

Surrogate Fitness via Factorization of Interaction Matrix

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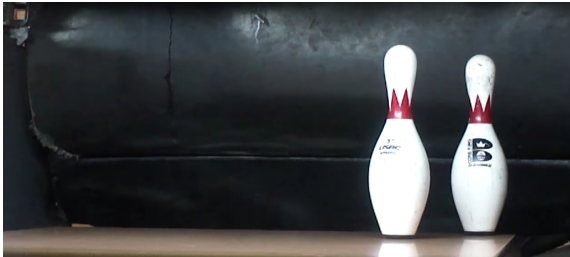


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Thought experiment



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Observation 1

GP algorithms do not let programs know **which** tests they solve.

Typical fitness function in GP *aggregates* program's behavior on *tests* by

- counting the number of passed tests (discrete domains).

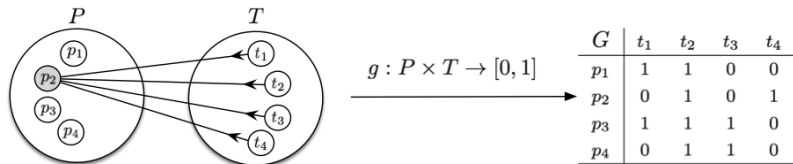
$$f(p) = |\{y_i \neq \hat{y}_i(p)\}|_i \quad (1)$$

- summing the errors on individual tests (continuous domains).

$$f(p) = \sum_i (y_i - \hat{y}_i(p))^2 \quad (2)$$

Observation 2

Detailed information on particular interactions with **is available** in GP.



- P : set of m programs,
- T : set of n tests (fitness cases)
- $g(p, t)$: interaction function between $p \in P$ and $t \in T$
- G : $m \times n$ matrix of interaction outcomes between P and T
- Test-based problems (Pollack, Bucci, de Jong, Popovici)

Observation 3

Interaction outcomes for particular tests are *partially* dependent.

Can be used to derive **alternative search objectives** (*search drivers*):

- *Derivation of Search Objectives*
(Krawiec & Liskowski, EuroGP 2015, ECJ 2016)

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Hypothesis

- An interaction outcome $g(p, t)$ can be reconstructed from other elements of G
- We may **reduce** so the number of program-test interactions.

The idea

Matrix factorization to estimate some program-test interactions in G .

Algorithm

- 1 Calculate **sparse** interaction matrix G between P and T
 - For each $p \in P$ draw a random subset of $\alpha|T|$ tests $T' \subset T$
 - Apply p to tests in T'
 - 2 **Factorize** G into non-negative components W and H ($\text{rank} \leq k$)
 - 3 **Reconstruct** the interaction outcomes by calculating $\hat{G} = WH$
- $\alpha \in (0, 1]$ - desired density of partial interaction matrix

Example: $P = \{p_1, \dots, p_4\}$, $T = \{t_1, \dots, t_5\}$, $\alpha = \frac{3}{5} = 0.6$

$$G = \begin{matrix} & t_1 & t_2 & t_3 & t_4 & t_5 \\ p_1 & \color{green}{2} & & 1 & 2 & \color{yellow}{} \\ p_2 & & 2 & 1 & & 1 \\ p_3 & 1 & & & 2 & 2 \\ p_4 & 2 & 1 & & \color{yellow}{} & 1 \end{matrix} \quad \begin{matrix} \leftarrow \\ \leftarrow \end{matrix} \quad \text{Missing outcomes due to } \alpha < 1$$

Example

$$G = \begin{matrix} & t_1 & t_2 & t_3 & t_4 & t_5 \\ p_1 & \begin{bmatrix} 2 \\ \end{bmatrix} & & 1 & 2 & \begin{bmatrix} \\ \end{bmatrix} \\ p_2 & & 2 & 1 & & 1 \\ p_3 & 1 & & & 2 & 2 \\ p_4 & 2 & 1 & & \begin{bmatrix} \\ \end{bmatrix} & 1 \end{matrix} \quad \begin{matrix} \nearrow \\ \searrow \end{matrix} \quad \text{Missing outcomes due to } \alpha < 1$$

$$W = \begin{matrix} & f_1 & f_2 & f_3 \\ p_1 & \begin{bmatrix} 0.46 & 1.96 & 0.6 \\ \end{bmatrix} \\ p_2 & \begin{bmatrix} 1.27 & 0.1 & 0.95 \\ \end{bmatrix} \\ p_3 & \begin{bmatrix} 1.37 & 0.02 & 2.83 \\ \end{bmatrix} \\ p_4 & \begin{bmatrix} 0.4 & 1.86 & 1.60 \\ \end{bmatrix} \end{matrix}, \quad H = \begin{matrix} & t_1 & t_2 & t_3 & t_4 & t_5 \\ f_1 & \begin{bmatrix} 0.48 \\ \end{bmatrix} & 1.50 & \begin{bmatrix} 0.01 \\ \end{bmatrix} & 0.41 & 0.41 \\ f_2 & \begin{bmatrix} 0.87 \\ \end{bmatrix} & 0.14 & \begin{bmatrix} 0.19 \\ \end{bmatrix} & 0.77 & 0.01 \\ f_3 & \begin{bmatrix} 0.11 \\ \end{bmatrix} & 0.09 & \begin{bmatrix} 1.02 \\ \end{bmatrix} & 0.50 & 0.51 \end{matrix}$$

$$\hat{G} = WH = \begin{matrix} & t_1 & t_2 & t_3 & t_4 & t_5 \\ p_1 & \begin{bmatrix} 2 & 1.02 & 1 & 2 & 0.52 \\ \end{bmatrix} \\ p_2 & \begin{bmatrix} 0.8 & 2 & 1 & 1.07 & 1 \\ \end{bmatrix} \\ p_3 & \begin{bmatrix} 1 & 2.31 & 2.1 & 2 & 2 \\ \end{bmatrix} \\ p_4 & \begin{bmatrix} 2 & 1 & 2.01 & 2.4 & 1 \\ \end{bmatrix} \end{matrix} \quad \xrightarrow{f(p_i) = \sum_{j=1}^n g_{ij}} \quad \begin{matrix} f(p_1) = 6.54 \\ f(p_2) = 5.87 \\ f(p_3) = 9.41 \\ f(p_4) = 8.41 \end{matrix}$$

- Sizes of W and H controlled by parameter $k \geq 1$ (here: $k = 3$)
- Technical realization: multiplicative update rule.
- Cost of evaluation **reduced** $\frac{1}{\alpha}$ **times**.

Experiment

- GP: 'vanila' GP, $|P| = 1000$
- SFIMX: $|P|$ increased $(1 - \alpha)$ times \implies same budget
 - FULL: $k = |T|$,
 - HALF: $k = \frac{|T|}{2}$,
 - LOG: $k = \log_2 |T|$
- RSS: Calculates fitness using $\alpha|T|$ random tests (same budget)
- $\alpha \in 0.1, 0.2, \dots, 1.0$

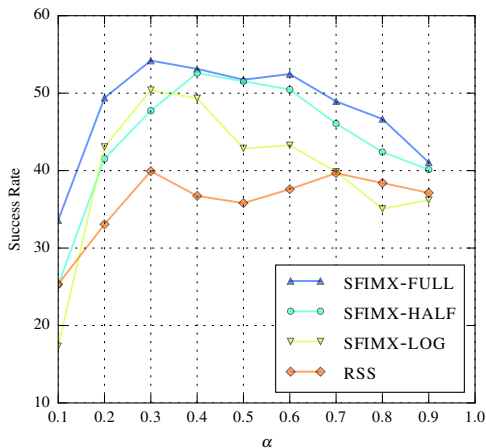
Domain	Instruction set	Problem	Variables	#tests
Boolean	and, nand or, nor	Cmp6	6	64
		Cmp8	8	256
		Par5	5	32
		Mux6	6	64
		Maj6	6	64
Algebras	$a_i(x, y)$	Disc-a1...a5	3	27
	$a_i(x, y)$	Malcev-a1...a5	3	15

Average ranks on success rate (Friedman's $p \ll 0.001$)

	SFIMX			GP	RSS
	HALF	FULL	LOG		
All problems	2.07	2.13	2.67	3.90	4.23
Boolean	2.4	1.7	3.3	3.2	4.4
Categorical	1.90	2.35	2.35	4.25	4.15

- Best results for $\alpha = 0.3$ and $\alpha = 0.4$
- Roughly the same performance as GP using only 10% of interactions
- LOG variant \rightarrow high compression without affecting the performance
 - \implies Interaction outcomes are indeed correlated.
- Low $k \rightarrow$ low computational overhead of factorization
 - For SFIMX-LOG: only 6% of the total cost of $1,000|T|$ interactions

Impact of α on success rates



Success rates improve as sparsity in G increases up to $\alpha = 0.3$

Conclusions

- SFIMX = well-informed and scalable surrogate fitness.
- Target domains:
 - Problems with expensive interaction functions
 - Problems with large numbers of tests
 - Evolving controllers, two-player games, image analysis, ...
- Replaces a discrete fitness function with a continuous one.
- Ongoing work: continuous domains

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Thank You