To appear in *Proc. 11th ACM-SIAM Symp. on Discrete Algorithms,* San Francisco, CA

Engineering the Compression of Massive Tables: An Experimental Approach

Adam L. Buchsbaum* Donald F. Caldwell* Kenneth W. Church* Glenn S. Fowler*
S. Muthukrishnan*

Abstract

We study the problem of compressing massive tables. We devise a novel compression paradigm—*training for lossless compression*—which assumes that the data exhibit dependencies that can be learned by examining a small amount of training material. We develop an experimental methodology to test the approach. Our result is a system, `pzip`, which outperforms `gzip` by factors of two in compression size and both compression and uncompression time for various tabular data. `Pzip` is now in production use in an AT&T network traffic data warehouse.

1 Introduction

We study the problem of compressing massive tables, which arises naturally in corporate data warehouses. Our goal is to provide a working system that can be put into production use and achieve 100:1 compression, in particular, one that can compress 10s of TB of data into 100s of GB. We devise a novel compression strategy—*training for lossless compression*—which can leverage standard compression methods, and we demonstrate its effectiveness experimentally. In the process, we identify the requirements for our compression application and design algorithmic solutions to various technical problems. The system we built, `pzip`, can compress 1 TB of data from AT&T's network traffic data warehouse into about 28 GB, small enough to fit on one PC disk and a two-fold improvement over existing solutions (in time as well as space). `Pzip` is now in production use in the warehouse.

Our motivating applications are tables of traffic data from telecommunication networks. For example, the AT&T voice communications network generates a record of each phone call it carries. A typical record consists of several hundred bytes and depicts network-level information (e.g., endpoint exchanges), time-stamp information (e.g., start and end times), and billing-level information (e.g., applied tariffs). This application generates about 1 TB of data per month and is just one example of the many different tables that AT&T and other corporations generate. Others include switch- and router-level traffic data, equipment sensor data (e.g., alarm status), and credit card transaction records. These data have certain unifying characteristics: they have fixed-length records and fields, they are written once but read many times, and they are truly massive (TBs per year). Furthermore, they typically contain much redundancy.

On the other hand, they are **not** text corpora (English, DNA, etc.), multimedia (images, audio, etc.), or WWW data (catalogs, bibliographies, XML files, etc.) Developing semantic compression techniques for each of these is an independent research area. Such methods can exploit domain-specific information, which is problematic in our setting for reasons explained below. Furthermore, our data sets are larger than most commercial data sets. Most dictionaries, corpora, etc., also are not this large. (For example, The Oxford English Dictionary consumes less than 10 GB; the Associated Press Newswire generates about one million words of text per week.)

Traditionally, compression is desirable because it saves not only storage space but also the I/O bandwidth (to disks, tapes, etc.) for accessing data. An added benefit is the savings in network bandwidth for transmitting data. This interests AT&T, where traffic tables may be shipped repeatedly to many centers: for fraud detection, billing, report generation, auditing, marketing, archival, customer care, and data analysis in general. The benefit of compression is thus saving not only storage space for a single copy of the data, with proportional effects on capital requirements for data warehouses, but also the cumulative cost of storing and transporting multiple copies of the data over the system for its entire lifespan, which may well be several years.

Any solution to the problem of compressing massive tables must satisfy the following constraints. (1) The compression must be lossless, as the information in the records must be preserved. (2) The algorithms must work on-line, processing the data as a stream, because there are applications, such as fraud detection, that require immediate access to the data. (3) The system must work fast, in particular in better than real time: the total time to process one day's worth of data cannot exceed one day, and compression accounts for a small fraction of the total processing time. There are additional requirements that are dictated by the peculiar circumstances under which the problem arises. Large corporations have legacy data, legacy systems feeding on such data, and large bodies of personnel managing them. Thus any system-level solution must work on legacy data formats, be integrable with legacy systems, and be easily deployed

*AT&T Labs, Shannon Laboratory, 180 Park Ave., Florham Park, NJ 07932; {alb,dfwc,kwc,gsf,muthu}@research.att.com.

and maintained. Finally, it is preferable that any solution be general, applying to the many different tables, or portions of tables, that are processed. Thus we cannot exploit domain-specific syntactic or semantic information.

Studying massive tables is a new focus in compression research. To distinguish our context from extant ones, consider the related field of database compression, where relational data may be viewed as tables. This differs from our table compression problem in many ways. First, the goals are different. Database compression stresses the preservation of indexing—the ability to retrieve an arbitrary record—under compression [7]. Table compression does not require indexing to be preserved. Next, the data are different. Database records are often dynamic, unlike table data, which have a write-once discipline. Databases consist of heterogeneous data, possibly with several string fields of variable length; table data are more homogeneous, with fixed field lengths. Also, non-tabular databases are not routinely TBs in size. (An exception is NASA's EOSDIS database [13], which anticipates processing 1 TB of satellite images every two weeks.) Finally, the approaches to database compression include lightweight techniques such as compressing each tuple by simple encodings [7, 8] and tiling the entire table [8]. These approaches are not appropriate for table compression: the former is too wasteful, and the latter too expensive and cumbersome.

Our contribution is a novel approach for the table compression problem: *lossless compression via training*. The idea is to construct a *compression plan* for the table by studying a very small training set off line. To do so, we assume that the data can be modeled by an underlying source that can be learned from a small sample. We further assume and exploit dependencies in the columns of the data in one of two ways: (1) implicitly, by grouping the columns that compress well together; and (2) explicitly, by determining a dependency tree among the columns. We then employ the compression plan on the entire dataset. To test our assumptions, we implement algorithms to construct compression plans on some training sets, and we compress test sets with respect to the plans. We compare the resulting compression to the straightforward approach of treating the tables as text and applying Lempel-Ziv compression [20, 21]. It will be clear that comparable performance would falsify our assumptions about the data dependencies. In all cases, however, our algorithms provide substantial compression improvements. While training has been applied to lossy compression, e.g., in speech coding [12, 15], ours is the first known instance of applying training to lossless compression.

For our primary application, compression exploiting implicit dependencies outperformed that using explicit dependencies. We have implemented the corresponding algorithm—*optimum partitioning*—in `pzip`, a fully working software system for compressing table data, which has been deployed in the AT&T network traffic data warehouse. `Pzip` achieves factors of about 2 improvement in compression size and both compression and uncompression time over `gzip`, the method previously used in this application.

In Section 2, we discuss the table compression problem further and define our assumptions regarding data dependencies. In Section 3, we present technical problems that exploit our assumptions, and we give algorithmic solutions to these problems. In Section 4, we present our experimental results, and in Section 5, we discuss the `pzip` system and some additional applications. In Section 6, we summarize our contributions and present directions for future work.

2 Problem Discussion

Our input consists of a table, T, of a large number of rows, each of length n bytes. We define *column* i to be the projection of the ith byte of each row, for $1 \leq i \leq n$. (A byte is the smallest unit of data that can be easily and rapidly accessed; moreover, this level of granularity captures patterns among larger lexical units.) The *table compression problem* is to compress T, such that the requirements discussed in Section 1 are satisfied.

From an information-theoretic point of view, T can be treated as a string, e.g., of bytes in row-major order. It would thus suffice to perform Lempel-Ziv [20, 21] or Huffman [9] compression, yielding provably optimal asymptotic performance in terms of certain ergodic properties of the source that generates the table. This does not, however, adequately solve the table compression problem. For specific classes of inputs, e.g., tables of network traffic data, the optimality results may not necessarily hold. In particular, the optimality results hold only with respect to compression methods that likewise treat T as a (byte) string; i.e., methods that do not account for complex dependencies in T. Some compression does result, however, and we use this method as our benchmark in Section 4.

We need a few technical definitions. Denote by $T[i]$ the ith column of T. Denote by $T[i,j]$ the interval of columns i through j of T. Finally, denote by $\mathcal{S}(C)$ the size of the result of compressing some interval C of columns, in row-major order, using an arbitrary but fixed compressor.

2.1 Assumptions.

Our approach to the table compression problem assumes that there are dependencies among the columns of T. In particular, we will consider dependencies of two types: *combinational* and *differential*.

DEFINITION 2.1. *Two contiguous intervals of columns* $T[i,j]$ *and* $T[j+1,\ell]$ *are* combinationally dependent *if*

$$\mathcal{S}(T[i,j]) + \mathcal{S}(T[j+1,\ell]) > \mathcal{S}(T[i,\ell]).$$

Combinational dependency is an *implicit dependency* between intervals. It merely expresses that intervals of columns are dependent, without determining which columns are dependent on the others.

DEFINITION 2.2. *Column* $T[j]$ *is* differentially dependent *on column* $T[i]$ *if*

$$\mathcal{S}(T[j]) > \mathcal{S}(T[i] - T[j]),$$

where $T[i] - T[j]$ *is the column formed by taking the row-wise difference between columns* $T[j]$ *and* $T[i]$.

Differential dependency is an *explicit dependency* between columns, in that it determines which column is dependent on the other. In general, we might compress $T[j]$ and $T[i] - T[j]$ by different methods, and we might consider other transformations $T[i] \odot T[j]$. This does not affect the ensuing discussion.

Our approach also makes the important assumption that the data is generated by some source that is well behaved, in particular, that dependencies (such as those above) among columns, if they exist, can be captured by examining a small amount of data, independent of the size of T.

3 Algorithmic Issues

We design compression schemes based on the assumptions embodied in Definitions 2.1 and 2.2.

3.1 Combinational Approach. We can exploit combinational dependencies as follows. Consider a partition, P, of T into intervals $T[p_0+1, p_1], T[p_1+1, p_2], \ldots, T[p_{\ell-1}+1, p_\ell]$, such that $p_0 = 0$ and $p_\ell = n$. We refer to an interval $T[p_{i-1} + 1, p_i]$ in P as a *class*. We define the *cost* of P to be

$$\mathcal{S}(P) = \sum_{i=1}^{\ell} \mathcal{S}(T[p_{i-1} + 1, p_i]).$$

The goal is find an optimum partition, i.e., $\hat{P}$ such that $\mathcal{S}(\hat{P}) = \min_P \mathcal{S}(P)$.

We can find an optimum partition as follows. Define $E(i)$ to be the cost of an optimum partition of $T[1, i]$ for $i \geq 1$, and define $E(0) = 0$. Then for $i \geq 1$,

$$E(i) = \min_{0 \leq j \leq i-1} E(j) + \mathcal{S}(T[j + 1, i]).$$

Assuming that the cost $\mathcal{S}(T[j, i])$ has been computed for all $1 \leq j \leq i \leq n$, we can compute $E(n)$ (and the corresponding partition) in $O(n^2)$ time by simple dynamic programming.

We call this *optimum partitioning*. This gives the following *compression plan* for compressing T: compress each class in the optimum partition independently in row-major order.

We can further speed up the dynamic programming, under the assumption that there are many optimum or near optimum partitions for compressing T, and that among these are some in which the classes are not too wide. To do so, we develop a "chunking" approach, in which, for some $1 \leq k < n$, we divide the n columns into $\lceil n/k \rceil$ pairwise-disjoint intervals of size at most k each, and solve our general problem on each such interval. The running time becomes $O(nk)$. We call this *chunk partitioning*, and it likewise returns a compression plan.

3.2 Differential Approach. We can exploit differential dependencies as follows. Consider a partition of the n columns of T into two sets, P and $\bar{P} = [1, n] \setminus P$. We treat the columns in P as *source columns* and those in $\bar{P}$ as *derived columns*. Given a mapping $\sigma : \bar{P} \to P$, we define the *cost*, $\mathcal{S}(P, \sigma)$ to be

$$\sum_{p \in P} \mathcal{S}(T[p]) + \sum_{\bar{p} \in \bar{P}} \mathcal{S}(T[\sigma(\bar{p})] - T[\bar{p}]).$$

The goal is to find a pair (P, σ) of minimum cost.

This is precisely the facility location problem [17]. We will assume that the differential cost is a metric. In general, this depends on the base compressor. We apply the simple, greedy algorithm for this problem [14].

At any time, we have a candidate pair $(\hat{P}, \hat{\sigma})$. We determine the smallest cost solution, $(\hat{P}', \hat{\sigma}')$, obtained by

1. removing a column from $\hat{P}$,
2. adding a column to $\hat{P}$, or
3. substituting one of the columns in $\hat{P}$ for one not in $\hat{P}$.

(Ties are broken arbitrarily.) If $\mathcal{S}(\hat{P}', \hat{\sigma}') < \mathcal{S}(\hat{P}, \hat{\sigma})$, then we set $\hat{P} \leftarrow \hat{P}'$ and $\hat{\sigma} \leftarrow \hat{\sigma}'$ and iterate. Otherwise we are done. We call this *greedy differential compression*. The final solution is roughly 5-optimal under the metric assumption [14]. Better approximations [3, 4, 5, 11] are known, but the greedy algorithm suffices for our purpose of testing the presence of differential dependencies.

Greedy differential compression produces the following compression plan: compress each column in $\hat{P}$ independently, and for each column $\bar{p} \notin \hat{P}$, compress $T[\hat{\sigma}(\bar{p})] - T[\bar{p}]$.

3.3 Lossless Compression via Training. Our overall approach is thus the following.

1. Select a small subset $T' \subset T$ as training material.
2. Using T', compute a compression plan, P, for T by either the combinational or differential approach.
3. Compress T with the compression plan P.

Our assumption that the amount of training data needed is independent of the size of T implies that, once we have generated a compression plan, we can use it to compress future tables generated by the same source as T. Training is thus an off-line procedure.

So far, we have abstracted the base problem of computing $\mathcal{S}(T[i])$ and $\mathcal{S}(T[i, j])$. Rather than develop our own base compression method, we decided to use one of the standard programs, which have already been well optimized: e.g., `compress` [18, 21], `gzip` [20], and `vdelta` [10]. Each is fast, on-line, and well-suited to our application. Of other available compressors, we note that `PPM` [6, 19], which exploits context sensitivity and thus seems applicable to table data, and `bzip` [1] are too slow for our environment, although attempts have been made to tune `PPM` for speed at the expense of compression size [16]. We therefore do not use `bzip` and `PPM` in our compression scheme, but we do compare our scheme against `bzip` and `PPM` by themselves. We note but do not consider in this paper hybrid approaches, in which we pick the best compressor for a given interval. We can even nest the differential approach within the combinational approach.

4 Experiments

4.1 Methodology. We summarize our assumptions as follows.

1. Our data sets present combinational dependencies.
2. The combinational approach is likely to induce some (near) optimum partition in which no class is wide.
3. Our data sets present differential dependencies.
4. The above dependencies can be detected with a small amount of training data, independent of the size of T.

We fix `gzip` as our underlying compression method. While this does not explore the range of possible base compressor options, it suffices to test our approach. As *benchmark R*, we apply `gzip` to T in row-major order, corresponding to the usage of `gzip` without off-line training; as *benchmark C*, we apply `gzip` to T in column-major order, corresponding to the other extremal partition in which no combinational or differential dependencies exist. We thus designed experiments to compare the performance of

1. optimum partitioning to the benchmarks,
2. chunk partitioning to optimum partitioning, and
3. the greedy differential compression to both optimum partitioning and benchmark C.

Each experiment has the potential to falsify one of our assumptions. If either benchmark outperforms optimum partitioning (with respect to output size), then our data sets do not present combinational dependencies. If optimum partitioning significantly outperforms chunk partitioning, then all (near) optimum partitions must have at least one wide class. If benchmark C outperforms the greedy differential compression, then our data sets do not present differential dependencies. We discuss testing assumption (4) below.

For each experiment, we produced a compression plan by running the corresponding algorithm on a training data set. Using the resulting plan, we compressed a disjoint test data set, and we compared the compression performance (time and size) to that of the benchmark(s) for that goal. Although size of compressed output is the metric by which our assumptions can be falsified, we also measured running times, to assess the practicality of our methods. This methodology extends to assess other, similar compression systems.

We also varied the amount of training data available, to gauge the effect of training size on compression performance. This is only the first step in testing assumption (4). If we do not see compression performance stabilize at some point as we increase the amount of training data, then assumption (4) is likely falsified. After observing this stabilization, however, a second test will be required: namely, to fix the training set size above the point at which we observed stability and increase the test set size arbitrarily. If the relative performance of the compression systems being compared does not remain stable, again assumption (4) is likely falsified. Otherwise, we will have evidence supporting assumption (4). Although this second experiment remains to be conducted, based on our results we do not expect assumption (4) to be falsified.

Finally, we compared the best results from the above experiments with isolated usages of compressors based on the Burrows-Wheeler transform [1] and prediction by partial match (PPM) [6, 19]. The goal was to assess empirically the benefit of our training scheme, which leverages standard compression technology, versus other methods that claim improved compression via sophisticated analyses of the source data.

Data. We used 100,000 records from a network traffic data warehouse. Each record is 781 bytes and pertains to an individual network event. The warehouse receives approximately one billion records per month, so effective compression is critical to this application. From the 781 columns of bytes, we extracted the 90 with the highest *frequency*: i.e., the number of times the value of the byte changed as the column was scanned top-down. We explain this in Section 5; basically, in our real application, the other 691 columns were compressed more effectively using incomparable methods.

We divided the 100,000 (now 90-byte) records into training and test sets. The training set was 1/11th of the data; the test set was the rest. We chose the training set in two ways: (1) the first 9091 records, which we will call the *ordered training set*, and (2) a randomly chosen set of 9091 records, which we will call the *random training set*. Each way left the corresponding rest of the data as the test set. In all our experiments, we used the training sets to generate the corresponding compression plans, and we conducted the compression experiments using those plans and the test sets.

Software. To run the experiments, we implemented the following tools.

`pin`. Given a training set, `pin` computes a compression plan based on optimum partitioning.

`pzip`. Given a compression plan computed by `pin`, `pzip` compresses a test set with respect to the plan. It encodes enough of the plan into the output (which is included in the output size results reported) so that, given a compressed file, `pzip` will uncompress it without needing the original plan. (`Pin` and `pzip` actually form our working system, and we discuss them in greater detail in Section 5.)

`colsel`. Given a training set, `colsel` computes a compression plan based on the greedy differential algorithm.

`cszip`. Given a compression plan computed by `colsel`, `cszip` compresses a test set with respect to the plan. It encodes enough of the plan into the output (which is included in the output size results reported) so that, given a compressed file, `cszip` will uncompress it without needing the original plan.

`Pzip` and `cszip` use the `zlib` library, version 1.1.3,[1] to compress the intervals and columns, respectively.

System. All the training and experiments were run on one 250 MHz MIPS R10000 processor on a 16-processor SGI Origin 2000 running IRIX 6.5, with 10 GB of main memory. Each time reported is the median of five runs, summing user and system time for each run.

4.2 Experiments and Results.

Optimum Partitioning. To test assumption (1) and assess how optimum partitioning affects compression performance, we used `pin` to compute optimum partitions on pieces of the training data of increasing size. We ran `pzip` with each resulting compression plan on the test set and compared the compression time and resulting size to those of the benchmarks; we also compared uncompression times. We performed this experiment using both the ordered and random training sets.

Figures 1 and 2 displays the results, as a function of the amount of training material used. Training on the 2%-size (w.r.t. the test set size) data set, at which we see the results stabilize, took about 2.27 CPU minutes. Because we anticipate using the same compression plan with multiple tables from a fixed source, though, training should be viewed as an off-line procedure. The results suggest that optimum partitioning offers significant improvement over both benchmarks and thus fail to falsify assumption (1). We saw 30–35% improvement in compression for this application. We suspect that most of the 15–25% degradation in compression and uncompression time vs. benchmark R can be attributed to the work required for `pzip` to organize the columns. Analogous effort is required to compress benchmark C, but not benchmark R. We argue in Section 5 that the resulting size improvement is worth this time overhead.

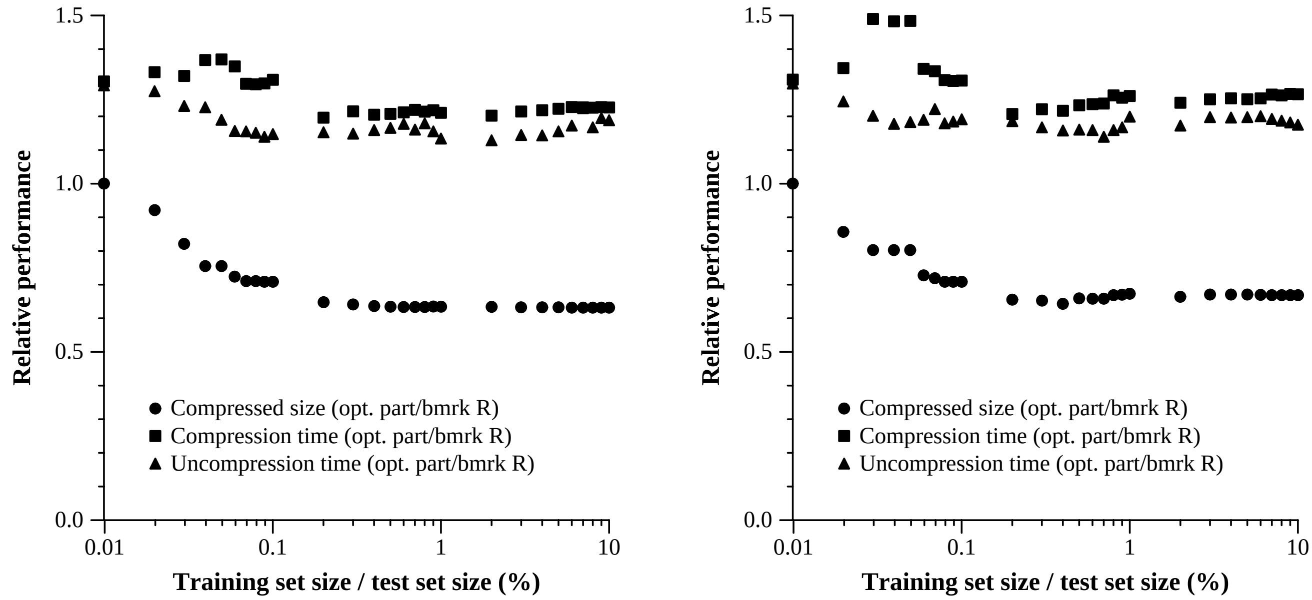
Chunk Partitioning. To test assumption (2) and assess the degradation in partition quality from using chunk partitioning, we computed chunk partitions on the training sets that were 2% of the test set size. (The optimum partitioning experiment suggests that larger training sets offer no increased benefits in compression performance.) Using `pin` on the individual chunks, we computed an optimum chunk partition for each possible chunk size. We used `pzip` with each resulting compression plan to compress the test set. We compared each result to that given by `pzip` using an optimum partition (from the 2% training size), measuring relative output size, compression and uncompression speeds, and training time. We performed this experiment using both the ordered and random training sets, comparing chunk partitioning to the corresponding optimum partition.

Figure 3 displays the results, as a function of chunk size. The results fail to falsify assumption (2) and furthermore suggest that chunk partitioning is worthwhile, as small chunk sizes (10–20 in this experiment) yielded almost identical performance as optimum partitioning, but required only about 2–6% of the training time.

Greedy Differential Compression. To test assumption (3) and assess how greedy differential compression affects performance, we computed greedy differential compression plans using `colsel` on pieces of the training data of increasing size. We compressed the test set using `cszip` with the resulting plans and compared the resulting size, compression and uncompression time to that of `pzip` using an optimum partition (from the 2% training size) and also to benchmark C. For the comparison to optimum partitioning, we also compared the time to compute the greedy assignment (using `colsel`) to that to compute the optimum partition (using `pin`). We performed this experiment using both the ordered and random training sets.

Figure 4 displays the results, as a function of the amount of training material used. (For brevity, we display only the results for the ordered training set. As in the previous experiments, using the random training set yielded similar results.) The results show that greedy differential compression offers slight improvement over benchmark C, in particular a 2.5% improvement in compression, and thus fail to falsify assumption (3). On the other hand, greedy differential compression does not compare favorably to optimum partitioning, except

[1] `ftp://ftp.cdrom.com/pub/infozip/zlib`



(a) (b)

Figure 1: Results of optimum partition compression, as a function of amount of training material. Shown is the relative performance of optimum partitioning over benchmark R in terms of compressed size, compression time, and uncompression time. (a) Ordered training set; (b) random training set.

in training time.

We offer a caveat: `pzip` has undergone significantly more code optimization than `cszip`, which partially explains the relative difference in running times. We believe that we can improve the running time of `cszip` by combining the column differencing and compression of the derived columns into a single pass.

4.3 General Discussion. In all the experiments above, the difference between using ordered and random training sets was negligible, although the ordered sets did provide slightly better results, suggesting the need for future experiments to assess the effects of contiguity in the training data.

We did observe stabilization of compression performance in all the experiments. Perhaps most remarkable is that this stabilization occurred at training set sizes of 1–2% of the test set size. Again, further experiments with increasingly larger test sets and a fixed training set size are required before assumption (4) can be assumed with confidence.

4.4 Comparison to Other Methods. We compared the result of optimum partitioning (using the 2% training size) to Burrows-Wheeler [1] and PPM [6, 19] compression in isolation. For Burrows-Wheeler, we used Seward's `bzip2`, version 0.9.5d.[2] For PPM, we used Bloom's `ppmz`, version 9.1;[3] we used coder 9, which offers the best (albeit the slowest) compression, with the rationale that if best PPM compression turned out to be less than that of optimum partitioning, faster PPM variants would not offer interesting comparisons.

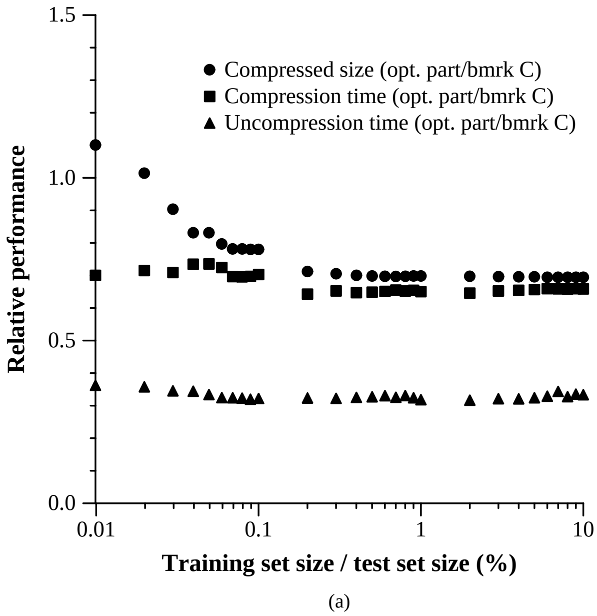
Table 1: Comparison to other methods. Size and times are ratios of optimum partitioning values to the corresponding other-method values.

Method	Size	Compress. time	Uncompress. time
`gzip`			
row-major	6.340e-1	1.202e-0	1.129e-0
col-major	6.977e-1	6.457e-1	3.168e-1
`bzip`	7.768e-1	4.344e-1	2.165e-1
`PPM`	8.786e-1	2.950e-3	4.010e-4

Table 1 details the results. For completeness, we include comparisons to `gzip` used in row-major order (i.e., benchmark R), corresponding to off-the-shelf use of `gzip`, and to `gzip` in column-major order (i.e., benchmark C). Optimum partitioning achieved greater compression than all the other methods used in isolation. Furthermore, it was faster than all the other methods, except for row-major `gzip`; compared to

[2] `http://sourceware.cygnus.com/bzip2/index.html`

[3] `http://www.cco.caltech.edu/~bloom/src/ppmz.html`



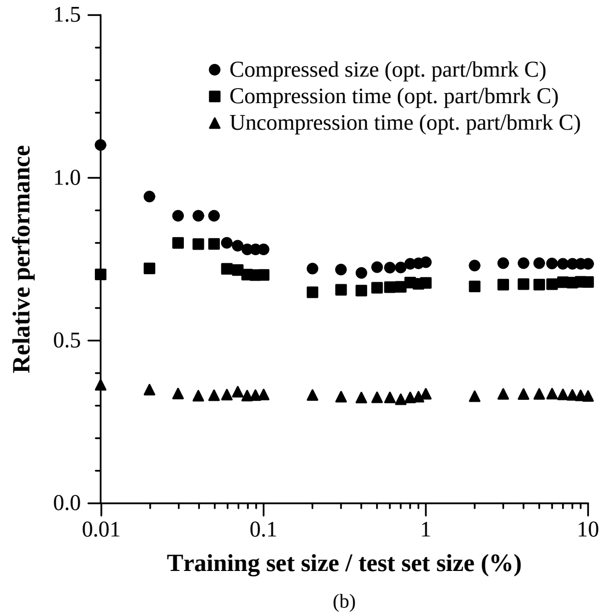


Figure 2: Results of optimum partition compression, as a function of amount of training material. Shown is the relative performance of optimum partitioning over benchmark C in terms of compressed size, compression time, and uncompression time. (a) Ordered training set; (b) random training set.

PPM, the relative speed difference was orders of magnitude.

The results suggest that, for our table application, optimum partitioning using `gzip` as the underlying compression method outperforms isolated usage of `bzip` and `PPM`, which by themselves purport to outperform `gzip`. Since `bzip` did out-compress `gzip` with only a slight time penalty, it is worth future experimentation to assess the performance of optimum partitioning using `bzip` as the underlying compression method.

5 Partition Compression System and Applications

`Pin` and `pzip` actually form our production compression system. Recall that the experiments in Section 4 used only the 90 highest frequency columns from the original data set. Prior to determining an optimum partition, `pin` calculates column frequencies. It actually computes the optimum partition only on the projection of the high frequency columns. (How it determines low from high is a heuristic outside the scope of this paper.) Furthermore, before computing the partition, it employs another heuristic to reorder the high frequency columns to improve compression size further. Again, this heuristic is outside the scope of this paper and was turned off for the experiments in Section 4.

`Pzip` then compresses the low frequency columns by differential encoding, additionally `gzip`ping the output of of that phase, and the high frequency columns with respect to the (reordered) partition. On the low frequency columns of the full network traffic data set, this method outperformed the `gzip` benchmark (R) by two orders of magnitude in compression size and almost an order of magnitude in compression time. To measure how the full system works on the original data set, we repeated the structure of the optimum partitioning experiment, allowing `pin` to detect the low frequency columns and `pzip` to use differential encoding on them. The system setup was as in Section 4, and again we fixed `gzip` as the underlying compression method. We compared to benchmark R, corresponding to off-the-shelf use of `gzip`, which was the method of choice in the AT&T network traffic data warehouse prior to our work. The results are shown in Figure 5. For this experiment, we used only the ordered training set, as the random training set destroys the frequency information.

The results indicate overall improvements relative to straight `gzip` of 55% in compression size **and** 40–50% in both compression and uncompression time, supporting the argument that the space improvement by optimum partitioning is worth the extra time. The time savings for the low frequency columns more than paid for the extra time needed to compress the high frequency columns via optimum partitioning. Again, training sets of 1–2% of the test set size sufficed to achieve these results. Applied to the network traffic warehouse, `pin/pzip` compresses the raw data for an entire month from the original 1 TB to about 28 GB, small enough to fit on a large PC disk. By comparison, `gzip` compressed the data only to about 65 GB.

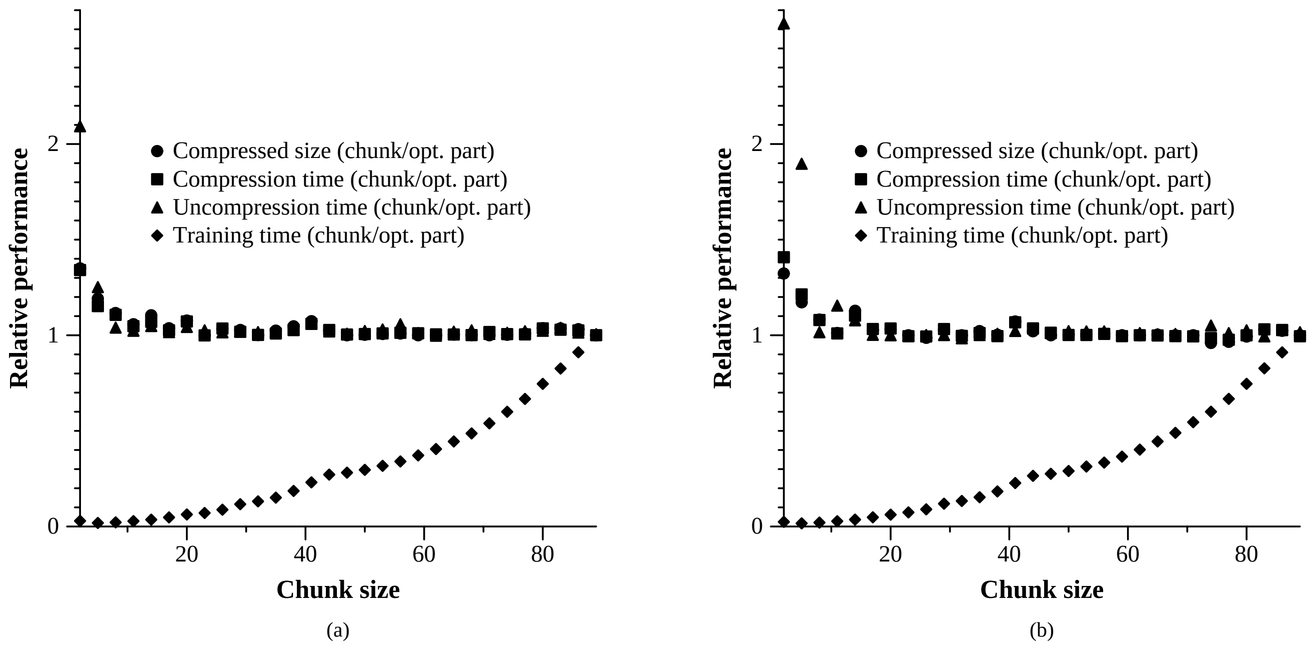


Figure 3: Results of chunk partition compression, as a function of chunk size. Shown is the relative performance of chunk partitioning over optimum partitioning in terms of compressed size, compression time, uncompression time, and training time. (a) Ordered training set; (b) random training set.

5.1 Additional Test Sets.

The AT&T network switch statistics project. In this project, statistics are collected at 15-minute intervals from ATM switches in a network. A record corresponds to a replaceable circuit component in one of the switches and consists of a 16-byte hardware identifier, a 4-byte statistic identifier, a 4-byte time stamp, and a 4-byte count value. Each 15-minute interval produces a file with about 80,000 records for a 6-switch network. The items are sorted by the 16-byte hardware identifier; sorted identifiers usually differ by one byte from one item to the next. The file format is determined by the switch manufacturer and has an irregular structure: variable length headers and interspersed sequencing records make the records variable length in general. The average file size is about 2.2 MB and `gzip`s to about 192 kB, making the daily space requirement 18.4 MB.

To use `pzip`, each record was padded to a fixed 32 bytes. This expanded the average file size to about 2.6 MB. Training data produced 10 high frequency columns, for which an optimum (reordered) partition was generated. The resulting average `pzip`ped file size was 10.3 kB, for a daily space requirement of 1 MB, a 95% improvement over straight `gzip`. Compression and uncompression time improvement was only about 20%.

U.S. census data. We took a portion of the United States *1990 Census of Population and Housing Summary Tape File 3A* (a.k.a. *STF3A*) [2]. The data format is fixed length ASCII records. We used field group 301, level 090, for all states.

Table 2: Summary of results. Size and times are ratios of `pzip` values to the corresponding `gzip` values.

Data	Size	Compression time	Uncompression time
Ntwk. traffic	.45	.62	.54
Ntwk. switch	.05	.80	.80
U.S. census	.56	.50	.33

This generated a 342 MB file with 932-byte records. `Gzip` compressed the file to 31.5 MB.

`Pin` determined that 186 columns were high frequency. In the optimum partition generated, the largest class was 56 bytes wide, indicating high combinational dependence. `Pzip` compressed the file to 17.5 MB, a 44.4% improvement over `gzip`. The compression time improvement was 50%, and uncompression time improvement was 67%.

5.2 Discussion. Table 2 summarizes the results in this section.

Based on its performance on the network traffic data, `pzip` has been put into production use in the AT&T network traffic warehouse, using a compression plan generated by `pin` on about 100,000 records. Although not in a controlled setting, this will provide an “in-production” experiment that

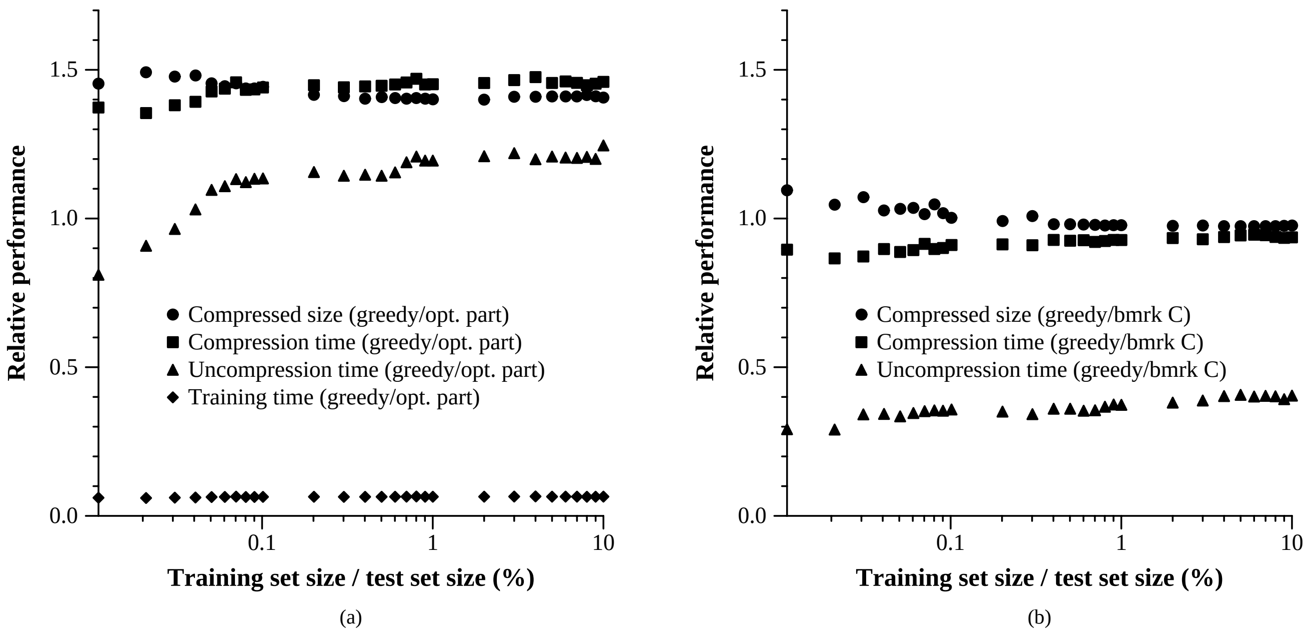


Figure 4: Results of greedy differential compression, as a function of amount of ordered training material. (a) Shows the relative performance of greedy differential compression over optimum partitioning in terms of compressed size, compression time, uncompression time, and training time. (b) Shows the relative performance of greedy differential compression over benchmark C in terms of compressed size, compression time, and uncompression time.

can help assess assumption (4), because going forward, `pzip` will be compressing an arbitrary amount of data based on the fixed-size training set.

6 Concluding Remarks

We have presented massive tables as a new focus in data compression research. We have given a systematic approach for solving the problem, based on the experimental validation of data dependency assumptions. The result is a new compression paradigm: training for lossless compression. By exploiting data dependencies, our scheme outperforms standard methods based on information theoretic results, e.g., Lempel-Ziv [20, 21]. We tested two such dependencies. For our application, optimum partitioning is better, and it is in production use within AT&T, in the `pzip` system. We anticipate instances for which the differential approach will outperform the combinational approach and also instances that favor a hybrid approach. We leave as an open problem to find other data dependencies.

Our results demonstrate the utility of training for lossless compression. Given multiple tables from a common source, training becomes an off-line operation, suitable for computationally expensive optimizations. The bottleneck in our dynamic programming algorithm for optimum partitioning is the computation of $\mathcal{S}(T[j,i])$ for all $1 \leq j \leq i \leq n$, which requires running the base compressor (`gzip`, in our case) on $\Theta(n^2)$ intervals of columns. A quick way to estimate the compressed size of an interval of columns, such as providing a suitable lower bound on their joint entropy—a fundamental problem of independent interest—would therefore be valuable in speeding the overall algorithm.

Two aspects of our work that are now only heuristic are as follows. Permuting the columns before partitioning them effects greater compression. The problem of optimally permuting the columns can be abstracted in combinatorial optimization terms as versions of the Hamiltonian path problem or clustering. We suspect that these formulations will prove to be hard, but proving their hardness is non-trivial. Any reduction must capture required costs by constructing columns whose compressed size using a particular program (such as `gzip`) will match required costs in the reduction. From a practical point of view, an efficient heuristic with good performance is desirable. Our second heuristic involves the choice of low frequency columns that are removed prior to training. In our data sets, simple rules of thumb sufficed to identify such columns, but a formal approach would be desirable.

In the differential approach, we focused on the case in which derived columns can be assigned only to source columns. In general, however, we can build a tree of derivations, which implies an interesting variation of the facility location problem that can be solved exactly by a reduction to minimum spanning trees. We also leave as open problems to explore the effect on compression plans

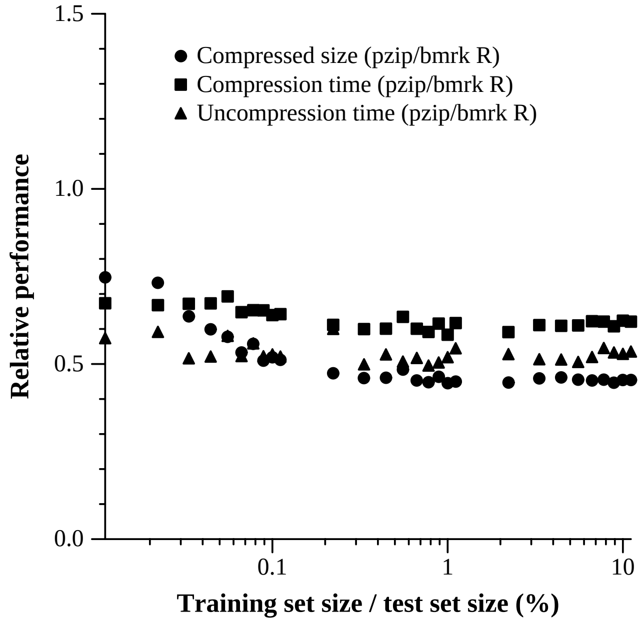


Figure 5: Results of using `pin/pzip` with all heuristics and optimum partition compression, as a function of amount of ordered training material. Shown is the relative performance of `pzip` over benchmark R in terms of compressed size, compression time, and uncompression time.

of using other approximations to the metric facility location problem [3, 11], and to explore hybrid approaches in which we apply optimum partitioning and differential compression to disjoint intervals of T.

Our experimental methodology—assuming dependencies, deriving algorithms based on them, and testing to support or falsify them—may be applied to other compression-based scenarios. It remains to conduct the second test of assumption (4)—that the amount of training material needed is independent of the size of the test set—by fixing a compression plan for an arbitrarily large amount of test material. The production use of `pzip` is providing an uncontrolled version of this experiment that supports the assumption. Finally, assessing the impact of data contiguity on training remains to be studied rigorously.

Acknowledgement

We thank the anonymous reviewers for many helpful comments.

References

[1] M. Burrows and D. J. Wheeler. A block-sorting lossless data compression algorithm. Technical Report 124, DEC SRC, May 1994.

[2] Census of population and housing, 1990: Summary tape file 3 on CD-ROM. U.S. Bureau of the Census, Washington, 1992.

[3] M. Charikar and S. Guha. Improved combinatorial algorithms for the facility location and k-median problems. In *Proc. 40th IEEE FOCS*, pages 378–88, 1999.

[4] F. A. Chudak. Improved approximation algorithms for uncapacitated facility location. In *Proc. 6th IPCO*, volume 1412 of *LNCS*, pages 180–94. Springer-Verlag, 1998.

[5] F. A. Chudak and D. B. Shmoys. Improved approximation algorithms for the uncapacitated facility location problem. Unpublished manuscript, 1998.

[6] J. G. Cleary and I. H. Witten. Data-compression using adaptive coding and partial string matching. *IEEE Trans. Comm.*, 32(4):396–402, 1984.

[7] G. Cormack. Data compression in a data base system. *C. ACM*, 28(12):1336, 1985.

[8] J. Goldstein, R. Ramakrishnan, and U. Shaft. Compressing relations and indexes. In *Proc. 14th Int'l. Conf. on Data Eng.*, pages 370–9, 1998.

[9] D. A. Huffman. A method for the construction of minimum-redundancy codes. *Proc. IRE*, 49(9):1098–101, 1952.

[10] J. J. Hunt, K.-P. Vo, and W. F. Tichy. An empirical study of delta algorithms. In *IEEE Software Configuration and Maintenance Wks.*, 1996.

[11] K. Jain and V. V. Vazirani. Primal-dual approximation algorithms for metric facility location and k-median problems. In *Proc. 40th IEEE FOCS*, pages 2–13, 1999.

[12] J.-H. Juang, D. Y. Wong, and A. H. Gray, Jr. Distortion performance of vector quantization for LPC voice coding. *IEEE Trans. Acous., Spch., and Sig. Proc.*, ASSP-30(2):294–304, 1982.

[13] B. Kobler, J. Berbert, P. Caulk, and P. C. Hariharan. Architecture and design of storage and data management for the NASA Earth Observing System Data and Information System (EOSDIS). In *Proc. 14th IEEE Symp. on Mass Storage Systems*, pages 65–76, 1995.

[14] M. Korupolu, G. Plaxton, and R. Rajaraman. Analysis of a local heuristic for facility location problems. In *Proc. 9th ACM-SIAM SODA*, pages 1–10, 1998.

[15] J. D. Markel and A. H. Gray, Jr. *Linear Prediction of Speech*. Springer-Verlag, 1976.

[16] A. Moffat. Implementing the PPM data-compression scheme. *IEEE Trans. Comm.*, 38(11):1917–21, 1990.

[17] D. Shmoys, E. Tardos, and K. Aardal. Approximation algorithms for facility location problems. In *Proc. 29th ACM STOC*, pages 265–74, 1997.

[18] T. A. Welch. A technique for high performance data compression. *IEEE Computer*, 17(6):8–19, 1984.

[19] I. H. Witten, R. M. Neal, and J. G. Cleary. Arithmetic coding for data-compression. *C. ACM*, 30(6):520–40, 1987.

[20] J. Ziv and A. Lempel. A universal algorithm for sequential data compression. *IEEE Trans. Inf. Thy.*, IT-23(3):337–43, 1977.

[21] J. Ziv and A. Lempel. Compression of individual sequences via variable-rate coding. *IEEE Trans. Inf. Thy.*, IT-24(5):530–36, 1978.