Delta Lake & Databricks

BI-BIG, 29.4.2025, Jan Lukány



About Speaker

- Jan Lukany
- lukany.jan@gmail.com
- https://www.linkedin.com/in/jan-lukany/
- CTU FIT 2014-2020 (Bc Theoretical Informatics, Mgr Knowledge Engineering)
- Datamole 2015-
 - 2015-2017 Junior Software Developer
 - 2017–2020 Data Scientist
 - 2020–2024 ML Engineer
 - 2024- ML Engineering Team lead





a Czech data and Al company of 80+ people founded in 2015. We develop custom AI, IoT & UI solutions that innovate industrial companies worldwide - in agriculture, machinery or biotech.







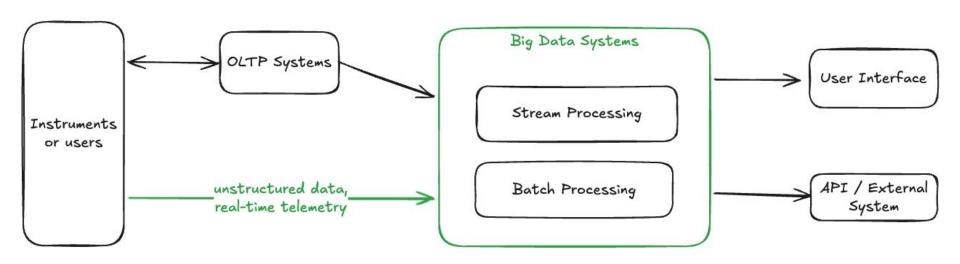










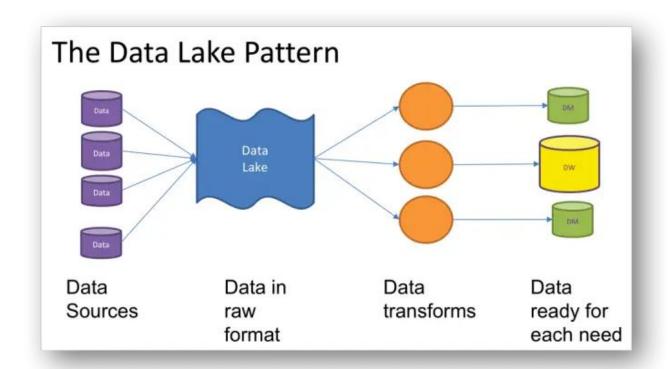




This Lecture

- Delta Lake Reliable Storage Protocol/Format
 - Data Lake with ACID
 - Core concepts and practical usage (Python Polars and Pyspark)
- Databricks Data Intelligence Platform (Spark + Delta Lake)
 - Practical example with free Community Edition











Delta Lake





ACID Transactions

Protect your data with serializability, the strongest level of isolation



Unified Batch/Streaming

Exactly once semantics ingestion to backfill to interactive queries



Scalable Metadata

Handle petabyte-scale tables with billions of partitions and files with ease



Schema Evolution / Enforcement

Prevent bad data from causing data corruption



Time Travel

Access/revert to earlier versions of data for audits, rollbacks, or reproduce



Open Source

Community driven, open standards, open protocol, open discussions



Audit History

Delta Lake log all change details providing a fill audit trail

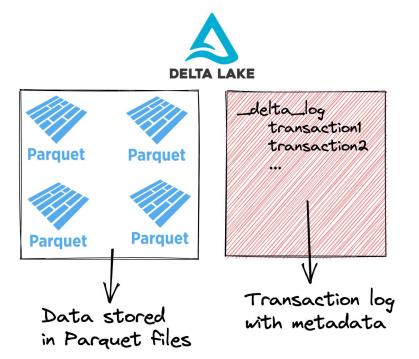


DML Operations

SQL, Scala/Java and Python APIs to merge, update and delete datasets

Delta Lake - Delta Table

Contents of a Delta table





Delta Lake - Demo



Delta Lake – on cheap cloud storages

- Azure Blob Storage
- Amazon S3
- Google Cloud Storage



Delta Lake - ACID

- Atomicity process all or nothing
- Consistency always valid state
- Isolation read while writing, safe multiple writes
- Durability transactions are permanent

Guarantees over one table only



Delta Lake - scalability

- Data file skipping using statistics (e.g. min/max)
- Columnar format of parquets
 - Read only parts of data files
- Optimization techniques
 - Storing similar data close together
 - Liquid clustering, Z-Ordering, partitioning



Delta Lake – time travel

- transaction log
- selecting specific version from the log
- optimize and vacuum operations
 - optimize compact multiple small files into large ones
 - vacuum delete unused data files

df = spark.read.format("delta").option("versionAsOf", 0).load("data/delta_census")



Delta Lake - Change Data Capture/Feed

- Tracking row-level changes for updates and deletes
 - no need for append-only (no update/delete) transaction log is enough.

```
SQL

ALTER TABLE myDeltaTable SET TBLPROPERTIES (delta.enableChangeDataFeed = true)
```

```
# providing a starting version
spark.readStream.format("delta") \
    .option("readChangeFeed", "true") \
    .option("startingVersion", 0) \
    .table("myDeltaTable")
```



Delta Lake - schema evolution and enforcement

- allow adding new columns and changing (some) data types
- prevent bad data from being written



Delta Lake - Unified Batch and Streaming

- Batch historical data processing in bulk
- Streaming real-time data processing
- Same API for both



Example Batch Processing with Spark

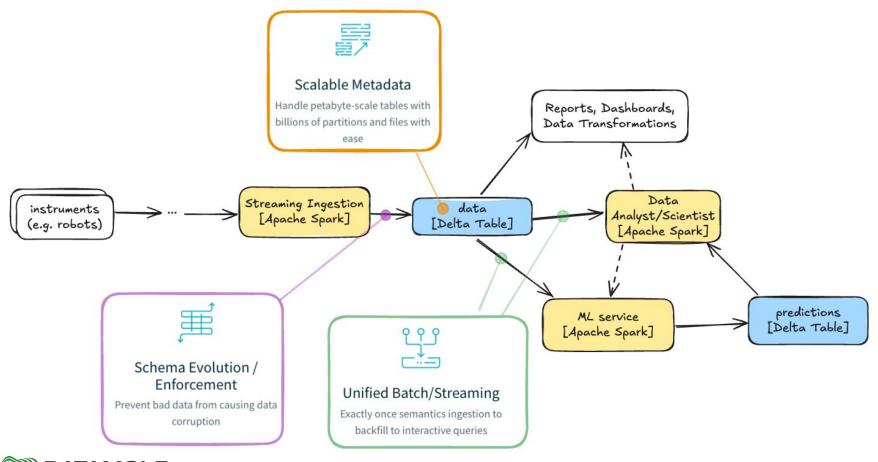
```
# Read data from Delta table
input_df = spark.read.format("delta").load("input-table-path")
# Perform simple processing (e.g., filtering and adding a column)
processed_df = (
    input df
    .filter(col("column name") > 100)
    .withColumn("new_column", col("column_name") * 2)
# Write processed data back to a Delta table
    processed_df
    .write.format("delta")
    .mode("overwrite")
    .save("output-table-path")
```



Example Stream Processing with Spark

```
# Read data from Delta table as a streaming source
input_stream = spark.readStream.format("delta").load("input-table-path")
# Perform simple processing (e.g., filtering and adding a column)
processed stream = (
    input_stream.filter(col("column_name") > 100)
    .withColumn("new_column", col("column_name") * 2)
# Write processed data to Delta table as a streaming sink
query = (
    processed stream.writeStream.format("delta")
    .outputMode("append")
    .option("checkpointLocation", "/path/to/checkpoint-dir")
    .start("output-table-path")
```











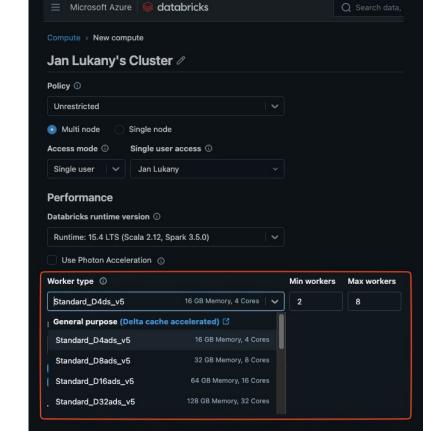
Databricks

- Compute
 - Apache Spark cluster management
 - Built-in orchestration for workflows
- Data Lakehouse
 - Delta Lake as default storage layer
 - Unity Catalog "one" database, data governance
 - Delta tables
 - External volumes
 - Federated access
- Other
 - Development workspace (similar to Jupyter Lab) with collaborative features
 - Machine learning support (training, deployment)
 - Native integrations with major cloud providers (Azure, AWS, GCP)



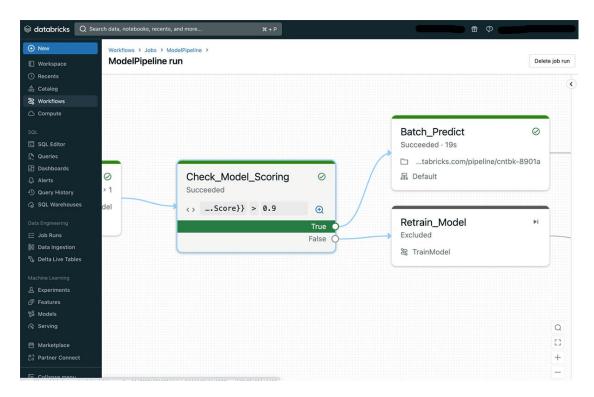
Databricks - Apache Spark cluster management

- Azure VMs
- AWS FC2
- Google Compute Engine





Databricks - Workflows (job orchestration)





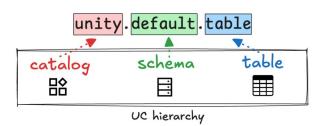
Databricks - Delta Tables on Cloud

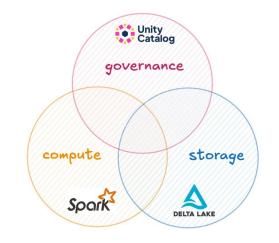
- Amazon S3
- Azure Blob Storage
- Google Cloud Platform

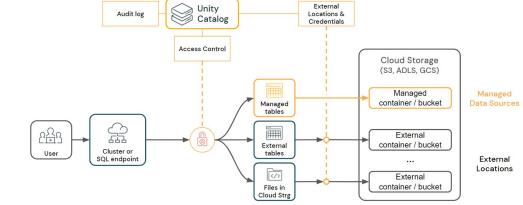


Databricks - Unity Catalog

- "one" database from the perspective of consumers
- data governance at one place
- can include e.g.:
 - Delta tables
 - ML models
 - Unstructured data on cloud storages
 - External databases









Databricks - Demo (community edition)



Summary

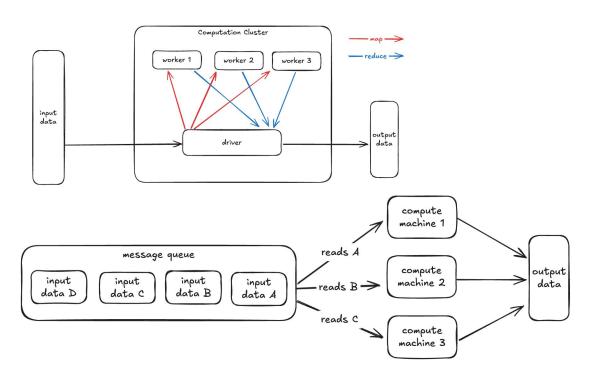
- Delta Lake
 - Reliable, ACID
 - Integration: Apache Spark, Python Polars, delta-rs
 - Open-source
- Unity Catalog
 - Data governance (e.g. easy access, discoverability)
 - Open-source
- Databricks
 - Cloud platform on top of Apache Spark, Delta Lake and Unity Catalog
 - Unity Catalog
 - ML experiments and serving
 - Closed-source / paid



Q&A



Bonus: Map-Reduce vs Competing Consumers



Example tech stack:

- Apache Spark
- Delta Lake
- (Databricks)

Example tech stack:

- Azure Event Hub
- Kubernetes, Docker, Python
- Azure Tables (NoSQL)

