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Transformed Search Based Software Engineering: A New Paradigm of SBSE

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Outline

- ❑ Roadmap of Search Based Software Engineering
- ❑ Transformed Search Based Software Engineering
- ❑ Search Space Reduction for the NRP
- ❑ Search Space Smoothing for the NRP
- ❑ Related Work

Roadmap of Search Based Software Engineering



1. Problem Transfer

EA

ACO

TS

Challenges:

1. Numerous Local Optimal Solutions

2. Rugged Landscape of Search Space

/Debugging

3. Apply Result



- across all the stages of the software lifecycle

- many search algorithms are employed



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Transformed Search Based Software Engineering



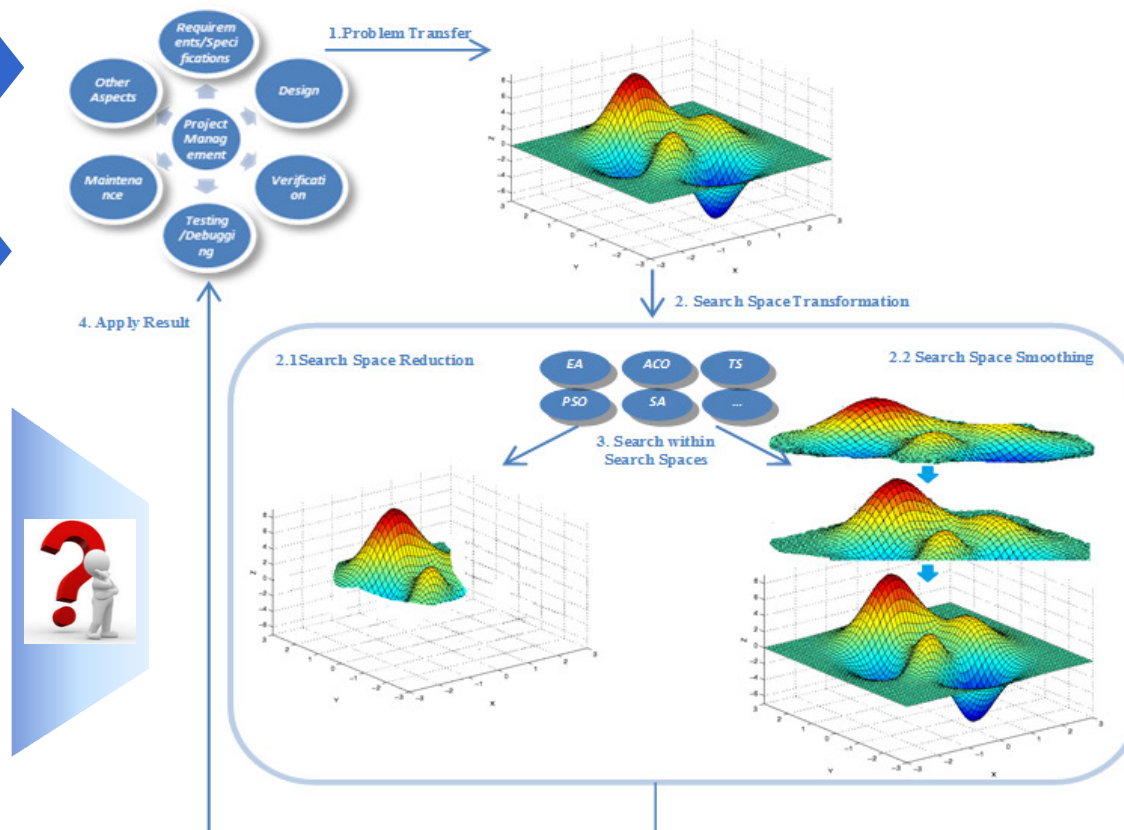
Transformed Search Based Software Engineering (TSBSE): we firstly transform the search space to facilitate the process of searching solutions, by 1) search space reduction 2) search space smoothing. Then search the solution of the SE task on the transformed search space.

Search out of the sea
Search in the pool

Search space reduction
Search space smoothing

1. How to incorporate the search space reduction into SBSE

2. How to apply search space smoothing techniques into SBSE

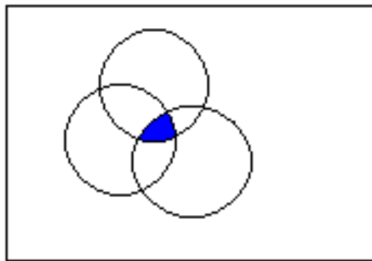


Backbone Based Search Space Reduction

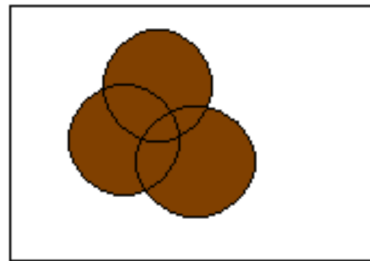


Search space reduction by the backbone

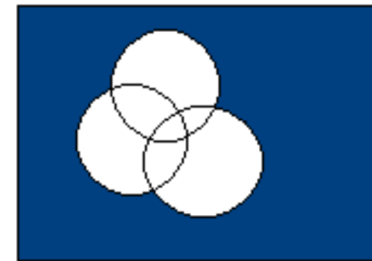
Backbone: the shared common parts of the optimal solutions



backbone



muscle



fat

Related Problems

•Intractability

– Can we achieve backbone within polynomial time?

•Approximating backbone

– How to achieve approximate backbone

•Backbone based reduction

– How to apply (approximate) backbone onto the search space reduction?

Backbone Based Search Space Reduction

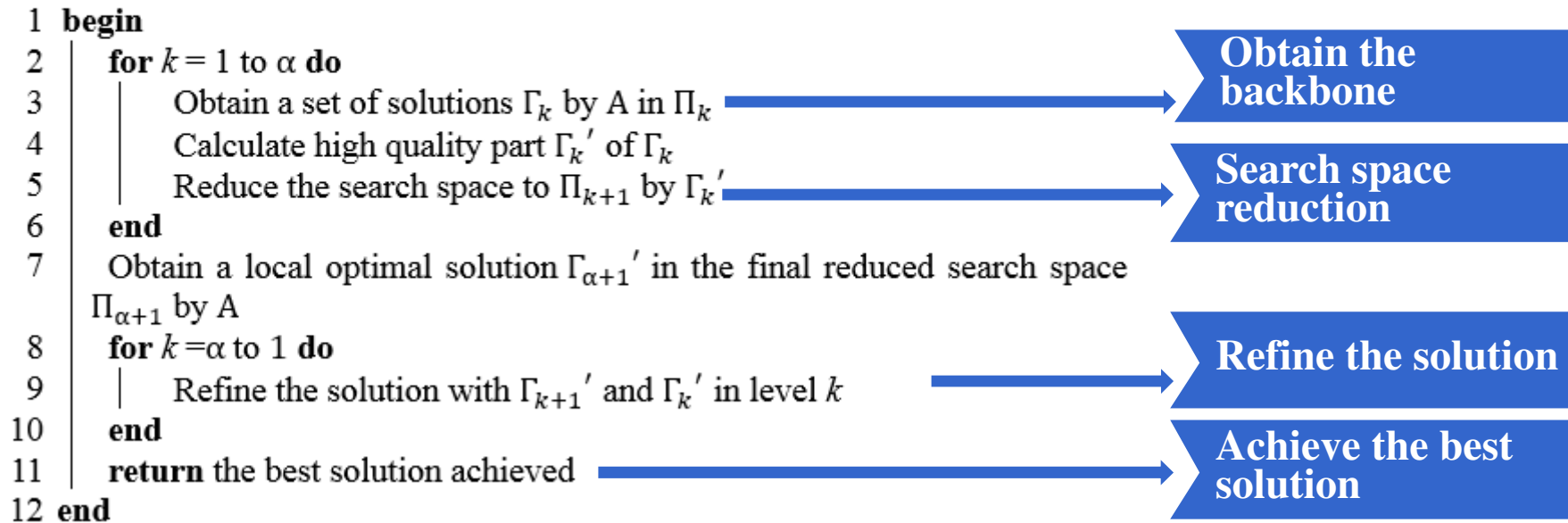


TSBSE: framework for search space reduction

Algorithm 1: Search Space Reduction

Input: search space Π , search algorithms A , maximum number α of reduction levels, a set of solutions Γ

Output: best solution

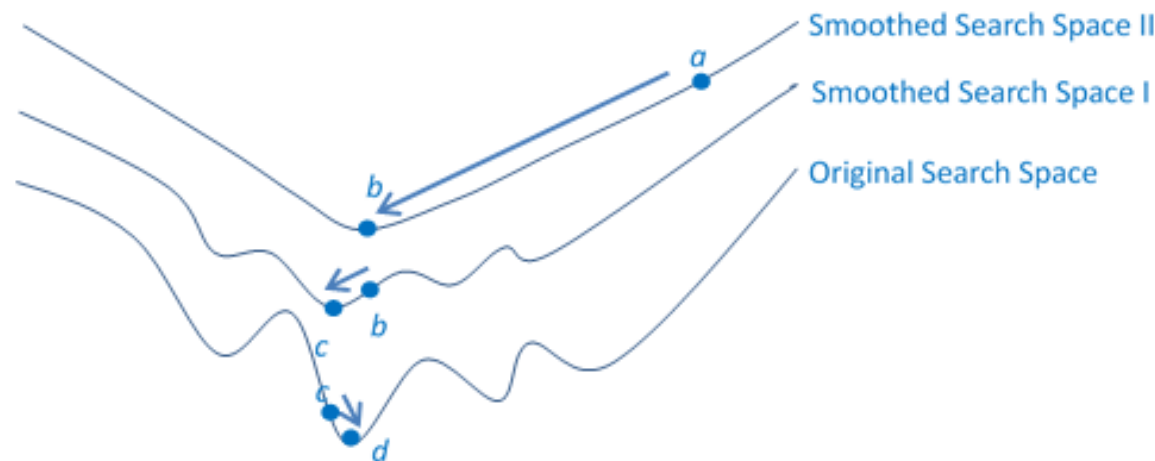


Search Space Smoothing for SBSE



Design search space smoothing techniques for SBSE

Smoothing: normalizing the rugged search space



Related Problems

•Smoothing techniques

–How to design smoothing techniques for SE tasks?

•Time cost

–To balance between time cost and solution quality

Search Space Smoothing for SBSE



TSBSE: framework for search space smoothing

Algorithm 2: Search Space Smoothing

Input: search space Π , search algorithms A , maximum number β of smoothing levels, a set of solutions Γ

Output: best solution

```
1 begin
2   Generate a smoothed search space  $\Pi_0$ 
2   Generate initial solutions  $\Gamma_0$  in  $\Pi_0$ 
3   for  $k = 1$  to  $\beta$  do
4     Tune the search space to  $\Pi_k$ , towards the original, rugged space.
5     Assign the current best solutions  $\Gamma_{k-1}$  as the initial solution
6     Apply  $A$  with  $\Gamma_{k-1}$  in  $\Pi_k$  to get the current best solutions  $\Gamma_k$ 
7   end
8   return the best solution achieved
9 end
```

Generate initial solutions and search space

Smoothing iteratively

Searching

Achieve the best solution



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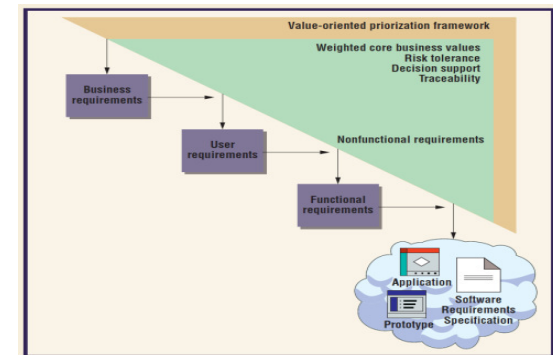
Search Space Reduction for the NRP



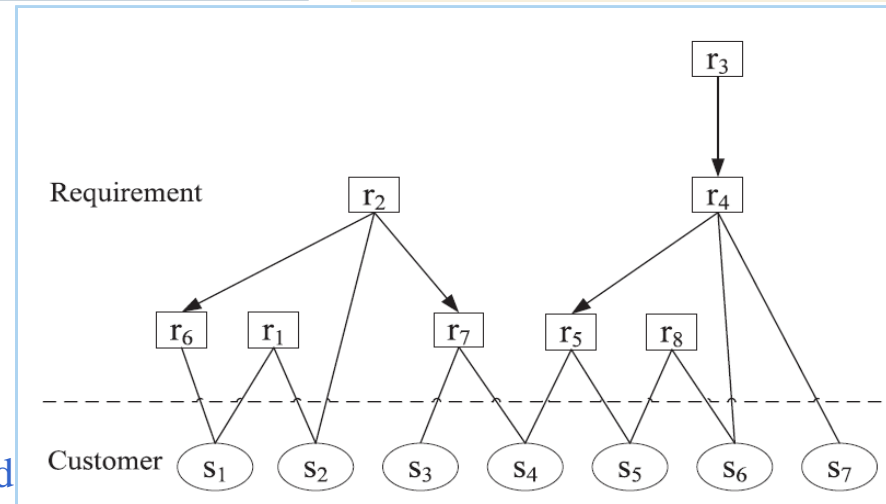
The NRP Problem

Given a directed acyclic requirements dependency graph $G = (R, E)$, each customer $s_i \in S$ directly requests a set of requirements R_i . The profit of s_i is $w_i \in W$ and the cost of requirement $r_j \in R$ is $c_j \in C$. A predefined budget bound is b .

The goal of the NRP is to find an optimal solution X^* , to maximize $\omega(X)$, subject to $\text{cost}(X) \leq b$.



- In the requirements analysis phase
 - ◆ Each requirement need a budget
 - ◆ The candidate requirements may interdependency
 - ◆ Each customer provides a potential profit for the company when being satisfied
- Determine a subset of customers to achieve maximum profits under a predefined budget bound



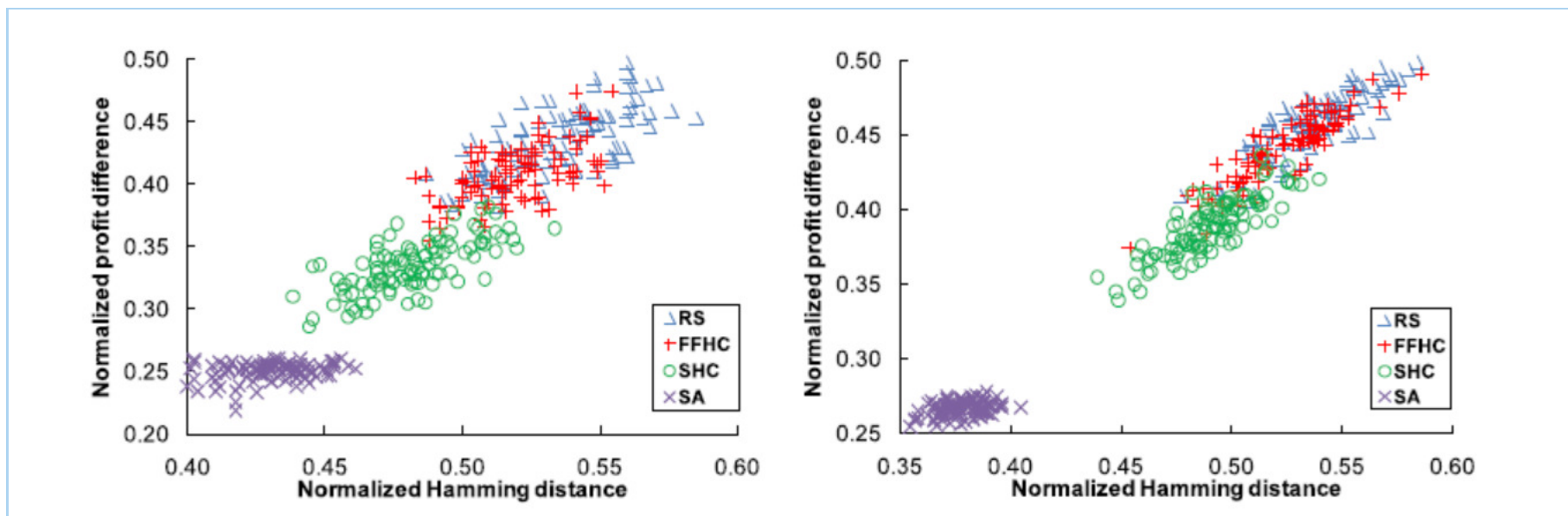
Search Space Reduction for the NRP



The NRP: **time complexity for obtaining the backbone**

It is intractable to obtain the backbone within polynomial time. NP-Hard.

The NRP: **approximate backbone**



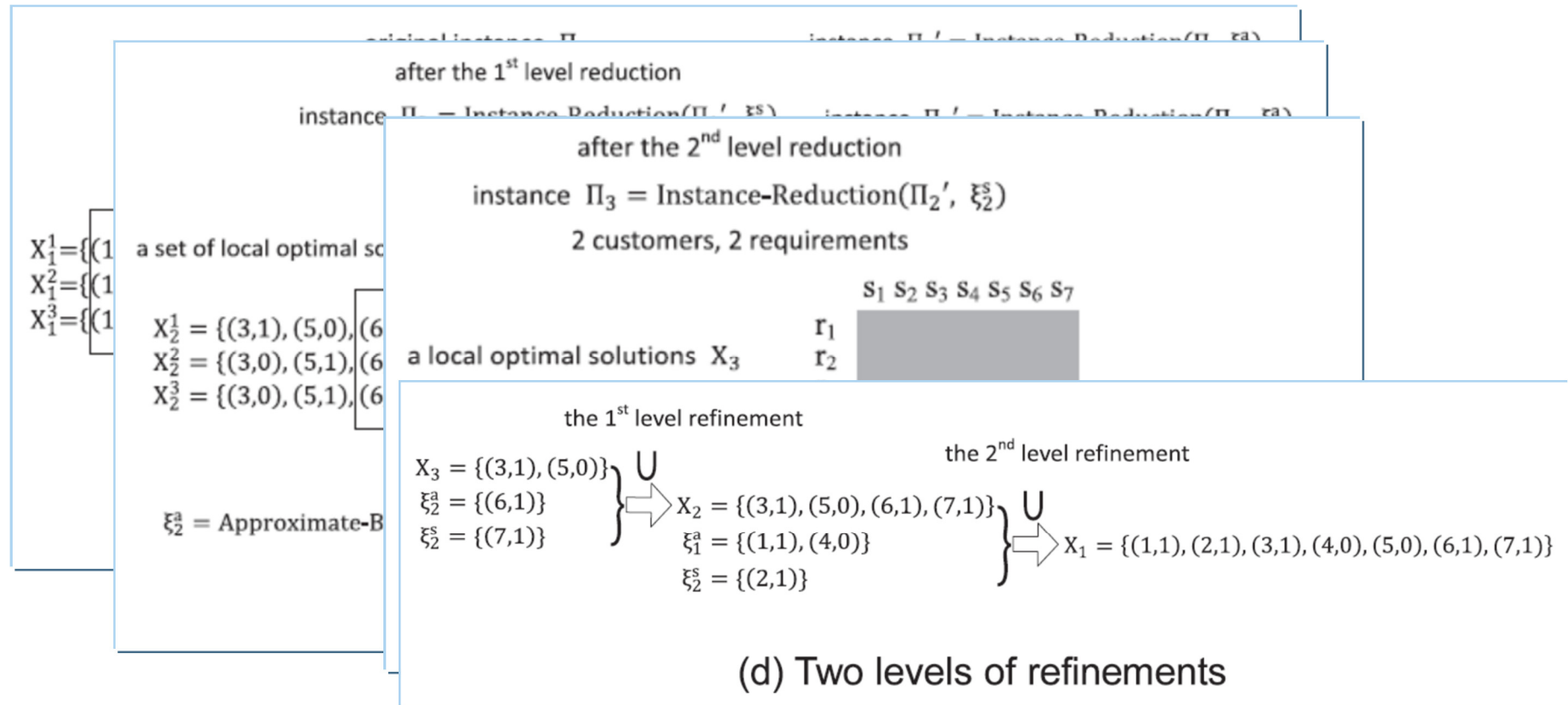
Obtain the approximate backbone from the common part of local optimal solutions.

Xuan, Jifeng, Jiang, He(*), Ren, Zhilei, Luo, zhongxuan, Solving the Large Scale Next Release Problem with a Backbone Based Multilevel Algorithm, IEEE Transactions on Software Engineering, 2012

Search Space Reduction for the NRP



The NRP: backbone based search space reduction



Search Space Reduction for the NRP



The NRP: **backbone based search space reduction**

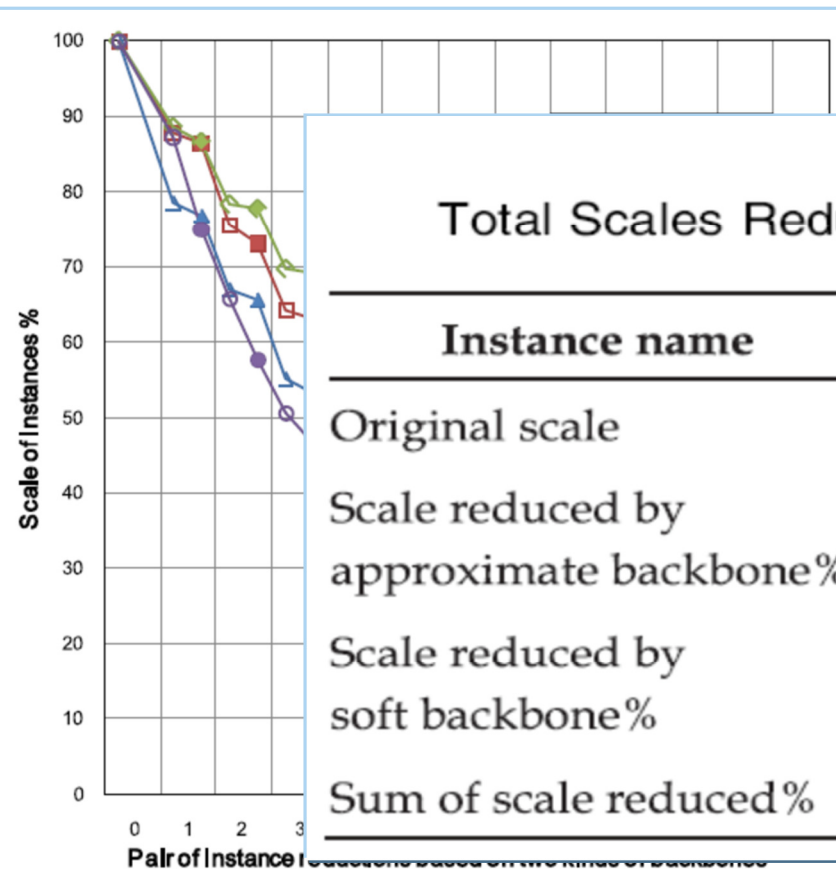


TABLE 4
Total Scales Reduced by 12 Instance Reductions

Instance name	nrp-2-0.5	nrp-3-0.5	nrp-4-0.5	nrp-5-0.5
Original scale	500	500	750	1000
Scale reduced by approximate backbone%	88.4	88.6	79.9	60.8
Scale reduced by soft backbone%	11.2	7.6	7.2	32.4
Sum of scale reduced%	99.6	96.2	87.1	93.2

Xuan, Jifeng, Jiang, He(*), Ren, Zhilei, Luo, zhongxuan, Solving the Large Scale Next Release Problem with a Backbone Based Multilevel Algorithm, IEEE Transactions on Software Engineering, 2012

Search Space Reduction for the NRP



The NRP: backbone based search space reduction

TABLE 8
Performance for MSSA, GA, and BMA on 15 Classic Instances

Instance		MSSA			GA			BMA			MSSA%		Profit distribution %
Name	Bound	Best	Average	Time	Best	Average	Time	Best	Average	Time	MSSA%	GA%	
nrp-1-0.3	257	998	976.5	108.65	1187	1178.1	85.63	1201	1188.3	52.68	21.69	0.87	
nrp-1-0.5	429	1536	1505.2	98.93	1820	1806.1	99.22	1824	1796.2	55.91	19.33	-0.55	
nrp-1-0.7	600	2301	2273.6	91.70	2507	2505.4	79.19	2507	2507.0	34.51	10.27	0.06	
nrp-2-0.3	1514	3220	3158.3	320.76	2794	2737.0	654.23	4726	4605.6	246.14	45.83	68.27	
nrp-2-0.5	2524	5229	5094.1	288.70	5363	5276.4	891.55	7566	7414.1	280.87	45.54	40.51	
nrp-2-0.7	3534	8002	7922.6	255.52	9018	8881.1	911.55	10987	10924.7	277.47	37.89	23.01	
nrp-3-0.3	2661	5147	5088.8	461.21	5851	5719.0	910.99	7123	7086.3	436.90	39.25	23.91	
nrp-3-0.5	4435	8725	8553.4	420.66	9639	9574.2	542.22	10897	10787.2	438.80	26.12	12.67	
nrp-3-0.7	6209	13600	13518.2	489.79	12454	12360.7	265.23	14180	14159.2	215.90	4.74	14.55	
nrp-4-0.3	6648	6797	6708.4	1153.34	6675	6595.7	1849.15	9818	9710.5	854.48	44.75	47.22	
nrp-4-0.5	11081	11355	11120.6	1017.39	12781	12595.4	1587.22	15025	14815.5	907.03	33.23	17.63	
nrp-4-0.7	15513	19077	18830.1	1104.26	17327	17189.9	549.71	20853	20819.7	672.60	10.57	21.12	
nrp-5-0.3	1198	11421	11279.2	502.87	10689	10507.0	3069.26	17200	17026.9	475.85	50.96	62.05	
nrp-5-0.5	1996	17843	17756.6	472.48	18950	18732.9	1696.38	24240	24087.5	459.05	35.65	28.58	
nrp-5-0.7	2794	28347	28232.5	628.25	22174	22026.5	376.57	28909	28894.2	171.70	2.34	31.18	

Xuan, Jifeng, Jiang, He(*), Ren, Zhilei, Luo, zhongxuan, Solving the Large Scale Next Release Problem with a Backbone Based Multilevel Algorithm, IEEE Transactions on Software Engineering, 2012



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Search Space Smoothing for the NRP



The NRP: smoothing techniques

Power law, Reciprocal, Sigmoidal Smoothing, etc.

The NRP: **Power law** .

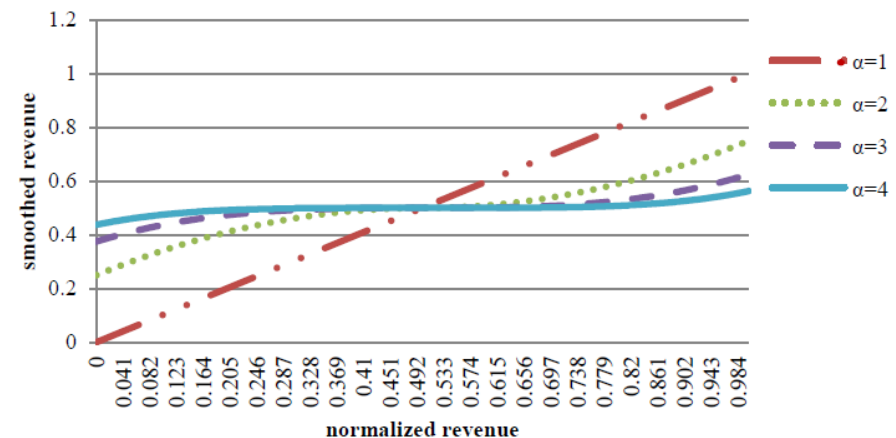
Formula^[1] (Memetic Algo.)

α : the degree of smoothing

$$w_i(\alpha) = \begin{cases} \bar{w} + (w'_i - \bar{w})^\alpha, & w'_i \geq \bar{w} \\ \bar{w} - (\bar{w} - w'_i)^\alpha, & w'_i < \bar{w} \end{cases} \quad (1)$$

■ where

- ◆ w'_i is the profit of customer i
- ◆ \bar{w} is the average profit of all customers
- ◆ α controls the degree of smoothing



Smoothing the rugged search space with α , and optimizing the initial solution

[1] Coy S. P., Golden B. L., Runger G. C., Wasil, E. A.: See the forest before the trees: fine-tuned learning and its application to the traveling salesman problem. IEEE SMCA (2004)

Search Space Smoothing for the NRP

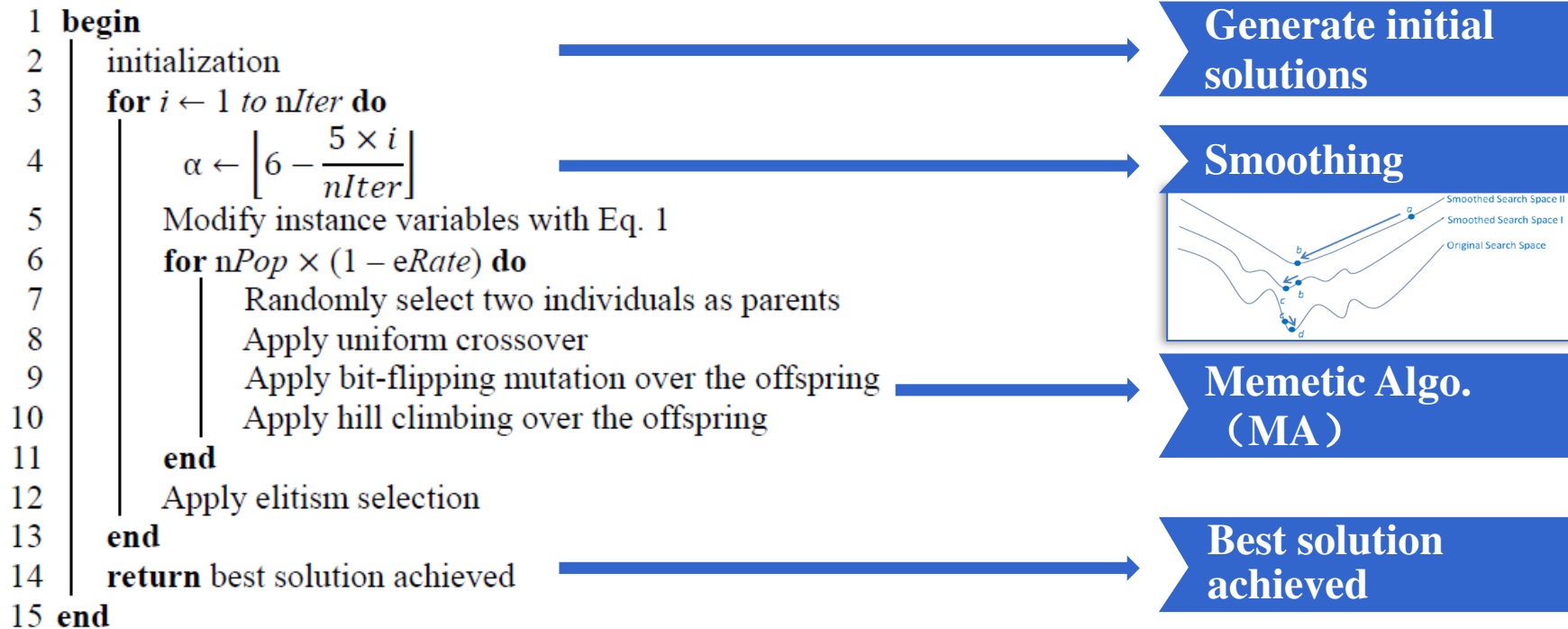


The NRP: search space smoothing for the NRP

Algorithm: Search Space Smoothing based Memetic Algorithm (SSS-MA)

Input: maximum iterator $nIter$, population size $nPop$, elitism rate $eRate$, mutation rate $mRate$

Output: best solution achieved



Search Space Smoothing for the NRP



The NRP: **search space smoothing for the NRP**

•Parameter α

•Small scale instances

•Large scale instances

Results: search space smoothing is effective for the NRP and obtains solutions that are better than the currently best known solutions over 6 instances

Instance	BMA		MA		SSS-MA		
	Best		Average		Best	Average	Time
	Best	Average	Time	Best	Average	Time	
nrp-e1-0.3	7572	7396	7344.5	12.95	7539	7460.8	20.63
nrp-e1-0.5	10664	10607	10555	15.16	10740	10676.3	22.90

Instance	BMA		MA		SSS-MA		
	Best	Average	Time	Best	Average	Time	
nrp1-0.3	1201	1204	1191.1	1.22	1200	1189.2	2.59
nrp1-0.5	1824	1836	1812.8	1.38	1834	1784.2	2.62
nrp1-0.7	2507	2507	2507	1.15	2507	2507	2.42
nrp2-0.3	4726	4007	3927.7	5.57	4365	4179.8	13.53
nrp2-0.5	7566	7034	6840.7	7.16	7353	7202.2	15.79
nrp2-0.7	10987	10585	10419	7.85	10683	10589.5	16.56
nrp3-0.3	7123	6846	6756	7.25	7001	6894.2	14.70
nrp3-0.5	10897	10566	10522.2	7.95	10758	10644.6	15.75
nrp3-0.7	14180	13867	13819.5	7.78	13990	13953	15.58
nrp4-0.3	9818	8950	8841.6	17.96	9164	9003.8	29.72
nrp4-0.5	15025	14609	14457.6	20.22	14794	14613.6	32.95
nrp4-0.7	20853	19996	19906.6	22.60	20205	20117.4	35.76
nrp5-0.3	17200	14873	14564.3	19.33	15417	15165.7	40.68
nrp5-0.5	24240	22409	22204.5	14.95	22785	22616.3	34.89
nrp5-0.7	28909	27494	27283.6	10.41	27854	27761.8	28.75



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Related Work

Jifeng Xuan, He Jiang(*), Yan Hu, Zhilei Ren, Weiqin Zhou, Towards Effective Bug Triage with Software Data Reduction Techniques, IEEE Transactions on Knowledge and Data Engineering, 2015, 27 (1) : 264-280

Zhilei Ren, He Jiang(*), Jifeng Xuan, Yan Hu, Zhongxuan Luo, New Insights Into Diversification of Hyper-Heuristics, IEEE Transactions on Cybernetics, 2014, 44 (10) : 1747-1761

Xuan, Jifeng, Jiang, He(*), Ren, Zhilei, Luo, zhongxuan, Solving the Large Scale Next Release Problem with a Backbone Based Multilevel Algorithm, IEEE Transactions on Software Engineering, 2012, 38(5): 1195-1212

Ren, Zhilei, Jiang, He(*), Xuan, Jifeng, Luo, Zhongxuan, An Accelerated-Limit-Crossing-Based Multilevel Algorithm for the p-Median Problem, IEEE Transactions on Systems, Man, and Cybernetics. Part B-Cybernetics, 2012, 42 (4) : 1187-1202

Xuan, Jifeng¹, Jiang, He¹(*), Ren, Zhilei¹, Zou, Weiqin¹, Developer prioritization in bug repositories, 34th International Conference on Software Engineering, 2012.7.2-2012.7.9

Webstie for TSBSE: oscar-lab.org/stbse/



Conclusion

- **Transformed Search Based Software Engineering (TSBSE) provides a new framework for SBSE, which can be incorporated into existing studies as you like.**
- **Future directions:**
 - **When it works?**
 - **Which one (reduction/smoothing) works better?**



Thanks!

