

## Lessons Learned from Automatically Optimizing Databases Using Machine Learning in the Real World

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# 01. Background

### **01. Background**

Databases are **notoriously** complex to deploy, optimize, and maintain.

Physical Design (Indexes, Partitioning)

Knob Configuration

**Query Optimization** 

Hardware Provisioning

Human experts are **scant**, **unscalable**, and **expensive**.



#### Occupational Employment and Wages, May 2021

#### 15-1242 Database Administrators

Administer, test, and implement computer databases, applying knowledge of database management systems. Coordinate changes to computer databases. Identify, investigate, and resolve database performance issues, database capacity, and database scalability. May plan, coordinate, and implement security measures to safeguard computer databases. Excludes "Information Security Analysis" (15-1212) and "Database Architects" (15-1243).

#### National estimates for Database Administrators:

Employment estimate and mean wage estimates for Database Administrators:

Employment <u>(1)</u>	Employment RSE <u>(3)</u>	Mean hourly wage	Mean annual wage <u>(2)</u>	Wage RSE <u>(3)</u>
85,870	1.5 %	\$46.42	\$ 96,550	0.9 %

Percentile wage estimates for Database Administrators:

Percentile	10%	25%	50% (Median)	75%	90%
Hourly Wage	\$ 23.50	\$ 30.36	\$ 46.50	\$ 59.88	\$ 72.79
Annual Wage <u>(2)</u>	\$ 48,880	\$ 63,160	\$ 96,710	\$ 124,550	\$ 151,400

### **01. Automated Database Optimization**

HTAP SUMMIT 2023

There is a long history of attempts in research to automate database management systems.

1970s: Self-Adaptive Databases



1990s/2000s: Self-Tuning Databases 2010/2020s: Self-Driving Databases



DRACLE

Research in the last decade has focused on applying **machine learning** (ML) methods to solve the tuning problem for databases.

**Colf Driving Database Management Systems** World's First Andrew Tod "Self-Driving" ABSTRA In the last to advisory to Database aspects of : which an driving I due to a Oracle provem 1. IN The is ment wa and deci approace they was store an Over data-int science and gro-tuning of word above could Autonomous Database No Human Labor – Half the Cost No Human Error – 100x More Reliable ORACLE oracle.com/selfdrivingdb an labor refers to tuning, patching, updating, and maintenance of database. Copyright © 2017, Oracle and/or its affiliates. All rights reserved.

### **01. Machine Learning for Databases**

#### Indexes:

Azure Auto Indexing, Oracle Autonomous Database Service, Cornell UDO, OpenGauss

**Partitioning:** 

**Cloud Partition Adviser** 

Knob Configuration:

OtterTune, CDBTune, Akamas, ResTune, QTune

**Query Optimization:** 

<u>Bao</u> (Join Algos), <u>Neo</u> (Join Ordering), <u>MySQL Heatwave</u> <u>Autopilot</u> (Plan Stitching)



### **01. OtterTune Overview**

OtterTune is an automated database tuning and resource optimization service.

Based on research developed at <u>Carnegie Mellon</u> <u>University</u> Database Group.

It uses **machine learning** to automatically optimize the configurations of DBMSs to improve performance, reduce costs, and maintain healthy operations.

Research: Knobs

Commercial: Knobs, Indexes, Queries, Cloud Config

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## 02. The Real World

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### **02. Real-World Databases**

# Challenge #1: Users do <u>not</u> maintain suitable staging databases.

Training models on staging DBs is **bad** because of inconsistent workloads and hardware.

Dev/Staging databases run on smaller hardware with a subset of the production databases because of cost.

Dynamic hardware scaling (burst credits) and serverless instances make this worse.



### **02. Real-World Databases**

# Challenge #2: Users <u>cannot</u> capture workloads and replay them.

Without a **repeatable workload** as a baseline, it is difficult for the ML models to learn whether they are improving a database.

Tools for open-source DBMSs are less sophisticated than commercial DBMSs.

Existing built-in slow query log methods do not capture transaction boundaries. It's super expensive to log all queries to disk.



### **02. Real-World Databases**

Challenge #3: Users mostly do <u>not</u> know what their database is doing. The production workload is dynamic.

Workload patterns and application **changes** make it difficult to measure whether a tuning tool is making things better or worse.

Most production workloads have daily or weekly patterns.







### **03.** Lessons Learned

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### **03. Production Database Tuning**

Tuning a staging database using a replayed workload is impractical in real-world scenarios.

Users do not maintain suitable staging databases.

Users <u>cannot</u> capture workloads and replay them.

Most customers allow us to **carefully** tune their production databases. But they need to have control over **what**, **when**, and **why** changes are applied.



### **03. Manual Controls & Explanations**

To reduce untimely performance degradations or downtime, a tuning service must provide controls to allow humans to specify **what** and **when** the service will optimize the database.

**Tuning Periods** 

**Restart Tracking & Scheduling** 

Human-in-the-loop Approval

To help build trust, provide users with datadriven explanations about recommendations. (why they should apply them)





### **03. Machine Learning & Domain Knowledge**

Machine Learning models can help find the (nearly) optimal database configurations.

No explanations about recommendations

Need time to converge

Heuristic-based approach using domain knowledge may not yield the optimal recommendations.

Provide explanations about recommendations

Do not need training data, recommend immediately

You don't need to pick just one. Integrate **both** methods for better recommendations.



### **03. Not A Machine Learning Problem**

Automated database tuning with ML works **better** in the real-world than in the research lab, but getting the full benefit of these optimizations and tuning production databases **safely** is **not a ML problem**.

Knob Bounds

...

**Tuning Periods & Schedule** 

Explanations about recommendations

We extend OtterTune to support three ML models. They all have **similar** performance:

**Gaussian Process Regression** 

Deep Neural Network

Deep Deterministic Policy Gradient





An Inquiry into Machine Learning-based Automatic Configuration Tuning Services on Real-World Database Management Systems VLDB 2021



## 04. LLMs For Databases

#### **04. Database Questions**

LLMs like ChatGPT may **not** be the ideal resource for addressing your database-related questions because it can give you **inaccurate** answers.

From ChatGPT, **jit** parameter can have the following values:

off 🗸 on 🗸 normal 🗙 all X

В	jit related knobs in postgres	C
	In PostgreSQL, JIT (Just-In-Time) compilation is a feature that allows the database to dynamically compile SQL queries into native machine code for improved query execution performance. As of my last update in September 2021, PostgreSQL introduced JIT compilation in version 11, and there might have been further developments since then. Here are some relevant parameters or "knobs" related to JIT compilation in PostgreSQL:	ΰ.
	<ol> <li>jit: This is a configuration parameter that can be set to control the overall behavior of JIT compilation. It can have the following values:         <ul> <li>`off': Disables JIT compilation.</li> <li>`on`: Enables JIT compilation for all statements.</li> <li>`normal`: Enables JIT compilation for statements considered worthwhile by the query planner (default).</li> <li>`all`: Enables IIT compilation for all statements.</li> </ul> </li> </ol>	

### **04. Database Optimizations**

LLMs like ChatGPT are trained on existing text that cannot account for an **application's** workload patterns.

> It can only give you some **generic** recommendations and cannot give you **exact** answers.

> We have found that "best practice" recommendations are often wrong.

The **`innodb\_adaptive\_hash\_index**` option in MySQL enables InnoDB to build a hash index on frequently accessed data pages in the buffer pool, which can speed up point queries (i.e., queries that retrieve a single row by its ID).

However, whether or not to enable this option depends on your workload and the nature of your queries. Given your high percentage of `**SELECT**' operations (77.60%), you might benefit from it, especially if those `**SELECT**' queries are mostly point queries.

That said, it's important to note that this setting can also consume additional memory and CPU resources for maintaining the hash index. In certain cases, especially in highly concurrent workloads, it can lead to contention issues and actually degrade performance.

Before you decide to enable it, you should test it in a non-production environment with a workload similar to your production environment. Monitor the performance and system resource usage closely to see if it provides a net benefit.

As of MySQL 8.0.23, note that this feature is deprecated, as improvements in the MySQL server and InnoDB make it less beneficial. Therefore, if you're using a version of MySQL where it's deprecated, it's recommended to keep it turned off.

#### **04. Database Queries**

LLMs like ChatGPT are actually very **good** at writing SQL queries. It can help rewrite queries with **hints**.

В	rewrite this query using IN operator: SELECT * FROM item WHERE id = 1 OR id = 2 OR id = 3	
<b>®</b>	You can rewrite the query using the 'IN' operator like this: sql SELECT * FROM item WHERE id IN (1, 2, 3);	Copy code
	This query will retrieve all rows from the `item` table where the `id` column the values within the parentheses.	matches any of

Rewrite this query using IN operator:

select \* from item where id = 1 OR id = 2 OR id =3

ChatGPT:

select \* from item where id IN (1, 2, 3)



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