Practical Course: Cloud-Based Data Processing

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Schedule

	Content	Lab Start	Lab End	Oral Discussions
16.06	Benchmarking in the Cloud	Project	Lab 6	Lab 4, Lab 5
23.06	Topic Selection			Lab 6
30.06	Q&A			
07.07	Q&A			
14.07	Project Presentations			

Lab 4: Cloud Storage

Goal: how fast can we read from Azure Blob Storage? **Theoretical Standard_B2 ceiling ≈ 700 MB/s.**

Two models

- **std::thread**
- **io_uring + curl_multi**

Four access patterns

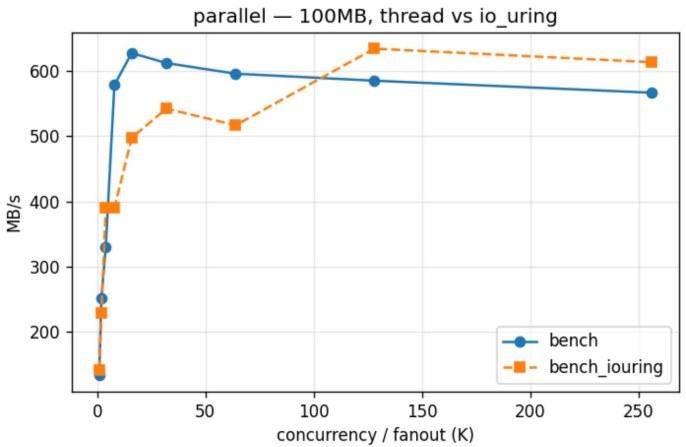
Sequential: one connection, one object
parallel: N concurrent full-object GETs
range: one object split into K byte-range GETs
tinyfanout: K tiny 4 KB range GETs

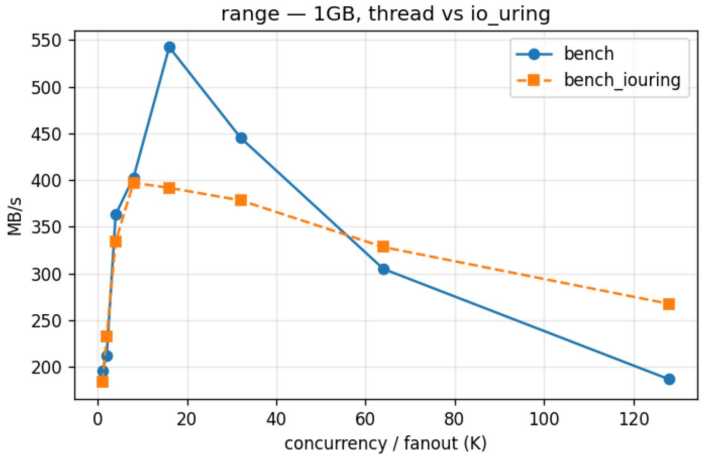
Lab 4: Findings per Access Pattern

Bandwidth-bound vs latency-bound — and the 4-connection cap shapes every curve.

Pattern	What binds it	Who wins	Key finding
sequential	Window / RTT (BDP)		One flow can't fill the NIC; larger objects increase throughput.
parallel	Link / aggregate window	threads (peak BW)	io_uring held back by MAX_HOST_CONNECTIONS = 4.
range	Same, but one object	parallel ≥ range	Splitting one object plateaus at the 4-conn cap.
tinyfanout	Handshake + RTT (latency)	io_uring, decisively	Warm-pool reuse wins; threads hit a ceiling and starve.

Lab 4: Findings per Access Pattern





	cross-region	in-region	factor
sequential 1 GB	82	172	2.1×
io_uring parallel @K=128	~100 (declining)	634	6×
io_uring tinyfanout peak	129 rps	317 rps	2.5×

Lab 4: Protocol & io_uring

HTTP/1.1 vs HTTP/2, and Range

- Keep-alive reuses a connection serially (one request in flight). HTTP/2 multiplexes many streams.
- Range Requests → 206 Partial Content.
- Azure Blob's REST endpoint is HTTP/1.1-compatible only only

How we actually used io_uring

Only as a readiness poll backend for curl_multi (a drop-in epoll).

- libcurl still owns recv/send and TLS. Operation = readiness; delivery = completion.

What did it buy us? Was it necessary?

Not strictly. The win over threads is the event loop (epoll would match it).

- io_uring's edge is syscall batching; the 4-conn cap and one-CQE-per-wait loop don't really amortize it.

Lab 4: io_uring + curl_multi Code Flow

1 Setup

- io_uring_queue_init(4096); curl_multi_init().
- Register socket_cb / timer_cb; set MAX_HOST_CONNECTIONS = 4.
- Build EasyCtx + curl_multi_add_handle.

2 Prime

- curl_multi_socket_action(CURL_SOCKET_TIMEOUT, 0).
- Fires socket_cb (“watch these fds”) and timer_cb (“wake in N ms”).
- still_running becomes the loop condition.

3 Event loop

- Arm one POLL_ADD per socket → io_uring_submit → wait_cqe_timeout.
- -ETIME: tell curl the timeout fired.
- Completion: drain all CQEs, decode fd, map to CURL_CSELECT_*.
- curl_multi_socket_action — libcurl does the real recv/send + TLS.

4 Teardown

- When still_running == 0, drain CURLMSG_DONE for errors.
- Sum body.size() across contexts; report throughput.
- Remove handles, cleanup multi + ring.

io_uring: Security Considerations

Why it worries defenders

- **Evasion / EDR blind spot:** async SQEs perform read/write/sendmsg/recvmsg in-kernel, so syscall hooks may never fire.
- **Large new attack surface:** novel kernel paths, replacing battle-tested code.
- **Hard to sandbox:** no fine-grained seccomp; functionality is opaque to BPF sandboxes, so it's effectively all-or-nothing.
- **Disabled for unprivileged users:** across Google's own production fleet / Google Cloud, they disabled it for unprivileged users stated they limit its use because they couldn't make it safe enough where untrusted code runs.

60%

of kernel exploits in Google's 2022 bounty targeted io_uring — since disabled by default in some environments.

~$1M

paid out by Google for io_uring vulnerabilities. Sandboxing via BPF isn't impossible and is on the roadmap.

Lab 5: Shuffle Substrates

A distributed shuffle is a **network workload** and the substrate you route it through is a **design choice**, not "the network."

Substrate	Equivalent	The trade-off
P2P TCP	Spark BlockManager, Lab 2/3	Fastest, but coupled — both ends live; no durability; N^2
Managed Redis	Memcached / dedicated Redis	Fast, decoupled — but volatile, RAM-bound, billed while idle
Storage Queue	Kafka / Kinesis / RabbitMQ	Decoupled + durable many→one; per-message overhead, size cap
Blob storage	S3 / GCS shuffle, Lab 4	Durable, elastic, cheap-at-rest — but high per-request latency

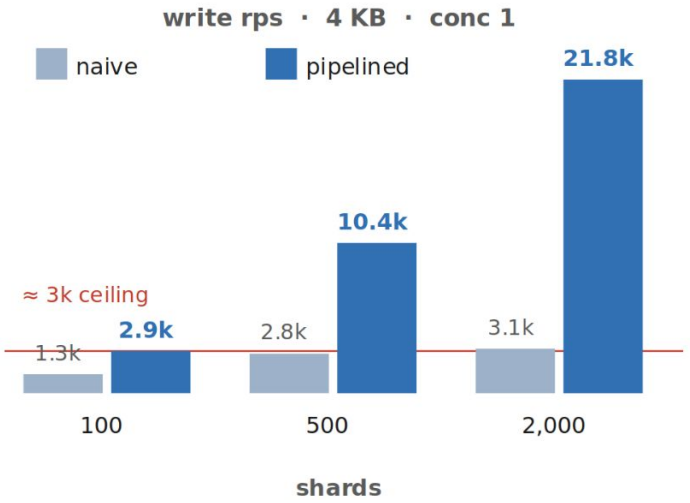
Lab 5: Findings per Substrate

No substrate wins everywhere

Substrate	Wins at	Watch out for
P2P TCP	Lowest latency; bulk streaming (1 RTT)	Coupled, fragile, no durability; N^2 connections
Redis	Fast small/medium — if pipelined	Naive = N×RTT; volatile; RAM-bound; billed idle
Storage Queue	Decoupled many→one work distribution	64 KB cap + base64; ≥3 ops/msg; at-least-once → dedupe
Blob	Durable, elastic, cheap bulk transfer	High Time-To-First-Byte; small-shard read amplification

Lab 5: Pipelining Unlocks Redis

Shards	naive rps	pipelined rps	speedup
100	1,330	2,940	2.2×
500	2,750	10,450	3.8×
2,000	3,100	21,800	7.0×



Naive Redis is RTT-bound at ≈3,000 rps (≈1/RTT at the ~0.3 ms intra-region round-trip). Pipelining (window W=512) pays the round-trip once per batch, not once per shard.

Lambada: The Serverless Shuffle → Lab 6

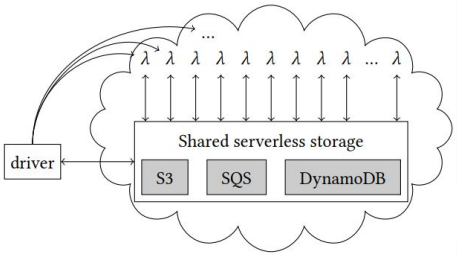
Three decoupled serverless stores (chosen by role & size)

S3: bulk data and the shuffle itself.

DynamoDB: small hot data.

SQS: short messages / coordination.

All scale to zero when idle — the bulk exchange runs on S3, not the key-value store.



The exchange operator is request-count-bound

A naive S3 shuffle needs $O(P^2)$ requests; at 256 workers the request cost already exceeds the worker cost.

Fix: multi-level exchange + write-combining → sub-linear requests. “Request count is the currency.”

The bridge to Lab 6: a serverless shuffle is only possible because storage decouples producers from consumers in time and identity.

Cloud Analytics Benchmarking

Benchmarking in the Cloud: Why It Is Different

- On-prem benchmarks (TPC-H, TPC-DS) measure **one engine on fixed hardware**: “which engine is fastest?”
- The cloud breaks that frame: resources scale **elastically**, services are **multi-tenant**, you may pay **per use**.
- The user-centric question becomes **cost (€) and latency**
  - not runtime on a fixed box.
- A cloud benchmark must capture elasticity, multi-tenancy, and handle different types of loads.

So: what does a **realistic** cloud workload even look like: and how do we benchmark it?

Existing Workload Telemetry Traces

Snowset (Snowflake)

Arrival Time	Exec. Time	CPU Time	Data Scanned	…
19:02	6 sec	50 sec	2 GB	…
19:04	2 sec	25 sec	100 MB	…
…	…	…	…	…

Redset (AWS Redshift)

Arrival Time	Was_ cached	# of scans	# of joins	…
19:02	Yes	7	6	…
19:04	No	3	2	…
…	…	…	…	…

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Can we get meaningful workloads out of these traces?

The Cloud Analytics Benchmark (CAB)

- Real workloads differ from TPC-H/DS: more variety in CPU/IO load, more **DML** (in-warehouse ETL), bursty multi-tenant arrivals.
- van Renen & Leis, PVLDB 2023: first to build a cloud benchmark based on an industry **trace** (Snowflake's Snowset, ≈69 M queries).
- CAB = TPC-H schema + per-tenant query streams + realistic arrival patterns; scored on **query latency and € per run**.

But the trace holds only **statistics: not the SQL**.

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But the trace holds only **statistics: not the SQL**.

- We are still running the same TPC-H queries as before, but also testing *concurrency* and *elasticity*.

Matching-Based Query Synthesis

Telemetry Dataset (unknown queries)

CPU Seconds	Data Scanned	Arrival Time
30	5	3
15	7	7

Known SQL Pool

Query	CPU Seconds	Data Scanned
Q1	30	5
Q2	5	3
Q3	10	4

Synthesized Dataset

Telemetry Query #	Target CPU Time	Target Data Scanned	Matched Query/-ies
1	30	5	Q1
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Workaround: LLM-Based Generation

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CPU Seconds	GB Scanned	Arrival Time
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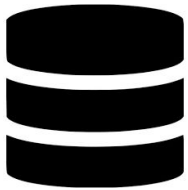
Synthesized Queries
`SELECT * FROM pizzas WHERE name = 'diavola'`
`SELECT COUNT(*) FROM pizzas WHERE type = 'vegetarian'`

Large Language Model

Target System



Example Systems:
SQLBarber(SIGMOD 2026) [4],
ResQ(aRxiV) [5]

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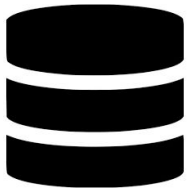

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SQL Pool

Query	CPU Seconds	GB Scanned
Q1	40	4
Q2	5	1

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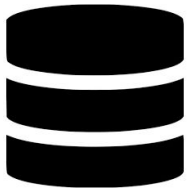

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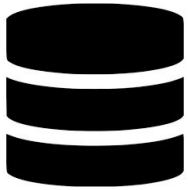

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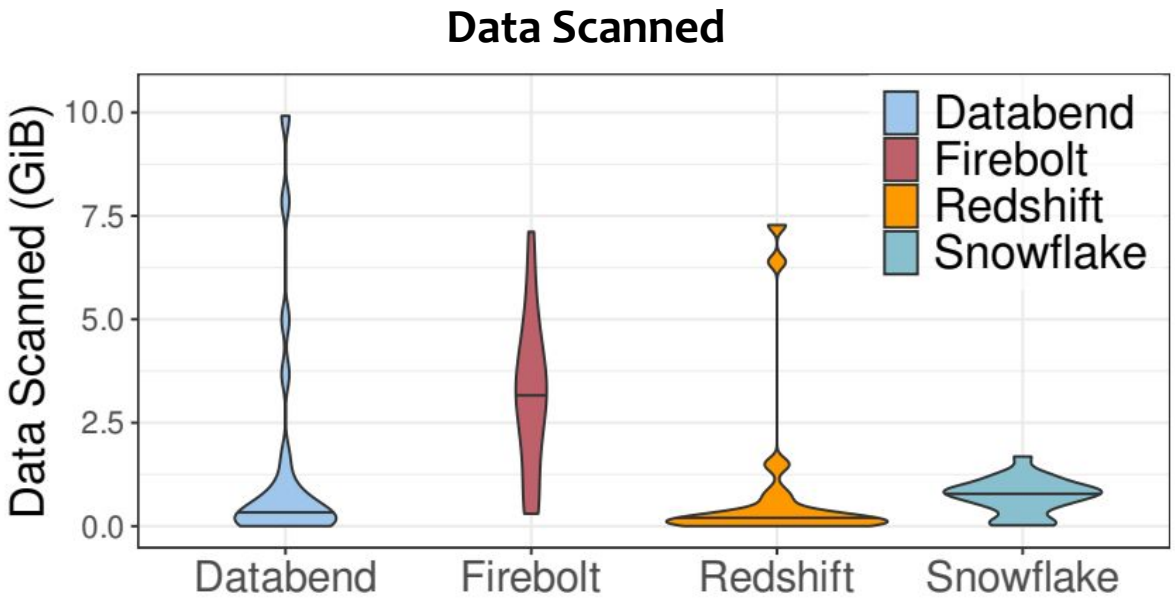
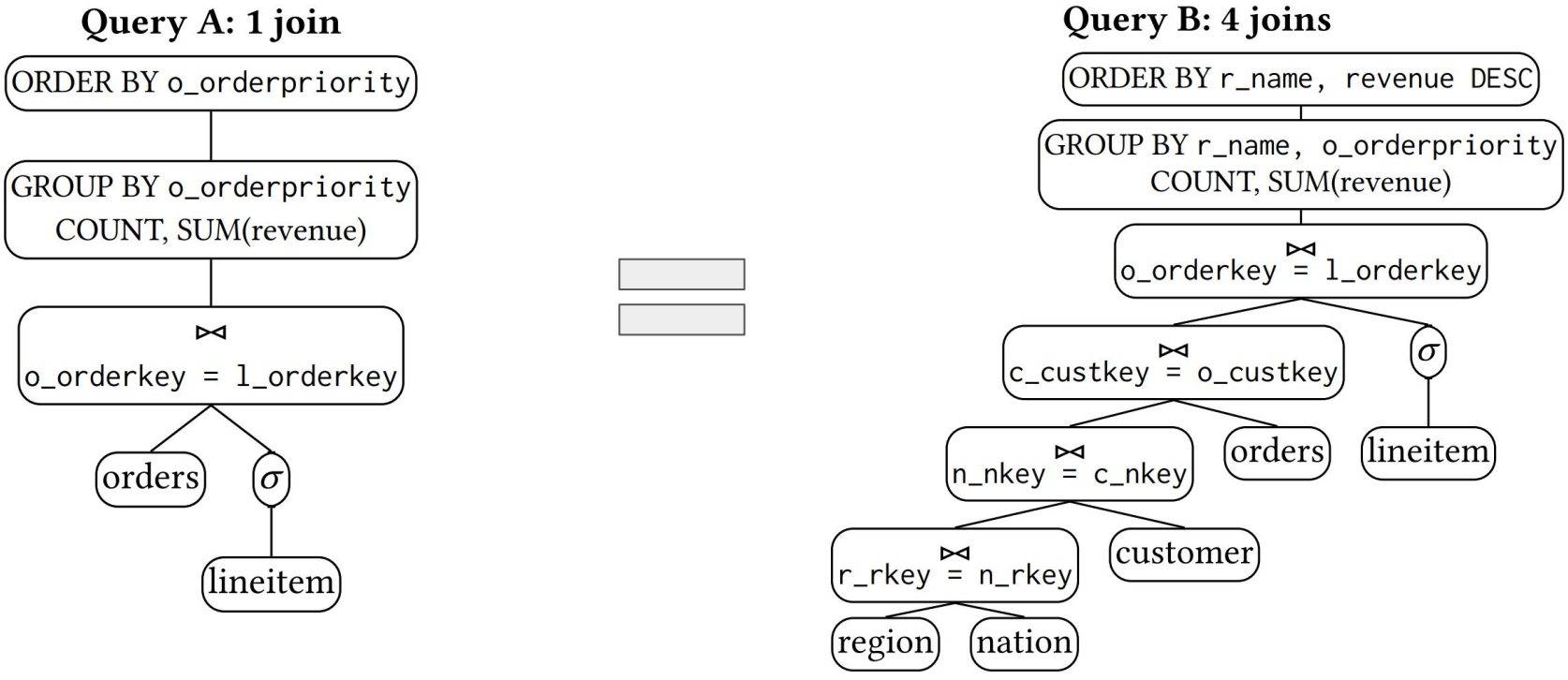
Repeats in a feedback loop until matching succeeds

Experiment 1: Varying the database system



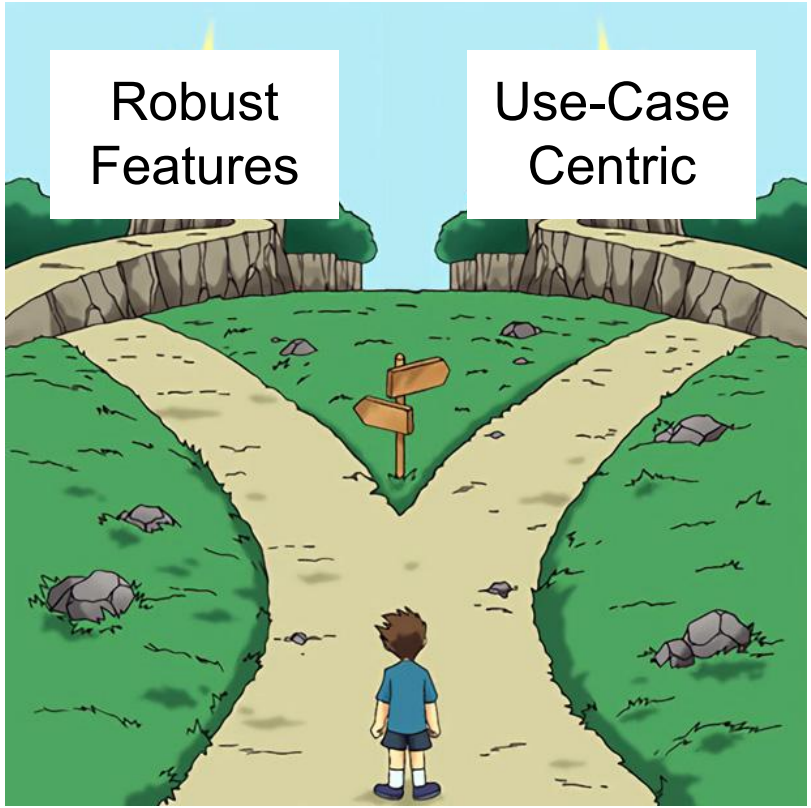
Insight 1: System telemetry describes how a particular engine executed a query

Consequence: No Guarantee on Structural Fidelity



These two queries produce nearly identical telemetry.

Where do we go from here?



Path 1: Transferable Workload Features

Enrich traces with engine-agnostic features beyond telemetry

Query Structure

E.g., subquery depth, CTEs, window functions

Data Characteristics

E.g., null fraction, data-type distribution

Plan-Shape Features

E.g., Join algorithm, parallelism, relative cardinalities

Workload-Level Features

Read/write ratio, access frequency, session type

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- *Privacy-preserving Query Anonymization: Open Challenge [6]*
- *Recent attempts of standardizing system-agnostic query representations (Substrait [7])*

Example: Our query similarity evaluation

We used 27 AST-based features to measure structural similarity between queries

Count Features (14)

n_tables, n_joins, n_filters,
n_aggregations, n_group_by_cols,
n_order_by_cols, n_select_cols,
n_subqueries, n_and, n_or,
n_comparison_ops, n_math_funcs,
n_string_funcs, n_date_funcs

Boolean Features (12)

has_having, has_limit,
has_distinct, has_union,
has_case, has_window,
has_exists, has_in_subquery,
has_cte, has_between,
has_like, has_not

Structural (1)

depth: maximum
AST nesting depth

Richer query structure information already enabled us to identify weaknesses of generated queries

Path 2: Use-Case-Centric Benchmarks

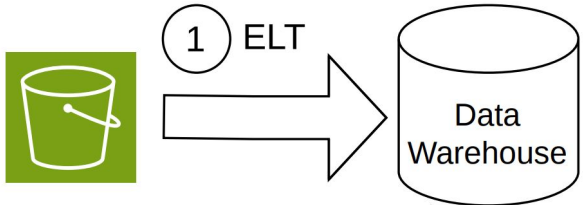
We know how data warehouses are used

- dbt, Superset, Airflow, …
- We also know that machine-generated queries from these tools favor specific SQL patterns (e.g., CTAS)

Instead of reverse-engineering queries, just run the tools.

Path 2: Use-Case-Centric Benchmarks

Jaffle Shop e-commerce: dbt (ELT) + Superset (BI) on Firebolt



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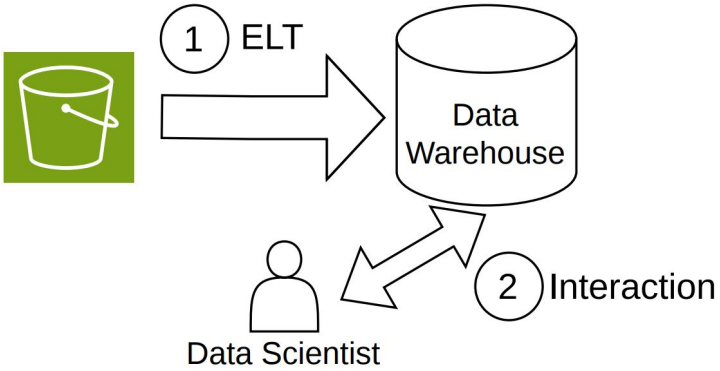

- Start with a well-defined analysis task
- Identify the relevant business questions

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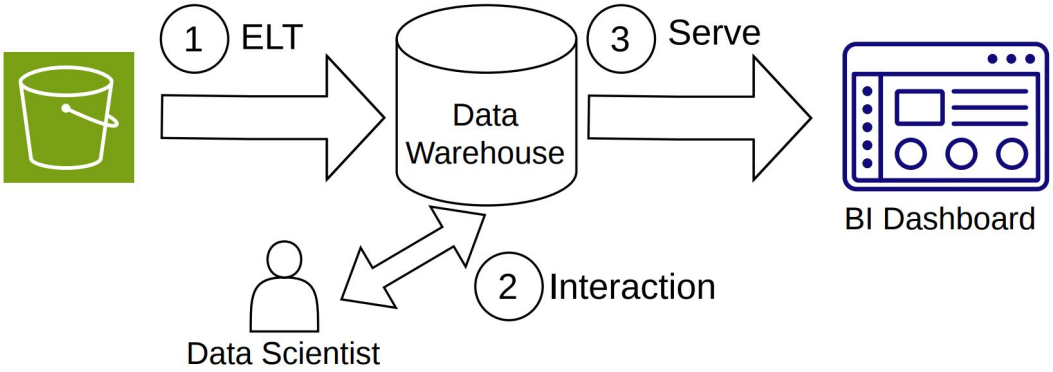

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- Let standard data-engineering tools generate the SQL (e.g., dbt, Apache Superset)

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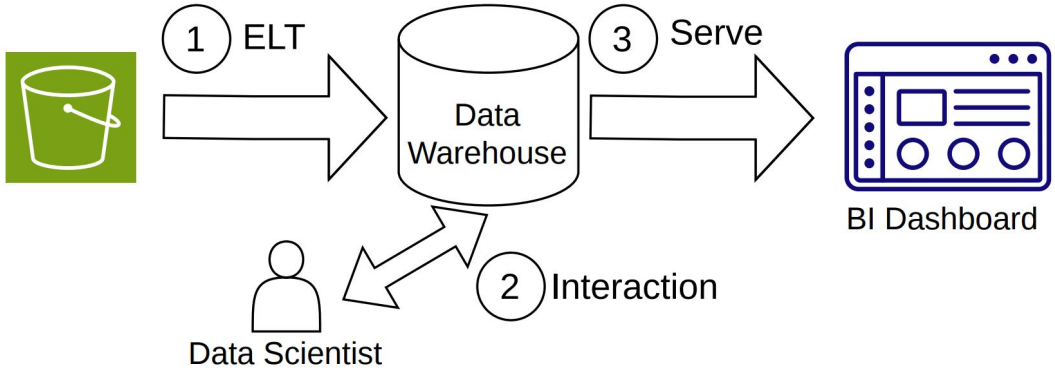

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Queries are transparent by construction

Preliminary Workload Insights

Patterns matching industry traces:

- Joins on string columns
- Timestamp operations
- Structural repetition: same template, different filter values

Patterns absent from synthesis tools:

- CTEs, LIKE, BETWEEN
- dbt compiles its DAG into CTAS sequences (Redset: CTAS accounts for 54.7% of runtimes)
- Real aggregation patterns (no SIN/MD5)

Final Projects

Project Guidelines

Deliverables

- **Code:** implementing the project (Git repo, reproducible).
- **Short report:** summary of findings.
- **Presentation:** ~10 minutes + questions.
- **Deadline:** 14.07

How it works

- 8–9 topics on offer: sign up for one.
- Up to 2 students per topic: two students each own a distinct part, not the same task.
- **Supervisor:** every project has one; check in with them.
- **Duration:** 4-weeks

Project Topic 1: Transferable Workload Features

Telemetry says how one engine ran a query. Can engine-agnostic features describe the query itself portably across systems?

Telemetry (CPU, bytes, op counts) underdetermines a workload — many different query structures hit the same numbers. So a synthetic stream can "match the metrics" yet look nothing like production.

Description: This project builds an engine-agnostic feature extractor and uses it in a loop: generate queries

→ generate a batch of queries

→ run them on the cloud-analytics benchmark; record telemetry and structural features

→ compare that profile against a target (real) workload: the differences show where the synthetic set is off

→ turn those differences into extra generation constraints and regenerate

Deliverables: Feature extractor + workload generator

Relevant Works:

- Cloud Analytics Benchmark
- Redbench

Supervisor: Michalis Georgoulakis (michalis.georgoulakis@tum.de)

Project Topic 2: Use-Case-Centric Benchmarks

Instead of reverse-engineering SQL from telemetry, start from a real application and let standard tools generate the workload.

Description: Synthetic benchmarks (TPC-H/DS) are shaped by a designer; real traces are private. This project takes a third path — build a workload from a real use case with real tools, so the SQL emerges from the stack instead of being hand-written:

→ pick an application scenario and its business questions

→ let dbt (ELT) and Superset (BI) generate the actual SQL — queries the tools emit, not a benchmark author

→ capture the resulting workload (the real SQL the stack runs)

→ characterize its patterns against synthetic benchmarks (TPC-H/DS) and industry traces (Snowset/Redset)

Deliver: A runnable use-case workload + a report contrasting its query patterns with a synthetic baseline.

Relevant works:

- Workload Insights from Snowflake
- Why TPC is not Enough: An Analysis of the Redshift Fleet

Supervisor: Michalis Georgoulakis (michalis.georgoulakis@tum.de)

Project Topic 3: Statistics for Object-Store Pruning

On object storage, request count is the currency. Which statistics let a reader skip data — and when does the metadata they cost outweigh what they save?

Given: Parquet data (optionally Delta / Iceberg tables) on Azure Blob; an engine that exposes pruning (e.g., DuckDB); selective queries spanning a range of selectivities.

Core task: Quantify, in object-store terms, how effective each pruning statistic is — partition pruning, row-group min/max (zone maps), the Parquet page index, and bloom filters. For each, report data skipped, object-store requests (metadata vs data), read amplification, and latency as a function of selectivity.

- Fine-grained stats trade extra metadata reads for skipping - find where each pays off.
- More metadata trade extra storage space for skipping.

Deliver: A report comparing pruning effectiveness per statistic across selectivities.

Resources:

- Pruning in Snowflake: Working smarter, not harder
- When metadata is big data

Supervisor: Michalis Georgoulakis (michalis.georgoulakis@tum.de)

Project Topic 4: Provisioned + Serverless Scheduling

Provisioned pools cost money while idle; serverless pay-per-query gets pricey under load. Can a scheduler route each query to the cheaper one without missing a latency target?

Given: Azure Synapse: a provisioned (dedicated) SQL pool (pay-per-hour, fixed capacity) and the serverless SQL pool (pay-per-TB-scanned, scales to zero) and an input workload with varying arrival patterns.

Core task: Build a scheduler that places each incoming query on the provisioned pool or on serverless SQL: based on its size and the current load to minimize cost subject to a latency target, or the opposite.

Deliver: Working scheduler and performance numbers

Bonus: Pause / resume or resize the provisioned pool to exploit idle windows.

Resources:

- Saving Money for Analytical Workloads in the Cloud

Supervisor: Michalis Georgoulakis (michalis.georgoulakis@tum.de)

Project Topic 5: Distributed DuckDB via Quack

How much of a hand-written distributed engine can a declarative layer recover? We “hack” Quack’s remote-scan capability to mimic distributed execution.

Given: DuckDB (a fast single-node, in-process engine) and Quack — one DuckDB issues remote scans against others with predicate pushdown. Note: Quack targets client-server-style access, not distribution; we repurpose it.

Goal: Hash-partition a relation across K DuckDB instances purely in SQL (the shuffle as remote scans + pushdown) and demonstrate a distributed aggregation. Characterize: scaling with K, bytes actually shuffled (and how much pushdown reduces them), and end-to-end latency vs a single DuckDB. Identify where the declarative path leaves performance on the table.

Optional: Extend to a distributed hash join by co-partitioning both inputs.

Resources:

- **Quack:** The DuckDB Remote Client-Server Protocol

Supervisor: Maximilian Rieger (riegerm@in.tum.de)

Broadcast vs. Partitioned Joins

An empirical study of when each strategy wins

The core question

A broadcast join replicates the build side to every worker; a partitioned (shuffle) join re-partitions **both** inputs by the join key. Which should the optimizer pick — and where exactly does the trade-off flip?

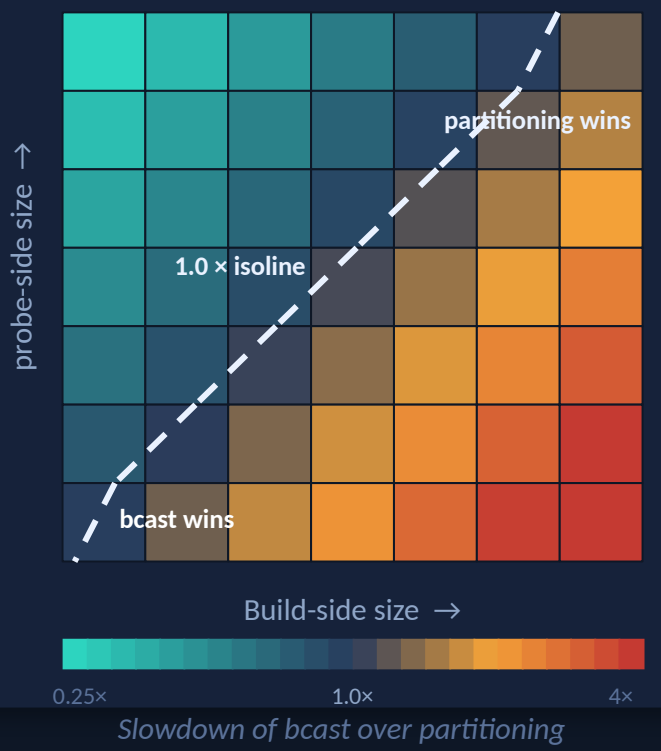
Build side drives cost

Conventional wisdom: the deciding factor is the size of the build-side hash table that must be broadcast.

Probe side is never shuffled

Broadcast's hidden edge — the (often huge) probe side stays put, avoiding a full re-partition over the network.

2D slowdown heatmap



Slowdown of bcast over partitioning

WHAT TO LOOK FOR

01

Where does the 1.0× isoline actually fall?

02

How far does a large probe side push the boundary toward bigger builds?

03

Two base table filters let you sweep the size space in 2D.

Contact: Abdelrahman Adel (abdelhaa@cit.tum.de)

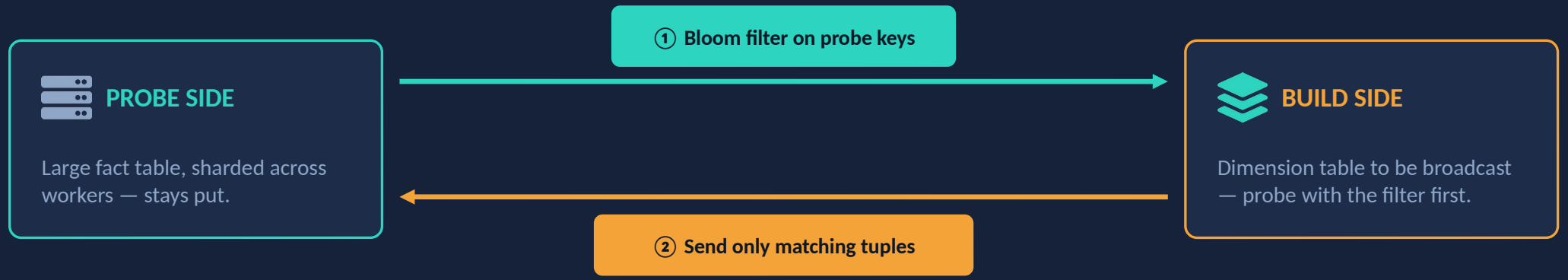
4-WEEK PROJECT PHASE

PROJECT 02

Semi-Join Reduction with Bloom Filters

Shrink the broadcast by filtering before you send

THE REDUCTION PIPELINE



QUESTION A

How big should the filter be?

Bits per key trades memory and network for a lower false-positive rate. Too small and junk tuples survive; too large and you erode the savings.

- Sweep bits/key vs. tuples sent
- Find the false-positive sweet spot
- When is it worth an extra round-trip (bloom filter on build-side AND probe side)?

QUESTION B

Per-worker or one combined filter?

Per-worker filters are cheap but each carries its own false positives. One merged (OR-combined) filter is tighter — but re-scanning the build side per worker costs passes.

- Per-worker FPR vs. combined filter
- Extra build-side scans/checks worth it?

Contact: Abdelrahman Adel (abdelhaa@cit.tum.de)

Project Topic 8: Open Table Formats on Object Storage

How do Delta Lake and Iceberg actually use object storage underneath a workload: and how have they changed since 2023?

Given: Spark + Delta Lake & Apache Iceberg (Hudi optional) on Azure Blob; Jain et al. (CIDR 2023) as the methodological starting point.

Core task: Bring Spark to current Delta / Iceberg releases and reproduce ONE workload class: point lookups, merge/upsert, or time-travel. Measure object-store behavior underneath: number & size of requests, metadata read amplification, and latency per format.

Deliver: (a) a results report for the chosen workload across both formats; (b) a current feature-and-version matrix showing how the formats evolved since 2023

Bonus: Add Apache Hudi to the comparison, and/or extend to a second workload class.

Supervisor: Tobias Götz (goetzt@in.tum.de)

Project Topic 9: Object-Store-Native Transactions

Can transactional reads be served purely through object-store semantics and no external coordinator? Characterize the request pattern that buys.

Given: The LakeVilla (LV) prototype (C++) with its existing Delta Lake path; hudi-rs (Hudi's Rust implementation) and its C++ bindings; Azure Blob Storage.

Core task: Characterize existing Azure Blob data path wrt throughput, latency, and the object-store request pattern LV generates to provide transactional reads with no external coordinator. Implement LV[Read] for Apache Hudi via the Rust C++ bindings (a Copy-on-Write snapshot read suffices) and compare its object-store behavior against the Delta baseline.

Bonus: LV[Write].

Resources:

- LakeVilla

Supervisor: Tobias Götz (goetzt@in.tum.de)

Next Week

- **Topic Selection Confirmation:** Everyone tells us what they plan to work on.

- **Praktikum Outlook:** Hardware trends in the cloud and open research directions

- **Lab 6:** Oral Discussion
  - Deadline: **18.06, 23:59:59**