Accessible and Portable LLM Inference by Compiling Computational Graphs into SQL

Wenbo Sun¹ Qiming Guo² Wenlu Wang² Rihan Hai¹

Abstract

Serving large language models (LLMs) often demands specialized hardware, dedicated frameworks, and substantial development efforts, which restrict their accessibility, especially for edge devices and organizations with limited technical resources. We propose a novel compiler that translates LLM inference graphs into SQL queries, enabling relational databases—one of the most widely used and mature software systems globally—to serve as the runtime. By mapping neural operators such as matrix multiplication and attention into relational primitives like joins and aggregations, our approach leverages database capabilities, including disk-based data management and native caching. Supporting key transformer components, such as attention mechanisms and key-value caching, our system generates SQL pipelines for end-to-end LLM inference. Using the Llama3 family as a case study, we demonstrate up to 30x speedup in token generation for memory-constrained scenarios comparable to competitive CPU-based frameworks. Our work offers an accessible, portable, and efficient solution, facilitating the serving of LLMs across diverse deployment environments.

1. Introduction

Large language models (LLMs) have proven highly effective across various applications, including enterprise analytics (Xie et al., 2024), personalized edge computing (Dong et al., 2023; Wu et al., 2024), and offline automation (Wilkins et al., 2024). However, many critical operational environments are limited by CPU-based infrastructure, which typically has less memory, computing power, and support for mainstream deep learning frameworks due to security, budget, or hardware constraints. Examples include

air-gapped systems (e.g., healthcare and defense) (Bagdasarian et al., 2024), legacy enterprise servers, and cost-sensitive edge devices such as Raspberry Pi clusters. This diverse range of underpowered, CPU-only environments poses a significant challenge to deploying large-scale LLMs.

Existing optimization techniques, such as weight pruning (Ma et al., 2023), low-bit quantization (Lin et al., 2025), and dynamic weight loading (Alizadeh et al., 2024; Sheng et al., 2023), offer partial solutions to reduce memory consumption. However, their implementations often depend on model architectures and require continuous engineering efforts to accommodate varying CPU architectures (e.g., x86, ARM, RISC-V) and vendor-specific optimizations.

Intermediate representation (IR)-based solutions (Lattner et al., 2021; Roesch et al., 2018; Tillet et al., 2019) compile LLMs into portable IRs. While effective in stable hardware environments, these methods need specialized backends and ongoing maintenance to handle evolving hardware/OS ecosystems. As hardware architectures become more fragmented, the repeated and continuous engineering overheads of IR-based solutions become an unsustainable burden for heterogeneous deployments.

Common model serving frameworks (e.g., TorchServe¹, Tensorflow Serving²) are widely used in GPU-rich environments but offer limited support for disk-backed execution, making them unsuitable for CPU-only environments where models exceed system memory. This raises the question: How can we enable LLM serving on underpowered, CPU-only infrastructure while ensuring accessibility and portability?

Relational databases offer a promising solution. They are widely deployed across computing environments—from SQLite³ instances in billions of edge devices to enterprise systems. With built-in features like cache management and query optimization, they can enable LLM inference without adaptation for diverse software/hardware stacks. However, prior work (Jankov et al., 2020; Lin et al., 2022) focuses on coarse-grained neural architectures (e.g., convolution lay-

¹Delft University of Technology ²Texas A&M University - Corpus Christi. Correspondence to: Wenbo Sun <w.sun-2@tudelft.nl>.

https://pytorch.org/serve/

²https://github.com/tensorflow/serving

³https://www.sqlite.org/

ers, pooling) rather than low-level operations fundamental to these components. This limits flexibility in supporting diverse architectures like transformer-based LLMs. Furthermore, existing work lacks a systematic compilation framework to automate SQL query translation for model serving.

In this paper, we propose a novel compiler that translates LLM inference graphs into optimized SQL, enabling relational databases to serve as accessible, hardware-agnostic runtimes. Our approach uniquely evaluate low-level tensor operations using relational primitives. Leveraging databases' native memory management and ANSI-standard SQL syntax, our compiler automatically generates queries that exploit database engines for efficient execution under strict memory constraints

Key contributions include:

- Operator Mapping. We systematically translate core LLM operations (e.g., matrix multiplication, softmax) into standard relational primitives (JOIN, GROUP BY, PROJECTION)This provides the foundation for a fully automated, SQL-based compilation pipeline.
- Two-stage Compiler. We develop a compiler that parses ONNX inference graphs and emits fully executable SQL queries, enabling any relational database to function as a general-purpose LLM serving engine.
- Real-World LLM Serving. We demonstrate how this
 compiler can serve models such as Llama in a diskmemory hybrid configuration, facilitating efficient inference on CPU-only, resource-constrained systems.
 Both interactive and large-sequence generation workloads become feasible without specialized hardware or
 abundant memory.

Our experiments show that the proposed approach achieves up to a $30\times$ speedup in token generation on constrained CPU-based systems compared to CPU-only baselines. By leveraging standard SQL interfaces that span ARM-based edge devices and x86 enterprise servers, our solution is both *accessible* (i.e., requiring minimal specialized expertise and no proprietary hardware) and *portable* (i.e., usable across diverse hardware/software environments). This allows resource-limited organizations to harness large language models with minimal ongoing engineering costs.

2. Compiling LLMs to SQL

We propose a systematic method to compile the computational graph of LLMs for model serving into SQL queries. The process involves two stages: (1) *Operator Mapping*, where each computational graph node is converted into a high-level relational function, and (2) *SQL Code Generation*, where these relational functions are translated into executable queries in the target database's dialect.

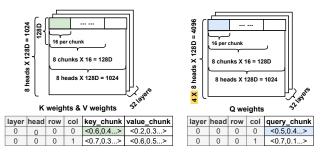


Figure 1. Illustration of slicing K, V, Q weights into chunks.

2.1. Matrix Multiplication in Relational Queries

Before introducing the compiler design, we briefly introduce the foundation of performing linear algebra within a database. Matrix multiplication (MM) is one of the most critical operations in LLM computations, especially for operations like self-attention, feed-forward layers, and the projection of embeddings. Let us denote the product of two matrices $\mathbf{A} \in \mathbb{R}^{m \times r}$ and $\mathbf{B} \in \mathbb{R}^{r \times n}$ by:

$$W = AB$$
,

where $\mathbf{W} \in \mathbb{R}^{m \times n}$. Each entry of \mathbf{W} is given by

$$w_{ij} = \sum_{k=1}^{r} a_{ik} b_{kj}.$$

Chunk-Based Representation. We represent matrices in a *chunked* format, an approach explored in prior research to enable linear algebra computations within databases (Jankov et al., 2020; Luo et al., 2021; Jankov et al., 2019). Matrices are divided into smaller block matrices, or tiles, indexed by tile row and tile column. However, since native support for matrix algebra is rare in databases, while many support vector operations (Raasveldt & Mühleisen, 2019; Schulze et al., 2024) such as dot products and elementwise arithmetic, we choose to partition matrices into vectors for broader compatibility. Fig. 1 illustrates an example of chunk-based representation for model weights.

Specifically, for a large matrix $\mathbf{W} \in \mathbb{R}^{m \times n}$, we split each row into $\lfloor \frac{n}{chunk_size} \rfloor$ chunks:

$$\mathbf{w}_i = \left[\mathbf{w}_i^{(0)}, \, \mathbf{w}_i^{(1)}, \, \dots, \, \mathbf{w}_i^{(C)}\right],$$

where each chunk $\mathbf{w}_{i}^{(c)}$ has a fixed dimension determined by a *chunk size* hyperparameter. In the database table, each row thus corresponds to:

$$(i, c, \mathbf{w}_i^{(c)}),$$

for $0 \le i < m$ and $0 \le c < \lfloor \frac{n}{chunk_size} \rfloor$. This chunking strategy provides flexibility by allowing trade-offs between the number of rows and the workload per thread when performing vector operations.

SQL Implementation of Matrix Multiplication. Within this chunked table structure, we emulate the summation $\sum_c a_{ic}b_{cj}$ by joining the chunked rows of the two matrices on their common index k. The relational engine then multi-

plies corresponding entries and aggregates the products to form each entry of the resulting matrix **W**. Formally, the SQL implementation follows a pattern like:

Here, $\mathbf{A}.\mathbf{w}_i^{(c)}$ and $\mathbf{B}.\mathbf{w}_j^{(c)}$ would each represent chunked slices of the matrices, typically stored as arrays or separate columns. The result is then reorganized (if needed) to match the output dimension $m \times n$.

This SQL-based matrix multiplication serves as a foundation for implementing other operations (e.g., elementwise activations, softmax) directly in the relational engine, enabling end-to-end inference within a database system.

2.2. Stage 1: Operator Mapping

In the first stage, operators are processed in topological order, extracting details such as operator type (e.g., MatMul, Add, Reshape), input/output shapes, and attributes like broadcast axes or chunk sizes. Each operator is mapped to a high-level relational function representing its equivalent relational primitives: π (projection), \bowtie (join), or γ (groupby with aggregation). These relational functions provide an intermediate abstraction, reinterpreting neural operators in LLMs for execution in a relational environment.

Definition 2.1. We define neural operators \mathcal{F} over p operands as:

$$\mathcal{F}\Big(\{\mathcal{O}_1,\ldots,\mathcal{O}_p\},\,\{fd_1,\ldots,fd_p\},\,\mathcal{S}\Big)$$

Each operand \mathcal{O}_i (for $1 \leq i \leq p$) is associated with some *free dimensions* in a tuple

$$fd_i = (fd_1^i, fd_2^i, \dots)$$

and $S = \{sd_1, sd_2, \ldots, sd_n\}$ is the set of *shared dimensions* among these operands. Intuitively, the free dimensions remain as independent axes in the output, whereas the shared dimensions indicate indices to be matched across the different operands.

Definition 2.2. The corresponding relational function of f is defined as:

$$\mathcal{R}(\lbrace R_1, \dots, R_p \rbrace, \lbrace \text{keys}_1, \dots, \text{keys}_p \rbrace, \text{keys}_{\text{join}})$$

where R_i is the chunk-based table representing operand \mathcal{O}_i , keys_i is the relational counterpart of the free dimensions fd_i (i.e., the row/column identifiers that remain in the final output), and keys_{join} encodes the shared dimensions \mathcal{S} as equi-join attributes for \bowtie .

Definition 2.3. The operator mapping in our compiler is a function op_map that maps a neural operator to a relational function, denoted by:

$$\mathcal{R} = op_map(\mathcal{F})$$

The resulting relational function is composed of standard relational operators (projections π , joins \bowtie , group-by/aggregation γ , and arithmetic). Conceptually, this translation reinterprets the original linear-algebraic operation in the framework of relational execution.

Matrix Multiplication Example. When the compiler encounters the operation $\mathbf{C} = \mathbf{A}\mathbf{B}$ in a computational graph, suppose

$$\mathbf{A} \in \mathbb{R}^{m \times r}, \quad \mathbf{B} \in \mathbb{R}^{r \times n}, \quad \mathbf{C} \in \mathbb{R}^{m \times n}.$$

We identify the free dimensions fd_1^A and fd_1^B and the shared dimension sd_1 as follows: $fd_1^A = \big\{i \mid 0 \leq i < m\big\},$ $fd_1^B = \big\{j \mid 0 \leq j < n\big\},$ and $sd_1 = \big\{k \mid 0 \leq k < r\big\}.$

Because our system employs a *chunk-based* representation, the dimension r is subdivided into chunks of size chunk-size. Concretely, the compiler replaces sd_1 with

$$C = \left\{ c \mid 0 \le c < \left\lfloor \frac{r}{\text{chunk_size}} \right\rfloor \right\},\,$$

so that each chunk index c corresponds to a slice of size chunk_size within the original dimension r.

Applying the general mapping,

$$op_map\Big(Matmul\big(\{\mathbf{A},\mathbf{B}\},\{(fd_1^A),(fd_1^B)\},\{\mathcal{C}\}\big)\Big) = \\ \gamma_{(i,j),\;\mathrm{SUM}(\mathbf{a}^{(c)}\otimes\mathbf{b}^{(c)})}\Big(R_A\;\bowtie_c\;R_B\Big)$$

where R_A and R_B are the chunked relational tables for **A** and **B**. The join on k aligns matching row fragments, and the aggregation (γ) sums partial products to form each \mathbf{c}_{ij} . This example demonstrates how free dimensions (i,j) are retained in the output and the shared dimension k is "consumed" by the join and subsequent aggregation.

Elementwise Matrix Arithmetic. Operators like Add, Sub, and Mul that apply elementwise arithmetic across two matrices are each mapped to a relational function involving a \bowtie on matching row and chunk indices, followed by a projection π that computes the desired operation. For example,

$$\begin{split} op_map\Big(Add\big(\{\mathbf{A},\mathbf{B}\},\varnothing,\{sd_1,\mathcal{C}\}\big)\Big) = \\ \pi_{sd_1,\,\mathbf{x}^{(c)}+\mathbf{y}^{(c)}}\Big(R_A \bowtie_{(sd_1,\mathcal{C})} R_B\Big) \end{split}$$

If either input is a scalar, the compiler omits the join and simply injects a scalar expression into the projection step.

Dimension Manipulation. Dimension manipulations can be categorized into two broad classes, depending on whether they affect *free dimensions* or *shared dimensions*. In the first class, operations that merely split, merge, or rename free dimensions can be handled by simple PROJECTION

expressions in SQL. For instance, suppose a tensor with free dimensions (i, j) where $0 \le i < 32$ and $0 \le j < 64$ is reshaped into (i_1, j_1, k_1) where $0 \le i_1 < 2, 0 \le j_1 < 16$, and $0 \le k_1 < 64$. The compiler can perform an integerbased remapping, e.g. $(i_1, j_1, k_1) \leftarrow (\lfloor \frac{i}{16} \rfloor, i \mod 16, j),$ via a single projection statement without additional tables or joins.

For dimension changes affecting shared chunking dimensions, advanced transformations are required. Operators like rotary encoding may need unrolling chunked vectors into individual elements. Modern relational databases like DuckDB and ClickHouse support such operations with built-in UNNEST functions (Raasveldt & Mühleisen, 2019; Schulze et al., 2024), enabling our compiler to reconfigure chunk layouts. Standard join and group-by operations then manipulate the shared dimension.

The compiler converts each neural operator into a relational function, creating a graph where edges represent inputoutput relations and nodes denote parameterized relationalalgebraic operations. This SQL node graph mirrors the original model structure while transitioning computation from matrix-based to relational primitives.

2.3. Stage 2: SQL Code Generation

SQL is a highly structured language. Once the required attributes and operands are identified, they can be combined with relational primitives to construct the final SOL query.

The compiler converts the SQL node graph into executable queries customized for the target database's SQL dialect, handling syntax variations and function compatibility across database engines like PostgreSQL and DuckDB. Standard relational primitives (e.g., projections, joins, group-bys) are directly translated into SELECT clauses, while vector operations such as inner products or specialized aggregations are implemented using user-defined functions (UDFs) when necessary.

To optimize execution, the compiler can merge nodes into common table expressions (WITH clauses) or CREATE VIEW statements, reducing intermediate result overhead. For instance, elementwise operations can be fused into a single projection if the database supports efficient inline expressions. The final SQL script replicates the original LLM model's functionality, including complex operators like multi-head attention and reshaping, all within standard relational constructs. An extensive list of other core operators and their SQL translations is provided in Appendix C, Tab. 2.

2.4. Attention Mechanism Example

In this section, we use the attention head—a core operation in LLM inference—as an example to illustrate how the compiler translates neural operators into relational functions.

Consider the single-head attention

$$\mathbf{S} = \operatorname{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\top}}{\sqrt{d}}\right)\mathbf{V},$$

 $\mathbf{S} \ = \ \operatorname{softmax}\!\!\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}}\right) \mathbf{V},$ where $\mathbf{Q}, \mathbf{K}, \mathbf{V} \in \mathbb{R}^{T \times d}$. Here, T is the sequence length and d the hidden dimension. Although the core multiplication QK can be handled as a standard matrix multiplication (as in Sec. 2.2), we now illustrate how the additional softmax and subsequent multiplication by V are mapped to relational functions.

Operator Mapping. Each of Q, K, V is split into chunks along the hidden dimension d. The compiler represents them as tables:

 $R_O(t, c, \mathbf{q}^{(c)}), R_K(t', c, \mathbf{k}^{(c)}), R_V(t', c, \mathbf{v}^{(c)})$ where t or $t' \in \{0, ..., T-1\}$ is the token index, $c \in \{0, \dots, \lfloor d/\text{chunk_size} \rfloor - 1\}$ is the chunk index, and $\mathbf{q}^{(c)}, \mathbf{k}^{(c)}, \mathbf{v}^{(c)}$ hold the corresponding slice of size chunk_size along the hidden dimension. The followings are operator mappings between neural operator and relational function in single head attention.

Form $\mathbf{A} = \mathbf{Q}\mathbf{K}^{\top}$.. From the MatMul pattern, the compiler creates a join \bowtie_c on matching chunk indices and aggregates over that chunk dimension. In relational algebra:

$$\mathbf{A}_{t,t'} = \gamma_{(t,t'), \text{SUM}(\mathbf{q}^{(c)} \otimes \mathbf{k}^{(c)})} \Big(R_Q \bowtie_{(t',c)} R_K \Big)$$

Here, R_Q : $(t, c, \mathbf{q}^{(c)})$ and R_K : $(t', c, \mathbf{k}^{(c)})$, so (t, t') are free dimensions and c is shared.

Elementwise scalar: $\mathbf{A} \leftarrow \frac{1}{\sqrt{d}} \mathbf{A}$. The compiler inserts an elementwise Mul-by-scalar operator. In SQL, this is typically a π - (projection) step that multiplies each $\mathbf{a}_{t,t'}$ by $1/\sqrt{d}$. No additional join or group-by is needed, only a column update:

$$\pi_{(t,t'),\frac{1}{\sqrt{d}}\times\mathbf{a}_{t,t'}}(R_A)$$

Softmax by rows of A.. Softmax requires exponentiating each element $\mathbf{a}_{t,t'}$, summing along t' per row t, and dividing. In relational terms, the compiler performs:

(i)
$$\gamma_{(t), SUM(\exp(a_{t,t'}))}(\dots)$$

(ii)
$$\pi_{(t,t'), \frac{\exp(a_{t,t'})}{\sum_{t'} \exp(a_{t,t'})}} (\dots)$$

This yields a row-stochastic matrix $\mathbf{M} \in \mathbb{R}^{T \times T}$ stored in a new relation.

Multiply M \times **V.** . Let R_M : $(t, t', m_{t,t'})$ hold the softmax result, chunked by (t',c) if needed. Meanwhile, R_V : $(t', c, \mathbf{v}^{(c)})$ stores \mathbf{V} . The final step mirrors a MatMul:

$$\mathbf{S}_{t,c} = \gamma_{(t,c), \, \mathrm{SUM}(m_{t,t'} \otimes \mathbf{v}^{(c)})} \Big(R_M \bowtie_{t'} R_V \Big)$$

Each entry $\mathbf{s}_t \in \mathbb{R}^d$ emerges by aggregating partial products over t' and chunk index c.

Discussion. This section illustrates how an attention layer— $\mathbf{Q}\mathbf{K}^{\top}$, scaling, softmax, and final multiplication—maps systematically to relational functions: chunkbased MatMul, elementwise functions, row-wise aggregations, and joins. Extending to multi-head attention or causal masks involves adding filters or parallel subgraphs.

3. Compiler Implementation

Our compiler converts an ONNX computational graph into chunked relational tables and then emits executable SQL queries for standard database engines. The overall process comprises four main components: *data conversion*, *pre-processing the computational graph*, *two-stage compilation*, and *post-optimization*.

3.1. Data Conversion

We begin by transforming each matrix, tensor, or model weight into a *chunked* relational table. Concretely, for a matrix \mathbf{W} of shape (m,n), we choose a chunk size c and create rows of the form $(i,c',\mathbf{w}^{(c')})$, where $0 \leq i < m$ indexes the original row, $0 \leq c' < \lfloor \frac{n}{c} \rfloor$ labels each chunk, and $\mathbf{w}^{(c')} \in \mathbb{R}^c$ holds a contiguous slice of size c. This same principle extends to higher-dimensional tensors: each dimension is broken into one or more chunk indices, ensuring that the final table remains manageable even when models contain billions of parameters. The database engine can thus store and page these chunked weights without exceeding memory.

3.2. Pre-processing the Computational Graph

We accept a topologically sorted ONNX graph as input, where each node lists its operator type and dependencies. Our pre-processing first *annotates shapes* on every operator and tensor, ensuring that each node carries information about free dimensions, shared dimensions, and scalars. This step enables relational functions to be constructed consistently. Once shapes are annotated, we apply a *pre-optimization* pass:

Constant Folding. Constant folding (Muchnick, 1998; Chen et al., 2018) is a classic compiler optimization technique. In computational graph, by examining the shape annotations and operator type, we detect whether an operator produces a scalar (e.g., constants or reduced values). If so, the compiler immediately evaluates such computations and stores them as constant attributes, avoiding runtime overhead in the relational plan. For example, when a dimension size can be multiplied or added at compile time, we do so and supply the result directly as a parameter in subsequent queries.

Shape-Manipulation Elimination. Operators such as

Reshape, Squeeze, and Expand, which operate on free dimensions, can be merged with their successor operators by adjusting the projection primitives. This optimization eliminates the need to translate these operators into separate SQL queries, reducing the overhead of table scans.

3.3. Two-stage Compilation

After the pre-processing step, the two-stage compiler converts each ONNX operator into a *relational function*, mapping computations like MatMul, elementwise arithmetic, and Softmax to joins, group-bys, and projections. These become a directed acyclic graph of relational functions, each describing chunk-based logic (e.g., MatMul as a join+SUM, Softmax as exponentiation+GROUP BY). The compiler then emits a final SQL queries: standard relational primitives (JOIN, GROUP BY, PROJECTION) produce most functionality, while vector-level operations (inner products, elementwise ops) are inserted as user-defined functions (UDFs). Any SQL-compliant engine with these UDFs can thus execute the entire LLM inference pipeline without relying on specialized deep learning runtimes or hardware accelerators.

3.4. Post-Optimization and KV-Cache Construction

After generating the raw SQL statements, the compiler applies post-optimizations to streamline execution and support advanced features like key-value caching. It reduces intermediate tables by using WITH common table expressions (CTEs) (Eisenberg & Melton, 1999), chaining logical query steps without creating large temporary relations. This minimizes disk I/O, and speeds up execution.

For key-value caching (KV-cache) (Pope et al., 2023), the compiler constructs or updates cache tables to store processed keys and values, indexed by sequence position or token index. For subsequent token generation, it reuses existing cache entries and emits compact queries to compute only new keys and values, avoiding redundant computations. This enhances throughput for interactive or streaming inference.

These optimizations ensure efficient execution, support for caching, and alignment with the model's original semantics, reducing runtime overhead for LLM workloads.

4. Experiments

In this section, we evaluate the performance of SQL queries generated by our proposed compiler using a real-world relational database and two models from the Llama3 family (Dubey et al., 2024). First, we analyze the impact of chunk size on performance. Next, we compare token generation time and memory usage across in-memory and disk-memory hybrid database modes (Disk+mem), bench-

marking against PyTorch (Ansel et al., 2024) and a C++ native model-serving framework. Finally, to assess the efficiency of our approach under resource-constrained conditions, we simulate an edge device environment by setting an 8GB memory cap.

4.1. Experiment Setup

Hardware Platforms. Experiments are conducted on a machine with 48 CPU cores, 96 GB of RAM, and DuckDB (Raasveldt & Mühleisen, 2019) as the analytical database engine. DuckDB's native vector inner-product operators are extended with custom user-defined functions (UDFs) for additional vector operations. Evaluations are performed in both disk-memory hybrid and in-memory modes. We also test with an 8GB memory limit and 6 CPU cores to simulate resource-constrained conditions.

Llama3 Models. We evaluate **transformer-based** Llama3 models in two sizes: i) Llama3.2 3B, a smaller model balancing resource efficiency and performance, and ii) Llama3.1 8B, a larger model showcasing scalability for handling extensive parameters. To assess performance variations with input size, we test prompts of four lengths: 10, 100, 200, and 500 tokens. All models are unquantized, which do not impact the comparative results. Incorporating quantization support is planned for future work.

Baselines. We compare against two baselines: i) PyTorch (CPU Only): Executes Llama3 models on CPU using default BLAS (Blackford et al., 2002) libraries. ii) Llama.cpp⁴: A lightweight C++ implementation for CPU inference, also relying on default BLAS libraries.

Metrics. Metrics include time to first token (TTFT) and time per output token (TPOT) to measure time consumption, and peak memory usage (in GB) to evaluate resource consumption. Peak memory is critical for assessing suitability on memory-constrained hardware.

Our goal is not to surpass optimized deep learning frameworks but to demonstrate comparable performance to CPUonly methods without requiring specialized hardware. Enhancing vector UDFs with BLAS libraries could further boost the performance of database-based LLM serving.

4.2. Chunk-Size Sensitivity Study

As discussed in Sec. 2.1, chunk size impacts performance when serving LLMs in a database. Larger chunks reduce table scan time but increase computational workload, while smaller chunks have the opposite effect. Our empirical study, as illustrated in Tab. 1, shows that in disk+mem mode, chunk size has minimal impact due to the data transfer bottleneck. In in-memory mode, smaller chunks increase

Table 1. Effect of varying chunk sizes on TTFT and TPOT for the 3B model, evaluated under both in-memory and (disk+mem) modes. Chunk size 64 offers a balance, minimizing TPOT while sustaining competitive TTFT.

Chunk size	Method	TTFT (s)	TPOT (s)
32		5.59	0.97
64	Disk+mem	5.80	1.00
128		5.15	1.36
32		4.81	0.34
64	In-memory	3.71	0.23
128		3.39	0.35

processing time per token, especially for TTFT. A chunk size of 64 offers the best balance and optimal TPOT. Therefore, we use chunk_size=64 in all subsequent experiments for consistency and highest throughput.

4.3. Memory Usage in Unlimited Memory Scenarios

Memory utilization is crucial in resource-constrained environments, where large language models often exceed available RAM, leading to failures or degraded performance. In this experiment, we compare the memory usage of our method with PyTorch and Llama.cpp using the same model, highlighting the efficiency of our disk+mem setting. Figure 2 shows memory usage for in-memory and disk+mem configurations with PyTorch and Llama.cpp. PyTorch loads all weights into memory, failing if the model exceeds device memory. Llama.cpp supports dynamic weight loading but, in our test with unlimited memory, shows similar memory usage to PyTorch. Our in-memory mode uses more memory than expected due to DuckDB's need to maintain metadata and indexes, introducing overhead.

However, our disk+mem configuration achieves significantly lower peak memory usage. For example, an 8B model (31GB) runs on disk+mem using less than 20GB. This demonstrates that our compiler-generated code, combined with DuckDB's intrinsic cache management, reduces memory usage without extra engineering effort, enhancing LLM accessibility.

4.4. Time Usage in Memory-Constraint Scenarios

We tested two systems with dynamic weight loading functions (disk+mem and Llama.cpp) under memory-constrained conditions (6 cores, 8GB RAM) to evaluate their performance in edge scenarios.

Figure 3 compares the time usage of disk+mem and Llama.cpp when serving an 8B model across varying prompt lengths. When the prompt length is less than 500 tokens, our disk+mem mode achieves significantly lower TTFT than Llama.cpp, highlighting the efficiency of our method even with edge-level hardware configurations. However, when

⁴https://github.com/ggerganov/llama.cpp

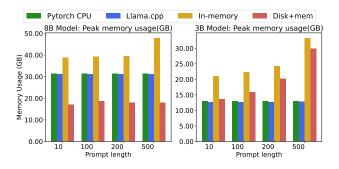


Figure 2. Peak memory usage under different inference configurations for Llama3 models. We compare the in-memory and disk+mem modes, highlighting how disk-based cache management reduces peak RAM usage while incurring additional I/O overhead.

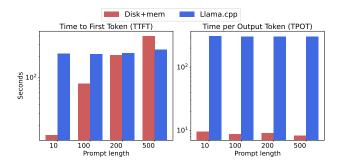


Figure 3. TTFT and TPOT under an 8GB memory limit, comparing Llama.cpp to the disk+mem approach for prompts of varying length.

the prompt length reaches 500 tokens, Llama.cpp performs faster due to the more complex data structures of database tables compared to naive matrices, which result in increased data communication. The performance degradation is especially significant when generating the first token, as it requires computing all Q, K, and V for all tokens.

In tests using TPOT, disk+mem maintains consistent time usage under 10 seconds, while Llama.cpp exceeds 300 seconds, making it 30 times slower for interactive use. By leveraging dynamic disk-memory cache management instead of relying on all-in-RAM strategies, disk+mem serves an 8B model (31GB) under the same memory constraints, offering a practical solution for resource-limited environments. This confirms the advantage of using databases as runtimes to serve LLMs in edge scenarios.

4.5. Time Usage for First Token and Subsequent Tokens

For completeness, we compared TTFT (Time-to-First-Token) and TPOT (Time-per-Token) across four methods and two model scales on server-level hardware. As shown in Fig. 4, the in-memory mode consistently outperforms the disk+mem mode for both metrics. For example, with the 8B model and a 10-token prompt, disk+mem introduces a

50% delay in TTFT due to overhead from on-demand loading of model weights and query results. A similar pattern is observed with the 3B model, where the in-memory mode consistently outperforms the disk+mem mode.

Compared to baseline methods like PyTorch CPU and Llama.cpp, database modes show higher TTFT—often by an order of magnitude—due to the computational overhead of relational primitives (JOIN, GROUP BY, Table Scan) and unoptimized vector UDFs, rather than using efficient neural operator kernels. However, for subsequent tokens, the in-memory mode delivers more competitive performance, while the disk-memory mode remains slower due to the overhead of data loading.

These results demonstrate that under unlimited resources, serving LLMs within a database does not match the performance of deeply optimized deep learning frameworks. However, there remains significant room for optimization. The current database setup does not leverage BLAS libraries for accelerating vector operations. Integrating such linear algebra libraries could substantially narrow the performance gap between in-database model serving and dedicated deep learning frameworks.

Takeaways.Our experiments show that SQL-based LLM inference enables efficient execution on resource-constrained CPUs, achieving 30x speedups over disk-memory hybrid frameworks while preserving model integrity. Although performance on high-resource hardware lags behind Py-Torch, integrating libraries like BLAS could bridge this gap. This work proves relational databases as viable, hardware-agnostic runtimes for LLM deployment in accelerator-limited environments.

5. Related Work

Serving LLMs with Limited Memory. Serving large language models (LLMs) under memory constraints involves three main strategies: weight pruning, low-bit quantization, and dynamic weight loading.

Weight pruning reduces a model's memory footprint by removing selected parameters. Common methods include magnitude-based pruning (Gupta et al., 2024) and structured pruning (Anwar et al., 2017; Wang et al., 2020; Ma et al., 2023). However, pruning often requires model-specific knowledge and additional fine-tuning, making it less flexible and more labor-intensive for new models or architectures.

Low-bit quantization uses fewer bits (e.g., 8-bit or 4-bit) to represent floating-point values, reducing memory usage and potentially speeding up computation on compatible hardware. Post-training quantization (Lin et al., 2025; Zhao et al., 2024; Yao et al., 2022) is favored for faster deployment, but hardware support for reduced data types (e.g., INT8) is cru-

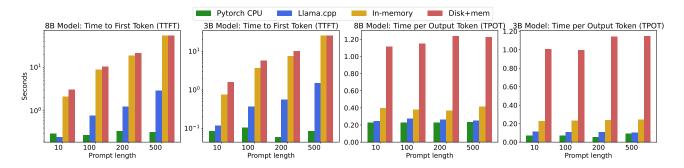


Figure 4. Comparison of time to generate the first token and the next token for various Llama3 models, prompt inputs, and methods.

cial. Many embedded CPUs (e.g., ARM, RISC-V) lack such support, negating the benefits of quantization on resource-limited devices.

Instead of keeping all parameters in memory, dynamic weight loading cache parameters from disk or slower memory on demand. Examples include DejaVu (Liu et al., 2023), which uses activation sparsity to load necessary weights, and FlexGen (Sheng et al., 2023), which offloads weights and caches to CPU DRAM. However, these methods often require specialized handling and sophisticated engineering to manage weight transfers across memory layers.

In summary, while these strategies mitigate memory bottlenecks, they introduce constraints such as accuracy degradation, hardware dependency, or specialized engineering. Our approach leverages relational databases' native cache management to handle models exceeding system memory, eliminating custom engineering and enhancing portability.

Intermediate Representations for Deep Learning. Deep learning compilers often use intermediate representations (IRs) like *MLIR* (Lattner et al., 2021), *Relay IR* (Roesch et al., 2018), and *ONNX IR* (onn, 2017) to enable crossplatform model execution and interoperability. While these approaches drive innovation, they require extensive maintenance to support evolving hardware and kernels, resulting in fragmented ecosystems and complex, toolchain-specific deployment pipelines.

Our approach uses *SQL* as an IR for deep learning inference, avoiding custom IRs or specialized runtimes. Relational engines, optimized over decades, efficiently handle data across platforms, from servers to embedded systems like SQLite. By compiling neural operators into SQL, we align deep learning tasks with familiar database abstractions, ensuring portability, reducing engineering effort, and providing a sustainable alternative to IR-based solutions.

Deep Learning in Databases. Recent database research has explored representing deep learning computations using relational algebra. Works like Dimitrije et al. (Jankov et al., 2020), SmartLite (Lin et al., 2023), and ModelJoin

(Kläbe et al., 2023) integrate matrix operations into relational databases but require extensive database-specific engineering, limiting portability and compatibility with traditional deep learning ecosystems.

DuckBrain (Schüle et al., 2024) and DL2SQL (Lin et al., 2022) take steps toward integrating deep learning with databases. DuckBrain handles simple neural networks but lacks a framework for complex models, serving as a proof of concept. DL2SQL translates basic convolution network modules (e.g., convolution layer, max pooling) into SQL queries but cannot automatically handle diverse modules like attention or rotary embeddings.

Our approach introduces a low-level operator mapping method, focusing on fundamental arithmetic operations like matrix multiplication and elementwise functions. This enables our compiler to support a wider range of deep learning models and automate the translation of LLMs into SQL queries.

6. Conclusion and Outlook

We present a method for converting neural operators into relational functions and a compiler that transforms LLM inference graphs into SQL queries, enabling relational databases to serve as a runtime for LLMs inference. While our token-generation time is slower than PyTorch in unlimited-memory scenarios, it remains competitive and outperforms in memory-constrained settings where PyTorch fails to load larger models. This database-driven approach reduces engineering overhead, avoids framework fragmentation, and expands access to LLM inference for low-resource environments and broader audiences.

Outlook. Future improvements include integrating BLAS libraries and quantization into our SQL compiler to accelerate vector operations, optimizing query plans for efficiency, and exploring lightweight database engines like SQLite for edge-level deployments. These advancements aim to further enhance resource efficiency and performance, extending the accessibility to large-scale language modeling.

Impact Statement

This paper presents work whose goal is to advance the field of Machine Learning and Database. There are many potential societal consequences of our work, none which we feel must be specifically highlighted here.

References

- Open Neural Network Exchange: The open standard for machine learning interoperability. https://github.com/onnx/onnx, 2017.
- Alizadeh, K., Mirzadeh, S., Belenko, D., Khatamifard, S., Cho, M., del Mundo, C. C., Rastegari, M., and Farajtabar, M. LLM in a flash: Efficient large language model inference with limited memory. In Ku, L., Martins, A., and Srikumar, V. (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics* (Volume 1: Long Papers), ACL 2024, Bangkok, Thailand, August 11-16, 2024, pp. 12562–12584. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.ACL-LONG.678. URL https://doi.org/10.18653/v1/2024.acl-long.678.
- Ansel, J., Yang, E. Z., He, H., Gimelshein, N., Jain, A., and et al. Pytorch 2: Faster machine learning through dynamic python bytecode transformation and graph compilation. In Gupta, R., Abu-Ghazaleh, N. B., Musuvathi, M., and Tsafrir, D. (eds.), *Proceedings of the 29th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 2, ASPLOS 2024, La Jolla, CA, USA, 27 April 2024- 1 May 2024*, pp. 929–947. ACM, 2024. doi: 10.1145/3620665.3640366. URL https://doi.org/10.1145/3620665.3640366.
- Anwar, S., Hwang, K., and Sung, W. Structured pruning of deep convolutional neural networks. *ACM J. Emerg. Technol. Comput. Syst.*, 13(3):32:1–32:18, 2017. doi: 10.1145/3005348. URL https://doi.org/10.1145/3005348.
- Bagdasarian, E., Yi, R., Ghalebikesabi, S., Kairouz, P., Gruteser, M., Oh, S., Balle, B., and Ramage, D. Airgapagent: Protecting privacy-conscious conversational agents. In *Proceedings of the 2024 on ACM SIGSAC Conference on Computer and Communications Security*, CCS '24, pp. 3868–3882, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400706363. doi: 10.1145/3658644.3690350. URL https://doi.org/10.1145/3658644.3690350.
- Blackford, L. S., Petitet, A., Pozo, R., Remington, K., Whaley, R. C., Demmel, J., Dongarra, J., Duff, I., Hammarling, S., Henry, G., et al. An updated set of basic

- linear algebra subprograms (blas). *ACM Trans. Math. Softw.*, 28(2):135–151, June 2002. ISSN 0098-3500. doi: 10.1145/567806.567807. URL https://doi.org/10.1145/567806.567807.
- Chen, T., Moreau, T., Jiang, Z., Zheng, L., Yan, E. Q., Shen, H., Cowan, M., Wang, L., Hu, Y., Ceze, L., Guestrin, C., and Krishnamurthy, A. TVM: an automated end-to-end optimizing compiler for deep learning. In Arpaci-Dusseau, A. C. and Voelker, G. (eds.), 13th USENIX Symposium on Operating Systems Design and Implementation, OSDI 2018, Carlsbad, CA, USA, October 8-10, 2018, pp. 578–594. USENIX Association, 2018. URL https://www.usenix.org/conference/osdi18/presentation/chen.
- Dong, X. L., Moon, S., Xu, Y. E., Malik, K., and Yu, Z. Towards next-generation intelligent assistants leveraging LLM techniques. In Singh, A. K., Sun, Y., Akoglu, L., Gunopulos, D., Yan, X., Kumar, R., Ozcan, F., and Ye, J. (eds.), *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, KDD 2023, Long Beach, CA, USA, August 6-10, 2023*, pp. 5792–5793. ACM, 2023. doi: 10.1145/3580305.3599572. URL https://doi.org/10.1145/3580305.3599572.
- Dubey, A., Jauhri, A., Pandey, A., and et al. The llama 3 herd of models. *CoRR*, abs/2407.21783, 2024.
- Eisenberg, A. and Melton, J. Sql: 1999, formerly known as sql3. *SIGMOD Rec.*, 28(1):131–138, March 1999. ISSN 0163-5808. doi: 10.1145/309844.310075. URL https://doi.org/10.1145/309844.310075.
- Gupta, M., Camci, E., Keneta, V. R., Vaidyanathan, A., Kanodia, R., James, A., Foo, C.-S., Wu, M., and Lin, J. Is Complexity Required for Neural Network Pruning? A Case Study on Global Magnitude Pruning. In 2024 IEEE Conference on Artificial Intelligence (CAI), pp. 747–754, Los Alamitos, CA, USA, June 2024. IEEE Computer Society. doi: 10.1109/CAI59869.2024.00144. URL https://doi.ieeecomputersociety.org/10.1109/CAI59869.2024.00144.
- Jankov, D., Luo, S., Yuan, B., Cai, Z., Zou, J., Jermaine, C., and Gao, Z. J. Declarative recursive computation on an RDBMS. *Proc. VLDB Endow.*, 12(7):822–835, 2019. doi: 10.14778/3317315.3317323. URL http://www.vldb.org/pvldb/vol12/p822-jankov.pdf.
- Jankov, D., Luo, S., Yuan, B., Cai, Z., et al. Declarative recursive computation on an RDBMS: or, why you should use a database for distributed machine learning. *SIGMOD Rec.*, 49(1):43–50, 2020.

- Kläbe, S., Hagedorn, S., and Sattler, K. Exploration of approaches for in-database ML. In *EDBT'23*, pp. 311–323, 2023.
- Lattner, C., Amini, M., Bondhugula, U., Cohen, A., Davis, A., Pienaar, J., Riddle, R., Shpeisman, T., Vasilache, N., and Zinenko, O. Mlir: Scaling compiler infrastructure for domain specific computation. In 2021 IEEE/ACM International Symposium on Code Generation and Optimization (CGO), pp. 2–14, 2021. doi: 10.1109/CGO51591.2021.9370308.
- Lin, J., Tang, J., Tang, H., Yang, S., Xiao, G., and Han, S. Awq: Activation-aware weight quantization for on-device llm compression and acceleration. *GetMobile: Mobile Comp. and Comm.*, 28(4):12–17, January 2025. ISSN 2375-0529. doi: 10.1145/3714983.3714987. URL https://doi.org/10.1145/3714983.3714987.
- Lin, Q., Wu, S., Zhao, J., Dai, J., Li, F., and Chen, G. A comparative study of in-database inference approaches. In 2022 IEEE 38th International Conference on Data Engineering (ICDE), pp. 1794–1807, 2022.
- Lin, Q., Wu, S., Zhao, J., Dai, J., Shi, M., Chen, G., and Li, F. Smartlite: A dbms-based serving system for DNN inference in resource-constrained environments. *Proc. VLDB Endow.*, 17(3):278–291, 2023.
- Liu, Z., Wang, J., Dao, T., Zhou, T., Yuan, B., Song, Z., Shrivastava, A., Zhang, C., Tian, Y., Ré, C., and Chen, B. Deja vu: contextual sparsity for efficient llms at inference time. In *Proceedings of the 40th International Conference* on Machine Learning, ICML'23. JMLR.org, 2023.
- Luo, S., Jankov, D., Yuan, B., and Jermaine, C. Automatic optimization of matrix implementations for distributed machine learning and linear algebra. In Li, G., Li, Z., Idreos, S., and Srivastava, D. (eds.), SIGMOD '21: International Conference on Management of Data, Virtual Event, China, June 20-25, 2021, pp. 1222–1234. ACM, 2021. doi: 10.1145/3448016.3457317. URL https://doi.org/10.1145/3448016.3457317.
- Ma, X., Fang, G., and Wang, X. Llm-pruner: on the structural pruning of large language models. In *Proceedings* of the 37th International Conference on Neural Information Processing Systems, NIPS '23, Red Hook, NY, USA, 2023. Curran Associates Inc.
- Muchnick, S. S. Advanced compiler design and implementation. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1998. ISBN 1558603204.
- Pope, R., Douglas, S., Chowdhery, A., Devlin, J., Bradbury, J., Heek, J., Xiao, K., Agrawal, S., and Dean, J. Efficiently scaling transformer inference. In *MLSys*'23, 2023.

- Raasveldt, M. and Mühleisen, H. Duckdb: an embeddable analytical database. In *Proceedings of the 2019 International Conference on Management of Data*, SIGMOD '19, pp. 1981–1984, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 9781450356435. doi: 10.1145/3299869.3320212. URL https://doi.org/10.1145/3299869.3320212.
- Roesch, J., Lyubomirsky, S., Weber, L., Pollock, J., Kirisame, M., Chen, T., and Tatlock, Z. Relay: a new IR for machine learning frameworks. In Gottschlich, J. and Cheung, A. (eds.), *Proceedings of the 2nd ACM SIG-PLAN International Workshop on Machine Learning and Programming Languages, MAPL@PLDI 2018, Philadel-phia, PA, USA, June 18-22, 2018*, pp. 58–68. ACM, 2018. doi: 10.1145/3211346.3211348. URL https://doi.org/10.1145/3211346.3211348.
- Schüle, M. E., Neumann, T., and Kemper, A. The duck's brain. *Datenbank-Spektrum*, 24(3):209–221, 2024.
- Schulze, R., Schreiber, T., Yatsishin, I., Dahimene, R., and Milovidov, A. Clickhouse lightning fast analytics for everyone. *Proc. VLDB Endow.*, 17(12):3731–3744, 2024. doi: 10.14778/3685800. 3685802. URL https://www.vldb.org/pvldb/vol17/p3731-schulze.pdf.
- Sheng, Y., Zheng, L., Yuan, B., Li, Z., Ryabinin, M., Chen, B., Liang, P., Ré, C., Stoica, I., and Zhang, C. Flexgen: high-throughput generative inference of large language models with a single gpu. In *Proceedings of the 40th International Conference on Machine Learning*, ICML'23. JMLR.org, 2023.
- Tillet, P., Kung, H. T., and Cox, D. Triton: an intermediate language and compiler for tiled neural network computations. In *Proceedings of the 3rd ACM SIGPLAN International Workshop on Machine Learning and Programming Languages*, MAPL 2019, pp. 10–19, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 9781450367196. doi: 10.1145/3315508.3329973. URL https://doi.org/10.1145/3315508.3329973.
- Wang, Z., Wohlwend, J., and Lei, T. Structured pruning of large language models. In Webber, B., Cohn, T., He, Y., and Liu, Y. (eds.), *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pp. 6151–6162. Association for Computational Linguistics, 2020. doi: 10.18653/V1/2020. EMNLP-MAIN.496. URL https://doi.org/10.18653/v1/2020.emnlp-main.496.
- Wilkins, G., Keshav, S., and Mortier, R. Offline energyoptimal llm serving: Workload-based energy models for

Ilm inference on heterogeneous systems. *arXiv preprint arXiv:2407.04014*, 2024.

- Wu, L., Zhao, Y., Wang, C., Liu, T., and Wang, H. A first look at llm-powered smartphones. In Filkov, V., Ray, B., and Zhou, M. (eds.), *Proceedings of the 39th IEEE/ACM International Conference on Automated Software Engineering Workshops, ASEW 2024, Sacramento, CA, USA, 27 October 2024 1 November 2024*, pp. 208–217. ACM, 2024. doi: 10.1145/3691621.3694952. URL https://doi.org/10.1145/3691621.3694952.
- Xie, L., Zhang, J., Li, Y., Wan, S., Zhang, X., Chen, M., Deng, G., and Wu, Z. Research and application of private knowledge-based llm in standard operating procedure scenarios of enterprises. In *Proceedings of the 2024 6th International Conference on Pattern Recognition and Intelligent Systems*, PRIS '24, pp. 82–86, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400718250. doi: 10.1145/3689218.3689328. URL https://doi.org/10.1145/3689218.3689328.
- Yao, Z., Aminabadi, R. Y., Zhang, M., Wu, X., Li, C., and He, Y. Zeroquant: Efficient and affordable post-training quantization for large-scale transformers. In Koyejo, S., Mohamed, S., Agarwal, A., Belgrave, D., Cho, K., and Oh, A. (eds.), Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28
 December 9, 2022, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/adf7fa39d65e2983d724ff7da57f00ac-Abstract-Conference.html.
- Zhao, Y., Lin, C., Zhu, K., Ye, Z., Chen, L., Zheng, S., Ceze, L., Krishnamurthy, A., Chen, T., and Kasikci, B. Atom:
 Low-bit quantization for efficient and accurate LLM serving. In Gibbons, P. B., Pekhimenko, G., and Sa, C. D. (eds.), Proceedings of the Seventh Annual Conference on Machine Learning and Systems, MLSys 2024, Santa Clara, CA, USA, May 13-16, 2024. mlsys.org, 2024. URL https://proceedings.mlsys.org/paper_files/paper/2024/hash/5edb57c05c81d04beb716ef1d542fe9e-Abstract-Conference.html.

A. Table Schema

In this section, we detail the table schema for model weights in the LLaMA3.1 8B model. The 8B model consists of 32 layers, each with an identical schema. Thus, we focus on describing the schema for a single layer.

```
vocabulary (token_encode INT32, chunk_id INT32, embedding FLOAT[])
freq_each_token (token_id INT32, freq_real FLOAT[], freq_img FLOAT[])
Q_weights_L1 (head_id INT32, row_id INT32, chunk_id INT32, chunk FLOAT[])
K_weights_L1 (head_id INT32, row_id INT32, chunk_id INT32, chunk FLOAT[])
V_weights_L1 (head_id INT32, row_id INT32, chunk_id INT32, chunk FLOAT[])
o_weights_L1 (row_id INT32, chunk_id INT32, chunk FLOAT[])
GLU_W1_L1 (row_id INT32, chunk_id INT32, chunk FLOAT[])
GLU_W2_1 1(row_id INT32, chunk_id INT32, chunk FLOAT[])
GLU_W3_L1 (row_id INT32, chunk_id INT32, chunk FLOAT[])
FFN_Norm_L1 (chunk_id INT32, chunk FLOAT[])
Attention_Norm_L1 (chunk_id INT32, chunk FLOAT[])
Final_Norm (chunk_id INT32, chunk FLOAT[])
```

B. Vector UDFs

In this section, we describe the user-defined functions (UDFs) for vector arithmetic operations. While some databases support array data types, their vector operation capabilities are often limited. To address this, we implement vector UDFs using native lambda functions, a feature widely supported in databases such as DuckDB, ClickHouse, and PostgreSQL. We illustrate this using DuckDB as an example.

```
create macro hadamard\_prod(arr1, arr2) as
(list_transform(list_zip(arr1, arr2), x -> x[1] * x[2]));

arr1 - arr2

create macro element_neg_sum(arr1, arr2) as
(list_transform(list_zip(arr1, arr2), x -> x[1] - x[2]));

arr1 + arr2

create macro element_sum(arr1, arr2) as
(list_transform(list_zip(arr1, arr2)) as
(list_transform(list_zip(arr1, arr2), x -> x[1] + x[2]));

concat(arr1, arr2)

create macro view_as_real(arr1, arr2) as (list_concat(arr1, arr2));
```

Collecting tuple (idx, value) as an array based on the positional index 'idx'.

```
create macro collect_as_array(idx, val) as (list_transform(list_sort(list_zip(idx, val)), x -> x[2]));

Extracting the first half of the input array as a new array.

create macro collect_real(ziped_arr, mid_pos) as (list_transform(ziped_arr[:mid_pos], x -> x[2]));

Extracting the second half of the input array as a new array.

create macro collect_img(ziped_arr, mid_pos) as (list_transform(ziped_arr[mid_pos:], x -> x[2]));

\sum_i chunk_i, \text{ sum all arrays}.

create macro sumForEach(arr) as
```

(list_reduce(arr, (acc, row)-> list_transform(acc, (acc_val, i) -> acc_val + row[i])));

C. Core Neural Operators and Corresponding SQL Queries

In this section, we illustrate the core modules of the LLaMA3.1 8B model, specifically self-attention and rotary positional encoding, each represented by distinct SQL query patterns. Other operators primarily reuse similar SQL queries derived from these three core components.

The self-attention mechanism involves multiple matrix multiplications (matmuls) and a softmax operation. The matmul operations are described in detail in the main text. The softmax function is a reduction operation that first sums all exponentiated values and then divides each value by the total sum.

Rotary positional encoding requires splitting a vector into two equal-sized subvectors representing the real and imaginary parts of a complex number array. After performing the necessary computations, the real and imaginary parts are concatenated.

In RMS normalization, an additional aggregation step is involved compared to the softmax operation. It first sums all vectors into a single vector and then reduces this vector to a scalar, resulting in longer computation times than the softmax implementation. The following Table 2 elaborates on these three core neural operators and their corresponding pseudo SQL queries.

<i>Table 2.</i> Core neural operators and corresponding pseudo SQL queries.				
Llama3 layers	Notation	Neural operators	SQL query	
Attention se	$softmax(\frac{QK^T}{\sqrt{d}})V$	Matmul	SELECT token, head, row, SUM(DOT(query_chunk, embedding)) AS q	
		Matmul	FROM query[key,value]_weights as A JOIN embedding as B	
		Matmul	ON A.col = B.col GROUP BY row	
		Matmul	SELECT Q.token, K.token, Q.head, EXP(SUM(q * k) / sqrt(head_dim)) as qk FROM Q	
			JOIN K on Q.row = K.row and Q.head//4 = K.head GROUP BY Q.token, K.token, Q.head	
		Softmax	WITH summation AS (SELECT Q.head, Q.token, SUM(qk) as s FROM QK	
			GROUP BY Q.token, Q.head) SELECT Q.head, Q.token, K.token, qk/s FROM	
			QK JOIN sumamtion ON Q.head, Q.token	
Rotary positional encoding	$\mathbf{x} = \mathbf{x}_1, \mathbf{x}_2 \in \mathbb{R}^{d/2}$	Split as complex	SELECT token, head, collect_real(collect_as_array(row), collect_as_array(r), 0) AS x_1 ,	
			collect_img(collect_as_array(row), collect_as_array(r), 1) AS x_2 FROM x	
			GROUP BY token, head	
	$\begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix}$	Rotation	SELECT token, head, hadamard.prod $(x_1,\; heta_1)$ - hadamard.prod $(x_2,\; heta_2)$ as real,	
			hadamard_prod (x_1, θ_2) + hadamard_prod (x_2, θ_1) AS img FROM complex_vectors as A	
			LEFT JOIN $rotation_{ heta}$ AS B ON A.token=B.token	
	$\operatorname{Concat}(\mathbf{x}_1^{(p)},\mathbf{x}_2^{(p)})$	Merge to vector	SELECT layer, token, head, VIEW_AS_REAL(real, img) as chunk	
			FROM positional_encoding	
RMS Norm	1	Squared mean	Select token, 1/SQRT(SUM(arraySum($x->x^2$,embedding)) / dim) + ϵ) as rep_sqmean	
	$\sqrt{(\sum x^2/\text{dim})}$	& rsqrt	FROM Embedding GROUP BY token	
	rep_sqmean*x*norm_weight	Weighted mean	SELECT token, col, rep_sqmean \star hadamard_prod(x , weight) AS new_embedding	
			FROM Embedding LEFT JOIN rsqrt ON rsqrt.token= Embedding.token	
			LEFT JOIN norm_weight ON Embedding.col = norm_weight.col	

Table 2. Core neural operators and corresponding pseudo SQL queries