Metaheuristic Optimization

21. Representations

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1 Introduction

2 Real-World VRP

3 Summary
• Search space $\mathcal{G}$ (genome, contains genotypes)
• Genotype-phenotype mapping (gpm) translate from $G$ to $X$
• Genotype-phenotype mapping (gpm) translate from $G$ to $X$
• Solution space $X$ (genome, contains phenotypes=candidate solutions)
- $f$: rates quality of candidate solutions

Search Space $\mathbb{G}$
Explored by Optimization Algorithm

$G = \mathbb{R}^n$

Genotype $g = \begin{pmatrix} 2.1 \\ 10.2 \\ 5.4 \\ 7.0 \\ 15.3 \\ 30.2 \end{pmatrix}$

Solution Space $\mathbb{X}$
Understood by User and Objective Function

Candidate solution $x =$

Mix 2.1g honey with 10.2g chocolate and 5.4g eggs and 7.0g sugar and 15.3g flour then bake for 30.2 minutes.

Objective Function $f$
Rates Quality of Solution

Objective function $f(x)$: Grandma bakes the cookie you eat it and rate it from 1 to 10.
• $f$: rates quality of candidate solutions

• Search Space $\mathbb{G}$, genotype-phenotype mapping $\text{gpm}$, and $\mathbb{X}$ together are called the *Representation*

Mathematical Representation:

- **Search Space $\mathbb{G}$**
  - Explored by Optimization Algorithm
  - $\mathbb{G} = \mathbb{R}^n$
  - Genotype $g = \begin{pmatrix} 2.1 \\ 10.2 \\ 5.4 \\ 7.0 \\ 15.3 \\ 30.2 \end{pmatrix}$

- **Solution Space $\mathbb{X}$**
  - Understood by User and Objective Function
  - Candidate solution $x =$
  - Mix 2.1g honey with 10.2g chocolate and 5.4g eggs and 7.0g sugar and 15.3g flour then bake for 30.2 minutes.

- **Objective Function $f$**
  - Rates Quality of Solution
  - Objective function $f(x)$:
    - Grandma bakes the cookie
    - You eat it and rate it from 1 to 10
• Search Space \( G \), genotype-phenotype mapping \( gpm \), and \( X \) together are called the *Representation*.

• Genotype-phenotype mapping becomes identity mapping if \( G = X \).
• Search Space $G$, genotype-phenotype mapping $gpm$, and $X X$ together are called the **Representation**

• Genotype-phenotype mapping becomes identity mapping if $G = X$

---

Search Space $G$
Explored by Optimization Algorithm

\[
G = \mathbb{R}^n \\
\text{genotype } g = \begin{pmatrix} 
2.1 \\
10.2 \\
5.4 \\
7.0 \\
15.3 \\
30.2 
\end{pmatrix}
\]

---

Solution Space $X$
Understood by User and Objective Function

candidate solution $x = \text{Mix } 2.1\text{g honey with } 10.2\text{g chocolate and } 5.4\text{g eggs and } 7.0\text{g sugar and } 15.3\text{g flour then bake for 30.2 minutes.}\$

---

Objective Function $f$
Rates Quality of Solution

\[
\text{objective function } f(x): \text{grandma bakes the cookie you eat it and rate it from 1 to 10}
\]

Representation (often $G = X$, but not always)
Incorporation of domain-specific knowledge (into EA) essential for good performance \[1\]
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But where to include it?
Incorporation of domain-specific knowledge (into EA) essential for good performance \(^\text{[1]}\)

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- “intelligent” /domain-specific/memetic search operators?
• Incorporation of domain-specific knowledge (into EA) essential for good performance \[1\]
• But where to include it?
  • “intelligent”/domain-specific/memetic search operators?
  • domain-specific search space (+operators)? \(\Rightarrow\) Representation
• Incorporation of domain-specific knowledge (into EA) essential for good performance \(^{[1]}\)
• But where to include it?
  • “intelligent”/domain-specific/memetic search operators?
  • domain-specific search space (+operators)?  \(\implies\) Representation
  • simple search space + “intelligent” GPM?  \(\implies\) Representation
Incorporation of domain-specific knowledge (into EA) essential for good performance \[1\]

But where to include it?

- “intelligent”/domain-specific/memetic search operators?
- domain-specific search space (+operators)? \[\implies \text{Representation}\]
- simple search space + “intelligent” GPM? \[\implies \text{Representation}\]
- domain-specific algorithm?
- …
Incorporation of domain-specific knowledge (into EA) essential for good performance \[1\]

But where to include it?

- “intelligent”/domain-specific/memetic search operators?
- domain-specific search space (+operators)? \implies\textbf{Representation}
- simple search space + “intelligent” GPM? \implies\textbf{Representation}
- domain-specific algorithm?
- …

Choice of representation has major impact on quality of results \[2–6\]
1 Introduction

2 Real-World VRP

3 Summary
Introduction

- Finished work contributing to a freight management system [7–11]
• Finished work contributing to a freight management system [7–11]
• Focus on container-based freight transportation
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• Focus on container-based freight transportation
Holistic Approach

Satellite-based location

Communication via Middleware

Swap Body + YellowBox

Software (e.g. Planner)

Visualization

Alert!
possible Optimization
VRP: in.west Project

- Holistic Approach
- Sensor Nodes

Satellite-based location

Communication via Middleware

Swap Body + YellowBox

Software (e.g. Planner)

Visualization

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- Holistic Approach
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Satellite-based location

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Visualization

Alert! possible Optimization

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VRP: in.west Project

- Holistic Approach
- Sensor Nodes
- Middleware
- Transportation Planner
- Web-based GUI

Satellite-based location

Communication via Middleware

Swap Body + YellowBox

Software (e.g. Planner)

Visualization

Communication

Metaheuristic Optimization

Thomas Weise
• *in west*: real-world vehicle routing problems of logistics company
• *in-west*: real-world vehicle routing problems of logistics company

• Orders/Containers/Trucks/Trains/Routes for...
VRP: Situation

- *in.west*: real-world vehicle routing problems of logistics company
- Orders/Containers/Trucks/Trains/Routes for...
- Multiple depots and pickup and delivery locations

[Diagram with VRP and its variants: MDVRP, DVRP, CVRP, VRPTW, VRPPD, VRPB, VRPSPD]

Metaheuristic Optimization Thomas Weise
• *in.west:* real-world vehicle routing problems of logistics company
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in west: real-world vehicle routing problems of logistics company

- Orders/Containers/Trucks/Trains/Routes for...
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- Vehicles (trucks and trains) have (different) capacity limits
- Time windows for pickup and delivery
VRP: Situation

- *in.west*: real-world vehicle routing problems of logistics company
- Orders/Containers/Trucks/Trains/Routes for...
- Multiple depots and pickup and delivery locations
- Vehicles (trucks and trains) have (different) capacity limits
- Time windows for pickup and delivery
- Constraints, laws, time limit: 1 day
• What is a solution/plan $x$ for such a scenario?
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VRP: Representation

- What is a solution/plan $x$ for such a scenario?
- Solution space $\mathbb{X}$: set of all such solutions
What is a solution/plan $x$ for such a scenario?

Search spaces such as integer or bit strings not convenient
What is a solution/plan \( x \) for such a scenario?
Search spaces such as integer or bit strings not convenient: encoding, decoding, meaningful modification too complex.
• What is a solution/plan $x$ for such a scenario?
• Use solution space $\mathbb{X}$ also as search space $\mathbb{G}$
VRP: Representation (Operators)

- Mutation 1: Add new tour for undelivered freight to plan
• Mutation 2: Integrate delivery in existing tour
• Mutation 3: Freight exchange / Truck-meets-Truck
• Mutation 4: Utilize trains with fixed schedules
VRP: Representation (Operators)

- Crossover 1: Join compatible tours
Optimization method: Evolutionary Algorithm [13]
- Initialization: random but *valid* plans that fulfill one randomly chosen task each
Transportation Plan = phenotype $x$ = genotype $g$ $\Rightarrow$ no genotype-phenotype mapping necessary.
• Criteria: no. of undelivered orders $f_1$
VRP: Solving with EA

- Criteria: no. of undelivered orders, distance

Evolutionary Algorithm

- Evaluation: compute the objective values of the solution candidates
- Fitness Assignment: use the objective values to determine fitness values
- Selection: select the fittest individuals for reproduction
- Reproduction: create new individuals from the mating pool by crossover and mutation
- GPM: apply the genotype-phenotype mapping and obtain the phenotypes
• Criteria: no. of undelivered orders, distance, spare capacity

VRP: Solving with EA

Evaluation
compute the objective values of the solution candidates

Fitness Assignment
use the objective values to determine fitness values

Reproduction
create new individuals from the mating pool by crossover and mutation

Selection
select the fittest individuals for reproduction

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apply the genotype-phenotype mapping and obtain the phenotypes

Evolutionary Algorithm
- Pareto Ranking as fitness assignment (see Lesson 15: *Multi-Objective Optimization*)

**Evolutionary Algorithm**

- **Evaluation**: compute the objective values of the solution candidates
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- **GPM**: apply the genotype-phenotype mapping and obtain the phenotypes
- **Reproduction**: create new individuals from the mating pool by crossover and mutation
- **Selection**: select the fittest individuals for reproduction
• Pareto Ranking as fitness assignment (see Lesson 15: *Multi-Objective Optimization*)
• Sharing in objective space: increase diversity \(^{[13]}\)
• Selection: tournament selection
VRP: Solving with EA

- 16 mutation + 3 crossover constellation-specific operators
VRP: Solving with EA

- 16 mutation + 3 crossover constellation-specific operators
- Each operator preserves validity; operators randomly chosen for application
Cycle starts again
• Original data from project partner
VRP: Experiments

- Original data from project partner

- 4th quarter 2007
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- \( \approx 800 \) swap bodies
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- \( \approx 800 \) swap bodies
- \( \approx 10 \) depots
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- $\approx 160 - 3000$ orders per day
VRP: Experiments

- Original data from project partner

- 4th quarter 2007
- ≈ 800 swap bodies
- ≈ 10 depots
- ≈ 800 pickup and delivery locations
- ≈ 160 – 3000 orders per day
- ≈ 75% fill rate, lean flow of goods
- Mon, 2007-12-24
- 642 orders
- original: 63 812km

VRP: Experiments

Distance in km

original performance

first time a complete plan was found

Generations

A

B
Mon, 2007-12-24
642 orders
original: 63,812km
A: assign all orders
VRP: Experiments

- Mon, 2007-12-24
- 642 orders
- original: 63,812 km
- A: assign all orders
- B: improve solutions

![Graph showing distance in km vs generations with two sections labeled A and B. Section A shows many points scattered around 70,000 km, while section B shows a more concentrated path with the label "first time a complete plan was found." A horizontal line indicates the original performance.](image-url)
- Mon, 2007-12-24
- 642 orders
- original: 63,812km
- A: assign all orders
- B: improve solutions
- 54,993km
Sat, 2007-11-03
1016 orders
original: 82 013 km

VRP: Experiments

Distance in km

A

B

first time a complete plan was found

original performance

Generations

all orders delivered
99% of orders delivered
• Sat, 2007-11-03
• 1016 orders
• original: 82 013km
• **A**: assign all orders
• **B**: improve solutions
- Sat, 2007-11-03
- 1016 orders
- original: 82 013km
- A: assign all orders
- B: improve solutions
- 100%: 79 463km
Sat, 2007-11-03
1016 orders
original: 82 013km
A: assign all orders
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100%: 79 463km
99%: 74 435km
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VRP: Summary

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VRP: Summary

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- Scalability is an issue!
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• Important Aspects
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• **Important Aspects:**
  • Domain-specific knowledge should be incorporated as much as possible
EAs are more than just selection, reproduction, and fitness assignment.

The choice of the representation may have much larger impact on their performance than other settings.

Representations can have many different characteristics.

**Important Aspects:**

- Domain-specific knowledge should be incorporated as much as possible.
- Scalability is an important issue!
谢谢

Thank you

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