CALF: Comparison of Attribute Layouts on Flash

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Abstract

Solid state drives(SSDs) are increasingly being used for database applications, due to their low seek latency and low power consumption. Solid state drives differ fundamentally in their characteristics from disk drives, which mandates that some core database design decisions, such as column layout, needs to take into account the specific characteristics of SSDs for optimal performance. This paper reexamines the question of column layout models for Flash based databases. We propose a flexible data storage model which partitions attributes based on a given workload, taking into account both reads and writes. We evaluate the performance of this intelligent partitioning against NSM and C-Store storage models.

1 Introduction

In recent years, the cost-per-byte of Flash drives has fallen to an extent where it is feasible to build fairly large applications on Flash storage. The lack of mechanical parts, fast random access, low power consumption and durability are some of the features which make it a storage medium of choice. While disk drives will be around for a while, Flash has the potential to replace magnetic disks in most applications.

As we will see in Section 3, Flash drives are inherently different from disk drives in many respects. A significant number of architecture and design decisions behind current database systems have (implicit or explicit) assumptions that work for disk based systems, but not for Flash drives. In this paper, we explore the decision of how columns of a relation are stored in secondary storage, and examine how it can be optimized for Flash databases. Instead of statically deciding column layout, we propose a way of coming up with a layout based on a given workload.

1.1 Organization of the paper

Section 2 briefly introduces the various column-organization alternatives available. Section 3 gives a short introduction to characteristics of Flash devices and how they are different from disk drives. Section 4 gives the analytical cost modeling of various operations. Section 5 describes our implementation and experimental setup. Section 6 describes the results of evaluating the performance of our layout with row,

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column based and CALF recommended page layouts.

2 Related Work

Column organization techniques can be roughly divided into two groups: *Horizontal* or *row-major* storage models, where all attributes of a tuple are stored together, and *Vertical* or *column-major* storage models in which the data belonging to the same attribute are stored together.

The typical row-major storage model in use is the *N-ary Storage model*(NSM). All the attributes of a tuple are laid out contiguously in a page. Each page maintains a *slot table* which maintains the offset of the beginning of each record. NSM is inefficient when only a few columns of the relation are being accessed, since all the attributes are loaded irrespective of whether they are used or not. CPU Cache performance is also bad, since loading unnecessary data pollutes the cache.

Decomposition Storage Model (DSM) [CK 85] was one of the first column-major layouts. DSM split a n-column relation into n sub-relations, duplicating the primary key or record-id in each sub relation. This method saves on data transfer when only a few columns are accessed, but pays a significant penalty joining the relations when multiple attributes are accessed in the query.

C-Store [SAB05] differs from DSM in that it doesn't explicitly store a record-id per sub relation. C-Store maintains a collection of columns, where an attribute of a column can be duplicated in multiple columns. Different columns can store the same attribute values in different orders, which can help in different queries.

Partition Attributes Across(PAX) [ADH01] improves upon the cache behavior of NSM by splitting a page into minipages, and storing the tuples in column-major order, each column in one minipage. While this improves cache performance, this has no impact on I/O transfer costs, since this just reorganizes data within a page, not across pages.

Data Morphing(DM) [HP 03] improves upon the cache performance of PAX, by making use of locality between attributes to group concurrently-accessed attributes together. As with PAX, DM only optimizes in-page layout, and doesn't help in reducing I/O transfer costs. This paper applies the same approach followed in DM to column layouts across pages to reduce I/O transfer costs as well.

Multiresolution Block Storage Model(MBSM) [ZR 03] extends the PAX model to include multiple pages or blocks. Blocks are arranged to superblocks, which are in turn grouped into Megablocks. Each block corresponds to a column. The relation is partitioned onto multiple superblocks. This approach has good cache performance and (somewhat) takes care of the data transfer problem. This model is no better than column store in systems with inexpensive random reads, since most of the organization is to make use of fast sequential access of disk drives.

There have been comparative studies of row-store vs. column-store organizations. Holloway et al. [HD 08] found that in most read-heavy cases, column stores beat row stores when I/O was the bottleneck. [HBN06] also found similar results, and proposed enhancing the row-storage model with some ideas from column-storage. All these comparisons were for disk drives based databases, hence the results may not hold true for Flash databases.

[SHW08] briefly touches upon storage models for Flash, and mentions that column-major layout is faster than row-major, for read queries. The authors also touch upon the fact that write queries pose a problem for column major layouts, incurring a heavy cost on inserts.

3 Characteristics of Flash

Flash drives have several traits that make them attractive for read-mostly enterprise applications such as web-page serving and search. Flash drives are divided into blocks and each block is further divided into pages. The memory can be read or programmed a byte or word in random access fashion at a time but the unit of erasure is a block. Because of these characteristics, flash drives offer more random read I/Os per second, offer comparable sequential bandwidth, and use a tenth of the power when compared to disks. Flash is also cheaper than DRAM and is non-volatile. Moreover, flash continues to get faster, cheaper, and denser at a rapid pace. However, flash drives are limited by their write endurance. Flash memory cells often wear out after 1000 to 10000 write cycles. Each write cycle requires erasing a super block before writing the actual data. Techniques exist to exploit wear levelling exist to extend the lifetime of the cells but an overhead of remapping fragments is incurred and this technique is useful only when there is a free super block available for the write. Flash memory also allows multiple memory locations to be erased or written in one programming operation and this is another major advantage with respect to disks. Flash memories also have improved on reliability which was one of it's major drawbacks during initial stages.

4 Our Contribution

We re-evaluate various storage models described in Section 2 for flash disks. Much work so far has been focused on exploiting random reading offered by flash disks. We also plan to focus on various workloads including writes and analyze relative performance of various storage techniques. The next section describes our cost model to start with and it has following assumptions or limitations which we plan to get rid of as time progresses.

- There are no variable length attributes. For example, if datatype is defined as *varchar(255)*, we assume that it is implemented as fixed size of 255 bytes.
- Database application does not have control on how to write a random page. Choosing an empty block instead of erasing and writing the block could minimize the costs associated. We consider average write cost in all our equations.
- No indexes on any of the columns. We plan to get rid of this assumption as early as possible, since it can have significant effect on the performance equations.

4.1 Cost Modeling

The key idea of Cost Modeling is to analytically estimate the cost of all operations in database for all possible layouts. Based on this cost model, we plan to organize the columns effectively in storage. Note that the cost model considers only bringing in pages from disk to memory. Some layouts may be cache-efficient and thus may improve performance, but we treat that as second order effect in our cost model. Some definitions:

- R : A relation in the database.
- A : The set of all columns of R $\{a_1, a_2, \cdots, a_n\}$.
- $sizeof(a_i)$: The maximum number of bytes a column can take.
- G : A *group* is a subset of columns $G \subseteq A$.
- $\mathcal{G}$: A *partition* is a set of disjoint groups $\{G_1, G_2, \cdots, G_k\}$ such that $\bigcup_{\mathcal{G}} G_i = A$.
- $cost_r$: The cost to read a random page.
- $cost_w$: The cost to write a random page.
- *pagesize*: The number of bytes in a page.
- N : number of tuples in the relation.
- k: Storage overhead per record in bytes. For example, in slotted page implementation, k is slot table entry size.

The read and write costs are assumed to be constant. More details about how these costs are estimated are given in Evaluation Section 6.1. Note that when $|\mathcal{G}| = 1$, this would reduce to N-ary storage model, and when $|\mathcal{G}| = |A|$, this reduces to column-store model.

The *records per page* for a group measures the number of tuples which can be stored in one page, considering only the columns in that group.

$$rpp(G) = \left\lfloor \frac{pagesize}{\sum_{a \in G} sizeof(a) + k} \right\rfloor$$

To ensure that each page holds at least one record, we can impose the constraint

$$\sum_{a \in G} sizeof(a) + k \leq pagesize.$$

For a given partition $\mathcal{G}$, the cost of a query depends on the type of query. The cost calculations for each type of query is shown below.

- Q : `select * from R`

  In this case, all the columns of the table are accessed for all rows.

  $$cost(Q) = cost_r \times \sum_{G \in \mathcal{G}} \left\lceil \frac{N}{rpp(G)} \right\rceil$$

  .

- Q : `select` $s_1, s_2, \cdots, s_p$ `from R`

  In this case, only some columns of the table are accessed for all rows. We incur a cost for a group if we access at least one attribute from it.

  $$cost(Q) = cost_r \times \sum_{G \in \mathcal{G}} cost'(G, \{s_1, s_2, \cdots, s_p\})$$

  where,

  $$cost'(G, X) = \begin{cases} 0 & X \cap G = \varnothing \\ \left\lceil \frac{N}{rpp(G)} \right\rceil & otherwise \end{cases}$$

- Q : `select` $s_1, s_2, \cdots, s_p$ `from R where` $p(w_1, w_2, \cdots, w_q)$ where p is a boolean predicate.

  In this case, the cost depends on the selectivity of the query. Let *row selectivity* of a predicate be defined as

  $$rowsel(p) = Pr_{tuple\ r \in R}\left[p(r) = true\right].$$

  Assuming that the distribution is uniform, the probability that none of the tuples in a given page belonging to a group G match the predicate is given by $(1 - rowsel(p))^{rpp}$. Hence the probability that at least one of the tuples in a page matches the predicate is $rowsel_G(p) = (1-(1-rowsel(p))^{rpp(G)})$. We incur a cost for a page if at least one record in that page matches the predicate.

Then the cost of query Q is

$$cost(Q) = cost_r \times (\sum_{G \in \mathcal{G}} cost''(G, W, S))$$

where,
$cost''(G, W, S) =$
$$\begin{cases} 0 & G \cap W = G \cap S = \varnothing \\ cost'(G, W) & G \cap W \neq \varnothing \\ cost'(G, S) & G \cap W = \varnothing, G \cap S \neq \varnothing \\ \times rowsel_G(p) & \end{cases}$$

- Q: `insert into R values`$(v_1, \cdots, v_n)$

  For each group, we have to read the last page and see if there is space available. If not, we have to allocate a new page and insert the record there. In terms of I/O, we incur one page read and one page write for each insert operation.

$$cost(Q) = (cost_r + cost_w) \times |\mathcal{G}|$$

- Q: `update table R set` $s_1 = v_1, \cdots, s_p = v_p$ `where` $p(w_1, \cdots, w_q)$

  The cost calculation is similar to the select case seen above. We incur a read and a write cost for a page if there is at least one attribute in that group in the set clauses, and there is at least one record in that page which matches the predicate.

$$cost(Q) = \sum_{G \in \mathcal{G}} cost''_u(G, W, S)$$

where,
$cost''_u(G, W, S) =$
$$\begin{cases} 0 \\ \qquad G \cap W = \varnothing, G \cap S = \varnothing \\ cost_r \times cost'(G, W) \\ \qquad G \cap W \neq \varnothing, G \cap S = \varnothing \\ rowsel_G(p) \times (cost_r + cost_w) \times cost'(G, S) \\ \qquad G \cap W = \varnothing, G \cap S \neq \varnothing \\ (cost_r + rowsel_G(p) \times cost_w) \times cost'(G, W) \\ \qquad G \cap W \neq \varnothing, G \cap S \neq \varnothing \end{cases}$$

- Q: `delete table R where` $p(w_1, \cdots, w_q)$

  Delete can be thought of as an update where every attribute needs to be updated (to a special 'deleted' value). So the cost calculation is similar to the above case.

$$cost(Q) = \sum_{G \in \mathcal{G}} cost''_d(G, W)$$

where,
$cost''_d(G, W) =$
$$\begin{cases} rowsel_G(p) \times cost_w \times cost'(G, A) \\ \qquad G \cap W = \varnothing \\ (cost_r + rowsel_G(p) \times cost_w) \times cost'(G, W) \\ \qquad G \cap W \neq \varnothing \end{cases}$$

Let $\mathcal{W} = \{Q_i\}$ be a given workload. Then the *optimal partitioning* of a relation R for the workload is given by

$$\mathcal{G}^*_{\mathcal{W}} = argmin_{\mathcal{G}} \sum_{Q_i \in \mathcal{W}} cost_{\mathcal{G}}(Q_i).$$

5 Implementation

Our Implementation is broadly divided into three modules.

- Query Processing Engine: A Query Processing Engine converts standard sql format to CALF format. The main difference between standard sql format and our format is adding selectivity as a part of the query. Since we have not reached the level of doing predicate matching and maintaining statistics about selectivity, we run the actual query on a real database. Get selectivity of the query and use it to selectively read pages. For example, sql query '`update table` $Table1$ `set` $column1 = 1$ `where` $column2 = 2$' with four different equally likely values for column2 will be transformed to CALF query '`update` $Table1$ `0.25` $column1 : 1$ $column2 = 2$'. Note that the third word in the CALF query is the selectivity.

- Optimal Partitioning Engine: Given schema and workload, the goal of Optimal Partitioning Engine is to split the columns into different groups in such a way that cost of workload according to the CALF analytical model is minimum. This can be reduced to Minimum cost Set Partitioning problem and is NP-Hard. We use Branch and Bound technique as an approximation to solve this problem. We start off by assuming table to have only one column. In this case, all the layouts are equivalent. We then consider adding second column to the table. There are two ways to do this. Put both the columns in same group or divide them into two different groups. We compute cost for these two approaches and select the best layout. The same approach is applied iteratively to reach final partition with all the columns in the schema. The ideal algorithm would require $i!$ comparisons in ith iteration while this approximation would require only i comparisons. But this approximation does not promise best possible partitioning. However, it gives fairly good partitions as shown in previous subsections. We are working on other better approximations to this problem that probably include domain knowledge as a part of heuristic.

- Database Engine: The Database Engine consists of Storage module that takes responsibility of persisting data and PageManager that interprets the stored data and helps in (un)marshalling of data. We follow Slotted Page structure for all the layouts. Thus, Column layout for a table with n-columns is actually stored as n-tables with one column each. We further have some Meta information on attribute to page number mapping. This Meta information helps in easily identifying the pages for a given group.

Figure 1 demonstrates the toolchain we developed for the evaluation.

- `calfproprocess`: Converts SQL files into a simpler form which the CALF engine can easily parse. It separates all the table creation statements into the schema file, and other statements into query files.

- `calfoptimize`: Finds the optimal partitioning of attributes based on the analytical cost model.

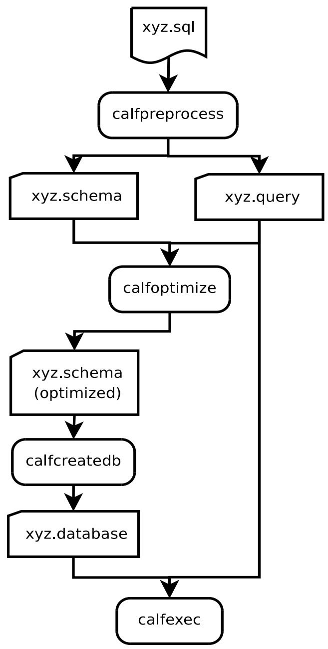


Figure 1: Toolchain for evaluation

- `calfcreatedb`: Creates database files, which link the schema produced with specific column layout implementations.
- `calfexec`: Executes the queries on the given database and measures the time it takes.
- `calfblkload`: For initial loading of data into the database.

6 Evaluation

Our experimental setup was as follows:

- Flash Device: Lenovo ChipsBnk 512MiB USB Stick over USB 2.0
- File System: ext2 [1]
- Operating system: Linux 2.6.27-2
- Page Size: 8KB

6.1 Measurement of read/write costs on flash

We measured the time taken to read and write one page from the file for different page sizes. This is used as $cost_w$ and $cost_r$ in the Cost Model calculations. We observed from our tests that random read and sequential read costs are equivalent. The following table shows the read and write costs for various block sizes. As we have no control over the actual erase operation, the erase costs are assumed to be amortized over the write costs.

Page Size	Read time (ms)	Write Time (ms)	$\frac{write}{read}$
8K	20.117	111.192	5.5637
16K	40.284	123.331	3.0610
32K	82.392	138.815	1.6767
64K	160.101	160.924	1.0511

As block size increases, the transfer cost begins to dominate the overall cost of the operation, especially over a USB connection. We chose a page size of 8K as a compromise between write-read ratio and the transfer rate.

6.2 Layout comparison results

We analyze a few workloads and see what our model predicts for row-store, column-store and CALF organizations. We then use the same workload and compare the results from actual CALF engine to our analytical model. For all the cases, we initially add 100,000 records to the

[1] We planned to use a log-structured file system like logFS instead of a conventional file system, but practical difficulties getting logFS prevented us from doing so.

database before executing the query that is being analyzed.

- Cost of `select * from R` while varying the number of attributes in R.

  Figure 2(a) shows the query cost using analytical model. Note that Optimal layout overlaps with the Row layout. This is obvious because size of actual data stored and retrieved in both the cases is same. But as the number of groups increase, the total slot table overhead increases and therefore requires reading more pages. Thus, N-ary model outperforms all the other layouts.

  Figure 2(b) shows the query cost by actually running the query on CALF database engine. The actual results follow the results from analytical model. But, we observe a knee when number of columns is a multiple of four. We attribute this to ratio of super block size (erase block size) to read block size on the flash drive.

- Cost of select $s_1, s_2 \ldots$ from R while varying the number of attributes in R, keeping the select clauses constant.

  Figure 3(a) shows performance of various layouts when a subset of columns in the table are selected. The read cost for Row layout remains same as in Case 1 because all the pages are read into memory always. Column layout reads relatively more pages with small number of columns because of added storage overhead, but with increasing number of columns, it outperforms Row layout. The Optimal layout in this case divides s_1, s_2 into one group and all the remaining columns into the other. It thus reduces extra storage overhead and reads only required data. Therefore, CALF predicts the best way to layout the columns.

  Figure 3(b) shows the actual measured time for the same schema and query. This graph is approximately similar to the expected one, but the column costs are much higher than the row costs. The optimal is slightly worse than the row for the first few cases, but is stable as the number of columns increases.

- Cost of select $s_1, \cdots, s_k$ from R while varying the number of attributes in the select clause, keeping the total number of attributes in R constant(9).

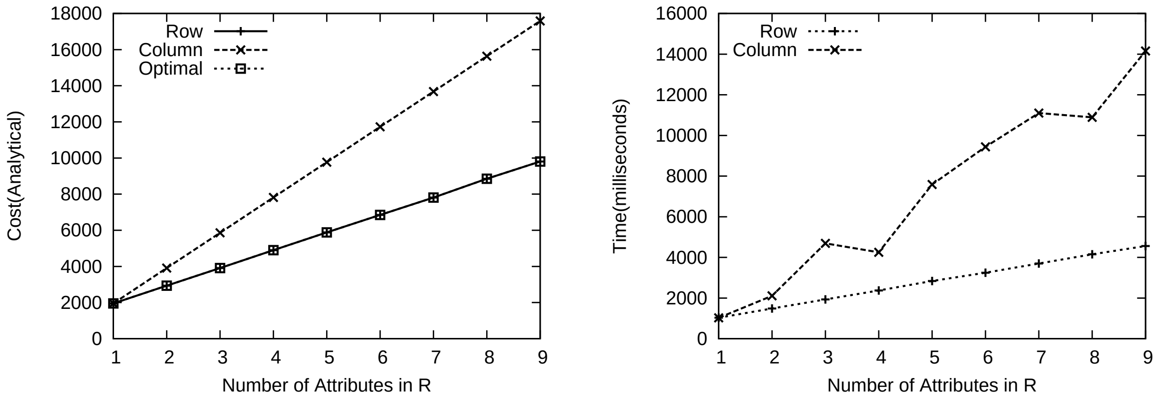
  Figure 4(a) shows the analytical cost of the query as the number of attributes in the select clause is varied. The cost of Row layout remains constant because all pages are read in always. Cost with column layout model increases linearly as expected as adding a new column in select clause requires reading additional pages corresponding to that column. Again, the CALF Optimal layout selects best partition of groups as the ones which contain exactly the same columns as those in the select clauses.

  Figure 4(b) shows the actual measurement. The graph is close to expected value. The optimal one is slightly worse than the group one because of extra overhead.

- Cost of select s_1, s_2 from R where $p(w_1, w_2 ...)$ with varying selectivity of predicate p.

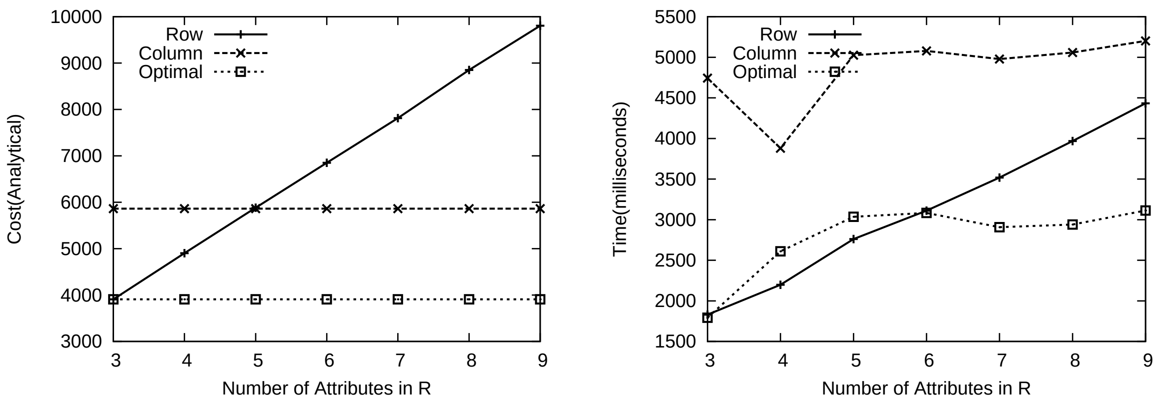
  Figure 5(a) shows the analytical cost as the selectivity of p is varied. This clearly shows a threshold phenomenon, since we read a page if at least one of the records in it match the predicate. We therefore skip a page only if the selectivity is $\approx \frac{1}{N}$.

  Figure 5(b) shows the measured cost. In the



(a) Analytical model (b) On CALF Engine

Figure 2: `select * from R`



(a) Analytical model (b) On CALF Engine

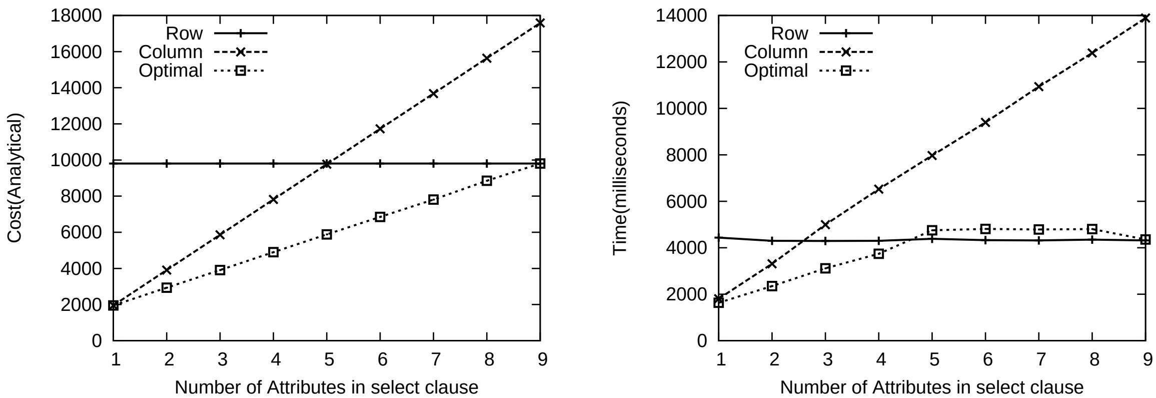
Figure 3: `select` s_1, s_2 `from R`

absence of indices, our implementation reads all the where clause pages, which is why the sharp threshold is not seen in our implementation. Contrary to the model, column layout actually performs worse than the row one, again due to the extra overhead per record.

- Cost of `update R` $sets_1 = v_1 \ldots$ `where p(`w_1, w_2`...)` with varying selectivity of predicate p.

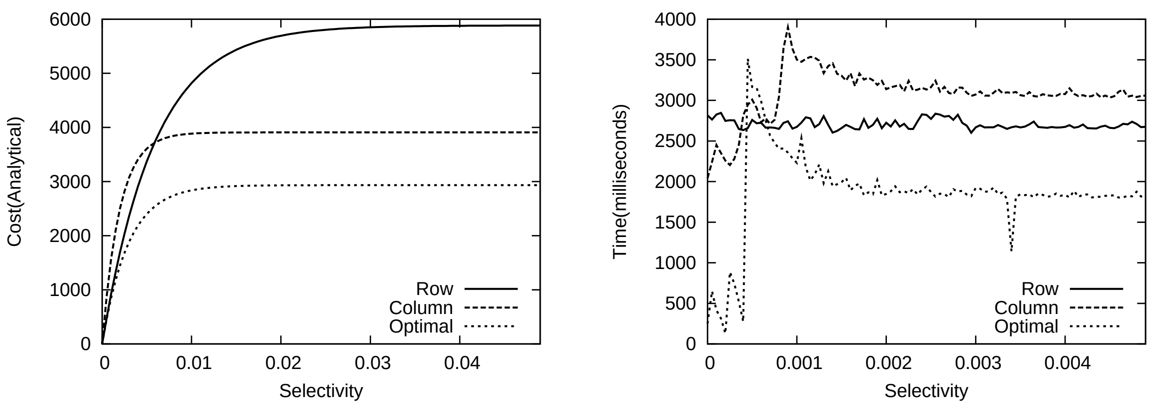
Figure 6(a) shows the analytical cost of a fixed query as the selectivity of the predicate is varied. This is similar to the previous case, other than the fact that if the predicate matches there is an additional write cost.

Figure 6(b) shows the actual measurement. For reasons not quite clear to us, there is sig-



(a) Analytical model (b) On CALF Engine

Figure 4: `select` $s_1, \cdots, s_k$ `from R`



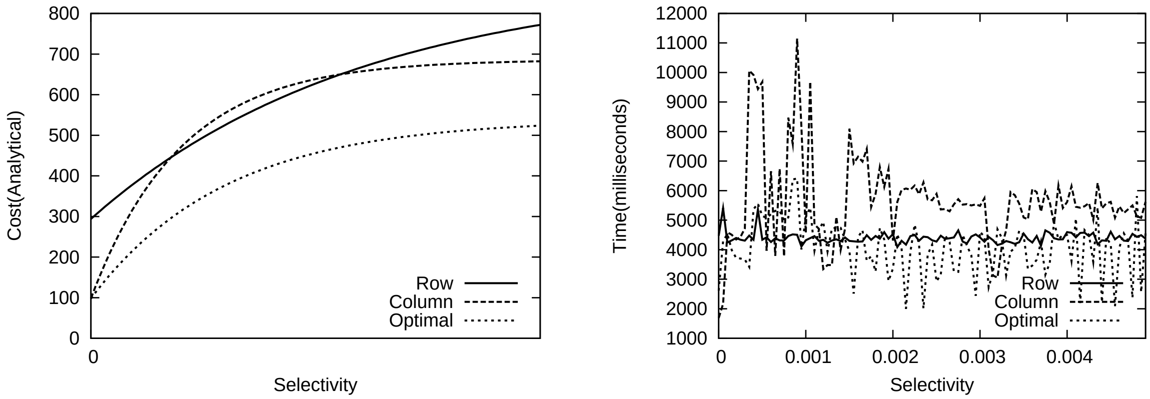
(a) Analytical model (b) On CALF Engine

Figure 5: `select` s_1, s_2 `from R where` $p(w_1, w_2 ...)$

nificant variation in the timings. We suspect that it interleaved reads and writes is the cause of this. Also column and CALF are the ones which seem to be affected, which might indicate that non sequential writes are causing problems.

7 Conclusions

In this report, we analyze the cost of various storage models for a solid state device. We introduce an analytical model that decides on best partitioning of columns based on given workload. In general, analytical model points out that NSM performs better when there are relatively fewer columns because of added overhead in Column



(a) Analytical model

(b) On CALF Engine

Figure 6: `update R set` $s_1 = v_1, ...$ `where p(`$w_1, w_2...$`)`

based approaches but as number of columns and tuples increase, Column layouts save lot of I/O. We show that actual costs match the predictions of analytical model and CALF correctly predicts optimal partitioning of columns. Of course, CALF layout may incur high penalties because the queries chosen for partitioning may not reflect the actual workload, and will not work well for frequently changing workloads. We assume real workloads to have fairly predictable set of queries in the long run.

8 Future work

Several directions suggest themselves for future work. Obviously, fine-tuning cost model and improving it by considering database operations such as join and including other meta information such as indices on a column will be an ongoing task. We would also like to extend the database engine to variable length attributes and support more datatypes. Providing atomicity and consistency by implementing locking is also top on our list as this could be a serious disadvantage to column layouts. In addition, we also plan to address improvements to Optimal Partitioning approximation algorithm and consider the effect of number of records in database on the cost model.

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