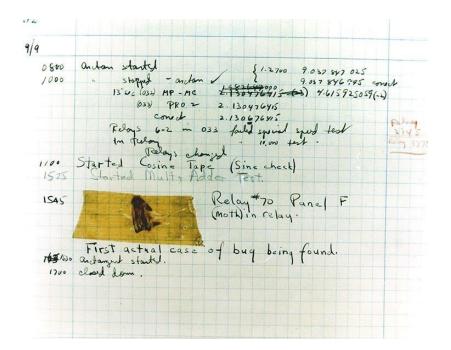


The Hitchhiker's Guide to

Search-Based Program Repair

Chris Timperley





Ever since...





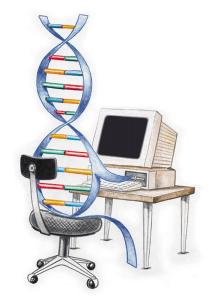


www.phdcomics.com

2008

Genetic Programming to modify existing programs, rather than building them from scratch.

Demonstrates concept of automated program repair.



Evolutionary Repair of Faulty Software

Andrea Arcuri

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Abstract

Testing and fault localization are very expensive software engineering tasks that have been tried to be automated. Although many successful tentingues have been designed, the actual change of the code for fixing the discovered faults is still a human only task. Even in the ideal case in which automated tools could tell us exactly where the location of a fault is, it is not always trivial how to fix the code. In this paper we analyse the possibility of automating the complex task of fixing faults. We propose to model this task as a search problem, and hence to use for example evolutionary algorithms to solve it. We then discuss the potential of this approach and how its current limits can be addressed in the future. This task is extremely challenging and mainly unceplored in literature. Hence, this paper only overs an initial investigation and gives directions for future work. A research prototype called JAFF and a case study are presented to give first validation of this approach.

Keyword: Repair, Fault Localization, Automated Debugging, Genetic Programming, Search Based Software Engineering, Coevolution.

1 Introduction

Software testing is used to reveal the presence of faults in computer programs [50]. Even if no fault is found, testing cannot guarantee that the software is fault-free. However, testing can be used to increase our confidence in the software reliability. Unfortunately, testing is expensive, time consuming and tedious. It is estimated that testing requires around 50% of the total cost of software development [14]. This is the reason why there has been a lot of effort spent to automate this expensive oftware engineering task.

Even if an optimal automated system for doing software testing existed, we still need to know where the faults are located, that in order to be able to fix them. Automated techniques can help the tester in this task [26, 65, 78].

Although in some cases it is possible to automatically locate the faults, there is still the need to modify the code to remove the faults. Is it possible to automate the task of fixing faults? This would be the natural next step if we seek a full automation of software engineering. And it would be particularly helpful in the cases of complex software in which, although the faulty part of code considerable, it is difficult to provide a patch for the fault. This would also be a step forward to achieve copporate visions like for example IBM's Autonomic Computing [40].

There has been work on fixing code automatically (e.g., [63, 61, 68, 25]). Unfortunately, in that work there are heavy constraints on the type of modifications that can be automatically done on the source code. Hence, only limited classes of faults can be addressed. The reason for putting these constraints is that there are infinite ways to do modifications on a program, and checking all of them is impossible.

1

GenProg

The Problem

Software engineering is expensive, summing to over one half of of the US GDP annually. Software maintenance accounts for over of that life cycle cost, and a key aspect of maintenance is fixing b existing programs. Unfortunately, the number of reported bugs i available development resources. It is common for a popular pro hundreds of new bug reports filed every day.

Software maintenance is expensive. GenProg reduces software maintenance costs by automatically producing patches (repairs) defects.

Our Approach

Many bugs can be fixed with just a few changes to a program's so Human repairs often involve inserting new code and deleting or existing code. GenProg uses those same building blocks to search automatically.

GenProg uses genetic programming to search for repairs. Our ev

Automatically Finding Patches Using Genetic Programming *

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Abstract

Automatic program repair has been a longstanding goal in software engineering, yet debugging remains a largely manual process. We introduce a fully automated method for locating and repairing bugs in software. The approach works on off-the-shelf legacy applications and does not require formal specifications, program annotations or special coding practices. Once a program fault is discovered, an extended form of genetic programming is used to evolve program variants until one is found that both retains required functionality and also avoids the defect in question. Standard test cases are used to exercise the fault and to encode program requirements. After a successful repair has been discovered, it is minimized using structural differencing algorithms and delta debugging. We describe the proposed method and report experimental results demonstrating that it can successfully repair ten different C programs totaling 63 000 lines in under 200 seconds, on overnee

1 Introduction

Fixing bugs is a difficult, time-consuming, and manual process. Some reports place software maintenance, traditionally defined as any modification made on a system after its delivery, at 90% of the total cost of a typical software project [27]. Modifying existing code, repairing defects, and otherwise evolving software are major parts of those costs 1241. The number of outstanding software defects typically exceeds the resources available to address them [4] Mature software projects are forced to ship with both known and unknown bugs [21] because they lack the development resources to deal with every defect. For example, in 2005, one Mozilla developer claimed that, "everyday, almost 300 bugs appear [...] far too much for only the Mozilla programmers to handle" [5, p. 363].

"This research was supported in part by National Science Foundation Grants CNS 0627523 and CNS 0716478, Air Force Office of Scientific Re-search grant FA9550-07-1-0532, as well as gifts from Microsoft Research.

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To alleviate this burden, we propose an automatic technique for repairing program defects. Our approach does not require difficult formal specifications, program annotations or special coding practices. Instead, it works on off-the-shelf legacy applications and readily-available testcases. We use genetic programming to evolve program variants until one is found that both retains required functionality and also avoids the defect in question. Our technique takes as input a program, a set of successful positive testcases that encode required program behavior, and a failing negative test case that demonstrates a defect.

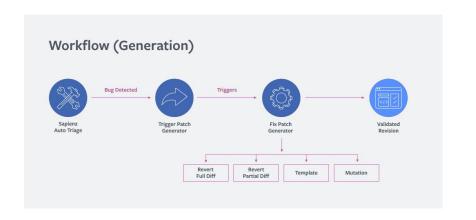
Genetic programming (GP) is a computational method inspired by biological evolution, which discovers computer programs tailored to a particular task [19]. GP maintains a population of individual programs. Computational analogs of biological mutation and crossover produce program variants. Each variant's suitability is evaluated using a userdefined fitness function, and successful variants are selected for continued evolution. GP has solved an impressive range of problems (e.g., see [1]), but to our knowledge it has not been used to evolve off-the-shelf legacy software.

A significant impediment for an evolutionary algorithm like GP is the potentially infinite-size search space it must sample to find a correct program. To address this problem we introduce two key innovations. First, we restrict the algorithm to only produce changes that are based on struc tures in other parts of the program. In essence, we hypothesize that a program that is missing important functionality (e.g., a null check) will be able to copy and adapt it from another location in the program. Second, we constrain the genetic operations of mutation and crossover to operate only on the region of the program that is relevant to the error (tha is, the portions of the program that were on the execution path that produced the error). Combining these insights, we demonstrate automatically generated repairs for ten C programs totaling 63,000 lines of code.

We use GP to maintain a population of variants of that program. Each variant is represented as an abstract syntax tree (AST) paired with a weighted program path. We modify variants using two genetic algorithm operations, crossover and mutation, specifically targeted to this repre

2009

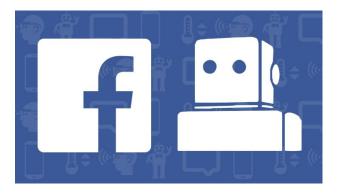
GenProg demonstrates program repair on real-world C programs

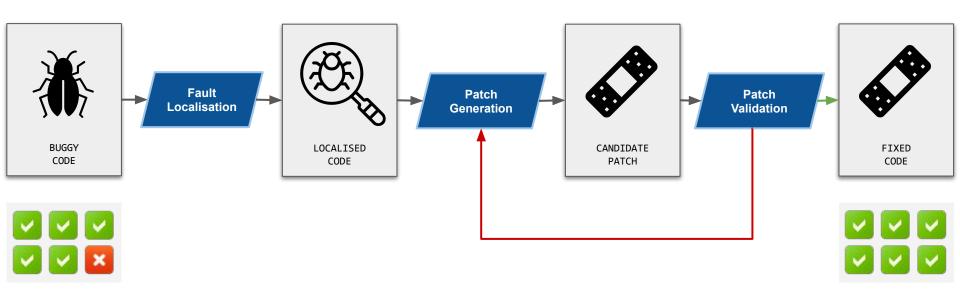


2018

Facebook unveils SapFix: a search-based program repair technique







Motivating Example







Can you spot the bug?

```
1: int getYear(int days) {
    int year = 1980;
    while (days > 365) {
4:
     if (isLeapYear(year)) {
    if (days > 366) {
 5:
     days -= 366;
6:
7:
     year += 1;
8:
9:
     } else {
10:
     days -= 365;
11:
     year += 1;
12:
13:
14: return year;
15: }
```

Determines the current year as a function of the number of days since 1st Jan 1980.

year(367) == 1981

year(-100) == 1980

year(1000) == 1982

year(0) == 1980

year(1826) == 1984

year(365) == 1980

year(2000) == 1985

year(10593) == 2008

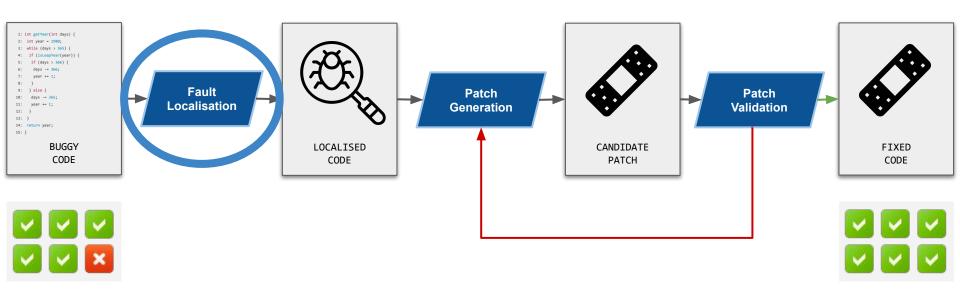
year(12054) == 2012

year(1827) == 1984

year(366) == 1980

Positive Tests

Negative Tests



Spectrum-Based Fault Localisation (SBFL)

Computes a measure of *suspiciousness* μ_c for each component c within the program (i.e., a line or statement), based on its correlation with positive and negative test execution.

- Components that are executed by passing tests are deemed less suspicious.
- Components that are executed by failing tests are deemed more suspicious.
- We restrict our attention to the set of *implicated* components:

$${c \in C \mid \mu_c > 0}$$

SBFL (1/4): Coverage

```
int getYear(int days) {
   int year = 1980;

while (days > 365) {
   if (isLeapYear(year)){
      if (days > 366) {
        days -= 366;
        year += 1;
      } else {
      days -= 365;
      year += 1;
    }
   }
   return year;
}
```

```
int getYear(int days) {
 int year = 1980;
 while (days > 365) {
   if (isLeapYear(year)){
     if (days > 366) {
       days -= 366;
       year += 1;
      } else { }
   } else {
     days -= 365;
     year += 1;
 return year;
```

```
int getYear(int days) {
  int year = 1980;
 while (days > 365) {
    if (isLeapYear(year)){
     if (days > 366) {
       days -= 366;
       year += 1;
      } else { }
     else {
      days -= 365;
     year += 1;
 return year;
```

```
int getYear(int days) {
 int year = 1980;
 while (days > 365) {
   if (isLeapYear(year)){
     if (days > 366) {
       days -= 366;
       year += 1;
     } else { }
   } else {
      days -= 365;
     year += 1;
 return year;
```

```
year(-366) == 1980
```

```
year(367) == 1981
```

year(1000) == 1982

year(366) == FAIL

SBFL (2/4): Fault Spectra

		year(-366)	year(367)	year(1000)	year(366)
S1	year = 1980;	1	1	1	1
S2	while (days > 365)	1	1	1	1
S3	<pre>if (isLeapYear(year))</pre>	0	1	1	1
S4	if (days > 366)	0	1	1	1
S5	days -= 366;	0	1	1	0
S6	year += 1;	0	1	1	0
S7	else { }	0	0	0	1
S8	else	0	0	1	0
S9	days -= 365;	0	0	1	0
S10	year += 1;	0	0	1	0
S11	return year;	1	1	1	0
		PASS	PASS	PASS	FAIL

SBFL (3/4): Fault Spectra

		ер	ef	np	nf
S1	year = 1980;	3	1	0	0
S2	while (days > 365)	3	1	0	0
S3	<pre>if (isLeapYear(year))</pre>	2	1	1	0
S4	if (days > 366)	2	1	1	0
S5	days -= 366;	2	0	1	1
S6	year += 1;	2	0	1	1
S7	else { }	0	1	3	0
S8	else	1	0	0	1
S9	days -= 365;	1	0	0	1
S10	year += 1;	1	0	0	1
S11	return year;	3	0	0	1

 e_n : num. passing tests that cover the line.

 e_f^{\prime} : num. failing tests that cover the line.

 $\vec{n_p}$: num. passing tests that don't cover the line.

 $n_f^{\rm F}$: num. failing tests that don't cover the line.

SBFL (4/4): Suspiciousness

		ер	ef	np	nf
S1	year = 1980;	3	1	0	0
S2	while (days > 365)	3	1	0	0
S3	<pre>if (isLeapYear(year))</pre>	2	1	1	0
S4	if (days > 366)	2	1	1	0
S5	days -= 366;	2	0	1	1
S6	year += 1;	2	0	1	1
S7	else { }	0	1	3	0
S8	else	1	0	0	1
S9	days -= 365;	1	0	0	1
S10	year += 1;	1	0	0	1
S11	return year;	3	0	0	1

$$\frac{e_f}{e_f + n_f + e_p}$$

$$\frac{e_f}{\sqrt{(e_f + n_f) \cdot (e_f + e_p)}}$$

$$\left| \frac{e_f}{e_f + n_f} - \frac{e_p}{e_p + n_p} \right|$$

$$\frac{\frac{e_f}{e_f + n_f}}{\frac{e_p}{e_p + n_p} + \frac{e_f}{e_f + n_f}}$$

$$\begin{cases} 0, & \text{if } \mathbf{e}_f + e_p = 0 \\ 1.0, & \text{if } \mathbf{e}_f > 0 \land e_p = 0 \\ 0.1, & \text{otherwise} \end{cases}$$

SBFL (4/4): Suspiciousness

		ер	ef	np	nf	μ
S1	year = 1980;	3	1	0	0	0.1
S2	while (days > 365)	3	1	0	0	0.1
S3	<pre>if (isLeapYear(year))</pre>	2	1	1	0	0.1
S4	if (days > 366)	2	1	1	0	0.1
S5	days -= 366;	2	0	1	1	0.0
S6	year += 1;	2	0	1	1	0.0
S7	else { }	0	1	3	0	1.0
S8	else	1	0	0	1	0.0
S9	days -= 365;	1	0	0	1	0.0
S10	year += 1;	1	0	0	1	0.0
S11	return year;	3	0	0	1	0.0

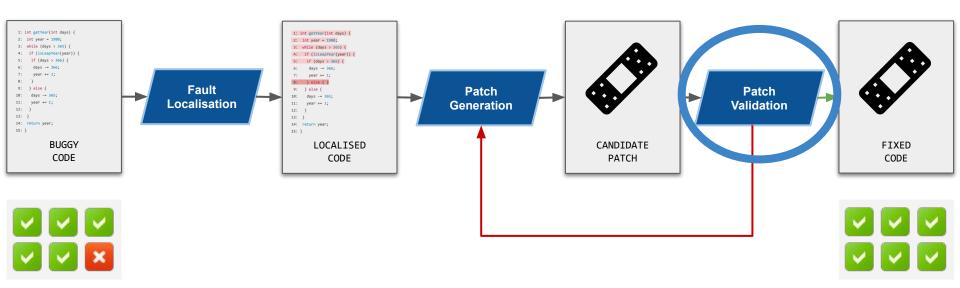
$$\frac{e_f}{e_f + n_f + e_p}$$

$$\frac{e_f}{\sqrt{(e_f + n_f) \cdot (e_f + e_p)}}$$

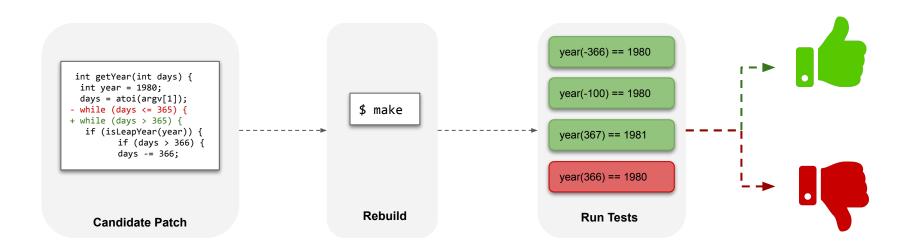
$$\left| \frac{e_f}{e_f + n_f} - \frac{e_p}{e_p + n_p} \right|$$

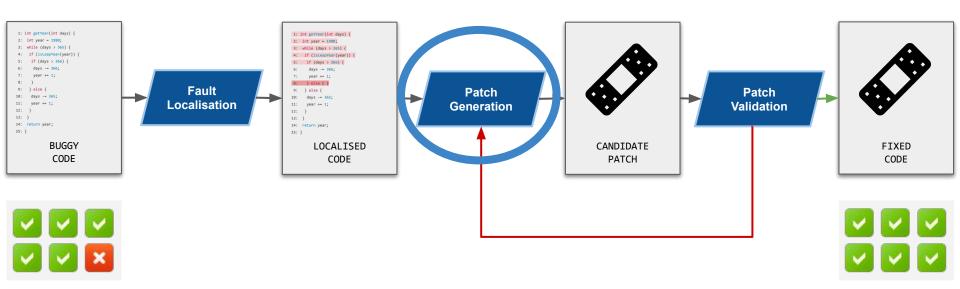
$$\frac{\frac{e_f}{e_f + n_f}}{\frac{e_p}{e_p + n_p} + \frac{e_f}{e_f + n_f}}$$

$$\begin{cases} 0, & \text{if } e_f + e_p = 0 \\ 1.0, & \text{if } e_f > 0 \land e_p = 0 \\ 0.1, & \text{otherwise} \end{cases}$$



Patch Validation





Patch Generation: Two Paradigms

Semantics-Based Repair

Angelix, SearchRepair, NOPOL, ...

```
if (\alpha_0) {
  days -= \alpha_1;
  year += \alpha_2;
}
```

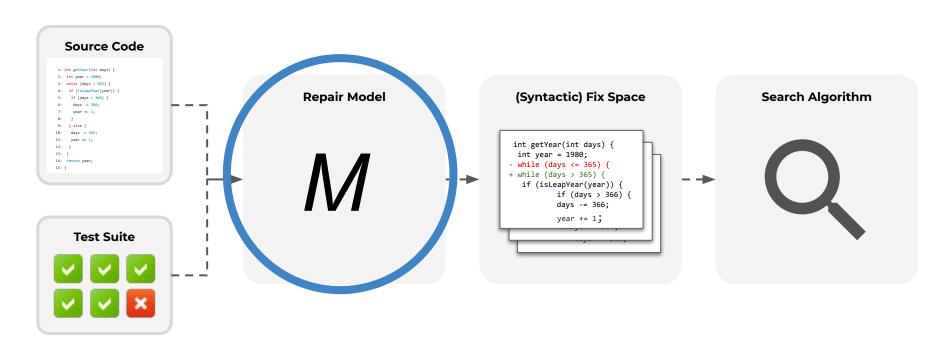
- Replaces suspicious expressions with symbolic variables (e.g., α_a).
- Uses concolic execution to find *angelic values* that would cause a given test to pass.
- Uses program synthesis to construct a replacement expression that produces the angelic values.
- Validate the candidate patch.

Syntax-Based Repair

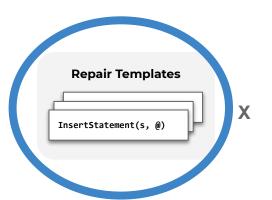
GenProg, RSRepair, SPR, AE, PAR, ...

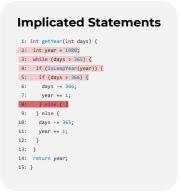
- Applies repair operators to suspicious statements within the program to produce concrete patches.
- Validate candidate patch.
- Operates directly on source code: searches over the space of possible syntactic changes.

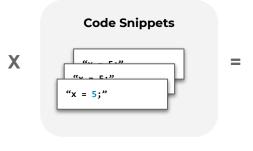
Syntax-Based Repair

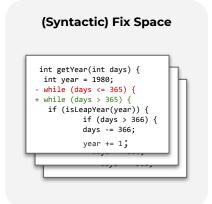


Repair Model









Repair Model: Templates

Describes a transformation to the AST of the buggy program, which may or may not take a set of code snippets as its arguments.

Generic Templates

Highly expressive: can represent most changes.

- Delete Statement
- Replace Statement
- Append Statement
- Swap Statements
- Replace Expression
- Insert Conditional
- Insert Conditional Control Flow
- ...

Specialised Templates

Low expressiveness: tailored to particular bugs.

- Insert null check
- Insert bounds check
- Insert class cast check
- Apply off-by-one correction to array access
- Assign lower bound to array access
- Assign upper bound to array access
- Add, remove, or replace parameter in method call
- Replace method
- ..

Repair Model: GenProg

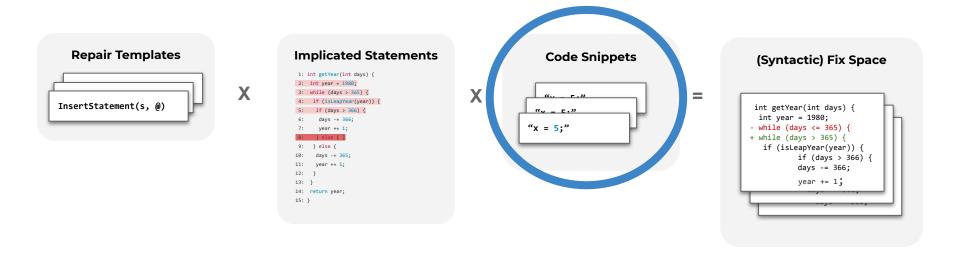
Uses a generic set of statement-level templates:

- Delete Statement
- Replace Statement
- Swap Statements
- Append Statement

In theory, this set of operators should be expressive enough to allow us to fix the vast majority of bugs.

Where do the statements come from?

Repair Model



Repair Model: Code Snippets

We need a source of code snippets to serve as template parameters.

- Searching the space of all possible statements is infeasible.
- We need a heuristic for selecting template parameter values.

Plastic Surgery Hypothesis

GenProg balances tractability and expressiveness by using code from the buggy program to compose its repairs. GenProg (and many other approaches) exploit what is now known as the plastic surgery hypothesis:

"Changes to a codebase contain snippets that *already exist* in the codebase at the time of the change, and these snippets can be *efficiently found* and exploited." [1]

- Barr et al. measure line-level *graftability* of 15,273 commits across several large Java projects.
- 43% of changes are graftable from the exact version of software being changed.
- 30% of grafts could be found within the same file at which the human-written change occurred.

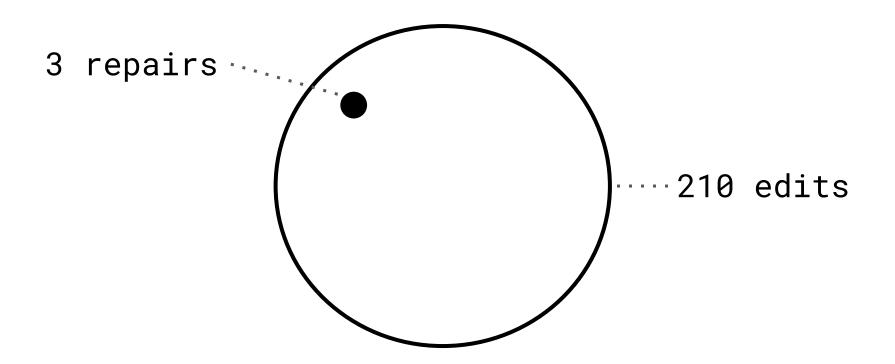
Exercise 1: Form pairs and find repairs.

```
1: int getYear(int days) {
     int year = 1980;
     while (days > 365) {
      if (isLeapYear(year)) {
      if (days > 366) {
     days -= 366;
      year += 1;
      } else { }
      } else {
      days -= 365;
10:
11:
      year += 1;
12:
13:
14:
    return year;
15: }
```

Repair Templates:

- Delete Statement
- Replace Statement
- Append Statement

```
while (days > 365) { ... }
vear = 1980;
davs -= 366;
vear += 1;
else { ... }
days -= 365;
return year;
else {}
if (days > 366) { ... }
if (isLeapYear(year)) { ... } else {}
if (days <= 365) { break; }
break;
```



Likelihood of picking a repair: ~1.43%

We can use *probabilistic models* to improve our odds of success.

Probabilistic Repair Models

Learn a classifier, $p(e \mid \mathbf{x})$, that estimates the probability that an edit e is correct based on the features \mathbf{x} of that edit:

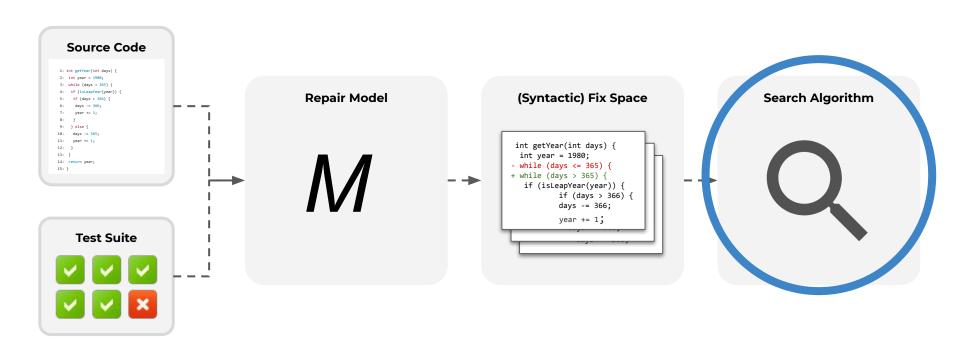
- Edit Location (i.e., use fault localisation)
- Repair Template [1]
- Statement Kind [2]
- Syntactic Features [3]

^[1] Fan Long and Martin Rinard. 2015. Staged program repair with condition synthesis. In Proceedings of the 2015 10th Joint Meeting on Foundations of Software Engineering (ESEC/FSE 2015). ACM, New York, NY, USA, 166-178. DOI: https://doi.org/10.1145/2786805.2786811

^[2] Mauricio Soto, Ferdian Thung, Chu-Pan Wong, Claire Le Goues, and David Lo. 2016. A deeper look into bug fixes: patterns, replacements, deletions, and additions. In Proceedings of the 13th International Conference on Mining Software Repositories (MSR '16). ACM, New York, NY, USA, 512-515. DOI: https://doi.org/10.1145/2901739.2903495

^[3] Fan Long and Martin Rinard. 2016. Automatic patch generation by learning correct code. In Proceedings of the 43rd Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (POPL '16). ACM, New York, NY, USA. 298-312. DOI: https://doi.org/10.1145/2837614.2837617

Syntax-Based Repair



Random and Exhaustive Search

Use the probabilistic model to either (a) sample and evaluate edits at random [1], or (b) rank all possible edits and evaluate them in ranked order [2].

- Simple and surprisingly effective. Used by most repair approaches.
- Usually restricted to single-edit patches. (Combinatorial explosion.)
- Treats the search as a decision problem: should I apply this patch?
- Allows us to substantially reduce the cost of candidate patch evaluation.

How can we reduce the cost of patch validation?

```
1: int getYear(int days) {
 2: int year = 1980;
    while (days > 365) {
 4:
     if (isLeapYear(year)) {
 5: if (days > 366) {
 6: days -= 366;
 7:
   vear += 1;
 8:
 9: } else {
10:
    days -= 365;
11:
   vear += 1;
12: }
13: }
14: return year;
15: }
```

```
assert getYear(365) == 1980;

assert getYear(0) == 1980;

assert getYear(367) == 1981;

assert getYear(1826) == 1984;

assert getYear(1827) == 1984;

assert getYear(366) == 1980;
```

Random and Exhaustive Search: Optimisations

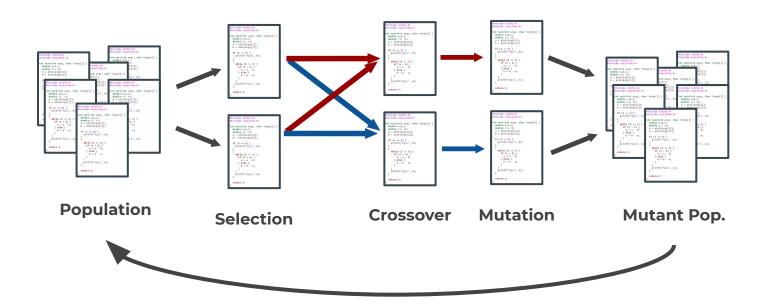
- 1. **Avoid redundant tests:** Only execute tests that cover the modified parts of the program.
- 2. **Short-circuit test suite evaluation:** Stop evaluating the rest of the test suite on the first instance of failure -- the outcome of the test suite evaluation (i.e., PASS or FAIL) won't be changed.
- Minimise number of test executions: Use (online) test prioritisation to minimise the expected number of test executions.

GenProg's Genetic Algorithm [1]

Uses feedback from patch validation to evolve *multi-edit patches*.

- Evolves a population of individuals that represent candidate patches.
- Each individual is represented as a sequence of edits.
- Each individual has a fitness value that is used to guide the search.
 - Indicates proximity to an acceptable repair.
 - Based on outcomes of test suite.

Genetic Algorithm



Fitness Function

Computes a weighted sum of number of positive/negative tests that passed.

$$f = W_{pos} T_{pos} + W_{neg} T_{neg}$$

Rewards fixing the bug $W_{\it neg}T_{\it neg}$, and punishes regressions $W_{\it pos}T_{\it pos}$

Problems:

- In practice, we usually only have a single negative test.
- Lack of gradient to guide the search. Difficult to identify partial solutions.
- Expensive to compute!

Exercise 2: A Cryptic Checksum Conundrum

```
while (next != '\n') {
    scanf("%c", &next);
    sum += next;
}
sum = sum % 64 + 22;
return sum;
```

Takes a single line as input. Should sum the integer codes of the ASCII characters, excluding the newline, modulo 64, plus the code for the space character. As before, you may only use the following repair operators:

- Delete Statement
- Replace Statement
- Append Statement

Hint: more than one edit is required.

```
while (next != '\n') { ... }

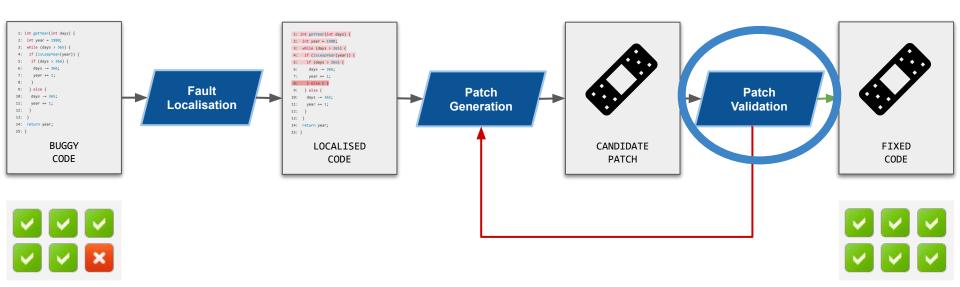
if (next == '\n') { break; }

scanf("%c", &next);

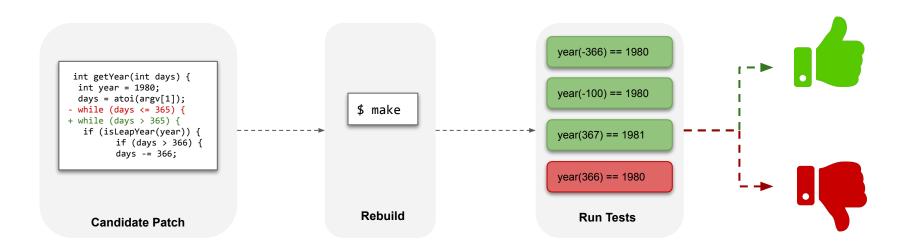
sum += next;

sum = sum % 64 + 22;

return sum;
```



Patch Validation



Warning: Don't trust your test suite

```
1: int getYear(int days) {
 2: int year = 1980;
     while (days > 365) {
      if (isLeapYear(year)) {
                                                            year(-366) == 1980
       if (days > 366) {
        days -= 366;
                                                            year(-100) == 1980
        year += 1;
       } else { return year; }
                                                            year(367) == 1981
      } else {
       days -= 365;
10:
       year += 1;
11:
                                                            year(366) == 1980
12:
13:
14: return year;
15: }
```

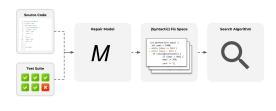
Summary



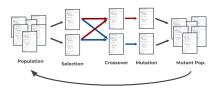
SBFL (1/4): Coverage

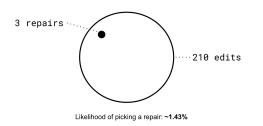


Syntax-Based Repair



Genetic Algorithm





Warning: Don't trust your test suite



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