On the Performance of Multiple Objective Evolutionary Algorithms for Software Architecture Discovery

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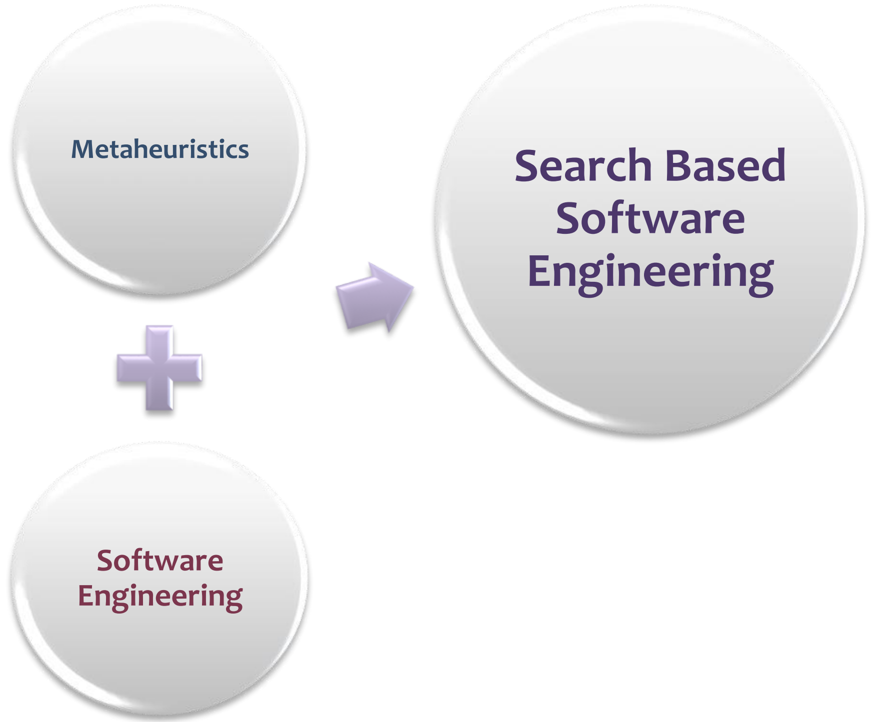
Introduction

- Search Based Software Engineering (SBSE)
  - Apply metaheuristics to Software Engineering tasks
  - All stages of the software development
- More specifically...
  - Design phase
  - Architectural analysis



Introduction

- Software architectures are important design artefacts in the early software conception

- Software architects face to:
  - Multiple functional and, mainly, non functional requirements
  - A wide set of design decisions
  - Discovery of software structures and their interactions

- SBSE can support in design tasks: efficient search of architectural alternatives

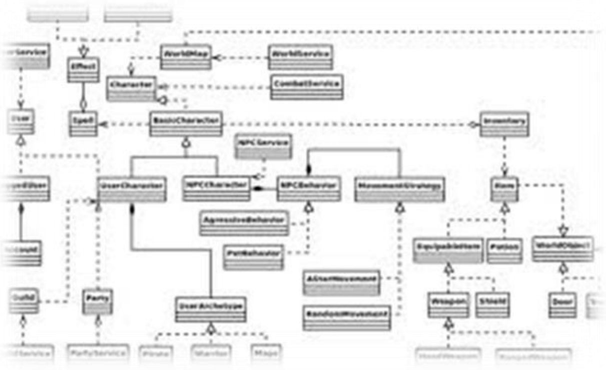
Introduction

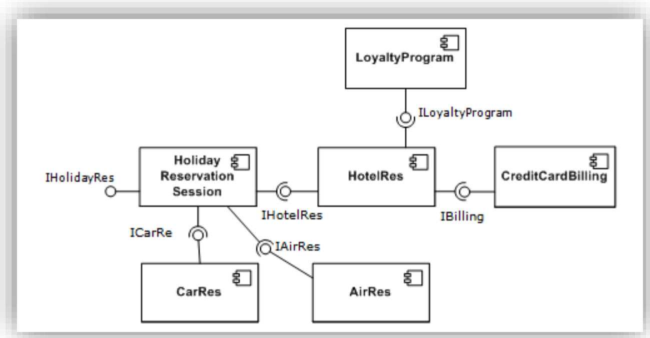
- Multi-objective Evolutionary Algorithms
  - Frequently applied in SBSE
  - Two or three objectives and classical algorithms (SPEA2, NSGA-II)
- Many-objective Evolutionary Algorithms
  - Rarely explored in problem domains like SBSE
  - Interesting alternative for high dimensional search spaces
- Architecture Discovery as a multi/many objective optimization problem
  - Comparative study of multi- and many-objective EAs
  - Scalability analysis: from 2 to 6 objectives
  - Different subsets of objectives related to software design

Evolutionary Discovery of Software Architectures

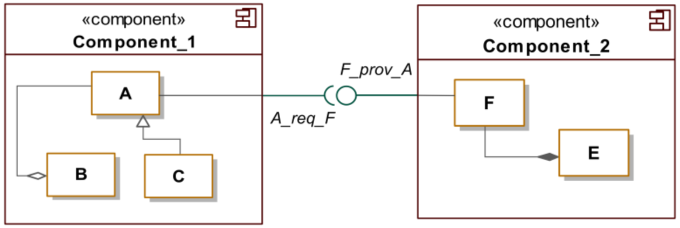
The software design problem

- Component-based software architectures in a nutshell:
  - **Component**: cohesive groups of classes
  - **Interface**: relationships between classes allocated in different components
  - **Connector**: pair of required and provided interfaces
- Focused on non-functional requirements
- Highly combinatorial problem
  - Different architectural styles
  - No prefixed structure

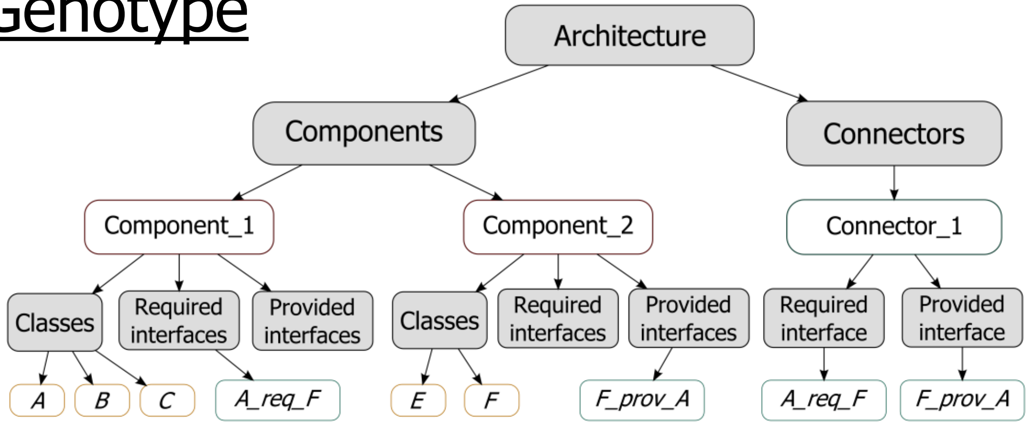




Phenotype



Genotype



Genetic operator

- A roulette-based mutation operator to:
  - Add a component
  - Remove a component
  - Merge two components
  - Split a component
  - Move a class

Initialization and constraints

1. Randomly distribution of classes
   - ✓ No empty components and no replicated classes
2. Set interfaces and connectors
   - ✗ Isolated or mutually dependant components

- The six objectives based on modularity and reusability
  - Intra-modular Coupling Density (ICD)

    $$ICD_i = \frac{CI_i^{in}}{CI_i^{in} + CI_i^{out}} \qquad ICD = \sum_{i=1}^{n} ICD_i$$

  - External Relations Penalty (ERP)

    $$ERP = \sum_{i=1}^{n}\sum_{j=1}^{n}\left[w_{as} \cdot n_{as_{ij}} + w_{ag} \cdot n_{ag_{ij}} + w_{co} \cdot n_{co_{ij}} + w_{ge} \cdot n_{ge_{ij}}\right]$$

  - Encapsulation (Enc)

    $$Enc_i = \frac{\#inner_{classes}}{\#total_{classes}} \qquad Enc = \frac{1}{n} \cdot \sum_{i=1}^{n} Enc_i$$

  - Critical Size (CS)

    $$CC_i = \begin{cases} 1 & if\ \ size(i) > threshold \\ 0 & otherwise \end{cases} \qquad CS = \sum_{i=1}^{n} CC_i$$

  - Instability (Ins)

    $$Ins_i = \frac{EC_i}{EC_i + AC_i} \qquad Ins = \frac{1}{n} \cdot \sum_{i=1}^{n} Ins_i$$

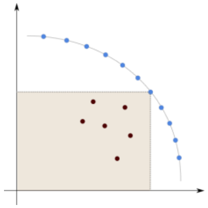
  - Groups/Components Ratio (GCR)

    $$GCR = \frac{\#cgroups}{\#components}$$

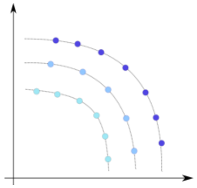
Multi- and many-objective evolutionary algorithms

SPEA2

- Generational algorithm
- Fitness = strength + density
- Binary tournament selection
- Archive with fixed size to store non dominated solutions

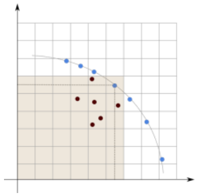


NSGA-II



- Non-dominated sorting
- Selection based on dominance and crowding distance
- Promotes the survival of non dominated solutions

ε-MOEA

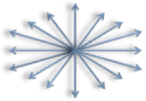


- Steady state algorithm
- Landscape partition in hypercubes
- ε-dominance relation
- Archive of solutions

GrEA

- Inspired by NSGA-II
- Number of divisions as a parameter
- Grid-based metrics for crowding distance and spread of solutions

MOEA/D



- Decomposition approach
- A weight vector for each individual
- Neighborhood information
- Fitness based on a reference point

Experiments and results

Problem instances and set-up

- 6 diverse software designs
- All possible combinations of 2, 4 and 6 objectives per instance
- 30 runs
- Quality indicators:
  - Hypervolume (HV)
  - Spacing (S)
- Friedman and Holm's statistical tests

Problem	*#Class*	*#Relationships*					*#Int*
		As	De	Ag	Co	Ge	
Aqualush	58	69	6	0	0	20	74
Datapro4j	59	3	4	3	2	50	12
Java2HTML	53	20	66	15	0	15	170
JSapar	46	7	33	21	9	19	80
Marvin	32	5	11	22	5	8	28
NekoHTML	47	6	17	15	18	17	46

Common parameters	
Population Size	100, 120, 126
Max. Evaluations	10,000, 15,000, 20,000
Min-Max. Components	2-8
Mutator weights	
	$w_{add} = 0.2, w_{remove} = 0.3, w_{merge} = 0.2$
	$w_{split} = 0.1, w_{move} = 0.2$
ERP metric weights	
	$w_{as} = 1, w_{ag} = 3, w_{co} = 1, w_{ge} = 5$
CS threshold	0.3
SPEA2 parameters	
Parents selector	Binary tournament
External population size	50
k-th neighboor	12
ϵ-MOEA parameters	
ϵ values	
	$\epsilon_{ICD} = 0.25,\ \epsilon_{ERP} = 5,\ \epsilon_{GCR} = 0.1$
	$\epsilon_{CS} = 1,\ \epsilon_{Ins} = 0.05,\ \epsilon_{Enc} = 0.05$
MOEA/D parameters	
Neighboorhood size (τ)	8
Max. Replacements (Nr)	2
H	99,7,4
GrEA parameters	
Number of divisions (div)	12

Experiments and results

From the perspective of the evolutionary performance

2 objectives

- Difficult trade-off between HV and S
- SPEA2 achieves good dispersion of the front
- NSGA-II, ϵ-MOEA and GrEA usually outperform SPEA2 and MOEA/D in HV
- Poor performance of MOEA/D

Objectives	SPEA2		NSGA-II		ϵ-MOEA		MOEA/D		GrEA	
	HV	S	HV	S	HV	S	HV	S	HV	S
ICD-ERP	3.67	2.67	2.58	3.42	**1.50**	**1.33**	*4.67*	*4.67*	2.58	2.92
ICD-GCR	*4.17*	**2.33**	2.75	2.66	2.17	3.67	*4.17*	3.83	**1.75**	2.50
ICD-Ins	*4.17*	**1.50**	*3.25*	2.83	**1.17**	*4.83*	*4.17*	2.33	2.25	3.50
ICD-CS	*4.50*	2.50	*3.25*	3.25	**1.17**	4.08	*3.83*	**2.08**	2.25	3.08
ICD-Enc	*4.17*	**1.33**	2.58	*4.08*	2.17	2.17	*4.17*	2.50	**1.92**	*4.92*
ERP-GCR	**2.83**	**3.00**	3.25	**3.00**	**2.83**	**3.00**	**2.83**	**3.00**	3.25	**3.00**
ERP-Ins	**2.83**	**3.00**	3.25	**3.00**	**2.83**	**3.00**	**2.83**	**3.00**	3.25	**3.00**
ERP-CS	**2.83**	**3.00**	3.25	**3.00**	**2.83**	**3.00**	**2.83**	**3.00**	3.25	**3.00**
ERP-Enc	1.92	**2.00**	**1.67**	2.75	3.50	2.67	3.67	3.50	*4.25*	4.08
GCR-Ins	**2.83**	**3.00**	3.25	**3.00**	**2.83**	**3.00**	**2.83**	**3.00**	3.25	**3.00**
GCR-CS	**2.83**	**3.00**	3.25	**3.00**	2.83	**3.00**	**2.83**	**3.00**	3.25	**3.00**
GCR-Enc	2.75	**1.67**	**1.67**	3.75	3.33	2.00	*4.17*	3.33	3.08	*4.25*
Ins-CS	**2.83**	**3.00**	3.25	**3.00**	**2.83**	**3.00**	**2.83**	**3.00**	3.25	**3.00**
Ins-Enc	3.08	**1.00**	**1.92**	*3.75*	2.92	*3.50*	3.92	2.17	3.17	*4.58*
CS-Enc	2.83	**1.33**	**1.75**	3.17	3.50	*4.08*	*4.33*	2.83	2.58	*3.58*

Algorithms perform similarly for some combinations of objectives (local and global optima)

Experiments and results

From the perspective of the evolutionary performance

4 objectives

Objectives	SPEA2		NSGA-II		ϵ-MOEA		MOEA/D		GrEA	
	HV	S	HV	S	HV	S	HV	S	HV	S
ICD-ERP-GCR-Ins	3.17	*2.33*	1.92	*4.75*	**1.50**	**1.83**	*4.00*	3.67	*4.42*	2.42
ICD-ERP-GCR-CS	*4.00*	*3.00*	2.25	*3.42*	**1.50**	**1.00**	*4.33*	*4.50*	2.92	*3.08*
ICD-ERP-GCR-Enc	3.17	1.83	1.92	*4.08*	**1.50**	**1.17**	*4.00*	*3.67*	*4.42*	*4.25*
ICD-ERP-Ins-CS	*4.33*	2.00	2.58	*4.42*	2.17	**1.00**	4.00	*3.67*	**1.92**	*3.92*
ICD-ERP-Ins-Enc	*4.00*	1.67	2.08	*4.08*	**1.33**	**1.33**	*3.83*	3.33	*3.75*	*4.58*
ICD-ERP-CS-Enc	*4.17*	1.83	2.08	*4.08*	**1.50**	**1.17**	*4.00*	3.00	3.25	*4.92*
ICD-GCR-Ins-CS	*4.17*	2.33	3.08	*4.08*	**1.50**	**1.00**	*4.17*	3.50	2.08	*4.08*
ICD-GCR-Ins-Enc	*4.17*	**1.33**	2.25	*3.75*	**1.17**	1.67	*4.00*	*3.67*	*3.41*	*4.58*
ICD-GCR-CS-Enc	*4.33*	2.00	2.25	*4.08*	**1.67**	**1.33**	*4.00*	3.00	2.75	*4.58*
ICD-Ins-CS-Enc	*4.17*	2.17	2.42	*4.25*	**1.67**	**1.17**	*4.17*	2.67	2.58	*4.75*
ERP-GCR-Ins-CS	**2.83**	**3.00**	3.25	**3.00**	**2.83**	3.00	**2.83**	**3.00**	3.25	**3.00**
ERP-GCR-Ins-Enc	2.33	2.00	**1.67**	*4.58*	3.17	**1.83**	3.08	3.83	*4.75*	2.75
ERP-GCR-CS-Enc	2.00	2.50	**1.75**	*4.58*	3.67	**1.17**	3.00	*3.33*	*4.58*	*3.42*
ERP-Ins-CS-Enc	2.33	2.17	**1.67**	*4.58*	3.33	**1.17**	2.92	*3.50*	*4.75*	*3.58*
GCR-Ins-CS-Enc	3.00	2.67	**1.67**	*3.75*	2.67	**1.00**	2.92	*3.17*	*4.75*	*4.42*

- Multi-objective algorithms decrease their performance
- ϵ-MOEA obtains the best rankings for both indicators

6 objectives

- ϵ-MOEA has significant differences with most of the algorithms (HV) and good spacing values
- SPEA2 maintains a substantial diversity

Objectives	SPEA2		NSGA-II		ϵ-MOEA		MOEA/D		GrEA	
	HV	S	HV	S	HV	S	HV	S	HV	S
ICD-ERP-GCR-Ins-CS-Enc	*3.83*	**1.17**	2.42	*3.58*	**1.33**	1.83	*3.50*	*4.33*	*3.92*	*4.08*

Experiments and results

From the perspective of the decision-maker

- SPEA2
  - 👍 Variety of architectures (types and number)
  - 👎 Low quality solutions
- NSGA-II
  - 👍 Good scalability
  - 👎 Problems with complex instances
- GrEA
  - 👍 Trade-off between metrics
  - 👎 Strong tendency to certain types of solutions
- MOEA/D
  - 👍 Generates more non-dominated solutions
  - 👎 Diversity is not preserved in the external population
- ϵ-MOEA
  - 👍 Good trade-off between high quality and diversity
  - 👍 Low execution time and ability to remove invalid solutions
  - 👎 Some problems with specific combinations of objectives

Experiments and results

From the perspective of the decision-maker

- The selection of metrics has an important influence on the solutions found
  - Number of components comprising the architecture
  - Types of components and interactions

- The trade-off between design criteria
  - Instability and Encapsulation can reach good values in all the problems
  - ERP and GCR tend to complement each other well
  - Critical Size is usually demoted by other metrics
  - ICD is the most difficult metric to optimize

Concluding Remarks

- **Conclusions**
  - A first comparative study of multi- and many-objective evolutionary algorithms in Search-based Software Design
  - Different number and combinations of objectives: close to the reality
  - Strengths and weaknesses of each algorithm from the architect's expectations
- **Future Work**
  - A more in-depth analysis of the most fitting algorithms for dealing with each specific set of architectural requirements
  - To extend the catalogue of metrics and used algorithms

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Thank you!