Parameter Tuning for Search-Based Test-Data Generation Revisited

Support for Previous Results

Anton Kotelyanskii

Gregory M. Kapfhammer

Software Testing

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Test Suites

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Automatic Generation

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Confronting Challenges

Software Testing

Test Suites

Automatic Generation

Confronting Challenges

Evaluation Strategies

Empirical Studies

Empirical Studies

Challenges

Empirical Studies

Challenges

Importance

Empirical Studies

Challenges
Importance
Replication

Empirical Studies

Challenges
Importance
Replication
Rarity


01010

EvoSuite

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Amazing test suite generator

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Uses a genetic algorithm

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http://www.evosuite.org/

Parameter Tuning

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RSM: Response surface methodology

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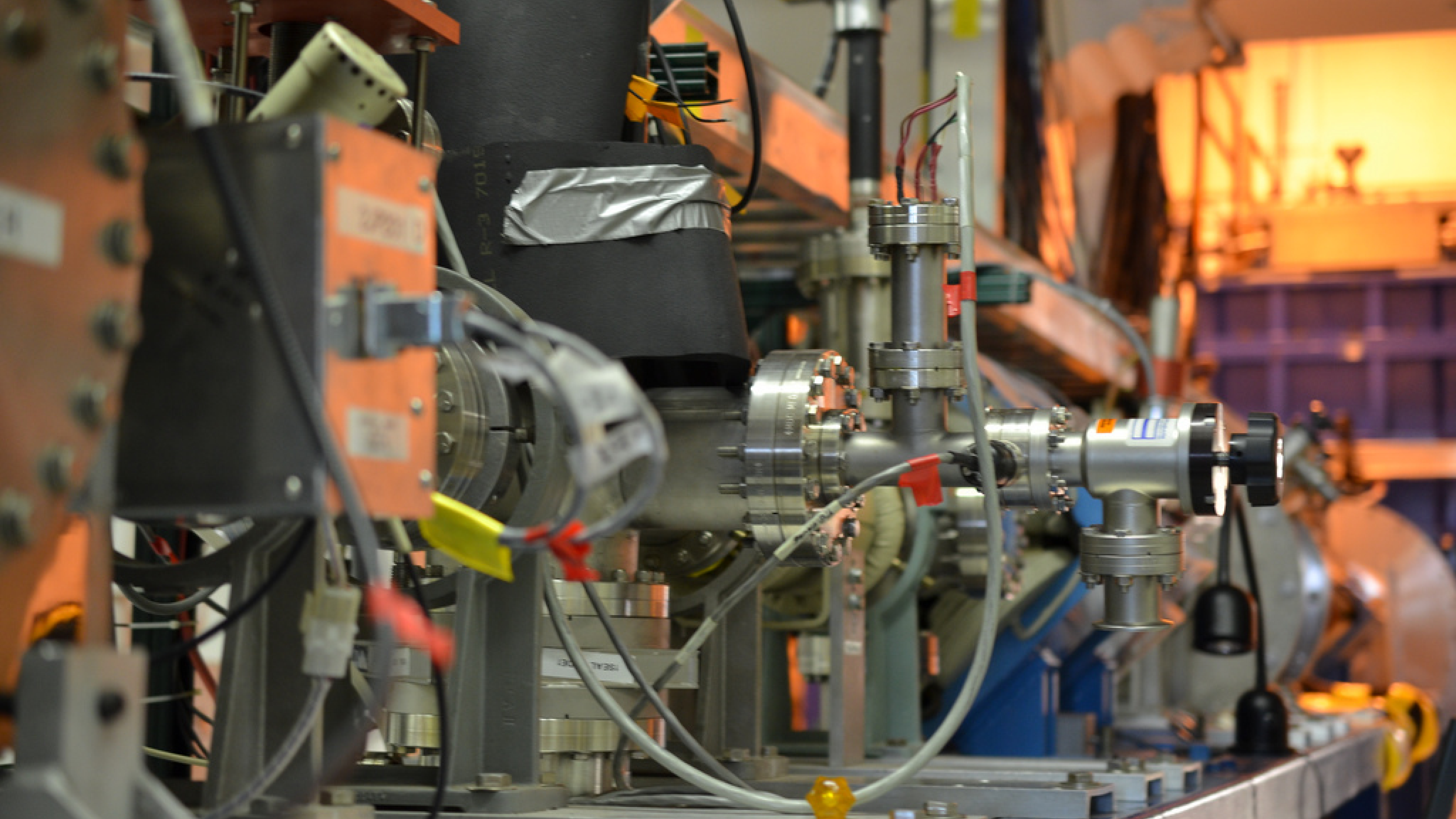
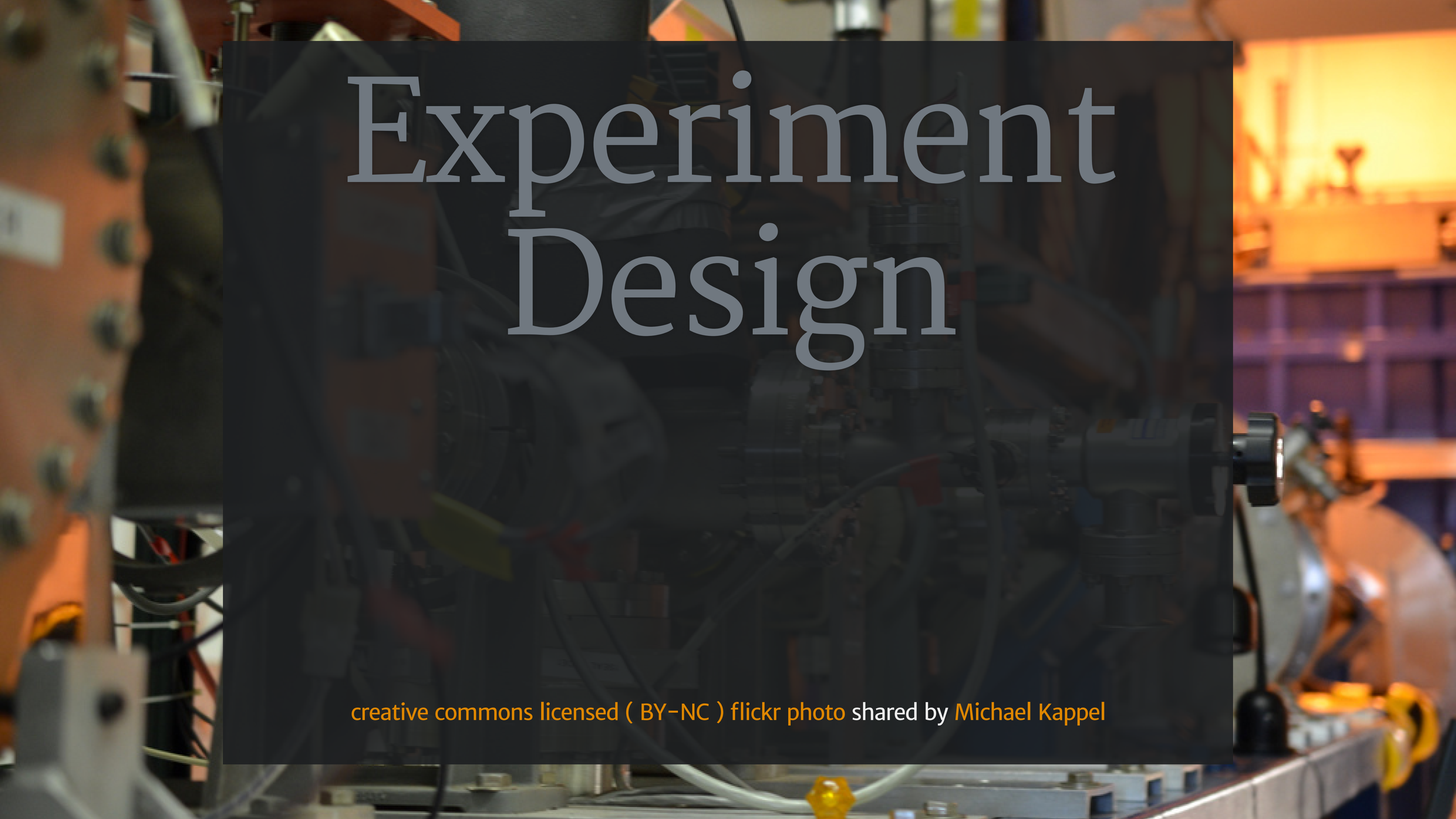
SPOT: Sequential parameter optimization toolbox

Successfully applied to many diverse problems!

Defaults or Tuned Values?



Experiment Design



Experiment Design

Eight EvoSuite parameters

Experiment Design

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Ten projects from SF100

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475 Java classes for subjects

Experiment Design

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Ten projects from SF100
475 Java classes for subjects
100 trials after parameter tuning

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Ten projects from SF100

475 Java classes for subjects

100 trials after parameter tuning

Aiming to improve statement coverage

Parameters

Parameter Name	Minimum	Maximum
Population Size	5	99
Chromosome Length	5	99
Rank Bias	1.01	1.99
Number of Mutations	1	10
Max Initial Test Count	1	10
Crossover Rate	0.01	0.99
Constant Pool Use Probability	0.01	0.99
Test Insertion Probability	0.01	0.99

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Cluster of 70 computers running for weeks

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Mann-Whitney U-test *and*
Vargha-Delaney effect size

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Results Across Trials and Classes	0.5029	0.1045
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Additional empirical results in the QSIC 2014 paper!

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Practical Implications

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Fundamental Challenges

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Tremendous Confidence

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Fundamental Challenges
Tremendous Confidence
Great Opportunities


33
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15
12
VACUUM
PUSH

Important Contributions

Important Contributions

Comprehensive Experiments

Important Contributions

Comprehensive Experiments

Conclusive Confirmation

Important Contributions

Comprehensive Experiments

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For EvoSuite, *Defaults* = *Tuned*