Lecture 9: Compression

Recap

Thread Safety

- A piece of code is **thread-safe** if it functions correctly during simultaneous execution by multiple threads.
- In particular, it must satisfy the need for multiple threads to access the same shared data (**shared access**), and
- the need for a shared piece of data to be accessed by only one thread at any given time (**exclusive access**)

2Q Policy

Maintain two queues (FIFO and LRU)

- Some pages are accessed only once (*e.g.*, sequential scan)
- Some pages are hot and accessed frequently
- Maintain separate lists for those pages
- **Scan resistant** policy

1. Maintain all pages in FIFO queue
2. When a page that is currently in FIFO is referenced again, upgrade it to the LRU queue
3. Prefer evicting pages from FIFO queue

Hot pages are in LRU, read-once pages in FIFO.

Today's Agenda

- Compression Background
- Naïve Compression
- OLAP Columnar Compression
- Dictionary Compression

Compression Background

Observation

- I/O is the main bottleneck if the DBMS has to fetch data from disk
- Database compression will reduce the number of pages
  - So, fewer I/O operations (lower disk bandwith consumption)
  - But, may need to decompress data (CPU overhead)

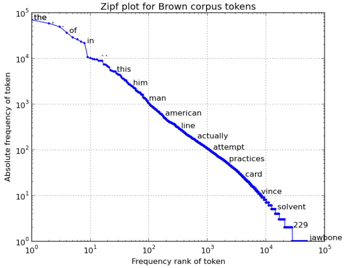
Observation

Key trade-off is **decompression speed vs. compression ratio**

- Disk-centric DBMS tend to optimize for compression ratio
- In-memory DBMSs tend to optimize for decompression speed. Why?
- Database compression reduces DRAM footprint and bandwidth consumption.

Real-World Data Characteristics

- Data sets tend to have highly **skewed** distributions for attribute values.
  - Example: Zipfian distribution of the Brown Corpus



Real-World Data Characteristics

- Data sets tend to have high **correlation** between attributes of the same tuple.
  - Example: Zip Code to City, Order Date to Ship Date

Database Compression

- Goal 1: Must produce fixed-length values.
  - Only exception is var-length data stored in separate pool.
- Goal 2: Postpone decompression for as long as possible during query execution.
  - Also known as **late materialization**.
- Goal 3: Must be a **lossless** scheme.

Lossless vs. Lossy Compression

- When a DBMS uses compression, it is always **lossless** because people don't like losing data.
- Any kind of **lossy** compression is has to be performed at the application level.
- Reading less than the entire data set during query execution is sort of like of compression. . .

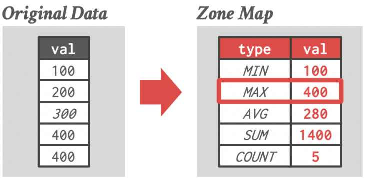
Data Skipping

- Approach 1: **Approximate Queries** (Lossy)
  - Execute queries on a sampled subset of the entire table to produce approximate results.
  - Examples: BlinkDB, Oracle
- Approach 2: **Zone Maps** (Lossless)
  - Pre-compute columnar aggregations per block that allow the DBMS to check whether queries need to access it.
  - Examples: Oracle, Vertica, MemSQL, Netezza

Zone Maps

- Pre-computed aggregates for blocks of data.
- DBMS can check the zone map first to decide whether it wants to access the block.

```
SELECT *
  FROM table
  WHERE val > 600;
```



Observation

- If we want to compress data, the first question is **what data** do want to compress.
- This determines what compression schemes are available to us

Compression Granularity

- Choice 1: Block-level
  - Compress a block of tuples of the same table.
- Choice 2: Tuple-level
  - Compress the contents of the entire tuple (**NSM-only**).
- Choice 3: Value-level
  - Compress a single attribute value within one tuple.
  - Can target multiple attribute values within the same tuple.
- Choice 4: Column-level
  - Compress multiple values for one or more attributes stored for multiple tuples (**DSM-only**).

Naïve Compression

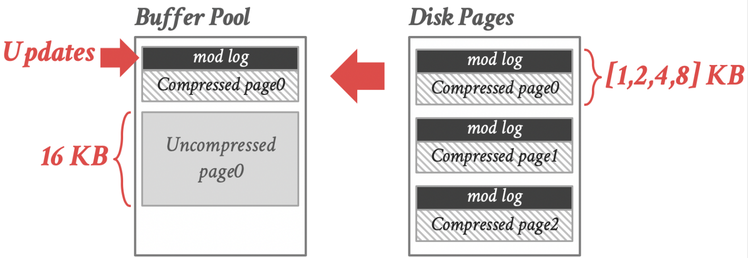
Naïve Compression

- Compress data using a general-purpose algorithm.
- Scope of compression is only based on the **type of data** provided as input.
- Encoding uses a dictionary of commonly used words
  - LZ4 (2011)
  - Brotli (2013)
  - Zstd (2015)
- Consideration
  - Compression vs. decompression speed.

Naïve Compression

- Choice 1: **Entropy** Encoding
  - More common sequences use less bits to encode, less common sequences use more bits to encode.
- Choice 2: **Dictionary** Encoding
  - Build a data structure that maps data segments to an identifier.
  - Replace the segment in the original data with a reference to the segment's position in the dictionary data structure.

Case Study: MySQL InnoDB Compression



Naïve Compression

- The DBMS must decompress data first before it can be read and (potentially) modified.
  - This limits the “complexity” of the compression scheme.
- These schemes also do not consider the high-level meaning or semantics of the data.

Observation

- We can perform exact-match comparisons and natural joins on compressed data if predicates and data are compressed the same way.
  - **Range predicates** are trickier. . .

```
SELECT *
  FROM Artists
  WHERE name = 'Mozart'
```

Original Table

Artist	Year
Mozart	1756
Beethoven	1770

```
SELECT *
  FROM Artists
  WHERE name = 1
```

Compressed Table

Artist	Year
1	1756
2	1770

Columnar Compression

Columnar Compression

- Null Suppression
- Run-length Encoding
- Bitmap Encoding
- Delta Encoding
- Incremental Encoding
- Mostly Encoding
- Dictionary Encoding

Null Suppression

- Consecutive zeros or blanks in the data are replaced with a description of how many there were and where they existed.
  - Example: Oracle's Byte-Aligned Bitmap Codes (BBC)
- Useful in wide tables with sparse data.
- Reference: Database Compression (SIGMOD Record, 1993)

Run-length Encoding

- Compress runs of the same value in a single column into triplets:
  - The value of the attribute.
  - The start position in the column segment.
  - The number of elements in the run.
- Requires the columns to be sorted intelligently to maximize compression opportunities.
- Reference: Database Compression (SIGMOD Record, 1993)

Run-length Encoding

Original Data

id	sex
1	M
2	M
3	M
4	F
6	M
7	F
8	M
9	M

Compressed Data

id
1
2
3
4
6
7
8
9

sex
(M,0,3)
(F,3,1)
(M,4,1)
(F,5,1)
(M,6,2)

RLE Triplet
- ***Value***
- ***Offset***
- ***Length***

```
SELECT sex, COUNT(*)
  FROM users
  GROUP BY sex
```

Run-length Encoding

Original Data

id	sex
1	M
2	M
3	M
4	F
6	M
7	F
8	M
9	M

Compressed Data

id	sex
1	(M,0,3)
2	(F,3,1)
3	(M,4,1)
4	(F,5,1)
6	(M,6,2)
7	
8	
9	

RLE Triplet
- ***Value***
- ***Offset***
- ***Length***

Bitmap Encoding

- Store a separate bitmap for **each unique value** for an attribute where each bit in the bitmap corresponds to the value of the attribute in a tuple.
  - The i^{th} position in the **bitmap** corresponds to the i^{th} tuple in the table.
  - Typically segmented into chunks to avoid allocating large blocks of contiguous memory.
-
- Only practical if the **cardinality** of the attribute is small.
- Reference: MODEL 204 architecture and performance (HPTS, 1987)

Bitmap Encoding

Original Data

id	sex
1	M
2	M
3	M
4	F
6	M
7	F
8	M
9	M

9 × 8-bits = 72 bits

Compressed Data

id	sex: M	sex: F
1	1	0
2	1	0
3	1	0
4	0	1
6	1	0
7	0	1
8	1	0
9	1	0

2 × 8-bits = 16 bits

9 × 2-bits = 18 bits

Bitmap Encoding: Analysis

```
CREATE TABLE customer_dim (
  id INT PRIMARY KEY,
  name VARCHAR(32),
  email VARCHAR(64),
  address VARCHAR(64),
  zip_code INT
);
```

- Assume we have 10 million tuples.
- 43,000 zip codes in the US.
  - 10000000×32-bits = 40 MB
  - $10000000 \times 43000 = 53.75$ GB
- Every time a txn inserts a new tuple, the DBMS must extend 43,000 different bitmaps.

Bitmap Encoding: Compression

- Approach 1: General Purpose Compression
  - Use standard compression algorithms (*e.g.*, LZ4, Snappy).
  - The DBMS must decompress before it can use the data to process a query.
  - Not useful for in-memory DBMSs.
- Approach 2: Byte-aligned Bitmap Codes
  - Structured run-length encoding compression.

Case Study: Oracle Byte-Aligned Bitmap Codes

- Divide bitmap into chunks that contain different categories of bytes:
  - **Gap Byte**: All the bits are 0s.
  - **Tail Byte**: Some bits are 1s.
- Encode each **chunk** that consists of some Gap Bytes followed by some Tail Bytes.
  - Gap Bytes are compressed with run-length encoding.
  - Tail Bytes are stored uncompressed unless it consists of only 1-byte or has only one non-zero bit.
- Reference: Byte-aligned bitmap compression (Data Compression Conference, 1995)

Case Study: Oracle Byte-Aligned Bitmap Codes

Bitmap

```
00000000 00000000 00010000
00000000 00000000 00000000
00000000 00000000 00000000
00000000 00000000 00000000
00000000 00000000 00000000
00000000 01000000 00100010
```

Compressed Bitmap

Bitmap

Gap Bytes *Tail Bytes*

```
00000000 00000000 00010000 #1
00000000 00000000 00000000
00000000 00000000 00000000
00000000 00000000 00000000 #2
00000000 00000000 00000000
00000000 01000000 00100010
```

Compressed Bitmap

Case Study: Oracle Byte-Aligned Bitmap Codes

Bitmap

```
00000000 00000000 00010000 #1
00000000 00000000 00000000
00000000 00000000 00000000
00000000 00000000 00000000
00000000 00000000 00000000
00000000 01000000 00100010
```

Compressed Bitmap

```
#1 (010)(1)(0100)
    1-3  4  5-7
```

- **Chunk 1** (Bytes 1-3)
- Header Byte:
  - Number of Gap Bytes (Bits 1-3)
  - Is the tail special? (Bit 4)
  - Number of verbatim bytes (if Bit 4=0)
  - Index of 1 bit in tail byte (if Bit 4=1)
- No gap length bytes since gap length < 7
- No verbatim bytes since tail is special.

Case Study: Oracle Byte-Aligned Bitmap Codes

Bitmap

```
00000000 00000000 00010000
00000000 00000000 00000000
00000000 00000000 00000000
00000000 00000000 00000000  #2
00000000 00000000 00000000
00000000 01000000 00100010
```

Compressed Bitmap

```
#1 (010)(1)(0100)
#2 (111)(0)(0010) 00001101
   01000000 00100010
```

- Original Data: 18 bytes
- Compressed Data: 5 bytes.

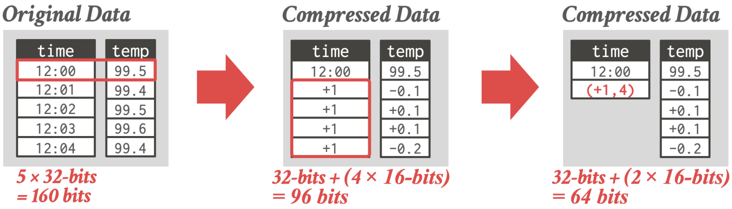
- Chunk 2 (Bytes 4-18)
- Header Byte:
  - 13 gap bytes, two tail bytes
  - of gaps is > 7, so have to use extra byte
-
- One gap length byte gives gap length = 13
- Two verbatim bytes for tail.

Observation

- Oracle's BBC is an obsolete format.
  - Although it provides good compression, it is slower than recent alternatives due to excessive branching.
  - Word-Aligned Hybrid (WAH) encoding is a patented variation on BBC that provides better performance.
- None of these support **random access** to a given value.
  - If you want to check whether a given value is present, you must start from the beginning and decompress the whole thing.

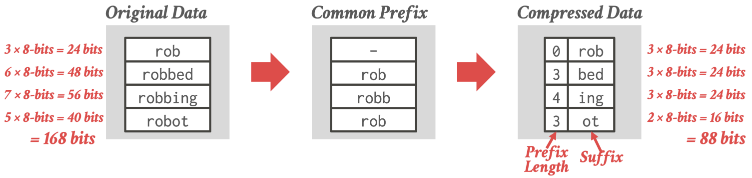
Delta Encoding

- Recording the difference between values that follow each other in the same column.
  - Store base value **in-line** or in a separate **look-up table**.
  - Combine with RLE to get even better compression ratios.



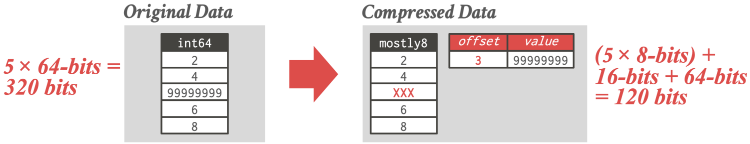
Incremental Encoding

- Variant of delta encoding that avoids duplicating common prefixes/suffixes between consecutive tuples.
- This works best with sorted data.



Mostly Encoding

- When values for an attribute are **mostly** less than the largest possible size for that attribute's data type, store them with a more compact data type.
  - The remaining values that cannot be compressed are stored in their raw form.
  - Reference: Amazon Redshift Documentation



Dictionary Compression

Dictionary Compression

- Probably the most useful compression scheme because it does not require pre-sorting.
- Replace frequent patterns with smaller codes.
- Most pervasive compression scheme in DBMSs.
- Need to support fast encoding and decoding.
- Need to also support range queries.

Dictionary Compression: Design Decisions

- When to construct the dictionary?
- What is the scope of the dictionary?
- What data structure do we use for the dictionary?
- What encoding scheme to use for the dictionary?

Dictionary Construction

- Choice 1: All-At-Once Construction
  - Compute the dictionary for all the tuples at a given point of time.
  - New tuples must use a separate dictionary, or the all tuples must be recomputed.
- Choice 2: Incremental Construction
  - Merge new tuples in with an existing dictionary.
  - Likely requires re-encoding to existing tuples.

Dictionary Scope

- Choice 1: Block-level
  - Only include a subset of tuples within a single table.
  - Potentially lower compression ratio but can add new tuples more easily. **Why?**
- Choice 2: Table-level
  - Construct a dictionary for the entire table.
  - Better compression ratio, but expensive to update.
- Choice 3: Multi-Table
  - Can be either subset or entire tables.
  - Sometimes helps with joins and set operations.

Multi-Attribute Encoding

- Instead of storing a single value per dictionary entry, store entries that span attributes.
  - I'm not sure any DBMS implements this.

Original Data

val1	val2
A	202
B	101
A	202
C	101
B	101
A	202
C	101
B	101

Compressed Data

val1+val2
XX
YY
XX
ZZ
YY
XX
ZZ
YY

val1	val2	code
A	202	XX
B	101	YY
C	101	ZZ

Encoding / Decoding

- A dictionary needs to support two operations:
  - Encode: For a given uncompressed value, convert it into its compressed form.
  - Decode: For a given compressed value, convert it back into its original form.
- No magic hash function will do this for us.

Order-Preserving Encoding

- The encoded values need to support **sorting** in the same order as original values.

```
SELECT *
  FROM Artists
  WHERE name LIKE 'M%'
```

Original Table

Artist	Year
Mozart	1756
Max Bruch	1838
Beethoven	1770

```
SELECT *
  FROM Artists
  WHERE name BETWEEN 10 AND 20
```

Compressed Table

Artist	Year
10	1756
20	1838
30	1770

Order-Preserving Encoding

```sql
SELECT Artist
  FROM Artists
  WHERE name  LIKE 'M%'     -- Must still perform sequential scan

SELECT DISTINCT Artist
  FROM Artists
  WHERE name  LIKE 'M%'     -- ??
```

Dictionary Data Structures

- Choice 1: Array
  - One array of variable length strings and another array with pointers that maps to string offsets.
  - Expensive to update.
- Choice 2: Hash Table
  - Fast and compact.
  - Unable to support range and prefix queries.
- Choice 3: B+Tree
  - Slower than a hash table and takes more memory.
  - Can support range and prefix queries.

Conclusion

- Dictionary encoding is probably the most useful compression scheme because it does not require pre-sorting.
- The DBMS can combine different approaches for even better compression.
- The DBMS can combine different approaches for even better compression.
- In the next lecture, we will learn about larger-than-memory databases.

References I