On the Value of Sampling and Pruning for Search-Based Software Engineering

PhD Defense

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Find this slides at `http://tiny.cc/jcdefense`

Dissertation Statement

For the optimization of search-based software engineering (SBSE) problems,

- *given a proper configuration selector or comparator built upon* ***decision space****,*
- **oversampling-and-pruning (OSAP)** *is better than a standard mutation based* **evolutionary approach (EVOL)***;*
- *where "better" is measured in terms of runtimes, number of evaluations and value of final results.*

Major content in this talk: Four generations of configuration selector/comparator, i.e. OSAP1, OSAP2,...

Publications List

- [ASE Submitted] **Jianfeng Chen** and Tim Menzies. "On the Benefits of Restrained Mutation: Faster Generation of Smaller Test Suites" Submitted to IEEE/ACM International Conference on Automated Software Engineering (ASE 2019).
- [TSE'18] **Jianfeng Chen**, Vivek Nair, Rahul Krishna, and Tim Menzies. ""Sampling" as a Baseline Optimizer for Search-based Software Engineering." IEEE Transactions on Software Engineering (2018).
- [IEEE CLOUD'18] **Jianfeng Chen**, and Tim Menzies. "RIOT: A Stochastic-Based Method for Workflow Scheduling in the Cloud." 2018 IEEE 11th International Conference on Cloud Computing.
- [IST'17] **Jianfeng Chen**, Vivek Nair, and Tim Menzies. "Beyond evolutionary algorithms for search-based software engineering." Information and Software Technology (2017).

* Covered in this talk.

- [FSE Submitted] **Jianfeng Chen**, Joymallya Chakraborty, Philip Clark, Kevin Haverlock, Snehit Cherian and Tim Menzies. "Predicting Breakdowns in Cloud Services (with SPIKE)". Submitted to ESEC/FSE 2019 - Industry Paper Track
- [TSE'19] Junjie Wang, *et al.*. "Characterizing Crowds to Better Optimize Worker Recommendation in Crowdsourced Testing ". IEEE Transactions on Software Engineering(2019).
- [EMSE'18] Tianpei Xia, *et al.*. "Hyperparameter optimization for effort estimation." Empirical Software Engineering (EMSE), 2018
- [MSR'18] Vivek Nair, *et al.*. "Data-Driven Search-based Software Engineering." The Mining Software Repositories (MSR) 2018.
- [SSBSE'16] Vivek Nair, *et al.*. "An (accidental) exploration of alternatives to evolutionary algorithms for sbse." In International Symposium on SBSE, 2016.

Impact on SE community

- 21 citations per year since 2017, according to the google scholar
- Extended by other researchers in software effort estimation.[1]
- Similar insights for space reduction in solving probabilistic constrained simulation optimization problems.[Horng'18] [2]
- and so on

[1] Sarro, Federica et al."Linear programming as a baseline for software effort estimation." ACM transactions on software engineering and methodology (TOSEM) 2018

[2] Horng, Shih-Cheng, and Shieh-Shing Lin. Embedding Ordinal Optimization into Tree-Seed Algorithm for Solving the Probabilistic Constrained Simulation Optimization Problems. Applied Sciences 8.11 (2018)

Feedback from the Oral Prelim Exam

- To answer: why does oversampling work
- When to use oversampling. Difference among developed methods
- To revisit: previous problem + improved method
- To explore: the testing problem
- Identify specific propriety in software engineering models

This talk ...

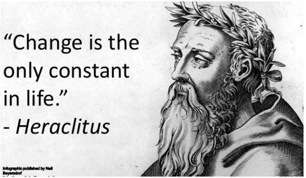
- review previous developed algorithms; analysis on their achievements and limitations
- latest oversampling technique
- revisit the old model and
- explore the testing problem.

Contents of this talk

- **Overview**
  - What is SBSE?
  - Motivation of this research
- **Early generations of OSAP**
  - OSAP1, OSAP2, OSAP3
  - Achievements and Limitations ← Why did they work/not work?
- **Delta-oriented surrogate model embedded OSAP**
  - OSAP4 ← addressing previous limitations
  - Revisiting XOMO & POM3 model ← old problems first
  - Test suite generation ← a more challenging problem
  - Critics on OSAP4
- **Conclusion and future work**

Modeling SE problems

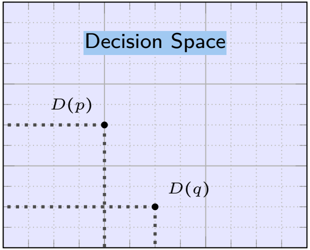
- (Requirement) What feature to include or develop in the project
- (Deployment) How to assign software to cloud environment
- (Test) How to find smaller set of test suite, converging more code

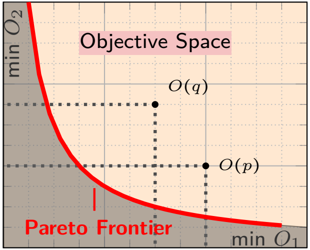


Search-based Software Engineering

- Modeling
- Decision space, objective space
- Search for optimal objective/goal within decision space

Search-based Software Engineering (SBSE)



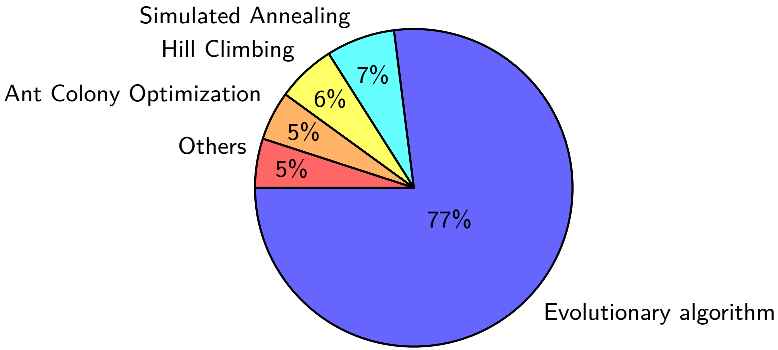


Dominance

p dominance q if and only if

- For every objective, p is no worse than q AND
- Exists at least one objective, p is better than q.

Existing Research



From CREST Center, UCL [3]

[3] [zhang18] A repository and analysis of authors and research articles on search-based Software Engineering.

How does Evolutionary algorithms (EVOL) work?

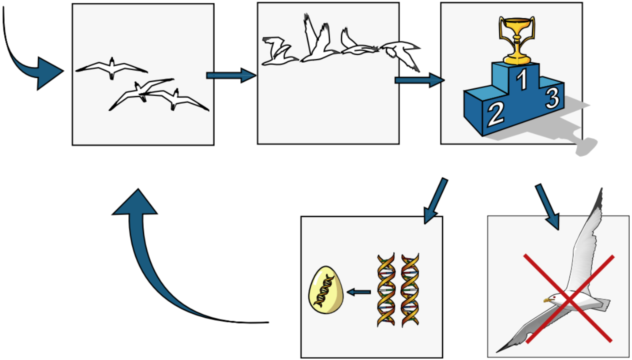


Figure: Framework[4] of the EVOL algorihtms.

[4] Doncieux, Stephane, et al. "The ROBUR project: towards an autonomous flapping-wing animat." Proceedings of the Journes MicroDrones, Toulouse (2004).

Is EVOL good enough?

- ☺ EVOL - Treats the problem as black-box
- ☺ EVOL - Easy to deploy to new problem
- ☹ Evaluates 1000s, 1,000,000s of configurations
  - Airspace operation model verification – 7 days [Krall'14] [5]
  - Test suite generation – weeks [Yoo'12] [6]
  - Software clone evaluation at pc – 15 years [Wang'13] [7]

Need a faster framework!

- Economic considerations – save computing resources
- Faster response to the environment changes
- As a baseline method – judge the problem before exploration
- Opens up a new research direction

[5] Krall, Joseph, Tim Menzies, and Misty Davies. "Learning the task management space of an aircraft approach model." (2014).

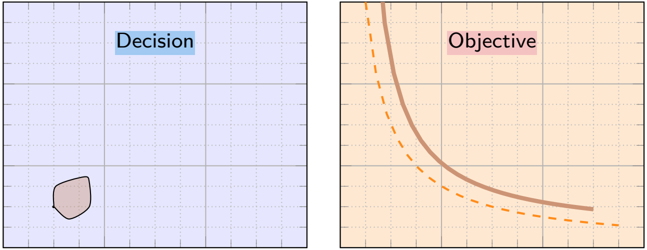
[6] Yoo, Shin, and Mark Harman. "Regression testing minimization, selection and prioritization: a survey." Software Testing, Verification and Reliability

[7] Wang, Tiantian, et al. "Searching for better configurations: a rigorous approach to clone evaluation." Proceedings of the 2013 9th Joint Meeting on Foundations of Software Engineering. ACM, 2013.

Roadmap

1. Overview
2. Early generations of OSAP
   - OSAP1 - Utilizing “golden” region assumption [SSBSE’16, IST’17]
   - OSAP2 - Utilizing the expert or domain knowledge [TSE’18]
   - OSAP3 - The linear surrogate model [Cloud’18]
3. Delta-oriented surrogate model embedded OSAP
4. Conclusion and future work

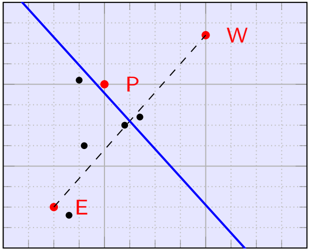
OSAP1 - “Golden” region assumption

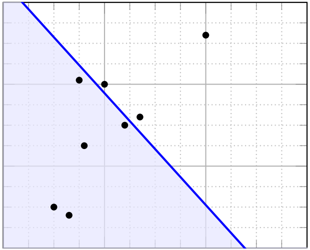


Assumption: A small region in the decision space covers the majority of the near-optimal configurations.

Question: How to figure out such region?
⇒ Similar decisions implies similar objectives

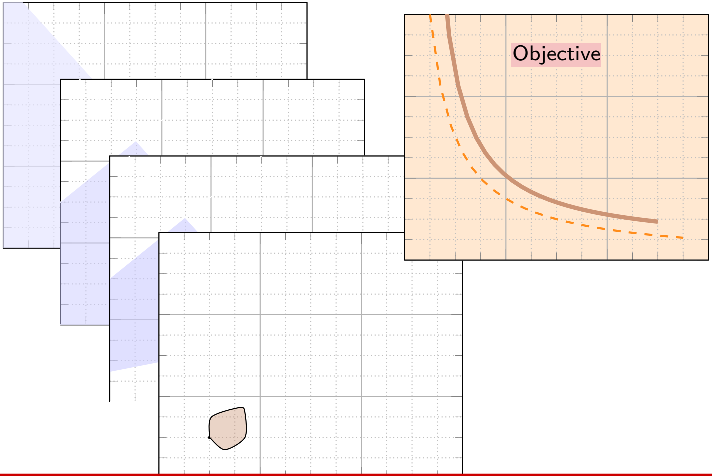
WHERE Geometric Learner





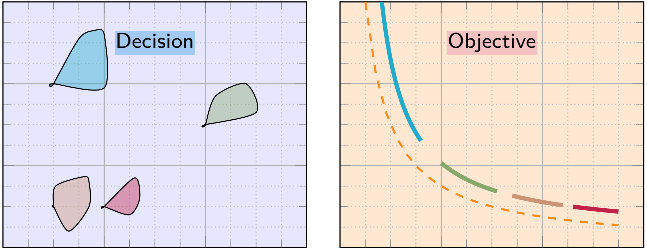
- step 1: get a random configuration, e.g. P
- step 2: find furthest point to P, as E
- step 3: find furthest point to E, as W
- step 4: connect EW. find medium line (hyperplane)
- step 5: compare E and W, select the half-space
- Recursively execute 1 - 5

WHERE Geometric Learner



OSAP2 - Just one "golden" region?

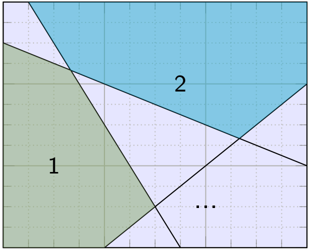
No!

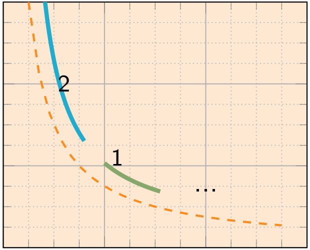


Improvement from OSAP1

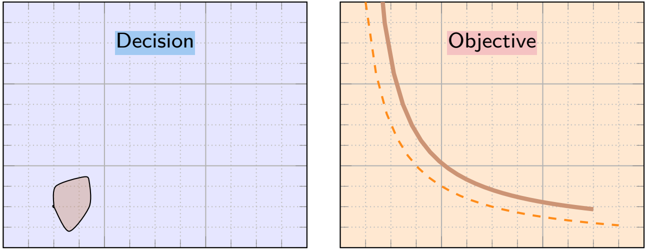
OSAP2: utilize the <u>domain or expert knowledge</u> to get the rough sub-space.

OSAP2 - Divide *with domain knowledge*, and conquer





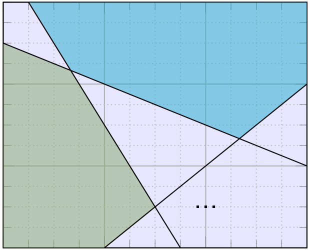
Comments

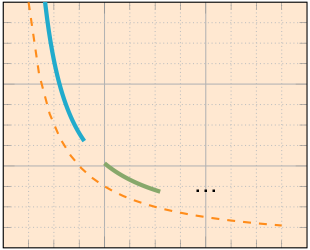


Achievements of OSAP1

- Oversampling can outperform the mutation based EVOL under some circumstances
- An effective geometric learner

Comments





Achievements of OSAP2

- Fixed OSAP1 via doing the decision space partition first, using the domain or expert knowledge
- Tested in two constrainted case studies

Comments

Limitations of OSAP1

- Majority of optimal solutions can be found in one small region
- Similar decisions implies similar objectives

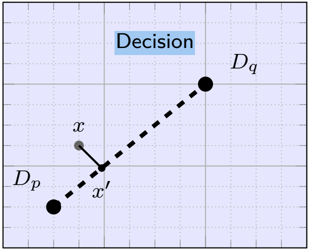
Limitations of OSAP2

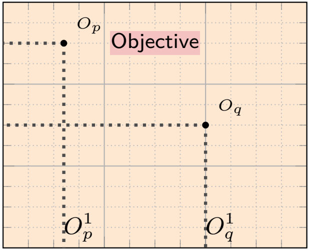
- Majority of optimal solutions can be found in <u>several</u> small regions
- Similar decisions implies similar objectives
- Requires the domain or expert knowledge

OSAP3 - Surrogate model

- ☹ Just figure out one (or more) region in the decision space is not enough
- Expecting: given any configurations, determine which one is better/best
- **Surrogate model:** an alternative model to replace the original SE model.
- Simple. fast.
- Estimating the objective is the most directed way
- If SE model has ≥ 2 objectives, build ≥ 2 surrogate models. (one surrogate for each objective)

OSAP3 - Linear surrogate model





$$\frac{|D_pD_q|}{|D_pD_{x'}|} = \frac{O_p^1 - O_q^1}{O_p^1 - O_x^1} = \frac{O_p^2 - O_q^2}{O_p^2 - O_x^2} = \dots$$

$$O_x^1 = O_p^1 - \frac{|D_pD_{x'}|}{|D_pD_{x'}|}(O_p^1 - O_q^1)$$

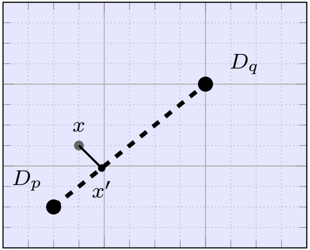
$$O_x^2 = O_p^2 - \frac{|D_pD_{x'}|}{|D_pD_{x'}|}(O_p^2 - O_q^2)$$

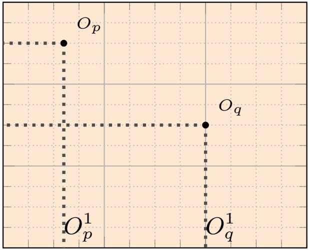
OSAP3 - Utilizing the linear surrogate model

- Need a few ≈ 100 evaluated configurations (anchors)
- Three ways to assign the anchors: 1) random , 2) diagonal, 3) 1+2
- Given evaluated anchors, estimate over $10,000$ other configurations via surrogate models.
- How to select the p and q? Nearest and furthest anchors

Anchors $\leftarrow n$ evaluated items;
Randoms $\leftarrow N \gg n$ un-evaluated items;
foreach $c \in$ *Randoms* **do**
    $A_n \leftarrow$ configurations in *Anchors* that nearest to c;
    $A_f \leftarrow$ configurations in *Anchors* that furthest to c;
    foreach $o \in \{o_1, o_2, ...\}$ **do**
        Accessing o_c using surrogate model;
Collect all items and return all frontiers;

Recap





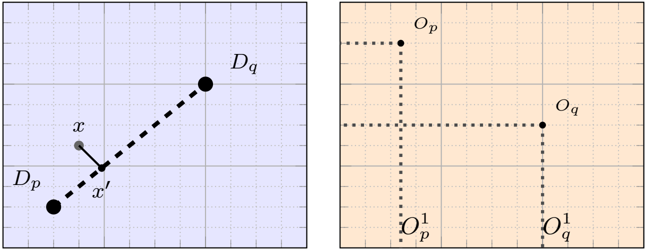
$$O_x^1 = O_p^1 - \frac{|D_p D_{x'}|}{|D_p D_{x'}|}(O_p^1 - O_q^1)$$

$$O_x^2 = O_p^2 - \frac{|D_p D_{x'}|}{|D_p D_{x'}|}(O_p^2 - O_q^2)$$

Achievements of OSAP3

- Replacing previous geometric learners by surrogate model
- Given a small number of configurations evaluated, any configurations' objectives can get estimated
- Successfully found the deployment plan for complex workflows

Recap



$$O_x^1 = O_p^1 - \frac{|D_p D_{x'}|}{|D_p D_{x'}|}(O_p^1 - O_q^1)$$

$$O_x^2 = O_p^2 - \frac{|D_p D_{x'}|}{|D_p D_{x'}|}(O_p^2 - O_q^2)$$

Limitations of OSAP3

OSAP3 is highly replied on the linear surrogate model.

What if the SE does not have linearity kernel, or the linearity inside is weak?

Roadmap

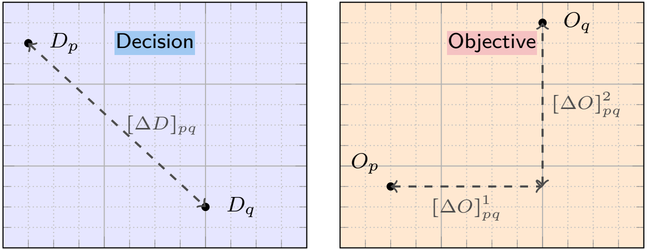
On the surrogate model...

- Ultimate purpose of the surrogate model is to compare or select the better configurations.
- The OSAP3 surrogate model was design to predict the objectives precisely
- Having the objectives, we can do comparisons
- For the purpose of configuration comparisons, is "predicting the objectives" a must?

Delta-oriented surrogate model

- Given any two configurations p, q, predict $[\Delta O]_{pq}$, i.e. $(O_p - O_q)$.
- Predict the $[\Delta O]_{pq}$ from $[\Delta D]_{pq}$ *(again, one predictor for each objective)*
- $[\Delta O]_{pq}$ need not be precise. **Correct sign is good enough.** $(\mathbf{O_p} <_? \mathbf{O_q})$

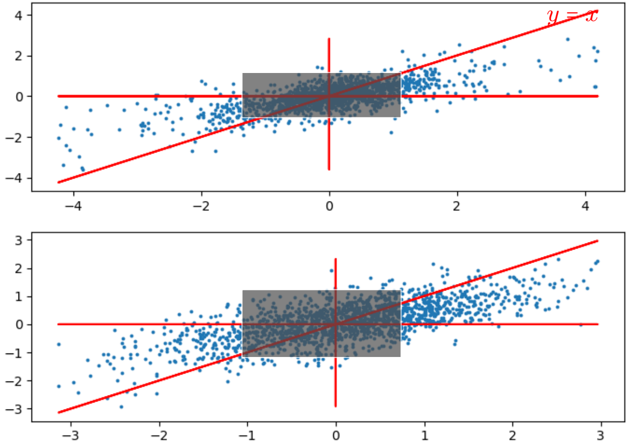
Delta-oriented surrogate model



$[\mathbf{\Delta D}]$ (vector)	$[\mathbf{\Delta O}]^{\mathbf{1}}$	$[\mathbf{\Delta O}]^{\mathbf{2}}$
(pq) ■ ■ ■ ■ ■	⋆	●
(pr) ■ ■ ■ ■ ■	⋆	●
(uv) ■ ■ ■ ■ ■	⋆	●
...	...	...

We found that **KNN** is a proper ML learner here.

Delta-oriented surrogate model



- Each chart is a actual $[\Delta O]$ vs. predicted $[\Delta O]$
- Quadrant I, III : FILLED
- **Quadrant II, IV: EMPTY**

Delta-oriented surrogate model

Framework of OSAP4

1 *Samples* $\leftarrow$ $(n = 100)$ <u>evaluated</u> items;
2 *PF* $\leftarrow$ pareto frontier in *Samples*;
3 **foreach** $x \in$ *PF* **do**
4   *Neighbors* $\leftarrow$ Configurations near x in decision space;
5   get all $[\Delta D]_{pq}$ and $[\Delta O]^i_{pq}(i = 1, 2, ...)$, where pq are pairs in *Neighbors*;
6   train KNN model to predict $[\Delta O]^i_{pq}$ from $[\Delta D]_{pq}$ (i=1,2,...#of objs);
7     $y \leftarrow$ random configuration;
8   predict $[\Delta O]^i_{xy}$ given $[\Delta D]_{xy}$;
9   If exists i such that $([\Delta O]^i_{xy} \ll 0)$, evaluate y using model;
10   repeat Line 7-9, or Goto 3;
11 Collect all new evaluated configurations, update *Samples*;
12 Goto 2 or Terminate;
13 Return all pareto frontiers achieved;

Roadmap

1. Overview
2. Early generations of OSAP
3. Delta-oriented surrogate model embedded OSAP
   - OSAP4 - Delta-oriented surrogate model [ASE'19*]
   - Case study I: revisit XOMO & POM3
   - Case study II: test suite generation
   - Summary of OSAP4
4. Conclusion and future work

Case study I: revisit XOMO and POM3

Objectives for the XOMO:

- Reduce risk;
- Reduce effort;
- Reduce defects;
- Reduce develop times.

Table: Descriptions of the XOMO decisions.

scale factors (exponentially decrease effort)	prec: have we done this before?
	flex: development flexibility
	resl: any risk resolution activities?
	team: team cohesion
	pmat: process maturity
upper (linearly decrease effort)	acap: analyst capability
	pcap: programmer capability
	pcon: programmer continuity
	aexp: analyst experience
	pexp: programmer experience
	ltex: language and tool experience
	: ...
lower (linearly increase effort)	rely: required reliability
	data: 2nd memory requirements
	cplx: program complexity
	ruse: software reuse
	docu: documentation requirements
	: ...
	stor: main memory requirements
	pvol: platform volatility

Case study I: revisit XOMO and POM3

Objectives for the POM3:

- Increase completion rates,
- Reduce idle rates,
- Reduce overall cost.

Table: List of POM3 decisions.

Decision	Description
Culture	Number (%) of requirements that change.
Criticality	Requirements cost effect for safety critical systems.
Criticality Modifier	Number of (%) teams affected by criticality.
Initial Known	Number of (%) initially known requirements.
Inter-Dependency	Number of (%) requirements that have interdependencies to other teams.
Dynamism	Rate of how often new requirements are made.
Size	Number of base requirements in the project.
Plan	Prioritization Strategy: 0= Cost Ascending; 1= Cost Descending; 2= Value Ascending; 3= Value Descending; 4= $\frac{Cost}{Value}$ Ascending.
Team Size	Number of personnel in each team

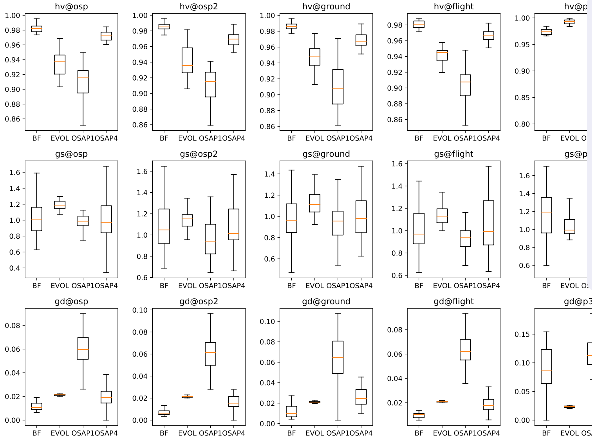
XOMO and POM3

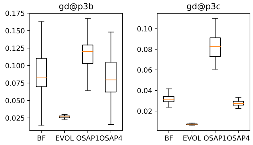
Benchmark scenarios

- XOMO-OSP : NASA flight guidance system
- XOMO-OSP2: Another NASA flight guidance system
- XOMO-Flight: NASA JPL general flight system
- XOMO-Ground: NASA JPL general ground system

- POM3a: A broad space of project
- POM3b: Critical small project
- POM3c: Highly dynamic large projects

Comparing the effectiveness





- BF ("brute force") = randomly sample 10,000 configurations; evaluate all; report the best;
- EVOL = evolutionary algorithms, with hyperparameter tuned
- OSAP1 = previous results, applying WHERE geometric learner
- OSAP4 = using delta-based surrogate model

Comparing the effectiveness (EVOL vs. OSAPs)

	Hypervolume		General Spread		Generated distance	
model	OSAP1	OSAP4	OSAP1	OSAP4	OSAP1	OSAP4
osp	🟢	🟢	🟢	🟢	🔴	🟢
osp2	🔴	🟢	🟢	🟢	🔴	🟢
ground	🔴	🟢	🟢	🟢	🔴	🟢
flight	🔴	🟢	🔴	🟢	🔴	🟢
pom3a	🔴	🟢	🟢	🟢	🔴	🔴
pom3b	🔴	🟢	🔴	🔴	🔴	🟢
pom3c	🔴	🔴	🔴	🟢	🔴	🔴
same+better	1/7	6/7	4/7	6/7	0/7	5/7

- **Hypervolume:** How large the area the obtained PF can covered?
- **General Spread:** Can PF provide enough choices to the users?
- **Generated distance:** How close the obtained PF to the theoretically-PF?

Observations

- In majority cases, OSAP4 is same or better than EVOL methods;
- OSAP1 is no good enough. Look back the digits, it was worse than EVOL by 27% on average.
- *OSAP1 conclusion not consistent with previous?* Following an updated HV/GS/GD calculation guidance [a]

[a] Li, Miqing et al. "A Critical Review of" A Practical Guide to Select Quality Indicators for Assessing Pareto-Based Search Algorithms in Search-Based Software Engineering" 2018 IEEE/ACM 40th International Conference on Software Engineering: New Ideas and Emerging Technologies Results (ICSE-NIER)

Comparing the effectiveness (EVOL vs. BF)

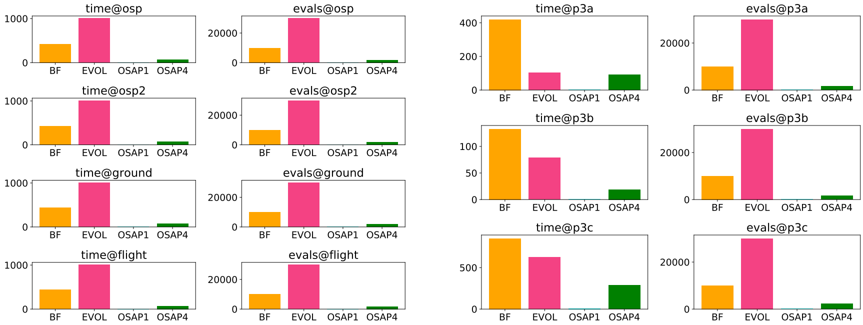
	Hypervolume	General Spread	Generated Distance
model	BF better?	BF better?	BF better?
osp	🟢	🟢	🟢
osp2	🟢	🟢	🟢
ground	🟢	🟢	🟢
flight	🟢	🟢	🟢
pom3a	🔴	🔴	🔴
pom3b	🟢	🟢	🔴
pom3c	🟢	🟢	🟢
better+same	6/7	6/7	5/7

- **Hypervolume:** How large the area the obtained PF can covered?
- **General Spread:** Can PF provide enough choices to the users?
- **Generated distance:** How close the obtained PF to the theoretically-PF?

Observations

- BF is good enough in majority cases
- If time permits, randomly selecting and evaluating large amount of candidates is a good strategy. *Simple! Effective!*
- Is the crossover, mutation in evolutionary algorithms really helpful in SBSE?

Comparing the efficiency (EVOL vs. OSAPs)



- 4 color bars, left to right: BF, EVOL, OSAP1, OSAP4
- Column 1-4: time@XOMOs, eval@XOMOs, time@POM3s, eval@POM3s
- **OSAP1 is always extremely fast.**
- **OSAP4 is frugal.**

Roadmap

Case study II: test suite generation

Get diverse solutions(models) to a 3-SAT problems could be helpful to in software testing.

```
1 int mid(int x, int y, int z) {
2  if (x < y) {
3    if (y < z) return y;
4    else if (x < z) return z;
5    else return x;
6  } else if (x < z) return x;
7  else if (y < z) return z;
8  else return y;
9 }
```

- `path 1: [C1: x < y < z] L2->L3`
- `path 2: [C2: x < z < y] L2->L3->L4`
- `path 3...`

- $\vee C_i$ (Disjunction form, meet any of formula)
- $\Rightarrow \wedge C'_j$ (Conjunction form, meet all formulas)
- Model checking tools transform a program to CNF (conjunctive normal form)
- A valid assignment to **CNF** $\leftrightarrow$ a test case
- A test suite with enough diverse $\leftarrow$ figure out enough amount of valid solutions meet the **CNF**
- NP-Complete – Easy to verify, hard to solve
- Decision space: $2^v (v = \#$ of variables) $\rightarrow$ valid configurations
- Objective space: not really interesting. Enough valid solution to guarantee diversity is more important.

Test suite generation::state-of-the-art[8]

Efficient Sampling of SAT Solutions for Testing

- Introduced by Dutra *et al.* in ICSE 2018
- Open sourced. Compared to former STOA
- Assert to be better than old STOA
- To achieve diversity, generates huge amount samples (> 2 millions)
- New samples fetched from crossover, or some mutations $\sim$ EVOL
- **Limitations:**
  - long execution time ≈ 3 hrs
  - samples are not verified. (may be invalid)
  - too many samples. Hard to test all suite

[8] Dutra, Rafael, et al. "Efficient sampling of SAT solutions for testing." 2018 IEEE/ACM 40th International Conference on Software Engineering (ICSE). IEEE, 2018.

Test suite generation::adapting OSAP4

1. *Samples* ← $(n = 100)$ evaluated items
2. *PF* ← pareto frontier in *Samples*
3. `foreach` $x \in$ PF
   3.1 *Neighbors* ← Configurations near x in decision space
   3.2 train delta-oriented surrogate model
   3.3 y ← random configuration
   3.4 predict $[\Delta O]^{xy}$
   3.5 if desired, evaluate y
   3.6 `repeat from 3.3`, or `Goto 3`
4. Collect all new evaluated configurations, update *Samples*
5. `Goto 2` or `Terminate`
6. `Return` all pareto frontiers achieved

- No PF here: k-means. centers of cluster
- $\Delta D = p \oplus q$, exclusive-or
- Local `neighbors`? To improve diversity, use global pairwise delta from `samples`
- Predict ΔO via ΔD → applying a ΔD to x, is it still valid?
- Surrogate model: answers ⇑
- Learn pairwise ΔD from the valid `samples`. Some ΔD are more common

Test suite generation::adapting OSAP4

1. *Samples* $\leftarrow (n = 100)$ valid items
2. *PF* $\leftarrow$ center of k-means clusters
3. Get the frequency of unique deltas among all pairs in *Samples* as the surrogate model
4. `foreach` $x \in$ PF
   4.1 pick one or more $[\Delta D]$, with high frequency ones in priority
   4.2 verify $x \oplus [\Delta D]$; fix by SAT solvers
   4.3 `repeat from 5.1` or `Goto 5`
5. Collect all valid configurations, update *Samples*
6. `Goto 2` or `Terminate`
7. `Return` all valid samples achieved

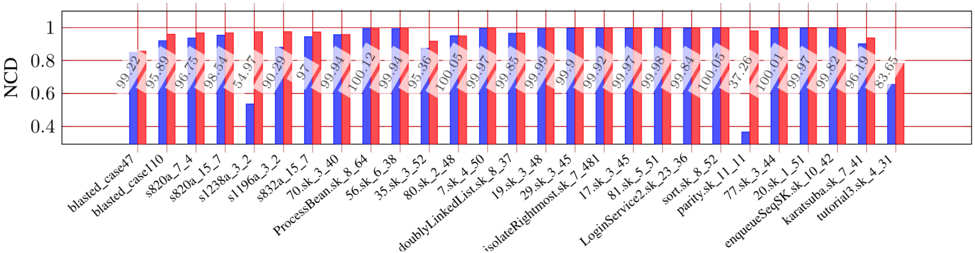
Test suite generation::experiments

Benchmarks	Vars
blasted_case47	118
blasted_case110	287
s820a_7_4	616
s820a_15_7	685
s1238a_3_2	685
...	
35.sk_3_52	4894
80.sk_2_48	4963
7.sk_4_50	6674
doublyLinkedList.sk_8_37	6889
19.sk_3_48	6984
29.sk_3_45	8857
isolateRightmost.sk_7_481	10024
...	
LoginService2.sk_23_36	11510
sort.sk_8_52	12124
...	
enqueueSeqSK.sk_10_42	16465
karatsuba.sk_7_41	19593
tutorial3.sk_4_31	486193

Research questions

- RQ1 - can delta-oriented sampling (OSAP4) return a diverse test suite?
- RQ2 - can OSAP4 return the test suite with less test cases?
- RQ3 - is the sampling procedure fast?

Test suite generation::RQ1 - got enough diversity?



- BLUE: OSAP4. RED: QuickSampler(STOA)
- NCD is the **diversity metrics** for this problem.
- Termination rule: NCD got improved by less than 5% within 10 minutes.
- Except in 2 benchmarks, **OSAP4 achieved more than 95% of the diverse of STOA**.

Test suite generation::RQ2 - less test cases?

Table: Number of unique cases in the test suite.

Benchmarks	OSAP4 O	QuickSampler Q	Q/O
blasted_case47	2799	71	0.00
blasted_case110	174	2386	13.71
s820a_7_4	37363	124457	3.30
80.sk_2_48	553	54440	98.44
...	...	...	...
doublyLinkedList.sk_8_37	178	12042	67.65
19.sk_3_48	104	200	1.90
29.sk_3_45	125	660	5.28
isolateRightmost.sk_7_481	15380	7510	0.49
7.sk_4_50	158	18090	114.49
doublyLinkedList.sk_8_37	178	12042	67.65
...	...	...	...
77.sk_3_44	145	33858	233.50
karatsuba.sk_7_41	39	4210	107.94
tutorial3.sk_4_31	236	2953	12.51

Observations

- Q/O is 91x (in average), 14x (in medium).
- That is, sharing the similar diverse, compared to QuickSampler's, running the test suites from OSAP4 can save $> 90\%$ testing times.

Test suite generation::RQ3 - sampling faster?

Table: Termination time (sorted by speedup)

Model	OSAP4	QuickSampler	Speedup
7.sk_4_50	2.47	1833.04	739.92
17.sk_3_45	2.18	1503.44	687.05
35.sk_3_52	1.85	966.40	520.44
81.sk_5_51	2.06	421.63	204.13
ProcessBean.sk_8_64	115.62	9296.81	80.40
20.sk_1_51	32.63	2595.68	79.54
...			
LoginService2.sk_23_36	75.35	99.3716	1.32
19.sk_3_48	29.84	23.43	0.79
isolateRightmost.sk_7_481	4031.86	1675.66	0.42
s832a_15_7	7193.96	1465.93	0.20
70.sk_3_40	2605.32	288.56	0.11

On average, it is 53X speedup.

Test suite generation::results

Summary

Comparing to the state-of-the-art QuickSampler, in majority benchmarks, the OSAP4

- finds test suite with similar diversity
- returns the test suite with much less cases
- terminates in much shorted time

Recap

Achievements of OSAP4

- No linearity dependence. Learning or transferring the deltas
- The learning model is not necessary to be accurate
- The initial sample size can be smaller than previous versions of OSAP

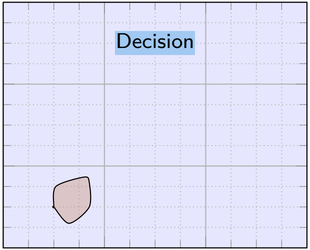
Limitations of OSAP4

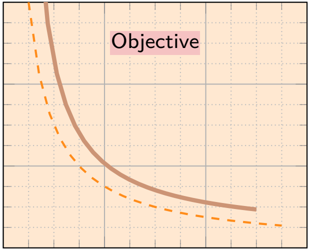
- More model evaluations than previous versions *(more uncertainty)*
- Other surrogate model kernel (in addition to KNN, or the frequency) needs to be explored
- Local monotonic?

Roadmap

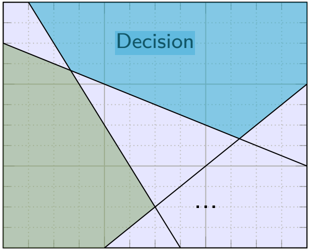
1. Overview
2. Early generations of OSAP
3. Delta-oriented surrogate model embedded OSAP
4. Conclusion and future work
   - Reviewing OSAP
   - Executive summary
   - Future work

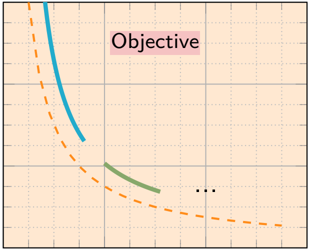
OSAP1



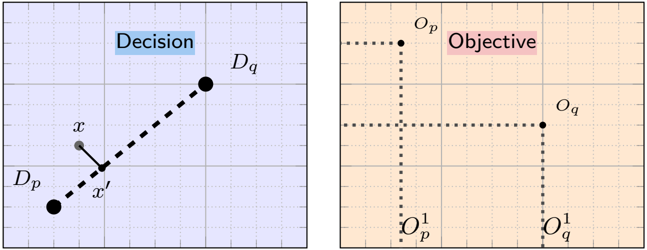


OSAP2



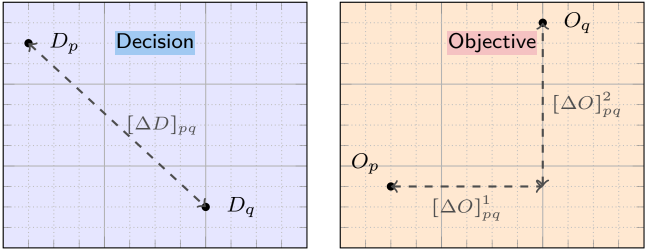


OSAP3



$$O_x^1 = O_p^1 - \frac{|D_pD_{x'}|}{|D_pD_{x'}|}(O_p^1 - O_q^1)$$

OSAP4



$[\mathbf{\Delta D}]$ (vector)	$[\mathbf{\Delta O}]^1$	$[\mathbf{\Delta O}]^2$
(pq) ■ ■ ■ ■ ■	⋆	•
(pr) ■ ■ ■ ■ ■	⋆	•
(uv) ■ ■ ■ ■ ■	⋆	•
...	...	...

OSAP generations

Gen	Assuming	Decision space	Objective space	Study cases	Constraint exists	Surrogate model
I	A "golden" region	numeric	numeric	XOMO POM3	✗	✗
II	n "golden" regions	boolean, discrete	numeric	SPL NRP	✓	✗
III	Linearity of the model	discrete	numeric	Workflow	✗	✓
IV	Local monotonic	numeric, discrete	numeric	XOMO POM3 Testing	✓	✓

Executive summary

- Try OSAP before the EVOL
- Always OSAP1 first. Simple, fast! Can use that as baseline method
- For the constraint model, which is not easy to get large amount of samples, OSAP4 could be helpful. (N samples can get $O(N^2)$ deltas)
- If the model is known to have some linearity features, OSAP3 is a good choice.
- "No free lunch theorem" [9]. No simple optimizer is the best for all problems.

[9] Wolpert, et al. "No free lunch theorems for optimization." IEEE transactions on evolutionary computation 1.1 (1997): 67-82.

Future work

- **Ensemble Learning** • random forest • hyperparameter tuning • ...
- **Incremental Sampling** • regression testing • dynamic cloud deployment • ...
- **More on the constraint models** • weighted sampling and counting[10] • AI applications• ...
- **Not just SBSE** • boosting stochastic gradient descent • feature reduction • ...

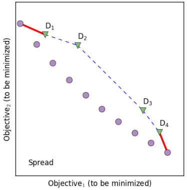
[10] Chakraborty, Supratik, et al. "Distribution-aware sampling and weighted model counting for SAT." Twenty-Eighth AAAI Conference on Artificial Intelligence. 2014.

Questions?

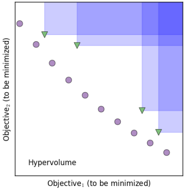
Backup slides

XOMO and POM3::Metrics

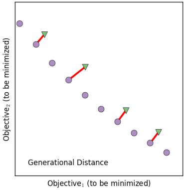
How to measure the results? What is a good pareto frontier?



Generated Spread (GS)



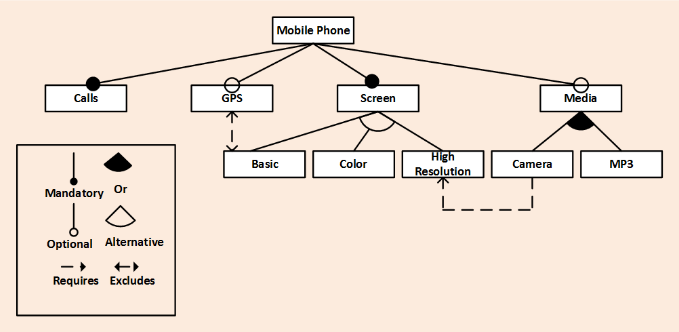
Hypervolume (HV)



Generational istance (GD)

GS, GD: Less is better
HV: Higher is better

Case study *(review)*: Software Product Line



- Constrained model. Initial configurations given from SAT solver.
- Divided via the number of features → small?, medium product? ...
- OSAP2 is **effective, and fast**, compared to [Henard'15] [11]

[11] Henard, Christopher, et al. "Combining multi-objective search and constraint solving for configuring large software product lines." Software Engineering (ICSE), 2015

Case study *(review)*: Next Release Problem

- Which requirements should be implemented for the next version?
- Subject to: customer satisfaction, budget, precedence constraints
- Objective: higher customer satisfaction + less development time + less cost

- Group (divide) the configurations via $WL(\mathbf{y}) = ||\{y_i < P/2\}||$
- i.e. how many features are scheduled in the first half of the plan
- Compared to the EVOL, OSAP2 was **effective and fast**.

Case study *(review)*: Workflow deployment

- A workflow is the combination of sub computing tasks
- Expressed as directed acyclic graph (DAG)
- For each task, what's the best AWS EC2 instance?
- Two objectives to minimize
  1. Time to complete the whole workflow
  2. $$$ spending
- More than 50 AWS EC2 types. (8 adopted in experiment)
- Experiment outputs:
  - (Efficiency) OSAP3 was 11 to 39 times faster than a state-of-the-art approach (EVOL based).
  - (Effectiveness) In the five largest workflows, OSAP3's results were better among 13/15 (87%) of all the quality indicators.