SEARCH-BASED APPROACHES FOR SOFTWARE DEVELOPMENT EFFORT ESTIMATION

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- Why do I choose to do a PhD?
  - I wish to pursue an academic career
    - I like teaching
      - Mutuo ista fiunt, et homines dum docent discunt
  - Intellectual curiosity
    - I like to spend time thinking about solutions to interesting problems and I get excited when coming up with a new idea

IF THIS IS TRUE, A PHD STUDY MAY BE AN ENJOYABLE JOURNEY FOR YOU

- What do I need to do a PhD?
  - PhD is more challenging than master degree but far more rewarding
    - It allows you to contribute to a discipline rather than just learn about what others in this discipline have done
  - I had moments varying from enthusiasm and excitement, to confusion and uncertainty…
    - It takes many failed attempts to finally succeed

YOU NEED PATIENCE AND PERSEVERANCE…

…BUT MOST OF ALL PASSION!

- Shift from *being consumers of knowledge* to be *producers of knowledge*[1]
  1. Work hard, read, and focus
  2. Seek out excellence in colleagues and supervisors, and emulate it
  3. Learn to be independent and creative
  4. Come up with new ideas and technologies

STAND ON THE SHOULDERS OF GIANTS…

…BEING ABLE TO LEAD YOUR RESEARCH

[1]E. Mendes, PROFES 2011 Doctoral Symposium

Outline

- Background
  - Software Development Effort Estimation
  - Effort Estimation with Search-Based Approaches
- Research Goals and Methodology
- Building Effort Estimation Models using Search-Based Approaches
  - Comparison of different Search-Based approaches
  - Analysis of the impact of design choice
  - Assessing the effectiveness of Search-Based approaches
- Enhancing Other Effort Estimation Techniques using Search-Based Approaches
  - Using Tabu Search to Configure Support Vector Regression

Software Development Effort Estimation

- Software development effort estimation is meant to predict the human effort needed to realize a software project
  - effort usually quantified as person-hours or person-months
- Obtaining accurate estimates is a critical activity
  - for planning and monitoring software project development
  - for delivering the product on time and within budget
- Significant over or under-estimates expose a software project to several risks
  - cancellation of activities, such as documentation and testing, impacts on software maintainability and quality

Software Development Effort Estimation

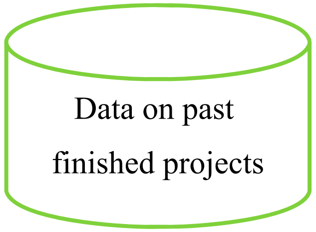
- Obtaining accurate estimates is a challenging activity
  - the estimation is needed early in the software lifecycle, when little information about the project is available

from http://www.dilbert.com/

- Several approaches have been proposed to support project managers in estimating software development effort

Data-Driven Approaches

Figure 1. Sequence used when estimating effort using a data-driven approach *



Project ID	TeamExp	ManagerExp	Transactions	Entities	PointsAdjust	RealEffort
1	1	4	253	52	305	5152
2	0	0	197	124	321	5635
3	4	4	40	60	100	805
4	0	0	200	119	319	3829
5	0	0	140	94	234	2149
6	0	0	97	89	186	2821
79	4	4	395	193	588	9520
80	4	3	469	176	645	5880

* *Adapted from E. Mendes, "Web Cost Estimation and Productivity Benchmarking", ISSSE 2008, LNCS 5413 Springer 2009, pp. 194-222.*

Data-Driven Approaches

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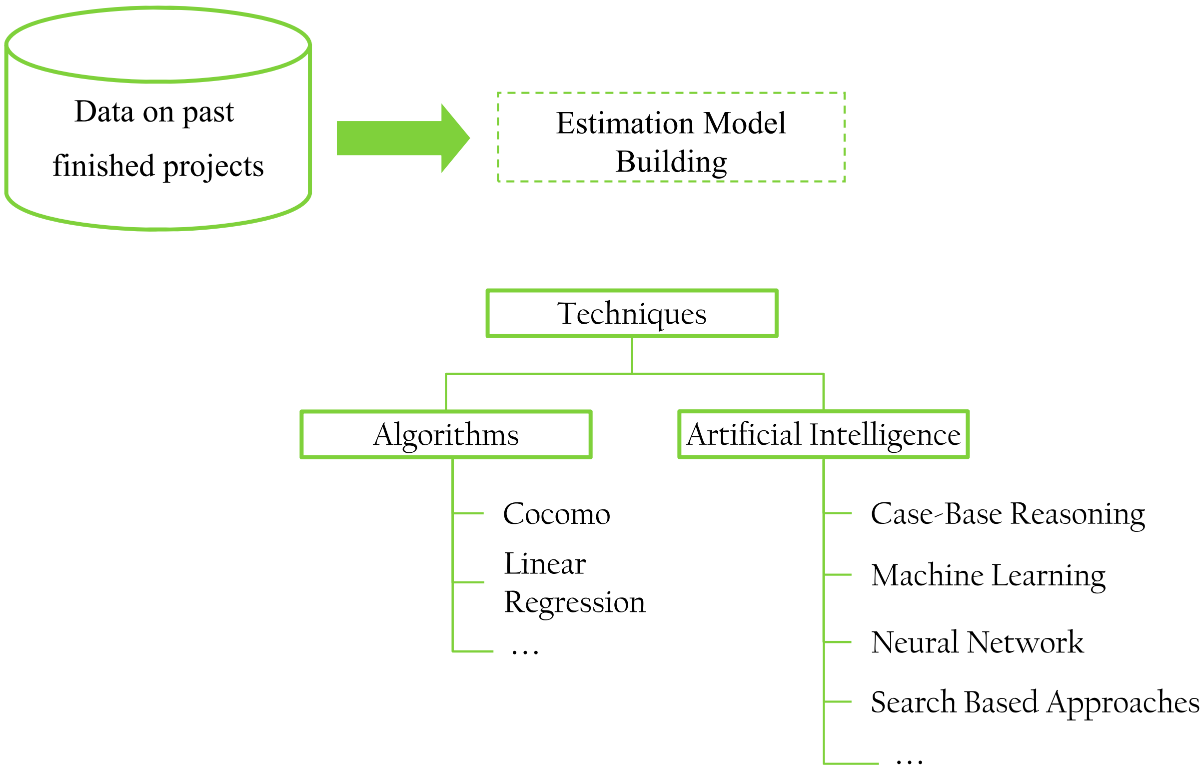

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Data-Driven Approaches

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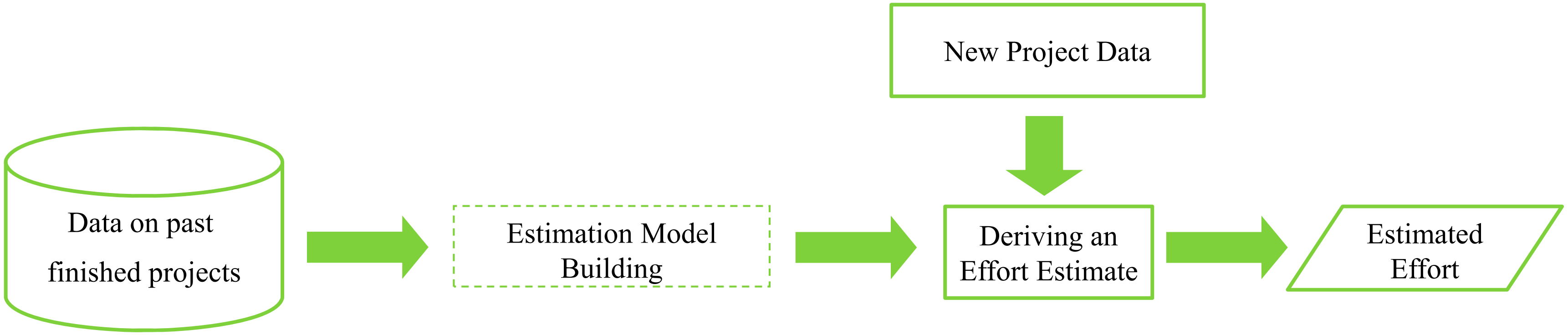


PredictedEffort = 4.0 ^ TeamExp - 97.0 / ManagerExp - 11.0 * Transactions + 14.628 * Entities + 2.414 * PointsAdjust + 0.76

Project ID	TeamExp	ManagerExp	Transactions	Entities	PointsAdjust	RealEffort
81	4	4	100	241	1127	-

New Project Data

PredictedEffort = 4.0 ^ 4 - 97.0 / 4 = 11* 100 + 14.628 * 241+ 2.414 * 1127+ 0.76 = **7578.436**

* *Adapted from E. Mendes, "Web Cost Estimation and Productivity Benchmarking", ISSSE 2008, LNCS 5413 Springer 2009, pp. 194-222.*

Effort estimation as an optimization problem

- Software development effort estimation can be also viewed as an optimization problem
  - the search space is represented by all the possible equations that can be generated assigning the values for c_i, C, and op_i and provide positive values for *EstimatedEffort*

$$\boldsymbol{EstimatedEffort = c_1\, op_1\, f_1\, op_2 \ldots\, op_{2n-2}\, c_n\, op_{2n-1} f_n\, op_{2n}}\ C$$

where c_i is the coefficient of the i^{th} project feature
f_i is the value of the i^{th} project feature
op_i $\{+, -, \cdot, /, f_i \wedge c_i, \ln(f_i)\}$
C is a constant
$Effort > 0$

  - we have to find among the possible estimation models *the most accurate*
    - min |RealEffort – EstimatedEffort|

Effort Estimation with Search-Based Approaches

SB approaches can be exploited to

- build effort estimation models
  - An SB technique builds many possible models - exploiting past projects data - and tries to identify the best one
    - i.e., the one providing the most accurate estimates
- enhance the use of other effort estimation methods
  - An SB technique can be used to improve critical steps of other estimation techniques
    - e.g., features subset selection or critical parameters setting

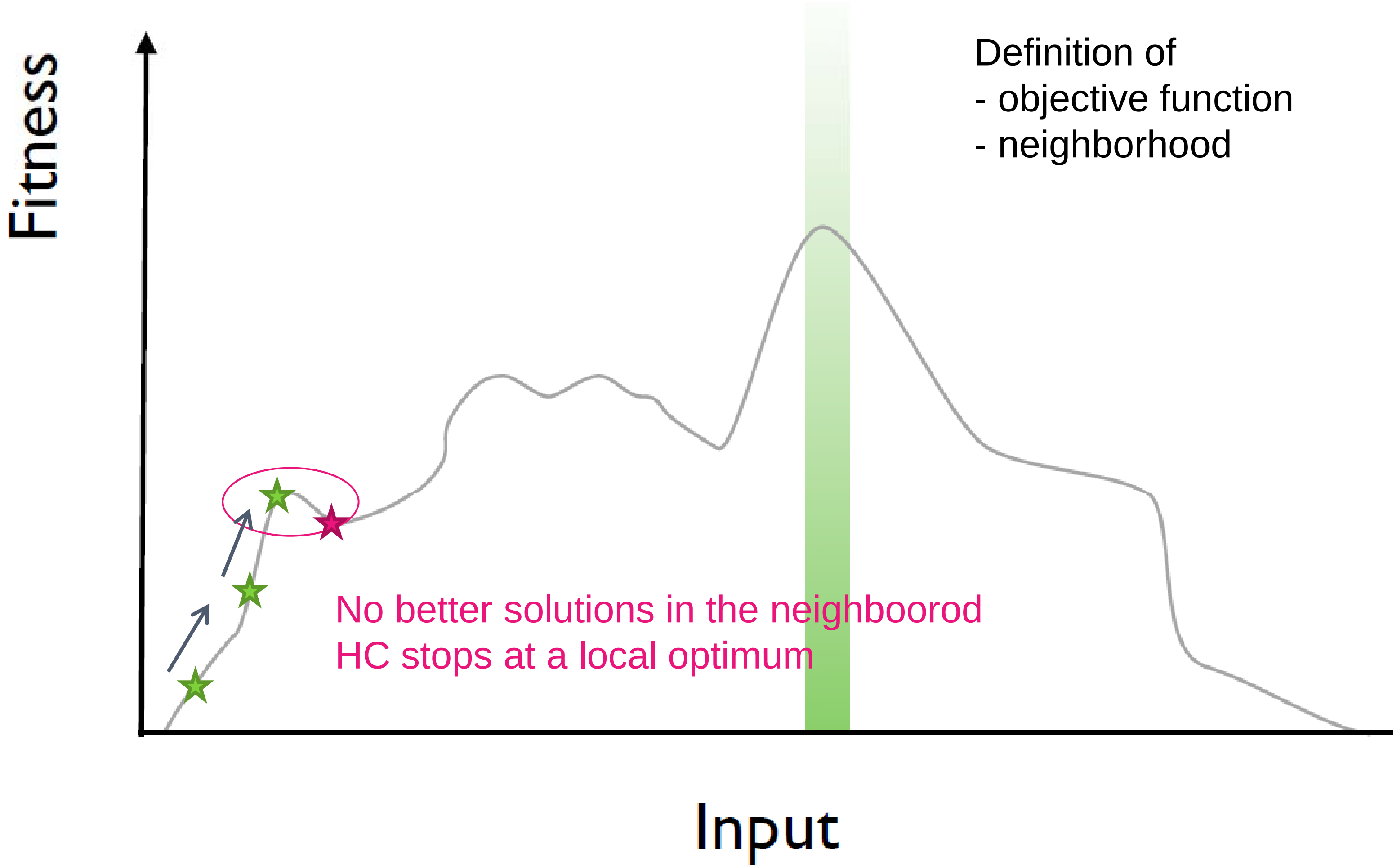
[B1] F. Ferrucci, C. Gravino, R. Oliveto, F. Sarro, "Using Evolutionary Based Approaches to Estimate Software Development Effort", in Evolutionary Computation and Optimization Algorithms in Software Engineering: Applications and Techniques, M. Chis, IGI Global

Research Goals

- **RG1.** Are there any differences in the use of different SB techniques?
- **RG2.** How the design choices (e.g., objective function) characterizing the use of SB approaches impact on the performance of these techniques?
- **RG3.** Are SB techniques effective to build effort estimation models?
- **RG4.** Are SB techniques effective to improve the accuracy of other effort estimation techniques?

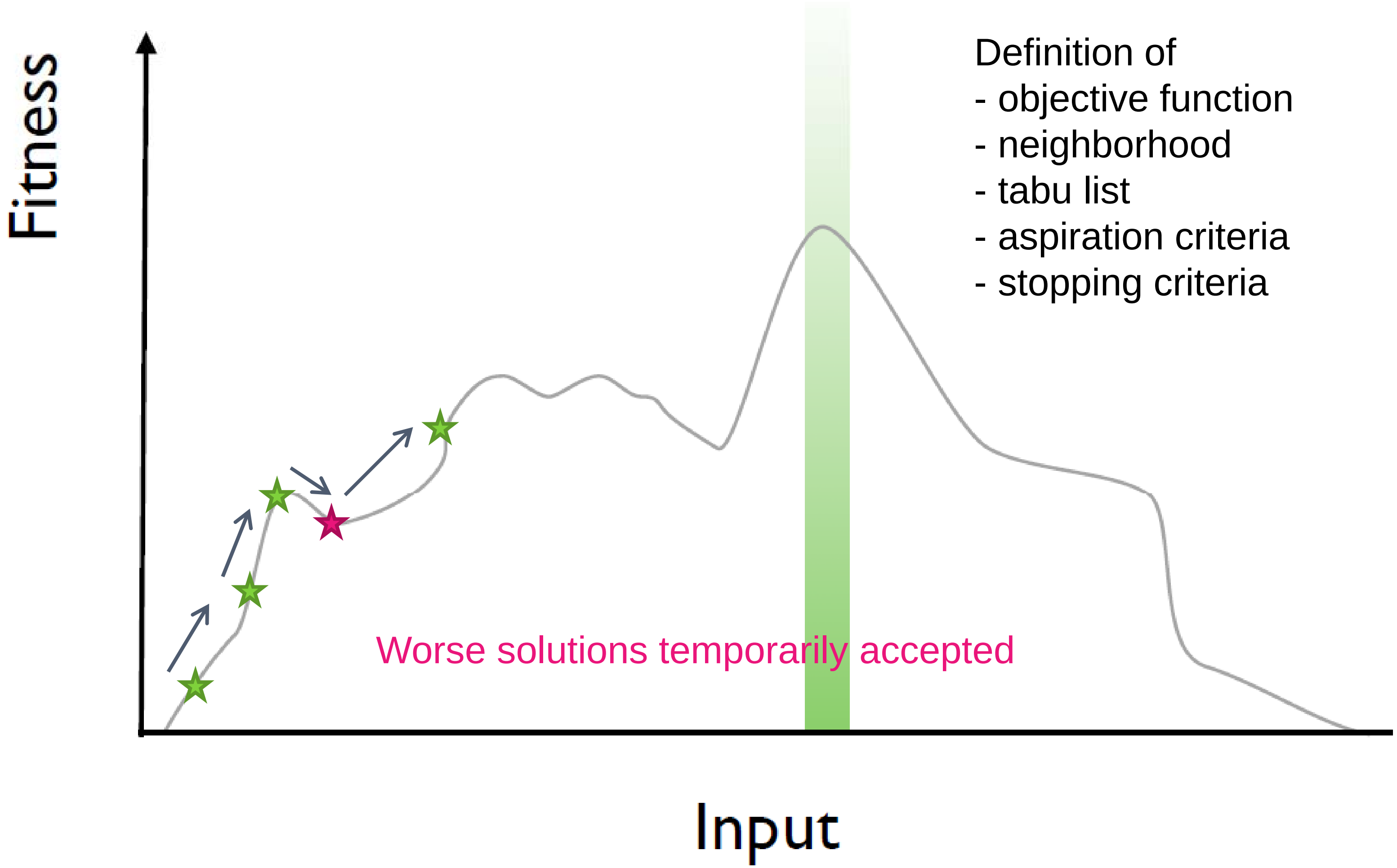
RG1: Are there any differences in the use of different SB techniques?

Hill Climbing



Adapted from P. Mcminn, "Search-Based Software Testing Tutorial"

Tabu Search



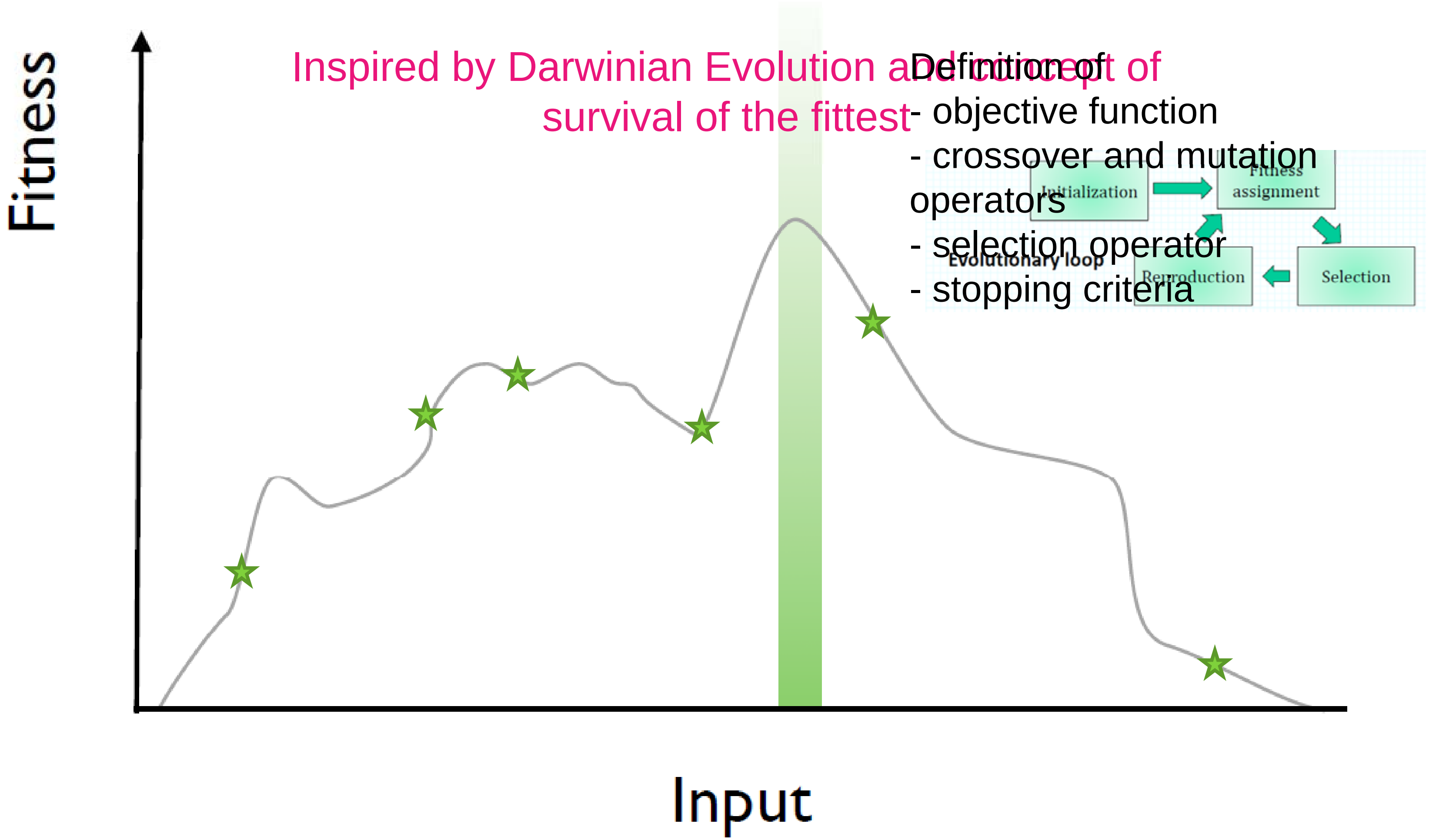
Definition of
- objective function
- neighborhood
- tabu list
- aspiration criteria
- stopping criteria

Adapted from P. Mcminn, "Search-Based Software Testing Tutorial"

Genetic Programming

Inspired by Darwinian Evolution and concept of survival of the fittest

Definition of
- objective function
- crossover and mutation operators
- selection operator
- stopping criteria



Adapted from P. Mcminn, P. Tonella "Search-Based Software Testing Tutorial"

Empirical Study

- Empirical study performed exploiting
  - 3 SB approaches: HC, TS and GP
  - 7 public datasets single and cross-company
    - China, Desharnais, Finnish, Kemerer, Maxwell, Miyazaki, Telecom,
  - 30 executions for each SB technique
  - 3-fold cross-validation
  - evaluation criteria: Sum of Squared Residuals (SSR) and statistical significance tests

Results RG1

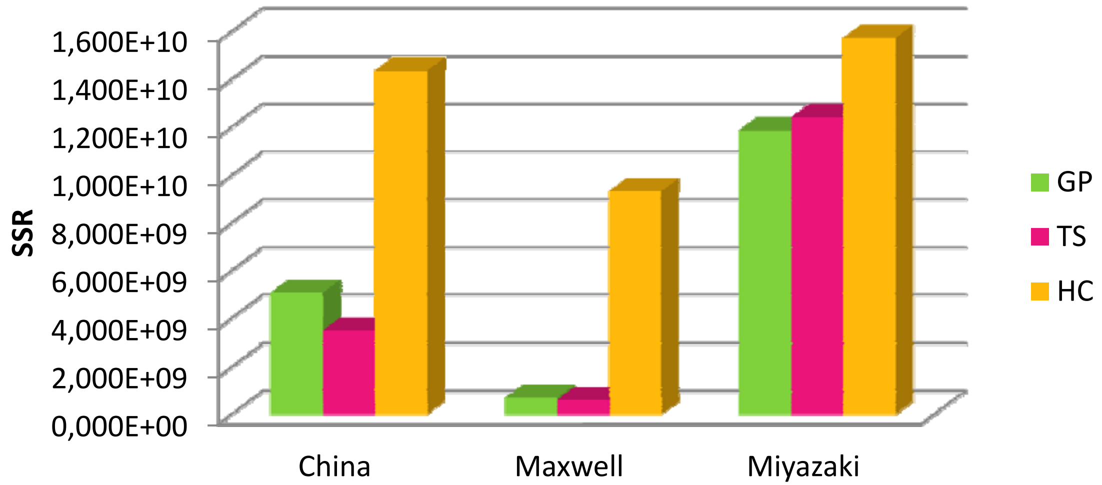
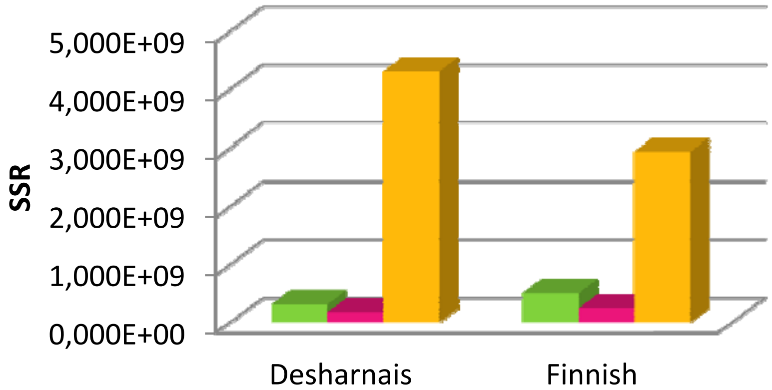
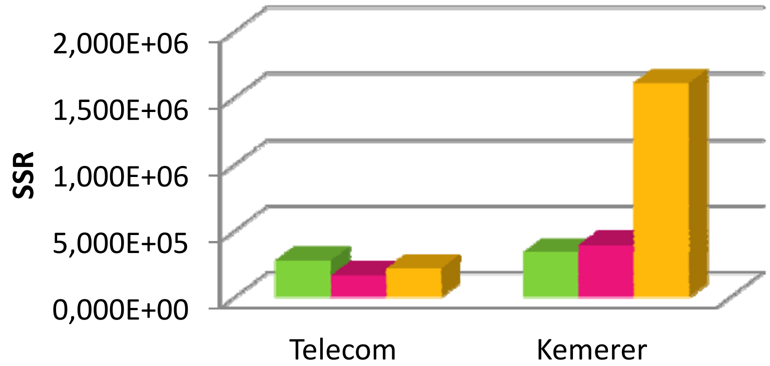


Table 1. Results of Wilcoxon Test

<	GP	TS	HC
GP	-	0,864	**0,017**
TS	0,136	-	**0,011**
HC	0,983	0,989	-





RG2: How the design choices characterizing the use of SB approaches impact on the performance of these techniques?

"When applying search-based software engineering (SBSE) techniques one is confronted with a multitude of different parameters that need to be chosen [...]

Which population size for a genetic algorithm?

Which objective function to use?

Tuning does have a critical impact on algorithmic performance [...] [1]"

Influence of Setting...

[1] A. Arcuri, G. Fraser: On Parameter Tuning in Search Based Software Engineering. SSBSE 2011: 33-47

To address RG2…

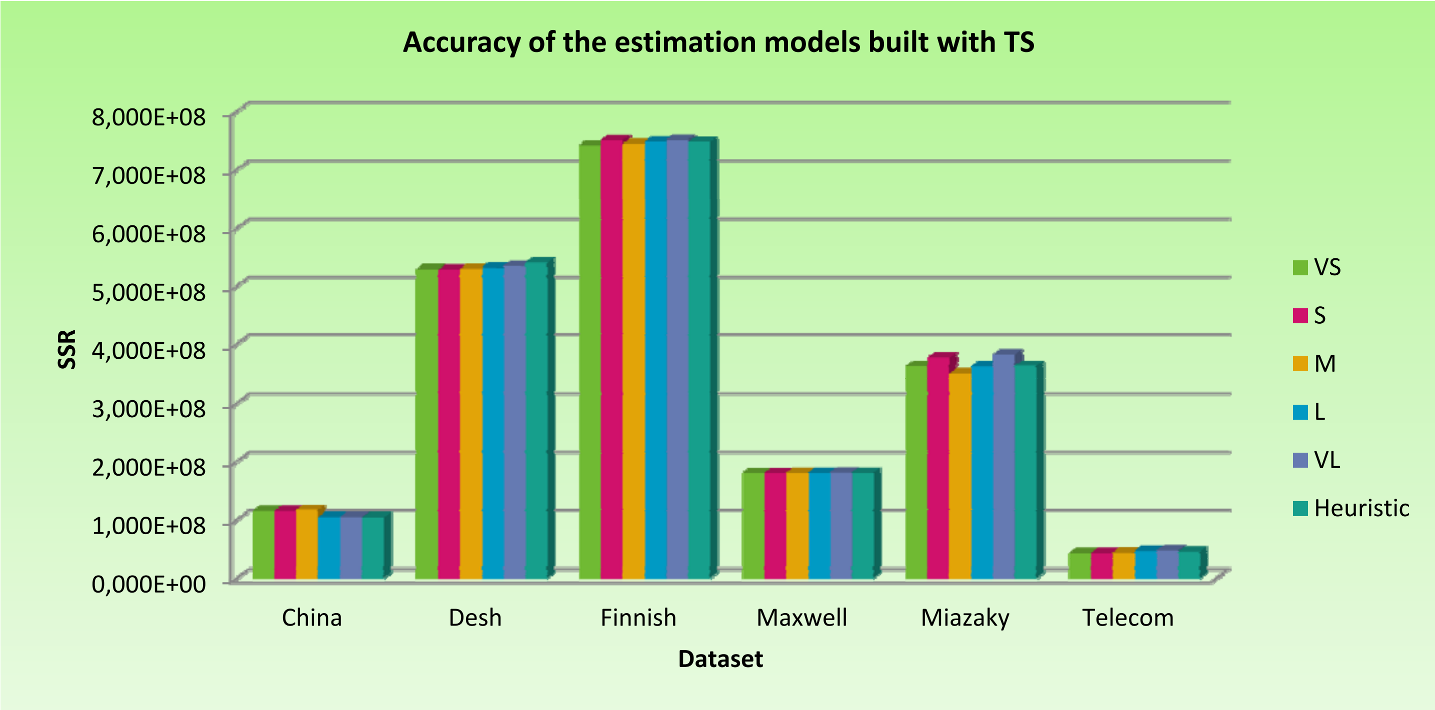
- Empirical study performed exploiting
  - TS and GP with six different configurations

Configuration	Individuals / Solutions	Generations/ Iterations	Tabu List Size
Very Small (VS)	50	5000	5
Small (S)	100	2500	10
Medium (M)	200	1250	20
Large (L)	500	500	50
Very Large (VL)	1000	250	100
Heuristic[1]	10V	1000V or100V if best sol does not change	V

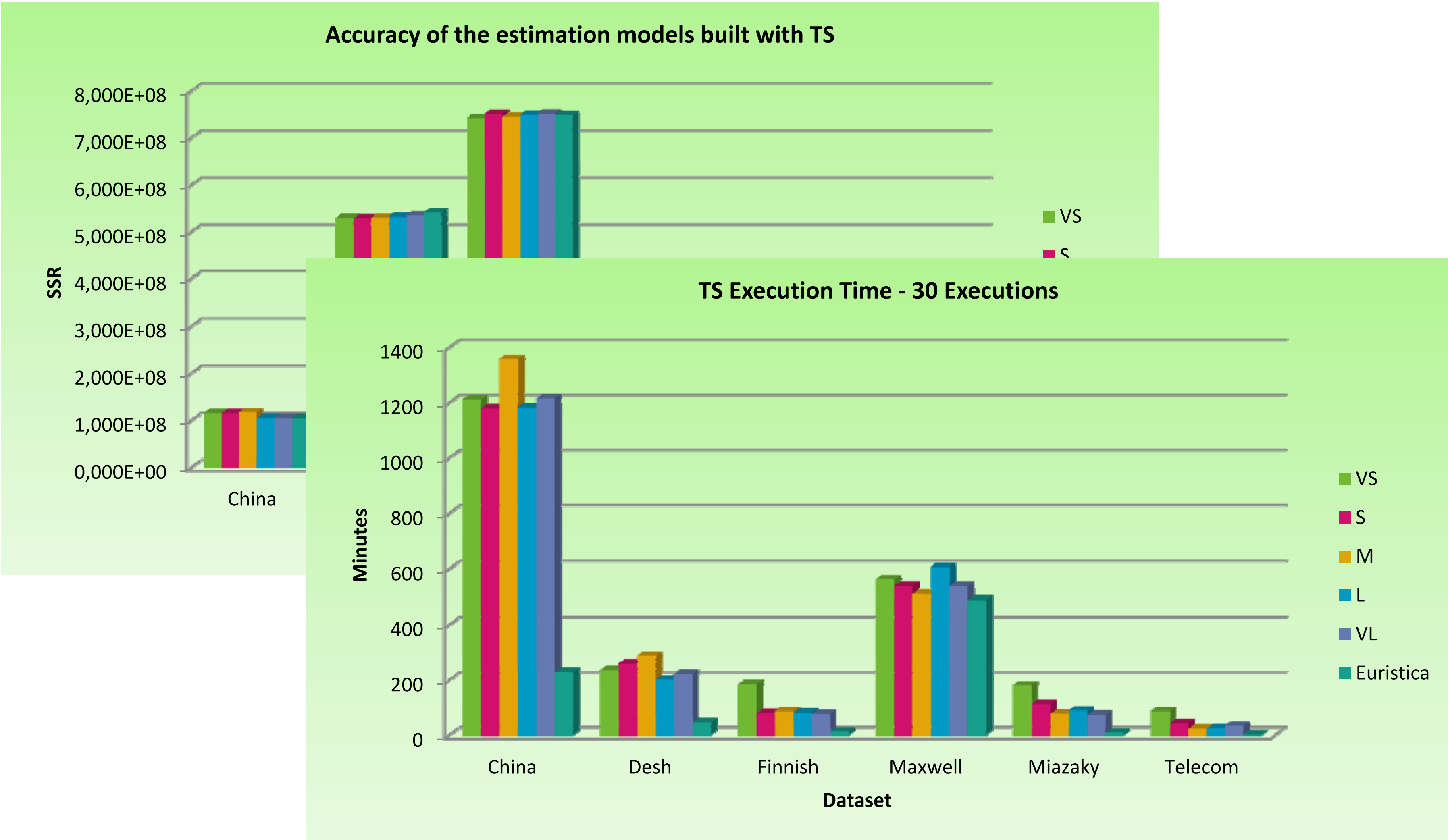
  - 6 public datasets single and cross-company
    - China, Desharnais, Finnish, Maxwell, Miyazaki, Telecom
  - 3-fold cross-validation, 30 executions for each technique
  - evaluation criteria: summary measures and statistical significance tests

[1] Huang, S.J., Chiu, N.H.: Optimization of analogy weights by genetic algorithm for software effort estimation. Journal of Systems and Software 48(11), 1034-1045 (2006)

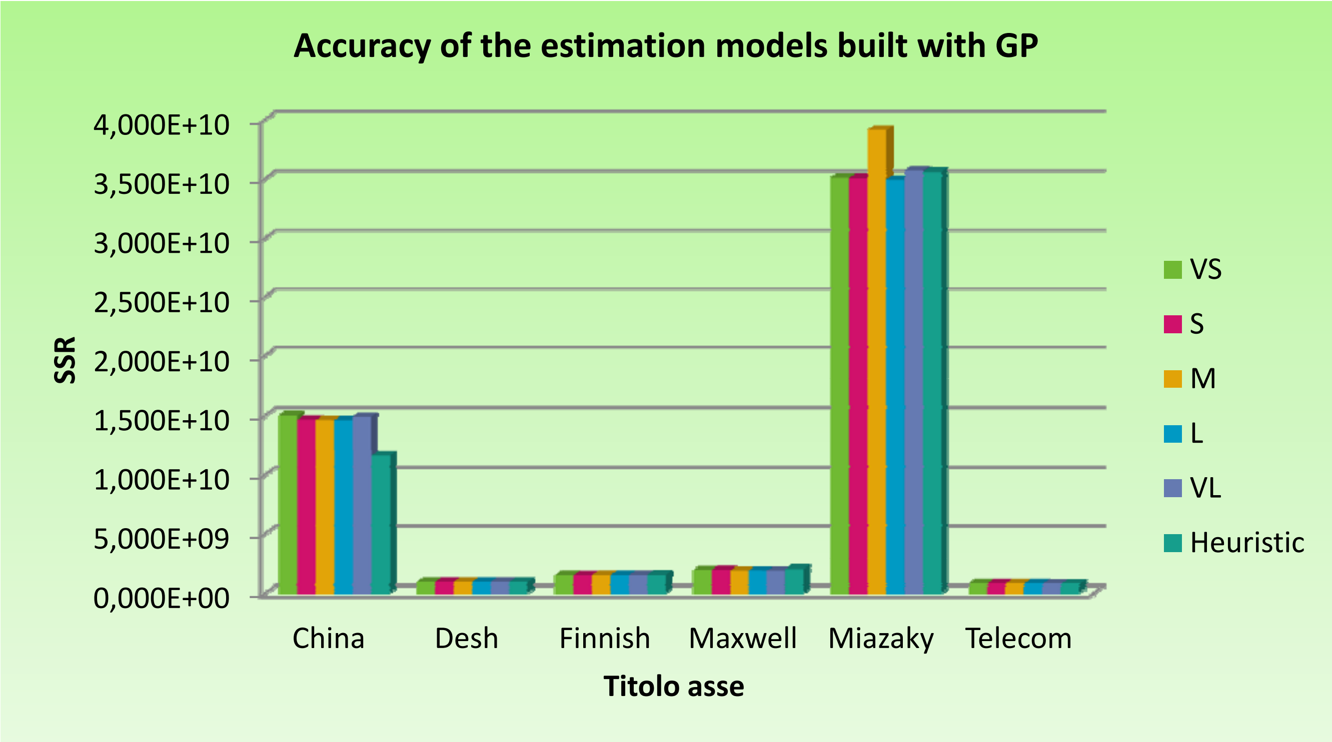
Results RG2
Tabu Search



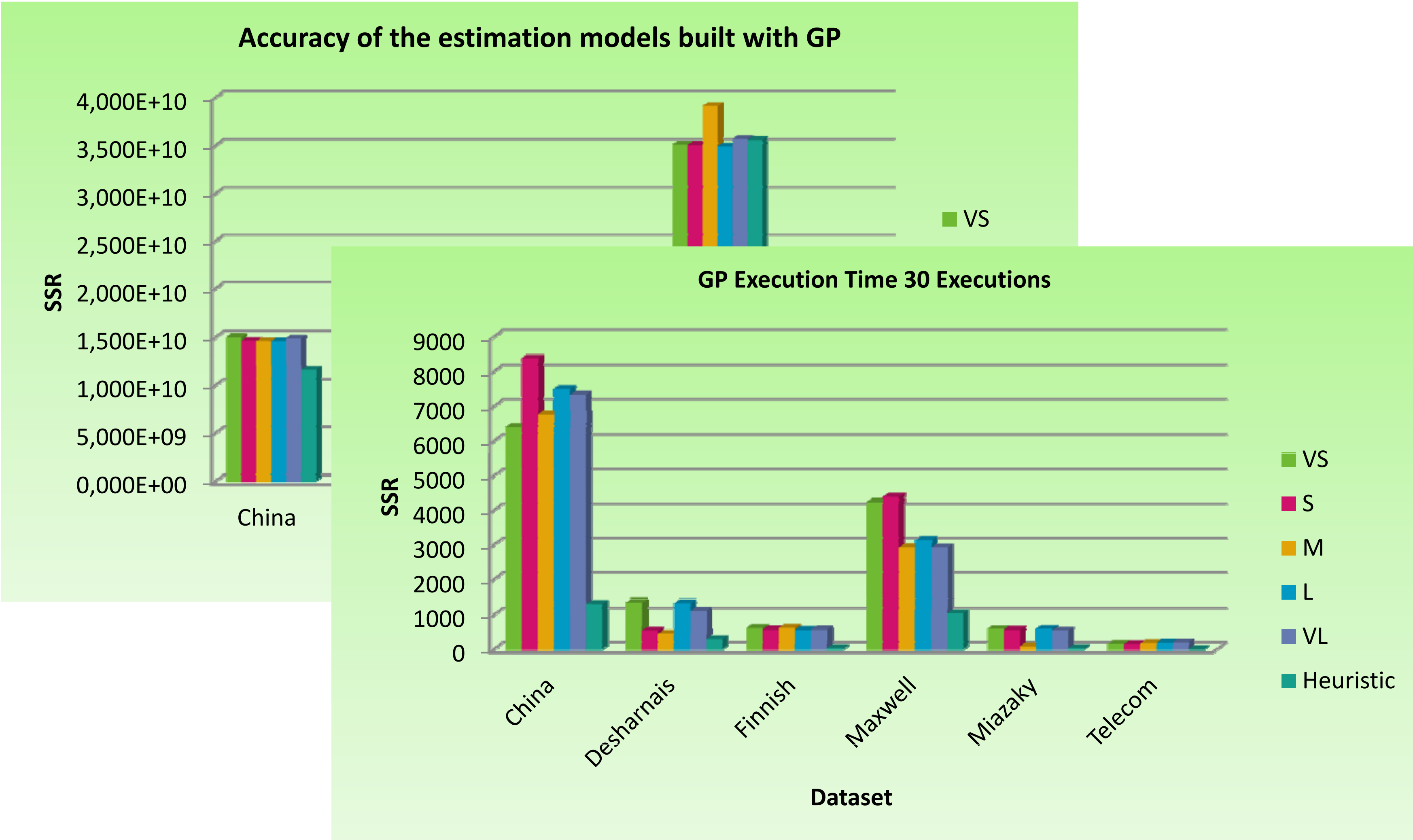
Results RG2
Tabu Search



Results RG2
Genetic Programming



Results RG2
Genetic Programming



"…no matter what search technique is employed, it is the fitness function that captures the crucial information; it differentiates a good solution from a poor one, thereby guiding the search."[1]

"…each measure used to evaluate properties of interest can be used as fitness function."[2]

…in the effort estimation context several criteria have been proposed to evaluate models' accuracy…

Influence of Objective Function…

(1) Harman, M., The current state and future of search-based software engineering. In Procs of IEEE FOSE 2007
(2) Harman,, M., Clark, J.A., Metrics Are Fitness Functions Too. In Procs of IEEE METRICS 2004

How to assess estimation model accuracy?

- Several evaluation criteria are employed for assessing the accuracy of effort estimation models

- The most commonly used are based on
  - **MRE** (Magnitude of Relative Error) $$MRE = \frac{|ActualEffort - EstimatedEffort|}{ActualEffort}$$
  - **EMRE** (Estimated MRE) $$EMRE = \frac{|ActualEffort - EstimatedEffort|}{EstimatedEffort}$$

- Summary Measures
  - **MMRE** (Mean MRE)
  - **MdMRE** (Median MRE)
  - **Pred(25)** (Prediction at level 25): percentage of the estimates whose MRE < 25
  - **MEMRE** (Mean EMRE)
  - **MdEMRE** (Median EMRE)

How to assess estimation model accuracy?

- Different accuracy measures take into account different aspects of model performance*
  - MMRE measures poor performance
  - MEMRE gives a stronger penalty to under-estimates
  - Pred(25) measures how well an estimation model performs
  - …
- Each measure used to evaluate properties of interest can be used as objective function**
  - the choice of the evaluation criterion can be a managerial issue
    - e.g., a project manager could prefer to optimize MEMRE to prevent under-estimates
  - SB approaches allow project managers to use their preferred evaluation criterion as objective function

(*) Kitchenham, B., Pickard, L. M., MacDonell, S. G., Shepperd, M. J., What accuracy statistics really measure, IEE Procs Software (2001)
(**) Harman,, M., Clark, J.A., Metrics Are Fitness Functions Too. IEEE METRICS 2004

To address RG2…

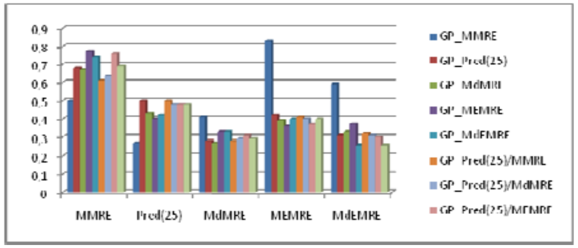
- Empirical study performed exploiting
  - 3*8*11*3*30= 23760 experiments
    - 3 approaches: HC, TS and GP
    - 7 public datasets single and cross-company
      - China, Desharnais, Finnish, Kemerer, Maxwell, Miyazaki, Telecom
    - 11 objective functions
    - 3-fold cross-validation
    - 30 executions for each technique
- Evaluation criteria: summary measures and statistical significance tests

Employed Objective Function	
Single	MMRE
	Pred(25)
	MdMRE
	MEMRE
	MdEMRE
	SSR
Combined	Avg(MMRE,MEMRE)
	Pred(25)/MMRE
	Pred(25)/MdMRE
	Pred(25)/MEMRE
	Pred(25)/MdEMRE

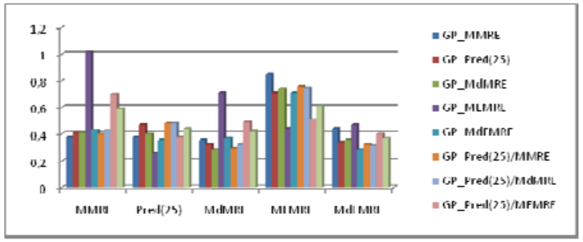
The observation that different accuracy measures take into account different aspects of predictions accuracy suggested us to investigate also the effectiveness of some combinations of those accuracy measures

RG2 Results
Influence of the objective function

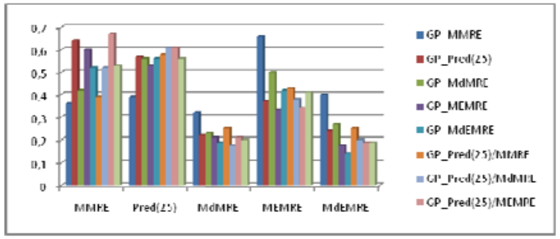
Desharnais



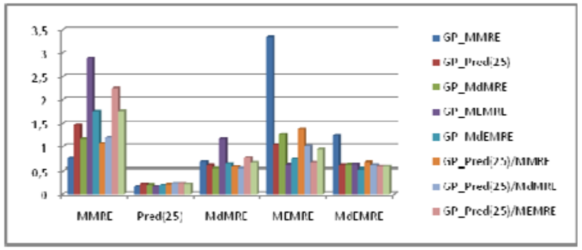
Maxwell



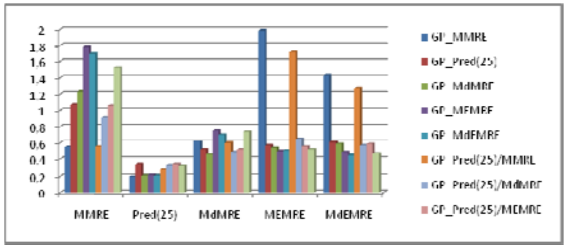
Telecom



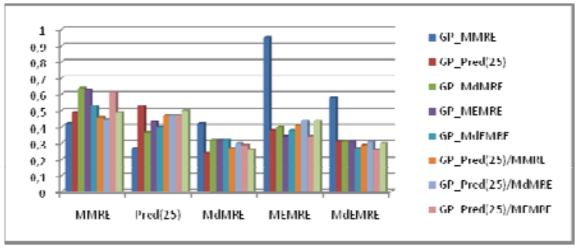
China



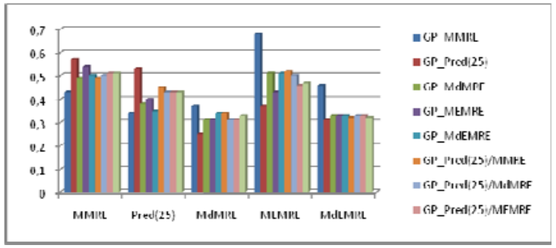
Finnish



Kemerer



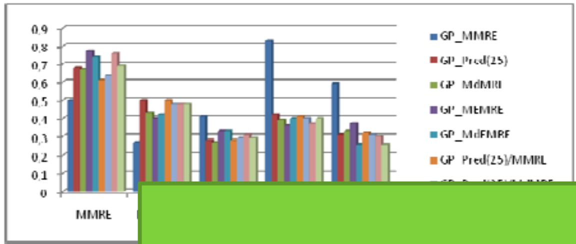
Miyazaki



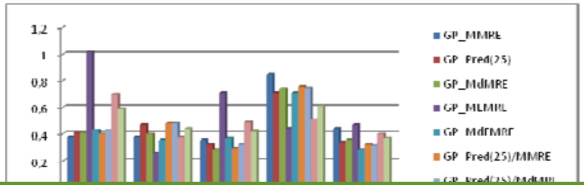
Results on Training Sets…
… to assess the models' ability to fit data

RG2 Results
Influence of the objective function

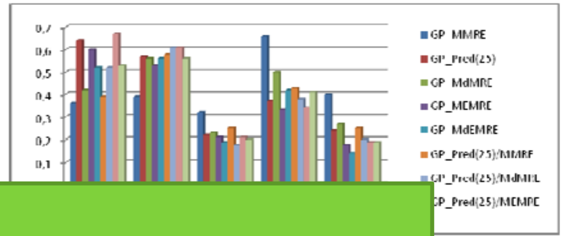
Deshamais



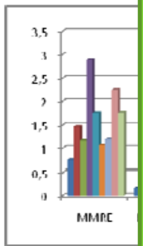
Maxwell

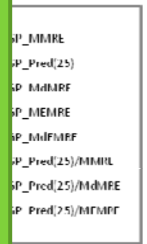


Telecom



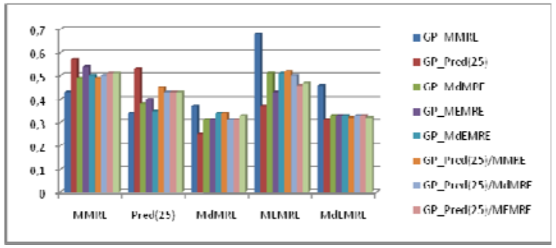
China





Our Running Example is GP on the Desharnais dataset
Note that the observations we will make hold also for the other datasets

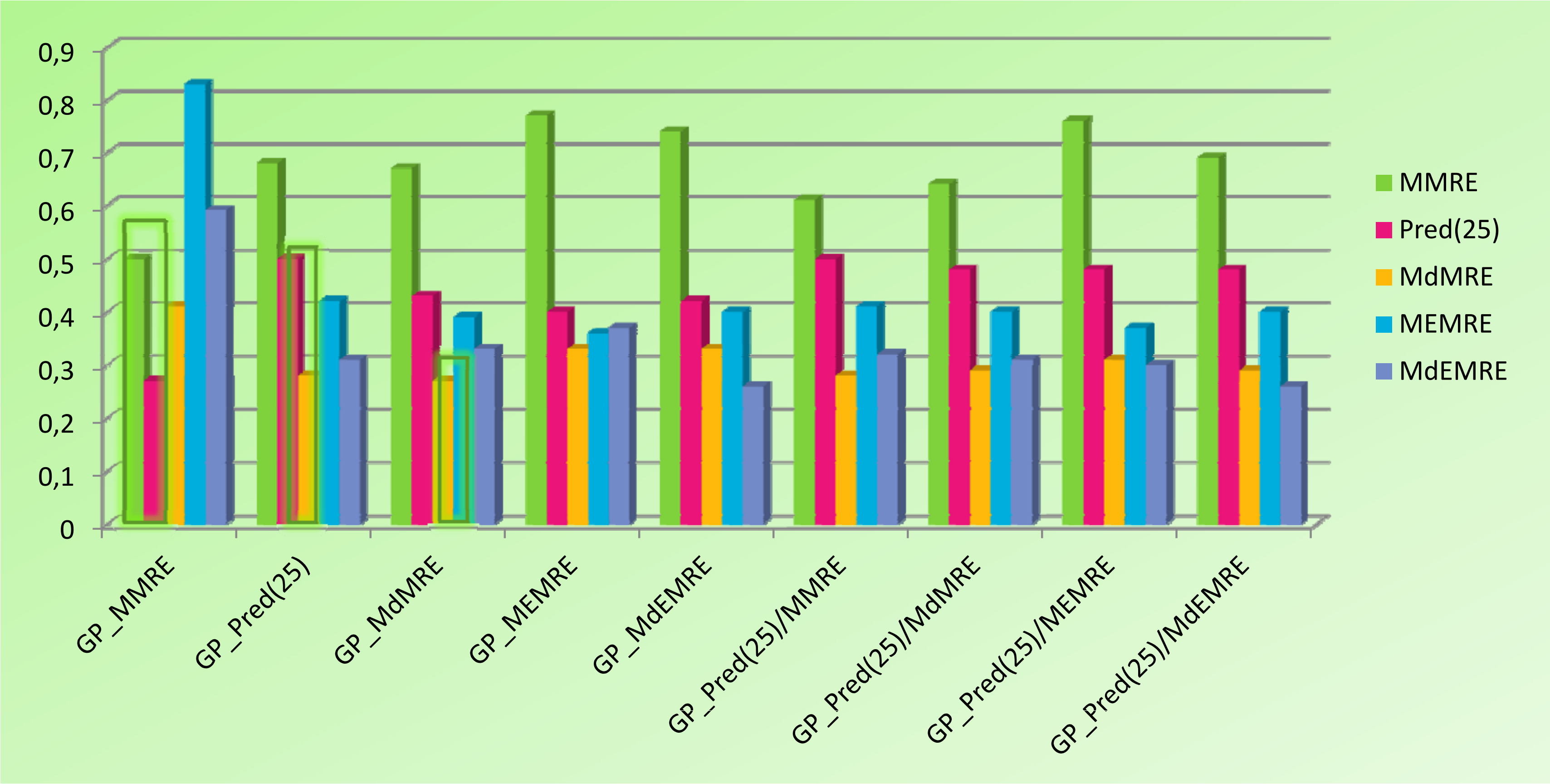
Miyazaki



Results on Training Sets…
… to assess the models' ability to fit data

RG2 Results
Influence of the objective function

Figure 2. Performance of using GP with different fitness functions in terms of MMRE, Pred(25), MdMRE, MEMRE, and MdEMRE on Desharnais dataset (TRAINING SETS)



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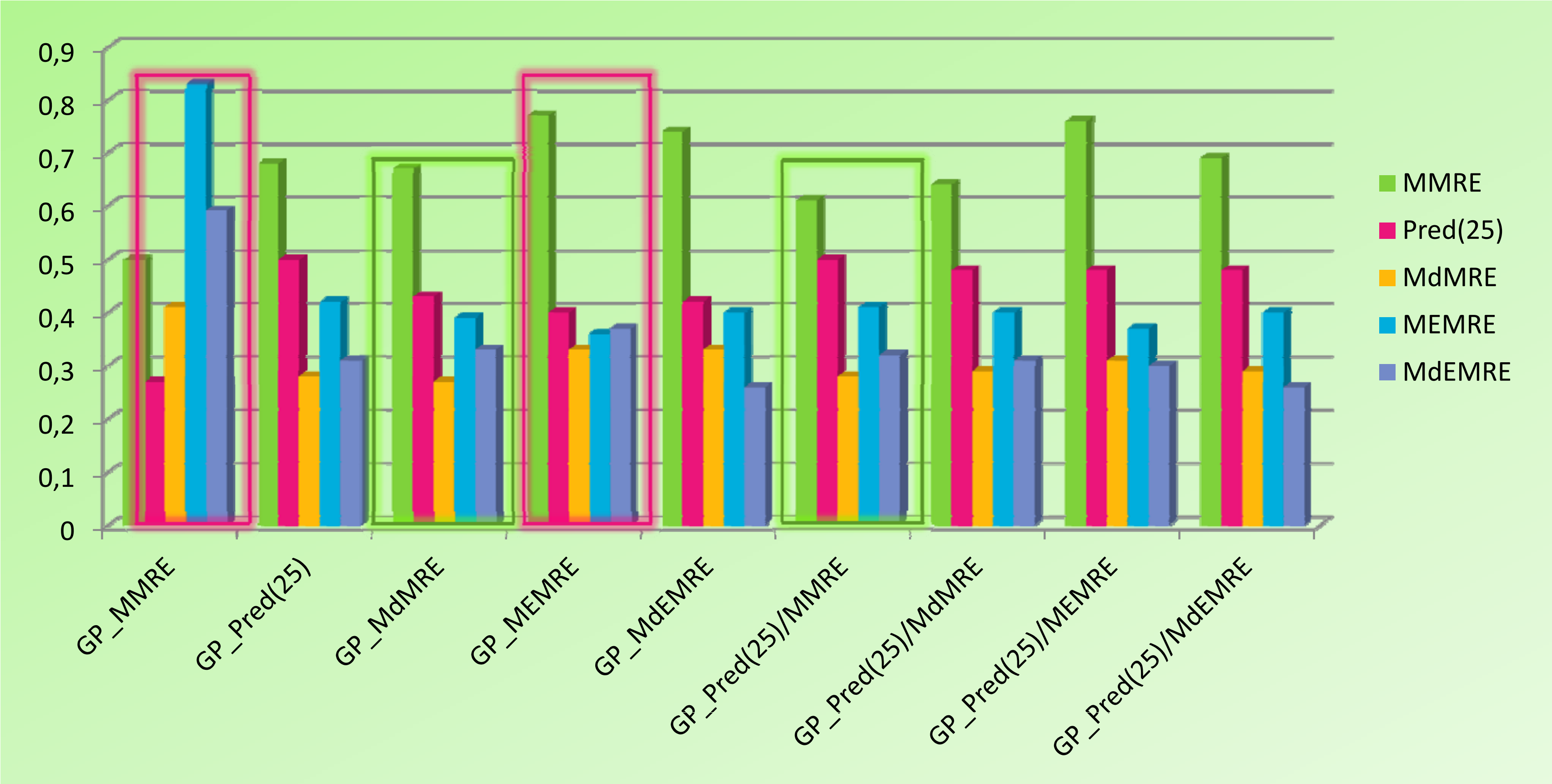
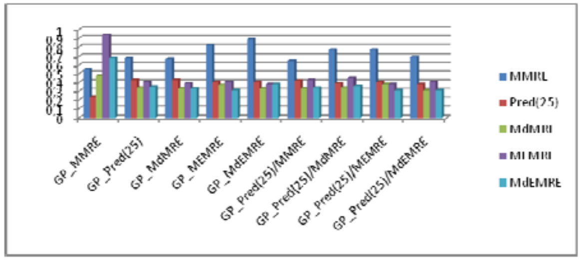
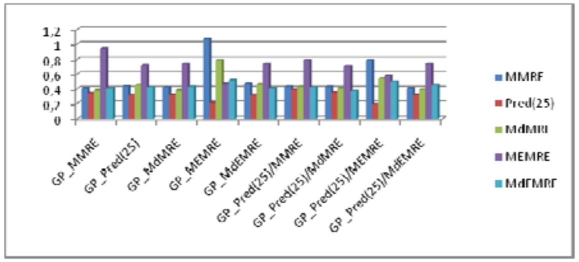


RG2 Results
Influence of the objective function

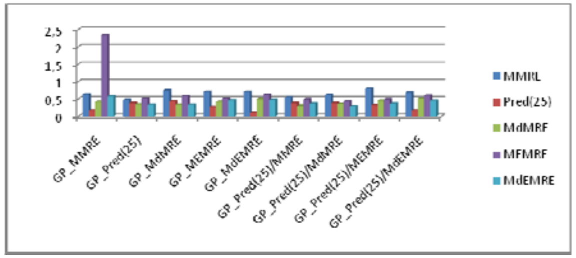
Desharnais



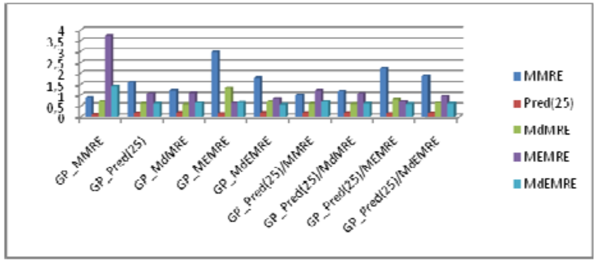
Maxwell Test Sets



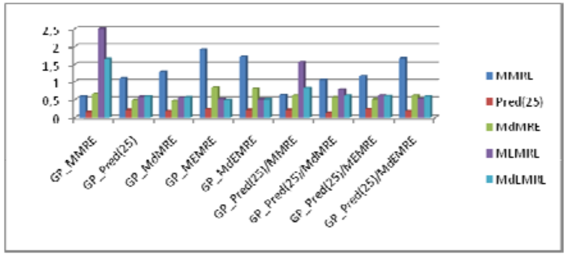
Telecom



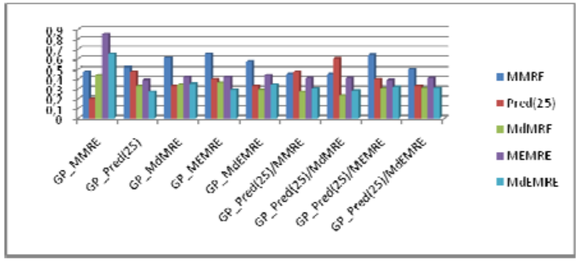
China



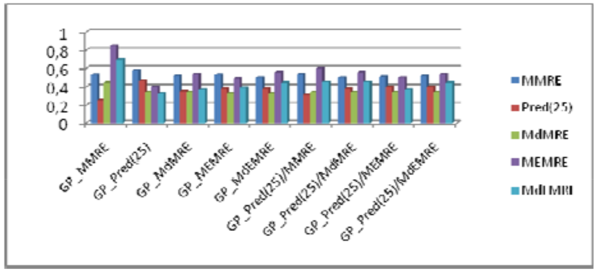
Finnish



Kemerer



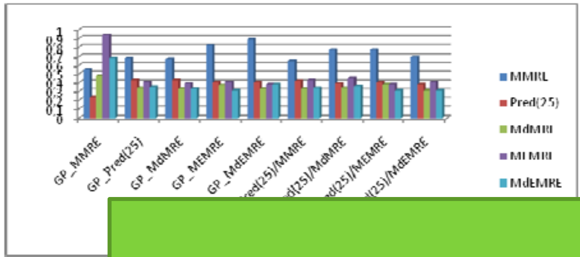
Miyazaki



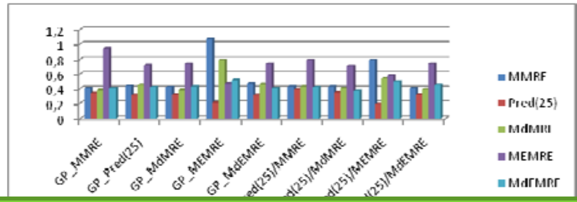
Results on Test Sets…
… to assess the models' predictive capability

RG2 Results
Influence of the objective function

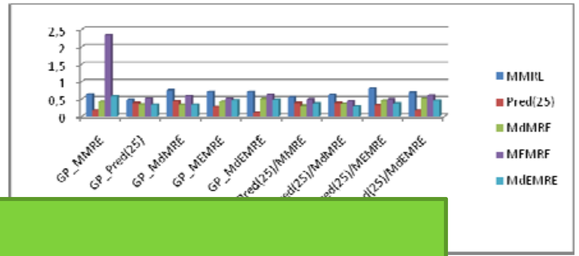
Desharnais



Maxwell Test Sets



Telecom



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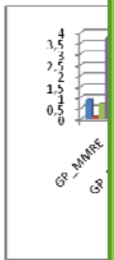

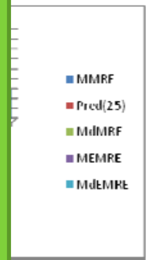

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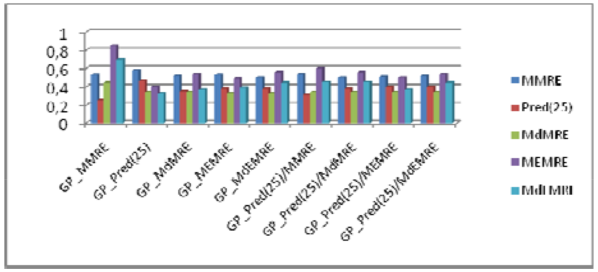
Miyazaki



Results on Test Sets…
… to assess the models' predictive capability

RG2 Results
Influence of the objective function

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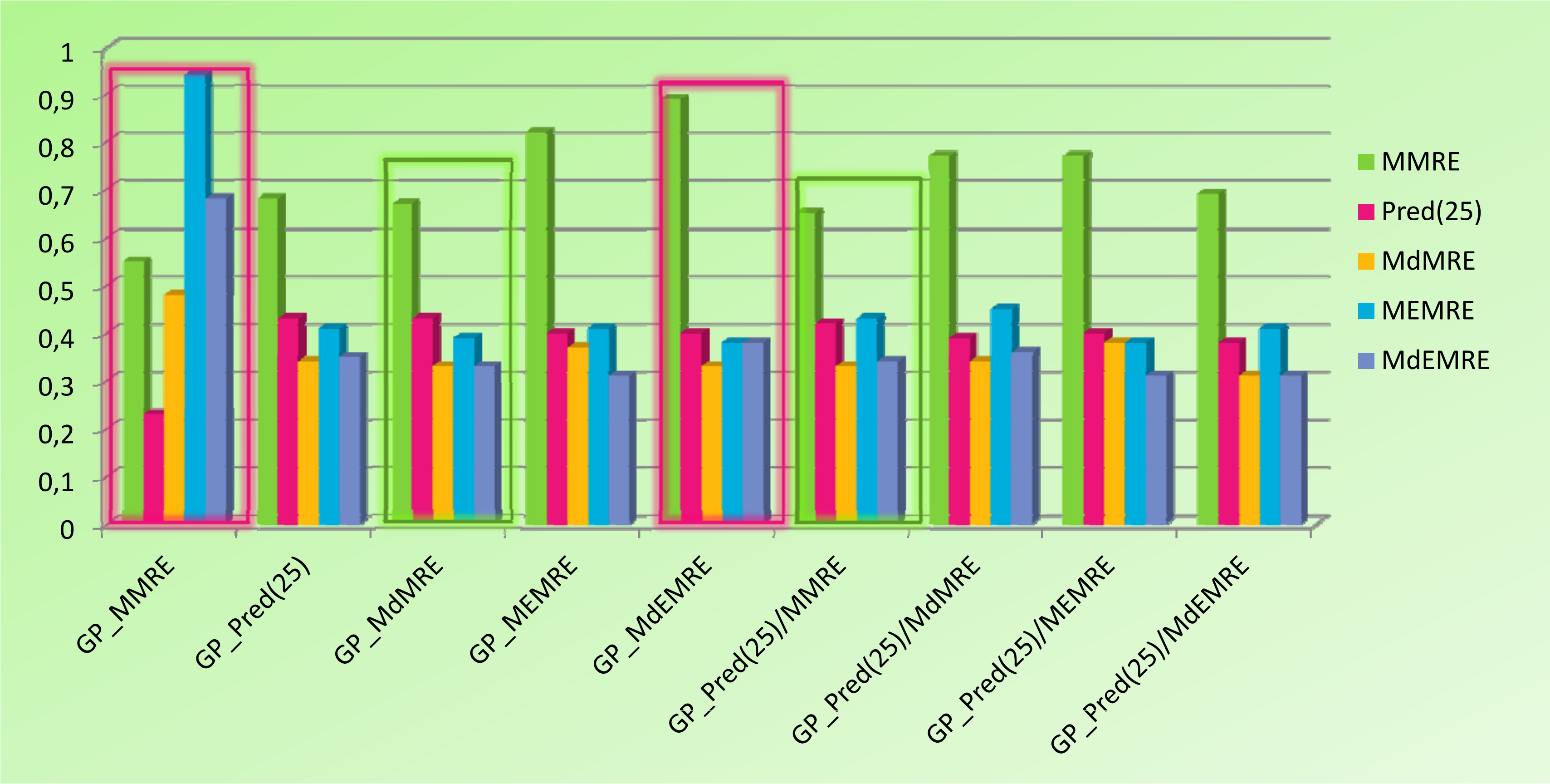


RG3: Are SB techniques effective to build effort estimation methods?

To address RG3…

- Empirical Study
  - RQ1: Do the proposed TS and GP provide significantly better results than the employed baseline benchmarks?
    - comparison with Mean and Median of Effort, Random Search
  - RQ2: Do the proposed TS and GP provide significantly better results than widely used effort estimation techniques?
    - comparison with Manual Stepwise Regression (MSWR) and Case-Based Reasoning (CBR)
  - 7 datasets (single and cross-company), Sum of Squared Residuals (SSR) as objective function, 3-fold cross-validation, 30 executions for each technique
  - Evaluation criteria: SSR and statistical significance tests

RG3 Results
SB approaches vs. Baseline Benchmark

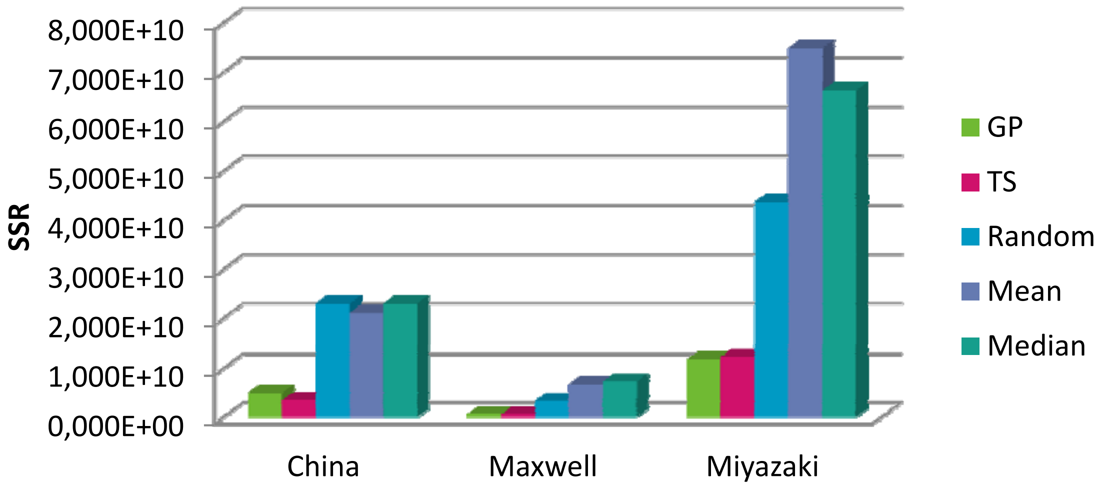
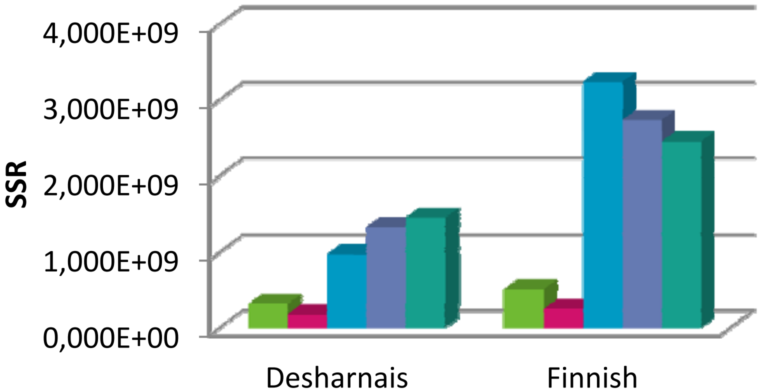


Table 2. Results of Wilcoxon Test

<	Random	Mean	Median
GP	**0.011**	**0.011**	**0.011**
TS	**0.011**	**0.011**	**0.011**



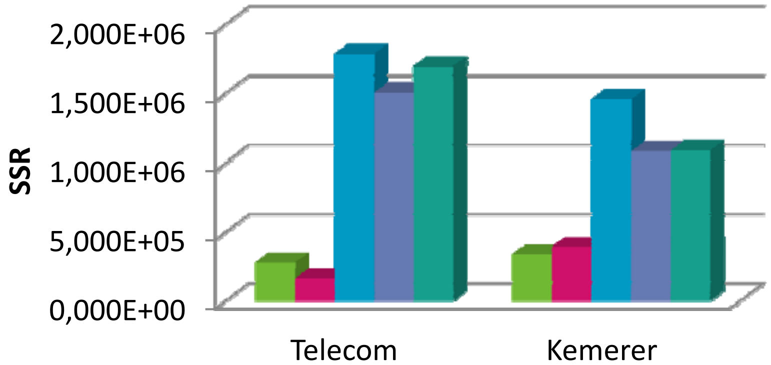


Figure 4. Comparison of SB approaches and benchmarks in terms of SSR

RG3 Results
SB approaches vs. MSWR and CBR

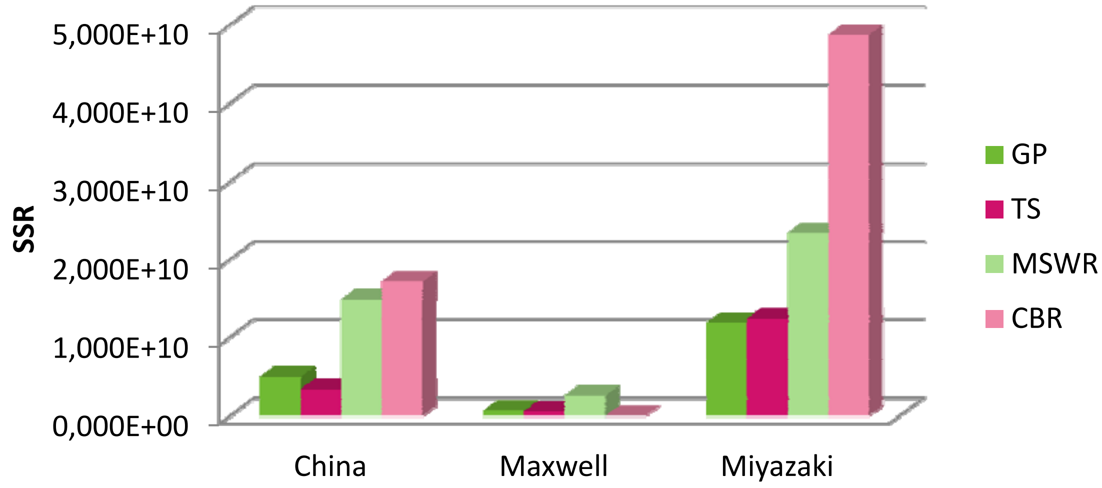
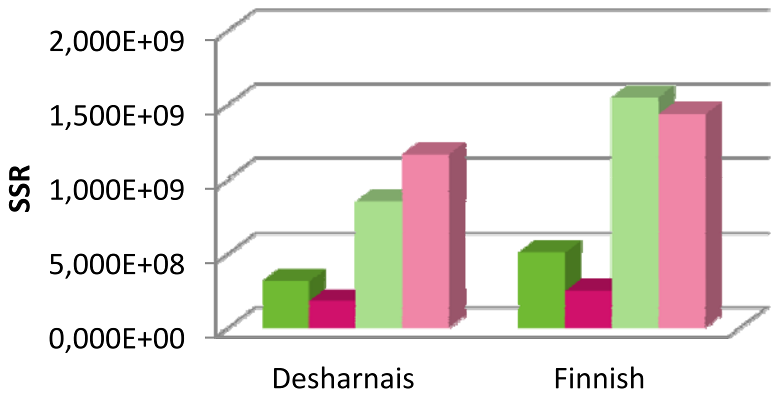


Table 3. Results of Wilcoxon Test

<	MSWR	CBR
GP	**0.011**	**0.038**
TS	**0.011**	**0.038**



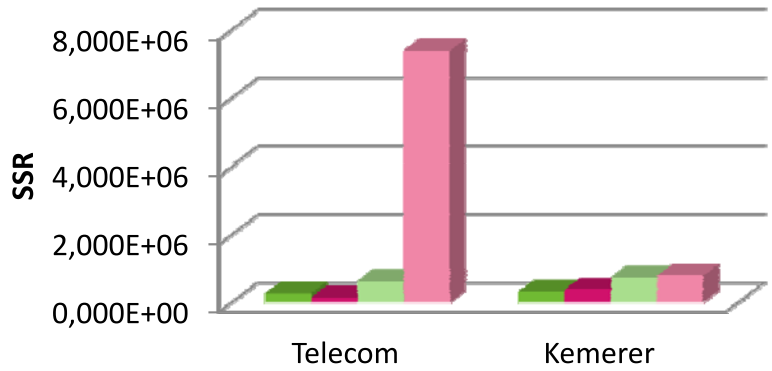


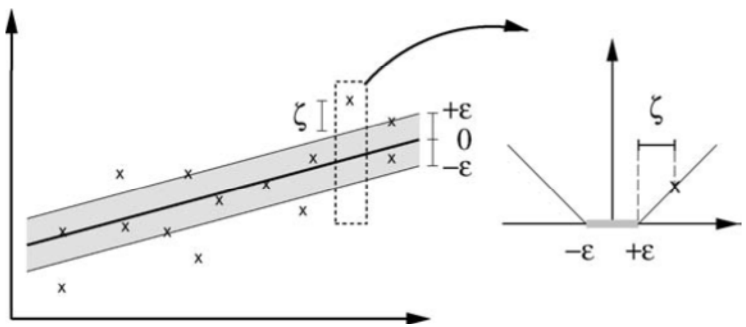
Figure 5. Comparison of SB approaches and benchmarks in terms of SSR

RG4: Are SB techniques effective to improve the accuracy of other data-driven effort estimation techniques?

Support Vector Regression (1)

- Support Vector Regression (SVR) is a regression technique based on the Support Vector Machine learning method

- SVR aims to find a function which emulates the training set points with an error on each point lower than a constant ε
  - among all the possible functions satisfying such constraint the flattest one is chosen
  - a constant C is used to weight errors larger than ε (SVR soft margin version)



Support Vector Regression (2)

- The use of kernel functions allows a better adaption to different problems (linear and non linear)
  - Linear
  - Radial Basis Function (RBF) $K(u,v) = exp(- \gamma |u - v|^2)$
  - Polynomial $K(u,v) = (s * u \cdot v + c0)degree$
  - …..
- Some parameters need to be specified
  - Linear Kernel: C and ε
  - RBF: C, ε, and γ
  - Polynomial: C, ε, s, c0,degree

Details about SVR can be found in

B. Scholkopf , Support Vector Learning. R. Oldenbourg Verlag, Munchen. Doktorarbeit, TU Berlin, 1997.
B. Scholkopf, A. Smola, “Learning with Kernels”. 2002, MIT Press
A. J. Smola , B. Schölkopf, “A tutorial on support vector regression”, Statistics and Computing, 14 (3) 2004

Support Vector Regression (3)

- The choice of parameters can have a strong impact on the application of the SVR technique
  - inappropriate setting can lead to over/under-fitting
- No general guidelines are available
  - the appropriate setting could depend on the characteristics of the employed dataset
  - the interaction among parameters complicates the setting
  - the exploration of all the possible settings is not computational affordable as the search space is too large

Using SB approaches to enhance effort estimation methods

- SVR's parameters are often selected by
  - a "Grid-Search" using an exponentially growing sequence of values
    - very coarse grain → optimal values can be missed
    - always the same values are explored, without taking into account the data under investigation

- A combination of Tabu Search (TS) with Support Vector Regression (SVR) was proposed

Using SB approaches to enhance effort estimation methods

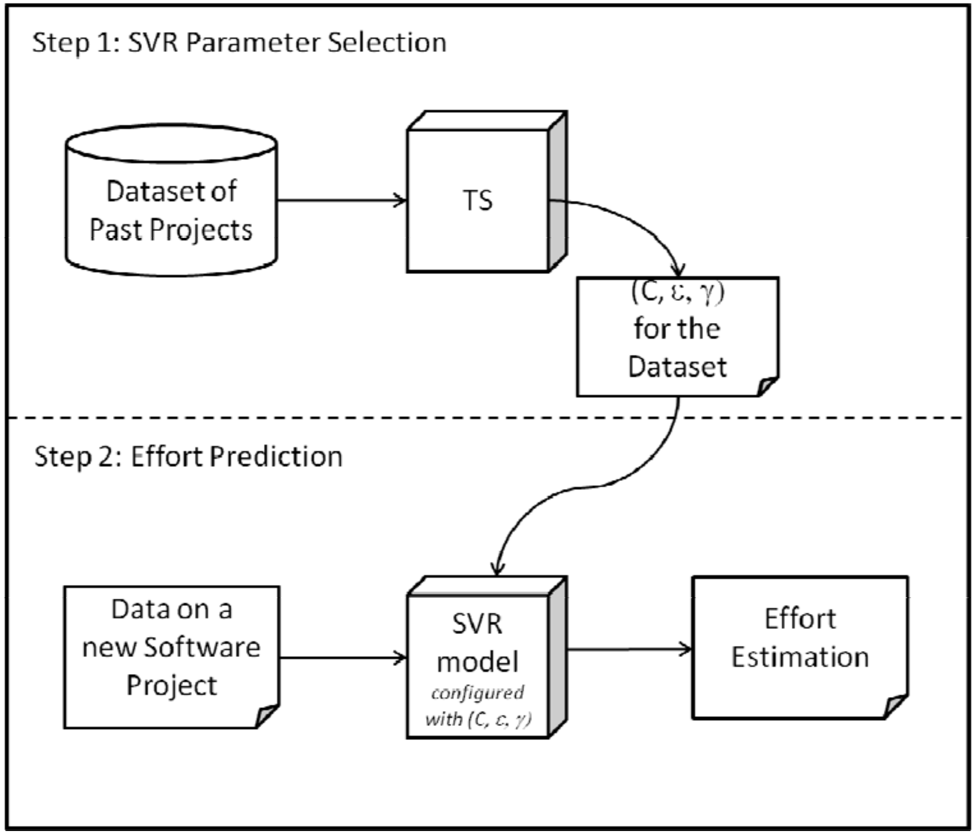
- SVR's parameters are often selected
  - a "Grid-Search" using an ex
    of values
    - very coarse grain → op
    - always the same values a
      account the data under i

Can we use a suitable heuristic to configure SVR?

- A combination of Tabu Search (TS) with Support Vector Regression (SVR) was proposed

Reformulating the problem of setting SVMs parameters…

- …as an optimization problem
  - among the possible configurations (solutions) identify the one which leads to optimal SVR performance



Empirical Study: Research Goals

- RG1: Is Tabu Search able to effectively set SVR configuration parameters?
  - comparison with baseline benchmarks
    - Random Search+SVR, Grid Search+SVR, WekaSVR
    - Mean and Median of Effort

- RG2: Are the effort predictions obtained using the combination of TS and SVR significantly superior to the ones obtained by other techniques?
  - comparison with widely used estimation methods
    - MSWR, CBR, CBR with feature subset selection

Empirical Study: Design

- 21 dataset containing industrial Web and software projects, single and cross company
  - 7 from the Tutukutu database, 14 from PROMISE repository
- Validation method
  - leave-one-out or 10-fold cross-validation depending on the dataset size
- Evaluation criteria
  - mean of absolute residuals (MAR) and statistical significance tests
- Comparison with several benchmarks
  - Random Search+SVR, Grid Search+SVR, WEKASVRDefaultSetting, Mean and Median of Effort, MSWR, CBR, CBR with feature subset selection

Empirical Study: Results

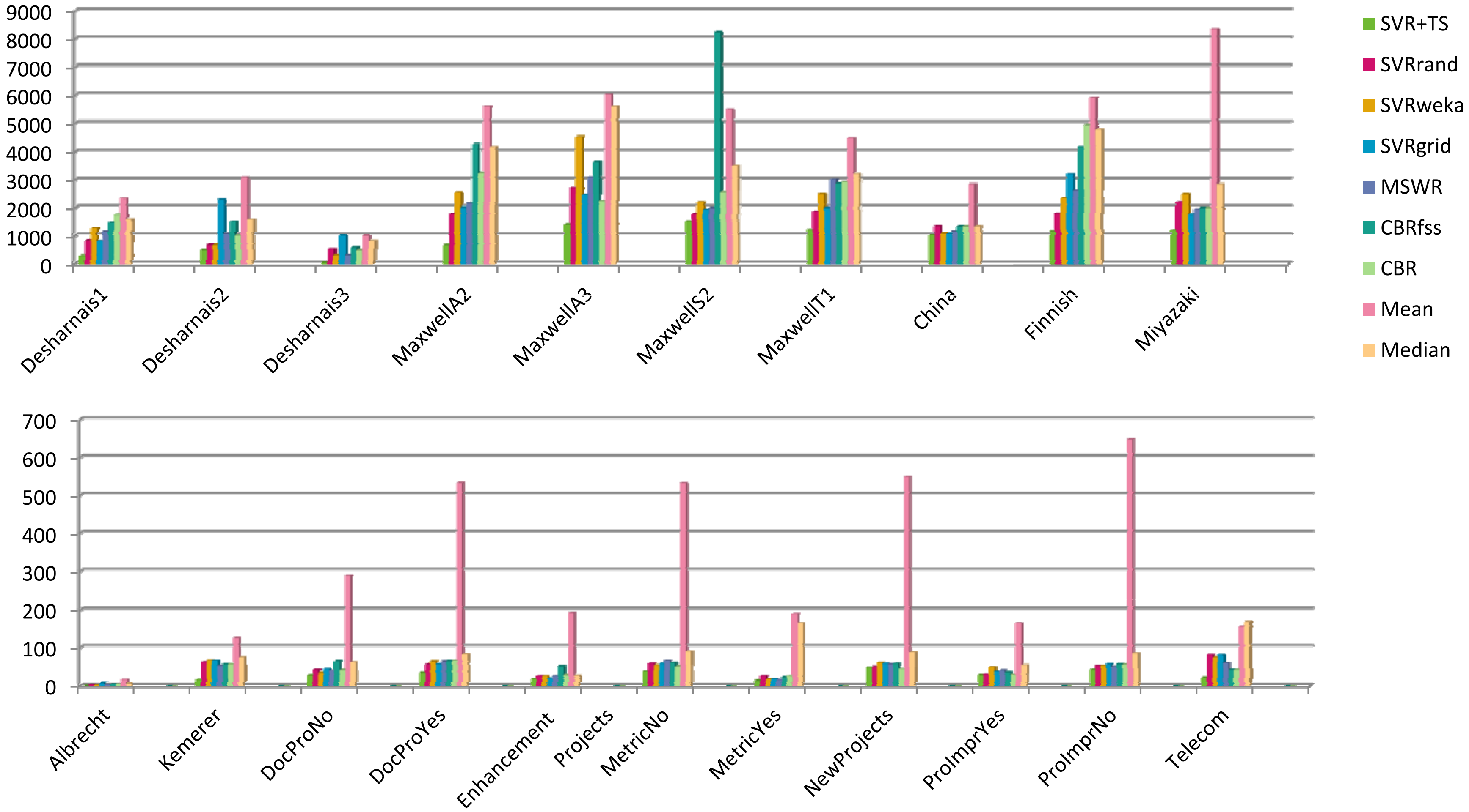


Figure 6. Comparison of TS+SVR and benchmarks in terms of MAR

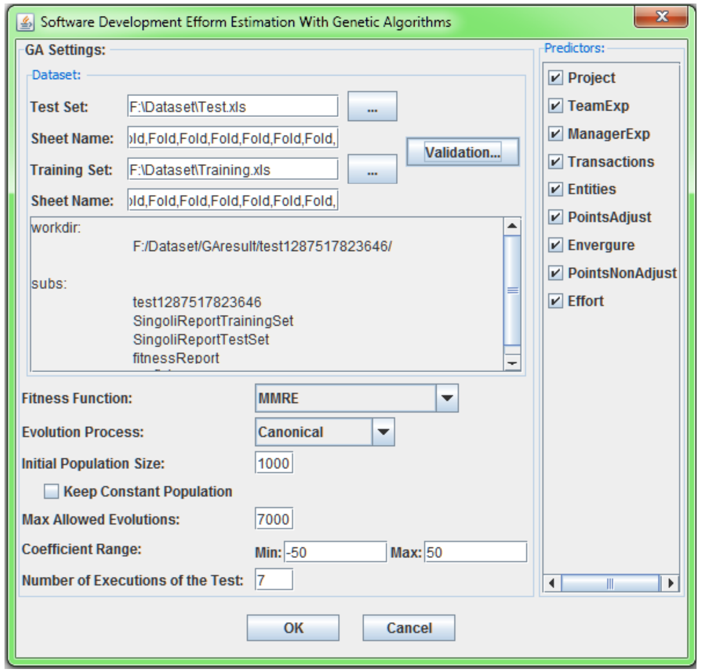
Empirical Study: Results

Table 4. Results of Wilcoxon Test

	Dataset	SVR rand	SVR Weka	SVR grid	MSWR	CBR fss	CBR	Median Effort	Mean Effort
Single-Company	Albrecht	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	Desharnais1	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	Desharnais2	Yes (<0.01)	Yes (0.046)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	Desharnais3	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (0.04)	Yes (<0.01)	Yes (<0.01)	Yes (0.012)	Yes (<0.01)
	MaxwellA2	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	MaxwellA3	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (0.015)	Yes (0.012)	Yes (0.018)	Yes (<0.01)	Yes (<0.01)
	MaxwellS2	Yes (0.047)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	MaxwellT1	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	Telecom	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
Cross-Company	China	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	Finnish	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	Kemerer	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	Miyazaki	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	DocProNo	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	DocProYes	Yes (<0.01)	Yes (<0.01)	Yes (0.025)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	Enhancement projects	Yes (0.014)	No (0.065)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	NewProjects	Yes (<0.01)	Yes (0.046)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (0.035)	Yes (<0.01)	Yes (<0.01)
	MetricsYes	Yes (<0.01)	Yes (<0.01)	Yes (0.011)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (0.012)	Yes (<0.01)
	MetricsNo	Yes (<0.01)	Yes (0.013)	No (0.111)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)
	ProImprYes	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	Yes (<0.01)	No (0.344)	Yes (<0.01)	Yes (<0.01)
	ProImprNo	Yes (<0.01)	Yes (<0.01)	Yes (0.012)	Yes (<0.01)	Yes (<0.01)	Yes (0.027)	Yes (<0.01)	Yes (<0.01)

From a Project Manager point of view....

- A Java tool has been realized to easily use the proposed search-based approaches
- A Project Manager interested in predicting effort has to
    1. Feed the tool with a CSV file, containing the historical data
    2. Feed the tool with a CSV file, containing the data about the new project
    3. Choose the preferred evaluation criterion
    4. Get the estimates



Conclusions

- SB approaches represent flexible methods that allow project managers to identify their preferred evaluation criterion
  - a manager has to be aware that the objective function choice influences the performance of the models built with GP (TS)
  - setting can be done by considering the number of feature of the datasets
- Hybridization (i.e., SB approaches + existing effort estimation techniques) provided very promising results
  - TS is effective for configuring SVR in estimating development effort allowing us to obtain
    - an automatic choice of the parameters required to run SVR
    - a significant improvement on prediction accuracy respect to several other widely used estimation techniques

Questions?

Thanks for your attention

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1. A. Corazza, S. Di Martino, F. Ferrucci, C. Gravino, F. Sarro, E. Mendes, “How Effective is Tabu Search to Configure Support Vector Regression for Effort Estimation?”, in Proceedings of International Conference on Predictor Models in Software Engineering (PROMISE10), ACM Inc, pp. 1-10. (Best Paper Award)
2. A. Corazza, S. Di Martino, F. Ferrucci, C. Gravino, F. Sarro, E. Mendes, “Using Tabu Search to Configure Support Vector Regression for Effort Estimation”, Empirical Software Engineering, doi 10.1007/s10664-011-9187-3.
3. F. Ferrucci, C. Gravino, R. Oliveto, F. Sarro, “Genetic Programming for Effort Estimation: an Analysis of the Impact of Different Fitness Functions”, in Proceedings of 2nd International Symposium on Search Based Software Engineering (SSBSE 2010). IEEE Computer Society, pp. 89-98.
4. F. Ferrucci, C. Gravino, R. Oliveto, F. Sarro, “Genetic Programming for Software Development Effort Estimation”, technical report.
5. F. Ferrucci, C. Gravino, R. Oliveto, F. Sarro, “Using Evolutionary Based Approaches to Estimate Software Development Effort”, in Evolutionary Computation and Optimization Algorithms in Software Engineering: Applications and Techniques, M. Chis (ed.), IGI Global.
6. F. Sarro, F. Ferrucci, C. Gravino, “Single and Multi Objective Genetic Programming for Software Development Effort Estimation”, in Proceedings of the 27th ACM Symposium On Applied Computing (ACM SAC 2012), Software Engineering Track, pp.1221-1226.
7. F. Sarro, "Search-Based Approaches for Software Development Effort Estimation", PROFES 2011 Doctoral Symposium (part of the 12th International Conference on Product-Focused Software Development and Process Improvement), ACM Inc., pp. 38-43.
8. F. Ferrucci, C. Gravino, R. Oliveto, F. Sarro, “Estimating Software Development Effort Using Tabu Search”, in Procs. of 2th International Conference on Enterprise Information Systems (ICEIS 2010), SciTePress, vol.1, pp. 236-241, ISBN: 978-989-8425-04-1.
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10. F. Ferrucci, C. Gravino, R. Oliveto, F. Sarro, “Using Tabu Search to Estimate Software Development Effort", in Procs. of IWSM/MENSURA 2009. LNCS 5891, pp. 307-320.