Efficiently Computing Edit Distance to Dyck Language

Barna Saha
AT&T Research Laboratory,
Florham Park, NJ 07932.
Email: barna@research.att.com.

Abstract

Given a string \( \sigma \) over alphabet \( \Sigma \) and a grammar \( G \) defined over the same alphabet, how many minimum number of repairs: insertions, deletions and substitutions are required to map \( \sigma \) into a valid member of \( G \)? We investigate this basic question in this paper for \textsc{Dyck}(s). \textsc{Dyck}(s) is a fundamental context free grammar representing the language of well-balanced parentheses with \( s \) different types of parentheses and has played a pivotal role in the development of theory of context free languages. It is also known a nondeterministic version of \textsc{Dyck}(s) is the hardest context free grammar. Computing edit distance to \textsc{Dyck}(s) has numerous applications ranging from repairing semi-structured documents such as XML to memory checking, automated compiler optimization, natural language processing etc. The problem also significantly generalizes string edit distance which has seen extensive developments over the last two decades and has attracted much attention in theoretical computer science as well as in computational biology community.

It is possible to develop a dynamic programming to exactly compute edit distance to \textsc{Dyck}(s) that runs in time cubic in the string length. Such algorithms are not scalable. In this paper we give the first near-linear time algorithm for edit distance computation to \textsc{Dyck}(s) that achieves a nontrivial (poly-logarithmic) approximation factor. In fact, given there exists an algorithm for computing string edit distance on input of size \( n \) in \( \alpha(n) \) time with \( \beta(n) \)-approximation factor, we can devise an algorithm for edit distance problem to \textsc{Dyck}(s) running in \( \tilde{O}(n + \alpha(n)) \) and achieving an approximation factor of \( O(\beta(n)(\log OPT)^{1.5}) \). In \( \tilde{O}(n^{1+\epsilon} + \alpha(n)) \) time, we get an approximation factor of \( O(\frac{1}{\epsilon} \beta(n) \log OPT) \) (for any \( \epsilon > 0 \)). Here \( OPT \) is the optimal edit distance to \textsc{Dyck}(s). Since the best known near-linear time algorithm for string edit distance problem has \( \beta(n) = \text{polylog} n \), we get the desired bound. Therefore, with the current state of the art, string and \textsc{Dyck}(s) edit distance can both be computed within poly-logarithmic approximation factor in near-linear time. This comes as a surprise since \textsc{Dyck}(s) is a significant generalization of string edit distance problem and their exact computations via dynamic programming show a marked difference in time complexity.

Rather less surprisingly, we show that the framework for efficiently approximating edit distance to \textsc{Dyck}(s) can be utilized for many other languages. We illustrate this by considering various memory checking languages such as \textsc{Stack}, \textsc{Queue}, \textsc{PQ} and \textsc{Deque} which comprise of valid transcripts of stacks, queues, priority queues and double-ended queues respectively. Therefore, any language that can be recognized by these data structures, can also be repaired efficiently by our algorithm.

\footnote{\( \tilde{O}(n) = O(n\text{poly log } n) \)}
1 Introduction

In this work, we consider the complexity of language edit distance problem. That is given \( \sigma \) over alphabet \( \Sigma \) and a grammar \( G \) again over the same alphabet, what is the time complexity of computing the minimum number of edits: insertions, deletions and substitutions, required to convert \( \sigma \) into a valid string of \( G \)? We ask this question with respect to \( \text{DYCK}(s) \). \( \text{DYCK}(s) \) is a fundamental context free grammar representing the language of well-balanced parentheses of \( s \) different types. For example, string such as “((()))” belongs to \( \text{DYCK}(1) \), but “((()”) does not and string such as “(([]))” belongs to \( \text{DYCK}(2) \) but “(([]])” does not.

Dyck language appears in many contexts. These languages often describe a property that should be held by commands in most commonly used programming languages, as well as various subsets of commands/symbols used in latex. Variety of semi-structured data from XML documents to JSON data interchange files to annotated linguistic corpora contain open and close tags that must be properly nested. They are frequently massive in size and exhibit complex structures with arbitrary levels of nesting tags (an XML document often encodes an entire database). For example, dblp.xml has current size of \( 1.2 \) GB, is growing rapidly, with 2.3 million articles that results in a string of parentheses of length more than 23 million till date. Furthermore, Dyck language plays an important role in the theory of context-free languages. As stated by the Chomsky-Schotzenberger Theorem, every context free language can be mapped to a restricted subset of \( \text{DYCK}(s) \) \(^{10}\). A comprehensive description of context free languages and Dyke languages can be found in \(^{17, 20}\).

The study of language edit distance problem dates back to early seventies. Such an algorithm for context free grammar was first proposed by Aho and Peterson that runs in \( O(|G|^2n^3) \) time where \( |\sigma| = n \) is the string length and \( |G| \) is the size of the grammar \(^{11}\). This was later improved by Myers to run in \( O(|G|n^3) \) time \(^{27}\). These works were motivated by developing automated parsers for compiler design. For \( \text{DYCK}(s) \) the following dynamic programming improves the running time to \( O(n^3) \) independent of \( |G| \) which is \( \Theta(s) \) in this case. The second condition in computing \( \text{Edit}[i,j]\) leads to \( O(n^3) \) running time as the \( j \)th parenthesis \( \sigma_j \) (considering it to be a close parenthesis) can be matched with any \( \sigma_k \) (considering it to be an open parenthesis), for \( k \in [1, j - 1] \).

\[
\text{Edit}[i,j] \leftarrow \min (\text{cost}[i,j] + \text{Edit}[i+1,j-1] , \min_{i \leq k < j} (\text{Edit}[i,k] + \text{Edit}[k+1,j])) , i \leq j
\]

\[
\text{cost}[i,j] = \text{cost of editing } \sigma_i \text{ to match } \sigma_j \text{ and is 1 if } i = j,
\]

\[
\text{Edit}[i,j] = \text{ edit distance of the substring } \sigma_i \sigma_{i+1} \ldots \sigma_j \text{ and is 1 if } i = j.
\]

Even a decade back, \(^{26}\) reported these algorithms with cubic running time to be prohibitively slow for parser design. With modern data deluge, the issue of scalability has become far more critical. Motivated by a concrete application of repairing semi-structured documents where imbalanced parenthesis nesting is one of the major reported errors (14% of XML errors on the web is due to malformedness\(^{16}\)) and lack of scalability of cubic time algorithms, the authors in \(^{19}\) study the problem of approximating edit distance computation to \( \text{DYCK}(s) \). Given any string \( \sigma \) if \( \text{cost} = \min_{x \in \text{DYCK}(s)} \text{Edit}(\sigma,x) \), they ask the question whether it is possible to design an algorithm that runs in near-linear time and returns \( \sigma'' \in \text{DYCK}(s) \) such that \( \text{Edit}((\sigma,\sigma'')) \leq \alpha \text{StrEdit}(\sigma,\sigma'') \) for some \( \alpha \geq 1 \) where \( \text{StrEdit} \) is the normal string edit distance function and \( \alpha \) is the approximation factor. Edit distance computation from a string of parentheses to \( \text{DYCK}(s) \) is a significant generalization of string edit distance computation.\(^2\) A prototypical dynamic

\(^2\)For string edit distance computation, between string \( \sigma_1 \) and \( \sigma_2 \) over alphabet \( C \), create a new alphabet \( T \cup \bar{T} \) by uniquely mapping each character \( c \in C \) to a new type of open parenthesis, say \( t_c \), that now belongs to \( T \). Let \( t_{\bar{c}} \) be the matching close parenthesis for \( t_c \) and we let \( \bar{t}_{\bar{c}} \in \bar{T} \). Now create strings \( \sigma_1' \) by replacing each character of \( \sigma_1 \) with its corresponding open parenthesis in \( T \), and create string \( \sigma_2' \) by replacing each character of \( \sigma_2 \) with its corresponding close parenthesis in \( \bar{T} \). Obtain \( \sigma \) by appending \( \sigma_1' \) with reverse of \( \sigma_2' \). It is easy to check the edit distance between \( \sigma \) and \( \text{DYCK}(s) \) is exactly equal to string edit distance between \( \sigma_1 \) and \( \sigma_2 \).
programming for string edit distance computation runs in quadratic time (as opposed to cubic time for DYCK(s) edit distance problem). There is a large body of works on designing scalable algorithms for approximate string edit distance computation \[^6, 7, 29, 5, 4\]. Though basic in its appeal, nothing much is known for approximately computing edit distance to DYCK(s).

In \[^19\], the authors proposed fast greedy and branch and bound methods with various pruning strategies to approximately answer the edit distance computation to DYCK(s). With detailed experimental analysis, they show the effectiveness of these edit distance based approaches in practice over rule based heuristics commonly employed by modern web browsers like Internet Explorer, Firefox etc. However, either their algorithms have worst-case approximation ratio as bad as \(\Theta(n)\) or has running time exponential in \(d\), where \(d\) is the optimal edit distance to DYCK(s) (see \[^19\] for worst case examples). It is to be noted that for DYCK(1), there exists a simple single pass algorithm to compute edit distance: just pair up matching open and close parentheses and report the number of parentheses that could not be matched in this fashion.

In this paper, we study the question of approximating edit distance to DYCK(s) for any \(s \geq 2\) and give the **first** near-linear time algorithm with nontrivial approximation guarantees. Specifically, given there exists an algorithm for computing string edit distance on input of size \(n\) in \(\alpha(n)\) time with \(\beta(n)\)-approximation factor, we can devise an algorithm for edit distance problem to DYCK(s) running in \(\tilde{O}(n + \alpha(n))\) and achieving an approximation factor of \(O(\beta(n)\log OPT)^{1.5}\). In \(\tilde{O}(n^{1+\epsilon} + \alpha(n))\) time, we get an approximation factor of \(O(\frac{1}{\epsilon}\beta(n)\log OPT)\) (for any \(\epsilon > 0\)). Here \(OPT\) is the optimal edit distance to DYCK(s).

Since the best known near-linear time algorithm for string edit distance problem has \(\beta(n) = \text{poly}\log n\), we overall get a poly-logarithmic approximation. Therefore, with the current state of the art, both string and DYCK(s) edit distance computation has poly-logarithmic approximation factor in near-linear time. This comes as a surprise since DYCK(s) is a significant generalization of string edit distance problem and their exact computations via dynamic programming show a marked difference in time complexity.

Any parentheses string \(\sigma\) can be viewed as \(Y_1X_1Y_2X_2...Y_zX_z\) for some \(z \geq 0\) where \(Y_i\)s and \(X_i\)s respectively consist of only consecutive open and close parentheses. The special case of string edit distance problem can be thought of having \(z = 1\). The approximation factor of our algorithm is in fact \(O(\beta(n)\log z)\), where it is possible to ensure \(z \leq OPT\) by a simple preprocessing. Our algorithm cleverly combines a random walk to guide selection of subsequences of the parentheses strings in multiple phases having only consecutive sequence of open parentheses followed by close parentheses. These subsequences are then repaired each by employing subroutine for STREEdit computation. The general framework of the algorithm and its analysis applies to languages far beyond DYCK(s). We discuss this connection with respect to several memory checking languages whose study was initiated in the seminal work of Blum, Evans, Gemmell, Kannan and Naor \[^8\], and followed up by several groups \[^2, 11, 13, 28, 9\]. We consider basic languages such as STACK, QUEUE, PQ, DEQUE etc. They comprise of valid transcripts of stacks, queues, priority queues and double-ended queues respectively. Given a transcript of any such memory-checking language, we consider the problem of finding the minimum number of edits required to make the transcript error-free and show that the algorithm for DYCK(s) can be adapted to return a valid transcript efficiently. Therefore, any language that can be recognized by these data structures, can also be repaired efficiently by our algorithm.

### 1.1 Related Work

Early works on edit distance to grammar \[^1, 27\] was motivated by the problem of correcting and recovering from syntax error during context-free parsing and have received significant attention in the realm of compiler optimization \[^14, 15, 26, 18\]. Many of these works focus on designing time-efficient parsers using local recovery \[^15, 26, 18\] rather than global dynamic programming based algorithms \[^1, 27\], but to the best of our knowledge, none of these methods provide approximation guarantee on edit distance in sub-cubic time. Approximating edit distance to DYCK(s) has recently been studied in \[^19\] for repairing XML documents,
but again the proposed subcubic algorithms all have worst case approximation factor $\Theta(n)$.

Recognizing a grammar is a much simpler task than repairing. Using a stack, it is straightforward to recognize $\text{DYCK}(s)$ in a single pass. When there is a space restriction, Magniez, Mathieu and Nayak [25] considered the streaming complexity of recognizing $\text{DYCK}(s)$ showing an $\Omega(\sqrt{n})$ lower bound and a matching upper bound within a $\log n$ factor. Even with multiple one-directional passes, the lower bound remains at $\Omega(\sqrt{n})$ [9], surprisingly with two passes in opposite directions the space complexity reduces to $O(\log^2 n)$. This exhibits a curious phenomenon of streaming complexity of recognizing $\text{DYCK}(s)$. Krebs, Limaye and Srinivasan extended the work of [25] to consider very restricted cases of errors, where an open (close) parenthesis can only be changed into another open (close) parenthesis [21]. Again with only such edits, computing edit distance in linear time is trivial: whenever an open parenthesis at the stack top cannot be matched with the current close parenthesis, change one of them to match. Allowing arbitrary insertions, deletions and substitutions is what makes the problem significantly harder. In the property testing framework, in the seminal paper Alon, Krivelevich, Newman and Szegedy [3] showed that $\text{DYCK}(1)$ is testable in time independent of $n$, however $\text{DYCK}(2)$ requires $\Omega(\log n)$ queries. This lower bound was further strengthened to $n^{1/11}$ by Parnas, Ron and Rubinfeld [30] where they also give a testing algorithm using $n^{2/3}/\epsilon^2$ queries. These algorithms can only distinguish between the case of 0 error with $\epsilon n$ errors, and therefore, are not applicable to the problem of approximating edit-distance to $\text{DYCK}(s)$.

Edit distance to $\text{DYCK}(s)$ is a significant generalization of string edit distance problem. String edit distance enjoys the special property that a symbol at the $i$th position in one string must be matched with a symbol at a position between $(i-d)$ to $(i+d)$ in the other string. Using this “local” property, prototypical quadratic dynamic programming algorithm can be improved to run in time $O(dn)$ which was later improved to $O(n+d^2)$ [31] to $O(n+d^4)$ [12] and then to $O(n+d^2)$ [22]. The later result implies a $\sqrt{n}$-approximation for string edit distance problem. However, all of these crucially use the locality property, which does not hold for parenthesis strings: two parentheses far apart can match as well. Also, it is known that parsing arbitrary context free grammar (CFG) is as hard as boolean matrix multiplication [23] and a nondeterministic version of $\text{DYCK}$ is the hardest CFG [10]. Therefore, exactly computing edit distance to $\text{DYCK}(s)$ in time much less than subcubic would be a significant accomplishment. For string edit distance, the current best approximation ratio of $(\log n)^{O(1/\epsilon)}$ in $n^{1+\epsilon}$ running time for any fixed $\epsilon > 0$ is due to Andoni, Krauthgamer and Onak [4]. This result is preceded by a series of works which improved the approximation ratio from $\sqrt{n}$ [22] to $n^{2/3}$ [6], then to $n^{3/5+o(1)}$ [7], all of which run in linear time and finally to $2^{\sqrt{\log n \log \log n}}$ that run in time $n2^{\sqrt{\log n \log \log n}}$ [5].

### 1.2 Techniques & RoadMap

**Definition 1.** The congruent of a parenthesis $x$ is defined as its symmetric opposite parenthesis, denoted $\bar{x}$. The congruent of a set of parentheses $X$, denoted $\bar{X}$, is defined as $\{\bar{x} \mid x \in X\}$.

We use $T$ to denote the set of open parentheses and $\bar{T}$ to denote the set of close parentheses. (Each $x \in T$ has exactly one congruent $\bar{x} \in \bar{T}$ that it matches to and vice versa.) The alphabet $\Sigma = T \cup \bar{T}$.

Consider a string $\sigma = \sigma_1...\sigma_n$, of length $n$, over some parenthesis alphabet $\Sigma = T \cup \bar{T}$, that is, $\sigma \in \text{DYCK}(s)$, $s = |T|$.

**Definition 2.** A well-balanced string over some parenthesis alphabet $\Sigma = T \cup \bar{T}$ obeys the context-free grammar $\text{DYCK}(s)$, $s = |T|$ with productions $S \rightarrow SS$, $S \rightarrow \varepsilon$ and $S \rightarrow aS\bar{a}$ for all $a \in T$.

**Definition 3.** The $\text{DYCK}$ Language Edit Distance Problem, given string $\sigma$ over alphabet $\Sigma = T \cup \bar{T}$, is to find $\arg \min_{\sigma'} \text{StrEdit}(\sigma, \sigma')$ such that $\sigma' \in \text{DYCK}(s)$, $s = |T|$.
A Simple Algorithm (Section 2)

We start with a very simple algorithm that acts as a stepping stone for the subsequent refinements. The algorithm is as simple as it gets, and we call it \textbf{Random-deletion}.

Initialize a stack to empty. Scan the parenthesis string $\sigma$ left to right. If the current symbol is an open parenthesis, insert it into the stack. If the current symbol is a close parenthesis, check the symbol at top of the stack. If both the symbols can be matched, match them. If the stack is empty, delete the current symbol. Else delete one of them independently with equal probability $\frac{1}{2}$. If the stack is nonempty when the scan has ended, delete all symbols from the stack.

We show

\textbf{Theorem 1.} \textbf{Random-deletion} obtains a $4d$-approximation for edit distance computation to $\text{DYCK}(s)$ for any $s \geq 2$ in linear time with constant probability, where $d$ is the optimum edit distance.

The probability can be boosted by running the algorithm $\Theta(\log n)$ times and considering the iteration which results in minimum number of edits. In the worst case, when $d = \sqrt{n}$, the approximation factor can be $4\sqrt{n}$. This also gives a very simple algorithm for string edit distance problem that achieves an $O(\sqrt{n})$ approximation.

The analysis of even such a simple algorithm is nontrivial and proceeds as follows. First, we allow the optimal algorithm to consider only deletion and allow it to process the string using a stack; this increases the edit distance by a factor of 2 (Lemma 5, Lemma 6). We then define for each comparison where an open and close parenthesis cannot be matched, a corresponding correct and wrong move. If an optimal algorithm also compares exactly the two symbols and decides to delete one, then we can simply define the parenthesis that is deleted by the optimal algorithm as the correct move and the other as a wrong move. However, after the “first” wrong move, the comparisons performed by our procedure vs the optimal algorithm can become very different. Yet, we can label one of the two possible deletions as a correct move in some sense of decreasing distance to an optimal state. Next, we show that if up to time $t$, the algorithm has taken $W_t$ wrong moves then it is possible to get a well-formed string using a total of $2(d + 2W_t)$ edit operations. These two properties help us to map the process of deletions to a one dimensional random walk which is known as the \textsc{Gambler’s Ruin} problem.

In gambler’s ruin, a gambler enters a casino with $d$ and starts playing a game where he wins with probability $\frac{1}{2}$ and loses with probability $\frac{1}{2}$ independently. The gambler plays the game repeatedly betting $\$1$ in each round. He leaves if he runs out of money or gets $\$n$. We can show that the number of steps taken by the gambler to be ruined is an upper bound on the number of edit operations performed by our algorithm. The expected number of such steps is $O(n)$ which is the string length in our case. Interestingly, the underlying probability distribution of the number of steps taken by the random walk is heavy-tailed and using that property, one can still lower bound the probability that gambler is ruined in $O(d^2)$ steps by a constant $\sim \frac{1}{d^2}$ (Lemma 12). This gives an $O(d)$ approximation.

A Refined Algorithm (Section 3)

We now refine our algorithm as follows. Given string $\sigma$, we can delete any prefix of close parentheses, delete any suffix of open parentheses and match well-formed substrings without affecting the optimal solution. After that, $\sigma$ can be written as $Y_1X_1Y_2X_2...Y_zX_z$, where each $Y_i$ is a sequence of open parentheses, each $X_i$ is a sequence of close parentheses and $z \leq d$. In the optimal solution $X_1$ is matched with some suffix of $Y_1$ possibly after doing edits. Let us denote this suffix by $Z_1$. If we can find the left boundary of $Z_1$, then we can employ \textsc{StRedit} to compute string edit distance between $Z_1$ and $X_1$ (we have to consider reverse of $X_1$ and convert each $t \in X_1$ to $t$—this is what is meant by \textsc{StRedit} between a sequence of open and a
sequence of close parentheses), as \( Z_1 X_1 \) consists of only a single sequence of open parentheses followed by a single sequence of close parentheses. If we can identify \( Z_1 \) correctly, then in the optimal solution \( X_2 \) is matched with a suffix of \( Y_1^{res} 2 \) after removing \( Y_1^{res} = Y_1 \setminus Z_1 \). Let us denote it by \( Z_2 \). If we can again find the left boundary of \( Z_2 \), then we can employ StrEdit between \( Z_2 \) and \( X_2 \) and so on. The question is how do we compute these boundaries?

We use Random-deletion again (repeat it appropriately \( \sim \log n \) times) to find these boundaries approximately (see Algorithm[1]). We consider the suffix of \( Y_1 \) which Random-deletion matches against \( X_1 \) possibly after multiple deletions (call it \( Z_1' \)) and use \( Z_1' \) to approximate \( Z_1 \). We show again using the mapping of Random-deletion to random walk, that the error in estimating the left boundary is bounded (Lemma[8] Lemma[16] Lemma[17]). Specifically, if \( StrEdit(Z_1, X_1) = d_1 \), then \( StrEdit(Z_1', X_1) \leq 2d_1 \sqrt{2 \log d_1} \). Note that this improves from \( O(d_1^2) \) by Random-deletion to \( O(d_1 \sqrt{\log d_1}) \). But, the error that we make in estimating \( Z_1 \) may propagate and affect the estimation of \( Z_2 \). Hence the gap between optimal \( Z_2 \) and estimated \( Z_2' \) becomes wider. If \( StrEdit(Z_2, X_2) = d_2 \), then we get \( StrEdit(Z_2', X_2) \leq 2(d_1 + d_2) \sqrt{2 \log (d_1 + d_2)} \). Proceeding, in this fashion, we get the following theorem.

**Theorem 2.** Algorithm[2] obtains an \( O(z\beta(n) \sqrt{\log d}) \)-approximation factor for edit distance computation from strings to DICO\( k(s) \) for any \( s \geq 2 \) in \( O(n \log n + \alpha(n)) \) time with probability at least \( (1 - \frac{1}{n} - \frac{1}{d}) \), where there exists an algorithm for StrEdit running in \( \alpha(n) \) time achieves an approximation factor of \( \beta(n) \).

Further Refinement: Main Algorithm (Section[4])

Is it possible to compute subsequences of \( \sigma \) such that each subsequence contains a single sequence of open and close parentheses in order to apply StrEdit, yet propagational error can be avoided? This leads to our main algorithm.

**Example.** Consider \( \sigma = Y_1 X_1 Y_2 X_2 Y_3 X_3 \ldots Y_2 X_2 \), and let the optimal algorithm matches \( X_1 \) with \( Z_{1,1} \), matches \( X_2 \) with \( Z_{1,2} Y_2 \), matches \( X_3 \) with \( Z_{1,3} Y_3 \), and so on, where \( Y_1 = Z_{1,z} Z_{1,z-1} \ldots Z_{1,2} Z_{1,1} \). In the refined algorithm, when Random-deletion finishes processing \( X_1 \) and tries to estimate the left boundary of \( Z_{1,1} \), it might have already deleted some symbols of \( Z_{1,2} \). It is possible that it deletes \( \Theta((d_1 + d_2) \sqrt{\log (d_1 + d_2)}) \) symbols from \( Z_{1,2} \). Therefore, when computing StrEdit between \( X_1 \) and \( Z_1' \), the portion of \( Z_{1,2} \) in \( Z_1' \) may not have any matching correspondence and results in increased StrEdit. More severely, the Random-deletion process gets affected when processing \( X_2 \). Since, it does not find the symbols in \( Z_{1,2} \) which ought to be matched with some subsequence of \( X_2 \), it penetrates \( Z_{1,3} \) and may delete \( \Theta((d_1 + d_2) \sqrt{\log (d_1 + d_2)}) \) symbols from \( Z_{1,3} \), and so on. To remedy this, view \( X_2 = X_{2,in} X_{2,out} \) where \( X_{2,in} \) is the prefix of \( X_2 \) that is matched with \( Y_2 \) and \( X_{2,out} \) is matched with \( Z_{1,2} \). Consider pausing the random deletion process when it finishes \( Y_2 \) and thus attempt to find \( X_{2,in} \). Suppose, Random-deletion matches \( X_{2,in} \) with \( Y_2 \), then compute StrEdit\((Y_2, X_{2,in}')\). While there could be still mistake in computing \( X_{2,in}' \), the mistake does not affect \( Z_{1,3} \). Else if Random-deletion process finishes \( X_2 \) before finishing \( Y_2 \), then of course it has not been able to affect \( Z_{1,3} \). In that case \( Y_2' \) is a suffix of \( Y_2 \) and we compute StrEdit\((Y_2', X_2)\). Similarly, when processing \( X_3 \), we pause whenever \( X_3 \) or \( Y_3 \) is exhausted and create an instance of StrEdit accordingly. Suppose, for the sake of this example, \( Y_2, Y_3, \ldots, Y_z \) are finished before finishing \( X_2, X_3, \ldots \). \( X_2 \) respectively and \( X_1 \) is finished before \( Y_1 \). Then, after creating the instances of StrEdits as described, we are left with a sequence of open parenthesis corresponding to a prefix of \( Y_1 \) and a sequence of close parenthesis, which is a combination of suffixes from \( X_2, X_3, \ldots, X_z \). We can compute StrEdit between them. Since much of \( Z_{1,z} Z_{1,z-1} \ldots Z_{1,2} \) exists in this remaining prefix of \( Y_1 \) and their matching parentheses in the created sequence of close parentheses, the computed StrEdit distance will remain within the desired bound.

Let us call each \( X_i Y_j \) a block. As the example illustrates, we create StrEdit instances corresponding to what Random-deletion does locally in each block. After the first phase, from each block we are either
left with a sequence of open parenthesis (call it a block of type O), or a sequence of close parentheses (call it a block of type C), or the block is empty. This creates new sequences of open and close parentheses by combining all the consecutive O blocks together (forget empty blocks) and similarly combining all consecutive C blocks together (forget empty blocks). We get new blocks, at most \( \lceil \frac{z}{2} \rceil \) of them after removing any prefix of close and any suffix of open parentheses, in the remaining string. Again, we look at what Random-deletion does locally in these new blocks and create instances of STREdit accordingly. This process can continue at most \( \lceil \log z \rceil + 1 \) phases, since the number of blocks reduces at least by a factor of 2 going from one phase to the next. This entire process is repeated \( O(n \log n) \) time and the final outcome is the minimum of the edit distances computed over these repetitions. The following theorem summarizes the performance of this algorithm.

**Theorem 3.** There exists an algorithm that obtains an \( O(\beta(n) \log z \sqrt{\frac{\log d}{z}}) \)-approximation factor for edit distance computation from strings to \( \text{DYCK}(s) \) for any \( s \geq 2 \) in \( O(n \log n + \alpha(n)) \) time with probability at least \( (1 - \frac{1}{n} - \frac{1}{z}) \), where there exists an algorithm for STREdit running in \( \alpha(n) \) time that achieves an approximation factor of \( \beta(n) \).

The \( \sqrt{\frac{\log d}{z}} \) factor in the approximation can be avoided if we consider iterating \( O(n^\epsilon \log n) \) times. Since, the best known near-linear time algorithm for STREdit anyway has \( \alpha(n) = n^{1+\epsilon} \) and \( \beta = (\log n)^{\frac{1}{z}} \), we obtain the following theorem.

**Theorem 4.** For any \( \epsilon > 0 \), there exists an algorithm that obtains an \( O(\frac{1}{2} \log z (\log n)^{\frac{1}{z}}) \)-approximation factor for edit distance computation from strings to \( \text{DYCK}(s) \) for any \( s \geq 2 \) in \( O(n^{1+\epsilon}) \) time with high probability.

The algorithm and its analysis gives a general framework which can be applied to many other languages beyond \( \text{DYCK}(s) \). Employing this algorithm one can repair footprints of several memory checking languages such as \( \text{STACK}, \text{QUEUE}, \text{PQ} \) and \( \text{DEQUE} \) efficiently. We discuss this connection in Section 5.

## 2 Analysis of Random-deletion

Here we analyse the performance of Random-deletion and prove Theorem 1.

Recall the algorithm. It uses a stack and scans \( \sigma \) left to right. Whenever it encounters an open parenthesis, the algorithm pushes it into the stack. Whenever it encounters a close parenthesis, it compares this current symbol with the one at the stack top. If they can be matched, the algorithm always matches them and proceeds to the next symbol. If the stack is empty, it deletes the close parenthesis and again proceeds to the next symbol. Else, the stack is non-empty but the two parentheses cannot be matched. In that case, the algorithm deletes one of the symbol, either the one at the stack top or the current close parenthesis in the string. It tosses an unbiased coin, and independently with probability \( \frac{1}{2} \) it chooses which one of them to delete. If there is no more close parenthesis, but stack is non-empty, then it deletes all the open parentheses from the stack.

We consider only deletion as a viable edit operation and under deletion-only model, assume that the optimal algorithm is stack based, and matches well-formed substrings greedily. The following two lemmas whose proofs are in the appendix state that we lose only a factor 2 in the approximation by doing so.

**Lemma 5.** For any string \( \sigma \in (T \cup \bar{T})^* \), \( \text{OPT}(\sigma) \leq \text{OPT}_d(\sigma) \leq 2\text{OPT}(\sigma) \), where \( \text{OPT}(\sigma) \) is the minimum number of edits: insertions, deletions, substitutions required and \( \text{OPT}_d(\sigma) \) is the minimum number of deletions required to make \( \sigma \) well-formed.

**Lemma 6.** There exists an optimal algorithm that makes a single scan over the input pushing open parenthesis to stack and when it observes a close parenthesis, it either pops the stack top, if it matches the observed
close parenthesis and removes both from further consideration, or edits (that is deletes) either the stack top or the observed close parenthesis whenever there is a mismatch.

From now onward we fix a specific optimal stack based algorithm, and refer that as the optimal algorithm.

Let us initiate time \( t = 0 \). At every step in Random-deletion when we either match two parentheses (current close parenthesis in the string with open parenthesis at the stack top) or delete one of them, we increment the time \( t \) by 1.

We define two sets \( A_t \) and \( A_t^{OPT} \) for each time \( t \).

**Definition 4.** For every time \( t \geq 0 \), \( A_t \) is defined as all the indices of the symbols that are matched or deleted by Random-deletion up to and including time \( t \).

**Definition 5.** For every time \( t \geq 0 \),

\[
A_t^{OPT} = \{ i \mid i \in A_t \text{ or } i \text{ is matched by the optimal algorithm with some symbol with index in } A_t \}.
\]

Clearly at all time \( t \geq 0 \), \( A_t^{OPT} \supseteq A_t \). We now define a correct and wrong move.

**Definition 6.** A comparison at time \( t \) in the algorithm leading to a deletion is a correct move if \( |A_t^{OPT} \setminus A_t| \leq |A_{t-1}^{OPT} \setminus A_{t-1}| \) and is a wrong move if \( |A_t^{OPT} \setminus A_t| > |A_{t-1}^{OPT} \setminus A_{t-1}| \).

**Lemma 7.** At any time \( t \), there is always a correct move, and hence Random-deletion always takes a correct move with probability at least \( \frac{1}{2} \).

*Proof.* Suppose the algorithm compares an open parenthesis \( \sigma[i] \) with a close parenthesis \( \sigma[j] \), \( i < j \) at time \( t \), and they do not match. If possible, suppose that there is no correct move.

Since Random-deletion is stack-based, \( A_t \) contains all indices in \([i,j]\). It may also contain intervals of indices \([i_1,j_1]\), \([i_2,j_2]\), ..., because there can be multiple blocks. It must hold \([1, j - 1] \setminus A_t \) does not contain any close parenthesis. Now for both the two possible deletions to be wrong, the optimal algorithm must match \( \sigma[i] \) with some \( \sigma[j'] \), \( j' > j \), and also match \( \sigma[j] \) with \( \sigma[i'] \), \( i' < i \), \( i' \notin A_t \). But, this is not possible due to the property of well-formedness.

Now consider the case that at time \( t \), the stack is empty and the current symbol in the string is \( \sigma[j] \). In that case Random-deletion deletes \( \sigma[j] \). Clearly, \( A_t = [1,j] \). For this to be a wrong move, the optimal algorithm should match \( \sigma[j] \) with \( \sigma[i] \), \( i < 1 \) which is not possible. Hence, in this case the move is correct.

Now consider the case that at time \( t \), the input is exhausted and the algorithm considers \( \sigma[i] \) from the stack top. In that case Random-deletion deletes \( \sigma[i] \). Clearly \( A_t \) contains indices of all close parenthesis. For this to be a wrong move, the optimal algorithm should match \( \sigma[i] \) with \( \sigma[j] \), \( j \notin A_t \) which is not possible. Hence, in this case the move is correct too.

**Lemma 8.** If at time \( t \) (up to and including time \( t \)), the number of indices in \( A_t^{OPT} \) that the optimal algorithm deletes is \( d_t \) and the number of correct and wrong moves are respectively \( c_t \) and \( w_t \) then \( |A_t^{OPT} \setminus A_t| \leq d_t + w_t - c_t \).

*Proof.* Clearly, the lemma holds at time \( t = 0 \), since \( d_0 = c_0 = w_0 = 0 \) and \( A_0 = A_0^{OPT} = \emptyset \).

Suppose, the lemma holds up to and including time \( t - 1 \). We now consider time \( t \). Let at time \( t \), the algorithm compares an open parenthesis \( \sigma[i] \) with a close parenthesis \( \sigma[j] \), \( i < j \). The following cases need to be considered.

Case 1. \( \sigma[i] \) is matched with \( \sigma[j] \), \( c_t = c_{t-1}, w_t = w_{t-1} \).

Subcase 1. The optimal algorithm also matches \( \sigma[i] \) with \( \sigma[j] \), hence \( d_t = d_{t-1} \). Now \( A_t^{OPT} = A_{t-1}^{OPT} \cup \{i,j\} \) and \( A_t = A_{t-1} \cup \{i,j\} \). So we have \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| \leq d_{t-1} + w_{t-1} - c_{t-1} \) (by induction hypothesis) \( = d_t + w_t - c_t \).
Subcase 2. The optimal algorithm does not match \( \sigma[i] \) with \( \sigma[j] \). It is not possible that the optimal algorithm matches \( \sigma[i] \) with \( \sigma[j'] \), \( j' > j \) and also matches \( \sigma[j] \) with \( \sigma[i'] \), \( i' < j \) simultaneously due to the property of well-formedness.

- First consider that \( \sigma[i] \) and \( \sigma[j] \) are both matched with some symbols in the optimal algorithm. So \( d_t = d_{t-1} \). Let \( \sigma[i] \) be matched with \( \sigma[j'] \) and \( \sigma[j] \) be matched with \( \sigma[i'] \). Then either \((a)i < j' < i'< j\), or \((b)i < i' < j < j'\), or \((c)i < i' < j < j'\).

  - For \((a)\), \( i,j \in A_{t-1}^{OPT} \) and \( A_t^{OPT} = A_{t-1}^{OPT} \). Also, \( A_t = A_{t-1} + \{i,j\} \). Hence \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| - 2 \leq d_{t-1} + w_{t-1} - c_{t-1} - 2 = d_t + w_t - c_t - 2 \).

  - For \((b)\), \( j \in A_{t-1}^{OPT} \) and \( A_t^{OPT} = A_{t-1}^{OPT} \setminus \{i,j'\} \). Also, \( A_t = A_{t-1} \setminus \{i,j\} \). Hence \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| \) (decreases 1 due to \( j \) and increases 1 due to \( j' \)) and thus \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| \leq d_{t-1} + w_{t-1} - c_{t-1} - 1 \) (by induction hypothesis) \( = d_t + w_t - c_t \).

  - For \((c)\), \( i \in A_{t-1}^{OPT} \) and \( A_t^{OPT} = A_{t-1}^{OPT} \setminus \{i',j\} \). Also, \( A_t = A_{t-1} \setminus \{i,j\} \). Hence \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| \) (decreases 1 due to \( i \) and increases 1 due to \( i' \)) and thus \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| \leq d_{t-1} + w_{t-1} - c_{t-1} - 1 \) (by induction hypothesis) \( = d_t + w_t - c_t \).

- Now consider that one of \( \sigma[i] \) or \( \sigma[j] \) gets deleted. Assume, w.l.o.g. that \( \sigma[i] \) is deleted (exactly similar analysis when only \( \sigma[j] \) is deleted). So \( d_t = d_{t-1} + 1 \). Then if \( \sigma[j] \) is matched with \( \sigma[i'] \) either \((a')i < i' < j \) or \((b')i' < i < j \).

  - For \((a')\), \( j \in A_{t-1}^{OPT} \) and \( A_t^{OPT} = A_{t-1}^{OPT} \setminus \{i\} \). Also, \( A_t = A_{t-1} \setminus \{i,j\} \). Hence \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| - 1 \) (decreases 1 due to \( j \)) and thus \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| - 1 \leq d_{t-1} + w_{t-1} - c_{t-1} - 1 \) (by induction hypothesis) \( < d_t + w_t - c_t \).

  - For \((b')\), \( A_t^{OPT} = A_{t-1}^{OPT} \setminus \{i,j\} \). Also, \( A_t = A_{t-1} \setminus \{i,j\} \). Hence \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| + 1 \) (increases 1 due to \( i' \)) and thus \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| + 1 \leq d_{t-1} + w_{t-1} - c_{t-1} + 1 \) (by induction hypothesis) \( = d_t + w_t - c_t \).

- Now consider that both \( \sigma[i] \) and \( \sigma[j] \) are deleted. \( d_t = d_{t-1} + 2 \). \( A_t^{OPT} = A_{t-1}^{OPT} \setminus \{i,j\} \). Also, \( A_t = A_{t-1} \setminus \{i,j\} \). Hence, \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| \leq d_{t-1} + w_{t-1} - c_{t-1} < d_t + w_t - c_t \).

Case 2. \( \sigma[i] \) is not matched with \( \sigma[j] \) and \( \sigma[i] \) is deleted.

- First consider that in the optimal algorithm, \( \sigma[i] \) and \( \sigma[j] \) are both matched with some symbols. So \( d_t = d_{t-1} \). Let \( \sigma[i] \) be matched with \( \sigma[j'] \) and \( \sigma[j] \) be matched with \( \sigma[i'] \). Then either \((a)i < j' < i' < j \), or \((b)i < i' < j < j'\), or \((c)i < i' < j < j'\).

  - For \((a)\), \( i,j \in A_{t-1}^{OPT} \) and \( A_t^{OPT} = A_{t-1}^{OPT} \). Also, \( A_t = A_{t-1} + \{i\} \). Hence \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| \leq d_{t-1} + w_{t-1} - c_{t-1} - 1 = d_t + w_t - c_t - 1 \) since \( c_t = c_{t-1} + 1 \).

  - For \((b)\), \( j \in A_{t-1}^{OPT} \) and \( A_t^{OPT} = A_{t-1}^{OPT} \setminus \{i,j\} \). Also, \( A_t = A_{t-1} \setminus \{i\} \). Hence \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| + 1 \) and thus \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| + 1 \leq d_{t-1} + w_{t-1} - c_{t-1} + 1 \) (by induction hypothesis) \( = d_t + w_t - c_t \), since \( w_t = w_{t-1} + 1 \).

  - For \((c)\), \( i \in A_{t-1}^{OPT} \) and \( A_t^{OPT} = A_{t-1}^{OPT} \). Also, \( A_t = A_{t-1} \setminus \{i\} \). Hence \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| - 1 \) (decreases 1 due to \( i \)) and thus \( |A_t^{OPT} \setminus A_t| = |A_{t-1}^{OPT} \setminus A_{t-1}| - 1 \leq d_{t-1} + w_{t-1} - c_{t-1} - 1 \) (by induction hypothesis) \( = d_t + w_t - c_t \), since \( c_t = c_{t-1} + 1 \).

- Now consider that one of \( \sigma[i] \) or \( \sigma[j] \) gets deleted by the optimal algorithm. Assume, first, that \( \sigma[i] \) is deleted. So \( d_t = d_{t-1} + 1 \). Then if \( \sigma[j] \) is matched with \( \sigma[i'] \) either \((a')i < i' < j \) or \((b')i' < i < j \).
In that case \( \sigma \) deletion takes action on \( \sigma \) and the optimal algorithm matches it. If \( \sigma[i] \) is matched with \( \sigma[j'] \) either \((a'')i < j' < j \) or \((b'')i < j < j' \).

- For \( (a'') \), \( i \in A^i_{t-1} \), \( A^i_{t-1} \) and \( A_t = A_{t-1} \cup \{i\} \). Hence \( |A^i_{t-1} \setminus A_t| = \sum_{k=1}^{n} A^i_{t-1} \setminus A_t| \) and thus \( |A^i_{t-1} \setminus A_t| = |A^i_{t-1} \setminus A_t| - 1 \leq d_{t-1} + w_{t-1} - c_{t-1} \) and thus \( A^i_{t-1} \setminus A_t = A^i_{t-1} \setminus A_{t-1} + 1 \) by induction hypothesis. Hence \( d_t = d_{t-1} + 1, \ c_t = c_{t-1} + 1 \) and \( w_t = w_{t-1} \).

- For \( (b'') \), \( A^i_{t-1} \setminus A_t = A^i_{t-1} \setminus A_{t-1} \) and thus \( |A^i_{t-1} \setminus A_t| = |A^i_{t-1} \setminus A_t| - 1 \leq d_{t-1} + w_{t-1} - c_{t-1} \) by induction hypothesis. Hence \( d_t = d_{t-1} + 1, \ c_t = c_{t-1} + 1 \) and \( w_t = w_{t-1} \).

\[ \sum_{k=1}^{n} A^i_{t-1} \setminus A_t = A^i_{t-1} \setminus A_{t-1} + 1 \]

• Now consider that both \( \sigma[i] \) and \( \sigma[j] \) get deleted by the optimal algorithm. \( d_t = d_{t-1} + 1, \ c_t = c_{t-1} + 1 \).

Case 3. \( \sigma[i] \) is not matched with \( \sigma[j] \) and \( \sigma[j] \) is deleted.

Same as Case 2.

Case 4. Now consider the case that at time \( t \), the stack is empty and the current symbol in the string is \( \sigma[j] \).

In that case \( \text{Random-deletion} \) deletes \( \sigma[j] \) and the move is correct. So \( c_t = c_{t-1} + 1 \) and \( w_t = w_{t-1} \). We have \( A_t = A_{t-1} \cup \{j\} \). If the optimal algorithm also deletes \( \sigma[j] \) then \( A^i_{t-1} \setminus A_t = A^i_{t-1} \setminus A_{t-1} + 1 \) and \( d_t = d_{t-1} + 1 \). Hence \( |A^i_{t-1} \setminus A_t| = |A^i_{t-1} \setminus A_{t-1}| - 1 \leq d_{t-1} + w_{t-1} - c_{t-1} \) by induction hypothesis. Hence \( d_t = d_{t-1} + 1, \ c_t = c_{t-1} + 1 \). On the other hand, if the optimal algorithm matches \( \sigma[j] \) with some \( \sigma[j'] \), \( j' < j \), then \( j \in A^i_{t-1} \) and \( A^i_{t-1} = A^i_{t-1} \setminus \{j\} \). Hence \( |A^i_{t-1} \setminus A_t| = |A^i_{t-1} \setminus A_{t-1}| - 1 \leq d_{t-1} + w_{t-1} - c_{t-1} \) by induction hypothesis. Hence \( d_t = d_{t-1} + 1, \ c_t = c_{t-1} + 1 \).

Case 5. Now consider the case that at time \( t \), the input is exhausted and the algorithm considers \( \sigma[i] \) from the stack top. In that case \( \text{Random-deletion} \) deletes \( \sigma[i] \). Then, again by similar analysis as in the previous case, the claim is established.

Let \( S_t \) denote the string \( \sigma \) at time \( t \) after removing all the symbols that were deleted by \( \text{Random-deletion} \) up to and including time \( t \).

**Lemma 9.** Consider \( d \) to be the optimal edit distance. If at time \( t \) \((\text{up to and including } t)\), the number of indices in \( A^i_t \) that the optimal algorithm deletes be \( d_t \) and \( |A^i_t \setminus A_t| = r_t \) at most \( r_t + (d - d_t) \) edits is sufficient to convert \( S_t \) into a well-balanced string.

**Proof.** Since \( |A^i_t \setminus A_t| = r_t \), there exists exactly \( r_t \) indices in \( S_t \) such that if those indices are deleted, the resultant string is same as what the optimal algorithm obtains after processing the symbols in \( A^i_t \). For the symbols in remaining \( \{1, 2, ..., n\} \setminus A^i_t \), the optimal algorithm does at most \( d - d_t \) edits. Therefore a total of \( r_t + (d - d_t) \) edits is sufficient to convert \( S_t \) into a well-balanced string.

**Lemma 10.** The edit distance between the final string \( S_n \) and \( \sigma \) is at most \( d + 2w_n \).
Proof. Consider any time \( t \geq 0 \), if at \( t \), the number of deletions by the optimal algorithm in \( A^{OPT} \) is \( d_t \), the number of correct moves and wrong moves are respectively \( c_t \) and \( w_t \), then we have \( |A^{OPT} \setminus A| \leq d_t + w_t - c_t \). The number of edits that have been performed to get \( S_t \) from \( S_0 \) is \( c_t + w_t \). Denote this by \( E(0, t) \). The number of edits that are required to transform \( S_t \) to well-formed is at most \( (d-d_t) + d_t + w_t - c_t = d + w_t - c_t \) (by Lemma \( \ref{lem:random-deletion} \)). Denote it by \( E'(t, n) \). Hence the minimum total number of edits required (including those already performed) considering state at time \( t \) is \( E(0, t) + E'(t, n) = d + 2w_t \). Since this holds for all time \( t \), the lemma is established.

In order to bound the edit distance, we need a bound on \( w_n \). To do so we map the process of deletions by \textbf{Random-deletion} to a random walk.

### 2.1 Mapping into Random Walk

We consider the following one dimensional random walk. The random walk starts at coordinate \( d \), at each step, it moves one step right (+1) with probability \( \frac{1}{2} \) and moves one step left (−1) with probability \( \frac{1}{2} \). We count the number of steps required by the random walk to hit the origin.

We now associate a modified random walk with the deletions performed by \textbf{Random-deletion} as follows. Every time \textbf{Random-deletion} needs to take a move (performs one deletion), we consider one step of the modified random walk. If \textbf{Random-deletion} takes a wrong move, we let this random walk make a right (away from origin) step. On the other hand if \textbf{Random-deletion} takes a correct move, we let this random walk take a left step (towards origin move). If the random walk takes \( W \) right steps, then \textbf{Random-deletion} also makes \( W \) wrong moves. If the random walk takes \( W \) right steps before hitting the origin, then it takes in total \( d + 2W \) steps, and \textbf{Random-deletion} also deletes \( d + 2W \) times. Therefore, hitting time of this modified random walk starting from \( d \) characterizes the number of edit operations performed by \textbf{Random-deletion}. In this random walk, left steps (towards origin) are taken with probability \( \geq \frac{1}{2} \) (sometimes with probability 1). Therefore, hitting time of this modified random walk is always less than the hitting time of an one-dimensional random walk starting at \( d \) and taking right and left step independently with equal probability.

We therefore calculate the probability of a one-dimensional random walk taking right or left steps with equal probability to have a hitting time \( D \) starting from \( d \). The computed probability serves as a lower bound on the probability that \textbf{Random-deletion} takes \( D \) edit operations to transform \( \sigma \) to well-formed.

The one dimensional random walk is related to GAMSBER’S RUIN problem. In gambler’s ruin, a gambler enters a casino with \( $d \) and starts playing a game where he wins with probability \( 1/2 \) and loses with probability \( 1/2 \) independently. The gambler plays the game repeatedly betting \$1 in each round. He leaves if he runs out of money or his total fortune reaches \$\( N \). In gambler’s ruin problem one is interested in the hitting probability of the absorbing states. For us, we are interested in the probability that gambler gets ruined. We can set \( N = n + d \) because that implies the random walk needs to take \( n \) steps at the least to reach fortune and \( n \) is a trivial upper bound on the edit distance.

Let \( P_d \) denote the probability that gambler is ruined or his fortune reaches \$\( N \) on the condition that his current fortune is \$\( d \) and also let \( E_d \) denote the expected number of steps needed for the gambler to be ruined or get \$\( N \) starting from \$\( d \). Then it is easy to see using Markov property that the distribution \( P_d \) satisfies the following recursion \( P_d = \frac{1}{2}P_{d+1} + \frac{1}{2}P_{d-1} \). It follows from the above that the expectation \( E_d \) satisfies \( E_d = \frac{1}{2}(E_{d+1} + 1) + \frac{1}{2}(E_{d-1} + 1) = \frac{1}{2}(E_{d+1} + E_{d-1}) + 1 \). Solving the recursion one gets \( E_d = d(N-d) \), which is useless in our case. But note that even though \( E_1 = N-1 \), with probability \( \frac{1}{2} \), the gambler is ruined in just 1 step. This indicates lack of concentration around the expectation. Indeed, the distribution \( P_d \) is heavy-tailed which can be exploited to bound the hitting time.

We now calculate the probability that the gambler is ruined in \( D \) steps precisely. Let \( P_d \) denote the law of a random walk starting in \( d \geq 0 \), let \( \{Y_i\}_{i=0}^\infty \) be the i.i.d. steps of the random walk, let \( S_D = d + Y_1 + Y_2 + \ldots + Y_D \)
Lemma 11. For the Gamblers Ruin problem \( \mathcal{P}_d(T_0 = D) = \frac{d}{D} \left( \frac{D}{D-d} \right) \frac{1}{2^2} \).

Proof. We first calculate \( \mathcal{P}_d(S_D = 0) \). In order for a random walk to be at position 0 starting at \( +d \), there must be \( r = (D - d)/2 \) indices \( i_1, i_2, ..., i_r \) such that \( Y_{i_1} = Y_{i_2} = ... = Y_{i_r} = +1 \). Rest of the \( \frac{D-d}{2} + d = r + d \) steps must be \(-1\). Hence \( \mathcal{P}_d(S_D = 0) = \left( \frac{D}{D-d} \right) \frac{1}{2^2} \), and the lemma follows from the following hitting time theorem.

Theorem (Hitting Time Theorem [32]). For a random walk starting in \( D \geq 1 \) with i.i.d. steps \( \{Y_i\}_{0}^{\infty} \) satisfying that \( Y_i \geq -1 \) almost surely, the distribution of \( T_0 \) under \( \mathcal{P}_d \) is given by

\[
\mathcal{P}_d(T_0 = D) = \frac{d}{D} \mathcal{P}_d(S_D = 0) .
\]

We now calculate the probability that a gambler starting with \( \$d \) hits 0 within \( cd \) steps. Our goal will be to minimize \( c \) as much as possible, yet achieving a significant probability of hitting 0.

Lemma 12. In Gamblers Ruin, the gambler starting with \( \$d \) hits 0 within \( 2d^2 \) steps with probability at least 0.194.

Proof. From Lemma (11) \( \mathcal{P}_d(T_0 = cd) = \frac{d}{cd} \left( \frac{cd}{d-cd} \right) \frac{1}{2^2} \). We now employ the following inequality to bound \( \left( \frac{cd}{d-cd} \right) \frac{1}{2^2} \).

 Lemma (Lemma 7, Ch. 10 [24]). (An estimate for a binomial coefficient.) Suppose \( \lambda m \) is an integer where \( 0 < \lambda < 1 \). Then

\[
\frac{1}{\sqrt{8m\lambda(1-\lambda)}} 2^{mH_2(\lambda)} \leq \left( \frac{m}{\lambda m} \right) \leq \frac{1}{\sqrt{2\pi m\lambda(1-\lambda)}} 2^{mH_2(\lambda)}
\]

where \( H_2 \) is the binary entropy function.

We have \( \lambda = \frac{1}{2} (1 - \frac{1}{c}) \) and

\[
\left( \frac{cd}{d-cd} \right) \geq \frac{2^{cdH_2(\frac{1}{2}(1-\frac{1}{c}))}}{\sqrt{2cd(1-\frac{1}{c}) (1+\frac{1}{c})}} = \frac{2^{cdH_2(\frac{1}{2})(1-\frac{1}{c})}}{\sqrt{2cd(1-\frac{1}{c})}} .
\]

Therefore, \( \mathcal{P}_d(T_0 = cd) = \frac{1}{c} \left( \frac{cd}{d-cd} \right) \frac{1}{2^2} \geq \frac{1}{c} \frac{2^{cdH_2(\frac{1}{2})(1-\frac{1}{c})}}{\sqrt{2cd(1-\frac{1}{c})}} . \) We now use the Taylor series expansion for \( H(x) \) around \( \frac{1}{2} \), \( 1 - H(\frac{1}{2} - x) = \frac{2}{\ln 2}(x^2 + O(x^4)) \). Hence,

\[
\mathcal{P}_d(T_0 = cd) \geq \frac{1}{c} \frac{1}{\sqrt{2cd(1-\frac{1}{c})}} 2^{-\frac{1}{\ln 2}cd^2} = \frac{1}{c} \frac{1}{\sqrt{2cd(1-\frac{1}{c})}} 2^{-\frac{1}{\ln 2}cd^2} > \frac{e^{-d}}{c} = \frac{1}{c \sqrt{2cd(e^d)}} ,
\]

Now set \( c = \alpha d, \alpha > 0 \) to get \( \mathcal{P}_d(T_0 = \alpha d^2) \geq \frac{1}{\alpha d^2 \sqrt{2ae^d}} = \frac{A(\alpha)}{d^2} \). where \( A(\alpha) = \frac{1}{\alpha \sqrt{2ae^d}} \). Now \( A(\alpha) \) is a decreasing function of \( \alpha \geq \frac{1}{3} \) (derivative of \( \ln A(\alpha) \) is negative for \( \alpha \geq \frac{1}{3} \)). Therefore, we have,

\[
\mathcal{P}_d(d^2 \leq T_0 \leq 2d^2) \geq d^2 \frac{A(2)}{d^2} = A(2) = 0.194 .
\]
Corollary 13. In Gambler’s Ruin, the gambler starting with $Sd$ hits 0 within $\frac{1}{2} d^2$ steps for any constant $\epsilon > 0$ with probability at least $\sqrt{\epsilon \log d} / d^{\epsilon/2}$.

Proof. Let $\epsilon' = 2\epsilon$. Set $c = \frac{1}{2} \epsilon \log d / d^2$ in the above proof, that is $\alpha = \frac{1}{2} \epsilon \log d$ to get $P_d(T_0 = \frac{1}{2} d^2) \geq \frac{(\epsilon' \log d)^{3/2}}{d^2 \sqrt{8 \epsilon' \log d}}$. Considering $A(\alpha)$ is an increasing function when $\alpha < \frac{1}{3}$, we get

$$P_d(\frac{1}{2} d^2 \leq T_0 \leq \frac{2}{\epsilon' \log d} d^2) \geq \sqrt{\frac{\epsilon' \log d}{2} d^2} \frac{1}{d^{\epsilon/2}}.$$ 

Now putting $\epsilon = \frac{\epsilon'}{2}$, we get the result. \qed

Theorem 14. Random-deletion obtains a 2$d$-approximation for edit distance with deletions only from strings to DYCK$(s)$ for any $s \geq 2$ in linear time with constant probability.

Proof. The theorem follows from the mapping that the edit distance computed by Random-deletion is at most the number of steps taken by gambler’s ruin to hit the origin starting from $Sd$ and then applying Lemma[12] \qed

Theorem (1). Random-deletion obtains a 4$d$-approximation for edit distance computations (substitution, insertion, deletion) from strings to DYCK$(s)$ for any $s \geq 2$ in linear time with constant probability.

Proof. Follows from the previous theorem, Lemma[5] and Lemma[6] \qed

3 Analysis of the Refined Algorithm

We revisit the description of the refined algorithm. Given a string $\sigma$, we first remove any prefix of close parentheses and any suffix of open parentheses to start with. Since any optimal algorithm will also remove them, this does not affect the edit distance. We also remove any well-formed substrings since that does not affect the edit distance as well (Lemma[4]). Now one can write $\sigma = Y_1 X_1 Y_2 X_2 \ldots Y_z X_z$ where each $Y_i$, $i = 1, 2, \ldots, z$ consists of only open parentheses and each $X_i$, $i = 1, 2, \ldots, z$ consists of only close parentheses. We call each $Y_i X_i$ a block. After well-formed substrings removal, each block requires at least one edit. Hence, we have $z \leq d$ where $d$ is the optimal edit distance of string $\sigma$.

We can write $\sigma$ based on the processing of the optimal algorithm as follows

$$\sigma = Z_{1,z} Z_{1,z-1} \ldots Z_{1,1} X_1 Z_{2,z} Z_{2,z-1} \ldots Z_{2,3} Z_{2,2} X_2 \ldots Z_{z-1,z} Z_{z-1,z-1} X_{z-1} Z_{z,z} X_z.$$

Here the optimal algorithm matches $X_1$ with $Z_{1,1}$, that is the close parentheses of $X_1$ are only matched with open parentheses in $Z_{1,1}$ and vice-versa. Some parentheses in $X_1$ and $Z_{1,1}$ may need to be deleted for matching $X_1$ with $Z_{1,1}$ using minimum number of edits. Similarly, the optimal algorithm matches $X_2$ with $Z_{2,1} Z_{2,2}$, matches $X_3$ with $Z_{1,3} Z_{2,3} Z_{3,3}$ and so on. Note that it is possible that some of these $Z_{i,j}$, $i = 1, 2, \ldots, z$, $j \geq i$ may be empty.

The algorithm proceeds as follows. It continues Random-deletion process as before, but now it keeps track of the substring with which each $X_a$, $a = 1, 2, \ldots, z$ is matched (possibly through multiple deletions) during this random deletion process. While processing $X_1$, the random deletion process is restarted $3 \log_3 n$ times, $b = \frac{1}{(1 - 0.194)} = 1.24$ and at each time the algorithm keeps a count on how many deletions are necessary to complete processing of $X_1$. It then selects the particular iteration in which the number of deletions is minimum. We let $Z_{1,min}$ to denote the substring to which $X_1$ is matched in that iteration. The algorithm then continues the random deletion process. It next stops when processing on $X_2$ finishes. Again,
the portion of random deletion process between completion of processing $X_1$ and completion of processing $X_2$ is repeated $3 \log_2 n$ times and the iteration that results in minimum number of deletions is picked. We define $Z_{a,\text{min}}$ accordingly. The algorithm keeps proceeding in a similar manner until the string is exhausted. In the process, $Z_{a,\text{min}}$ is matched with $X_a$ for $a = 1, 2, \ldots, z$. But, instead of using the edits that the random deletion process makes to match $Z_{a,\text{min}}$ to $X_a$, our algorithm invokes the best string edit distance algorithm $\text{StrEdit}(Z_{a,\text{min}}, X_a)$ which converts $Z_{a,\text{min}}$ to $R_a$ and $X_a$ to $T_a$ such that $R_aT_a$ is well-formed. Clearly, at the end we have a well-formed string. The pseudocode of the refined algorithm is given in the appendix (Algorithm 4).

3.1 Analysis

We first analyze its running time.

**Lemma 15.** The expected running time of Algorithm 4 is $O(n \log n + \alpha(n))$ where $\alpha(n)$ is the running time of $\text{STREdit}$ to approximate string edit distance of input string of length $n$ within factor $\beta(n)$.

**Proof.** First $\text{STREdit}(Z_{a,\text{min}}, X_a)$, $a = 1, 2, \ldots, z$ is invoked on disjoint subset of substrings of $\sigma$. Let us denote the length of these substrings by $n_1, n_2, \ldots, n_z$. Since the running time $\alpha(n)$ is convex, the total time required to run $\text{STREdit}(Z_{a,\text{min}}, X_a)$, $a = 1, 2, \ldots, z$ is

$$\alpha(n_1) + \alpha(n_2) + \ldots + \alpha(n_z) \leq \alpha(n_1 + n_2 + \ldots + n_z) = \alpha(n).$$

We now calculate the total running time of Algorithm 4 without considering the running time for $\text{STREdit}$. While processing $X_a$, in each of $3 \log_2 n$ rounds, the running time is bounded by number of comparisons that our algorithm makes with symbols in $X_a$. Each comparison might result in matching of a symbol in $X_a$—in that case it adds one to the running time, deletion of the symbol in $X_a$, again it adds one to the running time, and deletion of open parenthesis while comparing with a symbol in $X_a$—this might require multiple comparisons with the same symbol of $X_a$. If there are $\eta$ such comparisons with some symbol $x \in X_a$, then there are $\eta - 1$ consecutive comparisons with $x$, where random-deletion chooses to delete the open parenthesis. On the $\eta$th comparison, $x$ is either matched or deleted. Now the probability that random-deletion deletes $(\eta - 1)$ open parenthesis while comparing with $x$ is $\frac{1}{2^{\eta-1}}$. Therefore, the expected number of comparisons involving each symbol $x \in X_a$ before it gets deleted or matched is $\sum_{i=1}^{\eta} \frac{1}{2^i} \leq 2$. Hence the expected number of total comparisons in each iteration involving $X_a$ is at most $3|X_a|$. Therefore, the total expected number of comparison over all the iterations and $a = 1, 2, \ldots, z$ is at most $\sum_z a|X_a| \log_2 n$. Of course, if the running time becomes more than say 2 times the expected value, we can restart the entire process. By Markov inequality on expectation 2 rounds is sufficient to ensure that the algorithm will make at most $\sum_z 18|X_a| \log_2 n$ comparisons in at least one round. Hence the lemma follows. □

We now proceed to analyze the approximation factor. Let the optimal edit distance to convert $Z_aX_a$ into well-formed be $d_a$ for $a = 1, 2, \ldots, z$ where $Z_a = Z_{1,a}Z_{2,a} \ldots Z_{a,a}$.

While computing the set $Z_{a,\text{min}}$, it is possible that our algorithm inserts symbols outside of $Z_a$ to it or leaves out some symbols of $Z_a$. In the former case, among the extra symbols that are added, if the optimal algorithm deletes some of these symbols as part of some other $Z_{a'}$, $a' \neq a$, then these deletions are “harmless”. If we only include these extra symbols to $Z_{a,\text{min}}$, then we can as well pretend that those symbols are included in $Z_a$ too. The edit distance of the remaining substrings are not affected by this modification. Therefore, for analysis purpose, both for this algorithm and for the main algorithm in the next section, we always assume w.l.o.g that the optimal algorithm does not delete any of the extra symbols that are added.

**Lemma 16.** The number of deletions made by random deletion process to finish processing $X_1, X_2, \ldots, X_l$, for $l = 1, 2, \ldots, z$, that is to match $Z_{a,\text{min}}, X_a$, $a \leq l$, is at most $2(\sum_{a=1}^l d_a)^2$ with probability at least $(1 - \frac{1}{n^2})^l$. 

13
Proof. Consider \( l = 1 \), that is only \( X_1 \). The number of deletions made by random deletion process to finish processing \( X_1 \) is at most the hitting time of an one dimensional random walk starting from position \( d_1 \). This follows from Section 2.1 and noting that any deletion outside of \( Z \) is a wrong deletion. From Lemma 12 the hitting time of a random walk starting from \( d \) is at most \( 2d_1^2 \) with probability at least 0.194. Let \( b = \frac{1}{(1-0.194)} = 1.24 \). Since, we repeat the process \( 3 \log_b n \) times, the probability that the minimum hitting time among these \( 3 \log_b n \) iterations is more than \( 2d_1^2 \) is at most \((1 - 0.194)^{3 \log_b n} = \frac{1}{n^3} \). Therefore, the number of deletions made by random deletion process to finish processing \( X_1 \) is at most \( 2d_1^2 \) with probability \((1 - \frac{1}{n^3})\).

Now consider \( l = 2 \), the number of deletions made by random deletion process to finish processing \( X_1, X_2 \) is at most the hitting time of an one dimensional random walk starting from position \( d_1 + d_2 \). Start the random walk from \((d_1 + d_2)\) and first follow the steps as suggested by \( Z_{1,min} \) to hit \( d_2 \) in at most \( 2d_2^2 \) steps. Now, since we repeat the random deletion process from the time of completing processing of \( X_1 \) to completing processing of \( X_2 \), then by similar argument as in \( l = 1 \), the minimum hitting time starting from \( d_2 \) is at most \( 2d_2^2 \) with probability \((1 - \frac{1}{n^3})\). Hence, the minimum hitting time starting from \( d_1 + d_2 \) is at most \( 2d_1^2 + 2d_2^2 \leq 2(d_1 + d_2)^2 \) with probability \((1 - \frac{1}{n^3})^2\).

Proceeding in a similar manner for \( l = 3, \ldots, z \), we get the lemma. \( \square \)

Let us denote by \( C_l \) and \( W_l \) the number of correct and wrong moves taken by the random deletion process when processing of \( X_1, X_2, \ldots, X_l \) finishes. Since at each deletion, correct move has been taken with probability at least \( \frac{1}{2} \) then by standard Chernoff bound followed by union bound we have the following lemma.

**Lemma 17.** When the processing of \( X_1, X_2, \ldots, X_l \) finishes \( W_l - C_l \leq (2 \sum_{a=1}^l d_a) \sqrt{2 \log d} \) with probability at least \((1 - \frac{1}{n} - \frac{1}{4})\).

**Proof.** Probability that the number of deletions made by random deletion process is at most \( 2(\sum_{a=1}^l d_a)^2 \) is \( \geq (1 - \frac{1}{n^3})^l \). Let us denote the number of these deletions by \( D_l \), for \( l = 1, 2, \ldots, z \). Now by Azuma’s inequality

\[
\Pr \left[ W_l - C_l > (2 \sum_{a=1}^l d_a) \sqrt{2 \log d} \mid D_l \leq 2d_1^2 \right] \leq \exp \left( \frac{8(\sum_{a=1}^l d_a)^2 \log d}{4(\sum_{a=1}^l d_a)^2} \right) = \frac{1}{d^2}.
\]

Hence

\[
\Pr \left[ W_l - C_l > (2 \sum_{a=1}^l d_a) \sqrt{2 \log d} \right] \leq 1 - \left( 1 - \frac{1}{n^3} \right)^l + \left( 1 - \frac{1}{n^3} \right)^l \frac{1}{d^2} \leq \frac{l}{n^3} + \frac{1}{d^2}.
\]

Hence

\[
\Pr \left[ \exists l \in [1, z] \text{s.t.} W_l - C_l > (2 \sum_{a=1}^l d_a) \sqrt{2 \log d} \right] \leq \frac{z}{n^3} + \frac{z}{d^2} \leq \frac{1}{n} + \frac{1}{d}. \quad \square
\]

Now we define \( A_{OPT} \) and \( A_l \) in a similar manner as in the previous section. We only consider the iterations that correspond to computing \( Z_{a, min} \), \( a = 1, 2, \ldots, z \) to define the final random deletion process.

**Definition 7.** \( A_l \) is defined as all the indices of the symbols that are matched or deleted by Random-deletion process up to and including time when processing of \( X_l \) finishes.
Definition 8. For every time \( l \in [1, z] \),
\[
A_l^{OPT} = \{ i \mid i \in A_l \text{ or } i \text{ is matched by the optimal algorithm with some symbol with index in } A_l \}.
\]

We have the following corollary

Corollary 18. For all \( l \in [1, z] \), \(|A_l^{OPT} \setminus A_l| \leq \sum_{a=1}^{l} d_a + (2 \sum_{a=1}^{l} d_a) \sqrt{2 \log d} \) with probability at least \((1 - \frac{1}{n} - \frac{1}{d})\).

Proof. Proof follows from Lemma 8 and Lemma 17.

Lemma 19. For all \( a \in [1, z] \), \( \text{StrEdit}(Z_{a, \min}, X_a) \leq d_a + |A_{a-1}^{OPT} \setminus A_{a-1}| + |A_a^{OPT} \setminus A_a| \).

Proof. Let \( D(X_a) \) denote the symbols from \( X_a \) for which the matching open parentheses have already been deleted before processing on \( X_a \) started. Let \( D'(X_a) \) denote the symbols from \( X_a \) for which the matching open parentheses are not included in \( Z_{a, \min} \). Let \( E(Z_{a, \min}) \) denote open parentheses in \( Z_{a, \min} \) such that their matching close parentheses are in \( X'_a \), \( a' < a \), that is they are already deleted. Let \( E'(Z_{a, \min}) \) denote open parentheses in \( Z_{a, \min} \) such that their matching close parentheses are in \( X'_a \), \( a' > a \), that is they are extra symbols from higher blocks.

\[
\text{StrEdit}(Z_{a, \min}, X_a) = \text{StrEdit}(Z_a, X_a) + |D(X_a)| + |D'(X_a)| + |E(Z_{a, \min})| + |E'(Z_{a, \min})|.
\]

Now all the indices of \( D(X_a) \cup E(Z_{a, \min}) \) are in \( A_{a-1}^{OPT} \), but none of them are in \( A_{a-1} \). Hence

\[
|D(X_a)| + |E(Z_{a, \min})| \leq |A_{a-1}^{OPT} \setminus A_{a-1}|.
\]

Also, the indices corresponding to matching close parenthesis of \( E'(Z_{a, \min}) \) and \( D'(X_a) \) are in \( A_a^{OPT} \) but not in \( A_a \). Hence

\[
|D'(X_a)| + |E'(Z_{a, \min})| \leq |A_a^{OPT} \setminus A_a|.
\]

Therefore, the lemma follows.

In fact, we can have a stronger version of the above lemma, though it does not help in obtaining a better bound for Theorem 2.

Lemma 20. For all \( a \in [1, z] \), \( \text{StrEdit}(Z_{a, \min}, X_a) \leq d_a + |A_{a-1}^{OPT} \setminus A_{a-1}| + |\{A_a^{OPT} \setminus A_a\} \cup \{A_{a-1}^{OPT} \setminus A_{a-1}\}| \).

Proof. Follows from Lemma 19 and noting that

\[
|D'(X_a)| + |E'(Z_{a, \min})| \leq |\{A_a^{OPT} \setminus A_a\} \cup \{A_{a-1}^{OPT} \setminus A_{a-1}\}|.
\]

\[\square\]

Theorem 21. Algorithm 2 obtains an \( O(z\beta(n) \sqrt{\log d}) \) approximation factor for edit distance computation from strings to \( D\text{YCK}(s) \) for any \( s \geq 2 \) in \( O(n \log n + o(n)) \) time with probability at least \((1 - \frac{1}{n} - \frac{1}{d})\), where there exists an algorithm for \( \text{STRE} \text{D} \text{I} \text{T} \) running in \( \alpha(n) \) time achieves an approximation factor of \( \beta(n) \).

Proof. The edit distance computed by the refined algorithm is at most \( \sum_{a=1}^{z} \text{StrEdit}(Z_{a, \min}, X_a) \). Hence by Lemma 19, the computed edit distance (assuming we use optimal algorithm for \( \text{STRE} \text{D} \text{I} \text{T} \)) is at most

\[
\sum_{a=1}^{z} d_a + |A_{a-1}^{OPT} \setminus A_{a-1}| + |A_a^{OPT} \setminus A_a| = d + 2 \sum_{a=1}^{z} |A_a^{OPT} \setminus A_a|.
\]

15
Since, we use a $\beta(n)$-approximate algorithm for $\text{STREDIT}$ and that runs in $\alpha(n)$ time, we get an $O(\beta(n)z\sqrt{\log d})$-approximation with running time $O(n \log n + \alpha(n))$ (Lemma 15). Hence the theorem follows.

Note. Instead of repeating different portions of random deletion process and then stitching the random deletions corresponding to $Z_{a,\min}, a = 1, 2, \ldots, z$, we can simply repeat the entire Random-deletion $\Theta(\log n)$ time. For each repetition, run the entire algorithm and finally return the edit distance corresponding to the iteration that returns the minimum value. We get the same approximation factor and asymptotic running time by doing this. However, we need to calculate $\text{STREDIT}$ in each iterations, which is not the case in the described algorithm. Therefore, in practice, we save some running time.

4 Further Refinement: Main Algorithm & Analysis

We again view our input $\sigma$ as $Y_1X_1Y_2X_2\ldots Y_zX_z$, where each $Y_a$ is a sequence of open parentheses and each $X_a$ is a sequence of close parentheses. Each $Y_a, X_a, a = 1, 2, \ldots, z$, is a block. We know by preprocessing, $z \leq d$, where $d$ is the optimal edit distance to $\text{Dyck}(s)$.

As before, we first run the process of Random-deletion. For each run of Random-deletion, the algorithm proceeds in phases with at most $\lceil \log_2 z \rceil + 1$ phases. We repeat this entire procedure $3 \log_b n$ times, $b = 1.24$ (as before) and return the minimum edit distance computed over these runs and the corresponding well-formed string. We now describe the algorithm corresponding to a single run of random-deletion (also shown pictorially in Figure 1).

Let us use $X_1^a = X_a, Y_1^a = Y_a$ to denote the blocks in the first phase. Consider the part of Random-deletion from the start of processing $X_1^a$ to finish either $X_1^a$ or $Y_1^a$ whichever happens first. Since this part of the random deletion (from the start of $X_1^a$ to the completion of either $X_1^a$ or $Y_1^a$) remains confined within block $Y_1^a X_1^a$, we call this part local$^1$ to block $a$. Let $A_{a, \text{local}}$ denote the indices of all the symbols that are matched or deleted during the local$^1$ steps in block $a$. Let $A_{a, \text{OPT,local}}$ be the union of $A_{a, \text{local}}$ and the indices of symbols that are matched with some symbol with indices in $A_{a, \text{local}}$ in the optimal solution. We call $A_{a, \text{OPT,local}} \setminus A_{a, \text{local}}$ the local$^1$ error, denoted $\text{local-error}^1(Y_1^a, X_1^a)$.

Create substrings $L_2^a$ corresponding to local$^1$ moves in block $a, a = 1, \ldots, z$. Compute $\text{STREDIT}$ between $L_2^a \cap Y_2^a$ to $L_2^a \cap X_2^a$. Remove all these substrings from further consideration. The phase 1 ends here.

We can now view the remaining string as $Y_1^2 X_1^2 Y_2^2 X_2^2 \ldots Y_{z^2}^2 X_{z^2}^2$, after deleting any prefix of open parentheses and any suffix of close parentheses. Consider any $Y_2^a, X_2^a$. Let they span the original blocks $Y_1^a, X_1^a, Y_{a+1}^a X_{a+1}^a \ldots Y_2 X_2$. Consider the part of Random-deletion from the start of processing $X_1^a$ to the completion of either $Y_1^a$ or $X_2$ whichever happens first. Since this part of the random deletion remains confined within block $Y_2 X_2^a$, we call this part local$^2$ to block $a$. Let $A_{a, \text{local}}$ denote the indices of all the symbols that are matched or deleted during the local$^2$ steps in block $a$. Let $A_{a, \text{OPT,local}}$ be the union of $A_{a, \text{local}}$ and the indices of symbols that are matched with some symbol with indices in $A_{a, \text{local}}$ in the optimal solution. We call $A_{a, \text{OPT,local}} \setminus A_{a, \text{local}}$ the local$^2$ error, denoted $\text{local-error}^2(Y_2^a, X_2^a)$.

Create substrings $L_3^a$ corresponding to local$^2$ moves in block $a, a = 1, \ldots, z^2$. Compute $\text{STREDIT}$ between $L_3^a \cap Y_3^a$ to $L_3^a \cap X_3^a$. Remove all these substrings from further consideration.

We continue in this fashion until the remaining string becomes empty. We can define local$^i$ moves, $A_{a, \text{local}}^i, A_{a, \text{OPT,local}}^i$ and $\text{local-error}^i(Y_i^a, X_i^a)$ accordingly.

**Definition 9.** For $i$th phase blocks $Y_i^a, X_i^a$, if they span original blocks $Y_{a_1}^1 X_{a_1}^1 Y_{a_1+1}^1 X_{a_1+1}^1 \ldots Y_{a_2}^1 X_{a_2}^1$, then part of random deletion from the start of processing $X_{a_1}$ to finish either $Y_{a_1}$ or $X_{a_2}$ whichever happens first, remains confined in block $Y_i^a X_i^a$ and is defined as local$^i$ move.
**Definition 10.** For any \( i \in \mathbb{N} \), \( A_{a}^{\text{local}^{i}} \) denote the indices of all the symbols that are matched or deleted during the local\(^{i} \) steps in block \( a \).

**Definition 11.** For any \( i \in \mathbb{N} \), \( A_{a}^{\text{OPT, local}^{i}} \) denote the union of \( A_{a}^{\text{local}^{i}} \) and the indices of symbols matched with some symbol in \( A_{a}^{\text{local}^{i}} \).

**Definition 12.** For any \( i \in \mathbb{N} \), \( A_{a}^{\text{OPT, local}^{i}} \setminus A_{a}^{\text{local}^{i}} \) is defined as the local\(^{i}\) error, \( \text{local-error}^{i} \).

We now summarize the algorithm below.

**Algorithm:**

Given the input \( \sigma = Y_{1}X_{1}Y_{2}X_{2}...Y_{z}X_{z} \), the algorithm is as follows

- \( \text{MinEdit} = \infty \),
- For iteration = 1, iteration \( \leq 3 \log_{b} n \), iteration ++
  - Run Random-deletion process.
  - Set \( i = 1, z^{1} = z \), edit = 0, and for \( a = 1, 2, ..., z^{1} \), \( X_{a}^{1} = X_{a}, Y_{a}^{1} = Y_{a} \).
  - While \( \sigma \) is not empty
    * Consider the part of random-deletion from the start of processing \( X_{a}^{i} \) to finish either \( X_{a}^{i} \) or \( Y_{a}^{i} \) whichever happens first.
    * Create substrings \( L_{a}^{i}, a = 1, 2, ..., z^{i} \) which correspond to local\(^{i} \) moves. Compute \( \text{StrEdit}(L_{a}^{i} \cap Y_{a}^{i}, L_{a}^{i} \cap X_{a}^{i}) \) to match \( L_{a}^{i} \cap Y_{a}^{i} \) to \( L_{a}^{i} \cap X_{a}^{i} \) and add the required number of edits to edit.
    * Remove \( L_{a}^{i}, a = 1, 2, ..., z^{i} \) from \( \sigma \), write the remaining string as \( Y_{i+1}^{i+1}X_{i+1}^{i+1}Y_{i+1}^{i+1}X_{i+1}^{i+1}...Y_{z^{i+1}}^{z^{i+1}}X_{z^{i+1}}^{z^{i+1}} \), possibly by deleting any prefix of close parentheses and any suffix of open parentheses. The number of such deletions is also added to edit. Set \( i = i + 1 \)
  - End While
  - If (edit < MinEdit) set MinEdit = edit
  - End For
- Return MinEdit as the computed edit distance.

Of course, the algorithm can compute the well-formed string by editing the parentheses that have been modified in the process through \( \text{STREcD} \) operations.

**Lemma 22.** There exists at least one iteration among \( 3 \log_{b} n \) such that for all \( a' \leq b' \), \( (P1) \) the number of deletions made by random deletion process between the start of processing \( X_{a'} \) and finishing either \( X_{b'} \) or \( Y_{a'} \) whichever happens first is at most \( 2d(a', b')^{2} \), where \( d(a', b') \) is the number of deletions the optimal algorithm does starting from the beginning of \( X_{a'} \) to complete either \( X_{b'} \) or \( Y_{a'} \) whichever happens first with probability at least \( 1 - \frac{1}{n} \).

**Proof.** Consider the random source \( S \) that supplies the random coins for deciding which directional deletions to execute, and consider the outcomes of the random source for each of the \( 3 \log_{b} n \) iterations of Random-deletion.

Now consider any \( a', b', a \leq b' \). Suppose that the optimal algorithm finishes \( Y_{a'} \) first (the argument when the optimal algorithm finishes \( X_{b'} \) first is identical), and let the processing on \( Y_{a'} \) completes while comparing with \( X_{b''}, a' \leq b'' \leq b' \). Consider this portion of the substring, and let the number of deletions
performed by the optimal algorithm in this substring be $\gamma$. Then the number of deletions made by the random deletion process to finish processing $Y_a'$ is at most the hitting time of an one dimensional random walk starting from position $\gamma$. From Lemma 12, the hitting time of a random walk starting from $\gamma$ is at most $2\gamma^2$ with probability at least 0.194. Let $b = \frac{1}{(1 - 0.194)^n} = 1.24$. If, we repeat the process $3 \log_b n$ times, then the probability that there exists at least one iteration with hitting time not more than $2\gamma^2$ is at least $1 - (1 - 0.194)^{3 \log_b n} = 1 - \frac{1}{n^3}$. Now use the outcomes of the random source that have been applied for repeating the entire random walk corresponding to the portion of the random walk starting from $X_{a'}$ and finishing either $X_{b'}$ or $Y_{a'}$ whichever happens first. This has the same effect as repeating the process only for the portion of the random walk.

There are at most $z + (z - 1) + (z - 2) + \ldots + 1 < z^2$ possible values of $a', b'$. Hence the probability that there exists at least one iteration in which (P1) holds for all $a', b'$ is by union bound at least $1 - \frac{z^2}{n^3} = \left(1 - \frac{1}{n}ight)^3$.

\[\square\]

**4.1 Analysis of Approximation Factor**

**Lemma 23.** Considering phase $l$ which has $z^l$ blocks, the total edit cost paid in phase $l$ of the returned solution is $\sum_{a=1}^{z^l} StrEdit(L^l_a \cap Y^l_a, L^l_a \cap X^l_a) \leq \beta(n)(d+l+d\sqrt{20 \log d})$ with probability at least $1 - \frac{1}{n} - \frac{1}{d}$. 

18
Proof. Consider the iteration in which Lemma 22 holds, that is we have property (P1). We again fix an optimal stack based algorithm and refer to it as the optimal algorithm.

**Phase 1.**
Consider \( Y^1_a, X^1_a \). We know \( Y^1_a = Y_a \) and \( X^1_a = X_a \).

- If no symbols of either of \( Y_a \) or \( X_a \) is matched by the optimal algorithm outside of block \( a \) (that is they are matched to each other), then let \( d^1_a \) denote the optimal edit distance to match \( Y_a \) with \( X_a \).

By Lemma 22 the random deletion process takes at most \( 2(d^1_a)^2 \) steps within local \( a \) moves. Now from Lemma 8 local error, \( A_a^{OPT,local} \backslash A_a^{local} \leq d^1_a + W_{a^{local}} - C_{a^{local}} \), where \( W_{a^{local}} \) is the number of wrong moves taken during local steps in block \( a \) and similarly \( C_{a^{local}} \) is the number of correct steps taken during the local steps in block \( a \). Since the total number of local steps is at most \( 2(d^1_a)^2 \) and wrong steps are taken with probability at most \( \frac{1}{d^3} \), hence by standard application of Chernoff bound or by Azuma’s inequality as in Lemma 17 local error, \( local-error^1(Y^1_a, X^1_a) \leq d^1_a + d^1_a \sqrt{12 \log d^1_a} \leq d^1_a + d^1_a \sqrt{20 \log d^1_a} \) with probability at least \( 1 - \frac{1}{d^3} \).

Hence \( StrEdit(L^1_a \cap Y^1_a, L^1_a \cap X^1_a) \leq d^1_a + local-error^1(Y^1_a, X^1_a) \leq d^1_a + d^1_a \sqrt{20 \log d^1_a} \).

- If some suffix of \( X^1_a \) is matched outside of block \( a \), then let \( X^1_a \) be the prefix of \( X^1_a \) which is matched inside. Consider \( Y^1_a \) \( X^1_a \). Let \( d^1_a \) denote the optimal edit distance to match \( Y_a \) with \( X_a^* \). Now again, the total number of local steps is at most \( 2(d^1_a)^2 \) and wrong steps are taken with probability at most \( \frac{1}{d^3} \), hence by standard application of Chernoff bound or by Azuma’s inequality as in Lemma 17 local error, \( local-error^1(Y^1_a, X^1_a) \leq d^1_a + d^1_a \sqrt{12 \log d^1_a} \leq d^1_a + d^1_a \sqrt{20 \log d^1_a} \) with probability at least \( 1 - \frac{1}{d^3} \).

Hence again \( StrEdit(L^1_a \cap Y^1_a, L^1_a \cap X^1_a) \leq d^1_a + local-error^1(Y^1_a, X^1_a) \leq d^1_a + d^1_a \sqrt{20 \log d^1_a} \).

- If some prefix of \( Y^1_a \) is matched outside of block \( a \), then let \( Y^1_a \) be the suffix of \( Y^1_a \) which is matched inside. Consider \( Y^1_a \) \( Y^1_a \) and let \( d^1_a \) denote the optimal edit distance to match \( Y_a \) with \( X_a^* \). Again similar arguments lead to \( StrEdit(L^1_a \cap Y^1_a, L^1_a \cap X^1_a) \leq d^1_a + local-error^1(Y^1_a, X^1_a) \leq d^1_a + d^1_a \sqrt{20 \log d^1_a} \).

Hence due to phase 1, the total edit cost paid is at most \( \sum_{a=1}^s StrEdit(L^1_a \cap Y^1_a, L^1_a \cap X^1_a) \leq \sum_{a=1}^s d^1_a + d^1_a \sqrt{20 \log d^1_a} \leq d + d \sqrt{20 \log d} \).

**Phase 2.**
Consider \( Y^2_a, X^2_a \). Let \( Y^2_a, X^2_a \) spans original blocks \( Y_gX_gY_{g+1}X_{g+1}..., Y_hX_h \) (we drop the superscript 1 for the original blocks).

- If both \( Y^2_a \) and \( X^2_a \) are matched by the optimal algorithm inside \( g \) to \( h \) blocks, then let \( d^h_g \) denote the optimal edit distance to match \( Y_gX_gY_{g+1}X_{g+1}..., Y_hX_h \). By Lemma 22 the random deletion process takes at most \( 2(d^h_g)^2 \) steps within blocks \( g \) to \( h \). Hence \( local-error^2(Y^2_a, X^2_a) = A_a^{OPT,local} \backslash A_a^{local} \leq d^h_g + d^h_g \sqrt{12 \log d^h_g} \leq d^h_g \sqrt{20 \log d^h_g} \). Suppose, Random-deletion selects \( R \subset Y^2_a \) and \( T \subset X^2_a \) to match. Note that either \( R = Y^2_a \) or \( T = X^2_a \). Let \( D(R, T) \) denote all the symbols in \( R, T \) such that their matching parentheses belong to blocks either outside of index \( [g, h] \) or they exist at phase 2 but are not included. Let \( E(R, T) \) denote all the symbols in \( R, T \) such that their matching parentheses belong to blocks \([g, h]\) but have already been deleted in phase 1.

Then
\[
StrEdit(L^2_a \cap Y^2_a, L^2_a \cap Y^2_a) \leq d^h_g + |D(R, T)| + |E(R, T)|
\]
Now,
\[ |D(R, T)| \leq \text{local-error}^2(Y^2_a, X^2_a) = A^{OPT, local^2}_a \setminus A^{local^2}_a \leq d^b_y \sqrt{20 \log d^h} \]
For each \( x \in E(R, T) \) either its matching parentheses \( y \) belongs to the same block in phase 1, say \( a_i \in [g, h] \), or in different blocks, say \( a_i \) and \( a_i' \in [g, h] \). In the first case, \( x \) can be charged to some \( y \) (with which it matches) which contributes 1 to \( \text{local-error}^1(Y^1_{a_i}, X^1_{a_i}) \). In the second case, \( x \) can again be charged to some \( y \) which contributes 1 to \( \text{local-error}^1(Y^1_{a_i'}, X^1_{a_i'}) \). Hence,
\[ |E(R, T)| \leq \sum_{i=g}^{h} \text{local-error}^1(Y^1_i, X^1_i). \]
Thus, we get
\[
\text{StrEdit}(L^2_a \cap Y^2_a, L^2_a \cap Y^2_a) \leq d^h + \text{local-error}^2(Y^2_a, X^2_a) + \sum_{i=g}^{h} \text{local-error}^1(Y^1_i, X^1_i)
\]
\[ \leq d^h + d^h_y \sqrt{20 \log d^h_y} + d^h_y \sqrt{20 \log d^h_y} \n\]
\[ \leq d^h + 2d^h_y \sqrt{20 \log d^h_y} \]
- If some symbol of \( X^2_a \) is matched outside, let us denote the set of those indices by \( \Upsilon \). Consider the subsequence of \( X^2_a \) excluding \( \Upsilon \). Let us denote it by \( X^2_a \setminus \Upsilon \). Consider \( Y^2_a X^2_a \setminus \Upsilon \), and proceed as in the previous case.
- If some symbol of \( Y^2_a \) is matched outside, let us denote the set of those indices by \( \Upsilon \). Consider the subsequence of \( Y^2_a \) excluding \( \Upsilon \). Let us denote it by \( Y^2_a \setminus \Upsilon \). Consider \( Y^2_a \setminus \Upsilon X^2_a \), and proceed as in the previous case.

Hence due to phase 2, the total edit cost paid is at most \( \sum_{a=1}^{z^2} \text{StrEdit}(L^1_a \cap Y^1_a, L^1_a \cap X^1_a) \leq d + 2d \sqrt{20 \log d} \).

**Phase I.**

Proceeding exactly as in Phase 2, let \( Y^l_a \) and \( X^l_a \) contains blocks from index \([g^{l-1}, h^{l-1}]\) of level \( l - 1 \), all of which together contain blocks \([g^{l-2}, h^{l-2}]\) from level \( l - 2 \) and so on, finally \([g^1, h^1]\) = \([g, h]\) of blocks from level 1. Let \( d^h \) denote the optimal edit distance to match \( Y^l_a \) and \( X^l_a \) excluding the symbols that are matched outside of blocks \([g, h]\) by the optimal algorithm.

Suppose, Random-deletion selects \( R \subset Y^l_a \) and \( T \subset X^l_a \) to match. Note that either \( R = Y^l_a \) or \( T = X^l_a \). Let \( D(R, T) \) denote all the symbols in \( R, T \) such that their matching parentheses belong to blocks either outside of index \([g, h]\) or they exist at phase \( l \) but are not included. Let \( E(R, T) \) denote all the symbols in \( R, T \) such that their matching parentheses belong to blocks \([g, h]\) but have already been deleted in phases \( 1, 2, \ldots, l - 1 \).

Then
\[ \text{StrEdit}(L^1_a \cap Y^l_a, L^1_a \cap X^l_a) \leq d^h + |D(R, T)| + |E(R, T)| \]
Now,
\[ |D(R, T)| \leq \text{local-error}^l(Y^l_a, X^l_a) = A^{OPT, local^l}_a \setminus A^{local^l}_a \leq d^h + d^h_y \sqrt{12 \log d^h_y} \leq d^h_y \sqrt{20 \log d^h_y}. \]
For each $x \in E(R, T)$, consider the largest phase $\eta \in [1, 2, ..., l − 1]$ such that its matching parenthesis $y$ existed before start of the $\eta$th phase but does not exist after the end of the $\eta$th phase. It is possible, either $y$ belongs to the same block in phase $\eta$, say $r \in [g^\eta, h^\eta]$, or in different blocks, say $r$ and $s \in [g^\eta, h^\eta]$. In the first case, $x$ can be charged to $y$ which contributes 1 to local-error$^\eta(Y^\eta_r, X^\eta_r)$. In the second case, $x$ can again be charged to $y$ which contributes 1 to local-error$^\eta(Y^\eta_s, X^\eta_s)$.

Hence, 

$$|E(R, T)| \leq \sum_{j=l-1}^{1} \sum_{i=g^j}^{h^j} \text{local-error}^j(Y^j_i, X^j_i).$$

$$\text{StrEdit}(L^l_a \cap Y^l_a, L^l_a \cap Y^l_i) \leq d^h + \text{local-error}^d(Y^l_a, X^l_a) + \sum_{j=l-1}^{1} \sum_{i=g^j}^{h^j} \text{local-error}^j(Y^j_i, X^j_i)$$

$$\leq d^h + d^h \sqrt{20 \log d} + (l - 1) \sum_{i=g^j}^{h^j} \text{local-error}^j(Y^j_i, X^j_i)$$

Hence due to phase $l$, the total edit cost paid is at most 

$$\sum_{a=1}^{l} \text{StrEdit}(L^l_a \cap Y^l_a, L^l_a \cap X^l_a) \leq d + l \log d.$$

Now, since we are using a $\beta(n)$-approximation algorithm for STREDIT, we get the total edit cost paid during phase $l$ is at most $\beta(n)(d + l \sqrt{20 \log d})$.

For the above bound to be correct, all the local-error estimates have to be correct. The number of blocks reduces by $\frac{1}{2}$ from one phase to the next. Hence, the total number of local error estimates is $\Theta(z)$. We have considered the iteration such that property (P1) holds for all sequence of blocks (see Lemma 23). Given (P1) holds, since there are a total of $\Theta(z)$ blocks over all the phases, with probability at least $1 - \frac{\Theta(z)}{d^2} > 1 - \frac{1}{d}$, all the local-error bounds used in the analysis are correct. Since, (P1) holds with probability at least $(1 - \frac{1}{n})$, with probability at least $(1 - \frac{1}{n}) (1 - \frac{1}{d}) > 1 - \frac{1}{n} - \frac{1}{d}$, we get a total edit cost paid during phase $l$ is at most $\beta(n)(d + l \sqrt{20 \log d})$.

**Lemma 24.** The total edit cost paid is at most $O((\log z)^2 \beta(n) \sqrt{\log d})$ with probability at least $1 - \frac{1}{n} - \frac{1}{d}$.

**Proof.** By Lemma 23 summing up to and including phase 1, the total edit cost paid is at most $O(\beta(n)l^2d \sqrt{\log d})$ with probability $1 - \frac{1}{n} - \frac{1}{d}$ when the number of phases is $l$. Now each phase reduces the number of blocks at least by a factor of 2. Hence the total number of phases is $\leq \lceil \log z \rceil + 1$. Therefore, total edit cost paid is at most $O(\beta(n)(\log z)^2d \sqrt{\log d})$.

**Theorem 25.** There exists an algorithm that obtains an $O(\beta(n) \sqrt{\log d}(\log z)^2)$-approximation factor for edit distance computation from strings to DYCK(s) for any $s \geq 2$ in $O(n \log n + \alpha(n))$ time with probability at least $(1 - \frac{1}{n} - \frac{1}{d})$, where there exists an algorithm for STREDIT running in $\alpha(n)$ time that achieves an approximation factor of $\beta(n)$.

**Proof.** For a particular iteration, each STREDIT is run on a disjoint subsequence. Hence, the running time of the algorithm is $O(n \log n + \alpha(n))$. Therefore, from Lemma 24 we get the theorem.

### 4.2 Improving the Bound to $O(\beta(n) \log z \sqrt{\log d})$

The above argument can be easily strengthened to improve the approximation factor to $O(\beta(n) \log z \sqrt{\log d})$. 

21
Lemma 26. The total edit cost paid is at most $O(\beta(n) \log z \sqrt{\log d})$ with probability at least $1 - \frac{1}{n} - \frac{1}{d}$.

Proof. Consider any level $l \geq 1$. Let $Y_{g}^{l}$ and $X_{g}^{l}$ contain blocks from index $[g^{l-1}, h^{l-1}]$ of level $l - 1$, all of which together contain blocks $[g^{l-2}, h^{l-2}]$ from level $l - 2$ and so on, finally $[g^{1}, h^{1}] = [g, h]$ of blocks from level 1. Let $d_{g}^{h}$ denote the optimal edit distance to match $Y_{g}^{l}$ and $X_{g}^{l}$ excluding the symbols that are matched outside of blocks $[g, h]$ by the optimal algorithm.

We want to bound

$$
\sum_{j=l}^{1} \sum_{a=g^{j}}^{h^{j}} \text{StrEdit}(L_{a}^{j} \cap Y_{a}^{j}, L_{a}^{j} \cap X_{a}^{j})
$$

Let $R_{a}^{j} = L_{a}^{j} \cap Y_{a}^{j}$ and $T_{a}^{j} = L_{a}^{j} \cap X_{a}^{j}$. Note that either $R_{a}^{j} = Y_{a}^{j}$ or $T_{a}^{j} = X_{a}^{j}$.

Let $A(Y_{a}^{j})$ indicate the minimum index of original phase-1 block that $Y_{a}^{j}$ contains and $B(X_{a}^{j})$ indicate the maximum index of original phase-1 block that $X_{a}^{j}$ contains. Let $D(R_{a}^{j}, T_{a}^{j})$ denote all the symbols in $R_{a}^{j}, T_{a}^{j}$ such that their matching parentheses belong to blocks either outside of index $[A(Y_{a}^{j}), B(X_{a}^{j})]$ or they exist at phase $j$ but are not included. Let $E(R_{a}^{j}, T_{a}^{j})$ denote all the symbols in $R_{a}^{j}, T_{a}^{j}$ such that their matching parentheses belong to blocks $[A(Y_{a}^{j}), B(X_{a}^{j})]$ but have already been deleted in phases $1, 2, \ldots, j - 1$.

Then

$$
\text{StrEdit}(L_{a}^{j} \cap Y_{a}^{j}, L_{a}^{j} \cap X_{a}^{j}) = \text{StrEdit}(R_{a}^{j}, T_{a}^{j}) \leq d_{A(Y_{a}^{j})}^{B(X_{a}^{j})} | + | E(R_{a}^{j}, T_{a}^{j}) |
$$

where, $d_{A(Y_{a}^{j})}^{B(X_{a}^{j})}$ denotes the optimal edit distance to match $Y_{a}^{j}$ and $X_{a}^{j}$ excluding the symbols that are matched outside of blocks $[A(Y_{a}^{j}), B(X_{a}^{j})]$. Now, by definition

$$
|D(R_{a}^{j}, T_{a}^{j})| \leq \text{local-error}^{j}(Y_{a}^{j}, X_{a}^{j}) = A_{a}^{OPT, local^{j}} \setminus A_{a}^{local^{j}}
$$

$$
\leq d_{A(Y_{a}^{j})}^{B(X_{a}^{j})} + d_{A(Y_{a}^{j})}^{B(X_{a}^{j})} \sqrt{12 \log d_{A(Y_{a}^{j})}^{B(X_{a}^{j})}} \leq d_{A(Y_{a}^{j})}^{B(X_{a}^{j})} \sqrt{20 \log d_{A(Y_{a}^{j})}^{B(X_{a}^{j})}}.
$$

For each $x \in E(R_{a}^{j}, T_{a}^{j})$, consider the largest phase $\eta \in \{1, 2, \ldots, j - 1\}$ such that its matching parenthesis $y$ existed before start of the $\eta$th phase but does not exist after the end of the $\eta$th phase. It is possible, either $y$ belongs to the same block in phase $\eta$, say the $r$th block, or in different blocks, say the $r$th and the $s$th block. In the first case, $x$ can be charged to $y$ which contributes 1 to $\text{local-error}^{\eta}(Y_{r}^{\eta}, X_{s}^{\eta})$. In the second case, $x$ can again be charged to $y$ which contributes 1 to $\text{local-error}^{\eta}(Y_{r}^{\eta}, X_{s}^{\eta})$.

Therefore, since $x$ cannot belong to multiple $R_{a}^{j}, T_{a}^{j}$, we have

$$
\sum_{j=l}^{1} \sum_{a=g^{j}}^{h^{j}} |E(R_{a}^{j}, T_{a}^{j})| \leq \sum_{j=l}^{1} \sum_{a=g^{j}}^{h^{j}} \text{local-error}^{j}(Y_{a}^{j}, X_{a}^{j})
$$

We also have

$$
\sum_{j=l}^{1} \sum_{a=g^{j}}^{h^{j}} |D(R_{a}^{j}, T_{a}^{j})| \leq \sum_{j=l}^{1} \sum_{a=g^{j}}^{h^{j}} \text{local-error}^{j}(Y_{a}^{j}, X_{a}^{j})
$$

Therefore,

$$
\sum_{j=l}^{1} \sum_{a=g^{j}}^{h^{j}} \text{StrEdit}(L_{a}^{j} \cap Y_{a}^{j}, L_{a}^{j} \cap X_{a}^{j}) = d_{g}^{h} + \sum_{j=l}^{1} \sum_{a=g^{j}}^{h^{j}} (|D(R_{a}^{j}, T_{a}^{j})| + |E(R_{a}^{j}, T_{a}^{j})|)
$$

22
\[ \leq d^h_y + 2 \sum_{j=1}^{h} \sum_{a=g^j}^{h} \text{local-error}^j(Y^j_d, X^j_a) \leq d^h_y + 2ld^h_y\sqrt{20 \log d^h_y} \]

Since, this holds for any level, and \( l \leq \lceil \log z \rceil + 1 \), we get the desired bound stated in the lemma. The probabilistic bound comes from the same argument as in Lemma 23.

Therefore, we get the improved theorem

Theorem 3. There exists an algorithm that obtains an \( O(\beta(n) \log z \sqrt{\log d}) \)-approximation factor for edit distance computation from strings to \( \text{DYCK}(s) \) for any \( s \geq 2 \) in \( O(n \log n + \alpha(n)) \) time with probability at least \( (1 - \frac{1}{n} - \frac{1}{d}) \), where there exists an algorithm for \( \text{STREDIT} \) running in \( \alpha(n) \) time that achieves an approximation factor of \( \beta(n) \).

4.3 Getting Rid of \( \sqrt{\log d} \)-term in the Approximation Factor

We can improve the approximation factor to \( O(\beta(n) \log z) \), if we consider \( O(n^\epsilon \log n) \) iterations instead of \( O(\log n) \). We can then use Corollary 13 instead of Lemma 12 to bound the hitting time of the random walk to \( \frac{1}{\epsilon} d^2 \), and hence the number of deletions performed by Random-deletion process. Local error now improves from \( A^{OPT,local}_a \setminus A^{local}_a = O(d^h_y \sqrt{\log d^h_y}) \) to \( A^{OPT,local}_a \setminus A^{local}_a = O(\frac{1}{\epsilon} d^h_y) \) using the same Chernoff bound argument. Now following the same argument as before and noting that the best known algorithm for \( \text{STREDIT} \) also runs in \( n^{1+\epsilon} \) time returning an \( O((\log n)^{\frac{1}{2}}) \) approximation we get the following theorem.

Theorem 4. For any \( \epsilon > 0 \), there exists an algorithm that obtains an \( O(\frac{1}{\epsilon} \log z (\log n)^{\frac{1}{2}}) \)-approximation factor for edit distance computation from strings to \( \text{DYCK}(s) \) for any \( s \geq 2 \) in \( O(n^{1+\epsilon}) \) time with high probability.

Note. Due to local computations, it is possible to parallelize this algorithm.

5 Memory Checking Languages

Our algorithm and analysis for \( \text{DYCK}(s) \) gives a general framework which can be applied to the edit distance problem to many languages. Here we illustrate this through a collection of memory checking languages such as \( \text{PQ, QUEUE, STACK and DEQUE} \). These languages check whether a given transcript in memory corresponds to a particular data structures such as priority queue, queue, stack and double-ended queue respectively. Formally, we ask the following question, we observe a sequence of \( n \) updates and queries to (an implementation of) a data structure, and we want to report whether or not the implementation operated correctly on the instance observed and if not what is the minimum number of changes need to be done to make it a correct implementation. A concrete example is to observe a transcript of operations on a priority queue: we see a sequence of insertions intermixed with items claimed to be the results of extractions, and the problem is to detect a way to minimally change the transcript to make it correct. This is the model where checker is invasive and allowed to make changes. Most of the prior literature considered such invasive checkers \( 2, 13, 28 \).

Stack. Let \( \text{STACK}(s) \) denote the language over interaction sequences of \( s \) different symbols that correspond to stack operations. Let \( \text{ins}(u) \) correspond to an insertion of \( u \) to a stack, and \( \text{ext}(u) \) is an extraction of \( u \) from the stack. Then \( \sigma \in \text{Stack} \) iff \( \sigma \) corresponds to a valid transcript of operations on a stack which starts and ends empty. That is, the state of the stack at any step \( j \) can be represented by a string \( S^j \) so that \( S^0 = \phi \), \( S^j = uS^{j-1} \) if \( \sigma_j = \text{ins}(u) \), \( uS^j = S^{j-1} \) if \( \sigma(j) = \text{ext}(u) \) and \( S^n = \phi \).
It is easy to see that STACK$(s)$=DYCK$(s)$ by assigning $u$ to $\text{ins}(u)$ and $\bar{u}$ to $\text{ext}(u)$. Hence, we can employ the algorithm for DYCK$(s)$ to estimate the edit distance to STACK$(s)$ efficiently.

**Priority Queue.** Let PQ$(s)$ denote the language over interaction sequences of $s$ different symbols that correspond to priority queue operation. That is the state of priority queue at any time $j$ can be represented by a multiset $M^j$ such that $M^0 = M^n = \emptyset$. $M^j = M^{j-1}u$ if $\sigma_j = \text{ins}(u)$ and $M^j = M^{j-1} \setminus \{\min(M^{j-1})\}$ if $\sigma_j = \text{ext}(u)$. We view $\text{ins}(u)$ as $u$ and $\text{ext}(u) = \bar{u}$, but each $u$ now has a priority. Note that $\sigma$ can be represented as $Y_1X_1Y_2X_2...Y_kX_k$ where each $Y_i \in T^+$ and each $X_i \in T^*$. We proceed with Random-deletion but when the process starts considering symbols from $X_k$, we sort the prefix of open parenthesis by priority, so that highest priority element is at the stack top. After that using the boundaries computed by Random-deletion, one can employ the main refined algorithm from Section 4.

It can be verified by employing the same analysis that this results in a polylog-approximation algorithm for PQ in $O(n)$ time.

**Queue.** Let QUEUE$(s)$ denote the language over interaction sequences of $s$ different symbols that correspond to queue operations. That is the state of queue at any time $j$ can be represented by a string $Q^j$ such that $Q^0 = Q^n = \phi$. $Q^j = Q^{j-1}u$ if $\sigma_j = \text{ins}(u)$ and $uQ^{j-1} = Q^{j-1}$ if $\sigma_j = \text{ext}(u)$. Now QUEUE$(s)$ is nothing but a PQ$(s)$ with priority given by time of insertion, earlier a symbol is inserted, higher is its priority. Therefore using the algorithm for PQ$(s)$, we can estimate the edit distance to QUEUE$(s)$ efficiently.

**Deque.** Let DEQUE$(s)$ denote the language over interaction sequences that correspond to double-ended queues. That is, there are now two types of insert and extract operations, one operation for the head and one for the tail. We now create two strings $\sigma_1$ and $\sigma_2$ where $\sigma_1$ contains all the insertions and only extractions from the tail, whereas $\sigma_2$ contains again all the insertions and only extractions from the head. $\sigma_1$ is created according to STACK protocol, whereas $\sigma_2$ is created according to QUEUE protocol. We start running Random-deletion on both $\sigma_1$ and $\sigma_2$ simultaneously as follows. If Random-deletion is comparing (may lead to either matching or deletion) an extraction $\sigma_j$ in $\sigma_1$ and $\sigma_j'$ in $\sigma_2$, and $j < j'$, then we take one step of Random-deletion in $\sigma_1$ and if $j' < j$ then we take one step of Random-deletion in $\sigma_2$. If Random-deletion deletes an insertion from $\sigma_1$ which still exists in $\sigma_2$, we delete it from $\sigma_2$ as well and vice-versa. Once, we can perform Random-deletion, we can employ our main algorithm and the same analysis to show that this gives an $O(\text{poly log } n)$ approximation.

**6 Conclusion**

In this paper, we give the first nontrivial approximation algorithm for edit distance computation to DYCK$(s)$. DYCK$(s)$ is a fundamental context free language, and the technique developed here is general enough to be useful for a wide range of grammars. We illustrated this through considering languages accepted by common data structures. Is it possible to characterize this general class of grammars for which the method can be applied? What happens when there is a space restriction? From the hardness point of view, it is known a nondeterministic version of DYCK$(2)$ is the hardest context free grammar, and parsing any arbitrary context free grammar is as hard as boolean matrix multiplication. It will be an interesting result to show that exact computation of edit distance to DYCK$(s)$ also requires time same as boolean matrix multiplication. Finally, It would be good to get rid off $\log z$ term in the approximation factor, and otherwise establish a gap between approximation hardness of string and DYCK$(s)$ edit distance problem.
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8 Appendix

All missing proofs are provided here.

Lemma 5. For any string $\sigma \in (T \cup \bar{T})^*$, $OPT(\sigma) \leq OPT_d(\sigma) \leq 2OPT(\sigma)$.

Proof. Clearly, $OPT(\sigma) \leq OPT_d(\sigma)$, since to compute $OPT(\sigma)$, all edit operations: insertion, deletion and substitution were allowed but for $OPT_d(\sigma)$ only deletion was allowed and hence the number of edit operations can only increase.

To prove the other side of inequality, consider each type of edits that are done on $\sigma$ to compute $OPT(\sigma)$. First consider only the insertions. Let the positions of insertions are immediately after the indices $i_1, i_2, ..., i_l$. These insertions must have been done to match symbols, say at positions $j_1, j_2, ..., j_l$, otherwise, it is easy to refute that $OPT(\sigma)$ is not optimal. Instead of the $l$ insertions, we could have deleted the symbols at $j_1, j_2, ..., j_l$ with equal cost. Therefore, all insertions can be replaced by deletions at suitable positions without increasing $OPT(\sigma)$.

Next, consider the positions where substitutions have happened. Let these be $i_1', i_2', ..., i_l'$, for some $l' \geq 0$. If $l' = 0$, then $OPT(\sigma) = OPT_d(\sigma)$. Otherwise, let $l' \geq 1$. Consider the position $i_1'$. After substitution at position $i_1'$, the new symbol at $i_1'$ must match a symbol at some position $j$, such that either $j \in \{i_2', i_3', ..., i_l'\}$ or $j$ is outside of this set. When $j \in \{i_2', i_3', ..., i_l'\}$, instead of two substitutions at $i_1'$ and $j$, one can simply delete the symbols at these two positions maintaining the same edit cost. When $j$ does not belong to $\{i_2', i_3', ..., i_l'\}$, instead of one substitution at position $i_1'$, one can do two deletions at positions $i_1'$ and $j$. Therefore each substitution operation can be replaced by at most two deletions. Whereas each insertion can be replaced by a single deletion. Continuing in this fashion, overall, this ensures a 2 approximation, that is $OPT_d(\sigma) \leq 2OPT(\sigma)$.

Lemma 6. There exists an optimal algorithm that makes a single scan over the input pushing open parenthesis to stack and when it observes a close parenthesis, it either pops the stack top, if it matches the observed close parenthesis and removes both from further consideration, or edits (that is deletes) either the stack top or the observed close parenthesis whenever there is a mismatch.

Proof: The statement is true when there is 0 error. Suppose the statement is true when the number of minimum edits required is $d$. Now consider any string for which the minimum edit distance to DYCK language is $d + 1$. A stack based algorithm must find a mismatch at least once between stack top and the current symbol in the string. Consider the first position where it happens. Suppose, without loss of generality, at that point, the stack top contains “)” and the current symbol is “]”. Any optimal algorithm that does minimum number of edits must change at least one of these symbols. There are only two alternatives, (a) delete “(”, or (b) delete “[].” Our stack based algorithm can take exactly the same option as the optimal algorithm. This reduces the number of edits required in the remaining string to make it well-balanced and the induction hypothesis applies.

8.1 Pseudocode of Refined Algorithm
Algorithm 1 Improved Edit Distance Computation to DYCK(s)

Input $\sigma = Y_1X_1Y_2X_2...Y_zX_z$
Initialization: $\sigma' = \sigma$; $i = 1$

while $a \leq z$ do
  $N_{a,\text{min}} = \infty$; $Z_{a,\text{min}} = \emptyset$, $\text{startIn} = i$
  for $\text{count} = 1$; $\text{count} < 2 \log n$; $\text{count} += 1$ do
    $Z = \emptyset$, $d_a = 0$, $i = \text{startI}$
    while processing on $X_a$ is not completed do
      if $\sigma'[i] == o$ then
        Insert $\sigma'[i]$ in stack
        $i += 1$
      else if $\sigma'[i]$ matches top of stack then
        match $\sigma'[i]$ with top of stack, append top of stack to $Z$, and remove both of them
        $i += 1$
      else
        with probability $\frac{1}{2}$ each select one of $\sigma'[i]$ or top of stack to be deleted
        if top of stack is selected then
          append that to $Z$
        end if
        delete the selected symbol
        $d_a = d_a + 1$
        if $\sigma'[i]$ is deleted then
          $i += 1$
        end if
      end if
    end while
    if $d_a \leq N_{a,\text{min}}$ then
      $N_{i,\text{min}} = d_a$; $Z_{a,\text{min}} = Z$, $\text{endIn} = i - 1$
    end if
    Start again with $\sigma'$
  end for
  Remove $(Z_{a,\text{min}}, X_a)$ from $\sigma'$
  $(R_a, T_a) = \text{StrEdit}(Z_{a,\text{min}}, X_a)$
  Replace $(Z_{a,\text{min}}, X_{a,\text{min}})$ in $\sigma$ by $(R_a, T_a)$
  $a = a + 1$, $i = \text{endIn} + 1$
end while

if there are excess open parenthesis in $\sigma'$ then
  Delete those corresponding open parenthesis from $\sigma$
end if
return $\sigma$