Improving Patch Correctness Analysis via Random Testing and Large Language Models

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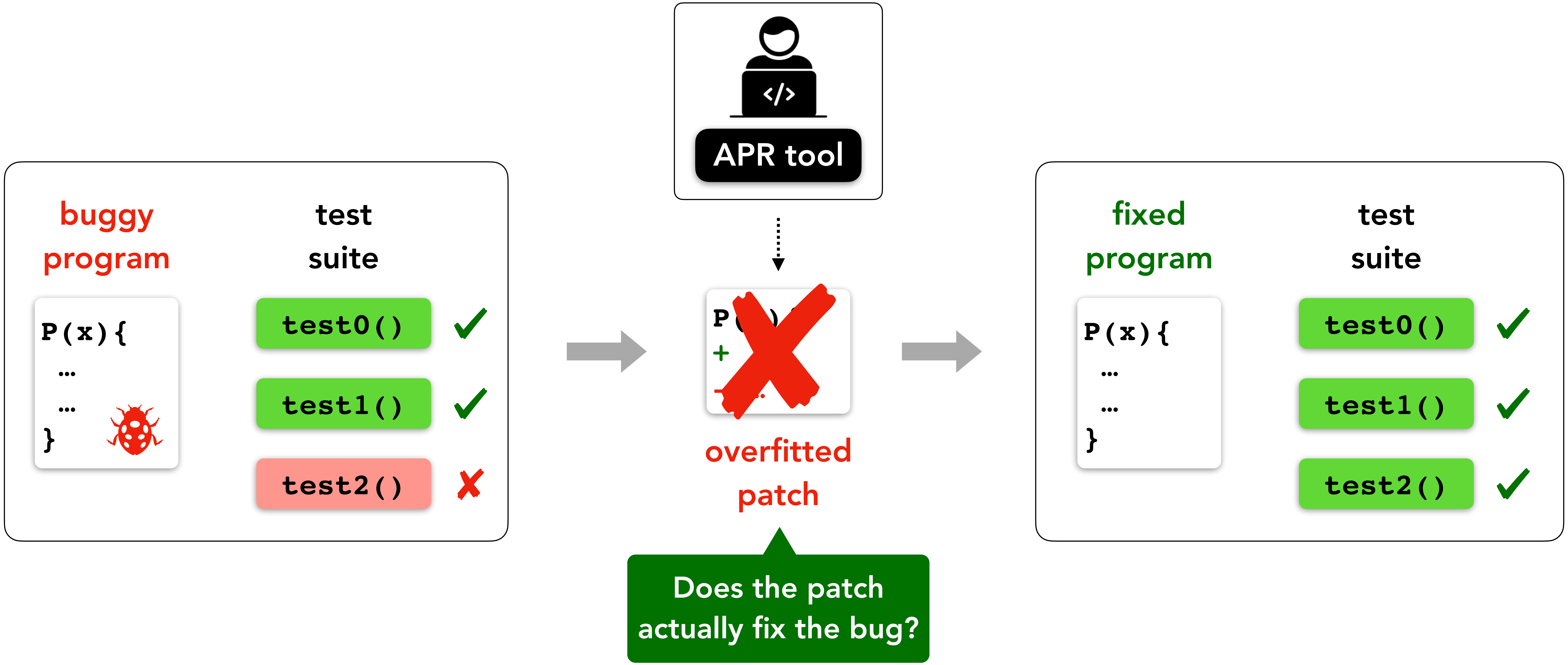
A Program Repair Scenario



buggy program

test suite

P(x){
…
…
}

test0() ✓

test1() ✓

test2() ✗

APR tool

P(x){
+
-…

overfitted patch

Does the patch actually fix the bug?

fixed program

test suite

P(x){
…
…
}

test0() ✓

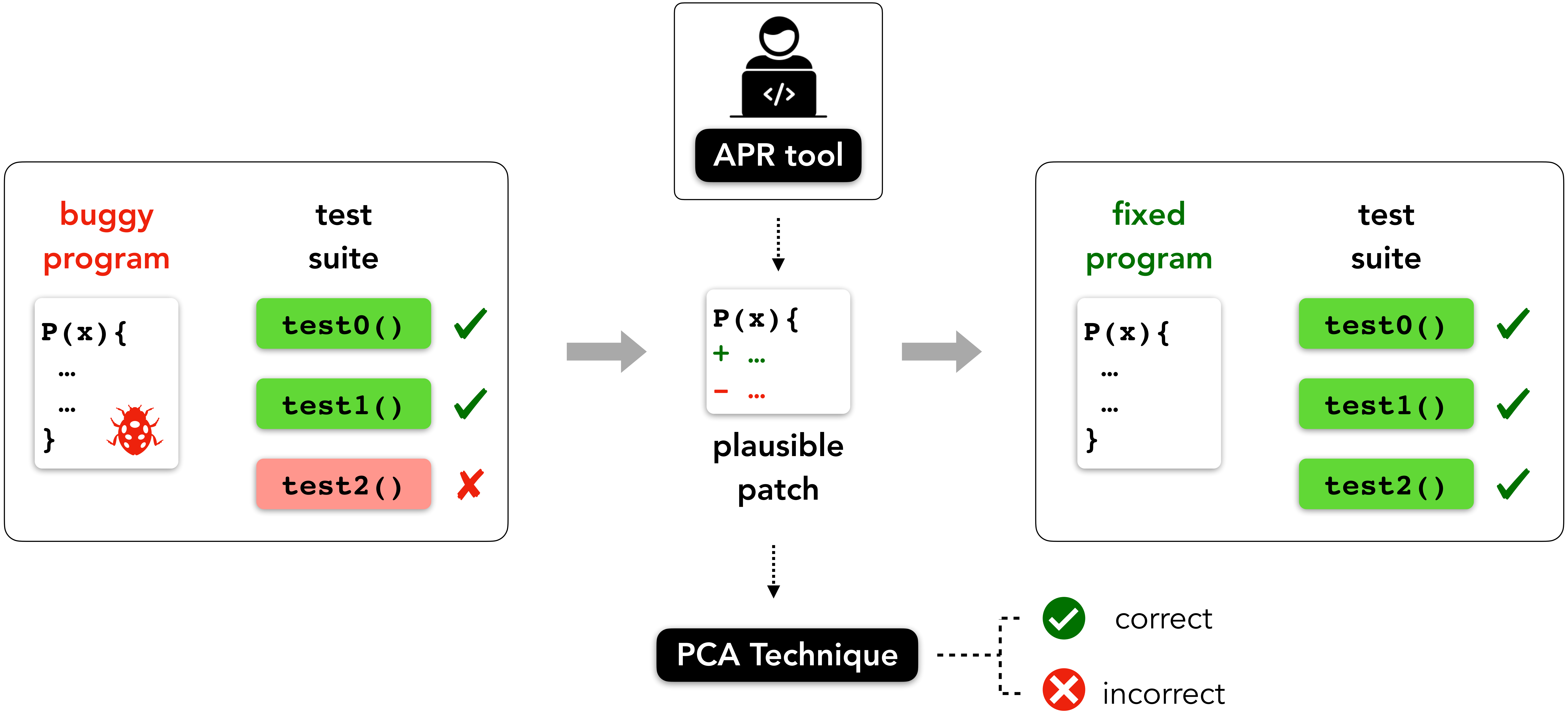
test1() ✓

test2() ✓

Plausible patches are prone to overfitting, leading to the creation of incorrect patches

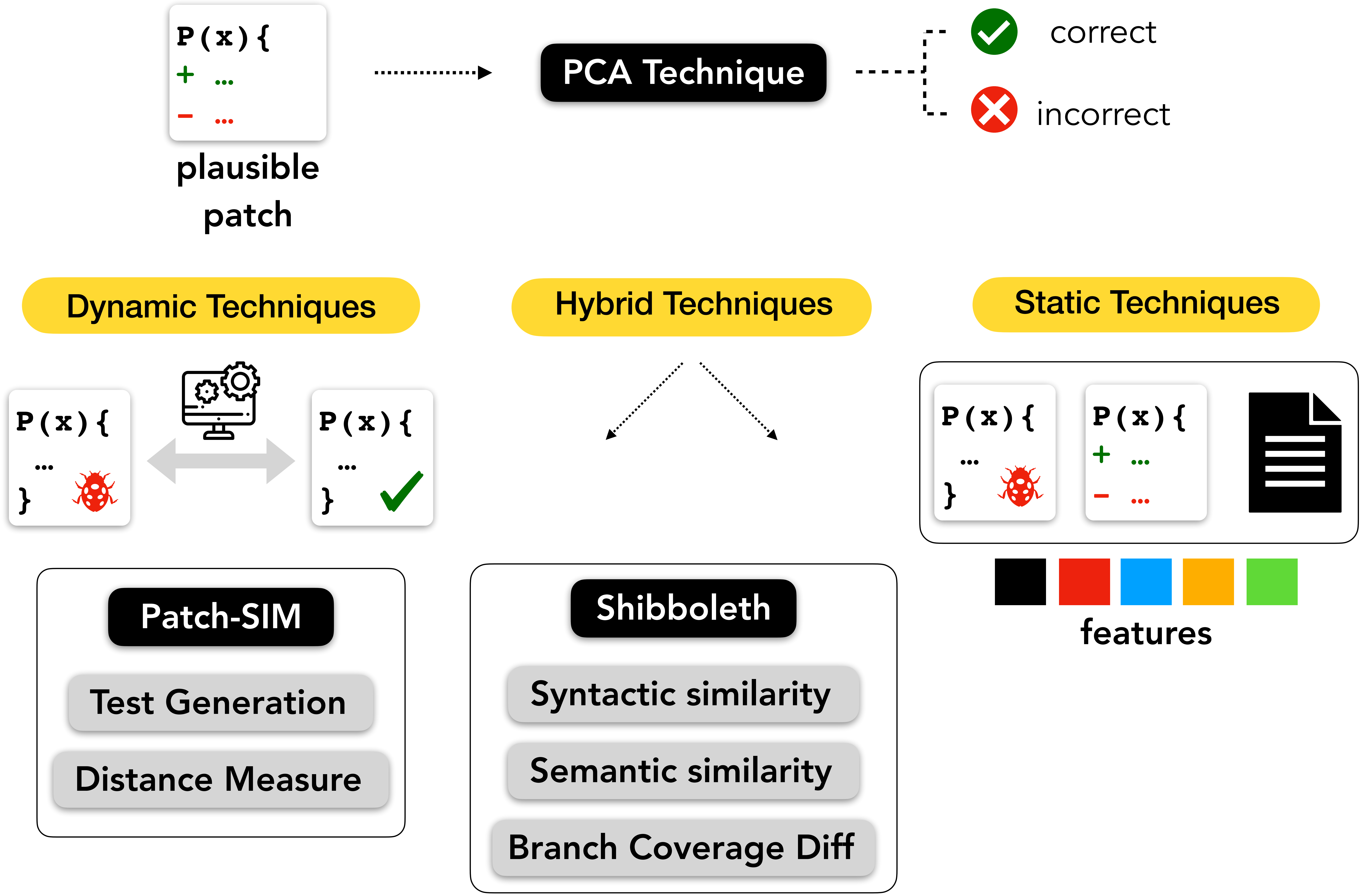
Claire Le Goues, Michael Pardal, and Abhik Roychoudhury. **Automated Program Repair.** Commun. ACM 2019

Patch Correctness Assessment



Shangwen Wang et al. **Automated Patch Correctness Assessment: How far are we?.** ASE 2020

Patch Correctness Assessment



plausible patch

PCA Technique

correct

incorrect

Dynamic Techniques

Hybrid Techniques

Static Techniques

features

Patch-SIM

Test Generation

Distance Measure

Shibboleth

Syntactic similarity

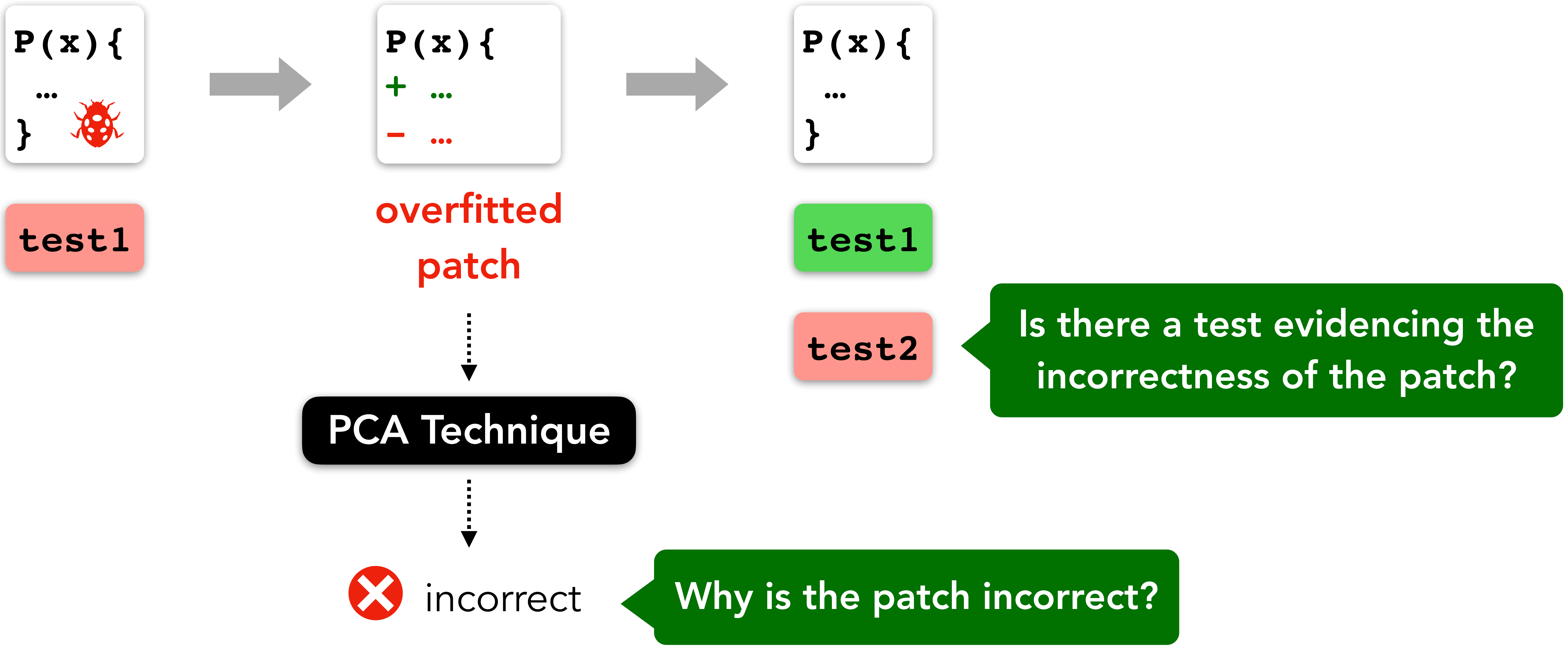
Semantic similarity

Branch Coverage Diff

Yingfei Xiong et al. **Identifying patch correctness in test-based program repair.** ICSE 2018

Ali Ghanbari and Andrian Marcus. **Patch correctness assessment in automated program repair based on the impact of patches on production and test code.** ISSTA 2022

Patch Correctness Assessment


P(x){
…
}
test1
P(x){
+ …
- …
overfitted patch
PCA Technique
incorrect
P(x){
…
}
test1
test2
Is there a test evidencing the incorrectness of the patch?
Why is the patch incorrect?

Goal: improve patch correctness analysis by generating tests highlighting and explaining the incorrectness of a patch

Shangwen Wang et al. **Automated Patch Correctness Assessment: How far are we?.** ASE 2020

Hypothesis

Jackson-databind example

```
P(x){
+ …
- …
```

plausible patch

We found that 70% of subsequent tests only differs from the initial fault-revealing test in the test input and in the corresponding assertions

```
public void testWithScalar118() {
  ObjectMapper mapper = new ObjectMapper();
  ExternalTypeWithNonPOJO input =
        new ExternalTypeWithNonPOJO(new Date(123L));
  String json = mapper.writeValueAsString(input);
  assertNotNull(json);
  // and back just to be sure:
  ExternalTypeWithNonPOJO result = mapper.readValue(json,
        ExternalTypeWithNonPOJO.class);
  assertNotNull(result.value);
  assertTrue(result.value instanceof java.util.Date);
}
```

✓

initial fault-revealing test

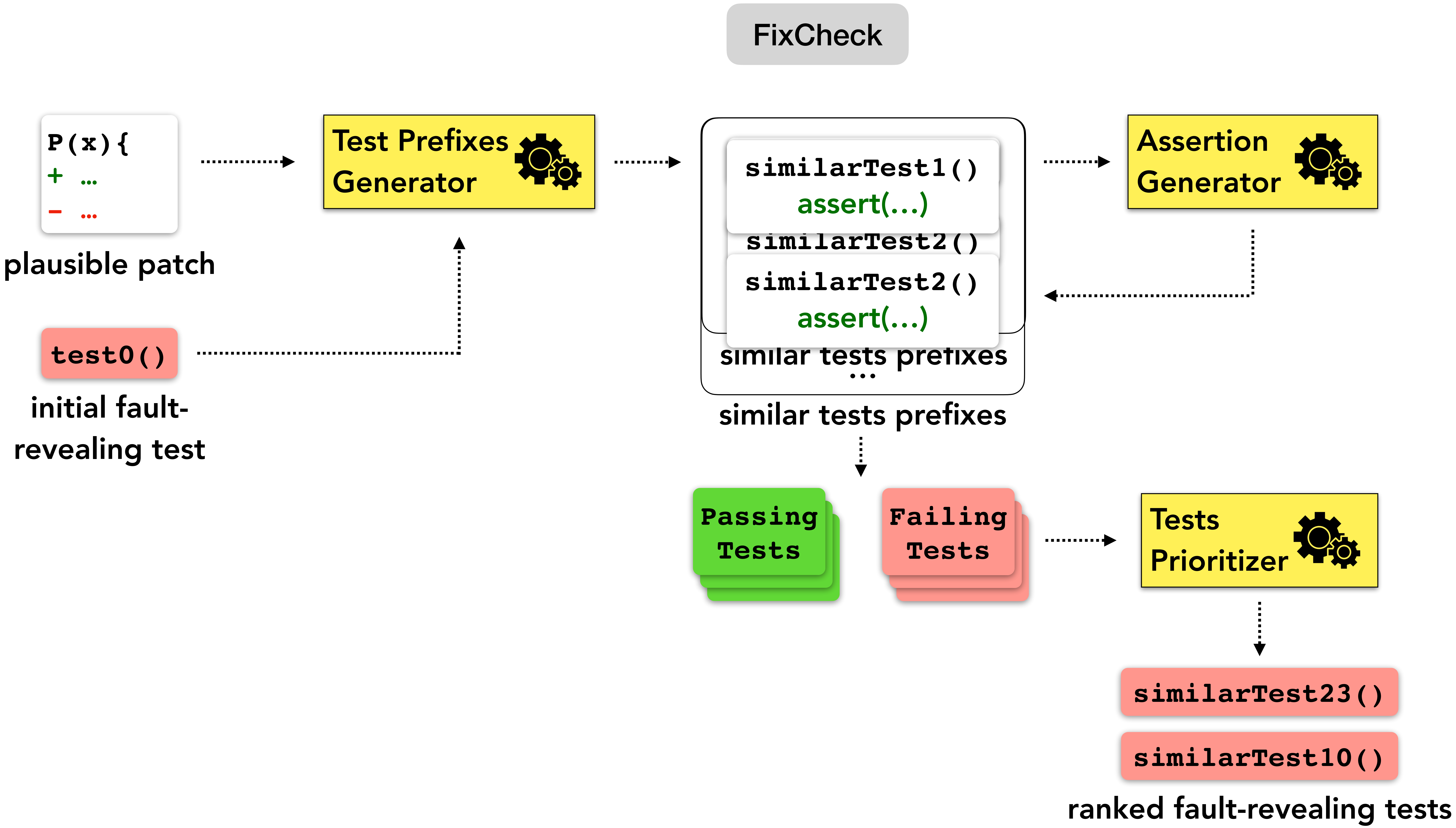
```
public void testWithNaturalScalar118() {
  ObjectMapper mapper = new ObjectMapper();
  ExternalTypeWithNonPOJO input =
        new ExternalTypeWithNonPOJO(Integer.valueOf(13));
  String json = mapper.writeValueAsString(input);
  assertNotNull(json);
  // and back just to be sure:
  ExternalTypeWithNonPOJO result = mapper.readValue(json,
        ExternalTypeWithNonPOJO.class);
  assertNotNull(result.value);
  assertTrue(result.value instanceof Integer);
}
```

✗

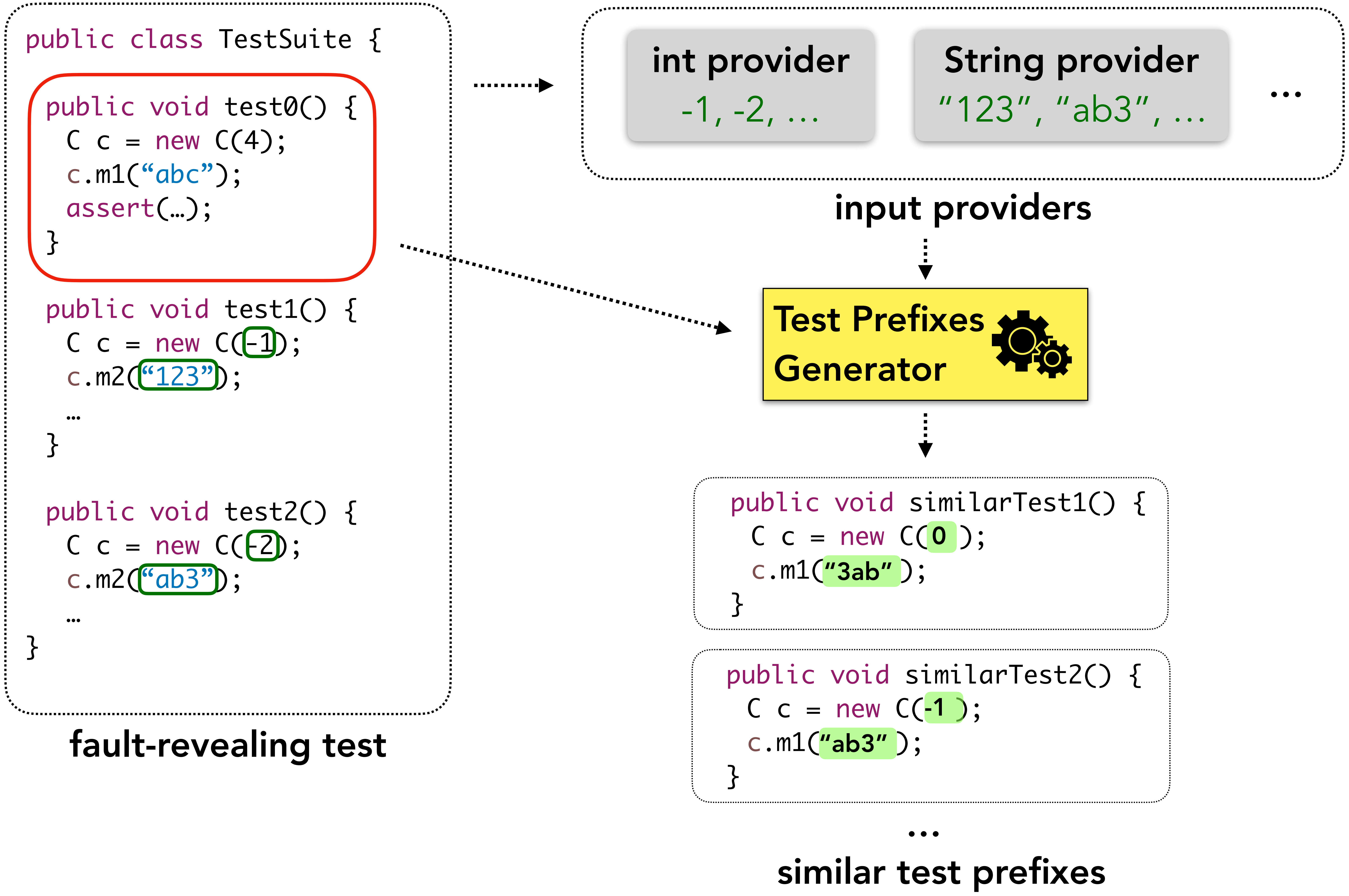
subsequent developer-written test

A test revealing the incorrectness of a patch is similar to the initial fault-revealing test case

Improving Patch Correctness Assessment



Test Prefixes Generation



```
public class TestSuite {

  public void test0() {
    C c = new C(4);
    c.m1(“abc”);
    assert(…);
  }

  public void test1() {
    C c = new C(-1);
    c.m2(“123”);
    …
  }

  public void test2() {
    C c = new C(-2);
    c.m2(“ab3”);
    …
}
```

fault-revealing test

input providers

```
public void similarTest1() {
  C c = new C(0);
  c.m1(”3ab”);
}
```

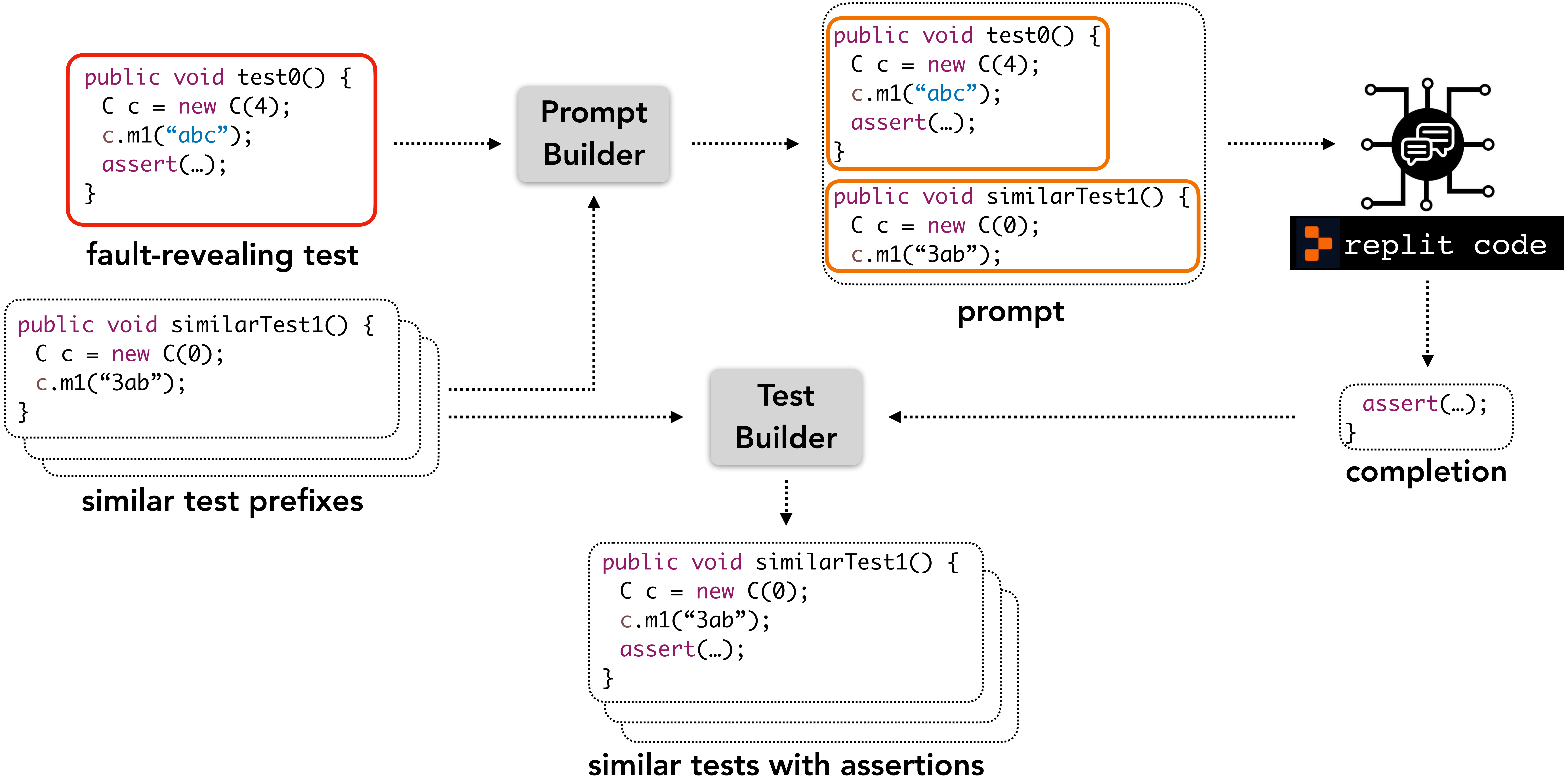
```
public void similarTest2() {
  C c = new C(-1);
  c.m1(”ab3”);
}
```

…

similar test prefixes

Generate tests prefixes that are *similar* to the initial fault-revealing test

Assertion Generation



```
public void test0() {
  C c = new C(4);
  c.m1("abc");
  assert(…);
}
```

```
public void test0() {
  C c = new C(4);
  c.m1("abc");
  assert(…);
}
public void similarTest1() {
  C c = new C(0);
  c.m1("3ab");
```

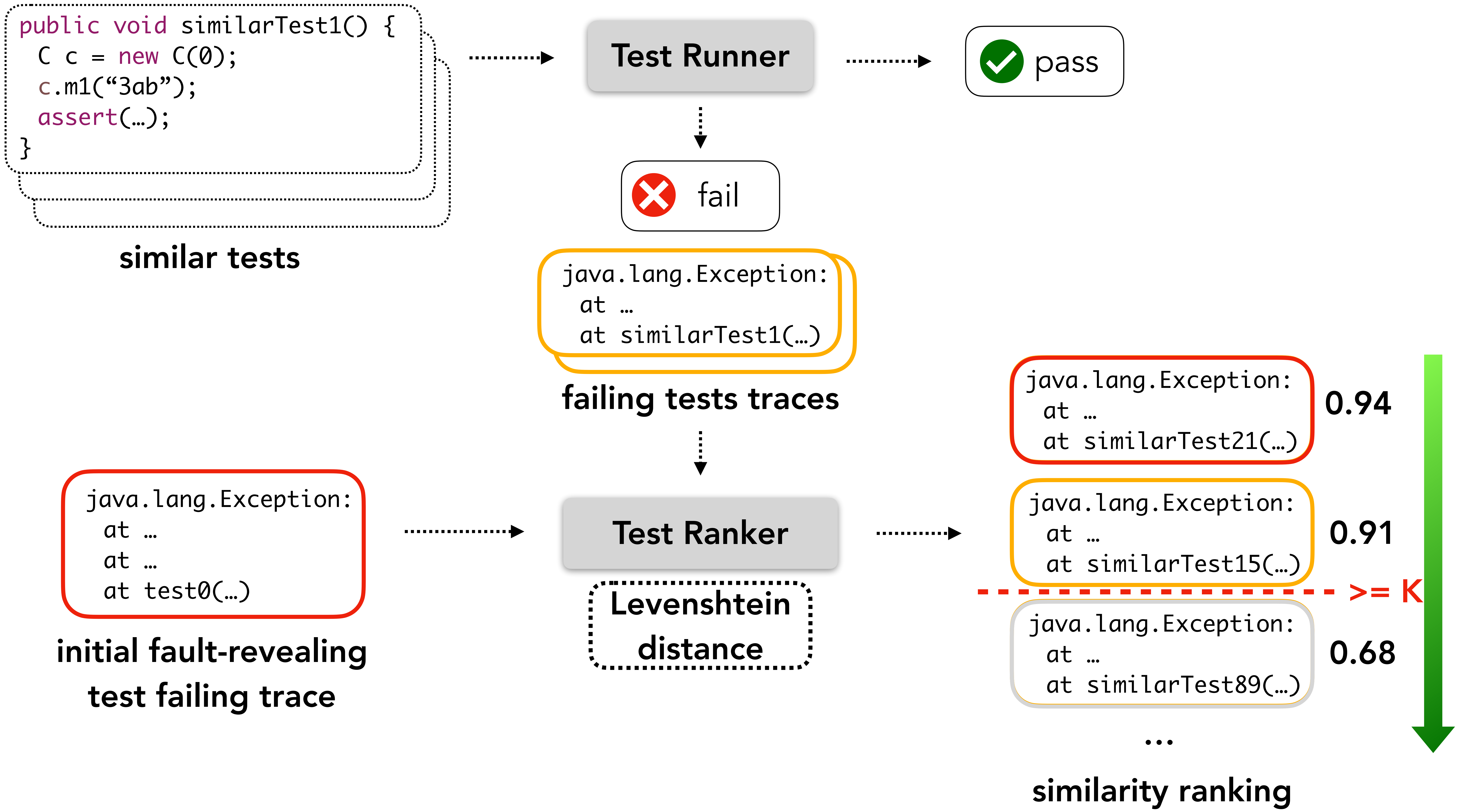
```
  assert(…);
}
```

```
public void similarTest1() {
  C c = new C(0);
  c.m1("3ab");
}
```

```
public void similarTest1() {
  C c = new C(0);
  c.m1("3ab");
  assert(…);
}
```

Equip the generated test prefixes with *meaningful* test assertions

Test Selection and Prioritization



```
public void similarTest1() {
  C c = new C(0);
  c.m1("3ab");
  assert(…);
}
```

similar tests

```
java.lang.Exception:
  at …
  at similarTest1(…)
```

failing tests traces

```
java.lang.Exception:
  at …
  at …
  at test0(…)
```

initial fault-revealing test failing trace

```
java.lang.Exception:
  at …
  at similarTest21(…)
```

0.94

```
java.lang.Exception:
  at …
  at similarTest15(…)
```

0.91

```
java.lang.Exception:
  at …
  at similarTest89(…)
```

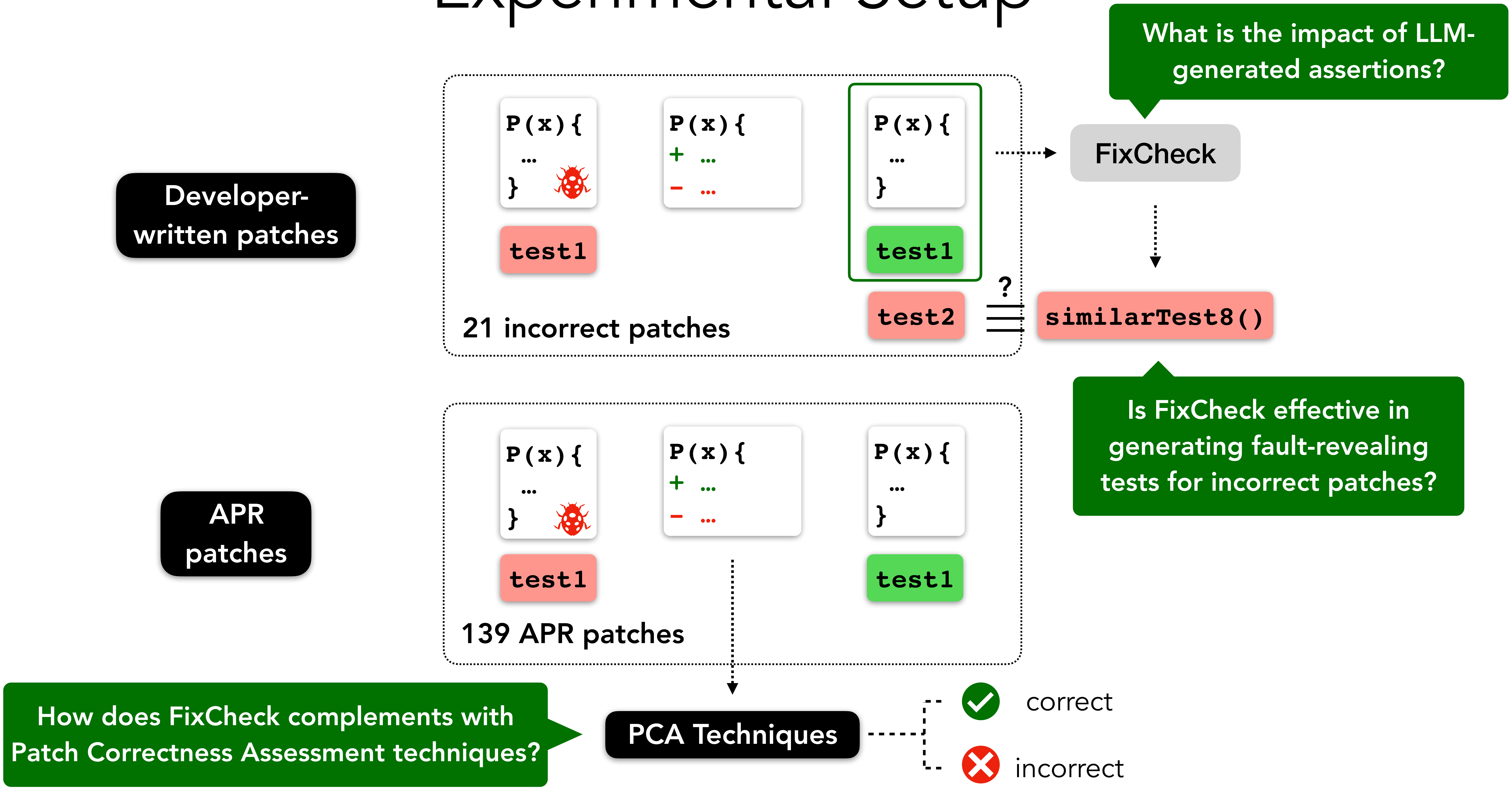
0.68

…

similarity ranking

Select and prioritise the failing tests based on their likelihood of actually revealing a defect in the patch

Experimental Setup



What is the impact of LLM-generated assertions?

Developer-written patches

```
P(x){
  ...
}
```

test1

```
P(x){
+ ...
- ...
```

```
P(x){
  ...
}
```

test1

test2 ≡? similarTest8()

FixCheck

21 incorrect patches

Is FixCheck effective in generating fault-revealing tests for incorrect patches?

APR patches

```
P(x){
  ...
}
```

test1

```
P(x){
+ ...
- ...
```

```
P(x){
  ...
}
```

test1

139 APR patches

How does FixCheck complements with Patch Correctness Assessment techniques?

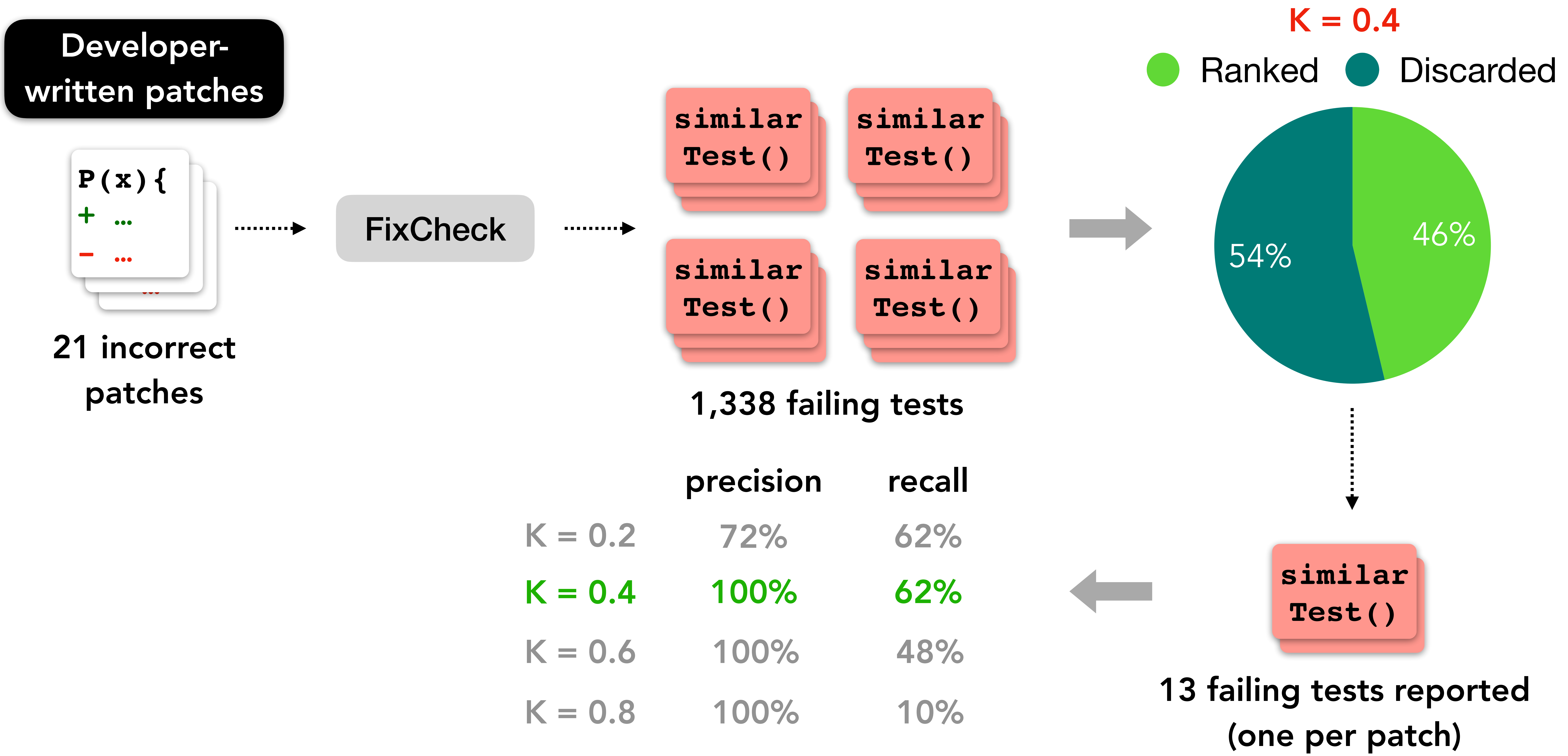
PCA Techniques

✓ correct

✗ incorrect

Yingfei Xiong et al. **Identifying patch correctness in test-based program repair.** ICSE 2018

Effectiveness of FixCheck

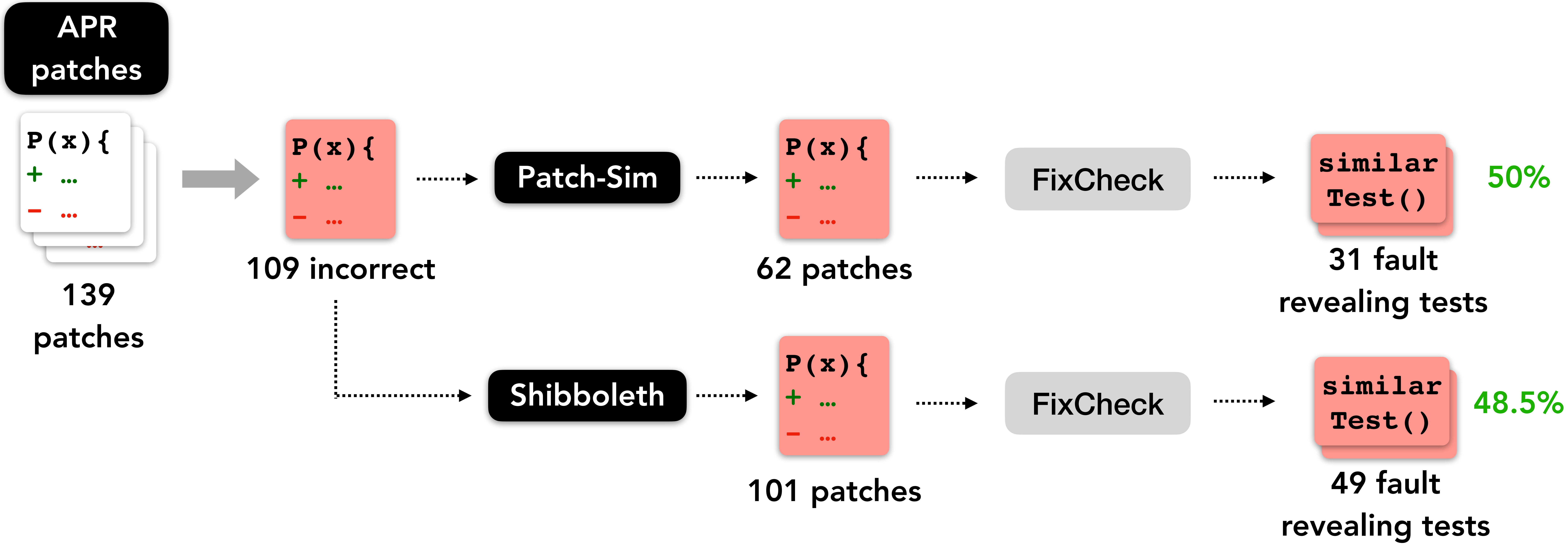


	precision	recall
K = 0.2	72%	62%
K = 0.4	100%	62%
K = 0.6	100%	48%
K = 0.8	100%	10%

FixCheck reports failing tests for up to 62% of incorrect patches

FixCheck reports failing tests for incorrect patches with a precision of 70-100%

Complementing Patch Correctness Assessment Techniques



APR patches

P(x){
+ ...
− ...

139 patches

P(x){
+ ...
− ...

109 incorrect

Patch-Sim

P(x){
+ ...
− ...

62 patches

FixCheck

similar Test()

50%

31 fault revealing tests

Shibboleth

P(x){
+ ...
− ...

101 patches

FixCheck

similar Test()

48.5%

49 fault revealing tests

FixCheck can generate fault-revealing tests for up to 50% of incorrect patches detected by patch correctness assessment tools

Remarks

✦ Automated Patch Correctness Assessment is a relevant problem for APR.

✦ FixCheck is a technique that combines static analysis, random testing, and large language models to effectively generate fault-revealing tests for incorrect patches.

✦ FixCheck can complement patch correctness analyses by providing fault revealing tests.

✦ Fault-revealing test generation for incorrect patches can still be improved:

Test Input Generation **Assertion Generation** **Applicability**