

Row-wise Parallel Predicate Evaluation

Ryan Johnson* Vijayshankar Raman Richard Sidle Garret Swart*
C.M.U. IBM Almaden Res. Ctr. IBM Almaden Res. Ctr. Oracle
ryanjohn@ece.cmu.edu ravijay@us.ibm.com rsidle@almaden.ibm.com garret.swart@oracle.com

ABSTRACT

Table scans have become more interesting recently due to greater use of ad-hoc queries and greater availability of multi-core, vector-enabled hardware. Table scan performance is limited by value representation, table layout, and processing techniques. In this paper we propose a new layout and processing technique for efficient one-pass predicate evaluation. Starting with a set of rows with a fixed number of bits per column, we append columns to form a set of banks and then pad each bank to a supported machine word length, typically 16, 32, or 64 bits. We then evaluate partial predicates on the columns of each bank, using a novel evaluation strategy that evaluates column level equality, range tests, IN-list predicates, and conjuncts of these predicates, simultaneously on multiple columns within a bank, and on multiple rows within a machine register. This approach outperforms pure column stores, which must evaluate the partial predicates one column at a time. We evaluate and compare the performance and representation overhead of this new approach and several proposed alternatives.

1. INTRODUCTION

Complex predicates are a common feature of queries in data warehouses. The typical decision support query is generated by a tool, and involves an aggregation over a subset of the database, where the subset is defined by a conjunction of *dozens* of predicates, some of which may in turn involve complex expressions and nested disjunctions.

E.g, the following is a **WHERE** clause from one of the simpler queries in a customer workload CUSTW1 that we use in this paper (the column names are anonymized and the query is varied slightly but the basic structure is unaltered):
A = a AND B = b AND C IN (c,d) AND D = 0 AND E = 0 AND F <= 11 AND G >= 2 AND H IN (e,f) AND (I IN (g,h) OR I > j) AND 9 other clauses (Q1)

Traditionally, DBMSs have considered the principal bottlenecks in query speed to be I/O and joins, and so have not optimized much for predicate evaluation, other than applying them as early as possible in the query plan.

*Work done while author was at IBM

Permission to make digital or hard copies of portions of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyright for components of this work owned by others than VLDB Endowment must be honored.

Abstracting with credit is permitted. To copy otherwise, to republish, to post on servers or to redistribute to lists requires prior specific permission and/or a fee. Request permission to republish from: Publications Dept., ACM, Inc. Fax +1 (212) 869-0481 or permissions@acm.org.

PVLDB '08, August 23-28, 2008, Auckland, New Zealand
Copyright 2008 VLDB Endowment, ACM 978-1-60558-305-1/08/08

However, more and more data warehouses store tables denormalized, in main memory, often in compressed form. For such warehouses, joins and I/O are no longer the issue. Accessing the denormalized table is the main cost, and in many cases this cost is mainly that of predicate evaluation.

1.1 Predicate Evaluation in Blink

In this paper we present a way to efficiently evaluate complex predicates in the context of Blink, a query processor that operates over a compressed main memory data format [9].

In Blink, every column is compressed by encoding its values with a fixed length, order preserving, dictionary code. For each column X , there is an array D_X (the *dictionary*) containing all the distinct values of that column. In each tuple, the entry for column X is a code of size $\lceil \log_2 |D_X| \rceil$ bits: a reference to a value in D_X . The values in D_X are stored in sorted order, so a range predicate (e.g., column $<$ literal) can be evaluated directly over the coded column.

In this paper we present two new techniques to speed up queries over such a format, in which tabular data is represented in fixed width columns. Our techniques are implemented in the Blink query processor, and we present experimental results using variations within Blink, and of Blink in comparison with MonetDB [13].

ALU Parallelism, exploiting Long Registers

Complex SQL **WHERE** clauses, as in Q1, are usually evaluated sequentially: an evaluator walks an operator tree, applying one predicate after another, repeating the process on each row. With order-preserving dictionary coding, all the standard predicates ($=, <, >, \leq, \geq$) map to integer comparisons between codes, irrespective of data type. As a result, each predicate can be evaluated using mask and compare instructions provided by the processor.

The drawback with this standard method is that it underutilizes the processor. Since code size grows only logarithmically with the domain size, the columns on which predicates are applied tend to compress very well. In Blink, the average code length for the columns in Q1 is under 6 bits. In contrast, most modern ALUs support operations on 128-bit registers. Applying predicates one at a time uses only 6/128th of the ALU.

We present a new method that avoids this drawback by applying predicates on multiple columns in parallel. Our layout packs the codes for multiple columns into a single 128-bit unit, and our method converts arbitrary numbers of comparisons on columns within this unit into a fixed sequence of operations over the 128-bit unit. This allows us to often evaluate the column comparisons on N column values that have been compressed to B bits each using only

$NB/128$ operations, as compared to N operations using the standard method.

We use this method as a primitive in evaluating a general WHERE clause containing arbitrary conjunctions of atomic predicates. We also present similar methods for disjunctions, as well as other more complex predicates such as in-lists (e.g. color in “violet”, “blue”, “purple”).

Later we show how these vector primitives can be incorporated into a query planner through the use of a packed vector data type and additional rewrite rules. While our experiments were conducted using a simple rule based optimization, the technique is easy to model so it can be incorporated into a cost-based optimizer.

Packing columns into word-sized banks

Besides CPU efficiency, another major factor driving query performance is (memory) bandwidth efficiency. While DBMSs since System R have laid out tables in row-major order, many recent systems use a column-major order, so that each query needs to only scan the columns it references (e.g., Sybase IQ [6], MonetDB [3], C-Store [1]). In this paper we argue that both row-major and column-major layouts are suboptimal: the former because queries have to scan columns that they don’t need, and the latter because columns must be padded to word boundaries for efficient access to the columns.

Instead, we propose a family of *Banked Layouts* that pack arbitrary width columns into fixed size banks, where the bank widths are chosen to allow efficient ALU operations: 8, 16, 32, or 64 bits. We then lay out the table in *bank-major* order.

Banked layouts present a size trade-off. Wide banks are more compact because we can pack columns together with little wasted space. When a query references many of the columns in the bank, this compactness results in efficient utilization of bandwidth, much like in a row-major layout.

On the other hand, narrow banks are beneficial for queries that reference only a few columns within each bank. In the extreme case, when each column is placed in a separate bank, we get a column-major layout, padded to the nearest machine word size. Banked layouts also make use of SIMD instruction sets on modern processors to allow a single ALU operation to operate on as many banks as can be packed into a 128 bit register. Narrow banks rely on SIMD processing for greater efficiency.

We explore this tradeoff between compactness and column-targeting and present multiple strategies for packing columns into banks. We experimentally compare the performance of these strategies, as well as the column-major layout, using an off-the-shelf column store (MonetDB). Our experiments show that banked layouts beat both row-major and column-major layouts.

2. BACKGROUND AND RELATED WORK

Blink is a query processing system that uses a compression method called *frequency partitioning* [9]. It partitions each table horizontally to allow for more efficient dictionary compression by allowing each partition to have its own set of dictionaries. Since each dictionary need only represent the values present in the partition the dictionaries can be shorter and shorter dictionaries means smaller column codes. In particular, if in partition P column C is coded using dictionary $D_{C,P}$ then the column width is $\lceil \log_2 |D_{C,P}| \rceil$

bits. Since each column has fixed width within a partition, each row has a fixed format in that partition. In [9] we show that frequency partitioning approaches the same efficiency as Huffman coding as we let the number of partitions grow, but has the advantage of generating fixed length codes within each partition. The partition level dictionaries are kept sorted, so that range and equality comparisons can be done without any decoding.

Queries in Blink are executed by compiling the query from value space to code space and then running the query directly on the compressed data without having to access the dictionary. This compilation from value space to code space has to be done separately for each partition, because the dictionaries are different for each partition. To limit this overhead we set an upper limit on the number of partitions.

Blink queries consist of a table scan with selection, followed by hash-based group by and aggregation. That is, for each tuple t , Blink evaluates the selection predicate, and if it passes, it computes the tuple’s group index and updates the aggregate values for that index with values extracted from the tuple. This process runs in parallel on as many cores as are available, each core running the query on a separate partition, and the resulting aggregates are finally combined to produce the final answer.

In this paper we focus on the efficiency of predicate evaluation in such a table scan. Predicate evaluation often dominates the query run time, because warehouse queries typically have low selectivity. This work is not specific to Blink, it is applicable to any system with fixed width columns. However it is especially interesting for use with Blink because the average column width is much smaller due to frequency partitioning. This means that the number of columns that can be packed into a machine word is higher, and thus opportunities to perform multiple column operations in each word operation are greater.

2.1 Related Work

We can categorize a physical data layout by three criteria: value coding, data placement, and data padding.

- Value Coding: Many systems have used variants of dictionary coding to encode column values. The scope of the dictionaries varies widely, and includes per column dictionaries[10], per table dictionaries[12], or per disk block dictionaries[8].
- Data Placement specifies how the coded data is arranged in memory or on the file system. There is a wide variation of techniques used. Some important ones are:
 - Row-wise Slotted Page. A portion of the page is used as an index into the rest of the page, mapping the slot number to a byte offset in the page. This allows for records to be rearranged inside the page without changing the Row IDs. This update-optimized format is used by all the major database vendors.
 - Column-wise File Packed. Each column is stored as a separate contiguous chunk, using the same ordering. An insert appends to each chunk. This format is used by C-Store[1] and Sybase IQ [6], and MonetDB [4].
 - Row-wise Paged, Column: Each page stores complete rows, but within a page each column is stored separately. Rows are joined positionally. This approach was pioneered in PAX [2].
 - Row-Partitioned and Column Banked: In Blink, rows are frequency partitioned, and within each partition the

columns are partitioned into vertical banks. Rows can be joined positionally.

- Data Padding is done to match the storage format of data with the word lengths and data formats of a particular machine. For example, Oracle RDBMS aligns and pads certain data structures stored on a page so that a pointer into a page can be cast to a pointer to a C struct, avoiding the need to copy data into an ancillary structure. Many databases optimized for fast execution align data on word boundaries (e.g., C-Store). However padded formats can take up more space in storage. MonetDB/X100[3] keeps data in memory without padding, but pads inside the processor cache.

A final dimension in physical design is the option of keeping multiple materializations of the same data. Placing data in multiple formats increases the odds that one will be more efficient for a particular query. Materialized views and C-Store projections fall in this category. Our bank design allows banks to contain redundant copies of columns, so as to decrease the number of banks that need to be accessed for an average query. All of these approaches suffer from the problem that the space of possible materializations is exponential in the schema size, and it is hard to choose the right materializations for a particular workload.

A general issue for query processing on SIMD hardware is that the natural bit width of a column often does not match any of the word widths of the processor. C-Store [1] and MonetDB/X100 [3] pad the columns to word width, C-Store as the data is being laid out, and X100 as the data is being read in. Blink does neither, packing columns into words to try and fill every bit. This approach not only obviates the unpacking pass of X100, but also packs each register full of interesting bits rather than zeros, making each ALU operation potentially more valuable. Zhou [11] uses SIMD processing for more than just scanning, but the scan processing is done at word level, as in C-Store.

3. REWRITING COLUMN EXPRESSIONS TO WORD EXPRESSIONS

The main challenge in efficient predicate evaluation is that the data types and operators used in an expression tree are not the operations and data types supported directly by the ALU. An expression tree for a **WHERE** clause uses operators such as $<$, $=$, **BETWEEN**, **IN**-list, Boolean **AND**, etc., on column values from domains like **VARCHAR**, **DATE**, etc. In contrast, the ALU performs compare, XOR, etc., on 128-bit units, which can be treated (using SIMD instructions) as vectors of machine words with width 8, 16, 32, or 64 bits.

Order-preserving dictionaries help to an extent, because they replace complex, variable width column domains with fixed width dictionary codes. However, these codes can have arbitrary widths that are not word sized, leaving open the question of how to map these column codes onto words.

The usual way of storing fixed width values in machine words is to pad each value on the left with 0s up to the next word boundary, so a 9 bit value would be stored in a 16 bit word, while a 2 bit value would be stored in an 8 bit word. The amount of this padding depends on the distribution of column widths. For example, in a table of 10 columns with widths 1, 2, ... 10 bits, column-level word padding expands the data from 55 to 96 ($8 \times 8 + 2 \times 16$) bits per row.

The difficulty with this padding is three fold:

- it increases the amount of space needed to store the data,
- it increases the amount of bandwidth needed to move the data into the CPU, and
- it increases the number of ALU ops needed to process the data (e.g., a comparison involving a 2 bit column has to use an 8-bit comparator).

Column store DBMSs like MonetDB/X100 [3] address the first two issues by packing the data tightly in memory and only padding after loading into cache, but this does not address the third issue. In fact, it further increases the number of ALU operations, because the processor has to do an extra pass to extract the column and pad the values to word width.

In this section, we present an alternative that packs columns tightly into words and processes them in parallel, by operating directly on the packed words. We start by specifying operator algebras over columns and over words, and describe how to map expressions on columns into equivalent expressions on words (Section 3.1). We then introduce rewrite rules for optimizing these word-expressions, by mapping patterns that operate sequentially on individual columns into more efficient expressions that operate simultaneously on many columns, making use of the full width of the ALU (Section 3.2). Finally, we present a policy for building an operation tree out of a general expression (Section 3.3) and invoking these rewrite rules on it (Section 3.4).

For ease of presentation, we assume initially that we can always operate on the the encoded value of each column. For expressions involving arithmetic, **LIKE**, or comparisons of multiple column values, we need to look at the decoded values. We present this generalization in Section 3.4.

3.1 Column and Word Algebra

SQL predicates apply operators on columns: binary comparisons, Boolean operators (**and**, **or**, **not**), **IN**-lists, etc. Because we use order-preserving dictionary codes, we can perform these operators directly on the encoded columns. We call these operators a *column algebra* (CA). The ALU implements a *word algebra* (WA): bit-wise $\&$, $|$, \sim (**not**), \oplus (**xor**), modular addition, subtraction, and comparison operators that produce *saturated results* – all 1s across the word width for true, and all 0s for false. Using SIMD instructions available on many processors, the word sizes for these operators can be 8, 16, 32, or 64 bits, while achieving the full parallelism of the 128-bit ALU. For example, we can do 16 compares of 8-bit words, or 4 compares of 32-bit words, in a single instruction.

To make this concrete, we use the following query written in CA as a running example:

$A = 7 \text{ AND } B=3 \text{ AND } C \geq 4 \text{ AND } D=0 \text{ AND } (F \leq 11 \text{ OR } G \geq 2) \text{ AND } H \text{ IN } \{7,99\}$ (Q2)

To write (Q2) in word algebra, we need to map the underlying columns into words. But this depends on how the columns and rows are formatted in memory, so we briefly digress to introduce this format.

Banks and Tuples

This paper introduces a new bank-major layout of relations. A *bank* represents a vertical partition containing a subset of the columns of the relation, with the fixed width dictionary codes for each column concatenated together and padded to the nearest word length. For example, a bank made up of 10 columns, with widths 1, 2, ... 10 would be padded from 55 bits to 64. The assignment of columns to banks affects

the bank width, the amount of padding, and the number of banks “touched” by a typical query. This is the subject of Section 4.

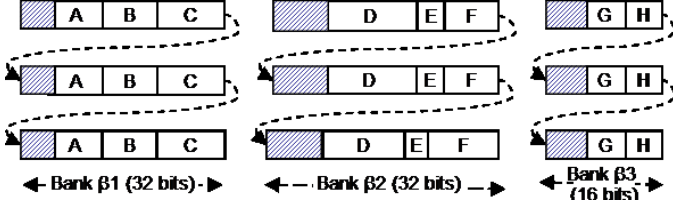


Figure 1: Banked Layout

Banking splits a tuple into multiple words, where each word is a concatenation of column codes. Figure 1 illustrates this with an example involving 3 banks and 3 tuples. We call an individual word-sized unit a *tuplelet*, as it represents a subset of column values from the full relational tuple. A bank is a vector of these tuplelets forming a vertical partition of the table. Note that the split into banks is lossless: the full tuples can be reconstituted by positionally joining tuplelets from each bank.

Now, we are ready to write our query in word algebra (WA).

From column expressions to word expressions

Within a bank, every tuplelet has the same word format, with each column occurring at the same bit offset in each tuplelet. We denote the set of columns associated with a tuplelet T as $C(T)$. Given a tuplelet T , for each column $c \in C(T)$, we can extract just the code for c , and place it right-justified in a word. We call that word operation $extract(T, c)$, and give it a short-form $T.c$. Extract works by doing a shift and mask on the tuplelet:

$$T.c \equiv extract(T, c) \equiv (T \gg shift_c) \& mask_c.$$

where $shift_c$ is the (little-endian) column offset in the bank, and $mask_c$ is a word with 1s in the bits where c occurs.

Having mapped each column into a word expression in this way, we next convert operations on columns into equivalent operations on words. Atomic operators ($=, <, \dots$) on a column c can be done on the word $T.c$, and the comparisons produce saturated results: e.g., $T.A = 7$ produces a word length bit-vector of 1s if true and a similar length vector of 0s if false. Boolean operators such as AND and OR map to their bitwise counterparts ($\&, |$).

Now let us apply this to Q2, with columns assigned to banks as in Figure 1. Let $T1, T2, T3$ be the tuplelet variables ranging (in lock-step) over banks $\beta_1, \beta_2, \beta_3$. Ignoring differences in tuplelet width, Q2 can be written in WA as:

$$T1.A=7 \& T1.B \geq 3 \& T1.C \geq 4 \& T2.D=0 \\ \& (T2.F \leq 11 | T3.G \geq 2) \& (T3.H=7 | T3.H=99)$$

Strictly speaking, the logical OR between $T2.F \leq 11$ and $T3.G \geq 2$ does not correspond directly to bitwise operations, because $T2$ and $T3$ are saturated to different widths. We have to interpose explicit “saturation-conversion” operations; we discuss this issue further in Section 3.2.3.

3.2 Optimizing Tuplelet Algebra

So far, our mapping from CA expressions to WA expressions has been straightforward. In this section, we show

how to run WA efficiently by optimizing commonly occurring patterns in WA expressions. We rewrite patterns that separately extract and operate on several columns from the same tuplelet into equivalent expressions that avoid extraction, and instead do word operations over the entire tuplelet.

3.2.1 Rules for conjunctions

Conjunctions of column-scalar comparisons ($=, <, >, \leq, \geq$), are the most common pattern in SQL WHERE clauses, so we address these first. The examples in the following rules refer to the banks in Figure 1. For ease of explanation, we assume that each column is encoded in exactly 3 bits.

Rule CCE (Complete-Conjunct-Equality) A conjunct of equality tests over all columns in a bank can be rewritten as a comparison of the bank tuplelet against a constant, yielding a saturated Boolean result. E.g., $T1.A = 3 \& T1.B = 7 \& T1.C = 5$ is equivalent to $T1 = 011111101$. Formally, for tuplelet T with n columns, $(T.c_1=a_1 \& \dots \& T.c_n=a_n) \equiv T=A$ where A is a word containing the constants $a_1 \dots a_n$.

Rule CE (Conjunct-Equality) Typically, a query will condition on only some of the columns in a bank. So we need to apply a mask of the missing columns to the tuplelet before comparing against a constant. As above, this yields a saturated Boolean result. E.g. $T1.A = 3 \text{ AND } T1.C = 5$ is equivalent to $T1 \& 111000111 = 111000101$. Formally, for tuplelet T and columns $C' \subseteq C(T)$,

$$T.c'_1=a'_1 \& \dots \& T.c'_m=a'_m \equiv (T \& M)=A'$$

where M is a word that masks out all columns $c_i \notin C'$ and A' is a word with a_i in the offsets of $c_i \in C'$ and zeros elsewhere.

Rule CR (Conjunct-Range) The most general of the conjunct patterns is a conjunct of closed range predicates, e.g.

$$T1.A \geq 2 \text{ and } T1.B \leq 6 \text{ and } T1.C \text{ between } 3 \text{ and } 5 \\ \text{By applying Rule CR, we will transform this into:} \\ ((T1 - 010000011) \oplus (111110101 - T1)) \& 1001001000 \\ = 0101110000$$

For tuplelet T , let m_i be the most significant bit position of column $c_i \in C(T)$. Also let $s_i = m_i + 1$ be a *sentinel* bit position immediately to the left¹ of $c_i \in C(T)$. Then

$$(a_1 \leq T.c_1 \& T.c_1 \leq b_1) \& \dots \\ \dots \& (a_i \leq T.c_i \& T.c_i \leq b_i) \& \dots \\ \dots \& (a_n \leq T.c_n \& T.c_n \leq b_n) \\ \equiv ((T - A) \oplus (B - T)) \& S = (A \oplus B) \& S$$

where A, B are words containing the values of $a_1 \dots a_n$ and $b_1 \dots b_n$, respectively, and S is a mask with bits $s_1 \dots s_n$ set to 1, and all other bits to 0. Figure 2 illustrates how s_i is related to the other bits in a tuplelet. In the example, the ranges on A, B were one-sided. To apply Rule CR, we synthesized the missing side by testing against zero or the maximum field value as appropriate.

Rules CCE and CE are straightforward, and allow us to deal with all equality predicates on a bank using only one or two ALU operations, respectively.

Rule CR is more general, but it is less obvious why it works. We give the formal proof in Appendix A, but here is

¹We use a little-endian numbering scheme for bits, where bit zero of the machine word is the the least significant bit.

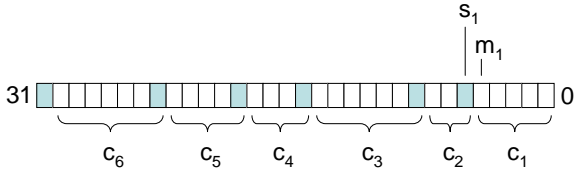


Figure 2: Depiction of a 32-bit tuple containing six columns, as well as the m_i (most significant) and s_i (sentinel) bit positions for column c_1 .

an intuitive argument. Suppose we have a bank containing only one column, x , and wish to test if $a \leq x \leq b$. Assuming that x , a , and b are non-negative (sign bit = 0), observe that

$$(x - a) \oplus (b - x) \geq 0 \quad \text{iff} \quad a \leq x \leq b$$

If $x < a$ the first term will become negative (i.e., a non-zero sign-bit), while the second term becomes negative if $x > b$. Both cannot happen at the same time (because $a \leq b$), so XORing them together produces a negative result if either input was negative.

In a general tuple, multiple fields are packed together, with no space reserved for a sign bit. Instead, we interpret the *sentinel* bit as a sign bit for x , even though that bit belongs to a neighboring column. Rule CR compensates for this via the $A \oplus B$ term. The mask with S is to ensure that the final comparison ignores non-sentinel bits.

Applicability of Rule CR

Rule CR as stated only deals with two-sided, closed range tests, on all the columns in a bank. But by appropriately setting the range bounds, it can handle all conjuncts of the form column op scalar, where op can be =, <, >, ≤, or ≥:

- equality tests: covered by setting $a_i = b_i$ for the appropriate columns (a_i, b_i are the range bounds).
- one-sided range tests: covered by setting $a_i = 0$ or $b_i = 2^{\text{col width}} - 1$.
- range tests on a subset of the columns in a bank: covered by setting $a_i = 0$ and $b_i = 2^{\text{col width}} - 1$ for the columns not being tested.
- open ranges (</>): A dictionary coded column always has a discrete domain, in which every value has a well defined successor and predecessor. So we convert open ranges into closed ranges by changing the literal.

Performance benefit of Rule CR

In the output of Rule CR, the $(A \oplus B)$ & S part is a constant that we precompute. So to apply Rule CR we only need five ALU operations on the tuple: two subtractions, two bitwise operations, and an equality comparison. Through microbenchmarks, we have measured that this method outperforms the `extract()`-based equivalent whenever the conjunction affects two or more columns within a bank.

While efficient, Rule CR suffers one limitation: the most significant bit of the tuple must be padding, or the left-most column will not participate in any comparisons. However, this limitation is minor because most bank layouts contain at least one padding bit anyway. Even if not, range tests on the left-most column can be handled using the machine’s native word comparison instructions, without a column extraction.

3.2.2 Rules for column-wise results

A significant number of SQL WHERE clauses contain dis-

junctions and arbitrary Boolean combinations of basic comparisons. Disjunctions in particular bring two new challenges compared with conjunctions. First, they often compare the same column against multiple constants (e.g. $3 \leq x$ or $x = 5$ or $x > 7$), which requires multiple operations on each tuple. Second, they tend to break up conjunctions within a bank. In the worst case, every column in a bank is involved in a predicate, but each column belongs to a different conjunct than the others. This again requires a separate operation for each conjunctive test. Another consequence of disjunctive break-up is that many conjuncts will combine columns from two or more banks, which imposes extra processing to make the results compatible with each other.

One way to improve the efficiency of arbitrary Boolean combinations is to develop rewrite rules that keep the results of each column comparison isolated from its neighbors and easily accessible in a single bit inside the tuple. Some of the conjunction rules (CE and CCE) do compute the independent results, but these results are spread unpredictably throughout the tuple. CR actually couples results such that failed comparisons can change the outcomes of other comparisons, making it impossible to use for other than computing conjunctions.

Independent and accessible comparisons greatly increase our flexibility in evaluating arbitrary Boolean combinations of comparisons. We can combine the results of many column comparison operations over the same bank before comparing the results (thanks to the results residing in a single bit), which significantly reduces the number of column extracts and comparisons that must be made. Because modern machines often have multiple ALU functional units but only one comparator, this approach also improves processor utilization. Using Rules SC and SD we can also choose subsets of columns for use in conjuncts or disjuncts. This allows a query optimizer to pack multiple unrelated tests on distinct columns into the same bank operation and then split the results afterward.

We start by giving an intuitive view of the rewrites we do, before going into detail.

Rule ME (Multiple-Equality)

If there are multiple equality tests involving different columns from the same bank, we can compute these column-wise partial results in parallel by applying a variant of Rule CE above, then post-processing the output to place an indicator in the most significant bit of each column. These individual partial results can then be used in an arbitrary Boolean combination, often using rules SC and SD below. E.g. (T1.A = 3) ... (T1.B = 7) is equivalent to

$$D = T \oplus 011111000$$

$$R = D \mid ((D \& \sim 100100000) + \sim 100100000)$$

Formally, let A be a constant tuple constructed as in Rule CE and let m_i be the most significant bit position of column c_i in tuple T

$$D = T \oplus A$$

$$R = D \mid ((D \& \sim M) + \sim M)$$

where M is a mask having 1s only at the m_i bits. Then $R[m_i]=0$ iff $T.c_i=A.c_i$

Rule MR (Multiple-Range) If there are multiple constant range tests involving columns from the same bank, we can compute these partial results in parallel by constructing two constant tuples, one representing the low end of each range, the other the high end, as in Rule CR

above. These two are then subtracted from the bank tuple in a careful way to determine which columns are in the range, placing the result in the high order bit of each column. These individual partial results can then be used in an arbitrary Boolean combination, often using rules MD, SC and SD below. E.g. if a predicate contains (T1.A BETWEEN 3 AND 5) as well as (T1.B BETWEEN 1 AND 6), we can compute both by doing:

$$\begin{aligned} L &= (T \mid 100100000) - 011001000 \\ U &= 010001000 - (L \ \& \ \sim 100100000) \\ R &= L \oplus U \oplus 001100000 \end{aligned}$$

Formally, let m_i be the most significant bit position of column c_i in tuple T . Let

$$\begin{aligned} C &= B - A \\ L &= (T \mid M) - (A \ \& \ \sim M) \\ U &= (C \ \& \ \sim M) - (L \ \& \ \sim M) \\ R &= L \oplus U \oplus (A \oplus C) \end{aligned}$$

where M is a bitmask selecting only the m_i bits, and A and B are tuples containing the lower and upper ranges to compare against T . Then

$$R[m_i]=0 \quad \text{iff} \quad A.c_i \leq T.c_i \leq B.c_i.$$

Performance benefit of Rule ME

An equality test on one column requires two operations: a mask to isolate the column and a saturating comparison against a constant value. In contrast, Rule ME requires six operations: XOR, AND, add, OR, mask, and saturating comparison. Therefore, it is only useful when a conjunction or disjunction touches three or more columns in the same bank. But, if the same tuple is to be compared against multiple constants (see Rule MIL, below), the banked layout wins when even two columns are used together. Finally, many machines feature multiple ALU units and only one comparator, further favoring the banked approach (which potentially requires fewer saturating comparisons)

Performance benefit of Rule MR

A two-sided range test on one column requires four operations: a mask to isolate the column, two saturating comparisons against constant values, plus an AND to combine the results. By comparison, Rule MR requires eight operations: OR, subtract, AND, subtract, two XORS, a mask to select the desired columns, and a saturating compare. Rule MR is therefore useful whenever at least two columns will be accessed together. Further, it uses far fewer (expensive) saturating comparisons.

Comparing Rule ME with Rule MR we conclude that Rule MR dominates in practice – many of the columns in a bank are likely to have range tests applied to them, at which point Rule MR is better. The one exception is IN-list evaluation, which involves many equality tests and no range tests (see Rule MIL).

Correctness of Rule ME

We present an intuitive argument for correctness here. The full proof is similar to that of Rule CR. First, we observe that D contains a set bit at every position where T and A differ, and that $T = A$ iff $D = 0$. Suppose that we treat $T1$ as containing three columns, each two bits wide and separated by one bit of padding. Then $D + 011011011$ would set bit s_i (see Figure 2) whenever $T.c_i \neq A.c_i$. This trick would not work without the padding, however, because a failed test on one column would produce a carry that prop-

agates into – and corrupts – the neighbor to its left.

In order to prevent carries from propagating between columns, we make m_i the *sentinel* rather than s_i . A comparison can then fail for one of two reasons: either $D[m_i]$ is set, or one of the other bits in c_i is set. Rule ME computes a partial result for all bits other than m_i , placing the output in position m_i , then ORs that result with D to obtain the final answer. In order to do this, it must mask out the m_i bits (the $D \ \& \ \sim M$ term) and generate a carry for non-zero columns (the $+ \sim M$ term).

Correctness of Rule MR

This rule uses the same split computation trick as Rule ME in order to stop carries at bit m_i of each column. It also exploits overflow in unsigned integer subtraction: if $x < a$ then $x - a$ will overflow and become a number larger than $b - a$, for any $b > a$. At the same time, if $x > b$, $x - a > b - a$ as well, allowing us to test both sides of the range simultaneously.²

The rest of the rule splits each of the three subtractions into two pieces, just like Rule ME does (the three $\ \& \ \sim M$ terms). This time, however, we use subtraction instead of addition, so we must start with bit m_i set to stop borrows from propagating to neighboring fields (the $T \mid M$ term).

3.2.3 Rules to combine column-wise results

Rule MD (Multiple-Disjunct) When computing the disjunct of two or more comparisons of the same column, we can rewrite the computation to use multiple applications of Rule ME or MR above and then combine the results by taking the OR of the resulting multiple result tuples. This gives us a separate disjunct value for each column. This may be applied to more than one column at a time. E.g. (T1.A \leq 3 OR T1.A = 5) ... (T1.B between 2 and 4 OR T1.B \geq 6) might become

$$\begin{aligned} &MR(T1, 000010000, 011100111) \\ &\mid MR(T1, 101110000, 101111111) \end{aligned}$$

Rule SC (Saturated-Conjunct) If there are some high order bit results (as produced by Rules ME and MR above) for which we want the conjunction, then we may rewrite this to mask and test the result bits, yielding a saturated Boolean result. E.g. (T1.A \leq 3) and (T1.B between 2 and 5) becomes

$$MR(T1, 000010000, 011101000) \ \& \ 100100000 = 0$$

Formally, let R be the output produced by applying Rule ME, MR, or MD to tuple T . Let M be a mask with bit m_i set for each column c_i included in the conjunction. Then

$$R \ \& \ M = 0 \quad \text{iff} \quad \text{all predicates passed}$$

Rule SD (Saturated-Disjunct) If there are some high order bit results (as produced by Rules ME, MR, and MD above) for which we want the disjunction, then we may rewrite this to mask and test the result bits, yielding a saturated Boolean result. E.g. (T1.A \leq 3) or (T1.B between 2 and 5) becomes

$$\begin{aligned} &MR(T1, 000010000, 011101000) \ \& \ 100100000 \\ &\neq 100100000 \end{aligned}$$

Formally, let R be the output produced by applying Rule ME, MR, or MD to tuple T . Let M be a mask with bit m_i set for each column c_i included in the conjunction.

²the same trick reduces the number of comparisons used in the scalar test by trading one comparison for a subtraction

predicate patterns and Blink currently processes top-level conjunctive single-column range and short in-list predicates (10 entries or less) in the Fastpath. Rules CR and MIL (and Rule ME, on which it depends) are used, respectively. We choose the more general CR rule over CCE and CE because it subsumes those rules, and in our experience, is almost as fast. We plan to push more patterns into the Fastpath by matching other rules to the expression tree. Rules MR and MD are high priority Fastpath candidates.

Rules CR and MIL are applied in the Fastpath stage to evaluate the range and short in-list conjunct predicates. Compilation clusters predicates of these types according to bank, computes the constants required by these rules per bank, and constructs register-sized (128 bit) vectors of the constants (e.g. there will be 4 copies of the constants in the vector for a 32 bit bank). Execution in the Fastpath stage operates on batches of contiguous tuples from a cell. The predicates are applied bank by bank to batches of vectors of tuples (again, for a 32 bit bank, 4 tuples are processed in each operation). The bitmap of predicate results for the batch is converted to a RID-list of the qualifying tuples, and the RID-list is passed to the next stage.

Batched, interpreted execution is used in the Residual stage. The remainder of the expression tree is compiled into an array of operators, each of which takes a vector of inputs and produces an output vector of equal size. For example, LoadBank is the leaf-level operator that takes the input RID list from Fastpath and loads the qualifying tuples into a result vector. (Each bank is loaded at most once.) The Rules presented in the prior sections apply to the Residual interpreter, but currently column operators such as the primitives for range predicates (e.g. disjunctive ones) and in-lists (short or long) use the standard mask and shift method to extract column values from tuples.

We have implemented multiple operators for expression tree node types where appropriate to provide efficient methods for a wide range of possible arguments. For example, we have bit map, hash (both perfect and standard), and simple array-based implementations for in-list predicates. The compiler chooses between them depending on the in-list entries (their number, value, and density).

Predicate expression trees frequently contain many nodes of the same type. When linearizing the tree into an operator array, we cluster together nodes of the same type when possible, because this allows us to amortize the function invocation overhead. A sort of the nodes by tree level (leaf nodes are at level 0), operator, and tree dependency accomplishes this clustering, and rather than generating the base operators for a cluster, a meta-operator is created. The meta-operator invokes the base operator function directly, in a loop, avoiding the usual interpretation overhead of dereferencing the function pointer. Sizeable savings are achieved through this simple optimization when applied to complex predicates.

Wherever possible operators process in compressed code space. Because we have constructed a dictionary of values, we can convert complex predicates on column values, such as LIKE predicates or even subqueries, into in-lists in code space by evaluating the predicate on each element of the dictionary. A Decode operator decompresses when necessary.

The interpreter produces a bit vector of predicate results, with one bit for each input RID. The final step of the Residual stage uses this bit vector to produce the final RID list

of qualifying tuples, that is then passed to Grouping and Aggregation.

Blink uses batched, multi-row execution at each stage of query processing as in [7, 3], to exploit ILP and SIMD. Short-circuiting for non-qualifying tuples only occurs between stages. Generally, batched execution on vectors reduces the benefits of short-circuiting and short-circuiting implies branches, which require careful (and suitably amortized) use, due to the high cost of misprediction.

4. BANKED LAYOUT SCHEMES

In Section 3 we briefly introduced the idea of banked layouts to understand row-wise parallel predicate evaluation.

Now we return to this topic: how to choose the right bank sizes and how to assign columns to banks. Recall that a bank is a vertical partition of a table that is sized to be a machine word in width. Fields within the bank are stored right justified, with 0-padding to make up the wasted space.

Wide Banks:

From a standpoint of compression, using wide banks (e.g., 64 bits)⁵ and bin-packing fields tightly into the banks yields the most compact layout. We use the standard first-fit decreasing heuristic for bin-packing that considers the column in order of decreasing width, and repeatedly packs the current column into the first bank with available space, starting a new one if none is found. This is known to pack within a factor of 11/9 of optimal [5].

This scheme, called *B64*, is very similar to a pure row store, except for the padding bits that wouldn't occur in a row-major layout. Also, the methods of Section 3 allow us to apply predicates on a set of columns in time proportional only to the cumulative size of the banks containing those columns. So if a query applies predicates on most of the columns in the table, the query's CPU time is proportional to the total row size, which is minimized with the *B64* layout.

Padded-Column Banks:

At the other extreme is a scheme that assigns each column to a separate bank: the smallest bank that will hold it. E.g. a 3 bit column is padded to a 8-bit bank and a 30-bit column to a 32-bit bank. We call this scheme *BCOL*. We believe that many column store systems use such padded representations: for example, MonetDB/x100 converts tightly packed columns into a (decompressed) word-sized representation [3], and Sybase IQ seems to pad to 16 and 32 bit sizes, according to their manuals.

This layout is ideal for a query that references very few columns, because each bank is as small as it can be for the particular column that it holds. But placing only one column in a bank leads to more padding than with *B64*, and is inefficient for queries that reference many columns, as we see experimentally in Section 5.

Variable-Width Banks:

As a compromise between these extremes, we propose banked layouts that use heterogeneous banks, i.e., have different widths. Having banks of different widths allows us to apply a variation of first-fit decreasing heuristic (as in *B64*) that limits the "expansion" of a column: (width of the bank holding a column) / (width of the column).

⁵We do not use 128 bit banks because ALUs do not support subtraction on 128-bit banks, preventing the parallel predicate evaluation methods of Section 3.

The disadvantage of B64 (as compared to BCOL) is that a narrow column may be placed in a wide bank: e.g, a 4 bit column in a 64-bit bank. With banks of different widths, we can restrict that narrow columns be placed only in narrow banks while allowing wide banks to be used for the wide columns. Specifically, our assignment occurs as follows:

1. $Banks \leftarrow \phi$ // $Banks$ is a list
2. Sort the columns by decreasing width.
3. For each column c of width c_w do:
4. Let b be the width of the smallest bank that will hold c (8 for widths 0-7, then 16, 32, and 64)
5. if $Banks$ has bank of width $\in \{b, 2b\}$ with space for c
6. Place c in the left-most such bank in $Banks$.
7. Else, create a new bank of size b , place c in it.

In addition to B64 and BCOL, Blink implements two variable-width banks: one with a maximum width of 32 bits: $VB32$, and one with a maximum width of 64 bits: $VB64$ ($VB32$ is usable only if there are no columns wider than 31 bits). Figure 4 illustrates these layout schemes on a table with 8 columns.

On top of these basic layout schemes, there are two additional enhancements.

Keeping measure fields separate

Queries do not access columns just for predicate evaluation: they also access them for grouping and aggregation. But there is an important distinction in the frequency of access to these columns.

Columns accessed for predicate evaluation are accessed once for each tuple (modulo short-circuiting, which we generally avoid, as discussed in Section 3.4). But columns that are used in aggregation and group-by are only accessed for each tuple that qualifies the query predicates. Data warehouse queries tend to select 10% or less of the rows in the database, so this difference in usage is significant.

It is hard to take advantage of this difference for group-by columns, because the same column is often used in predicates and in group-bys, for different queries in the same workload. But aggregation is done on the measure columns, which are usually distinct from the dimension columns used for applying predicates. We take advantage of this for the banked layouts by forming a separate bank of the measure columns, and only packing the non-measure columns as described above (we do not apply this optimization to BCOL because we want to retain it as a pure column major layout for experimental purposes). To be workload-insensitive, we identify measure columns purely based on the schema: decimal typed columns in the fact table are deemed as measures.

Keeping redundant copies of columns

A second optimization that is enabled by banked layouts is to keep redundant copies of columns in the padding space. For example, the padding space in bank β_2 of Figure 4 is wide enough that it can hold a redundant copy of column G. This redundant copy comes for free: no bank is made any wider and no query has to scan any extra bit because of this redundant copy. But for a query that needs this column, the redundant copy could save accessing other banks. For example, a query with predicates on G and D can access bank β_2 alone, instead of both β_2 and β_3 . We currently have not implemented this feature in Blink, but believe it is very promising. In particular, it is easy to see that this approach applied to BCOL always dominates or equals BCOL in the

cumulative width of banks accessed for a query, *irrespective of the number of columns referenced in the query.*

5. EXPERIMENTAL RESULTS

We now present a detailed experimental evaluation of the two main topics covered in this paper: the row-wise parallel predicate evaluation methods (Section 5.1), and the banked layout schemes (Section 5.2).

The main dataset we use for these experiments is an actual customer dataset CUST1, with about 120 columns and 28.6 million rows. The table occupies about 17GB (4910 bits/tuple) as a .csv and 25GB when stored uncompressed in a traditional commercial DBMS.

We denormalized and loaded this dataset into Blink, and ran experiments on an x86 server (4 Quad-core Opteron x2350 processor, 2.0GHz, 32GB RAM). We also ran the same queries against MonetDB (Feb 2008 release, from <http://monetdb.cw>) a column-store, on an identical machine. The entire dataset fit into memory for both DBMSs. All measurements were done by running each query 9 times, and taking the average of all but the worst and best number. All experiments were run single-threaded, to focus attention on CPU costs.

Some recent papers have compared column stores against commercial DBMSs and found differences of orders of magnitude in speed, and have generally attributed these to the layout: column-store vs row-store. But today's commercial DBMSs were not designed for modern memory-intensive hardware configurations or for read-mostly environments. Some of the banked layouts of Blink are quite similar to row-stores, especially B64, which uses wide banks. By comparing Blink against MonetDB, we study how row-store-like layouts compare against column-store layouts on two DBMSs that are both designed for modern hardware.

We wish to point out that MonetDB performance is known to suffer due to full materialization of intermediate results. This is one of the main motivations for MonetDB/X100, which avoids such materialization [3]. The MonetDB/X100 is not publicly available at the moment, we would like to rerun our experiments when it becomes available. MonetDB is designed to require no tuning and has automatic and self-tuning indexing. Other than following the standard installation and configuration instructions, we did no further tuning of MonetDB. We did denormalize the inputs and wrote the queries against this denormalized schema, so that neither Blink nor MonetDB had to do joins.

5.1 Value of Parallel Predicate Evaluation

We start with an investigation of the benefit of applying our rewrite rules for simultaneous predicate evaluation within a bank. We run a suite of queries of the form: `SELECT SUM(col), COUNT(*) FROM table WHERE conjunction of single column predicates GROUP BY cols`

Since our focus is on predicate evaluation, we choose the group-by columns so that there are always less than 10 distinct groups: this makes sure that the group-by and aggregation operations are cheap and do not factor in the results.

For our first experiment, the query WHERE clauses are a conjunction of range predicates, with ranges chosen to have a selectivity of 10% each. We choose one such predicate on each column, and form queries by gradually AND-ing together predicates from more and more columns. We use the B64 layout, and add predicates on columns in the same

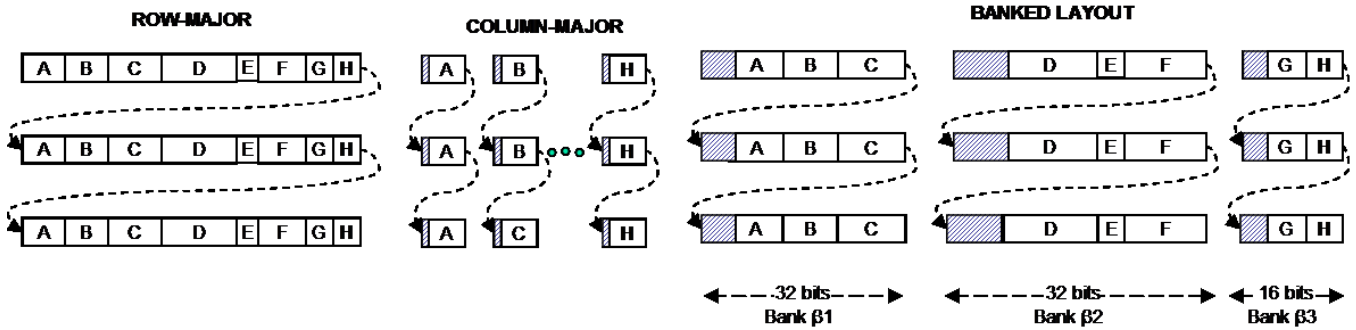


Figure 4: Banked Layout

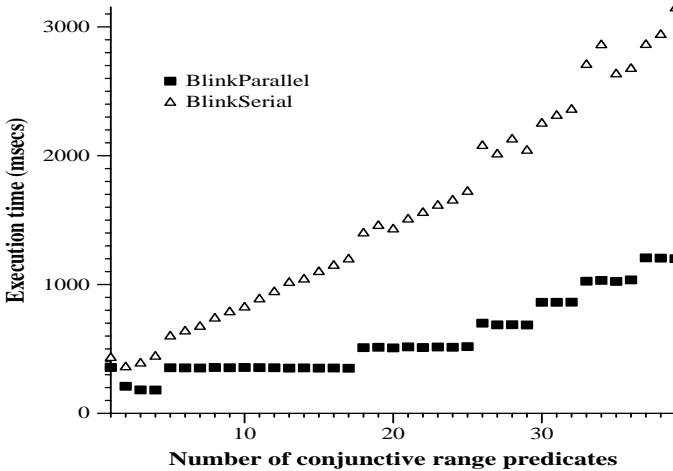


Figure 5: Synthetic queries with increasing number of predicates

order that columns are laid out in banks. Our motivation is to evaluate the benefit of simultaneous predicate evaluation within a bank, and validate our claim that simultaneous predicate evaluation allows us to apply arbitrary numbers of conjunctive predicates within a bank, for one fixed cost.

We run these queries on MonetDB and two versions of Blink: the mainline version that uses the rewrite rules of Section 3 (*BlinkParallel*), and one which uses the traditional sequential evaluation strategy of testing one predicate after another (*BlinkSerial*). The sequential evaluation strategy is also a carefully tuned one: in particular, it uses batched execution as described in Section 3.4 to amortize the overheads of function call invocations and branches, and uses SIMD instructions to apply predicates over banks from multiple tuples in parallel.

Figure 5 plots the running time as we add more predicates on more columns, for *BlinkSerial* and *BlinkParallel*. Notice that the numbers from *BlinkParallel* show a pronounced staircase behavior. The plateaus in the staircase correspond to the addition of predicates on the same bank, and the jump-points in the staircase correspond to the addition of the first predicate on a new bank. This staircase behavior shows the value of the rewrite rules of Section 3: the running time is determined by the number of banks accessed, irrespective of the number of predicates within that bank. In contrast, the times for *BlinkSerial* increase almost

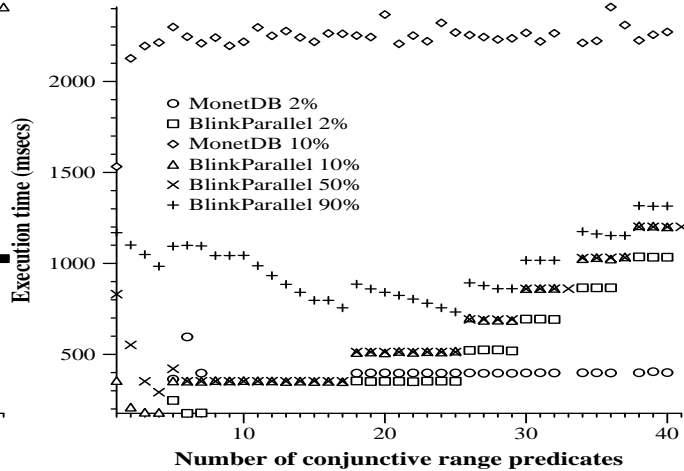


Figure 6: Synthetic queries with increasing number of predicates (full results for MonetDB is in Figure 13)

linearly with the number of predicates. This is to be expected because *BlinkSerial* does no short-circuiting and instead prefers the advantages from batched execution.

Figure 6 plots the same running times, but comparing *BlinkParallel* and MonetDB. MonetDB does short-circuiting by materializing results after each column has been processed; so selectivity is an important factor. We plot curves for per-predicate selectivities ranging from 2% to 90% (MonetDB timings for 50%, 90% are plotted in the appendix). At all selectivities above 2%, *BlinkParallel* outperforms MonetDB. At 2% selectivity, MonetDB outperforms Blink by a factor of two after multiple predicates are added. This is due to short-circuiting (at 2% selectivity, even after 5 predicates are added no tuples qualify). Notice also that the running times for MonetDB are linear in the number of predicates, as long as the selectivity is not too low, whereas the running times for Blink show up as flat lines – they are in fact step functions similar to that of Figure 5.

5.2 Speed & Compression of different Layouts

Next, we turn to an experimental study of the various layout schemes. Our primary goal is to see how the different banked layout schemes compare on compression and query speed, for different kinds of queries (those that touch few columns, those that touch many columns, etc.).

Experiment 1: Compression Ratios

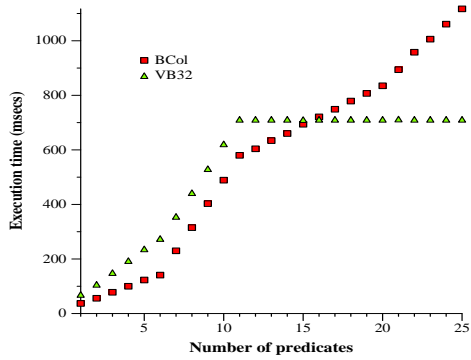


Figure 8: Query speeds vs layout, for random queries

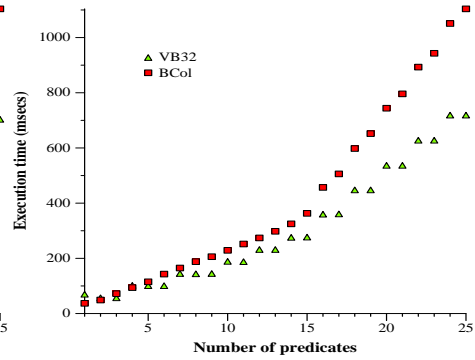


Figure 9: Query speeds vs layout, for clustered queries

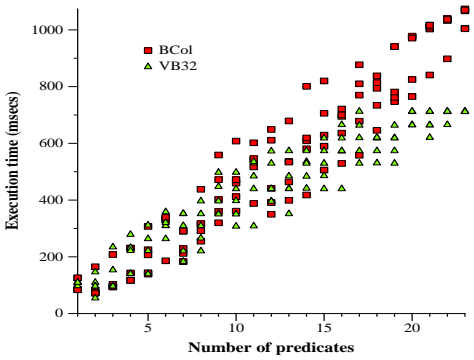


Figure 10: Query speeds vs layout, for partly clustered queries

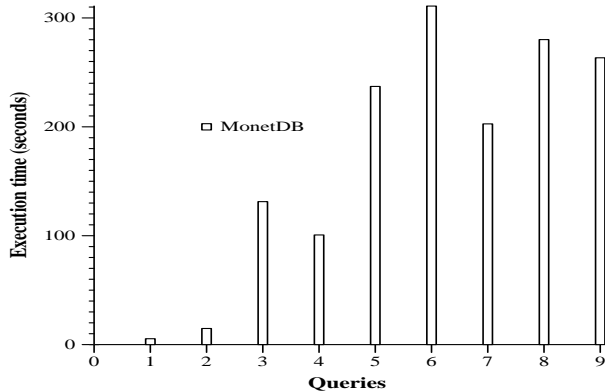


Figure 11: Query speeds for real queries (MonetDB)

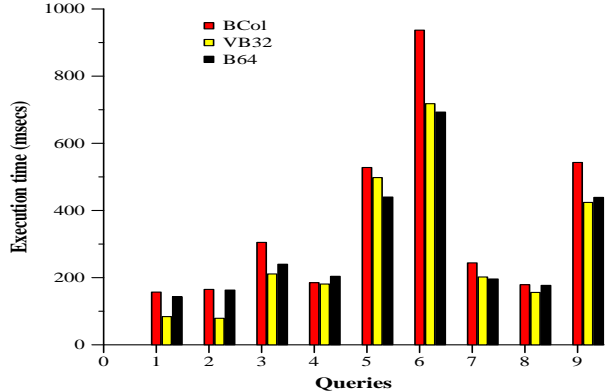


Figure 12: Query speeds for real queries (Blink)

We start with the compression achieved using each layout scheme. Figure 7 plots the compressed sizes and compression ratios for CUST1, a customer dataset. Notice that compression is maximum for the row stores, and least for the padded column store. The banked layouts fill out the spectrum between these, with wide banks behaving like row stores and narrow banks behaving like column stores.

Experiment 2: Speed

We now move to query speeds. The main way in which the column layout affects query speed is in terms of how much data is processed during the query. If each column goes into its own bank, each query processes the minimum number of columns needed, whereas if multiple columns are packed into a bank, the query can process more columns than it needs. But, as discussed, the number of columns processed is not well correlated with the number of bits processed: the thin-bank, one-column-per-bank layout has to do more padding than the wide-bank, many-columns-per-bank layouts.

To quantify this tradeoff, we run two kinds of experiments.

2a. Real Queries: First we run a suite of 9 real queries from a customer workload CUSTW1. These queries are all of the form: selection with group-by over key-foreign key joins on a star schema. The joins are removed because of our denormalization, so the query is a table scan with aggregation. The predicates are similar to query Q1 of Section 1. These are more complex than typical benchmark queries in that they contain many disjunctions and in-lists. Furthermore, each query computes 10-20 aggregations (all SUMs).

Figure 12 plots the run times on each layout. These timings show the banked layouts beat the padded column layout by up to 50%. Among the banked layouts, the variable-sized bank layout (VB32) wins on most queries. One disadvantage of the padded column layout BCOL for these queries is the large number of aggregations: the banked layouts place them in a single bank while the column layout has to access each aggregation column individually. This suggests that even a pure column store should keep measure attributes separately in a row-major bank.

Figure 11 plots the run times of the same query running on MonetDB. Notice that the MonetDB numbers are in *seconds*: about 3 orders of magnitude slower. This huge difference (as opposed to the small differences between BCOL and the other banked layouts within Blink) suggests that the reason goes beyond column vs bank major layout. MonetDB was comparatively slow in the previous experiments, but the difference was not so dramatic so we think that the materialization of intermediate results and the complexity of in-lists might be a possible cause. For Query 3 and up, we noticed via vmstat that MonetDB was doing I/O, even though the database fit comfortably in memory. For Query 1 and 2 we did not notice such I/O, but the MonetDB timings are still an order of magnitude slower than Blink. The rest of our experiments do not involve MonetDB.

Next, we run synthetic workloads to understand the tradeoffs between the layouts in greater depth.

2b. Random Queries:

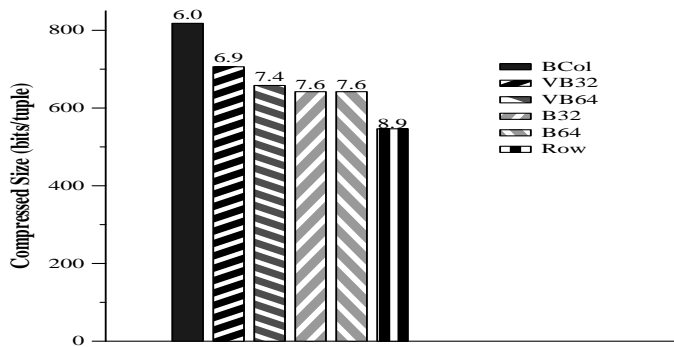


Figure 7: Compression ratios obtained by various layout schemes on a real dataset CUST1, of original (csv) size 17GB (4910 bits/tuple). BCol is the padded column layout, B32 (B64) uses 32-bit (64-bit) banks, VB32 (VB64) uses (64), 32, 16, and 8 bit banks, and Row is a pure rowstore that does no padding.

We start with a suite of queries that touch a random subset of columns in the table. Each query is of the form `SELECT SUM(a) GROUP BY b WHERE ...`, with an increasing number of conjunctive range predicates. To ensure that aggregation does not become the bottleneck, the predicates are chosen to be highly selective ($< 0.1\%$). Figure 8 plots the run times of these queries on Blink with two data layouts: BCOL and VB32. VB32 was chosen to represent the banked layouts because it is a good compromise that generally worked well. Notice that with VB32, run time increases until about 10 predicates (when there is a predicate against a column on every bank), and then stays constant. This is due to the simultaneous predicate evaluation within each bank. For the padded-column layout, run time continues to increase as more predicates are added.

2c. Predictable Queries: Next, we consider a situation in which the query workload is known up front and can be used to cluster columns into banks. Figure 9 reruns the same experiments, but with query predicates that are completely clustered by bank. That is, we add predicates on columns in the same order in which they are laid out in banks. Notice that the banked layout exhibits a staircase-like curve because additional predicates on the same bank do not affect run time. As the number of predicates increases, the banked layout beats the padded column layout by about 25%.

2d. Partially Predictable Queries: Lastly, we consider a situation between 2b and 2c in which with a 50% chance a predicate is over a random column and with a 50% chance a predicate is over a column that is adjacent (in the bank layout) to another column in the where clause. Figure 10 plots the run times on each layout. The result is not as clear but it is evident that VB32 generally outperforms BCOL, especially at higher predicate counts.

6. CONCLUSION

This paper has focused on two aspects of query processing: data layout, and the way predicates are evaluated. We have introduced a family of bank-major data layouts that vertically partition a table into machine-word sized banks. By packing multiple columns into each bank, bank-major

layouts achieve almost as tight a compression as a tightly packed, row-major layout, whereas a column-major layout achieves poorer compression due to padding. Column-major and narrow-bank layouts scan less data when queries touch only a small number of columns, but a bank-major layout with redundant columns dominates a column-major layout in this regard, irrespective of the query.

On predicate evaluation, our main finding is that traditional query processors utilize only a small portion of the ALU, because they place only one field at a time in a register. We have shown that a query processor can pack many fields into a single register and operate on all of them in parallel, by mapping SQL expressions on columns into machine operations on words. In future we hope to develop this word-algebra further, with more powerful rewrites to take advantage of the vector capabilities of modern ALUs.

Query processing in Blink looks much like a matrix-style computation. Predicate evaluation in a table scan is like computing dot-products on a sequence of field-vectors, where the dot product operator is a comparison. Such operations exploit the parallelism of the ALU well, because of their predictable data access and instruction flow. This points to two directions for work. Can we apply techniques from numerical computing to query processing? Can we do other operations, like grouping and aggregation, as matrix computations?

Acknowledgements: We wish to thank Lin Qiao and Fred Reiss for many useful suggestions during the course of this work.

7. REFERENCES

- [1] D. Abadi, S. Madden, and M. Ferreira. Integrating compression and execution in column-oriented database systems. In *SIGMOD*, 2006.
- [2] A. Ailamaki, D. J. DeWitt, and M. D. Hill. Data page layouts for relational databases on deep memory hierarchies. *The VLDB Journal*, 11(3):198–215, 2002.
- [3] P. Boncz, M. Zukowski, and N. Nes. MonetDB/X100: Hyper-Pipelining Query Execution. In *CIDR*, 2005.
- [4] P. A. Boncz et al. Database Architecture Optimized for the New Bottleneck: Memory Access. In *VLDB*, 1999.
- [5] G. Dosa. The Tight Bound of First Fit Decreasing Bin-Packing Algorithm Is $FFD(1)=(11/9)OPT(1)+6/9$. In *ESCAPE*, 2007.
- [6] R. MacNicol and B. French. Sybase IQ Multiplex - Designed for analytics. In *VLDB*, 2004.
- [7] S. Padmanabhan et al. Block Oriented Processing of Relational Database Operations in Modern Computer Architectures. In *ICDE*, 2001.
- [8] M. Poss and D. Potapov. Data compression in oracle. In *VLDB*, 2003.
- [9] V. Raman et al. Constant time query processing. In *ICDE*, 2008.
- [10] V. Raman and G. Swart. Entropy compression of relations and querying of compressed relations. In *VLDB*, 2006.
- [11] J. Zhou and K. A. Ross. Implementing database operations using SIMD instructions. In *SIGMOD*, 2002.
- [12] P. Zikopoulos, G. Baklarz, L. Katsnelson, and C. Eaton. *IBM DB2 9 New Features*. McGraw-Hill, 2007.
- [13] M. Zukowski et al. Super-Scalar RAM-CPU Cache Compression. In *ICDE*, 2006.

APPENDIX

A. PROOF OF RULE CR

Consider tuples A and X with n fields each. A and X are represented as unsigned N -bit integers with the n fields packed together in an aligned fashion i.e., if a field occupies bits $[p, q]$ in A then it occupies bits $[p, q]$ in X too.

Say the big-endian field start offsets in the tuples are s_1, s_2, \dots, s_n , with $1 = s_1 < s_2 < \dots < s_n = N - 1$. The MSB bit is denoted as offset 0, so 1 bit is left vacant before the leftmost field.

Let $b_i = s_i - 1, \forall 1 \leq i \leq n$.

Define $s_{n+1} = N$.

Let A_i denote the i^{th} bit of A , and

$A[i, j]$ denotes the integer $A_i A_{i+1} \dots A_j$, and

$A[i, j)$ denotes the integer $A_i A_{i+1} \dots A_{j-1}$

Rule CR involves conjunctions of both \leq and \geq predicates. We consider first the \geq predicates. We use \oplus to denote xor in the following.

Claim 1: Every field of A is \geq the corresponding field of X if and only if $(A - X \bmod 2^N)$ and $(A \oplus X)$ are identical on bits b_1, b_2, \dots, b_n

Proof of “only if” side:

We are given that $A[s_i, s_i + 1) \geq X[s_i, s_i + 1), \forall 1 \leq i \leq n$. This implies that $A[s_i, N) \geq X[s_i, N) \forall 1 \leq i \leq n$. Therefore⁶, $(A - X \bmod 2^N)[0, s_i) = (A[0, s_i) - X[0, s_i) \bmod 2^{s_i})$.

This means, LSB of $(A - X \bmod 2^N)[0, s_i)$ is the same as LSB of $(A[0, s_i) - X[0, s_i) \bmod 2^{s_i})$.

But, from the definition of subtraction, LSB of $(P - Q \bmod 2^x) =$ LSB of $(P \oplus Q)$ for all $x > 0$.

So, LSB of $(A[0, s_i) - X[0, s_i) \bmod 2^{s_i}) =$ LSB of $(A[0, s_i) \oplus X[0, s_i))$.

So, $(A - X \bmod 2^N)_{s_i-1} = (A \oplus X)_{s_i-1}$.

Proof of “if” side:

Suppose $A[s_i, s_i+1) < X[s_i, s_i+1)$ for some i . Then, $A[s_i, N) < X[s_i, N)$, for $1 \leq i \leq n$. So⁷, $(A - X \bmod 2^N)[0, s_i) = (A[0, s_i) - X[0, s_i) - 1 \bmod 2^{s_i})$. Continuing as in the proof of the “only if” side, we can show that $(A - X \bmod 2^N)_{s_i-1} = (A \oplus X \oplus 1)_{s_i-1}$.

A symmetric argument shows that:

⁶ $A = A[0, s_i)2^{N-s_i} + A[s_i, N)$, and $X = X[0, s_i)2^{N-s_i} + X[s_i, N)$.

So, $A - X = (A[0, s_i) - X[0, s_i))2^{N-s_i} + (A[s_i, N) - X[s_i, N)) \bmod 2^N$ (1)

Now, say that $A[0, s_i) - X[0, s_i) = \beta \bmod 2^{s_i}$.

Thus, $A[0, s_i) = X[0, s_i) + \alpha 2^{s_i} + \beta$, with $\alpha \geq 0$ and $\beta > 0$. Substituting in (1) and expanding, we get,

$A - X = \beta 2^{N-s_i} + \alpha 2^N + (A[s_i, N) - X[s_i, N)) \bmod 2^N$
 $= \beta 2^{N-s_i} + (A[s_i, N) - X[s_i, N)) \bmod 2^N$

Since $(A[s_i, N) - X[s_i, N)) \in [0, 2^{N-s_i})$, the first s_i bits of $A - X \bmod 2^N$ are β .

⁷ Reason: $A = A[0, s_i)2^{N-s_i} + A[s_i, N)$, and $X = X[0, s_i)2^{N-s_i} + X[s_i, N)$.

But $A - X \equiv (A[0, s_i) - X[0, s_i) - 1)2^{N-s_i} + (2^{N-s_i} + A[s_i, N) - X[s_i, N)) \bmod 2^N$.

Now, say that $A[0, s_i) - X[0, s_i) - 1 \equiv \beta \bmod 2^{s_i}$.

Continuing as in the previous footnote:

$A - X = \beta 2^{N-s_i} + (2^{N-s_i} + A[s_i, N) - X[s_i, N)) \bmod 2^N$.

But $(2^{N-s_i} + A[s_i, N) - X[s_i, N))$ lies in $[0, 2^{N-s_i})$ because $A[s_i, N) < X[s_i, N)$. So, the first s_i bits of $A - X$ are β .

Claim 2: Every field of B is \leq the corresponding field of X if and only if $(X - B \bmod 2^N)$ and $(B \oplus X)$ are identical on bits b_1, b_2, \dots, b_n

Rule CR tests for every field of $B \leq$ corresponding field of $X \leq$ corresponding field of A . The rule follows from Claim 1 and Claim 2 by straightforward Boolean algebra, treating the situation where a field of $A <$ a field of B as a don't care in the truth table (if this situation happens, we declare the conjunction as false without even looking at the data).

B. MORE DETAILS ON EXPERIMENTAL RESULTS

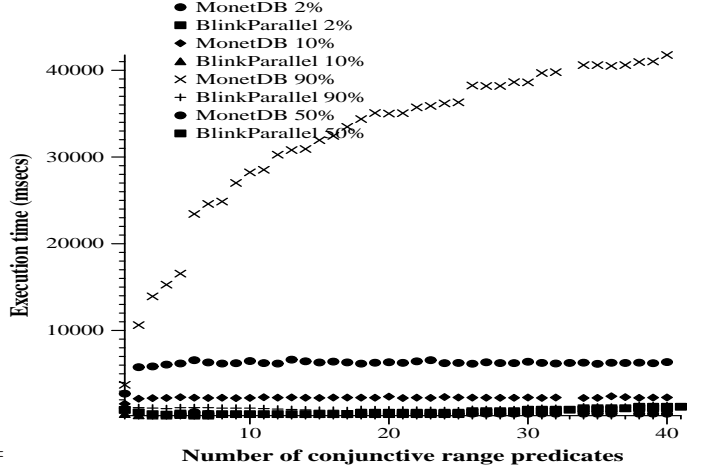


Figure 13: Query speeds for synthetic queries with increasing number of predicates