

Multi-objective Prediction

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**Annual "Humies" Awards
For Human-Competitive Results**

Produced By Genetic And Evolutionary Computation



Multi-objective Software Effort Estimation

F. Sarro*, A. Petrozziello**, M. Harman*

*CREST, Department of Computer Science, University College London, UK

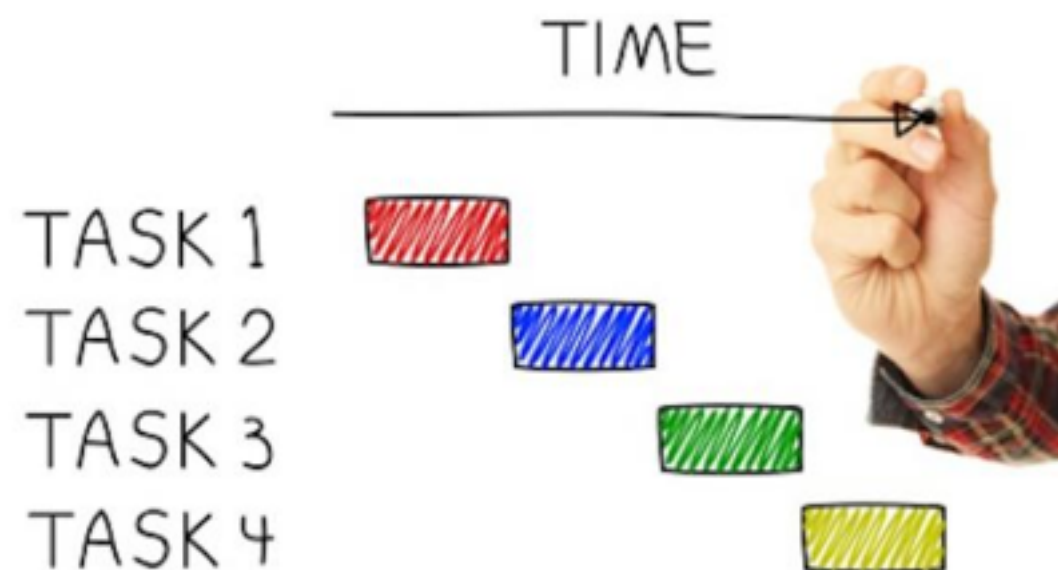
** School of Computing, University of Portsmouth, UK

*Would you ever
start producing
anything without
knowing the cost?*

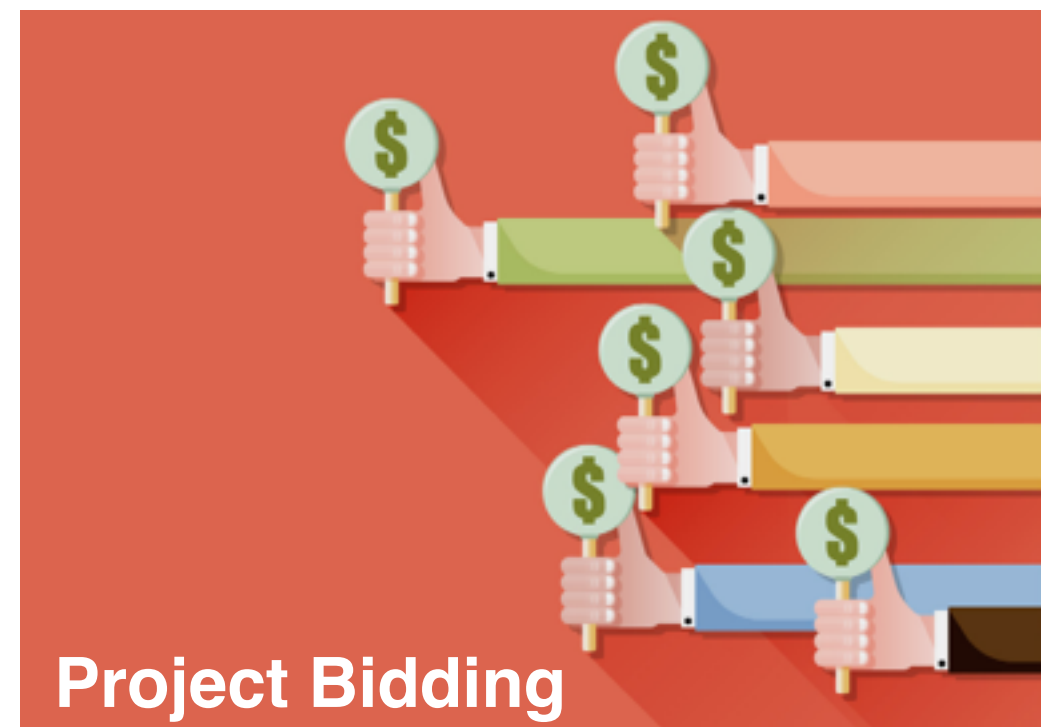


Software Effort Estimation (SEE)

Process of predicting the most realistic amount of effort required to realise a software project
(effort usually quantified in person-hours/person-months)



Project Scheduling /Staffing



Options for Estimation

Expert
Judgment



Experts tend to under-estimate
What is the margin of error?

Predictions of project effort lie within **30%-40%** of its true value

K. Molken and M. Jorgensen. A review of surveys on software effort estimation. ISESE'03.
S. McConnell. Software Estimation: Demystifying the Black Art. Microsoft Press, 2006

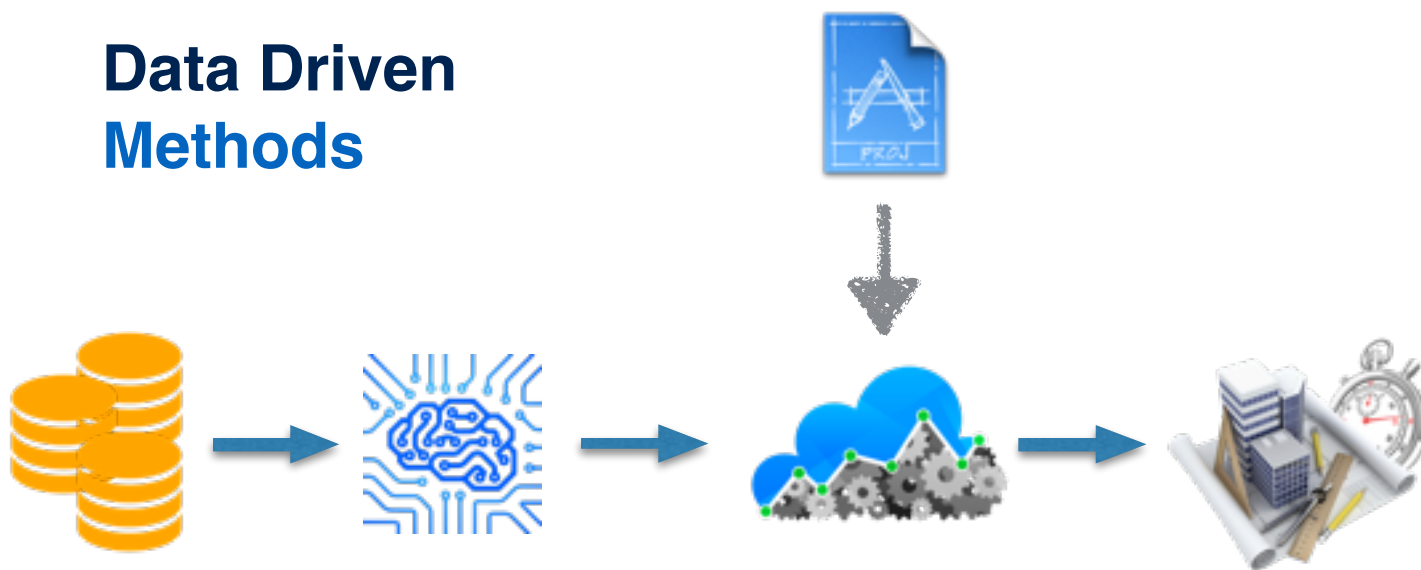
Options for Estimation

Expert Judgment



Experts tend to under-estimate within 30%-40% of the true value

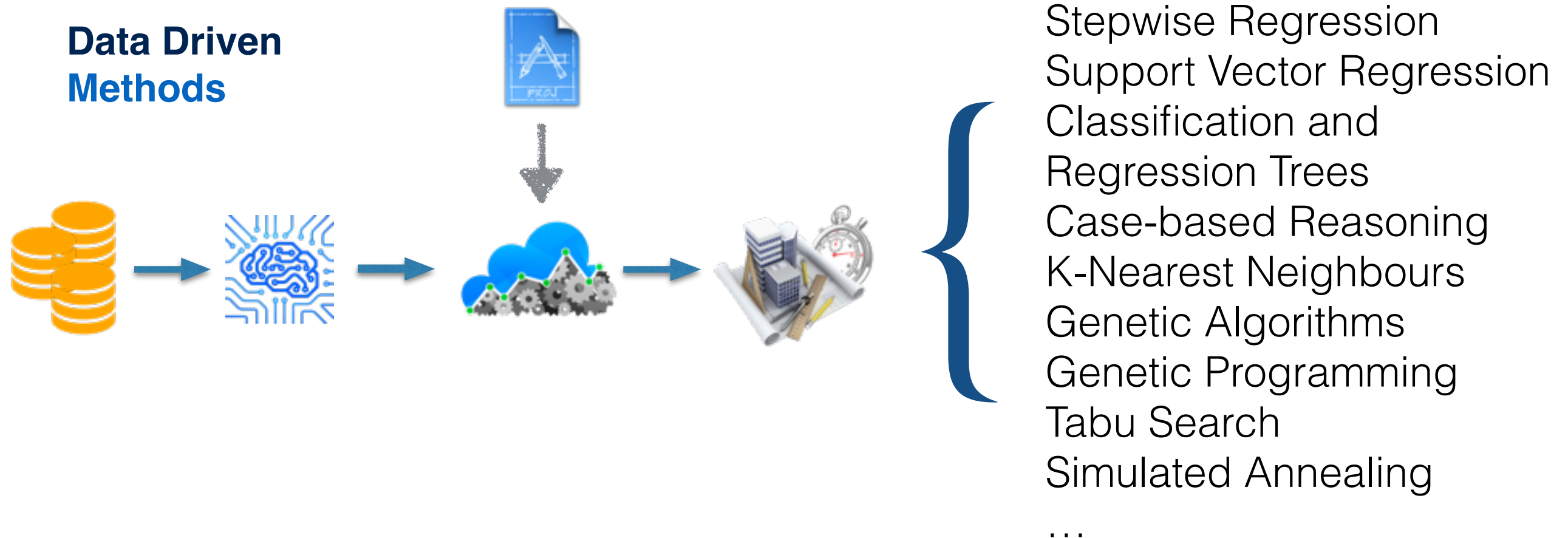
Data Driven Methods



Regression-based
Analogy-based
Search-based

Options for Estimation

After ~30 years of research...



... data-driven methods are still unable to beat human-estimates!

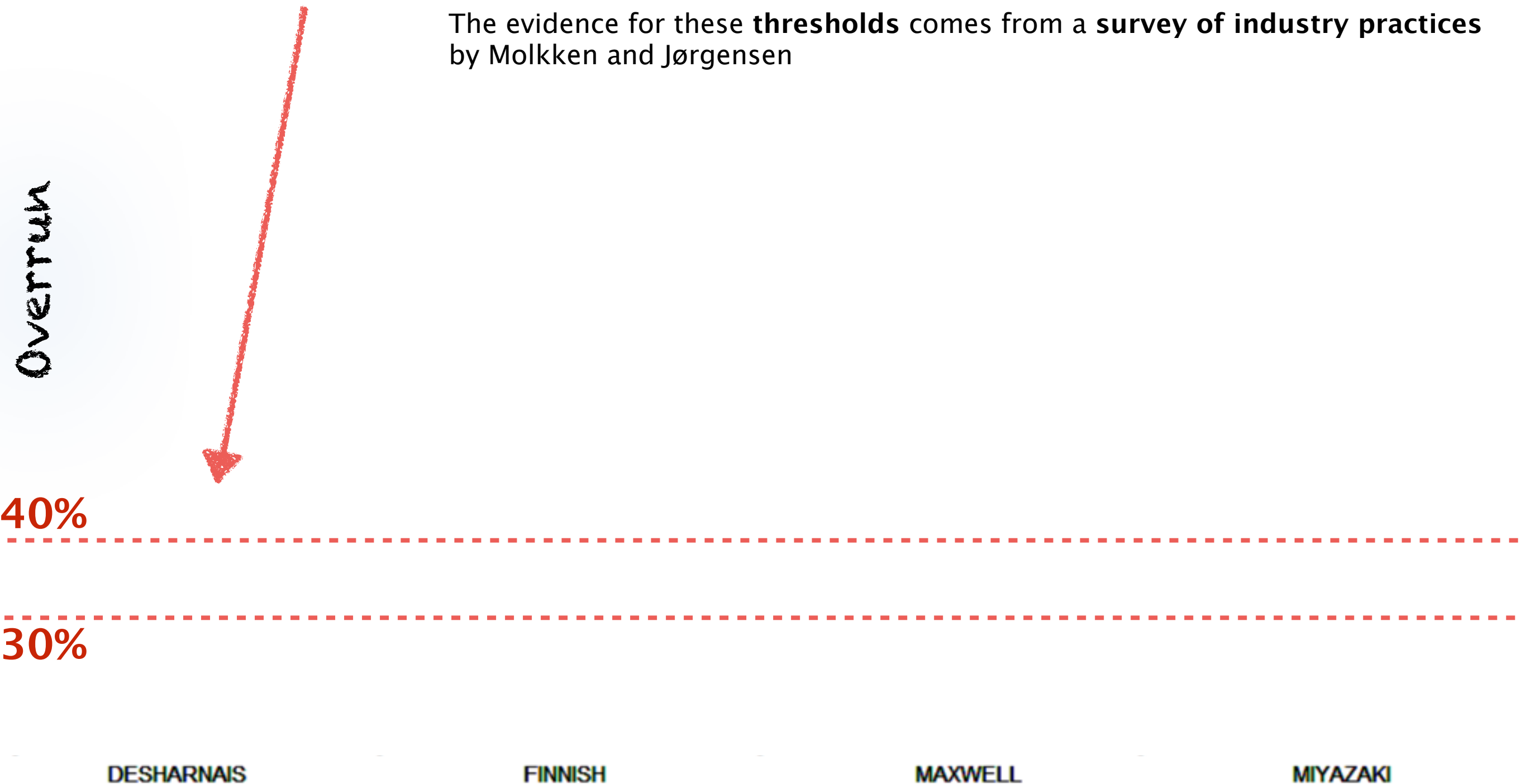
RQ4. Comparison to Industrial Practices

How does our approach, CoGEE, compare to human-expert-based estimates?

RQ4. Comparison to Industrial Practices

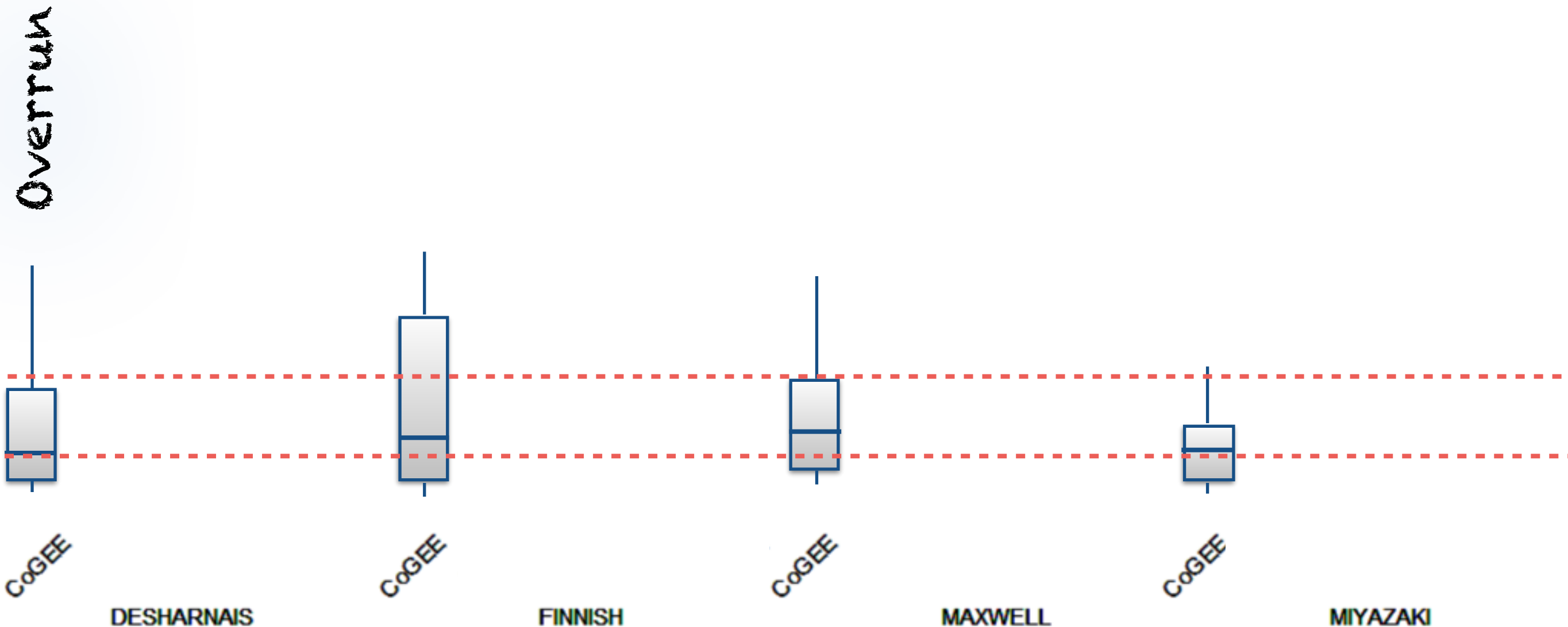
Human-expert-based predictions of project effort lie within 30% and 40% of the true value (overrun)

The evidence for these **thresholds** comes from a **survey of industry practices** by Molkken and Jørgensen



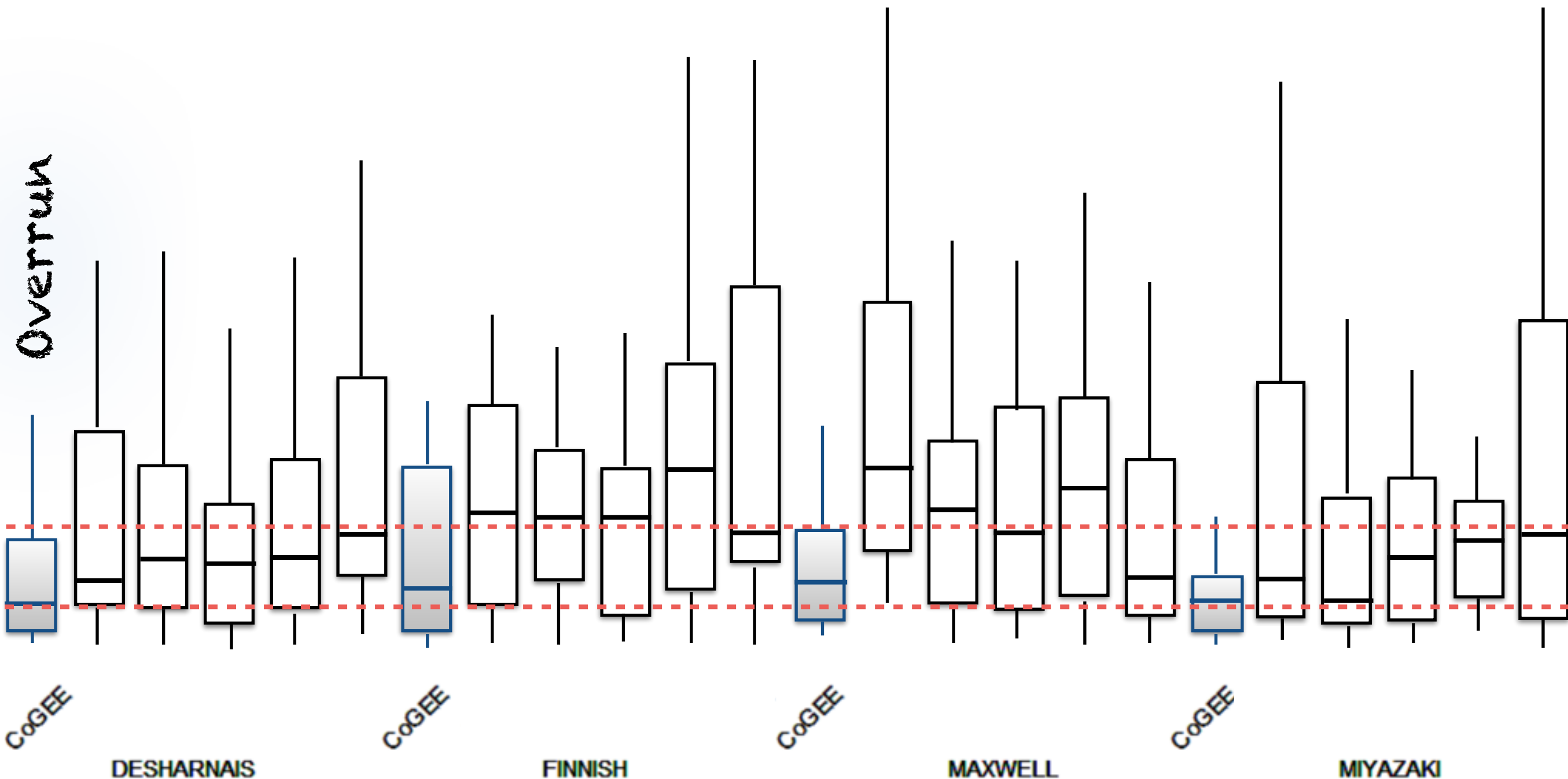
RQ4. Our Results are Human-Competitive

CoGEE provides effort estimates similar or better than those provided by human-experts



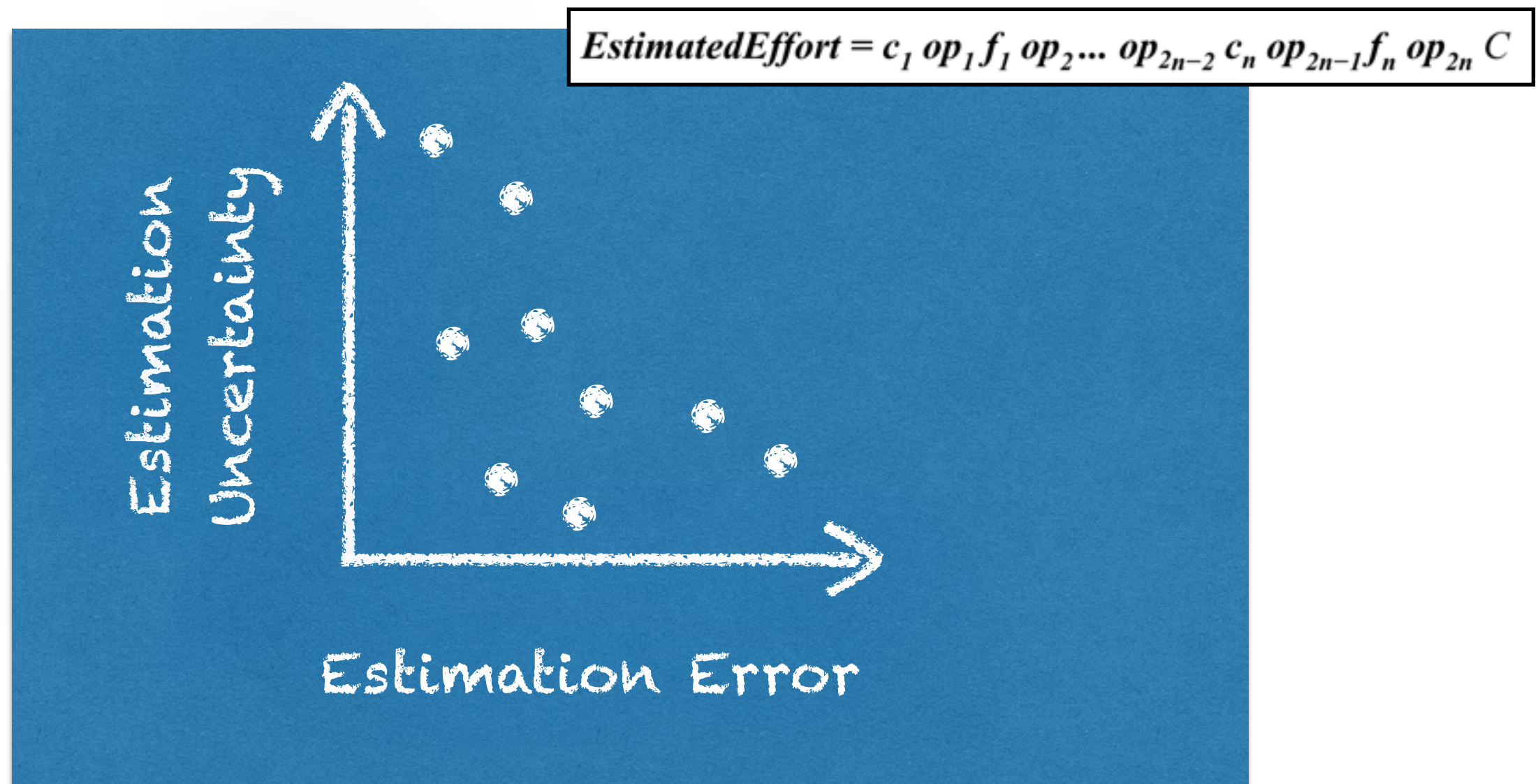
RQ2. Comparison with State-of-the-Art Benchmark

CoGEE outperforms popular automated estimation methods proposed over the last 30 years



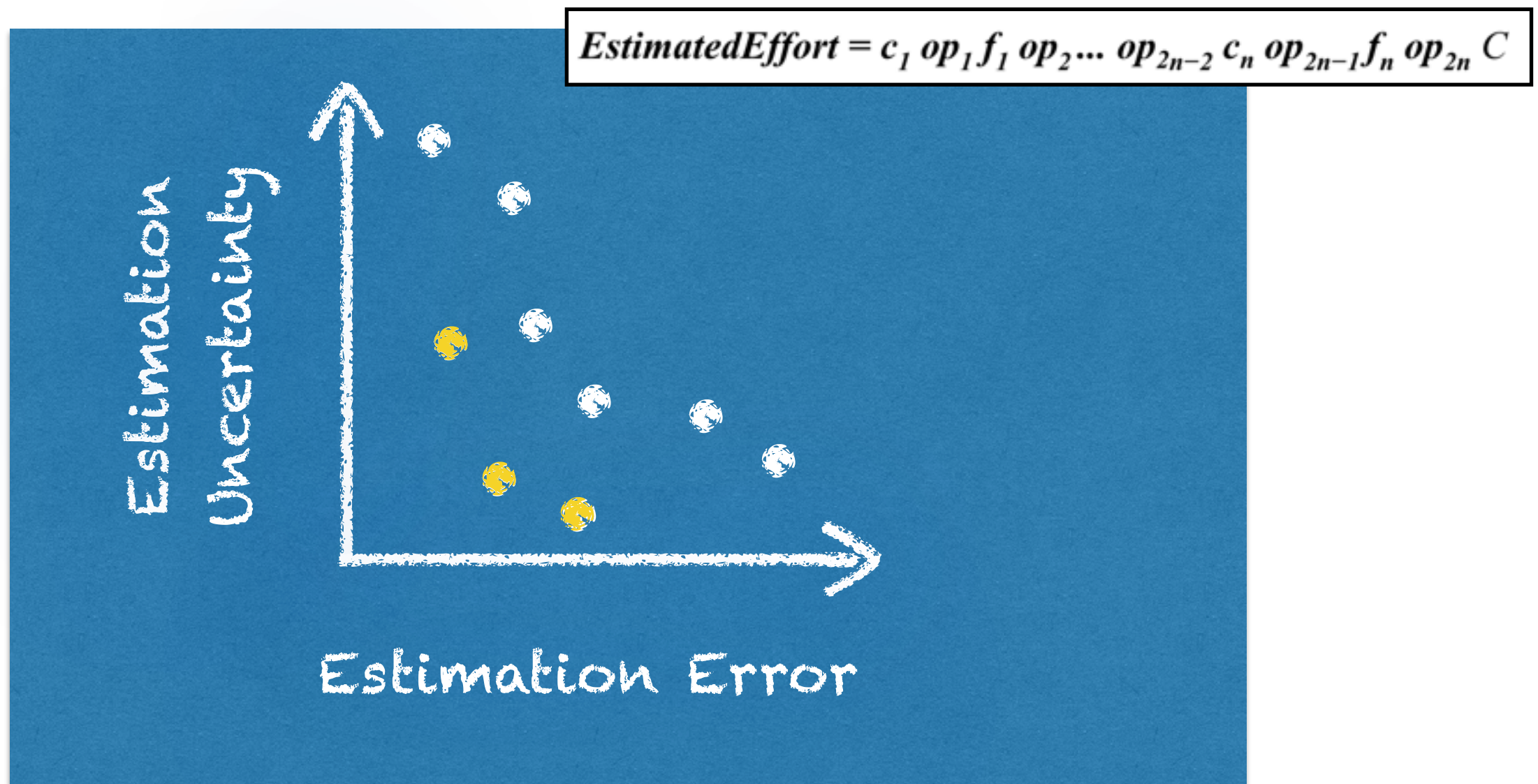
CoGEE: Confidence Guided Effort Estimator

CoGEE is a multi-objective evolutionary approach that builds robust estimation models



CoGEE: Confidence Guided Effort Estimator

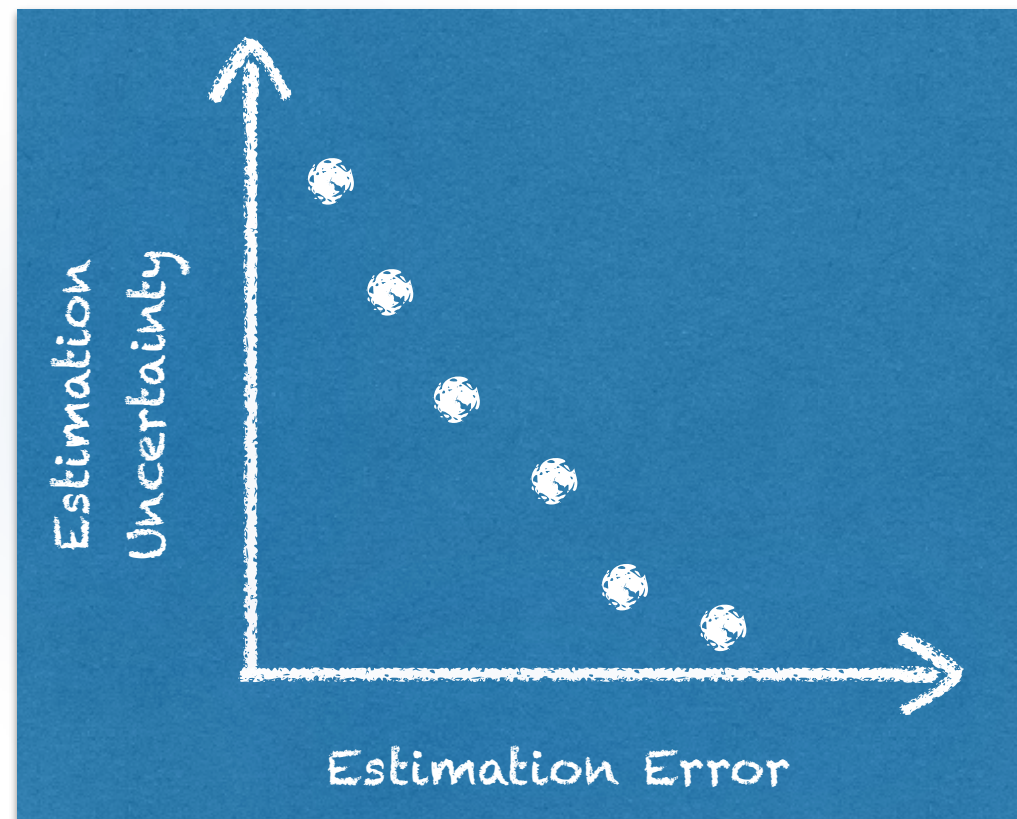
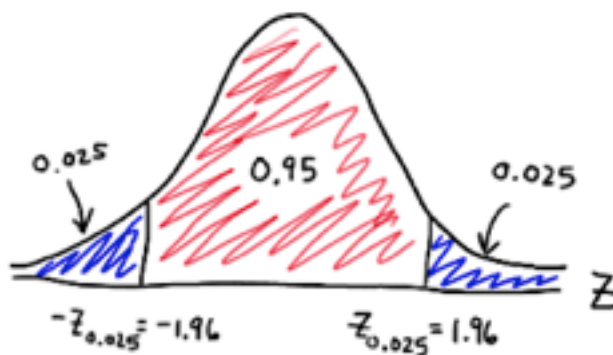
CoGEE is a multi-objective evolutionary approach that builds robust estimation models



CoGEE: Confidence Guided Effort Estimator

Bi-objective estimation

Confidence Interval



Sum of Absolute Error

$$SAE = \sum_{i=1}^N |RealEffort_i - EstimatedEffort_i|$$

**RQ1.
Sanity Check**

**RQ2. State of the Art
Benchmark**

**RQ3. Benefits from Multi-
objective Formulation**

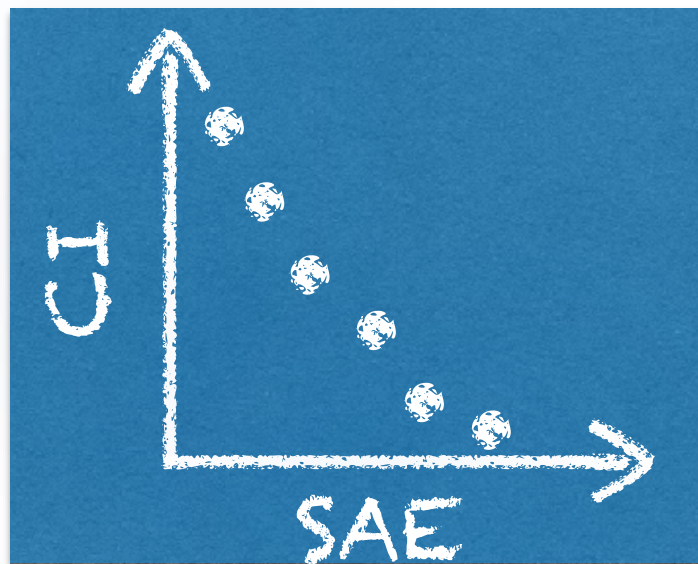
**RQ4. Comparison to
Industrial Practices**

RQ3. Benefits from Multi-objective Formulation

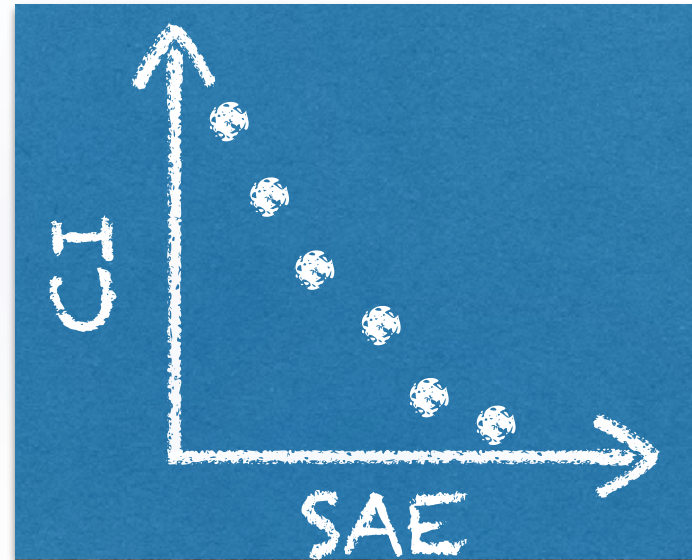
Does **CoGEE** provide more accurate estimates than *alternative single and multi-objective approaches*?

RQ3. Benefits from Multi-objective Formulation

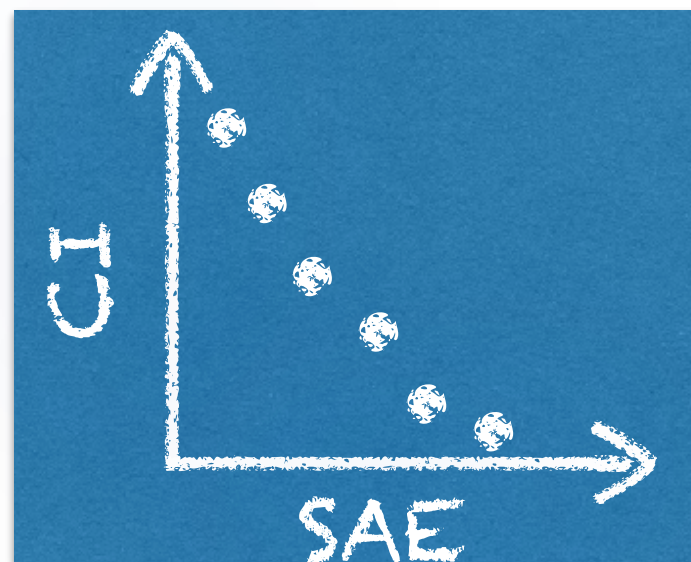
CoGEE



GA-SAE

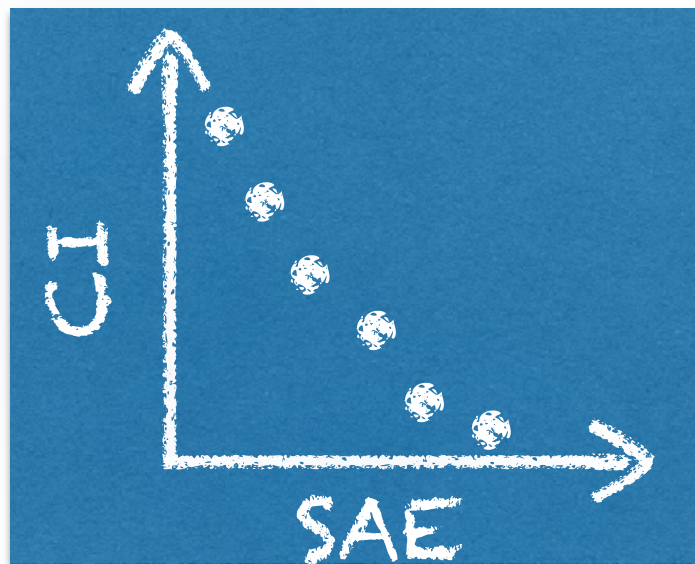


GA-CI

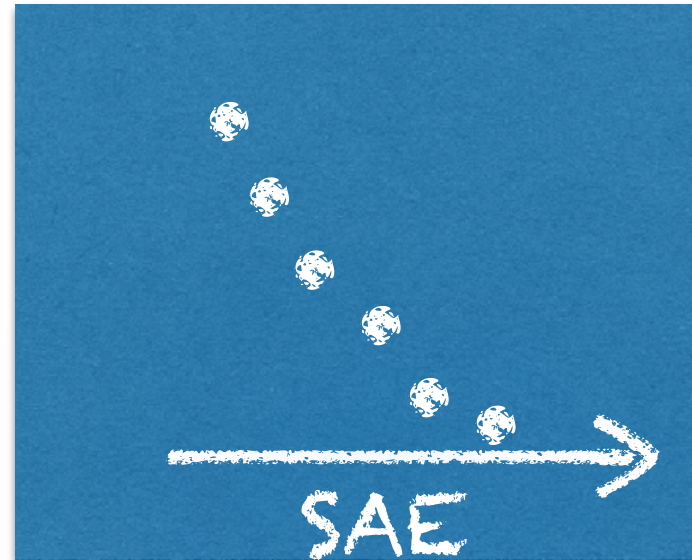


RQ3. Benefits from Multi-objective Formulation

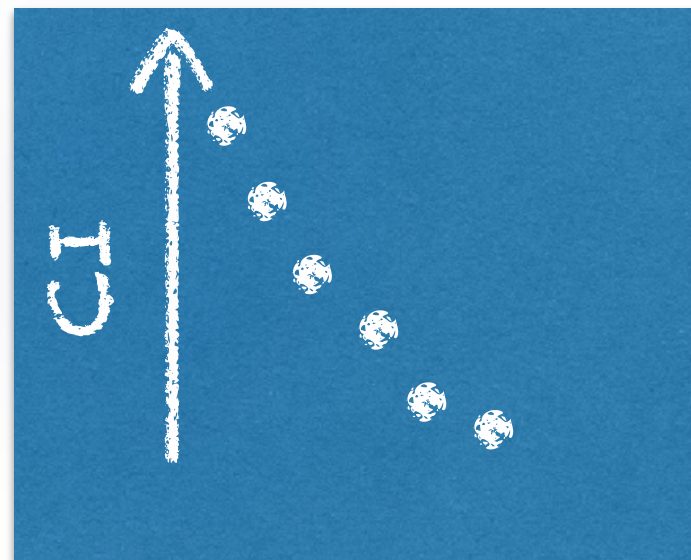
CoGEE



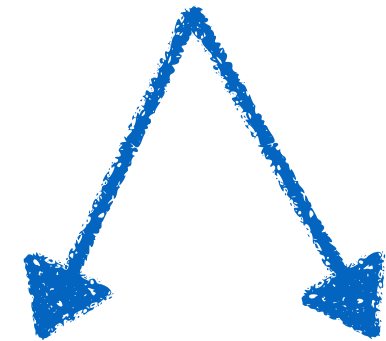
GA-SAE



GA-CI



$$SAE = \sum_{i=1}^N |RealEffort_i - EstimatedEffort_i|$$

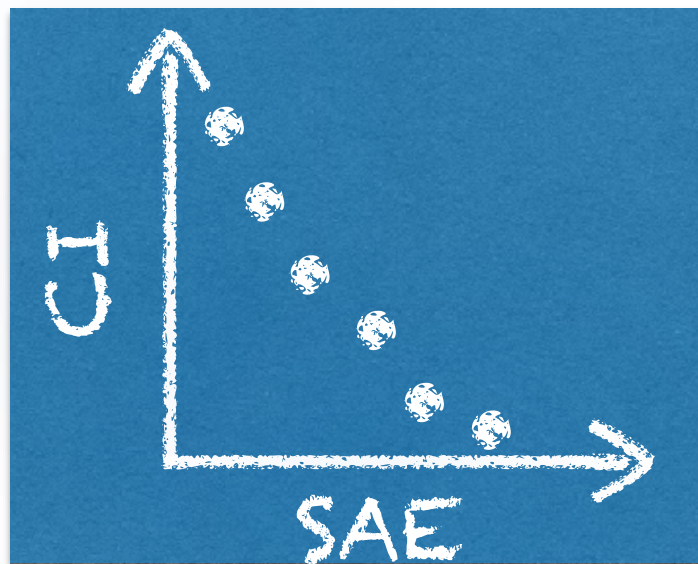


Underestimates
RealEffort -
EstimatedEffort > 0

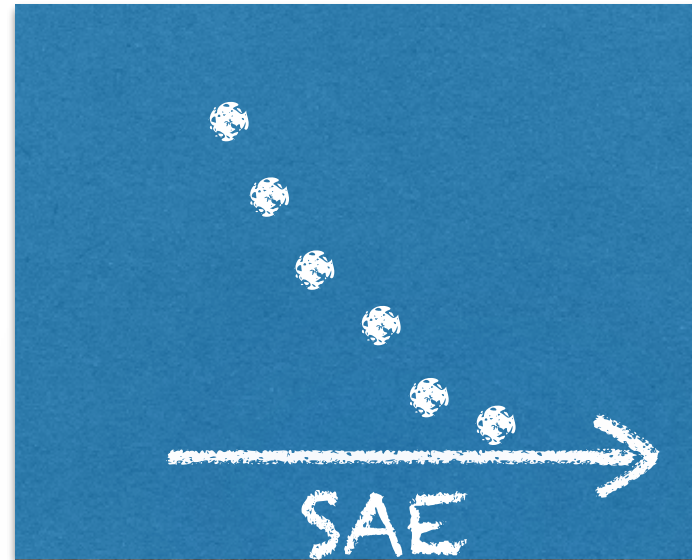
Overestimates
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RQ3. Benefits from Multi-objective Formulation

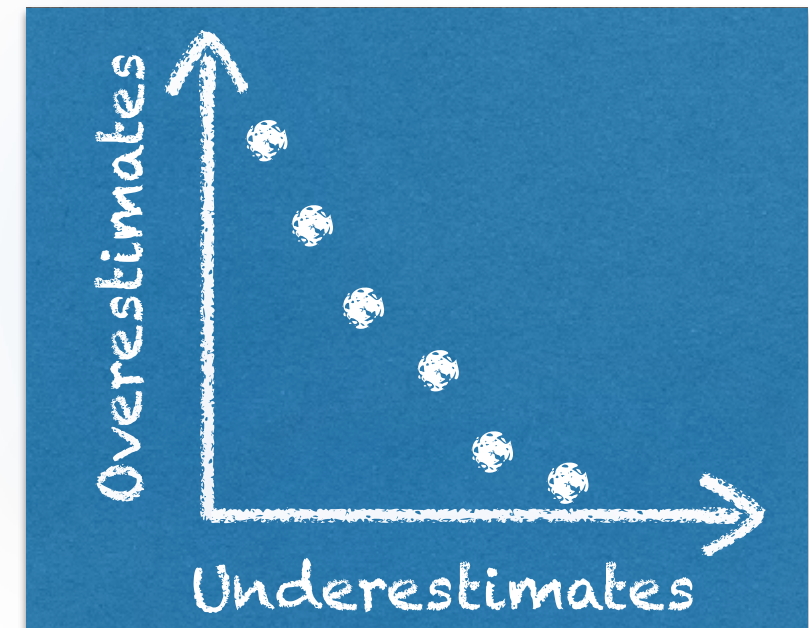
CoGEE



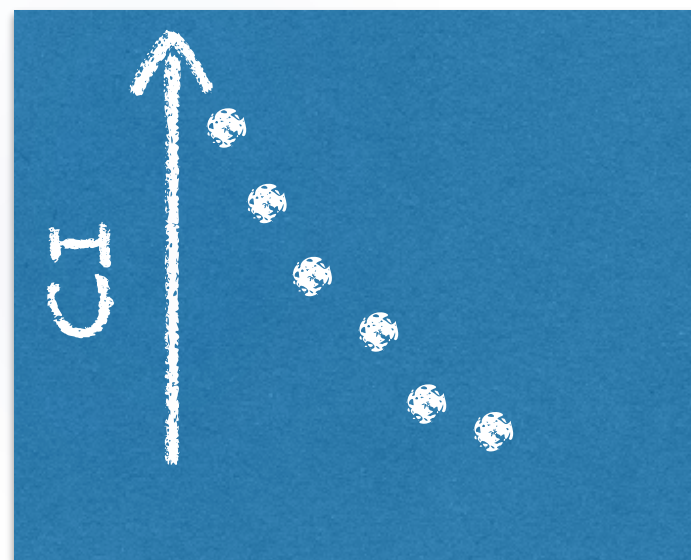
GA-SAE



NSGA-UO



GA-CI



RQ3. Benefits from Multi-objective Formulation

Dataset	Technique	I_{GD}	I_{HV}	I_C
China	CoGEE vs. GA-SAE	0.440 (0.49)	0.010 (0.60)	0.010 (0.42)
	CoGEE vs. GA-CI	0.830 (0.71)	0.010 (0.66)	0.010 (0.71)
	CoGEE vs. NSGAII-UO	<0.001 (0.26)	<0.001 (0.73)	<0.001 (0.94)
Desharnais	CoGEE vs. GA-SAE	0.010 (0.39)	<0.001 (0.33)	0.997 (0.39)
	CoGEE vs. GA-CI	0.005 (0.39)	<0.001 (0.88)	0.040 (0.66)
	CoGEE vs. NSGAII-UO	0.680 (0.56)	0.180 (0.56)	0.780 (0.44)
Finnish	CoGEE vs. GA-SAE	<0.001 (0.32)	0.130 (0.55)	0.640 (0.69)
	CoGEE vs. GA-CI	0.430 (0.51)	<0.001 (0.65)	0.920 (0.56)
	CoGEE vs. NSGAII-UO	<0.001 (0.70)	<0.001 (0.82)	<0.001 (0.71)
Maxwell	CoGEE vs. GA-SAE	<0.001 (0.08)	<0.001 (0.63)	<0.001 (0.98)
	CoGEE vs. GA-CI	<0.001 (0.25)	<0.001 (0.70)	<0.001 (0.92)
	CoGEE vs. NSGAII-UO	0.094 (0.03)	0.700 (0.72)	0.470 (0.53)
Miazaky	CoGEE vs. GA-SAE	<0.001 (0.25)	<0.001 (1.00)	<0.001 (1.00)
	CoGEE vs. GA-CI	<0.001 (0.25)	<0.001 (1.00)	<0.001 (1.00)
	CoGEE vs. NSGAII-UO	<0.001 (0.26)	<0.001 (0.95)	<0.001 (0.95)

RQ3. Results of the Wilcoxon test ($\hat{A}12$ effect size) which compare the quality indicators (I_{GD} , I_{HV} , I_C) of CoGEE to the ones of the other evolutionary approaches over 30 runs.

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**Human-competitive results to
a long-standing and difficult problem**



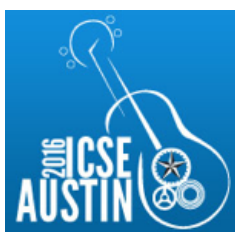
**Advances the
state of the art**



**Successful use
of EC in Software Engineering**



**Through Empirical Study
(724 real-word projects)**



**Breakthrough results published in ICSE'16
and awarded at the HUMIES-GECCO'16**

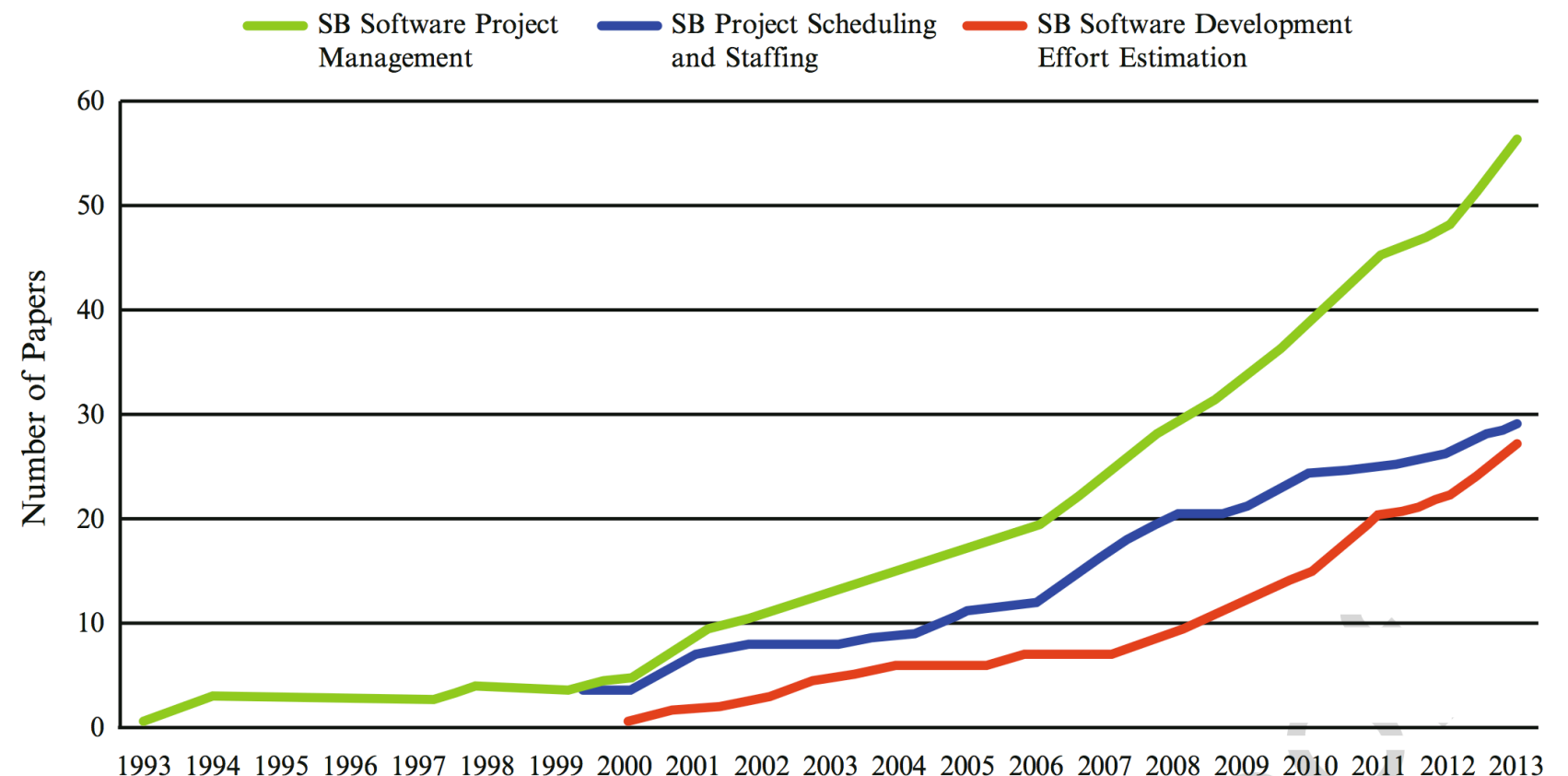


Want to Know More about Search-Based Software Effort Estimation?



Chapter 15 Search-Based Software Project Management

Filomena Ferrucci, Mark Harman, and Federica Sarro





Mutation-Aware Fault Prediction

David Bowes^{*}, Tracy Hall[†], Mark Harman[‡], Yue Jia[‡], Federica Sarro[‡], and Fan Wu[‡]

^{*}University of Hertfordshire, Hatfield, UK

[†]Brunel University London, Uxbridge, UK

[‡]University College London, London, UK

ABSTRACT

We introduce mutation-aware fault prediction, which leverages additional guidance from metrics constructed in terms of mutants and the test cases that cover and detect them. We report the results of 12 sets of experiments, applying 4 different predictive modelling techniques to 3 large real-world systems (both open and closed source). The results show that our proposal can significantly ($p \leq 0.05$) improve fault prediction performance. Moreover, mutation-based metrics lie in the top 5% most frequently relied upon fault predictors in 10 of the 12 sets of experiments, and provide the majority of the top ten fault predictors in 9 of the 12 sets of experiments.

12 sets of experiments.

provide the majority of the top ten fault predictors in 9 of the 12 sets of experiments, and provide the majority of the top ten fault predictors in 9 of the 12 sets of experiments.

HIGHLIGHTS

Important gaps addressed:

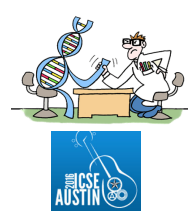
Testing information rarely used

Industrial data rarely used

Promising findings:

Adding mutation information
improves predictive performance

Worthwhile effect sizes occur



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Process of predicting the most realistic amount of effort required to realise a software project

(effort usually quantified in person-hours/person-months)



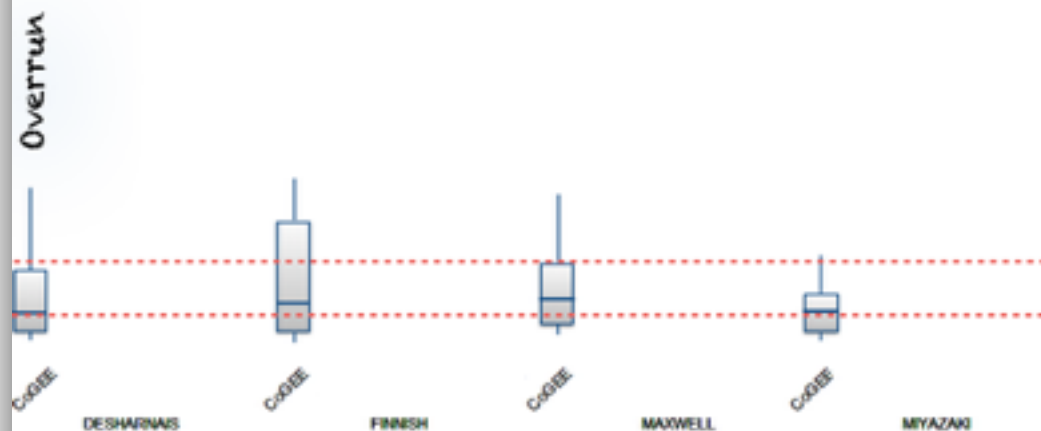
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CoGEE is a multi-objective evolutionary approach that builds robust estimation models



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RQ2. Comparison with State-of-the-Art Benchmark

CoGEE outperforms popular automated estimation methods proposed over the last 30 years

