Partial Sampling Operator and Tree-Structural Distance for Multi-Objective GP

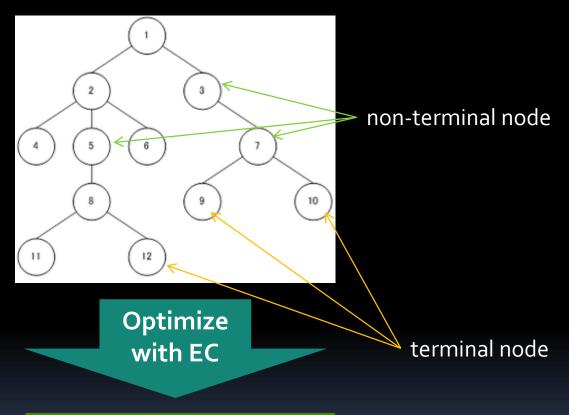
Makoto OHKI Tottori University, Japan

Program Synthesis

Function Generation

Rule Discovery

- Target of these application
 - → expressed by a tree structure.



Genetic Programming

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3.MOGP with SD

4. Verification

5.Conclusion

Effective Search **⇌** Bloat Control

- * Schema Theory for GP [Holland 1992]
- * Probabilistic Incremental Program Evolution [Salustowicz 1997]
- * Depth Limitation [Langdon 1999]
- * Size-Fair Model GP [Langdon 2000]
- * Grammar-Guided GP [Ratle 2000]
- * FREQT [Asai 2001]
- * Subtree Swapping Crossover [Poli 2003]
- * TAG₃P [Hoai 2004]
- * Tree Size Limitation [Ryan 2006]
- * Stochastic Grammar-based GP [Ratle 2006]
- * Semantic Building Blocks [McPhee 2008]
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In this paper,

- Partial Sampling (PS) operator instead of Crossover and Mutation
- A technique of Multi-Objective GP by applying NSGA-II.
 - index of goodness of the tree
 - the Size of the tree
 - tree position in the population by Tree-Structural Distance (TSD)
- Apply TSD instead of Crowding Distance (CD) of NSGA-II.
- Double Spiral Problem for verification

1.Introduction

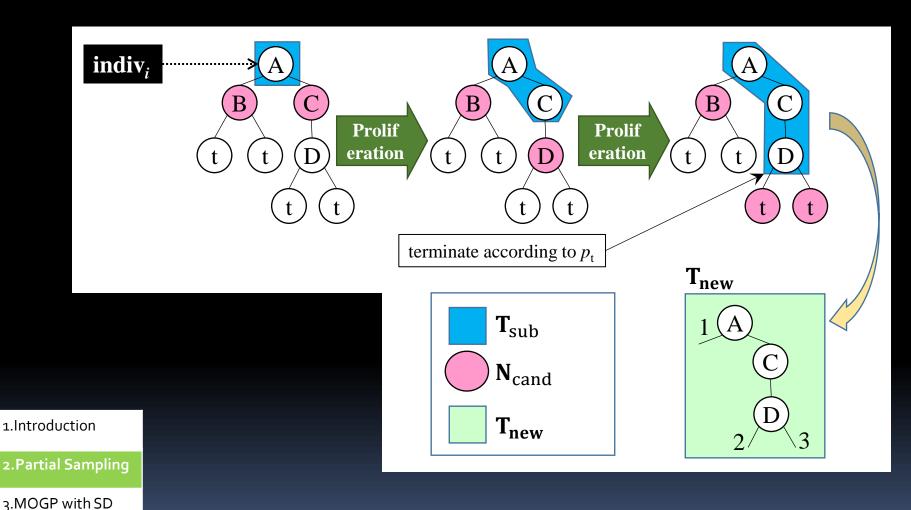
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2. Partial Sampling Operator for Mating

Proliferation in Partial Sampling (PS) Operator



4.Verification

2. Partial Sampling Operator for Mating

igcup Proliferation Termination Probability $p_{_t}$

$$p_t^0 = \frac{1}{\text{AverageSize } \mathbf{R}^g},$$

$$p_t^{g+1} = \frac{\frac{1}{\text{Succeed } \mathbf{P}^g} - p_t^0}{\frac{1}{\text{Succeed } \mathbf{R}^g} - p_t^0} p_t^g - p_t^0 + p_t^0,$$

 \mathbf{R}^g : population at g-th generation

 \mathbf{P}^g : parent set at g-th generation

AverageSize • : average size of tree structure

Secceed • : average size of partial tree structure of set succeeded from previous generation

1.Introduction

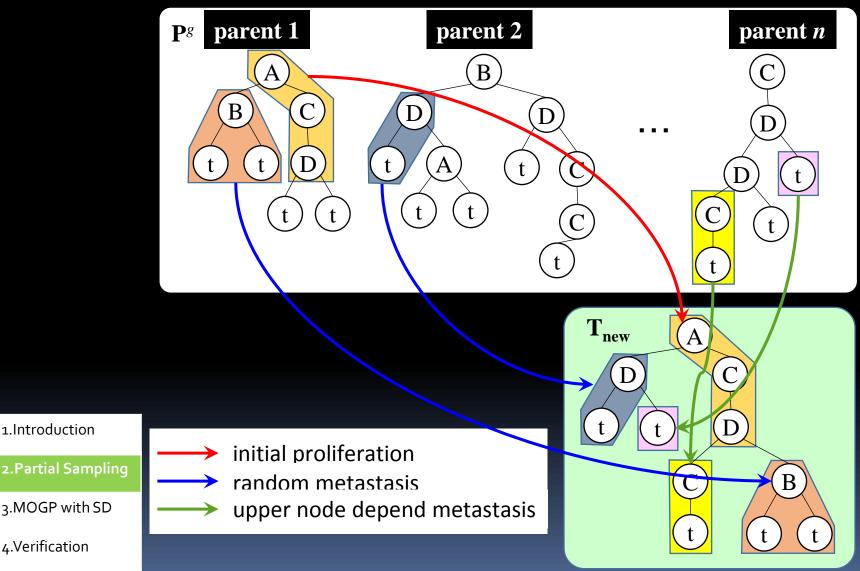
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2. Partial Sampling Operator for Mating

2 kinds of metastasis



5.Conclusion

4. Verification

1.Introduction

3 Objective Functions

① objective function according to Goodness of the tree structure

$$h_1(\text{indiv}_i) = \text{performance}(\text{root}_i)$$

2 objective function according to the size of the tree structure

$$h_2(\text{indiv}_i) = \frac{1}{\text{size}(\text{root}_i)}$$

③ objective function according to average of TSD in the population

2. Partial Sampling

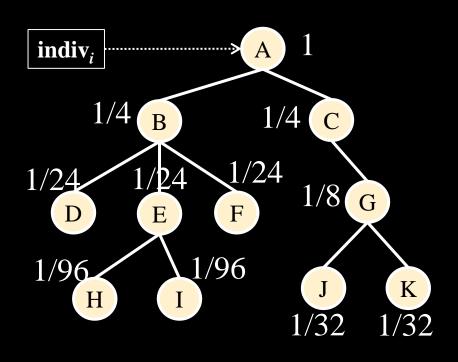
3.MOGP with SD

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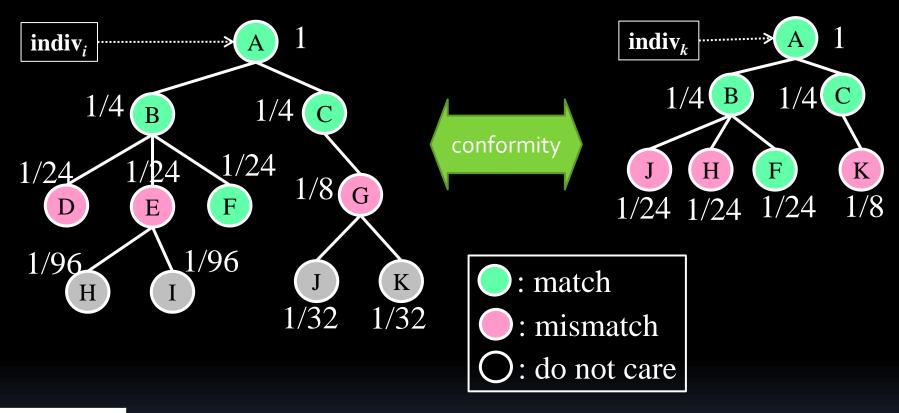
 $h_3(\text{indiv}_i) = \frac{1}{N_{\text{pop}}} \sum_{k=1}^{N_{\text{pop}}} \text{TSD indiv}_i, \text{indiv}_k$

Tree-Structural Distance (TSD)



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Tree-Structural Distance (TSD)



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2. Partial Sampling

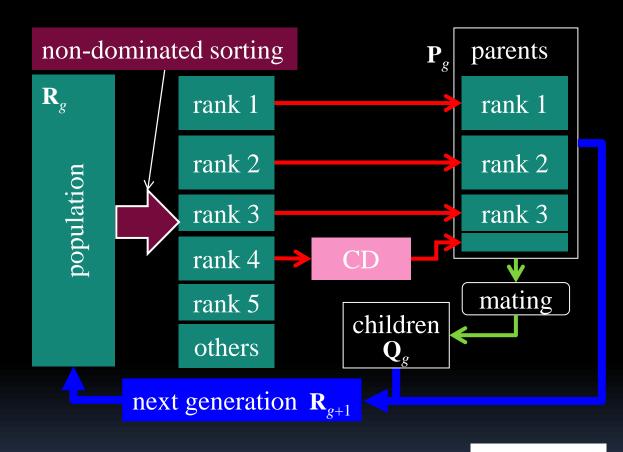
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 $TSD(root_i, root_k) = \frac{1}{24} + \frac{1}{24} + \frac{1}{8} = \frac{5}{24}$

NSGA-II (conventional)



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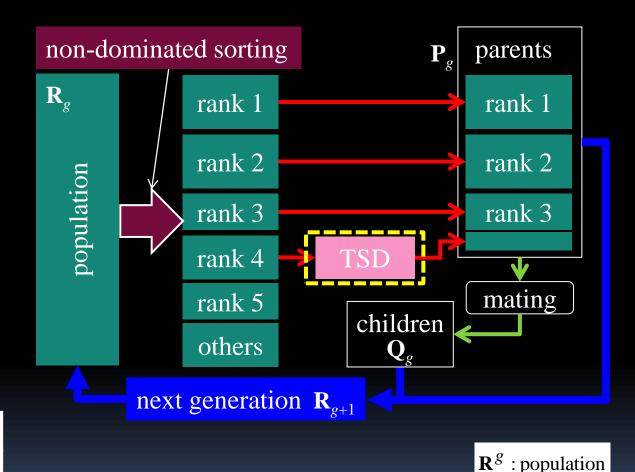
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 \mathbf{R}^g : population

 \mathbf{P}^g : parents

NSGA-II with TSD instead of CD



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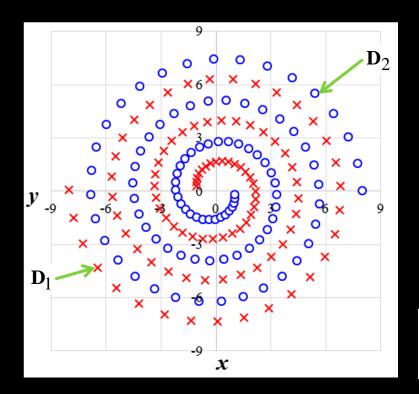
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 \mathbf{P}^g : parents



$$\begin{cases} f(x,y) > 0 \Leftrightarrow (x,y) \in \mathbf{D}_1 \\ f(x,y) < 0 \Leftrightarrow (x,y) \in \mathbf{D}_2 \\ f(x,y) = 0 \Leftrightarrow \text{FALSE} \end{cases}$$

difficult even by the neural network.



- o non-terminal node ∈ +,-,*,÷,sin,cos,tan, \underline{ifltz} o terminal node ∈ x, y, constant
 - ifltz $(a,b,c) \triangleq if \ a < 0 \text{ then } b \text{ else } c$

$$= \begin{cases} b & (a < 0) \\ c & (\text{otherwise}) \end{cases}$$

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lacksquare Objective function h_1 according to the goodness of tree

$$h_{\mathrm{l}}(\mathrm{indiv}_{i}) = \mathrm{performance}(\mathrm{root}_{i}) = \frac{1}{\left|\mathbf{D}_{1} \cup \mathbf{D}_{2}\right|} \sum_{k=1}^{\left|\mathbf{D}_{1} \cup \mathbf{D}_{2}\right|} \underbrace{g(x_{k}, y_{k})}_{g(x, y)}$$

$$g(x, y) = \begin{cases} 1 & f(x, y) > 0 \land (x, y) \in \mathbf{D}_{1}, \\ 0 & f(x, y) > 0 \land (x, y) \in \mathbf{D}_{2}, \\ 1 & f(x, y) < 0 \land (x, y) \in \mathbf{D}_{2}, \\ 0 & f(x, y) < 0 \land (x, y) \in \mathbf{D}_{1}, \\ 0 & f(x, y) = 0 \end{cases}$$

1.Introduction

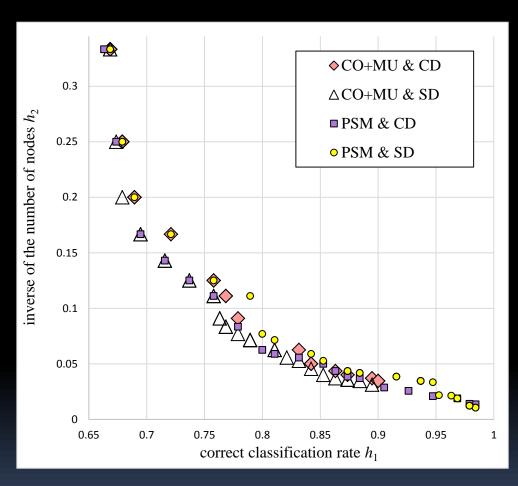
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Final Solution Distribution



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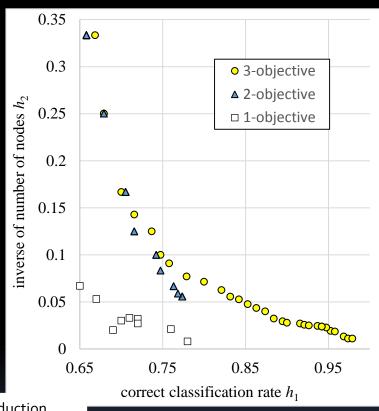
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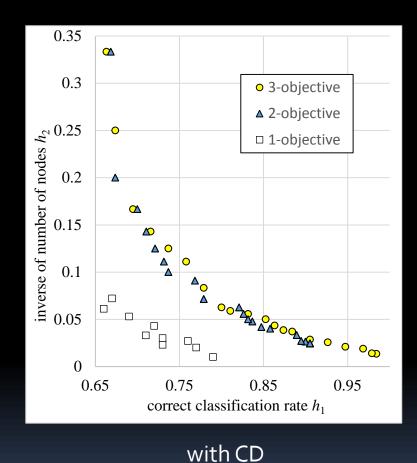
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Comparison among 3-Objective, 2-Objective, 1-Objective GPs



with SD



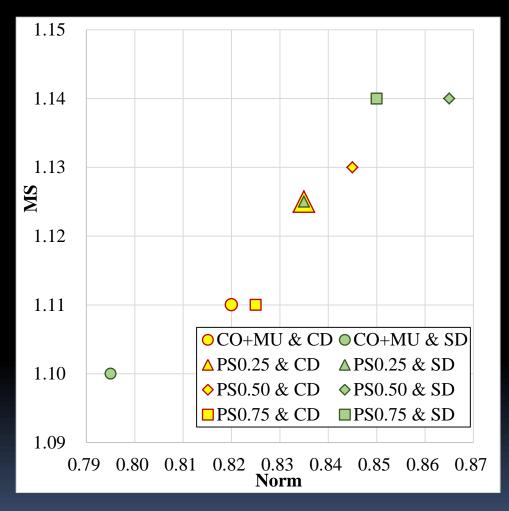
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Comparison of results on MS-Norm plane



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5. Conclusion

In this paper,

- Multi-Objective GP
- In addition to goodness of the tree, 2 objective functions
 - tree size
 - Tree-Structural Distance (TSD)
- Partial Sampling (PS) for mating
- Double Spiral Problem for verification.
- \bigcirc The proposed technique (PS + TSD \rightarrow NSGA-II) is effective.

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5. Conclusion

In the future,

- Enhance the capability of numerical optimization
- Ranking Selection technique harmonizing CD and TSD
- Mechanism to forcibly exit from PS

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Thank you very much!

Ask me simply, even if you have.

MS and Norm

degree of spread of \mathcal{FFS}

$$MS = \sqrt{\sum_{i=1}^{m} { |\mathcal{FFS}| \atop \max_{j=1}^{|\mathcal{FFS}|} f_i(\mathbf{x}_j) - \min_{j=1}^{|\mathcal{FFS}|} f_i(\mathbf{x}_j) }^2}$$

degree of convergence to POS

Norm =
$$\frac{1}{|\mathcal{FFS}|} \sum_{j=1}^{|\mathcal{FFS}|} \sqrt{\sum_{i=1}^{m} f_i(\mathbf{x}_j)^2}$$

Program Synthesis [David2017]

solution

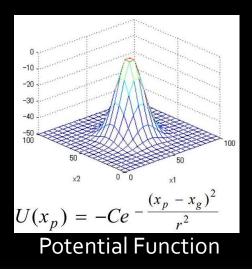
```
let rec sum_even x =
match x with
| Nil -> 0
| Cons (u, Nil) -> u
| Cons (u, Cons(_, us)) -> u + sum_even us
```

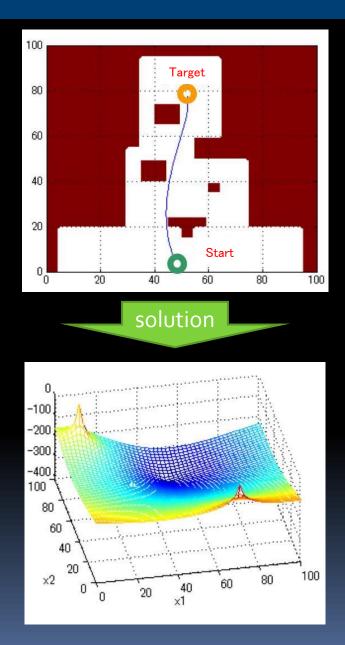
Applications of Genetic Programming (GP)

- Program Synthesis
- · Function Generation
- · Rule Set Discovery

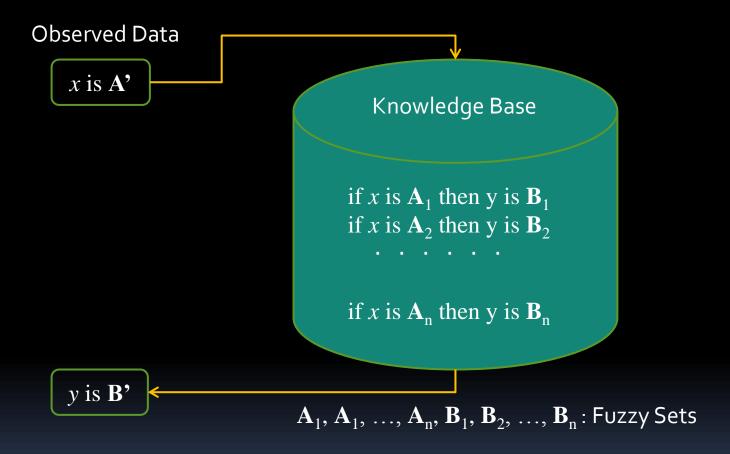
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Function Generation [Jamali2017]

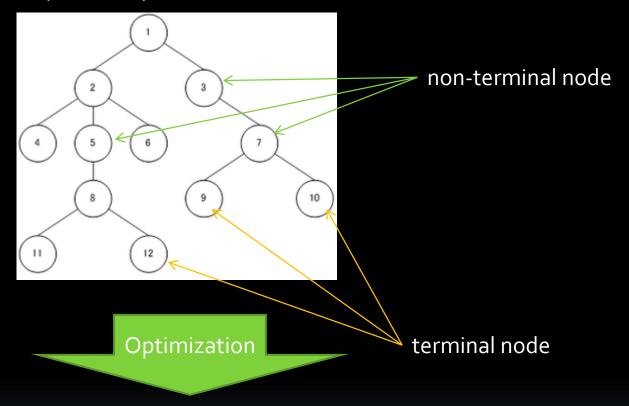




• Rule Set Discovery [Ohmoto2013]



They can be expressed by a tree structure data.



Genetic Programming: GP

