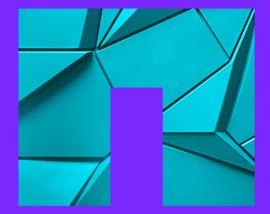


Building a Data Lakehouse with PostgreSQL

Dive into Formats, Tools, Techniques, and Strategies



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Josef Machytka

- Professional Service Consultant PostgreSQL specialist at NetApp Open Source Services / Credativ
- 30+ years of experience with different databases.
- PostgreSQL (12y), BigQuery (7y), Oracle (15y), MySQL (12y), Elasticsearch (5y), MS SQL (5y).
- 10+ years of experience with Data Ingestion pipelines, Data Analysis, Data Lake and Data Warehouse
- 2 years of practical experience with different LLMs / AI including their architecture and principles.
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What is Data LakeHouse?

- · Answer is surprisingly not simple
- · Big variety of opinions around this term
- Modern formats like Apache Iceberg, Hudi, Delta Lake
- · Object storage with structured and unstructured data
- Data pipelines processing structured and unstructured data
- Mesh of Data Lakes and Data Warehouses in the organization
- · Mesh of all existing data sources in the organization
- All of it together with Data Governance
- · All of it and AI and ML models



Data Formats

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Store only what you really need

- · Store only data necessary for your operations
- · And store them in efficient way
- · Avoid storing data just because it "might be useful in the future"
- Law regulations require Data Retention Policies
- Most companies need in long run only aggregated data
- · Some types of raw data can or must be deleted after processing
- · You pay for collecting, storing, and processing data
- · What about Return Of Investment from this data?



Relational Data Warehouses

- 20-30 years ago relational databases dominated
- · Mainly proprietary engines: Oracle, DB2, SQL Server
- In new millennia also PostgreSQL
- Engine-specific data storage formats
- Computation and storage were tightly coupled
- · Very difficult to scale to more machines
- · Almost exclusively row-oriented storage
- All processing done using SQL



Early Data Lakes Formats

- JSON key-value pairs, supports nested structures
- · Parquet compressed columnar storage format, optimized for data analysis
- Avro row oriented, schema-based, binary format
- ORC Optimized Row Columnar columnar storage format, for read-heavy workloads
- Data in these formats is hard to update append-only, immutable
- PostgreSQL has FDW for some of these formats or can import them
- · New extensions pg_analytics and pg_duckdb aim to allow direct querying of these formats
- · FerretDB with DocumentDB extension implements BSON data type and MongoDB wire protocol queries









Parquet Data Format

- · Parquet is a columnar storage format optimized for reading
- Repository: github.com/apache/parquet-format
- · Very efficient for numeric data types: INT32, INT64, FLOAT, DOUBLE, BOOLEAN
- Strings are less efficient, stored as BYTE_ARRAY
- · Optimized for read-heavy workloads, metadata includes min/max values for columns
- Most popular format, used in all modern Data LakeHouse solutions



(Image from the apache/parquet-format repository)

Modern Data LakeHouse Format Frameworks

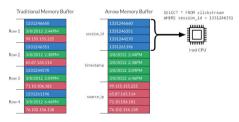
- · Apache Arrow platform for in-memory analytics, defines columnar data format
- · Apache Iceberg table format for large-scale data systems
- Delta Lake storage format for Data Lakehouse architecture
- Apache Hudi transactional data lake framework
- · Designed for managing and processing large data sets
- · Optimized for analytical queries and data processing
- Allow limited updates and deletes with ACID transactions





Apache Arrow - platform for in-memory analytics

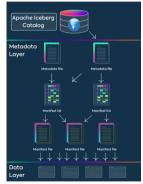
- · Cross-language platform for in-memory processing of large data sets
- Repository: github.com/apache/arrow
- Standardized, language-independent columnar in-memory format
- · Enables zero-copy reads across multiple processes
- · Closely integrated with Python for data analysis



(Image from the article Apache Arrow Overview)

Apache Iceberg Table Format

- Originated from Netflix, now an Apache project
- Repository: github.com/apache/iceberg
- · Immutable, append-only, and transactional
- Every change creates a new metadata file and snapshot
- · Components: catalog, metadata files, manifest files, Parquet data files
- Supports versioning, partitioning, and schema evolution
- Implements time travel to query historical data
- · Each snapshot provides full isolation and consistency
- · Allows multiple applications to work on the same data



(Image from the article What Is Apache Iceberg?)

Delta Lake Storage Format

- Open-source storage format for Data Lakehouse architecture
- · Created and maintained by Databricks
- Project page: delta.io
- · Transactional storage layer on top of cloud storage
- · ACID transactions and scalable metadata handling



(Image from the LinkedIn course

Fundamentals of Apache Iceberg)

Apache Hudi

- Originated from Uber, now an Apache project
- · Allows multiple updates and deletes
- · Changes are stored in a log file
- Brings database and data warehouse features to data lakes
- Project page: hudi.apache.org



(Image from the LinkedIn course

Fundamentals of Apache Iceberg)

PostgreSQL and Data LakeHouse Formats

- · PostgreSQL has columnar storage support for efficient analytics
- · Has FDW for CSV, JSON, Parquet, some other formats through JDBC
- · Arrow, Iceberg, Delta, and Hudi require more functionality
- · Currently closer integration with DuckDB looks very promising
- ParadeDB develops pg_analytics extension
- · Goal to provide a unified interface for various data formats & cloud storages
- DuckDB/MotherDuck team work on pg_duckdb extension
- It aims to provide full DuckDB functionality in PostgreSQL





DuckDB is a Powerful Analytical Database

- Created at the National Research Institute for Mathematics and Computer Science, Amsterdam
- · Open-source, column-oriented, in-memory relational database
- · Single-node database, intended for embedding in applications, like SQLite
- · Designed for heavy parallel analytical workloads
- Columnar-vectorized query processing engine
- · Direct selects from multiple formats and cloud storages
- Extremely portable, runs on all architectures, no dependences



(See details in my talk PostgreSQL and DuckDB on YouTube)

Examples of Data Pipelines

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One Solution does not fit All Cases

- · One solution does not fit all cases
- Classical data warehousing theory emphasized centralization
- Also some marketing articles see Data Lakehouse as centralized
- · Companies try sell "one size fits all" solutions
- · But special cases require decentralization



(Image from the article One Size Does Not Fit All)

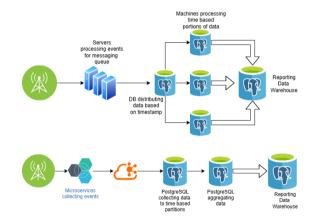
Examples of Data Pipelines

- Telecommunication software for events from mobile networks
- Widget predicting sizes for online stores selling clothes
- · Software for secure online logins and financial transactions
- They all need to calculate output for the clients very quickly
- All companies collect and process a lot data but in different ways
- · PostgreSQL heavily used in all these companies
- Multiple PostgreSQL instances in each company



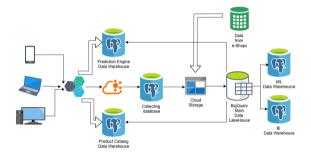
Telecommunication software for Events from Mobile Network

- · Probes collect events from the mobile network
- · Hundreds or tens of hundreds GBs per minute
- · Provider needs only aggregated summaries
- · Centralized model, storing only aggregated data
- · Raw data are discarded after processing
- originally multiple PostgreSQL dbs and PL/proxy
- · Later rebuilt with Kafka and quicker hardware



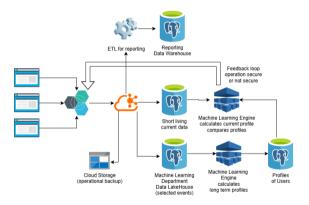
Widget predicting sizes for online stores selling clothes

- Calculates the best fit in dozens of milliseconds
- · Prediction uses only pre-aggregated data from ML
- · Scripts collect events from the website and devices
- · Raw data tens or hundreds of GBs per hour
- Mixed model, main Data LakeHouse is BigQuery
- Raw events stored for 2 years for Data Analysis
- Multiple other PostgreSQL instances for other tasks



Software for secure logins and financial transactions

- · Software analyzes behavior of users
- · Calculates current behavioral profile
- · Compares with stored profiles
- · Decides if operation is secure
- Response needed in milliseconds
- Strongly decentralized model
- · Storing only aggregated data
- PostgreSQL used multiple times
- · Raw data tens or hundreds of GBs per minute
- · Discarded soon after processing



PostgreSQL as Important Part of Data Pipelines

- PostgreSQL can play multiple roles in Data Pipelines
- · Multiple features and extensions for different tasks
- Very powerful partitioning, pg_partman
- Row level security for fine-grained access control
- JSONB implementation and multiple types of indexes
- · Multiple FDWs for different databases and file formats
- Citus distributed PostgreSQL, columnar format
- TimescaleDB sharding and columnar format
- Hydra and OrioleDB (beta) aim to improve analytical performance
- PostGIS for geospatial data
- Powerful build in full text search features, pg_search



Data Governance & Legal Aspects



Discipline is essential

- "Discipline is essential, you foolish lads!" Without it, you would be climbing trees like monkeys!"
- Every Data Lakehouse requires clear Data Governance
- Properly defined Data Life Cycles are crucial
- Clear Data Catalog and Lineage are necessary
- · Without these, we can "climb" every new technology
- · Jumping "like monkeys" from one new buzzword to another
- But we will end up in the same mess...



(Image by Mikoláš Aleš from the book "The Good Soldier Švejk")

Do not be overwhelmed by Data Governance

- · Abundance of articles and books on Data Governance
- · Majority of them overly maximalistic and complex
- · Marketing articles always sell something
- · Some proprietary solution, or consulting services
- Big companies really need complex Data Governance
- · But smaller companies can start with simple rules



(Picture from article Data Governance)

DAMA - Data Management Body of Knowledge

- DAMA International is a non-profit organization
- Website: data.org
- DAMA-DMBOK2 is a comprehensive guide to Data Management
- · It provides a very detailed view of Data Management





(Screenshots from dama.org page)

Business will suffer with poor quality data

- · If data belong to no one, no one will care about quality
- · If no one checks data quality, it will be poor
- Data Quality garbage in, garbage out
- · To know what is garbage, you need to know what is good
- · Basic Data Catalog and Data Definitions are needed
- Quality Checks and Data Profiling based on Data Catalog
- Data Producers/ Owners/ Stewards responsible for data quality



(Title page of EU Commission Data Governance Document)

Security and Privacy are crucial

- Data Security protect data from unauthorized access
- · Security is about safeguarding data
- · Data Privacy protect data from unauthorized use
- · Privacy is about safeguarding user identity
- · GDPR General Data Protection Regulation
- CCPA California Consumer Privacy Act
- HIPAA Health Insurance Portability and Accountability Act
- Principle of Least Privilege & Only for limited time
- · Minimize use of customer data, minimize access to them
- Delete or anonymize data at the end of their lifecycle



PostgreSQL and Data Governance

- Check constrains and triggers can help with data quality
- · Comments on all objects can help with data catalog
- pgTAP extension unit testing framework / data quality checks
- pg_analytics with DuckDB SQL features for data profiling
- · Data Governance uses mostly external tools and processes
- · Great Expectations / dbt for Data Quality checks
- Apache Atlas / OpenMetadata for Data Catalog/Lineage
- OpenLineage for Data Lineage for AI / ML
- Marquez for open source Metadata Service



AI and Data LakeHouse

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Over Promising AI Marketing Hype

- Do not believe every new AI marketing hype
- Everything these days is "AI powered", "AI driven"
- Many marketing ebooks over promise AI capabilities
- Yes, Al is the future, no doubt about it, but...
- Usefulness of AI in Data LakeHouse depends on use cases
- · Commercial Als can lead to privacy and security issues
- · Local Open Source AI solutions give more control
- · But are usually not that powerful



AI Answers Based on Probability

- We currently have Large Language Models (LLMs)
- LLMs use Transformer architecture
- · They use an "Attention mechanism" to understand context
- · LLMs generate text based on training data
- · Answers are the "most probable", not necessarily "correct"
- · For LLMs, there is no "correct" or "incorrect" answer
- Answers depend on activation of semantic associations
- · Prompt engineering and system prompts are crucial
- "Just because it sounds plausible, doesn't mean it's true"



Problematic Usability for Niche Topics

- · LLMs absolutely depend on the quality of training data
- · Amount, quality and topic coverage are crucial
- LLMs work amazingly for general topic data
- Like invoicing, financial reports, warehouse management
- If you have mainly these use cases, AI is perfect for you
- · More specialized topics often lead to hallucinations
- · But you can definitely use AI for brainstorming
- It can give you new ideas and perspectives
- · But you must always double-check the results



Most Common Issues with AI Outputs

- · Overgeneralization: wrong conclusions due to biased data
- · Misinterpretation: wrong conclusions due to wrong context
- · Underfitting: model too simple to capture details, too general
- · Overfitting: AI specialized on training data, cannot generalize
- Overinterpretation of the Input: wrong conclusions due to incomplete input, hallucinates missing parts of the input
- Out-of-distribution Generalization: wrong conclusions due to topic not covered by training data



Some Older AI Promises stayed Unfulfilled

- · Fine-tuning on domain specific data can shift performance
- · Model specializes on new data
- · But struggles with more general data
- · Can even lead to "catastrophic forgetting"
- Retrieval-Augmented Generation (RAG)
- · Depends fully on the quality of additional data
- · Very useful for chat-bots, and help-desk systems
- · Not that great for analysis of complex data
- Highly specific data require examples and explanations



Will Al-agents do better?

- Al-agents are new hype
- · They can run additional tasks like internet browsing
- · Could also run machine learning models
- · Could use multiple knowledge sources
- Capable of multi-step reasoning
- But still depend on quality of LLMs
- · We can expect best performance on well known topics
- · Niche topics can lead to multiple levels of hallucinations

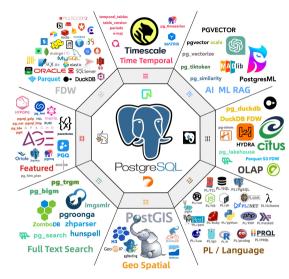


PostgreSQL and AI + ML

- AI, ML and PostgreSQL are a great match
- Has multiple extensions for AI and ML
- pgvector for vector similarity search for RAG
- Timescale pgvectorscale improved pgvector extension
- Timescale pgai automates creation of embeddings for RAG
- PostgresML for machine learning in PostgreSQL



Summary



(Image from the article Postgres is eating the database world on PIGSTY (PostgreSQL In Great STYIe) blog)

Resources

- · Other resources used for the talk, not mentioned in slides:
- Articles:
 - What is a Data Lakehouse?
 - History and evolution of data lakes
 - What is Data as a Product
 - Apache Iceberg main web page
 - Dremio.com: What is Apache Iceberg
 - Sqream.com: What is Apache Iceberg
 - Estuary.dev: Apache Iceberg vs Hudi
- · E-books:
 - T.Shiran, J.Hughes, A.Merced: Apache Iceberg, The Definitive Guide O'Reilly
 - · Bennie Haelen, Dan Davis: Delta Lake, Up & Running O'Reilly
 - · Dremio white paper: Optimizing the supply chain with a data lakehouse
 - · A.Kaplan, A.Kara: Data Lakehouse for Dummies Databricks
- Al tools:
 - NetAppAI GPT-4o, NetApp GitHub CoPilot AI
 - Paid tier ChatGPT-4o/ o1, Google Gemini Advanced 1.5/ 2.0

O'REILLY'

Apache Iceberg The Definitive Guide

Data Lakehouse Functionality, Performance, and Scalability on the Data Lake





THANK YOU

- Questions?
- Josef Machytka <josef.machytka@netapp.com>

