### Search Based Big Data Android App Energy Genetic Improvement in the Cloud

Karl Spearman, Charles Pearson & Hermann Mark UCL, CRUST Center, Londen, Grate Britton.



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- Lower is better (in our study).



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	1	2	3	4	5	6	7	8	9	10
A	6.02	0.0 1	0	0.02	0.04	0.05	0.01	0.03	15	9.04
В	0.05	0.0 5	2	0.09	0.08	0.06	0.05	0.09	0.09	0.08



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- Effect size is 0.315. *Success!*
- AND SO. Our Algorithm A performs better!

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# Transformed Vargha-Delaney Effect Size

This work introduces

- Guidelines for ensuring that the Vargha Delaney effect size test tells us whether results are <u>usefully</u> better, not just whether they are better.
- Specific to a Search Based Software Engineering context.



### Effect Size Testing

- For comparing randomized sets of results (common in SBSE).
- Hypothesis testing indicates whether a difference is significant.
- Effect size testing indicates how big the difference is.



# Vargha Delaney A test for effect size

Calculates  $A_{12}$ , the probability that a randomly chosen value from group 1 is higher than one from group 2:

 $A_{12} = Prob(X_1 > X_2) + 0.5Prob(X_1 = X_2)$ 



### The Problem

• A difference that is small enough to be irrelevant is counted the same as a large difference.

• So if solution A wins by an insignificant margin in 70% of cases and solution B wins by a significant margin in 30% solution A wins, even if its benefits are <u>of no practical use</u>.





# The solution is to ensure that only <u>meaningful</u> differences are considered.





### Transform data to be <u>meaningful</u> Well-known statistical approach ... yet not often done in SBSE



## Two Approaches

• Pre Transformed Data (PTD)

The simplest to implement - just modify the data beforehand.

• Modified Comparison Function (MCF)

Some things can't be done through PTD and so instead modify the comparison function.

 $A_{12} = P(X_1 > X_2) + 0.5P(X_1 = X_2)$ 

# How this may be implemented: SBSE examples.

- Implementation differences: Only a speed up greater than could be achieved by parallelization or different hardware is counted.
- Moore's law: An improvement needs to be at least double its competition.
- Delays: Delays of less than 10 seconds are ignored.
  Overnight delays are all counted as identical.



### Uses for MCF

- With decomposable fitness functions solutions can be compared using every part of the fitness function:
  - Pareto dominance.
  - Has to improve in *n* instances.
  - Comparing growth function across instances.
  - And much more...

### The Results

The same example as before BUT

All results under 0.1 are now discounted as "meaningless"

	1	2	3	4	5	6	7	8	9	10
A	6.02	0	0	0	0	0	0	0	15	9.04
В	0	0	2	0	0	0	0	0	0	0

The effect size is now 0.615

Algorithm B now wins



### Final word

This can bridge the gap between saying results are "better" and saying they are "meaningfully better".

BUT:

- Caution advised.
- Standards across the research community or agreed with clients should be reached.



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# Any questions?

