Don’t Panic! Better, Fewer, Syntax Errors for LR Parsers

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Abstract
Syntax errors are generally easy to fix for humans, but not for parsers, in general, and LR parsers, in particular. Traditional ‘panic mode’ error recovery, though easy to implement and applicable to any grammar, often leads to a cascading chain of errors that drown out the original. More advanced error recovery techniques suffer less from this problem but have seen little practical use because their typical performance was seen as poor, their worst case unbounded, and the repairs they reported arbitrary. In this paper we introduce an algorithm and implementation that addresses these issues. First, we report the complete set of minimum cost repair sequences for a given location, allowing programmers to select the one that best fits their intention. Second, on a corpus of 200,000 real-world syntactically invalid Java programs, we are able to repair 98.38% ± 0.018% of files within a cut-off of 0.5s. Finally, we use the existence of the complete set of minimum cost repair sequences to reduce one of the most frustrating consequences of error reporting: the cascading error problem. Across our corpus, we report 435,823.0 ± 478.0 error locations to the user, while the panic mode algorithm reports 981,628.0 ± 0.0 error locations: in other words, we reduce the cascading error problem by well over half.

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1 Introduction

Programming is a humbling job which requires acknowledging that we will make untold errors in our quest to perfect a program. Most troubling are semantic errors, where we intended the program to do one thing, but it does another. Less troubling, but often no less irritating, are syntax errors, which are (generally minor) deviances from the exacting syntax required by a compiler. So common are syntax errors that parsers in modern compilers are designed to cope with us making several: rather than stop on the first syntax error, they attempt to recover from it. This allows them to report, and us to fix, all our syntax errors in one go.

When error recovery works well, it is a useful productivity gain. Unfortunately, most current error recovery approaches are simplistic. The most common grammar-neutral approach to error recovery are those algorithms described as ‘panic mode’ algorithms (e.g. [13, p. 348]) which skip input until the parser finds something it is able to parse. A more grammar-specific variation of this idea is to skip input until a pre-determined synchronisation token (e.g. ‘;’ in Java) is reached [8, p. 3], or to try inserting a single synchronisation token. Such strategies are often unsuccessful, leading to a cascade of spurious syntax errors (see Figure 1 for an example). Programmers quickly learn that only the location of the first error in a file – not the reported repair, nor the position of subsequent errors – can be relied upon to be accurate.
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Figure 1 An example of a simple, common Java syntax error (a) and the problems traditional error recovery has in dealing with it. javac (b) spots the error when it encounters ‘y’. Its error recovery heuristic then repairs the input by inserting a semicolon before ‘y’ (i.e. making the input equivalent to ‘int x; y;’). This causes a (spurious) cascading parsing error, since ‘y’ on its own is not a valid statement. The CPCT+ error recovery algorithm we introduce in this paper produces the output shown in (c): after spotting an error when parsing encounters ‘y’, it uses the Java grammar to find the complete set of minimum cost repair sequences (unlike previous approaches which non-deterministically find one minimum cost repair sequence). In this case three repair sequences are reported to the user: one can delete ‘y’ entirely (‘int x;’), or insert a comma (‘int x, y;’), or insert an equals sign (‘int x = y;’).

A handful of parsers contain hand-written error recovery algorithms for specific languages. These generally allow better recovery from errors, but are challenging to create. For example, the Java error recovery approach in the Eclipse IDE is 5KLoC long, making it only slightly smaller than a modern version of Berkeley Yacc — a complete parsing system! Unsurprisingly, few real-world parsers contain effective hand-written error recovery algorithms.

Most of us are so used to these trade-offs (cheap generic algorithms and poor recovery vs. expensive hand-written algorithms and reasonable recovery) that we assume them to be inevitable. However, there is a long line of work on more advanced generic error recovery algorithms. Probably the earliest such algorithm is Aho and Peterson [1], which, upon encountering an error, creates on-the-fly an alternative (possibly ambiguous) grammar which allows the parser to recover. This algorithm has fallen out of favour in programming language circles, probably because of its implementation complexity and the difficulty of explaining to users what recovery has been used. A simpler family of algorithms, which trace their roots to Fischer et al. [11], instead try to find a single minimum cost repair sequence of token insertions and deletions which allow the parser to recover. Algorithms in this family are much better at recovering from errors than naive approaches and can communicate the repairs they find in a way that humans can easily replicate. However, such algorithms have seen little practical use because their typical performance is seen as poor and their worst case unbounded [17, p. 14]. We add a further complaint to this mix: such approaches only report a single repair sequence to users. In general – and especially in syntactically rich languages – there are multiple reasonable repair sequences for a given error location, and the algorithm has no way of knowing which best matches the user’s intentions.

In this paper we introduce a new error recovery algorithm in the Fischer et al. family, CPCT+. This takes the approach of Corchuelo et al. [5] as a base, corrects it, and then substantially expands it. CPCT+ is simple to implement (under 500 lines of Rust code), is able to repair nearly all errors in reasonable time, and reports the complete set of minimum cost repair sequences to users.

We validate CPCT+ on a corpus of 200,000 real, syntactically incorrect, Java programs (Section 6). CPCT+ is able to recover 98.38%±0.018% of files within a 0.5s timeout and does so while reporting well under half as many error locations to the user as a traditional panic mode algorithm: in other words, CPCT+ substantially reduces the cascading error problem.
Finally, we show — for, as far as we know, the first time — that advanced error recovery can be fairly easily added to a Yacc-esque system, allowing users to concisely make fine-grained decisions about what to do when error recovery has altered an input (Section 7). We believe that this shows that algorithms such as CPCT$^+$ are ready for wider usage, either on their own, or as part of a multi-phase recovery system.

1.1 Defining the problem

Formally speaking, we first test the following hypothesis:

H1 The complete set of minimum cost repair sequences can be found in acceptable time.

The only work we are aware of with a similar concept of ‘acceptable time’ is [6], who define it as the total time spent in error recovery per file, with a threshold of 1s. Since many compilers are able to fully execute in less time than this, we felt that a tighter threshold is more appropriate: we use 0.5s since we think that even the most demanding user will tolerate such a delay. We strongly validate this hypothesis. Relative to previous approaches, we are the clear beneficiaries of faster, modern hardware, which undoubtedly makes it easier to validate this hypothesis. However, it is important to note that we have stated a much stronger hypothesis than previous approaches: where they have aimed to find only a single minimum cost repair sequence, we find the complete set of minimum cost repair sequences, a much more challenging task.

The complete set of minimum cost repair sequences makes it much more likely that the programmer will see a repair sequence that best matches their original intention (see Figure 1 for an example; Appendix A contains further examples in Java, Lua, and PHP). It also opens up a new opportunity for error recovery algorithms. Previous error recovery algorithms find a single repair sequence, apply that to the input, and then continue parsing. While that repair sequence may have been a reasonable local choice, it may cause cascading errors later. Since we have the complete set of minimum cost repair sequences available, we can select from them a repair sequence which causes fewer cascading errors. We thus rank repair sequences by how far they allow parsing to continue successfully (up to a threshold — parsing the whole file would, in general, be too costly), and choose from the subset that gets furthest (note that the time required to do this is included in the 0.5s timeout). We thus also test a second hypothesis:

H2 The cascading error problem can be significantly reduced by ranking the complete set of minimum cost repair sequences and choosing from those which allow parsing to continue the furthest.

We also strongly validate this hypothesis. We do this by comparing ‘normal’ CPCT$^+$ with a simple variant CPCT$^+_{rev}$ which reverses the ranking process, always selecting from amongst the worst performing minimum cost repair sequence. CPCT$^+_{rev}$ models the worst case of previous approaches in the Fischer et al. family, which non-deterministically select a single minimum cost repair sequence. CPCT$^+_{rev}$ leads to 31.92%±0.293% more errors being reported (i.e. it substantially worsens the cascading error problem).

This paper is structured as follows. We describe the Corchuelo et al. algorithm (Section 4), filling in missing details from the original description and correcting its definition. We then expand the algorithm into CPCT$^+$ (Section 5). We then validate CPCT$^+$ on a corpus of 200,000 real, syntactically incorrect, Java programs (Section 6). To emphasise that our algorithms are grammar-neutral, we show examples of error recovery on different grammars in Appendix A.
2 Background

We assume a high-level understanding of the mechanics of parsing in this paper, but in this section we provide a handful of definitions, and a brief refresher of relevant low-level details, needed to understand the rest of this paper. Although the parsing tool we created for this paper is written in Rust, we appreciate that this is still an unfamiliar language to most readers: algorithms are therefore given in Python which, we hope, is familiar to most.

Although there are many flavours of parsing, the Fischer et al. family of error recovery algorithms are designed to be used with LR(k) parsers [10]. LR parsing remains one of the most widely used parsing approaches due to the ubiquity of Yacc [14] and its descendants (which include the Rust parsing tool we created for this paper). We use Yacc syntax throughout this paper so that examples can easily be tested in Yacc-compatible parsing tools.

Yacc-like tools take in a Context-Free Grammar (CFG) and produce a parser from it. The CFG has one or more rules; each rule has a name and one or more productions (often called ‘alternatives’); each production contains one or more symbols; and a symbol references either a token type or a grammar rule. One rule is designated the start rule. The resulting parser takes as input a stream of tokens, each of which has a type (e.g. INT) and a value (e.g. 123).

1 Strictly speaking, parsing is the act of determining whether a stream of tokens is correct with respect to the underlying grammar. Since this is rarely useful on its own, Yacc-like tools allow grammars to specify ‘semantic actions’ which are executed when a production in the grammar is successfully matched. Except where stated otherwise, we assume that the semantic actions build a parse tree, ordering the tokens into a tree of nonterminal nodes (which can have children) and terminal nodes (which cannot have children) relative to the underlying grammar.

The CFG is first transformed into a stategraph, a statemachine where each node contains one or more items (describing the valid parse states at that point) and edges are labelled with terminals or nonterminals. Since even on a modern machine, a canonical (i.e. unmerged) LR stategraph for a real-world grammar takes several seconds to build, and a surprising amount of memory to store, we use the state merging algorithm of [21] to merge together compatible states. The effect of this is significant, reducing the Java grammar we use later from 8908 to 1148 states. The stategraph is then transformed into a statetable with one row per state. Each row has a possibly empty action (shift, reduce, or accept) for each terminal and a possibly empty goto state for each nonterminal. Figure 2 shows an example grammar, its stategraph, and statetable.

The statetable allows us to define a simple, efficient, parsing process. We first define two functions relative to the statetable: action(s, t) returns the action for the state s and token t or error if no such action exists; and goto(s, N) returns the goto state for the state s and the nonterminal N or error if no such goto state exists. We then define a reduction relation →* for (parsing stack, token list) pairs with two reduction rules as shown in Figure 3. A full LR parse →* repeatedly applies the two →* rules until neither applies, which means that action(s_n, t_0) is either: accept (i.e. the input has been fully parsed); or error (i.e. an error has been detected at the terminal t_0). A full parse takes a starting pair of ([0], [t_0, ..., t_n, $]),

1 In practise, the system we outline requires a lexer which splits string inputs up into tokens. In the interests of brevity, we assume the existence of a tool such as Lex which performs this task.

2 Unfortunately [21] can over-merge states when conflict resolution is used [9, p. 3] (i.e. when Yacc uses its precedence rules to turn an ambiguous input into an unambiguous LR parser). Since our error recovery approach operates purely on the statetable, it should work correctly with other merging approaches such as that of [9].
Figure 2 An example grammar (top left), its corresponding stategraph (right), and statetable (split into separate action and goto tables; bottom left). Productions in the grammar are labelled (I) to (VI). In the stategraph: $S(x)$ means ‘shift to state $x$’; $R(x)$ means ‘reduce production $x$ from the grammar’ (e.g. action(3, '+') returns $R(IV)$ which references the production ‘Term: Factor;’).

Each item within a state $[N: \alpha \bullet \beta]$ references one of rule $N$’s productions; $\alpha$ and $\beta$ each represent zero or more symbols; with the dot (•) representing how much of the production must have been matched ($\alpha$) if parsing has reached that state, and how much remains ($\beta$).

where state 0 is expected to represent the entry point into the stategraph, $t_0 \ldots t_n$ is the sequence of input tokens, and ‘$\$$’ is the special End-Of-File (EOF) token.

3 Panic mode

Error recovery algorithms are invoked by a parser when it has yet to finish but there is no apparent way to continue parsing (i.e. when $\text{action}(s_n, t_0) = \text{error}$). Error recovery algorithms are thus called with a parsing stack and a sequence of remaining input (which, for simplicities sake, we represent as a list of tokens): they can modify either or both of the parsing stack and the input in their quest to get parsing back on track. The differences between algorithms are thus in what modifications they can carry out (e.g. altering the parse stack; deleting input; inserting input), and how they carry such modifications out.

The simplest grammar-neutral error recovery algorithms are called ‘panic mode’ algorithms. The precise origin of this family of algorithms seems lost in time; there are also more members of this family for LL parsing than there are for LR parsing. Indeed, for LR parsing, there is only one fundamental way of creating a grammar-neutral panic mode algorithm: we take
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\[
\text{action}(s_n, t_0) = \begin{cases} \text{shift } s' & \text{LR Shift} \\ \text{reduce } N \colon \alpha & \text{LR Reduce} \\ \end{cases}
\]

\[
\boxed{
\begin{array}{l}
(\text{action}(s_n, t_0) = \text{reduce } N \colon \alpha) \land (\text{goto}(s_{n-|\alpha|}, N) = s') \\
\text{LR Shift} \\
\text{LR Reduce}
\end{array}
}\]

**Figure 3** Reduction rules for \(\rightarrow_{LR}\), which operate on \((\text{parsing stack}, \text{token list})\) pairs. LR Shift advances the input by one token and grows the parsing stack, while LR Reduce unwinds (‘reduces’) the parsing stack when a production is complete before moving to a new (‘goto’) state.

```python
1 def holub(pstack, toks):
2     while len(toks) > 0:
3         npstack = pstack.copy()
4         while len(npstack) > 0:
5             if action(npstack[-1], toks[0]) != error:
6                 return (npstack, toks)
7             npstack.pop()
8             del toks[0]
9     return None
```

**Figure 4** Our version of the Holub [13] algorithm. This panic mode algorithm takes in a \((\text{parsing stack}, \text{token list})\) pair and returns: a \((\text{parsing stack}, \text{token list})\) pair if it managed to recover; or None if it failed to recover. The algorithm tries to find an element in the stack that has a non-error action for the next token in the input (lines 4–7). If it fails to find such an element, the input is advanced by one element (line 8) and the stack restored (line 3).

Our formulation from Holub [13, p. 348] works by taking the parsing stack and popping elements to see if an earlier part of the stack is able to parse the next input symbol. If no element in the stack is capable of parsing the next input symbol, the input symbol is skipped, the stack restored, and the process repeated. At worst, this algorithm guarantees to find a match at the EOF token. Figure 4 shows a more formal version of this algorithm.

The advantage of this algorithm is its simplicity and speed. For example, consider the grammar from Figure 2 and the input ‘2 + + 3’. The parser encounters an error on the second ‘+’ token, leaving it with a parsing stack of \([0, 2, 7]\) and the input ‘+ 3’ remaining. The error recovery algorithm now starts. It first tries action(7, ‘+’) which (by definition, since it is the place the parser encountered an error) returns error; it then pops the top element from the parsing stack and tries action(2, ‘+’), which returns shift. This is enough for the error algorithm to complete, and parsing resumes with a stack \([0, 2]\).

The fundamental problem with error recovery can be seen from the above example: the adjustment made to the parsing stack is not one that the user can replicate. Looked at another way, error recovery is a Deus ex machina: while panic mode managed to recover from the error, the only general way to report what was done is to show the parsing stack before and after recovery: this is challenging to interpret for small grammars like that of Figure 2 and completely impractical for anything larger. There is an important corollary to this: since the recoveries made often don’t match anything the user could have passed as input, they are often of poor quality, leading to a cascade of further parsing errors (as we will see later in Section 6.2).

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3 Note that step 2 in Holub causes valid repairs to be missed: while it is safe to ignore the top element of the parsing stack on the first iteration of the algorithm, as soon as one token is skipped, one must check all elements of the parsing stack. Our description simply drops step 2 entirely.
Section 4.3. Since the original description gives few details as to how the algorithm might shift \( y \), delete \( z \) which makes use of the relation which represents a different search state; configurations are searched for their neighbours until a successful configuration is found. The cost of a configuration is the cumulative cost of the repairs in its repair sequence. By definition, a configuration’s neighbours have the same, or greater, cost to it.

As with the original, we explain the approach in two parts. First is a new reduction relation \( \rightarrow_{CN} \) which defines a configuration’s neighbours (Figure 5). Second is an algorithm which makes use of the \( \rightarrow_{CN} \) relation to generate neighbours, and determines when a successful configuration has been found or if error recovery has failed (Figure 6). As well as several changes for clarity, the biggest difference is that Figure 6 captures semi-formally what

\[
\begin{align*}
\text{action}(s_n, t) \neq \text{error} \land t \neq \$ \land ([s_0 \ldots s_n], [t_0 \ldots t_n]) & \rightarrow^*_{LR} ([s'_0 \ldots s'_m], [t_0 \ldots t_n]) & \text{CR INSERT} \\
([s_0 \ldots s_n], [t_0, t_1 \ldots t_n]) & \rightarrow_{CR} ([s_0 \ldots s_n], [t_1 \ldots t_n], \text{[delete]}) & \text{CR DELETE} \\
([s_0 \ldots s_n], [t_0 \ldots t_n]) & \rightarrow^*_{LR} ([s'_0 \ldots s'_m], [t_j \ldots t_n]) & \land 0 < j \leq N_{shifts} \\
& j = N_{shifts} \land \text{action}(s'_m, t_j) \in \{\text{accept, error}\} \\
([s_0 \ldots s_n], [t_0 \ldots t_n]) & \rightarrow_{CR} ([s'_0 \ldots s'_m], [t_j \ldots t_n], \underline{\text{shift} \ldots \text{shift}}) & \text{CR Shift 1}
\end{align*}
\]

Figure 5 The repair-creating reduction rules [5]. CR INSERT finds all terminals reachable from the current state and creates insert repairs for them (other than the EOF token \( \$ \)). CR DELETE creates deletion repairs if user defined input remains. CR Shift 1 parses at least 1 and at most \( N_{shifts} \) tokens; if it reaches an accept or error state, or parses exactly \( N_{shifts} \) tokens, then a shift repair per token shifted is created.

4 Corchuelo et al.

There have been many attempts to create better LR error recovery algorithms than panic mode. Most numerous are those error recovery algorithms in what we call the Fischer et al. family. Indeed, there are far too many members of this family of algorithms to cover in one paper. We therefore start with one of the more recent – Corchuelo et al. [5]. We first explain the original algorithm (Section 4.1), although we use different notation than the original, fill in several missing details, and provide a more formal definition. We then make two correctness fixes to ensure that the algorithm always finds minimum cost repair sequences (Section 4.2). Since the original description gives few details as to how the algorithm might best be implemented, we then explain the steps we took to make a performant implementation (Section 4.3).

4.1 The original algorithm

Intuitively, the Corchuelo et al. algorithm starts at the error state and tries to find a minimum cost repair sequence consisting of: insert \( T \) (‘insert a token of type \( T \)’), delete (‘delete the token at the current offset’), or shift (‘parse the token at the current offset’). The algorithm completes: successfully if it reaches an accept state or shifts ‘enough’ tokens (\( N_{shifts} \), set at 3 in Corchuelo et al.); or unsuccessfully if it deletes and inserts ‘too many’ tokens (\( N_{total} \), set at 10 in Corchuelo et al.). Repair sequences are reported back to users with trailing shift repairs pruned i.e. \([\text{insert } x, \text{ shift } y, \text{ delete } z, \text{ shift } a, \text{ shift } b, \text{ shift } c] \) is reported as \([\text{insert } x, \text{ shift } y, \text{ delete } z] \).

In order to find repair sequences, the algorithm keeps a queue of configurations, each of which represents a different search state; configurations are searched for their neighbours until a successful configuration is found. The cost of a configuration is the cumulative cost of the repairs in its repair sequence. By definition, a configuration’s neighbours have the same, or greater, cost to it.

As with the original, we explain the approach in two parts. First is a new reduction relation \( \rightarrow_{CN} \) which defines a configuration’s neighbours (Figure 5). Second is an algorithm which makes use of the \( \rightarrow_{CN} \) relation to generate neighbours, and determines when a successful configuration has been found or if error recovery has failed (Figure 6). As well as several changes for clarity, the biggest difference is that Figure 6 captures semi-formally what
Corchuelo et al. explain in prose (spread amongst several topics over several pages): perhaps inevitably we have had to fill in several missing details. For example, Corchuelo et al. do not define what the cost of repairs is: for simplicities sake, we define the cost of insert and delete as 1, and shift as 0.

4.2 Ensuring that minimum cost repair sequences aren’t missed

CR Shift 1 has two flaws which prevent it from generating all possible minimum cost repair sequences.

First, CR Shift 1 requires at least one token to be shifted. However, after a non-shift repair, all that may be needed to reach a useful next configuration, or an accept state, is one or more reductions/gotos via LR Reduce. CR Shift 2 in Figure 7 shows the two-phase fix which addresses this problem. We first change the condition $0 < j \leq N_{\text{shifts}}$ to $0 \leq j \leq N_{\text{shifts}}$ (i.e. we don’t force the LR parser to consume any tokens). However, this then opens the possibility of an infinite loop. We avoid this by saying that, if the input is not advanced, the parsing stack must have changed. Put another way, in either case we require progress to be

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4 It is trivial to extend this to variable token costs if desired, and our implementation supports this. However, it is unclear whether non-uniform token costs are useful in practice [4 p.96].
(\langle s_0 \ldots s_n, t_0 \ldots t_n \rangle) \rightarrow_{CR} (\langle s'_0 \ldots s'_m, t_j \ldots t_n \rangle, \mathbb{X}) \quad \text{CR Shift 1}

\begin{align*}
\text{(a)} \quad & \text{Delete 3, Delete } + \\
& \quad \text{Delete 3, Shift } +, \text{ Insert Int} \\
& \quad \text{Insert } +, \text{ Shift 3, Shift } + , \text{ Insert Int} \\
& \quad \text{Insert } +, \text{ Shift 3, Shift } + , \text{ Insert Int} \\
\text{(b)} \quad & \text{Insert } * , \text{ Shift 3, Delete } + \\
& \quad \text{Insert } *, \text{ Shift 3, Delete } + \\
& \quad \text{CR Shift 3} \\
\end{align*}

Figure 7 CR Shift 1 always consumes input, when sometimes performing one or more reductions/gotos without consuming input would be better. CR Shift 2 addresses this issue. Both CR Shift 1 and CR Shift 2 generate multiple shift repairs in one go, which causes them to skip ‘intermediate’ (and sometimes important) configurations. CR Shift 3 generates at most one shift, exploring all intermediate configurations.

made, even if that progress does not require consuming any input.

Second, CR Shift 1 and CR Shift 2 generate multiple shifts at a time. This causes them to skip intermediate configurations from which minimum cost repair sequences may be found. The solution\footnote{The problem, and the basis of a fix, derive from [15, p. 12], though their suggestion suffers from the same problem as CR Shift 1.} is simple: at most one shift can be generated at any one time. CR Shift 3 in Figure 7 (as well as incorporating the fix from CR Shift 2) generates at most one shift repair at a time. Relative to CR Shift 1, it is simpler, though it also inevitably slows down the search, as more configurations are generated.

The problems with CR Shift 1, in particular, can be severe. Figure 8 shows an example input where CR Shift 1 is unable to find any repair sequences, CR Shift 2 some, and CR Shift 3 all minimum cost repair sequences.

4.3 Implementation considerations

The definitions we have given thus far do not obviously lead to an efficient implementation and Corchuelo et al. give few useful hints. We found that two techniques were both effective at improving performance while being simple to implement.

First, although Corchuelo et al. do not refer to it as such, it was clear to us that the most natural way to model the search is as an instance of Dijkstra’s algorithm. However, rather than use a general queue data-structure (probably based on a tree) to discover which element to search next, we use a similar queue data-structure to [11, p. 25]. This consists
of one sub-list per cost (i.e. the first sub-list contains configurations of cost 0, the second sub-list configurations of cost 1 and so on). Since we always know what cost we are currently investigating, finding the next todo element requires only a single \texttt{pop} (line 8 of Figure 6). Similarly, adding elements requires only an \texttt{append} to the relevant sub-list (lines 18, 21, 22). This data-structure is a good fit because costs in our setting are always small (double digits is unusual for real-world grammars) and each neighbour generated from a configuration with cost \(c\) has a cost \(\geq c\).

Second, we do not use lists to represent parsing stacks and repair sequences as Figure 6 may suggest. We found that this representation consumes noticeably more memory, and is slightly less efficient, than using parent pointer trees (often called ‘cactuses’). Every node in such a tree has a reference to a single parent (or \texttt{null} for the root node) but no references to child nodes. Since our implementation is written in Rust – a language without garbage collection – nodes are reference counted (i.e. a parent is only freed when it is not in a todo list and no children point to it). When the error recovery algorithm starts, it converts the main parsing stack (a list) into a parent pointer tree; and repair sequences start as empty parent pointer trees. The \(\rightarrow_{cr}\) part of our implementation thus operates exclusively on parent pointer trees. Although this does mean that neighbouring configurations are scattered throughout memory, the memory sharing involved seems to more than compensate for poor cache behaviour; it also seems to be a good fit with modern \texttt{malloc} implementations, which are particularly efficient when allocating and freeing objects of the same size. While we suspect this representation is always likely to be a reasonable choice, it is difficult to generalise from our experience whether it will always be the best in other contexts, in particular for garbage collected languages.

One seemingly obvious further improvement is to split the search into parallel threads. However, we found that the nature of the problem means that parallelisation is more tricky, and less productive, than might be expected. There are two related problems: we cannot tell in advance if a given configuration will have huge numbers of successors or none at all; and configurations are, in general, searched for successors extremely quickly. Thus if we attempt to seed threads with initial sets of configurations, some threads quickly run out of work whilst others have ever growing queues. If, alternatively, we have a single global queue then significant amounts of time can be spent adding or removing configurations in a thread-safe manner. This suggests that the right approach is likely to be a combination of the two approaches: threads would have a local queue which, if it gets too full, would be partly emptied into a global queue, from which otherwise idle threads can find new work. As we shall see in Section 6, \(CPCT^+\) runs fast enough that the additional complexity of such an approach is not, in our opinion, justified.

5 \(CPCT^+\)

In this section, we extend the Corchuelo \textit{et al.} algorithm to become what we call \(CPCT^+\). First we extend the algorithm to find the complete set of minimum cost repair sequences (Section 5.1). Since this significantly slows down the search, we introduce a significant optimisation in the form of merging compatible configurations (Section 5.2). The complete set of minimum cost repair sequences allows us to make an algorithm less susceptible to the cascading error problem (Section 5.3). We then change the criteria for terminating error recovery (Section 5.4).
5.1 Finding the complete set of minimum cost repair sequences

The basic Corchuelo et al. algorithm non-deterministically completes as soon as it has found a single minimum cost repair sequence. This is confusing in two different ways: the successful repair sequence found can vary from run to run; and the successful repair sequence might not match the user’s intention.

We therefore introduce the idea of the complete set of repair sequences: that is all equivalently good repair sequences. Although we will refine the concept of ‘equivalently good’ in Section 5.3 at this stage we consider all successful repair sequences with the minimum cost \( c \) to be equivalently good. In other words, as soon as we find the first successful repair sequence, its cost \( c \) defines the minimum cost.

An algorithm to generate this set is then simple: when a repair sequence of cost \( c \) is found to be successful, we discard all repair sequences with cost \( > c \), and continue exploring configurations in cost \( c \) (including, transitively, all neighbours that are also of cost \( c \); those with cost \( > c \) are immediately discarded). Each successful configuration is recorded and, when all configurations in \( c \) have been explored, the set of successful configurations is returned.

One of these successful configurations is then non-deterministically chosen, applied to the input, and parsing continued.

5.2 Merging compatible configurations

Relative to finding a single solution, finding the complete set of repair sequences can be extremely expensive because there may be many remaining configurations in \( c \), which may, transitively, have many neighbours. Our solution to this performance problem is to merge together compatible configurations on-the-fly, preserving their distinct repair sequences while still reducing the search space. Two configurations are compatible if:

1. their parsing stacks are identical,
2. they both have an identical amount of input remaining,
3. and their repair sequences are compatible.

Two repair sequences are compatible:

1. if they both end in the same number \( (n \geq 0) \) of shifts,
2. and, if one repair sequence ends in a delete, the other repair sequence also ends in a delete.

The first of these conditions is a direct consequence of the fact that a configuration is deemed successful if it ends in \( N_{shifts} \) shift repairs. When we merge configurations, one part of the merge is ‘dominant’ (i.e. checked for \( N_{shifts} \)) and the other ‘subsumed’. Thus we have to maintain symmetry between the dominant and subsumed parts to prevent the dominant part accidentally preventing the subsumed part from being recorded as successful. In other words, if the dominant part of the merge had fewer shifts at the end of its repair sequence than the subsumed part, then the \( N_{shifts} \) check (line 10, Figure 6) would fail, even though reversing the dominant and subsumed parts may have lead to success. It is therefore only safe to merge repair sequences which end in the same number of shifts.

The second condition relates to the weak form of compatible merging inherited from [5, p. 8]: delete repairs are never followed by an insert (see Figure 6) since \([\text{delete}, \text{insert} x]\) always leads to the same configuration as \([\text{insert} x, \text{delete}]\). Although we get much of the same effect through compatible configuration merging, we keep it as a separate optimisation because: it is such a frequent case; our use of the todo list means that we would not catch
every case; the duplicate repair sequences are uninteresting from a user perspective, so we
would have to filter them out later anyway; and each additional merge costs memory. We
thus have to make sure that merged repair sequences don’t accidentally suppress insert
repairs because one part of the repair sequence ends in a delete while the other does not.
The simplest way of solving this problem is thus to forbid merging repair sequences if one
sequence ends in a delete and the other does not.

Fortunately, implementing compatible configuration merging is simple. We first modify
the todo data-structure to be a list-of-ordered-hashset. This has near-identical append /
pop performance to a normal list, but filters out duplicates with near-identical performance
to an unordered hashset. We then make use of a simply property of hashsets: an object’s
hash behaviour need only be a non-strict subset of its equality behaviour. In other words,
while we need to ensure that two objects that compare equal always map to the same hash,
we can allow two objects that do not compare equal to map to the same hash. In our
context, this allows us to quickly find potentially compatible nodes using hashing, checking
for definitely compatible configurations using equality. We therefore hash configurations
based solely on their parsing stack and remaining input whereas configuration equality is
based on a configurations’ parsing stacks, remaining input, and repair sequences.

Conceptually, merging two configurations together is simple: each configuration needs
to store a set of repair sequences, each of which is updated as further repairs are found.
However, this is an extremely inefficient representation as the sets involved need to be copied
and extended as each new repair is found. Instead, we reuse the idea of graph-structured
stacks from GLR parsing which allows us to avoid copying whenever possible.
The basic idea is that configurations no longer reference a parent pointer tree of repairs
directly, but instead a parent pointer tree of repair merges. A repair merge is a pair (repair,
merged) where repair is a plain repair and merged is a (possibly null) set of repair merge
sequences. This structure has two advantages. First, the $N_{shifts}$ check can be performed
solely using the first element of repair merge pairs. Second, we avoid allocating memory
for configurations which have not yet been subject to a merge. The small downside to this
scheme is that expanding configurations into repair sequences requires recursively expanding
both the normal parent pointer tree of the first element as well as the merged parent pointer
trees of the second element.

Compatible configuration merging is a powerful optimisation even though it can only
merge configurations in the todo list (i.e. we cannot detect all possible compatible merges).
An example of compatible configuration merging can be seen in Figure 9.

5.3 Ranking repair sequences

In nearly all cases, members of the complete set of minimum cost repair sequences end with
$N_{shifts}$ (the only exception being if an error location is found less than $N_{shifts}$ from the end
of an input). Thus while the repair sequences we find are all equivalently good within the
range of $N_{shifts}$, some, but not others, may perform poorly beyond that range. This problem
is exacerbated by the fact that $N_{shifts}$ has to be a fairly small integer (we use 3, the value
suggested by Corchuelo et al.) since each additional token searched exponentially increases
the search space. From a user perspective this can mean that some members of the complete
set of minimum cost repair sequences can appear to be of much lower quality than others.

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6 An ordered hashset preserves insertion order, and thus allows list-like integer indexing as well as hash-based lookups.
Figure 9 An elided visualisation of a real run of \( \text{CPCT}^+ \) with the input ‘2 3 +’ and the grammar from Figure 2. The left hand side of the tree shows the ‘normal’ parser at work, which hits an error as soon as it has shifted the token ‘2’: at this point, \( \text{CPCT}^+ \) starts operating. As this shows, the search encounters various dead ends, as well as successful routes. As shown in Figure 8, this input has 6 minimum cost repair sequences, but the search only has 5 success configurations, because two configurations were merged together.

In order to lessen this problem, we rank configurations which represent the complete set of minimum cost repair sequences by how far they allow parsing to continue, up to a limit of \( N_{\text{try}} \) tokens (which we somewhat arbitrarily set at 250). Taking the furthest-parse point as our top rank, we then discard all configurations which parsed less input than this. The reason why we rank the configurations, and not the repair sequences, is that we only need to rank one repair sequence for each merged configuration, a small but useful optimisation.

We then expand the top ranked configurations into repair sequences and remove shifts from the end of those repair sequences. Since the earlier merging of compatible configurations is imprecise (it misses configurations that have already been processed), there can be some remaining duplicate repair sequences: we thus perform a final purge of duplicate repair sequences. Figure 9 shows a visualisation of \( \text{CPCT}^+ \) in action.

Particularly on real-world grammars, selecting the top-ranked repair sequences substantially decreases cascading errors (see Figure 10 for an example). It also does so for very little additional computational cost, as the complete set of minimum cost repair sequences is much smaller than the number of configurations searched. However, it cannot entirely reduce the cascading error problem. Since, from our perspective, each member of the top-ranked set is equivalently good, we non-deterministically select one of its members to repair the input and allow parsing to continue. This can mean that we select a repair sequence which performs less well beyond \( N_{\text{try}} \) tokens than other repair sequences in the top-ranked set.

5.4 Timeout

The final part of \( \text{CPCT}^+ \) relates to the use of \( N_{\text{total}} \) in Corchuelo et al.. As with all members of the Fischer et al. family, \( \text{CPCT}^+ \) is not only unbounded in time [17, p. 14], but also unbounded in memory. \( N_{\text{total}} \) is an attempt to stop the algorithm from running unacceptably long by limiting how much input the algorithm will consider for modification. Unfortunately
Figure 10 An example showing how the ranking of repair sequences can lessen the cascading error problem. The Java example (a) leads to a parsing error on line 3 at ‘y’, with three minimum cost repair sequences found: [insert ,], [insert ?], and [insert ()]. These repair sequences are then ranked by how far they allow parsing to continue successfully. [insert ,] leads to the rest of the file being parsed without further error. [insert ?] causes a cascading error at ‘;’ which must then be resolved by completing the ternary expression started by ‘?’ (e.g. changing line 3 to T ? y : this;). Similarly, [insert ()] causes a cascading error at ‘;’ which must then be resolved by inserting a ‘)’. Since [insert ,] is ranked more highly than the other repair sequences, the latter are discarded, leading to the parsing output shown in (b). javac in contrast attempts to insert ‘;’ before ‘y’ causing a cascading error on the next token.

6 Experiment

In order to understand the performance of CPCT+, we conducted a large experiment on real-world Java code. In this section we outline our methodology (Section 6.1) and results (Section 6.2). Our experiment is fully repeatable and downloadable from https://archive.org/download/error_recovery_experiment/0.3/. The results from our particular run of the experiment can also be downloaded from the same location.

6.1 Methodology

In order to evaluate error recovery implementations, we need a concrete implementation. We implemented a new Yacc-compatible parsing system grmtools in Rust which we use for our experiments. Including associated libraries for LR table generation and so on, grmtools is around 13KLoC. Although intended as a production library, it has accidentally played a part as a flexible test bed for experimenting with, and understanding, error recovery algorithms. We added a simple front-end nimbleparse which produces the output seen in e.g. Figure 1

There are two standard problems when evaluating error recovery algorithms: how to determine if a good job has been done on an individual example; and obtaining sufficient examples to get a wide perspective on an algorithm’s performance. To some extent, solutions to these problems are mutually exclusive: for real-world inputs, the only way to guarantee that a good job has been done is to manually evaluate it, which means that it is only practical to use a small set of input programs. Most papers we are aware of use at most 200 source files
with one using a single source file with minor variants \cite{15}. \cite{4} was the first to use a large-scale corpus of approximately 60,000 Java source files. Early in the development of our methodology, we performed some rough experiments which suggested that statistics only start to stabilise once a corpus exceeds 10,000 source files. We therefore prefer to use a much larger corpus than most previous studies. We are fortunate to have access to the Blackbox project \cite{3}, an opt-in data collection facility for the BlueJ editor, which records major editing events (e.g. compiling a file) and sends them to a central repository. Crucially, one can see the source code associated with each event. What makes Blackbox most appealing as a data source is its scale and diversity: it has hundreds of thousands of users, and a huge collection of source code.

We first obtained a Java 1.5 Yacc grammar and updated it to support Java 1.7. We then randomly selected source files from Blackbox's database (following the lead of \cite{28}, we selected data from Blackbox's beginning until the end of 2017-12-31). We then ran such source files through our Java 1.7 lexer. We immediately rejected files which didn’t lex, since such files cannot be considered for parsing. We then parsed candidate files with our Java grammar and rejected any which did parse successfully, since there is little point running an error recovery algorithm on correct input. The final corpus consists of 200,000 source files (collectively a total of 401MiB). Since Blackbox, quite reasonably, requires each person with access to the source files to register with them, we cannot distribute the source files directly; instead, we distribute the (inherently anonymised) identifiers necessary to extract the source files for those who register with Blackbox.

The size of our corpus means that we cannot manually evaluate repairs for quality. Instead, to evaluate this paper’s most important metric (the cascading error problem), we report the number of error locations found in the corpus for different algorithms. We know, by definition, that the corpus contains at least 200,000 manually created errors (i.e. at least one per file). Since it is likely that some files have more than one manually created error, the minimum possible number of error locations is likely to be bigger than this, but we have no way of knowing the true number. However, we can compare different algorithms: the fewer error locations an algorithm reports, the fewer cascading errors it has caused. This comes with an important caveat: a nefarious error recovery algorithm could simply skip all input after the first error encountered, thus reporting ‘only’ 200,000 error locations (i.e. one per file). Since, for other reasons, we also record the proportion of input skipped, we can confirm that this is not a significant factor in any of the algorithms we report on.

In order to test hypothesis H1 we ran each error recovery algorithm against the entire Java corpus, collecting for each file: the time spent in recovery (in seconds); whether error recovery on the file was successful (true or false); the number of error locations; the cost of repair sequences at each error location (only if error recovery was successful on the file as a whole); and the number of tokens skipped by error recovery (i.e. how many delete repairs were applied). Note that parsing fails if the timeout is exceeded or if the algorithm runs out of plausible candidate repair sequences. We measure the time spent in error recovery with a monotonic wall-clock timer, covering the time from when the main parser first invokes error recovery until an updated parsing stack and parsing index are returned along with minimum cost repair sequences. The timer is suspended when normal parsing restarts and resumed if

\footnote{Unfortunately, changes to the method calling syntax in Java 1.8 mean that it is an awkward, though not impossible, fit for an LR(1) formalism such as Yacc, requiring substantial changes to the current Java Yacc grammar. We consider the work involved beyond that useful for this paper.}

\footnote{Happily, this also excludes outputs which can’t possibly be Java source code. Some odd things are pasted into text editors.}
Figure 11 Summary statistics from running our error recovery algorithms over a corpus of 200,000 Java files (for all measures, lower values are better). Mean and median times report how long was spent in error recovery per file: both figures include files which exceeded the recovery timeout, so they represent the ‘real’ times that users would experience, whether or not all errors are repaired or not. Cost size reports the mean cost (i.e. the number of insert and delete repairs) of each error location repaired (this number is meaningless for Panic, which does not have a concept of costable repairs). The failure rate is the percentage of files which could not be fully repaired within the timeout (this number is semi-meaningless for Panic, which, at worst, is always able to find a repair at the EOF token). Tokens skipped is the percentage of input skipped (because of a delete repair).

In order to test hypothesis H2, we created a variant of CPCT+ called CPCT+rev, collecting the same data as for the other error recovery algorithms. Instead of selecting from the minimum cost repair sequences which allow parsing to continue furthest, CPCT+rev selects from those which allow parsing to continue the least far. This models the worst case for other members of the Fischer et al. family which non-deterministically select a single minimum cost repair sequence. In other words, it allows us to understand how many more errors could be reported to users of other members of the Fischer et al. family compared to CPCT+.

In order to understand the accuracy of the numbers we report, we provide 99% confidence intervals. We bootstrapped our results 10,000 times to produce confidence intervals. However, since, as Figure 12 shows, our distribution is heavy-tailed, we cannot bootstrap naively. Instead, we ran each error recovery algorithm 30 times on each source file; when bootstrapping we randomly sample one of the 30 values collected (i.e. our bootstrapped data contains an entry for every file in the experiment; that entry is one of the 30 values collected for that file). The only subtlety is when bootstrapping the mean cost size: this value only makes sense if the file was successfully recovered from, so we do not sample from runs where error recovery failed.

All experiments were run on an otherwise unloaded Intel Xeon E3-1240 v6 with 32GiB RAM running Debian 10. We disabled hyperthreading and turbo boost and ran experiments serially. Our experiments take approximately 4 days to complete. We used Rust 1.40.0 to compiler grmtools (the Cargo.lock file necessary to reproduce the build is included in our experimental repository).

### 6.2 Results

Figure 11 shows a summary of the results of our experiment. The overall conclusions are fairly clear. CPCT+ is able to repair nearly all input files within the 0.5s timeout; and while panic mode is able to repair every file within the 0.5s timeout, it reports well over twice as many error locations as CPCT+ (i.e. panic mode substantially worsens the cascading error problem). The fact that the median recovery time for CPCT+ is two orders of magnitude
lower than the mean recovery time suggests that only a small number of outliers cause error recovery to take long enough to be perceptible to humans; this is confirmed by the histogram in Figure 12. These results strongly validate Hypothesis H1.

\( CPCT^+ \) ranks the complete set of minimum cost repair sequences by how far parsing can continue and chooses from those which allow parsing to continue furthest. \( CPCT^+_{rev} \), in contrast, selects from those which allow parsing to continue the least far. \( CPCT^+_{rev} \) shows that the ranking technique used in \( CPCT^+ \) substantially reduces the potential for cascading errors: \( CPCT^+_{rev} \) leads to 31.92\%±0.293\% more error locations being reported to users relative to \( CPCT^+ \). As the histogram in Figure 13 shows, the distribution of error locations in \( CPCT^+ \) and \( CPCT^+_{rev} \) is similar, with the latter simply shifted slightly to the right. In other words, \( CPCT^+_{rev} \) makes error recovery slightly worse in a number of files (rather than making error recovery in a small number of files a lot worse). This strongly validates Hypothesis H2.

Interestingly, \( CPCT^+_{rev} \) has a noticeably higher mean cost of repair sequences relative to \( CPCT^+ \). In other words, \( CPCT^+_{rev} \) not only causes more error locations to be reported, but the repair sequences at the additional error locations have higher numbers of insert and delete repairs. This suggests that there is a double whammy from cascading errors: not only are more error locations reported, but the poorer quality repair sequences chosen make subsequent error locations disproportionately harder for the error recovery algorithm to recover from.

6.3 The impact of skipping input

As well as the much higher failure rate, the number of error locations reported by panic mode is well over twice that of \( CPCT^+ \). This led us to make an additional hypothesis:

H3 The more of the user’s input that is skipped, the greater the number of cascading parsing errors.
The intuition underlying this hypothesis is that, in general, the user’s input is very close to being correct: thus the more of the input that one skips, the less likely one is to get back to a successful parse. We thus added the ability to record how much of the user’s input is skipped as the result of delete repairs during error recovery. The figures surprised us: $CPCT^{+}$ skips very little of the user’s input; $CPCT_{rev}^{+}$ skips a little more; and panic mode skips an order of magnitude more. Although we do not have enough data points to make a definitive statement, our data seem to validate Hypothesis H3.

7 Using error recovery in practice

Although several members of the Fischer et al. family were implemented in parsing tools of the day, to the best of our knowledge none of those implementations have survived. Equally, previous approaches in the Fischer et al. family make no mention of how error recovery should be used or, indeed, if it has any implications for users at all.

We are therefore forced to treat the following as an open question: can one sensibly use error recovery in the Fischer et al. family in practice? In particular, given that the most common way to use LR grammars is to execute semantic actions as each production is reduced, what should semantic actions do when parts of the input have been altered by error recovery? This latter question is important for real-world systems (e.g. compilers) which can still perform useful computations (e.g. running a type checker) in the face of syntax errors.

While different languages are likely to require different solutions, in this section we show that grmtools allows sensible integration of error recovery in a Rust context. Readers who prefer to avoid Rust-specific details may wish to move immediately to Section 8.
7.1 A basic solution

Figure 14 shows a naive grmtools version of the grammar from Figure 2 that can evaluate numeric results as parsing occurs (i.e. given the input 2 + 3 * 4 it returns 14). This grammar should mostly be familiar to Yacc users: each production has a semantic action (i.e. Rust code that is executed when the production is reduced); and symbols in the production are available to the semantic action as pseudo-variables named \$n (a production of n symbols has n pseudo-variables with the first symbol connected to \$1 and so on). A minor difference from traditional Yacc is that grmtools allows rules to specify a different return type, an approach shared with other modern parsers such as ANTLR [22].

A more significant difference is in the contents of the \$n pseudo-variables and how user input is extracted from them. If a pseudo-variable references a rule R, then that pseudo-variable’s static type is R’s return type. However, if a pseudo-variable references a token T, then that pseudo-variable’s static type is (slightly simplified) Result<Lexeme, Lexeme>. We will explain the reasons for this shortly, but at this stage it suffices to note that we can extract tokens matching the user’s input by calling \$1.unwrap(), and obtain the actual string the user passed by using the globally available $lexer.lexeme_str function.

7.2 Can semantic action execution continue in the face of error recovery?

In Yacc, semantic actions can assume that each symbol in the production has ‘normal’ data attached to it (either a rule’s value or the string matching a token; Yacc’s error recovery is implicitly expected to maintain this guarantee). This assumption is unsafe in our setting, if we apply a repair sequence with an insert repair: the inserted token will have a type but no value. Given the input ‘(2 + 3’, the inserted close bracket is not hugely important, and our calculator returns the value 5. However, given the input ‘2 +’, CPCT finds a single repair sequence [Insert Int]: what should a calculator do with an inserted integer? Our naive
Don’t Panic! Better, Fewer, Syntax Errors for LR Parsers

Figure 15 A more sophisticated version of the grammar from Figure 14. Each rule now returns a `Result` type. If an integer is inserted by error recovery, the `Factor` rule returns `Err(() (line 18). All other rules simply percolate such errors upwards using the ‘?’ operator (which, if the `Result`-returning expression it is attached to evaluates to an `Err`, immediately returns that error; otherwise it unwraps the `Ok`). Note that other token types are unaffected: if error recovery inserts a bracket, for example, evaluation of the expression continues.

The approach we take is to allow users to easily differentiate normal vs. inserted tokens in a semantic action. Pseudo-variables that reference tokens have (slightly simplified) the Rust type `Result<Lexeme, Lexeme>`. Rust’s `Result` type is a sum type which represents success (`Ok(...)`) or error (`Err(...)`) conditions. We use the `Ok` case to represent ‘normal’ tokens created from user input and the `Err` case to represent tokens inserted by error recovery. Since the `Result` type is widely used in Rust code, users can avail themselves of standard idioms.

For example, we can then alter our calculator grammar to continue parsing, but stop executing meaningful semantic action code, when an inserted integer is encountered. We change grammar rules from returning type `T` to `Result<T, ()>` (where ‘()` is Rust’s unit type). When a rule cannot produce a value, for whatever reason, it simply returns `Err()`. It is then, deliberately, fairly easy to use with the `Result<Lexeme, Lexeme>` type: for tokens whose value we absolutely require, we map the `Err(Lexeme)` case to `Err()` with the (standard, if mildly clunky) idiom `$n.map_err(|l| ())?`. In essence, this first says ‘if `$n` is an `Err(Lexeme)`' convert it to `Err()`’ with `map_err` and then ‘if we have `Err(...)` percolate it upwards, otherwise unwrap the `Ok` case’ (the ‘?’ operator). While slightly verbose, this idiom is easily understood by Rust programmers. Figure 15 shows a version that changing the grammar to make use of this idiom requires relatively little extra code.

9 Equivalents are found in several other languages: Haskell’s `Either`; O’Caml’s `result`; or Scala’s `Either`. 
7.3 Avoiding insert repairs when possible

Although we now have a reasonable mechanism for dealing with inserted tokens, there are cases where we can bypass them entirely. For example, consider the input ‘2 + + 3’, which has two repair sequences: [Delete +], [Insert Int]; evaluation of the expression can continue with the former repair sequence, but not the latter. However, as presented thus far, these repair sequences are ranked equally and one non-deterministically selected.

We therefore added an optional declaration \%avoid_insert to grmtools which allows users to specify those tokens which, if inserted by error recovery, are likely to prevent semantic actions from continuing execution. In practise, this is synonymous with those tokens whose values (and not just their types) are important. In the calculator grammar only the INT token satisfies this criteria, so we add \%avoid_insert "INT" to the grammar. We then make a simple change to the repair sequence ranking of Section 5.3 such that the final list of repair sequences is sorted with inserts of such tokens at the bottom of the list. In our case, this means that we deterministically always select Delete + as the repair sequence to apply to the input ‘2 + + 3’ (though note that we still present the Insert Int repair sequence to the user, simply ranking it consistently as the second option).

8 Threats to validity

Although it might not be obvious at first, CPCT+ is non-deterministic, which can lead to different results from one run to the next. The root cause of this problem is that multiple repair sequences may have identical effects up to Ntry tokens, but cause different effects after that value. By running each file through each error recovery multiple times and reporting confidence intervals, we are able to give a good – though inevitably imperfect – sense of the likely variance induced by this non-determinism.

Blackbox contains an astonishingly large amount of source code but has two inherent limitations. First, it only contains Java source code. This means that our main experiment is limited to one grammar: it is possible that our techniques do not generalise beyond the Java grammar (though, as Appendix A suggests, our techniques do appear to work well on other grammars). Although [4, p. 109] suggests that different grammars make relatively little difference to the performance of such error recovery algorithms, we are not aware of an equivalent repository for other language’s source code. One solution is to mutate correct source files (e.g. randomly deleting tokens), thus obtaining incorrect inputs which we can later test: however, it is difficult to uncover and then emulate the numerous, sometimes surprising, ways that humans make syntax errors, particularly as some are language specific (though there is some early work in this area [7]). Second, Blackbox’s data comes largely from students, who are more likely than average to be somewhat novice programmers. It is clear that novice programmers make some different syntax errors – and, probably, make some syntax errors more often – relative to advanced programmers. For example, many of the files with the greatest number of syntax errors are caused by erroneous fragments repeated with variants (i.e. it is likely that the programmer wrote a line of code, copy and pasted it, edited it, and repeated that multiple times before deciding to test the syntactic validity). It is thus possible that a corpus consisting solely of programs from advanced programmers would lead to slightly different results. We consider this a minor worry, partly because a good error recovery algorithm should aim to perform well with inputs from users of different experience levels.

Our corpus was parsed using a Java 1.7 grammar, but some members of the corpus were almost certainly written using Java 1.8 or later features. Many – though not all – post-1.7
Java features require a new keyword: such candidate source files would thus have failed our initial lexing test and not been included in our corpus. However, some Java 1.8 files will have made it through our checks. Arguably these are still a valid test of our error recovery algorithms. It is even likely that they may be a little more challenging on average, since they are likely to be further away from being valid syntax than files intended for Java 1.7.

9 Related work

Error recovery techniques are so numerous that there is no definitive reference or overview of them. However, [8] contains an overall historical analysis and [4] an excellent overview of many members of the Fischer et al. family. Both must be supplemented with more recent works.

The biggest limitation of error recovery algorithms in the Fischer et al. family (including CPCT+) is that they find repairs at the point that an error is discovered, which may be later in the file than the cause of the error. Thus even when they successfully recover from an error, the repair sequence reported may be very different from the fix the user considers appropriate (note that this is distinct from the cascading error problem, which our ranking of repair sequences in Section 5.3 partly addresses). A common, frustrating example of this is a missing ‘}’ character in C/Java-like languages. Some approaches are able to backtrack from the source of the error in order to try and find more appropriate repairs. However, there are two challenges to this: first, the cost of maintaining the necessary state to backtrack slows down normal parsing (e.g. [6] only stores the relevant state at each line encountered to reduce this cost), whereas we add no overhead at all to normal parsing; second, the search-space is so hugely increased that it can be harder to find any repairs at all [8].

One approach to global error recovery is to use machine learning to train a system on syntactically correct programs [28]: when a syntax error is encountered, the resulting model is used to suggest appropriate global fixes. Although [28] also use data from Blackbox, their experimental methodology is both stricter – aiming to find exactly the same repair as the human user applied – and looser – they only consider errors which can be fixed by a single token, discarding 42% of the data [28, p. 8]) whereas we attempt to fix errors which span multiple tokens. It is thus difficult to directly compare their results to ours. However, by the high bar they have set themselves, they are able to repair 52% of single-token errors.

As CPCT_{rev} shows, choosing an inappropriate repair sequence during error recovery leads to cascading errors. The noncorrecting error recovery approach proposed by [28] explicitly addresses this weakness, eschewing repairs entirely. When a syntax error is discovered, noncorrecting error recovery attempts to discover all further syntax errors by checking whether the remaining input (after the point an error is detected) is a valid suffix in the language. This is achieved by creating a recogniser that can identify all valid suffixes in the language. Any errors identified in the suffix parse are guaranteed to be genuine syntax errors because they are uninfluenced by errors in the (discarded) prefix (though this does mean that some genuine syntax errors are missed that would not have been valid suffixes at that point in the user’s input had the original syntax error not been present). There seem to be two main reasons why noncorrecting error recovery has not been adopted. First, building an appropriate recogniser is surprisingly tricky and we are not currently aware of one that can handle the full class of LR grammars (though the full class of LL grammars has been tackled [32]), though we doubt that this problem is insoluble. Second, as soon as a syntax error is encountered, noncorrecting error recovery is unable to execute semantic actions, since it lacks the execution context they need.
Although one of our paper’s aims is to find the complete set of minimum cost repair sequences, it is unclear how best to present them to users, leading to questions such as: should they be simplified? should a subset be presented? and so on. Although rare, there are some surprising edge cases. For example, the (incorrect) Java 1.7 expression ‘x = f("a"b);’ leads to 23,067 minimum cost repair sequences being found, due to the large number of Java keywords that are valid in several parts of this expression leading to a combinatorial explosion: even the most diligent user is unlikely to find such a volume of information valuable. In a different vein, the success condition of ‘reached an accept’ state is encountered rarely enough that users sometimes forget it exists at all: they can then be surprised by an apparently unexplained difference in the repair sequences reported for some syntax errors in the middle of a file versus its end. There is a body of work which has tried to understand how best to structure compiler error messages (normally in the context of those learning to program). However, the results are hard to interpret: some studies find that more complex error messages are not useful [20], while others suggest they are [24]. It is unclear to us what the right approach might be, or how it could be applied in our context.

The approach of [17] is similar to Corchuelo et al., although the former cannot incorporate shift repairs. It tries harder than CPCT + to prune out pointless search configurations [17, p. 12], such as cycles in the parsing stack, although this leads to some minimum cost repairs being skipped [2]. A number of interlocking, sophisticated pruning mechanisms which build on this are described in [3]. These are significantly more complex than our merging of compatible configurations: since this gives us acceptable performance in practise, we have not investigated other pruning mechanisms.

The most radical member of the Fischer et al. family is that of [15]. This uses the A* algorithm, and a precomputed distance table to quickly generate repair sequences in the vein of Corchuelo et al. [15] works exclusively on the stategraph, assuming that it is unambiguous. However, Yacc systems allow ambiguous stategraphs and provide a means for resolving those ambiguities when creating the statetable. Many real-world grammars (e.g. Lua, PHP) make use of ambiguity resolution. In an earlier online draft, we created MF, a statetable-based algorithm which extends CPCT + with ideas from [15] at the cost of significant additional complexity. With the benefit of hindsight, we do not consider MF’s relatively small benefits (e.g. reducing the failure rate by approximately an additional 0.5%) to be worth that additional complexity.

CPCT + takes only the grammar and token types into account. However, it is possible to use additional information, such as nesting (e.g. taking into account curly brackets) and indentation when recovering from errors. This has two aims: reducing the size of the search space (i.e. speeding up error recovery); and making it more likely that the repairs reported matched the user’s intentions. The most sophisticated approach in this vein we are aware of is that of [6]. At its core, this approach uses GLR parsing: after a grammar is suitably annotated by the user, it is then transformed into a ‘permissive’ grammar which can parse likely erroneous inputs; strings which match the permissive parts of the grammar can then be transformed into a non-permissive counterpart. In all practical cases, the transformed grammar will be ambiguous, hence the need for generalised parsing. There is an intriguing similarity between our approach and that of [6]: our use of graph-structured stacks in configuration merging (see Section 5.1) gives that part of our algorithm a similar feel to

\[10\] In an earlier online draft of this paper we stated that this algorithm has a fundamental flaw. We now believe this was due to us incorrectly assuming that the ‘delete’ optimisation of Corchuelo et al. applied to [15]. We apologise to the authors for this mistake.
Don’t Panic! Better, Fewer, Syntax Errors for LR Parsers

GLR parsing (even though we never generate ambiguous strings). However, there are also major differences: LR parsers are significantly simpler to implement than GLR parsers; and the Fischer et al. family of algorithms do not require manually annotating, or statically increasing the size of, the grammar.

The approach we have taken in this paper can only repair errors on files which are fully lexed. Since many users are unaware of the distinction between these two stages, this can cause confusion: a minor lexing error does not lead to any parsing errors. Looked at another way, fixing a single lexing error can, surprisingly, lead to a slew of parsing errors being reported. Scannerless parsing [27] is one solution to this problem, since there is no distinction between lexing and parsing. However, scannerless parsing introduces new trade-offs: it is inherently ambiguous (e.g. is ‘if’ an identifier or a keyword?); ambiguity is, in general, undecidable and even the best ambiguity heuristics fail to find all ambiguous parts of a grammar [33]; and resolving those ambiguities can make the parser context sensitive [33]. Other possibilities are to intermingle parsing and lexing (see e.g. [34]) or to allow ‘fuzzy’ or partial matching of tokens (see [31, p. 8]).

A different approach to error recovery is that taken by [23]: rather than try and recover from errors directly, it reports in natural language how the user’s input caused the parser to reach an error state (e.g. “I read an open bracket followed by an expression, so I was expecting a close bracket here”), and possible routes out of the error (e.g. “A function or variable declaration is valid here”). This involves significant manual work, as every parser state (1148 in the Java grammar we use) in which an error can occur needs to be manually marked up, though the approach has various techniques to lessen the problem of maintaining messages as a grammar evolves.

Many compilers and editors have hand-written parsers with hand-written error recovery. Though generally ad-hoc in their approach, it is possible, with sufficient effort, to make them perform well. However, this comes at a cost. For example, the hand-written error recovery routines in the Eclipse IDE are approximately 5KLoC and are solely for use with Java code: CPCT+ is approximately 500LoC and can be applied to any LR grammar.

Although error recovery approaches have, historically, been mostly LR based, there are several non-LR approaches. A full overview is impractical, though a few pointers are useful. When LL approaches encounter an error, they generally skip input until a token in the follow set is encountered (an early example is [30]). Although this outperforms the simple panic mode of Section 3 it will, in general, clearly skip more input than CPCT+, which is undesirable. LL parsers do, however, make it somewhat easier to express grammar-specific error recovery rules. The most advanced LL approach that we are aware of is IntelliJ’s Grammar-Kit, which allows user to annotate their grammars for error recovery. Perhaps the most interesting annotation is that certain rules can be considered as fully matched even if only a prefix is matched (e.g. a partially completed function is parsed as if it was complete). It might be possible to add similar ideas to a successor of CPCT+, though this is more awkward to express in an LR approach. Error recovery for PEG grammars is much more challenging, because the non-LL parts of the grammar mean that there is not always a clearly defined point at which an error is determined to have occurred. PEG error recovery has thus traditionally required extensive manual annotations in order to achieve good quality recovery. [18] is the most advanced work we are aware of that tackles the problem of lessening the need for manual annotations for PEG error recovery. It does this by automatically adding many (though not necessarily all) of the annotations needed for good error recovery. However, deciding when to add, and when not to add, annotations is a difficult task and the two algorithms presented have different trade-offs: the Standard algorithm adds more
annotations, leading to better quality error recovery, but is more likely to change the input language accepted; the Unique algorithm adds fewer annotations, leading to poorer quality error recovery, but does not affect the language accepted. The quality of error recovery of the Unique algorithm, in particular, is heavily dependent on the input grammar: it works well on some (e.g. Pascal) but less well on others (e.g. Java). In cases where it performs less well, it can lead to parsers which skip large portions (sometimes the remainder) of the input.

While the programming language world has largely forgotten the approach of [1], there are a number of successor works, most recently that of [25]. These improve on the time complexity, though none that we are aware of address the issue of how to present what has been done to the user.

We are not aware of any error recovery algorithms that are formally verified. Indeed, as shown in this paper, some have serious flaws. We are only aware of two works which have begun to consider what correctness for such algorithms might mean: [36] provides a brief philosophical justification of the need and [12] provides an outline of an approach. Until such time as someone verifies a full error recovery algorithm, it is difficult to estimate the effort involved, or what issues may be uncovered.

10 Conclusions

In this paper we have shown that error recovery algorithms in the Fischer et al. family can run fast enough to be usable in the real world. Extending such algorithms to produce the complete set of minimum cost repair sequences allows parsers to provide better feedback to users, as well as significantly reducing the cascading error problem. The CPCT\(^+\) algorithm is simple to implement (less than 500LoC in our Rust system) and still has good performance.

Looking to the future, we (perhaps immodestly) suggest that CPCT\(^+\) might be ‘good enough’ to serve as a common representative of the Fischer et al. family. However, we do not think that it is the perfect solution. We suspect that, in the future, multi-phase solutions will be developed. For example, one may use noncorrecting error recovery (e.g. [26]) to identify syntax errors, and then use a combination of machine-learning (e.g. [28]) and CPCT\(^+\) to discover repair sequences that allow parsing to only error at those places.

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A Curated examples

In this section we show several examples of error recovery using $CPCT^+$ in different languages, to give some idea of what error recovery looks like in practise, and to emphasise that the algorithms in this paper are grammar neutral.

A.1 Java 7

Example 1 input:

```java
class C {
    int x y;
}
```

Example 1 output:

```
Parsing error at line 2 column 9. Repair sequences found:
1: Delete y
2: Insert ,
3: Insert =
```

Example 2 input:

```java
class C {
    void f() {
        if true {
        }
    }
}
```

Example 2 output:

```
Parsing error at line 2 column 9. Repair sequences found:
1: Delete y
2: Insert ,
3: Insert =
```

Parsing error at line 3 column 3. Repair sequences found:
1: Insert (, Shift true, Insert )

Parsing error at line 5 column 2. Repair sequences found:
1: Insert )
```
Example 3 (taken from [6, p. 10]) input:

```
1 class C {
2 void f() {
3     if (temp.greaterThan(MAX) // missing
4         fridge.startCooling();
5     }
6 }
```

Example 3 output:

```
Parsing error at line 4 column 7. Repair sequences found:
1: Insert )
```

Example 4 (taken from [6, p. 16]) input:

```
1 class C {
2     void methodX () {
3         if (true)
4             foo();
5     }
6     int i = 0;
7     while (i < 8)
8         i=bar(i);
9     }
10 }
```

Example 4 output:

```
Parsing error at line 7 column 5. Repair sequences found:
1: Insert {
Parsing error at line 11 column 1. Repair sequences found:
1: Delete }
```

Example 5 (taken from [19, p. 2]):

```
1 public class Example {
2     public static void main(String[] args) {
3         int n = 5;
4         int f = 1;
5         while(0 < n) {
6             f = f * n;
7             n = n - 1
8         };
9         System.out.println(f);
10     }
11 }
```

Example 5:

```
Parsing error at line 8 column 5. Repair sequences found:
1: Delete }
2: Insert ;
Parsing error at line 11 column 2. Repair sequences found:
1: Insert }
```

Example 6:

```
1 class C {
2     void f() {
3         x(((((
4     }
5 })
```

Example 6 output, showing the timeout being exceeded and error recovery unable to complete:

```
Parsing error at line 4 column 3. No repair sequences found.
```
A.2 Lua 5.3

Example 1 input:
1 print(“Hello World”)

Example 1 output:
Parsing error at line 1 column 20. Repair sequences found:
1: Insert )

Example 2 input. Note that ‘=’ in Lua is the assignment operator, which is not valid in conditionals; and that if/then/else blocks must be terminated by ‘end’.
1 function fact (n)
2 if n = 0 then
3 return 1
4 else
5 return n * fact(n-1)
6 end

Example 2 output:
Parsing error at line 2 column 8. Repair sequences found:
1: Delete =, Delete 0
2: Insert or, Delete =
3: Insert ==, Delete =
4: Insert --, Delete =
5: Insert >=, Delete =
6: Insert <=, Delete =
7: Insert >, Delete =
8: Insert <, Delete =
9: Insert |, Delete =
10: Insert &, Delete =
11: Insert >>, Delete =
12: Insert <<, Delete =
13: Insert -, Delete =
14: Insert +, Delete =
15: Insert .., Delete =
16: Insert %, Delete =
17: Insert //, Delete =
18: Insert /, Delete =
19: Insert *, Delete =
20: Insert //, Delete =
21: Insert -, Delete =
22: Insert <<, Delete =

Parsing error at line 6 column 4. Repair sequences found:
1: Insert end

Examples 3 and 4 (both derived from the Lua 5.3 reference manual) shows that CPCT+ naturally deals with an inherent ambiguity in Lua’s Yacc grammar involving function calls and assignments (which, following the Lua specification, is resolved by Yacc in favour of function calls). This example shows the ‘unambiguous’ case (i.e. if Lua forced users to use ‘;’ everywhere, the grammar would have no ambiguities):
1 a = b + c;
2 (print or io.write)’done’)

Example 3 output:
Parsing error at line 2 column 26. Repair sequences found:
1: Delete )
2: Insert (}

Example 4 shows what happens in the ‘ambiguous’ case (which Lua’s grammar resolves in favour of viewing the code below as a function call to c):
30 REFERENCES

Example 4 output:

```
Parsing error at line 2 column 26. Repair sequences found:
1: Delete )
```

Example 5 (taken from [19] p. 7):

```
if then print("that") end
```

Example 5 output:

```
Parsing error at line 1 column 4. Repair sequences found:
1: Insert [{<String>}]=
2: Insert "<String>"
3: Insert ...
4: Insert <Numeral>
5: Insert true
6: Insert false
7: Insert nil
8: Insert <Name>
```

A.3 PHP 7.3

Example 1 input:

```
function n() {
    $x = 1
}
```

Example 1 output:

```
Parsing error at line 3 column 1. Repair sequences found:
1: Insert ;
```

Example 2 input:

```
$a = array("foo", "bar");
```

Example 2 output:

```
Parsing error at line 2 column 5. Repair sequences found:
1: Insert ]
```

Example 3 input:

```
class X {
    function a($x) {
        if $x {
        }
    }
}
```

Example 3 output:

```
Parsing error at line 3 column 12. Repair sequences found:
1: Insert (, Shift $x, Insert )
Parsing error at line 5 column 2. Repair sequences found:
1: Insert )
```
Figure 16: The full histogram of the number of error locations. The small number of outliers obscures the main bulk of the data – see Figure 13 for the truncated version.