Workload Fingerprints:
The Precision Metric for Autonomous PostgreSQL Tuning

Moving From "Gut-Feel" Art to Rigorous Database Engineering

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Abstract: To an AI agent, a PostgreSQL database is a sea of noise. Traditional performance indicators like standard Average Query Runtime (AQR) are often too blunt to guide automated tuning, failing to account for shifting query frequencies or transient background system tasks. This poster presents the **Workload Fingerprint**, a novel approach to database observability spun out of research at DBtune. By isolating environmental noise and normalizing query distribution variations, this methodology provides the granular accuracy required for true autonomous optimization.

PROBLEM STATEMENT: THE TUNING CYCLE

Traditional database tuning creates a complex, continuous feedback loop where application owners and automated tuners must constantly evaluate fluctuating key performance indicators (KPIs) across testing and production environments. This process is severely hindered by measurement volatility, network jitter, and distribution shifts, demanding an architectural transition toward robust, isolated, and fingerprint-based statistical metrics.

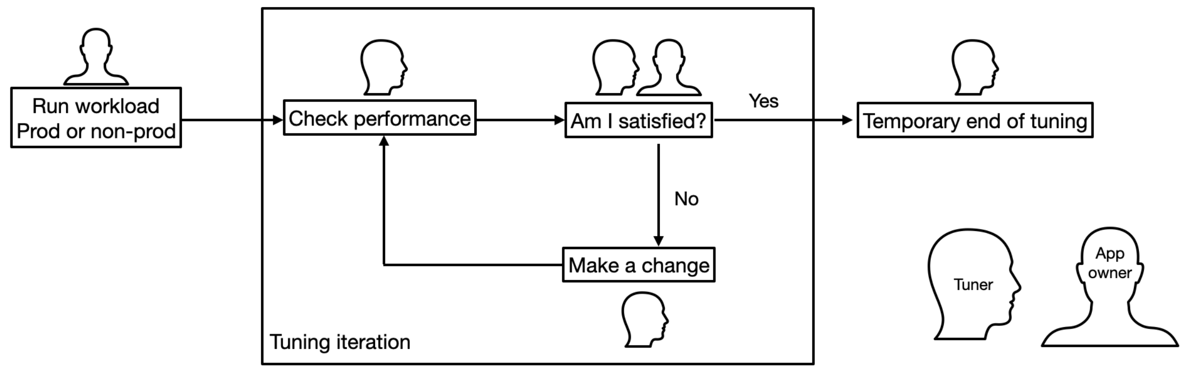

Figure 1: Standard iterative feedback loop between application owners and tuners.

1. THE PROBLEM: THE INACCURACY OF GENERIC METRICS

Traditional performance tuning relies heavily on global aggregates like Average Query Runtime (AQR) or generic Transactions Per Second (TPS). However, in production environments, these metrics are highly unstable due to:

- **Query Distribution Shifts:** A sudden influx of fast queries artificially lowers the aggregate AQR, while a few heavy reports inflate it, masking true performance changes.
- **Skewed Sampling Windows:** Truncated measurement cycles completely miss sporadic but high-impact analytical operations, producing misconfigured parameter targets.

2. ENVIRONMENTAL NOISE & RUNTIMES

Individual query latencies fluctuate dynamically due to ambient system interference rather than actual engine efficiency. Key production noise drivers include multi-tenancy overhead, shared network jitter, and transient cache eviction states.

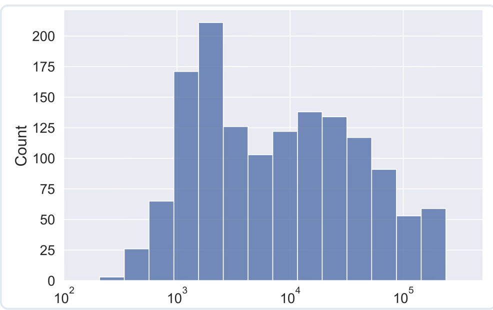

Figure 2: High variability of raw individual query runtimes.

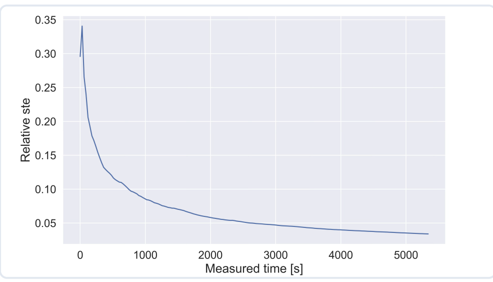

Figure 3: Relative Ste decay over measured window duration.

Solution: Standard Error (Ste) as a Stop Criterion

To explicitly isolate background interference and establish invariant baseline statistics, the autonomous tuning system must observe a target workload profile long enough for the Relative Standard Error to stabilize close to zero:

$$Ste = \sigma / \sqrt{n} \rightarrow 0$$

Minimizing the standard error guarantees that the captured localized sample mean accurately represents the true database population performance mean, ensuring reproducible optimization steps.

3. THE WORKLOAD FINGERPRINT METHOD

The **Workload Fingerprint (WF)** replaces global averages with a robust, comparable, and normalized measurement framework built in three sequential steps:

Step 1: Define Target Workload & Weights

Historical operational logs are statistically analyzed to map explicit importance weighting scores onto distinct, structured query signatures.

Step 2: Isolate Localized performance profiles

Track the separate performance distribution of every targeted query group independently, leveraging the Ste criteria to determine optimal window lengths.

Step 3: Weighted Global Aggregation

Recombine the isolated runtimes according to their static analytical weights to establish an immutable, production-comparable global performance metric:

$$WF\ AQR = \sum (Weight_i \times AQR_i)$$

3. THE WORKLOAD FINGERPRINT METHOD (CONTINUED)

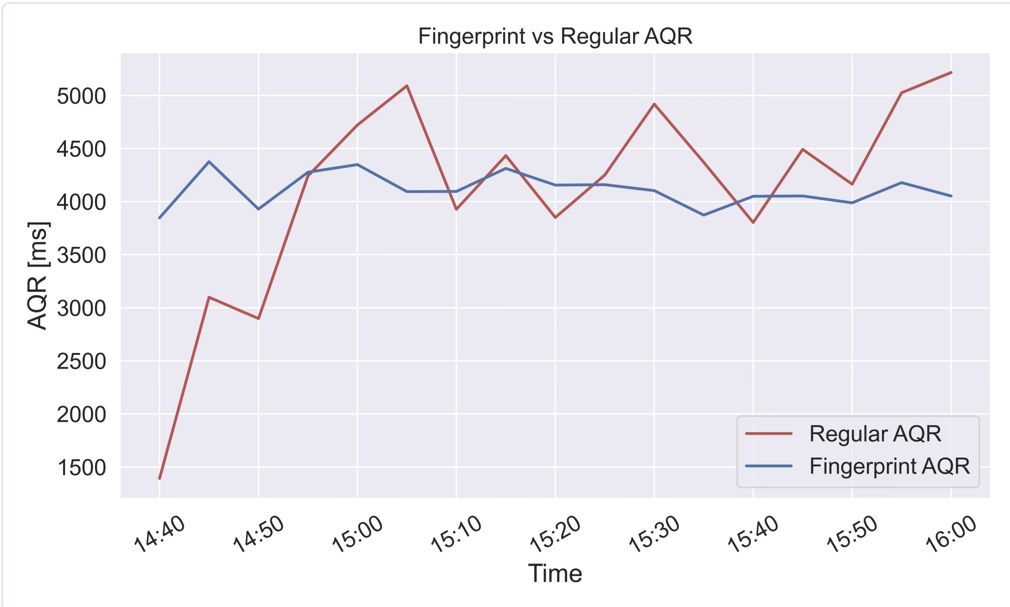

Figure 4: Comparative stability of Fingerprint AQR vs. volatile Regular AQR under identical load profiles.

4. QUERY CLASSIFICATION GRID

To systematically automate fingerprint generation across thousands of ad-hoc database queries, workloads are mapped into four deterministic quadrants based on volume and runtime:

Heavy & Infrequent **Analytical Reporting**	**Heavy & Frequent** **Critical Bottlenecks**
Light & Infrequent **Background Noise**	**Light & Frequent** **High-Volume OLTP**

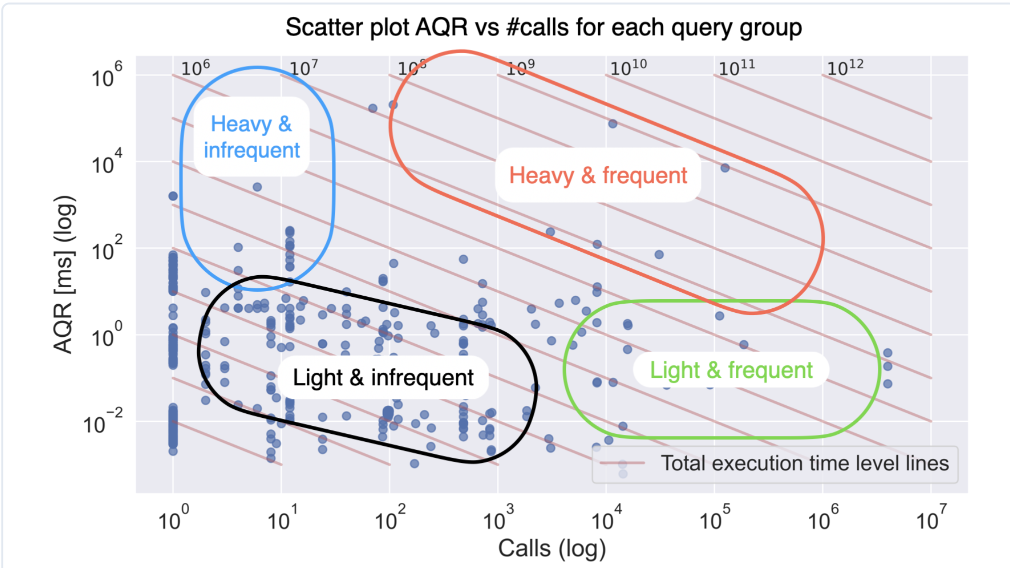

Figure 5: Empirical classification mapping of production query groups into target workloads.

PRESENTER & RESOURCES

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Luigi Nardi has a mixed background spanning industry and academia. He holds a Ph.D. in Computer Science from Sorbonne University, served as a Research Staff member at Stanford University, and is an Associate Professor in AI at Lund University. In 2020, he founded DBtune to bring AI-powered, autonomous database tuning solutions to the global enterprise market.

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