Efficient Query Processing with Optimistically Compressed Hash Tables & Strings in the USSR

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Motivation

Hash tables frequently used in analytical queries

Crucial for overall performance

But (large) HTs bottlenecked by main memory bandwidth

What can we do about it?

Motivation

Orthogonal approaches:

- Optimize access:
  - Partitioning
  - Prefetching
- Increase fill-rate:
  - Cuckoo*, Robin Hood^ hashing
  - Virtually eliminate empty rows (Concise HT)°
- <u>Shrink the table itself</u>

* R. Pagh, F. Rodler: Cuckoo Hashing

^ P. Celis: Robin Hood Hashing

° R. Barber, G. Lohman, I. Pandis et al: Memory-efficient Hash Joins

Shrinking Hash Tables

100 MiB, magically shrink by 10x:

a) Downsize your computer
b) Increase query throughput

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HT 10 MiB, fits into L3/LLC cache

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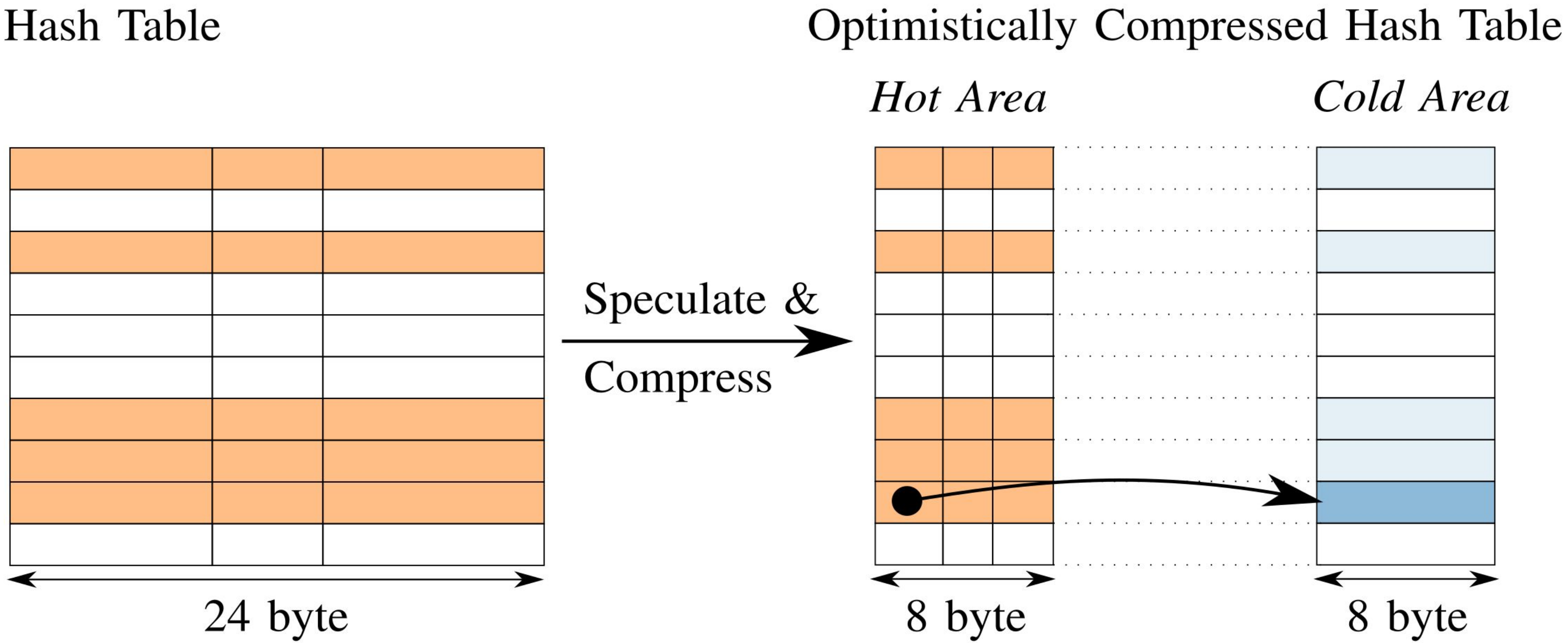
Better Latency & Throughput

Approach

Overview


Hash Table
Optimistically Compressed Hash Table
Hot Area
Cold Area
Speculate &
Compress
24 byte
8 byte
8 byte

Compression

Requirements:

- Very lightweight
- Support random access

Domain-Guided Prefix Suppression:

- Variant of bit-packing/null suppression
- Lightweight: Handful bitwise operations
- Fast random access: Rows independently compressed & word-aligned
- Fast equality comparisons on compressed data

Optimistic Splitting

- Decrease *effective* memory footprint
- Decompose HT into:

Hot HT:

- Frequently accessed
- Cache-resident
- Aggregates:

    SUM: sub-sums fit smaller data types

- Frequent strings

Cold HT:

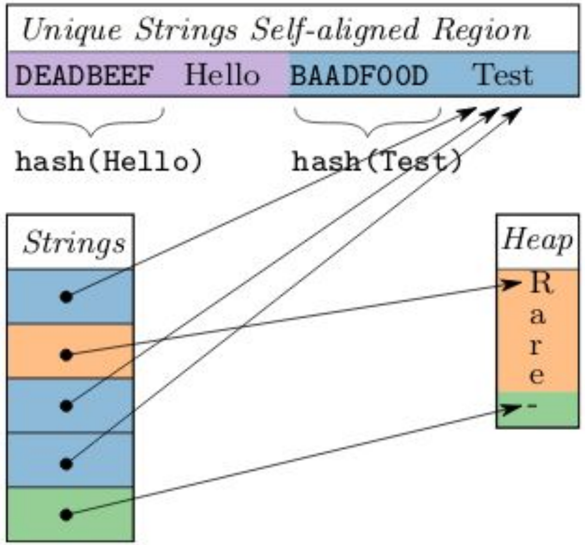
- Rarely accessed
- Main memory
- Aggregates:

    SUM: stores full SUM or overflow counter

- In-frequent strings

Strings in the USSR

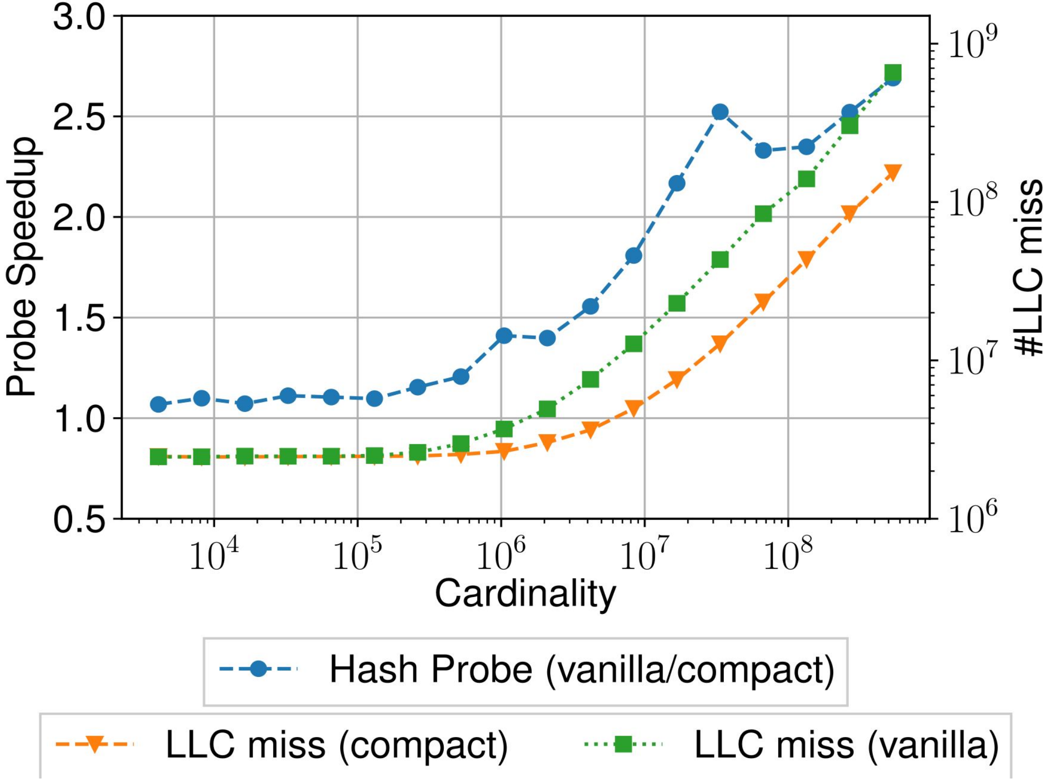
- Assumption: Many strings repeat
- Exploit dictionary-compression, **but**:
    - Global dictionaries come with huge challenges (updates, synchronization)
    - Per-block dictionaries need translation[*]
- Unique Strings Self-aligned Region (USSR):
    - *Query-wide* dictionary
    - Limited size (cache resident)
    - Only holds *frequent* strings
    - Built during scan: Exploit dictionary compression
    - *Easy to retrofit* into existing engines



* J.-G. Lee et al.: Joins on Encoded and Partitioned Data

Experiments

Faster HashJoin Probe



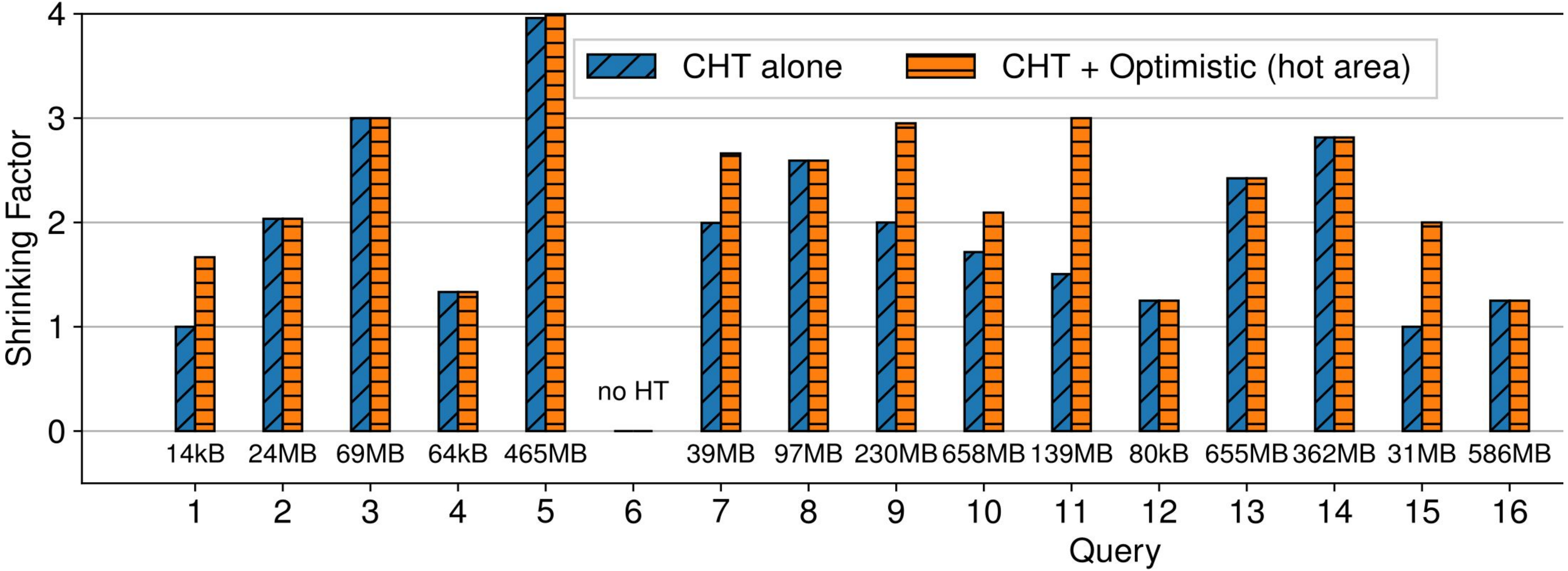
4 keys [0...1000] á 64 bit, 4 payloads [0...10] á 64 bit

Faster GroupBy on strings

- 10 unique strings
- Speedup S(x) over strings with varying length

Length	**2**	**4**	**8**	**16**	**32**	**64**	**128**	**256**	**512**
S(Query)	*1*	*2*	*1*	*2*	*3*	*3*	*5*	*10*	*22*
S(==)	2	2	2	3	3	4	10	20	50
S(Hash)	4	4	4	6	10	15	20	37	80

Smaller Hash Tables in TPC-H



Faster Real-World Workloads (Public BI*)

- String heavy^
- “CommonGovernment” workbook:

Query	1	2	3	4	5	6
Speedup	*2.1*	*1.4*	*2.2*	*1.4*	*1.3*	*1.0*
USSR size (kB)	1.8	0.5	2.0	0.3	66.1	512.0
Rejection Ratio (%)	0.0	0.0	0.0	0.0	0.0	18.3

* https://github.com/cwida/public_bi_benchmark
^ Adrian Vogelsgesang et al.: Get Real: How Benchmarks Fail to Represent the Real World

Summary

Hash tables can be made smaller via:

- Compression
- Optimistic Splitting
- Unique String Self-aligned Region (USSR)

Results in:

(a) Faster runtime
(b) Less memory footprint
(c) Composable (combinable with Cuckoo hashing, Concise HT, etc.)

Improved runtime:

- 50% on TPC-H
- 2x on Public BI (real workload)
- 22x GroupBy on strings
- 2.5x Hash Join probe

Improved memory footprint:

- 4x TPC-H (working set)
- 2x TPC-H (total)