Skipping-oriented Partitioning for Columnar Layouts

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Overview

- Introduced to Generalized Skipping Oriented Partitioning (GSOP): a hybrid data skipping framework that takes into account row-based and column-based store tradeoffs with partitioning data
  - GSOP generalizes the original SOP framework by removing the atomic-tuple constraint

Importance

- As data volumes continue to grow, data skipping mechanisms become more critical to improve performance in modern analytics databases and the Hadoop ecosystem
- Need a method of data skipping that is optimized for column-based stores rather than just row-based stores
- Finds balance between tuple reconstruction and skipping effectiveness

Vocab

- ***Tuple***: A single row of a table, which contains a single record for that relation
- ***Block***: tens of thousands of tuples, how data is organized
- ***Feature***: representative filters which can span many columns
- ***Feature Vector***: characterization of tuple
- ***Feature Conflict***: when the best partitioning schemes for different features do not overlap, happens often with complex workloads
- ***Tuple reconstruction***: the process of assembling requested column values back into tuples during query processing
- ***Data cell:*** each individual column value of a tuple

General Comparison SOP vs. GSOP

(a) original data (b) a SOP scheme (c) a GSOP scheme

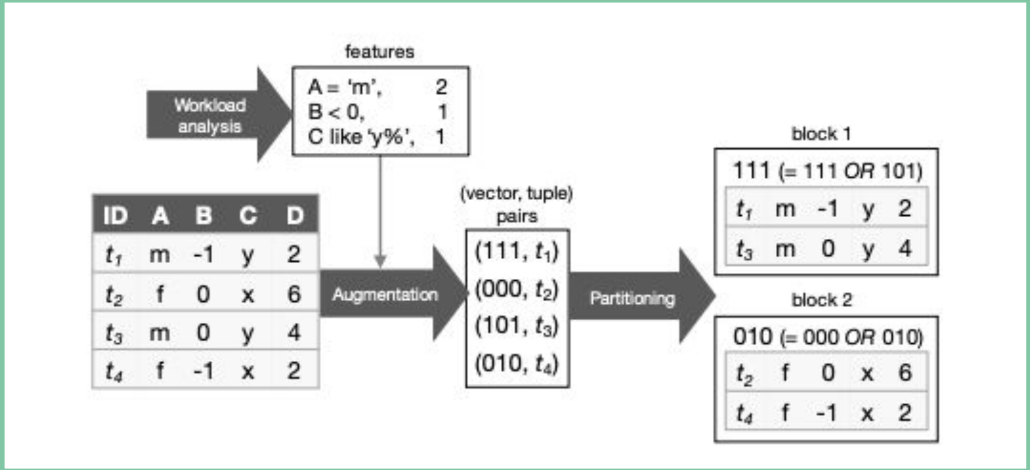
- Ex. two features to be extracted: F1: grade == ‘A’ and F2: year > 2011 AND course = ‘DB’
  - F1 – t1,t2 | t3, t4 (separate A’s from rest of rows)
  - F2 – t1,t4 | t2, t3 (separate year 2011 and separate DB’s)
- SOP produces only monolithic horizontal partitioning schemes, viewing every tuple as an ***atomic*** unit. This can result in ***feature conflicts.***
- GSOP solves feature conflicts, but can result in ***tuple reconstruction***.

SOP Framework

Based on two properties:

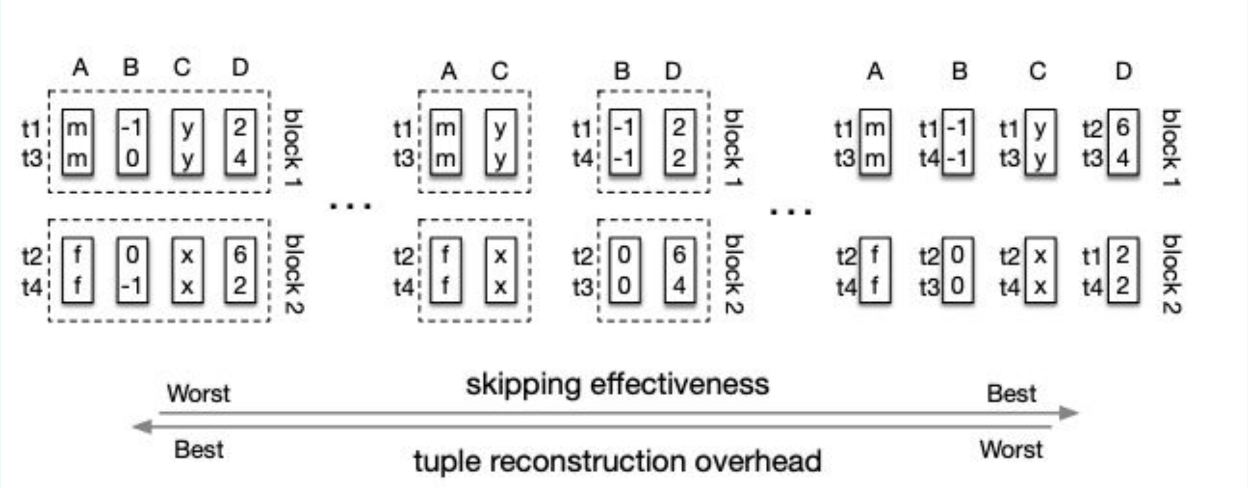
1. **Filter Commonality:** a small set of filters are commonly used by many queries (10% of filters used by 90% of queries)
    - Designing data layout based on small number of filters can benefit most queries
2. **Filter Stability**: a tiny fraction of query filters are newly introduced over time
    - Designing data layout based on past query filters can benefit future queries

Steps of SOP



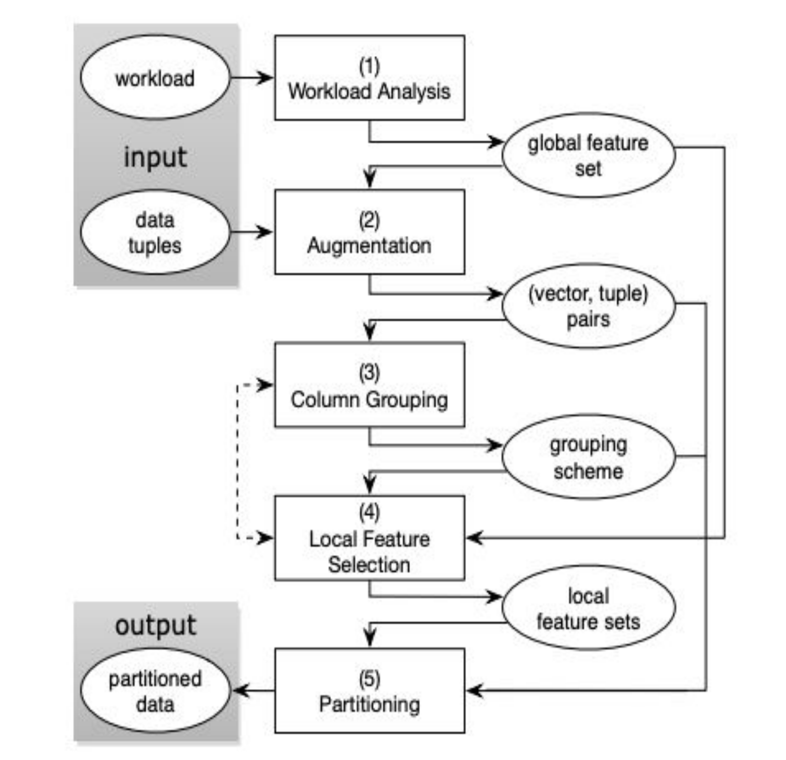
1. Workload Analysis
   - Extracts features using frequent item-set mining
   - ***Subsumption relations***
2. Augmentation
   - Data are scanned for given features and results stores in augmented ***feature vector***
3. Partitioning
   - Group vector, tuple pairs into vector, count pairs
   - Clustering algorithm generates ***partition map***
   - Each block gets a ***union map***

Partitioning Spectrum



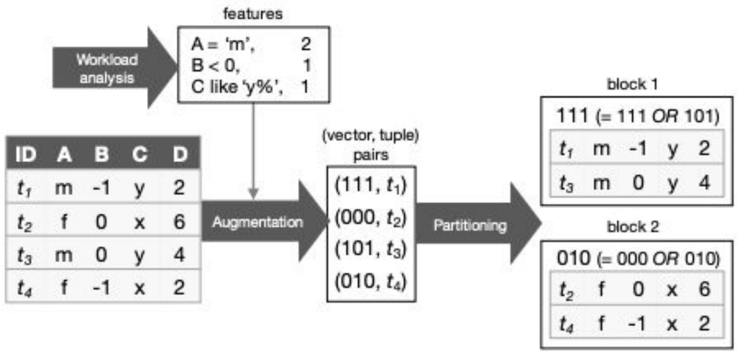
- Right end: partition each column individually, mitigates feature conflicts, introduces overhead for tuple reconstruction
- Left end: SOP framework, no separation of columns, no tuple reconstruction, a lot of feature conflicts
- Ex. SELECT B, D FROM T WHERE B<0 and D=2

GSOP Framework



1. Workload Analysis
   - ***Global features***
2. Augmentation
   - ***Global feature vector***
3. Column Grouping:
   - Divide columns into column groups based on ***objective function*** based on tradeoff
4. ***Local Feature*** Selection
   - Select subset of global features
   - Crucial step for skipping effectiveness
5. Partitioning
   - ***Local feature vectors***
   - Project global feature vectors to keep bits of local features

Column Grouping



Ex. Consider following workload:

Q1: SELECT A, C FROM T WHERE A = 'm'

Q2: SELECT B, D FROM T WHERE B < 0

Q3: SELECT B, C FROM T WHERE C like 'y%'

- AC, BC, BD equal weight of being grouped
- Need to account for filters
- T1, t3 both satisfy Q1 and Q3
- T2, t4 do NOT satisfy Q1 or Q3
- Prefer to group AC

Column Grouping Equations

Skipping Effectiveness:

$$\sum_{G_i \in \mathbb{G}^q} |G_i \cap C^q| \cdot r_i^q.$$

Objective Function:

$$\mathsf{COST}(q, \mathbb{G}) = \sum_{G_i \in \mathbb{G}^q} |G_i \cap C^q| \cdot r_i^q + \mathsf{overhead}(q, \mathbb{G})$$

$$\mathsf{COST}(W, \mathbb{G}) = \sum_{q \in W} \mathsf{COST}(q, \mathbb{G})$$

Tuple Reconstruction Overhead:

$$\mathsf{overhead}(q, \mathbb{G}) = \begin{cases} \sum_{G_i \in \mathbb{G}^q} (r_i^q + \mathsf{sort}(r_i^q)) & \text{if } |\mathbb{G}^q| > 1 \\ 0 & \text{otherwise} \end{cases}$$

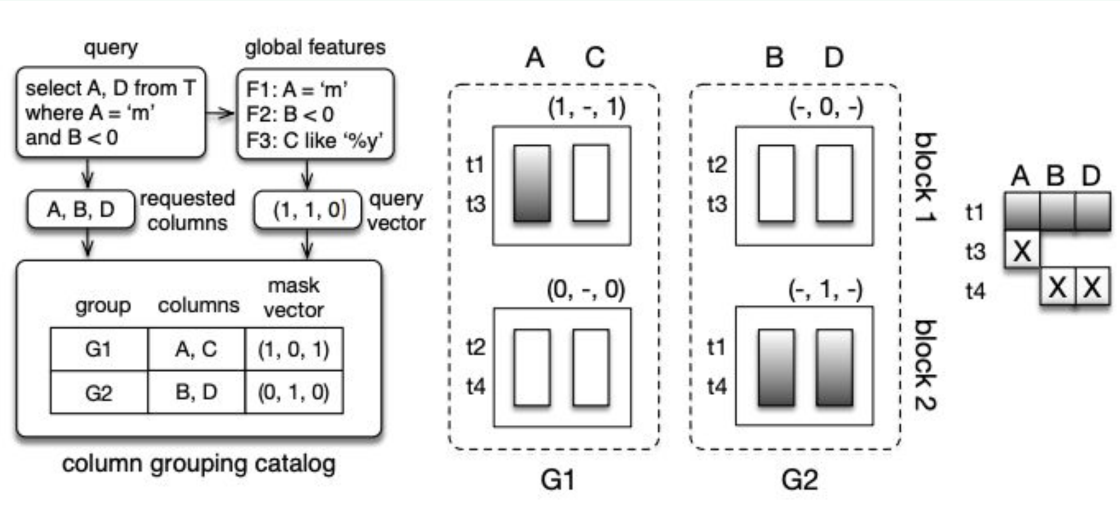
Efficient Cost Estimation

- Difficult to obtain the number of rows that a query needs to scan after skipping in a G_i
- Exact computation is extremely expensive, propose more efficient estimation
    - Huge cost bottleneck from applying partitioning to G_i, clustering problem
- Use selectivity of query q as an estimation of the r value
    - Not accurate if query has a highly selective predicate
- Need to account for block-based skipping mechanism
    - exploit a simple property of partitioning process-- preference to put rows with exactly same local feature vectors into the same block

Local Feature Selection

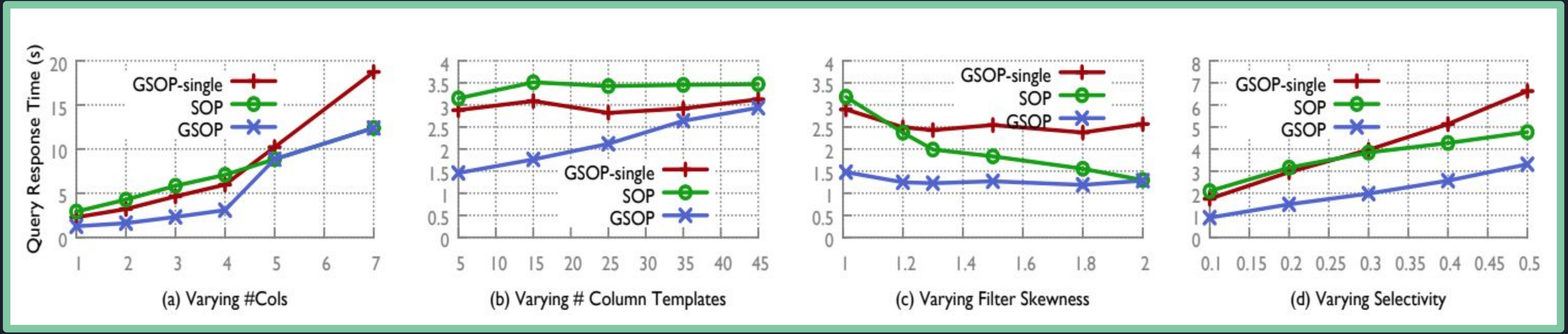
- Identifying Candidate Local Features:
  - CandSet(G) = $\cup_{q \in W^G} F^q$
  - F^q = features that subsume query q
  - W^G = set of queries that need to access data in column group G
- Feature Weighting and Selection:
  - Weight for local feature decided by importance in column group, not on all columns
  - weight(G, f) = $|\{q \mid f \in F^q \text{ and } q \in W^G\}|$ (f = given feature)
  - Number of distinctive feature vectors is a good indicator of whether the number of features selected is appropriate
    - Too few: add more features, does not affecting skipping of existing
    - Too many: existing features are very conflicting

Query Processing



1. Reading Data Blocks:
   - Check query against global features
   - Extract columns and pass to column catalog
   - Go through data blocks with union vectors
   - Read A from G1 and B, D from G2
2. Tuple reconstruction:
   - Tuple-ids stored as column within each block
   - Sort columns based on ids
   - Only return tuple t1, because t3 and t4 do not satisfy the full query

Results of Query Performance (Big Data)



- Figure a: vary parameter k (number of columns accessed)
  - As k increases, cost of GSOP-single increases, GSOP becomes SOP (70% accessed)
- Figure b: vary parameter t (number of column templates)
  - GSOP outperforms GSOP-single and SOP, especially at low t
- Figure c: vary parameter z (skewness of filter usage)
  - Greater z, less feature conflict, SOP can eventually outperform
- Figure d: vary parameter s (query selectivity)
  - Increase s results in higher execution cost for all 3, GSOP outperforms, single is worst

Results of Query Performance (TPC-H)

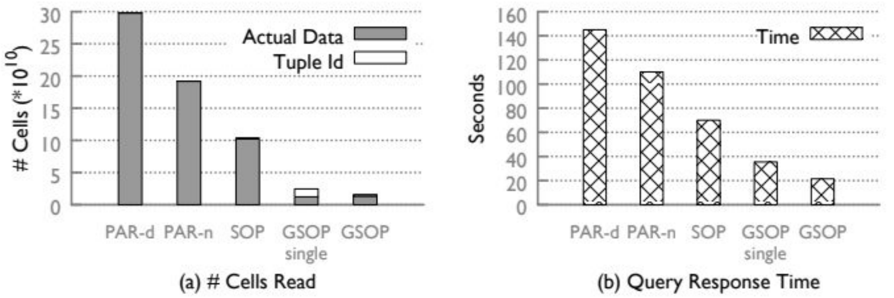


Figure 7: Query performance (TPC-H)

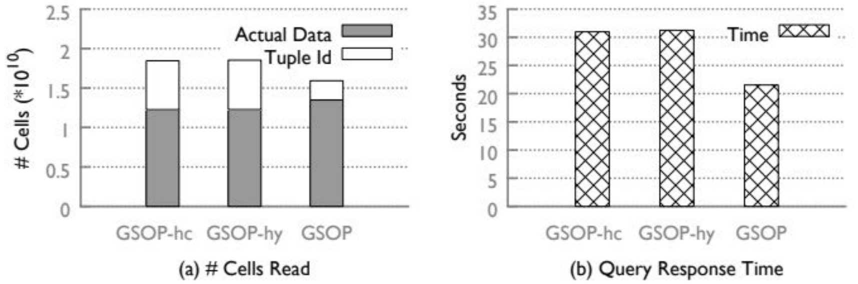


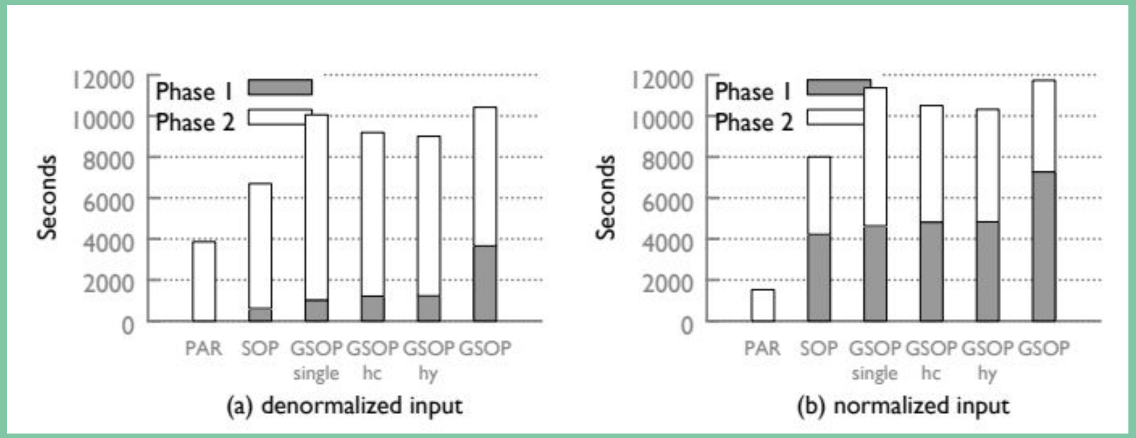
Figure 8: Query performance (TPC-H).

- Fig 7a: measure average number of actual data cells and tuple ids read by a test query
- Fig 7b: we show the end to end query response time.
- Fig 8a: forming smaller number of column groups results in less reads of tuple ids for GSOP while reading slightly more data
- Fig 8b: proposed column grouping techniques can balance the trade-off in GSOP better than GSOP-hy and GSOP-hc (35% better)

Objective Function Evaluation (TPC-H)

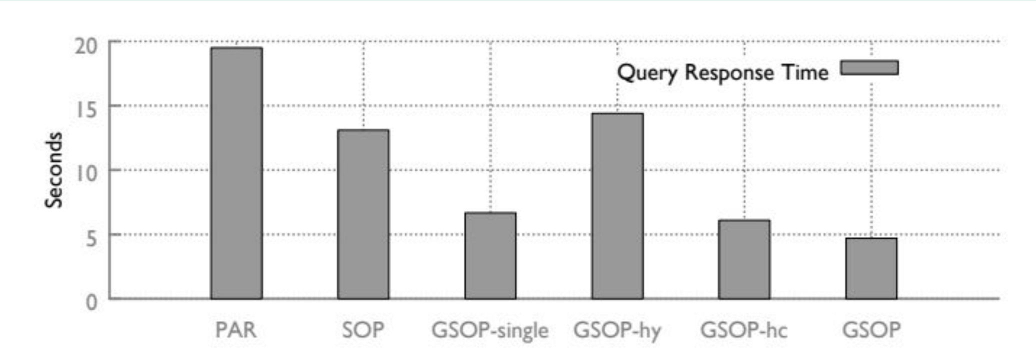
- Figure a: Efficiency comparison based on running time for different estimation approaches
  - Full computation is extremely time consuming compared to the estimations (a full day)
  - Sel. est. and Block est. take approximately the same amount of time (44 mins)
- Figure b: Quality comparison of different approaches based on workload cost
  - Sel. Est. involves most workload cost
  - Block est. only slightly more costly that full compt, thus the best choice

Loading Cost (TPC-H)



- Figure a: denormalized
  - GSOP spends most time in Phase 1
  - SOP has cheapest phase 2
- Figure b: normalized
  - Extra step of partial denormalization for GSOP
  - GSOP takes 2.6 times longer than the baseline
- Regardless, GSOP outperforms the other approaches
  - Worth the initial cost?

Query Performance (SDSS)



- Average query response times of 600 test queries against a baseline approach
- GSOP-hy and GSOP-hc are highly unreliable (do not take into account feature conflict or horizontal skipping)
- GSOP outperforms baseline by 4.7 times and outperforms SOP by 2.7 times

Evaluation

PROS:

- Good explanation of background & SOP framework
- Solid proof of better performance against multiple existing frameworks

CONS:

- Simplistic explanation of cost for trade-off -- does not explore impact of compression techniques
- Include more figures rather than refer to the same ones
- Need more experimentation comparing running time costs to overall performance improvements

Possible Next Steps

- Look into a dynamic layout for complex workloads that constantly change
- Can we change the layout of data to optimize the ideal case where tuple overhead is 0 and skipping is effective?
- Explore better ways to handle normalized data-- some way to avoid the step of partial denormalization?