A cost-aware strategy for merging differential stores in column-oriented in-memory DBMS

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Outline

- Preliminaries
- Value Distrib. in Enterprise Data
- Partial Merge Algorithm
- Evaluation

Motivation and Mission

Context of this work:

 SAP and HPI are working on consolidation of analytical and transactional workloads in a single column-oriented in-memory DBMS

Current Setting:

- Column-oriented DBMSs favor analytical queries, while write operations on read-optimized column structures are expensive
- Common solution: maintain a write-optimized delta structure in addition to the read-optimized structure (e.g., in C-Store, MonetDB, NewDB, HyRise)

General Problem:

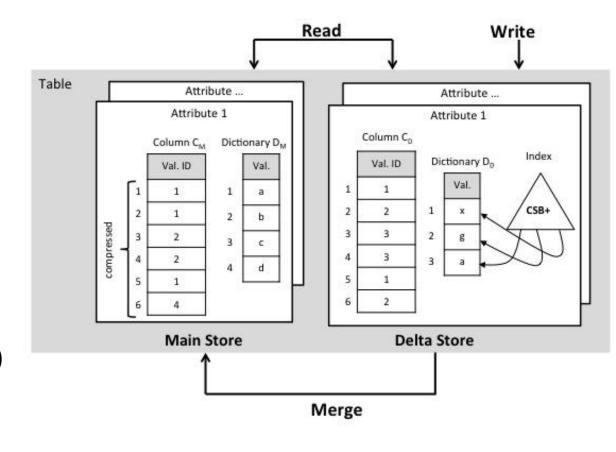
- Both structures must be merged for read performance and memory consumption
- Merging both structures induces substantial write overhead
- This work contributes on how to optimize this merge process

System Model and Data Structures

Tables consist of a main store (read-optimized) and delta store (write-optimized)

Main store:

- Sorted dictionary D_M
- Column data C_M is a vector of valueIDs
- valueIDs are defined
 by value position in D_M
- Compression
- Delta store:
 - Dictionary D_D is unsorted
 - Index (CSB+) is used for valueID lookup in $log(|D_{D}|)$
 - No compression but dictionary



Large delta store sizes compromise overall read performance and space consumption

Decreasing range select performance

- Range selects need an additional calculation and indirection in order to be answered for the delta store
- They can be calculated directly on valueIDs within the main store

Less efficient compression of data in delta structure

Run-length encoding, common value suppression, cluster coding, ...

Increasing size of index for delta dictionary

- CSB+-tree needed for fast lookups in unsorted delta dictionary while the main store's sorted dictionary allows for binary search directly -> additional space consumption
- For large delta dictionary sizes $|D_D|$ gains overall impact

Outline

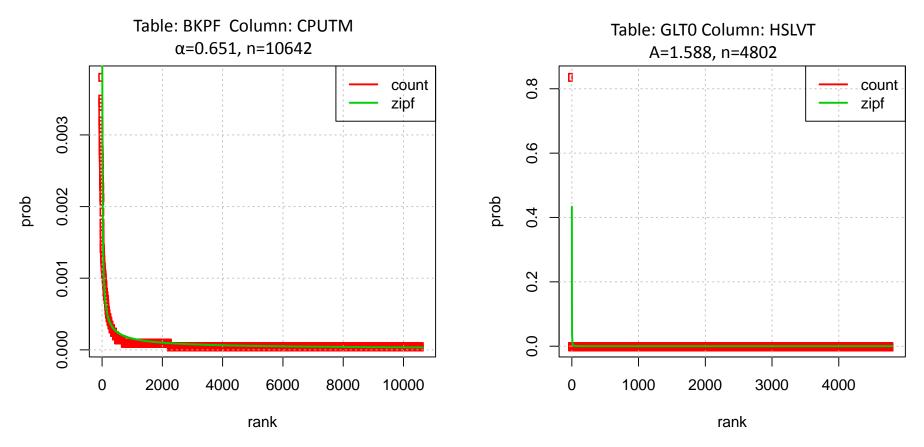
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Distribution of Values in Enterprise Data

- We analyzed 1864 attributes (i.e. columns) from two SAP customer's Financial and Sales Distribution module of SAPs Business Suite
 - Count distinct values & create histograms
 - Match against PDFs for fixed domains
 - ZIPF distribution or
 - Uniform distribution
 - Ignore ID columns and single-value columns

PDF	Fraction	Parameter
zipf	21.03%	α_{min} =0.001, α_{Q2} =1.581, α_{max} =4.884
uniform	20.02%	k _{min} =2, k _{Q2} =5, k _{max} =216
single value or key	58,95%	-

Distribution of Values in Enterprise Data (Examples)



Zipf: most frequent values have a high probability to exist in D_M

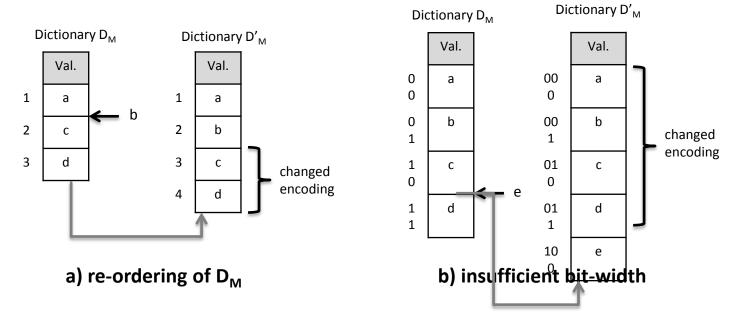
→ Data characteristics support partial merge strategy!

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Full Merge – High complexity

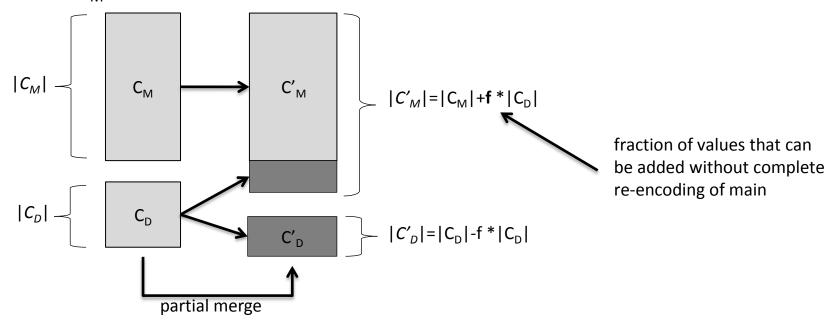
- Merging all delta values:
 - Complexity in $O(|C_M|+|C_D|)$ if dictionary encoding changes
 - Change of dictionary encoding necessary if:
 - a) Main dictionary D_M is re-ordered (with high probability)
 - b) Bit-width of D_M not sufficient any more



Merge operation induces significant write overhead!

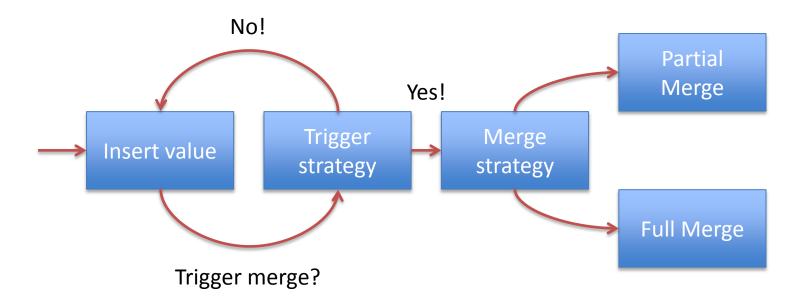
Partial Merge – Reduced Complexity

- *Idea*: Merge only those values, that don't cause event (a), i.e., don't change the existing main encoding
 - Only add values from the delta that exist already in D_{M} or do not cause re-ordering of D_{M}



- Complexity now in $O(|C_D|)$ instead of $O(|C_M|+|C_D|)$ with $|C_D| << |C_M|$
- Expected size of fraction f depends on PDF of distinct values

The Partial Merge Algorithm



- Continuous process with 2 decisions
 - Does the status of the delta store require a merge?
 - Is it feasible to conduct a partial merge?
- Strategies are aware of the read cost overhead and merge cost

Triggering Merge Operations possible with respect to cost

Fraction of optimum (fro) strategy:

- Trigger a merge after n-th insert, if current worst case select costs reach a defined distance f_{opt} from the theoretically opt. cost ($|C_D|=0$) (selectCost^{opt}(n))

$$selectCost(n) > f_{opt} \cdot selectCost^{opt}(n)$$

Since selectCost(n) and selectCost^{opt}(n) are only defined by current size
of the data structures, both can be easily computed at runtime

Other strategies possible

- Space consumption-aware
- Workload aware

– ...

Cost-based decision on Partial Merge guarantees upper bound on overhead

- Values that remain in delta still cause performance overhead
 - When is this too much?
- Cost aware strategy (coa): decide on merge strategy based on the possible improvement of worst case range select cost
- Partial merge is executed, if worst case range select cost after a partial merge (selectCost_P) are comparable to optimal cost after a full merge (selectCost_F), i.e. if:

$$selectCost_P \leq f_{to} \cdot selectCost_F$$

with f_{to} being a factor representing the tolerated overhead

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Evaluation

- Simulation of inserts (sampled from observed PDFs)
- Measure after every inserted value
 - selectCost(n): worst case range select
 - insertCost(n): amortized write cost (including potential merge)

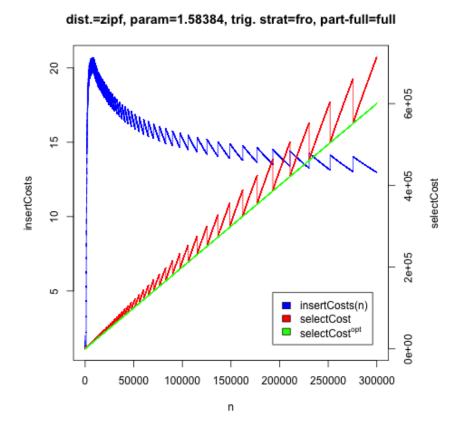
$$insertCost(n) = \frac{\sum_{i=0}^{n} writes(v_i)}{n}$$

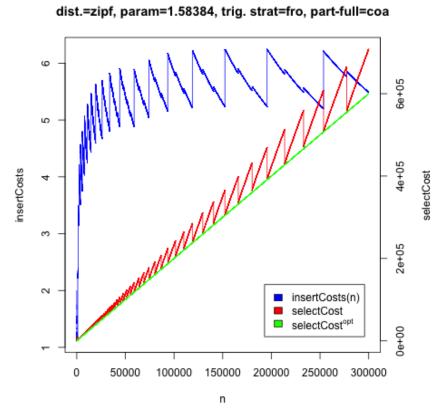
with writes(v_i) = #write operations required to insert v_i

Evaluation (1/3) – Zipf distributed distinct values

Full merge (always):

Partial merge (when possible):



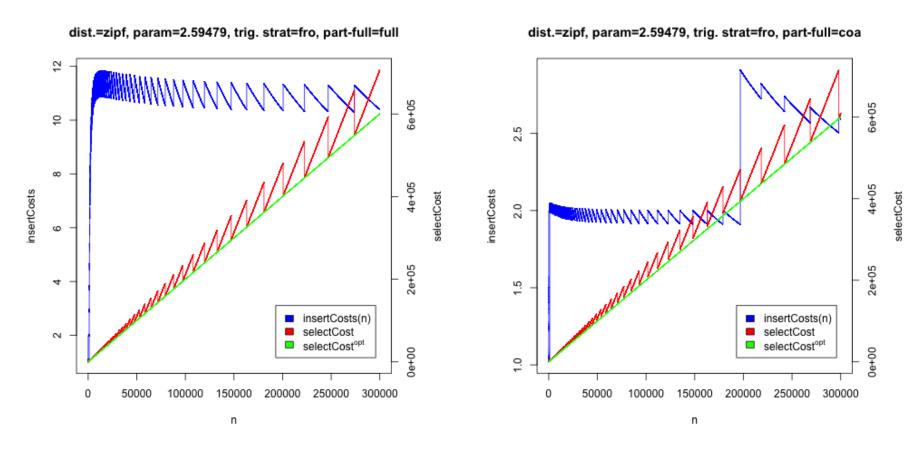


Amortized insert performance improved > 100%

Evaluation (2/3) – Zipf distributed distinct values

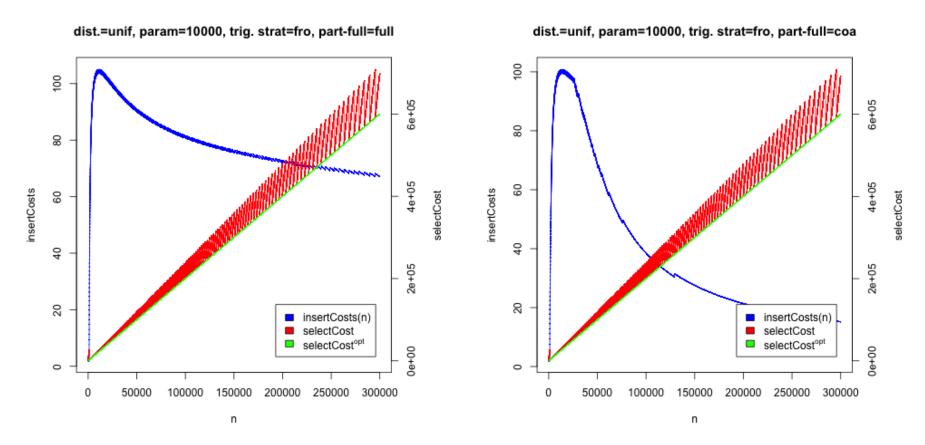
Full merge (always):

Partial merge (when possible):



Amortized insert performance improved > 400%

Evaluation (3/3) – Uniformly distributed distinct values Full merge (always): Partial merge (when possible):



Amortized insert performance improved about 400%

Future Work

- Analyze potential for tables (vs. single columns)
- Find more sophisticated strategies for trigger and merge
- Take workload into account (and find cost minima)
- Analyze more customer data
- Implement for existing DB prototypes

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Thank You!