A Baseline Method for Search-Based Software Engineering

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Search-Based Software Engineering

- Many issues of the software engineering field remain unresolved.
  - Scope (i.e. entire Java language, etc) makes many questions unanswerable.
- SBSE reformulates SE problems as search problems. [Harman '01]
- Great for problems with no *single* solution, instead a bunch of *good* ones.
- Great for finding an ideal *balance* of competing factors.

We Need a Baseline

- Many common, almost ubiquitous techniques, with thousands of different implementations and tweaks.
- Things like Random Search often used as a "sanity check," but…
  - Straw man – "In any problem worthy of study, the chosen technique should be able to convincingly outperform random search." [Harman '10]
- We need a standard baseline technique with a single implementation, simple concept.
- Gives a common method of comparison, a "quality bar," **lets us live up to the PROMISE mantra.**
  - "Repeatable, improvable, maybe even refutable research"

What Makes a Baseline

- Holte's 1R algorithm had factors that made it a good baseline for classification research: [Holte '93]
  - **Simplicity:** 1R is easy to understand, and easy to implement.
  - **Competitive Results:** It produces results within 5% of the C4.5.
  - **Stable Results:** Produced consistent outcomes for each trial on the same data set.
  - **Fast Runtimes:** 1R is faster than many competing techniques.
- A baseline **must** meet all four of these factors.
- Not a straw man, but a bar to beat.
- The KEYS2 algorithm meets all of these.

Theory of KEYS

- Theory: A minority of variables control the majority of the search space. [Menzies '07]
- If so, then a search that (a) finds those keys and (b) explores their ranges will rapidly plateau to stable, optimal solutions.

- This is not new: narrows, master-variables, back doors, and feature subset selection all work on the same theory.
  - [Amarel '86, Crawford '94, Kohavi '97, Menzies '03, Williams '03]
- Everyone reports them, but few exploit them!

KEYS2 Algorithm [Jalali ‘08, Gay ‘10]

- Two components: greedy search and a Bayesian ranking method (BORE = “Best or Rest”).
- Each round, a greedy search:
  - Generate 100 potential solutions.
  - Score them.
  - Sort top 10% of scores into “Best” grouping, bottom 90% into “Rest.”
  - Rank individual variable/value pairings using BORE.
  - An increasing number of top ranking pairs are fixed for all subsequent rounds. (1 in Round 1, 2 in Round 2, etc.)
- Stop when every variable has a value, return final fitness score.

BORE Ranking Heuristic

- We don't have to actually search for the keys, just keep frequency counts for "best" and "rest" scores.
- BORE [Clark '05] based on Bayes' theorem. Use those frequency counts to calculate:

$$P(best|E) = \frac{like(best|E)}{like(best|E) + like(rest|E)}$$

- To avoid low-frequency evidence, add support term:

$$P(best|E) * support(best|E) = \frac{like(best|E)^2}{like(best|E) + like(rest|E)}$$

Simulated Annealing

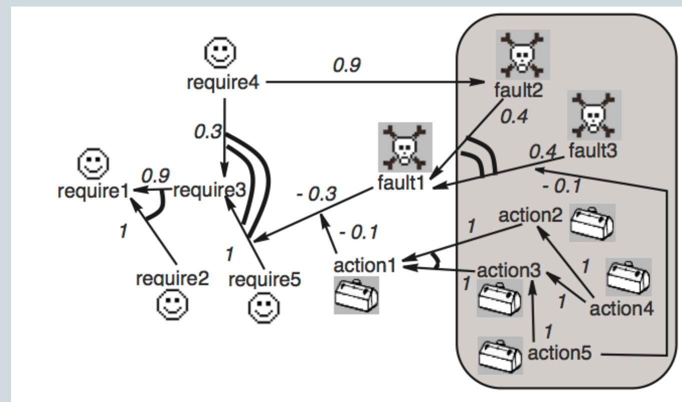
- Classic, yet common, approach. [Kirkpatrick ’83]
- Choose a random starting position.
- Look at a “neighboring” configuration.
  - If it is better, go to it.
  - If not, move based on guidance from probability function (biased by the current temperature).
- Over time, temperature lowers. Wild jumps stabilize to small wiggles.

Genetic Algorithms

- Influenced by Darwin's Theory of Evolution.
  - [Barricelli '54, Holland '75]
- Take a population, mutate over many generations.
- Evaluate each member of the population.
- Combine "best" solutions using mutation and crossover to get the new population (also carry over a few unchanged and generate a few random ones).
- Stop after X rounds, or once a fitness threshold has been met.

Case Study: Consider a requirements model…

- The Defect Detection and Prevention Model
  - Used at NASA JPL by Martin Feather's "Team X" [Cornford '01, Feather '02, Feather '08, Jalali '08]
  - Five models available in PROMISE repository.
- Early-lifecycle requirements model that contains:
  - Various goals of a project.
  - Methods for reaching those goals.
  - Risks that prevent those goals.
  - Mitigations that remove risks.
    - (but carry costs)
  - Directed mappings.



- A solution: balance between cost and attainment.

Using DDP

- Input = Set of enabled mitigations.
- Output = Two values: (Cost, Attainment)

- Those values are normalized and combined into a single score [Jalali '08]:

$$score = \sqrt{\overline{cost}^2 + (\overline{attainment} - 1)^2}$$

DDP Optimization as a SBSE Problem

No single solution, so reformulate as a search problem and find several!

- Four factors must be met: [Harman ’01, Harman ‘04]
  - 1. A large search space.
  - 2. Low computational complexity.
  - 3. Approximate continuity (in the score space).
  - 4. No known optimal solutions.
- DDP Problem fits all:
  - 1. Some models have up to ($2^{99} = 6.33*10^{29}$) possible settings.
  - 2. Calculating the score is fast, algorithms run in $O(N^2)$ [Gay ’10]
  - 3. Discrete variables, but continuous score space.
  - 4. Solutions depend on project settings, optimal not known.

Experiments

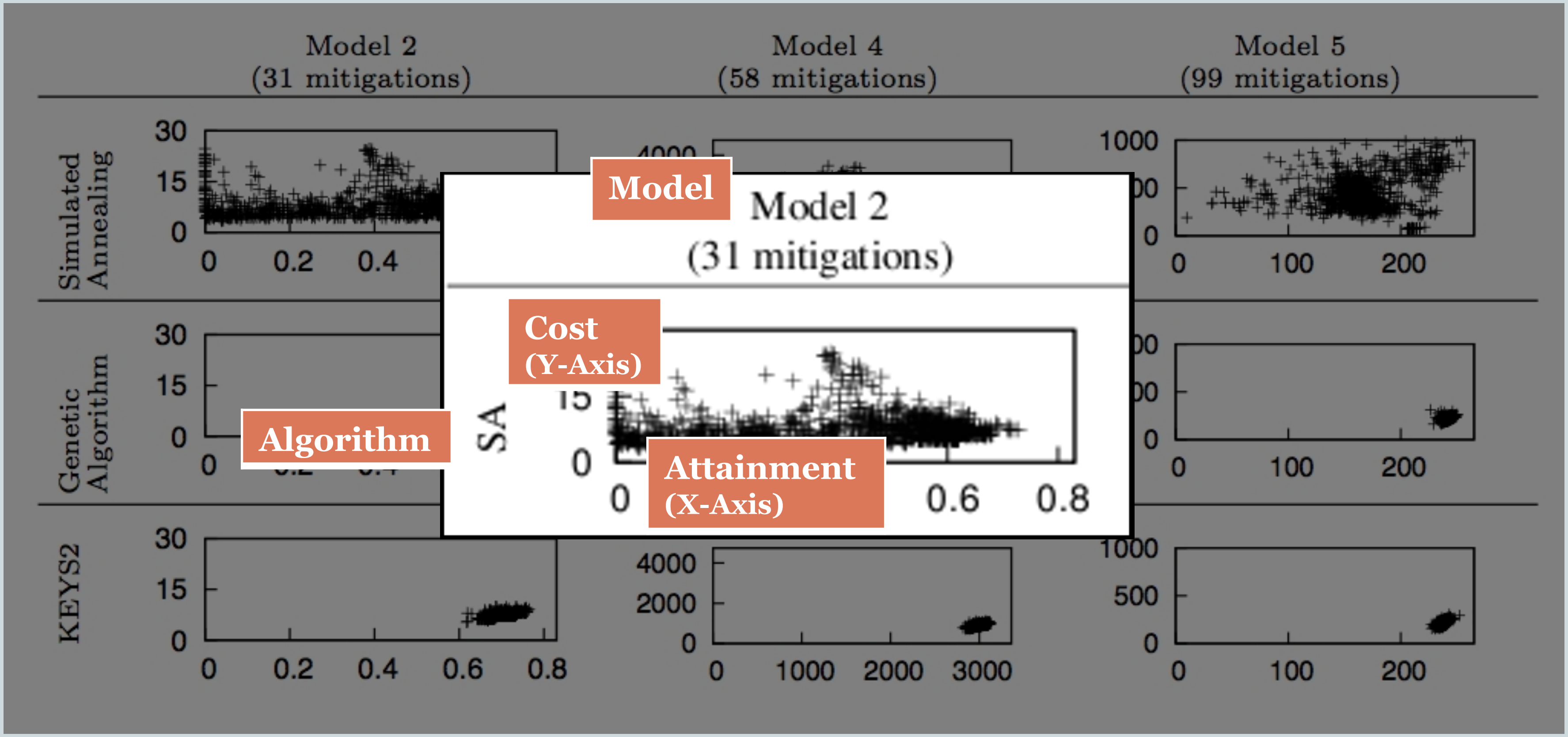
- Four requirements of a baseline:
  - Simple concept, competitive results, low variance, very fast.
- Can't experimentally "prove" that KEYS is simple
- Can qualitatively prove that KEYS2 fits the other three baseline criteria.

Algorithm	Simple	Competitive	Low Variance	Fast
KEYS2	Yes	?	?	?

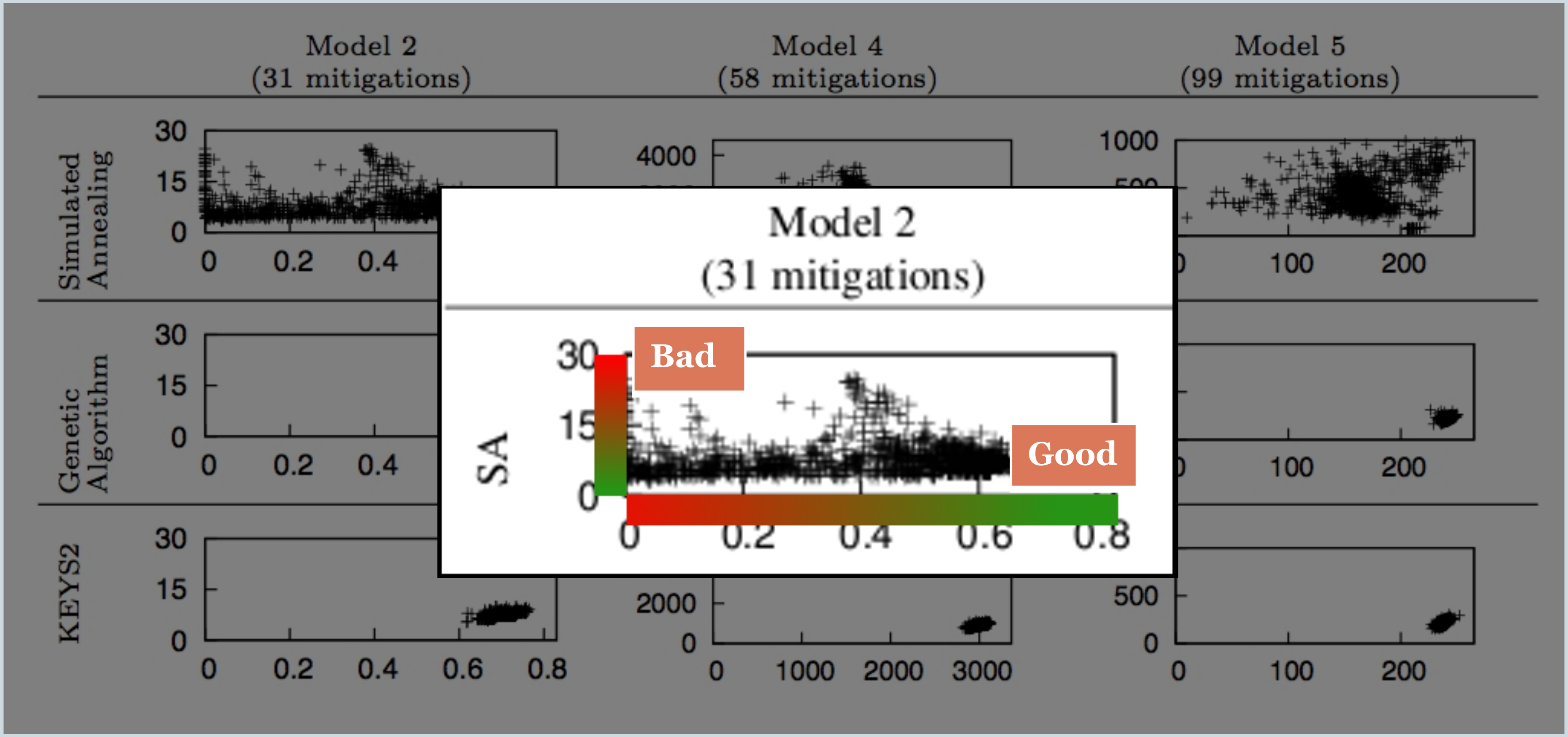
Experiment 1: Result Quality

- Using 3 real-world models (2, 4, and 5 from PROMISE repository).
  - Models discussed in [Feather '02, Jalali '08, Menzies '03]
- Run each algorithm 1000 times per model.
  - Removed outlier problems by generating a lot of data points.
  - Still a small enough number to collect results in a short time span.
- Graph cost and attainment values.
  - Values towards bottom-right better.

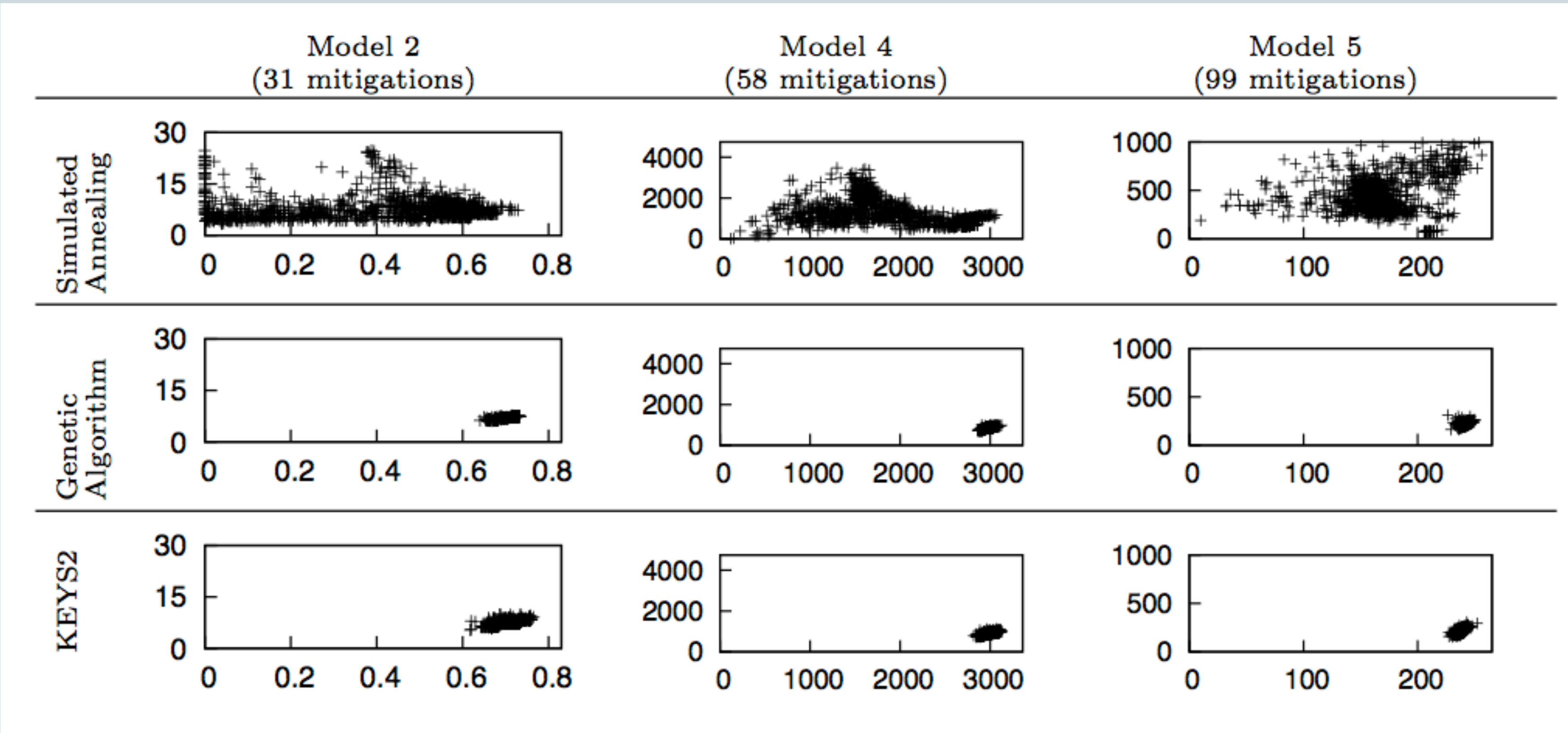
Experiment 1 Results



Experiment 1 Results



Experiment 1 Results



Experiment 1 Results

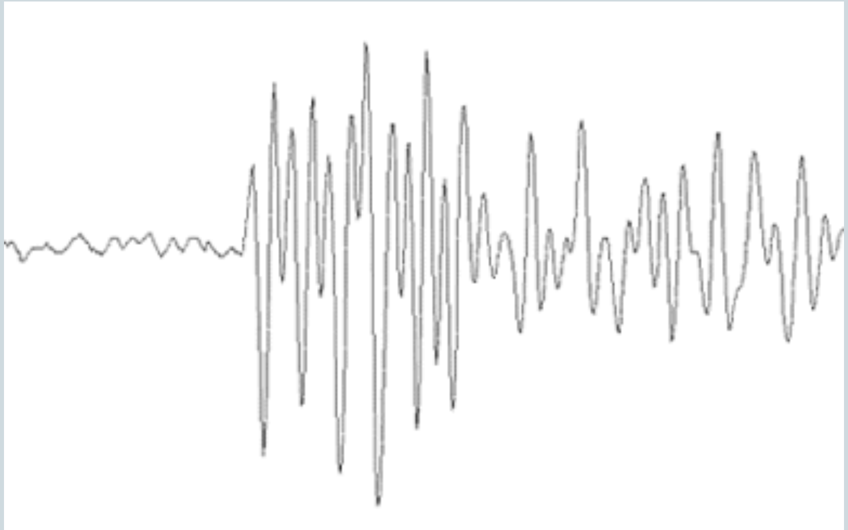
- Simulated Annealing *sometimes* obtains high-quality results.
  - Too much variance, more often gives *bad* results.
- KEYS2 and the GA *always* obtain high quality results.
  - Slightly less variance on the GA, but very similar results.

Algorithm	Wins	Losses	Ties	Wins-Losses
Simulated Annealing	4	8	0	-4
Genetic Algorithm	7	5	0	2
KEYS2	7	5	0	2

Algorithm	Simple	Competitive	Low Variance	Fast
KEYS2	Yes	Yes	?	?

Experiment 2: Stability

- Take the raw results from Experiment 1 for model 5
  - (Model 5 is the most complex model)
- Measure the spread of final cost and attainment values for each algorithm.
- This gives an idea of the level of variance in the final results.



Experiment 2 Results

Cost Quartiles – Model 5

	quartiles				
	min		med		max
	0	25%	50%	75%	100%
SA	163000	239025	248525	709025	1079000
GA	162369	205525	215197	227525	312052
KEYS2	154025	198025	211525	224525	305525

Attainment Quartiles – Model 5

	quartiles				
	min		med		max
	0	25%	50%	75%	100%
SA	46.3	201.1	207.4	217.0	255.2
GA	226.4	239.5	241.3	242.4	249.9
KEYS2	227.3	236.2	237.9	239.4	252.0

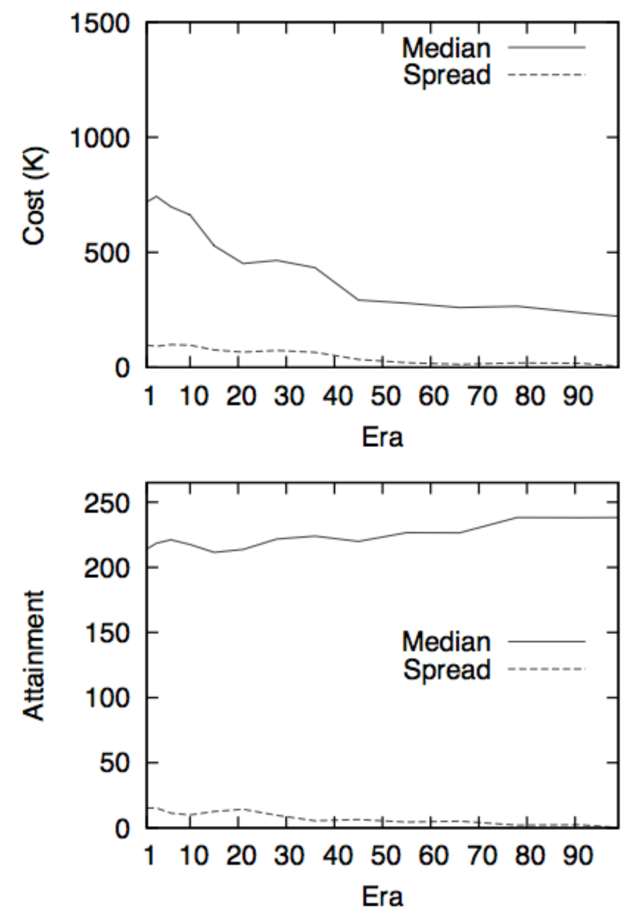
Experiment 2 Results

- Similar results to Experiment 1
  - Simulated Annealing returns seemingly random results, way too much variance.
  - GA and KEYs2 very similar, very stable
    - (GA has a slightly smaller spread of 22000 to 26500 for cost and 2.9 to 3.2 on attainment).

Algorithm	Simple	Competitive	Low Variance	Fast
KEYS2	Yes	Yes	Yes	?

Experiment 2 Results

- KEYS2 also offers guarantee of internal stability.
  - It generates a population of 100 potential solutions each round
  - Thus, we can measure the variance at each decision point in its execution



Algorithm	Simple	Competitive	Low Variance	Fast
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Experiment 3: Runtimes

- For each model:
- Run each algorithm 100 times.
- Record runtime using Unix "time" command.
- Divide runtime/100 to get average.

Experiment 3 Results

	Model 2 (31 mitigations)	Model 4 (58 mitigations)	Model 5 (99 mitigations)
Simulated Annealing	0.410	0.944	0.641
Genetic Algorithm	0.010	0.046	0.100
KEYS2	0.004	0.014	0.027

Runtimes In Seconds

Experiment 3 Results

- Simulated Annealing is slow, has trouble on more complex models.
- Genetic Algorithm is fast, but…
- KEYS2 is an order of magnitude faster.
- KEYS2 fast enough that it can be used without adding to overall experiment time.

Algorithm	Simple	Competitive	Low Variance	Fast
KEYS2	Yes	Yes	Yes	Yes

Conclusions

Algorithm	Simple	Competitive	Low Variance	Fast
KEYS2	Yes	Yes	Yes	Yes

- A baseline method is necessary to improve the quality and reliability of SBSE research.
  - But not just any will do…
- KEYS2 is one candidate baseline.
- KEYS2 has been experimentally shown to be:
  - Competitive with common SBSE algorithms.
  - Fast enough to not eat into precious experimentation time.
  - Stable enough to deliver trustworthy results.

Is KEYS2 the right choice?

- What about random search?
  - Random search is popular, but…
    - Straw man [Harman '10]
    - Results rarely competitive…
    - Unless it is allowed to run for a long time. [Ciupa '09]
    - Random = Too much variance
- Can KEYS2 apply to all problems?
  - Probably not, but…
  - In active use or planning to use in requirements optimization, defect detection, effort prediction, variable ordering for Bayesian Nets, monitoring of critical systems, and more.

The Discussion

- A single baseline for everything is unlikely.
  - But the field would benefit from a small set of agreed-upon baselines.
- Baselines provide benefits:
  - Common starting point
  - Unambiguous goal to beat
  - Easier to replicate, improve, or comment on other researcher's work.
- KEYS2 is a candidate baseline for a number of SBSE problems, but the important thing is that we think about baselines.

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Questions?

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