Learning Dialogue, Vilanova 2006

Exploration / Exploitation Inference for Statistical Software Testing

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Overview

- Software Testing
- Exploration/Exploitation for Statistical Software Testing
- ML for Computer Science

Autonomic Computing

Software Testing

A key task

Bugs may kill (airplanes, shuttles, stock market,...)

ST costs 50% percent of the development time

A challenging task

[Beizer 90]

Pesticide Paradox

Every method you use to prevent or find bugs leaves a residue of subtler bugs against which those methods are ineffectual.

Complexity Barrier

Software complexity (and therefore that of bugs) grows to the limits of our ability to manage that complexity.

Software Testing, Classification

By scope — **WHICH**

unit testing, component testing, integration testing, system testing.

By life-cycle phase — **WHEN**

requirements phase testing, design phase testing, program phase testing, evaluating test results, installation phase testing, acceptance testing, maintenance testing.

By purpose — **WHAT**

correctness testing, performance testing, reliability testing, security testing.

Correctness Testing

Black-box — Functional testing

Given: I/O of the program and specifications

Method: partitioning input space, exploring boundary conditions.

Issues: combinatorial explosion; error in specifications (30%)

White-box — Structural testing

Given: the program + oracle

Method: generate test cases (input vectors)

Criteria: coverage wrt program (syntactic or intrusive)

Issues: combinatorial explosion; undecidability.

Annotated-box — Formal testing

Given program + properties (formulas)

Method: Prove that program satisfies properties

Issues: combinatorial explosion; undecidability.

Criteria

Find criteria related to correctness...

- Product — Tested 80% of the lines of code
- Plan — Run 80% of the test cases
- Results — Discovered 417 bugs
- Efforts — Worked 80h a week for 4 weeks.

Standard: coverage-based

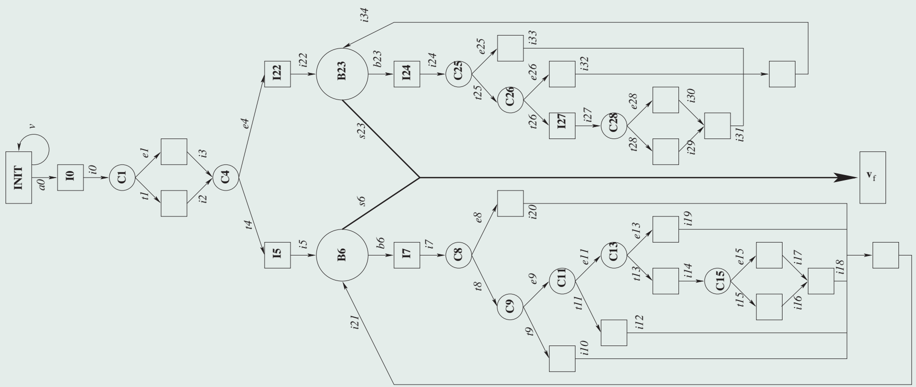
- Percentage of the lines of code
- Percentage of the transitions
- Percentage of the paths with bounded length

Hybrid Statistical/Structural Approach

Principle

[Denise et al. 04]

- Program $\equiv$ Finite State Automaton
- Path $\longrightarrow$ constraint satisfaction pb
- CSP $\longrightarrow$ Solution = value of input variables = test case exerting the program path



Example

Code

```
1 read (x, y)
2 if (x < 0)
3     then x := −x; y := 1/y;
4 p := 1;
5 while (x > 0)
6     do p := p ∗ y; x := x − 1;
7 print p;
```

Path

$s = 1.2.4.5.7$

Test case

Solution: $x = 0;$

Hybrid Statistical/Structural Approach, 2

Program = FSA = $\{$Nodes Σ, Edges $\subset \Sigma^2$ $\}$

Assumption: consider strings/paths with length $\leq T$

Approach : Uniform distribution in finite structured spaces

[Flajolet et al. 94]

Let

v_f (resp. v_s): accepting (resp. starting) node.

$suc(v)$: set of nodes w such that $v.w$ is an edge.

Define

$N(v,t) =$ Number of paths $v \ldots v_f$ of length t

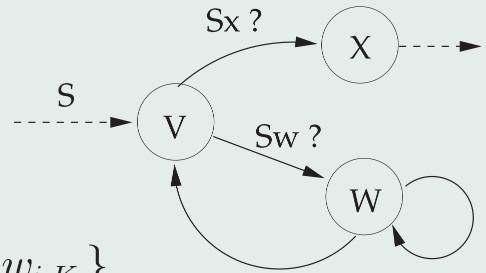
Then:

$$\begin{aligned} N(v,1) &= 1 \text{ iff } v_f \in suc(v) \\ N(v,t+1) &= \textstyle\sum_{w \in suc(v)} N(w,t) \end{aligned}$$

Uniform sampling of bounded program paths

For $t = 1 \ldots T$

$N(v, t) =$ Number of paths $v \ldots v_f$ of length t



Uniform Sampling

Init : $s[0] = v_s$

For $i = 1 \ldots T$

Candidates = $suc(s[i-1]) = \{w_{i,1}, ..w_{i,K_i}\}$

Select $w_{i,j}$ with probability $\propto N(w_{i,j}, T - i)$

$s[i+1] = w_{i,j}$

EndFor

Return s

Hybrid Statistical/Structural Approach, 3

Principle

Init: Test set = $\{\}$
Repeat
  Generate program path s
  Transform s into a constraint satisfaction pb CSP_s
  Call Oracle (constraint solver)
  If CSP_s satisfiable
    Find Solution = test case
    Test set $\longleftarrow$ Solution
  // Else s unfeasible path
Until stop criterion

Criterion

Pr (feasible path exerted by Test set).

Discussion

PROs

Uniform distribution.

No redundancy: each test case exerts a different program path

CONs

Mild: Undecidability *set a time limit on constraint solver*

SEVERE: Syntax is a very poor approximation of semantics

$\Longrightarrow$ huge fraction of unfeasible paths

$\Longrightarrow$ *modify the program by hand*

At last, ML comes into play !

1st: Discriminant/Active learning

Given $\left\{ \begin{array}{l} \text{FSA: } \{\Sigma, E\}. \\ \mathcal{L} = \{(x_i, y_i), x_i \in \Sigma^T, y_i = \pm 1\} \end{array} \right.$

Find : $\hat{y}$ estimating whether a program path is feasible

Wanted $\left\{ \begin{array}{l} \text{Now: Save the oracle cost} \\ \text{Later: Facilitate the generation of feasible paths} \end{array} \right.$

ML Settings

strings − RPNI, RedBlue

propositionalisation − C4.5, Ripper

Fails!

Insufficiently many positive examples

Active learning ? *[Dasgupta 05]*

2nd: Generative learning

Given $\begin{cases} \text{FSA: } \{\Sigma, E\}. \\ \mathcal{L} = \{(x_i, y_i), x_i \in \Sigma^T, y_i = \pm 1\} \end{cases}$

Find The distribution $\mathcal{D}$ of feasible paths

Principle :

1. Use $\mathcal{D}_t$ to generate x_t
2. Oracle: compute y_t *feasible/unfeasible*
3. Update $\mathcal{D}_t \rightarrow \mathcal{D}_{t+1}$.

Position of the problem

Goal

Find the maximal number of (distinct) feasible paths

Wrt online learning *[Cesa-Bianchi Lugosi 06]*

The criterion is not to minimize the regret

Wrt reinforcement learning
or estimation of distribution algorithms *[Larranaga 01]*

The goal is dynamic: after a feasible path has been found
it is not new anymore...

Domain knowledge and search space

What makes a path unfeasible?

Limits on Loops

If there are 17 or 19 uranium beams to be examined
the number of times in the loop is 17 or 19.

Violated dependencies

if (x) 1
    then $y := \ldots$ 2
    else $z := \ldots$ 3
[...] 4
if (x) 5
    then $u := \ldots$ 6
    else $w := \ldots$ 7

$s = ..12457\ldots$ is unfeasible.

Others

The last time a loop occurs, the closing instruction is executed.

Non Markovian problem

Representation: Parikh map

[Hopcroft Ullman 79]

Parikh map : each symbol u in $\Sigma \rightarrow$ integer attribute

$$\begin{aligned} a_u : X &\mapsto \mathbb{N} \\ a_u(s) &= \text{number of occurrences of } u \text{ in } s \end{aligned}$$

[Clark et al. 06]

Extended Parikh map : each (u, k) in $\Sigma \times \mathbb{N} \rightarrow$ categorical attribute

$$\begin{aligned} a_{u,k} : X &\mapsto \Sigma \\ a_{u,k}(s) &= \text{symbol successor of the } k\text{-th occurrence of } u \end{aligned}$$

Captures target concepts

- loops
- dependencies (XOR)
- closing instructions (reverse order on paths)

Distribution search space

Parikh map description

$s = v\,w\,v\,w\,v\,x\,y\,w \rightarrow$

$$\begin{aligned} &a_{v,1} = w,\; a_{v,2} = w,\quad a_{v,3} = x \\ &a_{w,1} = v,\; a_{w,2} = v,\quad a_{w,3} = \emptyset \\ &a_{x,1} = y,\; a_{x,2} = \emptyset,\; a_{x,3} = \emptyset \\ &a_{y,1} = w,\; a_{y,2} = \emptyset,\; a_{y,3} = \emptyset \end{aligned}$$

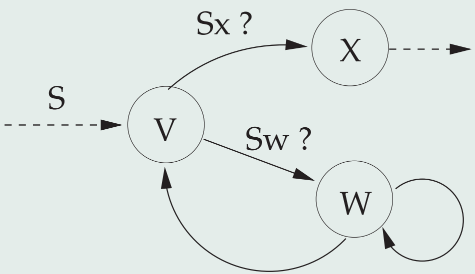
Distributions : $\Sigma \times \Sigma \times N \rightarrow [0, 1]$

- $n(v, w, i)$: number of paths st $a_{v,i} = w$
- $f(v, w, i)$: number of feasible paths st $a_{v,i} = w$
- $\mu(v, w, i) = f(v, w, i)/n(v, w, i)$

EXIST : Exploitation / Exploration Inference for Statistical Testing

Modules

- Initialise the current distribution
- Select the current symbol
- Update the distribution



Criteria

number of feasible NEW paths
[and their diversity]

Selection Module

Given the current string

$s = v_s \ldots v$ — v the last symbol

$a_v(s) = i$ — with i-th occurrences in s

$\mu(v, w, i)$ — frequency of feasible paths s' st $a_{v,i}(s') = w$

Select a node among $suc(v)$

- Greedy: $argmax_w \; \mu(v, w, i)$
- BandiST: $argmax_w \; \mu(v, w, i) + \sqrt{\frac{2 \log n(v,*,i)}{n(v,w,i)}}$
  [Auer, Cesa-Bianchi, Fischer 02]
- Roulette Wheel: select w proportionally to $\mu(v, w, i)$

Update Module

Global update after s is labelled

Increment $n(v, w, i)$

Increment $f(v, w, i)$ iff s is feasible and NEW

Local update: look ahead after selecting v

$n(v, w, i) \to n_s(v, w, i) =$ number of paths s'

such that $a_{v,i}(s') = w$ and $a_w(s') \geq a_w(s)$

Same for $f(v, w, i)$ and $\mu(v, w, i)$

Initialisation Module

Straightforward option

Set $n(v, w, i)$ and $f(v, w, i)$ to the initial number of *feasible* paths.

... fails same problem as finding XORs with decision trees...

Example:

$$([a_{v,1} = w] \wedge [a_{v,2} = w]) \vee ([a_{v,1} = z] \wedge [a_{v,2} = z])$$

$vwvwv \ldots$ feasible	but	$vwvzv \ldots$ unfeasible
$vzvzv \ldots$ feasible		$vzvwv \ldots$ unfeasible

$\rightarrow f(v, w, 1)$ and $f(v, w, 2)$ not informative...

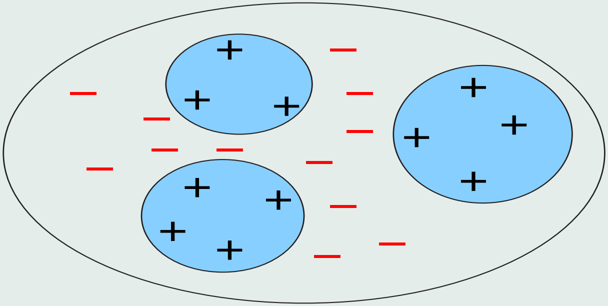
Seeded Initialization

Principle

Extract a subset E of positive paths in the same conjunctive concept

Criterion: the least general generalisation of E must be correct

not covering negative examples



Seeded Initialisation, 2

Seeded Initialization

Randomly order the positive examples $\{x_1, \ldots, x_n\}$

Init : $E' = \{e_1\}, tc_1 = e_1;$

For $i = 2 \ldots n$

$tc = lgg(tc_{i-1}, e_i)$

If tc is correct, $tc_i = tc$ and $E' = E' \cup \{e_i\}$

Else $tc_i = tc_{i-1}$

Uniform Seeded

Same except that the initial order favors the less previously selected examples

Fake Seeded

As in Seeded initialization, but without the correctness test

Summary of EXIST

Init Module

- Global, Seeded, Uniform Seeded, Fake Seeded

Selection Module

- Greedy, BandiST, Roulette Wheel

Update Module

- Global, Local, Restart

Experimental Validation

Real-world problem : FCT4

13 nodes and 26 edges (after pruning)

Length 120 $\rightarrow Pr(s$ feasible$) = 10^{-5}$.

target concept: loop and XORs.

Artificial problems randomly generated

nodes in [10,20]; length in [60,120]

target concept: loops and XORs

Feasibility:

cat. I	10^{-3}	$\leq Pr(s$ feasible $)$	$\leq$	10^{-2}
cat. II	10^{-5}	$\leq Pr(s$ feasible $)$	$\leq$	10^{-3}
cat. III	10^{-15}	$\leq Pr(s$ feasible $)$	$\leq$	10^{-12}

Experimental setting and goal

Goal

influence of initial size/balance of examples.

Training sets:

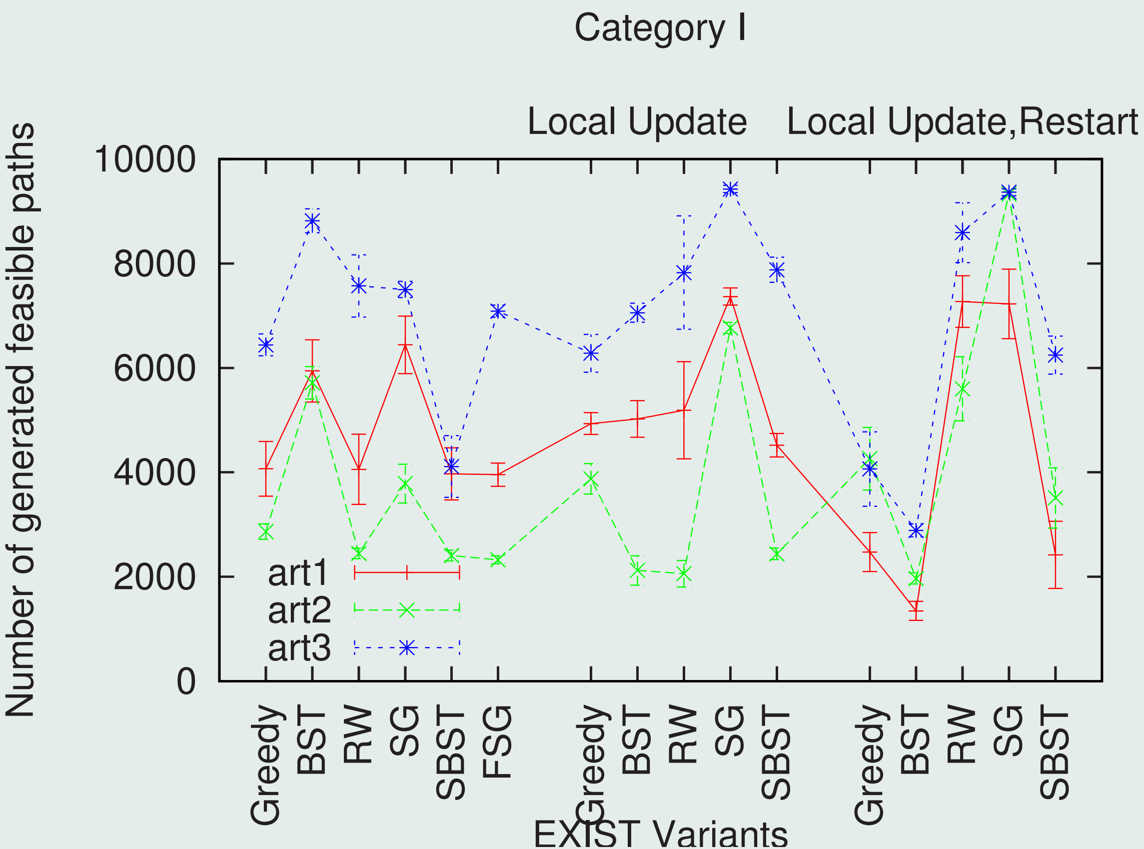
	1	2	3	4
feasible	50	200	1000	50
unfeasible	50	200	1000	1000

Assessment

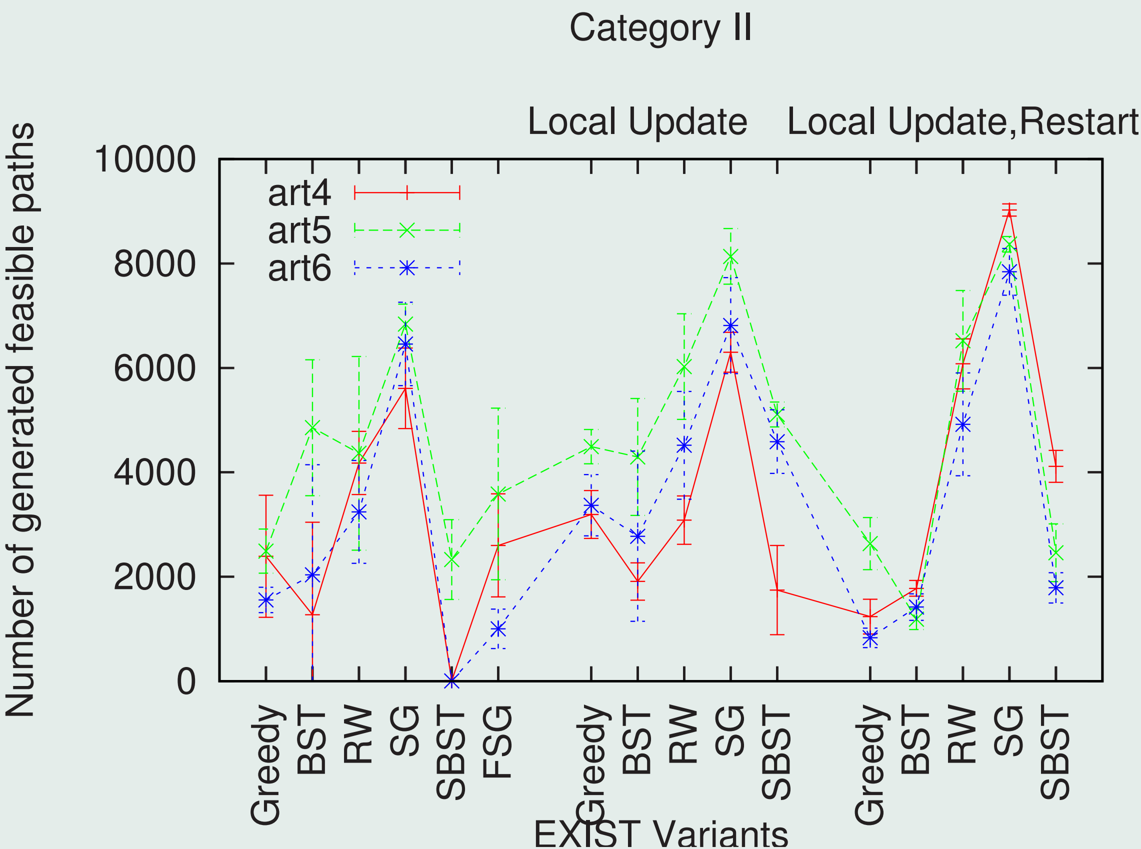
For every option and problem,

1 run: 10,000 paths are generated   #{ new feasible paths} recorded

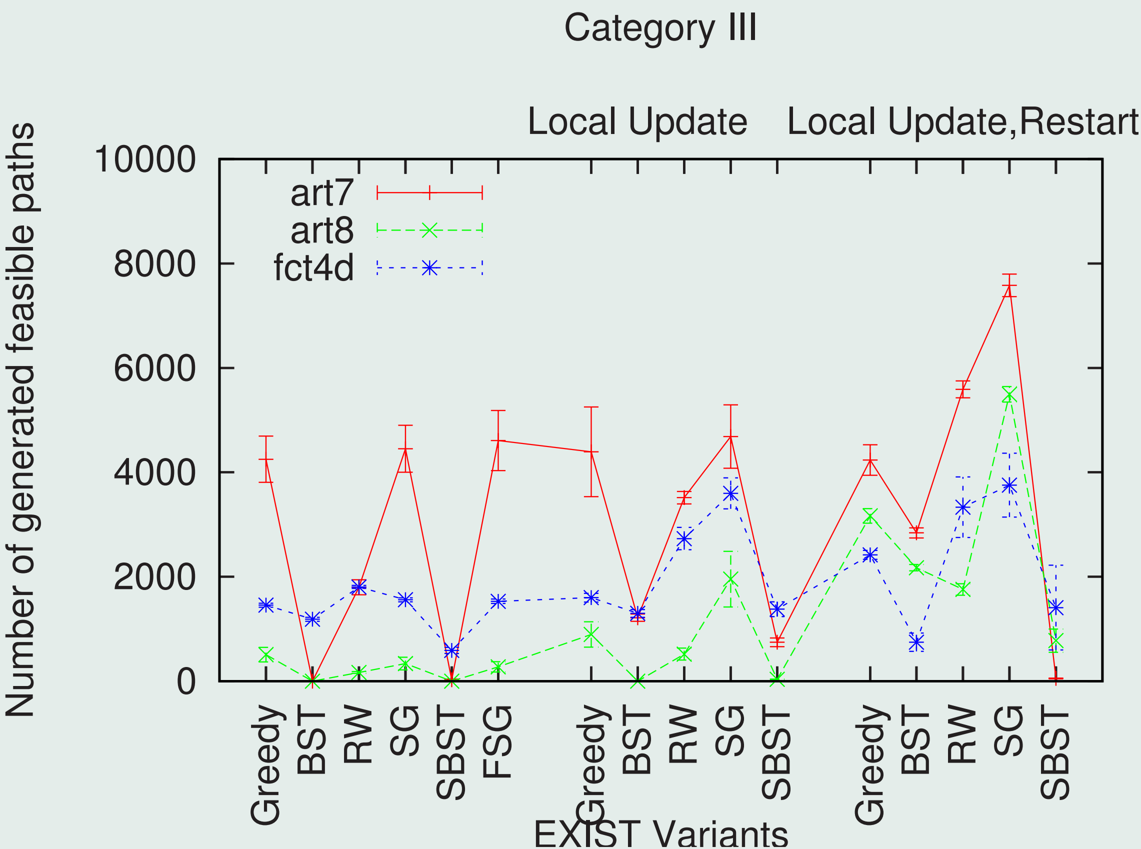
averaged on 10 runs.



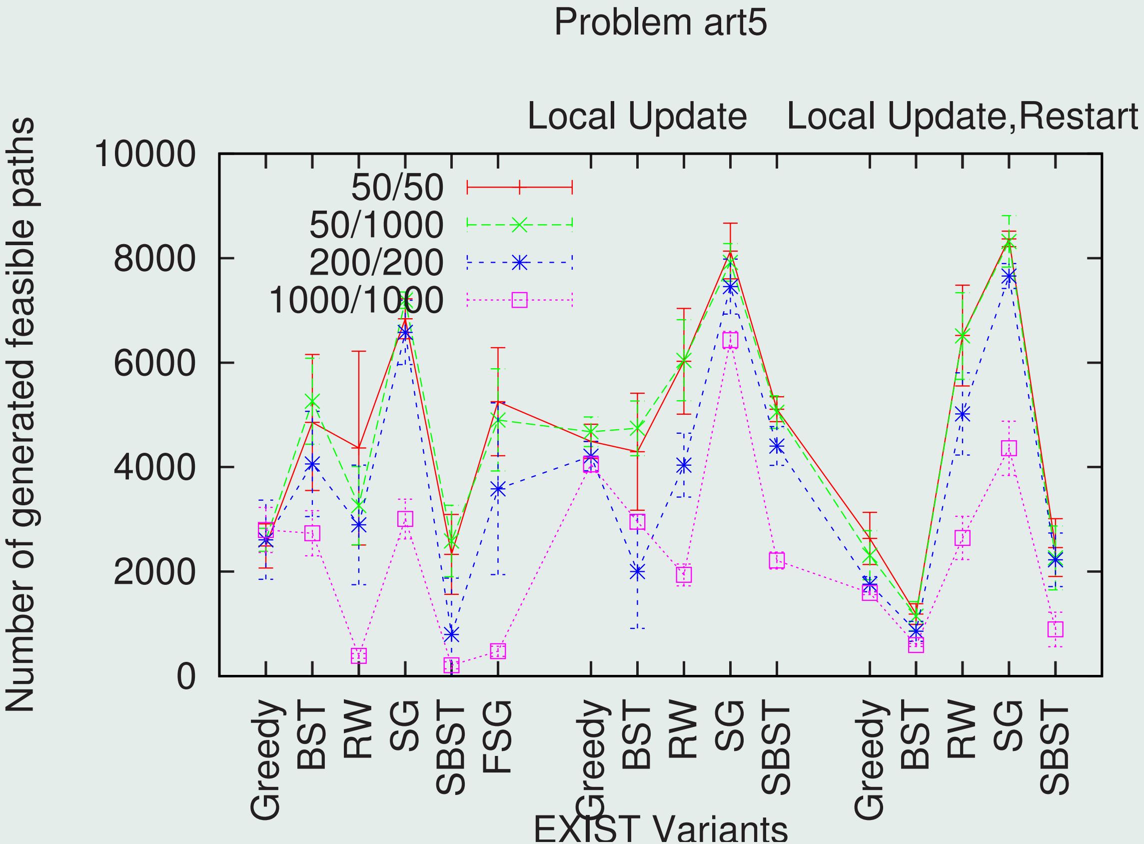
Best options = BandiST, Seeded Greedy, and Roulette Wheel



Best options = Seeded Greedy with restart



Best options = Seeded Greedy with restart



Remark : Seeded >>Fake seeded when nb examples $\nearrow$.

Discussion

It worked!

- Extended Parikh Map: a flexible and compact representation
- Seeded initialization: getting rid of non-Markovian issues
- Runtime $< 10min$

Next

- Convergence
- Diversity study
- Adapt EXIST for other coverage-based criteria
- Benchmarks for software testing

Related Works

- Ernst et al. 1999: Program invariants are learned from traces
- Brehelin et al. 2001: HMM are used to generalize test sequences for PLA.
- Vardan et al. 2004: Grammatical Inference is used to characterize paths relevant to constraint checking
- Zheng et al. 2003-6: Use traces to identify bugs (intrusive testing)
- Xiao et al. 05: Active learning for game player modeling (black box)

Overview

- Software Testing
- Exploration/Exploitation for Statistical Software Testing
- ML for Computer Science   Autonomic Computing

ML for Computer Science

Computers and networks

govern communication and information

Complex systems

Large-scale, heterogeneous components, dynamic interactions.

Number of skilled administrators ... doesn't scale up.

Need for

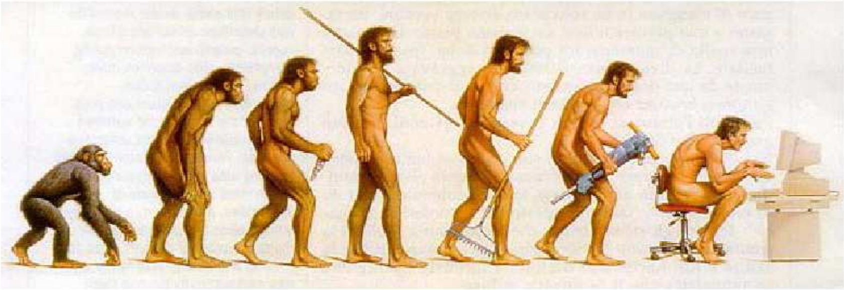
Autonomous Systems

First step

Self-Aware Systems

How ? ML

Evolution of Computing



"Considering current technologies, we expect that the total number of device administrators will exceed 220 millions by 2010."

-Gartner 6/2001

A case study
(upcoming EGEE-Pascal Challenge)

EGEE, Enabling Grids for e-Science in Europe

- Infrastructure project started in 2001
- 80 partners, 30,000 CPUs all over the world
- Web: www.eu-egee.org

Goal: Grid modelling

Heterogeneous systems : processors, storage, network, services.

State can at most be estimated

Mutualisation paradigm : load depends on collective behavior

... must be estimated on the fly

Needed : a grid model, in order to

- Control and maintain the system — detect ill-configured units
- Predict the application performances — dimension the capacities for jobs
- Optimize the system — refine the scheduler

Modelling the grid: an ML problem

Input data

Traces of the jobs:

- 800 Ko per job, including specifications and all events
- some hundred thousands jobs per trace
- spatio-temporal (redundant) structure

Goals

- Classification: jobs are *done*, *aborted*, or *lost*
- Early detection: predict as early as possible
- Clustering: provide the user with model chunks and/or outliers

Call to Arms

ML for Autonomic Computing

- The need
- The data
- The expertise

The big question mark: Learning or Optimization ?