Low Distortion Embeddings for Edit Distance[*]

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Abstract

We show that $\{0,1\}^d$ endowed with edit distance embeds into ℓ_1 with distortion $2^{O(\sqrt{\log d \log\log d})}$. We further show efficient implementations of the embedding that yield solutions to various computational problems involving edit distance. These include sketching, communication complexity, nearest neighbor search. For all these problems, we improve upon previous bounds.

1 Introduction

Given two metric spaces (X_1, d_1) and (X_2, d_2), an *embedding* $\varphi : (X_1, d_1) \hookrightarrow (X_2, d_2)$ has *distortion* c if and only if distances are preserved up to a factor of c (and uniform scaling). Easy to compute low distortion embeddings are extremely useful in computer science. Simply put, in many applications, if we can embed with small distortion a metric space which we do not understand well into some other metric space for which we do have efficient algorithms, then such an embedding provides an efficient algorithm for the original metric space. On a more fundamental level, studying embeddings of different metric spaces is a way to learn about the structure of these metric spaces and it has numerous implications in combinatorial optimization, discrete mathematics, functional analysis, and other areas.

In this paper we study the *edit distance* metric: Given two strings over a finite character alphabet, the *edit distance* (also known as *Levenshtein distance* [12]) measures the minimum number of character insertions, deletions, and substitutions needed to transform one string into the other. Edit distance plays a central role in genomics, text processing, web applications, and other areas. In particular, fast estimation of edit distance and efficient search

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according to the edit distance and its variants are the most investigated and used algorithms in computational biology. In this paper, we show that edit distance embeds in ℓ_1 with relatively small distortion. More specifically we show that $\{0,1\}^d$ endowed with edit distance embeds into ℓ_1 with distortion $2^{O\left(\sqrt{\log d \log\log d}\right)}$. Note that edit distance is well-defined even on strings over a larger alphabet, as well as on strings of varying length. Our results trivially extend to larger alphabet, and they can be applied to variable length strings using standard padding arguments. We omit the discussion on these extensions from this paper.

Furthermore, we show that our embedding can in fact be made *efficient*, thus implying improved algorithms for a number of problems, including sketching and approximate nearest neighbor search.

Given two d-bit strings, the best known running time to compute the exact edit distance, due to Masek and Paterson [13], is $O(d^2/\log d)$ (there is an easy quadratic-time dynamic programming algorithm). For approximating the edit distance, Batu et al. [3] show an algorithm that runs in time $O(d^{\max(\alpha/2, 2\alpha-1)})$ and can distinguish between edit distance $O(d^\alpha)$ and edit distance $\Omega(d)$. The best approximation achieved by a (nearly) linear time algorithm is the $d^{3/7}$ result of Bar-Yossef et al. [2]. If the edit distance metric is modified to allow "block operations" (i.e., swapping arbitrarily large blocks as a single operation), then the resulting *block edit* metric can be embedded into ℓ_1 with distortion $O(\log d \log^* d)$ [6, 14, 5]). Andoni et al. [1] showed that edit distance can not be embedded into ℓ_1 with distortion less than 3/2. This was the only lower bound known prior to the publication of the preliminary version of our paper. Recently, Khot and Naor [9] showed a lower bound of nearly $\sqrt{\log d}$ on the distortion of embedding edit distance into ℓ_1. Their lower bound was improved to $\Omega(\log d)$ by Krauthgamer and Rabani [10].

As mentioned above, we show an embedding into ℓ_1 with distortion $2^{O\left(\sqrt{\log d \log\log d}\right)}$. (Notice that distortion d is trivial.) It is also worth pointing out that our paper provides a theoretical foundation to the experimentally successful idea of Broder et al. [4] of estimating similarity between documents or web pages by looking at sets of "shingles" (substrings) covering the document. Our methods (as well as other constructions and results in [3, 7, 2]) can be considered as a refinement of the original approach of [4].

A notion related to embedding is the *sketching* model. In this model a probabilistic algorithm s computes, for any string x, a *sketch* (i.e., a small "fingerprint") $s(x)$ which is far shorter than x. Given two strings x and y, comparing their sketches $s(x)$ and $s(y)$ (computed using the same coin tosses) estimates their distance with high probability. Sketching is related to multi-scale dimension reduction methods and approximate nearest neighbor search [11, 8], to streaming algorithms, and to communication complexity of document exchange [6]. The sketching model is well understood for Hamming distance (and implicitly for ℓ_1), see [11]. For edit distance, Bar-Yossef et al. [2] show how to compute a constant size sketch that can distinguish between edit distance at most k and edit distance at least $(kd)^{2/3}$ for any $k \leq \sqrt{d}$. Our embedding results can be used to produce constant size sketches that can distinguish between edit distance at most k and edit distance at least $2^{O\left(\sqrt{\log d \log\log d}\right)} \cdot k$ for all feasible values of k.

Another important problem is that of approximate nearest neighbor search algorithms. Given a database of n points in an underlying metric space, we want to pre-process the database and provide a search algorithm which, given a query point, finds a database point which is close to the query point. There is a vast literature on this subject. We restrict our attention to some of the theoretical work where the pre-processing cost is polynomial in the input size (even for high dimensional data; for d-bit strings the input size is nd) and the search cost is polynomial in the size of the query and in $\log n$. Kushilevitz et al. [11] and Indyk and Motwani [8] consider databases in ℓ_1, ℓ_2, and the Hamming cube. Their search algorithms retrieve a database point at distance at most $1+\epsilon$ times the minimum. Muthukrishnan and Sahinalp [14] show how to extend this result to block edit distance. Indyk [7] gives a solution for edit distance where the search can return a point at distance at most d^ϵ times the minimum, for any $\epsilon > 0$. The Bar-Yossef et al. paper [2] gives similar bounds with a better pre-processing performance. Our embedding results imply a solution where the search returns a point at distance at most $2^{O\left(\sqrt{\log d \log\log d}\right)}$ times the minimum.

2 Preliminaries

We denote by $[i,j]$ the set $\{i, i+1, \ldots, j\}$ and we denote by $[j]$ the set $[1,j]$. (If $j < i$ then $[i,j]$ is the empty set.) Let $x \in \{0,1\}^*$. We denote by $|x|$ the length of x. Notice that a string x corresponds to a 0-1 vector in $\mathbb{R}^{|x|}$. We use x to denote both the string and the vector. For $i \in [|x|]$ we denote by x_i the i-th character in x (or, alternatively, the i-th coordinate of x). For $i,j \in [|x|]$ we define $x[i,j] = x_i x_{i+1} x_{i+2} \ldots x_j$. (If $j < i$ then $x[i,j]$ is the empty string.) Let $k \in [|x|]$. For $I = (i_1, i_2, \ldots, i_k) \in [|x|]^k$ we define $x_I = x_{i_1} x_{i_2} \cdots x_{i_k}$. We abuse notation and use $\{\cdot\}$ to denote a multiset of strings, i.e., multiple copies of the same string in the listed elements are counted as different elements of the set. Thus, the simplified notation $\{x^1, x^2, \ldots, x^n\}$ is used for the set

$$\left\{\left(x^j, k\right) : \; j \in [n] \wedge k = \left|\left\{i \in [j-1] : \; x^i = x^j\right\}\right|\right\}.$$

For $s \in \mathbb{N}$, we put

$$\text{shifts}(x,s) = \{x[1, |x|-s+1], x[2, |x|-s+2], \ldots, x[s, |x|]\}$$

Notice that this is a multiset containing exactly s elements. Let $x, y \in \{0,1\}^*$. We denote by xy the concatenation of x followed by y. We denote by $\text{ed}(x,y)$ the edit distance between x and y, which is the minimum number of insert, delete, and substitute operations needed to convert x to y (or vice versa). For x, y with $|x| = |y|$, we denote by $\mathcal{H}(x,y)$ the Hamming distance between x and y (i.e., the number positions i such that $x_i \neq y_i$). For a set X and $s \in \mathbb{N}$, we denote by $\binom{X}{s}$ the set of subsets of X of cardinality s. Let $x, y \in \{0,1\}^*$. Consider an optimal sequence of edit operations converting x into y. Any such sequence is equivalent to a function $f_{x,y} : [0, |x|+1] \to [0, |y|+1] \cup \{\varepsilon\}$ with the following properties.

1. $f_{x,y}(0) = 0$ and $f_{x,y}(|x|+1) = |y|+1$.

2. $\forall i \in [|x|]$, $f_{x,y}(i) \in [|y|] \cup \{\varepsilon\}$.

3. $\forall i, j \in [|x|]$ such that $i < j$ and $f_{x,y}(i), f_{x,y}(j) \neq \varepsilon$, it holds that $f_{x,y}(i) < f_{x,y}(j)$.

The interpretation of $f_{x,y}$ as a sequence of edit operations is as follows. Having $f_{x,y}(i) = \varepsilon$ corresponds to deleting x_i. If there is no i such that $f_{x,y}(i) = j$ that corresponds to inserting y_j. If $j = f_{x,y}(i) \in [|y|]$ and $x_i \neq y_j$ then that corresponds to substituting y_j for x_i. The extension of $f_{x,y}$ to 0 and $|x| + 1$ is useful in some of the calculations below. Notice that for $j \in [0, |y| + 1]$ we may put

$$f_{y,x}(j) = f_{x,y}^{-1}(j) = \begin{cases} i & \exists i \in [0, |x| + 1],\ f_{x,y}(i) = j; \\ \varepsilon & \text{otherwise.} \end{cases}$$

The following facts are trivial.

Fact 1. $\mathrm{ed}(x, y) \geq ||x| - |y||$.

Fact 2. $\mathrm{ed}(x, y) \geq |\{j :\ f_{x,y}(j) = \varepsilon\}| + \left|\left\{j :\ f_{x,y}^{-1}(j) = \varepsilon\right\}\right|$.

Fact 3. $|\{j :\ f_{x,y}(j) = \varepsilon\}| \geq |x| - |y|$.

Fact 4. Let $i, i' \in [|x|]$ and $j, j' \in [|y|]$ satisfy the following conditions: $i \leq i'$; $j \leq j'$; $f_{x,y}(i) = j$; $\forall i'' \in [i + 1, i']$, $f_{x,y}(i'') = \varepsilon$; and $\forall j'' \in [j + 1, j']$, $f_{x,y}^{-1}(j'') = \varepsilon$. Then,

$$\mathrm{ed}(x, y) = \mathrm{ed}(x[1, i'], y[1, j']) + \mathrm{ed}(x[i' + 1, |x|], y[j' + 1, |y|]).$$

For $x, y \in \{0, 1\}^*$, $\mathrm{ed}(x, y)$ can be estimated roughly by comparing substrings of x and y, as the following two lemmas quantify. Lemma 5 states that the strings in $\mathrm{shifts}(x, b)$ and $\mathrm{shifts}(y, b)$ can be matched so that no more than $\mathrm{ed}(x, y)$ matched pairs have edit distance greater than $2\,\mathrm{ed}(x, y)$. Lemma 6 applies this matching to a partition of x and y into equal length substrings.

Lemma 5. Let $x, y \in \{0, 1\}^*$ such that $|x| \leq |y|$, and let $b \in \mathbb{N}$, $b < |x|$. Then, there exists an injection

$$f : [|x| - b + 1] \rightarrow [|y| - b + 1]$$

such that

$$|\{i \in [|x| - b + 1] : \mathrm{ed}(x[i, i + b - 1], y[f(i), f(i) + b - 1]) > 2\,\mathrm{ed}(x, y)\}| \leq \mathrm{ed}(x, y).$$

Proof: Let $I = \{i \in [|x| - b + 1] :\ f_{x,y}(i) \in [|y| - b + 1]\}$. Put

$$i_{\max} = \max\{i \in [|x| - b + 1] :\ \forall j \in [i],\ f_{x,y}(j) \in [|y| - b + 1] \vee f_{x,y}(j) = \varepsilon\}.$$

By Fact 4,

$$\mathrm{ed}(x, y) = \mathrm{ed}(x[1, i_{\max}], y[1, |y| - b + 1]) + \mathrm{ed}(x[i_{\max} + 1, |x|], y[|y| - b + 2, |y|]).$$

We have that

$$\begin{aligned} |\{i \in [|x| - b + 1] :\ f_{x,y}(i) \in [|y| - b + 2, |y|]\}| &= |\{i \in [i_{\max} + 1, |x| - b + 1] :\ f_{x,y}(i) \neq \varepsilon\}| \\ &\leq |x| - b + 1 - i_{\max} \\ &\leq |y| - b + 1 - i_{\max} \\ &\leq \left|\left\{j \in [|y| - b + 1] :\ f_{x,y}^{-1}(j) = \varepsilon\right\}\right|, \end{aligned}$$

where the last inequality follows from Fact 3. Using Fact 2,

$$\begin{aligned}
|I| &= |\{i \in [|x|-b+1] :\ f_{x,y}(i) \neq \varepsilon\}| - |\{i \in [|x|-b+1] :\ f_{x,y}(i) \in [|y|-b+2, |y|]\}| \\
&= |x|-b+1 - |\{i \in [|x|-b+1] :\ f_{x,y}(i) = \varepsilon\}| - |\{i \in [|x|-b+1] :\ f_{x,y}(i) \in [|y|-b+2, |y|]\}| \\
&\geq |x|-b+1 - |\{i \in [|x|-b+1] :\ f_{x,y}(i) = \varepsilon\}| - \left|\{j \in [|y|-b+1] :\ f^{-1}_{x,y}(j) = \varepsilon\}\right| \\
&\geq |x|-b+1 - \operatorname{ed}(x[1, i_{\max}], y[1, |y|-b+1]) \\
&\geq |x|-b+1 - \operatorname{ed}(x, y).
\end{aligned}$$

For every $i \in I$, put $f(i) = f_{x,y}(i)$ and extend f arbitrarily to $[|x|-b+1]$. We show that for every $i \in I$, $\operatorname{ed}(x[i, i+b-1], y[f(i), f(i)+b-1]) \leq 2\operatorname{ed}(x, y)$. Let

$$g(i) = \max\{i+b-1, \max\{i' \in [i, |x|] :\ \exists j \in [f(i), f(i)+b-1],\ f_{x,y}(i') = j\}\},$$

and let

$$h(i) = \max\{f(i)+b-1, \max\{j \in [f(i), |y|] :\ \exists i' \in [i, i+b-1],\ f_{x,y}(i') = j\}\}.$$

Notice that either $g(i) = i+b-1$ or $h(i) = f(i)+b-1$. Moreover, $g(i) - (i+b-1) \leq \operatorname{ed}(x, y)$ and $h(i) - (f(i)+b-1) \leq \operatorname{ed}(x, y)$. Clearly, $\operatorname{ed}(x[i, g(i)], y[f(i), h(i)]) \leq \operatorname{ed}(x, y)$. Therefore,

$$\begin{aligned}
&\operatorname{ed}(x[i, i+b-1], y[f(i), f(i)+b-1]) \\
\leq\ &\operatorname{ed}(x[i, g(i)], y[f(i), h(i)]) + g(i) - (i+b-1) + h(i) - (f(i)+b-1) \\
\leq\ &2\operatorname{ed}(x, y),
\end{aligned}$$

as required. □

Lemma 6. Let $b, d, s \in \mathbb{N}$ with $\frac{d}{b} \in \mathbb{N}$ and $s < b$. For every $x, y \in \{0,1\}^d$ there exists a sequence $k_1, k_2, \ldots, k_{d/b}$ satisfying

$$\sum_{i=1}^{d/b} k_i \leq 2\operatorname{ed}(x, y),$$

such that for every $i \in [d/b]$ there exists a bijection

$$\tau_i : \text{shifts}\,(x[(i-1)b+1, ib], s) \to \text{shifts}\,(y[(i-1)b+1, ib], s)$$

such that

$$|\{z \in \text{shifts}\,(x[(i-1)b+1, ib], s) :\ \operatorname{ed}(z, \tau_i(z)) > k_i\}| \leq \operatorname{ed}(x, y).$$

Proof: Let $i \in [d/b]$. Put

$$a_i^x = \max\{(i-1)b+1, \max\{j \in [d+1] :\ f_{x,y}(j-1) \in [0, (i-1)b]\}\},$$

$$b_i^x = \min\{ib, \min\{j \in [d] :\ f_{x,y}(j+1) > ib\}\},$$

$$a_i^y = \max\{(i-1)b+1, \max\{j \in [d+1] :\ f^{-1}_{x,y}(j-1) \in [0, (i-1)b]\}\},$$

and

$$b_i^y = \min\left\{ib, \min\left\{j \in [d] :\ f_{x,y}^{-1}(j+1) > ib\right\}\right\}.$$

By Fact 4,

$$\mathrm{ed}(x,y) = \mathrm{ed}(x[1, a_i^x - 1], y[1, a_i^y - 1]) + \mathrm{ed}(x[a_i^x, b_i^x], y[a_i^y, b_i^y]) + \mathrm{ed}(x[b_i^x + 1, d], y[b_i^y + 1, d]).$$

Moreover, by Fact 1,

$$\mathrm{ed}(x[1, a_i^x - 1], y[1, a_i^y - 1]) \geq |a_i^x - a_i^y|$$

and

$$\mathrm{ed}(x[b_i^x + 1, d], y[b_i^y + 1, d]) \geq |b_i^x - b_i^y|\,.$$

We assume without loss of generality that $b_i^x - a_i^x \leq b_i^y - a_i^y$. Notice that if $z \in \mathrm{shifts}(x[(i-1)b+1, ib], s)$ (or $z \in \mathrm{shifts}(y[(i-1)b+1, ib], s)$) then $|z| = b - s + 1$. By Lemma 5, there exists an injection $f : [b_i^x - a_i^x - b + s + 1] \to [b_i^y - a_i^y - b + s + 1]$ such that the number of indices $j \in [b_i^x - a_i^x - b + s + 1]$ for which

$$\mathrm{ed}(x[a_i^x + j - 1, a_i^x + j + b - s - 1], y[a_i^y + f(j) - 1, a_i^y + f(j) + b - s - 1]) > 2\,\mathrm{ed}(x[a_i^x, b_i^x], y[a_i^y, b_i^y])$$

is at most $\mathrm{ed}(x[a_i^x, b_i^x], y[a_i^y, b_i^y])$. For every $j \in [b_i^x - a_i^x - b + s + 1]$ set

$$\tau_i(x[a_i^x + j - 1, a_i^x + j + b - s - 1]) = y[a_i^y + f(j) - 1, a_i^y + f(j) + b - s - 1]$$

and extend τ_i to the rest of shifts $(x[(i-1)b + 1, ib], s)$ arbitrarily, and set $k_i = 2\,\mathrm{ed}(x[a_i^x, b_i^x], y[a_i^y, b_i^y])$. Now,

$$\begin{aligned}
& |\{z \in \mathrm{shifts}\,(x[(i-1)b+1, ib], s) :\ \mathrm{ed}(z, \tau_i(z)) > k_i\}| \\
\leq\ & \mathrm{ed}(x[a_i^x, b_i^x], y[a_i^y, b_i^y]) + \max\{a_i^x, a_i^y\} - ((i-1)b + 1) + ib - \min\{b_i^x, b_i^y\} \\
\leq\ & \mathrm{ed}(x[a_i^x, b_i^x], y[a_i^y, b_i^y]) + \mathrm{ed}(x[1, a_i^x - 1], y[1, a_i^y - 1]) + \mathrm{ed}(x[b_i^x + 1, d], y[b_i^y + 1, d]) \\
=\ & \mathrm{ed}(x, y).
\end{aligned}$$

Moreover,

$$\begin{aligned}
\sum_{i=1}^{d/b} k_i &\leq 2\sum_{i=1}^{d/b} \mathrm{ed}(x[a_i^x, b_i^x], y[a_i^y, b_i^y]) \\
&\leq 2\,\mathrm{ed}(x, y).
\end{aligned}$$

This completes the proof. □

3 The Embedding

In this section we prove our main result, the following upper bound on the distortion of embedding edit distance into ℓ_1. The embedding given in this section ignores computational efficiency. In the next section we present an efficient implementation of the embedding.

Theorem 7. There exists a universal constant $c > 0$ such that for every $d \in \mathbb{N}$ there exists an embedding $\varphi : \left(\{0,1\}^d, \mathrm{ed}\right) \hookrightarrow \ell_1$ with distortion at most $2^{c\sqrt{\log d \log\log d}}$.

We first present an informal description of the embedding. Let $x \in \{0,1\}^d$ be any string. We partition x into $2^{\sqrt{\log d \log\log d}}$ disjoint substrings of (approximately) the same length. We refer to these substrings as *blocks*. Let $x^1, x^2, \ldots$ denote the blocks. We consider the multisets $\mathrm{shifts}(x^i, s)$ for s ranging over the non-negative integer powers of $\log d$ that are below the block length. Given $x, y \in \{0,1\}^d$, define the distance between $\mathrm{shifts}(x^i, s)$ and $\mathrm{shifts}(y^i, s)$ to be the minimum cost perfect matching between the two multisets, where the cost of an edge between two elements is the minimum of their edit distance and s. This is a metric on multisets of strings that are much shorter than x. (In fact, it can be viewed as a transportation metric on distributions of strings, where the frequency of a string is proportional to the number of times it appears in the multiset.) Ideally, we would like to embed this metric into ℓ_1. The edit distance-preserving embedding into ℓ_1 would then consist of concatenating the scaled embeddings of $\mathrm{shifts}(x^i, s)$ for all blocks i and all values of s. However, a good embedding of $\mathrm{shifts}(x^i, s)$ seems to be too strong an inductive hypothesis. Therefore, we inductively embed the strings in $\mathrm{shifts}(x^i, s)$ into ℓ_1 and redefine the edge costs for the matching to be the minimum of the ℓ_1 distance between the embedded strings and s. We embed this metric over sets of strings into ℓ_1. This embedding is not necessarily low distortion. The following lemma, which may be of independent interest, states the properties of this embedding.

Lemma 8. For every $\epsilon > 0$ and for every $d, s, t \in \mathbb{N}$ that satisfy $\ln(s/\epsilon) \le t \le d$ there is a mapping $\psi : \left(\{0,1\}^d\right)^s \to \ell_1$ such that for every two s-element multisets $A, B \in \left(\{0,1\}^d\right)^s$,

$$\|\psi(A) - \psi(B)\|_1 \le \frac{1}{s} \cdot \min_{\sigma} \left\{ \sum_{x \in A} \min\{t, 2\mathcal{H}(x, \sigma(x)) \ln(s/\epsilon)\} \right\}$$

(where the first minimum is taken over all bijections $\sigma : A \to B$), and furthermore if for all $x \in A$ and $y \in B$, $\mathcal{H}(x, y) \ge t$, then

$$\|\psi(A) - \psi(B)\|_1 \ge (1 - \epsilon)t.$$

Proof: Put $b = \frac{d \cdot \ln(s/\epsilon)}{t}$. Consider the function $\chi : \left(\{0,1\}^d\right)^s \to \mathbb{N}^{(2d)^b}$, which is defined as follows. Let $A = \{x^1, x^2, \ldots, x^s\} \in \left(\{0,1\}^d\right)^s$. To set $\chi(A)$, we generate a coordinate for every sequence $I \in [d]^b$ and for every string $z \in \{0,1\}^b$. Recall that $x_I = x_{i_1} x_{i_2} \cdots x_{i_b}$, where $I = (i_1, i_2, \ldots, i_b)$. We set

$$\chi(A)_{I,z} = \left| \{ j \in \{1, 2, \ldots, s\} :\ z = x^j_I \} \right|.$$

For all $A \in \left(\{0,1\}^d\right)^s$ put $\psi(A) = \frac{t}{2sd^b} \chi(A)$. (Notice that $\psi(A)$ is invariant to permuting the elements of A.)

Let $A, B \in \left(\{0,1\}^d\right)^s$. Let $\sigma : A \to B$ be a bijection that minimizes

$$\sum_{x \in A} \min\{t, 2\mathcal{H}(x, \sigma(x)) \ln(s/\epsilon)\}.$$

Let Pr denote the uniform distribution on $I \in [d]^b$. We have that

$$\begin{aligned}
\|\psi(A) - \psi(B)\|_1 &= \frac{t}{2sd^b} \sum_{I=(i_1,i_2,\ldots,i_b)\in[d]^b} \sum_{z\in\{0,1\}^b} |\chi(A)_{I,z} - \chi(B)_{I,z}| \\
&\leq \frac{t}{s} \cdot \sum_{x\in A} \Pr\left[x_I \neq \sigma(x)_I\right] \\
&= \frac{t}{s} \cdot \sum_{x\in A} \left(1 - \Pr\left[\bigwedge_{j=1}^{b} \left\{x_{i_j} = \sigma(x)_{i_j}\right\}\right]\right) \\
&= \frac{t}{s} \cdot \sum_{x\in A} \left(1 - \left(1 - \frac{\mathcal{H}(x,\sigma(x))}{d}\right)^b\right) \\
&\leq \frac{t}{s} \cdot \sum_{x\in A} \left(1 - e^{-\frac{2b\mathcal{H}(x,\sigma(x))}{d}}\right) \\
&= \frac{t}{s} \cdot \sum_{x\in A} \left(1 - e^{-\frac{2\mathcal{H}(x,\sigma(x))\ln(s/\epsilon)}{t}}\right) \\
&\leq \frac{t}{s} \cdot \sum_{x\in A} \min\left\{1, \frac{2\mathcal{H}(x,\sigma(x))\ln(s/\epsilon)}{t}\right\} \\
&= \frac{1}{s} \cdot \sum_{x\in A} \min\{t, 2\mathcal{H}(x,\sigma(x))\ln(s/\epsilon)\}.
\end{aligned}$$

Now assume that $\min\{\mathcal{H}(x,y) : \ x \in A \wedge y \in B\} \geq t$. Consider any $x \in A$. We have that

$$\begin{aligned}
\Pr\left[\chi(B)_{I,x_I} > 0\right] &\leq s \cdot \left(1 - \frac{t}{d}\right)^b \\
&= s \cdot \left(1 - \frac{t}{d}\right)^{\frac{d\ln(s/\epsilon)}{t}} \\
&\leq s \cdot e^{-\ln(s/\epsilon)} \\
&= \epsilon.
\end{aligned}$$

Therefore,

$$\begin{aligned}
\|\psi(A)-\psi(B)\|_1 &= \frac{t}{2sd^b}\sum_{I\in[d]^b}\sum_{z\in\{0,1\}^b}|\chi(A)_{I,z}-\chi(B)_{I,z}| \\
&\ge \frac{t}{2s}\cdot\sum_{x\in A}\Pr\left[\chi(B)_{I,z}=0:\ z=x_I\right] \\
&\quad +\frac{t}{2s}\cdot\sum_{x\in B}\Pr\left[\chi(A)_{I,z}=0:\ z=x_I\right] \\
&= \frac{t}{2s}\cdot\sum_{x\in A}\left(1-\Pr\left[\chi(B)_{I,z}>0:\ z=x_I\right]\right) \\
&\quad +\frac{t}{2s}\cdot\sum_{x\in B}\left(1-\Pr\left[\chi(A)_{I,z}>0:\ z=x_I\right]\right) \\
&\ge \frac{t}{2s}\cdot 2(1-\epsilon)s \\
&= (1-\epsilon)t,
\end{aligned}$$

completing the proof. □

For given values d,s and for $t=s$, $\epsilon=\frac{1}{2}$, we denote by $\psi_{d,s}$ the embedding ψ of Lemma 8.

Proof of Theorem 7. Let $\varphi_d:(\{0,1\}^d,\mathrm{ed})\hookrightarrow\ell_1$ denote the mapping (constructed below) for strings of length d. Let φ_d^{-1} denote the inverse mapping of the image of $\{0,1\}^d$ under φ_d. We show by induction on d a construction of φ_d such that $\|\varphi_d\|_{\mathrm{Lip}}$ and $\|\varphi_d^{-1}\|_{\mathrm{Lip}}$ are both at most $2^{c\sqrt{\log d\log\log d}}$, for some absolute constant c. Here $\|f\|_{\mathrm{Lip}}$ denotes the Lipschitz constant of a mapping $f:(X,D)\hookrightarrow(X',D')$; i.e.

$$\|f\|_{\mathrm{Lip}}=\sup_{x,y\in X,\ x\neq y}\frac{D'(f(x),f(y))}{D(x,y)}.$$

As the distortion of φ_d is given by $\|\varphi_d\|_{\mathrm{Lip}}\cdot\|\varphi_d^{-1}\|_{\mathrm{Lip}}$, this proves the theorem.

Clearly, the inductive hypothesis is true for d sufficiently small, using the identity map. We therefore assume that the inductive hypothesis holds for all strings of length less than d. Let $x\in\{0,1\}^d$. For $j\in\mathbb{N}$ let $s_j=(\log d)^j$. Put $i_{\max}=2^{\sqrt{\log d\log\log d}}$ and put $j_{\max}=\min\left\{j\in\mathbb{N}:\ s_j\ge\frac{d}{i_{\max}\cdot\log d}\right\}$. For $j\in[0,j_{\max}]$, put $d_j=\frac{d}{i_{\max}}-s_j+1$. For $i\in[i_{\max}]$ and $j\in[0,j_{\max}]$, put $A_{i,j}(x)=\mathrm{shifts}(x[(i-1)d/i_{\max}+1,id/i_{\max}],s_j)$, and put

$$B_{i,j}(x)=\left\{\varphi_{d_j}(y):\ y\in A_{i,j}(x)\right\}.$$

Finally, define the vector $\varphi_d(x)$ whose coordinates are indexed by I,z,i,j as follows.

$$\left(\varphi_d(x)\right)_{I,z,i,j}=\left(\psi_{d_j,s_j}(B_{i,j})\right)_{I,z}.$$

(Notice that for simplicity we assume that $i_{\max}$ divides d, and we partition x into $i_{\max}$ blocks of length $d/i_{\max}$ each. The assumption can be removed by increasing the length of some of the blocks by 1. The proof can be amended easily to handle blocks of two lengths varying by 1.)

Consider two strings $x, y \in \{0,1\}^d$, $x \neq y$. By Lemma 6, there is a sequence $k_1, k_2, \ldots, k_{i_{\max}}$ satisfying

$$\sum_{i=1}^{i_{\max}} k_i \leq 2\,\mathrm{ed}(x,y), \tag{1}$$

such that for every $i \in [i_{\max}]$ and for every $j \in [0, j_{\max}]$ there exists a bijection $\tau : A_{i,j}(x) \to A_{i,j}(y)$ such that

$$|\{z \in A_{i,j}(x) :\ \mathrm{ed}(z, \tau(z)) > k_i\}| \leq \mathrm{ed}(x,y). \tag{2}$$

Now, if $s_j < \mathrm{ed}(x,y)$ then, trivially, by Lemma 8,

$$\|\psi_{d_j,s_j}(B_{i,j}(x)) - \psi_{d_j,s_j}(B_{i,j}(y))\|_1 \leq s_j. \tag{3}$$

Otherwise, if $s_j \geq \mathrm{ed}(x,y)$, then by Equation (2) and the induction hypothesis,

$$\left|\left\{z \in B_{i,j}(x) :\ \mathcal{H}(z, \tau(z)) > \|\varphi_{d_j}\|_{\mathrm{Lip}} \cdot k_i\right\}\right| \leq \mathrm{ed}(x,y).$$

Therefore, by Lemma 8,

$$\begin{aligned}
\|\psi_{d_j,s_j}(B_{i,j}(x)) - \psi_{d_j,s_j}(B_{i,j}(y))\|_1 &\leq \frac{1}{s_j} \cdot \min_{\sigma} \left\{ \sum_{z \in B_{i,j}(x)} \min\{s_j, 2\mathcal{H}(z, \sigma(z)) \cdot \ln(2s_j)\} \right\} \\
&\leq \frac{1}{s_j} \cdot \sum_{z \in B_{i,j}(x)} \min\{s_j, 2\mathcal{H}(z, \tau(z)) \cdot \ln(2s_j)\} \\
&\leq \frac{1}{s_j} \cdot \left(\mathrm{ed}(x,y) \cdot s_j + s_j \cdot 2\|\varphi_{d_j}\|_{\mathrm{Lip}} \cdot k_i \cdot \ln(2s_j)\right) \\
&\leq \mathrm{ed}(x,y) + 2\|\varphi_{d_j}\|_{\mathrm{Lip}} \cdot k_i \cdot \ln(2s_j).
\end{aligned} \tag{4}$$

Summing Equations (3) and (4), over i, j, and using Condition (1), we get

$$\begin{aligned}
\|\varphi_d(x) - \varphi_d(y)\|_1 &= \sum_{i=1}^{i_{\max}} \sum_{j=0}^{j_{\max}} \left\|\psi_{d_j,s_j}(B_{i,j}(x)) - \psi_{d_j,s_j}(B_{i,j}(y))\right\|_1 \\
&\leq i_{\max} \cdot \sum_{j:\ s_j < \mathrm{ed}(x,y)} s_j + i_{\max} \cdot (j_{\max} + 1) \cdot \mathrm{ed}(x,y) + \\
&\quad + (j_{\max} + 1) \cdot 2\|\varphi_{d_0}\|_{\mathrm{Lip}} \cdot \sum_{i=1}^{i_{\max}} k_i \cdot \ln(2d) \\
&\leq \left(2i_{\max} \cdot \frac{\log d}{\log\log d} + 4\|\varphi_{d_0}\|_{\mathrm{Lip}} \cdot \frac{\log^2 d}{\log\log d}\right) \cdot \mathrm{ed}(x,y).
\end{aligned}$$

Thus, we obtain the recurrence relation

$$\|\varphi_d\|_{\mathrm{Lip}} \leq 4\|\varphi_{d_0}\|_{\mathrm{Lip}} \cdot \frac{\log^2 d}{\log\log d} + 2i_{\max} \cdot \frac{\log d}{\log\log d},$$

so $\|\varphi_d\|_{\rm Lip}$ (as a function of d) satisfies the conditions of Lemma 14 (in the appendix), and therefore the recurrence solves to $\|\varphi_d\|_{\rm Lip} = 2^{O(\sqrt{\log d \log\log d})}$.

We now proceed to bound $\|\varphi_d^{-1}\|_{\rm Lip}$. Define a sequence $j_1, j_2, \ldots, j_{i_{\max}}$ as follows. For $i \in [1, i_{\max}]$, if $x[(i-1)d/i_{\max}+1, id/i_{\max}] = y[(i-1)d/i_{\max}+1, id/i_{\max}]$ then put $j_i = -1$, otherwise put

$$j_i = \max\{j \in [0, j_{\max}] : \ \forall z \in A_{i,j}(x) \forall z' \in A_{i,j}(y), {\rm ed}(z,z') \geq \|\varphi_{d_j}^{-1}\|_{\rm Lip} \cdot s_j\}.$$

Put $s_{j_{\max}+1} = \frac{d}{i_{\max}}$. Let $I = \{i \in [1, i_{\max}] : \ j_i \geq 0\}$. Clearly,

$${\rm ed}(x,y) \leq \sum_{i \in I} \left(\|\varphi_{d_{j_i+1}}^{-1}\|_{\rm Lip} + 2 \right) \cdot s_{j_i+1}.$$

On the other hand, consider $z \in A_{i,j}(x)$ and $z' \in A_{i,j}(y)$. If ${\rm ed}(z,z') \geq \|\varphi_{d_j}^{-1}\|_{\rm Lip} \cdot s_j$, then by the induction hypothesis $\mathcal{H}(\varphi(z), \varphi(z')) \geq s_j$. Therefore, by Lemma 8,

$$\begin{aligned}
\|\varphi_d(x) - \varphi_d(y)\|_1 &\geq \sum_{i \in I} \left\| \psi_{d_{j_i}, s_{j_i}}(B_{i,j_i}(x)) - \psi_{d_{j_i}, s_{j_i}}(B_{i,j_i}(y)) \right\|_1 \\
&\geq \frac{1}{2} \sum_{i \in I} s_{j_i} \\
&\geq \frac{1}{2 \log d} \cdot \sum_{i \in I} s_{j_i+1} \\
&\geq \frac{1}{2 \left(\|\varphi_{d_{j_i+1}}^{-1}\|_{\rm Lip} + 2 \right) \log d} \cdot {\rm ed}(x,y).
\end{aligned}$$

Thus we get the recurrence

$$\|\varphi_d^{-1}\|_{\rm Lip} \leq 2 \|\varphi_{d/i_{\max}}^{-1}\|_{\rm Lip} \cdot \log d + 4 \log d,$$

which solves to $\|\varphi_d^{-1}\|_{\rm Lip} = 2^{O(\sqrt{\log d \log\log d})}$, by Lemma 14. □

4 Implementation and Applications

The embedding described in the previous section is computationally inefficient. An efficient implementation of the embedding is derived from the following algorithmic version of Lemma 8.

Lemma 9. There exists a probabilistic polynomial time algorithm ψ that satisfies the following properties.

1. For every $\delta > 0$, for every $d, s \in \mathbb{N}$ that satisfy $\ln(2s) \leq s \leq d$, and for every $A \in \left(\{0,1\}^d\right)^s$, $\psi(A) = \psi(A, d, s, \delta) \in \ell_1^{O(s \log(s/\delta))}$ always.

2. For $A, B \in \left(\{0,1\}^d\right)^s$, let $\psi(A)$ and $\psi(B)$ be computed using the same random choices for ψ. Then, with probability at least $1-\delta$ (over the coin tosses of ψ), the following two inequalities hold:
   (a) $\|\psi(A)-\psi(B)\|_1 \le \frac{1}{s} \cdot \min_\sigma \left\{\sum_{x\in A} \min\{2s, 4\mathcal{H}(x,\sigma(x))\ln(4s)\}\right\}$ (where the first minimum is taken over all bijections $\sigma : A \to B$);
   (b) if for all $x \in A$ and $y \in B$, $\mathcal{H}(x,y) \ge s$, then $\|\psi(A)-\psi(B)\|_1 \ge \frac{s}{4}$.

Proof: Put $b = \frac{d\ln(4s)}{s}$. Let r be a positive integer to be specified later. Let $I_1, I_2, \ldots, I_r$ be samples from the uniform distribution on $[d]^b$. Also, let $\tilde{H}$ be a distribution over hash functions $h : \{0,1\}^b \to \{1,2,\ldots,4s\}$ such that for every $z, z' \in \{0,1\}^b$ satisfying $z \ne z'$, $\Pr[h(z) = h(z')] = \frac{1}{4s}$. Let $h_1, h_2, \ldots, h_r$ be samples from $\tilde{H}$. We require that $I_1, I_2, \ldots, I_r, h_1, h_2, \ldots, h_r$ are mutually independent. The embedding ψ has one coordinate for every u, v such that $u \in [r]$ and $v \in [4s]$. Let $I_u = (i_1, i_2, \ldots, i_b)$, and let $A = (x^1, x^2, \ldots, x^s)$. Then, the coordinate indexed by u, v is given by

$$\psi(A)_{u,v} = \frac{1}{2r} \cdot \left|\{j \in \{1,2,\ldots,s\} :\ v = h_u(x^j_{I_u})\}\right|.$$

Let $A, B \in \left(\{0,1\}^d\right)^s$. Let $\sigma : A \to B$ be a bijection that minimizes

$$\sum_{x\in A} \min\left\{s, 2\mathcal{H}(x,\sigma(x))\ln(4s)\right\}.$$

Let Pr denote the product distribution of the uniform distribution on $[d]^b$ and $\tilde{H}$. Let $x \in A$. Then,

$$\begin{aligned}
\Pr\left[h(x_I) \ne h(\sigma(x)_I)\right] &\le \Pr\left[x_I \ne \sigma(x)_I\right] \\
&= \left(1 - \left(1 - \frac{\mathcal{H}(x,\sigma(x))}{d}\right)^b\right) \\
&\le \left(1 - e^{-\frac{2b\mathcal{H}(x,\sigma(x))}{d}}\right) \\
&= \left(1 - e^{-\frac{2\mathcal{H}(x,\sigma(x))\ln(4s)}{s}}\right) \\
&\le \min\left\{1, \frac{2\mathcal{H}(x,\sigma(x))\ln(4s)}{s}\right\} \\
&= \frac{1}{s} \cdot \min\left\{s, 2\mathcal{H}(x,\sigma(x))\ln(4s)\right\}.
\end{aligned}$$

Let p_x denote the last expression. Clearly, $p_x \ge \frac{1}{s}$. Let N_x denote the number of $u \in [r]$ such that $h_u(x_{I_u}) \ne h_u(\sigma(x)_{I_u})$. If $\Pr\left[h(x_I) \ne h(\sigma(x)_I)\right] = 0$ then clearly $\Pr[N_x > 2p_x r] = 0$. Otherwise, notice that $\mathrm{E}[N_x] \le p_x r$. Using standard Chernoff bounds,

$$\Pr[N_x > 2p_x r] < e^{-\frac{2}{27}p_x r} \le e^{-\frac{2r}{27s}}.$$

Notice that $\|\psi(A) - \psi(B)\|_1 \leq \frac{1}{r}\sum_{x\in A} N_x$. Therefore,

$$\Pr\left[\|\psi(A) - \psi(B)\|_1 > 2\sum_{x\in A} p_x\right] < se^{-\frac{2r}{27s}}.$$

On the other hand, consider any $x \in A$. Assuming that $\min\{\mathcal{H}(x,y) :\ x \in A \wedge y \in B\} \geq s$, we have that

$$\begin{aligned}\Pr\left[\exists y \in B :\ h(y_I) = h(x_I)\right] &\leq \frac{1}{4} + \sum_{y\in B}\Pr\left[y_I = x_I\right]\\ &\leq \frac{1}{4} + s\left(1 - \frac{s}{d}\right)^b\\ &\leq \frac{1}{2}.\end{aligned}$$

Let N_x denote the number of $u \in [r]$ such that for all $y \in B$, $h_u(y_{I_u}) \neq h_u(x_{I_u})$. As $\mathrm{E}[N_x] \geq \frac{r}{2}$, standard Chernoff bounds give

$$\Pr\left[N_x < \frac{r}{4}\right] < e^{-\frac{r}{16}}.$$

The same bound holds for N_y, for every $y \in B$, which is the number of $u \in [r]$ such that for all $x \in A$, $h_u(x_{I_u}) \neq h_u(y_{I_u})$. Obviously, $\|\psi(A) - \psi(B)\|_1 \geq \frac{1}{2r}\sum_{x\in A} N_x + \frac{1}{2r}\sum_{y\in B} N_y$. Therefore,

$$\Pr\left[\|\psi(A) - \psi(B)\|_1 < \frac{s}{4}\right] < 2se^{-\frac{r}{16}}.$$

To complete the proof, choose $r = O(s\log(s/\delta))$. □

Lemma 9 implies the following algorithmic version of Theorem 7.

Theorem 10. There exists a polynomial time algorithm φ that for every $\delta > 0$, for every $d \in \mathbb{N}$, and for every $x \in \{0,1\}^d$ computes $\varphi(x) = \varphi(x,d,\delta) \in \ell_1^{O(d\log(d/\delta))}$, such that for every $x, y \in \{0,1\}^d$, with probability at least $1 - \delta$,

$$2^{-O(\sqrt{\log d\log\log d})} \cdot \mathrm{ed}(x,y) \leq \|\varphi(x) - \varphi(y)\|_1 \leq 2^{O(\sqrt{\log d\log\log d})} \cdot \mathrm{ed}(x,y).$$

The proof of Theorem 10 follows closely the proof of Theorem 7, and is therefore omitted from the paper. Notice that at the top level of the recursion we take a total of $o(d)$ shingles from both strings, each of length at most $d/2^{\sqrt{\log d\log\log d}}$. Each scale s uses uniform length shingles. There are $o(logd)$ scales. For each scale, we use Theorem 10 inductively with failure probability $\delta/2d^2$. (In the base case we can afford complete enumeration and testing, so the probability of failure is 0.) The shingles are embedded in dimension $o(d\log d)$, and the probability that the embedding fails on any pair of shingles is at most $\delta/2$. Next we construct for each scale s a mapping ψ as per Lemma 9. We need to apply ψ to $2^{\sqrt{\log d\log\log d}}$ pairs of sets of shingles, one pair for each block. Thus, the total number of pairs of sets of shingles from all scales is $d^{o(1)}$. We use Lemma 9 with failure probability $\delta/2d$. The probability that the construction fails on any pair of sets is at most $\delta/2$. For each scale s, each block generates $O(s\log(ds/\delta)$ coordinates. There are $2^{\sqrt{\log d \log\log d}}$ blocks, and $s \le d/2^{\sqrt{\log d \log\log d}}$ is a power of $\log d$, hence the $O(d\log(d/\delta))$ bound on the dimension in Theorem 10.

Theorem 10 can be used to solve many data processing problems that involve edit distance, by first embedding the data into ℓ_1, and then applying previous results for ℓ_1 data. It is important in many applications that we can fix φ without knowing in advance the input points that it will be applied to. We discuss several examples to illustrate the issue. Our first example is a sketching algorithm, which is a basic building block for other tasks.

Theorem 11. There are universal constants $c, \alpha, \beta > 0$, $\alpha < \beta$, such that the following holds. There is a probabilistic polynomial time algorithm s that for every $\delta > 0$, for every $d, t \in \mathbb{N}$, and for every $x \in \{0,1\}^d$ computes a sketch $s(x) = s(x, d, t, \delta) \in \{0,1\}^{O(\log(1/\delta))}$ such that for every $x, y \in \{0,1\}^d$ with probability at least $1-\delta$ the following holds. If $\mathrm{ed}(x,y) \le t$ then $\mathcal{H}(s(x), s(y)) \le \alpha\log(1/\delta)$, and if $\mathrm{ed}(x,y) \ge 2^{c\sqrt{\log d \log\log d}} \cdot t$ then $\mathcal{H}(s(x), s(y)) \ge \beta\log(1/\delta)$.[1]

Proof: To compute $s(x)$, use Theorem 10 to embed x in ℓ_1, then use the ℓ_1 sketching algorithm implied in [11]. □

Corollary 12. There is $c > 0$ such that for every $\delta > 0$, for every $n, t \in \mathbb{N}$, there is a a one-round public-coin probabilistic two-party communication protocol that on input $x, y \in \{0,1\}^n$ exchanges $O(\log(1/\delta))$ bits and with probability at least $1-\delta$ outputs 1 if $\mathrm{ed}(x,y) \le t$ and 0 if $\mathrm{ed}(x,y) \ge 2^{c\sqrt{\log n \log\log n}} \cdot t$.

Proof: Suppose Alice gets x and Bob gets y. Alice computes $s(x)$, Bob computes $s(y)$ (on the same random string), then they exchange these bits. They output 1 if and only if $\mathcal{H}(s(x), s(y)) \le \alpha\log(1/\delta)$. By Theorem 11, the protocol succeeds with probability at least $1-\delta$. □

Another obvious application is approximate nearest neighbor search. This is a data structure problem that is defined as follows. The data set X consists of n points in an ambient distance space. A pre-processing algorithm can be used to generate a data structure D that represents in the input data set. The data structure D is then used by a search algorithm to answer nearest neighbor queries. (The query sequence is unknown to the pre-processing algorithm.) A nearest neighbor query q is just another point in the ambient space. A search algorithm gets D and q, and must return a point in X that closest to q. In the approximation version, the search algorithm may return a point in X at distance somewhat larger than the minimum. Using approximate nearest neighbor algorithms for points in ℓ_1 [11, 8], we get the following theorem.

Theorem 13. There is a probabilistic pre-processing algorithm D and a search algorithm N that satisfy the following conditions with high probability. On any input $X \subset \{0,1\}^d$, the pre-processing algorithm D computes in time polynomial in $|X|$ and d a pre-processed database $D(X)$. Using $D(X)$, on any input $q \in \{0,1\}^d$, the search algorithm N finds in

[1] The comparison of $s(x)$ and $s(y)$ is done using the same outcome of the algorithm's coin tosses in both cases.

time polynomial in d and $\log |X|$ a database point $N(q) \in X$ such that for every $x \in X$, $\mathrm{ed}(q, N(q)) \leq 2^{O(\sqrt{\log d \log\log d})} \cdot \mathrm{ed}(q, x)$. (Notice that with high probability the pre-processing algorithm D outputs a database $D(X)$ such that the search algorithm succeeds on all possible queries.)

Proof: Let φ be the algorithm from Theorem 10, taking $\delta \ll 2^{-2d}$. (So, φ embeds $\left(\{0,1\}^d, \mathrm{ed}\right)$ into $\ell_1^{O(d^2)}$.) To pre-process the database X, apply the ℓ_1 pre-processing algorithm of [11] to the database $\{\varphi(x) : x \in X\}$. To search a query q, apply the ℓ_1 search algorithm of [11] to $\varphi(q)$. □

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Appendix

Lemma 14. Consider a non-negative function $f : \mathbb{N} \to \mathbb{R}$ that satisfies the following. There exist $n_0 \in \mathbb{N}$ and constants $\alpha, \beta > 0$ such that for every $n > n_0$

$$f(n) \le f\left(\frac{n}{2^{\sqrt{\log n \log\log n}}}\right) \cdot (\log n)^{\alpha} + 2^{\beta\sqrt{\log n \log\log n}}.$$

Then, there exists a constant $c > 0$ such that for every $n \in \mathbb{N}$, $f(n) \le 2^{c\sqrt{\log n \log\log n}}$.

Proof: The proof is by induction on n. For the base case, if we take a sufficiently large constants c and $n_1 \ge n_0$, then for all $n \le n_1$, $f(n) \le 2^{c\sqrt{\log n \log\log n}}$, and for all $n > n_1$,

$$2^{c\sqrt{(\log n - \sqrt{\log n \log\log n})\log\log n}} \cdot (\log n)^{\alpha} \ge 2^{\beta\sqrt{\log n \log\log n}}.$$

So, let $n > n_1$ and assume that the claim holds for all $n' < n$. We have

$$\begin{aligned}
& \log f(n) \\
\le\ & \log\left(f\left(\frac{n}{2^{\sqrt{\log n \log\log n}}}\right) \cdot (\log n)^{\alpha} + 2^{\beta\sqrt{\log n \log\log n}}\right) \\
\le\ & \log\left(2^{c\sqrt{(\log n - \sqrt{\log n \log\log n})\log\log n}} \cdot (\log n)^{\alpha} + 2^{\beta\sqrt{\log n \log\log n}}\right) \\
\le\ & \log\left(2 \cdot 2^{c\sqrt{(\log n - \sqrt{\log n \log\log n})\log\log n}} \cdot (\log n)^{\alpha}\right) \\
=\ & c\sqrt{(\log n - \sqrt{\log n \log\log n})\log\log n} + \alpha \log\log n + 1 \\
=\ & c\sqrt{\log n \log\log n} \cdot \left(\sqrt{1 - \sqrt{\frac{\log\log n}{\log n}}} + \frac{\alpha}{c}\sqrt{\frac{\log\log n}{\log n}} + \frac{1}{c\sqrt{\log n \log\log n}}\right) \\
\le\ & c\sqrt{\log n \log\log n} \cdot \left(1 - \frac{1}{2}\sqrt{\frac{\log\log n}{\log n}} + \frac{\alpha}{c}\sqrt{\frac{\log\log n}{\log n}} + \frac{1}{c\sqrt{\log n \log\log n}}\right) \\
\le\ & c\sqrt{\log n \log\log n},
\end{aligned}$$

provided that c and n_1 are sufficiently large. □