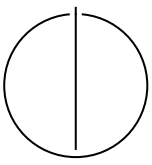
SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

Improved Symbol Table Construction for FSST Compression

Hedi Chehaidar



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Improved Symbol Table Construction for FSST Compression

Verbesserte Symboltabellenkonstruktion für die FSST-Komprimierung

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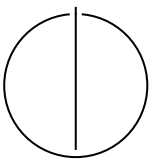

I confirm that this bachelor's thesis is my own work and I have documented all sources and material used.

Munich, January 8, 2026 Hedi Chehaidar

Acknowledgments

First and foremost, I would like to thank God for the guidance, strength and perseverance that made it possible to complete this work.

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Abstract

Modern analytical database systems process large volumes of string data, where efficient compression is essential for reducing memory footprint and improving performance. While the Fast Static Symbol Table (FSST) compression scheme provides excellent decompression speed and random-access capabilities, its effectiveness heavily depends on the quality of the constructed symbol table.

The original FSST algorithm relies on heuristic, greedy symbol selection, which can lead to suboptimal symbol choices and limit achievable compression ratios.

This thesis presents several enhancements to the FSST compression method that improve symbol table construction while preserving FSST's core advantages. The central contribution is a refined symbol selection process that systematically identifies more effective symbols and avoids redundant or conflicting choices.

First, a dynamic programming approach is introduced to evaluate and select higher-quality symbols within each generation, enabling a more globally informed optimization compared to the original greedy strategy. Second, an additional frequency counter is incorporated to accelerate the discovery of longer symbols and to explicitly favor them in subsequent generations, improving the exploitation of longer recurring patterns in the data. Third, a symbol pruning mechanism is applied to eliminate conflicting and redundant symbols, ensuring a more compact and effective symbol table.

Together, these techniques significantly improve the robustness and quality of the symbol table generation process. Experimental evaluation demonstrates that the proposed enhancements lead to consistently improved compression ratios compared to the original FSST algorithm, while maintaining its fast decompression and random-access properties. The results show that careful algorithmic refinement of symbol selection can yield substantial gains without altering the lightweight and practical nature of FSST, making the improved approach well suited for use in modern analytical systems.

Contents

1 Introduction

1.1 Motivation

Modern data management systems increasingly operate on large-scale, string-heavy datasets. In analytical databases, strings are omnipresent and appear in many forms, including URLs, file paths, identifiers, log messages, categorical attributes, and semi-structured data originating from web, cloud, and enterprise applications. Studies of real-world database workloads show that string columns often constitute a substantial fraction of the overall data volume, both in terms of storage and memory consumption. Prior analyses of analytical benchmarks and production systems report that strings can account for a significant portion of columnar storage, frequently dominating memory usage in dictionary-encoded or compressed representations [1], [2].

The growing prevalence of string data places strong demands on compression techniques used in analytical systems. Effective compression reduces memory footprint, improves cache utilization, and lowers memory bandwidth pressure, all of which are critical for high-performance query processing. At the same time, analytical workloads require fast random access to individual values, as queries often scan and decode only a subset of columns or rows. This combination of requirements makes general-purpose, block-based compressors such as Zstandard or LZ4 less suitable despite their strong compression ratios, as they typically require decompressing entire blocks before accessing individual strings.

To address this gap, lightweight string compression schemes have been proposed that prioritize fast decompression and random access. One prominent example is the FSST compression algorithm [3]. FSST compresses strings by replacing frequent byte sequences with compact symbols from a statically constructed symbol table. During decompression, symbols can be expanded independently, allowing direct access to individual strings without scanning neighboring data. As a result, FSST achieves decompression speeds that are competitive with, and often superior to, more heavyweight compression schemes, making it attractive for use in modern analytical databases.

However, the compression effectiveness of FSST critically depends on the quality of

its symbol table. The original FSST algorithm constructs this table using a greedy approach that iteratively selects symbols based on local heuristics. While this strategy is computationally efficient and aligns with FSST's design goal of lightweight processing, it can lead to suboptimal symbol choices. In particular, greedy selection may favor short or locally frequent symbols that conflict with longer or more informative sequences, limit the discovery of beneficial longer symbols, or introduce redundancy within the symbol table. Furthermore, once a symbol is selected, its impact on future generations of symbols is not globally optimized, which can prevent the algorithm from converging toward a symbol set that maximizes overall compression gain.

These limitations suggest that there is room for improvement in FSST's symbol table construction without compromising its core advantages. By revisiting the greedy nature of symbol selection and incorporating more informed decision-making into the construction process, it is possible to improve compression ratios while retaining FSST's fast decompression and random-access properties. This thesis explores such improvements, focusing on enhanced symbol selection strategies that address the shortcomings of the original greedy approach.

1.2 Thesis Outline

This thesis is structured as follows.

Chapter 2 (Background) introduces the fundamental concepts required to understand the techniques developed in this thesis. It begins with an overview of dynamic programming and contrasts it with greedy algorithmic approaches, highlighting their respective strengths and limitations. The chapter then introduces the core data structures used throughout the thesis, namely tries and max-heaps, which play a central role in symbol generation and selection.

Chapter 3 (Related Work) reviews existing work in the area of data compression. It first discusses widely used block-based compression algorithms such as LZ4 and Zstandard, explaining their general design principles and trade-offs. The chapter then presents the original FSST compression algorithm, detailing its symbol table construction and encoding process, which form the basis for the improvements proposed in this thesis.

Chapter 4 (Approach) describes the main contributions of this work. It introduces three enhancements to the FSST symbol table construction process: a dynamic programming-based method for improved symbol selection, the introduction of a third frequency counter to accelerate the discovery and prioritization of longer symbols,

and a symbol pruning strategy to eliminate conflicting and redundant symbols. Each technique is explained in detail and integrated into the overall compression pipeline.

Chapter 5 (Evaluation) evaluates the proposed enhancements experimentally. It presents the datasets, experimental setup, and benchmarking methodology used in the evaluation. The chapter analyzes the impact of the proposed techniques on compression ratio and runtime, comparing the improved FSST variants against the original algorithm.

Chapter 6 (Conclusion) summarizes the contributions and findings of the thesis. It reflects on the achieved improvements and discusses directions for future work, with emphasis on potential optimization opportunities to reduce the runtime overhead introduced by the enhanced symbol selection techniques.

2 Background

2.1 Dynamic Programming vs. Greedy

Many algorithmic problems involve selecting a sequence of decisions that together optimize a global objective. Two widely used approaches for solving such problems are greedy algorithms and dynamic programming (DP). While both aim to construct efficient solutions, they differ fundamentally in how they explore the solution space and reason about optimality.

2.1.1 Greedy Algorithms

Greedy algorithms build a solution incrementally by making locally optimal decisions at each step. At every stage, the algorithm selects the option that appears best according to a predefined heuristic, without reconsidering previous choices. This strategy is attractive due to its simplicity, low computational overhead, and ease of implementation.

Greedy approaches are particularly effective when a problem exhibits the greedy-choice property, meaning that a locally optimal decision can be shown to lead to a globally optimal solution.

An easy example illustrating the greedy-choice property is the problem where we are given a sequence of distinct numbers and we want to take a subset of K numbers with the goal of maximizing the sum of those numbers. The intuitive and correct way to choose the numbers is by selecting the largest K numbers of the sequence for the subset (denoted by S). We can prove this by contradiction: suppose there is an optimal solution where a number of the chosen subset does not belong to S, we can swap that number with an unchosen number of the set S and we would have a strictly better solution, which leads to contradiction.

An example of a problem that cannot be solved greedily and requires DP is the $0/1$ Knapsack problem.

Despite this limitation, greedy algorithms are frequently used in performance-critical systems where execution speed and simplicity are prioritized over absolute optimality.

2.1.2 Dynamic Programming

Dynamic programming (DP) addresses optimization problems by systematically exploring all relevant subproblems and combining their solutions to obtain a globally optimal result. The core idea is to decompose a problem into overlapping subproblems, solve each subproblem once, and store its result to avoid redundant computation.

Unlike greedy algorithms, dynamic programming evaluates the long-term consequences of decisions. By considering multiple possible choices at each stage and selecting the one that minimizes or maximizes a well-defined cost function, DP can guarantee optimality when the problem satisfies optimal substructure and overlapping subproblems.

We define the 0/1 Knapsack problem formally as follows: there are n items where each item i has value v_i and weight w_i and the knapsack capacity is W. We need to choose a subset of items that fits the capacity while maximizing the total value. Define the DP table: $DP[i][c]$ = maximum value achievable using the first i items with capacity c. So the result is stored in $DP[n][W]$. The base cases are $DP[i][0] = 0$ for all i and $DP[0][c] = 0$ for all c. The recurrence is defined for each item i and capacity c as follows: If $w_i > c$ (item does not fit): $DP[i][c] = DP[i-1][c]$. Otherwise choose best of taking or not taking the item: $DP[i][c] = max(DP[i-1][c], DP[i-1][c-w_i] + v_i)$. Time complexity is $O(nW)$.

The primary trade-off of dynamic programming is computational complexity. DP solutions often require more time and memory than greedy alternatives, especially when the state space is large. As a result, practical DP implementations frequently rely on carefully designed cost models, state compression, or bounded problem sizes to remain efficient.

2.2 Datastructures

Efficient algorithmic design relies not only on the choice of optimization strategy but also on the use of appropriate data structures. This section introduces the two core data structures used throughout this thesis: max-heaps and tries. Both play an important role in managing candidates and efficiently representing string data.

2.2.1 Max Heap

A max heap is a complete binary tree–based data structure that maintains the heap property: the key of each node is greater than or equal to the keys of its children. As a result, the maximum element is always stored at the root of the heap.

The primary operations supported by a max heap include insertion, extraction of the maximum element, and key updates. Each of these operations can be performed in logarithmic time with respect to the number of elements in the heap. This efficiency makes max-heaps particularly well suited for priority-based selection tasks, where the most valuable or promising element must be accessed repeatedly.

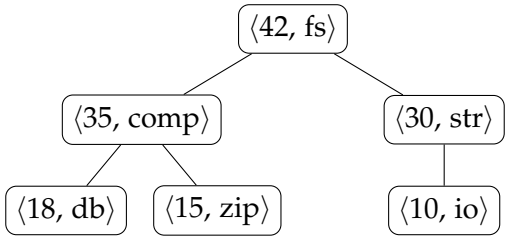

Figure 2.1: Initial max heap ordered by frequency.

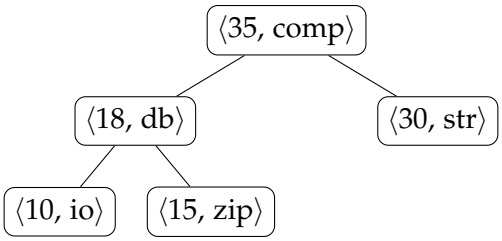

Figure 2.2: Max heap after extracting the maximum element ⟨42, fs⟩.

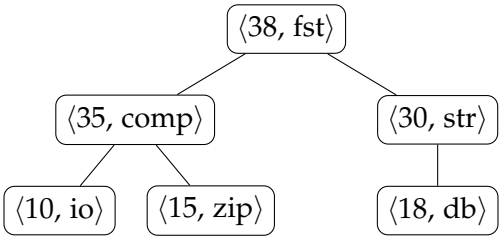

Figure 2.3: Max heap after inserting the element ⟨38, fst⟩.

In the context of algorithmic optimization, max-heaps are often used to manage candidate sets ordered by a score or heuristic value. They enable fast retrieval of the currently best candidate while allowing dynamic updates as new candidates are generated or existing ones are reweighted.

2.2.2 Trie

A trie, also known as a prefix tree, is a tree-based data structure used to store and retrieve strings efficiently by exploiting their shared prefixes. Each node in a trie represents a prefix of one or more strings, and edges correspond to individual characters or bytes. Strings are represented by paths from the root to terminal nodes which can also store other data related to the strings (like mappings).

Tries provide efficient operations for prefix-based queries, insertion, and lookup, all of which can be performed in time proportional to the length of the string rather than the number of stored strings. This makes them particularly suitable for applications involving multiple search operations for strings with commun prefixes.

Following trie stores the 5 strings "fs", "fst", "db", "dbms" and "zip" with a mapping for each string as an integer stored in the corresponding terminal node.

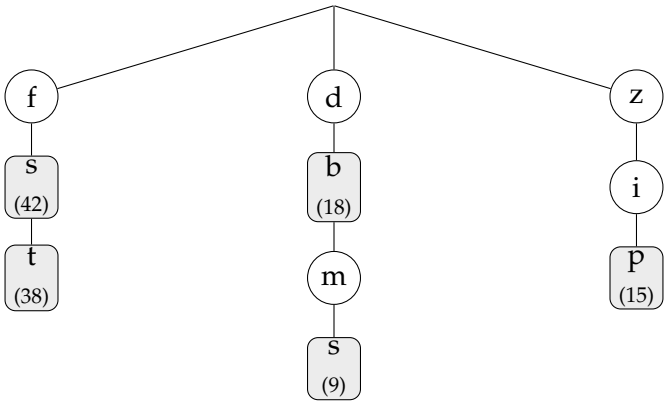

Figure 2.4: Example trie storing short strings. Terminal nodes are annotated with integer metadata.

3 Related Work

3.1 Block-based Compressors

3.2 FSST

4 Approach

4.1 Dynamic Programming

4.2 3^{rd} Counter

4.3 Symbol Pruning

5 Evaluation

5.1 Environment

5.2 Benchmarking Data

5.3 Results

6 Conclusion

6.1 Summary

6.2 Future Work

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