

Evolutionary Computation

2023/24

Master Artificial Intelligence

Arno Formella

Departamento de Informática
Escola Superior de Enxeñaría Informática
Universidade de Vigo

23/24

- active participation in class (10%)
- two major up-loads of homework (50%)
(probably week 19-23 Feb, and week 11-15 Mar)
- final exam (40%)
(28th May and/or 2th Jul)

- D. Simon, *Evolutionary Optimization Algorithms*, ISBN: 978-0-470-93741-9, Wiley, 2013
- A.E. Eiben, J.E. Smith, *Introduction to Evolutionary Computing*, second edition, ISBN 978-3-662-44873-1, Springer, 2015
- my webpage:
<http://formella.webs.uvigo.es/doc/ec23/index.html>

- Evolutionary computation is about **optimization**.
- **Evolutionary algorithms** are usually randomized or **probabilistic heuristic** algorithms.
- Many of them are called **nature-inspired** (or bio-inspired) algorithms as they exhibit some properties observed in nature (especially, but not only, from biology).
- Programs based on evolutionary algorithms are typically used to find **approximate solutions** to **difficult problems**.

Disclaimer: we are talking about *nature-inspired optimization algorithms*, we are not copying nature, mostly, because I've no idea what nature is doing. We are interested in mathematical models and certain types of algorithms that serve as powerful optimization methods.

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OPEN The cheetah optimizer: a nature-inspired metaheuristic algorithm for large-scale optimization problems

Mohammad Amin Akbari¹, Mohsen Zare², Rasoul Azizipanah-abarghooee³,
Seyedali Mirjalili^{4,5} & Mohamed Deriche^{1,2}✉

Motivated by the **hunting strategies of cheetahs**, this paper proposes a **nature-inspired algorithm** called the cheetah optimizer (CO). Cheetahs generally utilize three main strategies for hunting prey, i.e., searching, sitting-and-waiting, and attacking. These strategies are adopted in this work. Additionally, the leave the pray and go back home strategy is also incorporated in the hunting process to improve the proposed framework's population diversification, convergence performance, and robustness. We perform intensive testing over 14 shifted-rotated **CEC-2005 benchmark functions** to evaluate the performance of the proposed CO in comparison to state-of-the-art algorithms. Moreover, to test the power of the proposed CO algorithm over large-scale optimization problems, the CEC2010 and the CEC2013 benchmarks are considered. The proposed algorithm is also tested in solving one of the well-known and complex engineering problems, i.e., the economic load dispatch problem. For all considered problems, the results are shown to outperform those obtained using other conventional and improved algorithms. The simulation results demonstrate that the CO algorithm can successfully solve large-scale and challenging optimization problems and offers a significant advantage over different standards and improved and hybrid existing algorithms. Note that the source code of the CO algorithm is publicly available at <https://www.optim-app.com/projects/co>.

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A new human-inspired metaheuristic algorithm for solving optimization problems based on mimicking sewing training

Mohammad Deghani, Eva Trojovská[✉] & Tomáš Zuščák

This paper introduces a new **human-based metaheuristic** algorithm called **Sewing Training-Based Optimization (STBO)**, which has applications in handling optimization tasks. The fundamental inspiration of STBO is **teaching the process of sewing to beginner tailors**. The theory of the proposed STBO approach is described and then mathematically modeled in three phases: (i) training, (ii) imitation of the instructor's skills, and (iii) practice. STBO performance is evaluated on fifty-two benchmark functions consisting of unimodal, high-dimensional multimodal, fixed-dimensional multimodal, and the **CEC 2017 test suite**. The optimization results show that STBO, with its high power of exploration and exploitation, has provided suitable solutions for benchmark functions. The performance of STBO is compared with eleven well-known metaheuristic algorithms. The simulation results show that STBO, with its high ability to balance exploration and exploitation, has provided far more competitive performance in solving benchmark functions than competitor algorithms. Finally, the implementation of STBO in solving four engineering design problems demonstrates the capability of the proposed STBO in dealing with real-world applications.

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A novel hermit crab optimization algorithm

Jia Guo^{1,2}, Guoyuan Zhou¹, Ke Yan³, Binghua Shi^{1✉}, Yi Di^{1,2} & Yuji Sato⁴

High-dimensional optimization has numerous potential applications in both academia and industry. It is a major challenge for optimization algorithms to generate very accurate solutions in high-dimensional search spaces. However, traditional search tools are prone to dimensional catastrophes and local optima, thus failing to provide high-precision results. To solve these problems, a novel **hermit crab optimization algorithm** (the HCOA) is introduced in this paper. Inspired by the **group behaviour of hermit crabs**, the HCOA combines the optimal search and historical path search to balance the depth and breadth searches. In the experimental section of the paper, the HCOA competes with 5 well-known metaheuristic algorithms in the **CEC2017 benchmark functions**, which contain 29 functions, with 23 of these ranking first. The state of work BPSO-CM is also chosen to compare with the HCOA, and the competition shows that the HCOA has a better performance in the 100-dimensional test of the CEC2017 benchmark functions. All the experimental results demonstrate that the HCOA presents highly accurate and robust results for high-dimensional optimization problems.

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Pair barracuda swarm optimization algorithm: a natural-inspired metaheuristic method for high dimensional optimization problems

Jia Guo^{1,2}, Guoyuan Zhou³, Ke Yan⁴, Yuji Sato⁵ & Yi Di^{1,2✉}

High-dimensional optimization presents a novel challenge within the realm of intelligent computing, necessitating innovative approaches. When tackling high-dimensional spaces, traditional evolutionary tools often encounter pitfalls, including dimensional catastrophes and a propensity to become trapped in local optima, ultimately compromising result accuracy. To address this issue, we introduce the **Pair Barracuda Swarm Optimization** (PBSO) algorithm in this paper. PBSO employs a unique strategy for constructing barracuda pairs, effectively mitigating the challenges posed by high dimensionality. Furthermore, we enhance global search capabilities by incorporating a support barracuda alongside the leading barracuda pair. To assess the algorithm's performance, we conduct experiments utilizing the **CEC2017 standard function** and compare PBSO against five state-of-the-art natural-inspired optimizers in the control group. Across 29 test functions, PBSO consistently secures top rankings with 9 first-place, 13 second-place, 5 third-place, 1 fourth-place, and 1 fifth-place finishes, yielding an average rank of 2.0345. These empirical findings affirm that PBSO stands as the superior choice among all test algorithms, offering a dependable solution for high-dimensional optimization challenges.

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Mother optimization algorithm: a new human-based metaheuristic approach for solving engineering optimization

Ivana Matoušová¹, Pavel Trojovský¹, Mohammad Dehghani¹, Eva Trojovská¹ & Juraj Kostra²

This article's innovation and novelty are introducing a new metaheuristic method called mother optimization algorithm (MOA) that mimics the human interaction between a mother and her children. The real inspiration of MOA is to simulate the mother's care of children in three phases education, advice, and upbringing. The mathematical model of MOA used in the search process and exploration is presented. The performance of MOA is assessed on a set of 52 benchmark functions, including unimodal and high-dimensional multimodal functions, fixed-dimensional multimodal functions, and the CEC 2017 test suite. The findings of optimizing unimodal functions indicate MOA's high ability in local search and exploitation. The findings of optimization of high-dimensional multimodal functions indicate the high ability of MOA in global search and exploration. The findings of optimization of fixed-dimension multi-model functions and the CEC 2017 test suite show that MOA with a high ability to balance exploration and exploitation effectively supports the search process and can generate appropriate solutions for optimization problems. The outcomes quality obtained from MOA has been compared with the performance of 12 often-used metaheuristic algorithms. Upon analysis and

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A new human-based metaheuristic algorithm for solving optimization problems based on preschool education

Pavel Trojovský

In this paper, with motivation from the No Free Lunch theorem, a new human-based metaheuristic algorithm named **Preschool Education Optimization Algorithm** (PEOA) is introduced for solving optimization problems. Human activities in the preschool education process are the fundamental inspiration in the design of PEOA. Hence, PEOA is mathematically modeled in three phases: (i) the gradual growth of the preschool **teacher's educational influence**, (ii) **individual knowledge development** guided by the teacher, and (iii) **individual increase of knowledge and self-awareness**. The PEOA's performance in optimization is evaluated using **fifty-two standard benchmark functions** encompassing unimodal, high-dimensional multimodal, and fixed-dimensional multimodal types, as well as the **CEC 2017 test suite**. The optimization results show that PEOA has a high ability in exploration–exploitation and can balance them during the search process. To provide a comprehensive analysis, the performance of PEOA is compared against ten well-known metaheuristic algorithms. The simulation results show that the proposed PEOA approach performs better than competing algorithms by providing effective solutions for the benchmark functions and overall ranking as the first-best optimizer. Presenting a statistical analysis of the Wilcoxon signed-rank test shows that

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A new human-based metaheuristic optimization method based on mimicking cooking training

Eva Trojovská[✉] & Mohammad Dehghani

Metaheuristic algorithms have a wide range of applications in handling optimization problems. In this study, a new metaheuristic algorithm, called the chef-based optimization algorithm (CBOA), is developed. The fundamental inspiration employed in CBOA design is the **process of learning cooking skills in training courses**. The stages of the cooking training process in various phases are mathematically modeled with the aim of increasing the ability of global search in exploration and the ability of local search in exploitation. A collection of **52 standard objective functions** is utilized to assess the CBOA's performance in addressing optimization issues. The optimization results show that the CBOA is capable of providing acceptable solutions by creating a balance between exploration and exploitation and is highly efficient in the treatment of optimization problems. In addition, the CBOA's effectiveness in dealing with real-world applications is tested on four engineering problems. Twelve well-known metaheuristic algorithms have been selected for comparison with the CBOA. The simulation results show that CBOA performs much better than competing algorithms and is more effective in solving optimization problems.

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the problems we will look at

- search of minimum in real-valued **multi-dimensional functions**
- **traveling salesman** (or nowadays *salesperson*) problem (TSP)
- **sorting** as an optimization problem (just for fun)
- maybe: (0-1)-**knapsack** problem (KSP)
- some more problems as examples

- An algorithm is a **finite sequence of well-defined steps** (or instructions) to complete a task or solve a problem.
- In principal, the individual steps must be **executable by a human being**.
- The steps (or instructions) must realize a **finite change of state** (or configuration) on the system on which the algorithm is executed.
- Completing a task means that there is an other algorithm that can decide that the final configuration **has the required property**.
- The time complexity of an algorithm is the **number of steps** the algorithm executes before it stops.

- Algorithms can be **grouped into classes** according to their time complexity (same is true for space complexity).
- For an asymptotic upper bound according to some input size n we say:
function f is in the order of function g , whenever we have:

$$\exists c > 0 \exists n_0 \forall n > n_0 : |f(n)| \leq c \cdot g(n)$$

and write: $f(n) = \mathcal{O}(g(n))$.

- Example: if $f(n) = \mathcal{O}(n^3)$ then f does not grow faster than cubic.
- There are more notations for other **asymptotic characterizations**:
 \mathcal{o} , ω , Ω , Θ .
- If you like, take a look at the **complexity zoo**:

https://complexityzoo.net/Complexity_Zoo

computational complexity

- There are **arbitrary difficult** problems (there is a hierarchy of classes).
- There are problems that don't have a solution at all (**uncomputable problems**)
examples are: decide whether an arbitrary program stops, decide whether two formal languages are equivalent, among others.
- There are problems where we know that they are **computable** (i.e., there exists a solution) but **we don't know how to compute** one. Look into *forbidden graph minors in graph theory*.
- There are problems for which there are known algorithms, but we don't know the **smallest class they belong to**, e.g., unknotting an unknot (take a look into knot theory)
<https://en.wikipedia.org/wiki/Unknot> or factorization of numbers https://en.wikipedia.org/wiki/Integer_factorization.

runtime examples according to complexity

Assume we can deal with 1 million items in 1 second using a linear time algorithm (i.e., megahertz item processing):

size n	function	θ -notation	time
1000000	linear time	$\theta(n)$	1 second
	quasi-linear time	$\theta(n \log n)$	20 seconds
	quadratic time	$\theta(n^2)$	11.6 days
	cubic time	$\theta(n^3)$	31710 years
	quartic time	$\theta(n^4)$	32 billion year (2.3 times age of universe)
	exponential time	$\theta(2^n)$	eternal
	factorial time	$\theta(n!)$	no words any more

runtime examples according to complexity

Assume we can deal with 1 million items in 1 millisecond using a linear time algorithm (i.e., gigahertz item processing):

size n	function	\mathcal{O} -notation	time
1000000	linear time	$\mathcal{O}(n)$	1 millisecond
	quasi-linear time	$\mathcal{O}(n \log n)$	20 milliseconds
	quadratic time	$\mathcal{O}(n^2)$	16 minutes
	cubic time	$\mathcal{O}(n^3)$	31.7 years
	quartic time	$\mathcal{O}(n^4)$	32 million years
	exponential time	$\mathcal{O}(2^n)$	eternal
	factorial time	$\mathcal{O}(n!)$	no words any more

Note: **Parallelization** on a p -processor machine gives you at most a **linear speedup** of p (and most of the time not even that). **Quantum computation** offers sometimes (Grover algorithm) a quadratic speedup regarding input size n .

handable problem sizes according to complexity

Assume 1 nanosecond processing time per item (i.e., 1 GHz operating frequency), problem sizes **handable** in one hour:

function	θ-notation	problem size
linear time	$\theta(n)$	3.6 trillion
quasi-linear time	$\theta(n \log n)$	96.6 billion
quadratic time	$\theta(n^2)$	1.9 million
cubic time	$\theta(n^3)$	15.3 thousand
quartic time	$\theta(n^4)$	1377
exponential time	$\theta(2^n)$	41
factorial time	$\theta(n!)$	15

- deterministic algorithms
- **non-deterministic** algorithms
- randomized or **probabilistic** algorithms
- quantum algorithms

Note, all types compute the **same set** of computable functions, they differ only in time and space complexity (see below).

When do we consider a problem to be difficult?

A problem is **difficult** whenever we only know deterministic algorithms solving the problem that have at least exponential runtime (or polynomial runtime with a large exponent).

Side note: NP-complete and NP-hard problems

Evolutionary algorithms are often mentioned as a way to tackle NP-complete or NP-hard problems: What does that mean?

- A problem is **NP-complete** when we know a **polynomial** time deterministic algorithm that **checks a solution**, but we know only an **exponential** time deterministic algorithm to **find a solution**.
- A problem is, at least, **NP-hard** when we even don't know a polynomial time deterministic algorithm that **checks** a solution.
- There are problems where we know that they can be solved in exponential time, but we don't know whether they are NP-complete (or even simpler), e.g., the graph isomorphism problem, or the unknot problem.
- Essentially, we don't know whether the NP-complete problems (those that we know to have a polynomial time algorithm to check them) are the same class as the polynomial time solvable problems.

In other words, we **don't know** whether $P = NP$ or $P \neq NP$.



two main classes:

- **Monte Carlo** algorithm:
for a certain number of iterations do:
 - perform some randomized algorithm step towards a better solution
 - (usually keep track of your best solution found so far)
- Monte Carlo algorithms always terminate and (hopefully) find a somewhat good solution.
- **Las Vegas** algorithm:
while a certain end condition still not met do:
 - perform some randomized algorithm step towards a better solution
- Las Vegas algorithms only terminate with a correct solution (or do not terminate at all), but their runtime is probabilistic.

- backtracking
- branch and bound
- **brute-force** (or exhaustive) search
- divide and conquer
- **dynamic programming**
- **greedy** algorithm
- prune and search
- online algorithms

What are heuristic algorithms?

- Just **do something** you come up with and **be happy** with the result.

What are evolutionary algorithms?

- Evolutionary algorithms are **heuristic optimization algorithms** usually implemented with the Monte Carlo approach (and possibly a Las Vegas stopping condition when available)
- that exhibit, let's say, at least a **tendency to approach a global minimum** as solution of the optimization problem.
- (Often they are inspired by some phenomenon observable in nature or a *creative* name has been used.)

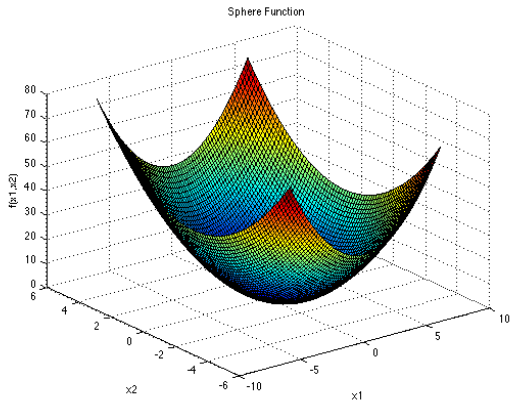
- Given a search space \mathbb{X} (called as well *search domain* or *problem space*) and
- a function f (bounded from below) from the search space to the real numbers (or at least a totally ordered set), e.g. $f : \mathbb{X} \rightarrow \mathbb{R}$,
- find an element $x^* \in \mathbb{X}$ such that $f(x^*) \leq f(x)$ for all $x \in \mathbb{X}$.
- i.e., we look for a **global minimum**.

Observe: whenever we look for a maximum, we can use just a negative sign and look for a minimum (and f must be bounded from above)!

local versus global minimum

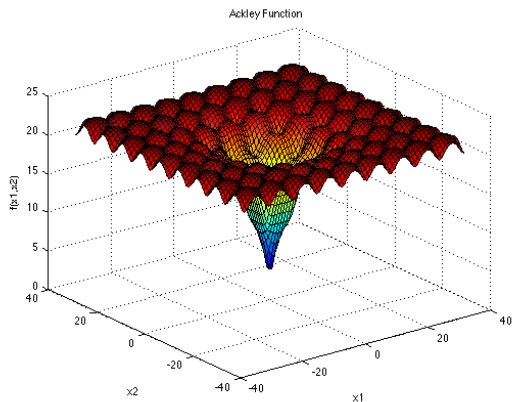
- If we can determine a **neighborhood** around each element $x \in \mathbb{X}$, we call $\mathcal{N}(x)$ the set of neighbors of x .
- and if we have for all such neighbors $x' \in \mathcal{N}(x)$, that $f(x) \leq f(x')$,
- then we call x a **local minimum** (sometimes written as \hat{x}).
- Reaching a local minimum is often somewhat easier, as we can take advantage of a possibly available **gradient** (local search algorithms).
- It happens to be an issue in optimization not to **get stuck** in a local minimum while searching for a global minimum.

optimization test functions: Sphere function



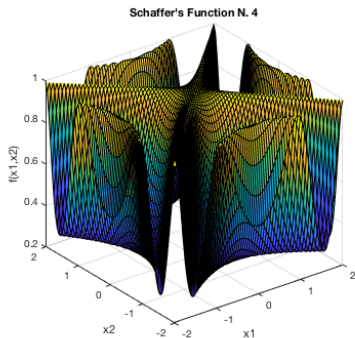
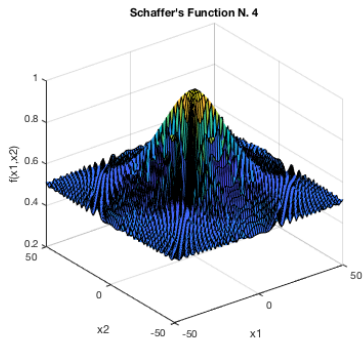
$$f(x) = \sum_{i=1}^d x_i^2$$

optimization test functions: Ackley function



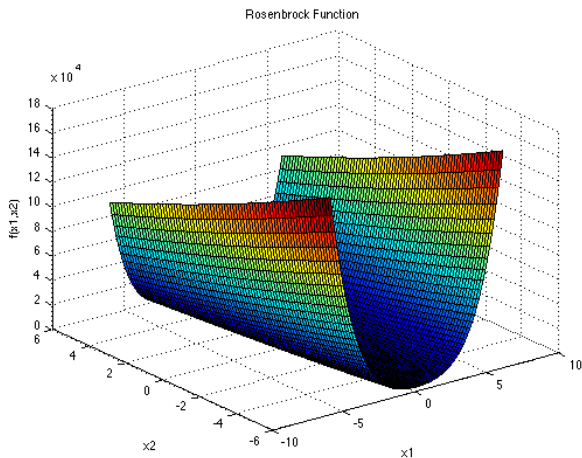
$$f(x) = -a \exp \left(-b \sqrt{\frac{1}{d} \sum_{i=1}^d x_i^2} \right) - \exp \left(\frac{1}{d} \sum_{i=1}^d \cos(cx_i) \right) + a + e$$

optimization test functions: Schaffer 4 function



$$f(x) = 0.5 + \frac{\cos^2(\sin(|x_1^2 - x_2^2|)) - 0.5}{[1 + 0.001(x_1^2 + x_2^2)]^2}$$

optimization test functions: Rosenbrock function



$$f(x) = \sum_{i=1}^{d-1} d - 1 [100 \cdot (x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$$

For more real-valued functions and common

- parameter settings,
- search areas,
- local/global optima,
- and code examples

take a look at

<https://www.sfu.ca/~ssurjano/optimization.html>

or look for CEC2017 benchmark <https://www.kaggle.com/code/kooaslansefat/cec-2017-benchmark>

the traveling salesperson problem (TSP)

The basic traveling salesperson problems are:

- Given n locations or cities and their interconnections in the 2D plane, tell whether there is a closed tour through all cities that visits each city exactly once and has a length below a certain threshold.

This is an NP-complete **decision problem**.

- Given n cities in the 2D plane, find a shortest closed tour through all cities that visits each city exactly once.

This is an NP-hard **search problem**.

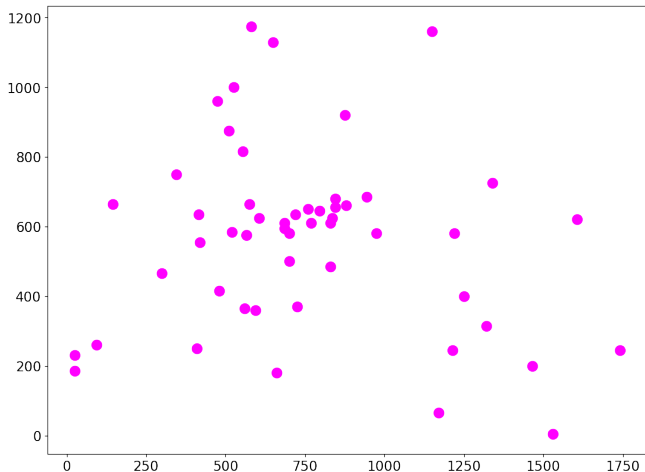
- Given n cities in the 2D plane, find all shortest closed tours through all cities that visit each city exactly once.

This is an exponential time **solver problem**.

- Note, there are $n!$ possible tours through the n cities.
- TSP is one of the best studied problems in computer science.
- There are more varieties of TSPs (some details later).

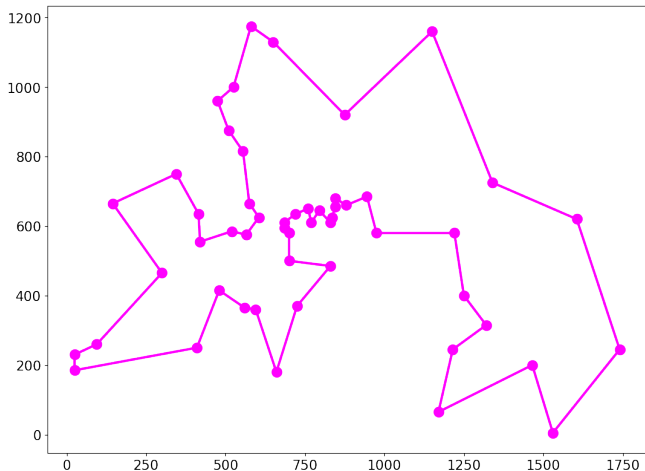


traveling salesperson problem: first impressions



the cities distributed geographically (dataset berlin52)

traveling salesperson problem: first impressions



the best tour (known for this example): 0% relative error