

# Liberate Analytical Data Management with DuckDB





D S QL 1337



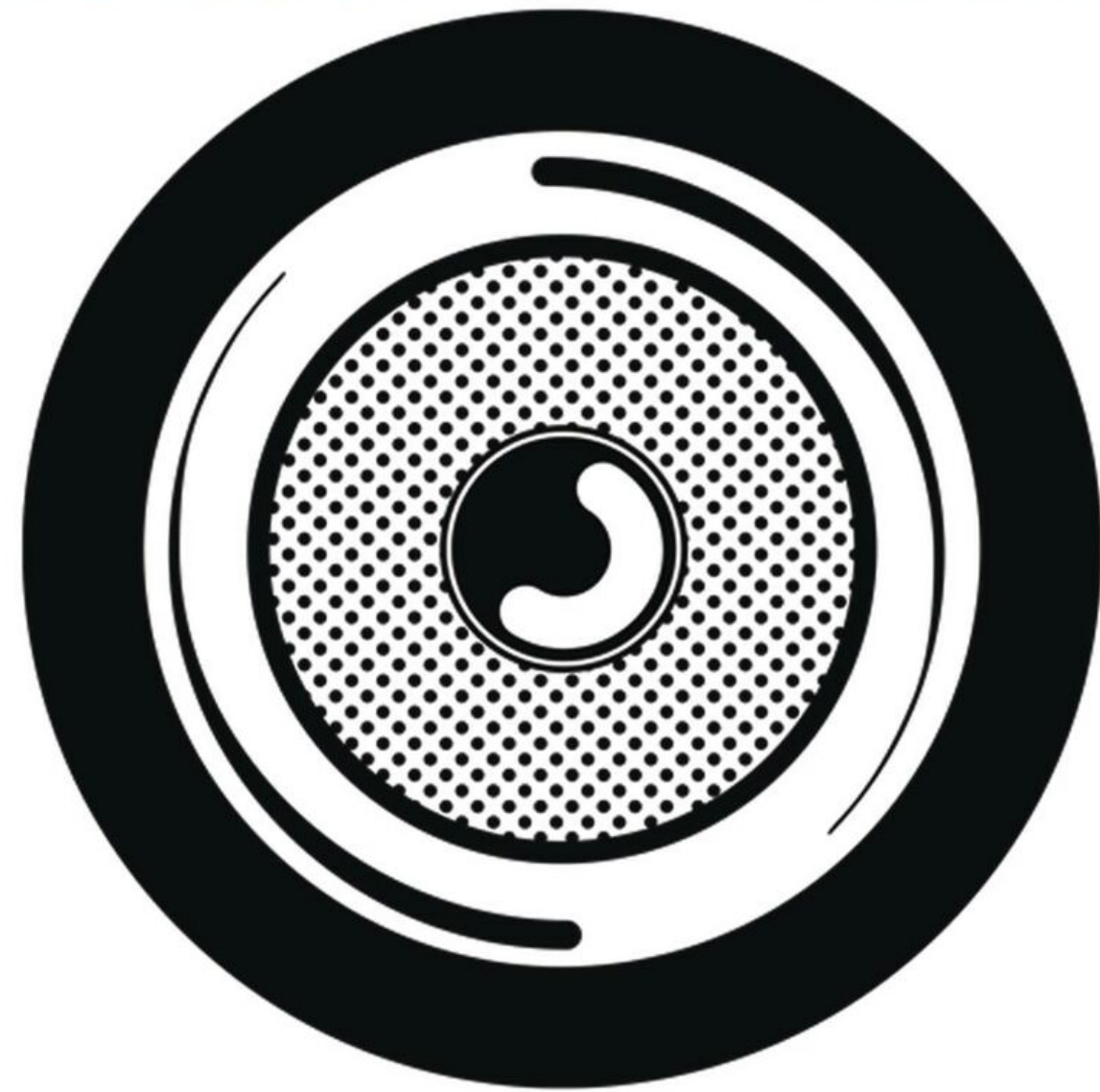
# Act 1: The Backstory



2015

MARK  
RONSON

FEAT: BRUNO  
MARS



UPTOWN FUNK!  
TRINIDAD JAMES REMIX





teradata.

VERTICA



ENTERPRISE SPECIAL



HADOOP-ISTAN



Google  
Big Query



amazon  
REDSHIFT

CLOUD TODDLERS

ORACLE®  
DATABASE



Microsoft®  
SQL Server®

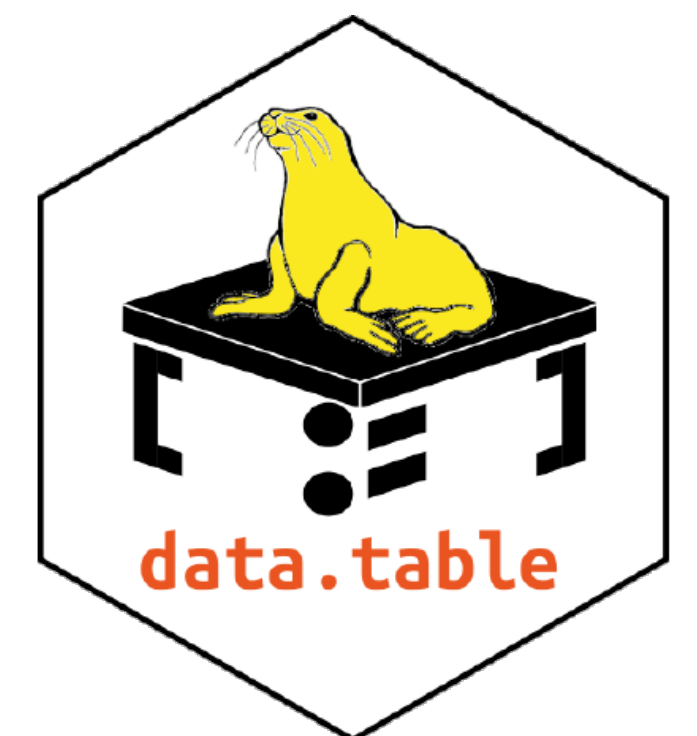
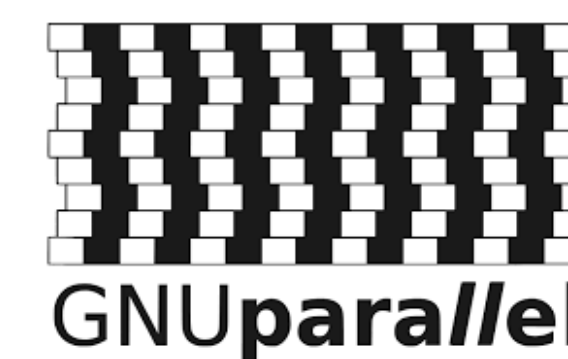


DINOSAUR ADD-ONS

# 2015 Analytics



OBSCUR E ACADEMIC SPIN-OFFS



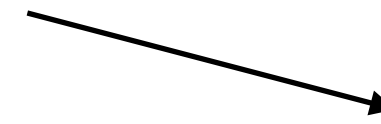
DESPAIR ENGINEERING



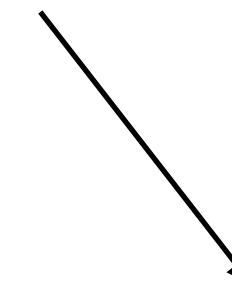




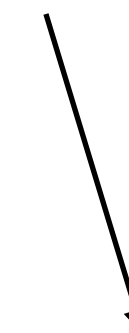
Can't  
pip import state\_of\_the\_art



have to build  
this ourselves?



100 people, 10 years  
Many \$\$\$



Pause

# Spite Engineering



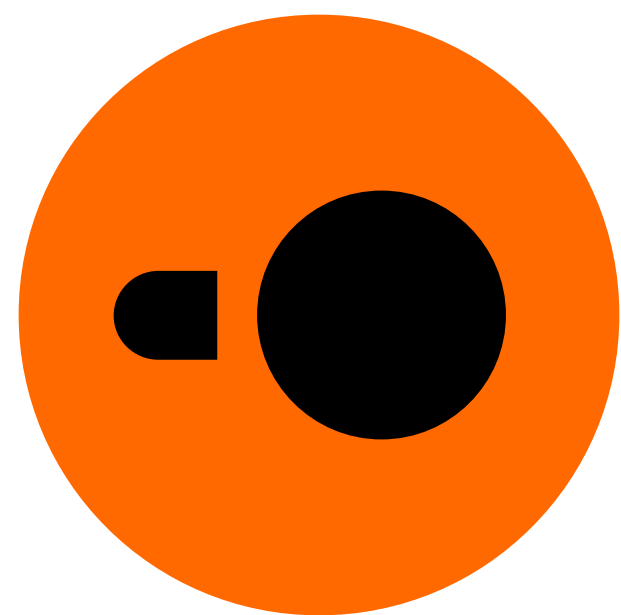






# SQLite for Analytics!







# **Act 2: Design Decisions**



# Distributed?





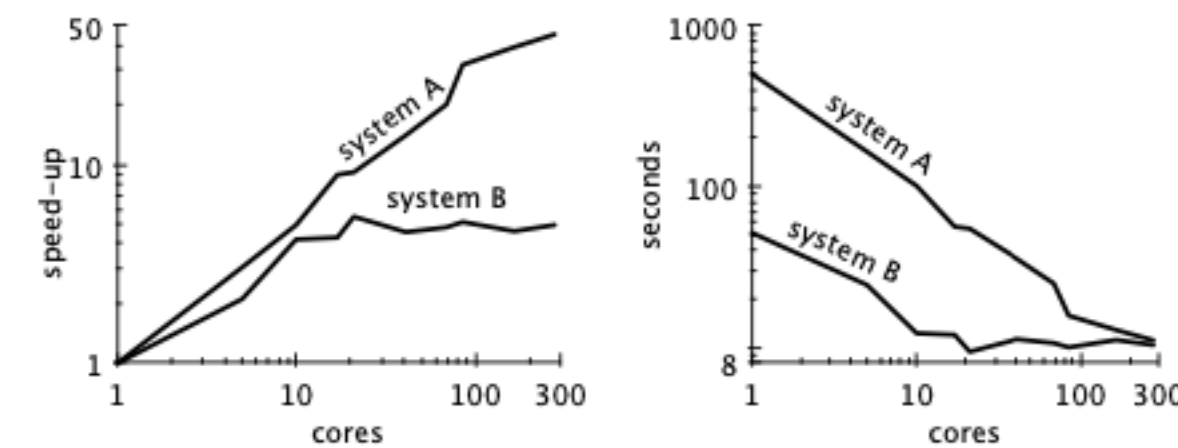
# Scalability! But at what COST?

Frank McSherry   Michael Isard   Derek G. Murray  
Unaffiliated   Unaffiliated\*   Unaffiliated<sup>†</sup>

## Abstract

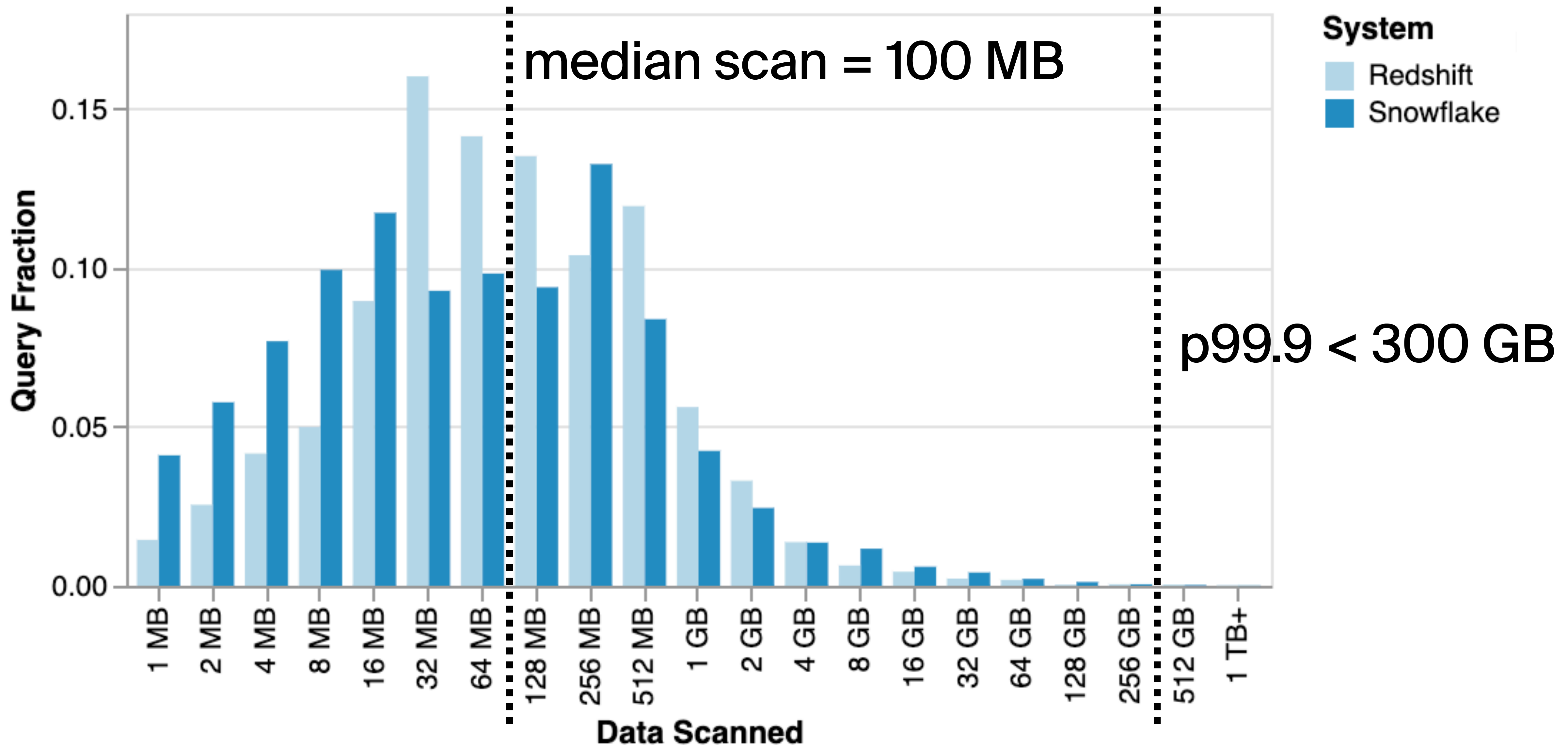
We offer a new metric for big data platforms, COST, or the Configuration that Outperforms a Single Thread. The COST of a given platform for a given problem is the hardware configuration required before the platform outperforms a competent single-threaded implementation. COST weighs a system’s scalability against the overheads introduced by the system, and indicates the actual performance gains of the system, without rewarding systems that bring substantial but parallelizable overheads.

We survey measurements of data-parallel systems recently reported in SOSP and OSDI, and find that many systems have either a surprisingly large COST, often



**Figure 1: Scaling and performance measurements for a data-parallel algorithm, before (system A) and after (system B) a simple performance optimization. The unoptimized implementation “scales” far better, despite (or rather, because of) its poor performance.**







# Single Node!







JIT



Vectorized





**GPU**



**CPU**





SIMD



Scalar



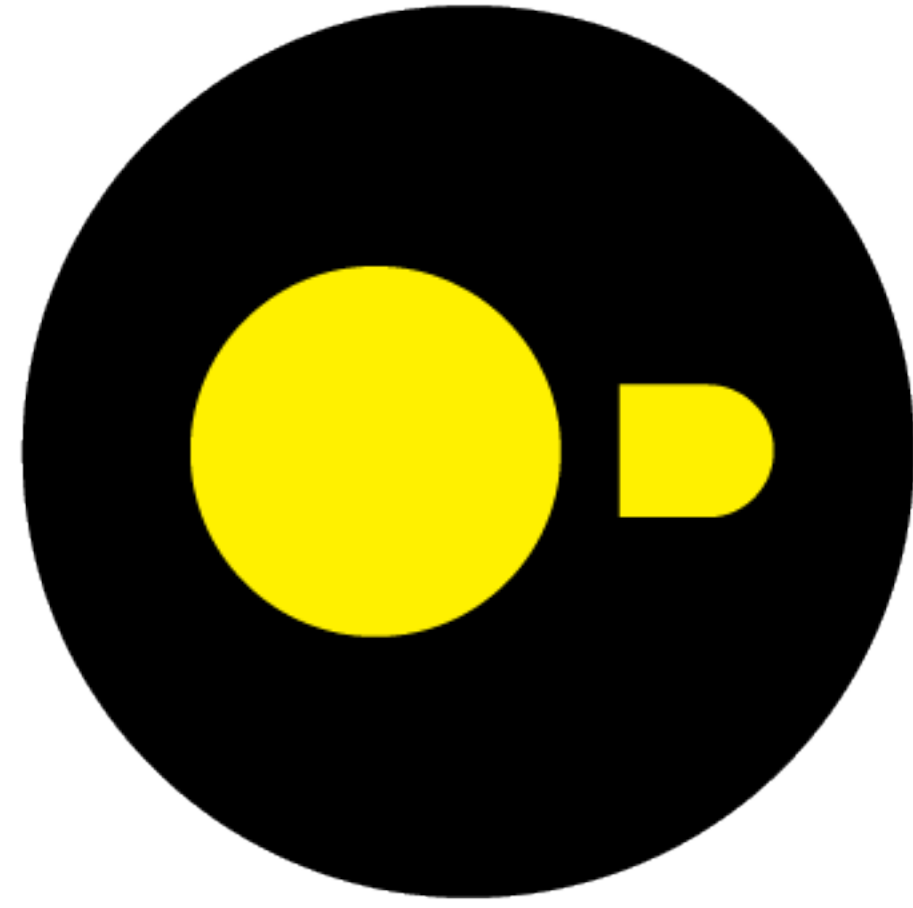


Proprietary



MIT





**DuckDB**

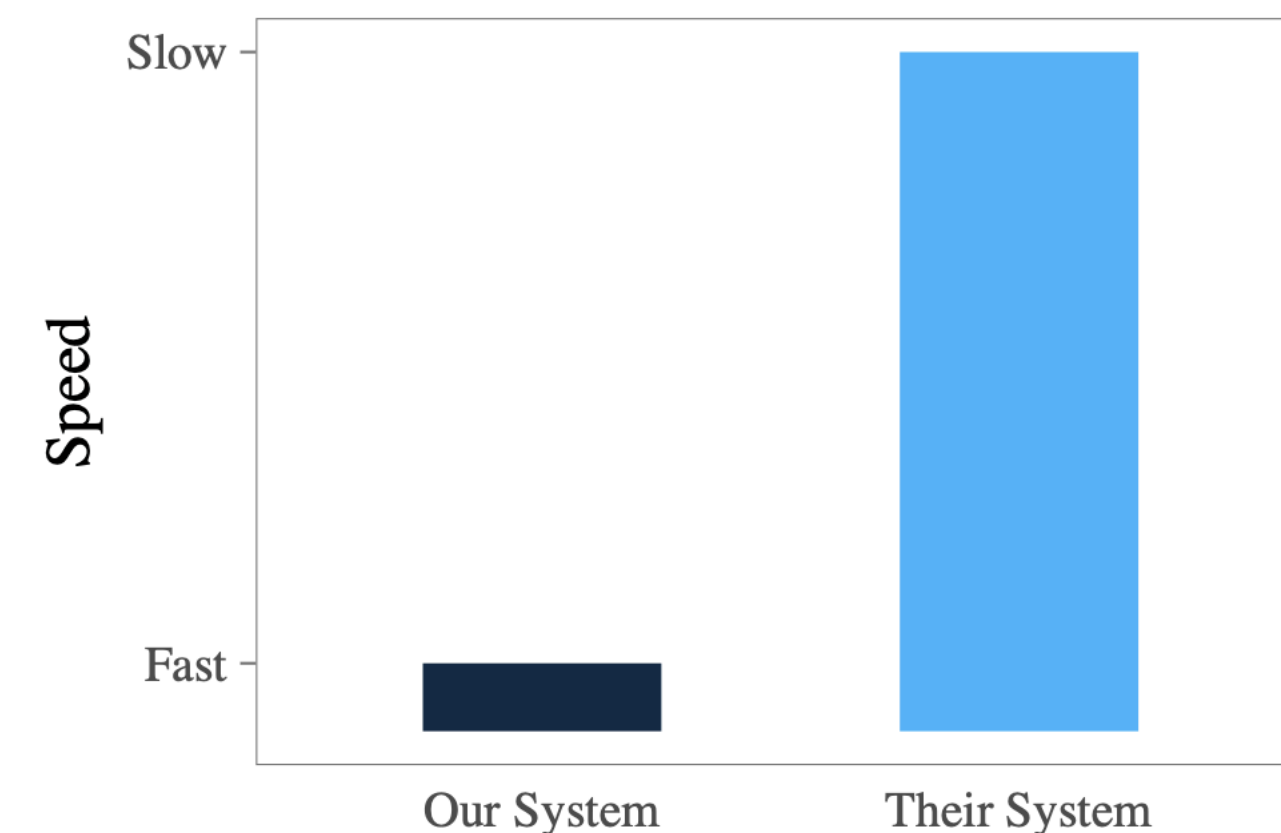


# Fair Benchmarking Considered Difficult: Common Pitfalls In Database Performance Testing

Mark Raasveldt, Pedro Holanda, Tim Gubner & Hannes Mühleisen  
Centrum Wiskunde & Informatica (CWI)  
Amsterdam, The Netherlands  
[raasveld,holanda,tgubner,hannes]@cwi.nl

## ABSTRACT

Performance benchmarking is one of the most commonly used methods for comparing different systems or algorithms, both in scientific literature and in industrial publications. While performance measurements might seem objective on the surface, there are many different ways to influence benchmark results to favor one system over the other, either by accident or on purpose. In this paper, we perform a study of the common pitfalls in DBMS performance comparisons, and give advice on how they can be spotted and avoided so a fair performance comparison between systems can be made. We illustrate the common pitfalls with a series of mock benchmarks, which show large differences in performance where none should be present.



**Figure 1: Generic benchmark results.**



# RTABench

a Benchmark For Real Time Analytics

Repo

System: 

All TimescaleDB ClickHouse Timescale Cloud MongoDB DuckDB Postgres ClickHouse Cloud (aws) MySQL

Database Type: 

All General Purpose Real-time Analytics Batch Analytics

Machine: 

All m5.4xlarge, 500gb gp2 c6a.4xlarge, 500gb gp2 4 vCPU 16GB 12 vCPU 48 GB (3x: 4vCPU 16GB) 16 vCPU 64GB 6 vCPU 24 GB (3x: 2vCPU 8GB) 8 vCPU 32GB 24 vCPU 96 GB (3x: 8vCPU 32GB)

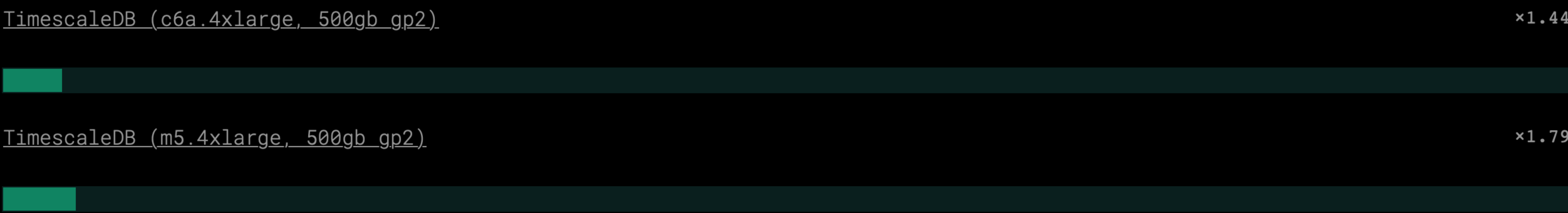
Cluster size: 

All 1 3

Metric: 

Cold Run Hot Run Load Time Storage Size

System and Machine Relative time (lower is better)





# RTABench

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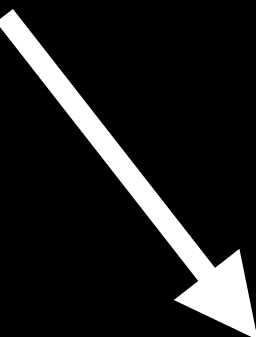
All m5.4xlarge, 500gb gp2 c6a.4xlarge, 500gb gp2 4 vCPU 16GB 12 vCPU 48 GB (3x: 4vCPU 16GB) 16 vCPU 64GB 6 vCPU 24 GB (3x: 2vCPU 8GB) 8 vCPU 32GB 24 vCPU 96 GB (3x: 8vCPU 32GB)

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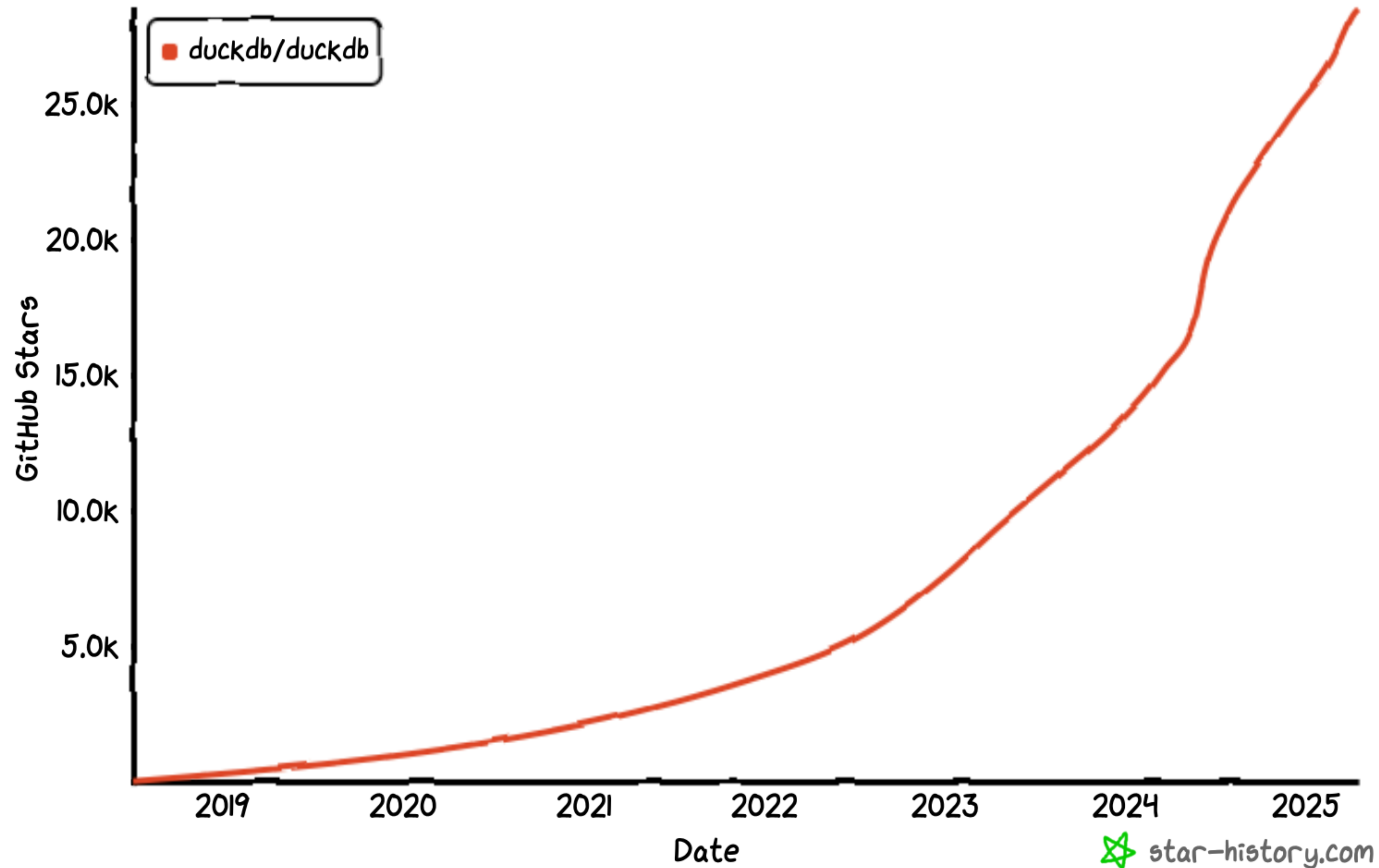
DuckDB (c6a.4xlarge, 500gb gp2)	×1.15
<div></div>	
DuckDB (m5.4xlarge, 500gb gp2)	×1.51
<div></div>	



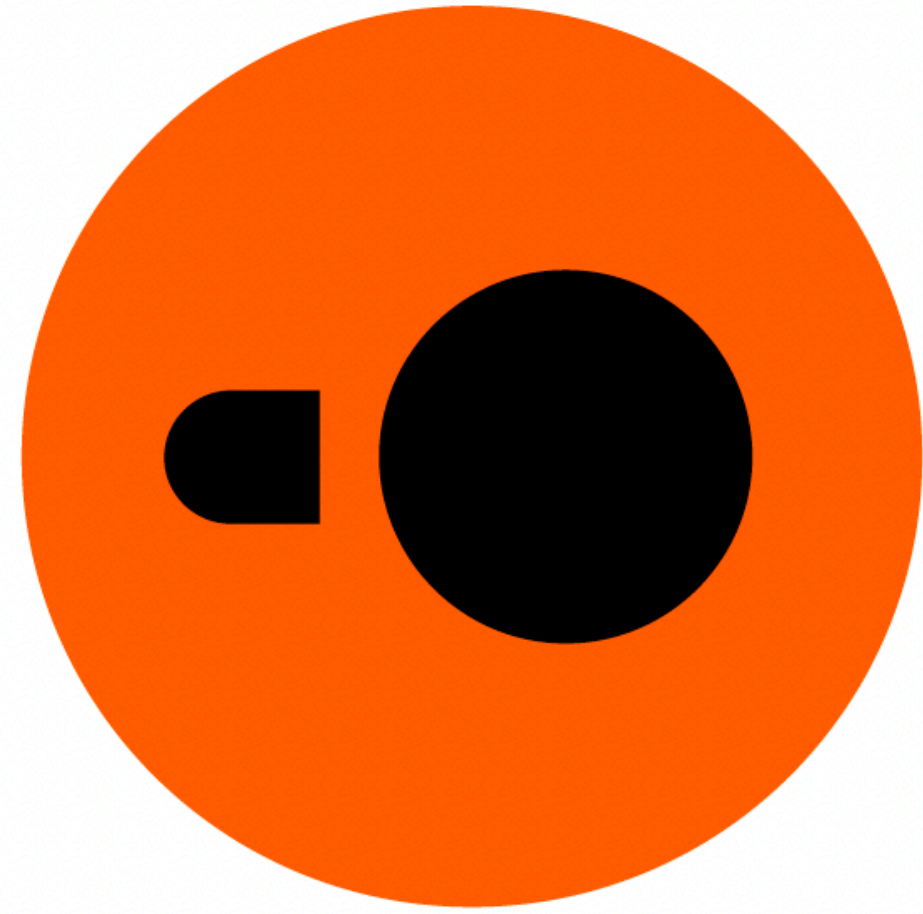
- DuckDB isn't built for real-time analytics, so it's excluded from the main results, but it was the fastest in the benchmark. Given its popularity, we included it in the benchmark to serve as a point of reference, and it surprised us: It was 3.5x faster than TimescaleDB and 7.3x faster than ClickHouse.



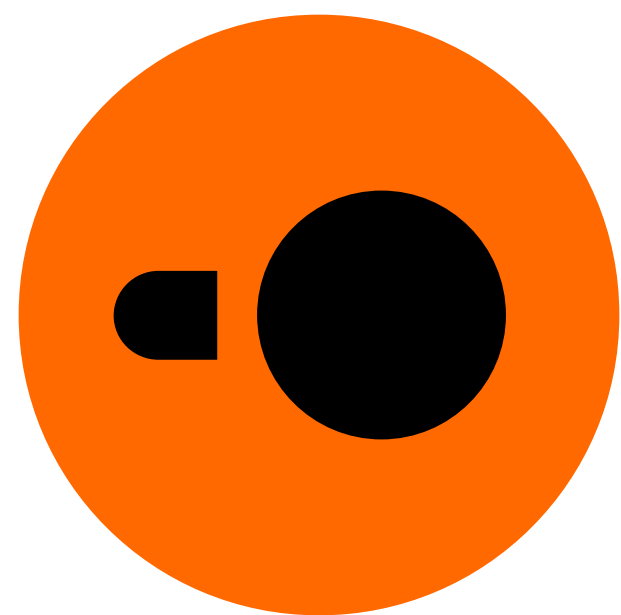
# Star History







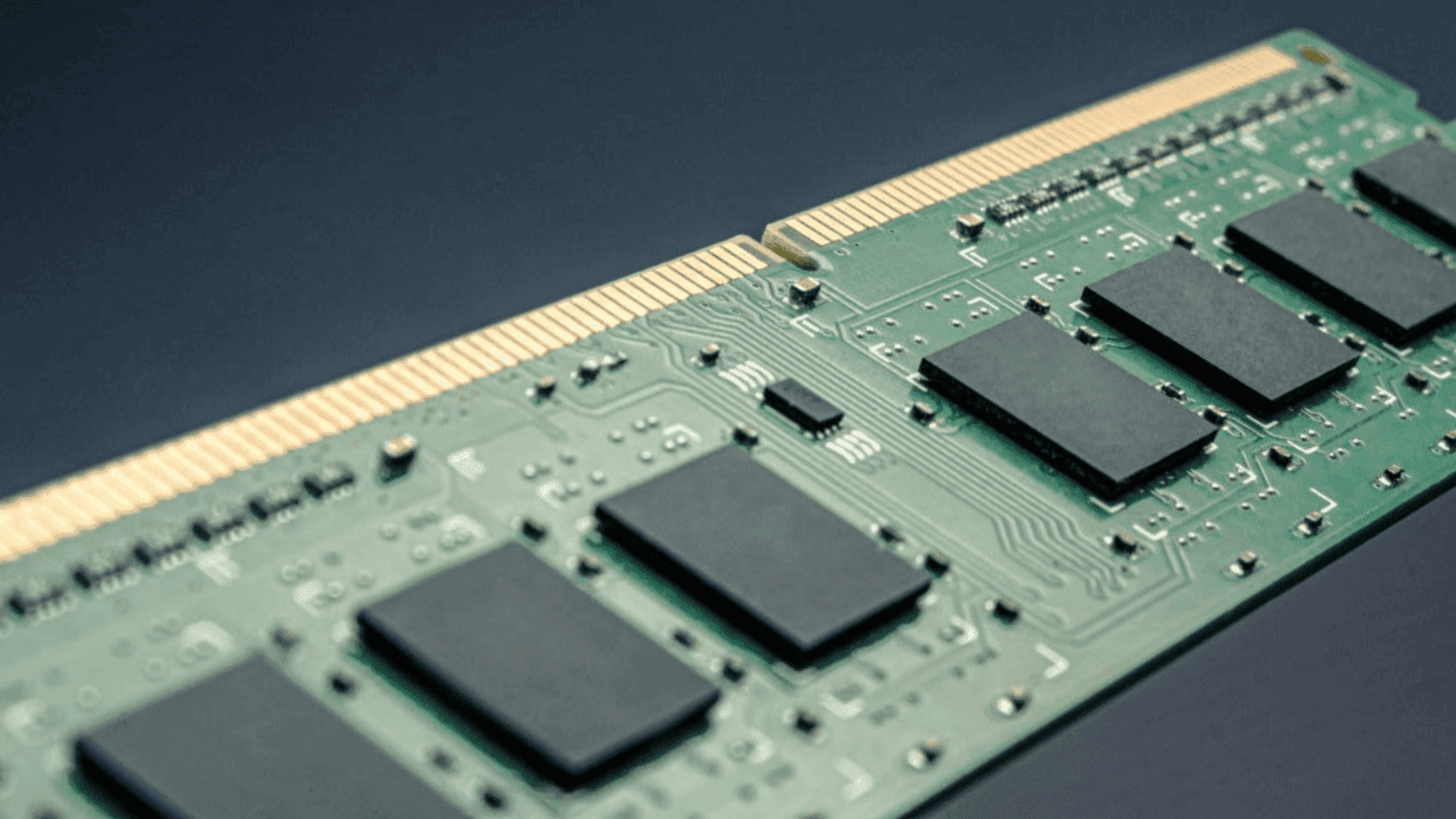
**DuckDB Labs**



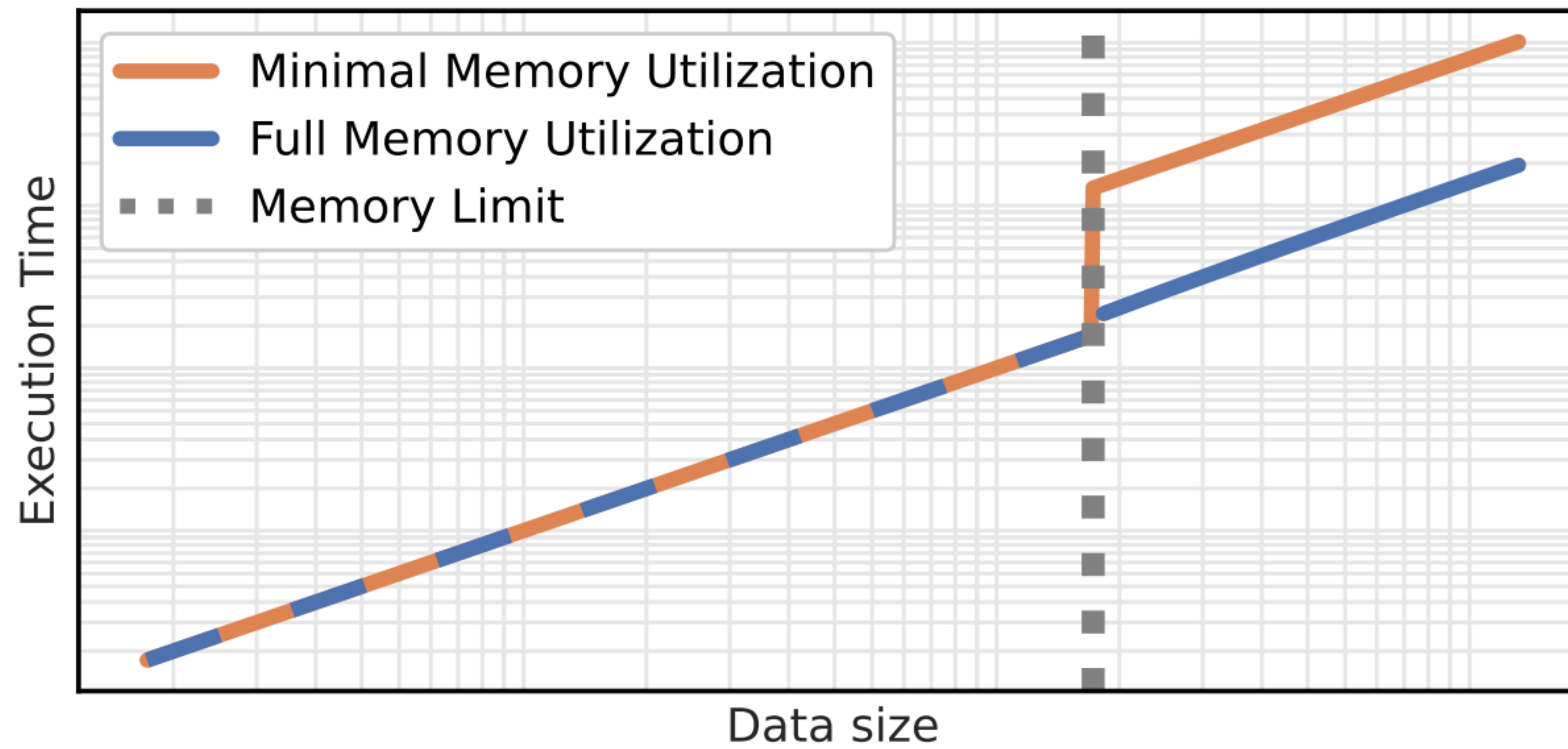


# Act 3: Going Deep









# **Saving Private Hash Join**

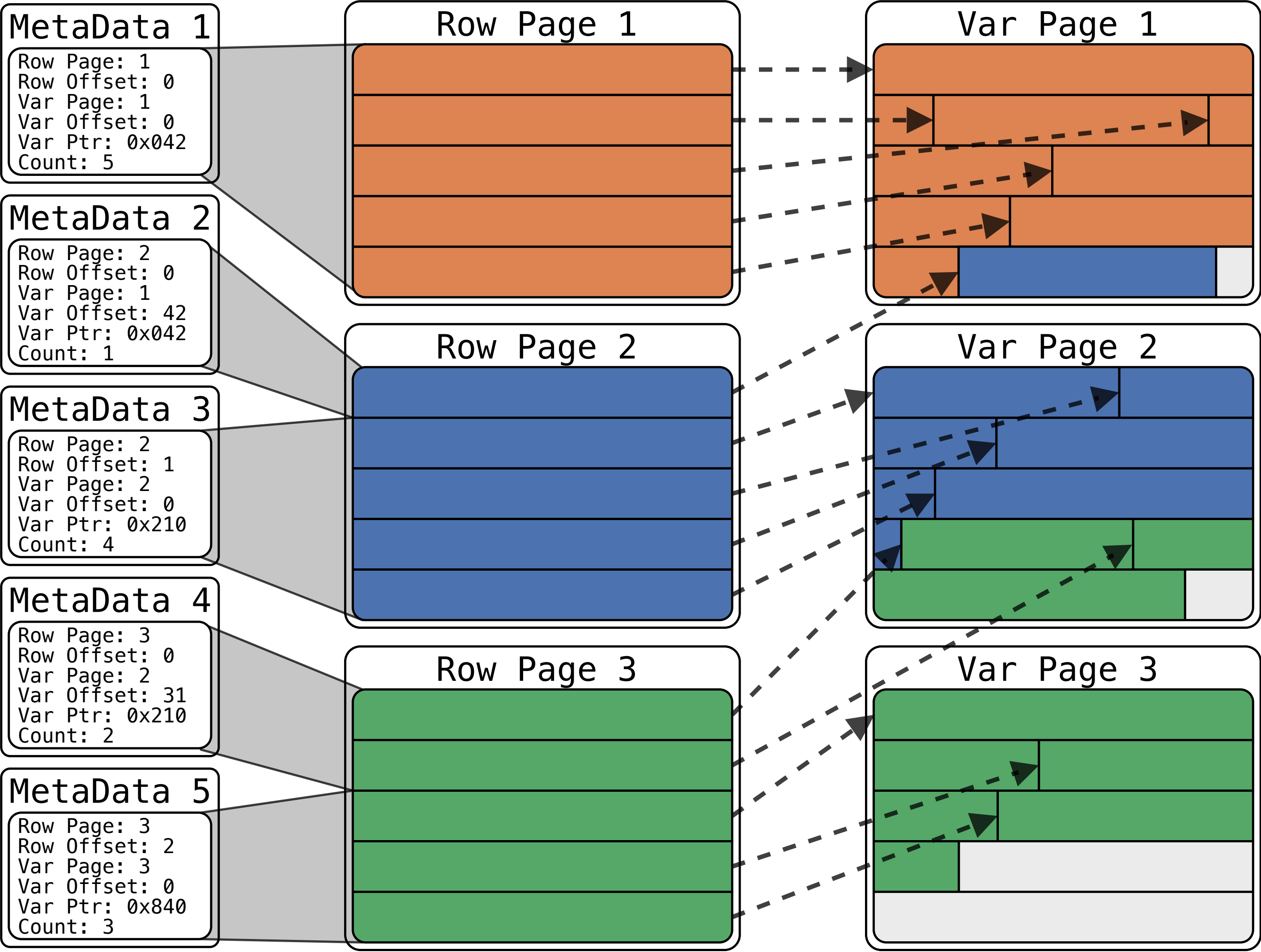
Laurens Kuiper, Paul Groß, Peter Boncz, Hannes Mühleisen

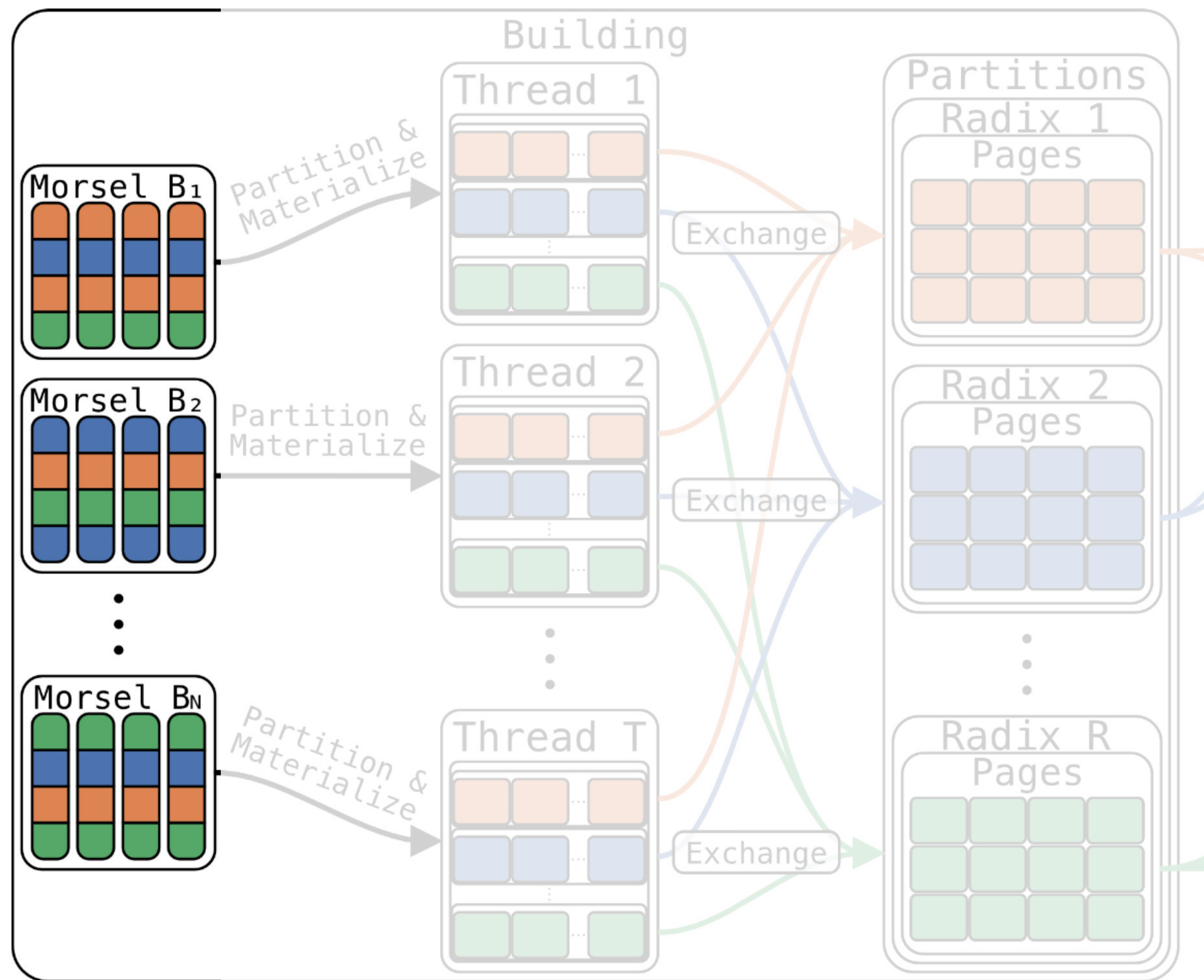
Centrum Wiskunde & Informatica

Amsterdam, The Netherlands

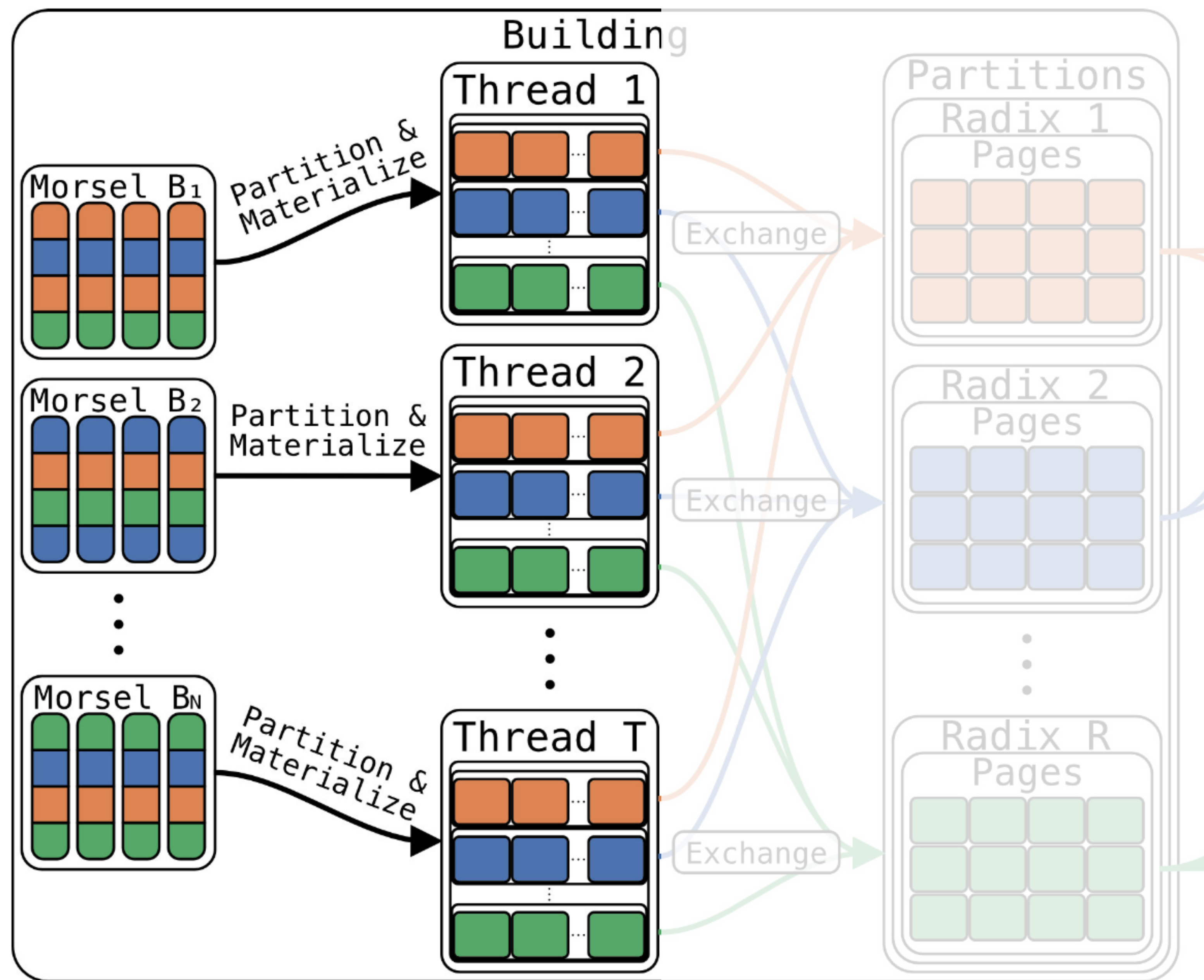
{laurens.kuiper,paul.gross,peter.boncz,hannes.muehleisen}@cwi.nl

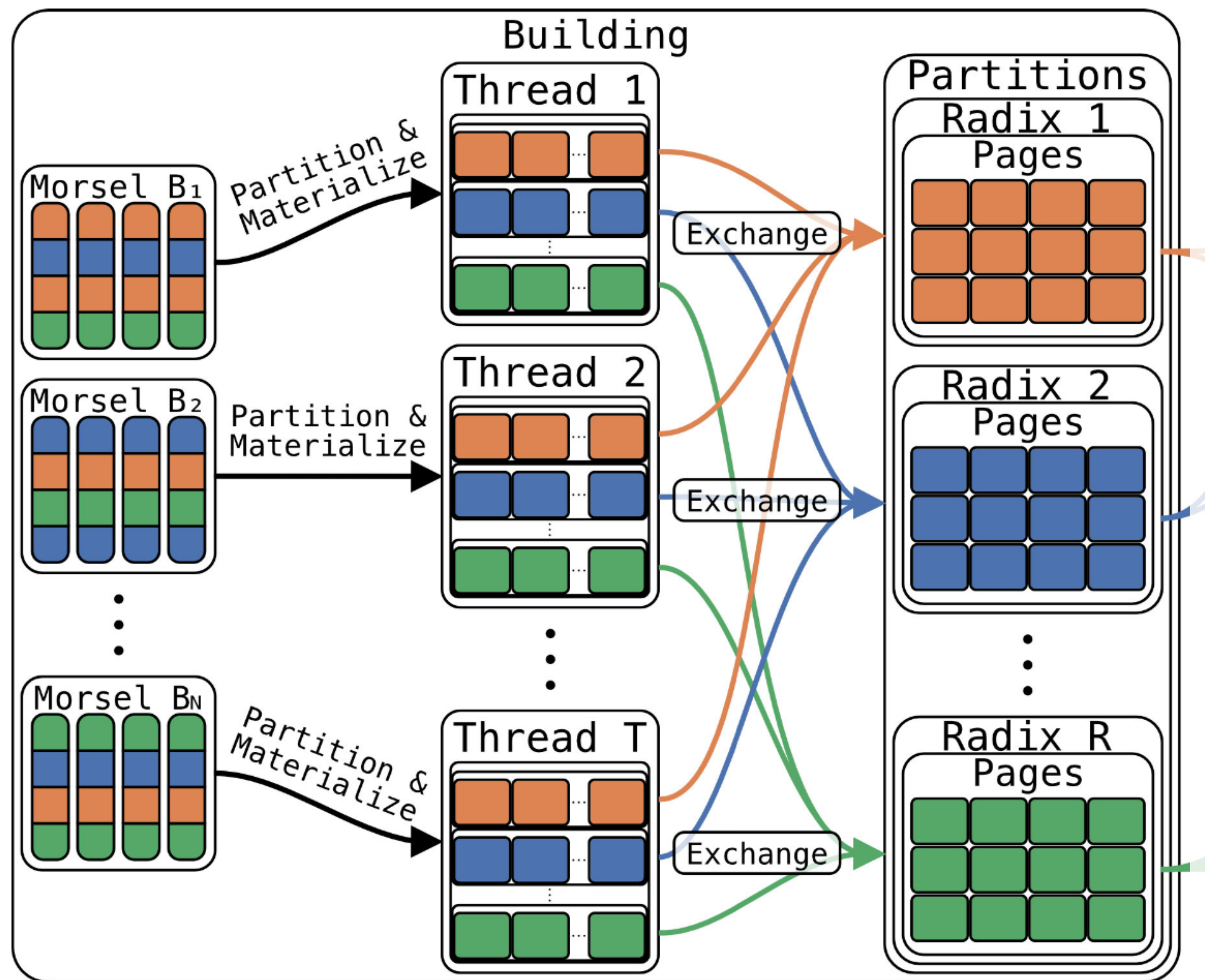




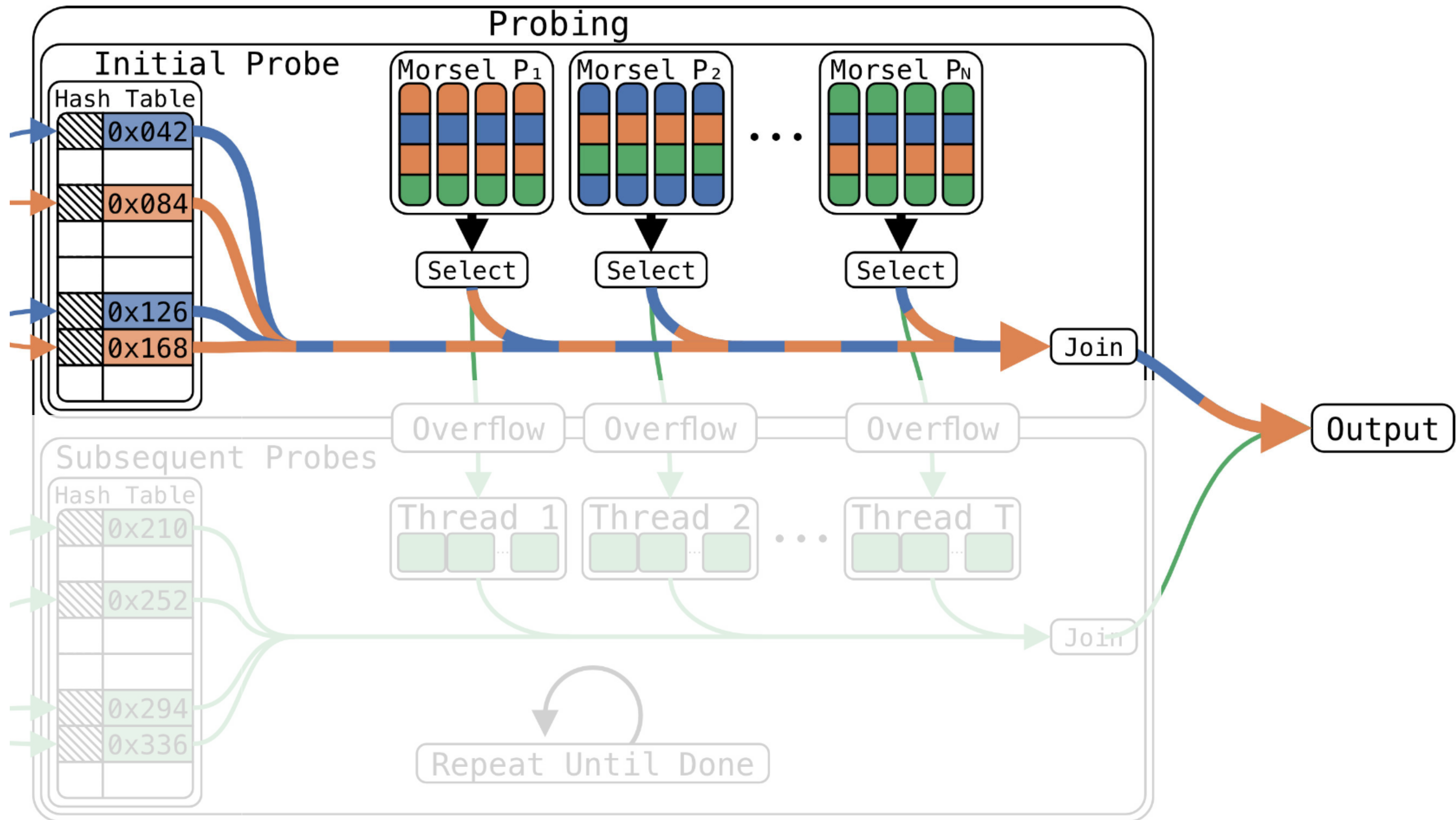


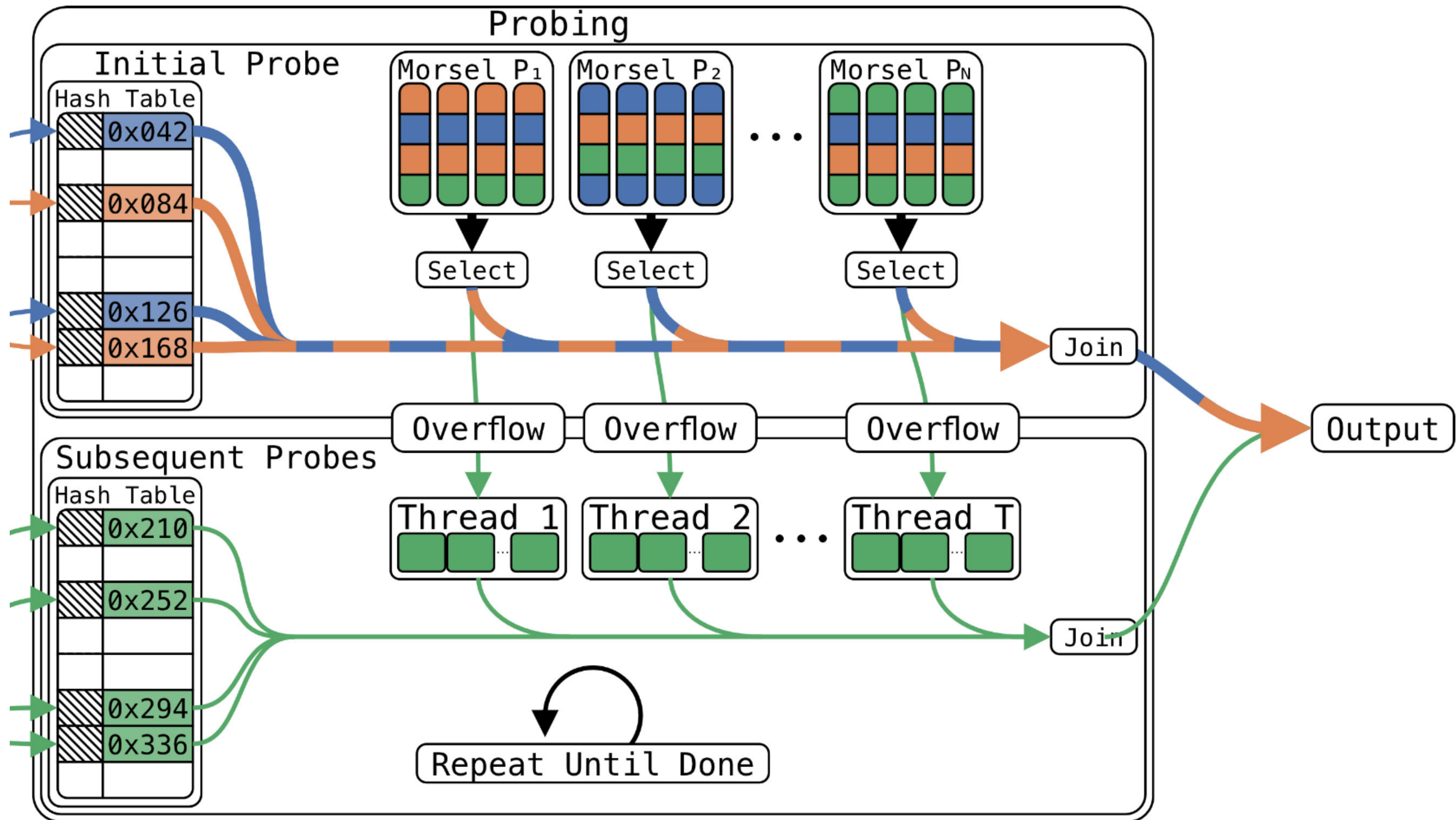




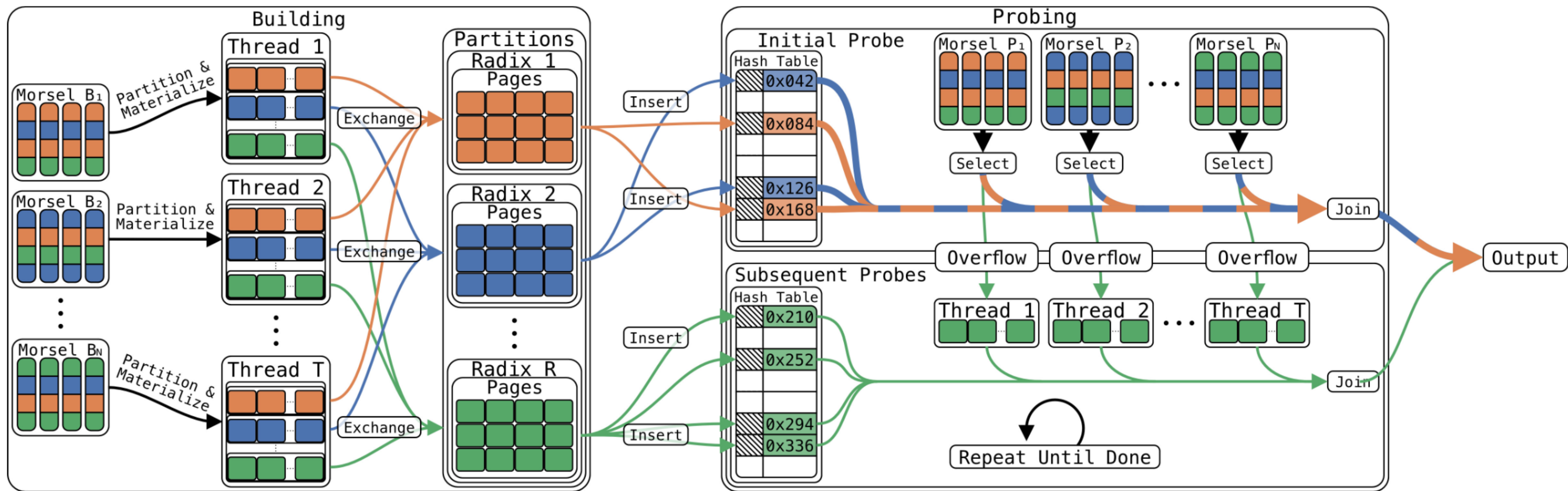


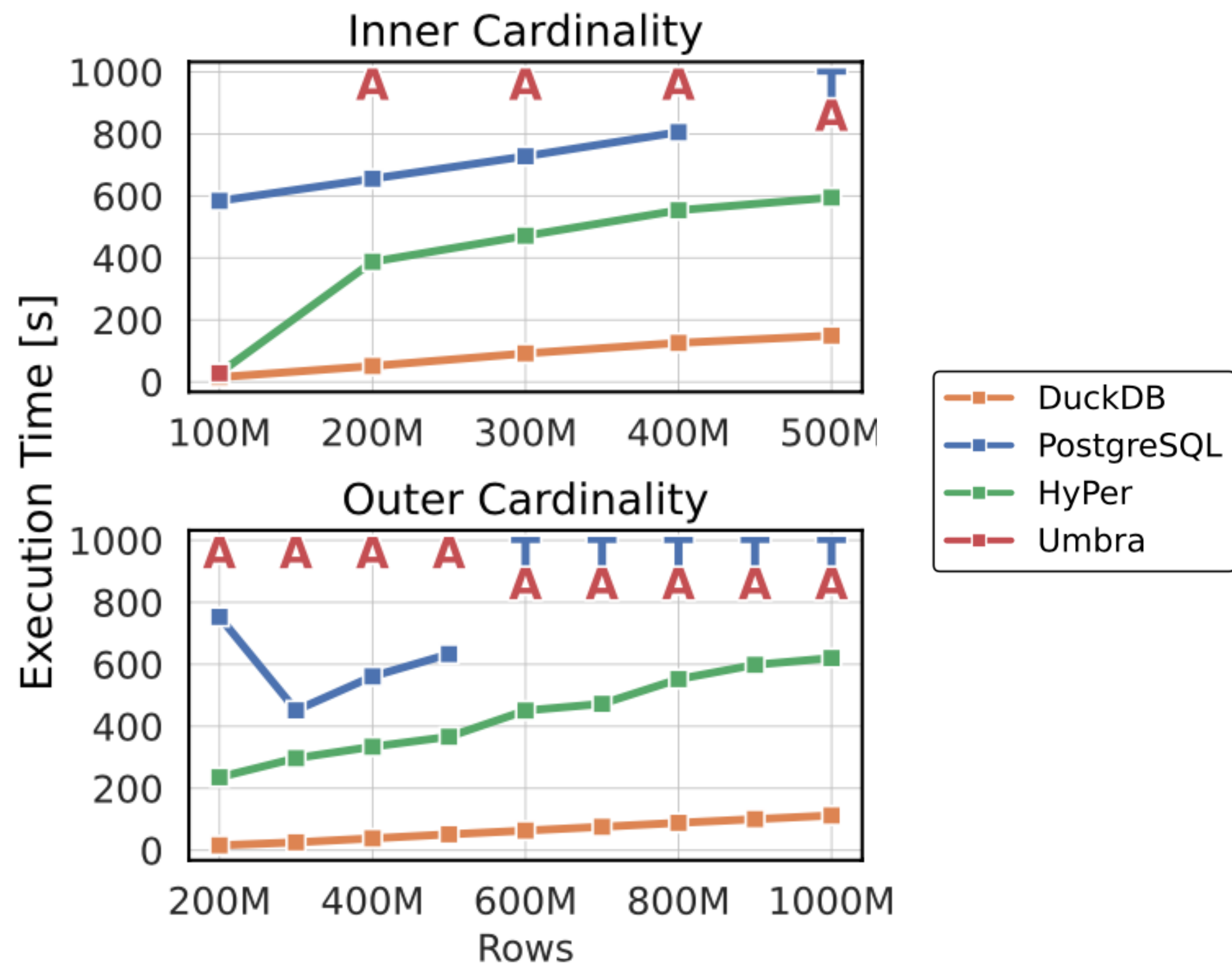




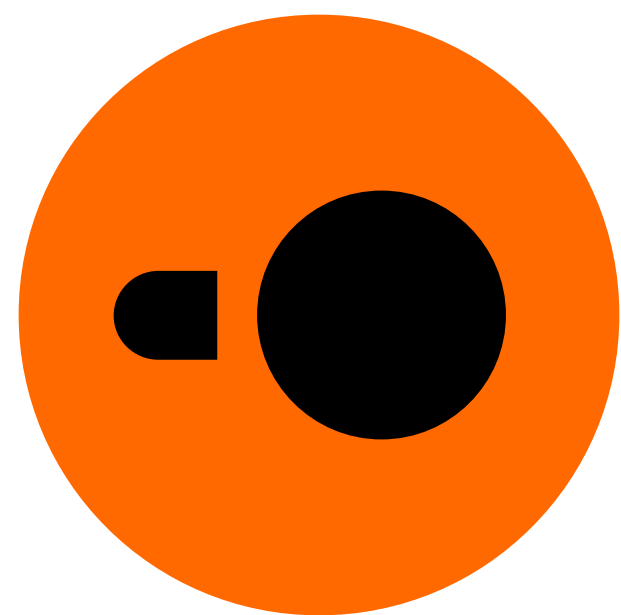






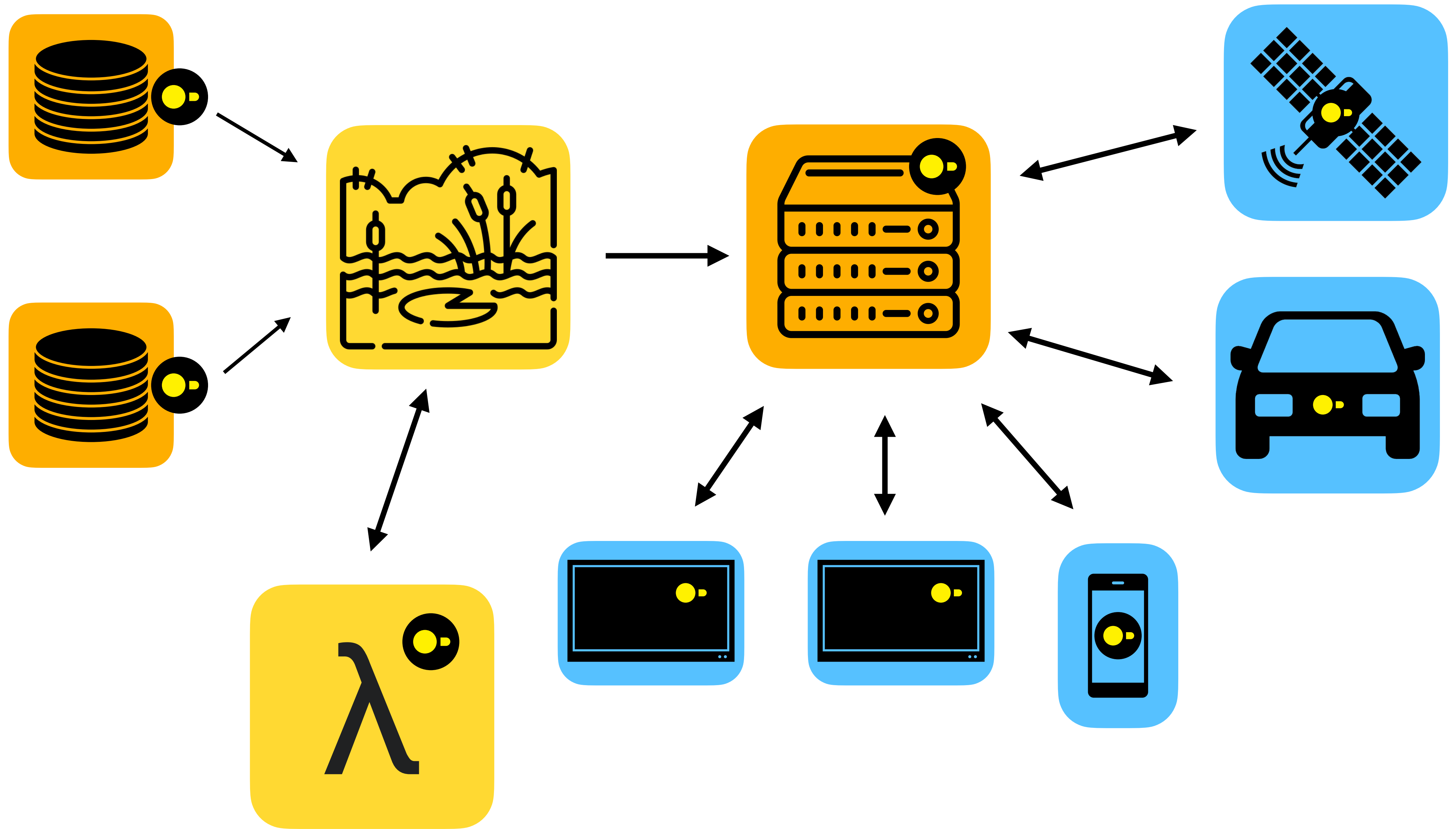




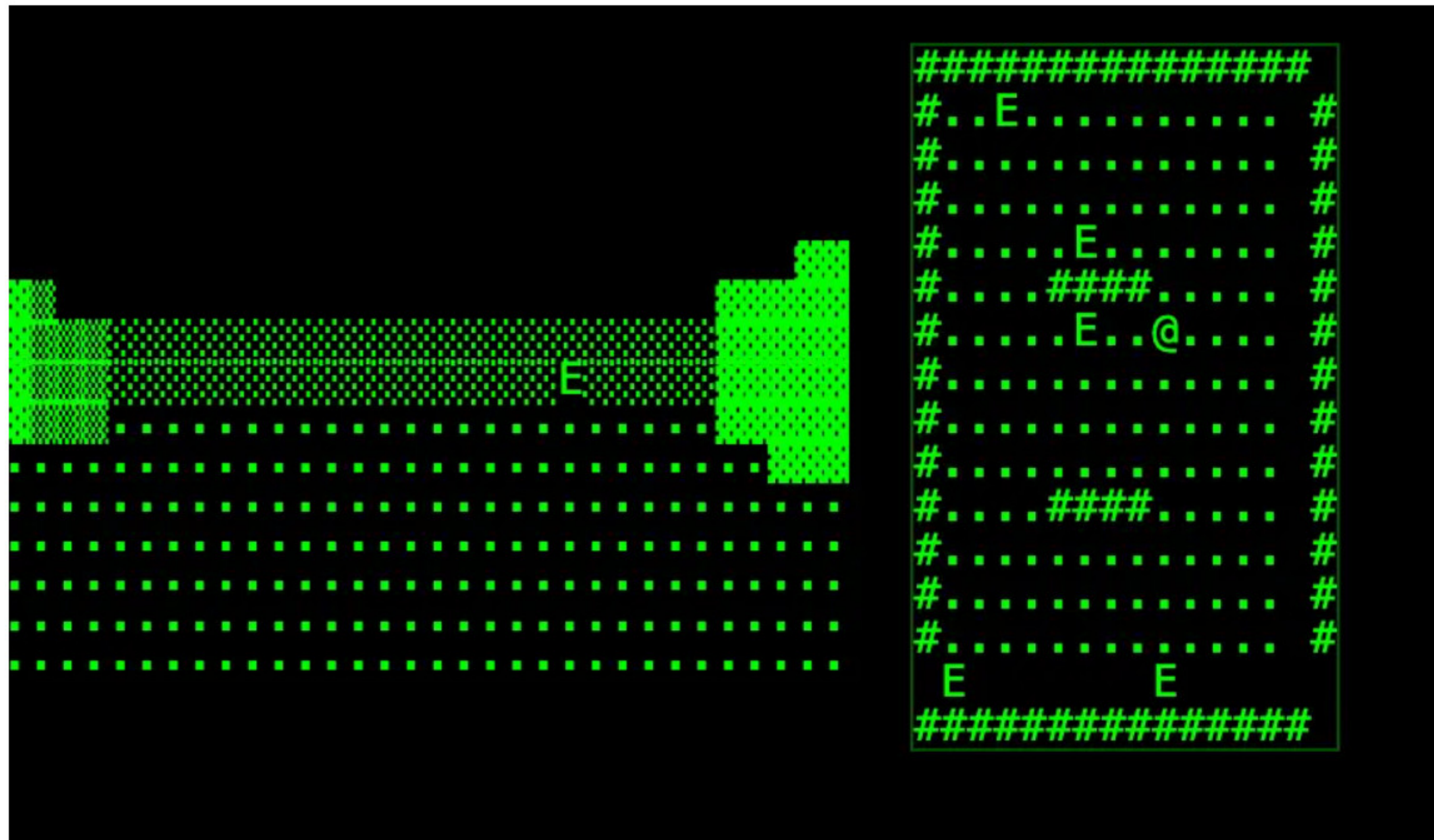


# Going Back Up



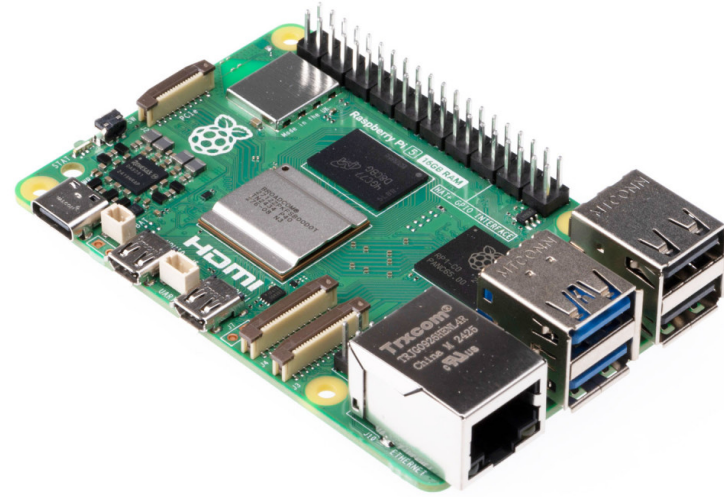


# Building a SQL-Powered Doom Clone in the Browser





SF 1 000



Raspberry Pi  
16 GB RAM

SF 10 000

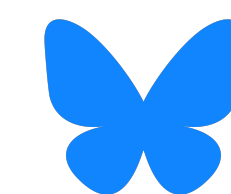
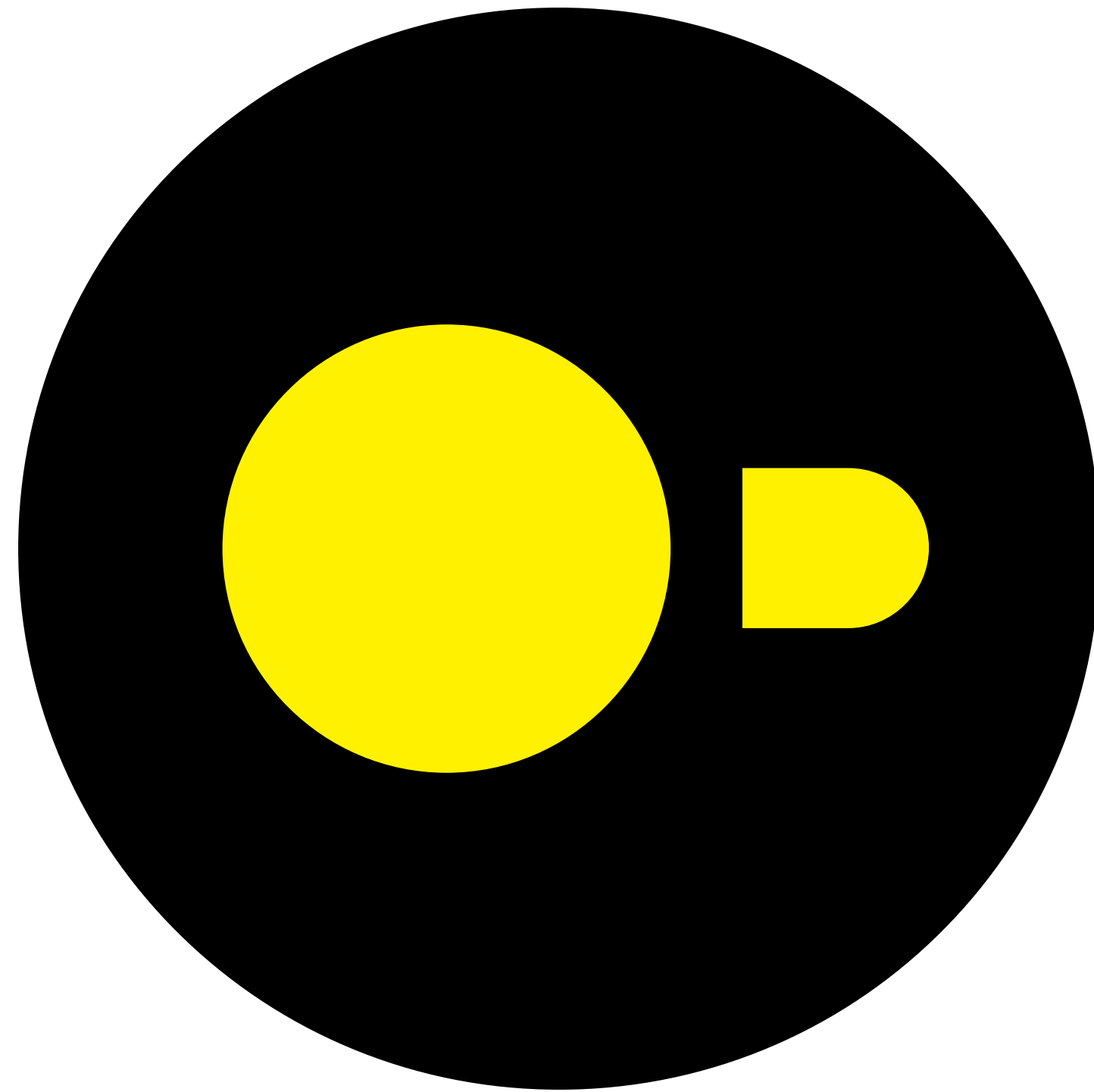


MacBook Pro  
128 GB RAM

SF 100 000



EC2 i7ie.48xlarge  
1.5 TB RAM



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