Index Estimation on column-oriented database

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September 9, 2025

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Background and motivation

Why column-oriented storage

- Traditional models store information row by row on disk.

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Hence, column-oriented databases are used mostly in analytical workloads (finance, e-commerce, data analysis, ...).

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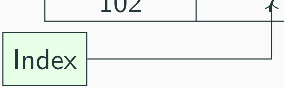


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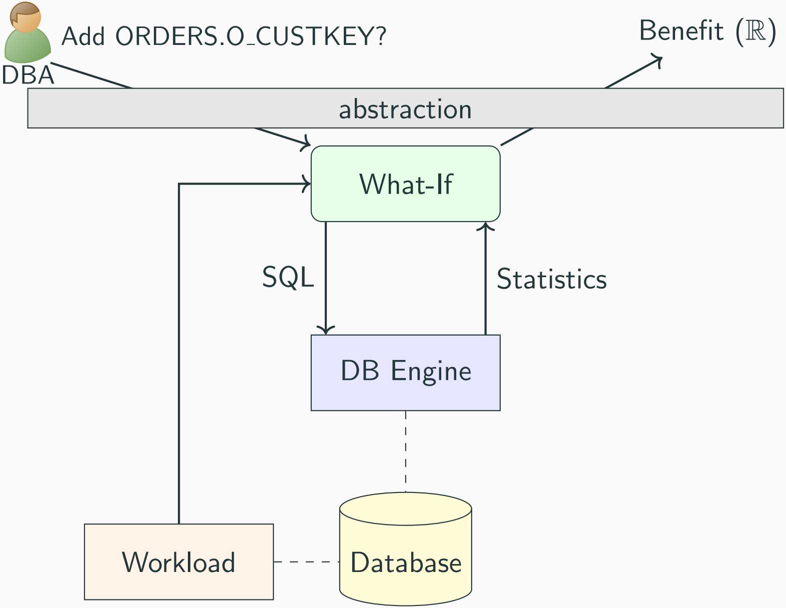
How to know if we should build an index ?

What-If Hypothetical Index Estimation



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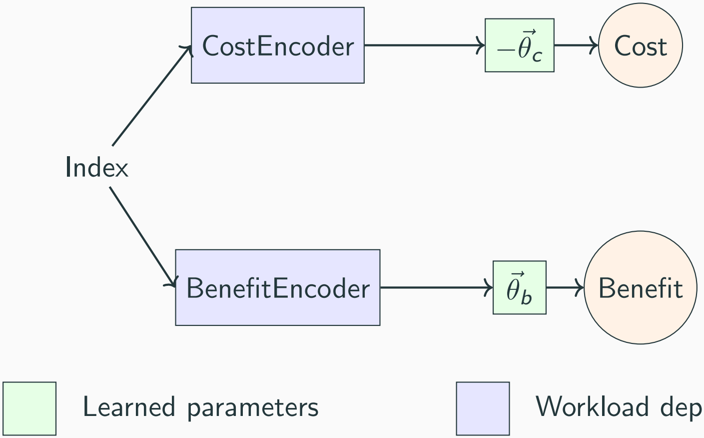
As this is the first work for column-oriented database, we want to provide a foundation that is: heuristics-based, extendable and tunable.

Hypothetical Index Benefit Estimation - Overview

QHICS benefit model

Quantile **H**ypothetical **I**ndex for **C**olumn-oriented **S**torage



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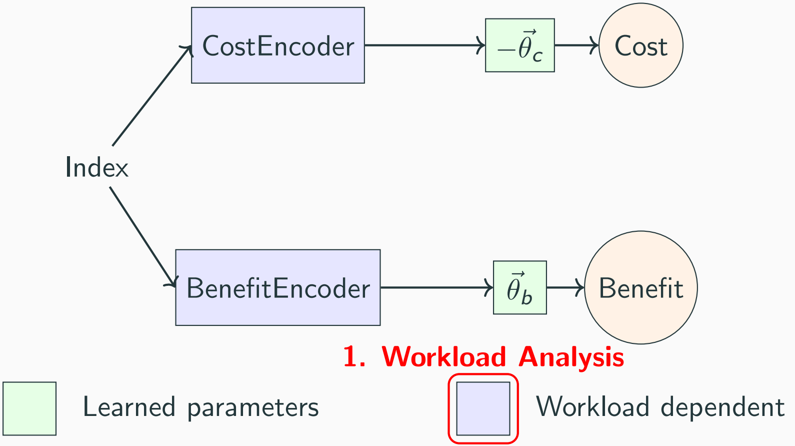

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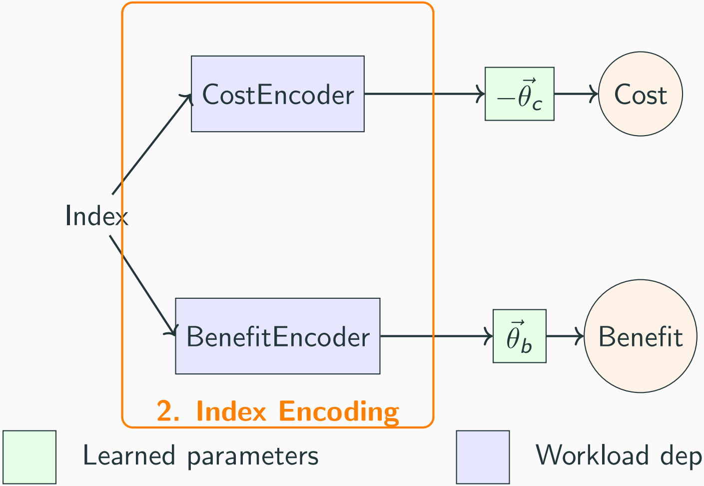

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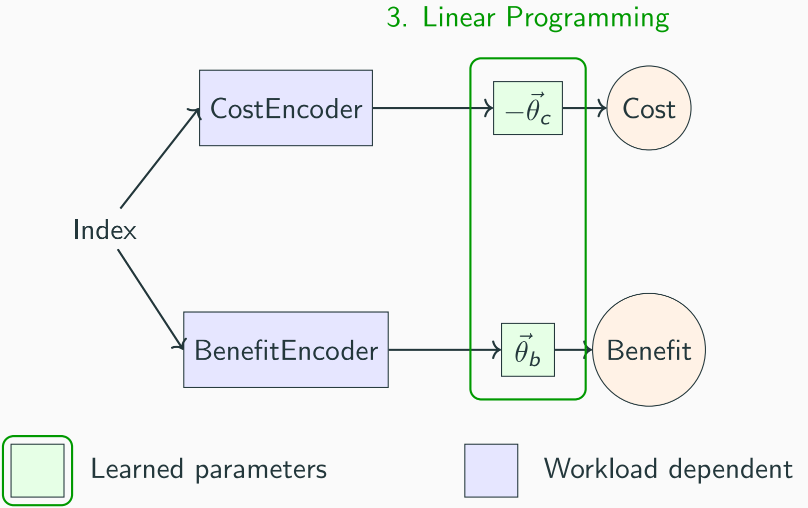
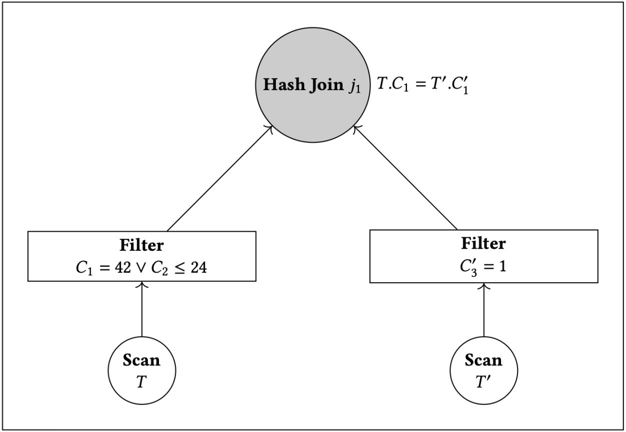


Workload Analysis

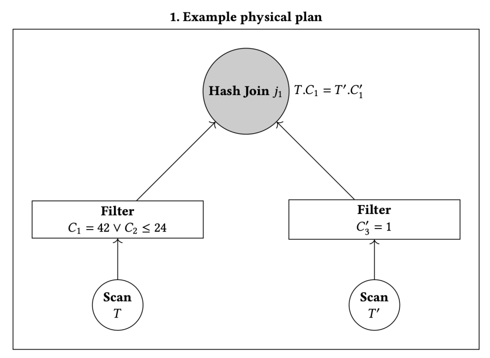
Given a query plan, analyze it and return objects that can be used to estimate the benefit of an index.

1. Example physical plan



What can be accelerated ?

Hash index are used to accelerate predicate checking (e.g. equality).



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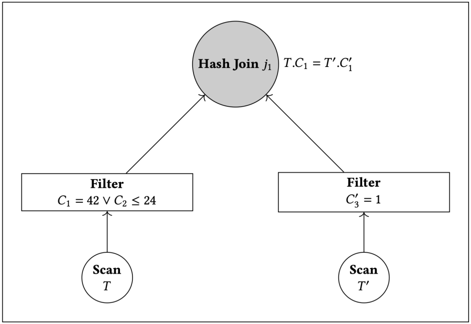

Hence, we estimate the difference of resource consumptions in access paths with and without new index.

Scan without index

Each column is cut in segments, each columnar segment stores min/max metadata.

A	B
[5,450]	[3,3]
[3,500]	[1,5]
[291,299]	[3,8]

```
SELECT * FROM T WHERE A <= 270 AND B = 2
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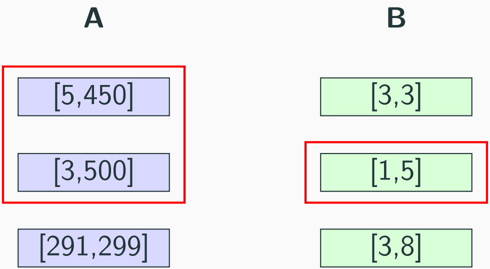


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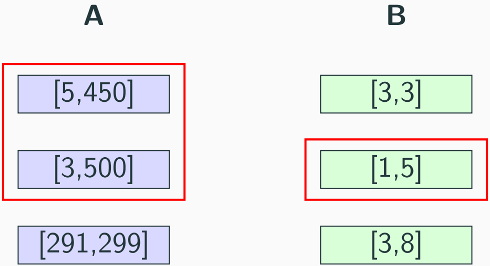


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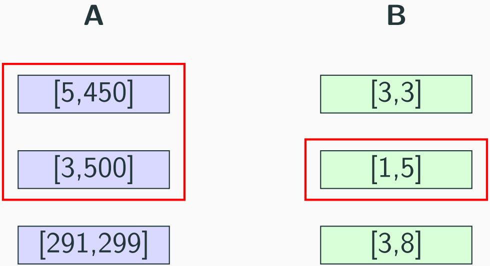


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To estimate the scan cost, we need an estimation of the hit factor.

Hit Factor Approximation

Let $h_C(v)$ for $v \in \texttt{Dom}(C)$ be the percentage of segments needed to get all rows with value v.

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Now we can use F-algebra:

- For two predicates p_1, p_2, $h(p_1 \wedge p_2) = h(p_1) \times h(p_2)$
- For two predicates p_1, p_2, $h(p_1 \vee p_2) = h(p_1) + h(p_2) - h(p_1) \times h(p_2)$
- For a predicate p_1, $h(\neg p_1) = 1 - h(p_1)$.

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We compute a map

$$\texttt{table} \mapsto \mathit{list}\left[\overbrace{\overbrace{\left(\texttt{col} \mapsto \texttt{list(Scan)}\right)}^{\text{Per operator}}, h}^{\text{Per Scan}}\right]$$

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- $\texttt{A} \rightarrow [(C_1 \rightarrow [=17]; C_2 \rightarrow [\leq 35])\,, 0.3]$
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We also capture Highly Selective Joins (example in appendix).

Index Encoding

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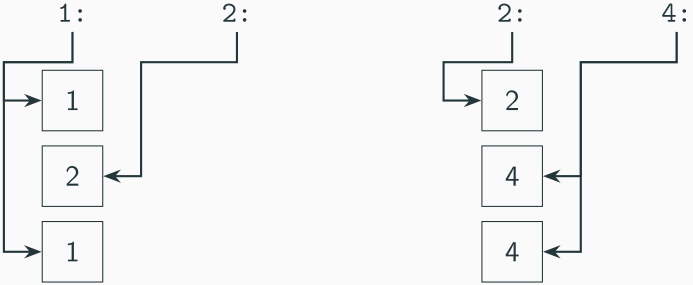

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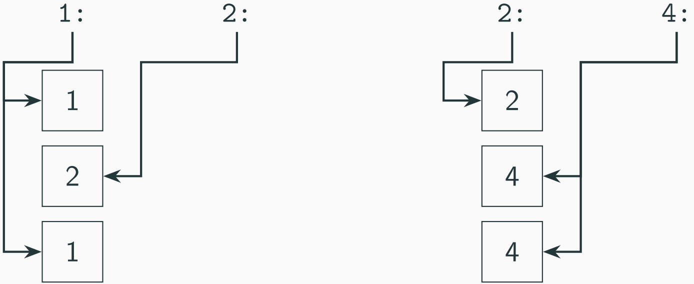

- A global index (LSM-based hash tables) is built to map from value to a list of inverted index positions. Here, 2 maps to `[seg:1,offset:2; seg:2, offset:0]`

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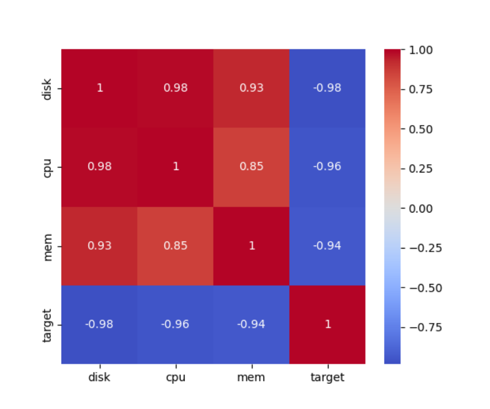

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Tuning QHICS

From Encodings to Execution Time

What we have: Resource vectors for cost and benefit.

$\vec{e}_{cost} = (c_{disk}, c_{cpu}, c_{mem})$ — $\vec{e}_{benefit} = (\Delta c_{disk}, \Delta c_{cpu}, \Delta c_{mem})$

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How to learn the optimal weights $\vec{\theta}_c$ and $\vec{\theta}_b$?

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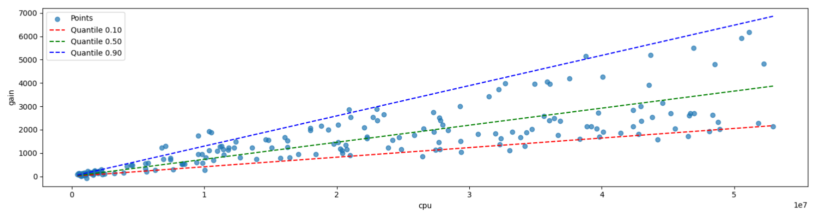

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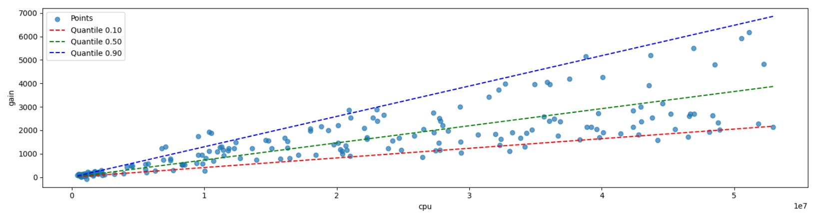

We restrict $\vec{\theta}$ to positive values $\Rightarrow$ Linear Programming.

Results

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We have implemented a toy QHICS to recommend indexes on Singlestore. It is limited to:

- `=,<=,>=,<,>,RANGE` condition predicates.
- `AND,OR,NOT` logical predicates.
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We also used another schema (TPC-DS) to test transferability.

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Configuration	Average error	Ranking	Underestimation
Lot	9%	97%	91%
Few	34%	92%	96%
None	Don't	81%	Don't

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Quantile allows to mitigate the needs of a huge starting dataset, and to fine tune over time.

Conclusion

In this work we have proposed:

- Heuristics for the number of segments needed for a query.
- Hypothetical Index estimation for column-oriented storage.
- The first use of Quantile Regression for risk-gain trade-off in WhatIf. Demonstrating that quantiles can be used to give early estimations while the system is being tuned on runtime information.

Appendix

Highly selective joins

A (unfiltered)		**B** (filtered)
Card=100,000 NDV(C) = 10,000	$\bowtie_C$	Card=10,000 NDV(C) = 50

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Once hash table on B is built:

- Without index, filter all A and probe H for each remaining tuples.

Highly selective joins

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- With index, probe A 50 times and filter matched tuples.

Highly selective joins

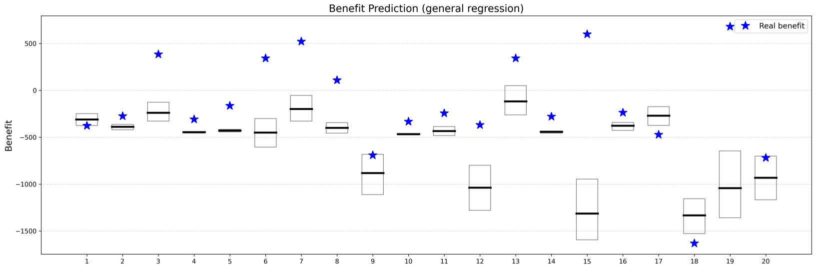
A (unfiltered)	C	**B** (filtered)
Card=100,000 NDV(C) = 10,000	$\bowtie$	Card=10,000 NDV(C) = 50

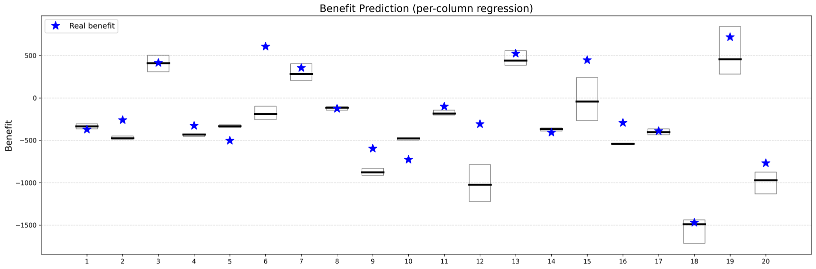
Once hash table on B is built:

- Without index, filter all A and probe H for each remaining tuples.
- With index, probe A 50 times and filter matched tuples.

QHICS captures this in its `JOIN` processing algorithm.

Visual example





Syntax of QHICS - creatung an instance

```
db_wrapper = DbWrapper(...)
db_utilities = DbUtilities(db_wrapper)

whatif = Qhics(db_wrapper,db_utilities)
```

Syntax of QHICS - Workload

```python
known_workload = [
    "SELECT c_nationkey FROM CUSTOMER WHERE c_acctbal > 150",
    "SELECT o_orderstatus, o_totalprice, o_shippriority FROM ORDERS WHERE o_orderdate >= '2004-02-04'",
    "SELECT l_shipinstruct FROM LINEITEM WHERE L_ORDERKEY = 190209"
]
whatif.set_workload(known_workload)

whatif.create_encoder()
whatif.create_cost_model(fit=True)
```

Syntax of QHICS - Configuration

```

new_indexes = [Index("CUSTOMER",["C_NATIONKEY"],["int"],"Hash")]
whatif.add_to_configuration(new_indexes)
whatif.remove_from_configuration(new_indexes)
```

Syntax of QHICS - Estimating

```
candidate1 = Index("LINEITEM",["L_QUANTITY"],["decimal"])
candidate2 =
↪ Index("LINEITEM",["L_LINENUMBER"],["integer"])
whatif.estimate_benefit(candidate1)
whatif.estimate_benefit(candidate2)
```

Positive Quantile Regression

We only accept positive coefficient for quantile regression, as we are modeling system costs. Hence, we need to write it as a Linear Programming problem:

$$
\begin{aligned}
\min_{\vec{\theta}, \vec{u}, \vec{v}} \quad & \sum_{i=1}^{n} \left[q\, u_i + (1-q)\, v_i \right] \\
\text{s.t.} \quad & y_i - X_i \vec{\theta} = u_i - v_i \quad \forall i \\
& \theta_j \geq 0 \quad \forall j \\
& u_i \geq 0, \;\; v_i \geq 0 \quad \forall i
\end{aligned}
$$

Appendix - Heuristics

Notations

- $S_{comp}(T.C)$ is the compressed size of the column.
- $S_{uncomp}(T.C)$ is the uncompressed size of the column.
- N_T is the number of tuples of the table.
- f_{op} is the time needed for one *op*.
- h is the hit factor.
- S_{offset} is the size of an offset in an inverted index.
- N_{res} is the number of resulting rows of a query.
- $ndv(T.C)$ is the number of distinct values of the column.

Creation Encoding

- $c_{disk} := S_{compressed} + \text{seg} \times S_{IV}$

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Creation Encoding

- $c_{disk} := S_{compressed} + \text{seg} \times S_{IV}$
- $c_{cpu} := S_{compressed} \times c_{decompress} + (N_{tuple} + \text{ndv}) \times c_{op}$
- $c_{mem} := S_{uncompressed}$
- For multi-column indexes we sum uni-column costs.

Gain encoding (Without Index)

For an index over $T.C$. If a scan reads h percentage of segments:

- Read $c_{disk}{:=}h \times S_{\text{comp}}(T.C)$ on the disk.
- Store $c_{mem} h \times S_{\text{uncomp}}(T.C)$ uncompressed data on the memory.
- Scan and check value using $c^1_{cpu}{:=}N_T \times h \times (f_{colscan} + f_{op})$.
- Uncompress data using $c^2_{cpu}{:=}S_{\text{comp}}(T.C) \times h \times f_{dec}$

Gain encoding (With Index) (1/3)

Assumptions:

- Inverted index are on disk, but a portion r_{meta} is cached in memory,
- The global index is read in memory *but this can be changed easily with a fixed parameter*,
- The database does not reverify that values have the one we are searching for (we trust the index).
- Leveraging seekable encoding adds a s_f seek factor to data needed.

Gain encoding (With Index) (2/3)

For an index over $T.C$, for each condition over $T.C$.

- The Inverted Index is estimated to $S_{iv}{:=}N \times S_{offset}$.
- At each level of the Global Index, we need to read each needed offsets: $S^1_{global}{:=}\log_k(N_{seg}(T)) \times \text{ndv}(T) \times S_{offset}$
- We need to read one offset per segments that contains the searched value: $S^2_{global}{:=}\text{ndv}(T) \times N_{seg}(T) \times h \times S_{offset}$

Gain encoding (With Index) (3/3)

For an index over $T.C$, for each equality condition over $T.C$.

- Read inverted index using the disk $c_{disk}^{1}{:=}(1 - r_{meta})S_{iv}$
- Read the remaining inverted index part using memory $c_{mem}^{1}{:=}r_{meta} \times S_{iv}$
- Read the global index using memory $c_{mem}^{2}{:=}S_{global}$
- Read needed data using the disk $c_{disk}^{2}{:=}s_f \frac{N_{res}}{N(T)} \times S_{\mathrm{comp}}(T.C)$
- Store all read data on memory $c_{mem}^{3}{:=}\frac{N_{res}}{N(T)} \times S_{\mathrm{uncomp}}(T.C)$
- Use the CPU to probe hash index $c_{cpu}^{1}{:=}\mathrm{ndv} \times \log_k(N_{seg}(T)) \times f_{op}$
- Use the CPU to decompress results $c_{cpu}^{2}{:=}S_{\mathrm{comp}}(T.C) \times \frac{N_{res}}{N(T)} \times f_{dec}$