Mark Raasveldt & Hannes Mühleisen

DuckDB
an Embeddable Analytical RDBMS

About Me

- Mark Raasveldt
- PhD Student @ CWI in Amsterdam
- Database Architectures group
- Supervised by Hannes Mühleisen and Stefan Manegold
- Me & Hannes made DuckDB

Outline

- Motivation for Using Database Systems
- Data Science and Database Systems
- DuckDB: Systems Overview

Motivation for Using Database Systems

Motivation

- Why **should** people use relational database systems?

- This is a strange question in our field (DBMS research)
- **Obviously** everyone should use RDBMSs!

- But for many people it is not so obvious
- So *why should you actually use a RDBMS?*

The Good

- Database systems offer ACID properties
  - Consistency, reliability
- Integrity checks
- Advanced query optimizers
- Fast and flexible query execution (SQL)
- Takes care of data layout for you (in theory)

The Bad

- Schema needs to be defined beforehand
  - Annoying at start of a project when there are many schema changes
- Database systems are **difficult to setup**
- Even PostgreSQL will take you an hour if you are new
- ...and then you still need to learn SQL!

The Ugly

- Database systems are **expensive**
- Oracle costs **$17.5K per processor**
- For the standard edition!

Section I

Prices in USA (Dollar)

Oracle Database

	Named User Plus	Software Update License & Support	Processor License	Software Update License & Support
Database Products				
Oracle Database				
Standard Edition 2	350	77.00	17,500	3,850.00
Enterprise Edition	950	209.00	47,500	10,450.00
Personal Edition	460	101.20	-	-
Mobile Server	-	-	23,000	5,060.00
NoSQL Database Enterprise Edition	200	44	10,000	2,200.00
Enterprise Edition Options:				
Multitenant	350	77.00	17,500	3,850.00
Real Application Clusters	460	101.20	23,000	5,060.00
Real Application Clusters One Node	200	44.00	10,000	2,200.00
Active Data Guard	230	50.60	11,500	2,530.00
Partitioning	230	50.60	11,500	2,530.00
Real Application Testing	230	50.60	11,500	2,530.00
Advanced Compression	230	50.60	11,500	2,530.00
Advanced Security	300	66.00	15,000	3,300.00
Label Security	230	50.60	11,500	2,530.00
Database Vault	230	50.60	11,500	2,530.00
OLAP	460	101.20	23,000	5,060.00
Advanced Analytics	460	101.20	23,000	5,060.00

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Motivation

- These problems lead to the rise of NoSQL systems
  - Thankfully (almost) everyone now realizes this was a bad idea*
- But these problems are still valid
- Lead to many people using inferior* technology

* In my completely unbiased opinion as RDBMS researcher

Data Science
and
Database Systems

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Data Science

- Data science seems like a prime target for RDBMS
  - After all, it has “data” in the name!
- Data scientists work with data
  - Thus they need to manage that data!
- Yet, many data scientists do not use RDBMS…

Data Science

- Instead of using RDBMS, they have invented their own solutions
- They manage data using flat files
  - CSV files, binary, HDF5, parquet…
- They created their own libraries for DBMS ops
  - dplyr, pandas, DataFrames

- **Flat File Management** - what is the problem?

- Manually managing files is cumbersome
- Loading and parsing e.g. CSV files is inefficient
- File writers typically do not offer resiliency
  - Files can be corrupted
  - Difficult to change/update
- It does not scale!

- The reason people use it:

```
# load a CSV file into a DataFrame
df <- read.csv("input.csv", sep="|")
# write a CSV file to a DataFrame
write.csv(df, sep="|")
```

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Data Science

- Start by using flat files because they are easy
  - But then never switch!

- At CWI:
- Genetics researchers asked us how they could speed up their data loading
- ...their data was 1TB of CSV files
- ...that they loaded every time they ran an analysis
- **Our answer:** use a RDBMS!

- **dplyr, pandas, DataFrames** - what is the problem?
- For those unfamiliar: these libraries are basically query execution engines

```
SELECT SUM(l_quantity)
FROM lineitem
GROUP BY l_returnflag, l_linestatus;
```

dplyr

```
lineitem %>% group_by(l_returnflag, l_linestatus) %>%
    summarise(sum_qty=sum(l_quantity))
```

```
SELECT *
FROM part JOIN partsupp ON (p_partkey=ps_partkey)
WHERE p_size=15 AND p_type LIKE '%BRASS';
```

dplyr

```
part %>%  filter(p_size == 15, grepl(".*BRASS$", p_type)) %>%
    inner_join(partsupp, by=c("p_partkey" = "ps_partkey"))
```

Data Science

- **dplyr, pandas, DataFrames** - what is the problem?
- The problem is that they are *very poor query engines*!
- Materialize huge intermediates
- **No** query optimizer
  - Not even for basics like filter pushdown
- No support for out of memory computation
- No support for parallelization
- Unoptimized implementations for joins/aggregations

Data Science

- Data scientists **need** the functionality RDBMSs offer
- But they opt not to use RDBMSs
- Often this leads to problems down the road
  - When the data gets bigger…
  - When a power outage corrupts their data…

Can we save these lost souls and unite them with the RDBMS?

DuckDB
an Embeddable Analytical RDBMS

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SQLite

- **Problem**: Databases are difficult to use
- What is the easiest to use database?

SQLite

SQLite

- SQLite is an embedded database
    - No external server management
- It has bindings for every language
- Database is stored in a single **file** (not directory)

* https://www.sqlite.org/famous.html

SQLite

- SQLite is great
- It is public domain and very easy to use
- It is secretly the most used RDBMS in the world
  - Runs on every phone, browser and OS*
  - It even runs inside airplanes!

* https://www.sqlite.org/famous.html

SQLite

- SQLite has one problem: designed for OLTP

- Row store (basically a giant B-tree)
- Tuple-at-a-time processing model
- Does not utilise memory to speed up computation
- Query optimizer is very limited

- Great for OLTP, not so good for analytics

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DuckDB

- DuckDB: The SQLite for Analytics

- **Core Features**
- Simple installation
- Embedded: no server management
- Single file storage format
- Fast analytical processing
- Fast transfer between R/Python and RDBMS

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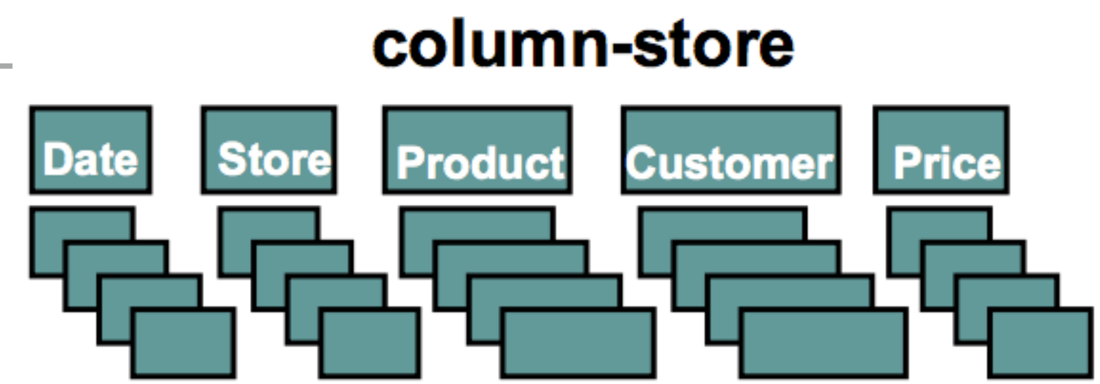
DuckDB

- Why "Duck" DB?

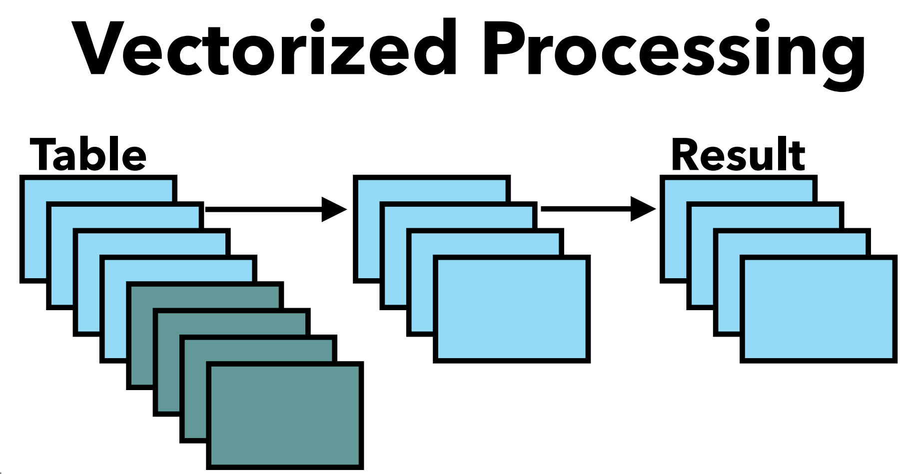
- Ducks are amazing animals
- They can fly, walk and swim
- They are resilient
- They can live off anything

- Also Hannes used to own a pet duck

DuckDB



- **DuckDB Internals**
- Column-storage database
- Vectorized processing model
- MVCC for concurrency control

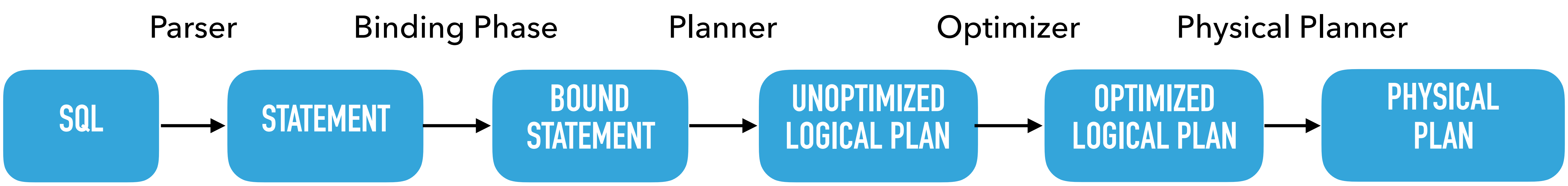


- ART index, used also for maintaining key constraints
- Combination of both cost/rule based optimizer

- We use the PostgreSQL parser
- Bindings for C/C++, Python and R

DuckDB

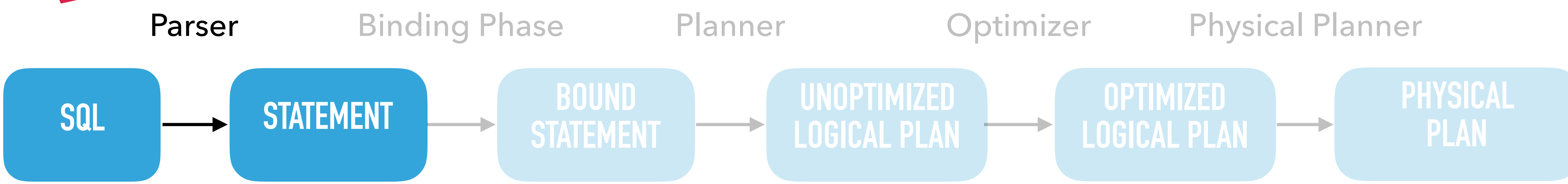
- DuckDB uses a typical pipeline for query processing

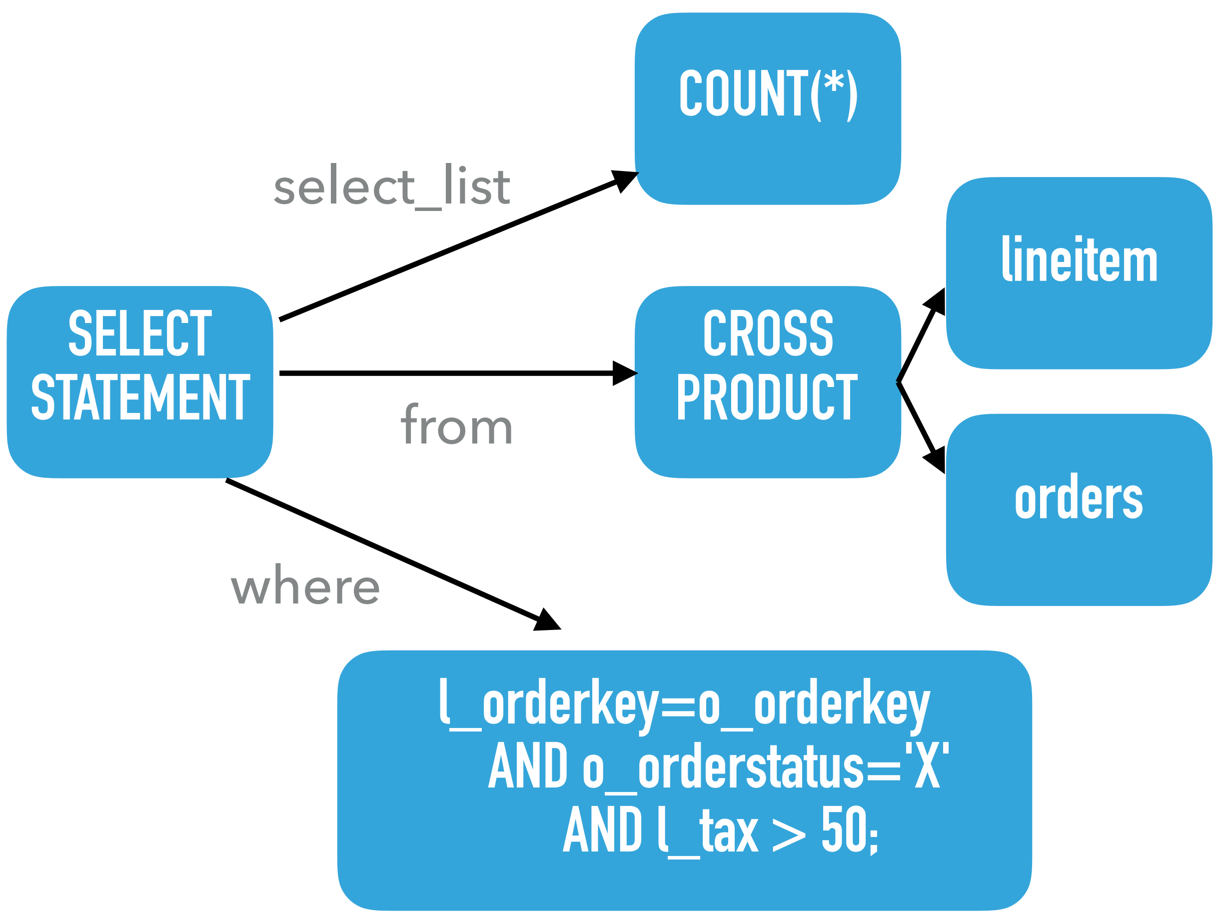


Life of a Query

```
SELECT COUNT(*)
FROM lineitem, orders
WHERE l_orderkey=o_orderkey
      AND o_orderstatus='X'
      AND l_tax > 50;
```

DuckDB






```sql
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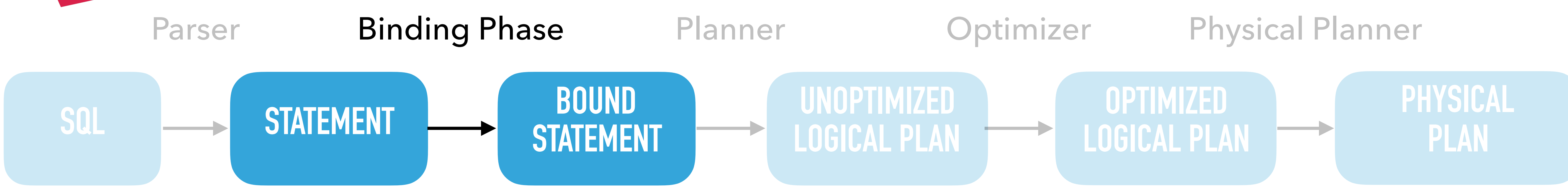
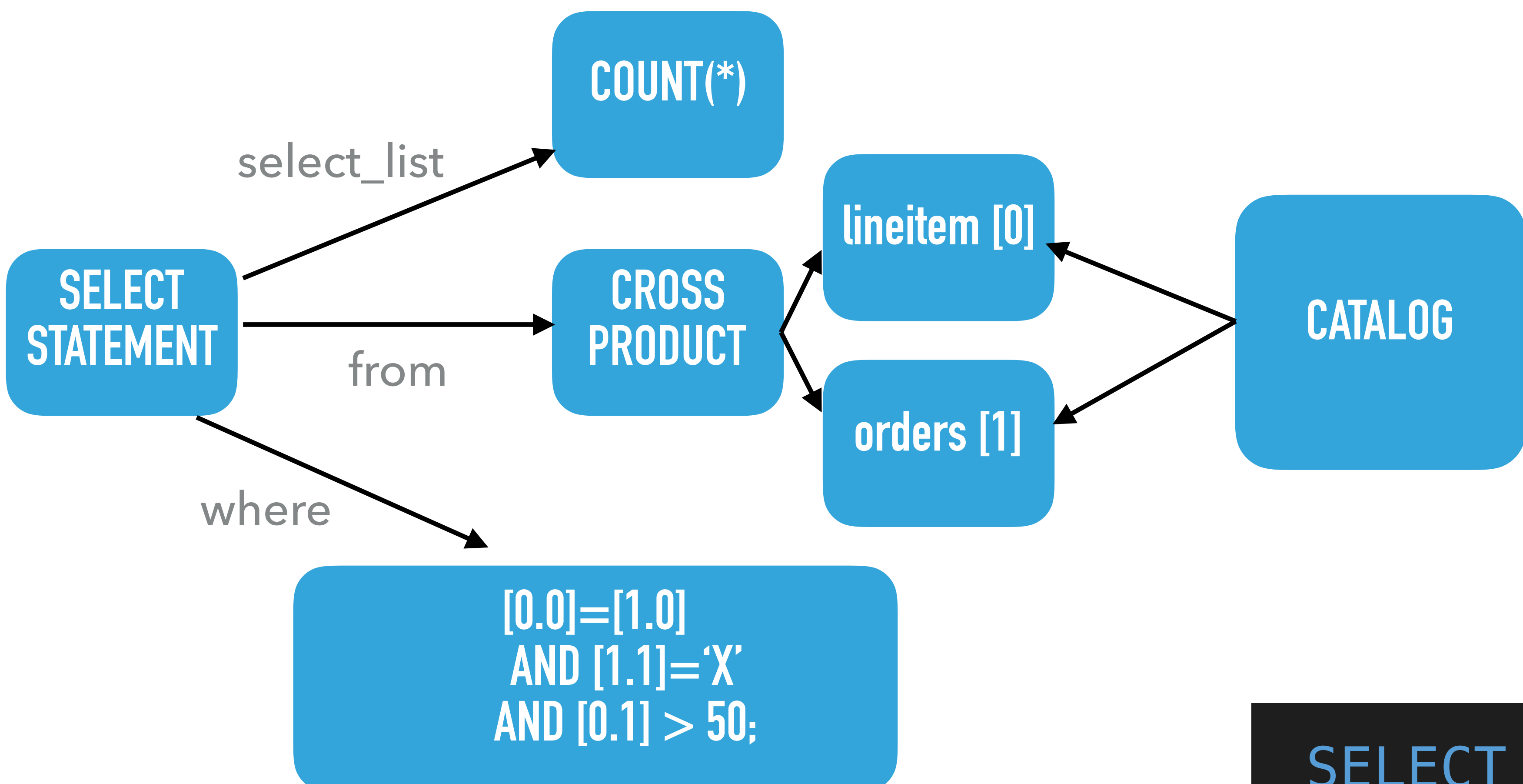
DuckDB



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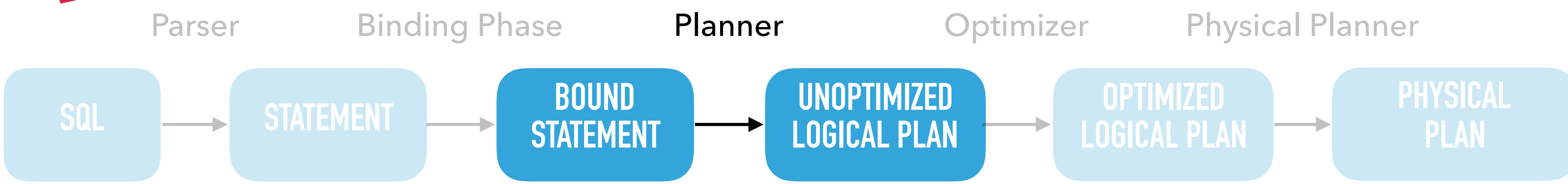

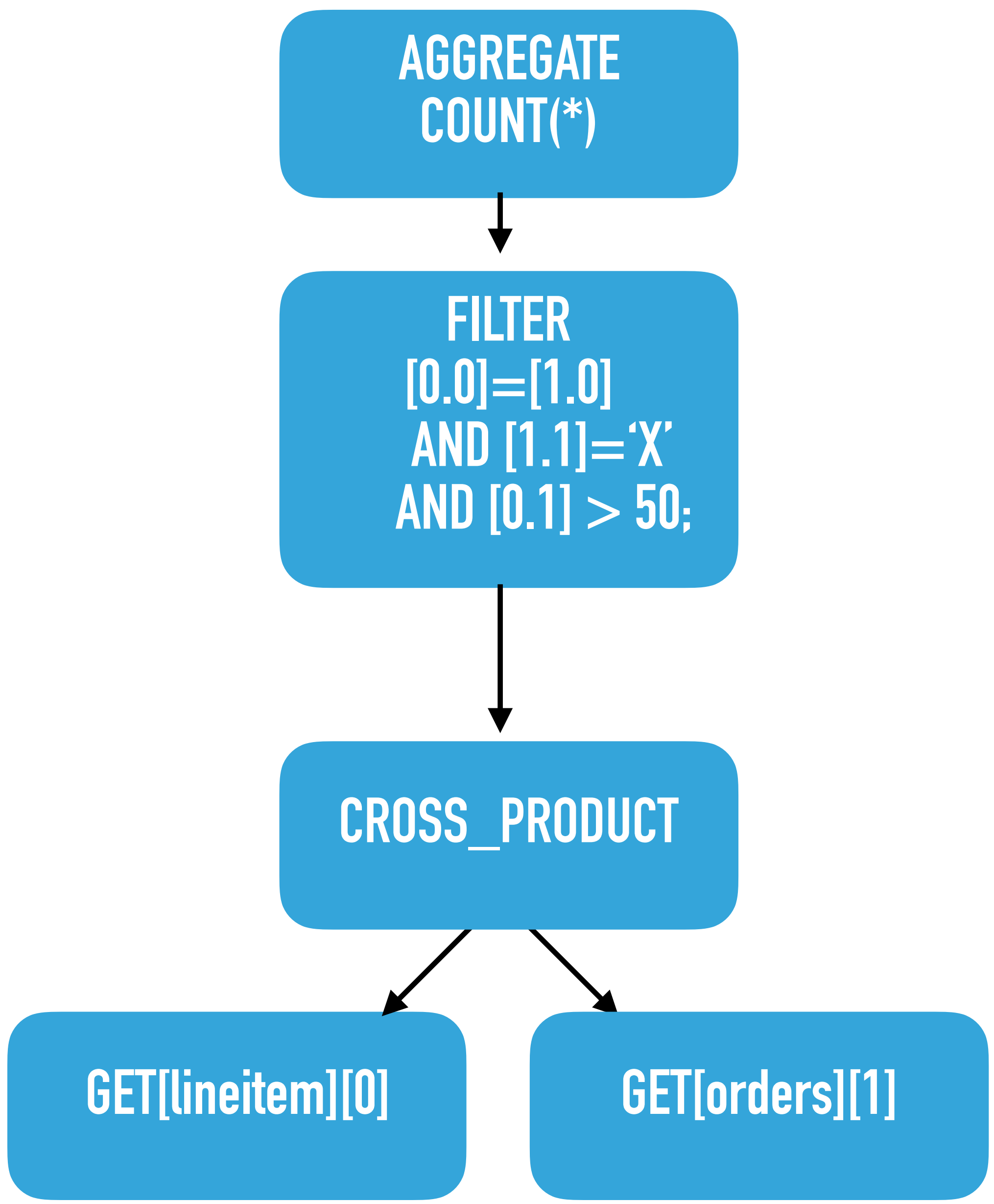


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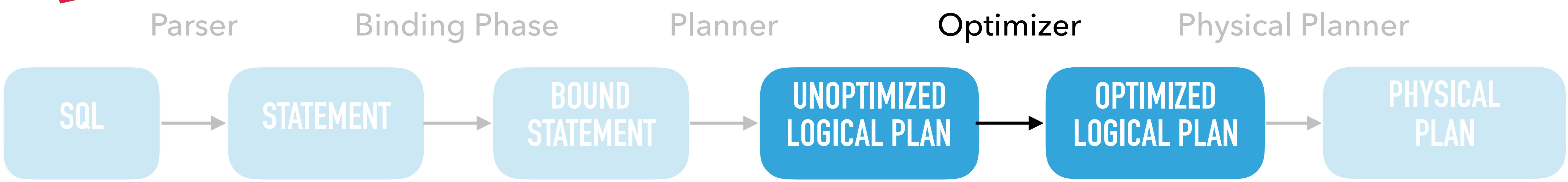
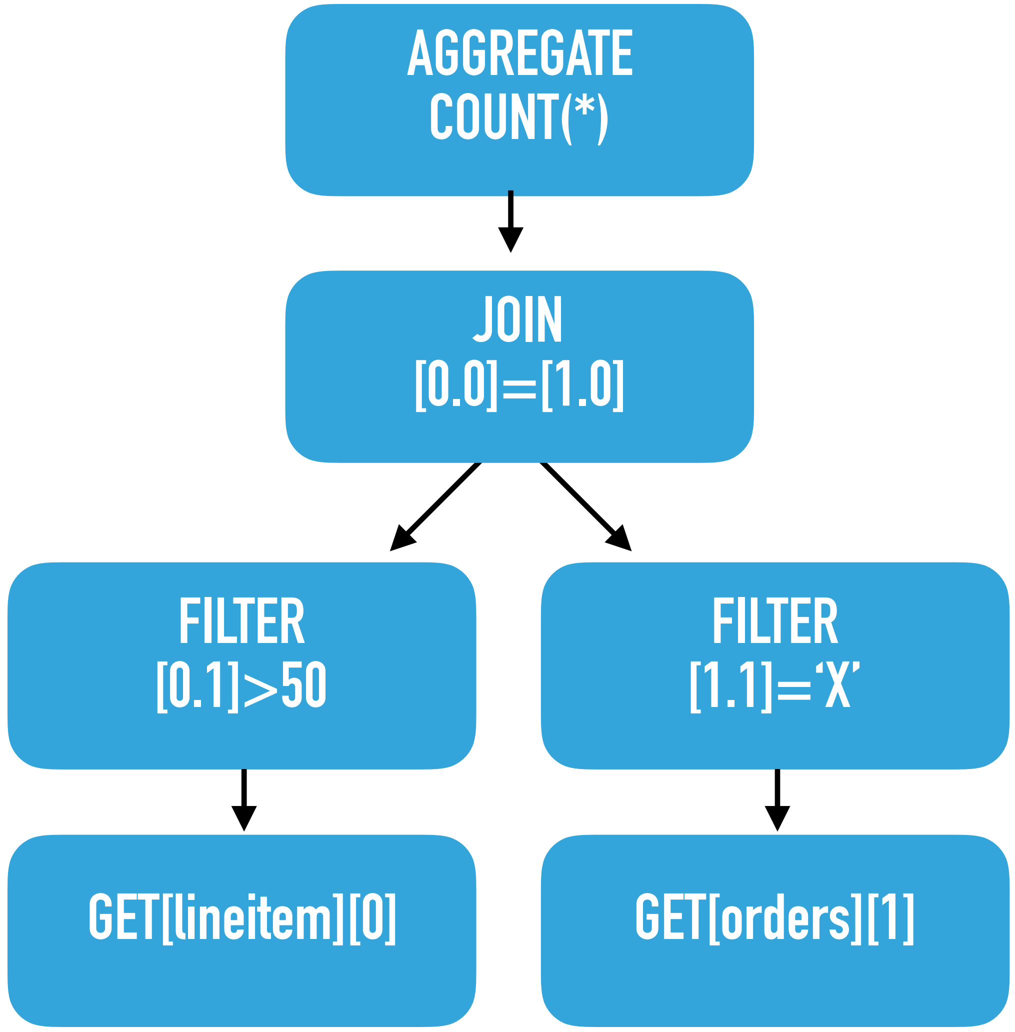
DuckDB



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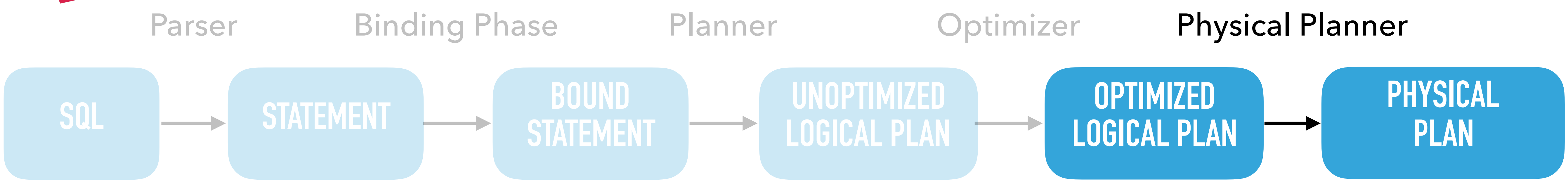
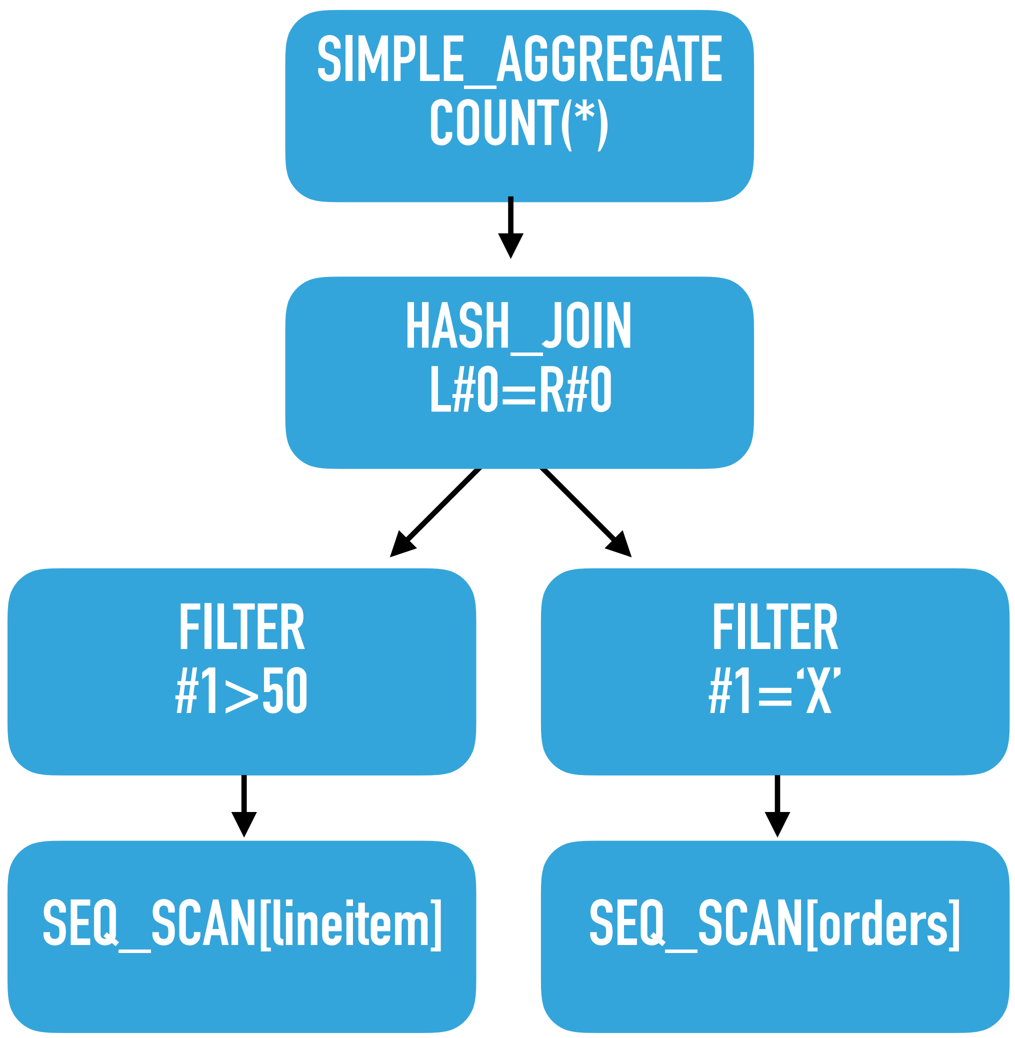
DuckDB






```sql
SELECT COUNT(*)
FROM lineitem, orders
WHERE l_orderkey=o_orderkey
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      AND l_tax > 50;
```
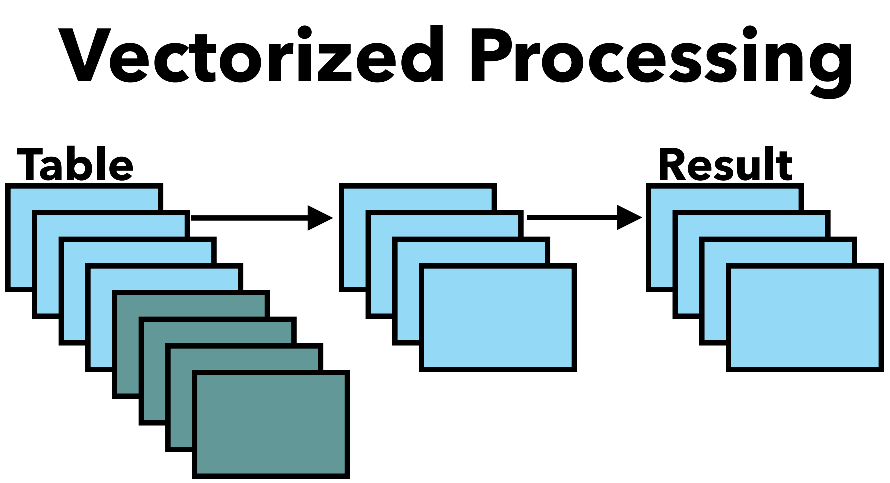
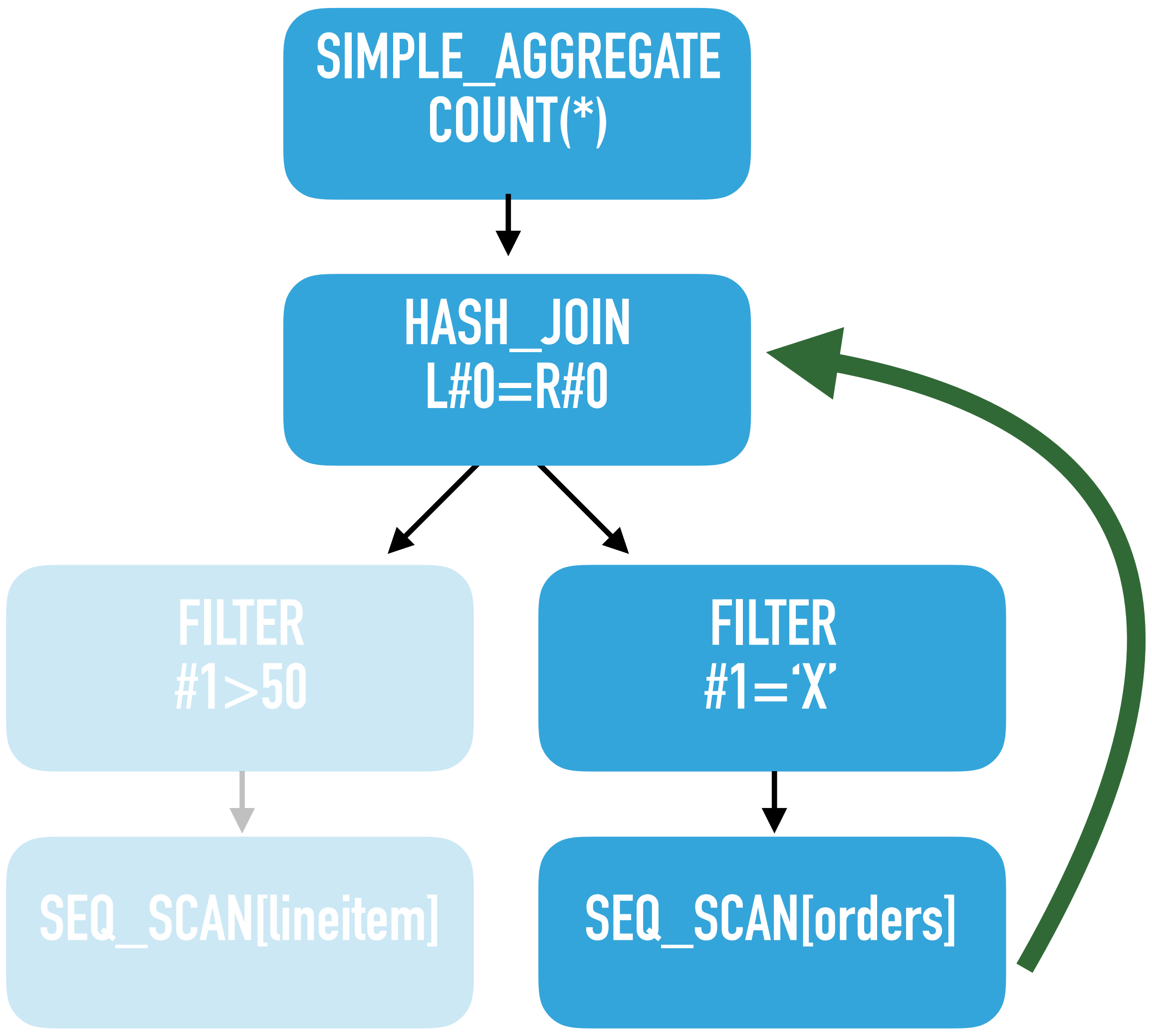

DuckDB

- **Query Execution**
- DuckDB uses a vectorized pull-based model ("vector volcano")
- Each operator calls "*GetChunk*" on its child operators to fetch an input chunk (= set of vectors)
- Scans fetch data from the base tables



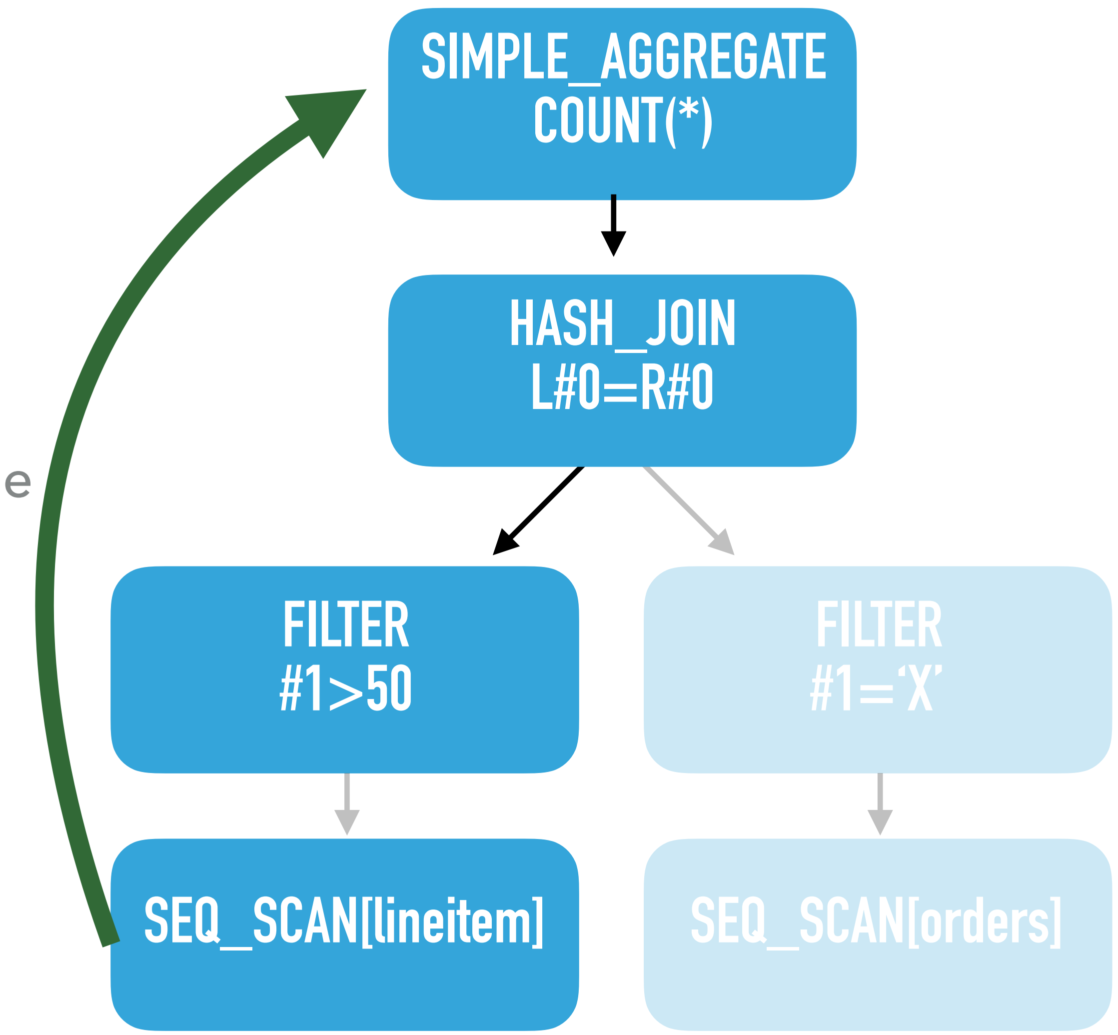
DuckDB



HT Build: Vectors flow from right side into HT

DuckDB

After build is completed chunks flow from left side to root aggregate



DuckDB

- DuckDB is free and open-source
- Currently in pre-release (v0.1)

- We have a website: www.duckdb.org
- Source Code: https://github.com/cwida/duckdb

- Feel free to try it
- And send us a bug report if anything breaks!

DuckDB

- **Lessons Learned for Building a RDBMS**
- Use an existing SQL parser
  - Writing a robust parser is difficult!
  - PostgreSQL parser saved us so much time
- Write many, many tests
  - Also steal tests from other systems!
- Read all of Thomas Neumann's papers