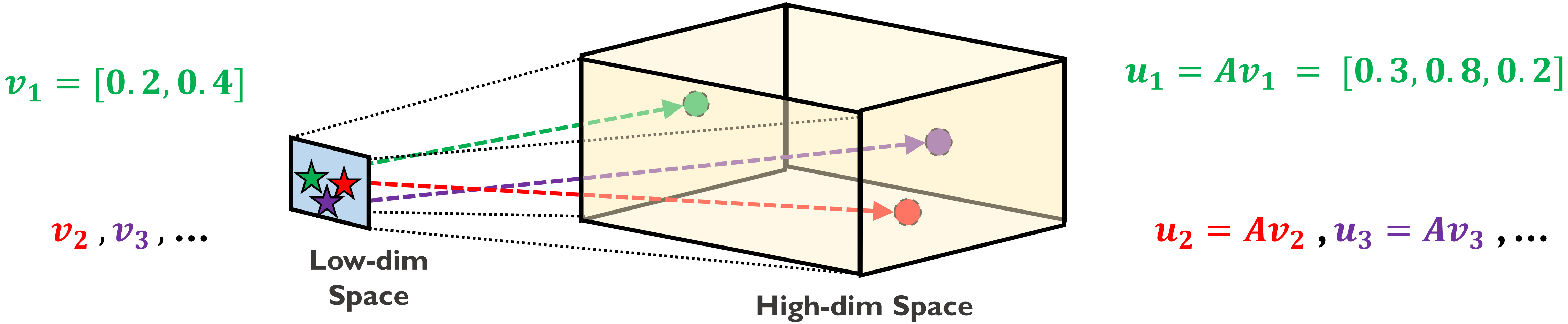
Low-Dimensional Projections

Theoretically-sound proposals from the ML / BO community

- Assume low-dim space has d dimensions; high-dim space has D
- Define a *projection* matrix A, to map points from low-dim to high-dim space

Input: estimate of the *number* of important dimensions (knobs) [d]

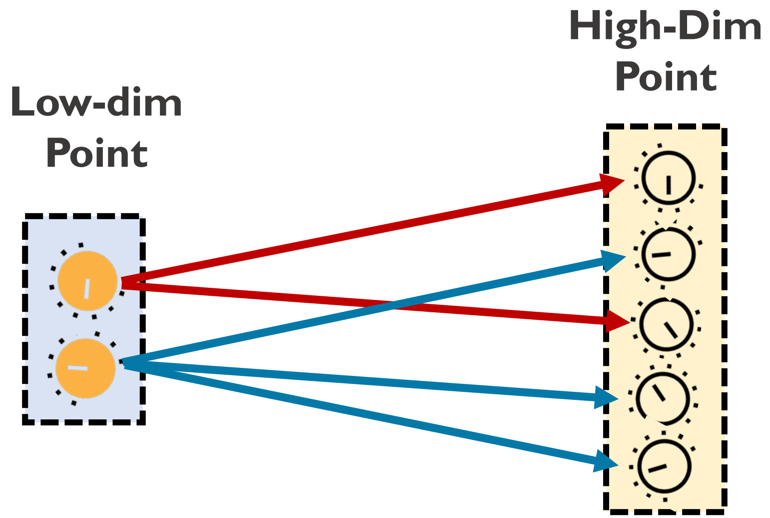
Output: definition of low-dim search space & projection matrix [$d \rightarrow D$]



Low-Dimensional Projections

Hashing-Enhanced Subspace BO (HesBO) [3]

- Random one-to-many *linear* projection
- Based on Count-Sketch projection
- Adequately preserves the characteristics of up to d (important) dimensions (e.g., pairwise distances)

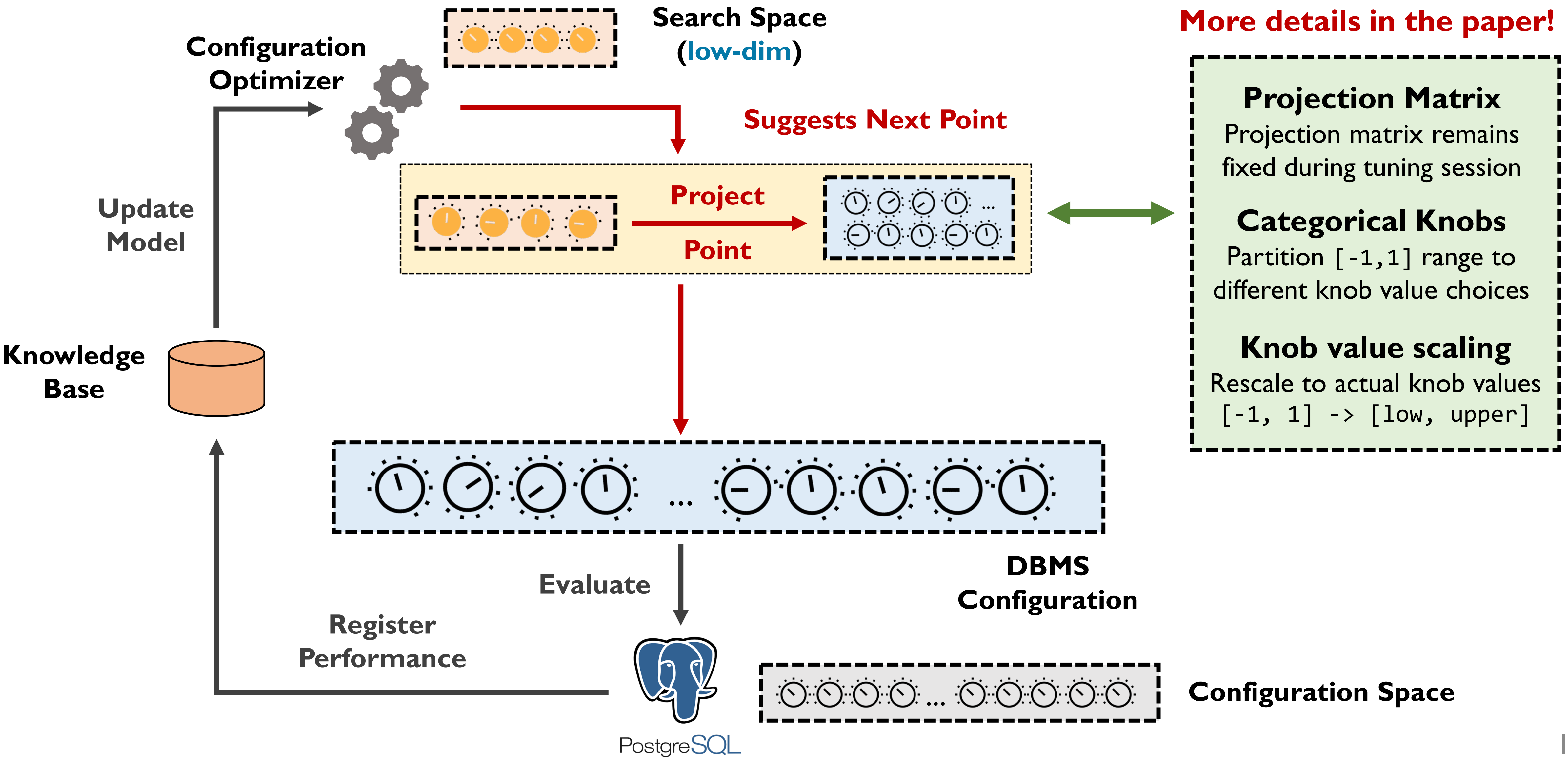


Low-dim space dimensions [d] **>** True # of important dimensions [d_e]

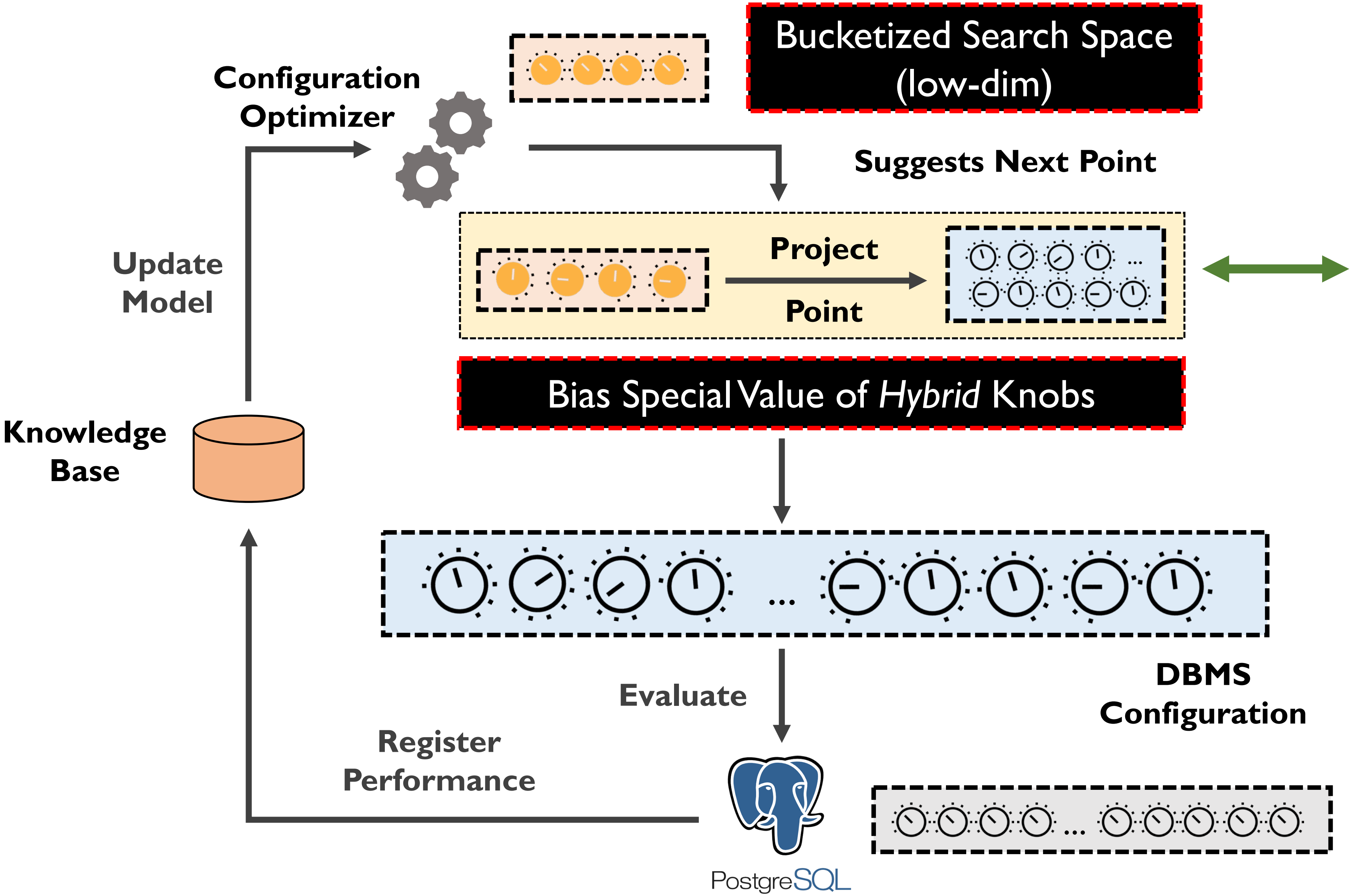
Optimal point(s) in low-dimensional space, with **high-probability**!

[3] Munteanu et al. A Framework for Bayesian Optimization in Embedded Subspaces (PMLR'19)

LlamaTune Architecture (low-dim tuning)



LlamaTune Architecture (complete)



More details in the paper!

Projection Matrix
Projection matrix remains fixed during tuning session

Categorical Knobs
Partition `[-1,1]` range to different knob value choices

Knob value scaling
Rescale to actual knob values
`[-1, 1] -> [low, upper]`

Evaluation

CloudLab

End-to-end evaluation with *six* diverse workloads

- TPC-C, SEATS, Twitter, YCSB-A, YCSB-B, ResourceStresser

Multiple performance *targets*

- Max throughput, 95-th% tail latency

Different underlying configuration optimizer

- SMAC, Gaussian-Based Bayesian Optimizer (GP-BO) ; DDPG (RL-Based)

Generalization to *newer* PostgreSQL version

Ablation Studies

- Measure *how much* each component contributes

Sensitivity analysis for each individual component

Overhead of the configuration optimizer

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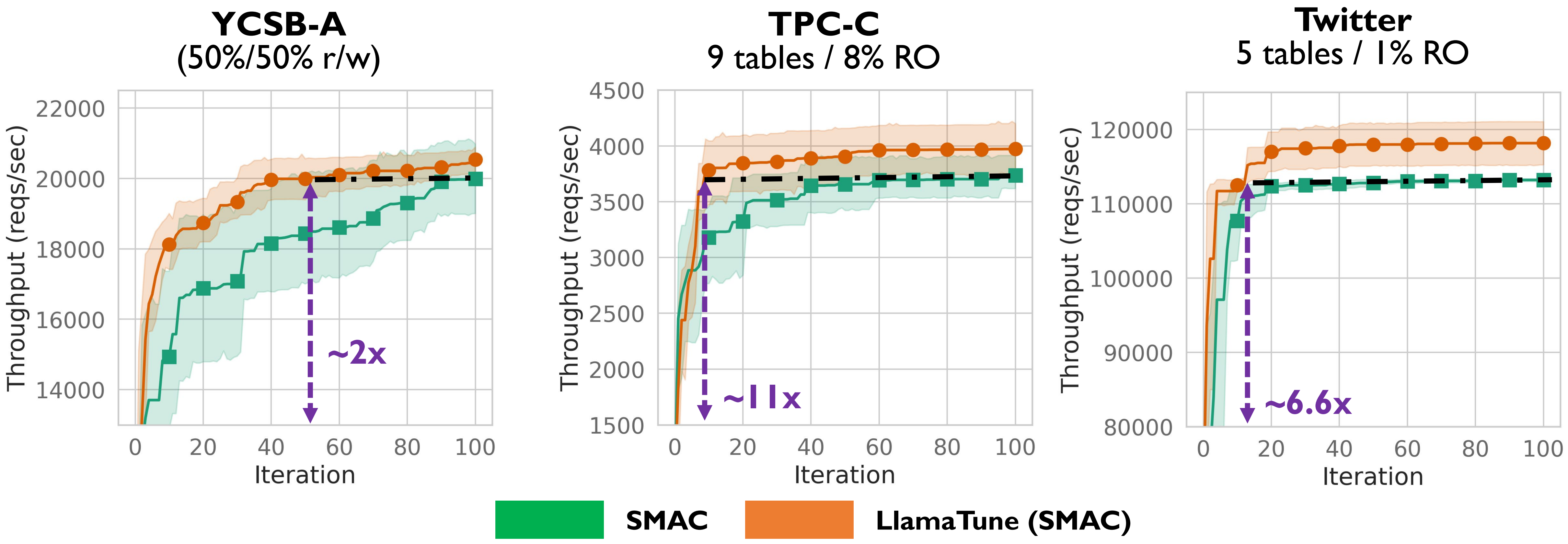
End-to-End Evaluation

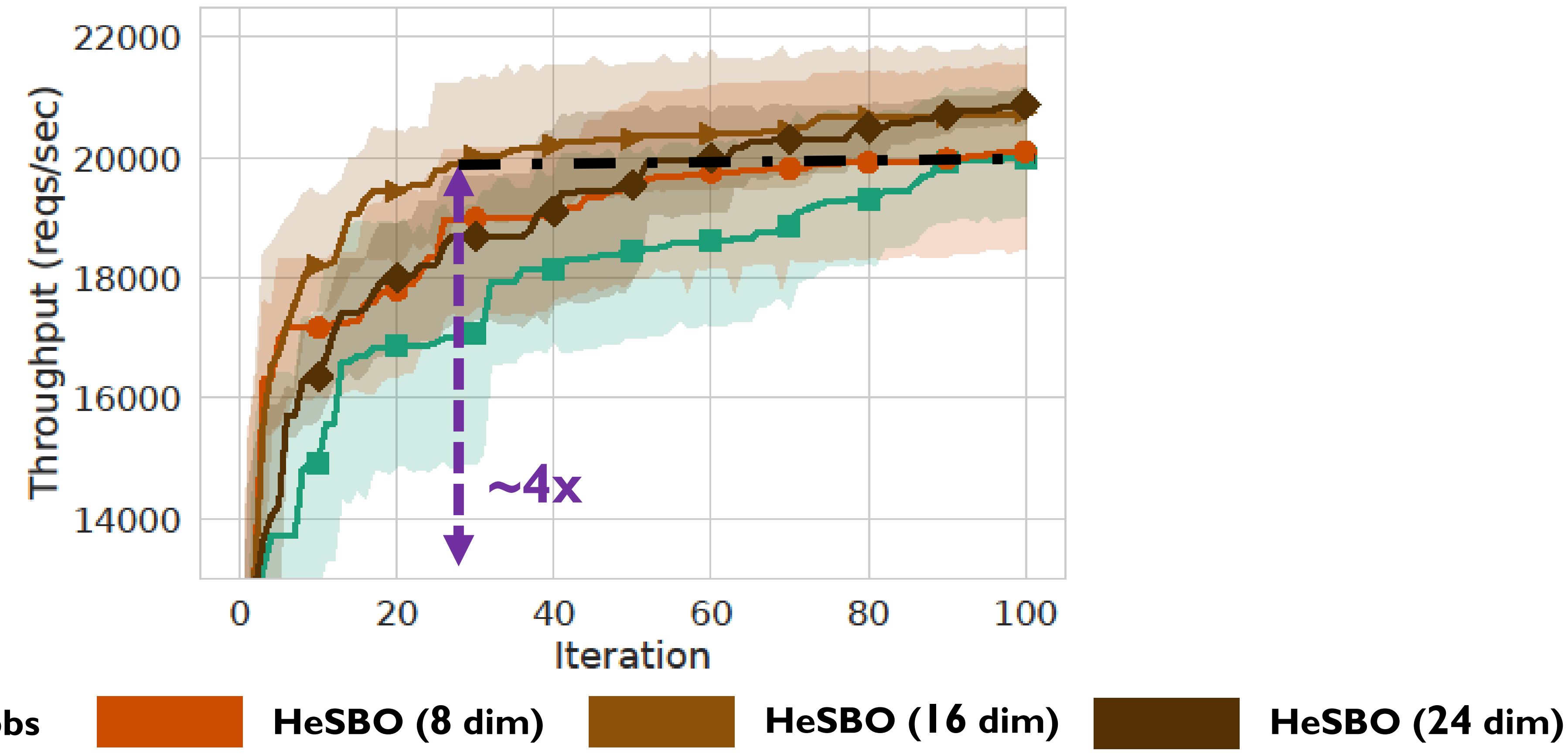
PostgreSQL v9.6, 90 knobs, SMAC, average of 5 runs



LlamaTune reaches baseline perf. **~5.6x** faster – improves final perf. **~11%**

Sensitivity Analysis – Low-Dim Tuning

PostgreSQL v9.6, 90 knobs, **YCSB-A** (50%/50% read/write), SF=20, SMAC, average of 5 runs



Conclusion

Feel free to reach out for questions!

Zero-knowledge DBMS tuners require ~100 samples to find good-performing conf.

- Sample-efficiency is *crucial*; reduces required time / resources utilization

LlamaTune: exploits domain knowledge

- Use low-dimensional projections to *indirectly* tune important knobs
- Handles *special values*, *bucketizes* knob values – search space easier to explore!

Outperforms SOTA optimizers [*SMAC*, *GP-BO*, *DDPG*]: up to 11x fewer evaluations

`github.com/uw-mad-dash/llamatune/` `kkanellis@cs.wisc.edu`

Thank you! Questions?

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