



School of Computer Science and Engineering

Faculty of Engineering

The University of New South Wales

pgx-lower: Productionising Database Compiler Research

by

Nicolaas Johannes van der Merwe

Thesis submitted as a requirement for the degree of
Bachelor of Computer Science (Honours)

Submitted: November 2024

Supervisor: Dr Zhengyi Yang

Student ID: z5467476

Abstract

Abbreviations

ACID Atomicity, consistency, isolation, durability

AST Abstract Syntax Tree

CPU Central Processing Unit

DB Database

EXP Expression (expressions inside queries)

IR Intermediate Representation

JIT Just-in-time (compiler)

JVM Java Virtual Machine

LLC Last Level Cache

MLIR Multi-Level Intermediate Representation

QEP Query Execution Plan

RA Relational Algebra

SQL Structured Query Language

SSD Solid State Drive

TPC-H Transaction Processing Performance Council - Decision Support Benchmark
H

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Chapter 1

Introduction

Databases are a heavily used type of system that rely on correctness and speed. Nowadays, they are often the primary bottleneck in many systems - especially on web servers and other large data applications [Kle19].

With modern hardware advances, the optimal way to structure these databases has drastically changed, but most databases are using architectures defined by older hardware. Older databases assume the disk operations are the vast majority of runtime, but that has shifted to the CPU for heavy queries.

Research projects typically create standalone databases. However, this approach makes distribution harder, requiring projects to implement all supporting infrastructure themselves. For serious projects, this involves many additional implementation steps. To productionise the system, this might include implementing ACID, MVCC, query plan optimisation, and more. By using an established database, we can address this issue.

pgx-lower replaces PostgreSQL's execution engine with LingoDB's compiler to bridge the gap of modern compilers with established systems. PostgreSQL's extension system is utilised to override the executor, and shows there are features that can be used within PostgreSQL that can assist with this research. One concern, however, is the additional complexities in implementation and testing.

This thesis is separated into a background in Chapter 2 which includes fundamental concepts and the definition/goal of the project, then a light literature survey will be conducted in Chapter 3. The project's solution will be introduced in Chapter 4, and finally conclusions will be drawn in Chapter 6.

Chapter 2

Background

2.1 Database Background

The majority of databases are structured like Figure 2.1. Structured Query Language (SQL) is parsed, turned to RA (relational-algebra), optimized, executed, then materialized into a table [SKS19].

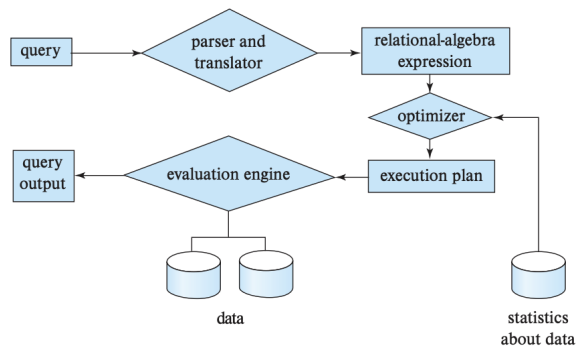


Figure 2.1: Database Structure
[SKS19]

For non-compiler databases, a volcano operator model tree is used, such as Figure 2.2 [ZVBB11]. The root node has a `produce()` function which calls its children's `produce()`, until it calls a leaf node, which calls `consume()` on itself, then that calls its parent's

`consume()` function. In other words, a post-order traversal through this tree where tuples are dragged upwards.

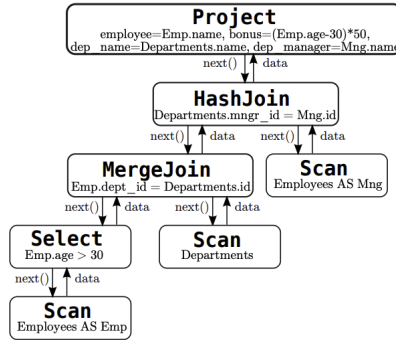


Figure 2.2: Volcano operator model tree.
[ZVBB11]

The fundamental issue with this classical model is that it is heavily under-utilising the hardware [ADHW99]. If only a single tuple is pulled, our CPU caches are barely used. An i5-570, a popular CPU in 2010 had an 8 megabyte L3 cache, but in 2024 an i5-14600K has a 24 megabyte L3 cache [Pas25], [Tec25]. For disks, in 2010 the Seagate Barracuda 7200.12 was popular, which had a sustained read of 138 MB/s, but in 2022 the Samsung V-NAND SSD 990 PRO released with a sustained read of 7450 MB/s [Sea07] [Sam24]. Such dramatic increases could mean the algorithms can fundamentally change.

This has led to the vectorized execution model and the compiled model. With the vectorized model, multiple tuples are pulled up in a group rather than one at a time. A core advantage is that instructions per CPU cycle (IPC) can increase through single instruction, multiple data (SIMD) operations [KLK⁺18]. However, this can cause deep copy operations to be required, or more disk spillage than necessary [Zuk09]. For instance, if a sort or a join allocates new space that is too much for the cache, the handling can become poor. The alternative approach, compilation, will be explored in section 2.2 and chapter 3.

Relational databases prioritise ACID requirements - Atomicity, Consistency, Isolation and Durability [SKS19]. This is a critical requirement in this type of system, and

usually one of the main reasons people pick a relational database. Atomicity means transactions are a single unit of work, while consistency means it must be in a valid state before and after the query. Isolation means concurrent transactions do not interact with each other, and durability means once something is committed it will stay committed. [SKS19]

It is common for on-disk databases to consider the cost of CPU operations to be constant or cost-free [SKS19]. This is partially due to the era in which these systems were developed, when disks were much slower and the caches were much smaller. In part A of this project, this was disproved for PostgreSQL as it was found that the time spent in the CPU was substantial: between 34.87% and 76.56% with an average of 49.32% across the tested queries.

Most of the recent databasing research has focused on the optimiser, which is visible in figure 2.1. Common optimization techniques include reordering join statements where the left and right sides are flipped, and predicate push down, where a conditional/filter on a node is moved onto a lower node [Ine21]. Additionally, extracting common subexpressions prevents recomputation, while constant folding evaluates constant operations inside the optimiser rather than at runtime. Despite these advances, query optimisers frequently produce suboptimal plans [LGM⁺15, LRG⁺17]. Another essential pattern involves genetic algorithms being used in optimisers for determining things like join orders, which can cause the outputted plan to be non-deterministic [Ute97]. A thesis could be written just to summarise the list of optimisations.

Within traditional and volcano databases, the cache is managed through a set of buffer techniques while reading tuples. This works by the database reading a page, which usually has a fixed size and can be configured, such as eight kilobytes. This is loaded into a buffer pool object which holds it in RAM. The operating system or environment manages where this memory goes inside the context of the L1/L2/L3 and ram caches depending on the access patterns [SKS19]. This buffer pool can change caching strategies depending on the situation, such as last-recently-used, most-recently-used, and more, which can be decided in the optimiser [EH84]. The effectiveness of this can

be measured with last level cache hit rate measurements (LLC) which represents how many of the instructions were resolved inside the CPU cache [FRMK19].

Databases are commonly split into Online Transaction Processing (OLTP) and Online Analytical Processing (OLAP). OLTP focuses on supporting atomicity, running multiple queries at once, and typically handles the work profile of an online service that frequently performs key-value lookups. On the other hand, OLAP databases focus on analytical work profiles where aggregations are requested or operations span large chunks of the database [Kle19]. OLAP systems can be highly distributed, such as Apache Hive, which allows compute to be distributed across the system [CRCG⁺19]. In the context of PostgreSQL, it is a hybrid architecture that supports both OLTP and OLAP operations [HRTVVA21]. There is currently debate about whether this hybrid architecture is still useful, as putting pressure on a database serving users commonly causes reliability issues [Moo24].

2.2 JIT Background

Just-in-time (JIT) compilers work with multiple layers of compilation such as raw interpretation of bytecode, unoptimized machine code, and optimized machine code. They are primarily used with interpreted languages to eliminate the ill-effects on performance [ZVBB11]. Advanced compilers can run the primary program, then dedicate background threads to improving code optimisation and swap in the optimized version when ready [KLN18]. This provides benefits such as faster initial compilation and faster development cycles.

Due to branch-prediction optimisation, JIT compilers can be faster than ahead of time compilers. In 1999, a benchmarking paper measured four commercial databases and found 10% – 20% of their execution time was spent fixing poor predictions [ADHW99]. Modern measurements still find 50% of their query times are spent resolving hardware hazards, such as mispredictions, with improvements in this area making their queries 2.6x faster [Ker21]. The Azul JIT compiler measured that their JIT solution’s

speculative optimisations can lead up to 50% performance gains [Azu22].

Evaluating a good branch prediction value is difficult. A reasonable baseline is that a 1% misprediction rate is too high and should be optimised in a low latency environment [Far25]. This baseline is not formal; it is based on empirical knowledge [Jos21]. Depending on the CPU, a branch mispredict can cost between 10 and 35 CPU cycles, with a safe range being 14-25 cycles. With 1 branch every 10 instructions and a 5% misprediction rate, a 20 cycle penalty per misprediction translates to approximately 10% of runtime spent resolving mispredictions [ESE06].

In the context of databases, compilers fall into two categories: those that compile only expressions (typically called EXP), and those that compile the entire Query Execution Plan (QEP) [MYH⁺24]. Within PostgreSQL itself, they have EXP support using `llvm-jit`. A variety of research databases will be examined in chapter 3.

2.3 LLVM and MLIR

The LLVM Project is a compiler infrastructure that eliminates the need to re-implement common compiler optimisations, making it easier to build compilers [LA04]. Multi-Level Intermediate Representation (MLIR) is another, newer toolkit that is tightly coupled with the LLVM project [LAB⁺20]. It provides a framework to define custom dialects and progressively lower them to machine code. A key benefit is that developers can define high-level dialects that others can target and build upon.

LLVM defines a language-independent intermediate representation (IR) based on Static Single Assignment (SSA) form, while MLIR extends this concept [LA04]. The architecture follows a three-phase design: a front-end parses source code and generates LLVM IR, an optimiser applies a series of transformation passes to improve code quality, and a back-end generates machine code for the target architecture. MLIR extends this concept by introducing a flexible dialect system that enables progressive lowering through multiple levels of abstraction [LAB⁺20]. This addresses software fragmentation in the compiler ecosystem, where projects were creating incompatible high-level IRs in front

of LLVM, and improves compilation for heterogeneous hardware by allowing target-specific optimisations at appropriate abstraction levels.

LLVM’s On-Request-Compilation (ORC) JIT is a system for building JIT compilers with support for lazy compilation, concurrent compilation, and runtime optimisation [LLV25b]. ORC can compile code on-demand as it is needed, reducing startup time by deferring compilation of functions until they are first called. The JIT supports concurrent compilation across multiple threads and provides built-in dependency tracking to ensure code safety during parallel execution. This makes ORC particularly suitable for dynamic language implementations, REPLs (Read-Eval-Print Loops), and high-performance JIT compilers.

2.4 WebAssembly and others

The V8 compiler used for WebAssembly has a unique architecture because it targets short-lived programs. Majority of JIT applications are used for long-running services, but this is used for web pages which are opened and closed frequently. To mitigate this, they have a two-phase architecture where code is first compiled with Liftoff for a quick startup, then hot functions are recompiled with TurboFan [HRS⁺17]. Liftoff aims to create machine code as fast as possible and skip optimisations.

Other common JIT compilers are the Java Virtual Machine (JVM), SpiderMonkey (Mozilla Firefox’s JIT), JavaScriptCore/Nitro (Safari/Webkit), PyPy, various python JIT compilers, LuaJIT for Lua, HHVM for PHP, Rubinius for Ruby, RyuJIT for C#, and more [DCL25]. The JVM has also been used for compiled query execution engines [RPML06]. These all target different work profiles.

2.5 PostgreSQL Background

PostgreSQL relies on memory contexts, which are an extension of arena allocators. An arena allocator is a data structure that supports allocating memory and freeing the entire data structure. This improves memory safety by consolidating allocations into a single location. A memory context can create child contexts, and when a context is freed it also frees all the children of this context, turning it into a tree of arena allocators. There is a set of statically defined memory contexts: `TopMemoryContext`, `TopTransactionContext`, `CurTransactionContext`, `TransactionContext`, which are managed through PostgreSQL’s Server Programming Interface (SPI) [Pos25b].

PostgreSQL defines query trees, plan trees, plan nodes, and expression nodes. A query tree is the initial version of the parsed SQL, which is passed through the optimiser which is then called a plan tree. These stages are visible in figure 2.1. The nodes in these plan trees can broadly be identified as plan nodes or expression nodes. Plan nodes include an implementation detail (aggregation, scanning a table, nest loop joins) and expression nodes consist of individual operations (binaryop, null test, case expressions) [Pos25d].

PostgreSQL provides the `EXPLAIN` command to inspect query execution plans, which is essential for understanding and optimizing query performance [Pos25a]. This command displays the execution plan that the planner generates, including cost estimates and optional execution statistics, making it a critical tool for database optimisation and analysis.

2.6 Database Benchmarking

Benchmarking a database is a difficult task because there is a variety of workloads. Many systems create their own benchmarking libraries, such as `pg_bench` by PostgreSQL [Pos25c] or `LinkBench` [APBC13] by Facebook, but in academics the more common benchmarks are from the Transaction Processing Council, which is a group

that defines benchmarks [BNE14]. Over the years they have made TPC-C for an order-entry environment, TPC-E, for a broker firm’s operations, TPC-DS for a decision support benchmark. The most common one in research appears to be TPC-H, where the H informally means ”hybrid”. It has a mix of analytical and transactional elements inside it [BNE14].

When evaluating benchmark results, the *coefficient of variation* (CV) is used. This is a standardized measure of dispersion that expresses the standard deviation as a percentage of the mean [Sta25]. It is calculated as $CV = \frac{s}{\bar{X}} \cdot 100$, where s is the sample standard deviation and \bar{X} is the sample mean. The coefficient of variation is particularly useful when comparing datasets with different units or scales, providing a unit-free measure for relative comparison of measurement precision.

Chapter 3

Related Work

This chapter summarises relevant works in the compiled query space and their architectures. The database industry originally favoured compiled query engines [CAB⁺81], but the volcano model subsequently dominated because it simplified implementation with minimal performance cost at the time. However, modern analytical engines are revisiting compilation approaches [KLK⁺18].

This chapter begins with PostgreSQL’s extension system in section 3.2, followed by System R in section 3.3 as a classical example of early compilation. HyPer and Umbra (sections 3.4 and 3.5) re-introduced compilation in modern databases. Two research databases are then examined: Mutable (section 3.6) and LingoDB (section 3.7). Finally, PostgreSQL’s own expression-based JIT compilation and prior compilation attempts are discussed.

3.1 OLAP Systems

Compiled query engines primarily benefit OLAP workloads, since OLTP workloads typically involve simpler retrieval queries [Kle19]. At scale, Apache Hive is commonly used, but it is a data warehouse system rather than a database, storing data in Hadoop’s distributed file system, which is closer to flat storage [CRCG⁺19]. The common OLAP

databases are MonetDB, Snowflake, ClickHouse, RedShift and Vectorwise [SZC⁺24]. For our context, understanding ClickHouse, NoisePage, DuckDB and extensions that turn PostgreSQL into an OLAP database are important.

ClickHouse and NoisePage are standalone systems, while DuckDB is embedded and in-process, similar to SQLite. ClickHouse is a columnar, disk-oriented database with a vectorised execution engine with optional LLVM compilation for expressions (EXP) [SSY⁺24]. NoisePage was created by the Carnegie Mellon Database group, and is columnar and in-memory with full query expression compilation (QEP), with a single node. They targeted ML-driven self optimisation in their research, but they were archived in February 21, 2023 [MZJ⁺21]. DuckDB is marketed as the SQLite for analytical loads with in-memory disk spillage, or like a more sophisticated Pandas DataFrame [RM19]. Their engine supports vectorised execution because JIT would add too much overhead to their lightweight philosophy.

3.2 PostgreSQL and Extension Systems

PostgreSQL is a battle-tested system and the most popular database, with 51.9% of developers in a Stack Overflow survey reporting extensive use in 2024 [Ove24]. In the context of compiled queries, this means PostgreSQL cannot be treated as a research prototype. Direct modifications require extensive testing, and such changes face casual code review via pull requests rather than formal peer review.

Building extensions for PostgreSQL and making entire companies around these extensions is not a new endeavour. Three such examples are Citus [CEP⁺21], TimescaleDB [Tim24a], and Apache AGE [Apa24]. Citus aims to add more horizontal scaling through sharding, TimescaleDB, now rebranded as TigerData, transforms the engine into a time series database, and Apache AGE turns it into a graph database. These all have thousands of GitHub stars, but TimescaleDB especially had over 500 paying customers in 2022, and claimed their revenue climbed 20x by 2024 [Tim24b] [Bus22]. This shows that the model of relying on the extension system is a robust, travelled road.

There have also been several extensions that attempt to make PostgreSQL more suited to OLAP workloads, with the most relevant one being `pg_duckdb` [Duc24]. This system replaces PostgreSQL’s engine with DuckDB which allows it to take advantage of the vectorised engine, and it is reasonably popular with roughly 2700 stars on GitHub. Hydra is also worth mentioning, but this is closer to TimescaleDB [Hyd24] and makes the system columnar with compression support. ParadeDB’s `pg_analytics` initially started in the same way as `pg_duckdb`, but pivoted into supporting search functionality instead, similar to Elasticsearch.

There has been significant discussion about HyPer and JIT in regard to PostgreSQL in 2017 [Fre16, Fre17]. The general response expressed doubt that someone would add support for full query compilation, noting that rearchitecting such a core component introduces significant risk.

However, in September 2017 Andres Freund started implementing JIT support for expressions [Fre18]. The reasoning was that most of the CPU time is in the expression components, (such as `y < 8` in `SELECT * from table WHERE x < 8`). Furthermore, there are significant benefits to tuple deformation as it interacts with the cache and has poor branch prediction. PostgreSQL’s JIT implementation is documented in the official PostgreSQL documentation [Pos24].

```
On 3/9/18 15:42, Peter Eisentraut wrote:
> The default of jit_above_cost = 500000 seems pretty good. I constructed
> a query that cost about 450000 where the run time with and without JIT
> were about even. This is obviously very limited testing, but it's a
> good start.

Actually, the default in your latest code is 100000, which per my
analysis would be too low. Did you arrive at that setting based on testing?
```

Figure 3.1: Peter Eisentraut asking whether the defaults are too low.
[Fre17]

In a pull request, Peter Eisentraut questioned whether the default JIT settings were too low. Despite this concern, PostgreSQL version 11 was released with JIT disabled by default. This conservative approach resulted in limited adoption initially, so they later decided to enable JIT by default to increase exposure and testing opportunities [She17]. However, when released, the United Kingdom’s critical service for a COVID-

19 dashboard automatically updated and spiked to a 70% failure rate as some of their queries ran 2,229x slower [Xen21]. This incident reinforced the view that JIT features should be disabled by default, and has led to negative opinions about JIT and compiled queries.

Two cases where QEP query compilation with PostgreSQL was implemented were found. The first is Vitesse DB, which made a series of public posts about getting people to assist with testing it. They became generally available in 2015, but their website is offline now and there is not much mention of them. The second was at a PgCon presentation and achieved a 5.5x speed-up on TPC-H query 1, and has more documentation [ISP17]. However, they did not publicize their implementation or show that it's easy for people to use.

This implementation of full JIT in PostgreSQL was preceded by profiling work which showed that different TPC-H benchmarks place pressure on different nodes, as shown in figure 3.2. This is important because they can make informed decisions about where to focus their efforts. Their core method is generating a function that represents a node in the plan tree, then inlining the function into the final LLVM IR [ISP17] in a push-based model. Another interesting method that is used is pre-compiling the C code into LLVM, then inlining that into the LLVM IR. This avoids runtime linking back to the C code [ISP17], similar to approaches taken by HyPer [Neu11].

Function	TPC-H Q1	TPC-H Q2	TPC-H Q3	TPC-H Q6	TPC-H Q22
ExecQual	6%	14%	32%	3%	72%
ExecAgg	75%	-	1%	1%	2%
SeqNext	6%	1%	33%	-	13%
IndexNext	-	57%	-	-	13%
BitmapHeapNext	-	-	-	85%	-

Figure 3.2: PGCon Dynamic Compilation of SQL Queries Profiling [ISP17].
[Fre17]

Other database systems also support extensions, and there are many systems that rely

on PostgreSQL’s extension system. MySQL, ClickHouse, DuckDB, Oracle Extensible Optimizer all support similar operations. This means more than only PostgreSQL can be extended in this same manner rather than creating databases from scratch.

3.3 System R

System R is a flagship paper in the databasing space that introduced SQL, compiling engines, and ACID [CAB⁺81]. Their vision described ACID requirements, but was explained as seven dot points as it was not a concept yet. Their goal was to run at a ”level of performance comparable to existing lower-function database systems.” Reviewers commented that the compiler is the most important part of the design.

Due to the implementation overhead of parsing, validity checking, and access path selection, a compiler was appealing. These were not supported within the running transaction by default, and they leveraged pre-compiled fragments of Cobol for the reused functions to improve their compile times. This was completely custom-made at the time because there were not many tools to support writing compilers. System R shows the idea of compiled queries is as old as databases, and over time the priorities of the systems changed.

3.4 HyPer

HyPer was a flagship system, and Umbra supersedes it. These are important systems in the JIT-database space as they developed many of the core features. Both were made by Thomas Neumann, and a core sign of its viability is that HyPer was purchased by Tableau in 2016 to be used in production [Tab18]. This shows that it is possible to use an in-memory JIT database at scale. The project began in 2010, with their flagship paper releasing in 2011 for the compiler component [Neu11], and in 2018 they released another flagship paper about adaptive compilation [KLN18]. However, the database

being commercialised poses issues for outside research because the source code is not accessible, but there is a binary on their website that can be used for benchmarking.

Their 2011 paper on the compiler identifies that translating queries into C or C++ introduced significant overhead compared to compiling into LLVM. As a result, they suggested using pre-compiled C++ objects of common functions then inlining them into the LLVM IR. This LLVM IR is executed by the LLVM’s JIT executor. By utilising LLVM IR, they can take advantage of overflow flags and strong typing which prevent numerous bugs in their original C++ approach.

	Q1	Q2	Q3	Q4	Q5
HyPer + C++ [ms]	142	374	141	203	1416
compile time [ms]	1556	2367	1976	2214	2592
HyPer + LLVM	35	125	80	117	1105
compile time [ms]	16	41	30	16	34
VectorWise [ms]	98	-	257	436	1107
MonetDB [ms]	72	218	112	8168	12028
DB X [ms]	4221	6555	16410	3830	15212

Figure 3.3: HyPer OLAP performance compared to other engines.
[Neu11]

Figure 3.3 demonstrates that HyPer reduced compile time by many multiples. Figure 3.4 shows they achieved many times fewer branches and branch mispredictions compared to their MonetDB baseline [BZN05]. This improvement resulted from HyPer’s output containing less code in the compiled queries.

	Q1		Q2		Q3		Q4		Q5	
	LLVM	MonetDB	LLVM	MonetDB	LLVM	MonetDB	LLVM	MonetDB	LLVM	MonetDB
branches	19,765,048	144,557,672	37,409,113	114,584,910	14,362,660	127,944,656	32,243,391	408,891,838	11,427,746	333,536,532
mispredicts	188,260	456,078	6,581,223	3,891,827	696,839	1,884,185	1,182,202	6,577,871	639	6,726,700
I1 misses	2,793	187,471	1,778	146,305	791	386,561	508	290,894	490	2,061,837
D1 misses	1,764,937	7,545,432	10,068,857	6,610,366	2,341,531	7,557,629	3,480,437	20,981,731	776,417	8,573,962
L2d misses	1,689,163	7,341,140	7,539,400	4,012,969	1,420,628	5,947,845	3,424,857	17,072,319	776,229	7,552,794
I refs	132 mil	1,184 mil	313 mil	760 mil	208 mil	944 mil	282 mil	3,140 mil	159 mil	2,089 mil

Figure 3.4: HyPer branching and cache locality benchmarks.
[Neu11]

Hyper continues on in 2018 where they separated the compiler into multiple rounds. They introduced an interpreter on the byte code generated from LLVM IR, then they can run unoptimised machine code, and on the final stage they can run optimised machine code. Figure 3.5 visualises this with the compile times of each stage. However,

they had to create the byte code interpreter themselves to enable this.

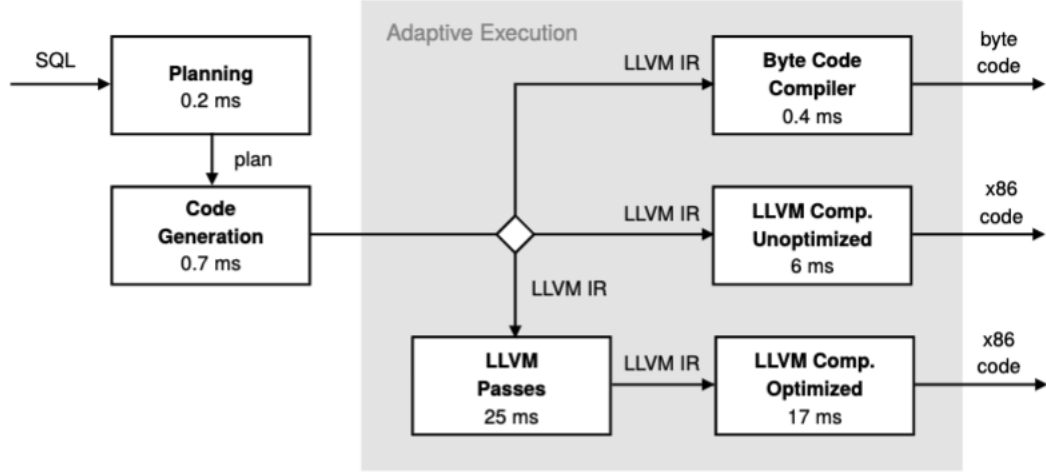


Figure 3.5: HyPer execution modes and compile times.
[KLN18]

The 2018 paper also improved their query optimisation by adding a dynamic measurement for how long live queries are taking. This is because the optimiser’s cost model did not lead to accurate measurements for compilation timing. Instead, they introduced an execution stage for workers, then in a ”work-stealing” stage they log how long the job took. With a combination of the measurements and the query plan, they calculate estimates for jobs and optimal levels to compile them to.

This approach was evaluated using TPC-H Query 11 with 4 threads. The adaptive execution strategy outperformed bytecode-only execution by 40%, unoptimised compilation by 10%, and optimised compilation by 80%. This improvement occurs because the single-threaded compilation can run in parallel with query execution on other threads.

Utilising additional stages of the LLVM compiler, improving the cost model, and supporting multi threading the compilation and execution combined into a viable JIT compiled-query application. The primary criticism is that they effectively wrote the JIT compiler from the ground-up, which requires large amounts of engineering time. Majority of the additions here are not unique to a database’s JIT compiler, and are mostly ways to target the compiler’s latency.

3.5 Umbra

Umbra, created in 2020 by Thomas Neumann (creator of HyPer), demonstrates that HyPer’s in-memory database concepts can be applied to on-disk systems [NF20]. This became possible due to recent improvements in SSDs and buffer management. Umbra integrates concepts from LeanStore for buffer management and latching, combined with multi-version concurrency, compilation, and execution strategies from HyPer. This hybrid approach produced an on-disk database that is scalable, flexible, and faster than HyPer itself.

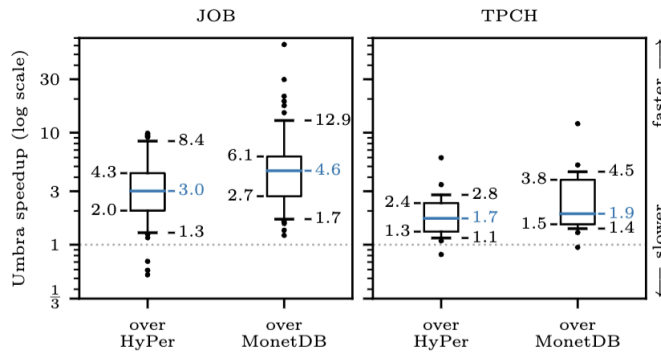


Figure 3.6: Umbra benchmarks.
[NF20]

A novel optimisation they introduced later was enabling the compiler to change the query plan [SFN22]. That is, they can use the metrics collected during execution to swap the order of joins, or the type of join being used. This improved the runtime of the data-centric queries by a factor of two. Some other databases introduce this concept by invoking the query optimiser multiple times, but since their compiler is invoked multiple times during execution this adds additional benefit.

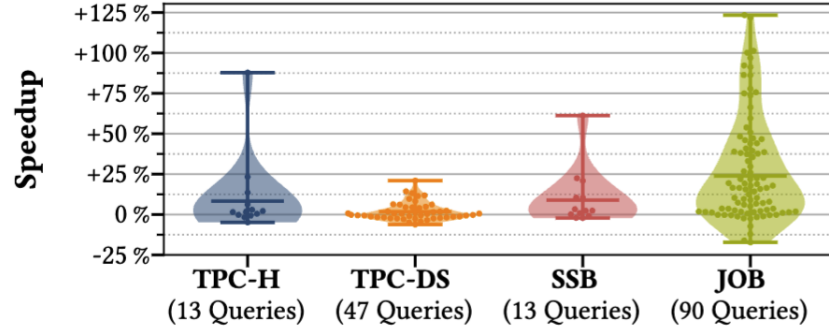


Figure 3.7: Umbra benchmarks after adaptive query processing (AQP).
[SFN22]

Umbra is currently ranked as the most effective database on ClickHouse’s benchmarking [Cli24]. The main complaint of the compiler being too heavy is still there, but it shows the advantage of having direct access to the JIT compiler with its adaptive compilation to change optimisation choices. Additionally, Umbra supports user-defined operators, enabling efficient integration of custom algorithms into the database [SN22].

3.6 Mutable

In 2023, Mutable presented the concept of using a low-latency JIT compiler (WebAssembly) rather than a heavy one in their initial paper [HD23a]. Its primary purpose, however, is to serve as a framework for implementing other concepts in database research so that they do not need to rewrite the framework later [HD23b]. However, using WebAssembly meant they can omit most of the optimisations that HyPer did while maintaining higher performance. Furthermore, they have a minimal query optimiser and instead rely on the V8 engine.

The V8 engine contains a ”Liftoff” component that adds an early-stage execution step to lower the initial overhead of running the query [Ham18]. The LiftOff component produces machine code as fast as possible while skipping optimisations, then ”turbofan” is a second-stage compiler that runs in the background while execution is running. However, HyPer has a direct bytecode interpreter which can result in a lower time to

execution.

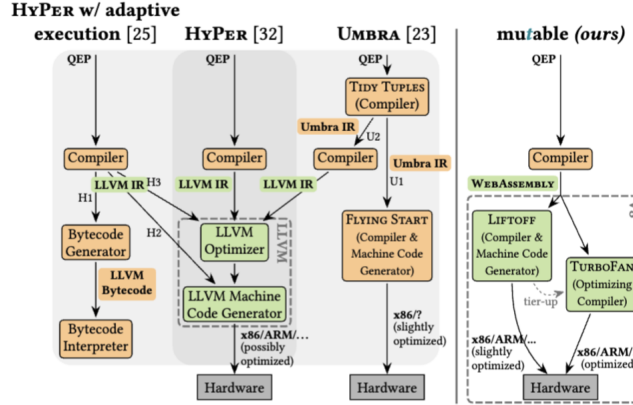


Figure 3.8: Comparison of mutable to HyPer and Umbra.
[HD23b]

Mutable’s benchmarks show they achieve similar compile and execution times to HyPer, and outperform them in many cases [HD23b]. While pushing Mutable to the same performance as HyPer or Umbra would require re-architecting, achieving this performance within the implementation effort is a significant outcome.

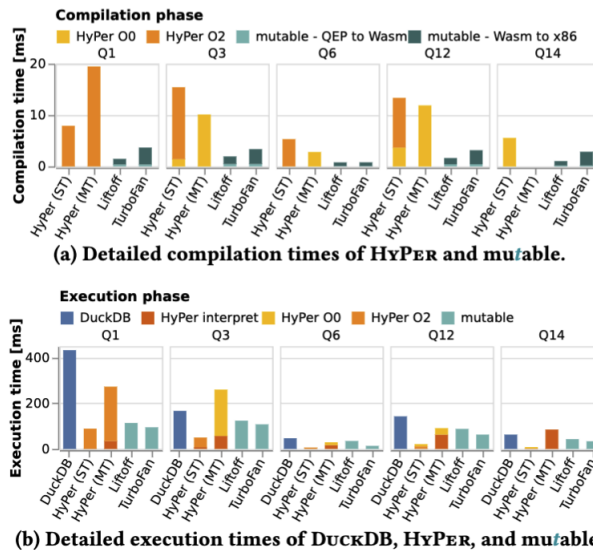


Figure 3.9: Benchmarks produced by Mutable.
[HD23b]

3.7 LingoDB

LingoDB, introduced in 2022, proposed using the MLIR framework for optimisation layers [JKG22]. Traditional databases follow a standard pipeline: parsing SQL into a query tree, converting to relational algebra, optimizing using manual implementations, creating a plan tree, and either executing or compiling to a binary. MLIR streamlines this by parsing directly to a high-level MLIR dialect, applying optimisation passes to the plan, and using LLVM compilation directly without intermediate conversions.

The LingoDB architecture can be seen in figure 3.10, which begins by parsing SQL into a relational algebra dialect. These dialects are defined using MLIR’s dialect system and code generation. The compiler consists of multiple dialect layers: a relational algebra dialect for high-level queries, a database dialect for database-specific types and operations, a DSA dialect for data structures and algorithms, and a utility dialect for support functions. This multi-stage design splits the intermediate representation into three levels: relational algebra, a mixed dialect layer, and finally LLVM code [JKG22].

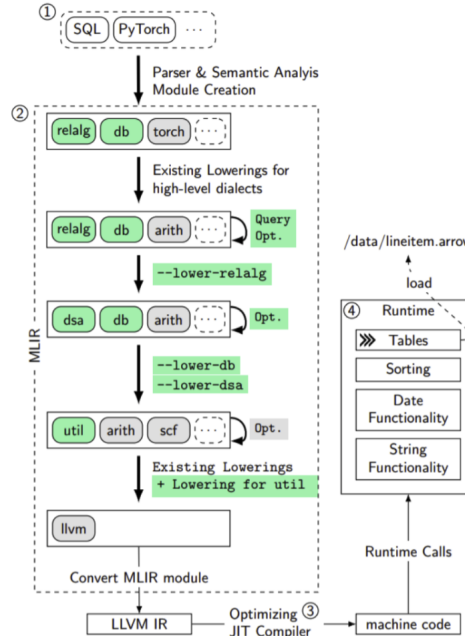


Figure 3.10: LingoDB architecture [JKG22]
[JKG22]

Their result is that they are less performant than HyPer, but do better than DuckDB [JKG22]. This performance is not their key output, rather, it is that they can implement the standard optimisation patterns within the compiler. Another feat is that they are approximately 10,000 lines of code in the query execution model, and Mutable is at 22,944 lines for their code despite skipping query optimisation. Within LingoDB’s paper they also compare this to being three times less than DuckDB and five times less than NoisePage.

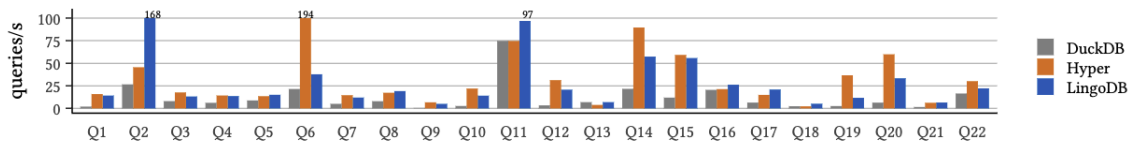


Figure 9: Query execution performance (compilation not included) for DuckDB, Hyper and LingoDB (SF=1)

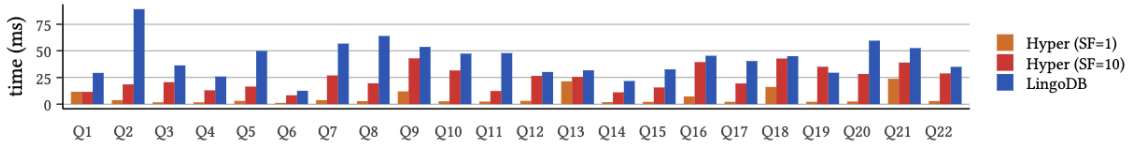


Figure 3.11: LingoDB benchmarking.
[JKG22]

In later research, LingoDB also explores obscure operations such as GPU acceleration, using the Torch-MLIR project’s dialect, representing queries as sub-operators for acceleration, non-relational systems, and more [JG23]. For our purposes, the appealing part of their architecture is that they use `pg_query` to parse the incoming SQL, which means their parser is the closest to PostgreSQL’s. This will be explored in the design in Section 4.1.

3.8 Benchmarking

These systems produced their own benchmarks and could selectively pick which systems to involve, so a recreation of the benchmarks was done. DuckDB, HyPer, Mutable, LingoDB and PostgreSQL were all compared to one another, and is visible in Figure 3.12.

TPC-H was used as most of the involved pieces used it themselves [BNE14], and docker containers were chosen to make deploying it easier. These benchmarks were created by relying on the Mutable codebase as they had significant infrastructure to support this, and is visible at <https://github.com/zyros-dev/benchmarking-dockers>.

The benchmarks show that PostgreSQL is significantly slower than the rest, likely because it is an on-disk database and most of the others are in-memory. With PostgreSQL removed from the graph, HyPer and DuckDB are the fastest, and with a single core DuckDB is the slowest.

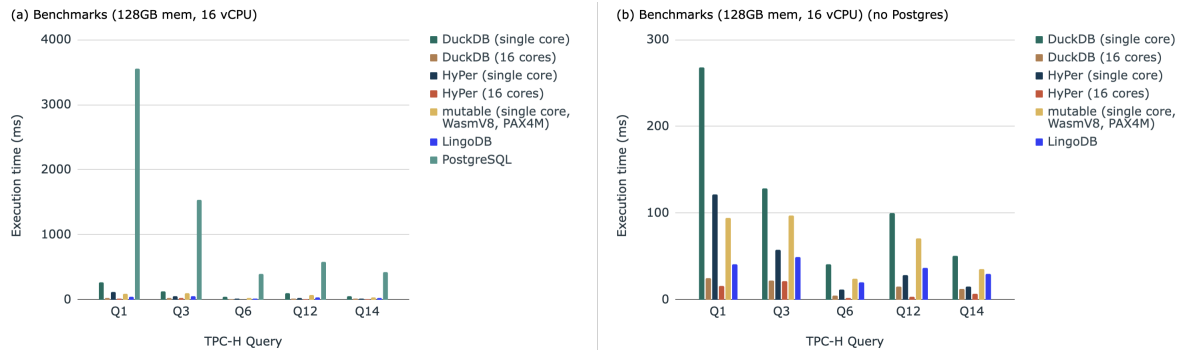


Figure 3.12: Benchmarking results.

To identify how much potential gain there is in a major on-disk database, **perf** was used on PostgreSQL during TPC-H queries 1, 3, 6, 12 and 14 in figure 3.13 [Linnd]. These queries were chosen because the Mutable code infrastructure directly supported them. This shows that the CPU time varied from between 34.87% and 76.56%, with an average of 49.32%. These metrics were identified using the **prof** graph. With this much time in the CPU, it is clear that the queries can become several times faster if optimised.

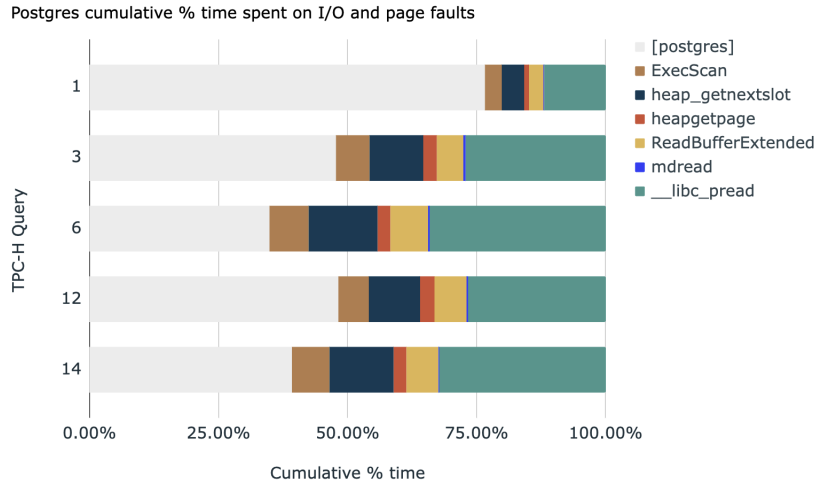


Figure 3.13: PostgreSQL’s time spent in the CPU, measured with prof.

3.9 Gaps in Literature

A core gap is the extension system within existing database. HyPer and Umbra managed to commercialise their systems, but the other databases are strictly research systems and some do not support ACID, multithreading, or other core requirements such as index scans. Michael Stonebraker, a Turing Award recipient and the founder of PostgreSQL, writes that a fundamental issue in research is that they have forgotten the use case of the systems and target the 0.01% of users [Sto18]. These commercial databases reaching high performance is a symptom of this. Testing the wide variety of ACID requirements is a significant undertaking.

The other issue is writing these compiled query engines is a large undertaking, and the core reason why vectorised execution has gained more popularity in production systems. Debugging a compiled program within a database is challenging, and while solutions have been offered, such as Umbra’s debugger [KN20], it is still challenging and questionable how transferable those tools are.

Relying on an extension system such that it’s an optional feature means users can install the optimisations, and tests can be done with production systems without requesting

pull requests into the system itself. Since these are large source code changes, it adds political complexity to have the solution added to the official system without production proof of it being used. The result of this would be an useable compiler accelerator, that can easily be installed into existing systems, and once used in many scenarios is easier to add to the official system.

3.10 Aims

Tying this together, this piece aims to integrate a research compiler into a battle-tested system by using an extension system. This addresses the gap of these systems being difficult to use widely, and potential to integrate it into the original system once stronger correctness and speed optimisations have been shown. Accomplishing this shows there is a way to rely on previous ACID-compliance and supporting code infrastructure. Users can install the extension, have faster queries with rollbacks, and the implementation effort is lowered since core systems and algorithms can be skipped.

A key output is showing that the system can operate within the same order of magnitude as the target system. The purpose of this is to ensure other optimisations can be applied to fit the surrounding database later, but the expectation is not to be faster than it.

One concern is these databases are large systems while the research systems are smaller. This increases the testing difficulty because a complete system has more variables, such as genetic algorithms in the query optimiser that makes performance non-deterministic. To counter this, benchmarks can be executed multiple times, and a standard deviation can be calculated.

Chapter 4

Method

In section 4.1 the overarching design is described, then section 4.2 goes over the implementation.

4.1 Design

The first decision is which database and which compiler this project should use. Something with strong extension support, wide-spread usage, high performance, and a volcano execution model is needed as a base. For the compiler, it would be ideal if they already use a similar interface to the target database when they parse SQL, and have promising results in their performance. This removes HyPer, Umbra, and System R, and leaves Mutable and LingoDB. LingoDB parses its inputs with `pg_query`, so it matches with PostgreSQL.

As a result, PostgreSQL and LingoDB were chosen. PostgreSQL offers strong support for extensions, and it is possible to override its execution engine using runtime hooks. An example of this is TimescaleDB (now TigerData) [Tim24a], which was explored in section 3.2. The primary challenge with this is that LingoDB is a columnar, in-memory database, so adjustments will be needed. Furthermore, LingoDB does not support indexes, which can make the benchmarks against PostgreSQL unfair. Another

detail is that LingoDB’s newer versions contain numerous features and optimisations that are not relevant to us, so to simplify implementation effort the 2022 version was used from their initial paper.

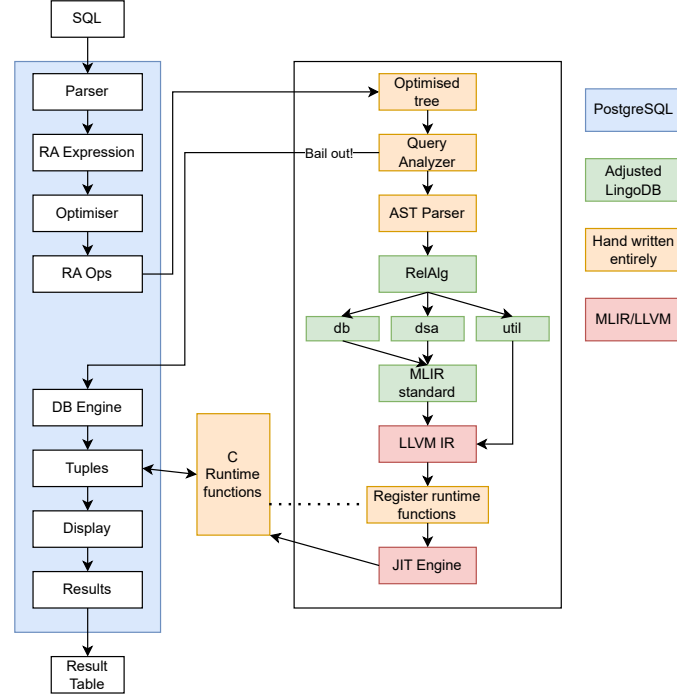


Figure 4.1: System design with labels of component sources.

LingoDB was integrated into PostgreSQL as seen in figure 4.1. The blue represents PostgreSQL components, with the pipeline on the left being the whole of PostgreSQL. A query reaches the runtime hooks, which gets analyzed by a handwritten analyser for whether the query can be executed, and then parsed. These hand written components are annotated in light-peach. This goes through the code LingoDB created, but with custom runtime hooks and other small edits, annotated with green. Finally, this is compiled into LLVM IR, which has the runtime hooks for reading from PostgreSQL embedded inside.

In the case that a query fails, the system should still support returning the results and gracefully roll over to PostgreSQL. This was done by ensuring the AST parser entrance

has a try-catch pattern that routes back to PostgreSQL even in failures. However, this does not protect from system panics such as segmentation faults.

The most time-consuming part of this is expected to be the AST Parser section, because it will be receiving the plan tree with the optimisations from PostgreSQL. LingoDB was designed to parse the query tree, which would come from the "Parser" stage in figure 4.1. 18 plan nodes and 14 expression nodes were implemented.

The final goal here is to support the TPC-H query set. To drive this implementation, a test-driven approach was used where PostgreSQL's `pg_regress` module added support for creating SQL queries and defining expected outputs. With this, a test set of basic queries was created which built up to TPC-H queries. This allowed progressive node implementation during development, and a quick way to validate changes are safe.

Table 4.1 shows the complete regression test suite, organized to progressively build complexity from single-row operations to full TPC-H queries.

Table 4.1: Regression test suite files and their aims

File Name	Aim
1_one_tuple.sql	Single row insertion and selection
2_two_tuples.sql	Multiple row retrieval
3_lots_of_tuples.sql	Large dataset handling (5000 rows)
4_two_columns_ints.sql	Multiple integer columns
5_two_columns_diff.sql	Mixed column types (INTEGER, BOOLEAN)
6_every_type.sql	All supported data types with projections
7_sub_select.sql	Column subsetting across Boolean columns
8_subset_all_types.sql	Column subsets from multi-type tables
9_basic_arithmetic_ops.sql	Arithmetic operators (+, -, *, /, %)
10_comparison_ops.sql	Comparison operators (=, <, !=, >, <=, >=, <=)
11_logical_ops.sql	Logical operators (AND, OR, NOT)
12_null_handling.sql	NULL operations (IS NULL, COALESCE)
13_text_operations.sql	Text operations (LIKE,)
14_aggregate_functions.sql	Aggregates without GROUP BY (SUM, COUNT, AVG, MIN, MAX)

Continued on next page

Table 4.1 – *Continued from previous page*

File Name	Aim
15_special_operators.sql	BETWEEN, IN, CASE WHEN
16_debug_text.sql	CHAR(10) with LPAD
17_where_simple_conditions.sql	WHERE with simple comparisons
18_where_logical_combinations.sql	WHERE with AND/OR/NOT combinations
19_where_null_patterns.sql	WHERE with NULL checks and COALESCE
20_where_pattern_matching.sql	WHERE with LIKE and IN operators
21_order_by_basic.sql	ORDER BY single columns (integers, strings, decimals)
22_order_by_multiple_columns.sql	ORDER BY multiple columns with mixed directions
23_order_by_expressions.sql	ORDER BY expressions (not supported - placeholder)
24_order_by_with_where.sql	ORDER BY combined with WHERE
25_group_by_simple.sql	GROUP BY with aggregations and ORDER BY
26_before_check_types.sql	All PostgreSQL types with casts and aggregations
27_group_by_having.sql	GROUP BY with HAVING clause
28_group_by_with_where.sql	GROUP BY with WHERE filtering
29_expressions_in_aggregations.sql	Expressions in aggregates (arithmetic, ABS)
30_test_missing_expressions.sql	PostgreSQL expression types coverage
31_distinct_statement.sql	DISTINCT in SELECT and aggregates
32_decimal_maths.sql	Decimal arithmetic operations
33_basic_joins.sql	INNER JOIN
34_advanced_joins.sql	LEFT, RIGHT, SEMI, ANTI joins
35_nested_queries.sql	Nested and correlated subqueries
36_tpch_minimal.sql	TPC-H minimal schema variant 1
37_tpch_minimal_2.sql	TPC-H minimal schema variant 2
38_tpch_minimal_3.sql	TPC-H minimal schema variant 3
39_tpch_minimal.sql	TPC-H minimal schema variant 4
40_tpch_not_lowered.sql	TPC-H queries without lowering
41_sorts.sql	Sorting with joins
42_test_relalgl_function.sql	Direct RelAlg MLIR execution
init_tpch.sql	TPC-H table initialization
tpch.sql	Full TPC-H benchmark in pgx-lower
tpch_no_lower.sql	TPC-H inside pure PostgreSQL for validation

Node implementation ordering followed the dependency analysis. Foundational nodes such as the sequential scan and projection are in virtually every query, while other

nodes build on top. By implementing in the dependency order, each new node could be tested using the previously implemented nodes, and bugs can be isolated.

4.2 Implementation

The primary system this project was developed on was a x86_64 CPU (Ryzen 3600) and on Ubuntu 25.04. The database was not tested on MacOS or Windows, and this may lead to issues when installing it independently.

4.2.1 Integrating LingoDB to PostgreSQL

The project was started from https://github.com/mkindahl/pg_extension, then `ExecutorRun_hook` inside of `executor.h` in PostgreSQL was used https://doxygen.postgresql.org/executor_8h_source.html as the entrance. Within PostgreSQL there are some surrounding steps since the intention is not usually to replace the entire executor with these hooks, so the memory context had to be activated and switched into.

Next, the `QueryDesc` pointer, which contains the query request, needed to be passed through to C++. This causes a design decision. Good practice here is to use smart pointers to prevent memory leaks, but this object is large and the source of truth about the request. Furthermore, the memory is handled by the PostgreSQL memory contexts. It was decided that these objects will remain as raw pointers, causing the C++ to break conventions.

LingoDB was installed as a git submodule and set to a read-only permission. This was maintained for reference purposes only, and the compilation phases would be extracted. LingoDB used LLVM 14, and was upgraded to LLVM 20 to modernise it and slightly better support with C++20 (some workarounds were required with LLVM 14 that could be skipped with LLVM 20). However, since this is the C++ API for LLVM, a large amount of the LingoDB code had to be adjusted to compile.

4.2.2 Logging infrastructure

PostgreSQL has its own logging infrastructure that routes through its `eelog` command, but it was decided that a two-layer logging infrastructure was required. The first layer is the level, (`DEBUG`, `IR`, `TRACE`, `WARNING_LEVEL`, `ERROR_LEVEL`, and more), and the second represents which layer of the design the log is inside of (`AST_TRANSLATE`, `RELALG_LOWER`, `DB_LOWER`, and more). This meant if the AST translation was being worked on, all the logs in only that section of the codebase could be enabled. The core benefit of this is that the logs are lengthy so it becomes easier to navigate.

An issue that was encountered was that the LLVM/MLIR logs would route through `stderr`, and this caused difficult-to-debug issues until the hook was found to redirect this into `eelog` as well. Subsection 4.2.3 will explore one of the workarounds that was needed at this stage.

Lastly, for error handling mostly `std::runtime_error` was utilised. This served as a global way to log the stack trace and roll back to PostgreSQL's execution. There initially was an implementation of error handling with severity levels and messages, but the simplicity of a single command that rolled back to PostgreSQL was more generally useful. If an error is thrown in `pgx-lower`, the progress in compiling is dumped then it fully falls over to PostgreSQL, even if the result is half-complete.

4.2.3 Debugging Support

An important property of PostgreSQL is that each client connection creates a new process. This means there are several debugging layers to navigate: the PostgreSQL postmaster, the client connection, the runtime hook entrance, C++ code, and the JIT runtime. Bugs can occur at any of these levels, making debugging challenging. This poses a particular difficulty when dealing with segmentation faults and other errors that lack logging information.

This was solved with a combination of the regression tests, unit testing, and a script

to connect `gdb` to dump the stack. The regression tests were already explored, but the unit tests test components unconnected to PostgreSQL. The issue is that this extension creates a `pgx_lower.so` which is loaded into PostgreSQL, and the PostgreSQL libraries are used from that context. This means if we run without being inside PostgreSQL, no `psql` libraries can be used. As a result, unit tests can only test MLIR functions. Most of the unit tests were highly situational, and are used when a proper interactive GDB connection was required within the IDE. Furthermore, unit tests allow the `stderr` to be visible, which assists greatly with MLIR/LLVM errors that go to `stderr` and nowhere else.

For the stack-dumping, a script was written, `debug-query.sh`, which proved to be the most useful approach for complex issues. It has the ability to create a `psql` connection, get the process ID of the client connection, then connect GDB, run a desired query, and dump the stack trace. In this way, the majority of errors were tackled.

4.2.4 Data Types

PostgreSQL has a large set of data types (<https://www.postgresql.org/docs/current/datatype.html>), and LingoDB has significantly less. However, for TPC-H we only require a subset of these. Table 4.2 shows which of the LingoDB types are used, and table 4.3 shows the type mappings. The two primary workarounds that were implemented were for decimals and the various types of strings. For decimals, `i128` provides enough precision for most TPC-H tests, which is what LingoDB was using. However, adjustments had to be made to prevent values that cannot be allocated from appearing, so the precision was capped at `<32, 6>`. That is, 32 digits in the integer part and 6 digits in the decimal places.

For the date types, a compromise was made that when it receives an interval type with a months column, it will turn this into days and introduce errors. However, since the TPC-H queries never use month intervals, this is acceptable.

DB Dialect Type	LLVM Type	Used by pgx-lower?
!db.date<day>	i64	Yes
!db.date<millisecond>	i64	No
!db.timestamp<second>	i64	Only if typmod specifies
!db.timestamp<millisecond>	i64	Only if typmod specifies
!db.timestamp<microsecond>	i64	Yes (default)
!db.timestamp<nanosecond>	i64	Only if typmod specifies
!db.interval<months>	i64	No
!db.interval<daytime>	i64	Yes
!db.char<N>	{ptr, i32}	No (uses !db.string)
!db.string	{ptr, i32}	Yes
!db.decimal<p,s>	i128	Yes
!db.nullable<T>	{T, i1}	Yes

Table 4.2: LingoDB type system full capabilities

PostgreSQL Type	DB Dialect Type	LLVM Type
<i>Integers</i>		
INT2 (SMALLINT)	i16	i16
INT4 (INTEGER)	i32	i32
INT8 (BIGINT)	i64	i64
<i>Floating Point</i>		
FLOAT4 (REAL)	f32	f32
FLOAT8 (DOUBLE)	f64	f64
<i>Boolean</i>		
BOOL	i1	i1
<i>String Types</i>		
TEXT / VARCHAR / BPCHAR	!db.string	{ptr, i32}
BYTEA	!db.string	{ptr, i32}
<i>Numeric</i>		
NUMERIC(p,s)	!db.decimal<p,s>	i128
<i>Date/Time</i>		
DATE	!db.date<day>	i64
TIMESTAMP	!db.timestamp<s ms μ s ns>	i64
INTERVAL	!db.interval<daytime>	i64
<i>Nullable</i>		
Any nullable column	!db.nullable<T>	{T, i1}

Table 4.3: PostgreSQL type translation through DB dialect to LLVM

4.2.5 LingoDB Dialect Changes

The MLIR dialects from LingoDB required modifications to support LLVM 20 and pgx-lower’s specific needs. Table 4.4 summarizes the key changes across the DB, DSA, RelAlg, and Util dialects. The changes were primarily API compatibility updates with minimal semantic modifications. The scope included 94 operations total across all dialects (93 in LingoDB, 94 in PGX) and 21 types (identical count), with most changes addressing LLVM 20 API compatibility.

Category	Count	Description
MLIR API Updates	30 changes	NoSideEffect \rightarrow Pure, Optional \rightarrow std::optional, added OpaqueProperties
Include Path Changes	100% of files	mlir/Dialect/ \rightarrow lingodb/mlir/Dialect/
Dialect Renames	1	Arithmetic \rightarrow Arith (MLIR core change)
New Operations	1	SetDecimalScaleOp in DSA
Modified Operations	2	DSA.SortOp (supports collections), BaseTableOp (added column_order)
Namespace Clarifications	6 interfaces	Added explicit cppNamespace declarations
Convenience Features	4 dialects	Added useDefaultTypePrinterParser = 1
Fastmath Support	2 patterns	Added fastmath flags to arithmetic canonicalization
Code Cleanup	5 locations	Removed comments, simplified logic

Table 4.4: Summary of key differences between LingoDB and pgx-lower dialects

This defines most of the supporting details. The main two components of the implementation are the runtime patterns and the plan tree translation.

4.2.6 Query Analyser

While the query analyser is fully written, in the final state it routes all queries through pgx-lower for testing. This enables testing new features and identifying where failures occur. It functions by doing a depth-first search through the plan tree and validating that the nodes are supported by the engine. In the future, this component could be enhanced to decide whether a query is worth running based on its cost metrics.

4.2.7 Runtime patterns

Runtime functions are used in LingoDB for methods that are difficult to implement in LLVM, such as sorting algorithms. `pgx-lower` adds several custom runtime implementations: reading tuples from PostgreSQL and storing them for streaming, modifying LingoDB’s runtime implementations, and replacing the sort and hash table implementations to use PostgreSQL’s API instead of standard library functions.

Figure 4.2 shows the high-level components in a runtime function. During SQL translation to MLIR, the frontend creates `db.runtimecall` operations with a function name and arguments. These operations are registered in the runtime function registry, which maps each function name to either a `FunctionSpec` containing the mangled C++ symbol name, or a custom lowering lambda. During the `DBToStd` lowering pass, the `RuntimeCallLowering` pattern looks up each runtime call in the registry and replaces it with a `func.call` operation targeting the mangled C++ function. The JIT engine then links these function calls to the actual compiled C++ runtime implementations, which handle PostgreSQL-specific operations like tuple access, sorting via `tuplesort`, and hash table management using PostgreSQL’s memory contexts. This pattern allows complex operations to be implemented once in C++ and reused across all queries, while maintaining type safety and null handling semantics through the MLIR type system.

LingoDB had a code generation step in their CMakeLists, `gen_rt_def`, which supports this. It parses a given C++ file, then generates a header file in the build files which has the mangled name lookup, so that the developer does not need to reimplement that section repeatedly.

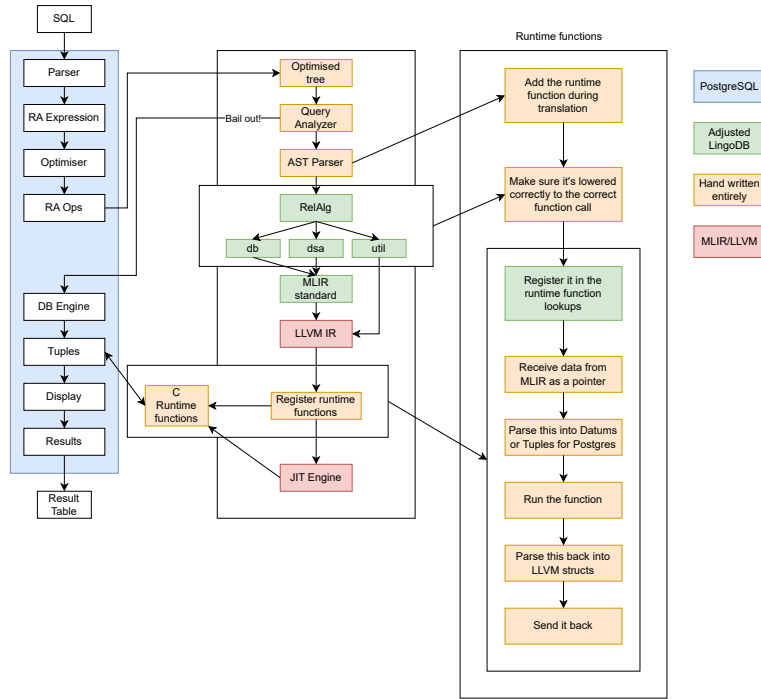


Figure 4.2: System design with labels of component sources.

The PostgreSQL runtime implements zero-copy tuple access for reading and result accumulation for output. When scanning a table, `open_postgres_table()` creates a heap scan using `heap_begin_scan()`, and `read_next_tuple_from_table()` stores a pointer (not a copy) to each tuple in the global `g_current_tuple_passthrough` structure. JIT code extracts fields via `extract_field()`, which uses `heap_get_attr()` and converts PostgreSQL `Datum` values to native types. For results, `table_builder_add()` accumulates computed values as `Datum` arrays in `ComputedResultStorage`. When a result tuple completes, `add_tuple_to_result()` streams it back through PostgreSQL's `TupleStreamer` by populating a `TupleTableSlot` and calling the destination receiver, enabling direct integration with PostgreSQL's tuple pipeline.

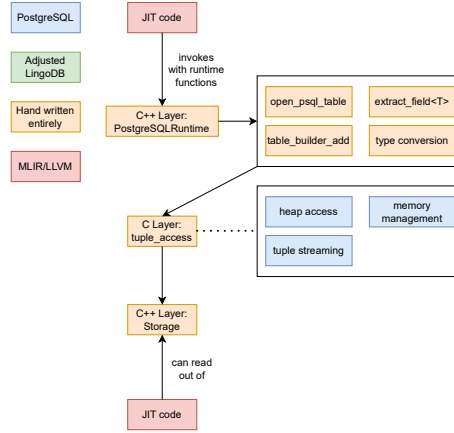


Figure 4.3: PostgreSQLRuntime.h component design

The PostgreSQL runtime allows the JIT runtime to read from the psql tables, and the design of it is visible in Figure 4.3. Generated JIT code invokes runtime functions implemented in the C++ layer, including table operations (`open_psql_table`), field extraction (`extract_field<T>`), result building (`table_builder_add`), and type conversions between PostgreSQL’s `Datum` representation and native types. These runtime functions interface with PostgreSQL’s C API layer, which handles heap access for reading tuples, memory management through PostgreSQL’s context system, and tuple streaming for returning results to the executor. An important part is that when tuples are read from Postgres, only the pointers are stored within the C++ storage layer to maintain zero-copy semantics.

Once stored, the JIT code can read from the batch and stream tuples back through the output pipeline as well. Streaming the tuples out from JIT means that the entire table does not build up in RAM, and instead tuples are returned one by one. This was tested by doing larger table scans as avoiding this buildup is essential.

LingoDB’s sort and hashtable runtimes were relying on `std::sort` and `std::unordered_map` respectively. This is problematic because as an on-disk database we need to handle disk spillage in these scenarios. Rather than reinventing these, leaning on psql’s implementation of these solves these issues and creates a blueprint for further implementations.

Most of the LingoDB lowerings bake metadata (such as table names) into the compiled binary by JSON-encoding it as a string. Instead of that, for the sort and hash table runtimes a specification pointer was used. Inside the plan translation stage, a struct was built and allocated with the transaction memory context, then the pointer to this was baked into the compiled binary instead. This enabled these runtimes to trigger without doing JSON deserialisation, and creating the operations them could skip this stage. This is something that a regular compiler would be incapable of doing, because the binary needs to be a standalone program, but in this context it can be relied upon.

4.2.8 Plan Tree Translation

The plan tree translation converts PostgreSQL’s execution plan nodes into RelAlg MLIR operations. Figure 4.4 shows where this fits into the broader design. Within the AST Parser component, we examine the PostgreSQL tag on the node to determine the plan node type, then a recursive descent parser starts translating. Each translation function follows a consistent pattern. First, children of the plan are translated using post-order traversal. Then, the node is translated into the MLIR relational algebra dialect, and a ”translation result” is returned.

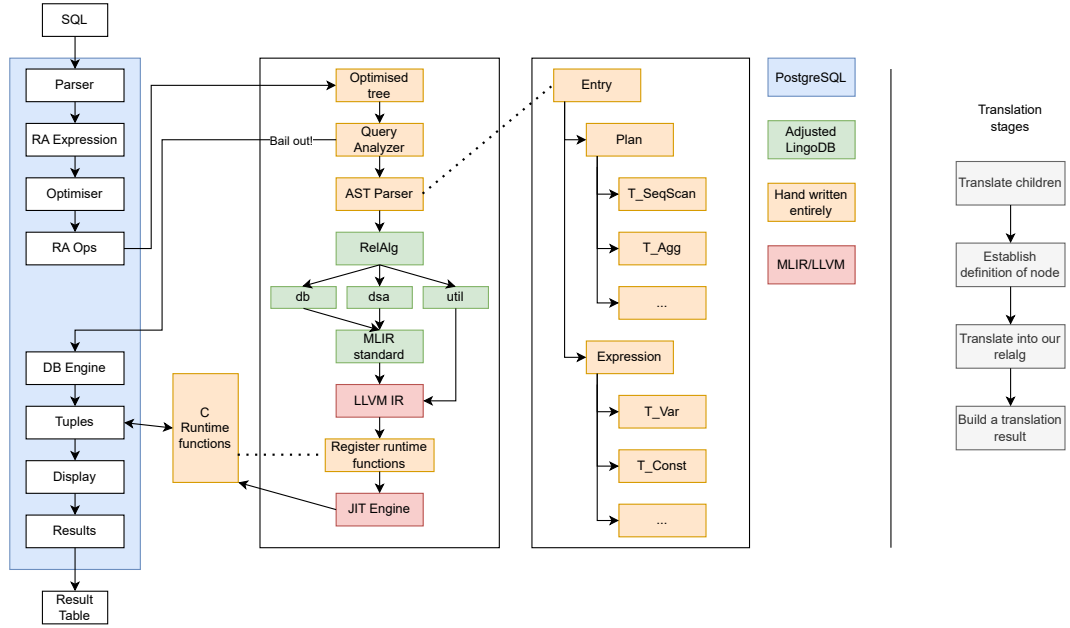


Figure 4.4: AST translation design and high-level steps in each function

The translation functions follow a consistent pattern, as shown in Listing 4.1. Each function takes the query context and a PostgreSQL plan node pointer, performs the translation, and returns a `TranslationResult`. The `QueryCtxT` object is passed down the tree, and when mutated, a new instance is created for child nodes. Meanwhile, `TranslationResults` flow upward to represent each node's output, providing strong type-correctness in theory. However, this pattern is not strictly enforced in practice.

Listing 4.1: Plan node translation method signatures. The expression nodes follow the same pattern.

```

1 auto translate_plan_node(QueryCtxT& ctx, Plan* plan) -> TranslationResult;
2 auto translate_seq_scan(QueryCtxT& ctx, SeqScan* seqScan) -> TranslationResult;
3 auto translate_index_scan(QueryCtxT& ctx, IndexScan* indexScan) -> TranslationResult;
4 auto translate_index_only_scan(QueryCtxT& ctx, IndexOnlyScan* indexOnlyScan) -> TranslationResult;
5 auto translate_bitmap_heap_scan(QueryCtxT& ctx, BitmapHeapScan* bitmapScan) -> TranslationResult;
6 auto translate_agg(QueryCtxT& ctx, const Agg* agg) -> TranslationResult;
7 auto translate_sort(QueryCtxT& ctx, const Sort* sort) -> TranslationResult;
8 auto translate_limit(QueryCtxT& ctx, const Limit* limit) -> TranslationResult;
9 auto translate_gather(QueryCtxT& ctx, const Gather* gather) -> TranslationResult;
10 auto translate_gather_merge(QueryCtxT& ctx, const GatherMerge* gatherMerge) -> TranslationResult;
11 auto translate_merge_join(QueryCtxT& ctx, MergeJoin* mergeJoin) -> TranslationResult;
12 auto translate_hash_join(QueryCtxT& ctx, HashJoin* hashJoin) -> TranslationResult;
13 auto translate_hash(QueryCtxT& ctx, const Hash* hash) -> TranslationResult;
14 auto translate_nest_loop(QueryCtxT& ctx, NestLoop* nestLoop) -> TranslationResult;
15 auto translate_material(QueryCtxT& ctx, const Material* material) -> TranslationResult;

```

```

16 auto translate_memoize(QueryCtxT& ctx, const Memoize* memoize) -> TranslationResult;
17 auto translate_subquery_scan(QueryCtxT& ctx, SubqueryScan* subqueryScan) -> TranslationResult;
18 auto translate_cte_scan(QueryCtxT& ctx, const CteScan* cteScan) -> TranslationResult;

```

The 14 expression node types are documented in Table 4.5, and the 18 plan node types in Table 4.6. These will be explained more specifically in the subsections.

File	Node Tag	Implementation Note
basic	T.BoolExpr	Boolean AND/OR/NOT - with short-circuit evaluation
basic	T.Const	Constant value - converts Datum to MLIR constant
basic	T.CoalesceExpr	COALESCE(...) - first non-null using if-else
basic	T.CoerceViaIO	Type coercion - calls PostgreSQL cast functions
basic	T.NullTest	IS NULL checks - generates nullable type tests
basic	T.Param	Query parameter - looks up from context
basic	T.RelabelType	Type relabeling - transparent wrapper
basic	T.Var	Column reference - resolves varattno to column
complex	T.Aggref	Aggregate functions - creates AggregationOp
complex	T.CaseExpr	CASE WHEN ... END - nested if-else operations
complex	T.ScalarArrayOpExpr	IN/ANY/ALL with arrays - loops over elements
complex	T.SubPlan	Subquery expression - materializes and uses result
functions	T.FuncExpr	Function calls - maps PostgreSQL functions to MLIR
operators	T.OpExpr	Binary/unary operators

Table 4.5: Expression node translations

File	Node Tag	Implementation Note
agg	T.Agg	Aggregation - AggregationOp with grouping keys
joins	T.HashJoin	Hash join - InnerJoinOp with hash implementation
joins	T.MergeJoin	Merge join - InnerJoinOp with merge semantics
joins	T.NestLoop	Nested loop join - CrossProductOp or InnerJoinOp
scans	T.BitmapHeapScan	Bitmap heap scan - SeqScan with quals
scans	T.CteScan	CTE scan - looks up CTE and creates BaseTableOp
scans	T.IndexOnlyScan	Index-only scan - treated as SeqScan
scans	T.IndexScan	Index scan - treated as SeqScan
scans	T.SeqScan	Sequential scan - BaseTableOp with optional Selection
scans	T.SubqueryScan	Subquery scan - recursively translates subquery
utils	T.Gather	Gather workers - pass-through (no parallelism)
utils	T.GatherMerge	Gather merge - pass-through (no parallelism)
utils	T.Hash	Hash node - pass-through to child
utils	T.IncrementalSort	Incremental sort - delegates to Sort
utils	T.Limit	Limit/offset - LimitOp with count and offset
utils	T.Material	Materialize - pass-through (no explicit op)
utils	T.Memoize	Memoize - pass-through to child
utils	T.Sort	Sort operation - SortOp with sort keys

Table 4.6: Plan node translations

Several common node definitions are helpful to understand. Nodes commonly have an `InitPlan` parameter, which is a function called before the node executes and initializes variables such as parameters and catalogue lookups. `targetlist` contains the output of the node, and `qual` specifies which tuples should pass through. Join nodes have left and right child trees, typically referred to as inner and outer children. These signify the inner and outer loops of the nested for-loop that is created.

Expression Translation - Variables, Constants, Parameters

PostgreSQL identifies values using variable nodes and parameter nodes. These are tracked in a schema/column manager class and the `QueryCtxT` object. Variables are typically defined within scans, while parameters are intermediate products. Identifying them presented challenges due to multiple interacting identifiers (`varno`, `varattno`, and special values for index joins). To handle this complexity, a generic function was added to the `QueryCtxT` object: `resolve_var`. This function is used extensively throughout the translation logic.

Parameters are mostly defined within the `InitPlan`, and one key novel type is the cached scalar type.

Plan translation - Scans

PostgreSQL supports multiple scan types: sequential scans, subquery scans, index scans, index-only scans, bitmap heap scans, and CTE scans. However, all scan types except subquery and CTE scans map to sequential scans in this implementation. This trade-off reduces implementation complexity at the cost of query optimisation, particularly for index scans.

Index scans use special annotations for variables via `INDEX_VAR`, which requires custom variable resolution. Additionally, we handle the qualifiers (scan filters) `indexqual` and `recheckqual` as generic filters. In PostgreSQL, these qualify at different stages, but

since we skip index implementation, both become generic filters here.

CTE scan plans are defined within the `InitPlan` of nodes, but still route through the primary plan switch statement logic. Neither CTE plans nor subqueries currently offer de-duplication to simplify implementation. That is, if a query uses the same CTE reference or writes the same subquery twice, they will currently be lowered into two different LLVM chunks of code rather than congregated and referenced.

Plan translation - Aggregations

Aggregation is a complicated node type with many properties. It includes an aggregation strategy (ignored in favour of a simpler algorithm), splitting specification (not utilised), and group columns. The node tracks the number of groups it produces and manages its own operators such as `COUNT`, `SUM`, and more. Additionally, it uses special varnos for variable lookups (represented as -2), requiring a new context object, and supports `DISTINCT` statements.

Most of the pain was with specific edge cases that arise in the simplification. For instance, `COUNT(*)` behaves differently in combining mode where parallel workers provide partial counts rather than raw rows, requiring translation to `SUM` instead of `CountRowsOp`. Similarly, `HAVING` clauses can reference aggregates not present in the `SELECT` list, necessitating a discovery pass with `find_all_aggrefs()` to ensure all required aggregates are computed before filtering. The use of magic number `varno=-2` to identify aggregate references, while necessary to distinguish them from regular column references, breaks the normal variable resolution flow and requires special handling throughout the expression translator.

Plan translation - Joins

For joins, there are two layers to translating them: the type of join, and the algorithm used by the join. The type of join refers to inner, semi, anti, right-anti, left/right

joins, and full joins. The semi and anti join types are not specifically translated, and instead rely on `EXISTS`/`NOT EXISTS` translations because they are semantically the same operation.

The algorithm used by the join refers to merge, nestloop, or hash joins. Following LingoDB's pattern, the merge joins are turned into hash joins so that there does not have to be additional lowering code. A challenge was that nest loops can carry parameters, so a new query context has to be created, the parameter has to be registered and inserted into the lookups.

One issue in the joins implementation is preventing double computations. LingoDB handles this by computing the inner join separately, building a vector of results, and then iterating over the outer operation while reusing the pre-computed inner section. This approach prevents duplicated computation at the cost of increased memory usage. While theoretically acceptable, the vector would need to implement disk spillage. In practice, memory usage did not become problematic enough to require this feature.

Expression Translation - Nullability

PostgreSQL tracks nullability information in the plan tree passed to `pgx-lower`. However, LingoDB's lowering operations can create situations where previously non-null objects become nullable through outer joins, aggregations, unions, and predicate evaluation. Since nullability propagates like not-a-number (affecting everything it touches), this introduces significant implementation complexity.

One note to be aware of is that LingoDB and PostgreSQL have inverted null flags. That is, in LingoDB 1 means valid, and in PostgreSQL 1 means null. This causes confusion with the runtime functions needing to invert flags back and forth.

Expression Translation - Operators and OID strings

Within operators, the primary challenge is the type conversions and quirks. Comparing two BPCHARs requires adding padding for the surrounding space. To implement implicit upcasting, a class was extracted from LingoDB’s DB dialect: `SQLTypeInference`. Rather than relying on PostgreSQL’s OID system for finding operations, operators are converted to strings (“l”, “i”, etc.) for lookup. This prevents issues with OID precision specifications that lead to unidentified operations. The same approach is used in function nodes, aggregation functions, sort operations, and scalar maths. When performing operations on different types, `SQLTypeInference` automatically upcasts both operands to the larger datatype. For example, with `i16 + i32`, both values are cast to `i32`.

Translation - Others

Many of these nodes are pass through nodes or delegated to another, sibling node, such as `T.Hash`, `T.Material`, `T.Memoize`, and `T.RelabelType`. Furthermore, nodes also come with executor hints and cost metrics which were skipped over rather than dragged through LingoDB, as the optimisations were already done by Postgres. `IN/ANY` operations are also converted into `EXISTS` operations, a number of operations such as scalar subqueries are always marked as nullable, and `CastOps` are also made frequently to defer casting to later layers.

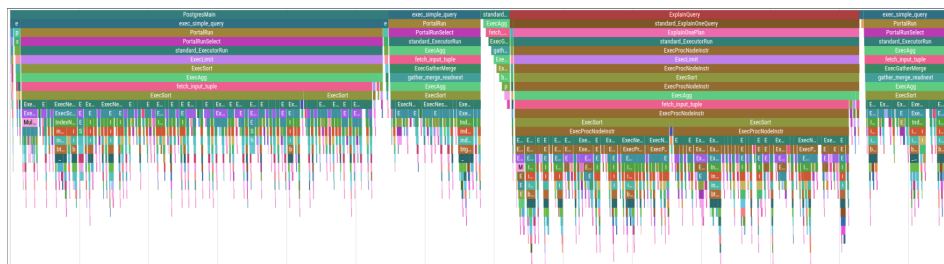
4.2.9 Configuring JIT compilation settings

Not much tinkering was done with the JIT optimisation flags, the minimum optimisation passes were used so that it can compile end-to-end, and `llvm::CodeGenOptLevel::Default` was used as the optimisation level. These optimisation passes consist of `SROA`, `InstCombinePass`, `PromotePass`, `LICM` pass, reassociation pass, `GVN` pass, and simplify `GVN` pass.

These passes perform fundamental optimisations [LLV25a]. `SROA` (Scalar Replacement

The consensus appeared to be that -02 should be used on it and moved on. This means it is possible to do more tuning work on this.

Code infrastructure was written to support magic-trace for profiling and isolating issues. A dedicated machine was configured for this purpose: an Intel i5-6500T with 16 GB of RAM and a Samsung MZVLB256HAHQ-000L7 NVMe disk. This was particularly useful for isolating obvious bottlenecks within the system and understanding the latency when compared to PostgreSQL. Figure 4.5 represents the flame chart for query 3, and has a runtime of approximately 260 milliseconds. The functions that it calls are clear, and you can see how the query runs over time.



The flame chart before any optimisations were applied is visible in figure 4.6. In that chart it is visible that too much time is spent inside the LLVM execution (those spikes in

the last 2/3rds are table reads). After adjusting how tuples are read, ensuring joins go to the correct algorithm, introducing Postgres’s tuple-slot reading API, and disabling logs, the chart looks like figure 4.7. These adjustments improved the latency from 4.5 seconds to approximately 400 milliseconds.

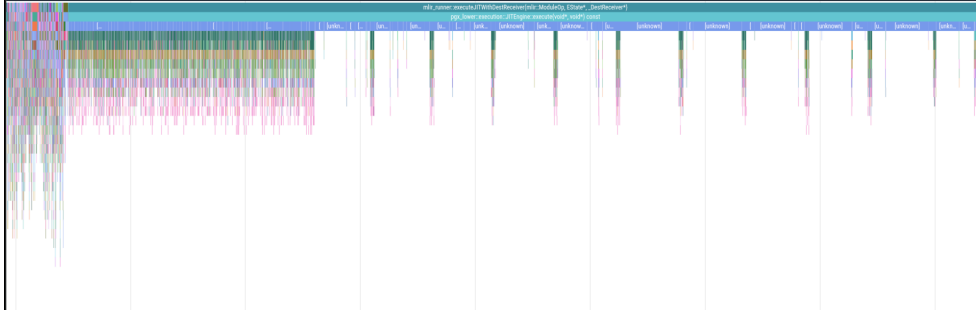


Figure 4.6: pgx-lower’s magic-trace flame chart for TPC-H query 3 at scale factor 0.05 before optimisation

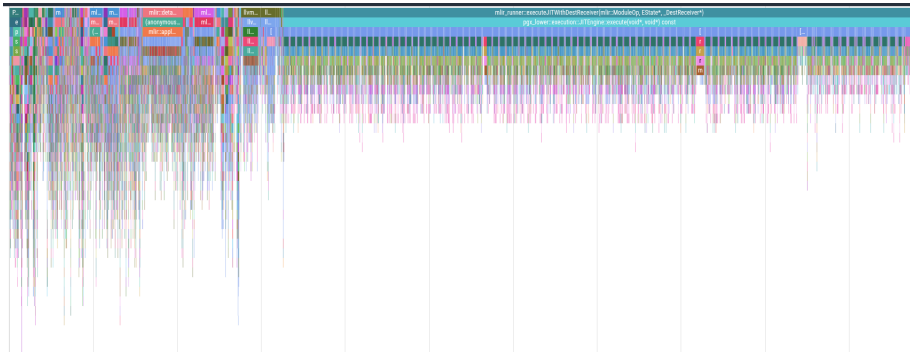


Figure 4.7: pgx-lower’s magic-trace flame chart for TPC-H query 3 at scale factor 0.05 after optimisation

The specifics of running these in a stable way will be explained in subsection 4.2.12.

4.2.11 Website

A small website was prepared so that users can interact with the lowerings and the compiler without installing the system themselves at <https://pgx.zyros.dev/query>. Keep in mind that it relies on caching the results, it has a scale factor of 0.01 (10 megabytes of data), and the pgx-lower system there is (as of writing), running a de-

bug build which has significantly longer runtimes. The implementation for this is at <https://github.com/zyros-dev/pgx-lower-addons>. The implementation uses several technologies: Python for the backend server, SQLite for query caching, and React for the frontend. Docker containers support the reverse proxy with Nginx, while a private Grafana dashboard provides health monitoring.

4.2.12 Benchmarking and Validation

A challenge is that PostgreSQL contains a non-deterministic optimiser, and many small factors can affect runs. For this reason, a python script was created that reads from a YAML file, and does a benchmark run. This means we can specify runs beforehand, and run them robustly over a long period. Also, this benchmarking run computes a hash of the outputs between PostgreSQL and pgx-lower to validate the outputs are correct between all the runs, and the hashes were compared. This avoids storing large amounts of data over time, while the issue can still be rediscovered in a large batch of runs.

The benchmark configurations used are displayed in Listing 4.2. These configurations allow testing across different scale factors, with and without indexes, and with varying iteration counts to understand performance characteristics. With multiple iterations, graphs that contain distributions can be created. These were decided by bucketing queries into small scale factor (0.01, or 1 megabyte of data) to show the overhead cost of the JIT compiler, medium scale factor (0.16) to show how Postgres scales while still keeping all the queries enabled with indexes, and lastly scale factor 1 with the very time-consuming queries completely disabled. These disabled queries would take on the order of hours in PostgreSQL, so benchmarking them was too time-consuming.

To disable indexes, `cur.execute("SET enable_indexscan = off;")` and `cur.execute("SET enable_bitmapscan = off;")` were used in conjunction. This means when the benchmarks say index scan is disabled, the bit map scan is as well.

Listing 4.2: Benchmark configurations for TPC-H testing

```
1 full:
```

```
2 runs:
3   - container: benchmark
4     scale_factor: 0.01
5     iterations: 5
6     profile: false
7     indexes: false
8     skipped_queries: ""
9     label: "SF=0.01, indexes disabled, 5 iterations"
10
11  - container: benchmark
12    scale_factor: 0.01
13    iterations: 100
14    profile: false
15    indexes: false
16    skipped_queries: "q07,q20"
17    label: "SF=0.01, indexes disabled - excluding postgres {q07,q20}, 100 iterations"
18
19  - container: benchmark
20    scale_factor: 0.01
21    iterations: 100
22    profile: false
23    indexes: true
24    skipped_queries: ""
25    label: "SF=0.01, indexes enabled, 100 iterations"
26
27  - container: benchmark
28    scale_factor: 0.16
29    iterations: 5
30    profile: false
31    indexes: true
32    skipped_queries: ""
33    label: "SF=0.16, indexes enabled, 5 iterations"
34
35  - container: benchmark
36    scale_factor: 0.16
37    iterations: 100
38    profile: false
39    indexes: true
40    skipped_queries: "q17,q20"
41    label: "SF=0.16, indexes enabled, excluding {q17,q20}, 100 iterations"
42
43  - container: benchmark
44    scale_factor: 1
45    iterations: 100
46    profile: false
47    indexes: false
48    skipped_queries: "q02,q17,q20,q21"
49    label: "SF=1, indexes disabled, excluding {q02,q17,q20,q21}, 100 iterations"
```

One thing to note here is that it was decided that only PostgreSQL and pgx-lower would be compared, rather than all the databases mentioned in chapter 3. As section 3.8 showed that the impact of PostgreSQL’s architecture being on disk makes it significantly slower than any of the other databases.

The magic trace profiling also functions through this script, which is what the `profile` tag there is for.

Chapter 5

Results and Discussion

5.1 Results

The following results were produced with the method detailed in subsection 4.2.12. Box plots were stacked on top of the graphs, representing the 5th, 25th, 50th, 75th, and 95th percentiles. Any outliers were marked with a hollow circle, and if they were inconvenient to show (such as in figure 5.4), an arrow annotation is utilised. Matplotlib and Seaborn were used to make these in Python.

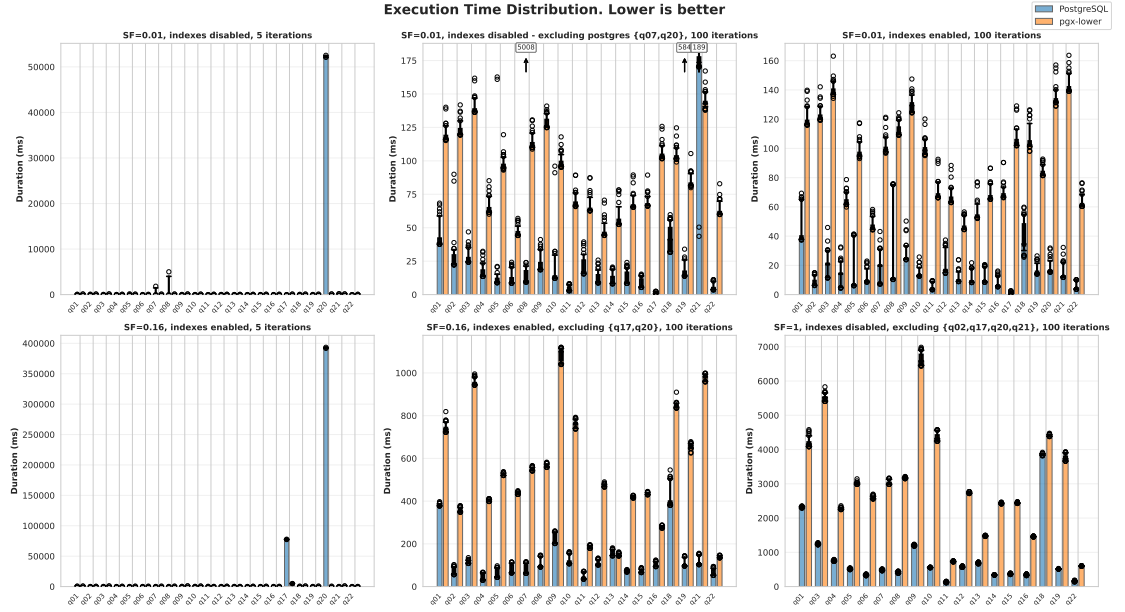


Figure 5.1: Overall benchmarking represented with box plots

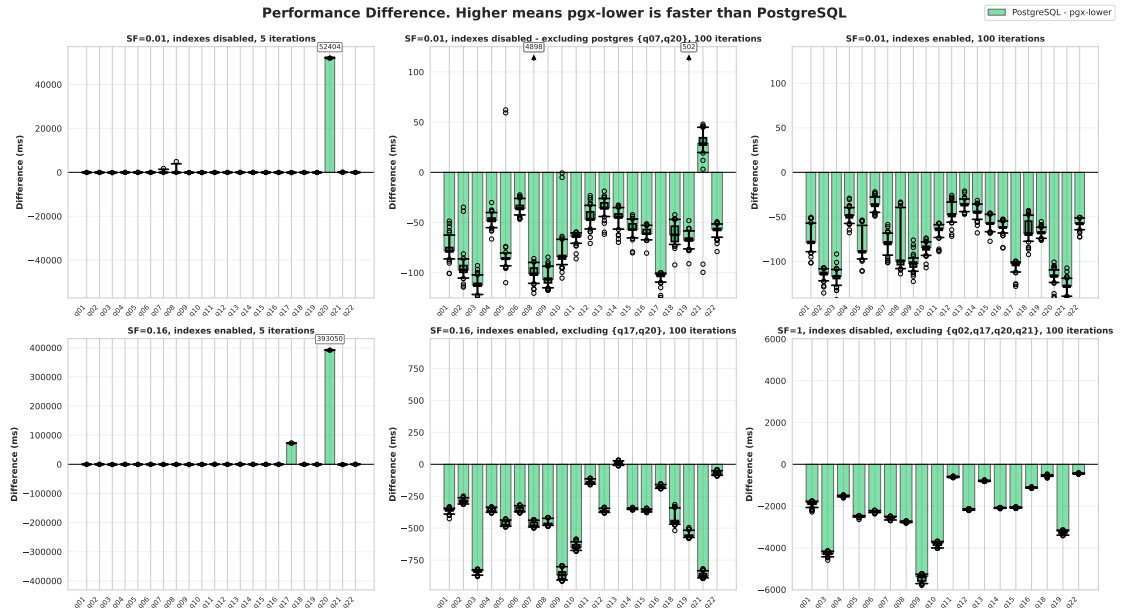


Figure 5.2: Difference in latency benchmarks between PostgreSQL and pgx-lower

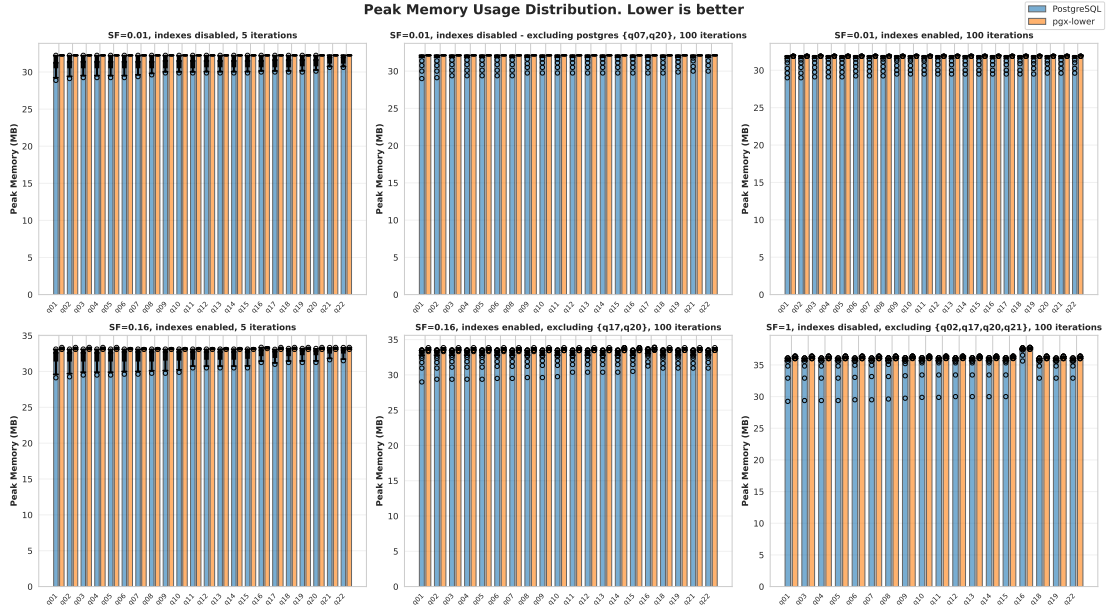


Figure 5.3: Peak memory usage of queries

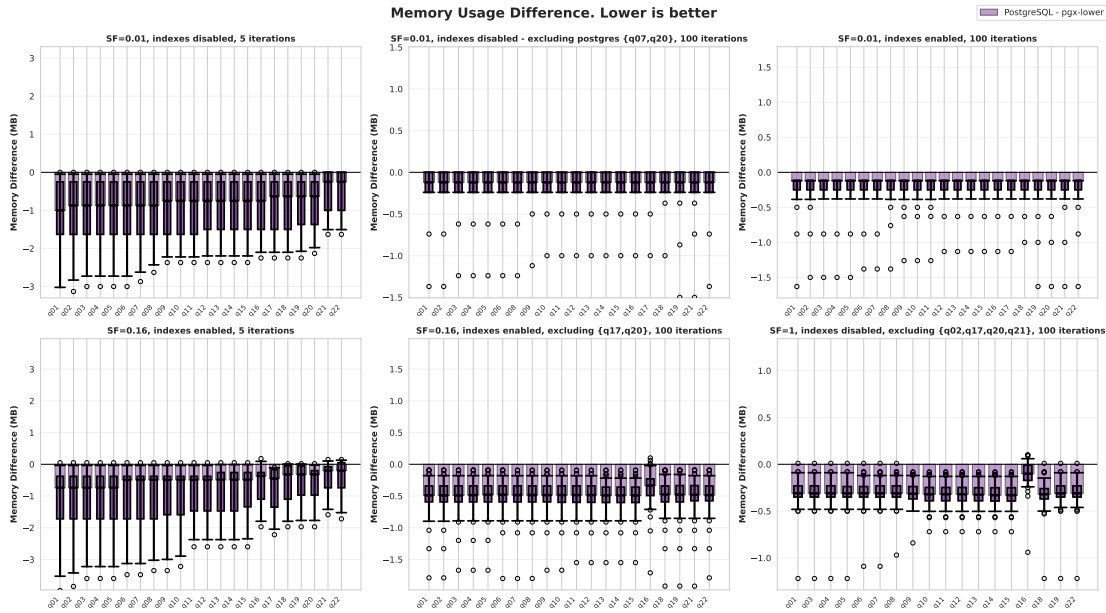


Figure 5.4: Difference in peak memory usage of queries

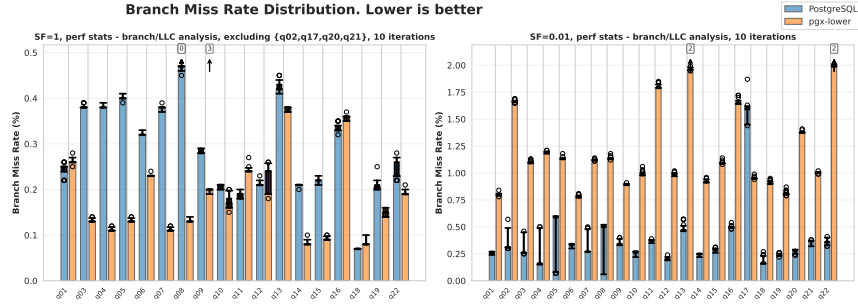


Figure 5.5: Branch miss rate

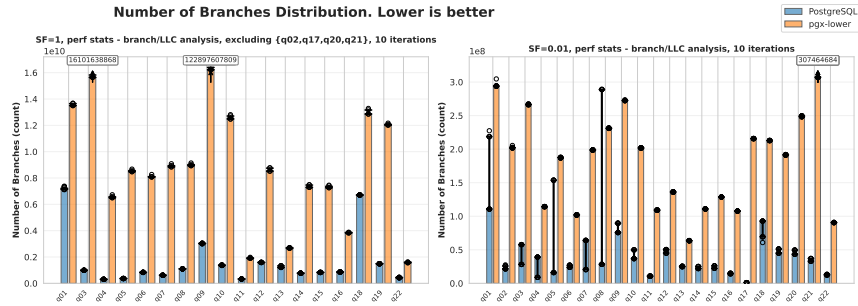


Figure 5.6: Number of branches

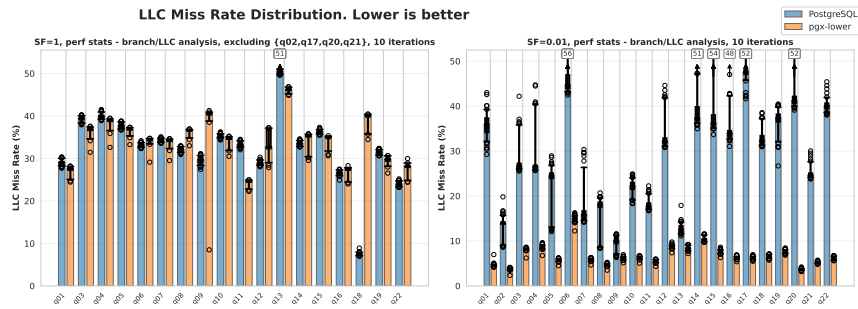


Figure 5.7: Last-level-cache miss plots

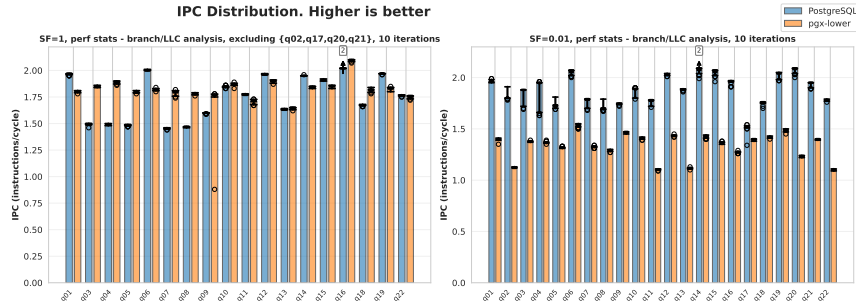


Figure 5.8: Instructions per (CPU) cycle plot



Figure 5.9: PostgreSQL TPC-H query 20 indexes enabled at SF = 0.16. Runtime: 15 minutes

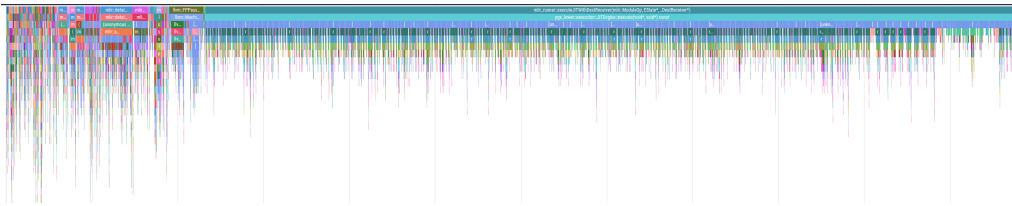


Figure 5.10: pgx-lower TPC-H query 20 indexes enabled at SF = 0.16. Runtime: 1.18 seconds

5.2 Discussion

To reiterate, the goal is to show that using the extension system is a viable approach to introduce compiled queries into battle-tested databases while maintaining their ACID properties. Previous studies have already found that this model has speed benefits.

In terms of latency, results are mixed. Figures 5.1 and 5.2 show that without indexes at scale factor 0.01, queries 7 and 20 are orders of magnitude slower than other queries. This pattern repeats at scale factor 0.16 even with indexes enabled. In contrast,

pgx-lower shows consistent performance across these queries. The reason is visible in figures 5.9 and 5.10: PostgreSQL uses a nested loop join while pgx-lower uses a hash join. Appendices A.1, A.2, and A.3 show the query and both systems’ plan trees. In pgx-lower’s output, joins are annotated with "hash", indicating hash join usage. This comparison is not entirely fair because pgx-lower uses a hash join while PostgreSQL uses a nested loop join (NestLoop_T), which would benefit from indexing.

A notable detail in figure 5.10 is the minimal time spent in LLVM code generation. Of the 1.18 second total query execution time, only 14.93 milliseconds is spent in `llvm::SelectionDAGISel::runOnMachineFunction`, the LLVM IR to machine code conversion step. However, total compilation time is 236 milliseconds, with most of this spent in MLIR passes. This suggests MLIR optimization is more expensive than LLVM code generation. One explanation is that the LLVM ORC JIT does minimal work per query and spreads compilation across the execution in the background.

For RAM usage, figures 5.3 and 5.4 show pgx-lower and PostgreSQL have similar peak memory usage. This is encouraging because it demonstrates that LingoDB’s in-memory operations were successfully adapted to PostgreSQL’s disk-oriented architecture. Figure 5.4 shows the maximum difference is just over 3 megabytes, with a mean difference of 0.34 megabytes across all queries.

The branch prediction in figure 5.5 shows potential. At scale factor 1, pgx-lower’s median branch miss rate was 0.16%, compared to Postgres’s 0.28%. However, at a smaller scale factor with smaller queries this is inverted such that PostgreSQL had a median of 0.38% and pgx-lower had 1.09%. This means that the compiled JIT runtime has a better branch prediction rate, but potentially the code within the compilation stage, or before warm-up, has a worse rate. The difference could be attributed to the number of branches, visible in figure 5.6. PostgreSQL had a median of 28,430,465 branches, while pgx-lower had 195,299,021.50; 6.87 times more than PostgreSQL. This increase in the number of branches could mean that there are more low-hanging fruit.

For the last level cache miss rate, pgx-lower appears to perform better than PostgreSQL at smaller scale factors and appears similar to PostgreSQL at larger ones, which can be

seen in figure 5.7. PostgreSQL has a median 31.20% miss rate at scale factor 0.01, while pgx-lower has a median of 6.19%. When increased to a scale factor of 1, PostgreSQL has a median of 33.16%, and pgx-lower has a median of 34.81%. An explanation for this could be that the LLVM compiler stage uses its cache much more effectively, but the actual JIT is approximately the same. This is expected with the current approach, but this would improve if the JIT stage is permitted to dynamically change the plan, such as how HyPer does.

5.2.1 Test Validity

Increasing the number of iterations to make the outputs more reliable seems to be successful, and the variation is not too large. Some queries, such as in scale factor 0.01 with indexes disabled, in figure 5.1, show the outliers do become extreme. On query 8, PostgreSQL had an outlier of 5008 milliseconds while the median was 12.42 milliseconds. However, the coefficient of variation was only 0.44% overall during the latency measurements in the scale factor 0.01. It's stable overall, but vital to do repeated tests to exclude these outliers from the system.

These variations will primarily be caused by PostgreSQL's optimiser containing genetic algorithms, as mentioned in section 2.5. It can cause plans to change significantly and makes them non-deterministic. While these tests were done on an isolated docker container in a Linux machine running minimal processes, system interrupts can also affect the results.

5.2.2 Future work

Since replacing PostgreSQL's execution engine with a JIT-focused one is quite generic, there are a number of directions future work can take. The system itself can be improved by fully implementing the plan nodes, and it could be optimised further. However, it's important to ensure the final product is useful, so other base databases, compilers, languages, and execution engines that could be integrated can be considered.

To progress this system further and make it a full extension, the plan tree nodes need to be fully implemented, and the query analyser can be improved. Only the minimum amount for TPC-H was implemented here, but `pg_bench` and `isolationtester` should also be used before suggesting this system to users. This includes implementing indexes, WINDOW functions, the other 22 missing plan nodes, and the missing execution nodes.

The other core work is optimising the system, both with existing research and clearer ways to use the PostgreSQL API. Namely: pre-compiling functions in PostgreSQL into LLVM, then inlining them instead of crossing the LLVM-C++ boundary; adaptive compilation/query planning; and Umbra’s LeanStore-style buffering system. Most of these optimisations are only applicable inside an LLVM/MLIR system, though if WebAssembly is used instead, many of them can be skipped. More generally, parallelism can be improved, JIT compilation tuning, cross-platform support, subquery deduplication, and further optimisations.

In databasing and research broadly, it is vital to keep in mind whether the research is useful and impactful, as per Michael Stonebraker’s concern that the field is merely polishing a round ball [Sto18]. For successful projects, database costs are typically minor compared to overall profitability, making higher throughput a lower priority. In practice, better latency gains often come from application-level caching solutions like Redis rather than database optimization. These complex queries are primarily in OLAP systems, and large-scale OLAP systems will usually move away from PostgreSQL and into a more scalable database such as ClickHouse, or Apache HIVE. For this reason, there may be better systems to develop this architecture on.

PostgreSQL was chosen due to its large popularity and LingoDB was used because it reasonably matched PostgreSQL’s interfaces while being open source. While PostgreSQL is reasonably good for this approach, and this can solve a real problem with it, there might be a better database. Most of these dedicated OLAP systems will already be using a JIT or vectorized approach, though.

During development, using LingoDB provided helpful constraints and made development easier since it is an established system. However, LingoDB’s columnar, in-memory

architecture required extensive modifications to suit its needs. It also contains a query optimisation engine, which is unnecessary because PostgreSQL already has a thorough optimisation system. It would be better to build the engine, or find a better suited base system. The ideal here would be Umbra based on its description, but it is closed source. Another potential approach is to take an established OLAP system's engine (such as ClickHouse), and route to that instead of PostgreSQL's depending on the analyser's rules.

MLIR was useful to give a strong set of dialect systems, but the main reason LingoDB used it was to give database optimisations clear layers. Furthermore, the LLVM/MLIR ecosystem targets ahead of time compilation, or longer-running JIT systems. While WebAssembly is appealing here because it targets short-lived processes, we would not be able to inline functions in the future. Either way, switching to a different compiler, or away from C++ into C or Rust is appealing.

This establishes a large set of different directions this research can take. The most appealing direction is attempting to take NoisePage or ClickHouse and inserting it into PostgreSQL as a drop-in engine replacement. This is a more complete ecosystem, and the primary work will be around the adapters to adjust queries. Furthermore, pg_duckdb has already done this, but it is a vectorised engine.

Chapter 6

Conclusion

Lorem Ipsum

Acknowledgements

This work has been inspired by the labours of numerous academics in the Faculty of Engineering at UNSW who have endeavoured, over the years, to encourage students to present beautiful concepts using beautiful typography.

Further inspiration has come from Donald Knuth who designed T_EX, for typesetting technical (and non-technical) material with elegance and clarity; and from Leslie Lamport who contributed L^AT_EX, which makes T_EX usable by mortal engineers.

John Zaitseff, an honours student in CSE at the time, created the first version of the UNSW Thesis L^AT_EX class and the author of the current version is indebted to his work.

Lastly my supervisor and assessor for supporting me throughout this project.

Appendices

This appendix contains the execution plans for TPC-H Query 20, demonstrating the differences between PostgreSQL's traditional query execution plan and pgx-lower's MLIR-based compilation approach.

A.1 Query 20 SQL

```
1  select
2      s_name,
3      s_address
4  from
5      supplier,
6      nation
7  where
8      s_suppkey in (
9          select
10             ps_suppkey
11         from
12             partsupp
13         where
14             ps_partkey in (
15                 select
16                     p_partkey
17                 from
18                     part
19                 where
20                     p_name like 'forest%'
21             )
22         and ps_availqty > (
23             select
24                 0.5 * sum(l_quantity)
25             from
26                 lineitem
27             where
28                 l_partkey = ps_partkey
29                 and l_suppkey = ps_suppkey
30                 and l_shipdate >= date '1994-01-01'
31                 and l_shipdate < date '1995-01-01'
32         )
33     )
34  and s_nationkey = n_nationkey
```

```

35         and n_name = 'CANADA'
36 order by
37         s_name

```

A.2 PostgreSQL Execution Plan

```

1 Sort (cost=46847.99..46848.00 rows=1 width=52) (actual time=69.713..69.728 rows=1 loops=1)
2   Sort Key: supplier.s_name
3   Sort Method: quicksort Memory: 25kB
4   -> Nested Loop Semi Join (cost=0.42..46847.98 rows=1 width=52) (actual time=68.025..69.569 rows=1 loops=1)
5     -> Nested Loop (cost=0.14..29.27 rows=1 width=56) (actual time=0.493..0.667 rows=3 loops=1)
6       Join Filter: (nation.n_nationkey = supplier.s_nationkey)
7       Rows Removed by Join Filter: 97
8       -> Index Scan using supplier_pkey on supplier (cost=0.14..15.64 rows=100 width=60) (actual time=
9         =0.029..0.131 rows=100 loops=1)
10      -> Materialize (cost=0.00..12.13 rows=1 width=4) (actual time=0.004..0.005 rows=1 loops=100)
11      -> Seq Scan on nation (cost=0.00..12.12 rows=1 width=4) (actual time=0.414..0.421 rows=1 loops=1)
12        Filter: (n_name = 'CANADA'::bpchar)
13        Rows Removed by Filter: 24
14      -> Nested Loop (cost=0.28..46818.70 rows=1 width=4) (actual time=22.958..22.958 rows=0 loops=3)
15        -> Seq Scan on part (cost=0.00..66.00 rows=20 width=4) (actual time=0.111..1.250 rows=16 loops=3)
16          Filter: ((p_name)::text ~ 'forest%'::text)
17          Rows Removed by Filter: 1973
18        -> Index Scan using partsupp_pkey on partsupp (cost=0.28..2337.63 rows=1 width=8) (actual time=1.355..1.355
19          rows=0 loops=48)
19          Index Cond: ((ps_partkey = part.p_partkey) AND (ps_suppkey = supplier.s_suppkey))
20          Filter: ((ps_availqty)::numeric > (SubPlan 1))
21          Rows Removed by Filter: 0
22          SubPlan 1
23            -> Aggregate (cost=2330.51..2330.52 rows=1 width=32) (actual time=31.616..31.617 rows=1 loops=2)
24              -> Seq Scan on lineitem (cost=0.00..2330.50 rows=1 width=5) (actual time=25.850..31.589 rows
25                =2 loops=2)
26                Filter: ((l_shipdate >= '1994-01-01'::date) AND (l_shipdate < '1995-01-01'::date) AND (
27                  l_partkey = partsupp.ps_partkey) AND (l_suppkey = partsupp.ps_suppkey))
28                Rows Removed by Filter: 60173
29 Planning Time: 16.634 ms
30 Execution Time: 70.580 ms

```

A.3 pgx-lower MLIR Execution Plan

```

1 // MLIR Module Debug Dump: Phase 3a AFTER: RelAlg -> Optimised RelAlg
2 // Generated: 2025-11-23 23:21:32
3 // Total Operations: 120
4 // Module Valid: YES
5
6 module {
7   func.func @main() -> !dsa.table {
8     %true = arith.constant true
9     %0 = relalg.basetable {column_order = ["l_orderkey", "l_partkey", "l_suppkey", "l_linenum", "l_quantity", "
10       l_extendedprice", "l_discount", "l_tax", "l_returnflag", "l_linestatus", "l_shipdate", "l_commitdate", "
11       l_receiptdate", "l_shipinstruct", "l_shipmode", "l_comment"], rows = 0.000000e+00 : f64, table_identifier = "
12       lineitem[oid:16425]"} columns: {l_comment => @lineitem::l_comment({type = !db.string}), l_commitdate =>
13       @lineitem::l_commitdate({type = !db.date<day>}), l_discount => @lineitem::l_discount({type = !db.decimal<12,
14       2>}), l_extendedprice => @lineitem::l_extendedprice({type = !db.decimal<12, 2>}), l_linenum => @lineitem::
15       l_linenum({type = i32}), l_linestatus => @lineitem::l_linestatus({type = !db.string}), l_orderkey =>
16       @lineitem::l_orderkey({type = i32}), l_partkey => @lineitem::l_partkey({type = i32}), l_quantity => @lineitem
17       ::l_quantity({type = !db.decimal<12, 2>}), l_receiptdate => @lineitem::l_receiptdate({type = !db.date<day>}),
18       l_returnflag => @lineitem::l_returnflag({type = !db.string}), l_shipdate => @lineitem::l_shipdate({type = !db.
19       date<day>}), l_shipinstruct => @lineitem::l_shipinstruct({type = !db.string}), l_shipmode => @lineitem::
20       l_shipmode({type = !db.string}), l_suppkey => @lineitem::l_suppkey({type = i32}), l_tax => @lineitem::l_tax({
21       type = !db.decimal<12, 2>})}
22
23     %1 = relalg.selection %0 (%arg0: !relalg.tuple){
24       %39 = relalg.getcol %arg0 @lineitem::l_shipdate : !db.date<day>
25       %40 = db.constant(-2191 : i32) : !db.date<day>
26       %41 = db.constant(-1826 : i32) : !db.date<day>
27       %42 = db.between %39 : !db.date<day> between %40 : !db.date<day>, %41 : !db.date<day>, lowerInclusive : true,
28       upperInclusive : false
29     }
30     relalg.return %42 : i1
31   } attributes {cost = 1.000000e+00 : f64, rows = 1.000000e+00 : f64}
32
33   %2 = relalg.basetable {column_order = ["ps_partkey", "ps_suppkey", "ps_availqty", "ps_supplycost", "ps_comment"], rows
34     = 0.000000e+00 : f64, table_identifier = "partsupp[oid:16410]"} columns: {ps_availqty => @partsupp::ps_availqty
35     ({type = i32}), ps_comment => @partsupp::ps_comment({type = !db.string}), ps_partkey => @partsupp::ps_partkey
36     ({type = i32}), ps_suppkey => @partsupp::ps_suppkey({type = i32}), ps_supplycost => @partsupp::ps_supplycost({
37     type = !db.decimal<12, 2>})}

```

```

18      %3 = relalg.basetable {column_order = ["n_nationkey", "n_name", "n_regionkey", "n_comment"], rows = 0.000000e+00 : f64
      , table_identifier = "nation[oid:16395]" columns: {n_comment => @nation::@n_comment({type = !db.string}), n_name
      => @nation::@n_name({type = !db.string}), n_nationkey => @nation::@n_nationkey({type = i32}), n_regionkey =>
      @nation::@n_regionkey({type = i32})}}
19      %4 = relalg.selection %3 (%arg0: !relalg.tuple){
20          %39 = relalg.getcol %arg0 @nation::@n_name : !db.string
21          %40 = db.constant("CANADA") : !db.string
22          %41 = db.compare eq %39 : !db.string, %40 : !db.string
23          relalg.return %41 : i1
24      } attributes {cost = 1.000000e-01 : f64, rows = 1.000000e-01 : f64}
25      %5 = relalg.basetable {column_order = ["s_supplier", "s_name", "s_address", "s_nationkey", "s_phone", "s_acctbal", "
      s_comment"], rows = 0.000000e+00 : f64, table_identifier = "supplier[oid:16405]" columns: {s_acctbal =>
      @supplier::@s_acctbal({type = !db.decimal<12, 2>}), s_address => @supplier::@s_address({type = !db.string}),
      s_comment => @supplier::@s_comment({type = !db.string}), s_name => @supplier::@s_name({type = !db.string}),
      s_nationkey => @supplier::@s_nationkey({type = i32}), s_phone => @supplier::@s_phone({type = !db.string}),
      s_supplier => @supplier::@s_supplier({type = i32})}}
26      %6 = relalg.join %4, %5 (%arg0: !relalg.tuple){
27          %39 = relalg.getcol %arg0 @nation::@n_nationkey : i32
28          %40 = relalg.getcol %arg0 @supplier::@s_nationkey : i32
29          %41 = db.compare eq %39 : i32, %40 : i32
30          relalg.return %41 : i1
31      } attributes {cost = 1.110000e+00 : f64, impl = "hash", rows = 0.010000000000000002 : f64}
32      %7 = relalg.projection all [@supplier::@s_name, @supplier::@s_address, @supplier::@s_supplier] %6
33      %8 = relalg.tmp %7 [@supplier::@s_address, @supplier::@s_name, @supplier::@s_supplier]
34      %9 = relalg.projection distinct [@supplier::@s_supplier] %8
35      %10 = relalg.tmp %9 [@supplier::@s_supplier]
36      %11 = relalg.join %2, %10 (%arg0: !relalg.tuple){
37          %39 = relalg.getcol %arg0 @partsupp::@ps_supplier : i32
38          %40 = db.as_nullable %39 : i32 -> <i32>
39          %41 = relalg.getcol %arg0 @supplier::@s_supplier : !db.nullable<i32>
40          %42 = db.compare eq %40 : !db.nullable<i32>, %41 : !db.nullable<i32>
41          %43 = db.derive_truth %42 : !db.nullable<i1>
42          relalg.return %43 : i1
43      } attributes {cost = 2.100000e+00 : f64, impl = "hash", rows = 1.000000e-01 : f64}
44      %12 = relalg.basetable {column_order = ["p_partkey", "p_name", "p_mfgr", "p_brand", "p_type", "p_size", "p_container",
      "p_retailprice", "p_comment"], rows = 0.000000e+00 : f64, table_identifier = "part[oid:16400]" columns: {
      p_brand => @part::@p_brand({type = !db.string}), p_comment => @part::@p_comment({type = !db.string}),
      p_container => @part::@p_container({type = !db.string}), p_mfgr => @part::@p_mfgr({type = !db.string}), p_name
      => @part::@p_name({type = !db.string}), p_partkey => @part::@p_partkey({type = i32}), p_retailprice => @part::
      @p_retailprice({type = !db.decimal<12, 2>}), p_size => @part::@p_size({type = i32}), p_type => @part::@p_type({
      type = !db.string})}}
45      %13 = relalg.selection %12 (%arg0: !relalg.tuple){
46          %39 = relalg.getcol %arg0 @part::@p_name : !db.string
47          %40 = db.constant("forest") : !db.string
48          %41 = db.runtime_call "Like"(%39, %40) : (!db.string, !db.string) -> i1
49          relalg.return %41 : i1
50      } attributes {cost = 1.000000e-01 : f64, rows = 1.000000e-01 : f64}
51      %14 = relalg.tmp %13 [@part::@p_partkey]
52      %15 = relalg.projection distinct [@part::@p_partkey] %14
53      %16 = relalg.tmp %15 [@part::@p_partkey]
54      %17 = relalg.join %11, %16 (%arg0: !relalg.tuple){
55          %39 = relalg.getcol %arg0 @partsupp::@ps_supplier : i32
56          %40 = db.as_nullable %39 : i32 -> <i32>
57          %41 = relalg.getcol %arg0 @part::@p_partkey : !db.nullable<i32>
58          %42 = db.compare eq %40 : !db.nullable<i32>, %41 : !db.nullable<i32>
59          %43 = db.derive_truth %42 : !db.nullable<i1>
60          relalg.return %43 : i1
61      } attributes {cost = 3.110000e+00 : f64, impl = "hash", rows = 0.010000000000000002 : f64}
62      %18 = relalg.tmp %17 [@partsupp::@ps_availability, @partsupp::@ps_supplier, @supplier::@s_supplier, @part::@p_partkey, @partsupp
      ::@ps_partkey]
63      %19 = relalg.projection distinct [@partsupp::@ps_supplier, @partsupp::@ps_partkey] %18
64      %20 = relalg.join %1, %19 (%arg0: !relalg.tuple){
65          %39 = relalg.getcol %arg0 @lineitem::@l_supplier : i32
66          %40 = relalg.getcol %arg0 @partsupp::@ps_supplier : i32
67          %41 = db.compare eq %39 : i32, %40 : i32
68          %42 = relalg.getcol %arg0 @lineitem::@l_partkey : i32
69          %43 = relalg.getcol %arg0 @partsupp::@ps_partkey : i32
70          %44 = db.compare eq %42 : i32, %43 : i32
71          %45 = db.and %44, %41 : i1, i1
72          relalg.return %45 : i1
73      } attributes {cost = 2.010000e+00 : f64, impl = "hash", rows = 0.010000000000000002 : f64}
74      %21 = relalg.crossproduct %20, %10
75      %22 = relalg.crossproduct %21, %16
76      %23 = relalg.aggregation %22 [@partsupp::@ps_supplier, @partsupp::@ps_partkey, @part::@p_partkey, @supplier::@s_supplier]
      computes : [@agg0::@agg_0({type = !db.nullable<!db.decimal<32, 6>})] (%arg0: !relalg.tuplstream, %arg1: !
      relalg.tuple){
77          %39 = relalg.aggrfn sum @lineitem::@l_quantity %arg0 : !db.nullable<!db.decimal<32, 6>
78          relalg.return %39 : !db.nullable<!db.decimal<32, 6>
79      }
80      %24 = relalg.map %23 computes : [@postmap::@postproc_1({type = !db.nullable<!db.decimal<32, 6>})] (%arg0: !relalg.
      tuple){
81          %39 = db.constant("0.5") : !db.decimal<32, 6>
82          %40 = db.as_nullable %39 : !db.decimal<32, 6> -> <!db.decimal<32, 6>
83          %41 = relalg.getcol %arg0 @agg0::@agg_0 : !db.nullable<!db.decimal<32, 6>
84          %42 = db.mul %40 : !db.nullable<!db.decimal<32, 6>, %41 : !db.nullable<!db.decimal<32, 6>
85          relalg.return %42 : !db.nullable<!db.decimal<32, 6>
86      }
87      %25 = relalg.renaming %24 renamed : [@renaming::@renamed0({type = i32})=[@partsupp::@ps_supplier], @renaming::@renamed1({
      type = i32})=[@partsupp::@ps_partkey]]

```

```

88 %26 = relalg.renaming %25 renamed : [@renaming1::@renamed0({type = i32})]=[@part::@p_partkey]]
89 %27 = relalg.renaming %26 renamed : [@renaming3::@renamed0({type = i32})]=[@supplier::@s_supkey]]
90 %28 = relalg.singlejoin %18, %27 (%arg0: !relalg.tuple){
91   %39 = relalg.getcol %arg0 @partsupp::@ps_supkey : i32
92   %40 = relalg.getcol %arg0 @renaming::@renamed0 : i32
93   %41 = db.compare eq %39 : i32, %40 : i32
94   %42 = relalg.getcol %arg0 @partsupp::@ps_partkey : i32
95   %43 = relalg.getcol %arg0 @renaming::@renamed1 : i32
96   %44 = db.compare eq %42 : i32, %43 : i32
97   %45 = relalg.getcol %arg0 @part::@p_partkey : i32
98   %46 = relalg.getcol %arg0 @renaming1::@renamed0 : i32
99   %47 = db.compare eq %45 : i32, %46 : i32
100  %48 = relalg.getcol %arg0 @supplier::@s_supkey : i32
101  %49 = relalg.getcol %arg0 @renaming3::@renamed0 : i32
102  %50 = db.compare eq %48 : i32, %49 : i32
103  %51 = db.and %50, %44, %41, %47 : i1, i1, i1, i1
104  relalg.return %51 : i1
105 } mapping: { @singlejoin::@sjattr({type = !db.nullable<!db.decimal<32, 6>>})=[@postmap::@postproc_1]} attributes {cost
    = 3.000000e+00 : f64, impl = "hash", rows = 1.000000e+00 : f64}
106 %29 = relalg.selection %28 (%arg0: !relalg.tuple){
107   %39 = relalg.getcol %arg0 @partsupp::@ps_availqty : i32
108   %40 = db.cast %39 : i32 -> !db.decimal<38, 0>
109   %41 = db.cast %40 : !db.decimal<38, 0> -> !db.decimal<32, 6>
110   %42 = db.as_nullable %41 : !db.decimal<32, 6> -> <!db.decimal<32, 6>>
111   %43 = relalg.getcol %arg0 @singlejoin::@sjattr : !db.nullable<!db.decimal<32, 6>>
112   %44 = db.compare gt %42 : !db.nullable<!db.decimal<32, 6>>, %43 : !db.nullable<!db.decimal<32, 6>>
113   %45 = db.derive_truth %44 : !db.nullable<i1>
114   relalg.return %45 : i1
115 } attributes {cost = 3.000000e+00 : f64, rows = 1.000000e+00 : f64}
116 %30 = relalg.renaming %29 renamed : [@renaming2::@renamed0({type = i32})]=[@part::@p_partkey]]
117 %31 = relalg.join %14, %30 (%arg0: !relalg.tuple){
118   %39 = relalg.getcol %arg0 @part::@p_partkey : i32
119   %40 = relalg.getcol %arg0 @renaming2::@renamed0 : i32
120   %41 = db.compare eq %39 : i32, %40 : i32
121   %42 = db.and %true, %41 : i1, i1
122   relalg.return %42 : i1
123 } attributes {cost = 2.100000e+00 : f64, impl = "hash", rows = 1.000000e-01 : f64}
124 %32 = relalg.projection all [@partsupp::@ps_supkey, @supplier::@s_supkey] %31
125 %33 = relalg.map %32 computes : [@map::@tmp_attr0({type = i32})] (%arg0: !relalg.tuple){
126   %39 = db.constant(1 : i32) : i32
127   relalg.return %39 : i32
128 }
129 %34 = relalg.renaming %33 renamed : [@renaming4::@renamed0({type = i32})]=[@supplier::@s_supkey]]
130 %35 = relalg.semijoin %8, %34 (%arg0: !relalg.tuple){
131   %39 = relalg.getcol %arg0 @supplier::@s_supkey : i32
132   %40 = relalg.getcol %arg0 @renaming4::@renamed0 : i32
133   %41 = db.compare eq %39 : i32, %40 : i32
134   relalg.return %41 : i1
135 } attributes {cost = 2.100000e+00 : f64, impl = "hash", rows = 1.000000e-01 : f64}
136 %36 = relalg.projection all [@supplier::@s_name, @supplier::@s_address] %35
137 %37 = relalg.sort %36 [(@supplier::@s_name, asc)]
138 %38 = relalg.materialize %37 [ @supplier::@s_name, @supplier::@s_address ] => ["s_name", "s_address"] : !dsa.table
139 return %38 : !dsa.table
140 }
141 }

```


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