

WTF is an Analytics Lake

Building an open data service layer with Arrow, DuckDB and Semantic Layer

Raise your hands!

Who likes writing boilerplate code?



Building an Analytics Stack is Hard!

Developer Velocity

You want to build an analytics stack powering a BI/analytics platform

With every new **data service**, developers have to solve the same problems again and again. For instance:

- Server handling, interfaces
- Config management
- Routing, Load balancing

Often you spend 80% of your time with boiler-plating

Developers Wish For ...

Skeleton data service

• Implement only the service logic, e.g. pivoting

Examples

• Real and meaningful data services

Performance

- Have you ever seen a really responsive end-user experience?
- Example: Tableau server

Our Initial Motivation

GoodData 1.0

We built the first version of our analytics stack more than **15** years ago! We combined it with large amounts of our own proprietary code

• with the technology available at that time



GoodData 2.0

We decided to rewrite the platform on greenfield 4 years ago

- Reuse open-source and SaaS services as much as possible
- We fell in love first with Apache Arrow and later with DuckDB
- Some prospects even ask for embedding custom data services into our platform



Anatomy of an Analytics Lake

Physical Execution

Usually it consists of:

- **Querying** the data source(s) or pre-aggregations
- Post-processing the data e.g. pivoting, ML
- Caching

We call this GD-specific stack FlexQuery

It's powered by (GD-agnostic) engine called Longbow

- Built on top of Apache Arrow, DuckDB, and Pandas (TODO: Polars)
- We are considering an open sourcing of Longbow engine

The Importance of Semantic Layer

Business users

- -> Semantic(logical) report definition SUM(amount) BY product_category
- -> Semantic layer with mapping to data [SALES] -> [PRODUCTS]
- -> Physical execution plan (SQL) SELECT SUM(amount) FROM JOIN GROUP BY

We use <u>Apache Calcite</u> for translation of business requests to SQL

• Thanks to the community, especially to Julian Hyde ;-)



Analytics Lake = FlexQuery + Semantic Layer



Why we chose Apache Arrow

Arrow format

- Language-independent
- Columnar memory format

Efficient for

- Analytic operations on modern hardware (CPUs, GPUs)
- Communication of services over the network

Zero-copy reads!



But You Get Much More Out of the Box!

I/O operations with the data - disk, object storages, ...

Convertors - CSV, Parquet, from JDBC, ...

Streaming computation on top of Arrow data - Acero engine

Flight RPC - API blueprint and infrastructure

Arrow Database Connectivity (ADBC) - query external data sources



Easy to Integrate

Arrow is becoming de facto standard

• Even big players like <u>Snowflake(JDBC, 2020)</u> are adopting it

Other technologies we found valuable and integrated:

- Transform
 - Pandas (2.0), Polars
 - \circ DuckDB
- Federate
 - DuckDB

What we set out to build

FlexCache - tiered storage

Memory <-> Disk <-> Object Storage (S3, ABS, GCS)

Arrow tables

Policies

- Various rules for promoting, demoting
- Enforce limits, isolate tenants, define replicas
- Leverage for pricing

```
cache_tier.in_memory = {
  type = "memory", max_flight_size = '512M', upload_spill_to = "mapped_disk",
  move_after = 60, move_to = "mapped_disk", spill_to = "parking_lot", priority = 10
}
cache_tier.mapped_disk = {
  type = "disk_mapped", max_flight_size = '2048M', upload_spill_to = "parking_lot", spill_to = "parking_lot"
}
cache_tier.parking_lot = {
  type = "disk", promote_after_hits = 10, promote_hits_window = 5, promote_to = "*best_fit"
}
```





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Data Source Connectors

TurboODBC -> ADBC

• Fallback to JDBC is possible

Flexible deployment / Limit enforcement

- Max connections, timeouts, ...
- Per node or per data source type

Streaming to FlexCache



Limit

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Limit

Result Post-Processing

Dataframe operations

- Even easier to implement new operations than modules dataframe IN/OUT
- Pivoting, sorting, paging for BI
- Three ML algorithms in Beta, created in a few days

Federation

- Query hybrid data sources, stream to FlexCache
- Object stores, databases
- Query FlexCache with DuckDB

Real UX/DX From Developers to Developers

Self-service drag&drop

- freeing hands of developers



Must not forget about Al chat bot



DX - Analytics Lake with UI SDK

About this dashboard

This is a demo dashboard created to showcase a complete data pipeline with GoodData for VS Code.

Read more about the dashboard contents in <u>the article on Pluto</u>. If you're interested in technical details check out <u>the technical article</u> or <u>the source code on GitHub</u>.

How big is Pluto, anyway?

Pluto's moons are quite massive and some astronomers suggest to call Pluto-Charon a binary dwarf-planet. Here is how it compares to Earth's and Jupiter's planetary systems. We are comparing dimensions here, the difference is even more stark when translated to masses (volume is proportional to radius^3).



Earth planetary system



DX - Analytics Lake with Python SDK - connect



Demo for how GoodData Python SDK can be used inside notebooks

GoodData Python SDK is an open-source set of libraries derived from GoodData OpenAPI specification. It provides an additional layer of abstraction of the raw APIs. Besides gooddata-sdk (core) library, we provide gooddata-pandas exposing report results as data frames.

Import libraries ¶

In [5]: M from pathlib import Path import pandas as pd from gooddata_sdk import GoodDataSdk from gooddata pandas import GoodPandas

Init GoodData

In [4]: M profiles= Path.home() / ".gooddata" / "profiles.yaml"
gd_sdk = GoodDataSdk.create_from_profile(profile="demo_cicd", profiles_path=profiles)
gd_pandas = GoodPandas.create_from_profile(profile="demo_cicd", profiles_path=profiles)
workspace_id = "cicd_demo_production"
gd_frames = gd_pandas.data_frames(workspace_id)

DX - Analytics Lake with Python SDK - query stored report

Jupyter report_execution Last Checkpoint: 49 seconds ago		
* File Edit View Run Kernel Settings Help		
🖻 + 🛠 🗇 🖹 🕨 🔳 C 🕨 Markdown 🗸		🗸 Open in 👙 Python 3 (i
9 sum_days_to_solve	Sum days to solve	
10 sum_stargazers	Sum of stargazers	

Execute Already Defined Report

[8]: insight_df = gd_frames.for_insight('contribution_of_top_25_users_per_repository')
insight_df

ribution_of_top_25_usersmerged_pr			8]:
	repo_name	closed_at.month	
0.500000	gooddata-ui-sdk	2019-09-01	
0.357143	gooddata-ui-sdk	2019-10-01	
0.850000	gooddata-ui-sdk	2019-11-01	
0.680000	gooddata-ui-sdk	2019-12-01	
0.411765	gooddata-ui-sdk	2020-01-01	
1.000000	gooddata-dashboard-plugins	2024-02-01	
0.750000	gooddata-python-sdk		
0.615385	gooddata-ui-sdk		
1.000000	gooddata-python-sdk	2024-03-01	
0.750000	gooddata-ui-sdk		

121 rows × 1 columns

DX - Analytics Lake with Python SDK - custom report

	xecute a Cus	stom Repo	ort						
In [22]: ₩	<pre>from gooddata exec_def = Exe attributes Attrib Attrib], metrics=[Simple], filters=[F dimensions)</pre>	sdk import E cutionDefini =[uute(local_id uute(local_id Metric(local Metric(local Metric(local Metric(local CelativeDateF =[["created_	<pre>xecutionDefi tion(="created_at ="repo_name" _id="count_c _id="count_p filter(datase at"], ["repo</pre>	nition, Attr ", label="cr , label="rep ommits", ite ull_requests t=ObjId(id=" _name", "mea	<pre>ibute, Simple eated_at.mon o_name"), m=ObjId(id=" ", item=ObjId created_at", sureGroup"]] exec_dat)</pre>	eMetric, Obj th"), commit_id", d(id="count_ type="datase ,	Id, Relative[type="label") pull_requests et"), granula	DateFilter), aggregatic 5", type="met arity="YEAR",	on="COUNT"), ric")), from_shift=
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DX - FlexQuery - TPC-H Q4

```
select o_orderpriority, count(*) as order_count
from orders
where
    o_orderdate >= date '1993-07-01'
    and o_orderdate < date '1993-07-01' + interval '3' month
    and exists (
        select 1 from lineitem where l_orderkey = o_orderkey and l_commitdate < l_receiptdate
    )
group by o_orderpriority order by o_orderpriority</pre>
```

DX - FlexQuery - Federation

```
tpch4_exec = SqlQuery(
    sql=tpch_q4,
    tables=(
        TableData(
            table_name="orders",
            data=ConnectorQuery(
                payload=orjson.dumps(
                    {"type": "parquet-file", "path": "tpch/orders.parquet",
                     "columns": ["o_orderpriority", "o_orderdate", "o_orderkey"]}
                sink_method=qc.SinkToFlightPath(flight_path="org1/tenant1/tpch/datasets/orders"),
            ).to flight descriptor(ds id="my-s3").
        ).
        TableData(
            table_name="lineitem",
            data=ConnectorQuery(
                payload=SqlPayload(sql='SELECT "l_orderkey", "l_commitdate", "l_receiptdate" FROM lineitem'),
                sink_method=qc.SinkToFlightPath(flight_path="org1/tenant1/tpch/datasets/lineitem"),
            ).to_flight_descriptor("postgres")
```

sink_method=qc.SinkToFlightPath(flight_path="org1/tenant1/tpch/reports/4.result"),

DX - Call FlexQuery

q = qc.QuiverClient("grpc://localhost:16004")

with q.flight_descriptor(tpch4_exec.to_flight_descriptor()) as stream: result: pyarrow.Table = stream.read_all() result.sort_by(sorting: "order_count", descending=True) # noinspection PyArgumentList df = result.to_pandas(split_blocks=True, self_destruct=True) st.bar_chart(data=df, x="o_orderpriority", y="order_count")

A Taste of the Future

DX - AI Explain - Using FlexCache

```
AIExplainAction(
    source_data="org1/tenant1/tpch/reports/4.result",
    explain_parameters={
        "max_sample_size": 1000,
        "method": "OpenAIWithRAG",
    },
    gpt_cache=True
```

DX - AI Explain - Chain of Commands

```
a = AIExplainAction(
    source_data=SqlQuery(
        sql=tpch_q4
        tables=(
        sink method=qc SinkToFlightPath(
            flight_path="org1/tenant1/tpch/reports/4.result", skip_if_exists=True
        ),
   explain_parameters={
        "max_sample_size": 1000,
        "method": "OpenAIWithRAG",
    }.
    gpt_cache=True
```

AI and Analytics Lake Architecture



Try it out



Live app for fun



Blueprint repository

Meet with us



Set time with us

- Meet the team
- Get a demo

Pick up swag

Visit our booth - ####

Admins Wish For ...

Consistent and meaningful metrics

Flexible deployment

Easy (auto)scaling

Base

Node - Arrow Flight server

Modules - config for loading modules to nodes

Shared features, e.g. requests cancellation

Tooling - CLI, operations(metrics)

Deployment options - bare metal, VM, K8S

Clients - Python, Java(Kotlin)