The Automated Modeling and Optimization of Part DNA Substructures Employing Evolutionary Computation

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Overview

Part-DNA Overview

Goals:

- Model and map the flow of goods and components through a system

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- Model and map the flow of goods and components through a system
- Track the changes to components over time
- Help identify relationships between components
- Makes analyzing the system easier

How We Fit into the Part-DNA Model

1. Choose a substructure of the Part-DNA Model

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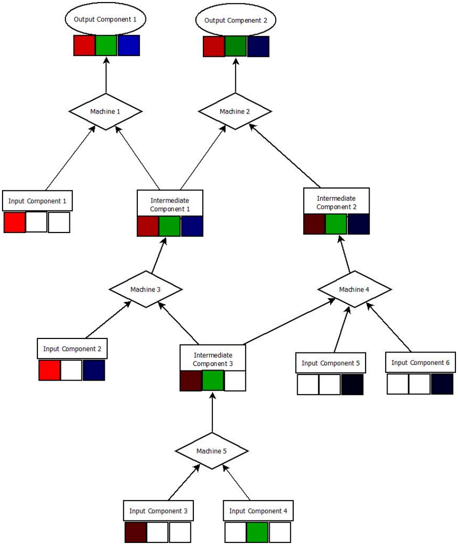
2. Modeling the substructure (GP)

Modeling the Substructure

1. Map the layout into a well-defined ordering

Our Model Concept



Modeling the Substructure

1. Map the layout into a well-defined ordering
2. Gather data on input-output component transformations

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3. Model the transformations of components

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2. Modeling the substructure (GP)
3. Optimize input combinations (MOEA)

Optimizing the Substructure

With the model in hand:

1. Gather data on possible input components

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With the model in hand:

1. Gather data on possible input components
2. Test new input combinations to map Pareto Trade-Off surface

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- Individual **A** is better than individual **B** if **A** has a higher fitness than **B**

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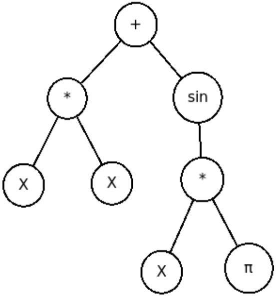
$$Y = X^2 + sin(X * \pi) \tag{1}$$



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  - **A:** `Accuracy 60%, Affordability 2`
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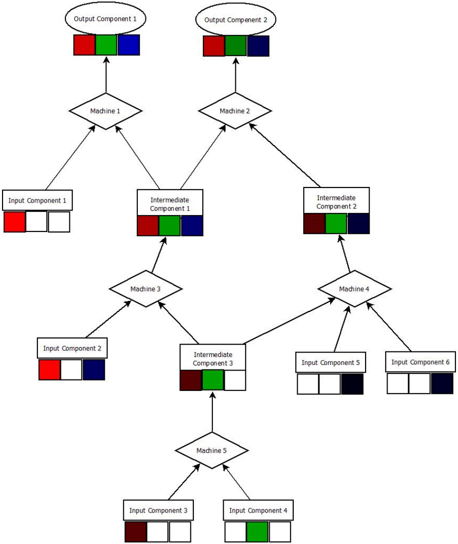
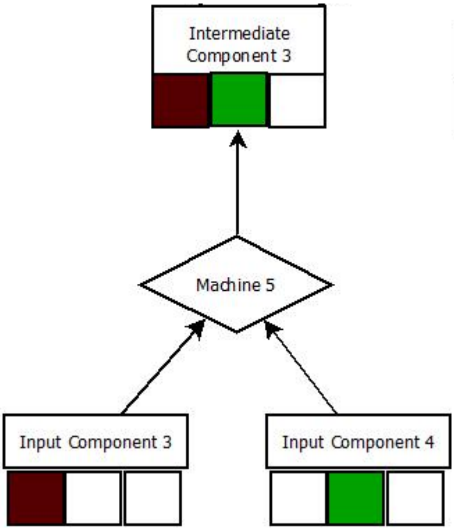
- **A** does *not dominate* **B**
  - **A:** `Accuracy 60%, Affordability 1`
  - **B:** `Accuracy 50%, Affordability 2`

GP Section



Output Component 1
Output Component 2
Machine 1
Machine 2
Input Component 1
Intermediate Component 1
Intermediate Component 2
Machine 3
Machine 4
Input Component 2
Intermediate Component 3
Input Component 5
Input Component 6
Machine 5
Input Component 3
Input Component 4

GP Section


Intermediate Component 3
Machine 5
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GP Process

Given a dataset of input-output combinations
For each output attribute:

- Generate population of randomized functions from the input domain

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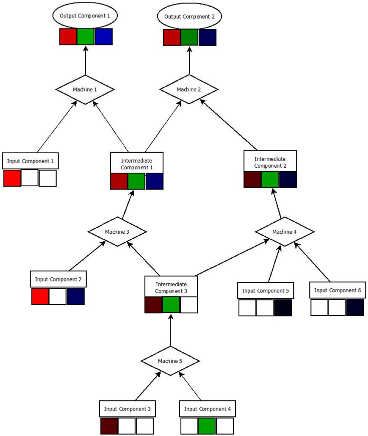
- Explore the function domain through recombination and mutation of functions

Repeat for each transformation object

MOEA Section

With the modeled functions in hand, we apply our MOEA to the whole process to optimize for the output parameters



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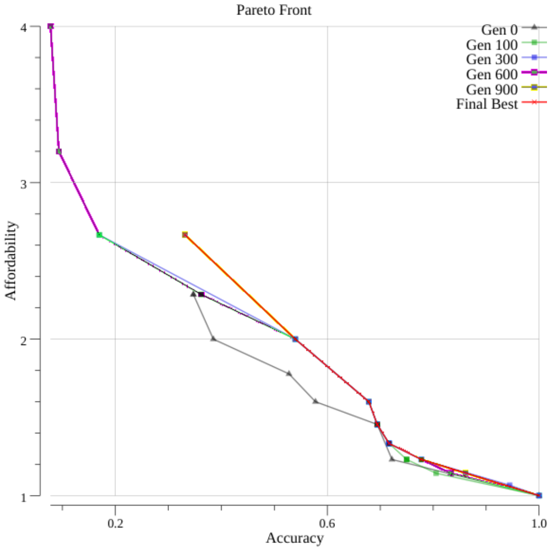
- Simulate the system with each input combination
- Assign fitness values for Accuracy and Affordability
- Rate solutions based on their Pareto score
- Explore the input combination domain through recombination and mutation of solutions

End with a selection of Pareto Optimal solutions, and associated trade-off information.

Example Pareto Front over Time



Future of the Project

- Realistic datasets, both transformation machines and full substructure simulation

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- Realistic datasets, both transformation machines and full substructure simulation
- Possibility for optimizing full substructure layout/ordering

Questions?

References

- Dr. Tauritz's Intro to EA class slides
  - `http://web.mst.edu/~tauritzd/courses/ec/`