

Stock data processing in Delta Lake

CSCI E-63 Big Data Analytics Spring 2021, Astakhov Danil

Problem statement

Architecture construction of an ACID-compliant storage and streaming processing of stock market data based on Databricks Delta Lake.

Problem Description

Designing the storage architecture is an essential part in big data solutions engineering. The central issue of these tasks is the choice of persistent storage. Even though Data Lake and Data Warehouse are powerful tools, the classic solutions based on them have a high complexity of application architecture. Just as difficult is the implementation of CRUD scripts in storage. Architectures based on Delta Lake are designed to eliminate these drawbacks. This paper presents the implementation of Delta Lake architecture for stock market data. The stock market is a suitable data model for data streaming, moreover, there is a wide scope for Business Intelligence.

Lakehouse architecture

"We define a Lakehouse as a data management system based on low-cost and directly-accessible storage that also provides traditional analytical DBMS management and performance features such as ACID transactions, data versioning, auditing, indexing, caching, and query optimization. Lakehouses thus combine the key benefits of data lakes and data warehouses: low-cost storage in an open format accessible by a variety of systems from the former, and powerful management and optimization features from the latter." -
Armbrust Michael, Ghodsi Ali, Xin Reynold, Zaharia Matei, Databricks, UC Berkeley, Stanford University "Lakehouse: A New Generation of Open Platforms That Unify Data Warehousing and Advanced Analytics." The Conference on Innovative Data Systems Research (CIDR), 2021, p. 3,
cidrdb.org/cidr2021/papers/cidr2021_paper17.pdf.

The idea that lays under Lakehouse is to have low-cost store with a well-defined Apache Parquet format, and add a layer with transactional metadata.

Delta lake Delta Lake is extremely popular, and "now used in about half of Databricks' workload, by thousands of customers" as said on <https://delta.io>

Key features:

Stock data processing in Delta Lake

Your report will start with class name, year and semester, your name and the project title.

Problem statement

Architecture construction of an ACID-compliant storage and streaming processing of stock market data based on Databricks Delta Lake.

Problem Description

Architecture construction and building the storage are important design steps in Big Data solutions. Data Lake and Data Warehouse, while powerful tools, increase the complexity of the overall application architecture, as well as make consistent modification of data outside of the pipelines more complicated.

Stock market data is a good data model for data streaming, moreover, opens a wide field for Business Intelligence.

Lakehouse architecture

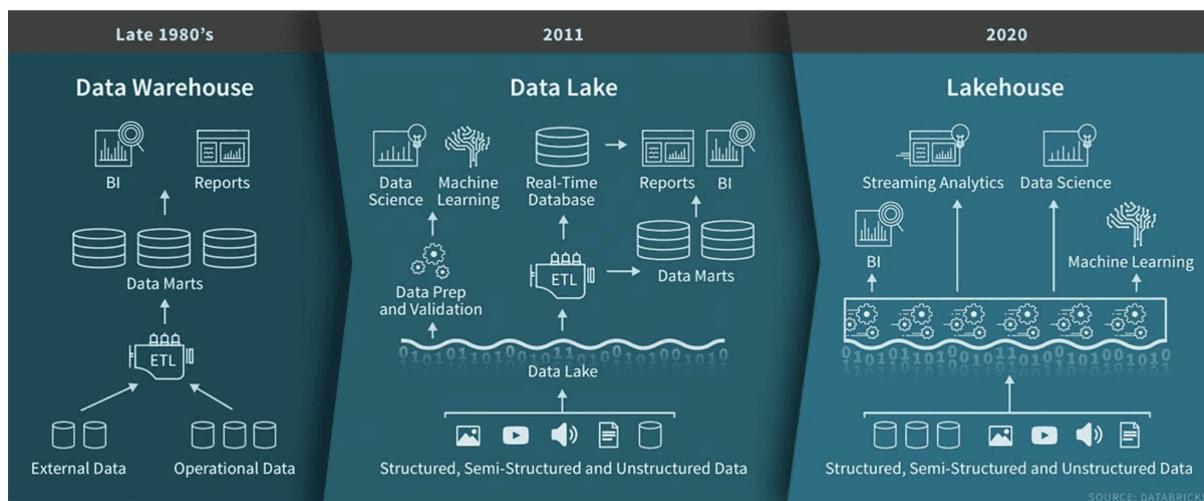
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Key features:

- Simple integration with Business Intelligence and Machine Learning
- Structure Streaming and Batch Processing compatibility
- Transaction management
- Schema enforcement
- Data in parquet
- DataFrame API
- Metadata API
- SQL API



Delta Lake

Delta Lake is an open source storage layer that brings reliability to data lakes. Delta Lake provides ACID transactions, scalable metadata handling, and unifies streaming and batch data processing. Delta Lake runs on top of your existing data lake and is fully compatible with Apache Spark APIs.

Specifically, Delta Lake offers:

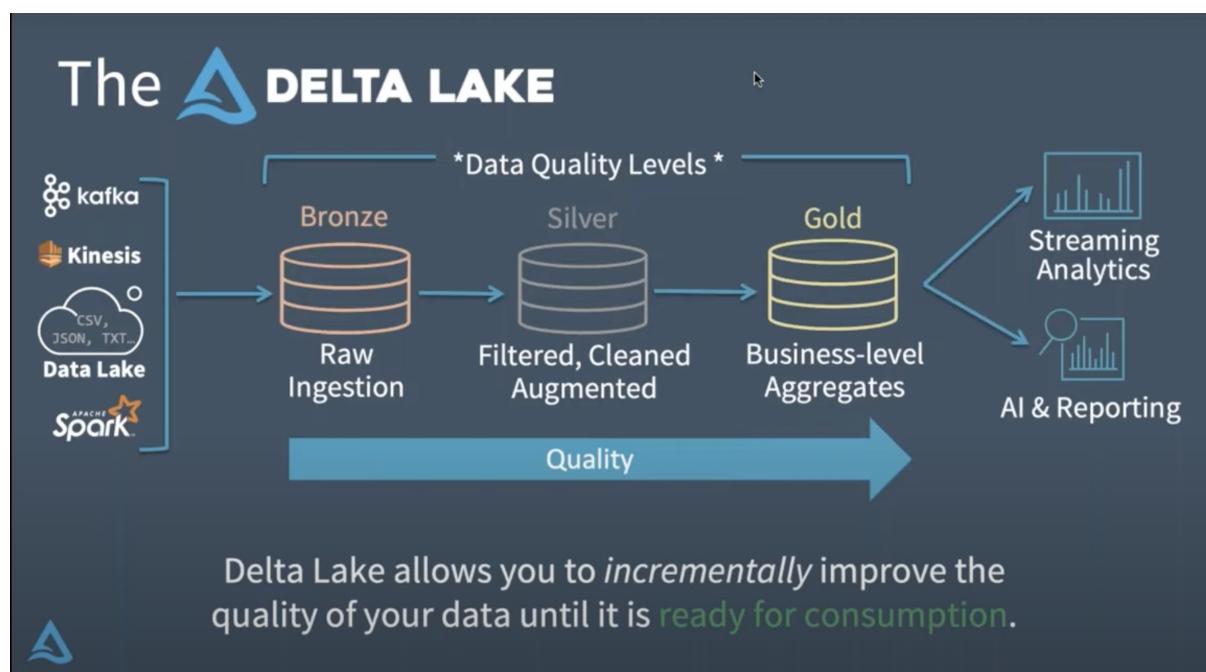
- ACID transactions on Spark: Serializable isolation levels ensure that readers never see inconsistent data.

- Scalable metadata handling: Leverages Spark's distributed processing power to handle all the metadata for petabyte-scale tables with billions of files at ease.
- Streaming and batch unification: A table in Delta Lake is a batch table as well as a streaming source and sink. Streaming data ingest, batch historic backfill, interactive queries all just work out of the box.
- Schema enforcement: Automatically handles schema variations to prevent insertion of bad records during ingestion.
- Time travel: Data versioning enables rollbacks, full historical audit trails, and reproducible machine learning experiments.
- Upserts and deletes: Supports merge, update and delete operations to enable complex use cases like change-data-capture, slowly-changing-dimension (SCD) operations, streaming upserts, and so on.

Source: "Introduction." Delta.io, Databricks, docs.delta.io/latest/delta-intro.html. Accessed 10 May 2021.

Pipeline

According to "Making Apache Spark™ Better with Delta Lake" YouTube video (<https://www.youtube.com/watch?v=LJtShrQqYZY>) on channel Databricks, it's good architectural approach to organise delta lake from layers, with separation data on quality and processing logic.



Software environment

macOS Big Sur Version 11.3.1 Darwin Kernel Version 20.4.0

Apache Spark: spark-3.1.1-bin-hadoop3.2

Python 3.9.2, Clang 12.0.0 (clang-1200.0.32.29) on darwin

Python packages:

- deltalake 0.4.7
- pandas 1.2.4
- plotly 4.14.3

Installations

Apache Spark and Python were installed according to the process completed in the lab work.

deltalake installation:

```
python3 -m pip install deltalake
```

Dataset

Dataset is a CSV Kaggle dataset downloaded from

<https://www.kaggle.com/camnugent/sandp500> that represents historical stock data for all current S&P 500 companies.

wc on datasource/all_stocks_5yr.csv shows 620 thousand rows:

```
→ solution git:(master) ✘ wc datasource/all_stocks_5yr.csv
619041 619041 29580549 datasource/all_stocks_5yr.csv
```

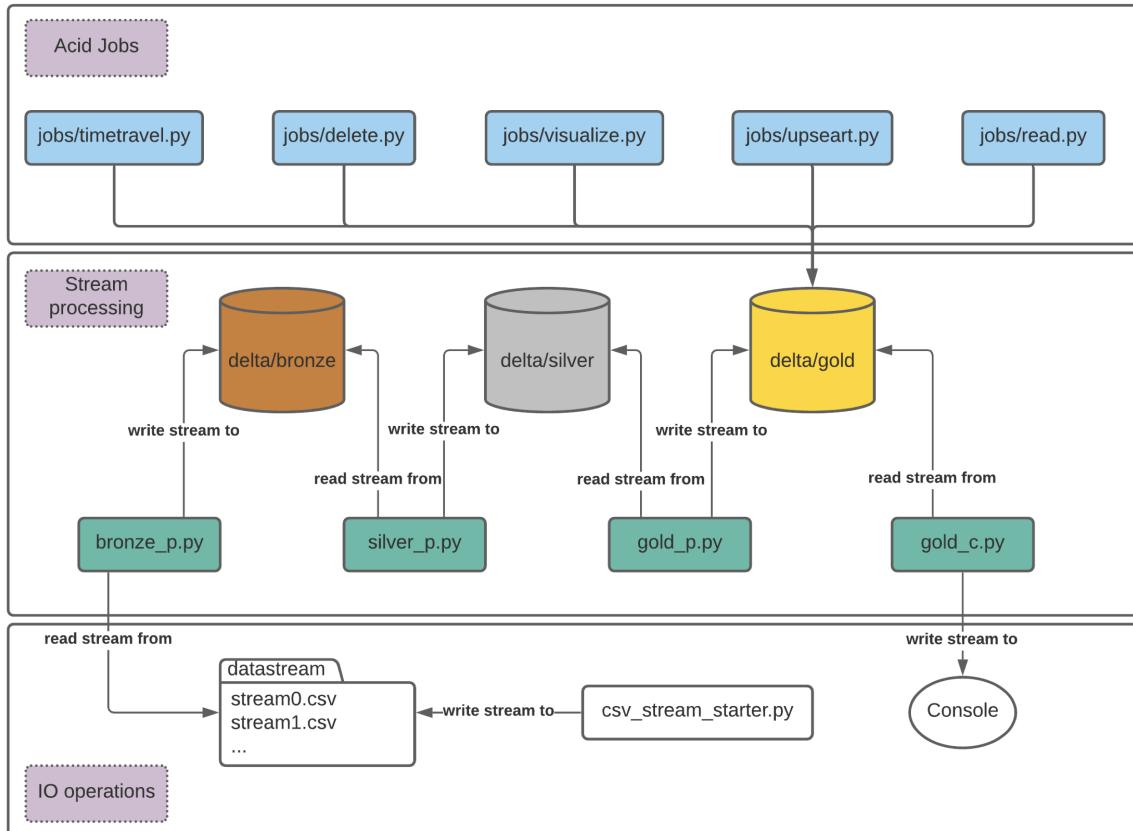
schema of CSV:

```
date,open,high,low,close,volume,Name
```

data source sample::

```
2013-02-08,15.07,15.12,14.63,14.75,8407500,AAL
```

Solution architecture



At first need to build a data producer. This is done with the stream server `csv_stream_starter.py`

`csv_stream_starter.py`

This module is a `CSV` stream server which sorts the input dataset by date, and sequentially sends a set of lines to the stream in the `datastream` directory.

Read from original dataset implemented with small generator-like Source object:

```
class Source():
    def __init__(self, filename):
        self.pos = 0
        self.data = []

        with open(filename, 'r') as rf:
            reader = csv.reader(rf)
            self.data = sorted([row for row in reader], key=lambda row: row[0]) # sort
```

```
by date

def read(self, strings_amount):
    new_pos = self.pos + strings_amount
    data = self.data[self.pos:new_pos]
    self.pos = new_pos
    return '\n'.join(['.'.join(row) for row in data])
```

Read is made with `strings_amount` parameter, which value currently is random range:

```
data = source.read(random.randint(30, 70)).strip('\n')
```

`wait_time` needed to control pauses between messages.

```
def start_csv_stream():
    idx = 0
    source = Source("datasource/all_stocks_5yr.csv")
    while True:
        produce_file(source, 'datastream', idx)
        idx += 1
        # reduce time
        wait_time = 1
        time.sleep(wait_time)
```

server started with

```
python3 csv_stream_starter.py
```

Each line indicates a successful stream writing, and the value represents length of the recorded message.

```
len(data)=531
len(data)=285
len(data)=326
len(data)=284
len(data)=670
len(data)=424
len(data)=370
```

`datastream` (stream directory) looks like:

```

→ solution git:(master) ✘ ls datastream
source0.csv source1.csv source2.csv source3.csv source4.csv source5.csv source6.csv
→ solution git:(master) ✘ cat datastream/source0.csv
2013-02-08,15.07,15.12,14.63,14.75,8407500,AAL
2013-02-08,67.7142,68.4014,66.8928,67.8542,158168416,AAPL
2013-02-08,78.34,79.72,78.01,78.9,1298137,AAP
2013-02-08,36.37,36.42,35.825,36.25,13858795,ABBV
2013-02-08,46.52,46.895,46.46,46.89,1232802,ABC
2013-02-08,34.39,34.66,34.29,34.41,10237828,ABT
2013-02-08,73.01,73.71,72.82,73.31,2000477,ACN
2013-02-08,38.31,39.45,38.145,39.12,5104545,ADBE
2013-02-08,44.72,45.9,44.45,45.7,2962576,ADI
2013-02-08,30.31,30.48,30.16,30.22,4789484,ADM
2013-02-08,60.71,61.0,60.51,60.925,1813162,ADP%

```

Bronze level

Bronze is the first level of the deltalake. All incoming messages go to the bronze storage. Bronze - is a level that in general is unprocessed.

In this case, writing into delta table comes from stream, but also there could be just batch and stream + batch solution.

A `delta` folder has been created. The delta folder will be a "database" and store the "tables". Each table in the delta folder consists of the regular parquet files and transaction log (`_delta_log`). Transaction log allows the ACID support to exist and solves the problem of the parquet files database growth.

```

→ solution git:(master) ✘ mkdir -p delta/events datasource
→ solution git:(master) ✘

```

Here and in next Spark constructed with Delta extensions:

```

spark = pyspark.sql.SparkSession.builder.master('spark://127.0.0.1:7077').appName("MyApp") \
    .config("spark.jars.packages", "io.delta:delta-core_2.12:0.8.0") \
    .config("spark.sql.extensions", "io.delta.sql.DeltaSparkSessionExtension") \
    .config("spark.sql.catalog.spark_catalog", "org.apache.spark.sql.delta.catalog.DeltaCatalog") \
    .config("spark.sql.streaming.forceDeleteTempCheckpointLocation", True) \
    .getOrCreate()

```

Here and in next scripts started with Delta extensions:

```

spark-submit --packages io.delta:delta-core_2.12:0.8.0,org.apache.spark:spark-sql-kafka-0-10_2.12:3.0.1 --conf "spark.sql.extensions=io.delta.sql.DeltaSparkSessionExtension" --conf "spark.sql.catalog.spark_catalog=org.apache.spark.sql.delta.catalog.DeltaCatalog" bronze_p.py

```

schema of incoming data is defined:

```
import pyspark.sql.types as stypes
schema = stypes.StructType().add('date', stypes.DateType()) \
    .add('open', stypes.FloatType()).add('high', stypes.FloatType()) \
    .add('low', stypes.FloatType()).add('close', stypes.FloatType()) \
    .add('volume', stypes.FloatType()).add('name', stypes.StringType())
```

csv stream read:

```
df = spark.readStream.option("host","localhost").option("port","9999") \
    .option('includeTimestamp', 'true').schema(schema).csv('datastream')
```

schema checked:

```
df.printSchema()
```

```
root
 |-- date: date (nullable = true)
 |-- open: float (nullable = true)
 |-- high: float (nullable = true)
 |-- low: float (nullable = true)
 |-- close: float (nullable = true)
 |-- volume: float (nullable = true)
 |-- name: string (nullable = true)
```

Data stream written to `delta/bronze`:

Checkpoints are needed to be able to reduce transaction log expansion.

```
query = df.writeStream.format("delta").outputMode("append") \
    .option("checkpointLocation", "checkpoints/etl-from-csv") \
    .option("mergeSchema", "true") \
    .start("delta/bronze/")
query.awaitTermination()
```

Silver level

`silver_p` is the second layer of data processing and storage. A streaming job has been created that loads data from the `bronze` table into the `silver` table. The architecture assumes that primary data processing, e.g. removing `NULL` values, can also be performed while this layer is running.

The `deltatable`, from which the stream reading is performed, can be worked with in the same way as a regular DF:

```
df = spark.readStream.format("delta").load("delta/bronze/")
```

The schema is unnecessary: the schema was set when the data was written and will now be inherited.

`NULL` values have been removed from df. For each column a `NULL` value is replaced by a value from another column (`column_pairs`). This is done in view of the further logic of the application (aggregations).

There could also be a different logic of data processing.

```
column_pairs = [('open', F.col('close')),
                 ('high', F.col('low')),
                 ('low', F.col('high')),
                 ('close', F.col('open')),
                 ('volume', 0)
                ]

for column, target in column_pairs:
    df = df.withColumn(
        column,
        F.when(
            F.isnan(column) |
            F.col(column).isNull() |
            (F.col(column) == "NA") |
            (F.col(column) == "NULL"),
            target).otherwise(F.col(column)).cast(stypes.DoubleType()))
```

Clean data written to `delta/silver`.

```
query = df.writeStream.format("delta").outputMode("append") \
    .option("checkpointLocation", "checkpoints/bronze-to-silver") \
    .option("mergeSchema", "true") \
    .start("delta/silver/")
query.awaitTermination()
```

When jobs run, `delta/silver` files are printed:

```
→ delta git:(master) ✘ ls silver/_delta_log
00000000000000000000000000000000.json      00000000000000000000000000000010.json
00000000000000000000000000000001.json      00000000000000000000000000000011.json
00000000000000000000000000000002.json      00000000000000000000000000000012.json
00000000000000000000000000000003.json      00000000000000000000000000000013.json
00000000000000000000000000000004.json      00000000000000000000000000000014.json
00000000000000000000000000000005.json      00000000000000000000000000000015.json
00000000000000000000000000000006.json      00000000000000000000000000000016.json
00000000000000000000000000000007.json      00000000000000000000000000000017.json
00000000000000000000000000000008.json      00000000000000000000000000000018.json
00000000000000000000000000000009.json      00000000000000000000000000000019.json
00000000000000000000000000000010.checkpoint.parquet 00000000000000000000000000000020.checkpoint.parquet
00000000000000000000000000000010.json      000000000000000000000000000000120.json
00000000000000000000000000000011.json      000000000000000000000000000000121.json
00000000000000000000000000000012.json      000000000000000000000000000000122.json
00000000000000000000000000000013.json      000000000000000000000000000000123.json
00000000000000000000000000000014.json      000000000000000000000000000000124.json
00000000000000000000000000000015.json      000000000000000000000000000000125.json
00000000000000000000000000000016.json      000000000000000000000000000000126.json
00000000000000000000000000000017.json      000000000000000000000000000000127.json
00000000000000000000000000000018.json      000000000000000000000000000000128.json
00000000000000000000000000000019.json      000000000000000000000000000000129.json
00000000000000000000000000000020.checkpoint.parquet 000000000000000000000000000000130.checkpoint.parquet
```

```
→ delta git:(master) ✘ cat silver/_delta_log/00000000000000000000000000000000.json
{"commitInfo":{"timestamp":1620868097267,"operation":"STREAMING UPDATE","operationParameters":{"outputMode":"Append","queryId":"f9497d19-946e-47f5-b9f6-6dbde13184c3","epochId":"0"}, "isBlindAppend":true,"operationMetrics":{"numRemovedFiles":0,"numOutputRows":5314,"numOutputBytes":186218,"numAddedFiles":8}}}
{"protocol":{"minReaderVersion":1,"minWriterVersion":2}}
{"metaData":{"id":"2fc208a9-bc2b-42b7-b7b9-605130451870","format":{"provider":"parquet","options":{}}, "schemaString":"{\\"type\\":\"struct\\\", \"fields\": [{\"name\\\":\"date\\\", \"type\\\":\"date\\\", \"nullable\\\":true, \"metadata\\\":{}}, {\"name\\\":\"open\\\", \"type\\\":\"double\\\", \"nullable\\\":true, \"metadata\\\":{}}, {\"name\\\":\"high\\\", \"type\\\":\"double\\\", \"nullable\\\":true, \"metadata\\\":{}}, {\"name\\\":\"low\\\", \"type\\\":\"double\\\", \"nullable\\\":true, \"metadata\\\":{}}, {\"name\\\":\"close\\\", \"type\\\":\"double\\\", \"nullable\\\":true, \"metadata\\\":{}}, {\"name\\\":\"volume\\\", \"type\\\":\"double\\\", \"nullable\\\":true, \"metadata\\\":{}}, {\"name\\\":\"name\\\", \"type\\\":\"string\\\", \"nullable\\\":true, \"metadata\\\":{}}]}, \"partitionColumns\":[], \"configuration\":{}, \"createdTime\":1620868095608}}
{"txns":[{"appId": "f9497d19-946e-47f5-b9f6-6dbde13184c3", "version": 0, "lastUpdated": 1620868097241}]
["add": {"path": "part-0000-44f80cac-89ed-42a9-8a54-592267517c73-c000.snappy.parquet", "partitionValues": {}}, "size": 55209, "modificationTime": 1620868097000, "dataChange": true}
{"add": {"path": "part-0001-9ab6f8ac-038b-4721-8217-e8ff88c753c4-c000.snappy.parquet", "partitionValues": {}}, "size": 44856, "modificationTime": 1620868097000, "dataChange": true}
{"add": {"path": "part-0002-0bdd477-e467-4d60-adbe-86bae286f1ee-c000.snappy.parquet", "partitionValues": {}}, "size": 34655, "modificationTime": 1620868097000, "dataChange": true}
{"add": {"path": "part-0003-c11f62fd-274b-4285-ba7e-a435458efba0-c000.snappy.parquet", "partitionValues": {}}, "size": 20693, "modificationTime": 1620868097000, "dataChange": true}]}
```

Gold level

`gold_p` is the third layer of data processing and storage. A streaming job has been created that loads data from the silver table into the gold table. The architecture assumes that high level data processing - (like aggregation) can also be performed while this layer is running.

Silver Delta table read:

```
silver = spark.readStream.format("delta").load("delta/silver/")
```

To implement `output mode = append`, `timestamp` is added to the grouping expression. Aggregation is by `name` field, aggregated values:

- `max_range` - maximum subtraction between high and low columns
- `volume_sum` - sum of the volume column
- `delta_total_percents` - how many percent change in open

```
import pyspark.sql.functions as F

query = silver.withColumn('timestamp', F.unix_timestamp(F.col('date'), "yyyy-MM-dd").cast(stypes.TimestampType())) \
    .withWatermark("timestamp", "1 minutes") \
    .select('*').groupby(silver.name, "timestamp").agg(
        F.max(F.col('high') - F.col('low')).alias('max_range'),
        F.sum(silver.volume).alias('volume_sum'),
        F.sum((F.col('open') - F.col('close')) / F.col('open') * 100).alias('delta_total_percents')
    )
```

<code>name</code>	<code>timestamp</code>	<code>max_range</code>	<code>volume_sum</code>	<code>delta_total_percents</code>
NEE	2013-02-12 00:00:00	0.529998779296875	1779632.0	-0.4990997144873778
GLW	2013-02-11 00:00:00	0.20999908447265625	1.0352591E7	-0.9740250692497617
GD	2013-02-12 00:00:00	0.4949951171875	1950788.0	0.3735245762140945
CCI	2013-02-15 00:00:00	1.58489990234375	4525800.0	-1.8296358955001792
PH	2013-02-08 00:00:00	0.7900009155273438	566484.0	-0.5222187511535973
KLAC	2013-02-14 00:00:00	0.6599998474121094	2182742.0	-0.16068586910364147
CVS	2013-02-13 00:00:00		0.375	4837994.0
PH	2013-02-14 00:00:00		1.5	1044842.0
KMI	2013-02-14 00:00:00	0.40000152587890625	2910025.0	0.1329060034028074
AYI	2013-02-13 00:00:00	1.2600021362304688	251358.0	-1.5125535543636806
HP	2013-02-12 00:00:00	0.9200057983398438	961950.0	-0.4144230801885063
LLY	2013-02-11 00:00:00	0.5800018310546875	1.8307288E7	-0.6348023597277948
KSU	2013-02-08 00:00:00	1.989501953125	640499.0	0.47101169491781236
NEE	2013-02-14 00:00:00	0.7957000732421875	1779659.0	0.19352971625063228
HD	2013-02-13 00:00:00	0.48999786376953125	3668687.0	0.10367253895799323
EQIX	2013-02-11 00:00:00		2.5	447442.0
L	2013-02-13 00:00:00	0.3899993896484375	663122.0	-0.7542898995535714
KEY	2013-02-08 00:00:00	0.12000083923339844	7594244.0	-0.7368388928865132
D	2013-02-12 00:00:00	0.470001220703125	1564869.0	-0.7190254011427634
MYL	2013-02-11 00:00:00	0.20000076293945312	2686982.0	-0.2432233952541217

This query is written to `gold` level.

```
query = query.writeStream.format("delta").outputMode("append") \
    .option("checkpointLocation", "checkpoints/etl-third-to-fourth") \
```

```

.option("mergeSchema", "true") \
.start("delta/gold/")
query.awaitTermination()

```

Gold level console consumer

`gold_c` is the part of the pipeline that streams data from the `gold` level to the console.

```

df = spark.readStream.format("delta").load("delta/gold/")
query = df.writeStream.outputMode('update') \
    .format('console').option('truncate', 'false').start()

```

Streaming output:

```

-----
Batch: 58
-----
+-----+-----+-----+-----+
|name|timestamp|max_range|volume_sum|delta_total_percents|
+-----+-----+-----+-----+
|KIM |2013-06-07 00:00:00|0.5 |2660709.0 |-0.1810729194314875 |
|STZ |2013-06-07 00:00:00|0.9010009765625 |2679510.0 |-1.4261266359077838 |
|SO |2013-06-07 00:00:00|0.6800994873046875 |6141049.0 |0.2693059759508 |
|RE |2013-06-07 00:00:00|1.8300018310546875 |376024.0 |0.1562598262209997 |
|IT |2013-06-07 00:00:00|1.0499992370605469 |351507.0 |-0.27826060419497284 |
|BAC |2013-06-07 00:00:00|0.24000072479248047 |1.20915168E8 |-0.3750952064594014 |
|GT |2013-06-07 00:00:00|0.25999927520751953 |2675855.0 |0.2020248207060221 |
|STX |2013-06-07 00:00:00|0.8299980163574219 |3291695.0 |0.856051077585392 |
|HUM |2013-06-07 00:00:00|1.3700027465820312 |902021.0 |-0.7210270811250076 |
|CI |2013-06-07 00:00:00|1.4799957275390625 |1405529.0 |-1.4074028862847223 |
|SYY |2013-06-07 00:00:00|0.3600006103515625 |3953825.0 |-0.5959384387908775 |
|BF.B|2013-06-07 00:00:00|0.6550025939941406 |856138.0 |-0.18634926811513602 |
|KMI |2013-06-07 00:00:00|0.9500007629394531 |2961857.0 |-0.9446075156454211 |
|WEC |2013-06-07 00:00:00|0.6300010681152344 |837179.0 |-0.6341422476419588 |
|CVS |2013-06-07 00:00:00|0.7100028991699219 |3914124.0 |0.0 |
|FISV|2013-06-07 00:00:00|0.470001220703125 |1070018.0 |-0.4878027600332078 |
|SPG |2013-06-07 00:00:00|3.44000244140625 |1348037.0 |0.13732818603168095 |
|CRM |2013-06-07 00:00:00|1.3699989318847656 |1.0148789E7 |-3.204792881723416 |
|GLW |2013-06-07 00:00:00|0.3099994659423828 |1.501403E7 |-1.8543028205138246 |
|EA |2013-06-07 00:00:00|0.43000030517578125 |3476129.0 |-0.4680877036236702 |
+-----+-----+-----+-----+
only showing top 20 rows

-----
Batch: 59
-----
+-----+-----+-----+-----+
|name|timestamp|max_range|volume_sum|delta_total_percents|
+-----+-----+-----+-----+
|CSX |2013-06-10 00:00:00|0.279998779296875 |6823939.0 |0.31796472254066116 |

```

GILD	2013-06-10 00:00:00 1.4500007629394531	8744157.0	2.0728303009635902	
STZ	2013-06-10 00:00:00 0.9500007629394531	1377841.0	1.2715039472630223	
BLL	2013-06-10 00:00:00 0.1849994659423828	908044.0	0.5040119427548982	
DOV	2013-06-10 00:00:00 1.28900146484375	920249.0	1.1665834055886366	
ESS	2013-06-10 00:00:00 2.9399871826171875	298738.0	0.08326707150882279	
PM	2013-06-10 00:00:00 1.3199996948242188	3888447.0	0.6828580839205263	
ROP	2013-06-10 00:00:00 1.0	301264.0	0.37817929298324066	
APC	2013-06-10 00:00:00 1.0999984741210938	1886003.0	0.04539368393164887	
YUM	2013-06-10 00:00:00 1.69000244140625	3975062.0	1.2670303621831502	
KMX	2013-06-10 00:00:00 0.7462005615234375	1458434.0	0.2330521368082962	
AET	2013-06-10 00:00:00 0.8987998962402344	2197540.0	-1.1446623347365277	
ANSS	2013-06-10 00:00:00 1.410003662109375	259039.0	1.1772538507263797	
PFE	2013-06-10 00:00:00 0.31999969482421875	6.6492012E7	0.03523016853018487	
WY	2013-06-10 00:00:00 0.7399997711181641	5194843.0	1.3559309102721133	
VMC	2013-06-10 00:00:00 1.9799995422363281	501905.0	-2.022896045280164	
DISCA	2013-06-10 00:00:00 2.2099990844726562	1497131.0	2.5940040736747814	
XLNX	2013-06-10 00:00:00 0.6399993896484375	3002325.0	0.7132339316666315	
ETR	2013-06-10 00:00:00 1.1299972534179688	1607675.0	-0.40409694847345495	
IDXX	2013-06-10 00:00:00 0.6899986267089844	744852.0	0.17828824602544624	
+-----+-----+-----+-----+-----+				

Gold jobs

Because deltalake has the power of ACID transactions, additional queries to the database can be made while the pipelines are running, without having to worry about consistency of data.

Delete

This job removes all values from the gold table for which `delta_total_percents > 2`.

Gold DeltaTable loaded:

```
gold = DeltaTable.forPath(spark, ".../delta/gold/")
```

delete query:

```
gold.delete(F.abs(F.col("delta_total_percents")) > 2) # predicate using Spark
```

checked using `toDF()`

```
gold.toDF().select('*').where(F.col("delta_total_percents") > 1.7).show()
```

Read data before job run:

name	timestamp	max_range	volume_sum	delta_total_percents
TWX	2013-02-25 00:00:00	1.7299995422363281	6431525.0	2.5660388874557785
ISRG	2013-02-28 00:00:00	28.169998168945312	2746851.0	11.082234764221248
CVX	2013-02-25 00:00:00	3.839996337890625	7522969.0	2.5407717463284603
ECL	2013-02-25 00:00:00	2.5699996948242188	1443306.0	2.933329264322917
INCY	2013-02-20 00:00:00	0.7749996185302734	1378199.0	3.1078538569894696
WFC	2013-02-25 00:00:00	1.1800003051757812	2.70318E7	2.929685358789625
NSC	2013-02-25 00:00:00	2.0699996948242188	2690751.0	2.603948292362565
GPC	2013-02-19 00:00:00	2.6200027465820312	2308667.0	3.046119800531852
REGN	2013-02-19 00:00:00	6.8899993896484375	1018693.0	2.4624569962294176
APC	2013-02-25 00:00:00	3.9300003051757812	3865033.0	4.5089926343146205
DHI	2013-02-20 00:00:00	1.3299999237060547	1.2674507E7	4.569187371525791
UNP	2013-02-20 00:00:00	1.660003662109375	7028462.0	2.2067315674740113
HUM	2013-02-22 00:00:00	2.6700057983398438	3795289.0	2.794601867227108
CF	2013-02-20 00:00:00	2.128002166748047	1.330919E7	4.549642761183847
CNP	2013-02-25 00:00:00	0.6499996185302734	3592201.0	2.0057309722167442
MAS	2013-02-20 00:00:00	1.25	8109855.0	5.784706574836333
MS	2013-02-20 00:00:00	1.1199989318847656	1.7434108E7	3.937650194908662
PVH	2013-02-20 00:00:00	3.8899993896484375	956101.0	2.703814026360912
ROP	2013-02-25 00:00:00	4.055000305175781	470345.0	2.8122703112690335
KLAC	2013-02-20 00:00:00	1.6599998474121094	1675158.0	2.780236693617465

only showing top 20 rows

Output:

name	timestamp	max_range	volume_sum	delta_total_percents
GS	2013-02-21 00:00:00	4.1499993896484375	8318209.0	1.847512565273212
GT	2013-03-04 00:00:00	0.3399991989135742	2881577.0	1.934984508697554
TPR	2013-02-20 00:00:00	1.5	4446174.0	1.8155842132544933
JEC	2013-02-20 00:00:00	1.0999984741210938	1143897.0	1.887168772466949
HRB	2013-02-25 00:00:00	0.5599994659423828	3962992.0	1.7408918700155076
FRT	2013-02-25 00:00:00	2.2300033569335938	420451.0	1.7129615501121238
CAT	2013-02-20 00:00:00	2.0499954223632812	8571002.0	1.873682925575658
ALK	2013-02-20 00:00:00	0.7549991607666016	1035072.0	1.9119679386123194
SLB	2013-02-20 00:00:00	1.7299957275390625	6395447.0	1.9233182482788127
NOV	2013-02-15 00:00:00	1.970001220703125	4415727.0	1.9516295733074123
STI	2013-02-13 00:00:00	0.6750011444091797	4857578.0	1.7651003617617635
NEM	2013-03-13 00:00:00	0.9199981689453125	7470774.0	1.9612742527505005
MHK	2013-02-21 00:00:00	4.040000915527344	1759249.0	1.7211547264685996
TXT	2013-02-21 00:00:00	0.829999237060547	3385823.0	1.8543986949334155
AIZ	2013-02-20 00:00:00	0.7900009155273438	1058179.0	1.7606421252956095
HIG	2013-02-20 00:00:00	0.5500011444091797	6051037.0	1.9758055894853404
MA	2013-02-20 00:00:00	1.1300010681152344	5376220.0	1.7413800449096555
SWKS	2013-02-15 00:00:00	0.6100006103515625	2876718.0	1.8036102171502972
ADM	2013-02-20 00:00:00	0.6599998474121094	7775251.0	1.78301646983144
USB	2013-03-05 00:00:00	1.1499977111816406	1.7875032E7	1.8292603906476115

only showing top 20 rows

The ability to remove from the table without fear opens up possibilities - such as convenient GDPR compliance.

Read job

The read job is set up to print gold layer values for which `delta_total_percents > 2;`

```
df.select('*').where(F.col("delta_total_percents") > dtp_threshold).show()
show_df(gold.toDF(), 2)
```

Job started after completion of deletion:

```
+---+-----+-----+-----+
|name|timestamp|max_range|volume_sum|delta_total_percents|
+---+-----+-----+-----+
+---+-----+-----+-----+
```

Upseart job

Data can be added or changed consistently in deltalake. Add data from upseart.csv dataset to gold table.

upseart.csv contains two entries.

NFPK name is not in the gold data, rows for the SWKS name exists.

```
name,timestamp,max_range,volume_sum,delta_total_percents
NFPK,2013-02-15 00:00:00,1.1206103515625,3875718.0,3.1
SWKS,2013-02-15 00:00:00,0.6100006103515625,2876718.0,2.80361
```

upseart.csv is loaded as DF:

```
upseart_data = spark.read.format("csv").option("header", "true").load("../datasource/upseart.csv")
```

Upseart is performed on the name field - as a result, an additional record is created with the name NFPK and delta_total_percents value is changed in all SWKS records.

```
gold.alias("gold").merge(
    upseart_data.alias("upseart"),
    "gold.name = upseart.name") \
.whenMatchedUpdate(set = { "delta_total_percents" : "upseart.delta_total_percents" })
) \
.whenNotMatchedInsert(values =
{
    "name": "upseart.name",
    "timestamp": "upseart.timestamp",
    "max_range": "upseart.max_range",
    "volume_sum": "upseart.volume_sum",
    "delta_total_percents": "upseart.delta_total_percents",
})
) \
.execute()
```

Execution checked:

```
gold.toDF().select('*').where(F.col("delta_total_percents") > 2).show()
```

name	timestamp	max_range	volume_sum	delta_total_percents
NFPK	2013-02-15 00:00:00	1.1206103515625	3875718.0	3.1
SWKS	2013-03-06 00:00:00	0.760000228818359	6465013.0	2.80361
SWKS	2013-02-15 00:00:00	0.6100006103515625	2876718.0	2.80361
SWKS	2013-02-08 00:00:00	0.4399986267089844	2522548.0	2.80361
SWKS	2013-03-12 00:00:00	0.3299999237060547	2783107.0	2.80361
SWKS	2013-03-01 00:00:00	0.5799999237060547	5449368.0	2.80361
SWKS	2013-02-11 00:00:00	0.6100006103515625	2387664.0	2.80361
SWKS	2013-02-13 00:00:00	0.4400005340576172	2684874.0	2.80361
SWKS	2013-03-08 00:00:00	0.46000099182128906	2690506.0	2.80361
SWKS	2013-03-05 00:00:00	0.5999984741210938	6769540.0	2.80361
SWKS	2013-02-22 00:00:00	0.7399997711181641	9045861.0	2.80361
SWKS	2013-02-12 00:00:00	0.4699993133544922	2991270.0	2.80361
SWKS	2013-02-19 00:00:00	0.6200008392333984	2511078.0	2.80361
SWKS	2013-03-14 00:00:00	0.510000228818359	2863779.0	2.80361
SWKS	2013-03-04 00:00:00	0.5750007629394531	5358110.0	2.80361
SWKS	2013-03-11 00:00:00	0.4850006103515625	2944899.0	2.80361
SWKS	2013-03-07 00:00:00	0.4699993133544922	2768163.0	2.80361
SWKS	2013-02-28 00:00:00	0.4399986267089844	3672172.0	2.80361
SWKS	2013-05-13 00:00:00	0.3699989318847656	2688511.0	2.80361
SWKS	2013-05-31 00:00:00	1.0720996856689453	5957220.0	2.80361

Timetravel job

`_delta_log` allows a database version from the past to be loaded as `DF`. Loading is possible either by time or by version.

Because the metadata in deltalake is also big data, it can be interacted with via the `DF` interface.

History of transactions printed:

```
gold = DeltaTable.forPath(spark, "delta/gold/")
gold_history = gold.history()
print('gold history:')
gold_history.show()
```

version	timestamp	userId	userName	operation	operationParameters	job	notebook	clusterId	readVersion
74	2021-05-13 04:37:56	null	null	MERGE	[predicate -> (go... null null null null null null null null nu)				
73	2021-05-13 04:35:10	null	null	DELETE	[predicate -> ["(... null null null null null null null null nu)]				
72	2021-05-13 04:20:16	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
71	2021-05-13 04:20:10	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
70	2021-05-13 04:20:02	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
69	2021-05-13 04:19:54	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
68	2021-05-13 04:19:46	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
67	2021-05-13 04:19:39	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
66	2021-05-13 04:19:33	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
65	2021-05-13 04:19:26	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
64	2021-05-13 04:19:19	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
63	2021-05-13 04:19:13	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
62	2021-05-13 04:19:05	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
61	2021-05-13 04:18:59	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
60	2021-05-13 04:18:52	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
59	2021-05-13 04:18:44	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
58	2021-05-13 04:18:35	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
57	2021-05-13 04:18:28	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
56	2021-05-13 04:18:21	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				
55	2021-05-13 04:18:14	null	null	STREAMING UPDATE	[outputMode -> Ap... null null null null null null null null nu]				

only showing top 20 rows

Version without `upsert` operation chosen.

```
version = 73
```

Time travel initiated:

```
gold_timetravel = spark.read.format("delta").option("versionAsOf", version).load("delta/gold")
```

```
print(f"Chosen {version}={version}")
gold_timetravel.select('*').where(F.col('version') == version).show()
```

version	timestamp	userId	userName	operation	operationParameters	job	notebook	clusterId	readVersion
73	2021-05-13 04:35:10	null	null	DELETE	[predicate -> ["(... null null null null null null null null nu)]				

```
print(f>Data for that version:")
gold_timetravel.show()
```

```
Data for that version:
+---+-----+-----+-----+-----+
| name | timestamp | max_range | volume_sum | delta_total_percents |
+---+-----+-----+-----+-----+
| AFL | 2013-02-13 00:00:00 | 1.0499992370605469 | 6063028.0 | 1.5779865961586932 |
| SJM | 2013-03-04 00:00:00 | 1.1399993896484375 | 391094.0 | -0.5619156338204953 |
| MTD | 2013-02-08 00:00:00 | 3.429901123046875 | 166815.0 | -0.8068141919393976 |
| DISH | 2013-02-08 00:00:00 | 0.6399993896484375 | 1449533.0 | -1.1827919830241873 |
| LLL | 2013-03-06 00:00:00 | 1.3899993896484375 | 626860.0 | 0.8958645054340371 |
| WMT | 2013-03-01 00:00:00 | 1.1200027465820312 | 8902516.0 | -1.3563140732258048 |
| CBG | 2013-02-14 00:00:00 | 0.5100002288818359 | 3224715.0 | -1.4373732073370962 |
| RF | 2013-02-21 00:00:00 | 0.21000003814697266 | 2.397351E7 | 1.1718708041976822 |
| MAR | 2013-02-14 00:00:00 | 0.43000030517578125 | 1381230.0 | -0.5865143919995018 |
| TSN | 2013-02-14 00:00:00 | 0.45999908447265625 | 4730889.0 | -1.508795866697278 |
| MU | 2013-03-08 00:00:00 | 0.31999969482421875 | 3.4767488E7 | -1.882614411086026 |
| HES | 2013-02-08 00:00:00 | 0.9899978637695312 | 2760327.0 | -1.0196435451823962 |
| AVY | 2013-03-05 00:00:00 | 0.5900001525878906 | 911836.0 | -1.1127215354977695 |
| JEC | 2013-02-22 00:00:00 | 0.5699996948242188 | 711554.0 | -0.47063545582823235 |
| MTD | 2013-02-11 00:00:00 | 3.92999267578125 | 165521.0 | 0.742047613415832 |
| PCAR | 2013-02-28 00:00:00 | 0.6300010681152344 | 1543304.0 | 0.021066838866573526 |
| WDC | 2013-02-14 00:00:00 | 0.8600006103515625 | 2032534.0 | -0.5148270035624527 |
| MOS | 2013-02-11 00:00:00 | 0.5600013732910156 | 1249907.0 | 0.4072324523302649 |
| AES | 2013-02-14 00:00:00 | 0.1700000762939453 | 4892310.0 | 0.8841766380156829 |
| ROST | 2013-03-06 00:00:00 | 0.37000083923339844 | 4865492.0 | -0.7935188660063585 |
+---+-----+-----+-----+-----+
only showing top 20 rows
```

`delta_total_percents` by threshold 2 printed:

```
print("DTP threshold 2 for that version:")
from read import show_df
show_df(gold_timetravel, 2)
```

```
DTP threshold 2 for that version:
+---+-----+-----+-----+
| name | timestamp | max_range | volume_sum | delta_total_percents |
+---+-----+-----+-----+
+---+-----+-----+-----+
```

As can seen, upseart was cancelled.

Visualize job

Also, based on reading from the database, the data could be visualised. There could also be a machine learning mechanism.

The names for which plots will be plotted are selected:

```
names = ['WYNN', 'BLL', 'IT', 'BA']
```

The dependency of the `delta_total_percents` parameter on time is plotted.

```
for name in names:
    plot_data = gold_df.select(F.col('timestamp'), F.col('delta_total_percents')).wher
```

```

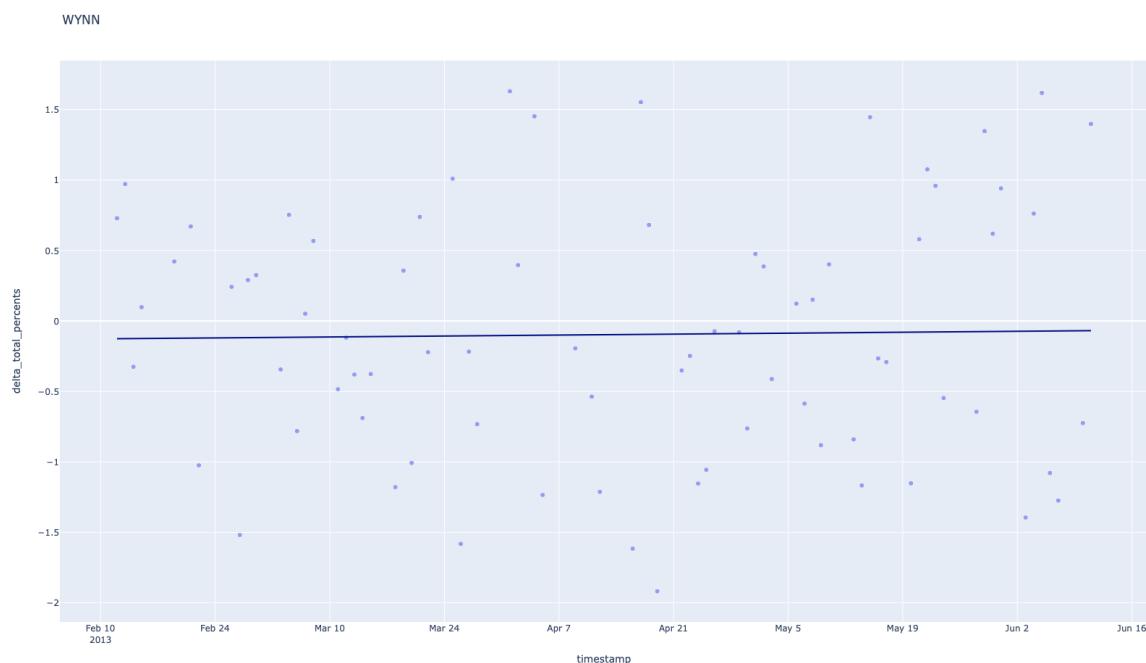
e(F.col('name') == name)
print(f'{name}:')
plot_data.show()

import plotly.express as px

fig = px.scatter(
    plot_data.toPandas(), x='timestamp', y='delta_total_percents', opacity=0.65,
    title=name, trendline='ols', trendline_color_override='darkblue'
)
fig.show()

```

Plot for **WYNN** name:



Summary

In this study, architecture construction of an ACID-compliant storage and streaming processing of stock market data based on Databricks Delta Lake was made.

Delta Lake is a new chapter in the development of Big Data solutions. Combination of convenient DataFrame interface, storage organisation transparency, ACID-compatibility, batch-stream processing, metadata as DataFrame opens up opportunities for building extremely large, scalable and durable storages and Big Data processing systems in financial and other fields.

[Youtube](#)

Github

Brief Demo <https://youtu.be/DfgN8cHtpLg>

Full Demo <https://youtu.be/4nye3nRV1R4>

Github: <https://github.com/vo0xr0c/deltalake>