

ParquetDB: A Lightweight Python Parquet-Based Database

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Summary

ParquetDB is a Python library serving as a “medium ware” solution, bridging the gap between file-based storage and full database systems. A key driver for its development was the need to support iterative research workflows, requiring schema evolvability, the ability to manage complex and evolving nested data structures without predefined rigidity, and the ability to handle table and field level metadata. Additionally, its “classically serverless” nature was a crucial design point for deployment in environments such as HPC clusters with limited connectivity. Leveraging Apache Parquet (“Parquet,” n.d.; *Welcome to The Apache Software Foundation*, n.d.), it combines file storage portability with advanced querying capabilities, enabling efficient compression and read performance without dedicated server overhead. ParquetDB addresses limitations in both traditional approaches by seamlessly handling complex data types (arrays, nested structures, Python objects), simplifying data interaction compared to direct file manipulation or manual serialization. Performance benchmarks show competitive read/write speeds and effective query performance via predicate pushdown, demonstrating its utility for managing medium-to-large datasets where database complexity is unwarranted but basic file I/O is insufficient.

Statement of need

The demand for efficient, scalable, and adaptable data storage solutions is critical across research domains. Traditional file formats (e.g., CSV, JSON, TXT) offer simplicity but suffer from inefficiencies, particularly with numerical data due to ASCII/UTF encoding overhead, leading to larger files and slower I/O. While binary formats like HDF5 (?) improve efficiency for large numerical datasets, they function primarily as structured file containers, lacking the rich querying APIs and transactional integrity features common in databases. These file-based approaches often require manual data relationship management and lack built-in indexing, hindering agility as projects scale or require rapid iteration.

Database systems like SQLite (Allen & Owens, 2010) or MongoDB (Guo, 2017) provide robust encoding, indexing, and querying. Relational databases ensure integrity via structured schemas but can be rigid when data models evolve (Pascal, 2000). NoSQL options offer flexibility but may introduce consistency challenges or require complex optimization (Pivert, 2018). Furthermore, many databases involve server configurations or lack transparent file-based portability, adding overhead unsuitable for lightweight experimentation or simpler deployment scenarios. While SQLite is serverless and ubiquitous, its row-based nature can be less performant for analytical queries scanning wide datasets compared to columnar formats, and managing complex nested data can be cumbersome.

42 Directly using libraries like Apache Arrow (PyArrow) to work with Parquet files offers access
43 to columnar efficiency and querying primitives like predicate pushdown. However, this still
44 requires developers to build abstractions for database-like operations (CRUD), manage schema
45 consistency across multiple files, handle serialization of complex Python objects, and orchestrate
46 data updates or deletions manually.

47 While powerful dataframe manipulation libraries like Pandas([Pandas - Python Data Analysis](#)
48 [Library, n.d.](#)), Dask([Dask | Scale the Python Tools You Love, n.d.](#)), and Polars([Polars, n.d.](#)),
49 or embedded analytical databases such as DuckDB([User, n.d.](#)), are invaluable for many tasks,
50 they may not holistically address the specific needs that motivated ParquetDB. For researchers
51 dealing with evolving, complexly nested scientific data, ParquetDB offers a more streamlined
52 approach to schema evolvability and native Python object persistence directly within a serverless
53 Parquet-based ecosystem. This focus distinguishes it from tools that might require more
54 manual setup for schema management across multiple files, or lack the same emphasis on
55 integrated metadata handling and a 'classically serverless' model for environments like HPC
56 clusters.

57 ParquetDB addresses this gap, providing a "medium ware" layer built upon Python and the
58 Parquet format. It offers a familiar database-like interface (CRUD operations) while leveraging
59 columnar storage for compression and read performance benefits. Crucially, ParquetDB adds
60 value beyond direct Parquet file manipulation by automating schema management (including
61 evolution), simplifying the storage/retrieval of complex Python objects, and providing a unified
62 API to manage collections of Parquet files as a single logical datastore. It supports predicate
63 and column pushdown for optimization within a lightweight, serverless architecture, offering a
64 pragmatic balance for scenarios demanding more than basic files but less than a full database
65 system, particularly where schema flexibility and ease of use are paramount. For a comprehensive
66 feature list, visit our documentation (<https://parquetdb.readthedocs.io/en/latest/>).

67 Benchmarks

68 We evaluated ParquetDB's performance against SQLite and MongoDB using synthetic datasets
69 (100 integer columns, varying record counts). Our first experiment compared write and read
70 performance. ParquetDB's create times are competitive, performing second best behind
71 SQLite as dataset size increases. For bulk read operations, ParquetDB initially lags slightly but
72 significantly outperforms both competitors on larger datasets (beyond several hundred/thousand
73 rows), benefiting from Parquet's columnar efficiency. (See Figure 1)

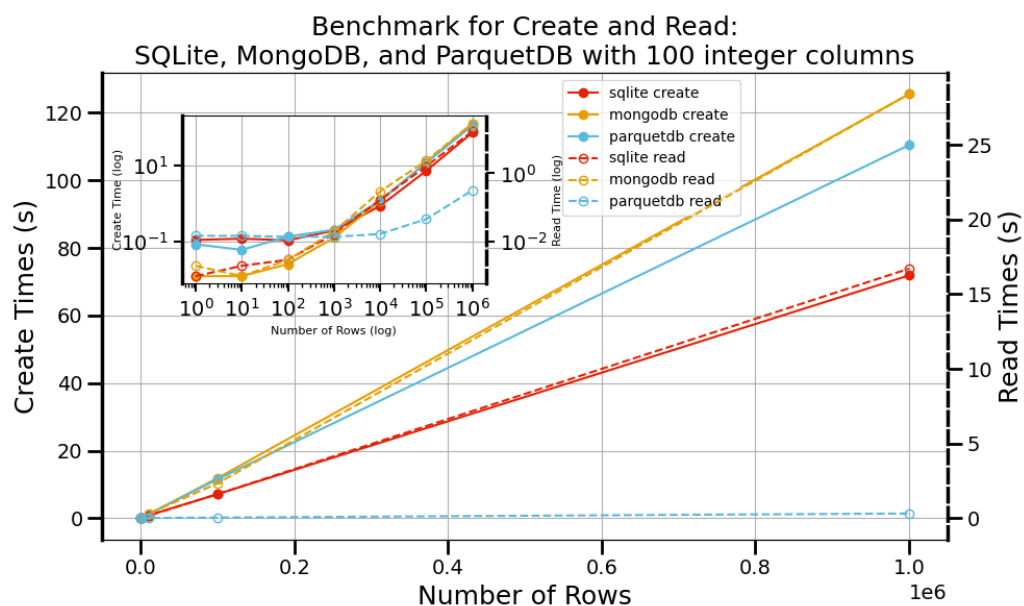


Figure 1: Benchmark Create and Read Times for Different Databases. Create time is plotted on the left y-axis, read time on the right y-axis, and the number of rows on the x-axis. A log plot is shown in the inset.

A “needle-in-a-haystack” benchmark assessed specific record retrieval. While lacking traditional B-tree indexes, ParquetDB uses predicate pushdown leveraging Parquet’s field-level statistics for efficient filtering without full scans. It is important to note that performance advantages depend on the workload; for instance, complex analytical queries involving aggregations or returning small, highly filtered results might favor the mature query engine and indexing of systems like SQLite. ParquetDB excels when querying or returning substantial portions of wide datasets. Detailed benchmarks are in our extended paper (<https://arxiv.org/abs/2502.05311>)(?).

Installation

For installation, please use pip:

```
pip install parquetdb
```

For more details, please visit the [GitHub repository](#). The repository contains additional examples, API documentation, and guidelines for contributing to the project.

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101 equipment identified are necessarily the best available for the purpose.

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