

DeltaSort: Incremental repair of sorted arrays with known updates

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Abstract

Reading sorted data is a fundamental requirement in almost all data processing systems. When dealing with large sorted datasets that require great read performance, sorting-on-read is not feasible. A standard approach is to have a derived sorted read-replica that is updated with the latest snapshot whenever the system-of-record gets updated. For updating read-replicas, most production systems resort to either full re-sorting or Binary-Insertion-Sort or Extract-Sort-Merge. In this paper, we dive into why the traditional approaches are sub-optimal and how we can do better. This paper also formulates an alternative model in which sorting routine is explicitly informed of the indices updated since the previous sort. Under this model, we present *DeltaSort*, an incremental repair algorithm for arrays that batches multiple updates instead of applying them independently. We present experimental evidence that shows that *DeltaSort* outperforms existing approaches for a wide range of update batch sizes. These results suggest that tighter integration between update pipelines and sorting routines can yield significant performance gains in real incremental-sorting workloads at the cost of increased memory usage to track updated indices. We also explore limitations of this approach and show that there is a clear crossover point depending on array size where full re-sorting becomes preferable.

1 Introduction

Sorting is among the most optimized primitives in modern systems backed by decades of deep research. Standard library implementations—TimSort [10], Introsort [8], and PDQSort [9] deliver excellent performance for general inputs by exploiting partial order, cache locality, and adaptive strategies. However, these algorithms operate under a *blind* model: they rediscover structure dynamically rather than being explicitly informed about which elements have changed since the previous sort.

In many practical systems, this assumption is unnecessarily pessimistic. Sorted arrays are often maintained incrementally in read-heavy workloads where updates affect only a subset of elements and the indices of those updates can be easily tracked if needed. Nevertheless, this information is typically not tracked or utilized, and systems fall back to blind re-sorting or sub-optimal repair approaches using binary-insertion or extract-sort-merge. As an example, consider a web application that shows a real-time game leaderboard. Being able to efficiently update the sorted view on updates directly impacts user experience. The traditional approaches don't serve us very well - full re-sort can block the main UI thread for long durations, while Binary-Insertion-Sort can be slow for large number of updates. To address these limitations, this paper makes the following contributions:

1. **Update-aware sorting model:** We formulate an incremental sorting model in which the sorting routine is explicitly informed of the indices updated since the previous sort. Under

this model, a couple standard algorithms are Binary-Insertion-Sort and Extract-Sort-Merge because they help maintain sorted order by processing incremental updates.

2. **DeltaSort algorithm:** We present *DeltaSort*, an incremental repair algorithm for sorted arrays designed for the update-aware model. DeltaSort batches updates and repairs them jointly, reducing redundant comparison work and overlapping element movement by exploiting update locality and batching. DeltaSort achieves multi-fold speed ups over traditional approaches and also beats Native-Sort for a wide range of update batch sizes.

2 Related Work

Adaptive sorting algorithms exploit existing order in the input to improve performance on nearly sorted data. TimSort [10] and natural merge sort [6] identify monotonic runs dynamically and merge them efficiently, yielding improved performance when such structure is present. A substantial body of work formalizes measures of presortedness and studies sorting algorithms whose complexity depends on these measures rather than input size alone [7]. These approaches, however, must discover structure through full-array scans and do not assume explicit knowledge of which elements were modified.

Dynamic data structures offer a different trade-off. Self-balancing trees such as AVL trees [1], red-black trees [5], B-trees [2], and skip lists [11] support efficient ordered updates with logarithmic cost, but sacrifice contiguous memory layout and cache locality. Library sort [3] reduces insertion cost by maintaining gaps in the array, but addresses online insertion and incurs additional space overhead.

In contrast, this work focuses on maintaining sorted order in arrays under batched updates where the indices of modified elements are explicitly available. This update-aware model enables efficient repair without auxiliary data structures, and distinguishes DeltaSort from prior adaptive and incremental approaches.

3 Problem Model

Definition 1 (Update-Aware Sorting). Let $A[0..n-1]$ be an array sorted according to a strict weak ordering defined by a comparator **cmp**. Suppose a set of indices $D = \{d_1, \dots, d_k\} \subseteq \{0, \dots, n-1\}$ is given such that the values at these indices may have been arbitrarily modified, while values at all other indices remain unchanged.

The *update-aware sorting problem* is to restore A to a state that is sorted with respect to **cmp**, given explicit knowledge of the set D .

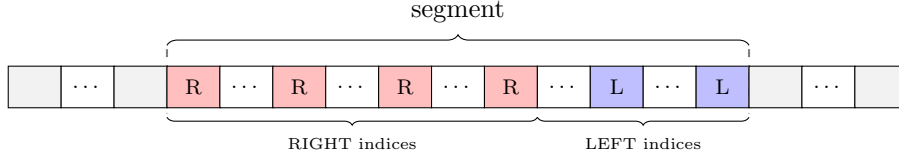
4 DeltaSort Algorithm

4.1 Overview

Definition 2 (Violation). For a dirty index i , we classify its *violation* based on local order:

- **LEFT (L):** Element **must** move left — $\text{cmp}(A[i-1], A[i]) > 0$ (for $i > 0$).
- **RIGHT (R):** Element **may** move right or stay stable. Essentially, all dirty indices that are not LEFT.

Definition 3 (Segment). A *segment* is a *maximal* contiguous subsequence of D (with respect to this ordering) whose elements follow the pattern $(R)^*(L^+ \mid \epsilon)$: zero or more RIGHT violations followed by one or more LEFT violations, or the empty suffix if the sequence ends.



DeltaSort operates in two phases:

1. **Phase 1 (Preparation):** Extract dirty values sort them, write back to dirty positions in index order. This establishes direction segments in the array which are disjoint and can be repaired independently.
2. **Phase 2 (Repair):** Repair each segment left-to-right, deferring RIGHT indices to a stack until the first LEFT index is encountered. Flush and repair the RIGHT indices in stack in LIFO order. Then repair all LEFT indices left-to-right.

4.2 Key Insight: Directional segmentation enables localized repair

The key insight behind DeltaSort is that pre-sorting dirty values induces a *directional segmentation* of updates. After Phase 1, dirty indices partition into disjoint segments of the form $(R)^*L^+$.

Lemma 4 (Movement Confinement). *Element movement is bounded within each segment: no element crosses a segment boundary.*

Proof. Let S be a segment with RIGHT indices R_1, \dots, R_m followed by LEFT indices L_1, \dots, L_p . After Phase 1, dirty values are monotonically ordered by index, so $A[R_1] < \dots < A[R_m] < A[L_1] < \dots < A[L_p]$.

1. *RIGHT elements cannot pass the leftmost LEFT.* Since $A[R_i] < A[L_1]$ for all i .
2. *LEFT elements cannot pass the rightmost RIGHT.* Since $A[R_m] < A[L_j]$ for all j .

Since no element exits its segment, segments can be repaired independently. □

4.3 Detailed Algorithm

Algorithm 1 DeltaSort

Require: Array $A[0..n-1]$, dirty indices D , comparator cmp

Ensure: A is sorted

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1: Phase 1: Prepare
2:  $\text{dirty} \leftarrow \text{sort}(D)$  ▷ Sort indices ascending
3:  $\text{values} \leftarrow [A[d] : d \in \text{dirty}]$ 
4:  $\text{values} \leftarrow \text{sort}(\text{values}, \text{cmp})$ 
5: for  $i \leftarrow 0$  to  $|\text{dirty}| - 1$  do
6:    $A[\text{dirty}[i]] \leftarrow \text{values}[i]$ 
7: end for

8: Phase 2: Repair
9:  $\text{pending} \leftarrow []$ ;  $\text{leftBound} \leftarrow 0$ 
10: for  $p \leftarrow 0$  to  $|\text{dirty}| - 1$  do
11:    $i \leftarrow \text{dirty}[p]$ 
12:   if  $\text{ISLEFTVIOLATION}(A, i)$  then
13:      $\text{FLUSHPENDING}(\text{pending}, i - 1)$  ▷ Fix pending before LEFT
14:      $\text{leftBound} \leftarrow \text{FIXLEFTVIOLATION}(A, i, \text{leftBound}) + 1$ 
15:   else
16:      $\text{pending.push}(i)$  ▷ Defer RIGHT indices
17:   end if
18: end for

19:  $\text{FLUSHPENDING}(\text{pending}, n - 1)$  ▷ Fix remaining RIGHT violations

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1: function  $\text{ISLEFTVIOLATION}(A, i)$ 
2:   return  $i > 0 \wedge \text{cmp}(A[i-1], A[i]) > 0$ 
3: end function

4: function  $\text{ISRIGHTVIOLATION}(A, i)$ 
5:   return  $i < n - 1 \wedge \text{cmp}(A[i], A[i+1]) > 0$ 
6: end function

1: function  $\text{FIXLEFTVIOLATION}(A, i, \text{leftBound})$ 
2:    $t \leftarrow \text{BINARYSEARCHLEFT}(A, A[i], \text{leftBound}, i - 1)$ 
3:    $\text{MOVE}(A, i, t)$ 
4:   return  $t$ 
5: end function

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1: function FLUSHPENDING(pending, rightBound)
2:   while pending  $\neq \emptyset$  do
3:      $s \leftarrow \text{pending.pop}()$  ▷ Process in LIFO order
4:     if ISRIGHTVIOLATION( $A, s$ ) then
5:        $t \leftarrow \text{BINARYSEARCHRIGHT}(A, A[s], s + 1, \text{rightBound})$ 
6:       MOVE( $A, s, t$ )
7:     end if
8:   end while
9: end function

1: function MOVE( $A, from, to$ )
2:    $v \leftarrow A[from]$ 
3:   if  $from < to$  then
4:     Shift  $A[from + 1..to]$  left by one
5:   else if  $from > to$  then
6:     Shift  $A[to..from - 1]$  right by one
7:   end if
8:    $A[to] \leftarrow v$ 
9: end function

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4.4 Correctness Proof

Claim 5 (Segment Boundary Invariant). Segment boundaries are never violated. For any two consecutive segments S_i and S_{i+1} , all values in S_i remain less than all values in S_{i+1} throughout the repair process.

Proof sketch. After Phase 1, dirty values are monotonically ordered by index. A segment boundary occurs where a LEFT dirty index is followed by a RIGHT dirty index. At such a boundary, the RIGHT element satisfies $A[d_{i+1}] \geq A[d_{i+1} - 1]$, establishing sorted order. By Lemma 4, movement is confined within segments, so boundaries remain intact. A fully rigorous proof is deferred to future work. \square

Lemma 6 (Fixing Does Not Introduce Violations). *When a LEFT or RIGHT element is moved to its correct position via binary search, no new violations are introduced.*

Proof. LEFT fix: Binary search finds position $t < i$ where the element belongs. Elements in $A[t..i - 1]$ shift right by one. The shift preserves relative order. By binary search, the moved element satisfies $A[t - 1] \leq A[t] < A[t + 1]$.

RIGHT fix: Binary search finds position $t > s$ where the element belongs. Elements in $A[s + 1..t]$ shift left by one. The shift preserves relative order. By binary search, the moved element satisfies $A[t - 1] < A[t] \leq A[t + 1]$.

In both cases, no new violations are introduced. \square

Theorem 7 (Correctness). *DeltaSort produces a correctly sorted array.*

Proof. Phase 2 processes each dirty index exactly once, fixing its violation if any. By Lemma 6, each fix resolves a violation without introducing new ones. After all dirty indices are processed, each segment is internally sorted.

By Claim 5, segment boundaries maintain sorted order throughout. Since each segment is internally sorted and boundaries preserve global order, the entire array is sorted. \square

4.5 Algorithm Analysis

Theorem 8 (Time Complexity). *DeltaSort runs in $O(k \log k + k \log n + M)$ time, where M is total movement.*

Proof. **Phase 1:** Sort k indices: $O(k \log k)$. Sort k values: $O(k \log k)$. Write back: $O(k)$.

Phase 2: Each dirty index: $O(1)$ direction check, $O(\log n)$ binary search. Total: $O(k \log n)$. Movement: $O(M)$. \square

Theorem 9 (Space Complexity). *DeltaSort uses $O(k)$ auxiliary space.*

Proof. Phase 1 stores k dirty indices and k dirty values. Phase 2 maintains a pending stack of at most k indices. No $O(n)$ auxiliary structures are required. \square

Remark 10 (Movement Efficiency). While worst-case movement is $O(kn)$, the segmentation created by Phase 1 tends to reduce movement in practice in the average case. Empirical results in §5 demonstrate substantial speedups, validating that movement is typically much less than the worst case.

Here we compare algorithm complexity with other standard baseline approaches which we use in experiments to compare DeltaSort’s performance:

- **NativeSort (NS):** Re-sort the array using the natively available sort function. $O(n \log n)$ comparisons and movements.
- **Binary-Insertion-Sort (BIS):** Extract dirty values, then for each: binary search for correct position, reinsert. $O(k \log n)$ comparisons, $O(kn)$ worst-case movement. Searches the full array range for each insertion.
- **Extract-Sort-Merge (ESM):** Extract dirty values, sort them, merge with clean elements. $O(k \log k + n)$ comparisons, $O(n)$ movement. Requires $O(n)$ auxiliary space.

Table 1: Algorithm complexity comparison.

Algorithm	Comparisons	Movement	Space
NativeSort	$O(n \log n)$	$O(n \log n)$	$O(n)$
Binary-Insertion-Sort	$O(k \log n)$	$O(kn)$	$O(1)$
Extract-Sort-Merge	$O(k \log k + n)$	$O(n)$	$O(n)$
DeltaSort	$O(k \log n)$	$O(kn)^*$	$O(k)$

*Worst case; average case is closer to $O(n)$.

5 Experimental Evaluation

All experiments are run using a Rust implementation of DeltaSort [4] on a synthetic dataset of user objects with composite keys (country, age, name) on a M3 Pro Macbook Pro with 18GB RAM. DeltaSort is compared against three baselines: NativeSort (Rust’s `sort_by`), Binary Insertion Sort (BIS), and Extract-Sort-Merge (ESM).

5.1 Correctness

Correctness is verified by an extensive set of randomized unit tests [4] across various scales and update sizes. The test routine generates a sorted base array of size N , applies k random updates at random indices, runs DeltaSort, and asserts that the final array is sorted and contains all original elements with updated values. All tests pass successfully.

5.2 Execution Time

The graph below shows execution time (in microseconds) for $n = 50,000$ elements as a function of dirty count k . DeltaSort consistently outperforms all alternatives up to approximately $k = 15K$ (crossover point), achieving significant speedups of 6–20 \times over Native sort in the intermediate range. Also note the orders-of-magnitude gap between DeltaSort and the baseline incremental algorithms (BIS and ESM) across the full range of k values.

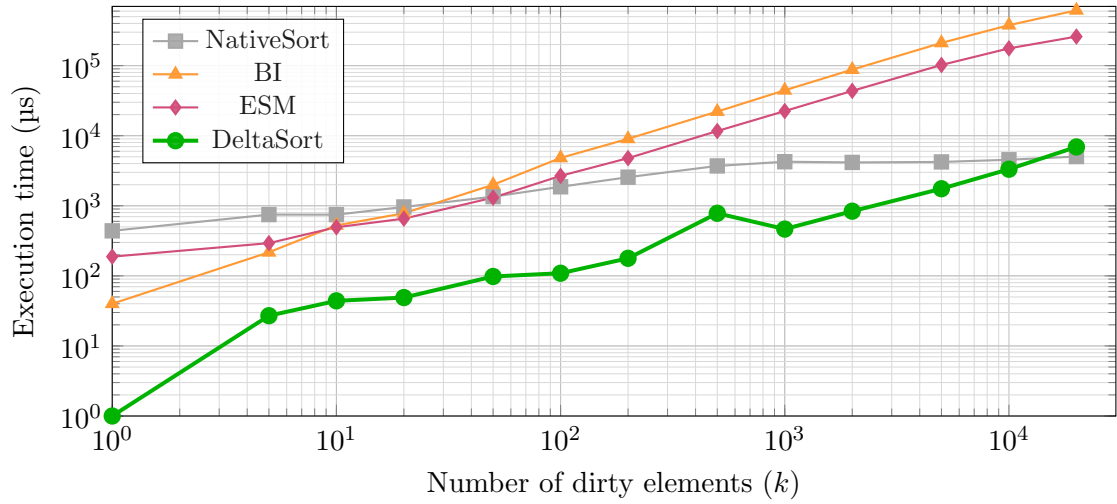


Figure 1: Execution time comparison of all algorithms for $n = 50,000$ (log-log scale)

5.3 Comparator Invocation Count

The following chart shows the number of comparator invocations for each algorithm. DeltaSort and BIS both achieve $O(k \log n)$ comparisons, substantially fewer than Native Sort’s $O(n \log n)$ and ESM’s $O(k \log k + n)$. The comparison counts for DeltaSort are 10–40% higher than BIS, indicating that DeltaSort’s performance advantage comes from reduced data movement.

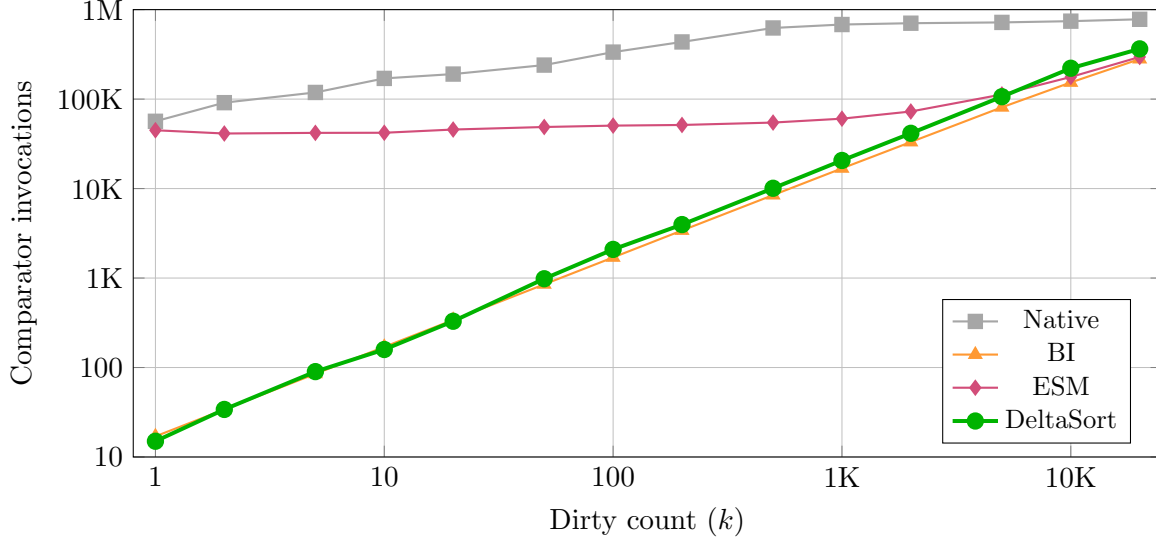


Figure 2: Comparator invocation count for $n = 50,000$ elements. DeltaSort and BI both achieve $O(k \log n)$ comparisons, while Native uses $O(n \log n)$ regardless of k , and ESM uses $O(k \log k + n)$. The similar comparison counts for DeltaSort and BI confirm that DeltaSort’s speedup derives from movement efficiency, not fewer comparisons.

5.4 Crossover Threshold Analysis

A key practical question is: at what delta size should one switch from DeltaSort to Native sort? A binary search was conducted for the crossover point k_c across array sizes from 1K to 10M elements.

Figure 3 visualizes how the crossover ratio k_c/n varies with array size. The ratio peaks around 31% for medium-sized arrays ($n \approx 50K$) and declines for very large arrays, suggesting that DeltaSort’s advantage narrows as arrays grow very large. More study is needed to understand this trend fully.

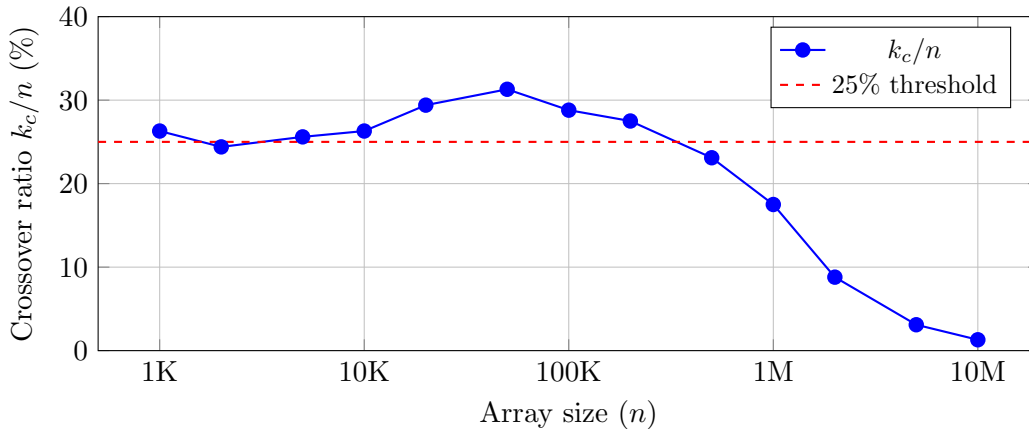


Figure 3: Crossover ratio k_c/n as a function of array size. DeltaSort outperforms Native sort when the dirty fraction is below this curve. The 25% rule of thumb (dashed line) is conservative for small-to-medium arrays but optimistic for very large arrays where the crossover drops significantly.

The key takeaway is that DeltaSort is beneficial for **large** ranges of update sizes. So DeltaSort

remains a viable choice even when delta sizes are large. The exact threshold depends on the scenario specifics (array sizes, data types, comparator cost, etc.) but the results suggest that a **25% dirty fraction** is a reasonable rule of thumb for the upper limit of delta size before which DeltaSort remains advantageous.

5.5 Performance in managed execution environments

DeltaSort was also implemented in JavaScript [4] running on Node.js v20 (V8 engine). While the implementation passes all correctness tests, the performance results show higher variance due to JIT compilation behavior, garbage collection pauses, and other engine-level effects. The JavaScript benchmarks will be refined in a future revision to provide more stable measurements. The Rust implementation provides the authoritative performance characterization.

6 Future Work

This work suggests several directions for future investigation:

- **Stronger theoretical characterization:** While the correctness argument and extensive randomized testing establish that DeltaSort produces a correctly sorted array, certain invariants—particularly those governing inter-segment boundaries—deserve a more formal treatment that could yield sharper theoretical guarantees.
- **Average-case movement bounds:** Beyond worst-case correctness and empirical evaluation, establishing average-case bounds on data movement under reasonable update distributions will help explain observed speedup and crossover behavior and clarify when segmented repair is most effective.
- **Structured workload analysis:** The current evaluation relies on randomized updates, whereas many real workloads exhibit additional structure, such as gradual value changes in leaderboards or localized updates in interactive list views. Studying such patterns may reveal regimes where DeltaSort’s advantages are amplified or diminished.
- **Runtime variance analysis.** Performance variance in managed runtimes warrants deeper investigation. Understanding the impact of factors such as memory allocation, garbage collection, and JIT compilation could improve result interpretability and guide implementation choices.
- **Block-structured storage.** Although this work focuses on in-memory arrays, the update-aware model naturally extends to block-structured storage. Exploring how DeltaSort-style segmentation interacts with page- or block-based layouts may clarify its applicability to database and external-memory settings.

7 Conclusion

This paper introduced *DeltaSort*, an incremental repair algorithm for maintaining sorted arrays under batched updates. The central insight is that pre-sorting updated values induces *directional segmentation*: dirty elements naturally partition into segments that can be repaired independently.

DeltaSort leverages this segmentation through stack-based processing. LEFT-moving elements are repaired immediately with progressively narrowed search ranges, while RIGHT-moving elements

are deferred and processed in reverse order to ensure stable target positions. This segmentation avoids redundant comparisons and overlapping element movement that arise from repeated binary insertion.

An experimental evaluation in Rust demonstrates that DeltaSort consistently outperforms both blind native sorting and repeated binary insertion across a wide range of array sizes and update volumes. In practice, DeltaSort remains advantageous until approximately 25% of the array is dirty, providing a clear and actionable decision boundary.

More broadly, this work highlights the value of integrating application-level update information into core algorithms. When sorting routines are informed of which elements changed, batching and segmentation becomes possible, enabling performance improvements that blind algorithms cannot realize. DeltaSort illustrates how modest structural insight—segmentation combined with disciplined processing order—can yield substantial practical gains.

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