LeCo: Lightweight Compression via Learning Serial Correlations

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ABSTRACT

Lightweight data compression is a key technique that allows column stores to exhibit superior performance for analytical queries. Despite a comprehensive study on dictionary-based encodings to approach Shannon's entropy, few prior works have systematically exploited the serial correlation in a column for compression. In this paper, we propose LeCo (i.e., Learned Compression), a framework that uses machine learning to remove the serial redundancy in a value sequence automatically to achieve an outstanding compression ratio and decompression performance simultaneously. LeCo presents a general approach to this end, making existing (ad-hoc) algorithms such as Frame-of-Reference (FOR), Delta Encoding, and Run-Length Encoding (RLE) special cases under our framework. Our microbenchmark with three synthetic and eight real-world data sets shows that a prototype of LeCo achieves a Pareto improvement on both compression ratio and random access speed over the existing solutions. When integrating LeCo into widely-used applications, we observe up to 3.9× speed up in filter-scanning a Parquet file and a 16% increase in RocksDB 's throughput.

1 INTRODUCTION

Almost all major database vendors today have adopted a column-oriented design for processing analytical queries [29, 31, 42, 51, 59, 71, 73, 91]. One of the key benefits of storing values of the same attribute consecutively is that the system can apply a variety of lightweight compression algorithms to the columns to save space and disk/network bandwidth [26, 27, 101]. These algorithms, such as Run-Length Encoding (RLE) [27] and Dictionary Encoding, typically involve a single-pass decompression process (hence, lightweight) to minimize the CPU overhead. A few of them (e.g., Frame-of-Reference or FOR [57, 113]) allow random access to the individual values. This is a much-preferred feature because it allows the DBMS to avoid full-block decompression for highly-selective queries, which are increasingly common, especially in hybrid transactional/analytical processing (HTAP) [17, 60, 66, 75, 87, 90] and real-time analytics [13, 73].

Given a sequence of values of the same data type, there are generally two sources of information redundancy that we can exploit to achieve compression. The first (i.e., Source 1) is embedded in the probability distribution of the values. Here, we assume that the values are generated independently from an information source (i.e., a random variable), and the goal of compression is to approach Shannon's Entropy [95]. All forms of dictionary encoding, including

those that exploit substring patterns (e.g., FSST [35], HOPE [110]), belong to this category. An optimal compression ratio is achieved when the code length for each dictionary entry is reversely proportional to its appearance frequency (i.e., by applying Huffman Encoding [61], Arithmetic Encoding [103], etc.). Nevertheless, most column-store engines prefer fixed-length codes. They are willing to sacrifice part of the compression ratio for more efficient query processing with vectorized instructions [26, 114].

Shannon's Entropy, however, is not the lower bound for compressing an existing sequence. The second source of redundancy (i.e., Source 2) lies in the serial correlation between values: the value of the current position depends on its preceding values in the sequence. The insight is that if we can model serial patterns concisely, we can use the model to predict individual values and only store error-correction bits if necessary. As opposed to Source 1, which is thoroughly studied, only a few attempts were made to explore Source 2 for lightweight compression [34], let alone formulating it systematically as a learning problem. Although common algorithms such as RLE, FOR, and Delta Encoding [27, 77] follow this paradigm implicitly (elaborated in Section 2), they are ad-hoc solutions for particular patterns. For example, RLE only models consecutive repetitions, and the "prediction" must be accurate.

As a result, we have missed many opportunities to achieve a compressed size beyond Shannon's Entropy. Figure 1, for example, depicts a column of movie IDs from a real data set [9], where the values exhibit clear serial patterns. After learning a piecewise-linear model that can predict a value based on its position for the data set, we need fewer bits to record the prediction errors (i.e., deltas) because the learned model (light green lines in Figure 1) eliminates the serial redundancy in the original values (marked as dark green dots). Compared to FOR, this approach improves the compression ratio on the data set from 4.84% to 91.05% (refer to Section 4).

We, thus, propose a framework called LeCo (i.e., Learned Compression) to automatically learn serial patterns from a sequence and use the models for compression. Our framework addresses two subproblems. The first is that given a subsequence of values, how to best fit the data using one model? This is a classic regression problem, but instead of minimizing the sum of the squared errors, we minimize the maximum error. The reason is that we choose to store the deltas (i.e., prediction errors) in fixed length to support fast decompression and random access during query processing. A smaller max delta reduces the size of each element in the delta array and, therefore, improves the compression ratio.

The second subproblem is data partitioning: given the type(s) of the regression model, how to partition the sequence to minimize the overall compression ratio? Proactive partitioning is critical to achieving high prediction accuracy in the regression tasks above because real-world data sets typically have uneven distributions [67, 111]. Having smaller partitions might be beneficial for reducing the local max errors, but it increases the overall model (and metadata) size. Because optimal partitioning is an NP-hard problem, we developed different heuristic-based algorithms for different
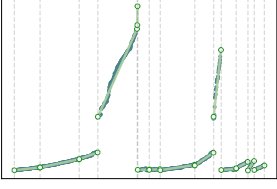
Figure 1: A Motivating Example. – On `movieid` data set.
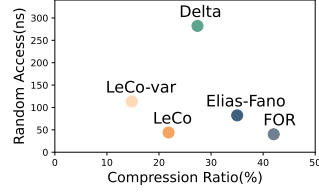
Figure 2: Performance-space trade-offs.

regression models to obtain approximate solutions in a reasonable amount of time. Another design trade-off is between fixed-length and variable-length partitions. Variable-length partitions produce a higher compression ratio but are slower in random access.

We implemented a prototype of LeCo to show the benefit of using machine learning to compress columnar data. For each partition, we store a pre-trained regression model along with an array of fixed-length deltas to record the prediction error at each position. Decompressing a value only involves a model inference plus a random access to the delta array (without decompressing the entire partition). LeCo is highly-extensible with built-in support for various model types and for both fixed-length and variable-length partition schemes.

We compared LeCo against state-of-the-art lightweight compression algorithms including FOR, Elias-Fano, and Delta Encoding using a microbenchmark consisting of eleven single-column data sets (three synthetic, eight real-world). As illustrated in Figure 2[1], LeCo achieves a Pareto improvement over these algorithms. Compared to FOR and Elias-Fano, LeCo improves the compression ratio by up to 81% while retaining a comparable decompression and random access performance. Compared to Delta Encoding, LeCo is an order-of-magnitude faster in random access with a competitive or better compression ratio. We then extended the microbenchmark with nine multi-column data sets and demonstrated that LeCo still holds the advantage over existing algorithms on relational tables. We also showed the superiority of our data partitioning algorithms over existing solutions through a controlled study under the LeCo framework.

We further integrated LeCo into two widely-used applications to study its benefit on end-to-end system performance. We first implemented LeCo in Apache Parquet [5]. Enabling LeCo in Parquet speeds up a filter-scan query by up to 3.9×, and accelerates bitmap-scan up to 12.6×. We also use LeCo to compress the index blocks in RocksDB [14, 46] and observed a 16% improvement in RocksDB's throughput compared to its default configuration.

The paper makes four primary contributions. First, we identify that exploiting the serial correlation between values has a great potential for efficient column compression. Second, we propose the LeCo framework that uses machine learning systematically to remove serial redundancy in a value sequence. Third, we implement a prototype of LeCo that achieves a Pareto improvement on compression ratio and random access speed over the existing algorithms. Finally, we integrate LeCo into example applications and show that it helps improve query performance and save space at the same time.

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[1]Figure 2 is based on the weighted average result of nine data sets in Section 4.3.

2 THE CASE FOR LEARNED COMPRESSION

The performance of persistent storage devices has improved by orders of magnitude over the last decade [105]. Modern NVMe SSDs can achieve 7GB/s read throughput and over 500,000 IOPS [16]. The speed of processors, on the other hand, remains stagnant as Moore's Law fades [54]. Such a hardware trend is gradually shifting the bottleneck of a data processing system from storage to computation. Hence, pursuing a better compression ratio is no longer the dominating goal when developing a data compression algorithm. Many applications today prefer lightweight compression schemes because decompressing the data is often on the critical path of query execution. Meanwhile, the line to separate online analytical processing (OLAP) and online transaction processing (OLTP) is getting blurred in many real-world applications [86]. An analytical workload today is often mixed with OLTP-like queries featuring small range scans or even point accesses [12]. To handle such a wide range of selectivity, it is attractive for a data warehouse to adopt compression algorithms that can support fast random access to the original data without decompressing the entire block.

Dictionary encoding is perhaps the most widely-used compression scheme in the database management systems (DBMSs). In dictionary encoding, the DBMS maps each unique value in a column to an integer and uses those (smaller) integers to represent the entire column. For fixed-length integer symbols, the DBMS can bit-pack the codes so that each symbol only requires log_2N bits, where N is the total number of unique records. Most column stores choose to have fixed-length codes so that they can apply SIMD optimizations to speed up filtered scans and perform random accesses efficiently [72]. If variable-length codes are acceptable, however, the DBMS can apply entropy encoding (e.g., Huffman Encoding [61]) to the integer symbols, where more frequent values are assigned to shorter codes. Then, the compressed size of the column would approach the optimal in this case: Shannon's entropy.

For a mostly unique value sequence (e.g., timestamps), dictionary encoding does not bring compression. The root cause is that dictionary/entropy encoding assumes independence between the values within a column. Under this assumption, the values form a probability distribution instead of a sequence. According to Shannon [32], if the probability distribution is mostly uniform across the value domain, there is not much room for compression.

However, the assumption of value independence ignores the position information embedded in the sequence. Values in many real-world columns often exhibit strong serial correlations (e.g., sorted or clustered) where the probability distribution of a particular value in the sequence is determined by the values of its preceding positions. A compression algorithm can take advantage of such serial correlations to achieve a compression ratio beyond the entropy[2]. For example, if the DBMS detects N consecutive values of v in a column, it can use RLE to encode the sequence as a tuple (v, N). Unfortunately, to the best of our knowledge, there is no general solution proposed that can systematically leverage such positional redundancy for compression.

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[2]The lower bound for data compression is known as the Kolmogorov Complexity. It is the length of the shortest program that can produce the original data [78]. Kolmogorov Complexity is incomputable.

We argue that a learned approach is a natural fit. Extracting serial correlation is essentially a regression task. Once the regression model captures the "common pattern" of the sequence succinctly, we can use fewer bits to represent the remaining delta for each value. This Model + Delta framework (a.k.a., LeCo) is fundamental for exploiting serial patterns in a sequence to achieve lossless compression. A recent pioneer work by Boffa et al. attempted to use linear models for storing rank&select dictionaries specifically [34]. In fact, many widely-used compression algorithms such as Frame-of-Reference (FOR), Delta Encoding (Delta), and Run-length Encoding (RLE) can be considered special cases under our framework as well.

FOR divides an integer sequence into frames, and for each value v_i in a frame, it is encoded as $v_i - v_{min}$ where v_{min} is the minimum value of that frame. From a LeCo 's point of view, the regression function for each frame in FOR is a horizontal line. Although such a naive model is fast to train and inference, it is usually suboptimal in terms of compression ratio. RLE can be considered a special case of FOR, where the values in a frame must be identical. Delta Encoding achieves compression by only storing the difference between neighboring values. Similar to FOR, it uses the horizontal-line function as the model, but each partition/frame in Delta only contains one item. The advantage of Delta is that the models can be derived from recovering the previous values rather than stored explicitly. The downside, however, is that accessing any particular value requires a sequential decompression of the entire sequence.

LeCo helps bridge the gap between data compression and data mining. Discovering and extracting patterns are classic data mining tasks. Interestingly, these tasks often benefit from preprocessing the data set with entropy compression tools to reduce "noise" for a more accurate prediction [98]. As discussed above, these data mining algorithms can inversely boost the efficiency of compression by extracting away the serial patterns through the LeCo framework. The theoretical foundation of this relationship is previously discussed in [50]. Notice that although we focus on regression in this paper, other data mining techniques, such as anomaly detection, also reveal serial patterns that can improve compression efficiency [28, 37]. The beauty of LeCo is that it aligns the goal of value sequence compression with that of serial pattern extraction. LeCo is an extensible framework: it provides a convenient channel to bring related advance in data mining to the improvement of sequence compression.

Although designed to solve different problems, LeCo is related to the recent learned indexes [45, 53, 70] in that they both use machine learning (e.g., regression) to model data distributions. A learned index tries to fit the cumulative distribution function (CDF) of a sequence and uses that to predict the quantile (i.e., position) of an input value. Inversely, LeCo takes the position in the sequence as input and tries to predict the actual value. LeCo's approach is consistent with the mapping direction (i.e., position $\rightarrow$ value) in classic pattern recognition tasks and thus has a close relationship to data mining, as discussed above.

Moreover, most compression scenarios deal with (relatively) static data sets (e.g., a Parquet file). They often follow the pattern of "compress once and access many times". Unlike indexes where incremental updates are the norm, the learned approach fits well for these common compression tasks that rarely retrain models, thus avoiding the "Achilles' heel" (i.e., inefficiency in handling updates)
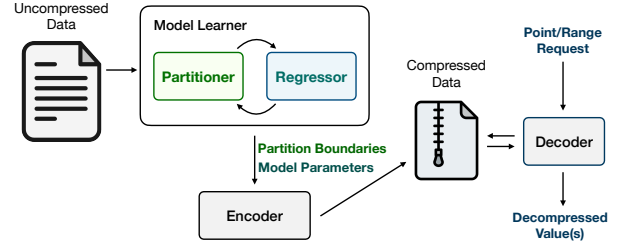
Figure 3: The LeCo Framework – An overview of the modules and the interactions with each other.

of learned indexes. Another key difference is that a learned index can overcome prediction errors through the "last-mile" search in the sequence. On the contrary, LeCo must record the exact prediction errors (i.e., the deltas) to guarantee a lossless compression. Because the size of the (fixed-length) delta array dominates the compression ratio and is proportional to the maximum delta size, the objective of the regression task in LeCo is to minimize the maximum delta instead of the sum of the squared deltas.

We next present the LeCo framework in detail, followed by an extensive microbenchmark evaluation in Section 4. We then integrate LeCo into two real-world applications and demonstrate their end-to-end performance in Section 5.

3 THE LECO FRAMEWORK

Let us first define the learned compression problem that the LeCo framework targets. Given a data sequence $\vec{v}_{[0,n)} = (v_0, ..., v_{n-1})$, let $P_0 = \vec{v}_{[k_0=0,k_1)}, P_1 = \vec{v}_{[k_1,k_2)}, ..., P_{m-1} = \vec{v}_{[k_{m-1},k_m=n)}$ be a partition assignment $\mathcal{P}$ with m non-overlap segments where each partition j has a model $\mathcal{F}_j$. Let $\delta_i = v_i - \mathcal{F}_j(v_i)$, for $v_i \in P_j$. The goal of learned compression is to find a partition assignment $\mathcal{P}$ and the associated models $\mathcal{F}$ such that the following is minimized:

$$\sum_{j=0}^{m-1} (\|\mathcal{F}_j\| + (k_{j+1} - k_j)(\max_{i=k_j}^{k_{j+1}-1} \lceil \log_2 \delta_i \rceil))$$

where $\|\mathcal{F}_j\|$ denotes the model size of $\mathcal{F}_j$.

As shown in Figure 3, LeCo consists of four modules: Regressor, Partitioner, Encoder, and Decoder. Given an uncompressed sequence of values, LeCo first enters the model learning phase, where the Regressor and the Partitioner work together to produce a set of regression models with associated partition boundaries. The Encoder receives the model parameters as well as the original sequence and then generates a compact representation of the "Model + Delta" (i.e., the compressed sequence) based on a pre-configured format. The compressed sequence is self-explanatory: all the metadata needed for decoding is embedded in the format. When a user issues a query by sending one or a range of positions, the Decoder reads the model of the relevant partition along with the corresponding locations in the delta array to recover the requested values.

A design goal of LeCo is to make the framework extensible. We first decouple model learning (i.e., the logical value encoding) from the physical storage layout because applying common storage-level optimizations such as bit-packing and null-suppression to a delta sequence is orthogonal to the modeling algorithms. We also divide the model learning task into two separate modules. The

Regressor focuses on best fitting the data in a single partition, while a Partitioner determines how to split the data set into subsequences to achieve a desirable performance and compression ratio.

Such a modular design facilitates integrating future advances in serial pattern detection and compressed storage format into LeCo. It also allows us to reason the performance-space trade-off for each component independently. We next describe our prototype and the design decisions made for each module (Sections 3.1 to 3.3). followed by the extension to handling string data in Section 3.4.

3.1 Regressor

The Regressor takes in a sequence of values $v_0, v_1, ..., v_{n-1}$ and outputs a single model that "best fits" the sequence. LeCo supports the linear combination of various model types, including constant, linear, polynomial, and more sophisticated models, such as exponential and logarithm. Given a model $\mathcal{F}(i) = \sum_j (\theta_j \cdot \mathcal{M}_j(i))$ where $\mathcal{M}_j$ denotes different model terms and i represents the position in the sequence, classic regression methods minimize the sum of the squared errors $\sum_i (v_i - \mathcal{F}(i))^2$ (i.e., the l_2 norm of deltas), which has a closed-form solution. If LeCo stores deltas in variable lengths, this solution would produce a delta sequence with minimal size. As we discussed before, real databases rarely choose to have variable-length values because the overhead of scanning and filtering on such a sequence is often too large.

LeCo, therefore, stores each value in the delta array in fixed-length. Specifically, LeCo adopts the bit-packing technique. Suppose the maximum absolute value in the delta array is δ_{maxabs}, then each delta occupies a fixed $\phi = \lceil log_2(\delta_{maxabs}) \rceil$ bits. The storage size of the delta array is thus determined by ϕ rather than the expected value of the deltas, and our regression objective becomes:

$$\begin{aligned} \text{minimize} \quad & \phi \\ \text{subject to} \quad & \lceil log_2(|\mathcal{F}(i) - \mathbf{v}_i|) \rceil \leq \phi, i = 0, \ldots, n-1 \\ & \phi \geq 0 \end{aligned}$$

The constrained optimization problem above can be transformed into a linear programming problem with $2n + 1$ constraints where we can get an approximated optimal solution in $O(n)$ time [94].

In general, a more complex model might fit some data partitions better to produce a smaller delta array, but the model itself occupies more space and takes longer to train and infer. Our observation suggests that unless there is prior knowledge about the value distribution, a linear model is often good enough for real-world data sets. There are cases, however, where higher-order terms are particularly beneficial (refer to Section 4.4). A deeper exploration of other sophisticated data mining techniques (e.g., domain transformation, Discrete Fourier Transform) is beyond the scope of this paper.
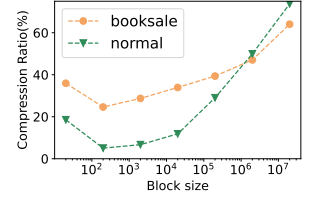
3.2 Partitioner

Given a Regressor, the Partitioner divides the input sequence $\vec{v}_{[0,n)} = v_0, v_1, ..., v_{n-1}$ into m consecutive subsequences (i.e., partitions) $\vec{v}_{[0,k_1)}, \vec{v}_{[k_1,k_2)}, ..., \vec{v}_{[k_{m-1},k_m)}$ where a regression model is trained on each partition. The goal of the Partitioner is to minimize the overall size of the compressed sequences.

Although partitioning increases the number of models to store, it is more likely for the Regressor to produce a smaller delta array when fitting a shorter subsequence. Thus, we require the Partitioner to balance between the model storage overhead and the general
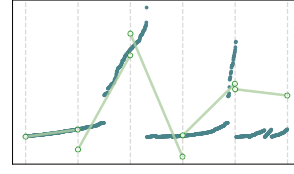
Figure 4: Fixed-length Partitioning Example.

Figure 5: Compression Ratio Trend. – Sweeping block size.

model fitting quality. We can find an optimal partition arrangement by computing the compressed size of each possible subsequence through dynamic programming [96]. Such an exhaustive search, however, is forbiddingly expensive with time complexity of $O(n^3)$ and space complexity of $O(n^2)$.

We next propose two practical partitioning schemes developed in LeCo that make different trade-offs between compression ratio and compression/decompression performance.

3.2.1 Fixed-Length Partitioning. The most straightforward (and most common) strategy is splitting the sequence into fixed-length partitions. This partitioning scheme is easy to implement and is friendly to random accesses. Because each partition contains a fixed number of items, given a position, an application can quickly locate the target partition without the need for a binary search in the metadata. The downside, however, is that fixed-length partitioning is not flexible enough to help the Regressor capture the desired patterns. For example, as shown in Figure 4, if we divide the Movie ID data set (the same one shown in the introduction) into fixed-length partitions, the Regressor and the Partitioner together fail to leverage the piecewise linearity in certain ranges.

We can find a relatively optimal point in the aforementioned trade-off by modifying the partition size. To approach an optimal partition size, we first sample a few subsequences randomly from the original values[3]. We next apply different partition sizes to the sampled data and compute the overall compression ratio. Because the compression ratio typically has a "U-shape" as we vary the partition size (illustrated in Figure 5), we first perform an exponential search to go past the global minimum. Then, we search back with smaller steps to approach the optimal partition size. Our evaluation in Section 4 shows that LeCo with the fixed-length partitioning scheme achieves a preferable balance between compression ratio and overall performance for many real-world data sets.

3.2.2 Variable-Length Partitioning. There exist variable-length partitioning algorithms for linear models when compressing time-series data [48, 49, 83, 84]. However, because the compression is lossy (i.e., the decompressed data is not required to recover the full precision), they only target minimizing the total size of the linear models rather than striking a balance between the model size and the delta sequence size. Our evaluation (Section 4.8) shows that the state-of-the-art variable-length partitioning algorithms [34, 39] are still suboptimal for general column compression.

We, therefore, propose a greedy algorithm for variable-length partitioning for an arbitrary Regressor discussed in Section 3.1 to approximate the optimal solution from the dynamic programming

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[3]We found that a sampling rate $< 1\%$ is often good enough empirically

approach. Distributions in real-world data sets are typically uneven: Some regions align with the regression models well, while others might have large prediction errors. Intuitively, we want larger partitions for the former to amortize the space for model storage; on the other hand, increasing the number of partitions in a region with irregular local distributions might be beneficial to reduce the size of the delta arrays.

Our greedy algorithm has two phases: **split** and **merge**. In the split phase, the algorithm groups consecutive data points into small partitions where the Regressor can predict with small errors. We impose strict constraints to limit the maximum prediction error produced by the Regressor for each partition. Because of our aggressive guarantee of prediction errors, the algorithm tends to generate an excessive number of partitions in the split phase, where the cumulative model size could dominate the final compressed size. To compensate for the over-splitting, the algorithm enters the merge phase where adjacent partitions are merged if such an action can reduce the final compressed size.

Specifically, in the **split** phase, we first pick a few starting partitions. A starting partition contains at least a minimum number of consecutive values for the Regressor to function meaningfully (e.g., three for a linear Regressor). Then, we examine the adjacent data point to determine whether to include this point into the partition. The intuition is that if the space cost of incorporating this data point is less than a pre-defined threshold, the point is added to the partition; otherwise, a new partition is created.

The splitting threshold is related to the model size S_M of the Regressor. Suppose the current partition spans from position i to $j-1$: $\vec{v}_{[i,j)}$. Let $\Delta(\vec{v})$ be a function that takes in a value sequence and outputs the number of bits required to represent the maximum absolute prediction error from the Regressor (i.e., $\lceil log_2(\delta_{maxabs}) \rceil$). Then, the space cost of adding the next data point v_j is

$$C = (j + 1 - i) \cdot \Delta(\vec{v}_{[i,j+1)}) - (j - i) \cdot \Delta(\vec{v}_{[i,j)})$$

We compare C against τS_M, where τ is a pre-defined coefficient between 0 and 1 to reflect the "aggressiveness" of the split phase: a smaller τ leads to more fine-grained partitions with more accurate models. If $C \leq \tau S_M$, v_j is included to the current partition $\vec{v}_{[i,j)}$. Otherwise, we create a new partition with v_j as the first value.

In the **merge** phase, we scan through the list of partitions $\vec{v}_{[0,k_1)}, \vec{v}_{[k_1,k_2)}, ..., \vec{v}_{[k_{m-1},k_m)}$ produced in the split phase and merge the adjacent ones if the size of the merged partition is smaller than the total size of the individual ones. Suppose the algorithm proceeds at partition $\vec{v}_{[k_{i-1},k_i)}$. At each step, we try to merge the partition to its right neighbor $\vec{v}_{[k_i,k_{i+1})}$. We run the Regressor on the merged partition $\vec{v}_{[k_{i-1},k_{i+1})}$ and compare its size $S_M + (k_{i+1} - k_{i-1}) \cdot \Delta(\vec{v}_{[k_{i-1},k_{i+1})})$ to the combined size of the original partitions $2S_M + (k_i - k_{i-1}) \cdot \Delta(\vec{v}_{[k_{i-1},k_i)}) + (k_{i+1} - k_i) \cdot \Delta(\vec{v}_{[k_i,k_{i+1})})$. We accept this merge if it results in a size reduction. We iterate the partition list multiple times until no qualified merge exists.

We next discuss two critical aspects that largely determine the efficiency of the above split-merge algorithm.

Computing $\Delta(\vec{v}_{[i,j)})$ Efficiently. The computational complexity of $\Delta(\vec{v}_{[i,j)})$ dominates the overall algorithm complexity because the function is invoked at every data point inclusion in the split phase. For a general k-degree *polynomial model* $\sum_{i \in [0,k]} \theta_i \cdot x^i$, we can use the method introduced in [94] to compute $\Delta(\vec{v}_{[i,j)})$

in linear time. To further speed up the process for the *linear Regressor* (which is most commonly used), we propose a much simpler metric $\widetilde{\Delta}(\vec{v}_{[i,j)}) = \log_2(\max_{k=i+1}^{j-1}(d_k) - \min_{k=i+1}^{j-1}(d_k))$, where $d_k = v_k - v_{k-1}$ to approximate the functionality of $\Delta(\vec{v}_{[i,j)})$ The intuition is that the proposed metric $\widetilde{\Delta}(\vec{v}_{[i,j)})$ indicates the difficulty of the linear regression task and has a positive correlation to max bit-width measure $\Delta(\vec{v}_{[i,j)})$.

As discussed in Section 2, Delta Encoding is considered a specific design point under the LeCo framework. The model in each Delta partition is an implicit step function, and only the first value in the partition is explicitly stored as the model. The prediction errors (i.e., the $\delta's$) of Delta Encoding are the differences between each pair of the adjacent values. Therefore, $\Delta(\vec{v}_{[i,j)}) = \lceil \log_2(\max_{k=i+1}^{j-1} d_k) \rceil$, where $d_k = v_k - v_{k-1}$. After adding the next data point v_j to this partition, we can directly compute $\Delta(\vec{v}_{[0,j+1)}) = \max\{\Delta(\vec{v}_{[0,j)}), d_j\}$.

Selecting Good Starting Positions. Because the algorithms used in both the split and merge phases are greedy, the quality of the algorithms' starting partitions can significantly impact the partition results, especially for the split phase. Suppose we start at a "bumpy" region $\vec{v}_{[i,j)}$ during splitting. Because $\Delta(\vec{v}_{[i,j)})$ of this partition is already large, there is a high probability that it stays the same when including an extra data point in the partition (i.e., $\Delta(\vec{v}_{[i,j+1)}) = \Delta(\vec{v}_{[i,j)})$). Therefore, the space cost of adding this point becomes a constant $C = \Delta(\vec{v}_{[i,j)})$. As long as $C \leq \tau S_M$, this "bad" partition would keep absorbing data points, which is destructive to the overall compression.

We define the first-order delta sequence as $d_1^1 = v_1 - v_0, d_2^1 = v_2 - v_1, ..., d_{n-1}^1 = v_{n-1} - v_{n-2}$. Then, the kth-order delta is $d_j^k = d_j^{k-1} - d_{j-1}^{k-1}$. For a general *polynomial model* of degree k, we select segments where the $(k+1)$th-order deltas are minimized as the positions to initiate the partitioning algorithm. The intuition is that the discrete $(k+1)$th-order deltas approximate the $(k+1)$th-order derivatives of a continuous function of degree k. If a segment has small $(k+1)$th-order deltas, the underlying function to be learned is less likely to contain terms with a degree much higher than k.

For Delta Encoding, a good starting partition is when the differences between the neighboring values are small (i.e., a small model prediction error) and when the neighboring points form roughly an arithmetic progression (i.e., the partition has the potential to grow larger). We, therefore, compute the bit-width for each delta in the sequence first ("required bits" in Figure 6). We then compute the second-order "delta bits" based on those "required bits" and pick the positions with the minimum value (the yellow-boxed zeros in Figure 6) as the initial partitions. The required bits are used as the tie-breaker to determine the partition growth precedence.

To summarize, we compared the split-merge partitioning algorithm with the linear Regressor against the optimal partitioning obtained via dynamic programming on real-world data sets introduced in Section 4.1 and found that our greedy algorithm imposes less than 3% overhead on the final compressed size.

3.3 Encoder and Decoder

The **Encoder** is responsible for generating the final compressed sequences. The input to the Encoder is a list of value partitions produced by the Partitioner, where each partition is associated with
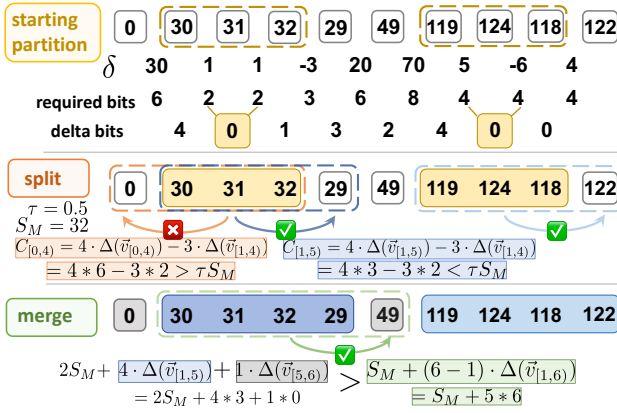
Figure 6: Variable-length Partitioning on Delta Encoding – Value 29 is successfully included into segment $\{30, 31, 32\}$ in the split phase because its inclusion cost $C_{[1,5)} = 6$ is less than the pre-defined threshold $\tau S_M = 16$. In the merge phase, the attempt to merge segment $\{30, 31, 32, 29\}$ and $\{49\}$ succeed because the space consumption of the segment formed is smaller than the summation of the two original segments.

Figure 7: LeCo's Storage Format for One Partition

a model. The Encoder computes the delta for each value through model inference and then stores it into the delta array.

The storage format is shown in Figure 7. There is a header and a delta array for each partition. In the header, we first store the model parameters. For the default linear Regressor, the parameters are two 64-bit floating-point numbers: intercept θ_0 and slope θ_1. Because we bit pack the delta array according to the maximum delta, we must record the bit-length b for an array item in the header.

For fixed-length partitions, the Encoder stores the partition size L in the metadata. If the partitions are variable-length, the Encoder keeps the start index (in the overall sequence) for each partition so that a random access can quickly locate the target partition. We use ALEX [45] (a learned index) to record those start positions to speed up the binary search.

To decompress a value given a position i, the **Decoder** first determines which partition contains the requested value. If the partitions are fixed-length, the value is located in the $\lfloor \frac{i}{L} \rfloor$th partition. Otherwise, the Decoder conducts a "lower-bound" search in the metadata to find the partition with the largest start index $\leq i$.

After identifying the partition, the Decoder reads the model parameters from the partition header and then performs a model inference using $i' = i - \text{start\_index}$ to get a predicted value $\hat{v}$. Then, the Decoder fetches the corresponding $\delta_{i'}$ in the delta array by accessing from the $(b \cdot i')$th bit to the $(b \cdot (i'+1)-1)$th bit. Finally, the Decoder returns the decompressed value $\lfloor \hat{v} \rfloor + \delta_{i'}$. Decoding a value involves at most two memory accesses, one for fetching the model (often cached) and the other for fetching the delta.

The basic algorithm for **range decompression** is to invoke the above decoding process for each position in the range. Because of
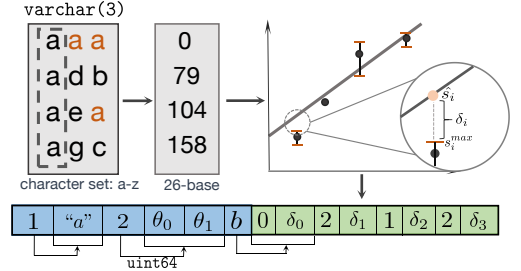
Figure 8: LeCo String Compression – An example including algorithm optimizations and storage format modifications.

the sequential access pattern, most cache misses are eliminated. For the default linear regression, the Decoder performs two floating-point calculations for model inference (one multiplication and one addition) and an integer addition for delta correction.

We propose an optimization to speed up range decompression by saving one floating-point operation per value. For position i, the model prediction is $\hat{v}_i = \theta_0 + \theta_1 \cdot i$. But if the previous prediction $\hat{v}_{i-1} = \theta_0 + \theta_1 \cdot (i-1)$ is available (which is true in range decompression), we can obtain $\hat{v}_i$ by computing $\hat{v}_{i-1} + \theta_1$, thus saving the floating-point multiplication. According to our experiments, this optimization improves the throughput of range decompression throughput by $10 - 20\%$.

There is an additional issue to fix for this optimization. Because of the limited precision in the floating-point representation, the value decoded through the θ_1-accumulation approach could be different from the one decoded via direct model inference at certain position i (i.e., $\lfloor \theta_0 + \sum_1^i \theta_1 \rfloor + \delta_i \neq \lfloor \theta_0 + \theta_1 \cdot i \rfloor + \delta_i$). Therefore, we append an extra list to the delta array to correct the deviation at those positions. The space cost of this error-correction list is negligible because the miscomputation caused by insufficient precision is rare.

3.4 Extension to Handling Strings

The (integer-based) algorithms discussed so far can already benefit a subset of the string columns in a relational table where the values are dictionary-encoded. In this section, we extend our support to string values under the LeCo framework. The idea is to create an order-preserving mapping between the strings and large integers so that they can be fed to the Regressor. The basic mapping is to treat a string as a 128-based integer. For example, a length-2 string "db" is equivalent to $100 \times 128 + 98 = 12898$ in base 10. To represent large integers, we use the built-in uint64 for a value less than 8 bytes. If the value is between 8 and 16 bytes, we use the built-in uint128. For values larger than 16 bytes, we rely on the multiprecision support from the Boost library [6]. We next present several optimizations to reduce the sizes of the mapped integers to speed up computation and facilitate regression.

Given a partition of string values, we first extract their common prefix (marked in dashed box in Figure 8) and store it separately in the partition header. This effectively shortens the string lengths and thus potentially reduces the sizes of the mapped integers. The next optimization is to shrink the size of the character set if possible. Because many string data sets refer to a portion of the ASCII table, we can use a smaller base to perform the string-integer mapping. In Figure 8, the data set only involves lower-case letters, we can treat

them as 26-based integers, and string "db" is mapped to $3 \times 26 + 1 = 79$ instead of 12898 in the 128-based conversion.

Notice that for an arbitrary M-based mapping, the computation required to recover each character from the integer is expensive. Given the mapped integer v, it requires an integer modulo $v \% M$ to decode the current character and an integer division v/M to prepare for decoding the next one. Both operations take tens of CPU cycles. To speed up decoding, we set M to its closest power of two (2^m) so that the modulo becomes a left-shift followed by a bit-wise AND ($v \& ((1 << m) - 1)$), and the division becomes a right-shift ($v >> m$). For example, for strings that only consist of lower-case characters, we set $M = 32$.

LeCo requires strings to be fixed-length. For a column of varchar(3), we pad every string to 3 bytes (padding bytes marked with orange "a" in Figure 8). An interesting observation is that we can leverage the flexibility in choosing the padding characters to minimize the stored deltas. Suppose the string at position i is s_i, and the smallest/largest valid string after padding is s_i^{min}/s_i^{max} (i.e., pad each bit position with the smallest/largest character in the character set). We then choose the padding adaptively based on the predicted value $\hat{s}_i$ from the Regressor to minimize the absolute value of the prediction error. If $\hat{s}_i < s_i^{min}$, we adopt the minimum padding and store $\delta_i = s_i^{min} - \hat{s}_i$ in the delta array; if $\hat{s}_i > s_i^{max}$, we use the maximum padding and produce $\delta_i = s_i^{max} - \hat{s}_i$; if $s_i^{min} \leq \hat{s}_i \leq s_i^{max}$, we choose $\hat{s}_i$ as the padded string directly and obtain $\delta_i = 0$.

The lower part of Figure 8 shows the updated storage format to accommodate varchars. Additionally, the header includes the maximum padding length (without prefix) along with the common prefix of the partition. We also record the length of each varchar value in the delta array. These lengths can be omitted for fixed-length strings (i.e., without padding).

4 MICROBENCHMARK EVALUATION

We evaluate LeCo in two steps. In this section, we compare LeCo against state-of-the-art lightweight compression schemes through a set of microbenchmarks. We analyze LeCo's gains and trade-offs in compression ratio, random access speed, and range decompression throughput. In Section 5, we integrate LeCo into two widely-used applications to show the end-to-end performance.

4.1 Compression Schemes and Data Sets

The baseline compression schemes under evaluation are Elias-Fano [85, 100], Frame-of-Reference (FOR) [57, 113], Delta Encoding (Delta) [27], and rANS [47]. FOR and Delta are introduced in Section 2. rANS is a variant of arithmetic encoding [103] with a decoding speed similar to Huffman [61]. Elias-Fano is an encoding mechanism to compress a sorted list of integers. Suppose the list has n integers, with m being the difference between the maximum and minimum value of the sequence. Elias-Fano stores the lower $\lceil log_2(\frac{m}{n}) \rceil$ bits for each value explicitly with bit packing. For the remaining higher bits, Elias-Fano uses unary coding to record the number of appearances for each possible higher-bit values.

We evaluate LeCo and the baseline solutions extensively on nine integer data sets and two string data sets:

- **linear, normal**: synthetic data sets with 200M 32-bit sorted integers following a clean linear (or normal) distribution.

- **poisson**: 87M 64-bit timestamps following a Poisson distribution that models events collected by distributed sensors [109].
- **ml**: 14M 64-bit sorted timestamps from the UCI-ML data set [18].
- **booksale**: 200M 32-bit sorted integers from the SOSD benchmark [67] representing book sale popularity data at Amazon.
- **facebook**: 200M 64-bit sorted integers from the SOSD benchmark representing Facebook user IDs.
- **wiki**: 200M 64-bit sorted integers from the SOSD benchmark representing edit timestamps of Wikipedia articles.
- **movieid**: 20M 32-bit "liked" movie IDs from MovieLens [9].
- **house_price**: 100K 32-bit sorted integers representing the distribution of house prices in the US [10].
- **email**: 30K email addresses (host reversed) with an average string length of 15 bytes [2].
- **hex**: 100K sorted hexadecimal strings (up to 8 bytes) [35].

Figure 9 visualizes the nine integer data sets where noticeable unevenness are observed frequently in real-world data sets.

4.2 Experiment Setup

We run the microbenchmark on a machine with Intel®Xeon®(Ice Lake) Platinum 8369B CPU @ 2.70GHz and 32GB DRAM. The three baselines are labeled as Elias-Fano, FOR, and Delta-fix. Delta-var represents our improved version of Delta Encoding that uses the variable-length Partitioner in LeCo. LeCo-fix and LeCo-var are *linear-Regressor* LeCo prototypes that adopt fixed-length and variable-length partitioning, respectively. The corresponding LeCo variants with *polynomial Regressor* are labeled LeCo-Poly-fix and LeCo-Poly-var. For all the fixed-length partitioning methods, the partition size is obtained through a quick sampling-based parameter search described in Section 3.2.1. For Delta-var, LeCo-var, and LeCo-Poly-var, we set the split-parameter τ to be small (in the range $[0, 0.15]$) in favor of the compression ratio over the compression throughput.

Given a data set, an algorithm under test first compresses the whole data set and reports the compression ratio (i.e., *compressed_size / uncompressed_size*) and compression throughput. Then the algorithm performs N uniformly-random accesses (N is the size of the data set) and reports the average latency. Finally, the algorithm decodes the entire data set and measures the decompression throughput. All experiments run on a single thread in the main memory. We repeat each experiment three times and report the average result for each measurement.

4.3 Integer Benchmark

Figure 10 shows the experiment results for compression ratio, random access latency, and decompression throughput on the nine integer data sets. Elias-Fano does not apply to poisson and movieid because these two data sets are not fully-sorted.

Overall, LeCo achieves a Pareto improvement over the existing algorithms. Compared to Elias-Fano and FOR, the LeCo variants obtain a significantly better compression ratio while retaining a comparable decompression and random access speed. When compared to Delta Encoding, LeCo remains competitive in the compression ratio while outperforming the Delta variants by an order of magnitude in random access.
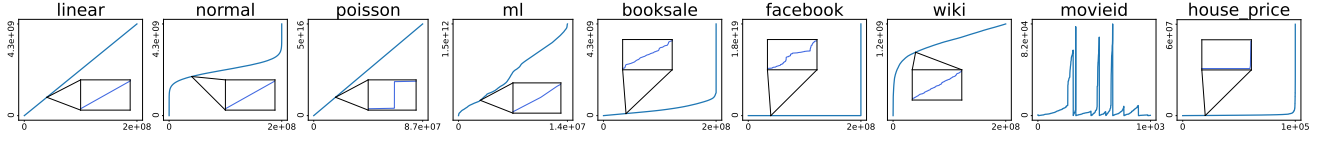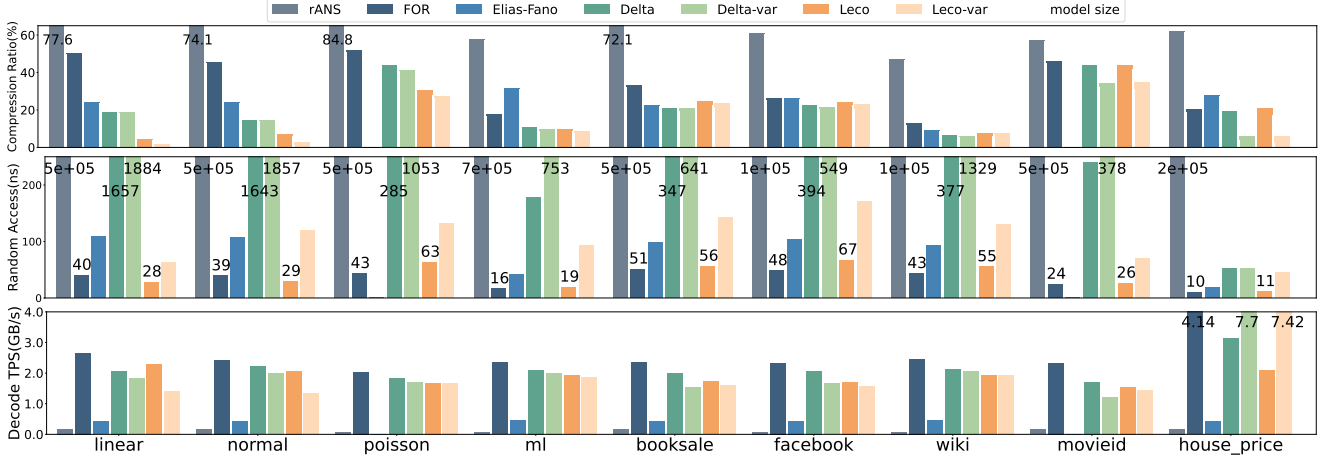
Figure 9: Data Distribution.

Figure 10: Compression Microbenchmark – Measurement of seven compression schemes on nine integer data sets from three aspects: Compression Ratio, Random Access Latency, and Full Decompression Throughput. We break down the compression ratio into model size (marked with the cross pattern) and delta size in the first row.

4.3.1 Compression Ratio. As shown in the first row of Figure 10, the compression ratios from the LeCo variants are strictly better than the corresponding ones from FOR. This is because FOR is a special case of LeCo: the output of its Regressor is fixed to a horizontal line (refer to Section 2).

LeCo also compresses better than Elias-Fano across (almost) all data sets. Although Elias-Fano is proved to be quasi-succinct, it fails to leverage the embedded serial correlation between the values for further compression. rANS remains the worst, which indicates that the redundancy embedded in an integer sequence often comes more from the serial correlation rather than the entropy.

Compared to Delta Encoding, LeCo shows a remarkable improvement on compression ratio for "smooth" (synthetic) data sets: linear, normal, and poisson. For the remaining (real-world) data sets, however, LeCo remains competitive. This is because many real-world data sets exhibit local unevenness, as shown in Figure 9. The degree of such irregularity is often at the same level as the difference between adjacent values.

Another observation is that variable-length partitioning is effective in reducing the compression ratio on real-world data sets that have rapid slope changes or irregular value gaps (e.g., movieid, house_price). Our variable-length partitioning algorithm proposed in Section 3.2 is able to detect those situations and create partitions accordingly to avoid oversized partitions caused by unfriendly patterns to the Regressor.

4.3.2 Random Access. The second row of Figure 10 presents the average latency of decoding a single value in memory for each compression scheme. The random access speed of LeCo-fix is comparable to that of FOR because they both require only two memory

accesses per operation. FOR is often considered the lower bound of the random access latency for lightweight compression because it involves minimal computation (i.e., an integer addition). Compared to FOR, LeCo-fix requires an additional floating-point multiplication. This overhead, however, is mostly offset by a better cache hit ratio because LeCo-fix produces a smaller compressed sequence.

LeCo-var is slower because it has to first search the metadata to determine the corresponding partition for a given position. This index search takes an extra $35-90$ ns depending on the total number of partitions. The Delta variants are an order of magnitude slower than the others in most data sets because they must decompress the entire partition sequentially to perform a random access.

4.3.3 Full Decompression. The third row in Figure 10 shows the throughput of each compression algorithm for decompressing an entire data set. In general, LeCo-fix is $14\% - 34\%$[4] slower than its fastest competitor FOR because LeCo-fix involves an extra floating-point operation upon decoding each record. Delta-var and LeCo-var perform exceptionally well on house_price. The reason is that part of the data set contains sequences of repetitive values. LeCo's Partitioner would detect them and put them into the same segment, making the decompression task trivial for these partitions.

Notice that the benefit of having a smaller compressed size is barely reflected in the above throughput measurements when everything is already in memory. We show in Section 5 that a better compression ratio (by LeCo) can improve the query performance in real-world applications.

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[4]except for house_price where the enhancement of FOR over LeCo-fix is 49%

FOR	Elias-Fano	Delta-fix	Delta-var	LeCo-fix	LeCo-var
0.81±0.28	0.58±0.17	1.04±0.14	0.04±0.01	0.78±0.11	0.02±0.01

Table 1: Compression Throughput (GB/s).

*4.3.4 **Compression throughput**.* Table 1 shows the compression throughput for each algorithm weighted averaged across all the nine data sets with error bars. LeCo-fix has a similar compression speed to the baselines because our linear Regressor has a low computational overhead. Algorithms that adopt variable-length partitioning (i.e., Delta-var and LeCo-var), however, are an order of magnitude slower because the Partitioner needs to perform multiple scans through the data set and invokes the Regressor (or an approximate function) frequently along the way. Such a classic trade-off between compression ratio and throughput is often beneficial to applications that do not allow in-place updates.

4.4 A Case For Higher-Order Models

Although linear models perform sufficiently well in the above integer benchmark[5], there are cases where higher-order models shine. In this section, we simulate a common situation in cosmology where a high-precision sensor keeps recording the signals from a particular cosmic ray for the cosmologists to query later. The sensor readings contain 100M integers[6] and are constructed by overlaying different *sine* functions plus a random noise[7]. As shown in Figure 11, LeCo with a polynomial Regressor (of degree three) reduces the data set size by an additional ∼ 30% compared to LeCo with a linear Regressor. Because such a sensor-reading data set is mostly read-only, it is usually worthwhile to spend more computation to compress the data once and then benefit from long-term space and query efficiency. Note that if domain knowledge is available in this case, we could include sinusoidal terms directly into the LeCo framework to obtain a more impressive compression ratio because integrating new models into LeCo requires minimal work.

4.5 Compressing Dictionaries

Building dictionaries that preserve the key ordering is a common technique to achieve compression and speed up query processing [33, 82, 110]. Reducing the memory footprint of such dictionaries is an important use case of LeCo. In the following experiment, we perform a hash join with the probe side being dictionary encoded. Specifically, we use the medicare[8] dataset as the probe-side column, and we pre-build a hash table of size 84MB in memory, which contains 50% of the unique values (i.e., 50% hash table hit ratio during the join). The probe side first goes through a filter of selectivity of 1% and then probes the hash table for the join. The probe-side values are encoded using an order-preserving dictionary compressed by LeCo (i.e., LeCo-fix), FOR, and Raw (i.e., no compression). We vary the memory budget from 3GB to 500MB and report the throughput (defined as the raw data size of the probe side divided by the query execution time) of executing this query.

Figure 11: Higher-Order Model Compression Ratio.

Figure 12: Hash Probe Throughput.

Figure 12 shows that applying LeCo improves the throughput up to 95.7× compared to FOR when the memory budget for this query is limited. This is because LeCo compresses the probe-side dictionary from 2.4GB to 5.5MB (cpr ratio = 0.23%) so that it constantly fits in memory. For comparison, the dictionary size compressed using FOR is still 400MB (cpr ratio = 17%). When the available memory is limited, this larger dictionary causes a significant number of buffer pool misses, thus hurting the overall query performance.

4.6 Multi-Column Benchmark

In this section, we evaluate the effectiveness of LeCo on multi-column tabular data sets[9]. As shown in Figure 13 (bottom right), the benchmark includes three tables from TPC-H [25] (i.e., lineitem, partsupp, and orders), three tables from TPC-DS [24] (i.e., inventory, catalog_sales, and date_dim), and three real-world tables (i.e., geo [20], stock [21], and course_info[22]). The benchmark considers numerical columns only. Each table is sorted by its primary-key column. We compute the "sortedness" of a table (in the range [0, 1]) by averaging the sortedness of each column using the portion of inverse pairs[38] as the metric.

From Figure 13 (the top row), we observe that LeCo achieves a better compression ratio than FOR in all nine tables. This is because columns in a table are often correlated [56, 62, 92]. Our "sortedness" metric indicates that non-primary-key columns have different degrees of correlation with the primary-key (i.e., sorting) column across tables, thus partially inheriting the serial patterns. Tables with high sortedness such as inventory and data_dim are more likely to achieve better compression ratios with the LeCo variants.

The bottom left of Figure 13 presents the compression ratios of the TPC-H tables with high-cardinality columns only (i.e., NDV > 10% #row). LeCo's has a more noticeable advantage over FOR on columns that are likely to select FOR as the compression method.

4.7 String Benchmark

We compare LeCo (i.e., LeCo-fix) against the state-of-the-art lightweight string compression algorithm FSST [35] using two string data sets email and hex. FSST adopts a dictionary-based approach by building a fine-grained static symbol table to map a partial string to a 1-byte code. Because each compressed string has a variable length, FSST must store a byte-offset array to support random access. An optimization (not mentioned in the FSST paper) is to delta-encode this offset array to trade its random access speed for a better compression ratio. To perform a fair comparison, we tested

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[5]Many data sets in the integer benchmark come from the SOSD benchmark [67], which favors linear models.

[6]Same as decimal numbers with fixed precision.

[7]We use $(\sin \frac{x+10}{60\pi} + \frac{1}{10} \sin \frac{3(x+10)}{60\pi}) \times 10^6 + \epsilon$, where ϵ is the random noise following a Gaussian distribution $\mathcal{N}(0, 100)$.

[8]The dataset contains 10M 64-bit integers and is from the public BI benchmark [23]. We augment the data to 1.5B records without modifying its distribution.
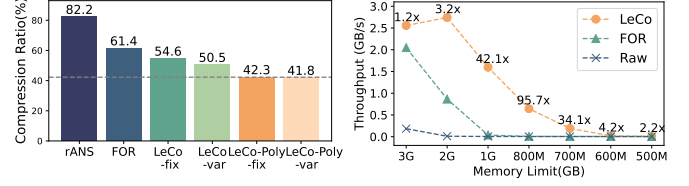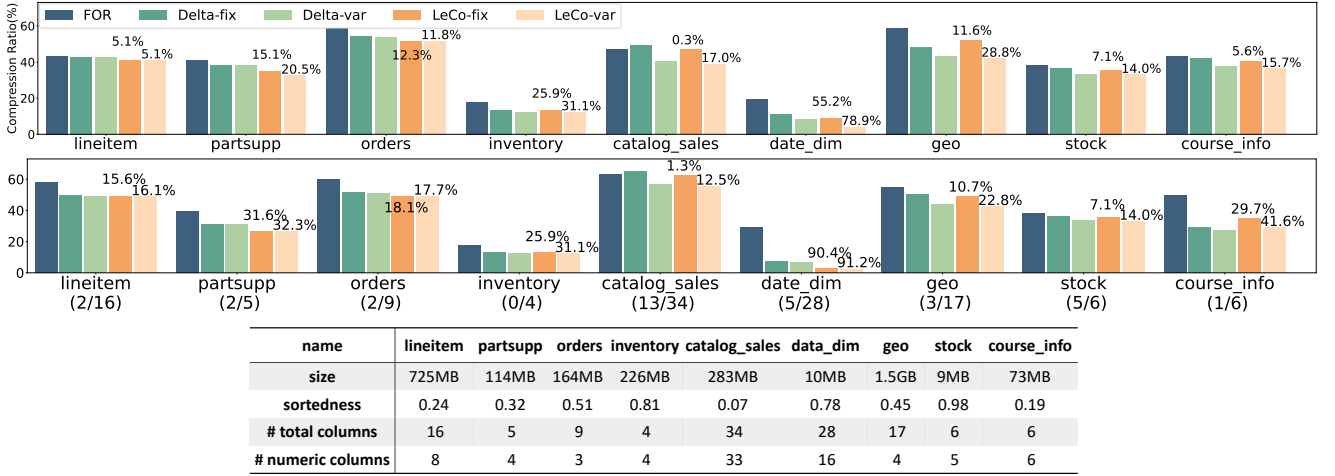
[9]Elias-Fano is not included as baseline because most columns are not strictly sorted.

| name	lineitem	partsupp	orders	inventory	catalog_sales	data_dim	geo	stock	course_info
size	725MB	114MB	164MB	226MB	283MB	10MB	1.5GB	9MB	73MB
sortedness	0.24	0.32	0.51	0.81	0.07	0.78	0.45	0.98	0.19
# total columns	16	5	9	4	34	28	17	6	6
# numeric columns	8	4	3	4	33	16	4	5	6

Figure 13: Multiple Column – Compression ratio of five methods on nine tabular data sets. The second row of the result only considers columns with cardinality $\geq 10\%$. We report the size in bytes, average sortedness (in the range $[0, 1]$), total column number, and integer/numerical column number of each table. We mark the enhancement ratio of LeCo variants over FOR above the bars.
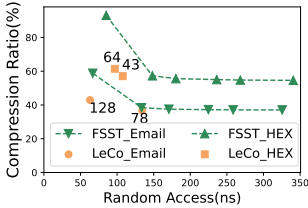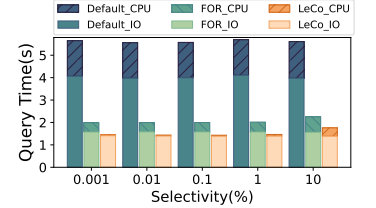

Figure 14: LeCo String Evaluation.
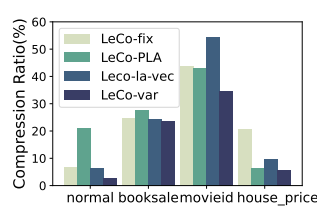
Figure 15: Space comparison of partitioning algorithms.
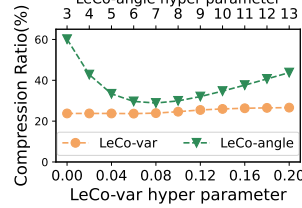
Figure 16: Hyper Parameter Sweep of partition algorithms.

Figure 17: Parquet Filter Scan Query.

six different block sizes of the delta encoding: 0 (i.e., no delta compression), 20, 40, 60, 80, and 100. For LeCo, we present two data points with different character-set sizes.

Figure 14 shows the random access latencies and compression ratios for different algorithm configurations. Each LeCo point is marked with the base value used to convert strings. We observed that LeCo's string extension provides a higher random access speed while retaining a competitive compression ratio, compared to FSST on both `email` and `hex` data sets.

4.8 Partitioner Efficiency

In this section, we compare LeCo's default Partitioner (as described in Section 3.2) to state-of-the-art partitioning algorithms, including the PLA algorithm adopted by time-series compression [69, 83] as well as FITing tree [55] and the la_vector algorithm proposed in [34]. The angle-based PLA predefines a fixed global prediction error bound (ϵ) and determines the partition boundaries greedily in one pass. On the other hand, la_vector translates each data point v_i into a vertex i, where the weight of edge (i, j) is defined as the compression ratio of segment $[v_i, v_j]$. The optimal partitioning problem is thus converted into finding the shortest path in the above graph $\mathcal{G}$. To reduce the computation complexity, la_vector approximates $\mathcal{G}$ with $\mathcal{G}'$ with fewer edges and proofs that the best compression ratio achieved on $\mathcal{G}'$ is at most $k \cdot l$ larger than that on $\mathcal{G}$ where k is a constant and l is the shortest path length.

We integrated PLA and la_vector into the LeCo framework (with the linear Regressor denoted by LeCo-PLA and LeCo-la-vec, respectively) and repeated the experiments in Section 4.3 on four representative data sets. As shown in Figure 15, both LeCo-PLA and LeCo-la-vec exhibit significantly worse compression ratios compared to LeCo-var. The globally-fixed error bound in LeCo-PLA fails to adapt to data segments with rapidly changing slopes. We also found that LeCo-PLA is more sensitive to its hyperparameter compared to LeCo-var, as shown in Figure 16 where we sweep the hyperparameters for LeCo-PLA (ϵ) and LeCo-var (τ) on the `books` data set. For LeCo-la-vec, although it finds the shortest path in the approximate "compression-ratio graph", it overlooked the length of the shortest path, resulting in an excessive number of models that dominates the compressed size on data sets such as `movieid`.

5 SYSTEM EVALUATION

To show how LeCo can benefit real-world systems, we integrated LeCo into two widely-used applications: Parquet [5] and RocksDB [14, 46]. For each application, we first introduce the implementations. Then, we present a set of experiments to demonstrate how LeCo improves query performance and storage cost simultaneously. All experiments are conducted on a machine with 4× Intel®Xeon® (Cascade Lake) Platinum 8269CY CPU @ 2.50GHz, 32GB DRAM, and a local NVMe SSD of 447GB with 250k maximum read IOPS. The setting is similar to RocksDB's recommendation [15].

We use Apache Arrow 8.0.0, Parquet version 2.6.0 and RocksDB Release version 6.26.1 in the following experiments.

5.1   Integration to Parquet

Apache Parquet [5] has become a standard open format for columnar data storage. In this section, we study how lightweight compression schemes such as LeCo can benefit the format in both query performance and storage cost. We integrated LeCo and FOR into Parquet using its C++ implementation [3]. Parquet uses dictionary encoding as the default compression method. It falls back to plain encoding if the dictionary grows too large. We refer to this mechanism as `Default`. We set Parquet's row group size to 10M rows for the experiments. Block compression is disabled unless specified otherwise.

5.1.1   Filter Scan. Filter scan is one of the most common operations performed against database storage. It applies a filter predicate on one column and then use the result bitmap or selection vector to filter another column (for engines that supports late materialization [36]). We created a table consisting of 200M rows and two columns: (1) `ts` is an almost-sorted timestamp column (in seconds) extracted from the `ml` [18] data set, and (2) `id` contains (randomly shuffled) Facebook user IDs [67]. The query returns a list of users who log in to the application in a specific time range per day: SELECT `id` FROM table WHERE *time_1* < `ts` % (24 * 60 * 60) < *time_2*. We adjust the time range (i.e., *time_2 - time_1*) to control the query selectivity. We generated three Parquet files with `Default`, `FOR`, and `LeCo-fix` as the encoding algorithm separately. For FOR and LeCo-fix, we set the partition size to 10K items. The resulting file size is 3.0GB, 1.3GB, and 1.1GB, respectively. We repeat each query three times and report the average execution time.

As shown in Figure 17, LeCo reduces the query execution time by 3.7× compared to Parquet `Default` and by 1.4× compared to FOR on average with varying selectivities. The I/O times across the algorithms are proportional to the corresponding file sizes because the I/O skipping is performed at the row-group level (via zone maps)[10]. Both FOR and LeCo support partition-level skipping in memory by reading the partition headers only. But interestingly, LeCo saves up to 9.2× CPU times compared to FOR in this filter-scan template. This is because LeCo can further skip decoding items *within* a partition. Suppose that the model of the partition is $\theta_0 + \theta_1 \cdot i$, and the bit-length of the delta array is b. For a less-than predicate $v < \alpha$, for example, once LeCo decodes the partition up to position k, where $\theta_0 + \theta_1 \cdot k - 2^{b-1} > \alpha$ (assume $\theta_1 \geq 0$), We can safely skip the values in the rest of the sequence because they are guaranteed to be out of range. FOR cannot perform such a computation pruning because the `ts` column is not *strictly* sorted.

5.1.2   Bitmap Selection. We zoom in to examine the bitmap selection operation separately. When Parquet receives a bitmap it applies the filter to the column and outputs a sequence of qualified values. We evaluate using a subset of the data sets introduced in Section 4.1: `normal`, `poisson`, `booksale`, and `ml`[11]). Given a data set, we create one Parquet file for each compression option (i.e., Default, FOR, and LeCo-fix). We then feed each Parquet file with

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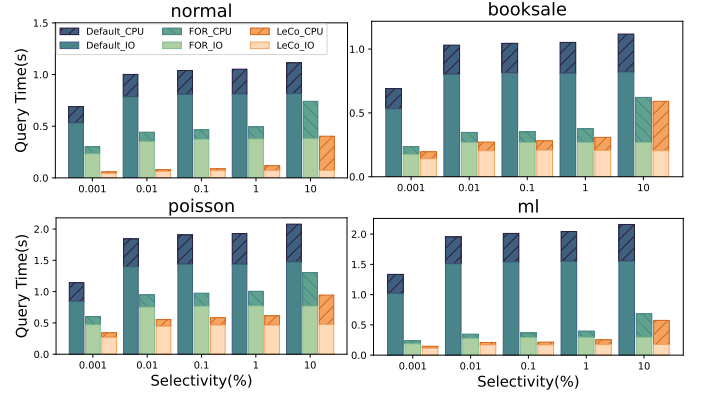[10]Zone maps at a finer granularity is currently unsupported Parquet's C++ version.
[11]Because the `ml` data set is too small compared to the others, we scale it to 200M rows while preserving its value distribution.
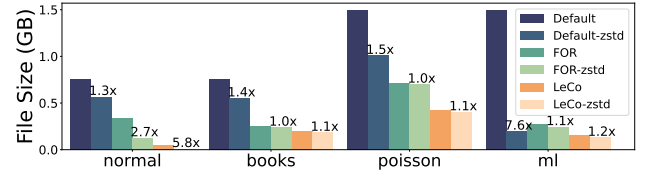

Figure 18: Parquet Bitmap Selection.

Figure 19: Parquet With zstd Compression – Numbers on bars indicating additional improvement introduced by zstd.

bitmaps having different ratios of "ones" (to represent a varying filter selectivity). Each bitmap includes ten set-bit clusters following a Zipf-like distribution. A row group is skipped if it does not contain any requested value.

Figure 18 shows the time consumed to perform a bitmap-scan on Parquet files with different compression options. We vary the filter selectivity on the x-axis. LeCo consistently outperforms Default (by up to 12.6×) and FOR (by up to 5.6×). Compared to FOR with a selectivity less than 1%, LeCo's speedup comes from both the I/O reduction (due to a better compression ratio) and the CPU saving (due to better caching). As the selectivity increases to 10%, the size advantage of LeCo is generally diluted by an increased computational cost for decoding[12].

5.1.3   Enabling Block Compression. People often enable block compression on columnar storage format such as Parquet and ORC [4] to further reduce the storage overhead. We repeat the Parquet loading phase of the above experiments with zstd [19] enabled to show how block compression algorithms affect the final file sizes.

As shown in Figure 19, the additional improvement introduced by zstd is marked above each bar. Applying zstd on top of the lightweight encoding schemes in Parquet can further reduce the file sizes. The relative improvement of LeCo + zstd over LeCo is higher than that in the case of FOR. This shows that LeCo's ability to remove serial redundancy is complementary to some degree to the general-purpose block compression algorithms.

The decompression overhead of zstd, however, can be significant. We repeated the bitmap selection experiments in Section 5.1.2 with zstd turned on for Parquet. Figure 20 shows an example result (`ml` data set, selectivity = 0.01). We observe that the I/O savings from

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[12]Because the "zone" skipping granularity in the current C++ implementation of Parquet is a row group, a 10% selectivity requires almost an entire file scan + decoding.
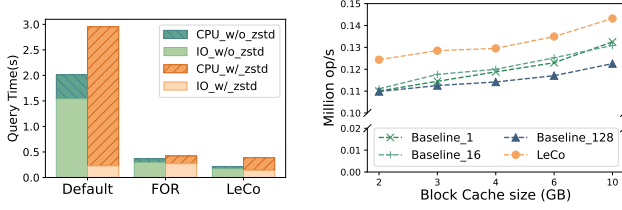
Figure 20: Time breakdown of zstd on Parquet.

Figure 21: RocksDB Seek Query Throughput.

zstd are outweighed by its CPU overhead, leading to an increase in the overall query time. The result confirms our motivation in Section 2 that heavyweight compression algorithms are likely to cause CPU bottlenecks in modern data processing systems.

5.2 RocksDB Index Block Compression

RocksDB is a key-value store based on log-structured merge trees. Each level consists of a sorted run of key-value pairs stored in a sequence of SSTables. Each SSTable is divided into multiple data blocks (4KB by default). RocksDB builds an index on top of the data blocks. For each pair of adjacent data blocks B_{i-1} and B_i, an index entry is created where the key is the shortest string greater than the last key in B_{i-1} and smaller than the first key in B_i. The value of the index entry is a "block handle" that records the byte offest and the size of B_i. To locate a particular key k, RocksDB performs a binary search in the index block and obtains the entry with the smallest key $\geq k$. It then reads the associated "block handle" and fetches the corresponding data block that (potentially) contains k.

RocksDB offers a native compression scheme for the index blocks. It includes a hyper-parameter called "restart interval" (RI) to make trade-offs between the lookup performance and the index size. The value of RI determines the size of a compression unit in an index block. Within each compression unit, RocksDB applies a variation of Delta Encoding to both the keys and values. For the index keys, suppose k_{i-1} proceeds k_i in the compressed sequence. Then k_i is encoded as (m_i, k'_i) where m_i denotes the length of the shared prefix between k_{i-1} and k_i, and k'_i is the remaining suffix. For the "block handles", RocksDB simply stores the offset of each block in a delta-encoded sequence.

We use LeCo to compress the keys and values separately in a RocksDB index block to shrink its size and to improve the lookup performance at the same time. We adopt LeCo-fix for both key and value sequences. Because all internal keys in RocksDB are strings, we use LeCo with the string extension to compress the keys.

We compare RocksDB with LeCo against[13] three baseline configurations: `Baseline_1`, `Baseline_16`, and `Baseline_128`. The number at the end of each label denotes the value of the RI parameter (1 is RocksDB's default). We configured RocksDB according to the settings in its Performance Benchmark [15][14]. We turned on direct I/O to bypass the large OS page cache.

In each experiment, we first load the RocksDB with 900 million record generated from the above RocksDB Performance Benchmark. Each record has a 20-byte key and a 400-byte value. The resulting RocksDB is around 110 GB. LeCo, `Baseline_1`, `Baseline_16`, and `Baseline_128` achieve a compression ratio of 28.1%, 71.3%, 18.9%

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[13]The fixed partition size are set to 64 entries for LeCo.

[14]block_size = 4096B; pin_l0_filter_and_index_blocks_in _cache is enabled.

and 15.9%, respectively on the index blocks in RocksDB. We then perform 200M non-empty Seek queries using 64 threads. The query keys are generated using YCSB [41] with a skewed configuration where 80% of the queries access 20% of the total keys. We repeat each experiment three times and report the average measurement.

Figure 21 shows the system throughputs for LeCo, and the baselines with a varying block cache size. RocksDB with LeCo consistently outperforms the three baseline configurations by up to 16% compared to the second-best configuration. The reasons are two-fold. First, compared to `Baseline_1` where no compression for the index blocks are carried out (each compression unit only contains one entry), LeCo produces smaller index blocks so that more data blocks can fit in the block cache to save I/Os. Such a performance improvement is more recognizable with a smaller block cache.

Second, compared to `Baseline_16` and `Baseline_128` where the index blocks are compressed using Delta Encoding. Although LeCo no longer exhibits an index-size advantage over these baselines, it saves a significant amount of computations. Compared to `Baseline_128` which need to decompress the entire 128-entry unit before it accesses a single entry, LeCo only requires two memory probes to perform a random access in the index block.

To sum up, applying LeCo speeds up binary search in the index blocks. Such a small change improved the performance of a complex system (RocksDB) noticeably. We believe that other systems with similar "zone-map" structures can benefit from LeCo as well.

6 RELATED WORK

Many prior compression algorithms leverage repetitions in a data sequence. Null suppression omits the leading zeros in the bit representation of an integer and records the byte length of each value [1, 27, 89, 93, 97]. Dictionary [30, 33, 35, 80, 82, 91, 110] and entropy-based compression algorithms [61, 103] build a bijective map between the original values and the code words. Block compression algorithms such as LZ77 [112], Gzip [7], Snappy [8], LZ4 [11], and zstd [19] achieve compression by replacing repeated bit patterns with shorter dictionary codes. These approaches, however, miss the opportunity to exploit the serial correlation between values to achieve a compressed size beyond Shannon's Entropy.

A pioneer work by Boffa et al. [34] proposed to use a similar linear model as in the PGM-Index [53] with a customized partitioning algorithm (i.e., la_vector) to compress a specific data structure called the rank&select dictionaries. Their approach represents a specific design point in the LeCo framework that is much more general and extensible in model types and partitioning algorithms. Also, LeCo's default variable-length partitioning algorithm is shown to be more efficient than la_vector for compressing columnar data (refer to Section 4.8).

Semantic compression [56, 62, 63] aims to compress tabular data by exploiting correlations between columns using complex models like Bayesian networks. LFR[107] and DFR[106] use linear model or Delta-like model to compress data without partitioning. Because their model parameters vary at each data point, they do not support quick random access.

Data partitioning plays an essential role in achieving a good compression ratio for various algorithms. Several prior work [85, 88] targeting inverted indexes proposed partitioning algorithms for

specific compression schemes like Elias-Fano [100] and VByte [99, 102]. The partitioning algorithms introduced in Section 3.2 are applicable to an arbitrary linear combination of regression models. In terms of storage format, FastPFOR [113] and NewPFD [108] stores outlier values separately in a different format to improve the overall storage and query efficiency.

Time-series/IoT data compression field adopts a similar idea with LeCo of approximating data distribution with models, but they target keeping the prediction error within a predetermined threshold and achieve **lossy** compression. Their optimization goal is to minimize the total space of model parameters. Partitioning algorithms for linear models [49, 83, 104] and constant value models [74] are designed to minimize the segment number. Sim-Piece[69] introduces a more compact format to keep the output models. Eichinger et al. [48] consider utilizing higher order models but require additional computation effort in the approximation process.

Both learned indexes and learned compression use regression to model data distributions. RMI [70] and RS [68] apply hierarchical machine learning models to fit the CDFs, while PGM-Index [53], FITing-Tree [55], and CARMI [111] put more effort into the partitioning strategies to reduce model prediction errors. ALEX [45] and Finedex [79] proposed techniques such as a gapped array and non-blocking retraining to improve the indexes' update efficiency.

Previous work [26, 114] have shown that heavyweight compression algorithms [7, 8, 61] designed for disk-oriented systems could incur notable computational overhead to the overall system performance. Algorithms such as FSST [35] and PIDS [64], therefore, emphasize on low CPU usage besides a competitive compression ratio. Other related work reduces the computational overhead by enabling direct query execution on compressed formats [27, 43, 65], including filter and aggregation/join pushdowns [40, 44, 52, 58, 72, 76, 81].

7 CONCLUSION

This paper introduces LeCo, a lightweight compression framework that uses machine learning techniques to exploit serial correlation between the values in a column. We provide a complementary perspective besides Shannon's entropy to the general data compression problem. The LeCo framework bridges data mining and data compression with a highly modular design. Both our microbenmark and system evaluation show that LeCo is able to achieve better storage efficiency and faster query processing simultaneously.

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