Froid: Optimization of Imperative Programs in a Relational Database

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ABSTRACT

For decades, RDBMSs have supported declarative SQL as well as imperative functions and procedures as ways for users to express data processing tasks. While the evaluation of declarative SQL has received a lot of attention resulting in highly sophisticated techniques, the evaluation of imperative programs has remained naïve and highly inefficient. Imperative programs offer several benefits over SQL and hence are often preferred and widely used. But unfortunately, their abysmal performance discourages, and even prohibits their use in many situations. We address this important problem that has hitherto received little attention.

We present Froid, an extensible framework for optimizing imperative programs in relational databases. Froid's novel approach automatically transforms entire User Defined Functions (UDFs) into relational algebraic expressions. and embeds them into the calling SQL query. This form is now amenable to cost-based optimization and results in efficient, set-oriented, parallel plans as opposed to inefficient, iterative, serial execution of UDFs. Froid's approach additionally brings the benefits of many compiler optimizations to UDFs with no additional implementation effort. We describe the design of Froid and present our experimental evaluation that demonstrates performance improvements of up to multiple orders of magnitude on real workloads.

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1. **INTRODUCTION**

SQL is arguably one of the key reasons for the popularity of relational databases today. SQL's declarative way of

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expressing intent has on one hand provided high-level abstractions for data processing, while on the other hand, has enabled the growth of sophisticated query evaluation techniques and highly efficient ways to process data.

Despite the expressive power of declarative SQL, almost all RDBMSs support procedural extensions that allow users to write programs in various languages (such as Transact-SQL, C#, Java and R) using imperative constructs such as variable assignments, conditional branching, and loops. These extensions are quite widely used. For instance, we note that there are of the order of tens of millions of Transact-SQL (T-SQL) UDFs in use today in the Microsoft Azure SQL Database service, with billions of daily invocations.

UDFs and procedures offer many advantages over standard SQL. (a) They are an elegant way to achieve modularity and code reuse across SQL queries, (b) some computations (such as complex business rules and ML algorithms) are easier to express in imperative form, (c) they allow users to express intent using a mix of simple SQL and imperative code, as opposed to complex SQL queries, thereby improving readability and maintainability. These benefits are not limited to RDBMSs, as evidenced by the fact that many popular BigData systems also support UDFs.

Unfortunately, the above benefits come at a huge performance penalty, due to the fact that UDFs are evaluated in a highly inefficient manner. It is a known fact amongst practitioners that UDFs are "evil" when it comes to performance considerations [35, 28]. In fact, users are advised by experts to avoid UDFs for performance reasons. The internet is replete with articles and discussions that call out the performance overheads of UDFs [34, 36, 37, 24, 25]. This is true for all popular RDBMSs, commercial and open source.

UDFs encourage good programming practices and provide a powerful abstraction, and hence are very attractive to users. But the poor performance of UDFs due to naïve execution strategies discourages their use. The root cause of poor performance of UDFs can be attributed to what is known as the 'impedance mismatch' between two distinct programming paradigms at play – the declarative paradigm of SQL, and the imperative paradigm of procedural code. Reconciling this mismatch is crucial in order to address this problem, and forms the crux of our paper.

We present Froid, an extensible optimization framework for imperative code in relational databases. The goal of Froid is to enable developers to use the abstractions of UDFs and procedures without compromising on performance. Froid

 $^{^*}$ Work done as an intern at Microsoft Gray Systems Lab.

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achieves this goal using a novel technique to automatically convert imperative programs into equivalent relational algebraic forms whenever possible. Froid models blocks of imperative code as relational expressions, and systematically combines them into a single expression using the *Apply* [14] operator, thereby enabling the query optimizer to choose efficient set-oriented, parallel query plans.

Further, we demonstrate how Froid's relational algebraic transformations can be used to arrive at the same result as that of applying compiler optimizations (such as dead code elimination, program slicing and constant folding) to imperative code. Although Froid's current focus is T-SQL UDFs, the underlying technique is language-agnostic, and therefore extending it to other imperative languages is quite straightforward, as we show in this paper.

There have been some recent works that aim to convert fragments of database application code into SQL in order to improve performance [12, 4]. However, to the best of our knowledge, Froid is the first framework that can optimize imperative programs in a relational database by transforming them into relational expressions. While Froid is built into Microsoft SQL Server, its underlying techniques can be integrated into any RDBMS.

We make the following contributions in this paper.

- 1. We describe the unique challenges in optimization of imperative code executing in relational databases, and analyze the reasons for their poor performance.
- 2. We describe the novel techniques underlying Froid, an extensible framework to optimize UDFs in Microsoft SQL Server. We show how Froid integrates with the query processing lifecycle and leverages existing subquery optimization techniques to transform inefficient, iterative, serial UDF execution strategies into highly efficient, set-oriented, parallel plans.
- 3. We show how several compiler optimizations such as dead code elimination, dynamic slicing, constant propagation and folding can be expressed as relational algebraic transformations and simplifications that arrive at the same end result. Thereby, Froid brings these additional benefits to UDFs with no extra effort.
- 4. We discuss the design and implementation of Froid, and present an experimental evaluation on several real world customer workloads, showing significant benefits in performance and resource utilization.

The rest of the paper is organized as follows. Section 2 gives the background. Sections 3, 4, 5 and 6 describe Froid and its techniques. Design details are discussed in Section 7 followed by an evaluation in Section 8. We discuss related work in Section 9 and conclude in Section 10.

2. BACKGROUND

In this section, we provide some background regarding the way imperative code is currently evaluated in Microsoft SQL Server and analyze the reasons for their poor performance. SQL Server primarily supports imperative code in two forms: UDFs and Stored Procedures (SPs). UDFs cannot modify the database state whereas SPs can. UDFs and SPs can be implemented in either T-SQL or Common Language Runtime (CLR). T-SQL expands on the SQL standard to include imperative constructs, various utility functions, etc. CLR integration allows UDFs and SPs to be

```
create function total_price(@key int)
    returns char(50) as
    begin
      declare @price float, @rate float;
1
2
3
      declare @pref_currency char(3);
      declare @default_currency char(3) = 'USD';
4
      select @price = sum(o_totalprice) from orders
                          where o_custkey = @key;
5
      select @pref_currency = currency
                   from customer_prefs
                   where custkey = @key;
¦6∏
      if(@pref_currency <> @default_currency)
      begin
7
        select @rate =
             xchg_rate(@default_currency,@pref_currency);
8
        set @price = @price * @rate;
      end
9
      return str(@price) + @pref_currency;
    end
    create function xchg_rate(@from char(3), @to char(3))
    returns float as
    begin
      return (select rate from dbo.xchg
1
           where from_cur = @from and to_cur = @to);
    end
            Sequential region
                                Conditional region
```

Figure 1: Example T-SQL User defined functions

written in any .NET framework language such as C# [5]. UDFs can be further classified into two types. Functions that return a single value are referred to as scalar UDFs, and those that return a set of rows are referred to as Table Valued Functions (TVFs). SQL Server also supports inline TVFs, which are single-statement TVFs analogous to parameterized views [13]. In this paper we focus primarily on *Scalar T-SQL UDFs*. Extensions to support other imperative languages are discussed in Section 7.3.

2.1 Scalar UDF Example

In SQL Server, UDFs are created using the CREATE FUNCTION statement [13] as shown in Figure 1. The function *total_price* accepts a customer key, and returns the total price of all the orders made by that customer. It computes the price in the preferred currency of the customer by looking up the currency code from the *customer_prefs* table and performs currency conversion if necessary. It calls another UDF *xchg_rate*, that retrieves the exchange rate between the two currencies. Finally it converts the price to a string, appends the currency code and returns it. Consider a simple query that invokes this UDF.

select c_name, dbo.total_price(c_custkey)
from customer;

For each customer, the above query displays the name, and the total price of all orders made by that customer. We will use this simple query and the UDFs in Figure 1 as an example to illustrate our techniques in this paper.

2.2 UDF Evaluation in SQL Server

We now describe the life cycle of an SQL query that includes a UDF. At the outset we note that this is a simplified description with a focus on how UDFs are evaluated currently. We refer the reader to [8, 2, 14] for details.

Parsing, Binding and Normalization: The query first goes through syntactic validation, and is parsed into a tree



Figure 2: Query plan for the query in Section 2.1

representation. This tree undergoes binding, which includes validating referenced objects and loading metadata. Type derivation, view substitution and optimizations such as constant folding are also performed. Then, the tree is normalized, wherein most common forms of sub-queries are turned into some join variant. A scalar UDF that appears in a query is parsed and bound as a UDF operator. The parameters and return type are validated, and metadata is loaded. The UDF definition is not analyzed at this stage.

Cost-based Optimization: Once the query is parsed and normalized, the query optimizer performs cost-based optimization based on cardinality and cost estimates. Execution alternatives are generated using transformation rules, and the plan with the cheapest estimated cost is selected for execution. SQL Server's cost-based optimizer follows the design of the Volcano optimizer [16]. SQL Server reuses query plans for queries and UDFs by caching chosen plans. A cache entry for a UDF can be thought of as an array of plans, one for each statement in the UDF.

Execution: The execution engine is responsible for executing the chosen plan efficiently. Relational query execution invokes a scalar evaluation sub-system for predicates and scalar computations, including scalar UDFs [10]. The plan for the simple query in Section 2.1 is shown in Figure 2. For every tuple that is emitted by the Table Scan operator, the execution engine calls into the scalar evaluation sub-system to evaluate the scalar UDF *total_price*.

At this point, the execution context switches to the UDF. Now, the UDF can be thought of as a batch of statements submitted to the engine. If the UDF contains SQL queries (e.g. lines 4 and 5 of Figure 1), the scalar subsystem makes a recursive call back to the relational execution engine. Once the current invocation of the UDF completes, the context switches back to the calling query, and the UDF is invoked for the next tuple – this process repeats. During the first invocation of the UDF, each statement goes through compilation, and the plan for the UDF is cached. During subsequent invocations, the cached plan for the UDF is used.

2.3 Drawbacks in UDF Evaluation

We now enumerate the main causes for poor performance of UDFs. While we describe the reasons in the context of UDFs in SQL Server, they are mostly true for other RDBMSs as well, though the finer details may vary.

Iterative invocation: UDFs are invoked in an iterative manner, once per qualifying tuple. This incurs additional costs of repeated context switching due to function invocation, and mutual recursion between the scalar evaluation sub-system and relational execution. Especially, UDFs that execute SQL queries in their body (which is common in real workloads) are severely affected.

These iterative plans can be highly inefficient, since queries within the function body are executed multiple times, once for each invocation of the UDF. This can be thought of as a nested loops join along with expensive context switches and overheads. As a consequence, the number of invocations of a UDF in a query has a huge impact on its performance. The query optimizer is rendered helpless here, since it does not look inside UDF definitions.

Lack of costing: Query optimizers treat UDFs as inexpensive black-box operations. During optimization, only relational operators are costed, while scalar operators are not. Prior to the introduction of scalar UDFs, other scalar operators were generally cheap and did not require costing. A small CPU cost added for a scalar operation was enough. This inadvertent simplification is a crucial cause of bad plan choices in cases where scalar operations are arbitrarily expensive, which is often true for scalar UDFs.

Interpreted execution: As described in Section 2.2, UDFs are evaluated as a batch of statements that are executed sequentially. In other words, UDFs are interpreted statement-by-statement.

Note that each statement itself is compiled, and the compiled plan is cached. Although this caching strategy saves some time as it avoids recompilations, each statement executes in isolation. No cross-statement optimizations are carried out, unlike in compiled languages. Techniques such as dead code elimination, constant propagation, folding, etc. have the potential to improve performance of imperative programs significantly. Naïve evaluation without exploiting such techniques is bound to impact performance.

Limitation on parallelism: Currently, SQL Server does not use intra-query parallelism in queries that invoke UDFs. Methods can be designed to mitigate this limitation, but they introduce additional challenges, such as picking the right degree of parallelism for each invocation of the UDF.

For instance, consider a UDF that invokes other SQL queries, such as the one in Figure 1. Each such query may itself use parallelism, and therefore, the optimizer has no way of knowing how to share threads across them, unless it looks into the UDF and decides the degree of parallelism for each query within (which could potentially change from one invocation to another). With nested and recursive UDFs, this issue becomes even more difficult to manage.

3. THE FROID FRAMEWORK

As mentioned earlier, Froid is an extensible, languageagnostic framework for optimization of imperative programs in RDBMSs. The novel techniques behind Froid are able to overcome all the limitations described above. We now describe the intuition and high level overview of Froid. Then, with the help of an example, we walk through the process of optimizing UDFs in Sections 4 and 5.

3.1 Intuition

Queries that invoke UDFs, such as the one in Section 2.1 can be thought of as queries with complex sub-queries. In nested sub-queries, the inner query is just another SQL query (with or without correlation). UDFs on the other hand, use a mix of imperative language constructs and SQL, and hence are more complex. A key observation that we make here is that iterative execution of UDFs is similar to correlated evaluation of nested sub-queries.

Optimization of sub-queries has received a lot of attention in the database literature and industry (see Section 9 for details). In fact, many of the popular RDBMSs are able to transform correlated sub-queries into joins, thereby enabling the choice of set-oriented plans instead of iterative evaluation of sub-queries.



Figure 3: Overview of the Froid framework

Given these observations, the intuition behind Froid can be succintly stated as follows. If the entire body of an imperative UDF can be expressed as a single relational expression R, then any query that invokes this UDF can be transformed into a query with R as a nested sub-query in place of the UDF. We term this semantics-preserving transformation as unnesting or inlining of the UDF into the calling query.

Once we perform this transformation, we can leverage existing sub-query optimization techniques to get better plans for queries with UDFs. This transformation forms the crux of Froid. Note that although we use the term *inlining* to denote this transformation, it is fundamentally different compared to inlining in imperative programming languages.

3.2 The APPLY operator

Froid makes use of the *Apply* operator while building a relational expression for UDFs. Specifically, it is used to combine multiple relational expressions into a single expression. The *Apply* operator (\mathcal{A}) was originally designed to model correlated execution of sub-queries algebraically in SQL Server [14, 10]. It accepts a relational input R and a parameterized relational expression E(r). For each row $r \in R$, it evaluates E(r) and emits tuples as a join between r and E(r). More formally, it is defined as follows [14]:

$$R \mathcal{A}^{\otimes} E = \bigcup_{r \in R} (\{r\} \otimes E(r))$$

where \otimes , known as the join type, is either cross product, left outer-join, left semijoin or left antijoin. SQL Server's query optimizer has a suite of transformation rules for subquery decorrelation, which remove the *Apply* operator and enable the use of set-oriented relational operations whenever possible. Details with examples can be found in [14, 10, 31].

3.3 Overview of Approach

For a UDF with a single RETURN statement in its body, such as the function *xchg_rate* in Figure 1, the transformation is straightforward. The body of such a UDF is already a single relational expression, and therefore it can be substituted easily into the calling context, like view substitution.

Expressing the body of a multi-statement UDF (such as the function *total_price* in Figure 1) as a single relational expression is a non-trivial task. Multi-statement UDFs typically use imperative constructs such as variable declarations, assignments, conditional branching, and loops. Froid models individual imperative constructs as relational expressions and systematically combines them to form one expression.

Figure 3 depicts the high-level approach of Froid, consisting of two phases: UDF algebrization followed by substitution. As a part of binding, the query tree is traversed and each node is bound, as described in Section 2.2. During binding, if a UDF operator is encountered, the control is transferred to Froid, and UDF algebrization is initiated. UDF algebrization involves parsing the statements of the UDF and constructing an equivalent relational expression for the entire UDF body (described in Section 4). This resulting expression is then substituted, or embedded in the query tree of the calling query in place of the UDF operator (described in Section 5). This query tree with the substituted UDF expression is bound using the regular binding process. If references to other (nested) UDF operators are encountered, the same process is repeated. This transformation finally results in a bound query tree, which forms the input to normalization and optimization.

3.4 Supported UDFs and queries

Froid currently supports the following imperative constructs in scalar UDFs.

- DECLARE, SET: Variable declaration and assignments.
- **SELECT:** SQL query with multiple variable assignments.
- IF/ELSE: Branching with arbitrary levels of nesting.
- **RETURN:** Single or multiple return statements.
- **UDF:** Nested/recursive function calls.
- Others: Relational operations such as EXISTS, ISNULL.

Table 1 (column 1) shows the supported constructs more formally. In Table 1, @var and @var1 denote variable names, *expr* is any valid T-SQL expression including a scalar subquery; *prj_expr* represents a projected column/expression; *sql_expr* is any SQL query; *pred_expr* is a boolean expression; *t_stmt* and *f_stmt* are T-SQL statements [33].

Froid's techniques do not impose any limitations on the size or depths of UDFs and complexity of queries that invoke them. The only precondition for our transformations is that the UDF has to use the supported constructs. However, in practice, there are certain special cases where we partially restrict the application of our transformations; they are discussed in Section 7.2.

4. UDF ALGEBRIZATION

We now describe the first phase of Froid in detail. The goal here is to build a single relational expression which is semantically equivalent to the UDF. This involves transforming imperative constructs into equivalent relational expressions and combining them in a way that strictly adheres to the procedural intent of the UDF. UDF algebrization consists of the following three steps.

4.1 Construction of Regions

First, each statement in the UDF is parsed and the body of the UDF is divided into a hierarchy of program *regions*. Regions represent structured fragments of programs such as basic blocks, if-else blocks and loops [17]. Basic blocks are referred to as sequential regions, if-else blocks are referred to as conditional regions, and loops are referred to as loop regions. Regions by definition contain other regions; the UDF as a whole is also a region.

Table 1: Relational algebraic expressions for imperative statements (using standard T-SQL notation from [33])

<u> </u>	•	
Imperative Statement (T-SQL)	Relational expression (T-SQL)	
DECLARE {@var data_type [= $expr$]}[, n];	SELECT $\{expr null \text{ AS } var\}[, \dots n];$	
SET { $@var = expr$ }[,n];	SELECT $\{expr \text{ AS } var\}[, \dots n];$	
SELECT { $@var1 = prj_expr1$ }[,n] FROM sql_expr;	{SELECT prj_expr1 AS $var1$ FROM sql_expr }; [,n]	
IF (mred amm) {t atmt: [m]] FI SF {f atmt: [m]]	SELECT CASE WHEN pred_expr THEN 1 ELSE 0 END AS pred_val;	
$\prod_{i=1}^{n} (p_i ea_exp_i) = \{i_{i=1}^{n}, \dots, i_{i_{i_{i_{i_{i_{i_{i_{i_{i_{i_{i_{i_{i$	$\{ \text{SELECT CASE WHEN } pred_val = 1 \text{ THEN } t_stmt \text{ ELSE } f_stmt; \} [\dots n]$	
RETURN expr;	SELECT expr AS returnVal;	

Function *total_price* of Figure 1 is a sequential region R0 (lines 1-9). It is in turn composed of three consecutive subregions denoted R1, R2 and R3. R1 is a sequential region (lines 1-5), R2 is a conditional region (lines 6-8), and R3 is a sequential region (line 9) as indicated in Figure 1. Regions can be constructed in a single pass over the UDF body.

4.2 **Relational Expressions for Regions**

Once regions are constructed, the next step is to construct a relational expression for each region.

4.2.1 Imperative statements to relational expressions

Froid first constructs relational expressions for individual imperative statements, and then combines them to form a single expression for a region. These constructions make use of the *ConstantScan* and *ComputeScalar* operators in SQL Server [20]. The *ConstantScan* operator introduces one row with no column. A *ComputeScalar*, typically used after a *ConstantScan*, adds computed columns to the row.

Variable declarations and assignments: The T-SQL constructs DECLARE, SET and SELECT fall under this category. These statements are converted into relational equivalents by modeling them as projections of computed columns in relational algebra as shown in Table 1 (rows 1, 2, 3). For example, consider line 3 of Figure 1:

set $@default_currency = 'USD';$

This is represented in relational form as

select 'USD' **as** default_currency.

Observe that program variables are transformed into attributes projected by the relational expression. The RHS of the assignment could be any scalar expression including a scalar valued SQL query (when the SELECT construct is used). In this case, we construct a *ScalarSubQuery* instead of *ComputeScalar*. For example, the assignment statement in line 4 of Figure 1 is represented in relational form as

select (select sum(o_totalprice) from orders

where $o_{-}custkey = @key)$ as price

Variable declarations without initial assignments are considered as assignments to *null* or the default values of the corresponding data types. Note that the DECLARE and SELECT constructs can assign to one or more variables in a single statement, but Froid handles them as multiple assignment statements. Modeling them as multiple assignment statements might lead to RHS expressions being repeated. However, common sub-expression elimination can remove such duplication in most cases.

Conditional statements: These are specified using the IF-ELSE T-SQL construct, consisting of a predicate, a *true* block, and a *false* block. This can be algebrized using SQL Server's CASE construct as given in Table 1 (row 4). The *switch-case* construct is also internally expressed as IF-ELSE, and behaves similarly. Consider the following example:

set @val = `low':

The above statement is represented in relational form as select(case when total > 1000 then 'high')

else 'low' end) as val.

This approach works for simple cases. For complex and nested conditional blocks, this approach may lead to redundant computations of the predicate thereby violating the procedural intent of the UDF. Re-evaluating a predicate multiple times not only goes against our principle of adherence to intent, but it might also hurt performance if the predicate is expensive to evaluate. Froid addresses this by assigning the value of the predicate evaluation to an implicit boolean variable (shown as *pred_val* in row 4 of Table 1). Subsequently, whenever necessary, it uses the CASE expression to check the value of this implicit boolean variable.

Return statements: Return statements denote the end of function execution and provide the value that needs to be returned from the function. Note that a UDF may have multiple return statements, one per code path. Froid models return statements as assignments to an implicit variable called *returnVal* (shown in row 5 of Table 1) followed by an unconditional jump to the end of the UDF. This unconditional jump means that no statement should be evaluated once the *returnVal* has been assigned a valid return value (note that *null* could also be a valid return value). Froid implicitly declares the variable *returnVal* at the first occurrance of a return statement. Any subsequent occurrance of a return statement is treated as an assignment to *returnVal*.

Unconditional jumps are modeled using the *probe* and *pass-through* functionality of the *Apply* operator [10]. The *probe* is used to denote whether *return Val* has been assigned, and the *pass-through* predicate ensures that subsequent operations are executed only if it has not yet been assigned.

Although unconditional jumps could be modeled without using probe and pass-through, there are disadvantages to that approach. First, it increases the size and complexity of the resulting expression. This is because all successor regions of a return statement would need to be wrapped within a case expression. Second, the introduction of case expressions hinders the applicability of scalar expression folding and simplification. As we shall describe in Section 6, Froid brings optimizations such as constant folding and constant propagation to UDFs. The applicability of these optimizations would be restricted by the use of case expressions to model unconditional jumps.

Function invocations: UDFs may invoke other functions, and may also be recursive. When a UDF invocation statement is encountered, Froid simply retains the UDF operator as the expression for that UDF. As part of binding, Froid is

Table 2: Derived tables for regions in function *total_price*.

Region	Write-sets (Derived table schema)
R1	DT1 (price <i>float</i> , rate <i>float</i> ,
	default_currency char(3), pref_currency char(3))
R2	DT2 (price <i>float</i> , rate <i>float</i>)
R3	DT3 (returnVal $char(50)$)

again invoked for the nested UDF, thereby inlining it. Some special cases with deeply nested/recursive functions, where we choose not to optimize are discussed in Section 7.2.

Others: Relational operations such as EXISTS, NOT EX-ISTS, ISNULL etc. can appear in imperative constructs such as the predicate of an IF-ELSE block. Froid simply uses the corresponding relational operators in these cases. In addition to the above constructs, we have prototyped algebrization of cursor loops. However, from our analysis of many real world workloads, we found that scalar UDFs with loops are quite rare (see Section 8). Therefore, we have currently disabled support for loops and may enable it in future.

4.2.2 Derived table representation

We now show how expressions for individual statements are combined into a single expression for a region using derived tables. A *derived table* is a statement-local temporary table created by a sub-query. Derived tables can be aliased and referenced just like normal tables. Froid constructs the expression of each region as a derived table as follows.

Every statement in an imperative program has a *read-set* and a *write-set*, representing sets of variables that are read from and written to within that statement respectively. Similarly, every region R can be seen as a compound statement that has a *read-set* and a *write-set*. Informally, the *read-set* of region R is the union of the *read-sets* of all statements within R. The *write-set* of R is the union of the *write-set* of all statements within R.

A relational expression that captures the semantics of a region R has to expose the *write-set* of R to its subsequent regions. This is because the variables written to in region R would be read/modified in subsequent regions of the UDF. The *write-set* of region R is therefore used to define the schema of the relational expression for R. The schema is defined by treating every variable in the *write-set* of R as an attribute. The implicit variable *returnVal* appears in the *write-set* of all regions that have a RETURN statement.

The *write-sets* of all the regions in function *total_price* of Figure 1 are given in Table 2. Using the schema, along with the relational expressions for each statement, we can construct a relational expression for the entire region R. A single *ConstantScan* followed by *ComputeScalar* operators, one per variable, results in a derived table with a single tuple. This derived table represents the values of all variables written to in R. The derived table aliases for regions R1, R2 and R3 are shown as DT1, DT2, and DT3 in Table 2.

4.3 Combining expressions using APPLY

Once we have a relational expression per region, we now proceed to create a single expression for the entire function. The relational expression for a region R uses attributes from its prior regions, and exposes its attributes to subsequent regions. Therefore, we need a mechanism to connect variable definitions to their uses and (re-)definitions.



Froid makes use of the relational Apply operator to systematically combine region expressions. The derived tables of each region are combined depending upon the type of the parent region. For a region R, we denote the corresponding relational expression as E(R). For the *total_price* function in Figure 1, E(R1) = DT1, E(R2) = DT2, E(R3) = DT3.

Figure 4 shows the relational expression for the entire UDF. The dashed boxes in Figure 4 indicate relational expressions for individual regions R1, R2 and R3. Note that Froid's transformations are performed on the relational query tree structure and not at the SQL language layer. Figure 4 shows an SQL representation for ease of presentation.

The relational expression for a sequential region such as R0 is constructed using a sequence of Apply operators between its consecutive sub-regions i.e.,

$$E(R0) = (E(R1) \mathcal{A}^o E(R2)) \mathcal{A}^o E(R3)$$

The SQL form of this equation can be seen in Figure 4. The *Apply* operators make the values in DT1 available for use in DT2, the values in DT1 and DT2 available for DT3, and so on. We use the outer join type for these *Apply* operators (\mathcal{A}°) . In the presence of multiple return statements, we make use of *Apply* with *probe* (which internally uses left semijoin) and *pass-through* (outer join) [10].

Consider the variable @pref_currency as an example. It is first computed in R1, and hence is an attribute of the derived table DT1 (as shown in Figure 4). R2 uses this variable, but does not modify it. Therefore @pref_currency is not in the schema of DT2. All the uses of @pref_currency in R2 now refer to it as DT1.pref_currency. R3 also uses @pref_currency but does not modify it. The value of @pref_currency that R3 uses comes from R1. Therefore R3 also makes use of DT1.pref_currency in its computation of returnVal.

Observe that the expression in Figure 4 has no reference to the intermediate variable @rate. As a simplification, we generate expressions for variables only when they are first assigned a value, and we expose only those variables that are live at the end of the region (i.e., used subsequently). The @rate variable gets eliminated due to these simplifications. Finally, observe that the only attribute exposed by R0 (the entire function) is the return Val attribute. This expression shown in Figure 4, is a relational expression that returns a value equal to the return value of the function total_price.

4.4 Correctness and Semantics Preservation

We now reason about the correctness of our transformations, and describe how they preserve the procedural semantics of UDFs. As described earlier, Froid first constructs equivalent relational expressions for individual imperative statements (Section 4.2.1). The correctness of these individual transformations directly follows from the semantics of the imperative construct being modeled, and the definition of the relational operations used to model it. The updated values of variables due to assignments are captured using derived tables consisting of a single tuple of values.

Once individual statements (and regions) are modeled as single-tuple relations (Section 4.2.2), performing an Applyoperation between these relations results in a single-tuple relation, by definition. By defining derived table aliases for these single-tuple relations and using the appropriate aliases, we ensure that all the data dependencies are preserved. The relational Apply operator is composable, allowing us to build up more complex expressions using previously built expressions, while maintaining correctness.

In order to strictly adhere to the procedural intent of the UDF, Froid ensures that any computation in the relational equivalent of the UDF occurs only if that computation would have occurred in the procedural version of the UDF. This is achieved by (a) using the *probe* and *pass-through* extensions of the *Apply* operator to ensure that unconditional jumps are respected, (b) avoiding re-evaluation of predicates by assigning their results into implicit variables, and (c) using CASE expressions to model conditional statements.

5. SUBSTITUTION AND OPTIMIZATION

Once we build a single expression for a UDF, the high-level approach to embed this expression into the calling query is similar to view substitution, typically done during binding. Froid replaces the scalar UDF operator in the calling query with the newly constructed relational expression as a scalar sub-query. The parameters of the UDF (if any) form the correlating parameters for the scalar sub-query. At substitution time, references to formal parameters in the function are replaced by actual parameters from the calling query.

SQL Server has sophisticated optimization techniques for sub-queries [14], which are then leveraged. In fact, SQL Server never chooses correlated evaluation for scalar valued sub-queries [10]. The plan (with Froid enabled) for the query in Section 2.1 is given in [27]. From the plan, we observe that the optimizer has (a) inferred the joins between *customer*, *orders*, *customer_prefs* and *xchg* – all of which were implicit in the UDF, (b) inferred the appropriate group by operations and (c) parallelized the entire plan.

Froid overcomes all limitations in UDF evaluation enumerated in Section 2.3. First, the optimizer now decorrelates the scalar sub-query and chooses set-oriented plans avoiding iterative execution. Second, expensive operations inside the UDF are now visible to the optimizer, and are hence costed. Third, the UDF is no longer interpreted since it is now a single relational expression. Fourth, the limitation on parallelism no longer holds since the entire query including the UDF is now in the same execution context.

In a commercial database with a large user base such as SQL Server, making intrusive changes to the query optimizer can have unexpected repercussions and can be extremely risky. One of the key advantages of Froid's approach is that it requires no changes to the query optimizer. It leverages existing query optimization rules and techniques by transforming the imperative program into a form that the query optimizer already understands.

6. COMPILER OPTIMIZATIONS

Froid's approach not only overcomes current drawbacks in UDF evaluation, but also adds a bonus: with no additional implementation effort, it brings to UDFs the benefits of several optimizations done by an imperative language compiler. In this section, we point out how some common optimization techniques for imperative code can be expressed as relational algebraic transformations and simplifications. As a result, Froid is able to achieve these additional benefits by leveraging existing sophisticated query optimization techniques present in Microsoft SQL Server.

Using a simple example, Figure 5 illustrates the working of Froid's transformations in contrast with compiler optimizations. The function getVal (Figure 5(a)) sets the value of variable @val based on a predicate. Starting with this UDF, a few common optimizations done by an imperative language compiler are shown in Figure 5(b) in three steps. Starting from the same input UDF, Figure 5(c) shows the output of Froid's algebrization. Then, Figure 5(d) shows relational algebraic transformations such as projection-pushdown and apply-removal that Froid uses, to arrive at the same result as the compiler optimizations in Figure 5(b).

6.1 Dynamic Slicing

Dynamic slicing is a program slicing technique that makes use of information about a particular execution of a program. A dynamic slice for a program contains a subset of program statements that will be visited in a particular execution of the program [18, 21]. For a particular invocation of the UDF in Figure 5(a), only one of its conditional branches is taken. For example, the dynamic slice for getVal(5000)is given in Figure 5(b)(i). As we can observe from Figure 5(d), Froid achieves slicing by evaluating the predicate (@x > 1000) at compile time and removing the case expression. In such cases where one or more parameters to a UDF are compile time constants, Froid simplifies the expression to use the relevant slice of the UDF by using techniques such as projection pushdown and scalar expression simplification.

6.2 Constant Folding and Propagation

Constant folding and constant propagation are related optimizations used by modern compilers [1, 18]. Constant folding is the process of recognizing and evaluating constant expressions at compile time. Constant propagation is the process of substituting the values of known constants in expressions at compile time.

SQL Server already performs constant folding within the scope of a single statement. However, since it does not perform cross-statement optimizations, constant propagation is not possible. This leads to re-evaluation of many expressions for every invocation of the UDF. Froid enables both constant propagation and folding for UDFs with no additional effort. Since the entire UDF is now a single relational expression, SQL Server's existing scalar simplification mechanisms simplify the expression. Figure 5(d) shows how the expression is simplified by evaluating both the predicate (@x > 1000) and then the string concatenation operation ('high' + ' value') at compile time, after propagating the constant 'high'.

6.3 Dead Code Elimination

Lines of code that do not affect the result of a program are called *dead code*. Dead code includes code that can never be executed (unreachable code), and code that only affects



Figure 5: Compiler optimizations as relational transformations. For ease of presentation, (c) and (d) are shown in SQL; these are actually transformations on the relational query tree representation.

dead variables (assigned, but never read). As an example, suppose the following line of code was present in function *total_price* (Figure 1) between lines 3 and 4:

select @t=count(*) from orders where $o_custkey=@key$ The above line of code assigns the result of a query to a variable that is never used, and hence it is dead code. In our experiments, we found many occurrences of dead code. As UDFs evolve and grow more complex, it becomes hard for developers to keep track of unused variables and code. Dead code can also be formed as a consequence of other optimizations. Dead code elimination is a technique to remove such code during compilation [1]. Since UDFs are interpreted, most forms of dead code elimination are not possible.

Now let us consider how Froid handles this. Since the variable @t is in the *write-set* of R1, it appears as an attribute of DT1. However, since it is never used, there will be no reference to DT1.t in the final expression. Since there is an explicit projection on the *returnVal* attribute, DT1.t is like an attribute of a table that is not present in the final projection list of a query. Such attributes are aggressively removed by the optimizer using projection pushdown. Thereby, the entire sub-expression corresponding to the variable @t gets pruned out, eliminating it from the final expression.

Summary: We showed how Froid uses relational transformations to arrive at the same end result as that of applying compiler optimizations on imperative code. One might argue that compiler optimizations could be implemented for UDFs without using Froid's approach. However, that would only be a partial solution since it does not address inefficiencies due to iterative UDF invocation and serial plans.

We conclude this section by highlighting two other aspects. First, the semantics of the *Apply* operator allows the query optimizer to move and reuse operations as necessary, while preserving correlation dependencies. This achieves the outcome of *dependency-preserving statement reorderings* and *common sub-expression elimination* [1], often used by optimizing compilers. Second, due to the way Froid is designed, these techniques are automatically applied across nested function invocations, resulting in increased benefits due to *interprocedural optimization*.

7. DESIGN AND IMPLEMENTATION

In this section, we discuss key design choices, trade-offs, and implementation details of the Froid framework.

7.1 Cost-based Substitution

One of the first questions we faced while designing Froid was to decide whether inlining of UDFs should be a costbased decision. The answer to this question influences the choice of whether substitution should be performed during Query Optimization (QO) or during binding.

If inlining has to be a cost-based decision, it has to be performed during QO. If not, it can be done during binding. There are trade-offs to both these design alternatives. One of the main advantages to doing this during binding is that it is non-intrusive – the QO and other phases of query processing require no modifications. On the other hand, inlining during query optimization has the advantage of considering the algebrized UDF as an alternative, and making a cost-based decision of whether to substitute or not.

In Froid, we chose to perform inlining during binding due to these reasons: (a) Our experiments on real workloads showed that the inlined version performs better in almost all cases (see Section 8), questioning the need for cost-based substitution. (b) It is non-intrusive, requiring no changes to the query optimizer – this is an important consideration for a commercial database system, (c) Certain optimizations such as constant folding are performed during binding. Inlining during QO would require re-triggering these mechanisms explicitly, which is not desirable.

7.2 Imposing Constraints

Although Froid improves performance in most cases, there are extreme cases where it might not be a good idea. Algebrization can increase the size and complexity of the resulting query (see Section 8.1). From our experiments, we found that transforming a UDF with thousands of lines of code may not always be desirable as it could lead to a query tree with tens of thousands of operators. Additionally, note that the query invoking the UDF might itself be complex as well (see Section 8.2.4). Optimizing such a huge input tree makes the job of the query optimizer very hard. The space of alternatives to consider would increase significantly.

To mitigate this problem, we have implemented a set of algebraic transformations that simplify the query tree reducing its size when possible. However, in some cases, the query tree may remain huge even after simplification. This has an impact on optimization time, and also on the quality of the plan chosen. Therefore, one of the constraints we imposed on Froid is to restrict the size of algebrized query tree. In turn, this restricts the size of UDFs that are algebrized by Froid. Based on our experiments, we found that except for a few extreme cases (see Section 8.2.5), imposing this constraint still resulted in significant performance gains.

Nested and Recursive functions: Froid's transformations can result in deep and complex trees (in the case of deeply nested function calls), or never terminate at all (in the case of recursive UDFs), if it is not managed appropriately. Froid overcomes this problem by controlling the inlining depth based on the size of the algebrized tree. This allows algebrization of deeper nestings of smaller UDFs and shallow nestings of larger UDFs. Note that if there is a deep nesting of large UDFs (or recursive UDFs), algebrizing a few levels might still leave UDFs in the query. This still is highly beneficial in terms of reducing function call overheads and enabling the choice of set-oriented plans, but it does not overcome the limitation on parallelism (Section 2.3).

7.3 Supporting additional languages

Relational databases allow UDFs and procedures to be written in imperative languages other than procedural SQL, such as C#, Java, R and Python. Although the specific syntax varies across languages, they all provide constructs for common imperative operations such as variable declarations, assignments and conditional branching. Froid is an extensible framework, designed in a way that makes it straightforward to incrementally add support for more languages and imperative constructs.

Froid models each imperative construct as a class that encapsulates the logic for algebrization of that construct. Therefore, adding support for additional languages only requires (a) plugging in a parser for that language and (b) providing a language-specific implementation for each supported construct. The framework itself is agnostic to the language, and hence remains unchanged. As long as the UDF is written using supported constructs, Froid will be able to algebrize them as described in this paper.

Note that while translating from a different language into SQL, data type semantics need to be taken into account to ensure correctness. Data type semantics vary across languages, and translating to SQL might lead to loss of precision, and sometimes different results.

7.4 Implementation Details

We now briefly discuss some special cases and other implementation details.

Security and Permissions Consider a user that does not have *execute* permissions on the UDF, but has *select* permissions on the referenced tables. Such a user will be able to run an inlined query (since it no longer references the UDF), even though it should be disallowed. To mitigate this issue, Froid enlists the UDF for permission checks, even if it was inlined. Conversely, a user may have *execute* permission on the UDF, but no *select* permissions on the referenced tables. In this case, by inlining, that user is unable to run the query even though it should be allowed. Froid handles this similar to the way view permissions are handled.

Plan cache implications: Consider a case where a user with administrative privileges runs a query involving this UDF, and consequently the inlined plan is now cached. Subsequently, if a user without UDF *execute* permissions but with *select* permissions on the underlying tables runs the same query, the cached plan will run successfully, even though

Table 3: Applicability of Froid on two customer workloads

Workload	W1	W2
Total $\#$ of scalar UDFs	178	93
# UDFs optimizeable by Froid	151 (85%)	86(92.5%)
UDF lines of code (avg,min,max)	(21, 6, 113)	(26, 7, 169)

it should not. Another implication is related to managing metadata version changes and cache invalidation. Consider the case as described above, where an inlined plan is cached. Now, if the user alters or drops the UDF, the UDF is changed or no longer available. Therefore, any query that referred to this UDF should be removed from the plan cache. Both these issues are solved by enlisting the UDF in schema and permission checks, even if it was algebrized.

Type casting and conversions: SQL Server performs implicit type conversions and casts in many cases when the datatypes of parameters and return expressions are different from the declared types. In order to preserve the semantics as before, *Froid* explicitly inserts appropriate type casts for actual parameters and the return value.

Non-deterministic intrinsics: UDFs may invoke certain non-deterministic functions such as GETDATE(). Inlining such UDFs might violate the user's intent since it may invoke the intrinsic function once-per-query instead of onceper-tuple. Therefore, we disable transforming such UDFs.

8. EVALUATION

We now present some results of our evaluation of Froid on several workloads and configurations. Froid is implemented in SQL Server 2017 in about 1.5k lines of code. For our experiments, SQL Server 2017 with Froid was run on Windows Server 2012(R2). The machine was equipped with Intel Xeon X5650 2.66 Ghz CPU (2 processors, 6 cores each), 96 GB of RAM and SSD-backed storage.

8.1 Applicability of Froid

We have analyzed several customer workloads from Azure SQL Database to measure the applicability of Froid with its currently supported constructs. We are primarily interested in databases that make good use of UDFs and hence, we considered the top 100 databases in decreasing order of the number of UDFs present in them. Cumulatively, these 100 databases had 85329 scalar UDFs, out of which Froid was able to handle 51047 (59.8%). The UDFs that could not be transformed contained constructs not supported by Froid. We also found that there are 10526 customer databases with more than 50 UDFs each, where Froid can inline more than 70% of the UDFs. The sizes of these UDFs range from a single line to 1000s of lines of code. These numbers clearly demonstrate the wide applicability of Froid.

In order to give an idea of the kinds of UDFs that are in these propreitary workloads, we have included a set of UDFs in Section 9 of our technical report [27]. These UDFs have been modified to preserve anonymity, while retaining program structure. We have randomly chosen two customer workloads (referred to as W1 and W2) for deeper study and performance analysis. The UDFs have been used with no modifications, and there were no workload-specific techniques added to Froid. As summarized in Table 3, Froid is able to transform a large fraction of UDFs in these workloads (85% and 92.5%). As described in Section 7, UDF algebrization results in larger query trees as input to query



Figure 6: Varying the number of UDF invocations



Figure 7: Elapsed time for Compilation and execution (using cold plan cache)



Figure 8: TPC-H queries using UDFs

create function discount_price(@price float, @disc float)
returns int as
begin
 return convert(int, @price * @disc);
end

Query: select o_orderkey, c_name from orders left outer join customer on o_custkey = c_custkey where discount_price(o_totalprice, 0.1) > 50000;

Figure 9: Example for Section 8.2.6

optimization. The largest case in W2 resulted in more than 300 imperative statements being transformed into a single expression, having more than 7000 nodes. Note that this is prior to optimizations described in Section 6. This illustrates the complexity of UDFs handled by Froid.

8.2 **Performance improvements**

We now present a performance evaluation of Froid on workloads W1 and W2. Since our primary focus is to measure the performance of UDF evaluation, the queries that invoke UDFs are kept simple so that UDF execution forms their main component. Evaluation of complex queries with UDFs is considered in Section 8.2.4.

8.2.1 Number of UDF invocations

The number of times a UDF is invoked as part of a query has a significant impact on the overal query performance. In order to compare the relationship between the number of UDF invocations and the corresponding performance gains, we consider a function F1 (which in turn calls another function F2). F1 and F2 are functions adapted from workload W1, and their definitions are given in [27]. We use a simple query to invoke this UDF, of the form

select dbo.F1(T.a, T.b) from T

Since the UDF is invoked for every tuple in T, we can control the number of UDF invocations by varying the cardinality of T. Figure 6 shows the results of this experiment conducted with a warm cache. The x-axis denotes the cardinality of table T (and hence the number of UDF invocations), and the y-axis shows the time taken in seconds, in log scale. Note that in this experiment, the time shown in the y-axis does not include query compilation time, since the query plans were already present in the cache.

We vary the cardinality of T from 10 to 100000. With Froid disabled, we observe that the time taken grows with cardinality (the solid line in Figure 6). With Froid enabled, we see an improvement of one to three orders of magnitude (the dashed line). The advantages start to be noticeable right from a cardinality of 10.

8.2.2 Impact of parallelism

As described in this paper, Froid brings the benefits of set-oriented plans, compiler optimizations, and parallelism to UDFs. In order to isolate the impact of parallelism from the rest of the optimizations (since enabling parallelism is a by-product of Froid's transformations), we conducted experiments where we enabled Froid but limited the Degree Of Parallelism (DOP). The dotted line in Figure 6 shows a result of this experiment. It includes all the optimizations of Froid, but forces the DOP to 1 using a query hint. For this particular UDF, SQL Server switches to a parallel plan when the cardinality of the table is greater than 10000 (indicated by the dashed line). The key observation we make here is that even without parallelism, Froid achieves improvements up to two orders of magnitude.

8.2.3 *Compile time overhead*

Since Froid is invoked during query compilation, there could be an increase in compilation time. This increase is not a concern as it is offset by the performance gains achieved. To quantify this, we measured the total elapsed time including compilation and execution by clearing the plan cache before running queries. This keeps the buffer pool warm, but the plan cache cold. The results of this experiment on 15 randomly chosen UDFs (sorted in descending order of elapsed time) of workload W2 are shown in Figure 7. The y-axis shows total elapsed time which includes compilation and execution. We observe gains of more than an order of magnitude for all these UDFs. Note that the compilation time of each of these UDFs is less than 10 seconds.

8.2.4 Complex Analytical Queries With UDFs

In the above experiments, we kept the queries simple so that the UDF forms the main component. To evaluate Froid in situations where the queries invoking UDFs are complex, we considered TPC-H [32] queries, and looked for opportunities where parts of queries could be expressed using scalar UDFs. We extracted several UDFs and then modified the queries to use these UDFs. The UDF definitions and rewritten queries are given in our technical report [27]. Figure 8 shows the results on a 10GB TPC-H dataset with warm cache for 6 randomly chosen queries. For each query, we show the time taken for (a) the original query (without UDFs), (b) the rewritten query with UDFs (with Froid OFF), and (c) the rewritten query with Froid ON.

Observe that for all queries, Froid leads to improvements of multiple orders of magnitude (compare (b) vs. (c)). We also see that in most cases, there is no overhead to using



Table 4: Benefits of Froid on row and column stores (total elapsed time with cold cache) for the example in Figure 9 .

Configuration	Froid OFF	Froid ON
Row store	24241 ms	822 ms
Column store	19153 ms	155 ms

UDFs when Froid is enabled (see (a) vs. (c)). These improvements are the outcome of all the optimizations that are enabled by Froid. For some queries (eg. Q5, Q14), there is a small overhead when compared with original queries. There are also cases (eg. Q11, Q22) where Froid does slightly better than the original. An analysis of query plans revealed that these are due to small variations in the chosen plan.

8.2.5 Factor of improvement

We now consider the overall performance gains achieved due to Froid on workloads W1 and W2 (row store), shown in Figures 10 and 11. The size of table T was fixed at 100,000 rows, and queries were run with warm cache (averaged over 3 runs). In these figures, UDFs are plotted along the xaxis, ordered by the observed improvement with Froid (in descending order). The y-axis shows the factor of improvement (in log scale). We observe improvements in the range of 5x-1000x across both workloads. In total, there were 5 UDFs that showed no improvement or performed slightly worse due to Froid. One of the main reasons for this was the presence of complex recursive functions. These can be handled by appropriately tuning the constraints as described in Section 7.2. UDFs that invoke expensive TVFs was another reason. Since our implementation currently does not handle TVFs, such UDFs do not benefit from Froid.

8.2.6 Columnstore indexes

We now present the results of our experiments on column stores. Column-stores achieve better performance because of high compression rates, smaller memory footprint, and batch execution [6]. However, encapsulating aggregations and certain other operations inside a UDF prevents the optimizer from using batch mode for those operations. Froid brings the benefits of batch mode execution to UDFs. Consider a simple example based on the TPC-H schema as shown in Figure 9. The results of running this on a TPC-H 1GB database with a cold cache are shown in Table 4.

For this example, without Froid, using a clustered columnstore index (CCI) led to about 20% improvement in performance over row store. With Froid, however, we get about 5x improvement in performance by using column store over row store. Along with other reasons, the fact that the pred-



Figure 11: Improvement for UDFs in workload W2

Table 5: Benefits of Froid with native compilation (total elapsed time with warm cache) for the UDF in [28].

Configuration	Froid OFF	Froid ON
Query and UDF interpreted	41729 ms	2056 ms
Interpreted query, native UDF	27376 ms	NA
Native query, native UDF	9230 ms	2005 ms

icate and discount computation can now happen in batch mode contributes to the performance gains.

8.2.7 Natively compiled queries and UDFs

Hekaton, the memory-optimized OLTP engine in SQL Server performs native compilation of procedures [9], which allows more efficient query execution than interpreted T-SQL [22]. Due to its non-intrusive design, Froid seamlessly integrates with Hekaton and provides additional benefits. For this expriment, we considered the UDFs (*dbo.FarePerMile*) used in an MSDN article about native compilation [28] (UDFs are reproduced in [27]). We considered a memory optimized table with 3.5 million rows and 25 columns, with a CCI. The results of this experiment are shown in Table 5.

First, in the classic mode of interpreted T-SQL, we see a 20x improvement due to Froid. Next, we natively compiled the UDF, but ran the query in interpreted mode. This results in a 1.5x improvement compared to the fully interpreted mode with Froid disabled. Froid is not applicable here since a compiled module cannot be algebrized.

Finally, we natively compiled both the UDF and the query, and ran it with and without Froid enabled. With Froid disabled, we see the full benefits of native compilation over interpreted mode, with a 4.5x improvement. With Froid enabled, we get the combined benefits of algebrization and native compilation. Froid first inlines the UDF, and then the resulting query is natively compiled, giving an additional 4.6x improvement over native compilation. Although native compilation makes UDFs faster, the benefits are limited as the query still invokes the UDF for each tuple. Froid removes this fundamental limitation and hence combining Froid with native compilation leads to more gains.

8.3 **Resource consumption**

In addition to significant performance gains, our techniques offer an additional advantage – they significantly reduce the resources consumed by such queries. The reduction in CPU time due to Froid is shown in Figure 12. Due to lack of space, we show the results for a randomly chosen subset of UDFs from workload W2; the results were similar across all the workloads we evaluated. Observe that Froid reduces the



begin declare @price float;

select @price = sum(o_totalprice) from orders where o_custkey = @key
return convert(varchar(20), @price) + 'USD';
end

Query: select c_custkey, total_price(c_custkey) from customer Figure 13: Example for I/O measurements

CPU time by 1-3 orders of magnitude for all UDFs. This reduction is due to elimination of expensive context-switches (see Section 2.2), and also due to optimizations such as setoriented evaluation, folding and slicing.

Due to the above-mentioned reasons, Froid also reduces I/O costs. The I/O metric is dependent upon the nature of operations in the UDF. For UDFs that perform data access, our transformations will lead to reductions in logical reads as it avoids repetition of data access for every invocation of the UDF. Consider a simple UDF such as the one in Figure 13. With Froid, the query requires about 3300 logical reads, whereas without Froid, it issued close to 5 million logical reads on a 1GB TPC-H dataset with cold cache. Such improvements lead to significant cost savings for our customers, especially for users of cloud databases, since they are billed for resources they consume.

9. RELATED WORK

Optimization of SQL queries containing sub-queries is wellstudied. There have been several techniques proposed over the years [19, 15, 30, 14, 7, 10, 23], and many RDBMSs can optimize nested sub-queries. Complementarily, there has been a lot of work spanning multiple decades, on optimization of imperative programs in the compilers community [1, 21, 18]. UDFs are similar to nested sub-queries, but contain imperative constructs. Hence, they lie in the intersection of these two streams of work; however, they have received little attention from either community.

Some databases perform sub-program inlining, which applies only to nested function calls [26]. This technique works by replacing the call to a function with the function body. Another technique is to cache function results [29], which is useful only when there are repeated UDF invocations with identical parameter values. Unlike Froid, none of these techniques offer a complete solution that addresses all drawbacks of UDF evaluation listed in Section 2.3.

There have been recent efforts that use programming languages techniques to optimize database-backed applications. Cheung et al. [4] consider applications written using objectrelational mapping libraries and transforms fragments of code into SQL using Query-By-Synthesis (QBS). The goals of QBS and Froid are similar, but the approaches are entirely different. QBS is based on program synthesis, whereas Froid uses a program transformation based approach. Although QBS is a powerful technique, it is limited in its scalability to large functions. We have manually analyzed all code fragments used in [4] (given in Appendix A of [4]), and found that none of those are larger than 100 lines of code. Even for these small code fragments, QBS suffers from potentially very long optimization times due to the space-exploration involved. They use a preset timeout of 10 mins in their experiments. Froid overcomes both these limitations – it can handle UDFs with 1000s of statements, and can transform them in less than 10 seconds (see Section 8.2.3).

The StatusQuo system [3] includes (a) a program analysis that identifies blocks of imperative logic that can be translated to SQL and (b) a program partitioning method to move application logic into imperative stored procedures. The SQL translation in StatusQuo uses QBS[4] to extract equivalent SQL. The program partitioning is orthogonal to our work. Once such partitioning is done, the resulting imperative procedures can be optimized using Froid.

Emani et al. [12, 11] present a static analysis based approach with similar goals. and can be adapted to extract equivalent SQL for UDFs. However, from a prototype implementation, we found that the generated SQL turns out to be larger and more complex compared to Froid. As discussed in Section 7.2, we prefer to minimize the size of input to the optimizer. Simhadri et al. [31] describe a technique to decorrelate queries in UDFs using extensions to the Apply operator. Froid's approach partly borrows its intuition from this work, but there are some key differences. First, Froid does not require any new operators or operator extensions unlike the approach of [31]. Second, their transformation rules are designed to be a part of a cost based optimizer. Froid, in contrast is designed as a precursor to query optimization. Third, they do not address vital issues such as handling multiple return statements and avoiding redundant computation of predicate expressions, which are found to be quite common in real workloads.

10. CONCLUSION

While declarative SQL and procedural extensions are both supported by RDBMSs, their primary focus has been the efficient evaluation of declarative SQL. Although imperative UDFs and procedures offer many advantages and are preferred by many users, their poor performance is a major concern. Often, using UDFs is discouraged for this reason.

In this paper, we address this important problem using novel techniques that automatically transform imperative programs into relational expressions. This enables us to leverage sophisticated query optimization techniques thereby resulting in efficient, set-oriented, parallel plans for queries invoking UDFs. Froid, our extensible, language-agnostic optimization framework built into Microsoft SQL Server, not only overcomes current drawbacks in UDF evaluation, but also offers the benefits of many compiler optimization techniques with no additional effort. The benefits of our framework are demonstrated by our evaluation on customer workloads, showing significant gains. We believe that our work will enable and encourage wider use of UDFs to build modular, reusable and maintainable applications without compromising performance.

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