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Solving the Space Optimization Competition 4 Challenge 2 of the European Space Agency

— Thomas Weise, Sina Abdipoor, Zhize Wu, and Mingxuan Li —

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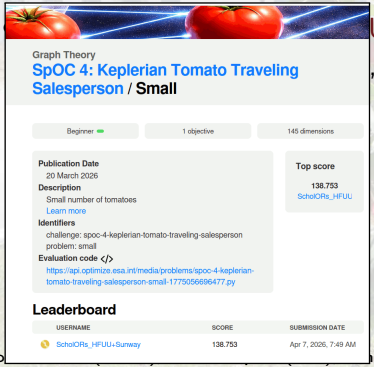

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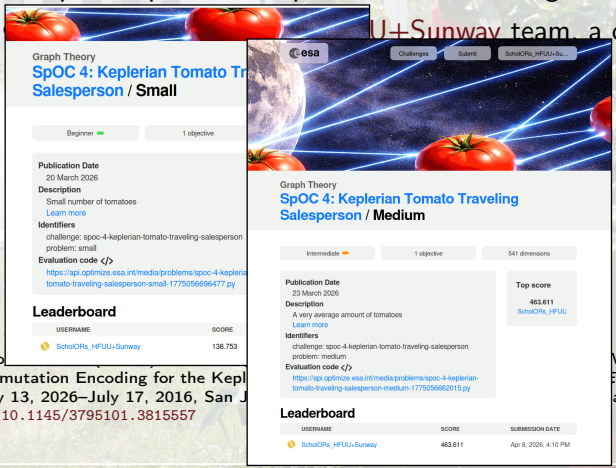

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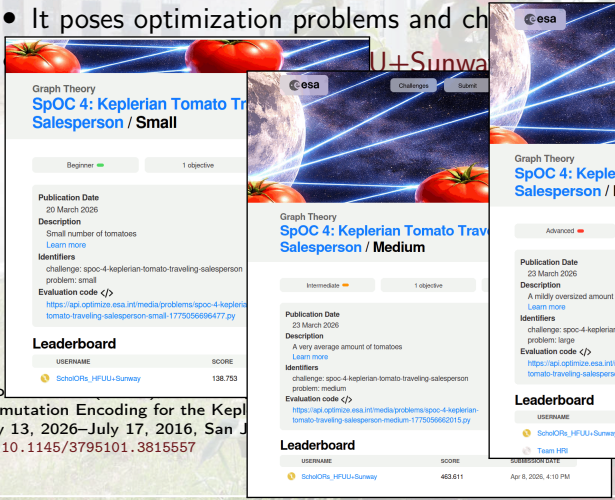

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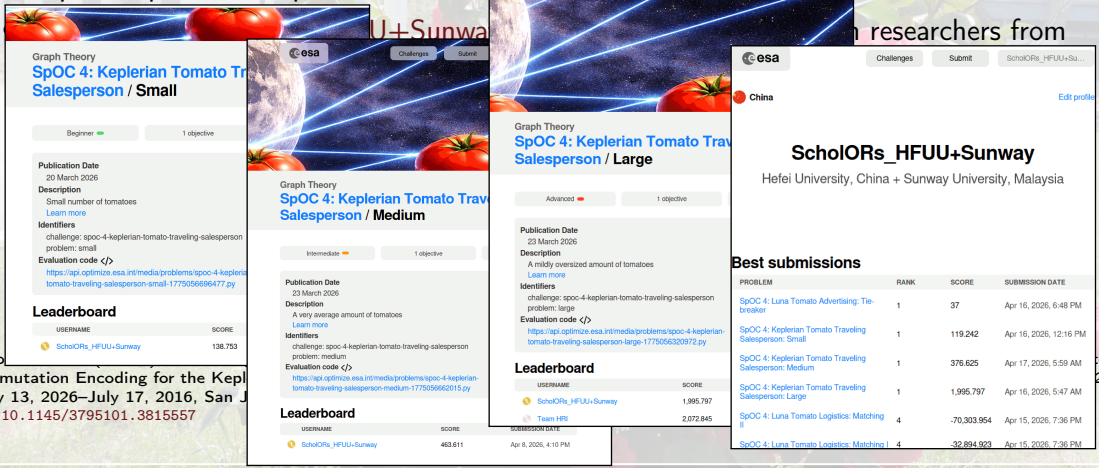

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- Limits for the shortest transfer and maximum total time are also given.

Computing Transfers

- We begin by developing a tool $opt\Delta V$ that finds the earliest transfer from one object to another one within a given time window $[t_s, t_d]$, given a ΔV-limit ΔV_{max}^{lim}.

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$$\psi(t_a, t_b) = \begin{cases} \Delta V & \text{if } \Delta V > \Delta V_{max}^{lim} \\ -1/t_b & \text{otherwise} \end{cases} \tag{1}$$

- If the transfer at times $\{t_a, t_b\}$ is infeasible, the positive ΔV value is returned and can further be minimized until $\Delta V \leq \Delta V_{max}^{lim}$ is reached.

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- We use a variety of algorithms, including Nelder&Mead, BFGS, and CMA-ES.
- If a feasible transfer with end time t' is found, we search again in $[t_s, t')$ until the search fails, retaining and returning the best result.

Infeasible Transfers and Preprocessing

- We first assemble a transfer matrix $\mathcal{T}$ for each instance, telling us whether we can travel from object to another either *not at all*, with excess velocity change, or with a normal velocity change.

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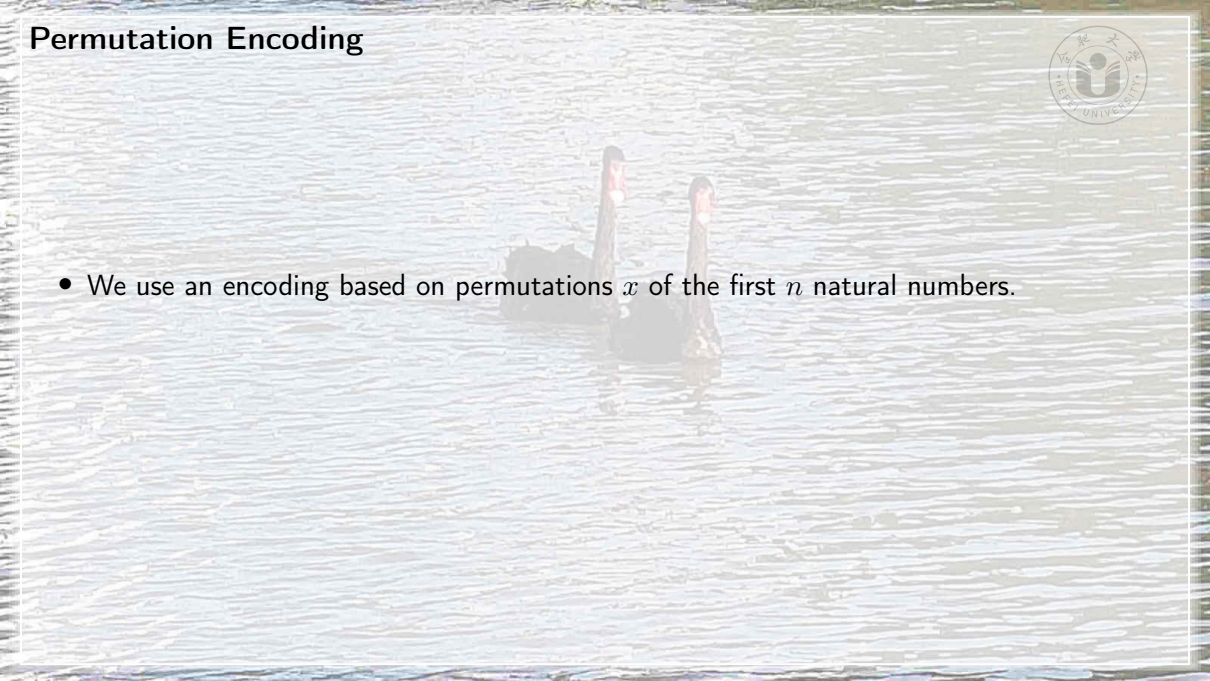
- The matrices $\mathcal{T}$ are sparse, most transfers are infeasible!
- On instance **small**, only 2.8 other objects can be reached with $\Delta V \leq \Delta V_{max}$ in average!
- The vast majority of visit sequences will not be feasible, so always using $opt\Delta V$ would be a huge waste of runtime...

Permutation Encoding



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Permutation Encoding

- We use an encoding based on permutations x of the first n natural numbers.
- A permutation x is decoded to a solution vector y with the actual travel times using a three-stage decoding function γ.

Permutation Encoding: Stage 1

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- This is repeated with the relaxed requirement to allow excess velocity changes.
- Finally, all remaining fragments are stitched together regardless, yielding a new permutation x'.

Permutation Encoding: Stage 2

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- If constraint violations are expected, the decoding stops — this is very fast, no physics computation needed at all.

Permutation Encoding: Stage 3

- Otherwise, we process the permutation x' from beginning to end computing transfers using the actual physics computation $opt\Delta V$.

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- Otherwise, we process the permutation x' from beginning to end computing transfers using the actual physics computation $opt\Delta V$.
- We make sure that each solution uses all 5 permitted excess velocity changes (even if it does not need them), because then we can make travel faster.

Optimization

- We apply a randomized local search (RLS) to minimize the objective function f:

$$f(y) = \begin{cases} p(y) & \text{if } p(y) > 0 \\ -1/t_{tot}(y) & \text{otherwise} \end{cases} \tag{2}$$

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- For feasible solutions, the total time t_{tot} is minimized.

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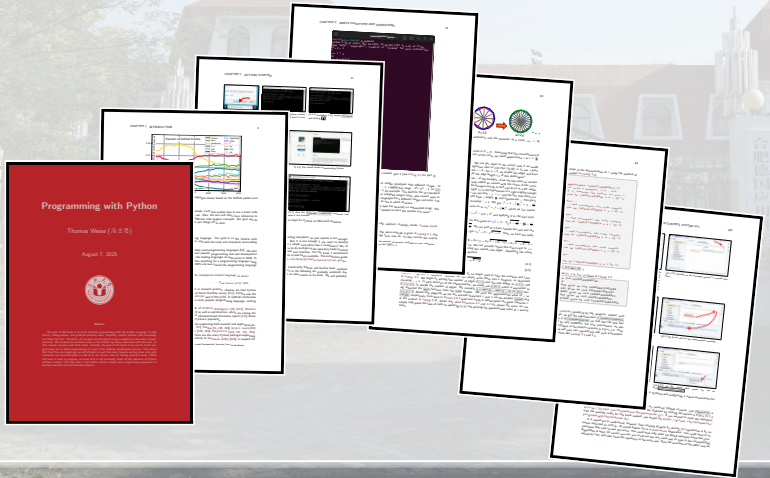
- Our results are obtained with low computational cost on off-the-shelf laptops.
- An early setup found a feasible solution with $t_{tot} = 2689.4$ for the **large** instance within 187 seconds.

Advertisement

Programming with Python

We have a freely available course book on *Programming with Python* at `https://thomasweise.github.io/programmingWithPython`, with focus on practical software development using the Python ecosystem of tools[15].

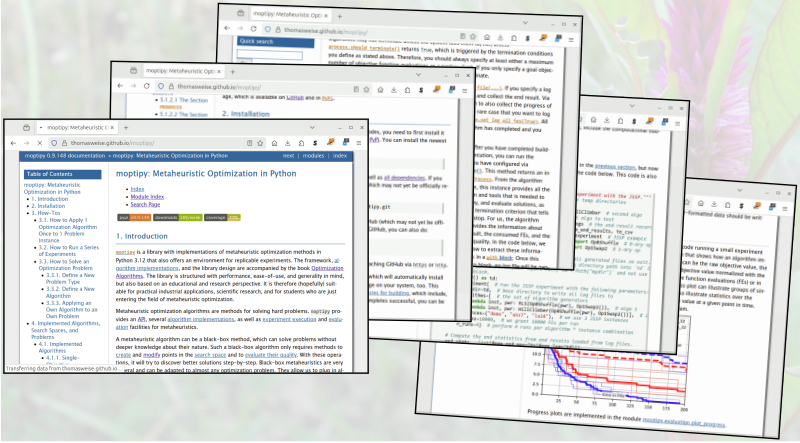


Databases

We have a freely available course book on *Databases* at `https://thomasweise.github.io/databases`, with actual practical examples using a real database management system (DBMS)[13].

Metaheuristic Optimization in Python: moptipy

We offer moptipy[17] a mature open source Python package for metaheuristic optimization, which implements several algorithms, can run self-documenting experiments in parallel and in a distributed fashion, and offers statistical evaluation tools.



谢谢您们！

Thank you!

Vielen Dank!

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Glossary I

$(1+1)$ EA The $(1+1)$ EA is a local search algorithm that retains the best solution x_c discovered so far during the search[2,4]. In each step, it applies a unary search operator to this best-so-far solution x_c and derives a new solution x_n. If the new solution x_n is *better or equally good* when compared with x_c, i.e., not worse, then it replaces it, i.e., is stored as the new x_c. If the search space are bit strings of length n, then the $(1+1)$ EA uses a unary search operator that flips each bit independently with probability m/n, where usually $m = 1$. This operator is the main difference to randomized local search (RLS). The $(1+1)$ EA is a special case of the $(\mu+\lambda)$ evolutionary algorithm ($(\mu+\lambda)$ EA) where $\mu = \lambda = 1$.

EA An *evolutionary algorithm* is a metaheuristic optimization method that maintains a population of candidate solutions, which undergo selection (where better solutions are chosen with higher probability) and reproduction (where mutation and recombination create a new candidate solution from one or two existing ones, repectively)[1,14].

$(\mu+\lambda)$ EA The $(\mu+\lambda)$ EA is an evolutionary algorithm (EA) where, in each generation, λ offspring solutions are generated from the current population of μ parent solutions. The offspring and parent populations are merged, yielding $\mu+\lambda$ solutions, from which then the best μ solutions are ratained to form the parent population of the next generation. If the search space is the bit strings of length n, then this algorithm usually applies a mutation operator flipping each bit independently with probability $1/n$.

DB A *database* is an organized collection of structured information or data, typically stored electronically in a computer system. Databases are discussed in our book *Databases*[13].

DBMS A *database management system* is the software layer located between the user or application and the database (DB). The DBMS allows the user/application to create, read, write, update, delete, and otherwise manipulate the data in the DB[19].

ESA The European Space Agency (ESA) is an international organization dedicated to space exploration, research, and technology development. Learn more at https://www.esa.int.

GECCO The Genetic and Evolutionary Computation Conference (GECCO) is one of the largest conferences in the field of EAs. It has been established in 1999 and its proceedings are published by ACM. Learn more at https://sig.sigevo.org/GECCOs.

Glossary II

moptipy is the *Metaheuristic Optimization in Python* library[17]. It has been used in several different research works, including[3,7–9,12,18,20,21]. Learn more at https://thomasweise.github.io/moptipy and https://thomasweise.github.io/moptipyapps.

Python The Python programming language[5,6,10,15], i.e., what you will learn about in our book[15]. Learn more at https://python.org.

RLS Randomized local search retains the best solution x_c discovered so far during the search and, in each step, it applies a unary search operator to this best-so-far solution x_c and derives a new solution x_n. If the new solution x_n is *better or equally good* when compared with x_c, i.e., not worse, then it replaces it, i.e., is stored as the new x_c. If the search space are bit strings of length n, then RLS uses a unary search operator that flips exactly one bit. This operator is the main difference to $(1+1)$ evolutionary algorithm ($(1+1)$ EA).

SpOC The Space Optimization Competition (SpOC) is a competition organized by the Advanced Concepts Team of ESA at GECCO since 2022, where various optimization problems related to space exploration and travel are posed and researchers worldwide can compete. Learn more at https://optimise.esa.int.

$f(y)$ The *objective function* $f : \mathbb{Y} \mapsto \mathbb{R}$ can compute a cost or rating for each candidate solution y in the solution space $\mathbb{Y}$. The smaller this value, the better the solution, i.e., in the context of this work, objective functions are subject to minimization. Objective functions are not necessarily continuous and it is also quite common that they have integer or natural numbers as results, e.g., we often have $f : \mathbb{Y} \mapsto \mathbb{N}_0$ instead of $f : \mathbb{Y} \mapsto \mathbb{R}$..

$\gamma(x)$ The decoding function $\gamma : \mathbb{X} \mapsto \mathbb{Y}$ translates point from the search space $\mathbb{X}$ to one point y in the solution space $\mathbb{Y}$. It is a very common case that $\mathbb{X} = \mathbb{Y}$ and that the decoding function γ is the identity mapping..

$\mathbb{N}_0$ the set of the natural numbers *including* 0, i.e., 0, 1, 2, 3, and so on. It holds that $\mathbb{N}_0 \subset \mathbb{Z}$.

Glossary III

$\mathbb{R}$ the set of the real numbers.

$\mathbb{X}$ The search space $\mathbb{X}$ is the space through which an optimization algorithm navigates in order to find good solutions. The search operators of metaheuristics are used to sample points $x \in \mathbb{X}$, for example. While it is often the case, these are not necessarily the same data structures that the user is interested in. It is also common that the search space $\mathbb{X}$ is a simple and plain data structure that can be tackled with standard operations or mathematical tools, such as real vectors $\mathbb{R}^n$, permutations, or bit strings, whereas the solution space $\mathbb{Y}$ can be something more complicated, like a Gantt chart. Then, the user only cares about the solutions $y \in \mathbb{Y}$ and not about the search space $\mathbb{X}$. A decoding $\gamma : \mathbb{X} \mapsto \mathbb{Y}$ is employed to translate the $x \in \mathbb{X}$ to $y = \gamma(x)$ with $y \in \mathbb{Y}$..

x a point in the search Space $\mathbb{X}$..

$\mathbb{Y}$ the set of candidate solutions of an optimization problem is called the *solution space* $\mathbb{Y}$. The solution space corresponds to the data structure holding the candidate solutions y. These are the elements that are passed to the user after the optimization process is completed. They are also the parameters of the objective function(s) $f : \mathbb{Y} \mapsto \mathbb{R}$..

y a candidate solution $y \in \mathbb{Y}$ is one possible solution to an optimization problem. After the optimization process is completed, one or multiple such solutions are passed to the user..

$\mathbb{Z}$ the set of the integers numbers including positive and negative numbers and 0, i.e., . . . , -3, -2, -1, 0, 1, 2, 3, . . . , and so on. It holds that $\mathbb{Z} \subset \mathbb{R}$.