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Search Based Test Case Generation

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Outline

- Search based algorithms
- Automated test case generation
- Object oriented testing
- Future internet testing
- Dynamic symbolic execution

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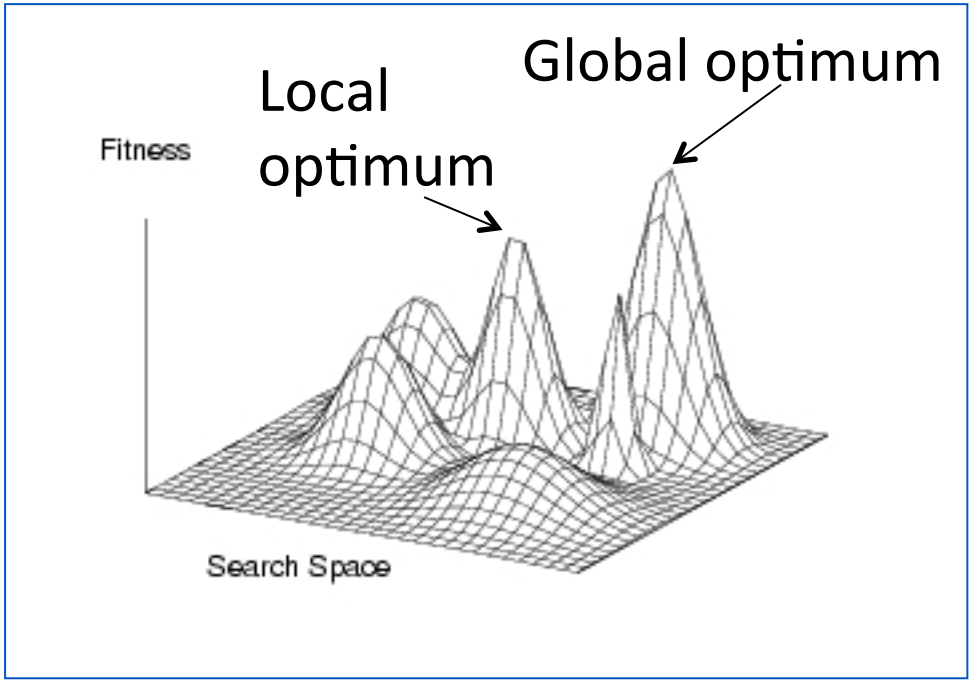
Search based algorithms

The search problem

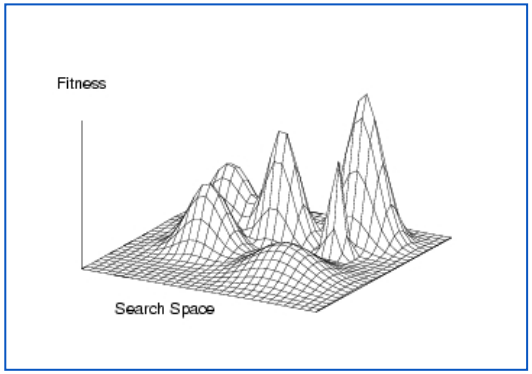
Find a value x^* which maximizes (minimizes) the objective (fitness) function f over the search space X:

$f: X \to \mathbb{R}$

$x^*: \forall x \in X, f(x^*) \geq f(x)$



Search algorithms



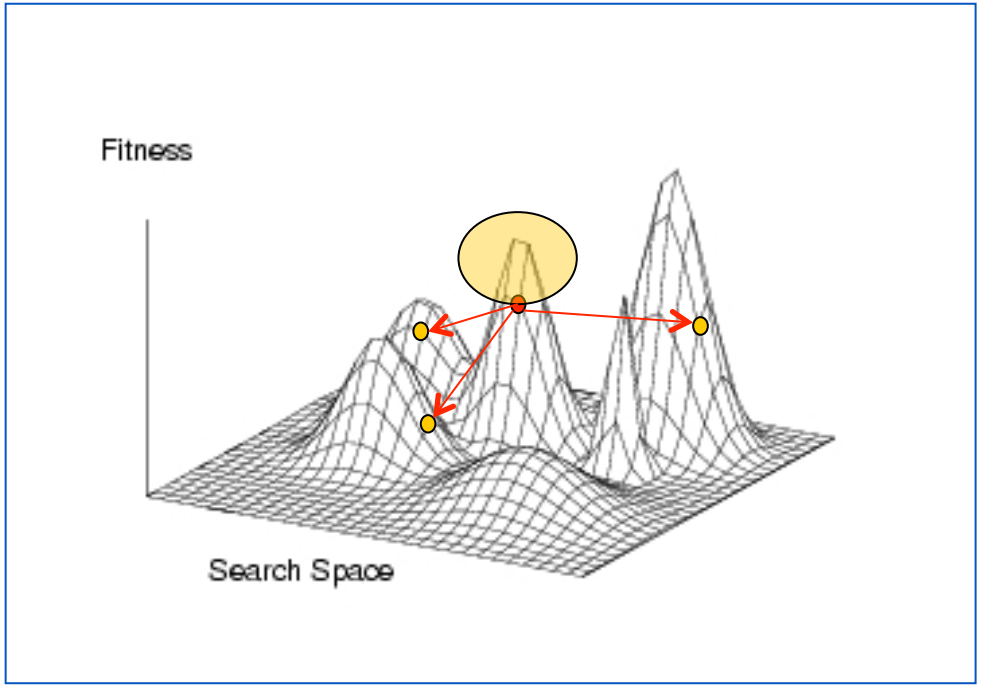
- Exhaustive search
- Random search
- Metaheuristic search

Metaheuristic algorithm: iterative optimization of candidate solutions for arbitrary problem instances. It is not ensured to find a global optimum, it finds a so-called *near-optimal solution*.

E.g.: find input that crashes `myFunc(int a, int b, int c){…}`

$$|X| = 2^{32} \times 2^{32} \times 2^{32} = 10^{28}$$

Exploration vs. exploitation



Since the search budget is finite, metaheuristic algorithms aim for a balance between:

- **local search**: exploitation (intensification);
- **global search**: exploration (diversification).

Search budget: max number of fitness evaluations (number of samples *x* taken) compatible with the max algorithm execution time.

No free lunch theorems

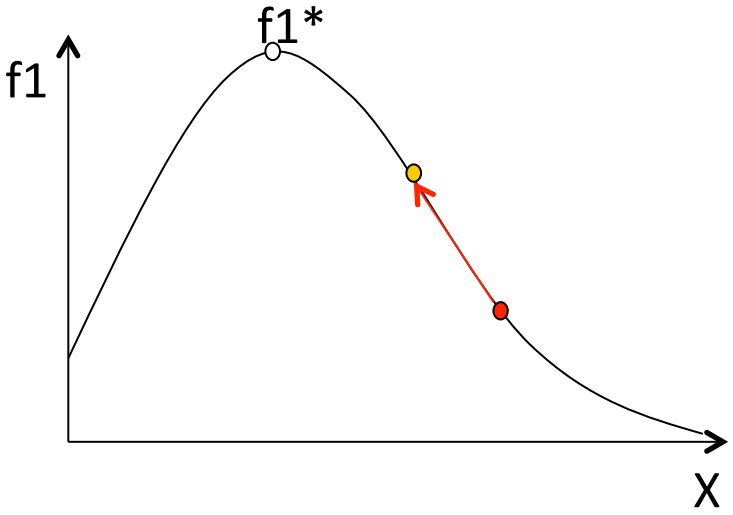
$$\sum_f P(f^*|f,m,A) = \sum_f P(f^*|f,m,B)$$

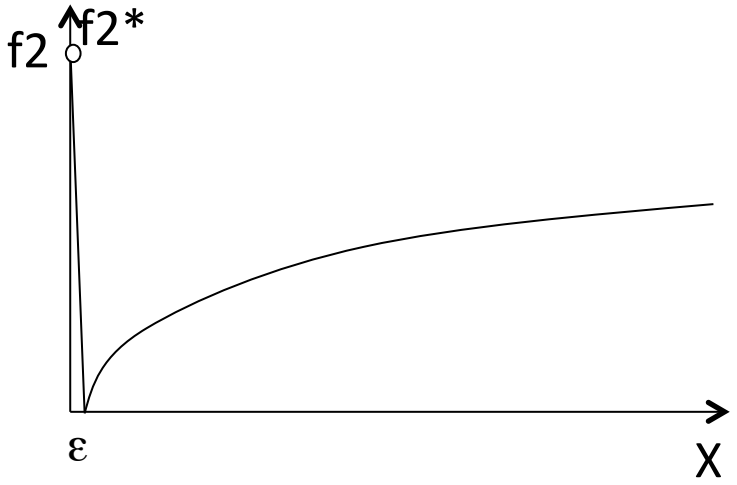
NFL theorem: given a search budget *m*, the average probability of obtaining the near-optimal value *f** using algorithm *A* is the same as the probability of obtaining the same near-optimal value using another, arbitrarily chosen algorithm *B*.

Hence, if metaheuristic *A* performs better than random search on problem instance *f1*, there will be another problem instance *f2* on which random performs better than *A*.

David H. Wolpert, William G. Macready: *No Free Lunch Theorems for Optimization*, IEEE Transactions on Evolutionary Computation, vol. 1, n. 1, April 1997.

Deceptive fitness function





P(f1*|f1, m, HC) = 1
P(f1*|f1, m, RND) = |m| / |X|

P(f2*|f2, m, HC) = |ε| / |X|
P(f2*|f2, m, RND) = |m| / |X|

HC = hill climbing (steepest ascent)
RND = random search

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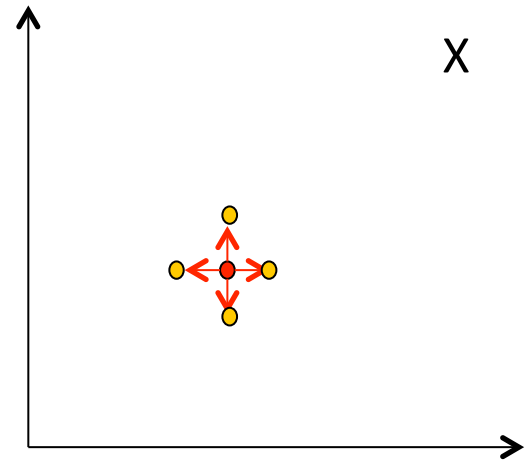
Metaheuristic algorithms

- Hill climbing
- Simulated annealing
- Tabu search
- Genetic algorithms
- Ant colony optimization
- Particle swarm optimization

Hill climbing

```
1.   x_opt = x0 // random
2.   max = f(x_opt)
3.   LOOP // with search budget m
4.     improved = FALSE
5.     FOR x IN Neighbors(x_opt)
6.       IF f(x) > max
7.         max = f(x)
8.         x_opt = x
9.         improved = TRUE
10.      END IF
11.    END FOR
12.    IF NOT improved
13.      RETURN x_opt
14.    END IF
15.  END LOOP
16.  RETURN x_opt
```



E.g.: find input that crashes `myFunc(int a, int b, int c){…}`

E.g.: (a±1, b±1, c±1)

Equivalent to greedy or steepest ascent: exploitation, no exploration.

Hill climbing variants

- **Stochastic hill climbing**: selects randomly among the improving solutions in the neighborhood.
- **Random-restart (shotgun) hill climbing**: randomly restarts when no improving solution is found (or the improvement is small).

They attempt to add more exploration, when local search is ineffective.

Simulated annealing

```
1.   x_opt = x0 // random
2.   k = 1      // time
3.   T = T_max  // temperature
4.   x = x_opt
5.   LOOP // with search budget m
6.     x_new = RNDNeighbor(x)
7.     Df = f(x_new) - f(x)
8.     IF Df > 0
9.        x_opt = x_new
10.    END IF
11.    IF Df > 0 OR
12.       P(Df, T) > rand(0, 1)
13.       x = x_new
14.    END IF
15.    T = cool(T, k)
16.    k = k + 1
17.  END LOOP
18.  RETURN x_opt
```

Parameters:

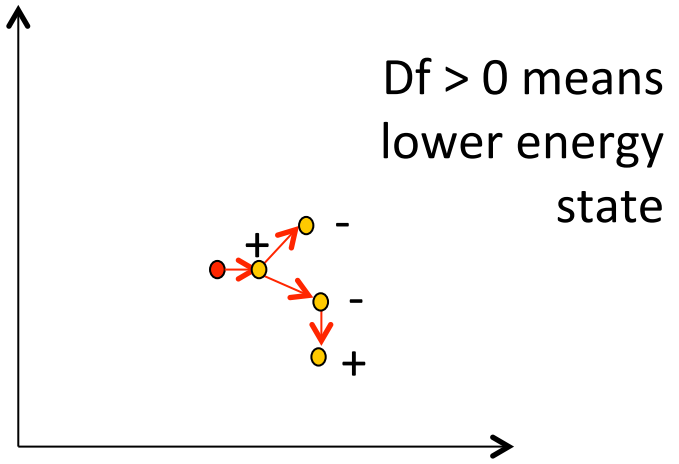
E.g.:

P(Df, T) = exp(Df / T)

if Df < 0; 1 otherwise

cool(T, k) = α T

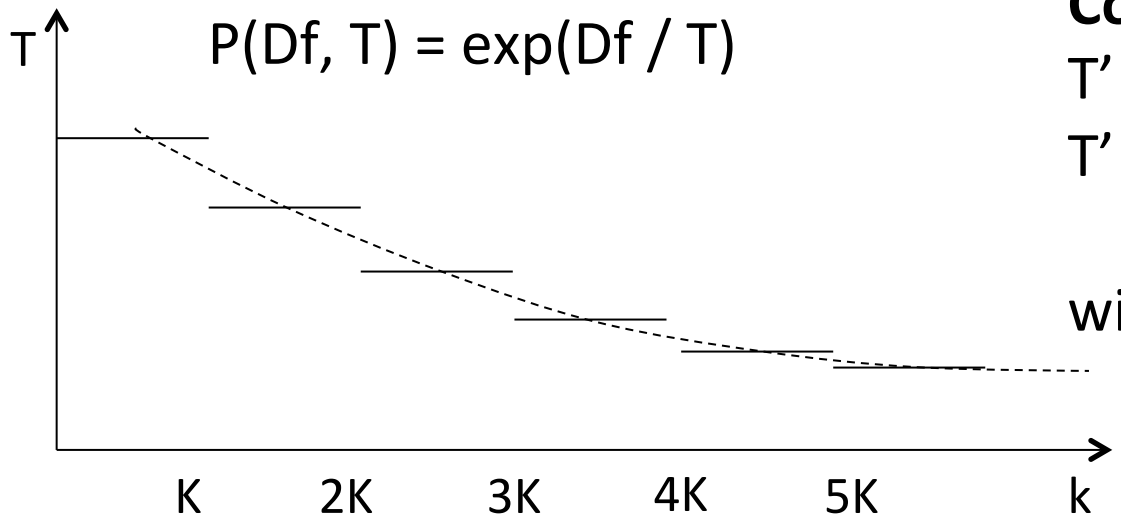
if k % K = 0; T otherwise



Df > 0 means lower energy state

Simulated annealing

- **Initial high temperature**: initially, exploration is privileged over exploitation: worsening solutions are initially accepted with high probability
- **Low temperature at the end**: only improving solutions are accepted at the end of the search (similar to hill climbing).



Cooling schedule:

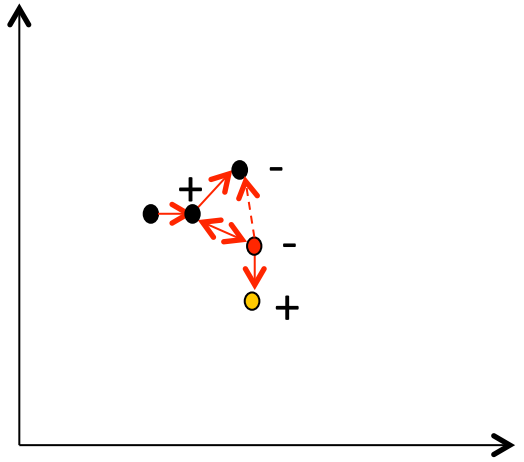
$T' = \alpha T$ if $k \% K = 0$

$T' = T$ otherwise

with $0 \leq \alpha \leq 1$

Tabu search

```
1.   x_opt = x0 // random
2.   add(tabuFIFOList, x_opt)
3.   LOOP // with search budget m
4.     x_new = RNDMutate(x_opt)
5.     IF x_new NOT IN tabuFIFOList
6.        add(tabuFIFOList, x_new)
7.        IF f(x_new) > f(x_opt)
8.           x_opt = x_new
9.        END IF
10.    END IF
11.  END LOOP
12.  RETURN x_opt
```



Local search (exploitation), optimized to avoid revisiting previously examined solutions

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Tabu search variants

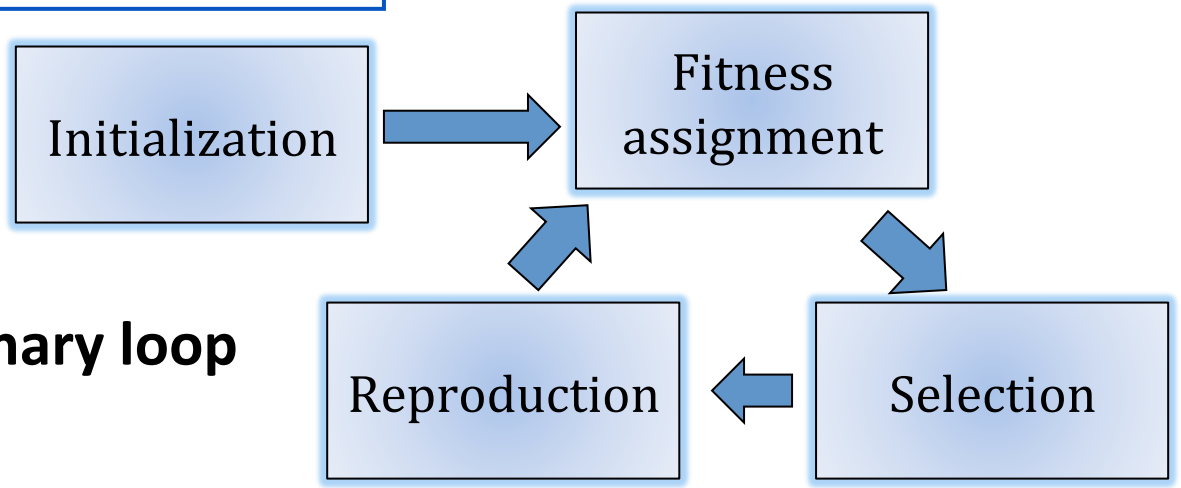
- **Neighborhood tabu**: the entire neighborhood of an already visited solution is declared tabu; mutations jump beyond such neighborhood.
- **Property based tabu list**: tabu solutions are characterized by their properties, such that any (even non visited) solution with the properties of a tabu solution is considered tabu as well.
- **Reactive tabu search**: when the same (tabu) solutions reappear frequently during the search, a random walk is made to explore a different portion of the search space.

Genetic algorithms

```
1.   Pop = {x0, …, xN} // random
2.   x_opt = NULL
3.   LOOP // with search budget m
4.     assignFitness(Pop)
5.     x_opt = best(Pop, x_opt)
6.     Pop = select(Pop)
7.     Pop = reproduce(Pop)
8.   END LOOP
9.   RETURN x_opt
```

Key decisions:

1. Representation
2. Fitness function
3. Selection
4. Reproduction (crossover and mutation)



Evolutionary loop

Representation

Fixed length chromosome:

y_1	y_2	y_3	y_4	y_5	y_6	…	y_k

y_i may be a single bit, a number, a character, etc.

E.g.: find input that crashes `myFunc(int a, int b, int c){…}`
Chromosomes = (2, 0, 3), (0, 0, -1)

Intron: portion of the chromosome that does not contribute to the phenotype (i.e., the fitness value)

E.g.: find input that crashes `myFunc(char* s){…}`
Chromosomes = ('a', 'b', 'c', '\0', 't'), ('z', '\0', 'a', 'g', 'h')

Variable length chromosome: *k* varies across individuals

Chromosomes = ('a', 'b', 'c', '\0'), ('z', '\0')

Selection

Pop = select(Pop)

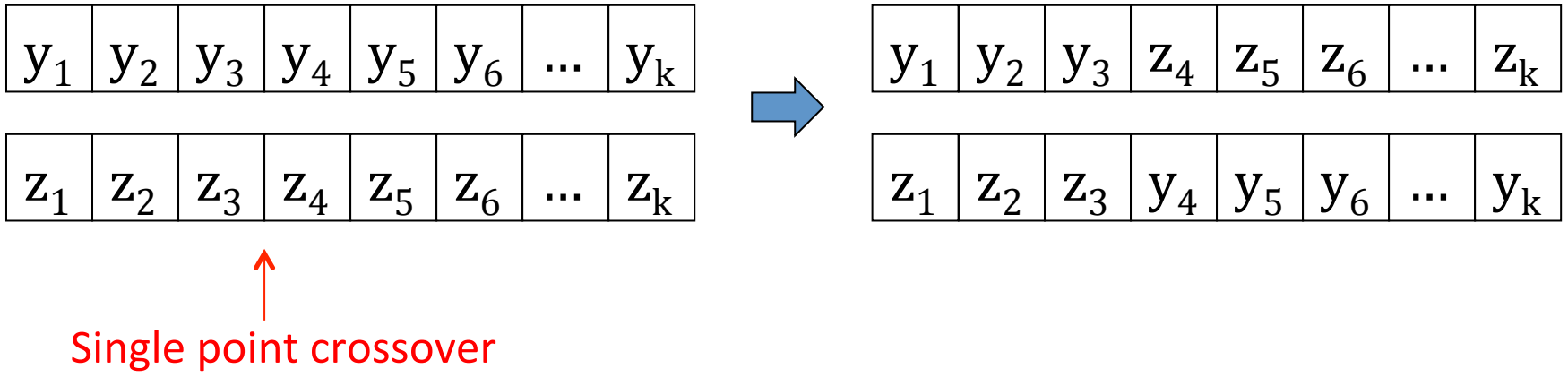
- **Truncation selection**: the best *M* individuals are selected; to obtain the number of individuals required to fill-in *Pop*, the selected individuals are replicated multiple times.
- **Roulette wheel selection**: the probability of selecting an individual is proportional to its fitness; individuals can be selected multiple times.
- **Tournament selection**: *T* individuals (e.g., 2) are randomly selected and compared (according to their fitness); the winner is inserted into the new population.
- **Ordered selection**: the probability of selecting an individual is proportional to its position in the list of all individuals ranked by increasing fitness.
- **Elitism**: at least one copy of the best individual(s) is propagated to the next generation.

Reproduction

Pop = reproduce(Pop)

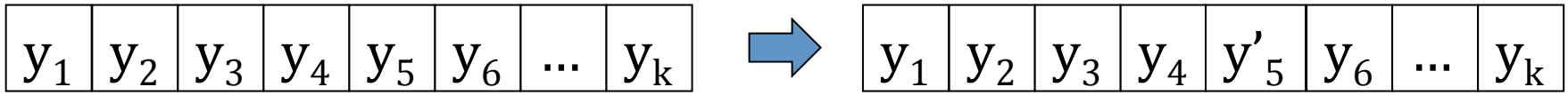
Crossover: $(y'_i, y'_j) = y_i \otimes y_j$

E.g., P = 80%



Mutation: $y'_i = \mu(y_i)$

E.g., P = 10%



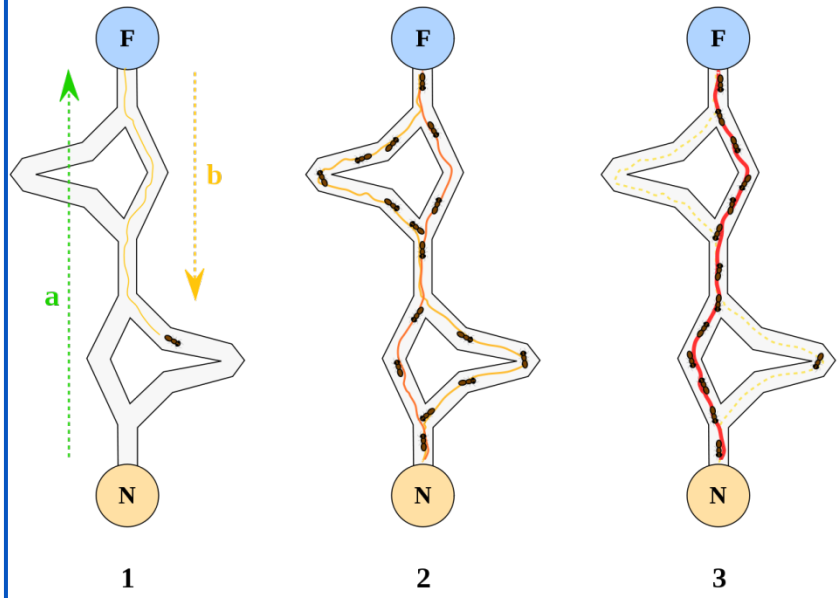
Genetic algorithms

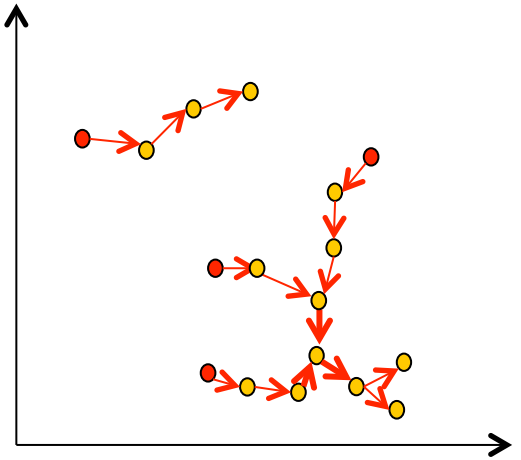
The parameters of these algorithms (population size, kind of selection, crossover and mutation rates, etc.) and the design of the mutation/crossover operators determine the trade-off between exploration and exploitation. E.g.:

- Neighborhood mutation / two-parent crossover / low mutation and crossover rate / elitism => **local search**.
- Disruptive mutation / multi-parent crossover / high mutation and crossover rate / ordered selection => **global search**.

Ant colony optimization

```
1.   Pop = {x0, …, xN} // random
2.   x_opt = NULL
3.   LOOP // with search budget m
4.     FOR x IN Pop
5.       FOR y IN Neighbors(x)
6.         computeProb(P(x, y))
7.       END FOR
8.       x = move(x, P(x, *))
9.     END FOR
10.    FOR EACH move (x, y)
11.      depositPheromone(x, y)
12.    END FOR
13.    updatePheromone()
14.    x_opt = best(Pop, x_opt)
15.  END LOOP
16.  RETURN x_opt
```





Stigmery principle: coordination between agents is achieved through traces left in the environment.

Pheromone calculation

computeProb(P(x, y))

$$P(x,y) = \frac{\tau_{xy}\eta_{xy}}{\sum_y \tau_{xy}\eta_{xy}}$$

τ_{xy} : amount of pheromone on (x, y)
η_{xy} : desirability of move (x, y) (e.g., f(y))

depositPheromone(x, y)

$$\tau_{xy} = \tau_{xy} + \Delta$$

updatePheromone()

$$\tau_{xy} = (1 - \rho)\tau_{xy}$$

ρ : pheromone evaporation coefficient

Ant colony optimization

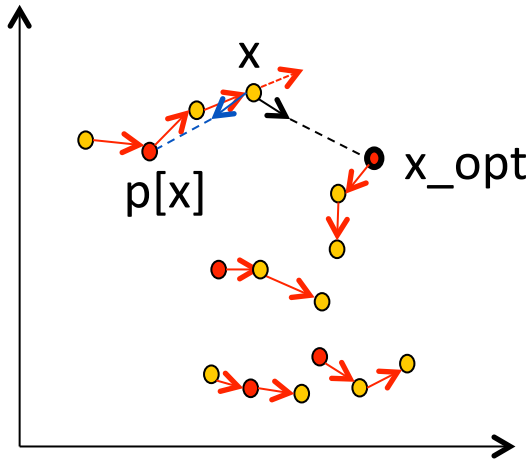
The decay of the pheromone (evaporation) determines the tradeoff between exploitation and exploration:

- Pheromone decays slowly: ants remain longer in the same region (local search).
- Pheromone decays quickly: ants move randomly to other regions (global search) after a limited amount of local search.

Particle swarm optimization

```
1.   Pop = {x0, …, xN} // random
2.   x_opt = NULL
3.   LOOP // with search budget m
4.     FOR x IN Pop
5.       IF f(x) > f(p[x])
6.         p[x] = x
7.       END FOR
8.       IF f(x) > f(x_opt)
9.         x_opt = x
10.      END FOR
11.      v[x] = updateVelocity(x)
12.      x = updatePosition(x)
13.    END FOR
14.  END LOOP
15.  RETURN x_opt
```

p[x]: best position of particle x
v[x]: speed of particle x
x: current position of particle x



Particle x tends to:

1. proceed along current direction;
2. be attracted by the best position in its trajectory
3. be attracted by the globally best position

Particle dynamics

updateVelocity(x)

$$v[x][d] = \omega\, v[x][d] + \varphi_p\, RND(0,1)\, (p[x][d] - x[d]) + \varphi_g\, RND(0,1)\, \left(x_{opt}[d] - x[d]\right)$$

updatePosition(x)

$$x[d] = x[d] + v[x][d]$$

Particle Swarm Optimization Variants

- **Neighborhood communication**: if any position in the neighborhood of a particle has been visited previously by other particles, the best position in the neighborhood determines a fourth direction to follow.

Particle swarm optimization

The parameters of the algorithm determine the tradeoff between exploitation and exploration:

ω: contributes to keeping current speed and direction, possibly moving towards unexplored regions.

φ_p: directs the search toward the best solution found by the current particle, usually increasing the amount of local search.

φ_g: directs the search toward the globally best solution, which may increase the local search in the region around x_{opt}.

Neighborhood communication increases the amount of local search.

Automated test case generation

Phil McMinn, *Search-based software test data generation: a survey*. Journal of Software Testing, Verification and Reliability, vol. 14, n. 2, pp. 105-156, June 2004.

Running example

```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;

  Triangle(int a, int b, int c) {…}
  void checkRightAngle(){…}
  void computeTriangleType() {…}
  boolean isTriangle() {…}
  public static void main(String args[]) {
    int a = Integer.parseInt(args[0]);
    int b = Integer.parseInt(args[1]);
    int c = Integer.parseInt(args[2]);
    Triangle t = new Triangle(a, b, c);
    if (t.isTriangle())
       t.computeTriangleType();
    System.out.println(typeToString(t.type));
  }
}
```

Running example

```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;

  Triangle(int a, int b, int c) {…}
  void checkRightAngle() {…}
  void computeTriangleType() {…}
  boolean isTriangle() {
    if (a <= 0 || b <= 0 || c <= 0)
        return false;
    if (a + b <= c || a + c <= b || b + c <= a)
        return false;
    return true;
  }
  public static void main(String args[]) {…}
}
```

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Running example

```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;

  Triangle(int a, int b, int c) {…}
  void checkRightAngle() {…}
  void computeTriangleType() {
    if (a == b)
        if (b == c) type = EQUILATERAL;
        else type = ISOSCELE;
    else if (a == c) type = ISOSCELE;
    else if (b == c) type = ISOSCELE;
    else checkRightAngle();
  }
  boolean isTriangle() {…}
  public static void main(String args[]) {…}
}
```

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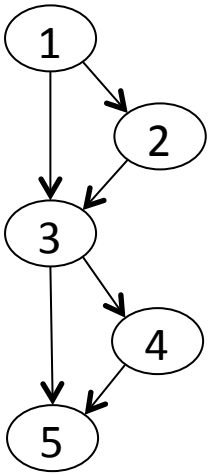
Running example

```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;

  Triangle(int a, int b, int c) {…}
  void checkRightAngle() {
    if (a*a + b*b == c*c)
        type = RIGHT_ANGLE;
    else if (b*b + c*c == a*a)
        type = RIGHT_ANGLE;
    else if (a*a + c*c == b*b)
        type = RIGHT_ANGLE;
    else type = SCALENE;
  }
  void computeTriangleType() {…}
  boolean isTriangle() {…}
  public static void main(String args[]) {…}
}
```

Coverage testing

```
void f(int a, int b) {
1    if (a < 0)
2        print("a is negative");
3    if (b < 0)
4        print("b is negative");
5    return;
}
```

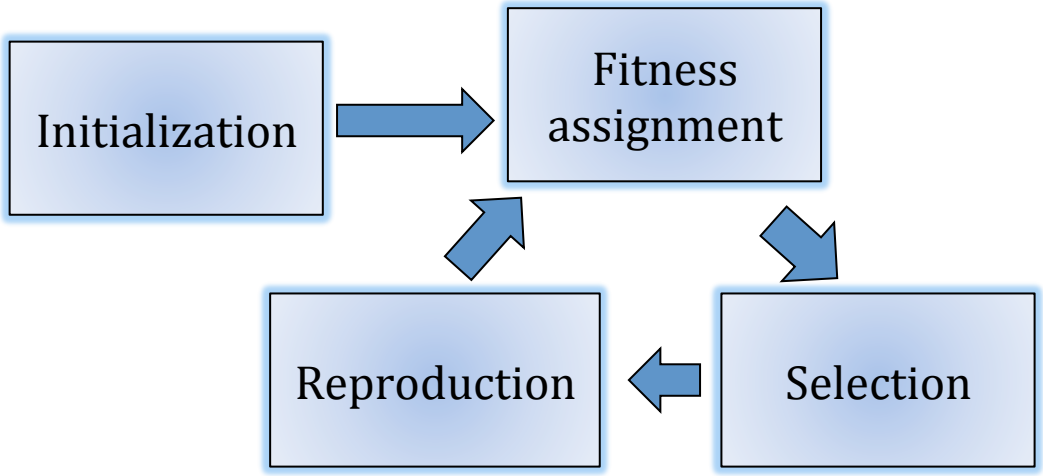


	Coverage targets	Test cases
Path coverage	{<1, 3, 5>, <1, 2, 3, 5>, <1, 3, 4, 5>, <1, 2, 3, 4, 5>}	f(-1, -1), f(1, -1) f(-1, 1), f(1, 1)
Branch coverage	{<1, 2>, <2, 3>, <1, 3>, <3, 4>, <4, 5>, <3, 5>}	f(-1, -1), f(1, 1)
Statement coverage	{1, 2, 3, 4, 5}	f(1, 1)

Running example

```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;
  Triangle(int a, int b, int c) {…}
  void checkRightAngle(){…}
  void computeTriangleType() {…}
  boolean isTriangle() {…}
  public static void main(String args[]){…}
}
```

Goal:
Automatic generation of test cases using genetic algorithms so as to achieve statement coverage.



Key decisions:

1. Representation
2. Fitness function
3. Selection
4. Reproduction (crossover and mutation)

Representation

The chromosome used for test case generation is the input vector, (sequence of input values used by the test case running the program) which may be fixed length or variable length.

E.g., in our running example:

Fixed length chromosome

a	b	c

Example of (randomly generated) initial population:
Pop = {(2, 2, -2), (2, 1, 1), (2, 1, 2), (3, 4, 2), (4, 3, 3), (4, -5, 6), (3, 5, 2), (-3, 0, -2)}

Fitness function

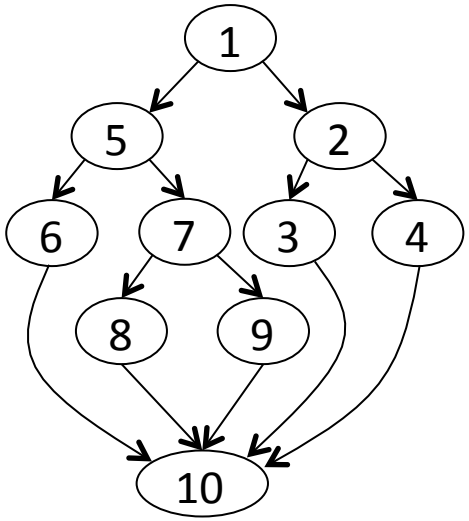
For statement and branch coverage, given a specific coverage target *t*, a widely used fitness function (to be minimized) is:

f(x) = approach_level(P(x), t) + branch_distance(P(x), t)

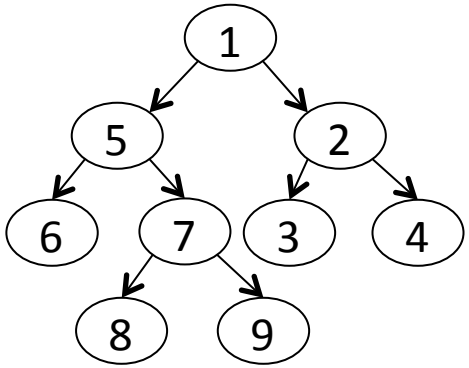
approach_level(P(x), t) :
Given the execution trace obtained by running program *P* with input vector *x*, the approach level is the minimum number of control nodes between an executed statement and the coverage target *t*.
branch_distance(P(x), t)
Given the first control node where the execution diverges from the target *t*, the predicate at such node is converted to a distance (from taking the desired branch), normalized between 0 and 1.

Approach level

```
class Triangle {
  void computeTriangleType() {
1     if (a == b)
2        if (b == c)
3           type = EQUILATERAL;
4        else type = ISOSCELE;
5     else if (a == c)
6           type = ISOSCELE;
7     else if (b == c)
8           type = ISOSCELE;
9     else checkRightAngle();
10    return;
  }
}
```



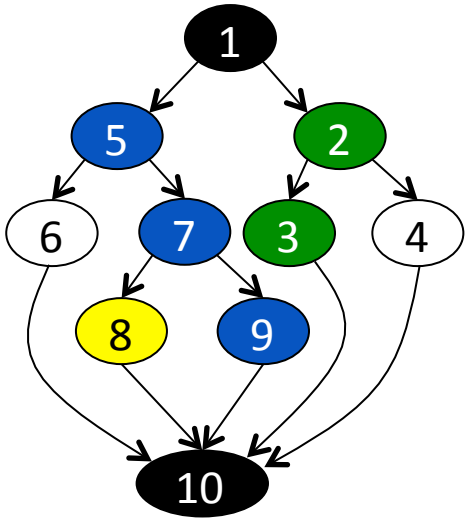
Control flow graph



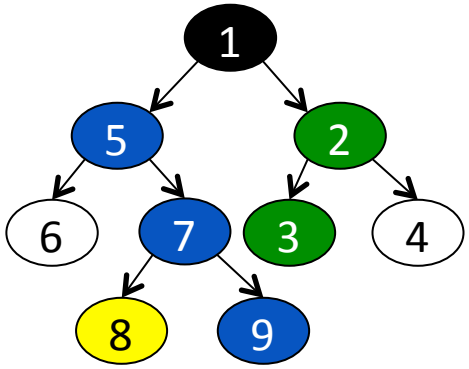
Control dependency graph

Approach level

```
class Triangle {
  void computeTriangleType() {
1     if (a == b)
2        if (b == c)
3           type = EQUILATERAL;
4        else type = ISOSCELE;
5     else if (a == c)
6           type = ISOSCELE;
7     else if (b == c)
8           type = ISOSCELE;
9     else checkRightAngle();
10    return;
  }
}
```



Control flow graph



Control dependency graph

Ch1 = (2, 2, 2) P(Ch1) = <1, 2, 3, 10> AL = 2

Ch2 = (2, 3, 4) P(Ch2) = <1, 5, 7, 9, 10> AL = 0

Branch distance

The predicate of the control node which is closest to the target is converted to a distance, which measures how far the test case is from taking the desired branch. For boolean/numeric variables a, b:

Condition c = atomic predicate	Distance BD(c) = d / (d + 1)
a	d = {0 if a == true; K otherwise}
!a	d = {K if a == true; 0 otherwise}
a == b	d = {0 if a == b; abs(a - b) + K otherwise}
a != b	d = {0 if a != b; K otherwise}
a < b	d = {0 if a < b; a - b + K otherwise}
a <= b	d = {0 if a <= b; a - b + K otherwise}
a > b	d = {0 if a > b; b - a + K otherwise}
a >= b	d = {0 if a >= b; b - a + K otherwise}

Branch distance

For string variables a, b:

Condition c = atomic predicate	Distance BD(c) = d / (d + 1)
a == b	d = {0 if a == b; edit_dist(a, b) + K otherwise}
a != b	d = {0 if a != b; K otherwise}
a < b	d = {0 if a < b; a[j] - b[j] + K otherwise}
a <= b	d = {0 if a <= b; a[j] - b[j] + K otherwise}
a > b	d = {0 if a > b; b[j] - a[j] + K otherwise}
a >= b	d = {0 if a >= b; b[j] - a[j] + K otherwise}

where j is the position of the first different character: *a[j] != b[j],* while *a[i] == b[i]* for *i < j* (*a[j] –b[j]* is set to zero if *a == b*).
Example of edit distance: edit_dist(“strqqvt”, “trwwv”) = 6

Branch distance

Condition c = composite predicate	Distance BD(c) = d / (d + 1)
!p	Negation is propagated inside p
p & q	d = d(p) + d(q)
p | q	d = min(d(p), d(q))
p XOR q = p & !q | !p & q	d = min(d(p)+d(!q), d(!p)+d(q))

Alternative normalizations of *d*:

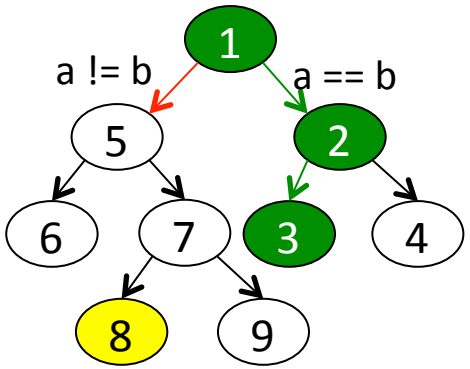
$$BD(c) = 1 - \alpha^{-d}$$

$$BD(c) = \frac{d}{d + \beta}$$

with $\alpha > 1$ and $\beta > 0$

Branch distance

```
class Triangle {
  void computeTriangleType() {
1     if (a == b)
2        if (b == c)
3           type = EQUILATERAL;
4        else type = ISOSCELE;
5     else if (a == c)
6           type = ISOSCELE;
7     else if (b == c)
8           type = ISOSCELE;
9     else checkRightAngle();
10    return;
  }
}
```



d(a != b) = K = 1

BD(a != b) = 1 / (1 + 1) = 0.5

f(Ch1) = 2 + 0.5 = 2.5

Ch1 = (2, 2, 2)

Ch2 = (2, 3, 4)

P(Ch1) = <1, 2, 3, 10>

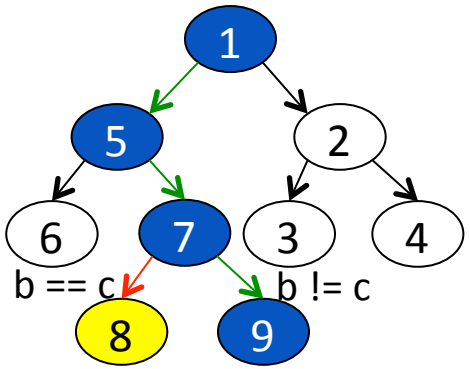
P(Ch2) = <1, 5, 7, 9, 10>

AL = 2 f = 2.5

AL = 0

Branch distance

```
class Triangle {
  void computeTriangleType() {
1     if (a == b)
2        if (b == c)
3           type = EQUILATERAL;
4        else type = ISOSCELE;
5     else if (a == c)
6           type = ISOSCELE;
7     else if (b == c)
8           type = ISOSCELE;
9     else checkRightAngle();
10    return;
  }
}
```



d(b == c) = abs(b - c) + K = 2
BD(b == c) = 2 / (2 + 1) = 0.66
f(Ch2) = 0 + 0.66 = 0.66

Ch1 = (2, 2, 2)
Ch2 = (2, 3, 4)

P(Ch1) = <1, 2, 3, 10>
P(Ch2) = <1, 5, 7, 9, 10>

AL = 2 f = 2.5
AL = 0 f = 0.66

Selection

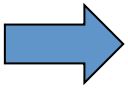
Ch1 = (2, 2, 2) f = 2.5
Ch2 = (2, 3, 4) f = 0.66
Ch3 = (-2, 3, 6) f = ∞
Ch4 = (2, 3, 7) f = ∞
Ch5 = (2, 2, 3) f = 2.5
Ch6 = (3, 4, 5) f = 0.66
Ch7 = (3, 5, 7) f = 0.75
Ch8 = (6, 8, 4) f = 0.83

```
class Triangle {
  void computeTriangleType() {
1     if (a == b)
2        if (b == c)
3           type = EQUILATERAL;
4        else type = ISOSCELE;
5     else if (a == c)
6              type = ISOSCELE;
7     else if (b == c)
8              type = ISOSCELE;
9     else checkRightAngle();
10    return;
  }
}
```

Selection

Truncation selection

Ch6 = (3, 4, 5) f = 0.66
Ch2 = (2, 3, 4) f = 0.66
Ch7 = (3, 5, 7) f = 0.75
Ch8 = (6, 8, 4) f = 0.83
Ch1 = (2, 2, 2) f = 2.5
Ch5 = (2, 2, 3) f = 2.5
Ch3 = (-2, 3, 6) f = ∞
Ch4 = (2, 3, 7) f = ∞



Ch6 = (3, 4, 5)
Ch2 = (2, 3, 4)
Ch7 = (3, 5, 7)
Ch8 = (6, 8, 4)
Ch6 = (3, 4, 5)
Ch2 = (2, 3, 4)
Ch7 = (3, 5, 7)
Ch8 = (6, 8, 4)

Selection

Roulette wheel selection

Ch6 = (3, 4, 5) P ≈ 1/f = 0.23
Ch2 = (2, 3, 4) P ≈ 1/f = 0.23
Ch7 = (3, 5, 7) P ≈ 1/f = 0.20
Ch8 = (6, 8, 4) P ≈ 1/f = 0.18
Ch1 = (2, 2, 2) P ≈ 1/f = 0.06
Ch5 = (2, 2, 3) P ≈ 1/f = 0.06
Ch3 = (-2, 3, 6) P ≈ 1/f = 0
Ch4 = (2, 3, 7) P ≈ 1/f = 0

Ch6 = (3, 4, 5)
Ch2 = (2, 3, 4)
Ch6 = (3, 4, 5)
Ch1 = (2, 2, 2)
Ch8 = (6, 8, 4)
Ch2 = (2, 3, 4)
Ch7 = (3, 5, 7)
Ch6 = (3, 4, 5)

Selection

Tournament selection

Ch1 = (2, 2, 2) f = 2.5	<Ch2, Ch7>	Ch2 = (2, 3, 4)
Ch2 = (2, 3, 4) f = 0.66	<Ch1, Ch5>	Ch5 = (2, 2, 3)
Ch3 = (-2, 3, 6) f = ∞	<Ch3, Ch8>	Ch8 = (6, 8, 4)
Ch4 = (2, 3, 7) f = ∞	<Ch3, Ch2>	Ch2 = (2, 3, 4)
Ch5 = (2, 2, 3) f = 2.5	<Ch6, Ch5>	Ch6 = (3, 4, 5)
Ch6 = (3, 4, 5) f = 0.66	<Ch6, Ch4>	Ch6 = (3, 4, 5)
Ch7 = (3, 5, 7) f = 0.75	<Ch8, Ch3>	Ch8 = (6, 8, 4)
Ch8 = (6, 8, 4) f = 0.83	<Ch8, Ch1>	Ch8 = (6, 8, 4)

Selection

				Ordered selection
1 Ch4 = (2, 3, 7)	f = ∞	P = 1/33 = 0.03		Ch2 = (2, 3, 4)
1 Ch3 = (-2, 3, 6)	f = ∞	P = 1/33 = 0.03		Ch2 = (2, 3, 4)
3 Ch5 = (2, 2, 3)	f = 2.5	P = 3/33 = 0.09		Ch6 = (3, 4, 5)
3 Ch1 = (2, 2, 2)	f = 2.5	P = 3/33 = 0.09		Ch4 = (2, 3, 7)
5 Ch8 = (6, 8, 4)	f = 0.83	P = 5/33 = 0.15		Ch8 = (6, 8, 4)
6 Ch7 = (3, 5, 7)	f = 0.75	P = 6/33 = 0.18		Ch2 = (2, 3, 4)
7 Ch6 = (3, 4, 5)	f = 0.66	P = 7/33 = 0.21		Ch7 = (3, 5, 7)
7 Ch2 = (2, 3, 4)	f = 0.66	P = 7/33 = 0.21		Ch6 = (3, 4, 5)

Rank sum = 33

Reproduction: crossover

Ch1 = (2, 3, 4)	-	Ch1 = (2, 3, 4)
Ch2 = (2, 2, 3)	<Ch2, Ch5>	Ch2 = (2, 4, 5)
Ch3 = (6, 8, 4)	<Ch3, Ch8>	Ch3 = (6, 8, 4)
Ch4 = (2, 3, 4)	<Ch4, Ch6>	Ch4 = (2, 3, 5)
Ch5 = (3, 4, 5)	SEL	Ch5 = (3, 2, 3)
Ch6 = (3, 4, 5)	SEL	Ch6 = (3, 4, 4)
Ch7 = (6, 8, 4)	-	Ch7 = (6, 8, 4)
Ch8 = (6, 8, 4)	SEL	Ch8 = (6, 8, 4)

One-point crossover, with P = 0.8

Reproduction: mutation

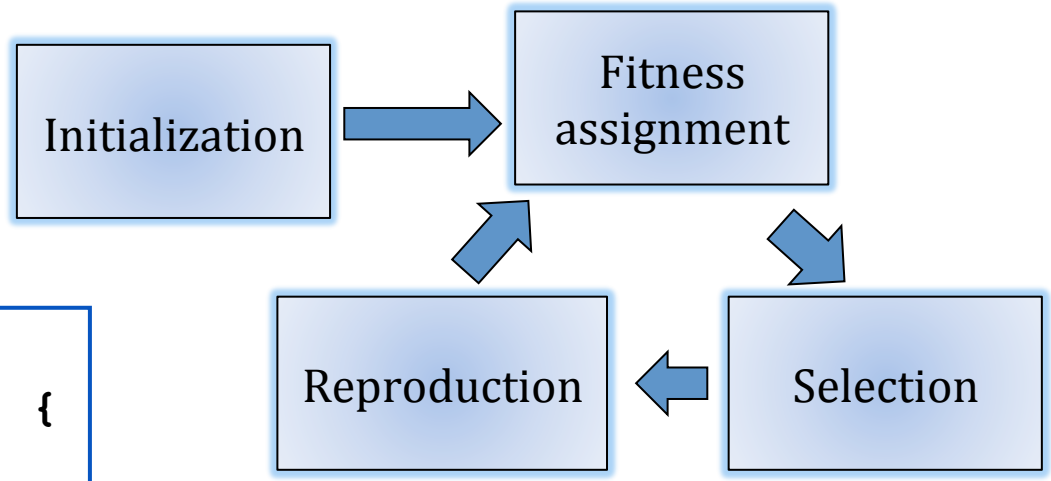
Ch1 = (2, 3, 4)	Ch1 = (2, 3, 4)
Ch2 = (2, 4, 5)	Ch2 = (2, 5, 5)
Ch3 = (6, 8, 4)	Ch3 = (6, 8, 4)
Ch4 = (2, 3, 5)	Ch4 = (2, 3, 5)
Ch5 = (3, 2, 3)	Ch5 = (2, 2, 3)
Ch6 = (3, 4, 4)	Ch6 = (3, 4, 4)
Ch7 = (6, 8, 4)	Ch7 = (6, 8, 4)
Ch8 = (6, 8, 4)	Ch8 = (6, 8, 4)

Mutation probability: P = 0.2

Mutation operators: increment/decrement (P = 50%)

Iterating

Until search budget (number of fitness evaluations) is over or target is covered.




```
class Triangle {
  void computeTriangleType() {
1     if (a == b)
2        if (b == c)
3           type = EQUILATERAL;
4        else type = ISOSCELE;
5     else if (a == c)
6              type = ISOSCELE;
7     else if (b == c)
8              type = ISOSCELE;
9     else checkRightAngle();
10    return;
  }
}
```

Then, select the next target (yet to cover statement) and repeat the test case generation cycle.

Collateral coverage

```
class Triangle {
  void computeTriangleType() {
1    if (a == b)
2       if (b == c)
3          type = EQUILATERAL;
4       else type = ISOSCELE;
5    else if (a == c)
6          type = ISOSCELE;
7    else if (b == c)
8          type = ISOSCELE;
9    else checkRightAngle();
10   return;
  }
}
```

When a target is covered accidentally (e.g., (2, 2, 3)) in a test case generation cycle, it is removed from the list of yet to cover targets and the related test case is stored, to be included in the final test suite.

Collateral (serendipitous) coverage: if test cases involved in collateral coverage are not detected and stored, it can be shown that random testing performs asymptotically better than search based testing.

Andrea Arcuri, Muhammad Zohaib Z. Iqbal, Lionel C. Briand: *Formal analysis of the effectiveness and predictability of random testing*. ISSTA, pp. 219-230, 2010.

Final test suite

```
class Triangle {
  void computeTriangleType() {
1    if (a == b)
2       if (b == c)
3          type = EQUILATERAL;
4       else type = ISOSCELE;
5    else if (a == c)
6            type = ISOSCELE;
7    else if (b == c)
8            type = ISOSCELE;
9    else checkRightAngle();
10   return;
  }
}
```

Ch1 = (2, 2, 3)
Ch2 = (2, 5, 5)
Ch3 = (2, 2, 2)
Ch4 = (4, 3, 4)
Ch5 = (3, 4, 5)

The final test suite consists of all chromosomes that have been found to cover (even accidentally) one or more yet to cover statements.

The final test suite might contain redundancies that can be eliminated in a post-processing (by keeping only the test cases that cover at least one target uniquely).

Object oriented testing

Paolo Tonella, *Evolutionary testing of classes*. Proc. of the International Symposium on Software Testing and Analysis (ISSTA), pp. 119-128, Boston, USA, July 2004.
Gordon Fraser, Andrea Arcuri, *Whole test suite generation*. IEEE Transactions on Software Engineering, vol. 38, n. 2, pp. 276-291, 2013.

Unit testing of classes

1. An object of the class under test is created using one of the available constructors.
2. A sequence of zero or more methods is invoked on it.
3. The method currently under test is executed.
4. The final state of the object is examined to produce the pass/fail result.

Drivers/stubs are created whenever necessary.
Steps 1, 2 are repeated for each parameter of object type.

Example of test case

```
1    A a = new A();
2    B b = new B();
3    b.f(2);
4    a.m(5, b);
```

Let us assume that **m** is the method under test.

- Object **b** is created because it is required to call **m**.
- Its state is changed by calling **f** on it.
- Sequence of required input values: <2, 5>.

Features of object-oriented unit testing

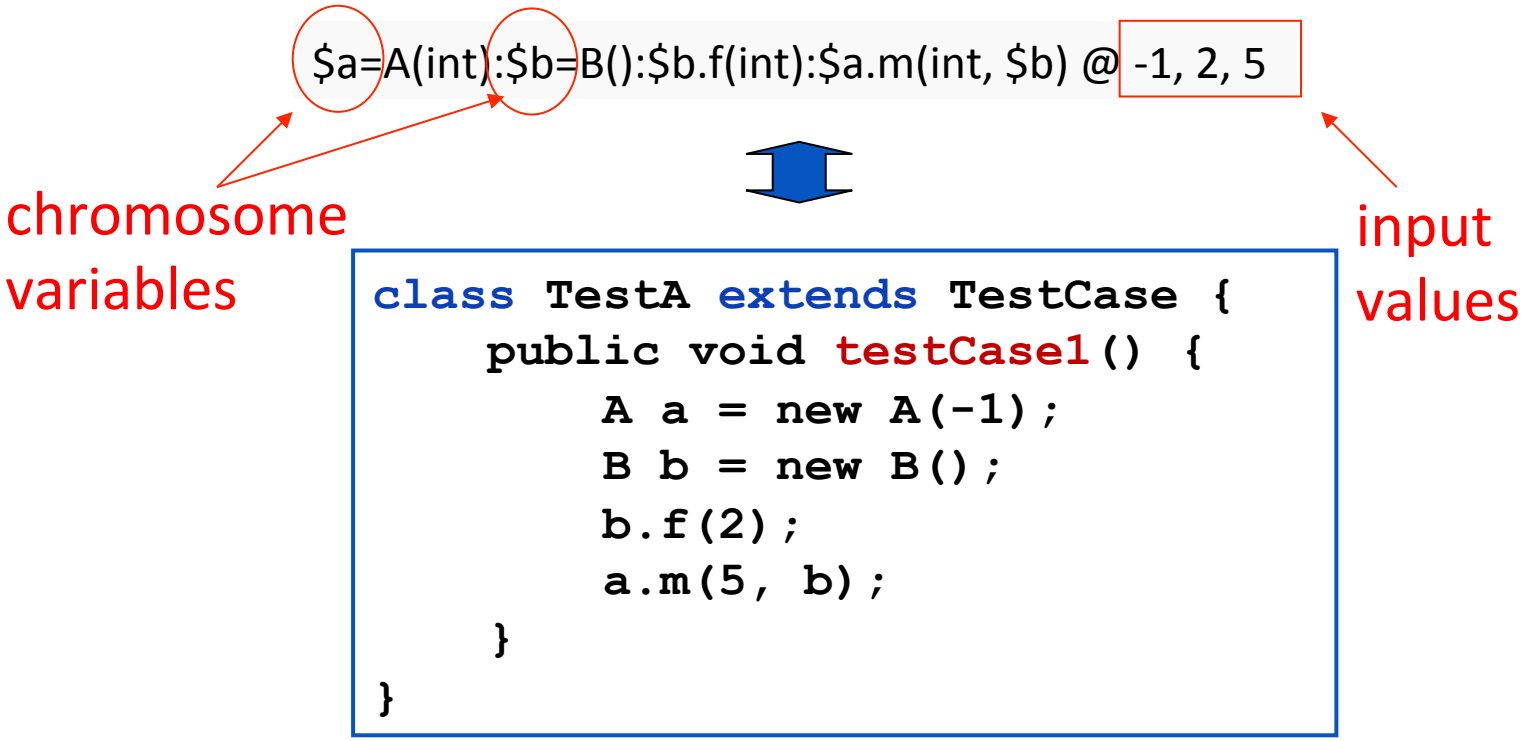
- The number and order of method invocations is variable.
- The number of input values is also variable.
- Some parameters in method calls are objects themselves, thus requiring further object constructions.
- The state of the object under test and of the object parameters affects the result.

Chromosomes are not just sequences of input values

Chromosomes

Procedural code: (v1, v2, …, vN)

Object-Oriented code: $x0=A(): $x0.f(): $x0.g() @ v1, v2, …, vN



Random chromosome construction

1. A constructor for the object under test is randomly selected: `$a=A(int)@-1`
2. The invocation of the method under test is appended: `$a=A(int):$a.m(int,$b)@-1,5`
3. All required object constructions are inserted: `$a=A(int):$b=B():$a.m(int,$b)@-1,5`
4. Method invocations to change the state of the created objects are randomly inserted: `$a=A(int):$b=B():$b.f(int):$a.m(int,$b)@-1,2,5`

Steps 3 and 4 are repeated until all chromosome variables used as method or constructor parameters are properly initialized (*well-formedness* of the resulting chromosome).

Random input data generation

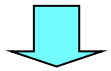
Default, parameterized, pooled and customized input generators:

`A.m(int)`	Default integer generator: uniform selection in [0, 100]
`A.m(int[-2;2])`	Parameterized integer generator: uniform selection in [-2, 2]
`A.m(int<pool>)`	Randomly selected from the program's pool of integer constants
`A.m(int[MyIntGenerator])`	Customized integer generator: method newIntValue() from class MyIntGenerator is called to obtain the value
`A.m(boolean)`	Default boolean generator: **true** and **false** are equally likely
`A.m(String)`	Default string generator: characters are uniformly chosen from [a-zA-Z0-9], with the string length decaying exponentially
`A.m(String<pool>)`	Randomly selected from the program's pool of string constants
`A.m(String[DateGenerator])`	Customized string generator: only strings representing legal dates are produced (e.g., "3/3/2003")

Mutation operators

Change input value:

```
$a=A(int):$b=B():$b.f(int):$a.m(int, $b) @ -1, 2, 5
```

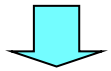


```
$a=A(int):$b=B():$b.f(int):$a.m(int, $b) @ -1, 4, 5
```

Mutation operators

Change constructor:

```
$a=A(int):$b=B():$b.f(int):$a.m(int, $b) @ -1, 2, 5
```

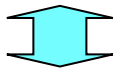


```
$a=A():$b=B():$b.f(int):$a.m(int, $b) @ 2, 5
```

Mutation operators

Insert/remove method call:

```
$a=A(int):$b=B():$b.f(int):$a.m(int, $b) @ -1, 2, 5
```



```
$a=A(int):$b=B():$a.m(int, $b) @ -1, 5
```

Crossover

$a=A(int):$b=B():$b.g():$a.m(int, $b) @ 0, -3

$a=A():$b=B():$b.f(int):$a.m(int, $b) @ -1, 2

Well-formedness must be maintained

$a=A(int):$b=B():$b.g():$b.f(int):$a.m(int, $b) @ 0, -1, 2

$a=A():$b=B():$a.m(int, $b) @ -3

$a=A():$b=B(int):$c=C(int):$b.h($c):$b.f():$a.m(int, $b) @ 1, 4, 5

$a=A(int, int):$b=B():$a.m(int, $b) @ 0, 3, 6

The alternative would be to use **null**

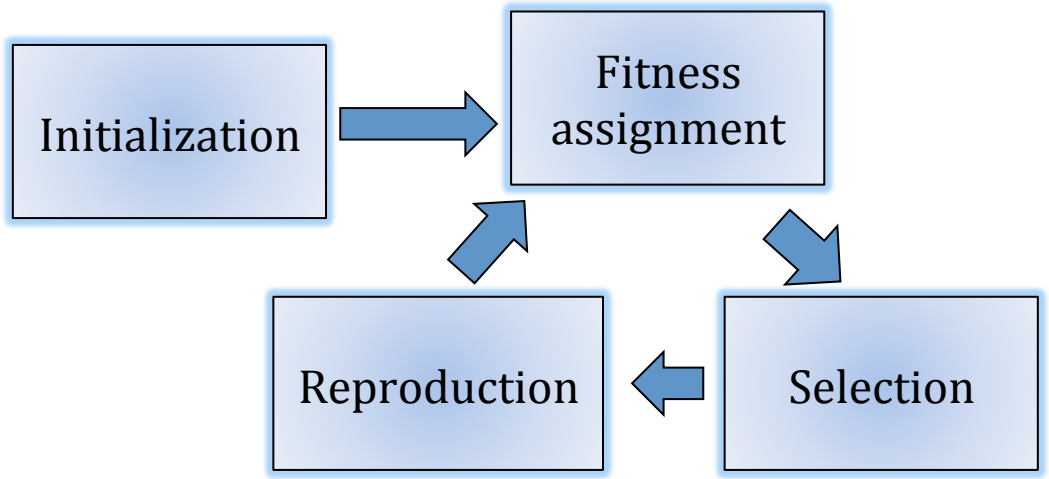
$a=A():$b=B(int):$a.m(int, $b) @ 1, 6

$a=A(int, int):$b=B():$c=C():$b.h($c):$b.f():$a.m(int, $b) @ 0, 3, 5

Fitness

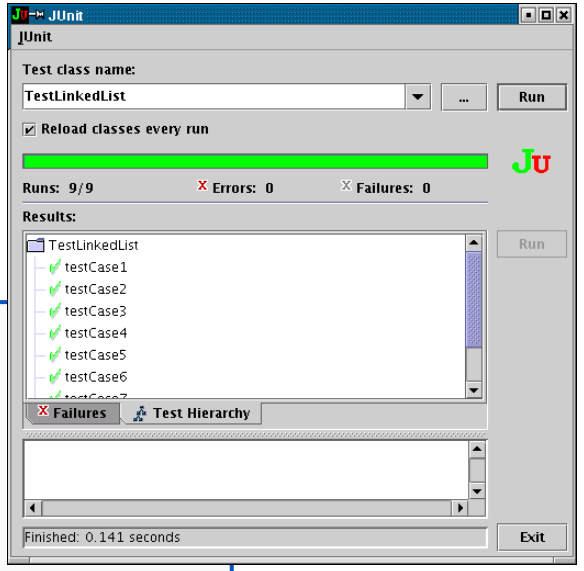
f(x) = approach_level(P(x), t) + branch_distance(P(x), t)

- **Truncation selection**
- **Roulette wheel selection**
- **Tournament selection**
- **Ordered selection**
- **Elitism**



Test case generator

$x0=BinaryTree(): $x1=Integer(int): $x2=BinaryTreeNode($x1): $x0.insert($x2): $x3=Integer(int): $x0.search($x3) @ 5, 5




```
class TestBinaryTree extends TestCase {
    ...
    public void testCase2() {
        BinaryTree x0 = new BinaryTree();
        Integer x1 = new Integer(5);
        BinaryTreeNode x2 = new BinaryTreeNode(x1);
        x0.insert(x2);
        Integer x3 = new Integer(5);
        assertTrue(x0.search(x3));
    }
}
```

Assertion added manually

Assertions

Assertions are inserted manually as follows:

- The **value returned** from each method call is compared with the expected one.
- If a method call can raise an **exception**, an assertion on its actual occurrence is added.
- At the end of each test case, the **final state** of the object under test is compared with the expected one.

Assertions

Assertions are added at method calls to check the actually **returned values** vs. the expected ones.

```
class TestLinkedList extends TestCase {
    public void testCase1() {
        LinkedList x0 = new LinkedList();
        …
        Integer x1 = null;
        x0.addFirst(x1);
        Integer x2 = null;
        assertTrue(x0.remove(x2));
        …
    }
}
```

Assertions

Assertions are added at method calls possibly raising exceptions.

```
class TestLinkedList extends TestCase {
    public void testCase2() {
        LinkedList x0 = new LinkedList();
        …
        boolean thrownException1 = false;
        try {
            x0.listIterator(78);
        } catch(IndexOutOfBoundException e) {
            thrownException1 = true;
        }
        assertTrue(thrownException1);
        …
}
```

Assertions

Assertions are added at to check the **final object state**.

```
class TestLinkedList extends TestCase {
    public void testCase3() {
        LinkedList x0 = new LinkedList();
        …
        Integer x1 = new Integer(2);
        x0.addLast(x1);
        assertTrue(x0.toString().equals("[2]"));
    }
}
```

Whole test suite generation

- Some coverage targets may be infeasible.
- Some coverage targets may be very difficult to achieve.

Since a limited search budget is available for test case generation:

- Infeasible targets may use the entire search budget without achieving any target.
- Difficult targets may use most of the search budget, leaving lots of easier coverage targets uncovered.
- The order in which targets are considered affects the final result.

Whole test suite generation addresses all these problems:

- A set of test cases is generated to cover all targets at the same time.
- The result is independent of the order of the targets and the presence of infeasible or difficult targets.

Example

```
class Stack {
    int[] values = new int[INIT_SIZE];
    int size = 0;

    void push(int x) {
      if (size >= values.length)
          resize();
      if (size < values.length)
          values[size++] = x;
    }
    int pop() {…}
    private void resize() {…}
}
```

Difficult to cover

Else branch is infeasible

Whole test suite generation

Gordon Fraser, Andrea Arcuri, *Evolutionary generation of whole test suites*. Proc. of the Int. Conference on the Quality of Software (QSIC), pp. 31-40, Madrid, Spain, July 2011.

Chromosome

An individual is an entire test suite, i.e. a set of test cases:

Ch1 = {TC1, TC2, …} =

{<$a=A(int):$b=B():$b.f(int):$a.m(int, $b) @ -1, 2, 5>,
<$a=A(int):$b=B():$a.m(int, $b) @ 3, 7>, …}

Ch1: cov = 30
Ch2: cov = 15
Ch3: cov = 17
Ch4: cov = 34
Ch5: cov = 21
Ch6: cov = 11
Ch7: cov = 13
Ch8: cov = 45

Intuitively, individuals (test suites) with higher coverage are better, so fitness must be based on coverage.

Fitness

Sum of the branch distances for branches that lead to uncovered test targets [to be minimized]:

$$f(ch) = |M| - |exec(M)| + \sum_{c \in Uncov} MinBD(c)$$

where *c* is any predicate condition leading to an uncovered test target; *minBD* gives the minimum normalized branch distance over all executions of the predicate containing *c* (=1 if the predicate was never executed or was executed just once, taking the other branch and covering other targets).

The number of non executed methods accounts for the entry branch.

Ties are resolved by rewarding the chromosomes representing smaller test suites (i.e., test suites with less statements).

Mutation

In addition to the mutation operators for the individual test cases:

- Remove method/constructor call;
- Insert method/constructor call;
- Change input value.

Mutation operators that work on whole test suites include:

- **Add test case**: Ch = {TC1, …} → Ch' = {TC_new, TC1, …}
- **Remove test case**: Ch = {TC_k, TC1, …} → Ch' = {TC1, …} if TC_k becomes empty after (repeatedly) applying remove method/ constructor call to it.

Crossover

Each test suite is partitioned into two non empty subsets, which are exchanged between the two individuals.

Ch1 = {TC1, TC2, TC3, TC4} Ch2 = {TC5, TC6, TC7}

Ch1’ = {TC1, TC2, TC7} Ch2’ = {TC5, TC6, TC3, TC4}

Tool

EvoSuite: http://www.st.cs.uni-saarland.de/evosuite/

by Gordon Fraser & Andrea Arcuri.

- Implements the genetic algorithm for whole test suite generation
- Instruments the Java bytecode under test for coverage analysis.
- Uses Java reflection to execute test cases encoded as chromosomes and to determine the execution traces.
- Only mutated test cases need to be re-executed from one iteration to the next one.
- Test case execution is timed out to prevent non-termination.
- Produces a JUnit test class as output.

Future internet testing

FITTEST

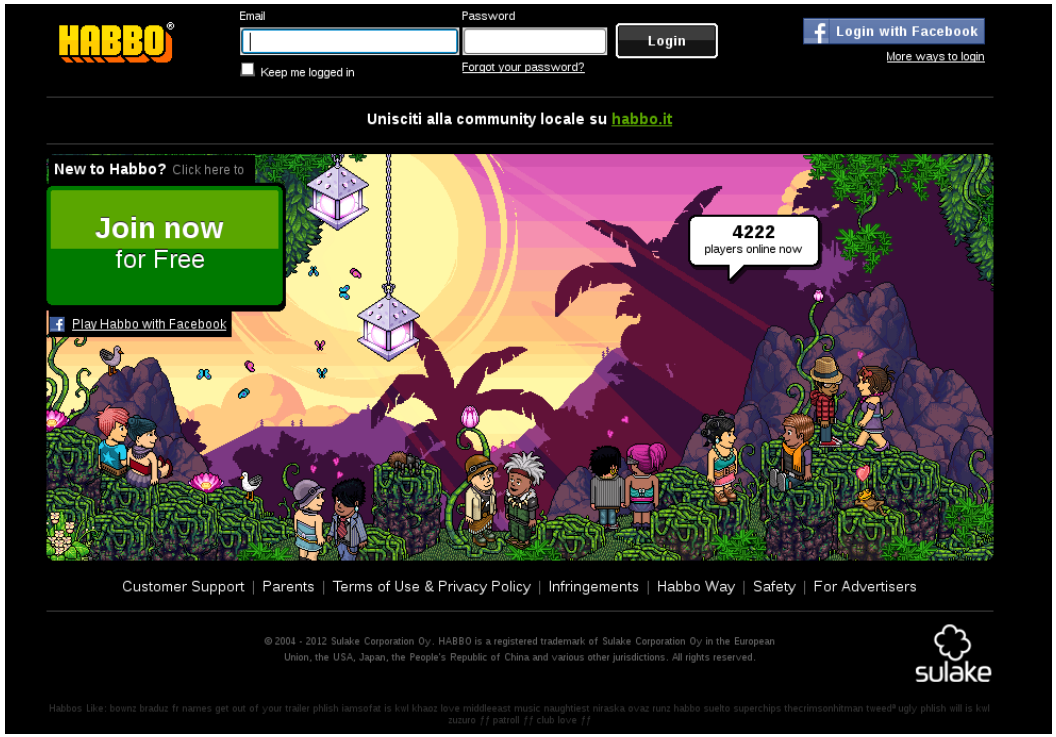
EU FP7 STREP project n. 257574

Sep 1, 2010 – Dec 31, 2013

Participant organisation	Country
Universidad Politécnica de Valencia (coordinator)	Spain
University College London	United Kingdom
Berner & Mattner Systemtechnik	Germany
IBM	Israel
Fondazione Bruno Kessler	Italy
Utrecht University	The Netherlands
SOFTeam	France
Sulake	Finland

Goal: automated, continuous testing of Future Internet applications

Future internet



- Highly interactive
- Communicating asynchronously with server
- Based on Web 2.0 technologies (e.g., Ajax, Flash/ActionScript)
- Composed and updated dynamically

THE FUTURE INTERNET (FI): A COMPLEX INTERCONNECTION OF SERVICES, APPLICATIONS, CONTENT AND MEDIA

FI testing challenges

- **CH1** Self modification
  - Rich clients have increased capability to dynamically adapt the structure of the Web pages; server-side services are replaced and recomposed dynamically based on Service Level Agreements (SLA) and newly discovered services; components are dynamically loaded

- **CH2** Autonomic behaviour
  - FI applications are highly autonomous; their correct behaviour cannot be specified precisely at design-time.

- **CH3** Low observability
  - FI applications are composed of an increasing number of 3rd-party components and services,accessed as a black box, which are hard to test.

FI testing challenges

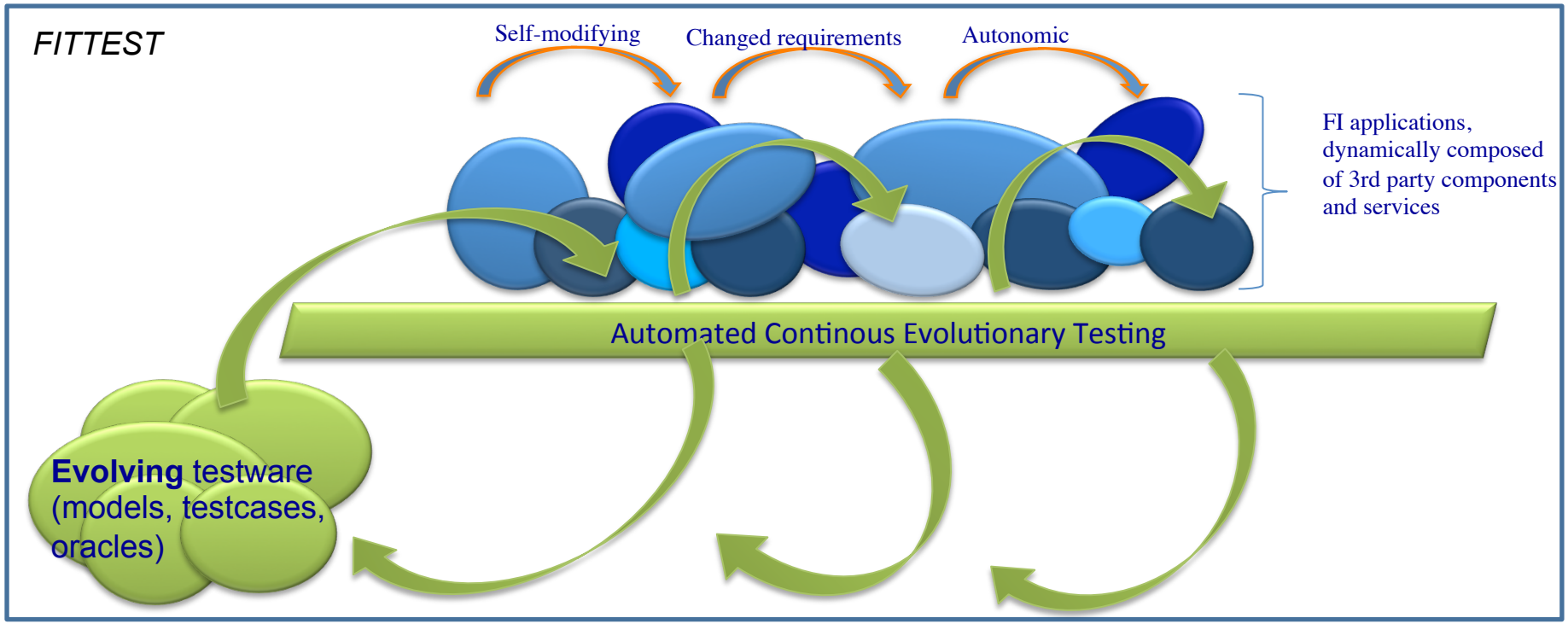
- **CH4** Asynchronous interactions
  - FI applications are highly asynchronous and hence hard to test. Each client submits multiple requests asynchronously; multiple clients run in parallel; server-side computation is distributed over the network and concurrent.

- **CH5** Time and load dependent behaviour
  - For FI applications, factors like timing and load conditions make it hard to reproduce errors during debugging.

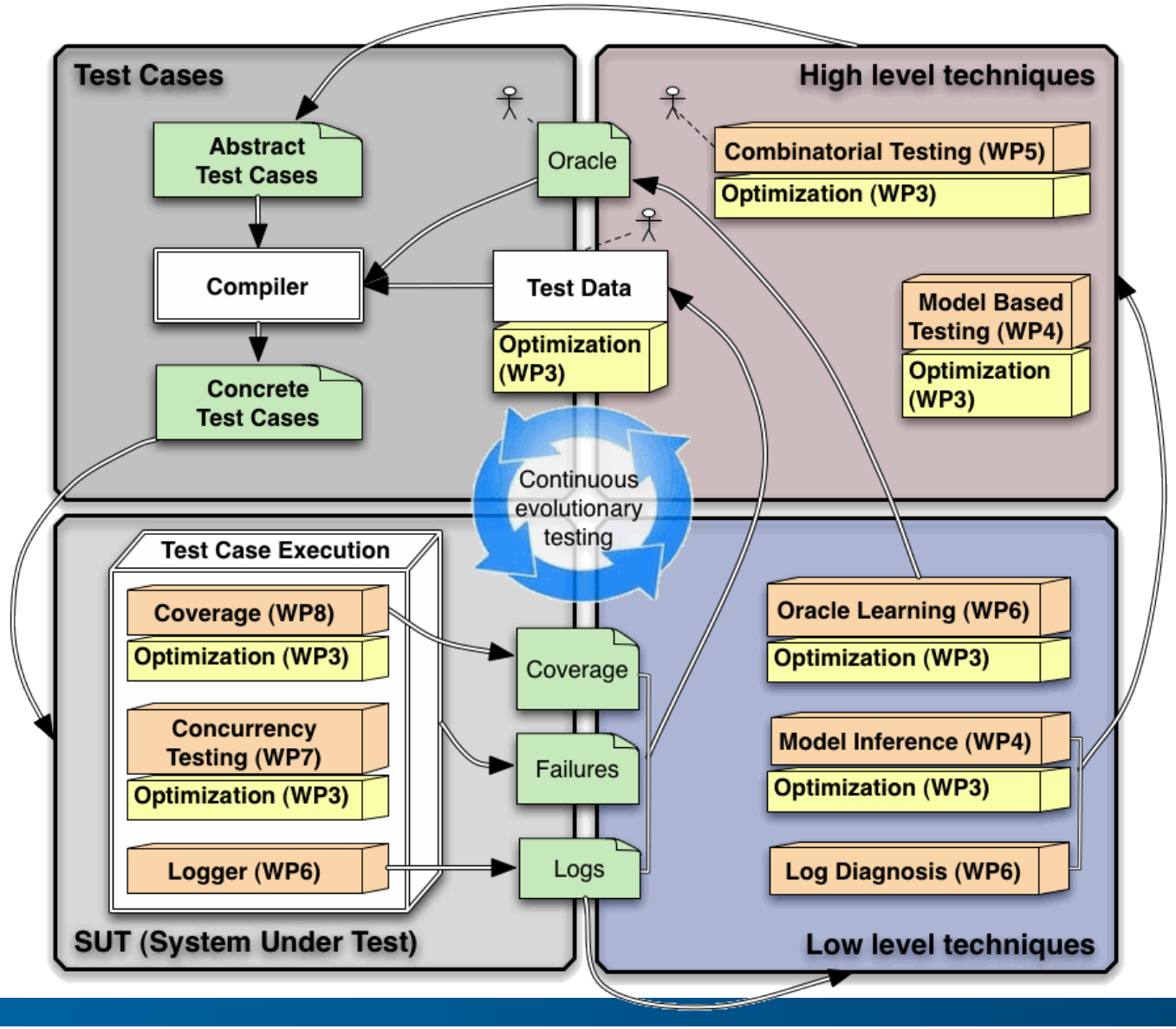
- **CH6** Huge feature configuration space
  - FI applications are highly customisable and self-configuring, and contain a huge number of configurable features, such as user-, context-, and environment-dependent parameters.

- **CH7** Ultra-large scale
  - FI applications are often systems of systems; traditional testing adequacy criteria cannot be applied, since even in good testing situations low coverage will be achieved.

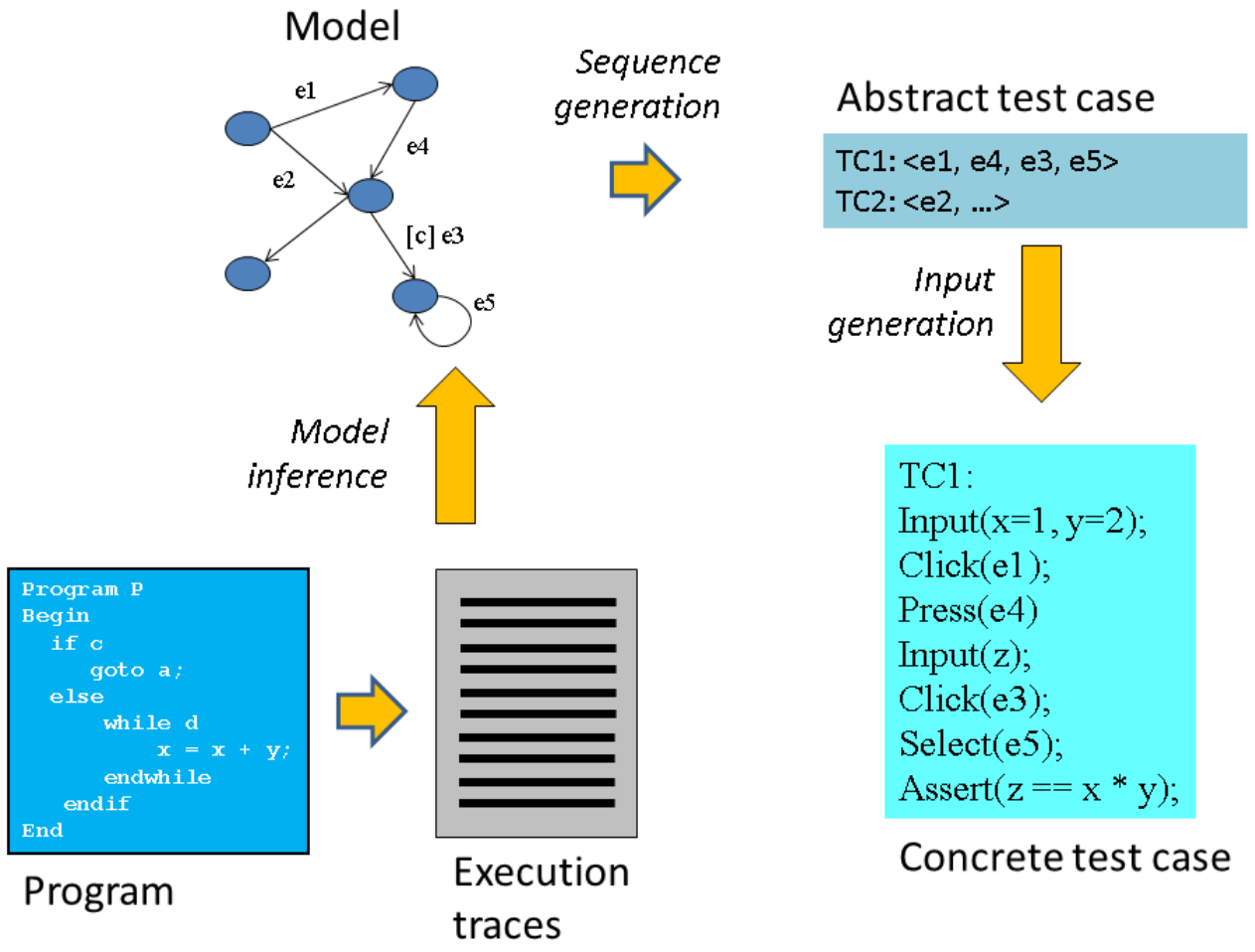
FI testing approach



Global picture

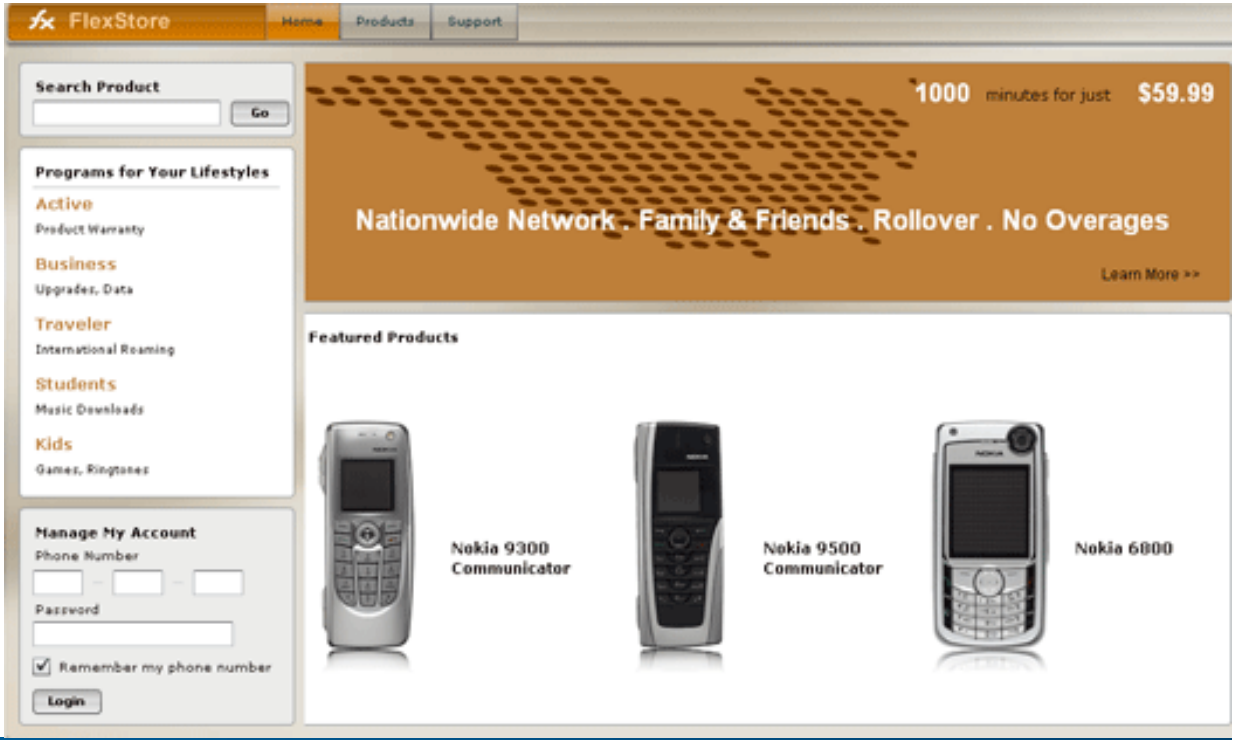


Model-based FI testing

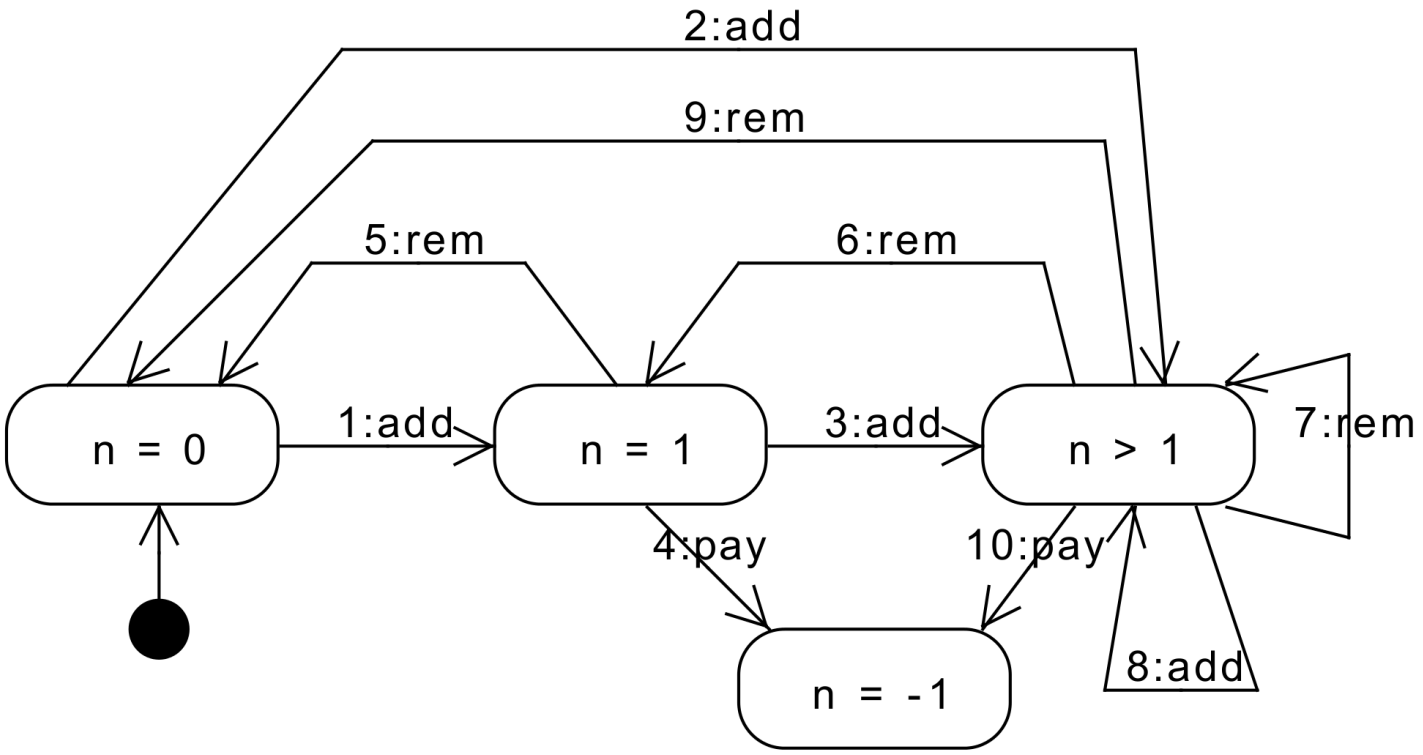


FI example: Cart

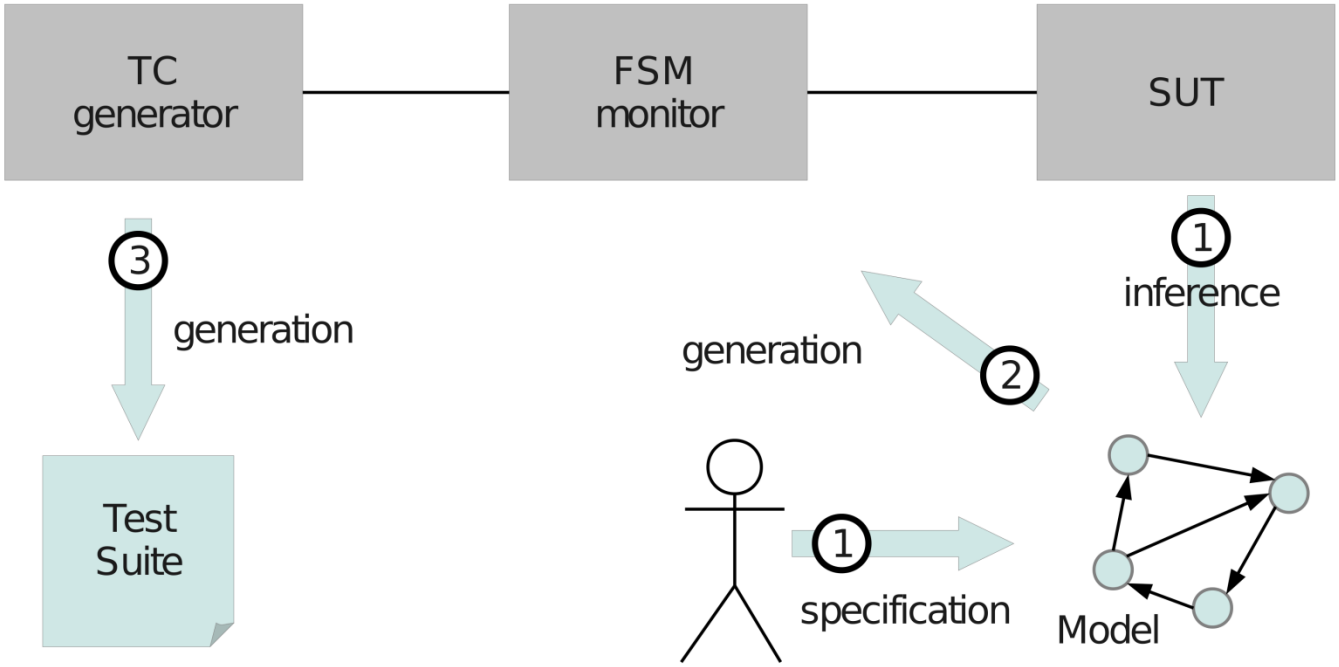
```
public class Cart {
    public Cart() { ... }
    public void add(int c) { ... }
    public void rem(int c) { ... }
    public void pay()
        { ... }
    public int n()
        { ... }
}
```



Inferred model

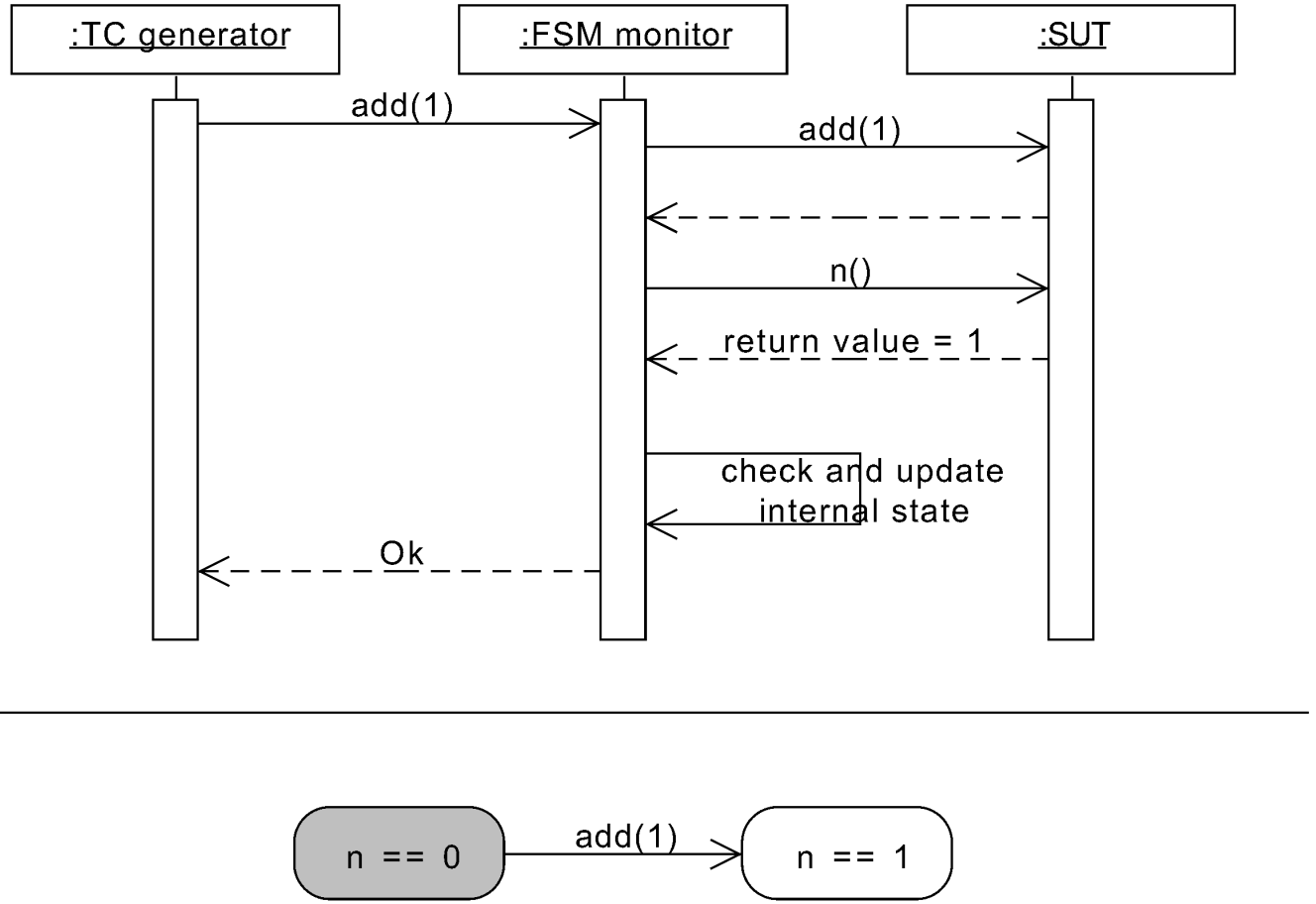


Architecture

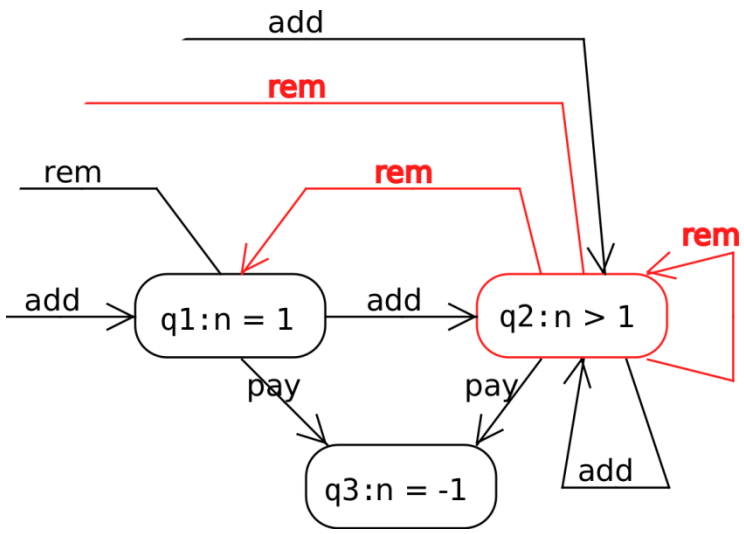


Branch coverage of the FSM monitor is equivalent to transition coverage of the model

FSM monitor as a “man in the middle”



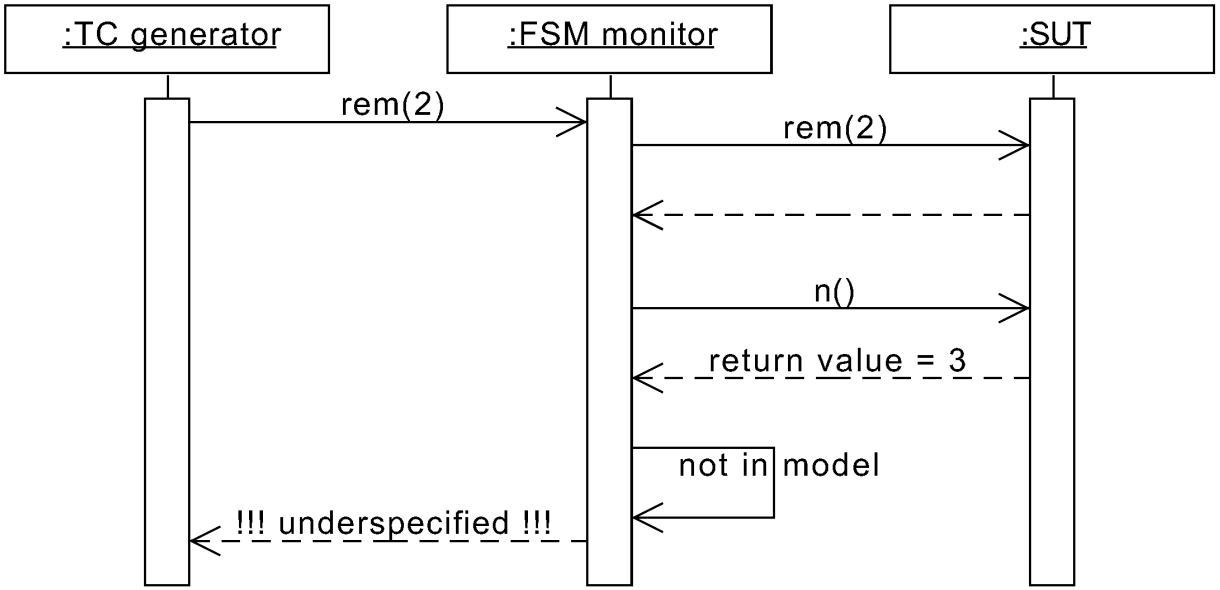
FSM monitor generation through testability transformation

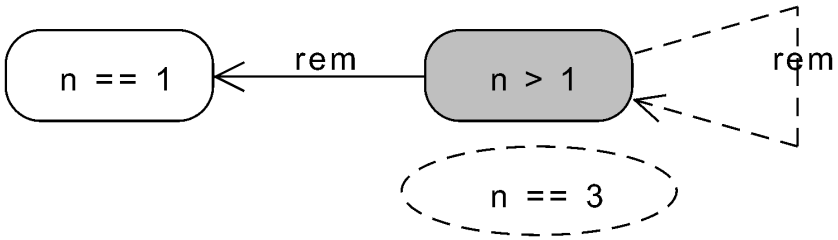



```
void rem(int n) {
  sut.rem(n);
  switch (s_state) {

  case 2:
    if ( n > 1 ) {
      s_state = 2;
    } else if ( n == 1 ) {
      s_state = 1;
    } else if ( n == 0 ) {
      s_state = 0;
    } else {
      throw new UnderSpecEx(...);
    }
    break;

  case 1:
    ...
}
```

Branch conditions become branch distances in the fitness function of the search based TC generator

Underspecified model





From Branch to Transition Coverage

- **Theorem**: given the FSM model, we can apply a testability transformation to the model, which builds a class *FSM_monitor* such that, if the SUT is compliant with the FSM, then:

All-transition coverage on the FSM is satisfied

iff

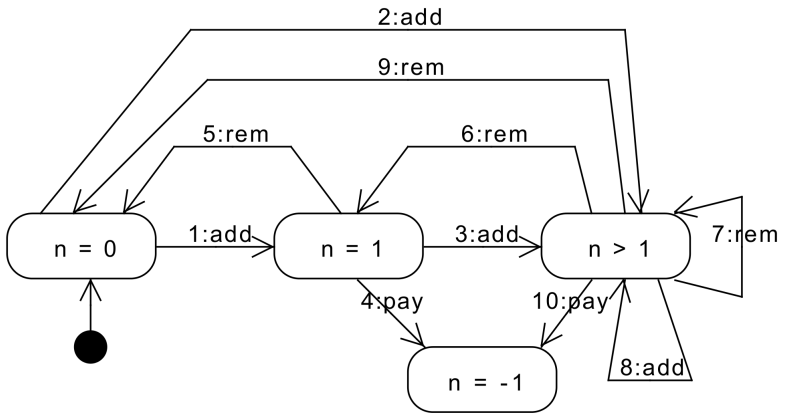
All (non-error) branch coverage on the FSM_monitor is satisfied

Implementation

- Existing search-based test case generators (e.g., *EvoSuite*) can be used
- *FSM_monitor* generator:
  - java
  - template based (Velocity)
    - highly configurable
    - different implementation styles can be supported
    - graphical representations can be produced, with proper templates

Test Suite

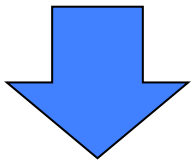
```
//Test case number: 0
   testCart0.add(1);
   testCart0.add(1);
   testCart0.add(1);

//Test case number: 1
   testCart0.add(2);
   testCart0.pay();

//Test case number: 2
   testCart0.add(11);
   testCart0.rem(11);
```




```
//Test case number: 3
   testCart0.add(1);
   testCart0.rem(1);

//Test case number: 4
   testCart0.add(1734);
   testCart0.rem(1);

//Test case number: 5
   testCart0.add(2);
   testCart0.rem(1);

//Test case number: 6
   testCart0.add(1);
   testCart0.pay();
```

FI testing

- Models are inferred continuously
- Test case generators cover all branches of the FSM monitor ➔ all model transitions
- Test suites are updated and re-executed incrementally



The testware evolves autonomously with the FI application under test

Dynamic symbolic execution

Slides are partially based on the ESEC-FSE'05 presentation: http://srl.cs.berkeley.edu/~ksen

Static symbolic execution

Path coverage:

1. Select a path *p* to be covered.
2. Determine the path condition (path constraint), by propagation of symbolic input values along the path (expressions are evaluated symbolically). The path condition is a boolean expression containing only input variables.
3. Solve the path condition using an SMT solver.

Static symbolic execution

```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;

  Triangle(int a, int b, int c) {…}
  void checkRightAngle() {…}
  void computeTriangleType() {
    if (a == b)
        if (b == c) type = EQUILATERAL; // target
        else type = ISOSCELE;
    else if (a == c) type = ISOSCELE;
    else if (b == c) type = ISOSCELE;
    else checkRightAngle();
  }
  boolean isTriangle() {…}
  public static void main(String args[]) {…}
}
```

Static symbolic execution

```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;

  Triangle(int a, int b, int c) {…}
  void checkRightAngle(){…}
  void computeTriangleType() {…}
  boolean isTriangle() {…}
  public static void main(String args[]) {
    int a = Integer.parseInt(args[0]);
    int b = Integer.parseInt(args[1]);
    int c = Integer.parseInt(args[2]);
    Triangle t = new Triangle(a, b, c);
    if (t.isTriangle())
       t.computeTriangleType();
    System.out.println(typeToString(t.type));
  }
}
```

Static symbolic execution

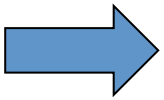
```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;

  Triangle(int a, int b, int c) {…}
  void checkRightAngle() {…}
  void computeTriangleType() {…}
  boolean isTriangle() {
    if (a <= 0 || b <= 0 || c <= 0)
        return false;
    if (a + b <= c || a + c <= b || b + c <= a)
        return false;
    return true;
  }
  public static void main(String args[]) {…}
}
```

Path condition = ! (a <= 0 || b <= 0 || c <= 0) && !(a + b <= c || a + c <= b || b + c <= a) && (a == b) && (b == c)

Yices SMT solver

Path condition = ! (a <= 0 || b <= 0 || c <= 0) && !(a + b <= c || a + c <= b || b + c <= a) && (a == b) && (b == c)
= (a > 0) && (b > 0) && (c > 0) && (a + b > c) && (a + c > b) && (b + c > a) && (a == b) && (b == c)

```
(define a::int)
(define b::int)
(define c::int)
(assert (> a 0))
(assert (> b 0))
(assert (> c 0))
(assert (> (+ a b) c))
(assert (> (+ a c) b))
(assert (> (+ b c) a))
(assert (= a b))
(assert (= b c))
(check)
```



```
sat
(= a 1)
(= b 1)
(= c 1)
```

Problems of static symbolic execution

In practice, **static** symbolic execution has several limitations that make it inapplicable for test case generation for not trivial programs:

- Loops must be unrolled a fixed number of times.
- Static symbolic execution may require a lot of (SMT-solving) time and does not scale to large programs.
- SMT solvers usually do not handle non linear constraints.
- SMT solvers cannot deal with black box functions.

Dynamic symbolic execution:
Start from an available (random), concrete execution and use symbolic execution to explore alternative paths.

FONDAZIONE BRUNO KESSLER

SE SOFTWARE ENGINEERING

In a nutshell

Goal: *to generate data inputs that exercise all feasible execution paths up to a given length.*

1. Execute a random test case.
2. Collect symbolic constraints along the concretely executed path.
3. Negate one branch condition in the path constraint.
4. Use constraint solvers to generate a new test input for the negated constraint.
5. Execute the new test case, covering a new path; iterate from 2.

In a nutshell

Problem: *the constraint solver may not be powerful enough to determine concrete values that satisfy the negated path constraint.*

```
4. Use constraint solvers to generate a new
   test input for the negated constraint.
4′ If necessary, simplify the path
   constraint by replacing some of the
   symbolic values with concrete values.
```

In particular, simplification may be necessary whenever non linear constraints are involved or black-box, external functions are called.

Implementation

Instrumentation can be used to perform concrete and symbolic execution at the same time.

```
x = y + 2;
Symb_exec("x=y+2");
…
if (x > z) {
   Symb_exec("x>z");
```

1. Update symbolic state
2. Accumulate path condition

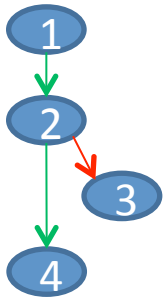
When a function is called for which the code is not available for symbolic execution, the outcome of its concrete execution is used as an approximation of its symbolic execution.

Example 1

Execution constraints are collected dynamically and negated to traverse alternative paths

```
int testme(int x) {
1  int y = x + 3;
2  if (y == 13)
3    target();
4 return 0;
}
```

concrete state	symbolic state	constraints
x = 0	x = x_0	(x_0 + 3 ≠ 13)
y = 3	y = x_0 + 3	

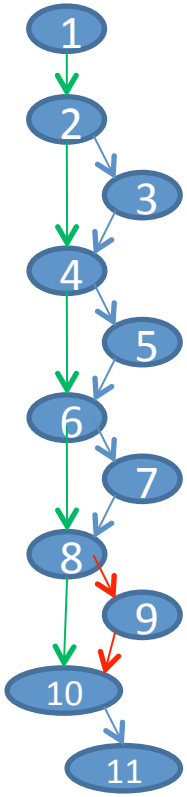


<x = 0> ➔ <1, 2, 4> ➔ (x_0 + 3 ≠ 13)

(x_0 + 3 = 13) ➔ <x = 10> ➔ <1, 2, 3>

Example 2

```
void testme(char x[4]) {
1   int n = 0;
2   if (x[0] == 'b')
3     n++;
4   if (x[1] == 'a')
5     n++;
6   if (x[0] == 'd')
7     n++;
8   if (x[0] == '!')
9     n++;
10  if (n >= 4)
11    target();
}
```

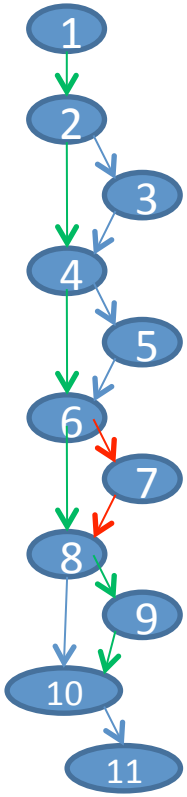


Concrete Execution	Symbolic Execution	
concrete state	symbolic state	constraints
x = "good"	x = {x_0, x_1, x_2, x_3}	(x_0 ≠ 'b') &
n = 0	n = 0	(x_1 ≠ 'a') &
		(x_2 ≠ 'd') &
		(x_3 ≠ '!') &
		(0 < 4)

(x_0 ≠ 'b') & (x_1 ≠ 'a') & (x_2 ≠ 'd') & (x_3 = '!') ➔ <x = "goo!">

Example 2

```
void testme(char x[4]) {
1   int n = 0;
2   if (x[0] == 'b')
3     n++;
4   if (x[1] == 'a')
5     n++;
6   if (x[0] == 'd')
7     n++;
8   if (x[0] == '!')
9     n++;
10  if (n >= 4)
11    target();
}
```



Concrete Execution

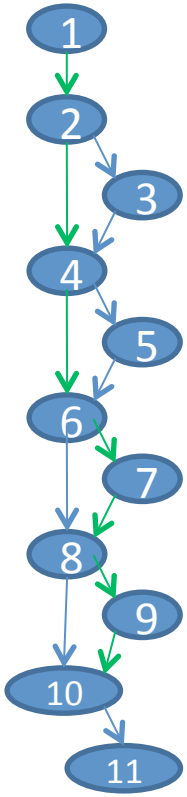
Symbolic Execution

concrete state	symbolic state	constraints
x = "goo!"	x = {x_0, x_1, x_2, x_3}	(x_0 ≠ 'b') &
		(x_1 ≠ 'a') &
n = 1	n = 1	(x_2 ≠ 'd') &
		(x_3 = '!') &
		(1 < 4)

(x_0 ≠ 'b') & (x_1 ≠ 'a') & (x_2 = 'd') & (x_3 = '!') ➔ <x = "god!">

Example 2

```
void testme(char x[4]) {
1   int n = 0;
2   if (x[0] == 'b')
3     n++;
4   if (x[1] == 'a')
5     n++;
6   if (x[0] == 'd')
7     n++;
8   if (x[0] == '!')
9     n++;
10  if (n >= 4)
11    target();
}
```

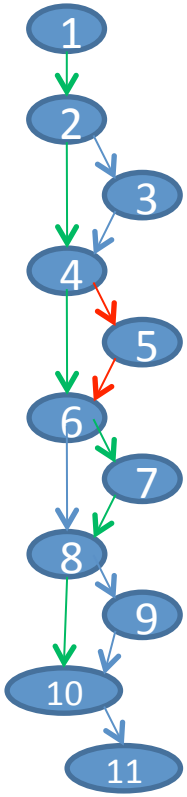


Concrete Execution	Symbolic Execution	
concrete state	symbolic state	constraints
x = "god!"	x = {x_0, x_1, x_2, x_3}	(x_0 ≠ 'b') &
n = 2	n = 2	(x_1 ≠ 'a') &
		(x_2 = 'd') &
		(x_3 = '!') &
		(2 < 4)

(x_0 ≠ 'b') & (x_1 ≠ 'a') & (x_2 = 'd') & (x_3 ≠ '!') ➔ <x = "godd">

Example 2

```
void testme(char x[4]) {
1   int n = 0;
2   if (x[0] == 'b')
3     n++;
4   if (x[1] == 'a')
5     n++;
6   if (x[0] == 'd')
7     n++;
8   if (x[0] == '!')
9     n++;
10  if (n >= 4)
11    target();
}
```



Concrete Execution

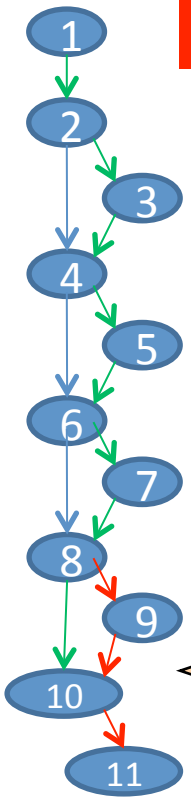
Symbolic Execution

concrete state	symbolic state	constraints
x = "godd"	x = {x_0, x_1, x_2, x_3}	(x_0 ≠ 'b') &
		(x_1 ≠ 'a') &
n = 1	n = 1	(x_2 = 'd') &
		(x_3 ≠ '!') &
		(1 < 4)

(x_0 ≠ 'b') & (x_1 = 'a') & (x_2 = 'd') & (x_3 ≠ '!') ➔ <x = "gadd">

Example 2

```
void testme(char x[4]) {
1   int n = 0;
2   if (x[0] == 'b')
3     n++;
4   if (x[1] == 'a')
5     n++;
6   if (x[0] == 'd')
7     n++;
8   if (x[0] == '!')
9     n++;
10  if (n >= 4)
11    target();
}
```



After 16 steps

Concrete Execution

Symbolic Execution

concrete state

x = "badd"

n = 3

symbolic state

x = {x_0, x_1, x_2, x_3}

n = 3

constraints

(x_0 = 'b') &

(x_1 = 'a') &

(x_2 = 'd') &

(x_3 ≠ '!') &

(3 < 4)

Target reached

(x_0 = 'b') & (x_1 = 'a') & (x_2 = 'd') & (x_3 = '!') ➔ <x = "bad!">

Non linear constraints

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        target();
    }
}
```

- Let initially x = -3 and y = 7 generated randomly

Non linear constraints

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        target();
    }
}
```

- Let initially x = -3 and y = 7 generated randomly
- concrete z = 9
- symbolic z = $x_0*x_0*x_0 + 3*x_0*x_0+9$
- take then branch with constraint $x_0*x_0*x_0+ 3*x_0*x_0+9 != y_0$

Non linear constraints

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        target();
    }
}
```

- Let initially x = -3 and y = 7 generated randomly
- concrete z = 9
- symbolic z = $x_0*x_0*x_0 + 3*x_0*x_0+9$
- take *then* branch with constraint $x_0*x_0*x_0+ 3*x_0*x_0+9 != y_0$
- solve $x_0*x_0*x_0+ 3*x_0*x_0+9 = y_0$ to take *else* branch
- Don't know how to solve !!
  - **Stuck ?**

Non linear constraints

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        target();
    }
}
```

- Let initially x = -3 and y = 7 generated by random test-driver
- concrete z = 9
- symbolic z = $x_0*x_0*x_0 + 3*x_0*x_0+9$
  - cannot handle symbolic value of z

Non linear constraints

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        target();
    }
}
```

- Let initially x = -3 and y = 7 generated by random test-driver
- concrete z = 9
- symbolic z = $x_0*x_0*x_0 + 3*x_0*x_0+9$
  - cannot handle symbolic value of z
  - make symbolic z = 9 and proceed

Non linear constraints

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        target();
    }
}
```

- Let initially x = -3 and y = 7 generated by random test-driver
- concrete z = 9
- symbolic z = $x_0*x_0*x_0 + 3*x_0*x_0+9$
  - cannot handle symbolic value of z
  - make symbolic z = 9 and proceed
- take *then* branch with constraint
  - 9 != y_0

Non linear constraints

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        target();
    }
}
```

- Let initially x = -3 and y = 7 generated by random test-driver
- concrete z = 9
- symbolic z = $x_0*x_0*x_0 + 3*x_0*x_0+9$
  - cannot handle symbolic value of z
  - make symbolic z = 9 and proceed
- take *then* branch with constraint
  - $9 != y_0$
- solve $9 = y_0$ to take *else* branch
- execute next run with x = -3 and y= 9
  - Target reached

Non linear constraints

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    }
}
```

Replace symbolic expression with concrete value when symbolic expression becomes unmanageable (e. g. non-linear)

- Let initially x = -3 and y = 7 generated by random test-driver
- concrete z = 9
- symbolic $z = x_0*x_0*x_0 + 3*x_0*x_0+9$
  - cannot handle symbolic value of z
  - make symbolic z = 9 and proceed
- take then branch with constraint
  - $9 != y_0$
- solve $9 = y_0$ to take else branch
- execute next run with x = -3 and y= 9
  - Target reached

Black-box functions

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        abort();
    }
}
```

```
void test_me(int x,int y){
    z = black_box_fun(x);
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        abort();
    }
}
```

The same approach is applied to any called function which cannot be executed or modeled symbolically.

Black-box functions

```
void test_me(int x,int y){
    z = x*x*x + 3*x*x + 9;
    if(z != y){
        printf("Good branch");
    }
}
```

```
void test_me(int x,int y){
    z = black_box_fun(x);
    if(z != y){
        printf("Good branch");
    } else {
        printf("Bad branch");
        abort();
    }
}
```

Use the concrete value returned by the function whenever the symbolic expression cannot be computed

The same approach is applied to *any* called function which cannot be executed or modeled symbolically.

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Properties

- **Incompleteness**: dynamic symbolic execution is complete only if the constraint solver can successfully solve all constraints without having to simplify them.
- **Approximation**: an input satisfying a simplified path condition, where some symbolic values are replaced by concrete ones, is not ensured to execute the path of interest (i.e., its execution may **diverge** from the expected one).
- **Soundness**: dynamic symbolic execution is always sound, since generated test cases are executable, hence revealed faults are real faults.

Example of approximation

```
class Triangle {
  int a, b, c; // sides
  int type = NOT_A_TRIANGLE;

  Triangle(int a, int b, int c) {…}
  void checkRightAngle() {
    if (a*a + b*b == c*c)
        type = RIGHT_ANGLE;
    else if (b*b + c*c == a*a)
        type = RIGHT_ANGLE;
    else if (a*a + c*c == b*b)
        type = RIGHT_ANGLE;
    else type = SCALENE;
  }
  void computeTriangleType() {…}
  boolean isTriangle() {…}
  public static void main(String args[]) {…}
}
```

Concrete input = (2, 3, 4) [SCALENE]

Path condition = ! (a <= 0 || b <= 0 || c <= 0) && !(a + b <= c || a + c <= b || b + c <= a) && !(a*a + b*b == c*c) && !(b*b + c*c == a*a) && !(a*a + c*c == b*b)

Example of approximation

Concrete input = (2, 3, 4) [SCALENE]

SMT solver:

(a > 0 && b > 0 && c > 0) && (a + b > c && a + c > b && b + c > a) &&
(a*a + b*b != c*c) && (b*b + c*c != a*a) &&
(a*a + c*c == b*b)

Error: feature not supported: non linear problem.

Simplified constraint:

(a > 0 && b > 0 && c > 0) && (a + b > c && a + c > b && b + c > a) &&
(2*a + 3*b != 4*c) && (3*b + 4*c != 2*a) &&
(2*a + 4*c == 3*b)

```
sat
(= a 4)
(= b 4)
(= c 1)
```

Not a right angle triangle!

Target not covered.

Strengths and weaknesses

Dynamic symbolic execution:

- **Incompleteness**: not all paths are covered if concrete values are used and the simplified constraint admits no solution.
- **Approximation**: solutions are not ensured to execute the path of interest if concrete values are used.
- **Soundness**: generated test cases are executable, faults are real.

Search based test case generation:

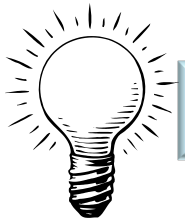
- **Incompleteness**: feasible coverage targets might be missed.
- **Robustness**: non linear expressions and black box functions do not represent any special problem in fitness function definition.
- **Soundness**: generated test cases are executable, faults are real.

Search based algorithms can easily accommodate approximations, but might miss exact solutions which are available via SMT solving.

Combining SBST & DSE

- Kobi Inkumsah, Tao Xie. *Improving Structural Testing of Object-Oriented Programs via Integrating Evolutionary Testing and Symbolic Execution*. Proc. of Automated Software Engineering (ASE), pp. 297-306, 2008.
- Jan Malburg, Gordon Fraser. *Combining search-based and constraint-based testing*. Proc. of Automated Software Engineering (ASE), pp. 436-439, 2011.
- Tao Xie, Nikolai Tillmann, Jonathan de Halleux, Wolfram Schulte. *Fitness-guided path exploration in dynamic symbolic execution*. Proc. of the International Conference on Dependable Systems and Networks (DSN), pp. 359-368, 2009.
- Arthur I. Baars, Mark Harman, Youssef Hassoun, Kiran Lakhotia, Phil McMinn, Paolo Tonella, Tanja E. J. Vos. *Symbolic search-based testing*. Proc. of Automated Software Engineering (ASE), pp. 53-62, 2011.

Generating new individuals by means of DSE

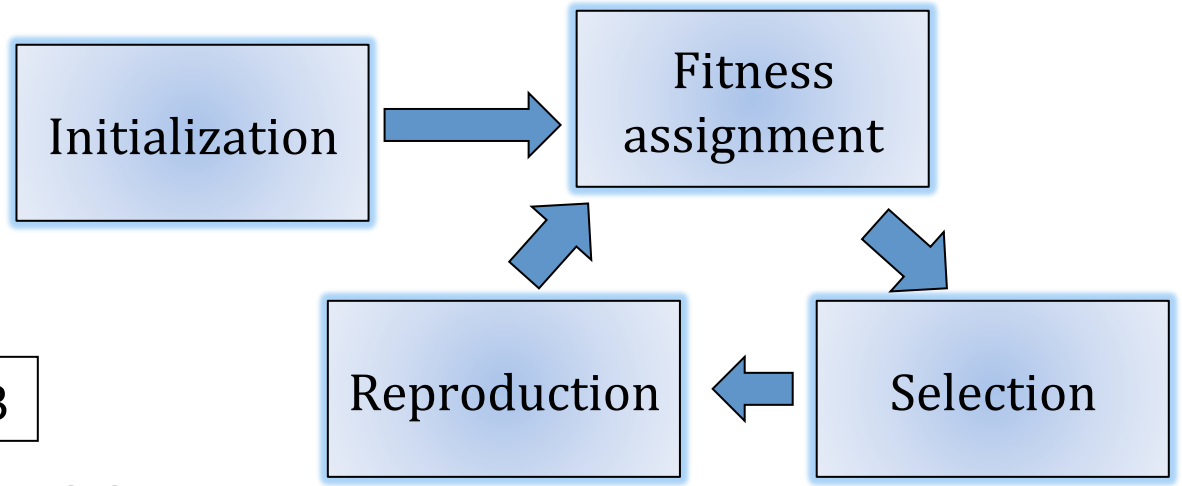


New individuals are generated using DSE.

Kobi Inkumsah, Tao Xie. *Improving Structural Testing of Object-Oriented Programs via Integrating Evolutionary Testing and Symbolic Execution*. Proc. of Automated Software Engineering (ASE), pp. 297-306, 2008.

Jan Malburg, Gordon Fraser. *Combining search-based and constraint-based testing*. Proc. of Automated Software Engineering (ASE), pp. 436-439, 2011.

Generating new individuals by means of DSE



- Mutation
- Crossover
- **DSE based mutation**

Ch1:

1	5	-1	0	3

pc1: C1 && C2 && **C3** && C4

pc1': C1 && C2 && !**C3**

Ch1':

1	0	2	1	1

Primitive values generation

$x0=BankAccount(): $x0.deposit(int): $x0.withdraw(int) @ 1, 20

Primitive values are made symbolic: z0, z1

Path condition (withdraw) = (z1 > z0)

Error handling branch:

```
void withdraw(int amount) {
  if (amount > balance) {
     printError();
     return;
  }
  balance = balance - amount;
  …
}
```

Primitive values generation

$x0=BankAccount(): $x0.deposit(int): $x0.withdraw(int) @ 1, 20

Primitive values are made symbolic: z0, z1

Path condition (withdraw) = (z1 > z0)

Negated path condition = (z1 <= z0)

```
sat
(= z1 1)
(= z0 20)
```

$x0=BankAccount(): $x0.deposit(int): $x0.withdraw(int) @ 20, 1

Added to current population

Non-error branch:

```
if (amount > balance) {
    printError();
    return;
} balance = balance - amount;
...
```

Primitive values generation

```
double testMe(int x, int y, double z) {
1  boolean flag = y > 1000;
2  //…
3  if (x + y == 1024)
4     if (flag)
5        if (Math.cos(z) - 0.95 < Math.exp(z))
6           abort();
7  return 0.0;
}
```

Ch1:

1024	0	0.0

Standard mutation may take a while to make y > 1000 and x + y = 1024

pc1: (x + y = 1024) && (y ≤ 1000)

pc1': (x + y = 1024) && (y > 1000)

Ch1':

23	1001	0.0

Normal mutation and crossover are still required for conditions such as 5.

Fitness guided path exploration

A **fitness function** is used to select which **path to explore** by means of DSE.

Tao Xie, Nikolai Tillmann, Jonathan de Halleux, Wolfram Schulte. *Fitness-guided path exploration in dynamic symbolic execution*. Proc. of the International Conference on Dependable Systems and Networks (DSN), pp. 359-368, 2009.

Fitness guided path exploration

```
bool testLoop(int x, int[] y) {
1   if (x == 90) {
2       for (int i = 0 ; i < y.length ; i++)
3           if (y[i] == 15)
4               x++;
5       if (x == 110)
6           abort();
    }
7   return false;
}
```

DSE

Initial random TC:

x = 0, y = {0}

p = <1F, 7>

pc = (x != 90)

pc' = (x == 90)

New TC:

x = 90, y = {0}

p = <1T, 2T, 3F, 2F, 5F, 7>

- The (randomly selected) size of y must be ≥ 20.
- DSE has ≥ 2^{20} paths to explore, among which only a small fraction contain exactly twenty 3T, which is required to make 5 true.

Fitness guided path exploration

```
bool testLoop(int x, int[] y) {
1   if (x == 90) {
2       for (int i = 0 ; i < y.length ; i++)
3           if (y[i] == 15)
4               x++;
5       if (x == 110)
6           abort();
    }
7   return false;
}
```

d_{5T} = {0 if x == 110; abs(x - 110) otherwise}

Fitness guided path exploration

```
bool testLoop(int x, int[] y) {
1   if (x == 90) {
2       for (int i = 0 ; i < y.length ; i++)
3           if (y[i] == 15)
4               x++;
5       if (x == 110)
6           abort();
    }
7   return false;
}
```

- f(TC0) = 1 + BD(1T) = 1.989
- d(TC1) = |90 – 110| = 20, BD = 0.952
- d(TC2) = |91 – 110| = 19, BD = 0.95
- d(TC3) = |91 – 110| = 19, BD = 0.95
- d(TC4) = |92 – 110| = 18, BD = 0.947

DSE

TC0:
TestLoop(0, {0})
p = <**1F**, 7>

TC1:
TestLoop(90, {0})
p = <1T, 2T, **3F**, 2F, 5F, 7>

TC2:
TestLoop(90, {15})
p = <1T, 2T, 3T, **2F**, 5F, 7>

TC3:
TestLoop(90, {15, 0})
p = <1T, 2T, 3T, 2T, **3F**, 2F, 5F, 7>

TC4:
TestLoop(90, {15, 15})
p = <1T, 2T, 3T, 2T, 3T, 2F, 5F, 7>

Fitness guided path exploration

```
bool testLoop(int x, int[] y) {
1   if (x == 90) {
2       for (int i = 0 ; i < y.length ; i++)
3           if (y[i] == 15)
4               x++;
5       if (x == 110)
6           abort();
    }
7   return false;
}
```

TC4 is selected for branching node flipping

- f(TC0) = 1 + BD(1T) = 1.989
- d(TC1) = |90 – 110| = 20, BD = 0.952
- d(TC2) = |91 – 110| = 19, BD = 0.95
- d(TC3) = |91 – 110| = 19, BD = 0.95
- d(TC4) = |92 – 110| = 18, BD = 0.947

DSE

TC0:
TestLoop(0, {0})
p = <**1F**, 7>

TC1:
TestLoop(90, {0})
p = <1T, 2T, **3F**, 2F, 5F, 7>

TC2:
TestLoop(90, {15})
p = <1T, 2T, 3T, **2F**, 5F, 7>

TC3:
TestLoop(90, {15, 0})
p = <1T, 2T, 3T, 2T, **3F**, 2F, 5F, 7>

TC4:
TestLoop(90, {15, 15})
p = <1T, 2T, 3T, 2T, 3T, 2F, 5F, 7>

Fitness gain

```
bool testLoop(int x, int[] y) {
1   if (x == 90) {
2       for (int i = 0 ; i < y.length ; i++)
3           if (y[i] == 15)
4               x++;
5       if (x == 110)
6           abort();
    }
7   return false;
}
```

DSE

TC4:

TestLoop(90, {15, 15})

p = <1T, 2T, 3T, 2T, 3T, 2F, 5F, 7>

Which branch shall be flipped?

Fitness gain: how much the fitness value has improved across paths after flipping a given branch in the past.

Fitness gain

```
bool testLoop(int x, int[] y) {
1   if (x == 90) {
2       for (int i = 0 ; i < y.length ; i++)
3           if (y[i] == 15)
4               x++;
5       if (x == 110)
6           abort();
    }
7   return false;
}
```

- Δd(3F) = (1 + 1 + 2) / 3 = 1.33
- Δd(3T) = (-1 - 1 - 2) / 3 = -1.33
- Δd(2F) = (0 + 1) / 2 = 0.5
- Δd(2T) = (0 - 1) / 2 = -0.5

DSE

TC0:
TestLoop(0, {0})
p = <**1F**, 7>

TC1: d = 20
TestLoop(90, {0})
p = <1T, 2T, **3F**, 2F, 5F, 7>

TC2: d = 19
TestLoop(90, {15})
p = <1T, 2T, 3T, **2F**, 5F, 7>

TC3: d = 19
TestLoop(90, {15, 0})
p = <1T, 2T, 3T, 2T, **3F**, 2F, 5F, 7>

TC4: d = 18
TestLoop(90, {15, 15})
p = <1T, 2T, 3T, 2T, 3T, 2F, 5F, 7>

Fitness gain

```
bool testLoop(int x, int[] y) {
1   if (x == 90) {
2       for (int i = 0 ; i < y.length ; i++)
3           if (y[i] == 15)
4               x++;
5       if (x == 110)
6           abort();
    }
7   return false;
}
```

DSE

TC4:

TestLoop(90, {15, 15})

p = <1T, 2T, 3T, 2T, 3T, 2F, 5F, 7>

Estimated distance: the new branch distance associated with flipping branch *b* is estimated as: *d'(TC) = d(TC) - Δd(b)*

- Flip **2T**: d'(TC4) = 18 + 0.5 = 18.5
- Flip **3T**: d'(TC4) = 18 + 1.33 = 19.33
- Flip **2F**: d'(TC4) = 18 - 0.5 = 17.5

Fitness guided path exploration

```
bool testLoop(int x, int[] y) {
1   if (x == 90) {
2       for (int i = 0 ; i < y.length ; i++)
3           if (y[i] == 15)
4               x++;
5       if (x == 110)
6           abort();
    }
7   return false;
}
```

41 paths are explored to cover 5T; full exploration of all paths would require $\geq 2^{20}$ test cases.

DSE

TC4: TestLoop(90, {15, 15}), p = <1T, 2T, 3T, 2T, 3T, **2F**, 5F, 7>, d = 18

TC5: TestLoop(90, {15, 15, 0}), p = <1T, 2T, 3T, 2T, 3T, 2T, **3F**, 2F, 5F, 7>, d = 18

TC6: TestLoop(90, {15, 15, 15}), p = <1T, 2T, 3T, 2T, 3T, 2T, 3T, **2F**, 5F, 7>, d = 17

…

TC40: TestLoop(90, {15, 15, …, 15}), p = <1T, 2T, 3T, 2T, 3T, 2T, 3T, 2T, …, 2F, 5T, 7>, d = 0

Fitness function improvement

The **fitness function is improved** by means of symbolic execution.

Arthur I. Baars, Mark Harman, Youssef Hassoun, Kiran Lakhotia, Phil McMinn, Paolo Tonella, Tanja E. J. Vos. *Symbolic search-based testing*. Proc. of ASE, pp. 53-62, 2011.

Fitness function improvement

- Concrete execution of SUT
- Symbolic execution of each path between critical node and target
- Compute cumulative branch distance for each path condition
- Return minimal distance

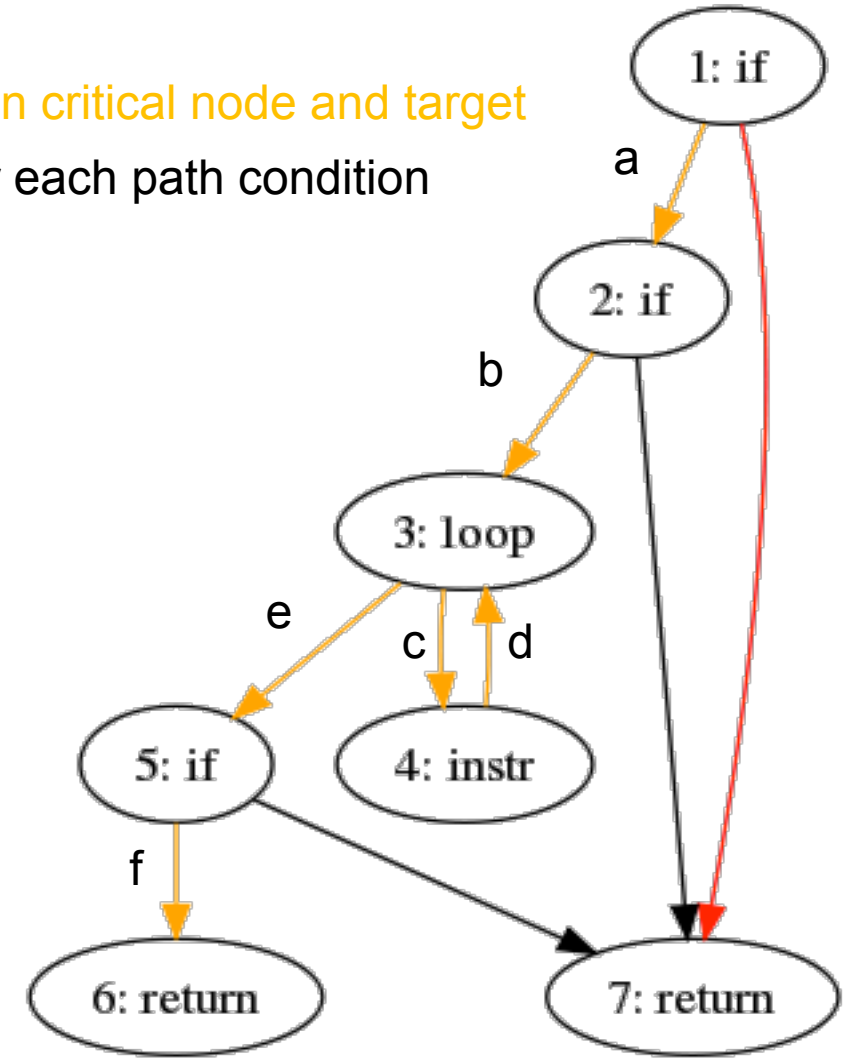
- Example:
  - abef

$Z > 0 \wedge X = Z \wedge Z \leq 0 \wedge Y = 10$

  - abcdef

$Z > 0 \wedge X = Z \wedge Z \leq 1 \wedge Y = 9$

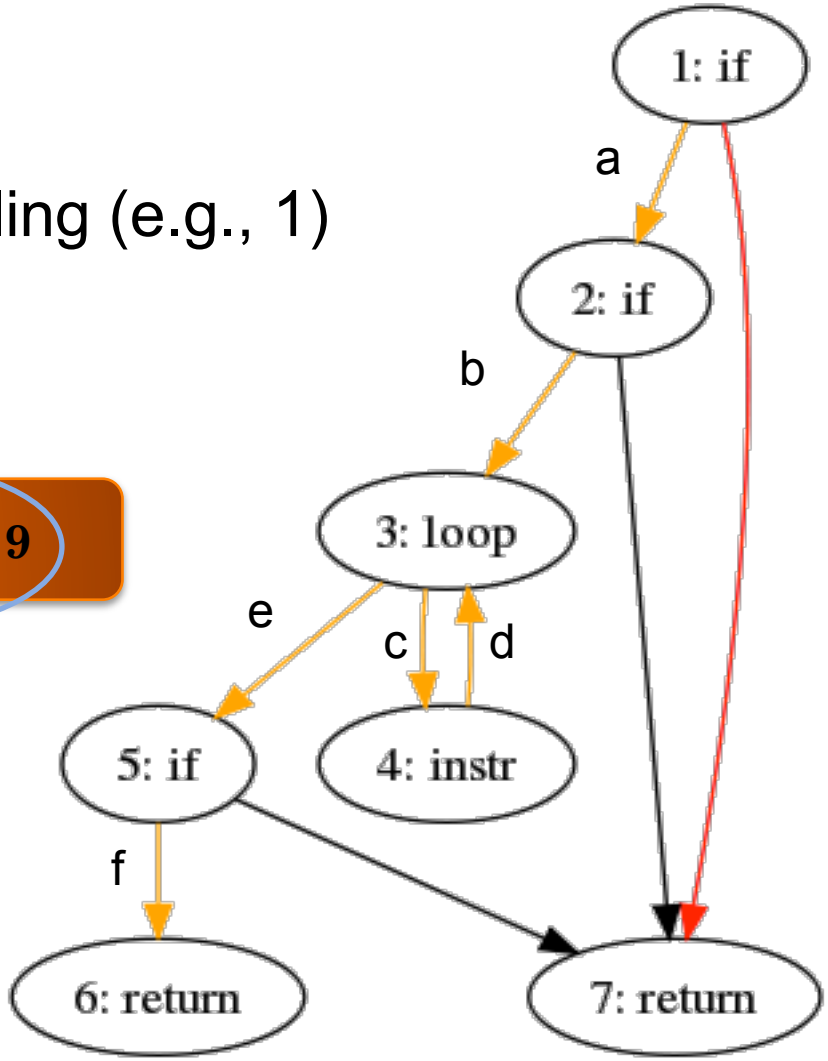
$bd_{>}(z,0) + bd_{=}(x,z) + bd_{<=}(z,1) + bd_{=}(y,9)$



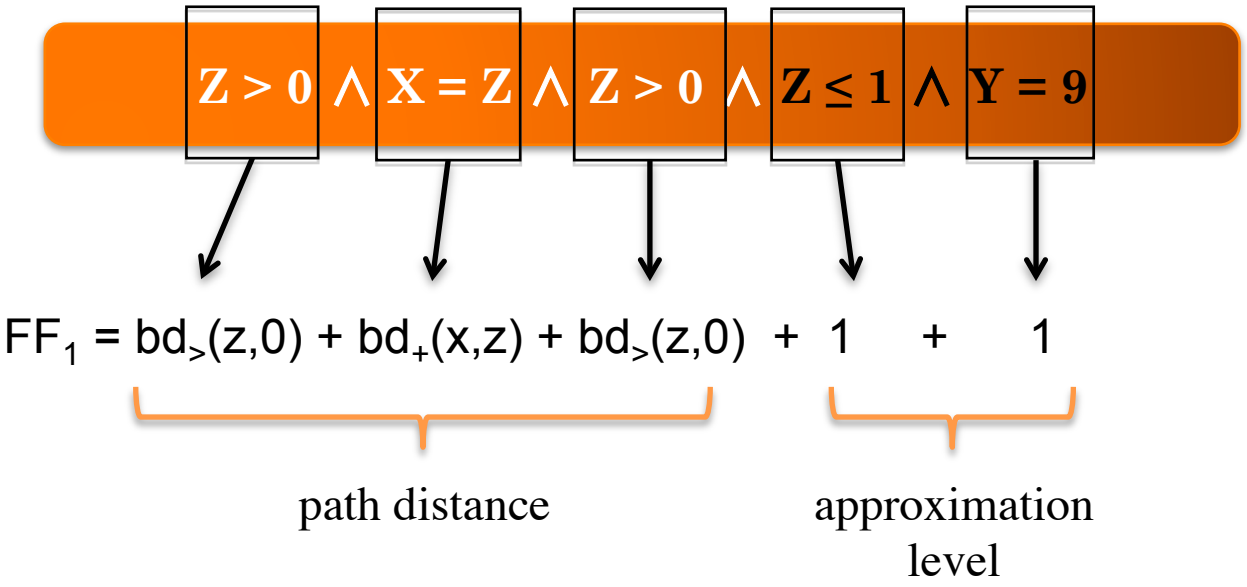
Fitness function improvement

- Path expression:
  - ab(cd)*ef
- Choose a maximum loop unrolling (e.g., 1)
  - abef
  - abcd***D[cd]***ef

$$Z > 0 \wedge X = Z \wedge Z > 0 \wedge Z \leq 1 \wedge Y = 9$$



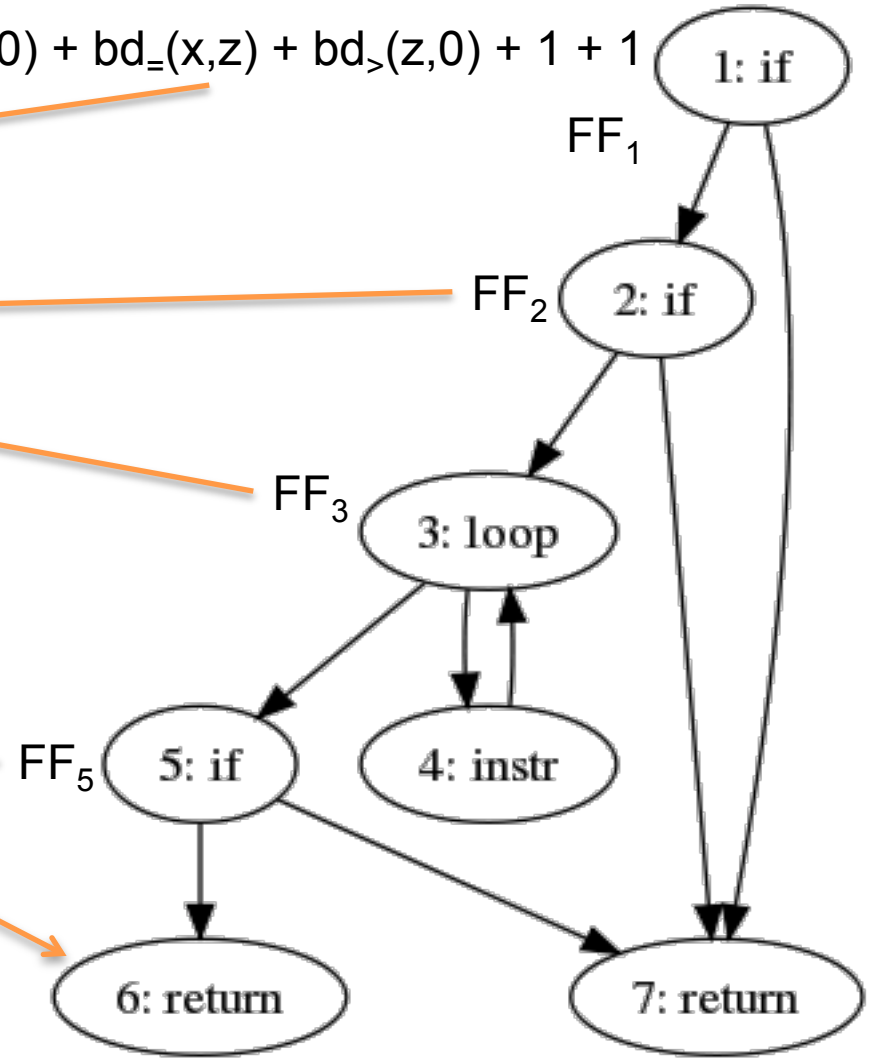
Fitness function improvement



Fitness function improvement

$FF_1 = bd_{>}(z,0) + bd_{=}(x,z) + bd_{>}(z,0) + 1 + 1$

```
int foo(int x, int y, int z) {
   if(z > 0)
      if(x == z) {
         for(int i = 0; i < z; i++)
            y++
         if(y == 10)
            return 0;
      }
   return 1;
```



Fitness = $\min(FF_1, FF_2, FF_3, FF_5)$

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Conclusions and future work

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Conclusions

- High coverage can be achieved automatically using search based test case generation.
- Functions and classes under test are exercised in a quite sophisticated way.
- Resulting test suites are generally quite compact and their size can be controlled as a further optimization objective.

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Future work

- Investigation of alternative adequacy criteria and testing goals (e.g., non-functional testing).
- Automating the generation of likely oracles (i.e., anomaly detectors), based on invariants and temporal properties of the functions and classes under test.
- Further empirical studies, especially on combined approaches.

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Slides on dynamic symbolic execution are partially based on the ESEC-FSE'05 presentation: http://srl.cs.berkeley.edu/~ksen