Syntax Repair as Language Intersection

ANONYMOUS AUTHOR(S)

We introduce a new technique for correcting syntax errors in arbitrary context-free languages. Our work stems from the observation that syntax errors with a small repair typically have very few unique small repairs, which can usually be enumerated up to a small edit distance then quickly reranked. We place a heavy emphasis on precision: the enumerated set must contain every possible repair within a few edits and no invalid repairs. To do so, we construct a grammar representing the language intersection between a Levenshtein automaton and a context-free grammar, then decode it in order of likelihood.

1 INTRODUCTION

Syntax errors are a familiar nuisance for programmers, arising due to a variety of factors, from inexperience, typographic error, to cognitive load. Often the mistake itself is simple to fix, but manual correction can disrupt concentration, a developer's most precious and fickle resource. Syntax repair attempts to automate the correction process by trying to anticipate which program, out of the many possible alternatives, the developer actually intended to write.

Early work on syntax repair by Irons [29] and Aho [2] use techniques from dynamic programming to find the smallest repair for an erroneous input. These methods guarantee correctness, but make no attempt to model naturalness, i.e., predict human edits. Instead, they find just one or a small number of repairs, which may not correspond to the author's intent. Nevertheless, these methods are appealing for their interpretability and well-understood algorithmic properties.

More recently, probabilistic repair techniques based on neural language models have been introduced [3, 41, 48]. These techniques can generate more natural repairs, but are costly to train, prone to misgeneralization and the released models often hallucinate false positive repairs. Such failures can be challenging to debug or interpret, and the models themselves are often too large to properly verify. Nonetheless, they are highly appealing for ability to predict human intent.

Taking inspiration from formal and statistical language modeling alike, we adapt a construction from Bar-Hillel [5] for formal language intersection, to the problem of syntax repair. Our work shows this approach, while seemingly intractable, can be scaled up to handle real-world program repair tasks. We will then demonstrate how, by decoding the Bar-Hillel construction with a Markov model, it is possible to predict human syntax repairs with the accuracy of large langauge models, while retaining the correctness and interpretability of classical repair algorithms.

In particular, we consider the problem of ranked syntax repair under a finite edit distance. We experimentally show it is possible to attain a significant advantage over state-of-the-art neural repair techniques by exhaustively retrieving every valid Levenshtein edit in a certain distance and scoring it. Not only does this approach guarantee both soundness and completeness, we find it also improves precision when ranking by naturalness. Our proposed solution is straightforward:

(1) We model syntax repair as a language intersection problem between the Levenshtein ball and a context-free language, then materialize the grammar using a specialized version of the Bar-Hillel construction to Levenshtein intersections. (§ 4.3)
(2) We design a data structure that compactly represents finite context-free languages. This data structure is used to both eliminate useless productions (§ 4.3, 4.6) from the intersection grammar and index parse trees in the resulting intersection language. (§ 4.7)
(3) We can decode the data structure by either (a) sampling parse trees and reranking them by likelihood or (b) translating to a DFA and decoding trajectories. We default to (b), but compare both methods. In either case, this returns a stream of concrete syntax repairs which are all sound, reachable within a few edits, and sorted by likelihood. (§ 4.8)

Our primary technical contributions are (1) the adaptation of the Levenshtein automaton and Bar-Hillel construction to syntax repair and (2) a method for enumerating or sampling valid sentences in finite context-free languages in order of naturalness. The efficacy of our technique owes to the fact it does not synthesize likely edits, but unique, fully-formed repairs within a given edit distance. This enables us to suggest correct and natural repairs with far less compute and data than would otherwise be required by a large language model to attain the same precision.

2 EXAMPLE

Syntax errors can usually be fixed with a small number of edits. If we assume the intended repair is small, this imposes strong locality constraints on the space of possible edits. For example, let us consider the following Python snippet: `v = df.iloc(5:, 2:)`. Assuming an alphabet of just a hundred lexical tokens, this tiny statement has millions of possible two-token edits, yet only six of those possibilities are accepted by the Python parser:

(1) `v = df.iloc(5:, 2,)` (3) `v = df.iloc(5[:, 2:])` (5) `v = df.iloc[5:, 2:]`

(2) `v = df.iloc(5), 2()` (4) `v = df.iloc(5:, 2:)` (6) `v = df.iloc(5[:, 2])`

With some semantic constraints, we could easily narrow the results, but even in their absence, one can probably rule out (2, 3, 6) given that `5[` and `2(` are rare bigrams in Python, and knowing `df.iloc` is often followed by `[`, determine (5) is the most likely repair. This is the key insight behind our approach: we can usually locate the intended fix by exhaustively searching small repairs. As the set of small repairs is itself often small, if only we had some procedure to distinguish valid from invalid patches, the resulting solutions could be simply ranked by likelihood.

The trouble is that any such procedure must be highly efficient. We cannot afford to sample the universe of possible d-token edits, then reject invalid samples – assuming it takes just 10ms to generate and check each sample, (1-6) could take 24+ hours to find. The hardness of brute-force search grows exponentially with edit distance, sentence length and alphabet size. We will need a more efficient procedure for sampling all and only small valid repairs.

We will now proceed to give an informal intuition behind of our method, then formalize it in the following sections. At a high level, our approach is to construct a language that represents all syntactically valid patches within a certain edit distance of the invalid code fragment. To do so, we first lexicalize the invalid source code, which simply abstracts over numbers and named identifiers.

From the lexical string, we build an automaton that represents all possible strings within a certain edit distance. Then, we proceed to construct a synthetic grammar, recognizing all strings in the intersection of the programming language and the edit ball. Finally, this grammar is reduced to a normal form and decoded with the help of a statistical model to produce a list of suggested repairs.

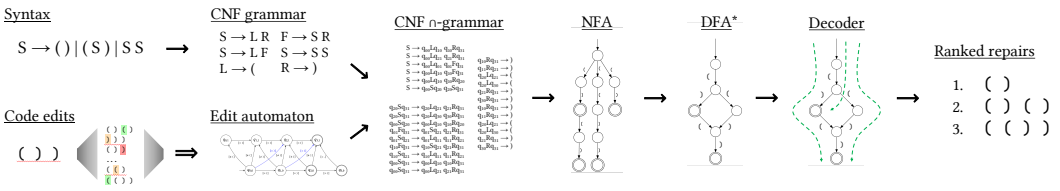


Fig. 1. Simplified dataflow. Given a grammar and broken code fragment, we create a automaton generating the langauge of small edits, then construct a grammar representing the intersection of the two languages. This grammar can be converted to a finite automaton, determinized, then decoded to produce a list of repairs.

This process is depicted in Fig. 1. We will now discuss the intersection step in slightly more detail.

By way of illustration, suppose we have a string ( )), and wish to find nearby repairs. To represent the language of small edits, there is an automaton, called the Levenshtein automaton, recognizing every single string that can be formed by inserting, substituting or deleting a parenthesis. We use a variant that removes some unnecessary edges, but does not affect the generated language.

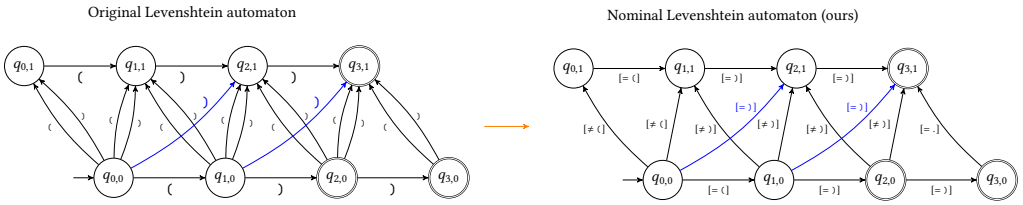


Fig. 2. Automaton recognizing every 1-edit patch. We nominalize the original automaton, ensuring upwards arcs denote a mutation, and use a symbolic predicate, which deduplicates parallel arcs in large alphabets.

Let us consider a very simple grammar: $G = \{S \to () \mid (S) \mid SS\}$. For convenience, G can be reduced into an equivalent normal form, G', by refactoring the right hand side of each production to be in either binary or unary form: $G' = \{S \to LR, S \to LF, S \to SS, F \to SR, L \to (, R \to)\}$. Now, we proceed to stitch together the automaton and grammar into new grammar, $G_\cap$, that will recognize every string in the intersection of their respective languages, and no other string.

This stitching process is known in the literature as the Bar-Hillel (BH) construction, and applies to any context-free grammar and nondeterministic finite automaton. It has three rules: first, for every initial state in the automaton (here there is just one, q_{00}) and every final state, (q_{20}, q_{30}, q_{31}), there will be a production $S \to q_{00}Sq_{xy}$. We call this rule $\sqrt{\ }$, and leave it unchanged.

Next, the BH construction states: for every production $A \to a$ and arc $q \xrightarrow{a} q'$ in the automaton, there will be a production, $qAq' \to a$ in the intersection grammar. Here is where our variation, the Levenshtein Bar-Hillel (LBH) construction, now diverges: we only consider unit productions matching the nominal predicate depicted in Fig. 2, and will call this modified rule $\hat{\uparrow}$.

So far, the intersection grammar now contains the following productions:

$\sqrt{\ }$	$\hat{\uparrow}$			
$S \to q_{00}Sq_{20}$	$q_{00}Rq_{01} \to)$	$q_{10}Lq_{11} \to ($	$q_{20}Rq_{21} \to)$	$q_{01}Lq_{11} \to ($
$S \to q_{00}Sq_{30}$	$q_{00}Rq_{11} \to)$	$q_{10}Lq_{21} \to ($	$q_{20}Rq_{31} \to)$	$q_{11}Rq_{21} \to)$
$S \to q_{00}Sq_{31}$	$q_{00}Lq_{10} \to ($	$q_{10}Rq_{20} \to)$	$q_{20}Lq_{30} \to ($	$q_{21}Rq_{31} \to)$
	$q_{30}Lq_{31} \to ($	$q_{10}Rq_{31} \to)$	$q_{30}Rq_{31} \to)$	$q_{00}Rq_{21} \to)$

The final and most expensive rule of the BH construction, $\bowtie$, stipulates: for every $w \to xz$ in G' and every state triplet $\langle p, q, r\rangle$, we will have $pwr \to (pxq)(qzr)$ in $G_\cap$. This rule creates a synthetic production recognizing every combination of NFA states consistent with every nonterminal in every production. Fortunately, most of these combinations are simply impossible. For example, we note that $q_{31}Sq_{00}$ is an impossible nonterminal, as there is no path from q_{31} to q_{00} in the Levenshtein automaton (Fig. 2). Likewise, the nonterminal $q_{i,j}Iq_{i+1,j}$ is clearly impossible, as the nonterminal I requires at least three tokens, and the only path from $q_{i,j}$ to $q_{i+1,j}$ has length one. Criteria such as these are essential for filtering out synthetic nonterminals generated by the original BH $\bowtie$ rule.

In Sec. 4.3, we will consider a refinement to the $\bowtie$ rule which eliminates many impossible productions from BH intersection grammars by a sound overapproximation to the Parikh image. Aggressively pruning synthetic productions from $G_\cap$ by (1) nominalizing the Levenshtein automaton and (2) refining the $\bowtie$ rule, are key insights to unlocking the full potential of the Bar-Hillel construction and scaling up this technique to handle real-world program repair scenarios.

3 PROBLEM STATEMENT

Source code in a programming language can be treated as a string over a finite alphabet, Σ. We use a lexical alphabet for convenience. The language has a syntax, $\ell \subset \Sigma^*$, containing every acceptable program. A syntax error is an unacceptable string, $\underset{\sim}{\sigma} \notin \ell$. We can model syntax repair as a language intersection between a context-free language (CFL) and a regular language. Henceforth, $\underset{\sim}{\sigma}$ will always and only be used to denote a syntactically invalid string whose target language is known.

Definition 3.1 (Bounded Levenshtein-CFL reachability). Given a CFL, ℓ, and an invalid string, $\underset{\sim}{\sigma} : \bar{\ell}$, find every valid string reachable within d edits of $\underset{\sim}{\sigma}$, i.e., letting Δ be the Levenshtein metric and $L(\underset{\sim}{\sigma}, d) = \{\sigma' \mid \Delta(\underset{\sim}{\sigma}, \sigma') \leq d\}$ be the Levenshtein d-ball, we seek to find $A = L(\underset{\sim}{\sigma}, d) \cap \ell$.

As the admissible set A is typically under-constrained, we want a procedure which surfaces natural and valid repairs over unnatural but valid repairs:

Definition 3.2 (Ranked repair). Given a finite language $A = L(\underset{\sim}{\sigma}, d) \cap \ell$ and a probabilistic language model $\mathrm{P}_\theta : \Sigma^* \to [0, 1] \subset \mathbb{R}$, the ranked repair problem is to find the top-k maximum likelihood repairs under the language model. That is,

$$R(A, P_\theta) = \underset{\boldsymbol{\sigma} \subseteq A, |\boldsymbol{\sigma}| \leq k}{\operatorname{argmax}} \sum_{\sigma \in \boldsymbol{\sigma}} \mathrm{P}_\theta(\sigma) \tag{1}$$

A popular approach to ranked repair involves learning a distribution over strings, however this is highly sample-inefficient and generalizes poorly to new languages. Approximating a distribution over Σ^* forces the model to jointly learn syntax and stylometry. Furthermore, even with an extremely efficient approximate sampler for $\sigma \sim \ell_\cap$, due to the size of ℓ and $L(\underset{\sim}{\sigma}, d)$, it would be intractable to sample either ℓ or $L(\underset{\sim}{\sigma}, d)$, reject duplicates, then reject invalid ($\sigma \notin \ell$) or unreachable ($\sigma \notin L(\underset{\sim}{\sigma}, d)$) edits, and completely out of the question to sample $\sigma \sim \Sigma^*$ as do many neural language models.

As we will demonstrate, the ranked repair problem can be factorized into a bilevel objective: first maximal retrieval, then ranking. Instead of working with strings, we will explicitly construct a grammar which soundly and completely generates the set $\ell \cap L(\underset{\sim}{\sigma}, d)$, then retrieve repairs from its language. By ensuring retrieval is sufficiently precise and exhaustive, maximizing likelihood over the retrieved set can be achieved with a much simpler, syntax-oblivious language model.

Assuming we have a grammar that recognizes the Levenshtein-CFL intersection, the question then becomes how to maximize the number of unique valid sentences in a given number of samples. Top-down incremental sampling with replacement eventually converges to the language, but does so superlinearly [23]. Due to practical considerations including latency, we require the sampler to converge linearly, ensuring with much higher probability that natural repairs are retrieved in a timely manner. This motivates the need for a specialized generating function. More precisely,

Definition 3.3 (Linear convergence). Given a finite CFL, ℓ, we want a randomized generating function, $\boldsymbol{\varphi} : \mathbb{N}_{\leq |\ell|} \to 2^\ell$, whose rate of convergence is linear in expectation, i.e., $\mathbb{E}_{i \in [1,n]} |\boldsymbol{\varphi}(i)| \propto n$.

This will ensure that if $|\ell_\cap|$ is sufficiently small and enough samples are drawn, $\boldsymbol{\varphi}$ is sure to include a representative subset, and additionally, will terminate after exhausting all valid repairs.

To satisfy Def. 3.3, we can construct a bijection from syntax trees to integers (§ 4.5), sample integers uniformly without replacement, then decode them as trees. This will produce a set of unique trees, and each tree, assuming grammatical unambiguity, will correspond to a unique sentence in the language. Finally, sentences can be scored and ranked by likelihood under a language model.

Otherwise, if the grammar, G_ℓ, is ambiguous, it can be translated into a DFA, then decoded (§ 4.9) using an autoregressive language model or any suitably fast scoring function of the implementer's choice. In our case, we use a low-order Markov model for its inference speed, data efficiency, and simplicity. So long as the decoder samples ℓ without replacement, it will satisfy Def. 3.3.

4 METHOD

The method we describe in this paper takes as input the invalid code fragment, and returns a set of plausible repairs. We assume to know the target syntax and a small dataset of valid programs to estimate the likelihood of candidate repairs. At a high level, our method can be decomposed into two main steps: (1) language intersection, (2) repair decoding.

First, we generate a synthetic grammar representing the intersection between the syntax and the Levenshtein ball around the source code, then during the decoding process, retrieve as many repairs as possible from the intersection grammar via enumeration or trajectory sampling, then rerank all unique repairs by naturalness. This can be depicted in more detail as a flowchart (Fig. 3).

More specifically, since the syntax of most programming languages is context-free, we construct a context-free grammar (CFG), $G_\cap$, representing the intersection between the programming language syntax (G) and an automaton recognizing the Levenshtein edit ball of a given radius, $L(\underset{\sim}{\sigma}, d)$. As the CFL family is closed under intersection with regular languages, the intersection language $\mathcal{L}(G_\cap)$ should contain every repair within a given Levenshtein distance and no invalid repairs. Either the grammar will be empty, in which case there are no repairs within the given radius, or it will be nonempty, in which case we can directly proceed to decode the repairs.

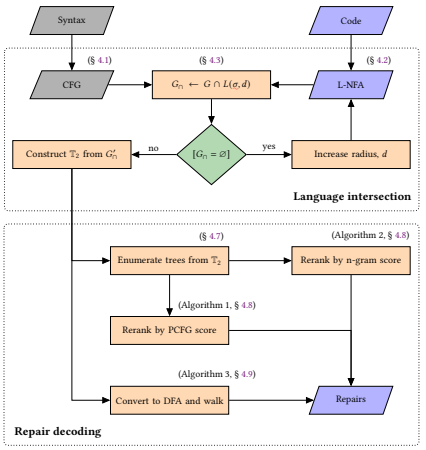


Fig. 3. Dataflow of our proposed method.

We present three basic methods for repair decoding: enumerate parse trees from the CFG, $G_\cap$, and rerank each tree by either (1) PCFG score, or (2) Markov chain likelihood, or (3) translate $G_\cap$ to an equivalent DFA, $\mathcal{A}_\cap$, minimize it using Brzozowski's algorithm to produce $\mathcal{A}^*_\cap$, then sample trajectories without replacement through the DFA according to a Markov chain until a fixed timeout is reached. We use (3) by default but will present a comparison of (1-3) in § 5.4.

In all cases, if the language is sufficiently small, this will generate every possible repair and halt early. Otherwise, if the language is too large to exhaustively search, it will draw a representative subset containing the most likely repairs with high probability, then halt. The decoders (1-3) essentially differ in the order they retrieve repairs, and the likelihood model they use to rank them.

We will first describe how to generate the intersection grammar (§ 4.2, 4.3), then, define a data structure compactly representing its language, allowing us to efficiently decode all repairs contained within (§ 4.5). Finally, we will show how to enumerate repairs from the CFG (§ 4.7), or sample them from an equivalent DFA (§ 4.9). As we build up our intuition for each component, we will periodically revisit the criteria from § 3, to ensure we remain on the right track.

4.1 Preliminaries

Recall that a CFG, $\mathcal{G} = \langle \Sigma, V, P, S \rangle$, is a quadruple consisting of terminals (Σ), nonterminals (V), productions ($P\colon V \rightarrow (V \mid \Sigma)^*$), and a start symbol, ($S$). Every CFG is reducible to so-called *Chomsky Normal Form*, $P'\colon V \rightarrow (V^2 \mid \Sigma)$, where every production is either (1) a binary production $w \rightarrow xz$, or (2) a unit production $w \rightarrow t$, where $w, x, z : V$ and $t : \Sigma$. For example:

$$G = \{\ S \rightarrow S\,S \mid (\ S\ ) \mid (\ )\ \} \Longrightarrow G' = \{\ S \rightarrow Q\,R \mid S\,S \mid L\,R,\quad R \rightarrow),\quad L \rightarrow (,\quad Q \rightarrow L\,S\ \}$$

Likewise, a finite state automaton (FSA) is a quintuple $\mathcal{A} = \langle Q, \Sigma, \delta, I, F \rangle$, where Q is a finite set of states, Σ is a finite alphabet, $\delta \subseteq Q \times \Sigma \times Q$ is the transition function, and $I, F \subseteq Q$ are the set of initial and final states, respectively. We will adhere to this notation in the following sections.

4.2 Modeling lexical edits with the nominal Levenshtein automaton

Levenshtein edits are recognized by an automaton known as the Levenshtein automaton. As the original construction defined by Schultz and Mihov [42] contains cycles and ε-transitions, we propose a variant which is ε-free and acyclic. Furthermore, we adopt a nominal form which supports infinite alphabets and considerably simplifies the language intersection to follow. Illustrated in Fig. 4 is an example of a small Levenshtein automaton recognizing $L(\sigma : \Sigma^5, 3)$. Unlabeled arcs accept any terminal from the alphabet, Σ. Equivalently, this transition system can be viewed as a kind of proof system within an unlabeled lattice. The following construction is equivalent to Schultz and Mihov's original Levenshtein automaton, but is more amenable to our purposes as it does not any contain ε-arcs, and instead uses skip connections to recognize consecutive deletions of varying lengths.

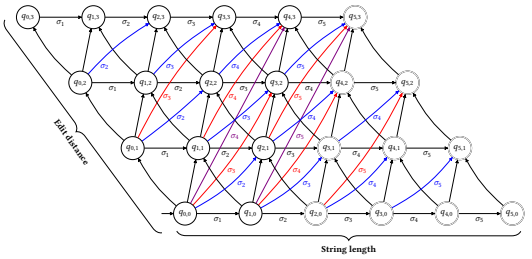


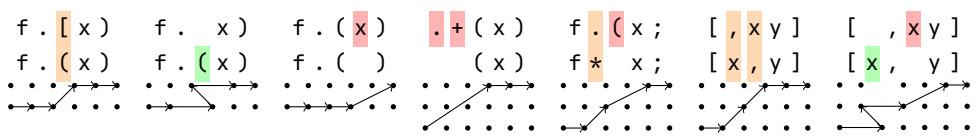
Fig. 4. NFA recognizing Levenshtein $L(\sigma : \Sigma^5, 3)$.

$$\frac{s \in \Sigma \quad i \in [0, n] \quad j \in [1, d_{\max}]}{(q_{i,j-1} \xrightarrow{s} q_{i,j}) \in \delta} \qquad \frac{s \in \Sigma \quad i \in [1, n] \quad j \in [1, d_{\max}]}{(q_{i-1,j-1} \xrightarrow{s} q_{i,j}) \in \delta}$$

$$\frac{i \in [1, n] \quad j \in [0, d_{\max}]}{(q_{i-1,j} \xrightarrow{\sigma_i} q_{i,j}) \in \delta} \qquad \frac{d \in [1, d_{\max}] \quad i \in [d+1, n] \quad j \in [d, d_{\max}]}{(q_{i-d-1,j-d} \xrightarrow{\sigma_i} q_{i,j}) \in \delta}$$

$$\frac{}{q_{0,0} \in I}\ \textsc{Init} \qquad \frac{q_{i,j} \qquad |n - i + j| \leq d_{\max}}{q_{i,j} \in F}\ \textsc{Done}$$

Each arc plays a specific role. ↖ handles insertions, ↗ handles substitutions and ⋰ handles deletions of one or more terminals. Let us consider some illustrative cases.



Note that the same patch can have multiple Levenshtein alignments. Done constructs the final states, which are all states accepting strings σ' whose Levenshtein distance $\Delta(\sigma, \sigma') \leq d_{\max}$.

To avoid creating a parallel bundle of arcs for each insertion and substutition point, we instead decorate each arc with a nominal predicate, accepting or rejecting σ_i. To distinguish this nominal variant from the original construction, we highlight the modified rules in orange below.

$$\frac{i \in [0, n] \quad j \in [1, k]}{(q_{i,j-1} \xrightarrow{[\neq \sigma_{i+1}]} q_{i,j}) \in \delta} \qquad \frac{i \in [1, n] \quad j \in [1, k]}{(q_{i-1,j-1} \xrightarrow{[\neq \sigma_i]} q_{i,j}) \in \delta}$$

$$\frac{i \in [1, n] \quad j \in [0, k]}{(q_{i-1,j} \xrightarrow{[= \sigma_i]} q_{i,j}) \in \delta} \qquad \frac{d \in [1, d_{\max}] \quad i \in [d+1, n] \quad j \in [d, k]}{(q_{i-d-1,j-d} \xrightarrow{[= \sigma_i]} q_{i,j}) \in \delta}$$

Nominalizing the NFA eliminates the creation of $e = 2(|\Sigma| - 1) \cdot |\sigma| \cdot d_{\max}$ unnecessary arcs over the entire Levenshtein automaton and drastically reduces the size of the construction to follow, but does not affect the underlying semantics. Thus, it is essential to first nominalize the automaton before proceeding to avoid a large blowup in the intermediate grammar.

4.3 Recognizing syntactically valid edits via language intersection

We now describe the Bar-Hillel construction, which generates a grammar recognizing the intersection between a regular and a context-free language, then specialize it to Levenshtein intersections.

Lemma 4.1. *For any context-free language ℓ and finite state automaton α, there exists a context-free grammar $G_\cap$ such that $\mathcal{L}(G_\cap) = \ell \cap \mathcal{L}(\alpha)$. See Bar-Hillel [5].*

Although Bar-Hillel [5] lacks an explicit construction, Beigel and Gasarch [8] construct $G_\cap$ like so:

$$\frac{q \in I \quad r \in F}{(S \to qSr) \in P_\cap}\ \surd \qquad \frac{(A \to a) \in P \qquad (q \xrightarrow{a} r) \in \delta}{(qAr \to a) \in P_\cap}\ \uparrow \qquad \frac{(w \to xz) \in P \qquad p,q,r \in Q}{(pwr \to (pxq)(qzr)) \in P_\cap}\ \bowtie$$

This, now standard, Bar-Hillel construction applies to any CFL and REG language intersection, but generates a grammar whose cardinality is approximately $|P_\cap| = |I|\cdot|F|+|P|\cdot|\Sigma|\cdot|\sigma|\cdot 2d_{\max}+|P|\cdot|Q|^3$. Applying the BH construction directly to practical languages and code snippets can generate hundreds of trillions of productions for even modestly-sized grammars and Levenshtein automata. Instead, we will describe a kind of reachability analysis that elides many superfluous productions, greatly reducing the number of synthetic productions in the intersection grammar, $G_\cap$.

Consider $\bowtie$, the most expensive rule. What $\bowtie$ tells us is each nonterminal in the intersection grammar $\langle q, v, q'\rangle$ matches a substring simultaneously recognized by (1) a pair of states q, q' in the original NFA and (2) a nonterminal, v, in the original CFG. A key observation is that $\bowtie$ generates the Cartesian product of every such triple, but this is a gross overapproximation for most NFAs and CFGs, as the vast majority of all state pairs and nonterminals recognize no strings in common.

To identify these superfluous triples, we define an interval domain that soundly overapproximates the Parikh image, encoding the minimum and maximum number of terminals each nonterminal can generate. Since some intervals may be right-unbounded, we write $\mathbb{N}^* = \mathbb{N} \cup \{\infty\}$ to denote the upper bound, and $\Pi = \{[a, b] \in \mathbb{N} \times \mathbb{N}^* \mid a \leq b\}^{|\Sigma|}$ to denote the Parikh image of all terminals.

Definition 4.2 (Parikh mapping of a nonterminal). Let $p : \Sigma^* \to \mathbb{N}^{|\Sigma|}$ be the Parikh operator [37], which counts the frequency of terminals in a string. We define the Parikh map, $\pi : V \to \Pi$, as a function returning the smallest interval such that $\forall\sigma : \Sigma^*, \forall v : V, v \Rightarrow^* \sigma \vdash p(\sigma) \in \pi(v)$.

In other words, the Parikh mapping computes the greatest lower and least upper bound of the Parikh image over all strings in the language of a nonterminal. The infimum of a nonterminal's Parikh interval tells us how many of each terminal a nonterminal *must* generate, and the supremum tells us how many it *can* generate. Likewise, we define a similar relation over NFA state pairs:

Definition 4.3 (Parikh mapping of NFA states). We define $\pi : Q \times Q \to \Pi$ as returning the smallest interval such that $\forall\sigma : \Sigma^*, \forall q, q' : Q, q \overset{\sigma}{\Longrightarrow} q' \vdash p(\sigma) \in \pi(q, q')$.

Next, we will define a measure on Parikh intervals representing the minimum total edits required to transform a string in one Parikh interval to a string in another, across all such pairings.

Definition 4.4 (Parikh divergence). Given two Parikh intervals $\pi, \pi' : \Pi$, we define the divergence between them as $\pi \parallel \pi' = \sum_{n=1}^{|\Sigma|} \min_{(i,i') \in \pi[n] \times \pi'[n]} |i - i'|$.

Now, we know that if the Parikh divergence between two intervals is nonzero, those intervals must be incompatible as no two strings, one from each Parikh interval, can be transformed into the other with fewer than $\pi \parallel \pi'$ edits.

Definition 4.5 (Parikh compatibility). Let q, q' be NFA states and v be a CFG nonterminal. We call $\langle q, v, q'\rangle : Q \times V \times Q$ *compatible* iff their divergence is zero, i.e., $v \lhd qq' \iff (\pi(v) \parallel \pi(q, q')) = 0$.

Finally, we define the modified Bar-Hillel construction for nominal Levenshtein automata as:

$$\frac{(A \to a) \in P \quad (q \xrightarrow{[\cdot]} r) \in \delta \quad a[\cdot]}{(qAr \to a) \in P_\cap} \hat{\uparrow} \frac{w \lhd pr \quad x \lhd pq \quad z \lhd qr \quad (w \to xz) \in P \quad p,q,r \in Q}{(pwr \to (pxq)(qzr)) \in P_\cap} \hat{\bowtie}$$

Once constructed, we normalize $G_\cap$ by removing unreachable and non-generating productions [22] to obtain $G'_\cap$, which is a recognizer for the admissible set, i.e., $\mathcal{L}(G'_\cap) = A$, satisfying Def. 3.1. Note, the original BH construction and our adapted version both reduce to the same CNF, $G'_\cap$, but normalization becomes significantly more tractable for large intersections, as far fewer useless productions are instantiated to only later be removed during normalization.

Now that we have a grammar to recognize nearby repairs, we will need a method to generate the repairs themselves. We impose certain criteria on such a procedure: it must generate only valid repairs and eventually generate all repairs in the language, preferably in a natural order. In the following sections, we will describe a constructor (§ 4.4) for a data structure (§ 4.5) representing parse forests in a length-bounded CFL. Among other features, this data structure provides an explicit way to construct the parameterized Parikh map (§ 4.6) for the Levenshtein Bar-Hillel (LBH) construction, and a method for sampling the language with or without replacement.

4.4 Code completion as idempotent matrix completion

In this section, we will introduce the porous completion problem and show how it can be translated to a kind of idempotent matrix completion, whose roots are valid strings in a context-free language. This technique is convenient for its geometric interpretability, parallelizability, and generalizability to any CFG, regardless of finitude or ambiguity. We will see how, by redefining the algebraic operations $\oplus, \otimes$ over different carrier sets, one can obtain a recognizer, porous synthesizer, parser, generator, Parikh map and other convenient structures for CFL intersection and membership.

Given a CFG, $G' : \mathcal{G}$ in Chomsky Normal Form (CNF), we can construct a recognizer $R : \mathcal{G} \to \Sigma^n \to \mathbb{B}$ for strings $\sigma : \Sigma^n$ as follows. Let 2^V be our domain, 0 be $\varnothing$, $\oplus$ be $\cup$, and $\otimes$ be defined as:

$$X \otimes Z = \left\{ w \mid \langle x, z \rangle \in X \times Z, (w \to xz) \in P \right\} \tag{2}$$

If we define $\hat{\sigma}_r = \{w \mid (w \to \sigma_r) \in P\}$, then construct a matrix with nonterminals on the superdiagonal representing each token, $M_0[r+1=c](G', \sigma) = \hat{\sigma}_r$, the fixpoint $M_{i+1} = M_i + M_i^2$ is uniquely determined by the superdiagonal entries. The fixedpoint iteration proceeds as follows:

$$M_0 = \begin{pmatrix} \varnothing & \hat{\sigma}_1 & \varnothing & \cdots & \varnothing \\ & \ddots & \ddots & & \\ & & & & \varnothing \\ & & & & \hat{\sigma}_n \\ \varnothing & & & & \varnothing \end{pmatrix} \Rightarrow \begin{pmatrix} \varnothing & \hat{\sigma}_1 & \Lambda & \cdots & \varnothing \\ & \ddots & \ddots & & \\ & & & & \Lambda \\ & & & & \hat{\sigma}_n \\ \varnothing & & & & \varnothing \end{pmatrix} \Rightarrow \ldots \Rightarrow M_\infty = \begin{pmatrix} \varnothing & \hat{\sigma}_1 & \Lambda & \cdots & \Lambda^*_\sigma \\ & \ddots & \ddots & & \\ & & & & \Lambda \\ & & & & \hat{\sigma}_n \\ \varnothing & & & & \varnothing \end{pmatrix}$$

Once obtained, the proposition $[S \in \Lambda^*_\sigma]$ decides language membership, i.e., $[\sigma \in \mathcal{L}(\mathcal{G})]$ [1]. So far, this procedure is essentially the textbook CYK algorithm in a linear algebraic notation [25].

This procedure can be lifted to the domain of strings containing free variables, which we call the *porous completion problem*. In this case, the fixpoint is characterized by a system of language equations, whose solutions are the set of all sentences consistent with the template.

Definition 4.6 (Porous completion). Let $\underline{\Sigma} = \Sigma \cup \{\_\}$, where _ denotes a hole. We denote $\sqsubseteq : \Sigma^n \times \underline{\Sigma}^n$ as the relation $\{\langle \sigma', \sigma \rangle \mid \sigma_i \in \Sigma \implies \sigma'_i = \sigma_i\}$ and the set of all inhabitants $\{\sigma' : \Sigma^+ \mid \sigma' \sqsubseteq \sigma\}$ as $\mathrm{H}(\sigma)$. Given a *porous string*, $\sigma : \underline{\Sigma}^*$ we seek all syntactically valid inhabitants, i.e., $A(\sigma) = \mathrm{H}(\sigma) \cap \ell$.

Let us consider an example with two holes, $\sigma = 1 \_ \_$, and the context-free grammar being $G = \{S \to NON, O \to + \mid \times, N \to 0 \mid 1\}$. This grammar will first be rewritten into CNF as

[1] Hereinafter, we use Iverson brackets to denote the indicator function of a predicate with free variables, i.e., $[P] \Leftrightarrow \mathbb{1}(P)$.

$G' = \{S \to NL, N \to 0 \mid 1, O \to \times \mid +, L \to ON\}$. Using the powerset algebra we just defined, the matrix fixpoint $M' = M + M^2$ can be computed as follows, shown in the leftmost column below:

	2^V	$\mathbb{Z}_2^{\lvert V\rvert}$	$\mathbb{Z}_2^{\lvert V\rvert} \to \mathbb{Z}_2^{\lvert V\rvert}$
M_0	$\begin{pmatrix} \{N\} & & \\ & \{N,O\} & \\ & & \{N,O\} \end{pmatrix}$	$\begin{pmatrix} \square\blacksquare\square\square & & \\ & \square\blacksquare\blacksquare\square & \\ & & \square\blacksquare\blacksquare\square \end{pmatrix}$	$\begin{pmatrix} V_{0,1} & & \\ & V_{1,2} & \\ & & V_{2,3} \end{pmatrix}$
M_1	$\begin{pmatrix} \{N\} & \varnothing & \\ & \{N,O\} & \{L\} \\ & & \{N,O\} \end{pmatrix}$	$\begin{pmatrix} \square\blacksquare\square\square & \square\square\square\square & \\ & \square\blacksquare\blacksquare\square & \blacksquare\square\square\square \\ & & \square\blacksquare\blacksquare\square \end{pmatrix}$	$\begin{pmatrix} V_{0,1} & V_{0,2} & \\ & V_{1,2} & V_{1,3} \\ & & V_{2,3} \end{pmatrix}$
$M_2 = M_\infty$	$\begin{pmatrix} \{N\} & \varnothing & \{S\} \\ & \{N,O\} & \{L\} \\ & & \{N,O\} \end{pmatrix}$	$\begin{pmatrix} \square\blacksquare\square\square & \square\square\square\square & \square\square\square\blacksquare \\ & \square\blacksquare\blacksquare\square & \blacksquare\square\square\square \\ & & \square\blacksquare\blacksquare\square \end{pmatrix}$	$\begin{pmatrix} V_{0,1} & V_{0,2} & V_{0,3} \\ & V_{1,2} & V_{1,3} \\ & & V_{2,3} \end{pmatrix}$

The same procedure can be translated, without loss of generality, into the bit domain ($\mathbb{Z}_2^{|V|}$) using a lexicographic nonterminal ordering, however M_∞ in both 2^V and $\mathbb{Z}_2^{|V|}$ represents a decision procedure, i.e., $[S \in V_{0,3}] \Leftrightarrow [V_{0,3,3} = \blacksquare] \Leftrightarrow [A(\sigma) \neq \varnothing]$. Since $V_{0,3} = \{S\}$, we know there exists at least one solution $\sigma' \in A$, but M_∞ does not explicitly reveal its identity.

To extract the inhabitants, we can translate the bitwise procedure into an equation with free variables. Here, we can encode the idempotency constraint directly as $M = M^2$. We first define $X \boxtimes Z = [X_2 \wedge Z_1, \bot, \bot, X_1 \wedge Z_0]$ and $X \boxplus Z = [X_i \vee Z_i]_{i \in [0,|V|)}$, mirroring $\oplus, \otimes$ from the powerset domain, now over bitvectors. Since the unit nonterminals O, N can only occur on the superdiagonal, they may be safely ignored by $\boxtimes$. To solve for M_∞, we proceed by first computing $V_{0,2}, V_{1,3}$:

$$\begin{aligned} V_{0,2} &= V_{0,j} \cdot V_{j,2} = V_{0,1} \boxtimes V_{1,2} \\ &= [L \in V_{0,2}, \bot, \bot, S \in V_{0,2}] \\ &= [O \in V_{0,1} \wedge N \in V_{1,2}, \bot, \bot, N \in V_{0,1} \wedge L \in V_{1,2}] \\ &= [V_{0,1,2} \wedge V_{1,2,1}, \bot, \bot, V_{0,1,1} \wedge V_{1,2,0}] \end{aligned}$$

$$\begin{aligned} V_{1,3} &= V_{1,j} \cdot V_{j,3} = V_{1,2} \boxtimes V_{2,3} \\ &= [L \in V_{1,3}, \bot, \bot, S \in V_{1,3}] \\ &= [O \in V_{1,2} \wedge N \in V_{2,3}, \bot, \bot, N \in V_{1,2} \wedge L \in V_{2,3}] \\ &= [V_{1,2,2} \wedge V_{2,3,1}, \bot, \bot, V_{1,2,1} \wedge V_{2,3,0}] \end{aligned}$$

Now we solve for the corner entry $V_{0,3}$ by dotting the first row and last column, which yields:

$$\begin{aligned} V_{0,3} &= V_{0,j} \cdot V_{j,3} = (V_{0,1} \boxtimes V_{1,3}) \boxplus (V_{0,2} \boxtimes V_{2,3}) \\ &= [V_{0,1,2} \wedge V_{1,3,1} \vee V_{0,2,2} \wedge V_{2,3,1}, \bot, \bot, V_{0,1,1} \wedge V_{1,3,0} \vee V_{0,2,1} \wedge V_{2,3,0}] \end{aligned}$$

Since we only care about $V_{0,3,3} \Leftrightarrow [S \in V_{0,3}]$, we can ignore the first three entries and solve for:

$$\begin{aligned} V_{0,3,3} &= V_{0,1,1} \wedge V_{1,3,0} \vee V_{0,2,1} \wedge V_{2,3,0} \\ &= V_{0,1,1} \wedge (V_{1,2,2} \wedge V_{2,3,1}) \vee V_{0,2,1} \wedge \bot \\ &= V_{0,1,1} \wedge V_{1,2,2} \wedge V_{2,3,1} \\ &= [N \in V_{0,1}] \wedge [O \in V_{1,2}] \wedge [N \in V_{2,3}] \end{aligned}$$

Now we know that $\sigma = 1\,\underline{O}\,\underline{N}$ is a valid solution, and we can take the product $\{1\} \times \hat{\sigma}_2^{-1}(O) \times \hat{\sigma}_3^{-1}(N)$ to recover the inhabitants, yielding $A = \{1+0, 1+1, 1\times 0, 1\times 1\}$. In this case, since G is unambiguous, there is only one parse tree satisfying $V_{0,|\sigma|,3}$, but in general, there can be multiple valid parse trees.

4.5 An algebraic datatype for context-free parse forests

The procedure described in § 4.4 generates solutions satisfying the matrix fixpoint, but forgets provenance. The question naturally arises, is there a way to solve for the parse trees directly? This would allow us to handle ambiguous grammars, whilst preserving the natural arborescent structure.

We will now describe a datatype for compactly representing CFL parse forests, then redefine the matrix algebra over this domain. This datatype is particularly convenient for tracking provenance under ambiguity, constructing the Parikh map for a CFG, counting the size of a finite CFL, and sampling parse trees with or without replacement.

We first define a datatype $\mathbb{T}_3 = (V \cup \Sigma) \rightharpoonup \mathbb{T}_2$ where $\mathbb{T}_2 = (V \cup \Sigma) \times (\mathbb{N} \rightharpoonup \mathbb{T}_2 \times \mathbb{T}_2)$[2]. Morally, we can think of $\mathbb{T}_2$ as an implicit set of possible trees that can be generated by a CFG in CNF, consistent with a finite-length porous string. Structurally, we may interpret $\mathbb{T}_2$ as an algebraic data type corresponding to the fixpoints of the following recurrence, which tells us each $\mathbb{T}_2$ can be a terminal, or a nonterminal and a (possibly empty) sequence of nonterminal pairs and their two children:

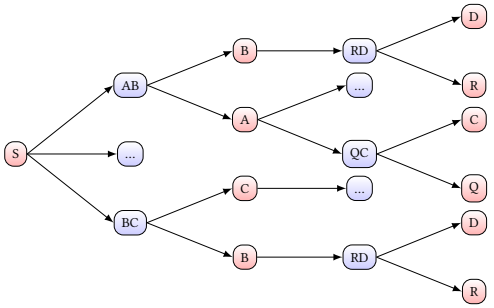


Fig. 5. A partial $\mathbb{T}_2$ corresponding to the grammar $\{S \to BC \mid \ldots \mid AB, B \to RD \mid \ldots, A \to QC \mid \ldots\}$.

$$L(p) = 1 + pL(p) \qquad P(a) = \Sigma + VL\left(V^2 P(a)^2\right) \tag{3}$$

Depicted in Fig. 5 is a partial $\mathbb{T}_2$, where red nodes are `roots` and blue nodes are `children`. The shape of type $\mathbb{T}_2$ is congruent with an acyclic CFG in Chomsky Normal Form, i.e., $\mathbb{T}_2 \cong \mathcal{G}'$, so assuming the CFG recognizes a finite language, as is the case for $G'_\cap$, then it can be translated directly. Since the RHS of CNF productions must each be nonterminals, we define $P(a)$ as $\Sigma + L\left(V^2 P(a)^2\right)$, otherwise, we could write $\Sigma + VL\left(P(a)^2\right)$ to allow productions containing mixed Σ and V.

It is also possible to construct $\mathbb{T}_2$ for infinite languages by using the matrix fixpoint technique. If the CFG is cyclic, we can slice the language, $\mathcal{L}(G) \cap \Sigma^n$, and solve the fixpoint for each slice $n \in [2, n]$. Given a porous string $\sigma : \underline{\Sigma}^n$ representing the slice, we construct $\mathbb{T}_2$ from the bottom-up, and read off structures from the top-down. Here, we define first upper diagonal $\hat{\sigma}_r = \Lambda(\sigma_r)$ as:

$$\Lambda(s : \underline{\Sigma}) \mapsto \begin{cases} \bigoplus_{s' \in \Sigma} \Lambda(s') & \text{if } s \text{ is a hole,} \\ \left\{ \mathbb{T}_2\left(w, \left[\langle \mathbb{T}_2(s), \mathbb{T}_2(\varepsilon) \rangle\right]\right) \mid (w \to s) \in P \right\} & \text{otherwise.} \end{cases} \tag{4}$$

This initializes the superdiagonal entries of M_0, enabling us to compute the fixpoint M_∞ in the same manner described in § 4.4, by redefining $\oplus, \otimes : \mathbb{T}_3 \times \mathbb{T}_3 \to \mathbb{T}_3$ as:

$$X \oplus Z \mapsto \bigcup_{k \in \pi_1(X \cup Z)} \left\{ k \Rightarrow \mathbb{T}_2(k, x \cup z) \mid x \in \pi_2(X \circ k), z \in \pi_2(Z \circ k) \right\} \tag{5}$$

$$X \otimes Z \mapsto \bigoplus_{(w \to xz) \in P} \left\{ \mathbb{T}_2\Big(w, \left[\langle X \circ x, Z \circ z \rangle\right]\Big) \mid x \in \pi_1(X), z \in \pi_1(Z) \right\} \tag{6}$$

These operators group subtrees by their root nonterminal, then aggregate their children. Instead of tracking sets, each Λ now becomes a dictionary of $\mathbb{T}_2$, indexed by their root nonterminals. This ensures each matrix entry $\Lambda_{i,j}$ contains at most $|V|$ separate $\mathbb{T}_2$ instances, each representing a reachable nonterminal and all possible ways to derive that nonterminal from $\sigma_{i..j}$, i.e., all parse forests sharing the same root, consistent with the porous substring in the first upper diagonal.

[2]Given a $T : \mathbb{T}_2$, we may also refer to $\pi_1(T), \pi_2(T)$ as $\texttt{root}(T)$ and $\texttt{children}(T)$ respectively.

4.6 Precomputing the parameterized Parikh map for a CFG

$\mathbb{T}_2$ is a convenient datatype for many operations involving CFGs. We can use it to approximate the Parikh image, compute the size of a finite CFG, and sample parse trees with or without replacement. For example, to obtain the Parikh map of a CFG (Def. 4.2), we may use the following recurrence,

$$\pi(T : \mathbb{T}_2) \mapsto \begin{cases} \left[[1,1] \text{ if } \texttt{root}(T) = s \text{ else } \varnothing\right]_{s\in\Sigma} & \text{if } T \text{ is a leaf,} \\ \bigoplus_{\langle T_1,T_2\rangle\in\texttt{children}(T)} \pi(T_1) \otimes \pi(T_2) & \text{otherwise.} \end{cases} \tag{7}$$

where the operations over Parikh maps $\oplus, \otimes : \Pi \times \Pi \longrightarrow \Pi$ are defined respectively as follows:

$$X \oplus Z \mapsto \left[[\min(X_s \cup Z_s), \max(X_s \cup Z_s)]\right]_{s\in\Sigma} \tag{8}$$

$$X \otimes Z \mapsto \left[[\min(X_s) + \min(Z_s), \max(X_s) + \max(Z_s)]\right]_{s\in\Sigma} \tag{9}$$

To obtain the parameterized Parikh map (PPM) of a length-bounded CFG, we abstractly parse the porous string and take the minimal cover of all intervals, which subsumes the Parikh image of every repair in the Levenshtein ball. Given a specific grammar, G, the following function can be evaluated and cached for all nonterminals $v : V$, and reasonable values of $m, n : \mathbb{N}$ for the sake of efficiency, then used to lookup the Levenshtein-Parikh-$\langle v, m, n\rangle$ map in constant time:

$$\pi(G : \mathcal{G}, v : V, m : \mathbb{N}, n : \mathbb{N}) : \Pi = \bigoplus_{i\in[m,n]} \pi\left(\Lambda^*(\{\_\}^i) \circ v\right) \tag{10}$$

By constructing the PPM for a grammar, G, we are effectively precomputing conditional upper and lower bounds on the Parikh image of any string generated by v whose length falls within a fixed interval – conditioned on that interval. Given a pair of FSA states $q, q' : Q$, let m and n be the greatest and least values, respectively, such that for all $\sigma \in \mathcal{L}(q \Longrightarrow q'), |\sigma| \in [m, n]$. To obtain the corresponding Parikh map for each $\langle q, v, q'\rangle$-triplet in $\hat{\bowtie}$, we can then directly lookup $\pi(G, v, m, n)$.

4.7 Sampling parse trees from $\mathbb{T}_2$ with and without replacement

One solution to decode repairs from $T : \mathbb{T}_2$ would be to treat it as a top-down generative model and perform some form of ancestral sampling. Constructing such a sampler for $\mathbb{T}_2$ is straightforward. Given a PCFG whose productions indexed by each nonterminal are decorated with a probability vector $\mathbf{p}$ (uniform in the non-probabilistic case), we define a tree sampler $\Gamma : (\mathbb{T}_2 \mid \mathbb{T}_2^2) \rightsquigarrow \mathbb{T}$ which recursively draws children according to a Multinoulli distribution:

$$\Gamma(T) \mapsto \begin{cases} \texttt{BTree}\Big(\texttt{root}(T), \Gamma\big(\text{Multi}(\texttt{children}(T), \mathbf{p})\big)\Big) & \text{if } T : \mathbb{T}_2 \\ \Big\langle \Gamma\big(\pi_1(T)\big), \Gamma\big(\pi_2(T)\big)\Big\rangle & \text{if } T : \mathbb{T}_2 \times \mathbb{T}_2 \end{cases} \tag{11}$$

This method is closely related to the generating function for the ordinary Boltzmann sampler,

$$\Gamma C(x) \mapsto \begin{cases} \text{Bern}\left(\frac{A(x)}{A(x)+B(x)}\right) \to \Gamma A(x) \mid \Gamma B(x) & \text{if } \mathcal{C} = \mathcal{A} + \mathcal{B} \\ \big\langle \Gamma A(x), \Gamma B(x)\big\rangle & \text{if } \mathcal{C} = \mathcal{A} \times \mathcal{B} \end{cases} \tag{12}$$

from analytic combinatorics, however unlike Duchon et al. [19], our work does not depend on rejection to guarantee exact-size sampling, as all trees from $\mathbb{T}_2 \cong \mathcal{G}'_\cap$ can be constrained to have the same size or fall within a small Levenshtein distance of each other.

However this approach, while plausible at first glance, is not a viable solution for decoding repairs, as it does not sample unique parse trees, nor guarantee uniformity over the set of all generable trees and converges extremely poorly to the language, failing to satisfy Def. 3.3.

To ameliorate this issue, we will instead define a replacement-free sampler based on an integer-tree bijection. To set up a proper bijection, we first need to compute the number of unique parse trees in the language represented by $T : \mathbb{T}_2$. This is a straightforward recurrence:

$$|T : \mathbb{T}_2| \mapsto \begin{cases} 1 & \text{if } T \text{ is a leaf,} \\ \sum_{\langle T_1, T_2 \rangle \in \texttt{children}(T)} |T_1| \cdot |T_2| & \text{otherwise.} \end{cases} \tag{13}$$

To sample all trees in a $T : \mathbb{T}_2$ uniformly without replacement, we precompute a histogram for each production, counting the size of its childrens' languages relative to the size of the root nonterminal's language, assign a commensurate integer range, and then construct a modular pairing function $\varphi : \mathbb{T}_2 \to \mathbb{Z}_{|T|} \to \texttt{BTree}$ that recursively selects values within each range:

$$\varphi(T : \mathbb{T}_2, i : \mathbb{Z}_{|T|}) \mapsto \begin{cases} \texttt{BTree}\big(\texttt{root}(T)\big) & \text{if } T \text{ is a leaf,} \\ \textbf{let } r = |\texttt{children}(T)|, & \\ \quad F(n) = \sum_{\langle l,r \rangle \in \texttt{children}[0 \ldots n]} |l| \cdot |r|, & \\ \quad F^{-1}(u) = \inf \big\{ x \mid u \le F(x) \big\}, & \\ \quad q = i - F\big(F^{-1}(i)\big), & \\ \quad l, r = \texttt{children}[t], & \\ \quad q_1, q_2 = \big\langle \lfloor \frac{q}{|r|} \rfloor, q \pmod{|r|} \big\rangle, & \\ \quad T_1, T_2 = \big\langle \varphi(l, q_1), \varphi(r, q_2) \big\rangle \textbf{ in} & \\ \texttt{BTree}\big(\texttt{root}(T), T_1, T_2\big) & \text{otherwise.} \end{cases} \tag{14}$$

Then, instead of top-down incremental sampling, we can create a randomized φ' from φ by sampling integers uniformly without replacement from $\mathbb{Z}_{|T|}$, then decode them into whole parse trees. Obtaining the concrete repair is then a simple matter of defoliating binary trees:

$$\mathscr{D}(t : \mathbb{T}) \mapsto \begin{cases} \texttt{root}(t) & \text{if } t \text{ is a leaf,} \\ \texttt{concatenate}(\texttt{left}(t), \texttt{right}(t)) & \text{otherwise.} \end{cases} \tag{15}$$

This procedure will converge to the language much more quickly than Eq. 11, as it never draws the same tree twice. Assuming the grammar is unambiguous, then letting $\boldsymbol{\varphi}(i) = \bigcup_{j \in [1,i]} \big\{ \mathscr{D}\big(\varphi'(T, j)\big) \big\}$ will satisfy Def. 3.3 by construction. Furthermore, this procedure is trivially parallelizable across an arbitrary number of processors, enabling communication-free sampling without replacement.

4.8 Scoring and reranking enumerated trees by likelihood

Returning to the ranked repair problem (Def. 3.2), the above procedure returns a set of syntactically consistent repairs, and we need an ordering over them. We note that any statistical distance metric is sufficient, such as the log-likelihood of the repair under a large language model. We compare two simple ranking methods: (1) the PCFG score and (2) the likelihood of a low-order Markov chain.

In the first method, we will use a reranking model based on PCFG log likelihood, which requires a treebank of parsed snippets in CNF and computes a log probability of each binary tree by the standard method, where $\alpha : V, \beta : V \mid V^2$ are amended nonterminals[3], and Score: $\mathbb{T} \to \mathbb{R}$ is defined:

$$\text{Score}(t : \mathbb{T}) \mapsto \begin{cases} 0 & \text{if } t \text{ is a leaf,} \\ -\ln \frac{\text{Count}(\alpha \to \beta)}{\sum_\gamma \text{Count}(\alpha \to \gamma)} + \text{Score}\big(\texttt{left}(t)\big) + \text{Score}\big(\texttt{right}(t)\big) & \text{otherwise.} \end{cases} \tag{16}$$

[3] n.b., To score trees from LBH grammars, we first strip off adjacent states from all synthetic nonterminals, i.e., $qvq' \equiv v$.

Finally, after enumerating distinct parse trees, we can simply rerank by PCFG score.

Algorithm 1 Enumerative tree sampling with PCFG reranking

Require: $T : \mathbb{T}_2$ intersection grammar, PCFG Score: $\mathbb{T} \to \mathbb{R}$

$\hat{A} \leftarrow \varnothing$, `seed` $\leftarrow 0$ ▷ Initialize set of parse trees.

for `seed` $< |T|$ and uninterrupted **do**

  $t \leftarrow \varphi'(T, \texttt{seed}\texttt{++})$ ▷ Draw unique $\mathbb{Z}_{|T|}$ and decode into fresh parse tree.

  $\hat{A} \leftarrow \hat{A} \cup \{t\}$

return $[\mathscr{D}(a) \mid a \in \hat{A}$ **ranked by** Score$(a)]$ ▷ Rerank by PCFG likelihood and defoliate.

This sampler is readily simple and fast, but gathering a treebank to calibrate the score function can be tedious. A more general method is to use a low-order Markov chain to rerank the repairs, which only requires a corpus of syntactically valid strings to estimate the Markov transition parameters.

Specifically, given a string $\sigma : \Sigma^*$, we factorize the probability $P_\theta(\sigma)$ as a product of conditionals $\prod_{i=1}^{|\sigma|} P_\theta(\sigma_i \mid \sigma_{i-1} \dots \sigma_{i-n})$, for some small $n \in \mathbb{N}$. To obtain the parameters θ, we use the standard maximum likelihood estimator for Markov chains. We approximate the joint distribution $P(\Sigma^n)$ directly from data, then the conditionals by normalizing n-gram counts with Laplace smoothing. Then, to score the repairs, we use the conventional length-normalized negative log likelihood:

$$\mathrm{NLL}(\sigma) = -\frac{1}{|\sigma|} \sum_{i=1}^{|\sigma|} \log P_\theta(\sigma_i \mid \sigma_{i-1} \dots \sigma_{i-n}) \tag{17}$$

Finally, for each retrieved set $\hat{A} \subseteq A$ drawn by the sampler before a predetermined timeout elapses and each $\sigma \in \hat{A}$, we score the repair and return $\hat{A}$ in ascending order.

Algorithm 2 Enumerative tree sampling with n-gram reranking

Require: $T : \mathbb{T}_2$ intersection grammar, $P_\theta : \Sigma^d \to \mathbb{R}$ Markov chain

$\hat{A} \leftarrow \varnothing$, `seed` $\leftarrow 0$ ▷ Initialize set of repairs.

for `seed` $< |T|$ and uninterrupted **do**

  $t \leftarrow \varphi'(T, \texttt{seed}\texttt{++})$ ▷ Draw unique $\mathbb{Z}_{|T|}$ and decode into fresh parse tree.

  $\hat{A} \leftarrow \hat{A} \cup \{\mathscr{D}(t)\}$

return $[a \in \hat{A}$ **ranked by** NLL$(a)]$ ▷ Rank by n-gram likelihood.

If $\hat{A} = A$ and the Markov chain is itself the language model being maximized, then this procedure satisfies Def. 3.2. Otherwise it is a heuristic, and the quality of the ranking will depend on the quality of $\hat{A}$, and how well the distribution P_θ approximates the true distribution of interest.

4.9 Decoding repairs in order of maximal likelihood using an FSA

The previous technique will enumerate parse trees in a given $\mathbb{T}_2$, but does not guarantee string uniqueness, as the same string may have more than one parse, i.e., the CFG may be ambiguous. While potentially insignificant, this becomes problematic for large finite CFLs and language intersections involving highly ambiguous CFGs. First, we make the following observation:

Lemma 4.7. *If the FSA, α, is ambiguous, then the intersection grammar, $G_\cap$, can be ambiguous.*

Proof. Let ℓ be the language defined by $G = \{S \to LR, L \to (, R \to)\}$, where $\alpha = L(\underset{\sim}{\sigma}, 2)$, the broken string $\underset{\sim}{\sigma}$ is `)(`, and $\mathcal{L}(G_\cap) = \ell \cap \mathcal{L}(\alpha)$. Then, $\mathcal{L}(G_\cap)$ contains the following two identical repairs: `)()` with the parse $S \to q_{00}Lq_{21}\ q_{21}Rq_{22}$, and `()` with the parse $S \to q_{00}Lq_{11}\ q_{11}Rq_{22}$. □

In practice, this means the tree sampler can produce multiple parse trees which represent the same string, impeding convergence. We can eliminate ambiguity and thereby improve the rate of convergence for natural syntax repair by translating $\mathbb{T}_2$ into a DFA, then sampling repair trajectories in order of decreasing string likelihood. To show this is possible, let us take note of the following:

Lemma 4.8. *The intersection grammar, $G_\cap$, is acyclic.*

Proof. Assume $G_\cap$ is cyclic. Then $\mathcal{L}(G_\cap)$ must be infinite. But since $G_\cap$ generates $\ell \cap \mathcal{L}(\alpha)$ by construction and α is acyclic, $\mathcal{L}(G_\cap)$ is necessarily finite. Therefor, $G_\cap$ must not be cyclic. □

Since $G_\cap$ is acyclic and thus finite, it must be representable as an FSA. Using an FSA for decoding has many advantages, notably, it can be efficiently minimized and sampling converges linearly regardless of syntactic ambiguity. It is also more readily steerable than a PCFG sampler, and can be decoded in order of n-gram likelihood using a standard pretrained autoregressive language model.

Constructively, let $+, * : \mathcal{A} \times \mathcal{A} \to \mathcal{A}$ be the automata operators corresponding to language union and concatenation satisfying $\mathcal{L}(A_1 + A_2) = \mathcal{L}(A_1) \cup \mathcal{L}(A_2)$, and $\mathcal{L}(A_1 * A_2) = \mathcal{L}(A_1) \times \mathcal{L}(A_2)$. This can be implemented using the standard textbook construction, recalling that FSAs are closed under these operations. We can translate the $\mathbb{T}_2$ ADT to an FSA, $\mathcal{A}$, as follows:

$$\mathcal{Y}(T : \mathbb{T}_2) \mapsto \begin{cases} \alpha \mid \mathcal{L}(\alpha) = \{T\} & T : \Sigma, \\ \sum_{\langle T_1, T_2 \rangle \in \texttt{children}(T)} \mathcal{Y}(T_1) * \mathcal{Y}(T_2) & T : VL\left(V^2 P(a)^2\right) \end{cases}$$

In the case of LBH intersection grammars, $\mathcal{Y}(G'_\cap)$ would then yield an NFA recognizing $\ell \cap L(\underset{\sim}{\sigma}, d)$, which can be determinized, minimized using Brzozowski's algorithm [11] and decoded using a k-best paths algorithm to obtain the top-k maximum likelihood repairs.

For example, let us return to the example given in § 2, where we have the syntactically invalid Python string, `v = df.iloc(5:, 2:)`. The CFG recognizing the language intersection can be translated into an equivalent DFA. After minimization, this will take the following form:

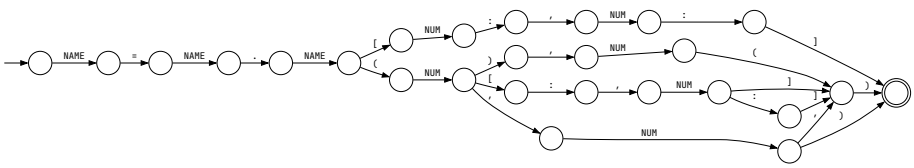


Fig. 6. Minimal DFA recognizing the langauge $L(\texttt{NAME = NAME . NAME (NUM : , NUM :)}, 2) \cap \ell_{\text{PYTHON}}$.

At the first bifurcation, we have a choice: assuming a 4-gram Markov chain, we estimate the probability of $P(\sigma_i \mid \sigma_{i-1..3} = \texttt{NAME . NAME})$ for $\sigma_i = \texttt{[}$ versus $\sigma_i = \texttt{(}$ by comparing the respective transition probabilities. At each subsequent junction, we clone the trajectory, estimate the likelihood of each branch, then greedily expand the most likely transition based on an ordering heuristic.

This procedure we call the steerable DFA walk (Alg. 3). It takes a DFA and a Markov chain, then samples trajectories through the DFA from the initial state to final states, in order of partial likelihood. During sampling, it maintains a priority queue of partial trajectories, ranked by length-normalized log likelihood, which are speculatively extended by the most likely available transition. A beam search and stochastic decoder is also feasible, however we omit them here for brevity.

Algorithm 3 Steerable DFA walk

Require: $\mathcal{A} = \langle Q, \Sigma, \delta, I, F\rangle$ DFA, $P_\theta : \Sigma^d \to \mathbb{R}$ Markov chain

$\mathcal{T} \leftarrow \varnothing, \mathcal{P} \leftarrow \left[\langle \varepsilon, i, 0\rangle \mid i \in I\right]$ ▷ Initialize priority queue of total and partial trajectories.
repeat
  let $\langle \sigma, q, \gamma\rangle = \texttt{head}(\mathcal{P})$ **in**
    $\mathbf{T} = \left\{\langle s\sigma, q', \gamma - \log P_\theta(s \mid \sigma_{1..d-1})\rangle \mid (q \xrightarrow{s} q') \in \delta\right\}$ ▷ Extend partial trajectories.
  for $\langle \sigma, q, \gamma\rangle = T \in \mathbf{T}$ **do**
    if $\exists s : \Sigma, q' : Q \mid (q \xrightarrow{s} q') \in \delta$ **then**
      $\mathcal{P} \leftarrow \texttt{tail}(\mathcal{P}) \oplus T$ ▷ Add partial trajectory to priority queue.
    if $q \in F$ **then**
      $\mathcal{T} \leftarrow \mathcal{T} \oplus T$ ▷ Accepting state reached, add trajectory into total queue.
until interrupted or $\mathcal{P} = \varnothing$.
return $\left[\sigma_{|\sigma|..1} \mid \langle \sigma, q, \gamma\rangle = T \in \mathcal{T}\right]$ ▷ Reverse string and return in order of likelihood.

Regardless of grammatical ambiguity, this procedure satisfies Def. 3.3 and Def. 3.2 simultaneously, as each repair will be unique and all repairs will be sorted in order of decreasing likelihood.

5 EVALUATION

We call our method Tidyparse and consider the following research questions:

- **RQ 1**: What statistical properties do human repairs exhibit? (e.g., length, edit distance)
- **RQ 2**: How performant is Tidyparse at fixing syntax errors? (i.e., vs. Seq2Parse and BIFI)
- **RQ 3**: Which design choices are most significant? (e.g., sampling, decoding, parallelism)

We address **RQ 1** in § 5.2 by analyzing the distribution of natural code snippet lengths and edit distances, **RQ 2** in § 5.3 by comparing Tidyparse against two existing syntax repair baselines, and **RQ 3** in § 5.4 by ablating various design choices and evaluating the impact on repair precision.

5.1 Experimental setup

We use syntax errors and fixes from the Python language to validate our approach. Python source code fragments are abstracted as a sequence of lexical tokens using the official Python lexer, erasing numbers and identifiers, but retaining all other keywords. Accuracy is evaluated across a test set by checking for lexical equivalence with the ground-truth repair, following Sakkas et al. (2022) [41].

To evaluate accuracy, we use the Precision@k statistic, which measures the frequency of repairs in the top-k results matching the true repair. Specifically, given a repair model, $R : \Sigma^* \to 2^{\Sigma^*}$ and a test set $\mathcal{D}_{\text{test}}$ of pairwise aligned errors ($\sigma^\dagger$) and fixes (σ'), we define Precision@k as:

$$\text{Precision@k}(R) = \frac{1}{|\mathcal{D}_{\text{test}}|} \sum_{\langle \sigma^\dagger, \sigma'\rangle \in \mathcal{D}_{\text{test}}} \mathbb{1}\left[\sigma' \in \underset{\boldsymbol{\sigma} \subseteq R(\sigma^\dagger), |\boldsymbol{\sigma}| \le k}{\operatorname{argmax}} \sum_{\sigma \in \boldsymbol{\sigma}} \text{Score}(\sigma)\right] \tag{19}$$

This is a variation on a standard metric used in information retrieval, and a common way of measuring the quality of ranked results in machine translation and recommender systems. Precision@All or completeness may be seen as a special case where $k = \infty$.

By default, Tidyparse uses the DFA decoder (Alg. 3) for all experiments, however, we also include a comparison of a naive rejection-based edit sampler, as well as enumerative sampling with PCFG reranking (Alg. 1) and n-gram reranking (Alg. 2) in our ablation study (§ 5.4).

We compare our method against two external baselines, Seq2Parse and Break-It-Fix-It (BIFI) [48] on a single test set. This dataset [47] consists of 20k naturally-occurring pairs of Python errors and their corresponding human fixes from StackOverflow, and is used to compare the precision of

each method at blind recovery of the ground truth repair across varying edit distances, snippet lengths and latency cutoffs. We preprocess all source code by filtering for broken-fixed snippet pairs shorter than 80 tokens and fewer than five Levenshtein edits apart, whose broken and fixed form is accepted and rejected, respectively, by the Python 3.8.11 parser. We then balance the dataset by sampling an equal number of repairs from each length and Levenshtein edit distance.

The Seq2Parse and BIFI experiments were conducted on a single Nvidia V100 GPU with 32 GB of RAM. For Seq2Parse, we use the default pretrained model provided in commit `7ae0681` [4]. Since it was unclear how to extract multiple repairs from their model, we only take a single repair prediction. For BIFI, we use the Round 2 breaker and fixer from commit `ee2a68c`[5], the highest-performing model reported by the authors, with a variable-width beam search to control the number of predictions, and let the BIFI fixer model predict the top-k repairs, for $k = \{1, 5, 10, 2 \times 10^4\}$.

The language intersection experiments were conducted on 40 Intel Skylake cores running at 2.4 GHz, with 150 GB of RAM, executing bytecode compiled for JVM 17.0.2. To train our scoring function, we use an order-5 Markov chain trained on 55 million BIFI tokens. Training takes roughly 10 minutes, after which re-ranking is nearly instantaneous. Sequences are scored using NLL with Laplace smoothing and our evaluation measures the Precision@{1, 5, 10, All} for varying latency cutoffs up to 90s, although it often exhausts the search space and halts before timeout.

5.2 Dataset

In the following experiments, we use a dataset of Python snippets consisting of 20,500 pairwise-aligned human errors and fixes from StackOverflow [47]. We preprocess the dataset to lexicalize all code snippets, then filter by length and distance shorter than 80 lexical tokens and under five edits, i.e., where pairwise Levenshtein distance is under five lexical edits ($|\Sigma| = 50, |\sigma| < 80, \Delta(\sigma, \sigma') < 5$). We depict the length, edit distance, normalized edit locations and stability profile in Fig. 7.

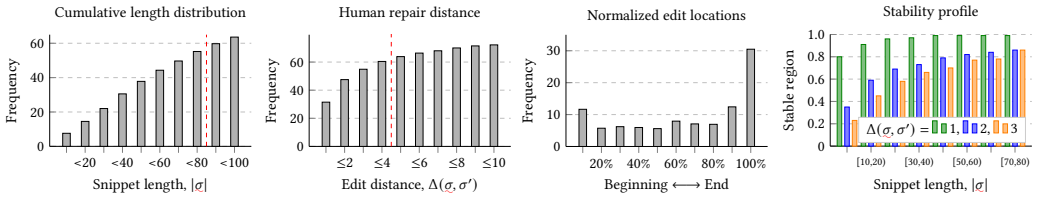


Fig. 7. Repair statistics across the StackOverflow dataset, of which Tidyparse can handle about half in under ~30s and ~150 GB. Larger repairs and edit distances are possible, albeit requiring additional time and memory.

We observe that slightly over half of the code snippet pairs in the StackOverflow dataset contain fewer than 80 tokens and five lexical edits, which our method can easily handle (§ 5.3). The distribution across edit locations indicates a large fraction of human edits occur near the boundaries of the broken code snippet, however we do not exploit this prior anywhere in the repair process.

For the stability profile, we enumerate repairs for each syntax error and estimate the average fraction of all edit locations that were never altered by any repair in the $L\big(\sigma, \Delta(\sigma, \sigma')\big)$-ball. For example, on average roughly half of the string is stable for 3-edit syntax repairs in the $[10 - 20)$ token range, whereas 1-edit repairs of the same length could modify only ~ 10% of all locations. For a fixed edit distance, we observe an overall decrease in the number of degrees of caret freedom with increasing length, which intuitively makes sense, as the repairs are more heavily constrained by the surrounding context and their locations grow more concentrated relative to the entire string.

[4] https://github.com/gsakkas/seq2parse/tree/7ae0681f1139cb873868727f035c1b7a369c3eb9
[5] https://github.com/michiyasunaga/BIFI/tree/ee2a68cff8dbe88d2a2b2b5feabc7311d5f8338b

5.3 StackOverflow evaluation

For our first experiment, we measure the precision of our repair procedure at various lengths and Levenshtein distances. We rebalance the StackOverflow dataset across each length interval and edit distance, sample uniformly from each category and compare Precision@1 of our method against Seq2Parse, vanilla BIFI and BIFI with a beam size and precision at 2×10^4 distinct samples.

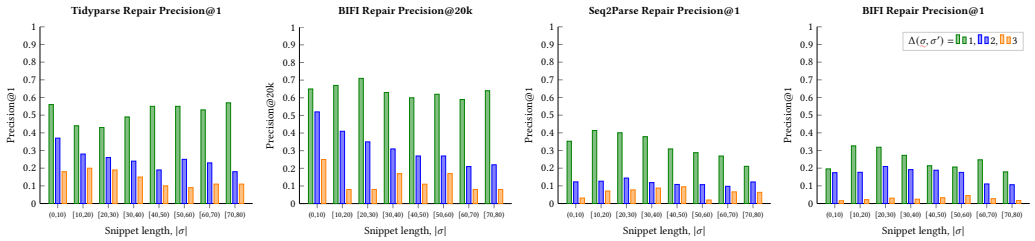


Fig. 8. Tidyparse, Seq2Parse and BIFI repair precision at various lengths and Levenshtein distances.

As we can see, Tidyparse has a highly competitive top-1 precision versus Seq2Parse and BIFI across all lengths and edit distances, and attains a significant advantage in the few-edit regime. The Precision@1 of our method is even competitive with BIFI's Precision@20k, whereas our Precision@All is Pareto-dominant across all lengths and edit distances, while requiring only a fraction of the data and compute. We report the raw data from these experiments in Appendix B.

Next, we measure the precision at various ranking cutoffs and wall-clock timeouts. Our method attains the same precision as Seq2Parse and BIFI for 1-edit repairs at comparable latency, however Tidyparse takes longer to attain the same precision for 2- and 3-edit repairs. BIFI and Seq2Parse both have subsecond single-shot latency but are neural models trained on a much larger dataset.

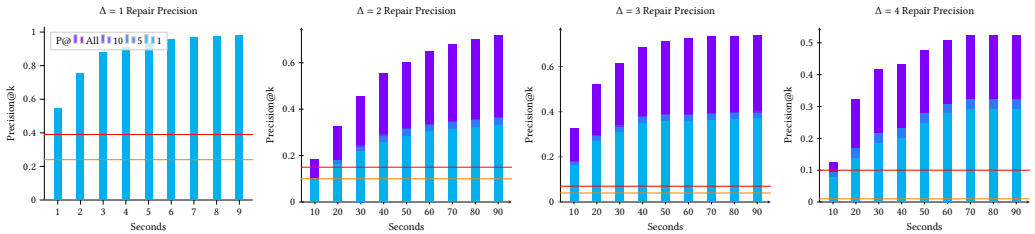


Fig. 9. Human repair benchmarks. Note the y-axis across different edit distance plots has varying ranges. The red line indicates Seq2Parse and the orange line indicates BIFI's Precision@1 on the same repairs.

We present a Sankey diagram of our repair pipeline in Fig. 10. We drew 2247 total repairs from the StackOverflow dataset balanced evenly across lengths and edit distances ($\lfloor |\sigma|/10 \rfloor \in [0, 8], \Delta(\sigma, \sigma') < 4$) with a timeout of 30s and tracked individual outcomes. In 101 cases, the intersection grammar was too large to construct and threw an out-of-memory (OOM) error, in 45 cases the human repair was not recognized, in 253 cases the sampler timed out before drawing the human repair, in 1226 cases the human repair was drawn but not ranked first, and in the remaining 622 cases the first prediction matched the human repair.

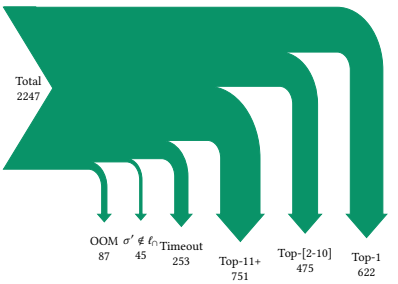


Fig. 10. Outcomes in the repair pipeline.

The remaining experiments in this section were run on a 10-core ARM64 M1 with 16 GB of memory. We balance the StackOverflow dataset across Levenshtein distances, then measure the number of samples required to draw the exact human repair across varying Levenshtein radii. This tells us of how many samples are required on average to saturate the admissible set.

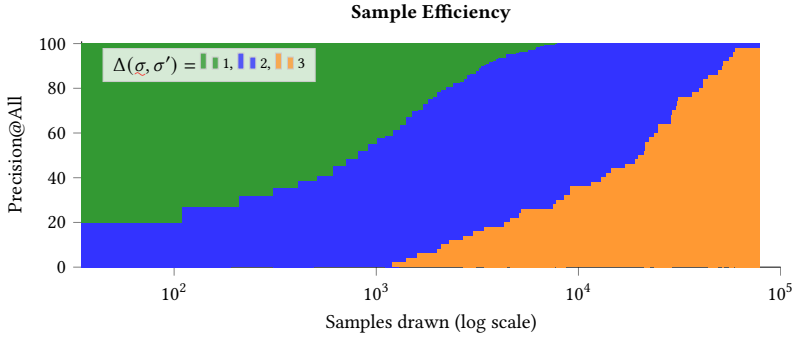


Fig. 11. Sample efficiency of Tidyparse at varying Levenshtein radii. After drawing up to $\sim 10^5$ samples without replacement we can usually retrieve the human repair for almost all repairs fewer than four edits.

End-to-end throughput varies significantly with the edit distance of the repair. Some errors are trivial to fix, while others require a large number of edits to be sampled before the ground truth is discovered. We evaluate throughput by sampling patches across invalid strings $|\sigma| \leq 40$ from the StackOverflow dataset balanced across length and distance, and measure the total number of unique valid patches discovered, as a function of string length and edit distance $\Delta \in [1, 4]$. Each trial is terminated after 10 seconds, and the experiment is repeated across 7.3k total repairs. Note the y-axis is log-scaled, as the number of admissible repairs increases sharply with edit distance. Our approach discovers a large number of syntactic repairs in a relatively short amount of time, and is able to quickly saturate the admissible set for $\Delta(\sigma, \sigma') \in [1, 4]$ before timeout.

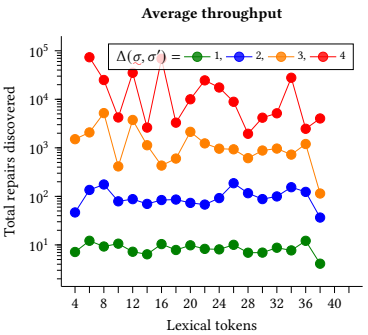


Fig. 12. Distinct repairs found in 30s.

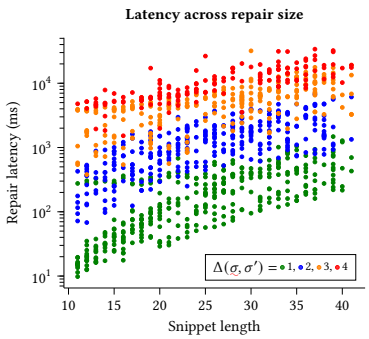


Fig. 13. End-to-end repair timings.

In Fig. 13, we plot the end-to-end repair timings by collecting 1000 samples balanced across length and edit distance, then measure the wallclock time until the sampler retrieves the human repair and report the log latency. While short repairs finish quickly, latency is positively correlated with length and edit distance. Our method is typically able to saturate the admissible set for 1- and 2-edit repairs before timeout, while 4+-edit throughput starts becoming constrained by compute around 30s, when Python's admissible set approaches a volume of 10^5 valid edits. This bottleneck can be relaxed with a longer timeout or additional CPU cores. We anticipate that a much longer delay will begin to tax the patience of most users, and so we consider 30s a reasonable upper bound for repair latency. As we will now show, end-to-end latency can be improved by doing rejection sampling, albeit at the cost of naturalness and sample efficiency.

5.4 Subcomponent ablation

Originally, we used an adaptive rejection-based sampler, which did not sample directly from the admissible set, but the entire Levenshtein ball, and then rejected invalid samples. Although rejection sampling has a much lower minimum latency threshold to return admissible repairs, i.e., a few seconds at most, the average time required to attain a desired precision on human repairs is much higher. We present the results from the rejection-based evaluation for comparison below.

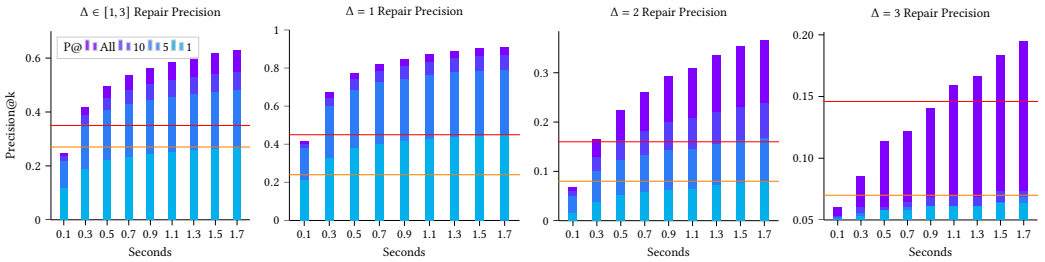
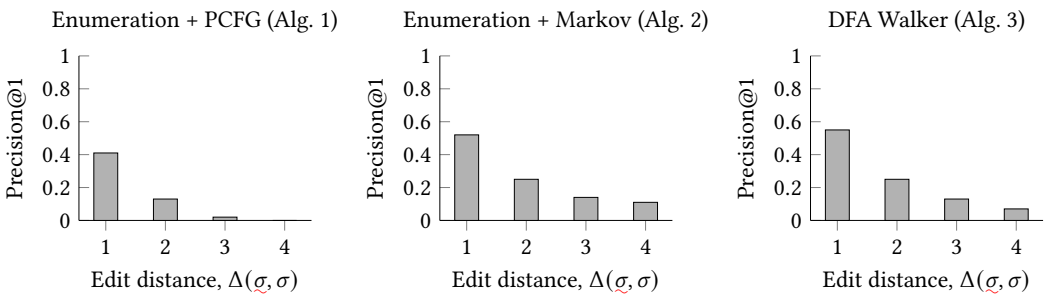


Fig. 14. Adaptive sampling repairs. The red line indicates Seq2Parse Precision@1, and the orange indicates BIFI's precision at single-shot repair, all three of which were evaluated on the exact same repairs.

We also evaluate Seq2Parse on the same dataset. Seq2Parse only supports Precision@1 repairs, and so we only report Seq2parse Precision@1 from the StackOverflow benchmark for comparison. Unlike our approach, which only produces syntactically correct repairs, Seq2Parse and BIFI also produce syntactically incorrect repairs in practice. The overall latency of Seq2Parse varies depending on the length of the repair, averaging 1.5s for $\Delta = 1$ to 2.7s for $\Delta = 3$, across the entire StackOverflow dataset, while BIFI consistently achieves subsecond latency across all repairs and distances.

Next, we conduct an ablation study across three decoding strategies to compare their relative effectiveness. In each experiment, we balance the StackOverflow dataset across edit distances and run the candidate sampler for up to 30 seconds. In Alg. 1, we use the enumerative sampler and rank all repairs by either PCFG score, in Alg. 2, we use the same approach but rank the repairs by n-gram log-likelihood, and in Alg. 3, we translate the BH intersection grammar into a DFA then sample trajectories according to a n-gram transition probability, as described in § 4.9. We compare the Precision@1 of each method at recovering the ground truth human repair.



In general, n-gram likelihood appears to have a significant advantage over PCFG scoring, however this margin may decrease with PCFG models that consider higher-order nonterminal dependencies. Alg. 1 is efficient, but also the least precise, being a poor model for lexical alignment. Alg. 2 offers competitive precision for Python, but can produce duplicate samples in highly ambiguous

CFGs. Alg. 2 has the best performance across all edit distances and langauges, but is also the most computationally expensive, requiring a determinization and minimization preprocessing step.

Finally, we evaluate the impact of increased parallelism on repair throughput. We balance the StackOverflow dataset across edit distances and run DFA sampler for up to 30 seconds, then measure the total number of unique valid repairs discovered as a function of the number of additional CPU cores assigned, which we exercise to both construct the intersection grammar and sample from it.

We measure the relative improvement in throughput (measured by the number of distinct repairs found after 30s) as a function of the number of additional CPU cores, averaged across 1000 trials. We observe from Fig.15 the relative throughput increases logarithmically with the number of additional CPU cores, with at least four CPU cores needed to offset the parallelization overhead. Generally, increasing parallelism only helps when the size of the admissible set is large enough to absorb the additional computation, which is seldom the case for small-radii Levenshtein balls. Further speedups are likely possible to realize by rewriting the sampler in CUDA, an engineering challenge which we leave for future work.

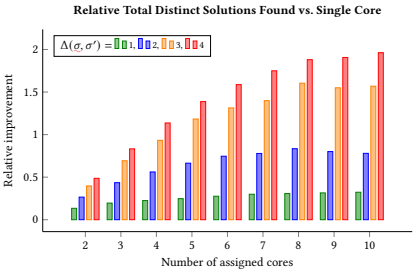


Fig. 15. Observed improvement in throughput relative to total CPU cores assigned.

6 DISCUSSION

The main lesson we draw from our experiments is that it is possible to leverage compute to compete with large language models on practical program repair tasks. Though sample-efficient, their size comes at the cost of expensive training, and domain adaptation requires fine-tuning or retraining on pairwise repairs. Our approach uses a small grammar and a relatively cheap ranking metric to achieve significantly higher precision. This allows us to repair errors in languages with little to no training data and provides far more flexibility and controllability during the repair process.

Our primary insight leading to state-of-the-art precision is that repairs are typically concentrated near the center of a small Levenshtein ball, and by enumerating or sampling it carefully, then reranking retrieved repairs can achieve a significant improvement over one-shot neural repair. This is especially true for small-radii Levenshtein balls, where the admissible set is small enough to be completely enumerated and ranked. For larger radii, we can still achieve competitive precision by using an efficient decoding mechanism to sample the admissible set and rank it by likelihood.

There is a clear tradeoff between latency and precision for any repair model. While existing neural syntax repair models scale poorly with additional time, Tidyparse is highly effective at exchanging more time for higher precision. We find that the Precision@1 of our method is competitive with BIFI's Precision@20k, while requiring only a fraction of the data and compute for training and inference. As Tidyparse uses its own grammar, it can sample directly from the formal language specification and does not require a stochastic language model to suggest nearby valid repairs, only to rank them by naturalness. The emphasis on completeness is especially useful for discovering small or contextually unlikely repairs, which may be overlooked by neural models.

Although latency and precision are ultimately the deciding usability factors, repair throughput is a crucial intermediate factor to consider when evaluating the performance of a repair system. Even with a perfectly accurate scoring function, if the correct repair is never retrieved, it will be for naught. By maximizing the total number of unique valid repairs, we increase the likelihood of retrieving natural repairs to give the scoring function the best chance of ranking them successfully. For this reason, we prioritize throughput heavily in our design (Def. 3.3) and evaluation (Fig. 12).

6.1 Limitations and future work

6.1.1 Naturalness. Firstly, Tidyparse does not currently support intersections between weighted CFGs and weighted finite automata, a la Pasti et al. [39]. This feature would allow us to put transition probabilities on the Levenshtein automaton corresponding to edit likelihood then construct a weighted intersection grammar. With this, one could preemptively discard unlikely productions from $G_\cap$ to reduce the complexity in exchange for relaxing completeness. We also hope to explore more incremental sampling strategies such as sequential Monte-Carlo [33].

The scoring function is currently computed over lexical tokens. We expect that a more precise scoring function could be constructed by splicing candidate repairs back into the original source code and then scoring plaintext, however this would require special handling for insertions and substitutions of names, numbers and identifiers that were absent from the original source code. For this reason, we currently perform the scoring in lexical space, which discards a useful signal, but even this coarse approximation is sufficient to achieve state-of-the-art precision.

Furthermore, the scoring function only considers each candidate repair $P_\theta(\sigma')$ in isolation, returning the most plausible candidate independent of the original error. One way to improve this would be to incorporate the broken sequence ($\underset{\sim}{\sigma}$), parser error message (m), original source (s), and possibly other contextual priors to inform the scoring function. This would require a more expressive probabilistic language model to faithfully model the joint distribution $P_\theta(\sigma' \mid \underset{\sim}{\sigma}, m, s, \ldots)$, but would significantly improve the precision of the generated repairs.

6.1.2 Complexity. Latency can vary depending on several factors including string length, grammar size, and critically the Levenshtein edit distance. This can be an advantage because, in the absence of any contextual or statistical information, syntax and minimal Levenshtein edits are often sufficiently constrained to identify a small number of valid repairs. It is also a limitation, because the admissible set expands rapidly with edit distance and the Levenshtein metric diminishes in usefulness without a very precise metric to discriminate natural solutions in the cosmos of equidistant repairs.

Space complexity increases sharply with edit distance and to a lesser extent with length. This can be partly alleviated with more precise criteria to avoid creating superfluous productions, but the memory overhead is still considerable. Memory pressure can be attributed to engineering factors such as the grammar encoding, but is also an inherent challenge of grammar intersection. Therefor, managing the size of the intersection grammar by preprocessing the syntax and automaton, then eliminating unnecessary synthetic productions is a critical factor in scaling up our technique.

6.1.3 Toolchain integration. Lastly and perhaps most significantly, Tidyparse does not incorporate semantic constraints, so its repairs whilst syntactically admissible, are not guaranteed to be type safe. It may be possible to add a type-based semantic refinement to our language intersection, however this would require a more expressive grammatical formalism than CFGs naturally provide.

Program slicing is an important preprocessing consideration which has so far gone unmentioned. The current implementation expects pre-sliced code fragments, however in a more practical scenario, it would be necessary to leverage editor information to identify the boundaries of the repairable fragment. This could be achieved by analyzing historical editor states or via ad hoc slicing techniques.

Additionally, the generated repairs must be spliced back into the surrounding context, which requires careful editor integration. One approach would be to filter all repairs through an incremental compiler or linter, however, the latency necessary to check every repair may be non-negligible.

We envision a few primary use cases for Tidyparse: (1) helping novice programmers become more quickly familiar with a new programming language, (2) autocorrecting common typos among proficient but forgetful programmers, (3) as a prototyping tool for PL designers and educators, and (4) as a pluggable library or service for parser-generators and language servers.

7 RELATED WORK

Three important questions arise when repairing syntax errors: (1) is the program broken in the first place? (2) if so, where are the errors located? (3) how should those locations then be altered? Those questions are addressed by three theoretical areas, (1) parsing, (2) language equations and (3) syntax repair. We survey each of those areas, then turn our attention to more engineering-oriented research, including (4) string solving, (5) error-correction, (6) decoding and finally (7) neural program repair.

7.1 Parsing

Context-free language (CFL) parsing is the well-studied problem of how to turn a string into a unique tree, with many different algorithms and implementations (e.g., shift-reduce, recursive-descent, LR). Many of those algorithms expect grammars to be expressed in a certain form (e.g., left- or right- recursive) or are optimized for a narrow class of grammars (e.g., regular, linear).

General CFL parsing allows ambiguity (non-unique trees) and can be formulated as a dynamic programming problem, as shown by Cocke-Younger-Kasami (CYK) [40], Earley [20] and others. These parsers have roughly cubic complexity with respect to the length of the input string.

As shown by Valiant [46], Lee [31] and others, general CFL recognition is in some sense equivalent to binary matrix multiplication, another well-studied combinatorial problem with broad applications, known to be at worst subcubic. This reduction opens the door to a range of complexity-theoretic speedups to CFL recognition, however large constants tend to limit their practical utility.

From a more applied perspective, parsers are ubiquituous in present-day software engineering, but none are designed to handle arbitrary CFGs or recover from arbitrary errors. Parr and Quong introduce ANTLR [38] which can handle LL(k) grammars and offers an IDE plugin with limited support for error recovery. Scott and Johnstone [43] introduce GLL parsing, which supports linear-time parsing for LL grammars and cubic for arbitrary CFGs, but does not support error correction. Inspired by their work, we introduce a method for repairing small syntax errors in arbitrary CFLs.

7.2 Language equations

Language equations are a powerful tool for reasoning about formal languages and their inhabitants. First proposed by Ginsburg et al. [24] for the ALGOL language, language equations are essentially systems of inequalities with variables representing *holes*, i.e., unknown values, in the language or grammar. Solutions to these equations can be obtained using various fixpoint techniques, yielding members of the language. This insight reveals the true algebraic nature of CFLs and their cousins.

Being an algebraic formalism, language equations naturally give rise to a kind of calculus, vaguely reminiscent of Leibniz' and Newton's. First studied by Brzozowski [11, 12] and Antimirov [4], one can take the derivative of a language equation, which can be interpreted as a kind of continuation or language quotient, revealing the suffixes that complete a given prefix. This technique leads to an elegant family of algorithms for incremental parsing [1, 35] and automata minimization [10].

Bar-Hillel [5] establishes the closure of CFLs under intersection with regular languages, but does not elaborate on how to construct the corresponding grammar in order to recognize it. Beigel [8] and Pasti et al. [39] provide helpful insights into the construction of the intersection grammar, and Nederhof and Satta [36] specifically consider finite CFL intersections, but neither considers Levenshtein intersections. Our work specializes Bar-Hillel intersections to Levenshtein automata in particular, and more generally acyclic automata using a refinement of Beigel's construction.

More concretely, we restrict our attention to language equations over CFLs whose variables coincide with edit locations in the source code of a computer program, and solutions correspond to syntax repairs. While prior work has studied the use of language equations for parsing [35], to our knowledge they were never specifically applied to code completion or syntax error correction.

7.3 Syntax repair

In finite languages, syntax repair corresponds to spelling correction, a more restrictive and largely solved problem. Schulz and Stoyan [42] construct a finite automaton that returns the nearest dictionary entry by Levenshtein edit distance. Though considerably simpler than syntax correction, their work shares similar challenges and offers insights for handling more general repair scenarios.

When a sentence is grammatically invalid, parsing grows more challenging. Like spelling, the problem is to find the minimum number of edits required to transform an arbitrary string into a syntactically valid one, where validity is defined as containment in a (typically) context-free language. Early work, including Irons [29] and Aho [2] propose a dynamic programming algorithm to compute the minimum number of edits required to fix an invalid string. Prior work on error correcting parsing only considers the shortest edit(s), and does not study multiple edits over the Levenshtein ball. Furthermore, the problem of actually generating the repairs is not well-posed, as there are usually many valid strings that can be obtained within a given number of edits. We instead focus on bounded Levenshtein reachability, which is the problem of finding useful repairs within a fixed Levenshtein distance of the broken string, which requires language intersection.

7.4 String solving

There is related work on string constraints in the constraint programing literature, featuring solvers like CFGAnalyzer and HAMPI [30], which consider bounded context free grammars and intersections thereof. Bojańczyk et al. (2014) [9] introduce the theory of nominal automata. Around the same time, D'Antoni et al. (2014) introduce *symbolic automata* [16], a generalization of finite automata which allow infinite alphabets and symbolic expressions over them. Hague et al. (2024) [26] use Parikh's theorem in the context of symbolic automata to speed up string constraint solving, from which we draw partial inspiration for the Levenshtein-Bar-Hillel construction in § 4.3. In none of the constraint programming literature we surveyed do any of the approaches specifically consider the problem of syntax error correction, which is the main focus of our work.

7.5 Error correcting codes

Our work focuses on errors arising from human factors in computer programming, in particular *syntax error correction*, which is the problem of fixing partially corrupted programs. Modern research on error correction, however, can be traced back to the early days of coding theory when researchers designed *error-correcting codes* (ECCs) to denoise transmission errors induced by external interference, e.g., collision with a high-energy proton, manipulation by an adversary or even typographical mistake. In this context, *code* can be any logical representation for communicating information between two parties (such as a human and a computer), and an ECC is a carefully-designed scheme which ensures that even if some portion of the message should become corrupted, one can still recover the original message by solving a linear system of equations. When designing ECCs, one typically assumes a noise model over a certain sample space, such as the Hamming [17, 45] or Levenshtein [6, 7, 32] balls, from which we draw inspiration for this work.

7.6 Decoding

Decoding is a key problem in machine translation, speech recognition, and other sequence-to-sequence tasks. Given a compressed encoding of some finite distribution, its goal is find the maximum likelihood samples. A classic example is Viterbi decoding, which is used to find the most likely sequence of hidden states in a hidden Markov model and is closely related to the CYK algorithm for parsing. For PCFGs, the problem is more challenging, as the solution space can be exponentially larger relative to the number of transitions.

In particular, we care about the problem of *top-k decoding*, which attempts to find the exact or approximate k-most likely samples in order of decreasing likelihood. This is closely related to the k-best enumeration [21] problem, a carefully studied problem in graph theory and combinatorial optimization. An exact solution to this problem for large acyclic PCFGs is often intractable, but we can approximate it using a beam search or cube-pruning technique.

A popular solution to k-best decoding in the NLP literature is a technique called cube-pruning [13, 27, 28], which samples maximum likelihood paths through a hypergraph. We take inspiration from this technique, and adapt it to the setting of constrained decoding from finite CFGs. Our approach is also complementary to work by Zhang and McDonald [49], but specialized to language intersections.

An alternate approach would be to use MCMC or sequential Monte Carlo method to steer a transformer-based large langauge model (LLM), as proposed by Lew et al. [33]. This technique is particularly useful for constrained sampling from LLMs, and could be adapted to our setting to improve sample efficiency. The downside is that it introduces a dependency on an LLM, which requires a very large dataset to train and is more computationally expensive than cube-pruning. Furthermore, distinct sampling is unclear how to do properly, as LLMs are not trained to generate unique samples, and sampling without replacement is a fundamentally non-Markovian process. One potential solution proposed by Shi and Bieber [44] assumes trace injectivity and constructs a trie, however their solution is not stateless and can introduce a significant latency overhead.

Our approach is complementary to existing work in constrained decoding. The bijection proposed in Eq. 14 guarantees that all repairs are well-formed and converge linearly to the exact top-k maximum likelihood samples. This method is completely stateless and can be used to enumerate a bounded Levenshtein ball with linear parallelization speedup. Alternately, in the case of approximate ranked repair over a very large sample space, this technique can be adapted to sample with high probability a representative subset of the most likely sentences in a finite but large PCFG.

7.7 Neural program repair

More recently, probabilistic repair techniques have been introduced using neural models to predict the most likely correction [3, 15, 18]. These approaches typically employ large language models (LLMs) and treat the problem as a sequence-to-sequence transformation. While capable of generating natural repairs, these models are suceptible to misgeneralization, costly to train, and challenging to customize thereafter. Furthermore, the generated repairs are not necessarily sound without additional filtering, and we observe the released models often hallucinate false positive repairs.

In particular, two papers stand out being closely related to our own: Break-It-Fix-It (BIFI) [48] and Seq2Parse [41]. BIFI adapts techniques from semi-supervised learning to generate synthetic errors in clean code and fixes them. This reduces the amount of pairwise training data, but tends to generalize poorly to lengthy or out-of-distribution repairs. Seq2Parse combines a transformer-based model with an augmented version of the Early parser to suggest error rules, but only suggests a single repair. Our work differs from both in that we suggest multiple repairs at much higher precision, do not require a pairwise repair dataset, and can fix syntax errors in any language with a well-defined grammar. We note our approach is complementary to existing work in neural program repair, and may be used to generate synthetic repairs for training or employ an LLM for ranking.

Recent work by Merrill et al. [34] and Chiang et al. [14] suggest that the issue with generalization may be more foundational: transformer-based language models, a popular class of neural language models used in probabilistic program repair, are fundamentally less expressive than context-free grammars, which formally describe the syntax of most programming languages. This suggests such models, despite their useful approximation properties, are ill-suited for the task of end-to-end syntax repair. Yet, they may still be useful for resolving ambiguity between valid repairs of differing likelihood or searching a large sample space for the most likely repair.

8 CONCLUSION

Our work, while a case study on syntax repair, is part of a broader line of inquiry in program synthesis that investigates how to weave formal language theory and machine learning into helpful programming tools for everyday developers. In some ways, syntax repair serves as a test bench for integrating learning and language theory, as it lacks the intricacies of type-checking and semantic analysis, but is still rich enough to be an interesting challenge. By starting with syntax repair, we hope to lay the foundation for more organic hybrid approaches to program synthesis.

Two high level codesign patterns have emerged to combine the naturalness of neural language models with the precision of formal methods. One seeks to filter the outputs of a generative language model to satisfy a formal specification, typically by some form of rejection sampling. Alternatively, some attempt to use language models to steer an incremental search for valid programs via a reinforcement learning or hybrid neurosymbolic approach. However, implementing these strategies is often painstaking and their generalization behavior can be difficult to analyze.

In our work, we take a more pragmatic tack - by incorporating the distance metric into a formal language, we attempt to exhaustively enumerate repairs by increasing distance, then use the stochastic language model to sort the resulting solutions by naturalness. The more constraints we can incorporate into formal language, the more efficient sampling becomes, and the more precise control we have over the output. This reduces the need for training a large, expensive language model to relearn syntax, and allows us to leverage compute for more efficient search and ranking.

There is a delicate balance in formal methods between soundness and completeness. Often these two seem at odds because the target language is too expressive to achieve them both simultaneously. In syntax repair, we also care about *naturalness*. Fortunately, syntax repair is tractable enough to achieve all three by modeling the problem using language intersection. Completeness helps us to avoid missing simple repairs that might be easily overlooked, soundness guarantees all repairs will be valid, and naturalness ensures the most likely repairs receive the highest priority.

From a usability standpoint, syntax repair tools should be as user-friendly and widely accessible as autocorrection tools in word processors. We argue it is possible to reduce disruption from manual syntax repair and improve the efficiency of working programmers by driving down the latency needed to synthesize an acceptable repair. In contrast with program synthesizers that require intermediate editor states to be well-formed, our synthesizer does not impose any constraints on the code itself being written and is possible to use in an interactive programming setting.

We have implemented our approach and demonstrated its viability as a tool for syntax assistance in real-world programming languages. Tidyparse is capable of generating repairs for invalid source code in a range of practical languages with little to no data required. We plan to continue expanding the prototype's autocorrection functionality to cover a broader range of languages and hope to conduct a more thorough user study to validate its effectiveness in practical programming scenarios.

DATA-AVAILABILITY STATEMENT

An artifact for Tidyparse is currently available as a browser application. [6] While the browser demo is single-threaded and does not support ranking synthetic repairs by naturalness, it is capable of automatically repairing syntax errors in arbitrary context-free languages. The data and source code for the experiments contained in this paper will be made available upon publication.

[6] https://tidyparse.github.io

REFERENCES

[1] Michael D Adams, Celeste Hollenbeck, and Matthew Might. 2016. On the complexity and performance of parsing with derivatives. In Proceedings of the 37th ACM SIGPLAN Conference on Programming Language Design and Implementation. 224–236.

[2] Alfred V Aho and Thomas G Peterson. 1972. A minimum distance error-correcting parser for context-free languages. SIAM J. Comput. 1, 4 (1972), 305–312.

[3] Miltiadis Allamanis, Henry Jackson-Flux, and Marc Brockschmidt. 2021. Self-supervised bug detection and repair. Advances in Neural Information Processing Systems 34 (2021), 27865–27876. https://arxiv.org/pdf/2105.12787.pdf

[4] Valentin Antimirov. 1996. Partial derivatives of regular expressions and finite automaton constructions. Theoretical Computer Science 155, 2 (1996), 291–319.

[5] Yehoshua Bar-Hillel, Micha Perles, and Eli Shamir. 1961. On formal properties of simple phrase structure grammars. Sprachtypologie und Universalienforschung 14 (1961), 143–172.

[6] Daniella Bar-Lev, Tuvi Etzion, and Eitan Yaakobi. 2021. On Levenshtein Balls with Radius One. In 2021 IEEE International Symposium on Information Theory (ISIT). 1979–1984. https://doi.org/10.1109/ISIT45174.2021.9517922

[7] Leonor Becerra-Bonache, Colin de La Higuera, Jean-Christophe Janodet, and Frédéric Tantini. 2008. Learning Balls of Strings from Edit Corrections. Journal of Machine Learning Research 9, 8 (2008).

[8] Richard Beigel and William Gasarch. [n.d.]. A Proof that if $L = L_1 \cap L_2$ where L_1 is CFL and L_2 is Regular then L is Context Free Which Does Not use PDA's. http://www.cs.umd.edu/~gasarch/BLOGPAPERS/cfg.pdf

[9] Mikołaj Bojańczyk, Bartek Klin, and Sławomir Lasota. 2014. Automata theory in nominal sets. Logical Methods in Computer Science 10 (2014).

[10] Janusz A Brzozowski. 1962. Canonical regular expressions and minimal state graphs for definite events. In Proc. Symposium of Mathematical Theory of Automata. 529–561.

[11] Janusz A Brzozowski. 1964. Derivatives of regular expressions. Journal of the ACM (JACM) 11, 4 (1964), 481–494.

[12] Janusz A. Brzozowski and Ernst Leiss. 1980. On equations for regular languages, finite automata, and sequential networks. Theoretical Computer Science 10, 1 (1980), 19–35.

[13] David Chiang. 2007. Hierarchical phrase-based translation. computational linguistics 33, 2 (2007), 201–228.

[14] David Chiang, Peter Cholak, and Anand Pillay. 2023. Tighter bounds on the expressivity of transformer encoders. In International Conference on Machine Learning. PMLR, 5544–5562. https://proceedings.mlr.press/v202/chiang23a/chiang23a.pdf

[15] Nadezhda Chirkova and Sergey Troshin. 2021. Empirical study of transformers for source code. In Proceedings of the 29th ACM joint meeting on European software engineering conference and symposium on the foundations of software engineering. 703–715.

[16] Loris D'Antoni and Margus Veanes. 2014. Minimization of symbolic automata. In Proceedings of the 41st ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages. 541–553.

[17] Dingding Dong, Nitya Mani, and Yufei Zhao. 2023. On the number of error correcting codes. Combinatorics, Probability and Computing (2023), 1–14. https://doi.org/10.1017/S0963548323000111

[18] Dawn Drain, Chen Wu, Alexey Svyatkovskiy, and Neel Sundaresan. 2021. Generating bug-fixes using pretrained transformers. In Proceedings of the 5th ACM SIGPLAN International Symposium on Machine Programming. 1–8.

[19] Philippe Duchon, Philippe Flajolet, et al. 2004. Boltzmann samplers for the random generation of combinatorial structures. Combinatorics, Probability and Computing 13, 4-5 (2004), 577–625.

[20] Jay Earley. 1970. An efficient context-free parsing algorithm. Commun. ACM 13, 2 (1970), 94–102.

[21] David Eppstein. 2014. k-best enumeration. arXiv preprint arXiv:1412.5075 (2014).

[22] Denis Firsov and Tarmo Uustalu. 2015. Certified normalization of context-free grammars. In Proceedings of the 2015 Conference on Certified Programs and Proofs. 167–174.

[23] Philippe Flajolet, Daniele Gardy, and Loÿs Thimonier. 1992. Birthday paradox, coupon collectors, caching algorithms and self-organizing search. Discrete Applied Mathematics 39, 3 (1992), 207–229.

[24] Seymour Ginsburg and H Gordon Rice. 1962. Two families of languages related to ALGOL. Journal of the ACM (JACM) 9, 3 (1962), 350–371.

[25] Joshua Goodman. 1999. Semiring parsing. Computational Linguistics 25, 4 (1999), 573–606. https://aclanthology.org/J99-4004.pdf

[26] Matthew Hague, Artur Jeż, and Anthony W Lin. 2024. Parikh's Theorem Made Symbolic. Proceedings of the ACM on Programming Languages 8, POPL (2024), 1945–1977.

[27] Liang Huang and David Chiang. 2005. Better k-best parsing. In Proceedings of the Ninth International Workshop on Parsing Technology. 53–64.

[28] Liang Huang and David Chiang. 2007. Forest rescoring: Faster decoding with integrated language models. In Proceedings of the 45th annual meeting of the association of computational linguistics. 144–151.

[29] E. T. Irons. 1963. An Error-Correcting Parse Algorithm. Commun. ACM 6, 11 (nov 1963), 669–673. https://doi.org/10.1145/368310.368385

[30] Adam Kiezun, Vijay Ganesh, Philip J Guo, Pieter Hooimeijer, and Michael D Ernst. 2009. HAMPI: a solver for string constraints. In Proceedings of the eighteenth international symposium on Software testing and analysis. 105–116.

[31] Lillian Lee. 2002. Fast context-free grammar parsing requires fast boolean matrix multiplication. Journal of the ACM (JACM) 49, 1 (2002), 1–15. https://arxiv.org/pdf/cs/0112018.pdf

[32] Vladimir I Levenshtein et al. 1966. Binary codes capable of correcting deletions, insertions, and reversals. In Soviet physics doklady, Vol. 10. 707–710. https://nymity.ch/sybilhunting/pdf/Levenshtein1966a.pdf

[33] Alexander K Lew, Tan Zhi-Xuan, Gabriel Grand, and Vikash K Mansinghka. 2023. Sequential monte carlo steering of large language models using probabilistic programs. arXiv preprint arXiv:2306.03081 (2023).

[34] William Merrill, Ashish Sabharwal, and Noah A Smith. 2022. Saturated transformers are constant-depth threshold circuits. Transactions of the Association for Computational Linguistics 10 (2022), 843–856.

[35] Matthew Might, David Darais, and Daniel Spiewak. 2011. Parsing with derivatives: a functional pearl. ACM sigplan notices 46, 9 (2011), 189–195.

[36] Mark-Jan Nederhof and Giorgio Satta. 2004. The language intersection problem for non-recursive context-free grammars. Information and Computation 192, 2 (2004), 172–184.

[37] Rohit J. Parikh. 1966. On Context-Free Languages. J. ACM 13, 4 (oct 1966), 570–581. https://doi.org/10.1145/321356.321364

[38] Terence J. Parr and Russell W. Quong. 1995. ANTLR: A predicated-LL (k) parser generator. Software: Practice and Experience 25, 7 (1995), 789–810.

[39] Clemente Pasti, Andreas Opedal, Tiago Pimentel, Tim Vieira, Jason Eisner, and Ryan Cotterell. 2023. On the Intersection of Context-Free and Regular Languages. In Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics, Andreas Vlachos and Isabelle Augenstein (Eds.). Association for Computational Linguistics, Dubrovnik, Croatia, 737–749. https://doi.org/10.18653/v1/2023.eacl-main.52

[40] Itiroo Sakai. 1961. Syntax in universal translation. In Proceedings of the International Conference on Machine Translation and Applied Language Analysis.

[41] Georgios Sakkas, Madeline Endres, Philip J Guo, Westley Weimer, and Ranjit Jhala. 2022. Seq2Parse: neurosymbolic parse error repair. Proceedings of the ACM on Programming Languages 6, OOPSLA2 (2022), 1180–1206.

[42] Klaus U Schulz and Stoyan Mihov. 2002. Fast string correction with Levenshtein automata. International Journal on Document Analysis and Recognition 5 (2002), 67–85.

[43] Elizabeth Scott and Adrian Johnstone. 2010. GLL parsing. Electronic Notes in Theoretical Computer Science 253, 7 (2010), 177–189.

[44] Kensen Shi, David Bieber, and Charles Sutton. 2020. Incremental sampling without replacement for sequence models. In International Conference on Machine Learning. PMLR, 8785–8795.

[45] Michalis K Titsias and Christopher Yau. 2017. The Hamming ball sampler. J. Amer. Statist. Assoc. 112, 520 (2017), 1598–1611.

[46] Leslie G Valiant. 1975. General context-free recognition in less than cubic time. Journal of computer and system sciences 10, 2 (1975), 308–315. http://people.csail.mit.edu/virgi/6.s078/papers/valiant.pdf

[47] Alexander William Wong, Amir Salimi, Shaiful Chowdhury, and Abram Hindle. 2019. Syntax and Stack Overflow: A methodology for extracting a corpus of syntax errors and fixes. In 2019 IEEE International Conference on Software Maintenance and Evolution (ICSME). IEEE, 318–322.

[48] Michihiro Yasunaga and Percy Liang. 2021. Break-it-fix-it: Unsupervised learning for program repair. In International Conference on Machine Learning. PMLR, 11941–11952.

[49] Hao Zhang and Ryan McDonald. 2012. Generalized higher-order dependency parsing with cube pruning. In Proceedings of the 2012 joint conference on empirical methods in natural language processing and computational natural language learning. 320–331.