Revisiting the Theory and Practice of Database Cracking

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ABSTRACT

Database cracking (DBC) provides an adaptive data storage environment that meets the needs of modern applications in business and science, reorganizing data on demand and adapting indexes on the fly, automatically, and collaterally to query processing. Despite intensive research on cracking and other adaptive indexing variants, their theoretical side has scarcely been investigated. Yet, quite surprisingly, as we show, an antecedent of database cracking in a pure, no-frills form had been developed in the theory community 24 years ahead of its time by the name of *deferred data structuring* (DDS). While lacking system implementations, DDS corresponds to what we would call, by the terminology used in the database community, *materialization-based data-driven center* cracking for point lookup queries, as well as a stochastic variant thereof. Further, DDS has gone beyond regular cracking proposals by suggesting a policy that reorganizes index ranges along the median of a *sample* set, i.e., a *mediocre* element.

In this paper, we reanalyze state-of-the-art database cracking algorithms with the benefit of hindsight provided by deferred data structuring, and propose new alternatives that use a mediocre element as cracking pivot instead of a random or a median one. In a thorough experimental study, we determine that a logarithmic or linear sample size yields best performance on a standard benchmark across the board of cracking algorithms.

1 INTRODUCTION

Database Cracking (DBC) [1–3] addresses the needs of dynamic environments where workload knowledge and idle time are scarce, queries follow an exploratory path, and new data arrive continuously [1]; as a form of adaptive indexing [6], it paves the way to self-organizing database management systems, eschewing the need for human administration in physical database design. Cracking builds and refines index data structures for a column-oriented database incrementally, in response to queries and arriving data, without a need for human intervention; its core operation, applied within the select operator, reorganizes a column into pieces [5], handles updates [4] and invites security features [8]. A *stochastic* alternative [1] improves performance by refraining from *blindly* following queries; it also creates *random cracks* on its own, and thereby avoids the deterioration of performance that skewed workloads may cause.

Surprisingly, while database cracking has been studied over the last decade, an antecedent thereof had been investigated from a theory perspective two decades in advance by the name of **Deferred Data Structuring** (DDS) [7]. Specifically, DDS suggested that, instead of processing a data set in advance, we may instead process it while responding to queries. Traditionally, to answer the query *"is integer x in list ℓ?"*, we would scan ℓ in $O(n)$. If the number of queries is high, it pays off to sort $O(n \log n)$ in a pre-processing step and then perform binary search in $O(\log n)$ for each query. By DDS, we create a data structure that represents the list *while* processing queries, achieving better performance in all cases. While DDS was proposed for lookup queries on a static data set only, we will argue that its main logic uncannily resembles that of database cracking.

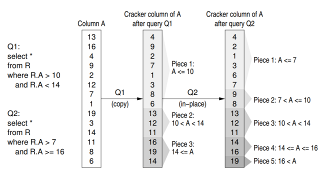
In this paper, we observe the resemblance between DBC and DDS and bring both concepts under the same roof. We conduct a thorough theoretical study of state-of-the-art DBC algorithms under the light of DDS methods. We implement existing DDS and DBC proposals and propose new intermediary, mediocre-based solutions, that inherit both the theoretical elegance of DDS and the practical applicability of DBC.

2 RELATED WORK

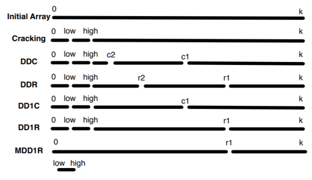
We discuss related works in two fields: database cracking and defferred data structuring.

2.1 Database Cracking

Database Cracking [2, 3] reorganizes and indexes columns in an adaptive manner triggered by user queries, within the SELECT operator. In the general case, a query requests all values within a range, [*low*, *high*]; when responding to that query, the a cracking system finds one or more *pieces* of the current index where the requested data resides, reorganizes (i.e., cracks) the column so as to bring the result values between query bounds *low* and *high* in a contiguous space, and updates the index accordingly. Figure 1a provides an example.



(a) Reorganizing a column.



(b) Cracking algorithms at work.

Figure 1: Database cracking illustration [1].

Stochastic Cracking [1] maintains performance when faced with pathological workloads; in addition to cracking using query bounds as pivots, it creates additional cracks while traversing the index towards query bounds. Figure 1b indicates how several stochastic cracking algorithms work. We discuss the six main alternatives: DDC, DDR, DD1C, DD1R, MDD1R, and PMDD1R.

The *Data-Driven Center* (**DDC**) algorithm divides (i.e., cracks) each value range it encounters while traversing the index along the *middle* (i.e., median) of its value domain *recursively*, as in an ideal case of pivot selection by quicksort. This recursive splitting process terminates when pieces become smaller than a size threshold. Thereafter, DDC cracks on query bounds as usual. Algorithm 1 illustrates the process. On the other hand, the *Data-Driven Random* (**DDR**) algorithm avoids the median-finding overhead: it uses a random element instead of the median as pivot when cracking each value range in Line 6 of Algorithm 1.

Both DDC and DDR incur an overhead on the first few queries, as they *recursively* introduce many cracks on the way to query bounds. Two lightweight alternatives, **DD1C** and **DD1R**, eschew the recursion, i.e., crack only *once* at a median or random pivot, respectively, in addition to cracking at query bounds, by turning the *while* loop in Line 5 of Algorithm 1 to an *if* statement.

ALGORITHM 1: DDC [1]

```
   Result: Cracks at center of each relevant piece and bounds
1  int DDCCrack(C:array, v:value)
2      Find the piece Piece that contains value v;
3      $pLow$ = $Piece$.firstPosition();
4      $pHigh$ = $Piece$.lastPosition();
5      while ($pHigh - pLow$ > CRACK-THRESHOLD)
6          $pMiddle = (pHigh + pLow)/2$;
7          Introduce crack at $pMiddle$;
8          if ($v < C[pMiddle]$)
9              $pHigh = pMiddle$
10         else
11             $pLow = pMiddle$
12     $position$ = crack($C[pLow, pHigh]$, $v$);
13     return $position$;
   /* Main Body : DDC                                    */
   /* Crack array C on bounds a and b                    */
14 $positionLow$ = DDCCrack($C$, $a$);
15 $positionLow$ = DDCCrack($C$, $b$);
16 result = createView($C$, $positionLow$, $positionHigh$);
```

Still, the hitherto presented algorithms create cracks at each query's bounds, which may hurt performance without bringing a benefit in the long run. **MDD1R**, a variation of DD1R, dispels the cracking at query bounds as well, and simply *materializes* query results while creating exactly *one* random crack per query. Algorithm 2 shows the corresponding pseudocode.

ALGORITHM 2: MDD1R [1]

```
   Result: Cracks at a random point in one relevant piece and bounds
1  array split-and-materialize(Piece, a, b)
2      $L = Piece$.firstPosition;
3      $R = Piece$.lastPosition;
4      $result$ = newArray;
5      $X = C[L + rand()\%(R - L + 1)]$;
6      while ($L \leq R$)
7          while ($L \leq Q$ and $C[L] < X$)
8              if ($a \leq C[L]$ and $C[L] < b$)
9                  $result.Add(C[L])$
10             $L = L + 1$;
11         while ($L \leq R$ and $C[R] \geq X$)
12             if ($a \leq C[R]$ and $C[R] < b$)
13                 $result.Add(C[L])$
14             $R = R - 1$;
15         if ($L < R$)
16             swap($C[L]$, $C[R]$)
17     Add crack on $X$ at position $L$;
18     return $result$;
   /* Main Body: MDD1R                                   */
   /* Crack array C on bound a, b                        */
19 Find the piece $P1$ that contains value $a$;
20 Find the piece $P2$ that contains value $b$;
21 if ($P1 == P2$)
22     $result$ = split-and-materialize($P1$, $a$, $b$)
23 else
24     $res1$ = split-and-materialize($P1$, $a$, $b$);
25     $res2$ = split-and-materialize($P2$, $a$, $b$);
26     $view$ = createView($C$, $P1.lastPosition + 1$, $P2.firstPosition - 1$);
27     $result$ = concat($res1$, $view$, $res2$);
```

In more detail, the algorithm first finds the pieces where the two bounds are. If they are in the same piece, it partitions that piece with respect to a random pivot, while collecting the query results in an array. Should they be in different pieces, it partitions the pieces where each bound belongs and then concatenates the query results, as well as all pieces in between to produce the response to the query. Note that MDD1R maintains a data-driven character: even though not cracking at query bounds, it introduces random cracks in the pieces where those bounds are.

Even with MDD1R, the initial queries of a workload need to reorganize almost all the the data. **PMDD1R** is a *progressive* instantiation of MDD1R that takes the incremental nature of cracking one step further. MDD1R performs a reorganization task on a given piece in smaller units, performed with each query touching that piece. A percentage p determines how much of the pending reorganisation task is done with each relevant query, while materializing and returning the query result.

2.2 Deferred Data Structuring

Deferred Data Structures [7] are tree-like structures built in response to queries. Their objective and rationale resembles database cracking, even though they were introduced two decades earlier with a focused theoretical intent and no accompanying system implementation. Consider a list $\ell = \{x_1, x_2, x_3, \ldots, x_n\}$ and *existence* queries thereupon, $q = \{q_1, q_2, q_3, \ldots, q_r\}$. A conventional approach would sort the list and answer each query by binary search. DDS performs sorting through query answering: it answers each query in $O(n)$ time, and partition the list as well while doing so. Algorithm 3 illustrates DDS. By the terms of Section 2.1, Algorithm 3 corresponds to a **DDC** variant of database cracking specialized on point lookup queries, without a size threshold: it cracks recursively on the median, like DDC does, and reports the existence or absence of the lookup query value; were there a size threshold, it would correspond to an **MDDC** variant, yet without such a threshold **MDDC** degenerates to **DDC**.

ALGORITHM 3: DDS via recursive median finding [7]

```
   Result: Create a tree structure representation of list l while responding to queries
1  boolean SEARCH(v:node, q:query)
2      if(v is not labeled)
3          $EXPAND(v)$;
4      if(label(v) == q)
5          return true;
6      if(v is a leaf node)
7          return false;
8      if(q < label(v))
9          return $SEARCH(left\_child(v), q)$;
10     if(q > label(v))
11         return $SEARCH(right\_child(v), q)$;
12 void EXPAND(v:node)
13     $S \leftarrow set(v)$;
14     $m \leftarrow MEDIAN - FIND(S)$;
15     $label(v) \leftarrow m$;
16     if($\|S\|$ == 1)
17         return ;
18     $S_l \leftarrow [x \mid x \text{ in } S \text{ and } x < m]$;
19     $S_r \leftarrow [x \mid x \text{ in } S \text{ and } x > m]$;
20     $set(left\_child(v)) \leftarrow S_l$;
21     $set(right\_child(v)) \leftarrow S_r$;
   /* Main Body                                          */
22 initialize the tree $T_X$ with the n data keys at the root;
23 Get a query $q$;
24 Result $\leftarrow SEARCH(root, q)$;
25 Output the result;
26 Goto Line 23;
```

Further, DDS [7] comes along with a *randomized* proposal, which replaces the exact median-finding operation with a *mediocre* function, i.e., the median of small sampled set of values, whose computed rank passes a sanity test, instead of the whole set, as Algorithm 4 shows; this choice improves the cost per query while it still creates a well-balanced tree structure in the long term. Once again, the rationale is reminiscent of what we would call **MDDR** in database cracking terms. In particular, a randomized DDS where the size of the sampled set is one element corresponds to an MDDR cracking algorithm specialized on point lookup queries and without a size threshold.

ALGORITHM 4: Mediocre finding function [7]

```
   Result: Finds mediocre of set $T$
1  int mediocreFind(T:set of values)
2      $t \leftarrow size(T)$;
3      Pick a random of sample $S$ of size $2 * \lceil t^{5/6} \rceil + 1$ from T;
4      $m \leftarrow MEDIAN - FIND(S)$;
5      Compute rank(m) by comparing with each element of $T - S$;
6      If rank(m) is not in the range $(t/2) \pm t^{2/3}$;
7      return $m$;
```

3 THEORETICAL ANALYSIS

Here, we analyze state-of-the-art database cracking algorithms by the tools of deferred data structuring, assuming a cracking size threshold of zero and point lookup queries. We also propose, study, and build upon an alternative stochastic cracking algorithm, **DDM**, which uses a *mediocre* element as cracking pivot, as in Algorithm 4, instead of a random one, as DDR algorithms do, or a median one, as DDC algorithms do.

Theorem 3.1. *DDC: The number of operations needed to process r queries on a list of n points is no more than $\lambda(n, r)$:*

$$\lambda(n,r) = \begin{cases} 3n\log r + r\log n, & if\, r \le n \\ (3n+r)\log n, & if\, r > n \end{cases}$$

Proof. In case $r \le n$, at any level of the tree, at most r nodes are expanded. For the top $\log r$ levels, the total cost is less than $3n\log r$, since all nodes have to be expanded. The creation of a crack includes finding the median, which requires $3|set(node)|$. The cost of node expansion at level i of the tree for $i > \log r$, is $O(rn/2^i)$, since the expansion of a node at this level costs at most $3n/2^i$. Summing over all but the first $\log r$ levels, we get an $O(n)$ cost, which is dominated by $3n\log r$. Searching for each query costs $O(\log n)$, since the tree is balanced, hence the $r\log n$ term. When $r > n$, expansion will complete the tree, with a cost of $3n\log n$, while search follows the same principles. □

Theorem 3.2. *DDR: The number of operations needed to process r queries on a list of n points is no more than $\lambda(n, r)$:*

$$\lambda(n,r) = n^2 + rn$$

and is expected to be no more than $\lambda(n, r)$ operations:

$$\lambda(n,r) = \begin{cases} 1.39n\log r + r\log n, & if\, r \le n \\ (1.39n+r)\log n, & if\, r > n \end{cases}$$

Proof. As there is no guarantee that the created tree will be balanced, in the worst case, the random numbers chosen to create cracks yield a completely unbalanced tree. A query may cause the entire tree to be created in $O(n^2)$. Due to the lack of balance, search can take up to n operations, producing the rn term. In the average case, we expect performance similar to quicksort [9], with 1.39 in place of 3 in Theorem 3.1. □

Theorem 3.3. *DDM: The number of operations needed for processing r queries in a list of n points is no more than $\lambda(n, r)$:*

$$\lambda(n,r) = \begin{cases} (1+\alpha)(n\log r + r\log n), & if\, r \le n \\ (1+\alpha)(n+r)\log n, & if\, r > n \end{cases}$$

with probability greater than $1 - \frac{\log r}{\beta n}$, where $\alpha \ll 1$ and β depends on the value of α.

Proof sketch. The proof follows from [7]. The height of the tree created only differs from $\log n$ by a constant, so the search operations are $r\log n$. Then, the probability of the first sample chosen rendering a median that passes the test is higher than $(1 - \frac{1}{4|set(node)|})$, which leads to the conclusion that the total cost of testing for mediocrity is at most $(1+\alpha)n\log r$ with probability higher than $1 - \frac{\log r}{k^2 n}$, where α and k are small constants, and β depends on α. The total cost of finding the medians for the first $\log r$ levels is $O(n^{\frac{5}{6}} r^{\frac{1}{6}})$ with probability higher than $1 - \frac{\log r}{\beta n}$, from which the complexity for $r \le n$ follows. If $r > n$ the tree will be complete with some extra costs, as in the DDR case. □

Theorem 3.4. *DD1C: The number of operations needed to process r queries in a list of n points is no more than $\lambda(n, r)$:*

$$\lambda(n,r) = \begin{cases} 14n + r\log n, & if\, r \le n \\ (3n+r)\log n, & if\, r > n \end{cases}$$

Proof. As the first query, q_1 is made to a list of length n, the median should be found in $3n$. Then, one of the two crack pieces is chosen and another crack is made, with regards to the query. The process of partitioning takes at most $\frac{n}{2}$ comparisons. For the second query, up to two comparisons are made based on the crack created in the first query, to choose a chunk of size at most $n/2$, find its median, and crack one of the resulting pieces, yielding $\frac{3n}{2} + \frac{n}{4}$. Following the same pattern until the rth query, we get a cost of:

$$\sum_{i=1}^{i=r} \frac{3n}{2^{i-1}} + \sum_{i=1}^{i=r} \frac{n}{2^i} = 7n \sum_{i=1}^{i=r} \frac{1}{2^i} < 14n$$

while the search component costs $r\log n$. When the number of queries reaches n, the tree will be complete, and the cost is as in the proof of Theorem 3.1. □

Theorem 3.5. *DD1R :The number of operations needed to process r queries in a list of n points is no more than $\lambda(n, r)$:*

$$\lambda(n,r) = \begin{cases} 3rn + r, & if\, r \le n \\ n^2 + rn, & if\, r > n \end{cases}$$

and is expected to be no more than $\lambda(n, r)$ operations:

$$\lambda(n,r) = \begin{cases} 7.56n + r\log n, & if\, r \le n \\ (1.39n+r)\log n, & if\, r > n \end{cases}$$

Proof. In the worst case in terms of random pivot choices, for query q_1 we pick a random point and partition based on it, in at most n operations. The pieces may be of size 1 and $n-1$. One of those two is partitioned based on the query in $n-1$ comparisons. The second query will partition a piece of size as large as $n-2$ for the random crack and one as large as $n-3$ for the query bound, and so on, in $[n - 2(i-1)] + [n - (2i-1)]$ operations for the i^{th} query. Going all the way to q_r, we have

$$\sum_{i=0}^{i=2r-1} (n-i) = 2rn - 2r^2 + r$$

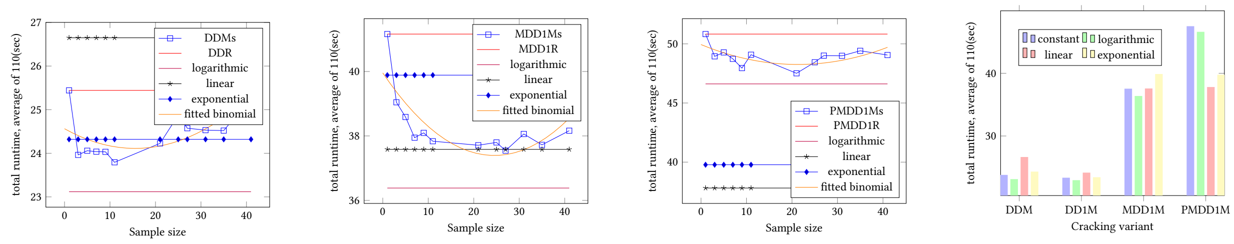
operations for expansion and rn operations for search. Should the number of queries exceed n, the tree is completed, hence n^2 operations. In the expected case, the tree resembles a balanced tree and results follow Theorem 3.4, with the quicksort complexity factor $1.39n$ replacing $3n$ in calculations, as in Theorem 3.2. □

Theorem 3.6. *DD1M: The number of operations needed to process r queries in a list of n points is no more than $\lambda(n, r)$:*

$$\lambda(n,r) = \begin{cases} (1+\alpha)(n\log r + r\log n), & if\, r \le n \\ (1+\alpha)(n+r)\log n, & if\, r > n \end{cases}$$

with probability greater than $1 - \frac{\log r}{\beta n}$.

Proof. By Lemma 3 in [7], with high probability we only need to compute a median over a sample once, as the first attempt passes the mediocrity test. For the first r queries, we compute the medians of nodes that will overall lead to $O(n^{\frac{5}{6}} r^{\frac{1}{6}})$ (Lemma 5 in [7]). The cost testing for mediocrity at level i, denoted by c_i, is proven to be less than $(1+\alpha)n\log r$. After cracking at the



(a) Recursive crack (b) Crack with materialization (c) Progressive materialization (d) All variants, constant $m = 21$

Figure 2: Total runtime, 160K queries; linear: $m = \frac{size}{1000}$, logarithmic: $m = log(size)$, exponential: $m = size^{\frac{5}{6}}$.

mediocre, we scan the list to find the query point and create another crack there, in at most s_i (Lemma 1 in [7]), yielding:

$$n^{\frac{5}{6}} r^{\frac{1}{6}} + \sum_{i=1}^{i=r} c_i + 1.5 s_{i+1} \leq$$

$$n^{\frac{5}{6}} r^{\frac{1}{6}} + (1+\alpha) n \log r + 2n(1-(0.5)^r) + 20 n^{\frac{2}{3}} \frac{1-2^{\frac{2r}{3}}}{1-2^{\frac{2}{3}}}$$

The cost of search remains similar to that of DDM. □

Overall, materialization-based algorithms have similar complexities as their default counterparts due to their common bases.

4 EXPERIMENTAL STUDY

We assess the performance of mediocre-based variants database cracking algorithms [1] inspired from our study of deferred data structures [7]. We conduct experiments on a Ubuntu Linux server release 18.04 machine with a 10-core 3.1GHz Intel E5-2687W processor and 377GB of RAM. All methods are implemented in C++ upon the code[1] of [1]; our code is also available[2] online. We use the 4TB SkyServer[3] data and workload [1], derived from an astronomy project mapping the universe. We filter selection predicates from 160K chronologically ordered queries using the right ascension attribute of the Photoobjall table, which contains 500 million tuples. Query patterns are complex, as users tend to focus in a specific area of the sky before moving on.

4.1 Compared Algorithms

We compare the state-of-the-art stochastic cracking algorithms presented in Section 2, namely DDR, DD1R, MDD1R, and PMDD1R with $p = 0.1$ and $CRACK\_THRESHOLD = 128$ to their median-based counterparts and to counterparts that use a mediocre cracking pivot, i.e., the median of a random *sample* set of a cracked piece, rather than a median or random one: DDM, DD1M, MDD1M, and PMDD1M, respectively.

The median-based counterparts of DDR, DD1R and MDD1R are DDC, DD1C and MDD1C respectively; we included those three in our study, but they proved to be too expensive. We do not include a median-based counterpart of PMDD1R, since median-finding operations are hard to render progressive. The mediocre-based policy is reduced to the median-based one for m equal to piece size, and to the randomized one for $m = 1$.

4.2 Results

We apply each algorithm on the same 160K-query workload and measure the total runtime, juxtaposing mediocre-based variants to their randomized and median-based counterparts, where such exist. Figure 2 shows the results when varying the sample set size m from 1 to 41, and as a linear, logarithmic, or exponential function of piece size, with the mediocre-based policy, averaging over 110 runs and foregoing the mediocrity check [7]. The case of single crack without materialization is very similar to that of single crack with materialization in Figure 2b, hence we omit a separate figure for that case.

In the case of a constant sample size, the cost of calculating the median of a small sample set is initially a worthwhile price to pay for the benefits it brings, yet the cost to benefit ratio deteriorates as m grows; binomial fit curves visualize the trends in Figure 2a, 2b, and 2c. However, cases where sample size is a simple function of piece size achieve the best performance in all variants. The logarithmic function is the best performer with recursive and simple crack with and without materialization. In the variant with progressive materialization, a linear function, $m = \frac{size}{1000}$, performs best.

5 CONCLUSION

We revisited the theory and practice of *database cracking*, which has been intensively studied in practice, yet scantily examined in theory. We provided the first thorough study of the complexity of the all state-of-the-art stochastic cracking algorithms, drawing from an overlooked 32-year-old study that introduced analogous concepts under the name of *deferred data structuring*. Inspired from deferred data structuring, we introduced a refined stochastic cracking policy that uses a sample-based *mediocre* pivot, rather than an arbitrary random or median one, for data-driven cracking. We showed that variants of state-of-the-art stochastic cracking algorithms using the mediocre-based policy have lower complexity than their median-based and randomized counterparts with high probability, and demonstrated experimentally that they stand out in terms of cumulative time efficiency.

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