

Rafiki: A Middleware for Parameter Tuning of NoSQL Databases for Dynamic Metagenomics Workloads

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Motivation

- DBMS have numerous configuration parameters
 - NoSQL Cassandra has 50+
 - NoSQL ScyllaDB has 25
- Configuration parameters control the system's behavior
- Parameter tuning is time-consuming for DBAs
- Optimal configurations are workload dependent
- Dynamic workloads
 - MG-RAST (Metagenomic Rapid Annotations using Subsystems Technology): automatic phylogenetic and functional analysis of metagenomes. It is also one of the biggest repositories for metagenomic data.
 - Wikipedia workloads

NoSQL Databases (Cassandra)

- Non-relational (flexible design)
- Distributed (fault tolerant)
- Horizontally scalable (performance scales with [# of instances])
- 25+ configuration parameters
- Interdependent parameters (one-by-one tuning provides sub-optimal performance)

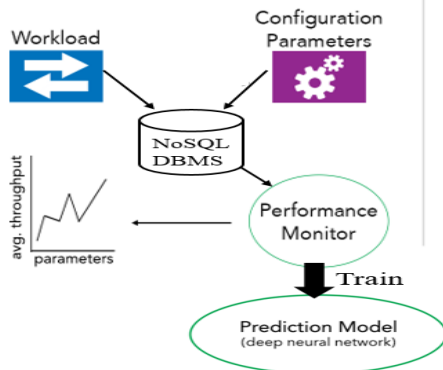
Challenges

- Configurations space is huge.
- Searching in runtime is non-practical
- A fast and efficient approach is needed to adapt with sudden workload shifts

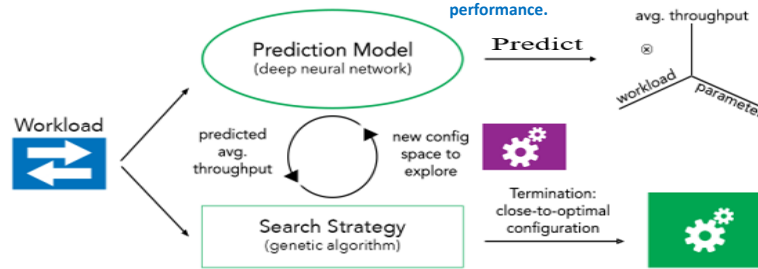
Rafiki reaches within 15% of grid search performance using only 1/10000-th of the search time

Phase 1: Varying workloads and configurations are applied to the NoSQL database to identify the key configuration parameters and to generate training data for a surrogate model.

Data Collection



Runtime



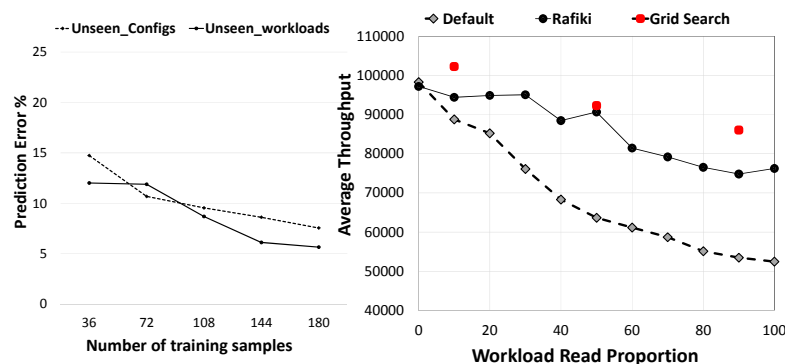
Phase 3: A search strategy is applied for a given workload to find close-to-optimal configurations.

Rafiki:
The sagacious monkey in Lion King



A high-level overview of Rafiki searching through the configuration parameters' space of NoSQL databases to achieve close-to-optimal performance. Rafiki is agile enough to quickly adapt to changing workloads, such as in the MG-RAST system.

Evaluation



Performance of Cassandra with optimal configuration selected by Rafiki vs. default configuration. Three points are shown for the theoretically optimal performance using exhaustive searching.

Prediction error for Cassandra using the surrogate performance model with Neural Network, as a function of the number of training samples.

Triumphs of Rafiki

- We design and develop Rafiki for automatically configuring NoSQL database parameters in a workload-centric manner, using traces from MG-RAST.
- We apply ANOVA-based analysis to identify the key parameters that are the most impactful toward improving database throughput.
- We create a DNN framework (surrogate model) to predict the performance for unseen configurations and workloads. It achieves a performance prediction with an error in the range of 5-7% for Cassandra and 7-8% for ScyllaDB.
- We then create a **Genetic Algorithm-based search** process through the configuration parameter space, which **improves the throughput for Cassandra by 41.4% for read-heavy workloads** (more relevant to MG-RAST), and 30% on average.
- To get an estimate of the upper bound of improvement, we compare Rafiki to an exhaustive search process and see that Rafiki, **using 4 orders of magnitude lower search time than exhaustive grid search**, reaches within 15% and 9.5% of the theoretically best achievable performances for Cassandra and ScyllaDB, respectively.

References

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Acknowledgments

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