UNIVERSITÄT PADERBORN

Software Engineering

Landscape depending parameter tuning for search-based software testing

Overview

1. Introduction
2. Fundamentals
3. Experimental
4. Adaptive parameter control
5. Evaluation
6. Conclusion
7. Conclusion

Introduction

- Unit tests
- maximize coverage (line, branch, exception)
- lack of sufficient tests
- costly and time-consuming
- => use search-based software testing

Motivation

- Tools... => EvoSuite state-of-the-art
- may not terminate => search budget
- optimal only with optimal configuration
- No Free Lunch theorem
  - impossible to find optimal configuration for all problems
- EvoSuite's default configuration is fairly good, but not perfect

Research goal

- wide variety of problem-cases
- concept landscape depending
- adaptive parameter control
- increase coverage of EvoSuite

State-of-the-art

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Challenges

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Delimitation

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Search-based software testing

- tests for object oriented languages
- sequence of method calls
-
-
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Fitness function

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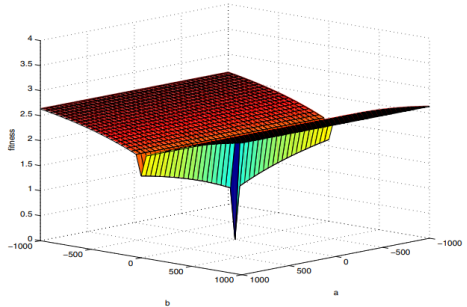
- function for e.g. coverage
- guidance for search algorithms
-
-

```
1 void bar(int x) {
2     if (x == 1) {
3         // uncovered code
4     }
5 }
```

Fitness landscape



Genetic algorithm

Heading

- start with random population
- iterate till termination condition
  - mutate and crossover
- return last generation

Heading

-
-
-

DynaMOSA

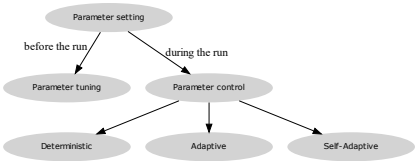
Heading

- start with random population
- multiple target
- keep track of target covering individuals

Heading

- iterate till termination condition
  - breed offspring
  - update targets
  - update archive
  - select by rank
- return archive as last generation

Parameter tuning and control



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Corpus

SF110

- 110 open-source Java projects
- 23,894 Java Classes
-
-
-

Panichella et al.

- 117 open-source Java projects
- 346 Java Classes
- non-trivial and complex
- often used

Prediction sample

- S_1
- 709 Java Classes
- randomly selected
- SF110

- 9.8 days on three machines
-
-
-

Evaluation sample

- S_2
- 346 Java Classes
- the whole Panichella corpus
-

- 4.8 days on tree machines
-
-
-

Sensitive sample

- S_3
- 20 Java Classes
- extracted from S_1
- high Standard Deviation

- 6.6 hours on tree machines
-
-
-

Comparisons

- 30 repeats for every Java Class
- Mann-Whitney U-test
- Vargha-Delaney effect size $\hat{A}_{12}$
-

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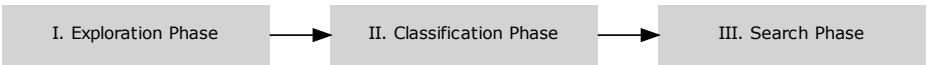
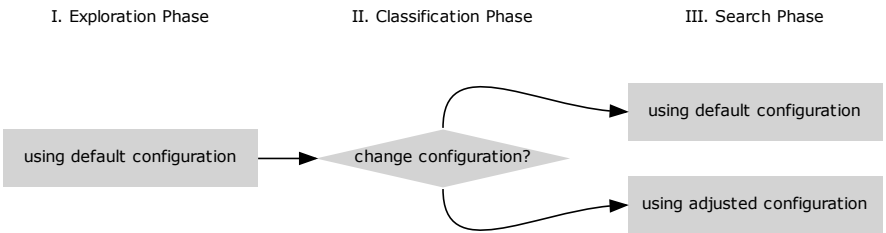
Concept

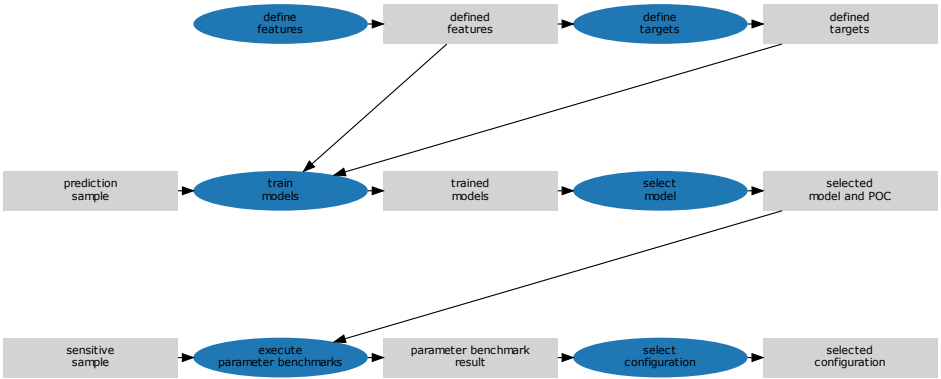
- use the beginning of the search to explore the search space
- classify the current search (”adjust” or ”default”)
- use configuration depending on class



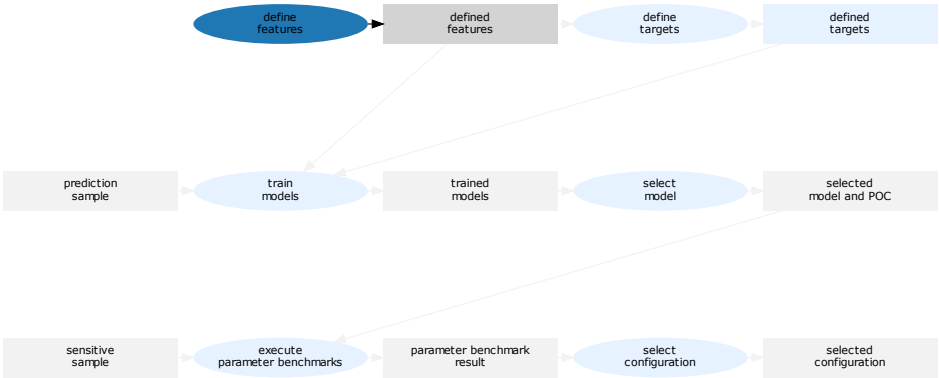
Configuration selection



Components


define features
defined features
define targets
defined targets
prediction sample
train models
trained models
select model
selected model and POC
sensitive sample
execute parameter benchmarks
parameter benchmark result
select configuration
selected configuration

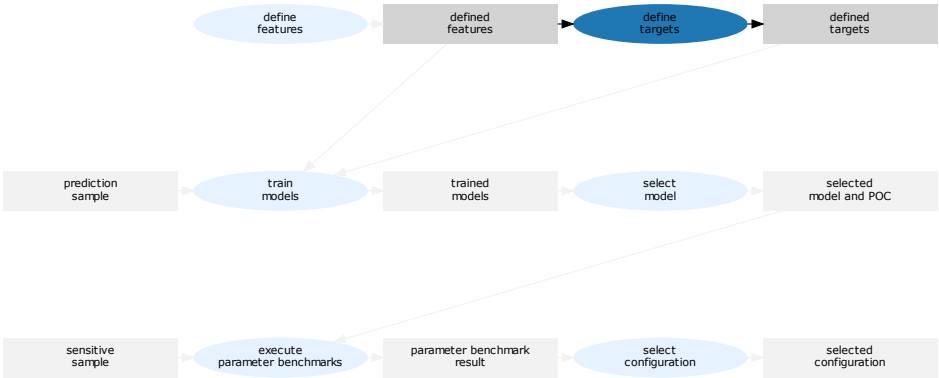
Landscape features



Landscape features

- Fitness and gradient
- Neutrality
- Neutrality Volume
- Information Content

Classification target



Target approximation

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-
-

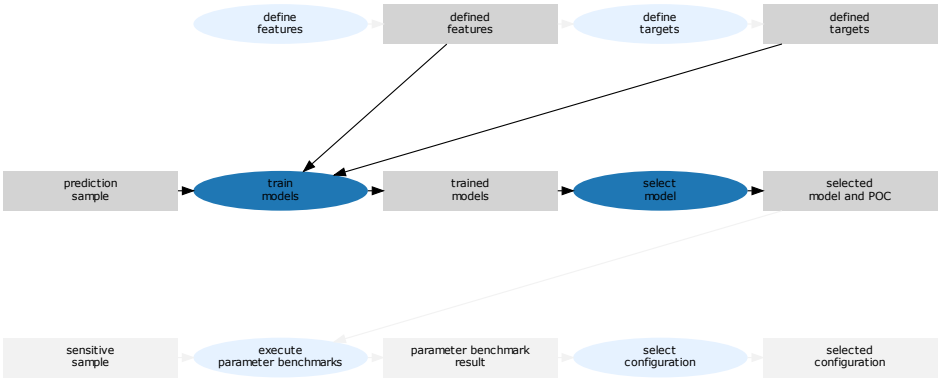
Targets

- Low end coverage $endcov. < 0.8$
- High standard deviation $stdev > 0.1$
- Relative low coverage $cov. < max(cov.) * 0.8$

Targets

target	n in class	description
$cov. < max(cov.) * 0.8$	447	End coverage less than 80% of the best execution
$endcov. < 0.8$	6687	End coverage less than 80%
$stdev > 0.1$	541	Standard deviation greater than 0.1
$stdev > 0$	6046	Standard deviation greater than 0.0
$p = 125$	1735	The median coverage with a population of 125 is greater than the median coverage with default settings
$stdev > 0.1$ & $cov. < max(cov.) * 0.8$	256	The boolean ”and” of the two targets
$stdev > 0$ & $cov. < max(cov.) * 0.8$	447	The boolean ”and” of the two targets
$stdev > 0.1$ & $endcov. < 0.8$	391	The boolean ”and” of the two targets
$pop = 125$ & $cov. < max(cov.) * 0.8$	254	The boolean ”and” of the two targets

Classification



Classification

Heading

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Heading

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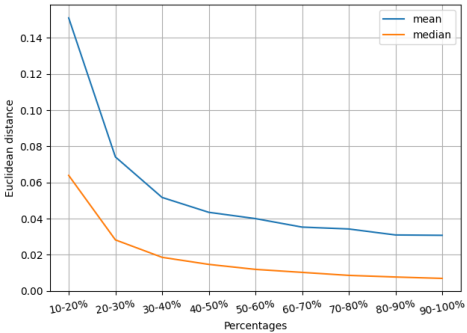
Length of Exploration Phase

- compare landscape features ever 10%
- using Euclidean distance
- trade-off between
  - time for exploration
  - time for adjusted configuration
- between 20 and 40% from search (percentage of classification)



Machine learning algorithm

Heading

- supervised learning
- fast classification
- few features
- decision tree

Heading

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-

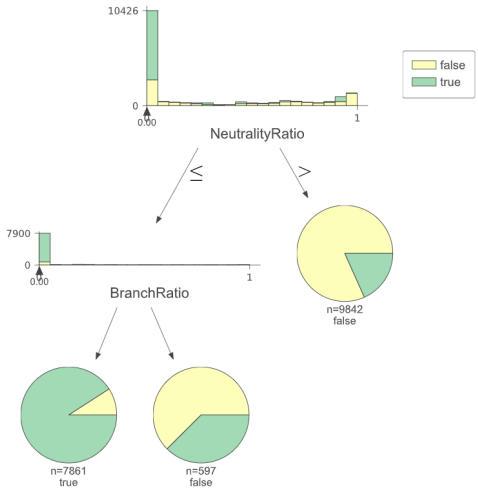
Hyper-parameter search

- only apply on as many as possible
  - TPR > 80%
- only apply if positive effect
  - FPR < 5%
- percentage of classification (POC)
- construction criteria (Gini Impurity, Entropy or Log-Loss)
- depth of decision tree

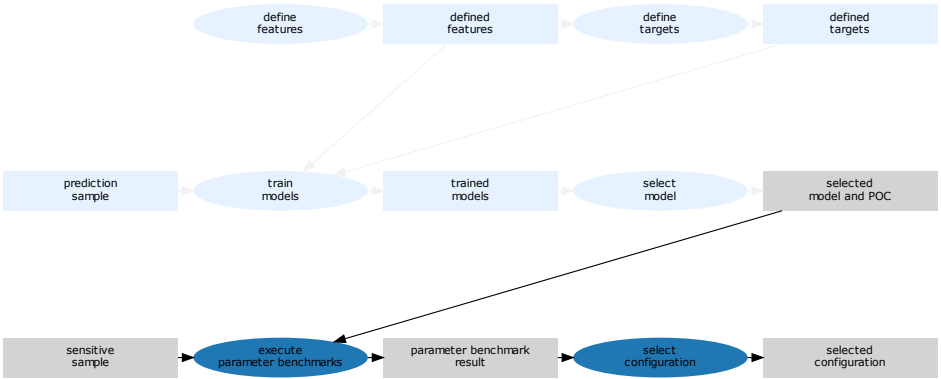
Component selection

Decision tree

- $stdev > 0.1 \& cov.max(cov.) * 0.8$
- depth of decision tree: 2
- Gini Impurity
- POC: 30%



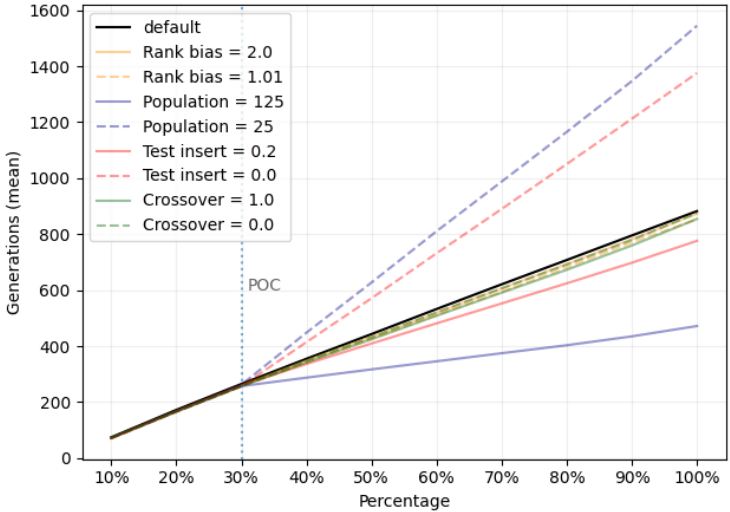
Parameter selection



Parameter selection

- EvoSuite parameter
- nearly infinite possible combinations
- small-scale experiments
- using small sample S_3

Influence on runtime



Event probability

- runtime in relation to event probability
  - insert
  - mutate
  - crossover
- trade-off
  - fitness evaluation
  - event occurrence

$$P_{adj}(e) = \frac{n_1 P_1(e) + n_2 P_2(e)}{n_1 + n_2} \quad (1)$$

$$\hat{P}(e) = \sum_{i=k}^{n} \frac{n!}{i!(n-i)!} P_{adj}(e)^i (1 - P_{adj}(e))^{n-i} \quad (2)$$

Component selection

configuration	gen.	n	P_{adj} mut.	cross.	ins.	$\hat{P}$ for $k = 5$ mut.	cross.	ins.	n_+	n_-
default	853	9	0.95	0.68	0.05	1.0	0.87	0.0		
p = 25	1,263	13	0.96	0.69	0.04	1.0	1.0 ↗	0.0	0	0
p = 125	572	6	0.95	0.68	0.04	0.77	0.15	0.0	3	0
cr = 0.0	841	8	0.95	0.0	0.05	1.0	0.0	0.0	1	0
cr = 1.0	849	8	0.95	0.95	0.05	1.0	1.0 ↗	0.0	0	0
bias = 2.0	912	9	0.95	0.68	0.05	1.0	0.88 ↗	0.0	1	0
bias = 1.01	824	8	0.95	0.68	0.05	1.0	0.77	0.0	0	0
pti = 0.0	1,154	12	1.0	0.75	0.0	1.0	1.0 ↗	0.0	0	4
pti = 0.2	770	8	0.92	0.63	0.08	1.0	0.66	0.0	0	0
p = 10, pti = 5.0	912	9	0.58	0.13	0.42	0.69	0.0	0.31 ↗	3	0
p = 25, pti = 1.0	**777**	**8**	**0.75**	**0.38**	**0.25**	**0.89**	**0.14**	**0.03** ↗	**4**	**0**

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Classification

Known sample S_1

- trained on S_1
- test on S_1
- TPR of 86%
- FPR of 8%
- acceptable reliability

Unknown sample S_2

- trained on S_1
- test on S_2
- TPR of 21%
- FPR of 7%
- not reliability

Adaptive parameter control

Known sample S_1

-

Unknown sample S_2

-

Selected configuration

Discussion

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Conclusion

- concept of APC-DynaMOSA
- pre-selected configuration
- pre-trained classification model
- mixed results improved and degraded Java classes

Future work

- long jump approach
- landscape feature
- real world use
- Fitness function for guidance


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