Optimizing Query Execution for Variable-Aligned Length Compression of Bitmap Indices

Ryan Slechta
University of St. Thomas
ryan@stthomas.edu

Jason Sawin
University of St. Thomas
jason.sawin@stthomas.edu

Ben McCamish
Washington State University
b.mccamish@wsu.edu

David Chiu
University of Puget Sound
dchiu@pugetsound.edu

Guadalupe Canahuate
The University of Iowa
guadalupe-canahuate@uiowa.edu

ABSTRACT

Indexing is a fundamental mechanism for efficient data access. Recently, we proposed the Variable-Aligned Length (VAL) bitmap index encoding framework, which generalizes the commonly used word-aligned compression techniques. VAL presented a variable-aligned compression framework, which allows columns of a bitmap to be compressed using different encoding lengths. This flexibility creates a tunable compression that balances the trade-off between space and query processing time. The variable format of VAL presents several unique opportunities for query optimization.

In this paper we explore multiple algorithms to optimize both point queries and range queries in VAL. In particular, we propose a dynamic encoding-length translation heuristic to process point queries. For range queries, we propose several column orderings based on the bitmap's metadata: largest segment length first (lsf), column size (size), and weighted size (ws). In our empirical study over both real and synthetic data sets, we show that our dynamic translation selection scheme produces query execution times only 3.5% below the optimal. We also found that the weighted size column ordering significantly and consistently out-performs other ordering techniques. Finally, we show that algorithms scale to data sets that are row-ordered.

Categories and Subject Descriptors

H.2.4 [**Systems**]: Query Processing

Keywords

bitmap indices, bitmap compression, query execution

1. INTRODUCTION

Popular applications including, but not limited to, web search, online shopping, and social media, are increasingly data-intensive, and billions of users rely on fast interactions with massive data stores. To offer high-performing data access and query processing time, such storage systems rely on advanced indexing techniques. One indexing scheme used for read-only databases, the *bitmap index* [1,2], has seen a surge in recent popularity, due to the increased prevalence and pressure of having to manage *Big Data*. As a result, bitmaps are now found in various scientific and business intelligence applications [3,4,5,6,7]. This rise in bitmap's popularity is spurred on by two of its characteristics. First, bitmaps reduce query execution down to simple logical operations, which are hardware-supported and fast. Second, bitmaps' sparsity is amenable to compression, and a number of encodings allow logical operations to be applied across bitmaps in their compressed state.

A bitmap index is a coarse representation of a relational table. In general, attributes are divided into distinct value-ranges, known as *bins*. For each attribute in a tuple, a 1-bit is placed in the column that represents its binned value. All other columns that do not represent possible values for that attribute are given a 0-bit. Table 1 presents an example of a simple relational table (left) and a possible corresponding bitmap (right). Each of the unique *Name* values is represented as a bin. *Salary* is a continuous attribute, so it is discretized into bins that represent ranges. To answer a query that seeks to retrieve tuples that have salaries in the range $\$10$K to $\$100$K, we perform a bitwise `OR` between the $5th$ and $6th$ bins (from the left). The rows with 1-bits set in the resulting vector correspond to the candidate tuples on disk.

Depending on the size of the relation being indexed, and the cardinality of bins used to discretize the attributes, bitmaps can easily out-grow core memory. Fortunately, many compression techniques have been developed that are uniquely suited for bitmaps. Most of these techniques are variations of a hybrid run-length encoding scheme, which represents each bin using a mix of literal and fill atoms. A literal atom encodes a sequence of bits exactly as they appear in their uncompressed form. The fill atoms compactly encode sequences, or runs, of homogeneous bits. For example, in the following two atoms $(L, 1000100)(F, 1, 110000)$, the L-bit and F-bit designate whether the atom is a literal or a fill, respectively. The fill atom contains a *value* bit, in this case 1, that encodes the value of the homogeneous bits being compressed. The *value* bit is followed by the length of the run, $110000_2 = 48_{10}$.

Several modern bitmap compression schemes are variants of a word-aligned encoding, the most popular being Word Aligned Hybrid (WAH) codes [8]. For instance, on a $w = 64$-bit machine, these word-aligned schemes decompose a bitmap column into *segments* of $s = w - 1 = 63$ bits and forms fills of homogeneous segments. A 64-bit fill atom is then $(flag, v, len)$, where $flag = 1$ signifies a fill atom, v is the fill-value bit, and len is the run-

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Name	Salary
Kat	1250 K
Zac	6 K
Ben	125 K
Kat	12 K
Zac	275 K

Kat	Zac	Ben	[0,10K)	[10K,100K)	[100K,250K)	[250K,1000K)	[1000K,∞)
1	0	0	0	0	0	0	1
0	1	0	1	0	0	0	0
0	0	1	0	0	1	0	0
1	0	0	0	1	0	0	0
0	1	0	0	0	0	1	0

Table 1: Example relation (left) and a corresponding bitmap (right)

length of consecutive segments. Similarly, 64-bit literal atoms are $(flag, v)$, where $flag = 0$ denotes a literal and v is the s-bit verbatim segment. Intuitively, because word-aligned schemes imposes a fixed segment length of $s = w-1$, it can efficiently compress extremely long runs of segments. It can also be seen that shorter runs can be represented more efficiently given smaller segment lengths.

To address segment size variability, we recently proposed the Variable Aligned Length (VAL) encoding scheme [9]. Unlike WAH, VAL enables varying segment lengths, so as long as they are *multiply-aligned*. For example, VAL might compress a noisier column by separating it into segments of length ($s = 15$) to efficiently represent shorter runs. A sparse column could be compressed using segment length $s = 60$ to emulate word-aligned encoding. We developed systematic methods to process queries between columns encoded using different segment lengths.

A particular challenge intrinsic to the VAL's query execution algorithm is to reconcile different segment lengths when applying a logical operation between two columns V_i and V_j. For instance, if we assume $V_i.seglen = 15$ and $V_j.seglen = 60$, it is unclear whether it is more efficient to decode V_i up to a single 60-bit segment, or conversely, decode V_j down to four 15-bit segments, before applying the logical operation.

This paper explores the unique challenges and opportunities that VAL's variable alignment represents for efficient query execution of point and range queries. We explore several novel range query algorithms for VAL. This study makes the following contributions:

- We evaluate and identify the tradeoff between two distinct segment length translation algorithms for query execution: decode up *vs.* decode down. We present a metadata-driven heuristic that can select the ideal translation algorithm with a high rate of accuracy for point queries.
- For range query execution, we gather the columns' metadata (*e.g.*, column size, segment length, etc.), which is then used to impose a total ordering in range query processing. We show that ordering impacts the efficiency of range query execution in VAL for several different types of data.
- We present a nuanced experimental study that uses both real and synthetic data sets to evaluate the effects of our ordering on five unique range query processing algorithms. The results of this study show that a column ordering based on size weighted by column composition is the most efficient. It also suggests that an accumulation approach to query processing is ideal for uniform data and a reentrant priority queue approach is better suited for skewed data.

The remainder of the paper is organized as follows. Section 2 provides an overview of the VAL bitmap compression scheme. Section 3 presents our proposed optimizations to VAL's range query algorithm. Section 4 presents the results of our empirical study. Related works are presented in Section 5. We conclude and present future avenues for this work in Section 6.

2. VAL COMPRESSION

The popular Word-Aligned Hybrid code (WAH) excels in compressing and accelerating the query processing of bitmaps containing super sparse columns. In general, depending on the application and data distribution, a bitmap can take on a spectrum of sparsity, which may not always favor WAH. In contrast, VAL analyzes each bit vector to be compressed, noting the bit distribution and run-lengths, then chooses an appropriate segment length and encoding algorithm. Like WAH, the bit vector is compressed by VAL into *atoms*, which are limited by hardware constraints, but the significant difference is that VAL can specify a *segment length* into which the word is broken and encoded. These words are then compressed using the specified compression method, determined by VAL during the analysis of the bit vector.

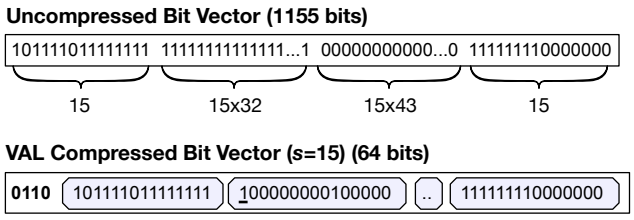


Figure 1: VAL Encoding Example

Consider the example shown in Figure 1, where the segment length is set to 15 with a word size of 64. The uncompressed bit vector (top) is 1155 bits long. Each word in the VAL compressed bit vector (bottom) will have a header of 4 bits representing whether the respective segment is a fill or a literal, reducing some of the overhead from decoding during query execution. The first and last segments are literals and represent the 15 verbatim bits from the original bit vector. The middle two segments are fills and are encoded such that the first bit is their fill bit (underlined in the figure) and the remaining bits encode the run-length of segments contained. Here, VAL was able to compress 1155 bits down to only a single 64 bit word. In contrast, 64-bit WAH would have require five words, or 320 bits. It can be observed even in this simple and contrived example that VAL's flexibility from being able to select different segment lengths for each bit vector can improve the compression of shorter runs.

To minimize the translation overhead, VAL only allows for segments that are multiply-aligned. For example, with alignment factor 15 and word size 64, the possible segments lengths are 15, 30, and 60. Consider two VAL bit vectors, $A_{m\times s}$ and B_s, encoded using segment lengths $m \times s$ and s, respectively. The operation $A_{m\times s} \circ Y_s$, where $\circ$ is a binary logical operator. Algorithm 1 shows the pseudocode for query processing. For each bit vector, one physical word (*currentWord*) is decoded at a time (Line 1-7). The parameter m (Line 3) indicates that the *currentWord* should be decoded into blocks, representing atoms, of segment length $m \times s$. Given the multiply-aligned restriction on segment lengths, m is always a power a 2. The decoded *currentWord* contains a number of *activeBlocks*. This *activeBlock* is tantamount to the *activeWord* structure used in WAH. The *currentWords* are iterated over one block at a time (Lines 8-14) and are operated together until exhausted. Two fill blocks can be operated together without explicit decompression (Lines 15-20). If one of the *activeBlocks* is a literal, then the values are operated together and the number of segments

in the fill, *nSegments*, is decremented by 1 with each *getLitValue()* call (Lines 21-23).

Algorithm 1: General Bitwise Logical Operation

```
   Input: Bit Vector A, B: (A.segLen=m × s and B.segLen=s)
   Output: Bit Vector Z: The resulting compressed bit vector
           after performing the logical operation X ∘ Y
1  while A and B are not exhausted do
2      if A.currentWord is exhausted and ∃ words in A then
3          A.decodeNextWord(m);
4      end
5      if B.currentWord is exhausted and ∃ words in B then
6          B.decodeNextWord(1);
7      end
8      while A.currentWord and B.currentWord are not
       exhausted do
9          if A.activeBlk.nSegments == 0 then
10             A.activeBlk = A.nextBlk();
11         end
12         if B.activeBlk.nSegments == 0 then
13             B.activeBlk = B.nextBlk();
14         end
15         if A.activeBlk.isFill() and B.activeBlk.isFill() then
16             nSegments = min(A.activeBlk.nSegments,
17                             B.activeBlk.nSegments);
18             Z.addFill(A.activeBlk.fill
19                         ∘ Y.activeBlk.fill, nSegments);
20             A.activeBlk.nSegments -= nSegments;
21             B.activeBlk.nSegments -= nSegments;
22         end
23         else
24             Z.addLiteral(A.activeBlk.getLitValue()
25                         ∘ B.activeBlk.getLitValue());
26         end
27     end
28 end
29 return Z;
```

Let us focus on Lines 3 and Line 5 of the algorithm. Due to segment length variation across bit vectors, it is necessary to align the bits appropriately before performing logical operations on them. Given $A_{m \times s}$ and B_s, there are two scenarios: the segment lengths between them are the same ($m = 1$), or they can differ ($m > 1$). In the former case, the bit vectors are already aligned, and the logical operation can proceed normally. In the latter case where the segment lengths differ (*e.g.*, A_{30} and B_{15}), the segments must be reconciled so that they are in alignment. Here, we have a choice: (1) the words in A_{30} could be split into segments of length 15. We name this method *DecodeDown*. (2) Conversely, the words in B_{15} can be merged to form segments of length 30. We refer to this method as *DecodeUp*. Note that the decision of the decoding direction occurs only once, prior to running Algorithm 1, which also defines the segment length of the result bit vector Z.

We now discuss *DecodeDown* (Algorithm 2) and *DecodeUp* (Algorithm 3). When decoding down there are two cases depending on whether the block being decoded is a fill or literal. If the block is a fill, then the new run length is equal to:

$$(segLen_{old}/segLen_{new}) \times runLength_{old} \quad (1)$$

Recall from before that, because m is a power of 2, the *DecodeDown* operation can be reduced to shifting bits to the right. Figure 2 (a) shows an example where the bits representing the number of segments represented can not translate into a single segment when decoding down from 60 to 15. Thus, two segments are created such that together they represent the same number of zeros in the bit vector. A literal segment is decoded down by dividing it into the smaller segment length and appending it onto the word. In this case a literal with segment length 60 would be broken down with segment length 15 into four literals.

Algorithm 2: DecodeDown()

```
   Input: Compressed word containing blocks of length s; N:
          the number of blocks in the word; m: the conversion
          factor to the new segment length
   Output: activeWord - VAL word containing decoded blocks
           using segments of length s/m
1  for i = 1 → N do
2      activeBlk = ith block;
3      if activeBlk.isLiteral() then
4          for j = 1 → m do
5              activeWord.addLiteral(activeBlk.val >>>
6                                     s × (N − i));
7          end
8      end
9      else
10         activeWord.addFill(activeBlk.val >>> (s − 1),
11                            activeBlk.nSegments ×m);
12     end
13 end
14 return activeWord;
```

Cost-wise, *DecodeUp* consists of more cases than *DecodeDown*. There is the use of an additional data structure called the alignedBlock which stores intermediate data such as remainder bits or partial words. There are four scenarios when decoding down depending on the activeBlock and the alignedBlock values. First, consider the case where the activeBlock is a fill and the alignedBlock is empty. The activeBlock is added to the currentWord with the number of segments being a fraction of the new segment length with any remaining bits being appended to the alignedBlock as a literal. The second scenario is when the activeBlock is a literal and the alignedBlock is empty. The literal is appended to the alignedBlock. The third scenario is when the alignedBlock is not empty and the activeBlock is a literal. The alignedBlock is then filled with bits from the literal in activeBlock until it is a complete segment. The fourth and final scenario is when the alignedBlock is not empty and the activeBlock is a fill. This is the example that is presented in Figure 2 (b). Literals are subtracted from the fill to complete the alignedBlock. In this example, all segments in the fill are needed to complete the block. In the case there are remaining segments in the activeBlock, they are added to the activeWord as a fill.

(a) Decode Down

(b) Decode Up

Figure 2: Segment Length Resolution Example

Algorithm 3: DecodeUp()

Input: Compressed word containing blocks of length s; N: the number of blocks in the word; m: the conversion factor to the new segment length
Output: $activeWord$ - VAL Word containing decoded blocks of length $s \times m$

```
for i = 1 → N do
    activeBlk= ith block;
    if alignedBlk.nSegments=0 then
        if activeBlk.isLiteral() then
            alignedBlk.addLiteral(activeBlk.value)
        end
        else
            activeWord.addFillBlock(activeBlk.fill,
            activeBlk.nSegments/m);
            store the leftover bits in alignedBlk, if any
        end
    end
    else
        if activeBlk.isLiteral() then
            alignedBlk.addLiteral(activeBlk.value);
            if alignedBlk.isComplete() then
                activeWord.addLiteralBlock(alignedBlk.value)
                alignedBlk.clear()
            end
        end
        else
            while alignedBlk.isNotComplete() do
                alignedBlk.addLiteral(activeBlk.fill)
                activeBlk.nSegments–
            end
            activeWord.addLiteralBlock(alignedBlk)
            alignedBlk.clear()
            activeWord.addFill(activeBlk.fill,
            activeBlk.nSegments/m) store the leftover bits in
            alignedBlk, if any
        end
    end
end
return activeWord
```

3. QUERY OPTIMIZATIONS

In this section, we present our proposed optimizations to VAL's query engine. We first discuss a heuristic for choosing a translation method when processing queries between columns with different segment lengths. Next, we present the various column orderings we propose to investigate for carrying out range queries. Finally, we discuss how the metadata can be collected at compression time to facilitate our optimizations.

3.1 Point Queries: Single Logical Operations

For fixed-length bitmap compression algorithms such as WAH, processing a query by applying a single logical operation is straightforward. The variable-length approach of VAL presents several unique challenges. The first is translating a column compressed with segment length s to that of a column compressed with segment length $m \times s$, or vice versa. The previous section presented two solutions to this problem, *i.e.*, *DecodeDown* and *DecodeUp*. The existence of two possible approaches for translation provides a second challenge: when to use one translation over the other.

Accurate selection of the most efficient decoding method used to answer a query of the form $A_a \circ B_b$, where $\circ$ is a bitwise operator, relies on *a priori* knowledge of the characteristics of A and B, including: the segment lengths a and b, the number of literal atoms, the number of fill atoms and the length of the runs they encode. Because gathering this information at query time would require both reading the columns into memory and completely parsing them, it is clear that any potential gains made by selecting the most efficient decoding method would be lost. We propose a heuristic that uses information gathered at compression-time to estimate the efficiency of each decoding method.

Our heuristic assumes that the efficiency of a decoding method depends on the amount of parsing required. Since no additional translation cost is incurred when both columns are compressed using the same segment length, we assume $a < b$. Calculating the number of parses required by *DecodeDown* to process a query is straightforward. Before any translation penalty is incurred, each atom in both A and B will require one parse operation. Since B has the larger segment length, it will require additional parsing, incurred by the literal atoms: each literal atom of B must be parsed into b/a smaller atoms. B's fill atoms will require no further parsing, their run lengths are simply adjusted to reflect the new $segLen$. The following formula calculates the parsing costs of processing a query using *DecodeDown*:

$$p_{down} = \left(\frac{b}{a} \times B_{\#lits}\right) + B_{\#fills} + A_{\#atoms} \qquad (2)$$

where $B_{\#fills}$ and $B_{\#lits}$ represent the number of fill and literal atoms in B respectively. $A_{\#atoms}$ represents the total number of atoms in column A.

Calculating the parsing cost required by *DecodeUp* is more complex. Since column B has the larger segment length, it will require no further parsing past isolating its individual atoms. Column A will incur the translation costs. Uniquely, *DecodeUp* actually presents opportunities to reduce the number of parses needed for literals in column A to under 1. This is due to VAL's word format: all flag bits for the atoms contained in a word are placed in the most significant bits. Thus, if a word in a column with a segment length of 15 contains only literal atoms, the 4 most significant bits of the word would be 0000 and the remaining bits is a segment of 60 literal bits. If this column were to be translated to segment length 60, it may be possible to translate it without further parsing, essentially saving four parses. Note that this is a specialization of Algorithm 3 which is not shown in the pseudocode for brevity. It will not be possible to realize these savings for all such "literal-words" because a previous word might not have translated exactly and thus the alignedBlock would contain leftover segments. In this situation, literals would have to be parsed from a literal-word to compensate for the leftovers.

Where the cost of parsing a literal is slightly reduced, using *DecodeUp* adds a slight cost to the parsing of the fill atoms of A. Consider a fill atom from A which encodes a run length of R. If $R \bmod b/a \neq 0$, then the atom cannot be directly translated to a run of b sized segments. A total of $R \bmod b/a$ segments will need to be removed from the run and treated as literals added to the alignedBlock. We use the following formula to estimate the parsing costs of processing a query using *decodeUp*:

$$p_{up} = \gamma\left(\frac{b}{a} \times A_{\#fills}\right) + \tau A_{\#lits} + B_{\#atoms} \qquad (3)$$

where $1 \geq \gamma, \tau \geq (a/b)$. A value of 1 for γ implies that every fill-value in A encodes run-lengths that are congruent to $b/a - 1 \bmod b/a$. This would be the worse-case and requires the most parsing. A lower γ value implies less parsing is needed due to fewer incongruent run-lengths. A τ value of a/b implies that all literals in A are stored in literal-words and no additional parsing is needed to translate them to b. A higher value implies the existence of fewer literal-words. These parameters could be thought of as *tuning variables*. Their ideal values would change from column to column.

Our *Dynamic Translation Selection* heuristic selects the decode

method that is estimated to require the least number of parses using the above formulas. We evaluate its performance in Section 4.

3.2 Range Queries

For discretized or binned columns, range queries are implemented using the *or-of-or's* form,

$$(A_1.b_1 \vee ... \vee A_1.b_m) \vee ... \vee (A_n.b_1 \vee ... \vee A_n.b_{m'})$$

where $A_i.b_j$ denotes the jth bin of attribute i. A previous study on WAH showed that the order in which the `OR` operations are applied to the columns of a range query can impact the overall execution time [10]. When columns A and B are *OR*'ed together, the resulting column can be at most $size(A) + size(B)$ large. Thus, given a series of WAH columns that generates the worse case, each successive operation produces a column that has a size equal to the sum of the sizes of the operands. Ordering the column in increasing order of size provides an optimal query execution time [10,11].

However, it is not obvious what effect column ordering would have on VAL range queries, because the assumption that execution time is proportional to column size does not necessarily hold for VAL. For example, an operation applied to two columns with a segment length of 15 might take longer than the same operation being applied to two columns with a segment length of 60 even though the 60 columns might be larger. This discrepancy is due to the increased parsing incurred by columns compressed with shorter segment lengths. Another factor that must be considered when ordering columns is the translation cost associated when applying an operation to columns with different segment lengths.

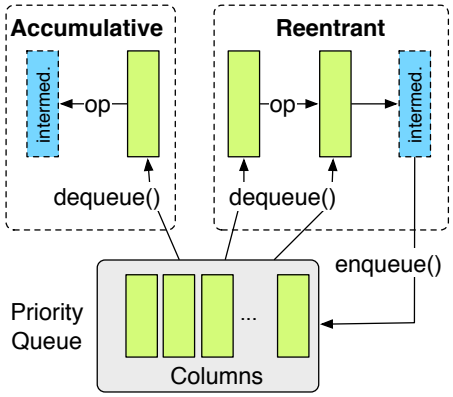


Figure 3: Range Query Processing Pattern

To impose column ordering, we use a priority queue keyed on:

- **Increasing Size (`size`)**: This ordering assumes that variations in processing time due to translation and parsing are subsumed by the advantages of always trying to produce the smallest result column.
- **Weighted Size (`ws`)**: Order the columns according to $size \times (60/segLen)$. This ordering takes into account that, for VAL, processing time is not directly proportional to size. It attempts to estimate the processing time by considering the number of atoms that will be processed in each column.
- **Largest Segment-Length First (`lsf`)** - Arrange the columns such that they will be grouped by largest $segLen$, within each group, we further order by increasing size. This ordering minimizes the translations needed for *DecodeDown* and ensures the result column is always the largest segment length for *DecodeUp*.

Another design decision involves the column holding the intermediate (and final) result. One way (*Accumulative*) is to allocate temporary column T to hold the result column. When a column A is dequeued, the logical operation is applied directly $T \leftarrow A \circ T$. This process continues until the priority is empty. Another processing method (*Reentrant*) is to dequeue two columns A and B, and apply the logical operation. The resulting column is then reenqueued into the priority queue. This is the approach taken by Wu, *et al.* [10]. The *Reentrant* approach can, in the worst case, require that $\log_2(n)$ temporary result columns be kept in memory, where n is the total number of columns being queried. The temporary columns that are generated by both approaches will require the needed metadata (*e.g.*, size) be collected while they are being generated. We illustrate these two approaches in Figure 3.

3.3 Column Metadata

The above querying algorithms rely on a priori knowledge about the bitmap columns being processed. We propose a process of gathering column metadata at compression time and storing it on disk. Gathering the information has a very low overhead and would not significantly impact the time needed to compress. The size of the metadata file will be proportional to the number of columns in a bitmap. However, depending on the amount of data being collected, the size of the metadata file will be insignificant when compared to the size of the compressed bitmap. For example, our point query algorithm requires 4 pieces of information per column: segment length, column size, number of literal atoms, and number of run atoms. This information can be stored in a byte for the segment length, and 4 32-bit integers for the remaining information. Prior to query processing, the metadata file can be read into memory and referenced as needed. This does slightly increase the memory footprint. However, this is much smaller than reading all the columns into memory, which is required to order by size without metadata.

4. EXPERIMENTAL RESULTS

In this section, we present an evaluation of our algorithms over both real and synthetic data sets. First, we describe the experimental setup. All experiments were performed on a machine equipped with two Intel Xeon E5-2630 processors (six 2.3 GHz cores with hyperthreading enabled), 128 GB DDR3 RAM, running Windows 7 Professional. Each experiment was repeated six times: results from the first run were discarded to warm the cache, and the average of the subsequent five runs are reported.

4.1 Data Preparation

We prepared both synthetic and real data sets for testing. Here, we describe the data generation process.

Synthetic Data: We generated 8 data sets, each containing 32 million rows and 10 attributes. The attributes' cardinalities vary between 10, 20, 40, and 80 resulting in bitmaps containing 100, 200, 400, and 800 columns, respectively. For each of these settings, two different distributions were used: uniform and zipf. The uniform distribution emulates real data sets that are discretized using equally-populated bins. In this approach, the data is binned such that each bin contains roughly the same number of objects, thus creating a uniform distribution of 1's in the bitmap. The zipf distributions represent a clustered approach to discretization. In this process, the density of data is represented in the bitmap, creating a skewed distribution. The zipf distribution generator assigns each bit a probability of: $p(k, n, skew) = (1/k^{skew}) / \sum_{i=1}^{n}(1/i^{skew})$ where n is the number of elements determined by cardinality, k is their rank, and the coefficient $skew$ creates an exponentially skewed distribution. The distribution is uniform when $skew = 0$. We generated data sets for $skew = 0$ (labeled `uniform`) and $skew = 2$ (labeled `zipf2`).

Real Data: For our real data experiments, we use the data set

from KDDCup'99 (labeled KDDCup), which captures network flow. The data set contains $4,898,431$ rows and 42 attributes[1]. Continuous attributes were discretized into 25 bins using Lloyd's Algorithm [12]. In total, there were 475 bins/columns. We run the range queries shown in Table 2.

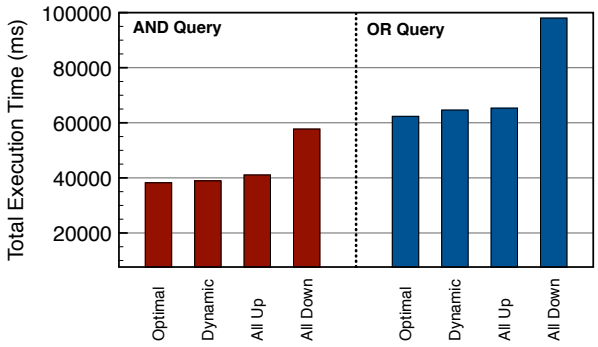
All data sets were compressed using segment lengths $s \in S = \{15, 30, 60\}$ in round-robin fashion, *i.e.*, $A_1.b_1$ compressed with $s = 15$, $A_1.b_2$ with $s = 30$, $A_1.b_3$ with $s = 60$, etc. To query over this data, we select the following set of columns:

$$\{A_i.b_j \mid j \mod (|S| + 1) = 0\} \ \forall i, j \quad (4)$$

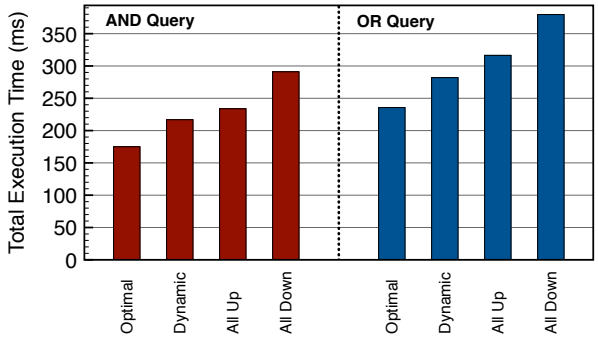
to ensure an equal distribution of segment lengths used.

4.2 Point Queries

The first set of experiments evaluates the performance of point query execution. We performed point queries (*e.g.*, AND/OR operations) over two randomly selected columns from our data sets. To test the performance of *DecodeUp* and *DecodeDown*, we only selected columns with mismatched segment lengths. We ensured an even distribution: $1/3$ of our queries were of each variety, *i.e.*, 15:60, 15:30, and 30:60.



(a) Point Query Execution Time (zipf2)



(b) Point Query Execution Time (KDDCup)

Figure 4: Point Query Execution Time

The run-settings are defined as follows: (a) All Up is when *DecodeUp()* is used to execute every query, (b) All Down refers to when *DecodeDown()* is used for every query, (c) Dynamic refers to the use of our equations from Section 3.1 to inform on decoding directions, and (d) Optimal is when the all decode directions minimize execution time.

Let us first consider the results for zipf2. The results for executing AND and OR 5000 queries are shown in the left-hand and right-hand side of Figure 4(a), respectively. Notice that AND queries are much faster to process than OR queries. This is due to 0s, the predominate value in skewed data, short-circuiting the logic. Our heuristic provided the closest performance to the optimal, coming only within 1.8% and 3.5% of the optimal for AND and OR queries, respectively. The next closest setting, using All Up, came within 6.9% and 4.6% of the optimal. We ran 1000 queries over KDDCup, and show the results in Figure 4(b). Our heuristic came within 17.6% and 18.2% of the optimal, while the next closest setting (again, All Up) came within 23.8% and 23.1% of the optimal for AND and OR queries, respectively. Although our heuristic was less accurate over this data set, it still obtained significantly higher performance than simply using a uni-directional scheme. We leave the calibration of our heuristic for future work.

In both data sets, we can see that All Down suffers for both types of queries. The reason for this can be seen by again investigating our formulas for estimating the parsing costs of *DecodeUp* and *DecodeDown* (Section 3.1.) If the worse case is assumed for *DecodeUp*, *i.e.*, $\gamma = \tau = 1$, the formula for when *DecodeDown* is preferable, $P_{up} > P_{down}$, can be simplified to $A_{\#fills} > B_{\#lits}$. This implies that *DecodeDown* is only optimal when the columns with the shorter segment length A has more fill atoms than B does literal atoms. This relationship was observed for all instances where *DecodeDown* was more efficient. In general, it is expected that a compressed bitmap would contain more literals than fills. If a run is interrupted, it is likely to result in at least one fill-literal pair. In the entire compressed version of KDDCup, there were 750K literal atoms and only 189K fill atoms.

4.3 Range Queries

We are interested in understanding the effects of our metadata-driven ordering algorithms for computing range queries. Recall the ordering schemes from Section 3, where columns $A_i.b_j$ can be ordered by size (size), largest segment length first (lsf), or weighted size (ws). We compare these orderings with a random column ordering (random). Each of these orderings was evaluated under six query processing algorithms: *DecodeUp Accumulation*, *DecodeUp Reentrant*, *DecodeDown Accumulation*, *DecodeDown Reentrant*, *Dynamic Accumulation*, and *Dynamic Reentrant*. The *DecodeDown* algorithm decodes down in translation, but due to it performing substantially slower than both *Dynamic* and *DecodeUp* algorithms (also observed in the Point Query evaluation), its results are not included in the interest of space.

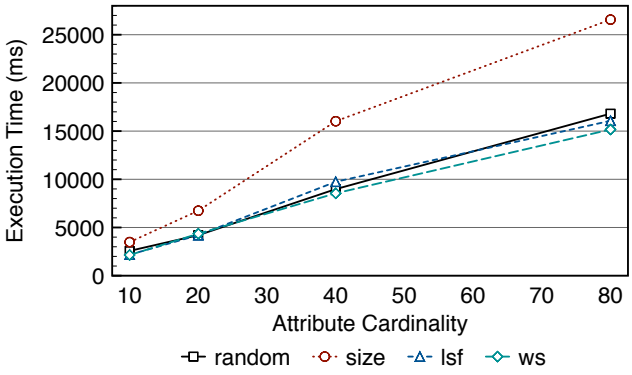
4.3.1 Synthetic Data

We first used range queries over: uniform and zipf2. Using Eq. 4 for data sets with bin cardinality 10, 20, 40, and 80, we *or* together 25, 50, 100, and 200 columns, respectively.

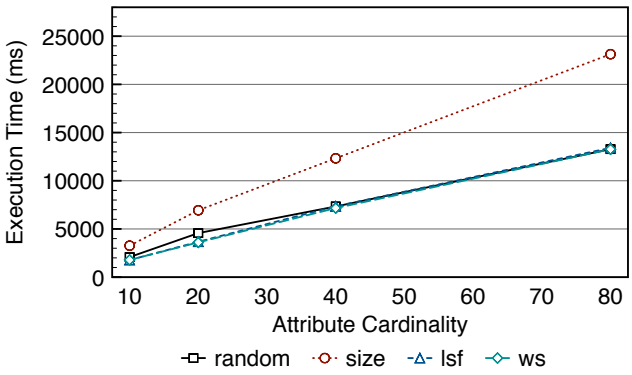
In Figure 5(a) and Figure 5(b), we show the range query execution time for *DecodeUp, Accumulation* and *Dynamic, Accumulation*, respectively, over uniform data. It is interesting to note that for both of these approaches, size generates the slowest results. This is because the smallest columns of uniform all have a segment length of 15. Unfortunately, the size difference between any two columns is not large. In uniform with cardinality 80, the largest column is only $2.5\times$ larger than the smallest column. In contrast, the largest column in zipf2 with the same cardinality is $705\times$ larger than the smallest column.

The size ordering favors columns with segment length of 15, which have a few more fill atoms than other columns, but those gains are lost after applying multiple logical OR operations. Because the result column will have a segment length of 15 until it is queried with a column of a greater segment length, it will be roughly the same size as the rest of the columns, but will require

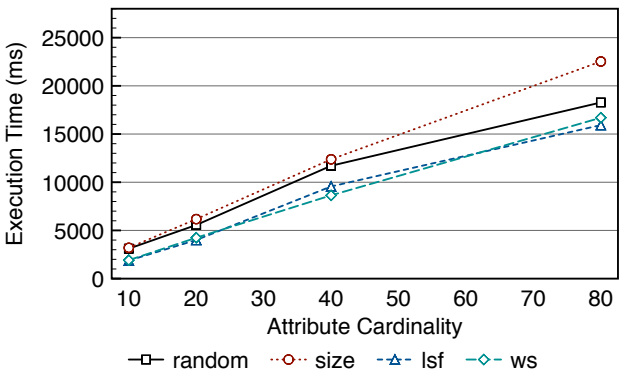
[1]http://archive.ics.uci.edu/ml/datasets/KDD+Cup+1999+Data



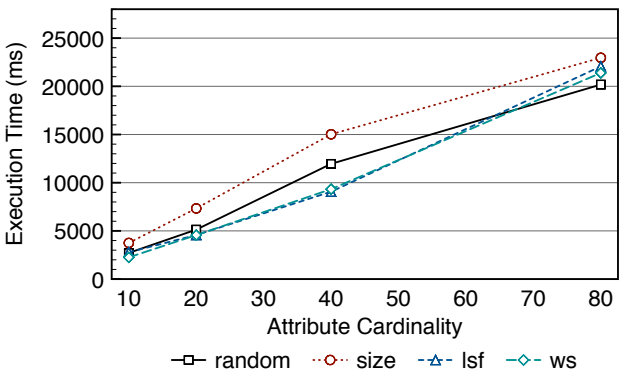
(a) DecodeUp, Accumulation



(b) Dynamic, Accumulation

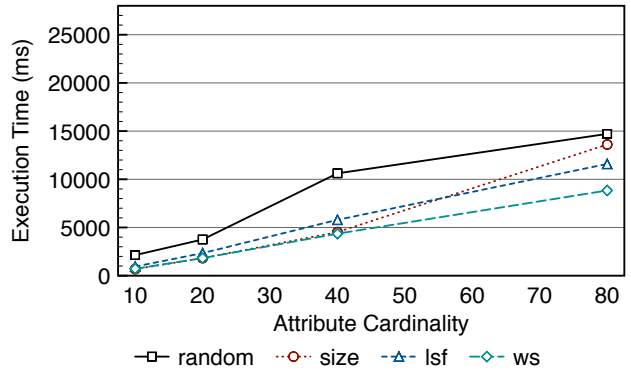


(c) DecodeUp, Reentrant

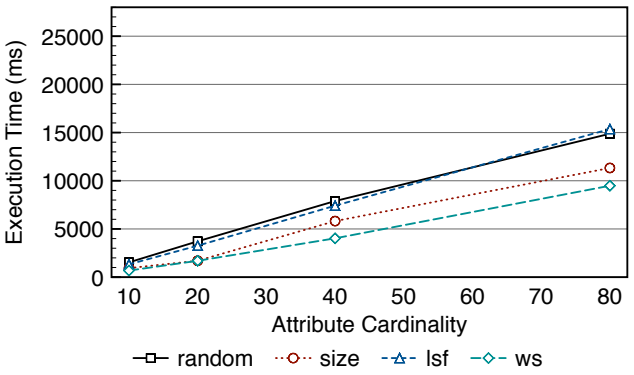


(d) Dynamic, Reentrant

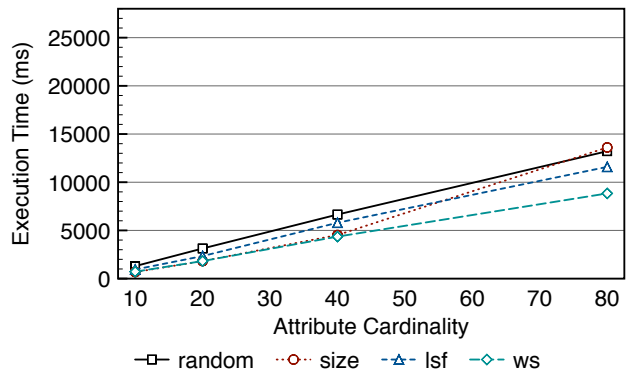
Figure 5: Execution Time (`uniform`)



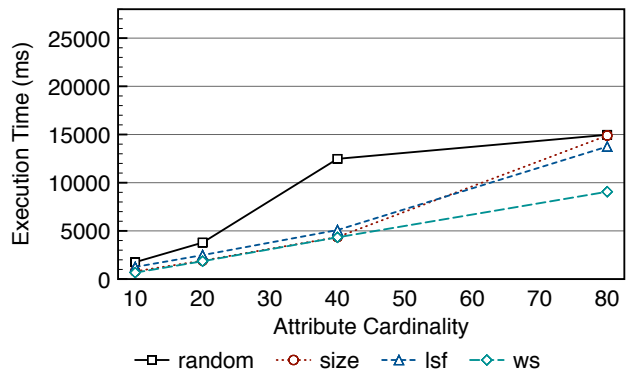
(a) DecodeUp, Accumulation



(b) Dynamic, Accumulation



(c) DecodeUp, Reentrant



(d) Dynamic, Reentrant

Figure 6: Execution Time (`uniform`, Row-Ordered)

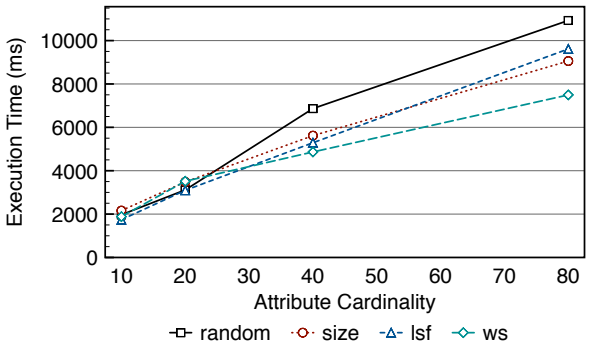
much more parsing. The other three orderings all achieve approximately the same times. This is because they all have a column with a segment length of 60 as one of their first three columns. Hence, the result column will have a segment length of 60 for the majority of the operations. Since the column sizes are so close, this reduction of parsing appears to be the key in query speedup. *Dynamic* selection of the translation method does provide a slight advantage for `uniform` offering a speedup of 1.14× for `ws`, the most efficient ordering.

The results for *DecodeUp, Reentrant* applied to `uniform` data are shown in Figures 5(c). The *Dynamic, Reentrant* results are shown in Figure 5(d). The timings for *Dynamic, Reentrant* are actually slower than its `Dynamic, Accumulation` counterpart for all orderings and all cardinalities. This suggests that our translation selection heuristic is not well-suited for the *Reentrant* approach. We believe this is because, even though *DecodeDown* might be most efficient for two columns, it can have negative ramifications on the remaining unprocessed columns. The consequences of a wrong decoding choice is magnified when conducting a range query. By examining the decoding method chosen by the `Dynamic` approach, we see that for the *Dynamic, Reentrant*, *DecodeDown* was selected more times than in the *Dynamic, Accumulation* approach.

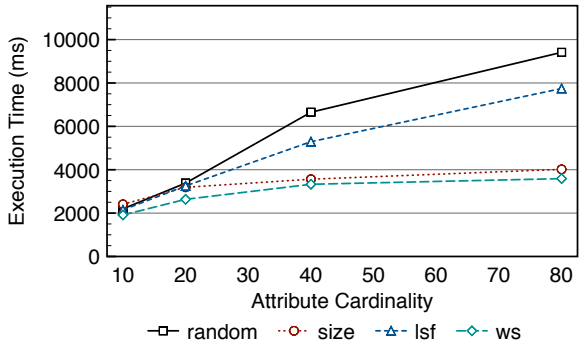
Several previous studies have shown that row reordering can drastically improve compression and query performance [13,14, 15]. One popular ordering schemes is graycode, *i.e.*, two adjacent rows differ by only one bit. In general, graycode maximizes runs in the first several columns of the data, and then the runs degrade into shorter runs before deteriorating into noise in the last several columns. To evaluate graycode's effect on our query algorithms, we sorted the rows using graycode ordering before compressing. The graphs shown in Figure 6 show the execution times of our range query algorithms on graycode sorted `uniform` data.

With row ordering, we see more variance in the execution times of the column orderings. Figure 6(a) presents the results for *DecodeUp, Accumulation* applied to graycode-ordered `uniform`. As can be seen, `ws` slightly outperforms `size` and both are approximately 1.3× to 1.5× faster than `random` ordering and 1.2× to 1.25× faster than `lsf`. This speedup is due to the size differential of the columns. Because graycode creates very long runs in the first few columns, some of the most compressed columns have a segment length of 60. By decoding up, the answer column will become 60 and reduce the total amount of parsing needed. The reason `size` and `ws` are beating `lsf` is because some of the columns compressed using a segment length of 30 and 15 are small enough to offset the increased parsing cost. Since `lsf` orders first by segment length and then by size, it does not realize the benefits of these very small columns. As shown in Figure 6(b), the *Dynamic, Accumulation* algorithm was less efficient than *DecodeUp, Accumulation* for all orderings.

There is very little difference in the timing results of `ws` for *DecodeUp, Reentrant* (Figure 6(c)) and approaches that use *Accumulation*. Though the *Reentrant* algorithm changes the ordering of the columns for the graycoded `uniform` data, the overall order is not radically different than that of the *Accumulation* approach. For cardinality 80, a typical temporary result column is used within 3 to 8 logical operations of its creation. This implies that the result columns of the logical operations are generating roughly the same number of atoms as the operand columns. The `size` ordering is performing slightly worse under *DecodeUp, Reentrant*. This is because with larger cardinality, `size` again begins to favor columns of segment length 15 and its performance degrades. Again, *Dynamic, Reentrant* (Figure 6(d)) is slower than `Accumulation, Reentrant`. This relationship of `DecodeUp` being faster than the `Dynamic` approach held for the remainder of our experiments. This indicates that our heuristic, though helpful for point queries, is not amenable to range queries. Due to space constraints, we only show the results of `DecodeUp` for the remaining experiments.



(a) DecodeUp, Accumulation

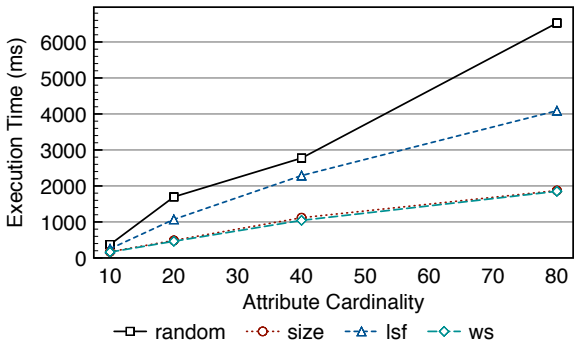


(b) DecodeUp, Reentrant

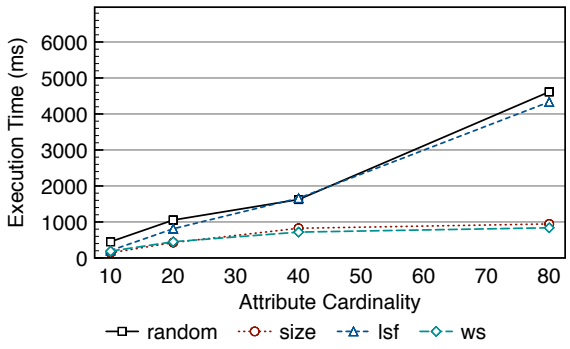
Figure 7: Execution Time (`zipf2`)

Next, we move on to skewed data. Figure 7(a) shows the results of *DecodeUp, Accumulation* applied to `zipf2`, without row-ordering. Again, we see that `ws` is the most efficient ordering and is 1.5× faster than `random` and 1.2× faster than `size`, for high cardinality. The `size` ordering is only slightly faster than `lsf`. In Figure 7(b), we observe the first significant speedup achieved by the *Reentrant* scheme. On `ws`, *Reentrant* achieves a speedup of 2.09× over *Accumulation* for cardinality of 80. This speedup occurs because, unlike the `uniform` data set, the growth of the result column does not remain approximate to the size of the operands. When `ws` is applied to cardinality 80, the first temporary result column is not removed from the queue until 32 operations had been processed. The fact that `size` is doing almost as well as `ws` indicates that many of the columns with shorter column lengths are aggressively compressed.

The `lsf` order does not see a substantial improvement (only 1.24× speedup) for the `Reentrant` approach. This is because after all of the columns of segment length 60 are processed, the *Reentrant* scheme essentially becomes `Accumulation`. Since `DecodeUp` always produces a result column with a segment length of 60 for `lsf`, after all of the columns of segment length 60 are processed, the first column polled from the priority queue will be the result column. This is the exact pattern of *Accumulation* for `lsf`. Figure 8 shows the results of our algorithms applied to graycode-ordered `zipf2`. The pattern of the results mimic those observed in unordered `zipf2`, only faster. The ordered data set produced results for `ws` that were over twice as fast as unordered.

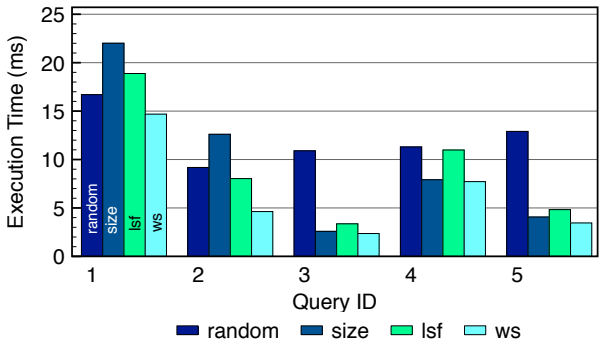


(a) DecodeUp, Accumulation

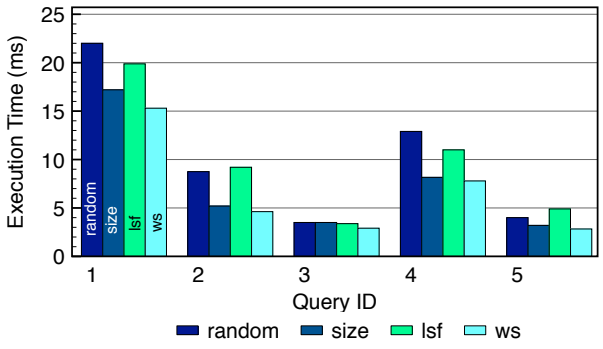


(b) DecodeUp, Reentrant

Figure 8: Execution Time (`zipf2`, Row-Ordered)



(a) DecodeUp, Accumulation



(b) DecodeUp, Reentrant

Figure 9: Execution Time (`KDDCup`)

4.3.2 *KDDCup'99 Data*

Table 2 shows a set of real queries posed over our `KDDCup` data set. The **Selection Criteria** column describes the data being selected for each query, and **Cols** displays the number of bitmap columns that must be processed to answer the query.

ID	Selection Criteria	Cols
1	$< 50\%$ of connections to different hosts for the same service and $< 10\%$ REJ and $\leq 10\%$ SYN error. This query could indicate that the host is accepting the connections and servicing them.	32
2	$< 50\%$ of connections to the same host (or $> 50\%$ to different hosts) were for the same service and less than 10% have REJ errors and $< 10\%$ SYN error. A client is primarily checking other hosts for a specific service and is not getting rejected often.	18
3	Connections with REJ or SYN errors to the same host, but not necessarily the same service.	39
4	src_bytes=2048 and dst_bytes < 1843. Indicates at least a 10% loss of data in the connection.	19
5	$< 10\%$ SYN and $< 10\%$ REJ error for the same service and the same hosts. This could be used to see if some kind of connection that is an attack is actually getting through.	32

Table 2: Queries over `KDDcup` Data Set

Figures 9(a) and Figure 9(b) show the time it took our different orderings to answer the queries using both *DecodeUp, Accumulation* and *DecodeUp, Reentrant* algorithms. Again, we observed that *Dynamic* selection did not significantly improve query performance, so we will not include those results. For queries 1 and 2, we see that `size` is actually slower than `random` when using the `Accumulation` algorithm. In these two queries, the smallest columns had a segment length of 15, but many were not compact enough to compensate for the increased processing costs. The `lsf` ordering is also slower than `random` for query 1. This is because several of the 60 columns in this query were some of the larger columns being processed. This meant the result column of `lsf` grew very quickly. Similar to the synthetic data results, the `ws` ordering outperformed all others for all queries.

As shown, there is only minor differences between the times of *Accumulations* vs. *Reentrant* for the fastest ordering, `ws`. This reaffirms our observation that significant speed up from the *Reentrant* algorithms is only realized for high cardinality queries. Though, it is interesting to note that the `size` ordering did perform better under the *Reentrant* scheme, though still not out performing `ws`.

4.4 Summary of Results

The salient findings from our experiments are as follows. For point queries, our dynamic translation selection heuristic consistently came within 3.5% of the optimal time for 1000 *OR* queries, and was more efficient than simply always using *DecodeUp* or *DecodeDown*. However, our heuristic did not extend well to range queries. For range queries, always selecting *DecodeUp* appears to be the most efficient processing method. Our study suggests that for data sets observing uniform distribution, the *Accumulation* approach to range query processing is the most efficient. The overhead of a *Reentrant* approach is not always surpassed for such data. However, for skewed data, the *Reentrant* approach appears to be much more efficient, providing up to a $2\times$ speedup for higher cardinality data. Regardless of the type of data and the processing algorithm used, the `ws` column ordering almost always produced the fastest times.

5. RELATED WORK

Our work relates to bitmaps indices compressed using VAL, however, there are many other bitmap compression algorithms. One of the earliest schemes was the Byte-aligned Bitmap Code (BBC) [16]. BBC is a patented encoding that uses four types of byte-aligned

atoms. The use of a 7-bit segment length allows BBC to compress compactly but is very CPU intensive when querying. The Word-Aligned Hybrid (WAH), which uses a word-aligned encoding, has been shown to typically use 60% more space but executes queries up to $12\times$ faster [8].

Several variants of WAH have emerged recently. PLWAH [17] and Concise [18] both modify WAH's version of a fill atom. They reserve $\lceil \log_2 w \rceil$ bits, where w is the total number of bits used for a fill atom. If the run being represented was interrupted by a near-fill segment, a segment containing a single dirty bit, the reserve bits are used to indicate the position of that dirty bit. Thus, there is no need to create an addition literal atom. PLWAH encodes near-fills that follow a run and Concise encodes those before a run. This approach can achieve $2\times$ the compression of WAH. Enhanced WAH (EWAH) also modifies the formatting of fill atoms [19]. EWAH divides the fill atoms in half. The upper half (the most significant bits) are used to encode the flag bit, value bit and run length in the same manner as WAH. The lower half is used to encode the number of literal atoms that follow the fill. When processing queries, this extra information allows EWAH to skip literal words when comparing to large runs. This extra information does mean that, in some instances, EWAH will need to use two words to encode long runs, whereas WAH would only use one.

We recently introduced Variable-Aligned Length code (VAL) [9] and compared it to WAH, PLWAH, and EWAH, and found that for skewed and sorted data, VAL achieved the best compression. We also compared timings of point query operations, using only *DecodeDown* algorithm, which our current study has suggested is slower than *DecodeUp* for most queries. Variable Length Compression (VLC) [20] could be considered a generalization of VAL. Like VAL, it allows each bitmap column to be compressed using a separate segment length. Unlike VAL, the segment lengths can be arbitrary. Corrales, *et al.* showed that using truly arbitrary lengths was impractical when processing queries [20]. Instead, they suggested limiting lengths to $m \times b$ where b is a common base. When two columns compressed using different segment lengths are queried, both are translated to the greatest common divisor of the two lengths. It was shown that the need to translate both columns could lead VLC to be 3 to 4 times slower than VAL. This high translation cost suggests that VLC may be amenable to query algorithm that clusters columns compressed using the same segment length similar to that of our `lsf` ordering.

Our work was inspired by Wu, *et al.* [10]. They evaluated the effect of ordering on range queries for both WAH and BBC. They also implemented a priority queue algorithm similar to the one we used. Our study varies from theirs in several significant aspects. We addressed the issue of column translation which is unique to variable-aligned compression schemes. We investigated orderings which are unique to VAL. We also used metadata to reduce the memory foot print of our query engine and we evaluated our algorithms on both real and synthetic data. Wu, *et al.* proposed an in-place algorithm where one uncompressed columns is used to store all the intermediate results from an aggregate range query to avoid compression costs. We plan to evaluate such an approach for VAL in the future.

6. CONCLUSION AND FUTURE WORK

Variable Aligned Length (VAL) Compression is a tunable framework that allows for bitmap indexes to be compressed using varying segment lengths. In this paper we explored optimizations to VAL's query engine. When VAL performs a logical operation on two columns that were compressed using different encoding lengths, one of the columns must be translated. We evaluated benefits of using two translation algorithms *DecodeDown* and *DecodeUp*. Our translation select heuristic determined which algorithm to use by analyzing parsing costs. The heuristic performed better than always using either *DecodeDown* or *DecodeUp*, and was within 3.5% of the optimal for or queries on skewed data, slightly besting *DecodeUp*. For range queries, we implemented column orderings that were dependent on metadata gathered at compression time. The `ws` ordering, which weights size by column composition, method was tested under five query processing algorithms, and was consistently able to outperform other orderings. The results of our study also suggests that an accumulation approach to query processing is ideal for uniform data and a reentrant priority queue approach is better suited for skewed data.

In the future we plan to extend our translation selection heuristic to make it more amenable to range queries. We think it would be interesting to investigate the effects of column orderings on sequences of logical *AND* operations. Additionally, there may be other range query algorithms which could be implemented in VAL.

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