



**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



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# 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



# Challenges





# Delimitation





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# Search-based software testing

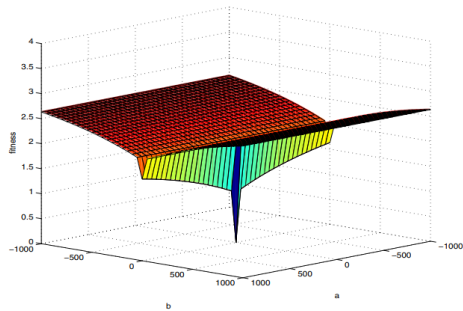
- tests for object oriented languages
- sequence of method calls
- 
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# Fitness function

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

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# DynaMOSA

## Heading

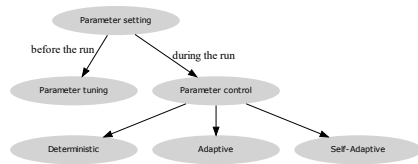
- start with random population
- multiple target
- keep track of target covering individuals

## 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
- 
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## 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

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# Evaluation sample

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

- 4.8 days on tree machines
- 
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# Sensitive sample

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

- 6.6 hours on tree machines

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# Comparisons

- 30 repeats for every Java Class
- Mann-Whitney U-test
- Vargha-Delaney effect size  $\hat{A}_{12}$
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**4. Adaptive parameter control**

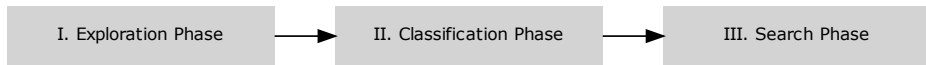
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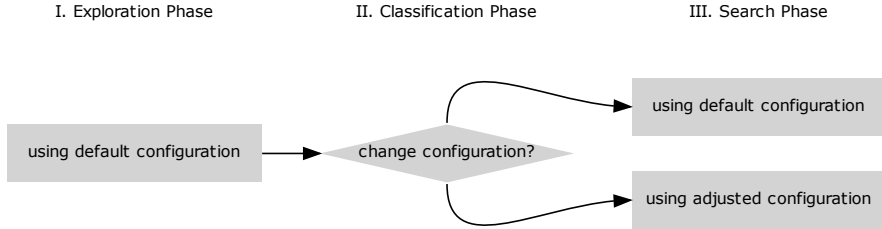
# Concept

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

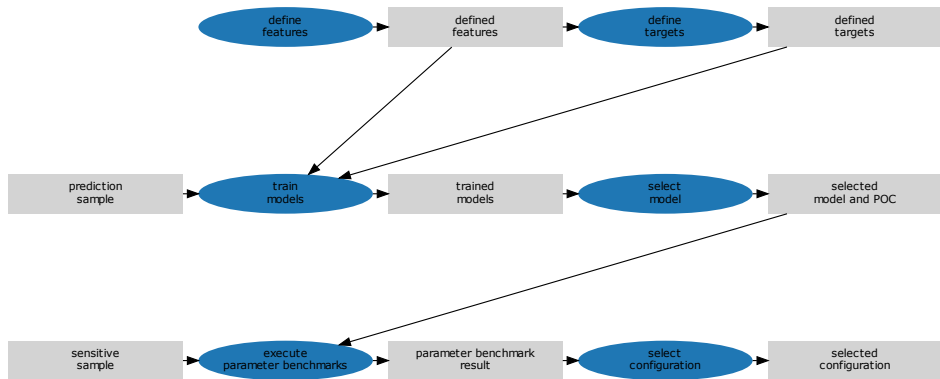




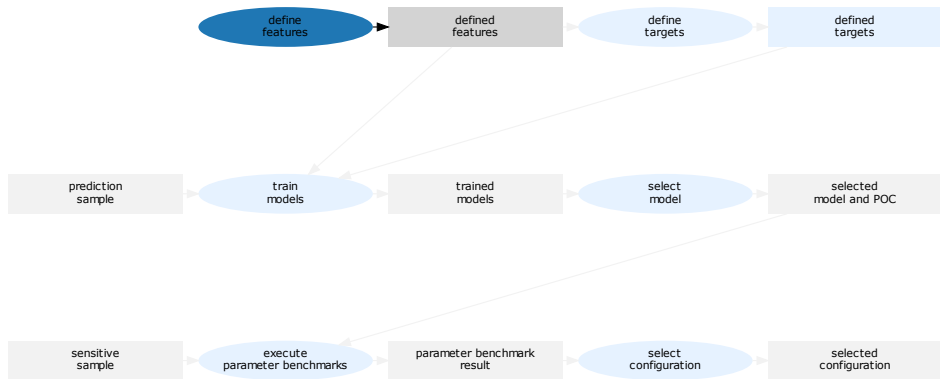
# Configuration selection



# Components



# Landscape features

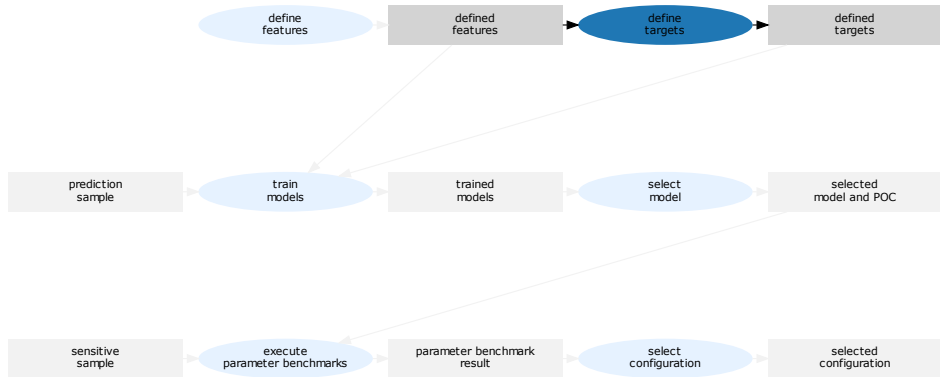


# Landscape features



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

# Classification target



# Target approximation

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# Targets

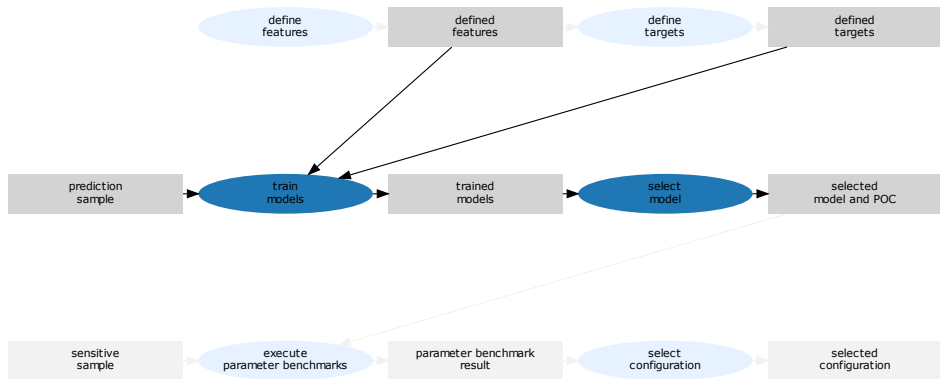
- Low end coverage  $endcov. < 0.8$
- High standard deviation  $stdev > 0.1$
- Relative low coverage  $cov. < max(cov.) * 0.8$

# 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

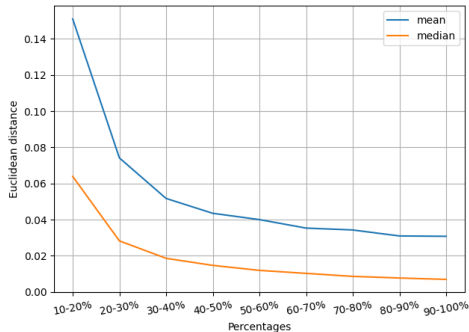
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## Heading

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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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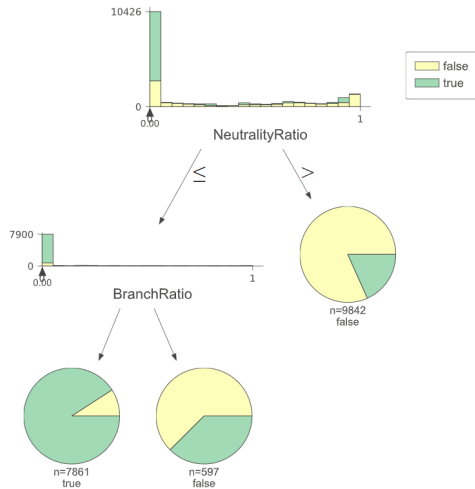
# Hyper-parameter search

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

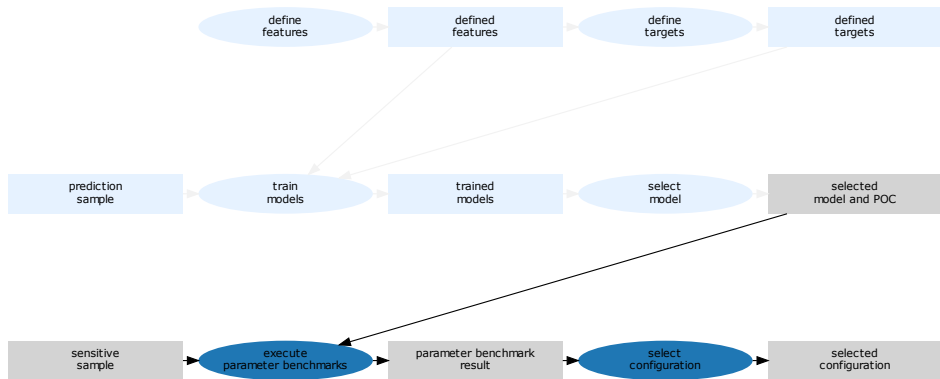
# Component selection

## Decision tree

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



# Parameter selection

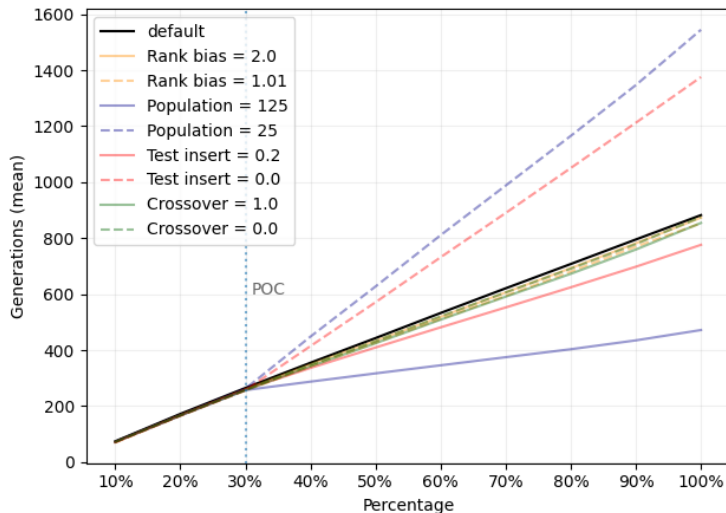


# Parameter selection

- 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	$P_{adj}$			$\hat{P}$ for $k = 5$			$n_+$	$n_-$
			mut.	cross.	ins.	mut.	cross.	ins.		
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
<b>p = 25, pti = 1.0</b>	<b>777</b>	<b>8</b>	<b>0.75</b>	<b>0.38</b>	<b>0.25</b>	<b>0.89</b>	<b>0.14</b>	<b>0.03</b> ↗	<b>4</b>	<b>0</b>



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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



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