DBMS-Benchmarker: Benchmark and Evaluate DBMS in Python

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Summary

DBMS-Benchmarker is a Python-based application-level blackbox benchmark tool for Database Management Systems (DBMS). It is intended for reproducible measurement and easy evaluation of the performance the user receives, even in complex benchmark situations. It connects to a given list of DBMS (via JDBC) and runs a given list of (SQL) benchmark queries. Queries can be parametrized and randomized. Results and evaluations are available via a Python interface and can be inspected with standard Python tools like pandas DataFrames. An interactive visual dashboard assists in multi-dimensional analysis of the results.

This module has been tested with Clickhouse, Exasol, Citus Data (Hyperscale), IBM DB2, MariaDB, MariaDB Columnstore, MemSQL (SingleStore), MonetDB, MySQL, OmniSci (HEAVY.AI), Oracle DB, PostgreSQL, SQL Server, SAP HANA, TimescaleDB, and Vertica.

See the homepage and the documentation for more details.

Statement of Need

Performance benchmarking of database management systems (DBMS) is an active research area and has a broad audience. It is used “by DBMS developers to evaluate their work and to find out which algorithm works best in which situation. Benchmarks are used by (potential) customers to evaluate what system or hardware to buy or rent. Benchmarks are used by administrators to find bottlenecks and adjust configurations. Benchmarks are used by users to compare semantically equivalent queries and to find the best formulation alternative”, Erdelt (2021). Approaches and their special implementations are also examined in benchmarks in academia. There is a large variety of DBMS types and products. For example, solid IT GmbH (2022) ranks 350 DBMS (150 Relational) and Carnegie Mellon Database Group (2022) lists 850 DBMS (280 Relational). We focus on Relational DBMS (RDBMS) in the following. Their types can be divided into, for example, row-wise, column-wise, in-memory, distributed, and GPU-enhanced. All of these products have unique characteristics, special use cases, advantages and disadvantages, and their own justification. In order to be able to verify and ensure performance measurements, we want to be able to create and repeat benchmarking scenarios. Repetition and thorough evaluation are crucial, in particular in the age of cloud-based systems with their diversity of hardware configurations (Kersten et al., 2018; Kouvev et al., 2020; Raasveldt et al., 2018).

Thus there is widespread need for a tool to support the repetition and reproducibility of benchmarking situations, and that is capable of connecting to all these systems.

When we collect a lot of data during benchmarking processes, we also need a tool that will help with the statistical, visual, and interactive analysis of the results. The authors advocate using Python as a common Data Science language, since “it is a mature language programming,
easy for the newbies, and can be used as a specific platform for data scientists, thanks to its large ecosystem of scientific libraries and its high and vibrant community”, Igual & Seguí (2017). This helps in implementing the tool within a pipeline, for example to make use of closed-loop benchmarking situations (He et al., 2019), or to closely inspect parts of queries (Kersten et al., 2018). It also allows the use of common and sophisticated tools to inspect and evaluate the results. To name a few: pandas (McKinney, 2010; The pandas development team, 2020) for statistical evaluation of tabular data, scipy (Virtanen et al., 2020) for scientific investigation of data, IPython and Jupyter notebooks (Kluyver et al., 2016) for interactive analysis and display of results, Matplotlib (Hunter, 2007) and Seaborn (Waskom, 2021) for visual analysis, or even machine learning tools. Moreover, Python is currently the most popular computer language (PYPL, 2022; TIOBE, 2022).

To our knowledge, there is no other such tool, c.f. also the studies in Seybold & Domaschka (2017) and Brent & Fekete (2019). There are other tools like Apache JMeter (Java), HammerDB (Tcl), Sysbench (LuaJIT), OLTPBench (Java), and BenchBase (Java) that provide very nice features. However they do not fit these needs, since they are not Python-based. Moreover some are limited in supported DBMS, in supporting repetition and (statistical) evaluation, or do not support randomized queries. The design decisions of this tool have been described in more detail in Erdelt (2021). DBMS-Benchmarker has been used as to support receiving scientific results about benchmarking DBMS performance in Cloud environments as in Erdelt (2021) and Erdelt (2022).

Summary of Solution

DBMS-Benchmarker is Python3-based and helps to **benchmark DBMS**. It
- connects to all DBMS having a JDBC interface
- requires only JDBC - no vendor specific supplements are used
- benchmarks arbitrary SQL queries
- supports planning of complex test scenarios
- allows easy repetition of benchmarks in varying settings
- allows randomized queries to avoid caching side effects
- investigates a number of timing aspects
- investigates a number of other aspects - received result sets, precision, number of clients
- collects hardware metrics from a Prometheus server (Rabenstein & Volz, 2015)

DBMS-Benchmarker helps to **evaluate results** - by providing
- metrics that can be analyzed by aggregation in multi-dimensions
- predefined evaluations like statistics
- in standard Python data structures
- in Jupyter notebooks - see rendered example
- in an interactive dashboard

Some features are inspired by **TPC-H** and **TPC-DS** - Decision Support Benchmarks, which are provided in part as predefined configs.

A Basic Example

The following simple use case runs the query SELECT COUNT(*) FROM test 10 times against one local (existing) MySQL installation.

Run `pip install dbmsbenchmarker` for installation. Make sure Java is set up correctly. We assume here we have downloaded the required JDBC driver, e.g., `mysql-connector-java-8.0.13.jar`.
Configuration

DBMS configuration file, e.g. in .:/config/connections.config

```
[
    {
      'name': "MySQL",
      'active': True,
      'JDBC': {
        'driver': "com.mysql.cj.jdbc.Driver",
        'url': "jdbc:mysql://localhost:3306/database",
        'auth': ["username", "password"],
        'jar': "mysql-connector-java-8.0.13.jar"
      }
    }
]
```

Queries configuration file, e.g. in .:/config/queries.config

```
{
    'name': 'Some simple queries',
    'connectionmanagement': {
      'timeout': 5 # in seconds
    },
    'queries': [
      {
        'title': "Count all rows in test",
        'query': "SELECT COUNT(*) FROM test",
        'numRun': 10
      }
    ]
}
```

Perform Benchmark and Evaluate Results

Run the CLI command: dbmsbenchmarker run -e yes -b -f ./config

After benchmarking has completed we will see a message like Experiment <code> has been finished. The script has created a result folder in the current directory containing the results. <code> is the name of the folder.

Run the CLI command: dbmsdashboard

This will start the evaluation dashboard at localhost:8050. Visit the address in a browser and select the experiment <code>. Alternatively you may use Python's pandas.

Description

Experiment

An experiment is organized in queries. A query is a statement that is understood by a Database Management System (DBMS).

Single Query

A benchmark of a query consists of these steps:
1. Establish a **connection** between client and server
   This uses `jaydebeapi.connect()` (and also creates a cursor - time not measured)
2. Send the query from client to server and
3. **Execute** the query on server
   These two steps use `execute()` on a cursor of the JDBC connection
4. **Transfer** the result back to client
   This uses `fetchall()` on a cursor of the JDBC connection
5. Close the connection
   This uses `close()` on the cursor and the connection

The times needed for the connection (1), execution (2 and 3), and transfer (4) steps are measured on the client side. A unit of connect, send, execute, and transfer of a single query is called a **run**. Connection time will be zero if an existing connection is reused. A sequence of units of sending, executing, and transmitting between establishing and discarding a connection is called a **session**. This is the same as a run, if we always reconnect prior to sending a query, but if we choose to reuse a connection this will cover multiple runs.

A basic parameter of a query is the **number of runs**. To configure sessions it is also possible to adjust

- the number of runs per connection (session length) and
- the number of parallel connections (to simulate several simultaneous clients)
- a timeout (maximum lifespan of a connection)
- a delay for throttling (waiting time before each connection or execution)

for the same query. Parallel clients are simulated using the `pool.apply_async()` method of a `Pool` object of the module`multiprocessing`. Runs and their benchmark times are ordered by numbering. Moreover we can randomize a query, such that each run will look slightly different. This means we exchange a part of the query for a random value.

**Basic Metrics**

We have several **timers** to collect timing information in milliseconds and per run, corresponding to the parts of query processing: `timerConnection`, `timerExecution`, and `timerTransfer`. The tool also computes `timerRun` (the sum of `timerConnection`, `timerExecution`, and `timerTransfer`) and `timerSession`.

We also measure and store the total **time** of the benchmark of the query, since for parallel execution this differs from the sum of times based on `timerRun`. Total time means measurement starts before the first benchmark run and it stops after the last benchmark run has finished. Thus total time also includes some overhead (for spawning a pool of subprocesses, computing the size of result sets, and joining results of subprocesses.) We also compute **latency** (measured time) and **throughput** (number of parallel clients per measured time) for each query and DBMS.
Additionally error messages and timestamps of the begin and end of benchmarking a query are stored.

**Comparison**

We can specify a dict of DBMS. Each query will be sent to every DBMS in the same number of runs. This also respects randomization, i.e., every DBMS receives exactly the same versions of the query in the same order. We assume all DBMS will give us the same result sets. Without randomization, each run should yield the same result set. The tool can automatically check these assumptions by comparison of sorted result tables (small data sets) or their hash value or size (bigger data sets). In order to do so, result sets (or their hash value or size) are stored as lists of lists and additionally can be saved as csv files or pickled pandas DataFrames.

**Monitoring Hardware Metrics**

To make hardware metrics available, we must provide the API URL of a Prometheus Server. The tool collects metrics from the Prometheus server with a step size of 1 second. We may define the metrics in terms of Prometheus’s `promql`. Metrics can be defined per connection.

**Results**

As a result, we obtain measured times in milliseconds for the query processing parts: connection, execution, and data transfer.

![Figure 2: evaluation cubes for time and hardware metrics.](image)

These are described in three dimensions: number of run, of query, and of configuration. The configuration dimension can consist of various nominal attributes like DBMS, selected processor, assigned cluster node, number of clients, and execution order. We also can have various hardware metrics like CPU and GPU utilization, CPU throttling, memory caching, and working set. These are also described in three dimensions: Second of query execution time, number of query, and of configuration.

**Evaluation**

**Python - Pandas**

The cubes of measurements can be sliced or diced, rolled-up, or drilled-down into the various dimensions and several aggregation functions for evaluation of the metrics can be applied: first, last, minimum, maximum, arithmetic, and geometric mean, range, and interquartile range, standard deviation, median, some quantiles, coefficient of variation, and quartile coefficient of dispersion. This helps in univariate analysis of center and dispersion of the metrics to evaluate measures and stability.

The package includes tools to convert the three-dimensional results into pandas DataFrames, like covering errors and warnings that have occurred, and timing and hardware metrics that...
have been collected or derived. For example the latency of execution, aggregated in the query dimension by computing the mean value, can be obtained as:

```python
df = evaluate.get_aggregated_query_statistics(type='latency', name='execution', query_aggregate='Mean')
```

**Figure 3:** example DataFrame: latency of execution times aggregated.

**GUI - Dashboard**

The package includes a dashboard that helps in interactive evaluation of experiment results. It shows predefined plots of various types, which can be customized and filtered by DBMS configuration and query.

**Figure 4:** screenshot of dashboard.
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