NiaPy Documentation

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Python micro framework for building nature-inspired algorithms.

Nature-inspired algorithms are a very popular tool for solving optimization problems. Since the beginning of their era, numerous variants of nature-inspired algorithms were developed. To prove their versatility, those were tested in various domains on various applications, especially when they are hybridized, modified or adapted. However, implementation of nature-inspired algorithms is sometimes difficult, complex and tedious task. In order to break this wall, NiaPy is intended for simple and quick use, without spending a time for implementing algorithms from scratch.

The main documentation is organized into a couple sections:

- *User Documentation*
- *Developer Documentation*
- *About NiaPy*

CHAPTER 1

Getting Started

It's time to write your first NiaPy example. Firstly, if you haven't already, install NiaPy package on your system using following command:

```
pip install NiaPy
```

When package is successfully installed you are ready to write you first example.

1.1 Basic example

In this example, let's say, we want to try out Gray Wolf Optimizer algorithm against Pintér benchmark function. Firstly, we have to create new file, with name, for example *basic_example.py*. Then we have to import chosen algorithm from NiaPy, so we can use it. Afterwards we initialize GreyWolfOptimizer class instance and run the algorithm. Given bellow is complete source code of basic example.

```
from NiaPy.algorithms.basic import GreyWolfOptimizer

# we will run 10 repetitions of Grey Wolf Optimizer against Pinter benchmark function
for i in range(10):
    # first parameter takes dimension of problem
    # second parameter is population size
    # third parameter takes the number of function evaluations
    # fourth parameter is benchmark function
    algorithm = GreyWolfOptimizer(10, 20 , 10000, 'pinter')

    # running algorithm returns best found minimum
    best = algorithm.run()

    # printing best minimum
    print(best)
```

Given example can be run with `python basic_example.py` command and should give you similar output as following:

```
5.00762243998e-61
2.67621982742e-57
1.07156289063e-65
8.43622715953e-61
1.20903733381e-57
6.32743651354e-62
8.5819291808e-59
8.10197009706e-59
2.91642600474e-66
5.73888425977e-54
```

1.1.1 Customize benchmark bounds

By default, Pintér benchmark has the bound set to -10 and 10. We can simply override those predefined values very easily. We will modify our basic example to run Grey Wolf Optimizer against Pintér benchmark function with custom benchmark bounds set to -5 and 5. Given bellow is complete source code of customized basic example.

```
from NiaPy.algorithms.basic import GreyWolfOptimizer
from NiaPy.benchmarks import Pinter

# initialize Pinter benchamrk with custom bound
pinterCustom = Pinter(-5, 5)

# we will run 10 repetitions of Grey Wolf Optimizer against Pinter benchmark function
for i in range(10):
    # first parameter takes dimension of problem
    # second parameter is population size
    # third parameter takes the number of function evaluations
    # fourth parameter is benchmark function
    algorithm = GreyWolfOptimizer(10, 20 , 10000, pinterCustom)

    # running algorithm returns best found minimum
    best = algorithm.run()

    # printing best minimum
    print(best)
```

Given example can be run with `python basic_example.py` command and should give you similar output as following:

```
7.43266143347e-64
1.45053917474e-58
1.01835349035e-55
6.50410738064e-59
2.18186445002e-61
3.20274657669e-63
3.23728585089e-62
1.78481271215e-63
7.81043837076e-66
7.30943390302e-64
```

1.2 Advanced example

In this example we will show you how to implement your own benchmark function and use it with any of implemented algorithms. First let's create new file named advanced_example.py. As in the previous examples we wil import algorithm we want to use from NiaPy module.

For our custom benchmark function, we have to create new class. Let's name it *MyBenchmark*. In the initialization method of *MyBenchmark* class we have to set *Lower* and *Upper* bounds of the function. Afterwards we have to implement a function which returns evaluation function which takes two parameters *D* (as dimension of problem) and *sol* (as solution of problem). Now we should have something similar as is shown in code snippet bellow.

```
from NiaPy.algorithms.basic import GreyWolfOptimizer

# our custom benchmark classs
class MyBenchmark(object):
    def __init__(self):
        # define lower bound of benchmark function
        self.Lower = -11
        # define upper bound of benchmark function
        self.Upper = 11

    # function which returns evaluate function
    def function(self):
        def evaluate(D, sol):
            val = 0.0
            for i in range(D):
                val = val + sol[i] * sol[i]
            return val
        return evaluate
```

Now, all we have to do is to initialize our algorithm as in previous examples and pass as benchmark parameter, instance of our *MyBenchmark* class.

```
for i in range(10):

    algorithm = GreyWolfOptimizer(10, 20, 10000, MyBenchmark())
    best = algorithm.run()

    print(best)
```

Now we can run our advanced example with following command python advanced_example.py. The results should be similar to those bellow.

```
1.99601075063e-63
1.03831459307e-65
6.76105610278e-63
2.39738295065e-64
1.11826744557e-46
1.95914350691e-65
6.33575259075e-58
9.84100808621e-68
2.62423542073e-66
4.20503964752e-64
```

1.3 Runner example

For easier comparison between many different algorithms and benchmarks, we developed a useful feature called *Runner*. Runner can take an array of algorithms and an array of benchmarks to compare and run all combinations for you. We also provide an extra feature, which lets you easily exports those results in many different formats (LaTeX, Excell, JSON).

Below is given a usage example of our *Runner*, which will run three given algorithms and four given benchmark functions. Results will be exported as JSON.

```
import NiaPy

class MyBenchmark(object):
    def __init__(self):
        self.Lower = -5.12
        self.Upper = 5.12

    def function(self):
        def evaluate(D, sol):
            val = 0.0
            for i in range(D):
                val = val + sol[i] * sol[i]
            return val
        return evaluate


algorithms = ['DifferentialEvolutionAlgorithm',
            'ArtificialBeeColonyAlgorithm',
            'GreyWolfOptimizer']
benchmarks = ['ackley', 'whitley', 'alpine2', MyBenchmark()]

NiaPy.Runner(10, 40, 10000, 3, algorithms, benchmarks).run(export='json',␣
↪verbose=True)
```

Output of running above example should look like something as following.

```
Running DifferentialEvolutionAlgorithm...
Running DifferentialEvolutionAlgorithm algorithm on ackley benchmark...
Running DifferentialEvolutionAlgorithm algorithm on whitley benchmark...
Running DifferentialEvolutionAlgorithm algorithm on alpine2 benchmark...
Running DifferentialEvolutionAlgorithm algorithm on MyBenchmark benchmark...
--------------------------------------------------
Running ArtificialBeeColonyAlgorithm...
Running ArtificialBeeColonyAlgorithm algorithm on ackley benchmark...
Running ArtificialBeeColonyAlgorithm algorithm on whitley benchmark...
Running ArtificialBeeColonyAlgorithm algorithm on alpine2 benchmark...
Running ArtificialBeeColonyAlgorithm algorithm on MyBenchmark benchmark...
--------------------------------------------------
Running GreyWolfOptimizer...
Running GreyWolfOptimizer algorithm on ackley benchmark...
Running GreyWolfOptimizer algorithm on whitley benchmark...
Running GreyWolfOptimizer algorithm on alpine2 benchmark...
Running GreyWolfOptimizer algorithm on MyBenchmark benchmark...
--------------------------------------------------
Export to JSON completed!
```

Results exported as JSON should look like this.

```
{
    "GreyWolfOptimizer": {
        "MyBenchmark": [
        6.766062076017854e-46,
        2.6426533581097554e-43,
        8.658015542865062e-44
        ],
        "ackley": [
        4.440892098500626e-16,
        4.440892098500626e-16,
        4.440892098500626e-16
        ],
        "whitley": [
        41.15672884009374,
        45.405829107898754,
        45.285854036223746
        ],
        "alpine2": [
        -334.17253174936184,
        -26.600888674701295,
        -214.48104063289853
        ]
    },
    "ArtificialBeeColonyAlgorithm": {
        "MyBenchmark": [
        1.381020772809769e-09,
        4.082544319484199e-09,
        2.5174669579239143e-11
        ],
        "ackley": [
        0.0001596817850928467,
        0.0017004800794961916,
        0.00018082865898749745
        ],
        "whitley": [
        20.622549664235308,
        14.085647205633876,
        1.838650658412531
        ],
        "alpine2": [
        -23686.224202267975,
        -23678.92101630358,
        -14320.040364388877
        ]
    },
    "DifferentialEvolutionAlgorithm": {
        "MyBenchmark": [
        1.692521623510217e-10,
        1.7135875905552047e-10,
        1.2860888219094234e-10
        ],
        "ackley": [
        0.00012939348497598147,
        0.00010798205896778157,
        0.00011202026154366607
        ],
        "whitley": [
```


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```
        59.35951990376928,
        58.805393587160424,
        63.532977687055386
        ],
        "alpine2": [
        -23698.80535644514,
        -19925.409402805282,
        -23500.48062034027
        ]
    }
}
```

CHAPTER 2

Guides

Here are gathered together user guides.

2.1 Git Beginners Guide

Beginner's guide on how to contribute to open source community

Note: If you don't have any previous experience with using Git, we recommend you take a 15 minutes long Git Tutorial.

Whether you're trying to give back to the open source community or collaborating on your own projects, knowing how to properly fork and generate pull requests is essential. Unfortunately, it's quite easy to make mistakes or not know what you should do when you're initially learning the process. I know that I certainly had considerable initial trouble with it, and I found a lot of the information on GitHub and around the internet to be rather piecemeal and incomplete - part of the process described here, another there, common hang-ups in a different place, and so on.

This short tutorial is fairly standard procedure for creating a fork, doing your work, issuing a pull request, and merging that pull request back into the original project.

2.1.1 Create a fork

Just head over to the our GitHub page and click the "Fork" button. It's just that simple. Once you've done that, you can use your favorite git client to clone your repo or just head straight to the command line:

```
git clone git@github.com:<your-username>/<fork-project>
```

Keep your fork up to date

In most cases you'll probably want to make sure you keep your fork up to date by tracking the original "upstream" repo that you forked. To do this, you'll need to add a remote if not already added:

```
# Add 'upstream' repo to list of remotes
git remote add upstream git://github.com/NiaOrg/NiaPy.git


# Verify the new remote named 'upstream'
git remote -v
```

Whenever you want to update your fork with the latest upstream changes, you'll need to first fetch the upstream repo's branches and latest commits to bring them into your repository:

```
# Fetch from upstream remote
git fetch upstream
```

Now, checkout your own master branch and rebase with the upstream repo's master branch:

```
# Checkout your master branch and merge upstream
git checkout master
git merge upstream/master
```

If there are no unique commits on the local master branch, git will simply perform a fast-forward. However, if you have been making changes on master (in the vast majority of cases you probably shouldn't be - see the next section *Doing your work*, you may have to deal with conflicts. When doing so, be careful to respect the changes made upstream.

Now, your local master branch is up-to-date with everything modified upstream.

2.1.2 Doing your work

Create a Branch

Whenever you begin work on a new feature or bug fix, it's important that you create a new branch. Not only is it proper git workflow, but it also keeps your changes organized and separated from the master branch so that you can easily submit and manage multiple pull requests for every task you complete.

To create a new branch and start working on it:

```
# Checkout the master branch - you want your new branch to come from master
git checkout master

# Create a new branch named newfeature (give your branch its own simple informative␣
↪name)
git branch newfeature

# Switch to your new branch
git checkout newfeature

# Last two commands can be joined as following: git checkout -b newfeature
```

Now, go to town hacking away and making whatever changes you want to

2.1.3 Submitting a Pull Request

Cleaning Up Your Work

Prior to submitting your pull request, you might want to do a few things to clean up your branch and make it as simple as possible for the original repo's maintainer to test, accept, and merge your work.

If any commits have been made to the upstream master branch, you should rebase your development branch so that merging it will be a simple fast-forward that won't require any conflict resolution work.

```
# Fetch upstream master and merge with your repo's master branch
git fetch upstream
git checkout master
git merge upstream/master

# If there were any new commits, rebase your development branch
git checkout newfeature
git rebase master
```

Now, it may be desirable to squash some of your smaller commits down into a small number of larger more cohesive commits. You can do this with an interactive rebase:

```
# Rebase all commits on your development branch
git checkout
git rebase -i master
```

This will open up a text editor where you can specify which commits to squash.

Submitting

Once you've committed and pushed all of your changes to GitHub, go to the page for your fork on GitHub, select your development branch, and click the pull request button. If you need to make any adjustments to your pull request, just push the updates to GitHub. Your pull request will automatically track the changes on your development branch and update.

When pull request is successfully created, make sure you follow activity on your pull request. It may occur that the maintainer of project will ask you to do some more changes or fix something on your pull request before merging it to master branch.

After maintainer merges your pull request to master, you're done with development on this branch, so you're free to delete it.

```
git branch -d newfeature
```

2.1.4 Copyright

This guide is modified version of original one, written by Chase Pettit.

Copyright

Copyright 2017, Chase Pettit

MIT License

Additional Reading

- Atlassian - Merging vs. Rebasing

Sources

- GitHub - Fork a Repo
- GitHub - Syncing a Fork
- GitHub - Checking Out a Pull Request

2.2 MinGW Installation Guide - Windows

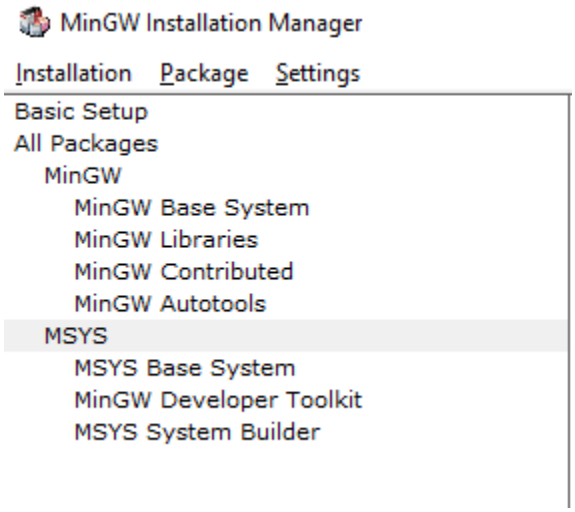
Download MinGW installer from here.

> **Warning:** **Important!** Before running the MinGW installer disable any running antivirus and firewall. Afterwards run MinGW installer as Administrator.

Follow the installation wizard clicking **Continue**.

After the installation procedure is completed MinGW Installation Manager is opened.

In tree navigation on the left side of window select **All Packages > MSYS** like is shown in figure below.



On the right side of window, search for packages **msys-make** and **msys-bash**. Right click on each package and select **Mark for installation** from context menu.

Next click on the **Installation** in top menu and select **Apply Changes** and again **Apply**.

The last thing is to add binaries to system variables. Go to **Control panel > System and Security > System** and click on **Advanced system settings**. Then click on **Environment Variables...** button and on list in new window mark entry with variable **Path**. Next, click on **Edit...** button and create new entry with value equal to: <MinGW_install_path>\msys\1.0\bin (by default it is: C:\MinGW\msys\1.0\bin). Click **OK** on every window.

That's it! You are ready to contribute to our project!

CHAPTER 3

Support

3.1 Usage Questions

If you have questions about how to use Niapy or have an issue that isn't related to a bug, you can place a question on StackOverflow.

You can also join us at our Slack Channel or seek support via niapy.organization@gmail.com.

NiaPy is a community supported package, nobody is paid to develop package nor to handle NiaPy support.

All people answering your questions are doing it with their own time, so please be kind and provide as much information as possible.

3.2 Reporting bugs

Check out Reporting bugs section in Contributing to NiaPy

CHAPTER 4

Changelog

We are using semantic versioning.

4.1 2.0.0rc2 (Aug 30, 2018)

- fix PyPI build

4.2 2.0.0rc1 (Aug 30, 2018)

Changes included in release:

- **Added algorithms:**
  - **basic:**
    - Camel algorithm
    - Evolution Strategy
    - Fireworks algorithm
    - Glowworm swarm optimization
    - Harmony search algorithm
    - Krill Herd Algorithm
    - Monkey King Evolution
    - Multiple trajectory search
    - Sine Cosine Algorithm
  - **modified:**
    - Dynamic population size self-adaptive differential evolution algorithm

    - **other:**
        * Anarchic society optimization algorithm
        * Hill climbing algorithm
        * Multiple trajectory search
        * Nelder mead method or downhill simplex method or amoeba method
        * Simulated annealing algorithm
- **Added benchmarks functions:**
    - Discus
    - Dixon-Price
    - Elliptic
    - HGBat
    - Katsuura
    - Levy
    - Michalewicz
    - Perm
    - Powell
    - Sphere2 -> Sphere with different powers
    - Sphere3 -> Rotated hyper-ellipsoid
    - Trid
    - Weierstrass
    - Zakharov
- **breaking changes** in algorithms structure
- various bugfixes

4.3 1.0.1 (Mar 21, 2018)

This release reflects the changes from Journal of Open Source Software (JOSS) review: - Better API Documentation - Clarification of set-up requirements in README - Improved paper

4.4 1.0.0 (Feb 28, 2018)

- stable release 1.0.0

4.5 1.0.0rc2 (Feb 28, 2018)

- fix PyPI build

4.6 1.0.0rc1 (Feb 28, 2018)

- version 1.0.0 release candidate 1
- added 10 algorithms
- added 26 benchmark functions
- added Runner utility with export functionality

CHAPTER 5

Installation

5.1 Setup development environment

5.1.1 Requirements

- Python: download (at least version 2.7.14, prefferable 3.6.x)
- Pip: installation docs
- **Make**
  - Windows: download [*MinGW Installation Guide - Windows*]
  - Mac: download
  - Linux: download
- pipenv: docs (run `pip install pipenv` command)
- Pandoc: installation docs * optional
- Graphviz: download * optional

To confirm these system dependencies are configured correctly:

```
make doctor
```

5.1.2 Installation of development dependencies

List of NiaPy's dependencies:

Package	Version	Platform
click	Any	All
numpy	1.14.0	All
scipy	1.0.0	All
xlsxwriter	1.0.2	All
matplotlib	•	All

List of development dependencies:

Package	Version	Platform
pylint	Any	Any
pycodestyle	Any	Any
pydocstyle	Any	Any
pytest	~=3.3	Any
pytest-describe	Any	Any
pytest-expecter	Any	Any
pytest-random	Any	Any
pytest-cov	Any	Any
freezegun	Any	Any
coverage-space	Any	Any
docutils	Any	Any
pygments	Any	Any
wheel	Any	Any
pyinstaller	Any	Any
twine	Any	Any
sniffer	Any	Any
macfsevents	Any	darwin
enum34	Any	Any
singledispatch	Any	Any
backports.functools-lru-cache	Any	Any
configparser	Any	Any
sphinx	Any	Any
sphinx-rtd-theme	Any	Any
funcsigs	Any	Any
futures	Any	Any
autopep8	Any	Any
sphinx-autobuild	Any	Any

Install project dependencies into a virtual environment:

```
make install
```

To enter created virtual environment with all installed development dependencies run:

```
pipenv shell
```

CHAPTER 6

Testing

Note: We suppose that you already followed the *Installation* guide. If not, please do so before you continue to read this section.

Before making a pull request, if possible provide tests for added features or bug fixes.

We have an automated building system which also runs all of provided tests. In case any of the test cases fails, we are notified about failing tests. Those should be fixed before we merge your pull request to master branch.

For the purpose of checking if all test are passing localy you can run following command:

```
make test
```

If all tests passed running this command it is most likely that the tests would pass on our build system to.

CHAPTER 7

Documentation

Note: We suppose that you already followed the *Installation* guide. If not, please do so before you continue to read this section.

To locally generate and preview documentation run the following command in the project root folder:

```
sphinx-autobuild docs/source docs/build/html
```

If the build of the documentation is successful, you can preview the documentation by navigating to the http://127.0.0.1:8000.

CHAPTER 8

API

This is the NiaPy API documentation, auto generated from the source code.

8.1 NiaPy

Python micro framework for building nature-inspired algorithms.

class NiaPy.**Runner**(*D*, *NP*, *nFES*, *nRuns*, *useAlgorithms*, *useBenchmarks*, ***kwargs*)

Runner utility feature.

Feature which enables running multiple algorithms with multiple benchmarks. It also support exporting results in various formats (e.g. LaTeX, Excel, JSON)

Initialize Runner.

__init__(self, D, NP, nFES, nRuns, useAlgorithms, useBenchmarks, ...)

Arguments: D {integer} – dimension of problem

NP {integer} – population size

nFES {integer} – number of function evaluations

nRuns {integer} – number of repetitions

useAlgorithms [] – array of algorithms to run

useBenchmarks [] – array of benchmarks to run

A {decimal} – laudness

r {decimal} – pulse rate

Qmin {decimal} – minimum frequency

Qmax {decimal} – maximum frequency

Pa {decimal} – probability

F {decimal} – scalling factor

F_l {decimal} – lower limit of scalling factor

F_u {decimal} – upper limit of scalling factor

CR {decimal} – crossover rate

alpha {decimal} – alpha parameter

betamin {decimal} – betamin parameter

gamma {decimal} – gamma parameter

p {decimal} – probability switch

Ts {decimal} – tournament selection

Mr {decimal} – mutation rate

C1 {decimal} – cognitive component

C2 {decimal} – social component

w {decimal} – inertia weight

vMin {decimal} – minimal velocity

vMax {decimal} – maximal velocity

Tao1 {decimal} –

Tao2 {decimal} –

n {integer} – number of sparks

mu {decimal} – mu parameter

omega {decimal} – TODO

S_init {decimal} – initial supply for camel

E_init {decimal} – initial endurance for camel

T_min {decimal} – minimal temperature

T_max {decimal} – maximal temperature

C_a {decimal} – Amplification factor

C_r {decimal} – Reduction factor

Limit {integer} – Limit

k {integer} – Number of runs before adaptive

8.2 NiaPy.algorithms

Module with implementations of basic and hybrid algorithms.

class NiaPy.algorithms.**Algorithm**(***kwargs*)

Bases: object

Class for implementing algorithms.

Data: 2018

Author: Klemen Berkovič

License: MIT

Initialize algorithm and create name for an algorithm.

Arguments:

name {string} – Full name of algorithm

shortName {string} – Short name of algorithm

NP {integer} – population size

D {integer} – dimension of problem

nGEN {integer} – nuber of generation/iterations

nFES {integer} – number of function evaluations

benchmark {object} – benchmark implementation object

task {Task} – task to perform optimization on

Raises:

TypeError – Raised when given benchmark function which does not exists.

See: Algorithm.setParameters(self, **kwargs)

normal(*loc*, *scale*, *D=None*)

Get D shape random normal distributed numbers.

Arguments:

loc {} –

scale {} –

D {array} or {int} – Shape of returnd random uniform numbers

rand(*D=1*)

Get random numbers of shape D in range from 0 to 1.

Arguments:

D {array} or {int} – Shape of return random numbers

randint(*Nmax*, *D=1*, *Nmin=0*, *skip=[]*)

Get D shape random full numbers in range Nmin to Nmax.

Arguments:

Nmin {integer} –

Nmax {integer} –

D {array} or {int} – Shape of returnd random uniform numbers

skip {array} – numbers to skip

run()

Start the optimization.

See: Algorithm.runTask(self, taks)

runTask(*task*)

Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

runYield(*task*)
Run the algorithm for only one iteration and return the gest solution.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of the best solution

setParameters(***kwargs*)
Set the parameters/arguments of the algorithm.

Arguments:

kwargs {dict} – Dictionary with values of the parametres

uniform(*Lower*, *Upper*, *D=None*)
Get D shape random uniform numbers in range from Lower to Upper.

Arguments:

Lower {array} or {real} or {int} – Lower bound

Upper {array} or {real} or {int} – Upper bound

D {array} or {int} – Shape of returnd random uniform numbers

class NiaPy.algorithms.**Individual**(***kwargs*)
Bases: object

Class that represent one solution in population of solutions.

Date: 2018

Author: Klemen Berkovič

License: MIT

evaluate(*task*)
Evaluate the solution.

Arguments:

task {Task} – Object with objective function for optimization

generateSolution(*task*, *rnd=<module 'numpy.random' from '/home/docs/checkouts/readthedocs.org/user_builds/niapy/env*
packages/numpy/random/__init__.py'>)
Generate new solution.

Arguments:

task {Task}

e {bool} – Eval the solution

rnd {random} – Object for generating random numbers

repair(*task*)
Reper solution and put the solution in the bounds of problem.

Arguments:

task {Task}

8.2.1 NiaPy.algorithms.basic

Implementation of basic nature-inspired algorithms.

class NiaPy.algorithms.basic.**BatAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Bat algorithm.

Algorithm: Bat algorithm

Date: 2015

Authors: Iztok Fister Jr., Marko Burjek and Klemen Berkovič

License: MIT

Reference paper: Yang, Xin-She. "A new metaheuristic bat-inspired algorithm." Nature inspired cooperative strategies for optimization (NICSO 2010). Springer, Berlin, Heidelberg, 2010. 65-74.

__init__(self, D, NP, nFES, A, r, Qmin, Qmax, benchmark).

See: Algorithm.__init__(self, **kwargs)

runTask(*task*)
Run algorithm with initialized parameters.

Return:

{decimal} – coordinates of minimal found objective function

{decimal} – minimal value found of objective function

setParameters(*NP*, *A*, *r*, *Qmin*, *Qmax*, ***ukwargs*)
Set the parameters of the algorithm.

Arguments:

NP {integer} – population size

A {decimal} – loudness

r {decimal} – pulse rate

Qmin {decimal} – minimum frequency

Qmax {decimal} – maximum frequency

class NiaPy.algorithms.basic.**FireflyAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Firefly algorithm.

Algorithm: Firefly algorithm

Date: 2016

Authors: Iztok Fister Jr, Iztok Fister and Klemen Berkovič

License: MIT

Reference paper: Fister, I., Fister Jr, I., Yang, X. S., & Brest, J. (2013). A comprehensive review of firefly algorithms. Swarm and Evolutionary Computation, 13, 34-46.

alpha_new(*a*, *alpha*)
Optionally recalculate the new alpha value.

getBest(*xb*, *xb_f*, *Fireflies*, *Intensity*)

move_ffa(*i*, *Fireflies*, *Intensity*, *oFireflies*, *alpha*, *task*)
Move fireflies.

runTask(*task*)
Run.

setParameters(*NP=20*, *alpha=1*, *betamin=1*, *gamma=2*, ***ukwargs*)
Set the parameters of the algorithm.

Arguments:

NP {integer} – population size

alpha {decimal} – alpha parameter

betamin {decimal} – betamin parameter

gamma {decimal} – gamma parameter

class NiaPy.algorithms.basic.**DifferentialEvolutionAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Differential evolution algorithm.

Algorithm: Differential evolution algorithm

Date: 2018

Author: Uros Mlakar and Klemen Berkovič

License: MIT

Reference paper: Storn, Rainer, and Kenneth Price. "Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces." Journal of global optimization 11.4 (1997): 341-359.

evalPopulation(*x*, *x_old*, *task*)
Evaluate element.

runTask(*task*)
Run.

selectBetter(*x*, *y*)

setParameters(*NP=25*, *F=2*, *CR=0.2*, *CrossMutt=<function CrossRand1>*, ***ukwargs*)
Set the algorithm parameters.

Arguments:

NP {integer} – population size

F {decimal} – scaling factor

CR {decimal} – crossover rate

CrossMutt {function} – crossover and mutation strategy

class NiaPy.algorithms.basic.**FlowerPollinationAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Flower Pollination algorithm.

Algorithm: Flower Pollination algorithm

Date: 2018

Authors: Dusan Fister, Iztok Fister Jr. and Klemen Berkovič

License: MIT

Reference paper: Yang, Xin-She. "Flower pollination algorithm for global optimization. International conference on unconventional computing and natural computation. Springer, Berlin, Heidelberg, 2012. Implementation is based on the following MATLAB code: https://www.mathworks.com/matlabcentral/fileexchange/45112-flower-pollination-algorithm?requestedDomain=true

levy()

repair(*x*, *task*)
Find limits.

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*NP=25*, *p=0.35*, *beta=1.5*, ***ukwargs*)
__init__(self, D, NP, nFES, p, benchmark).

Arguments:

NP {integer} – population size

p {decimal} – probability switch

beta {real} –

class NiaPy.algorithms.basic.**GreyWolfOptimizer**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Grey wolf optimizer.

Algorithm: Grey wolf optimizer

Date: 2018

Author: Iztok Fister Jr. and Klemen Berkovič

License: MIT

Reference paper: Mirjalili, Seyedali, Seyed Mohammad Mirjalili, and Andrew Lewis. "Grey wolf optimizer." Advances in engineering software 69 (2014): 46-61. Grey Wold Optimizer (GWO) source code version 1.0 (MATLAB) from MathWorks

repair(*x*, *task*)
Find limits.

runTask(*task*)
Run.

setParameters(*NP=25*, ***ukwargs*)
Set the algorithm parameters.

Arguments:

NP {integer} – Number of individuals in population

class NiaPy.algorithms.basic.**GeneticAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Genetic algorithm.

Algorithm: Genetic algorithm

Date: 2018

Author: Uros Mlakar and Klemen Berkovič

License: MIT

evolve(*pop*, *x_b*, *task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*NP=25*, *Ts=5*, *Mr=0.25*, *Cr=0.25*, *Selection=<function TurnamentSelection>*, *Crossover=<function UniformCrossover>*, *Mutation=<function UniformMutation>*, ***ukwargs*)
Set the parameters of the algorithm.

Arguments:

NP {integer} – population size

Ts {integer} – tournament selection

Mr {decimal} – mutation rate

Cr {decimal} – crossover rate

class NiaPy.algorithms.basic.**ArtificialBeeColonyAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Artificial Bee Colony algorithm.

Algorithm: Artificial Bee Colony algorithm

Date: 2018

Author: Uros Mlakar and Klemen Berkovič

License: MIT

Reference paper: Karaboga, D., and Bahriye B. "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm." Journal of global optimization 39.3 (2007): 459-471.

__init__(self, D, NP, nFES, benchmark).

See: Algorithm.__init__(self, **kwargs)

CalculateProbs()
Calculate probs.

checkForBest(*Solution*)
Check best solution.

init(*task*)
Initialize positions.

runTask(*task*)
Run.

setParameters(*NP=10*, *Limit=100*, ***ukwargs*)
Set the arguments of an algorithm.

Arguments:

NP {integer} – population size

Limit {integer} – Limit

class NiaPy.algorithms.basic.**ParticleSwarmAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Particle Swarm Optimization algorithm.

Algorithm: Particle Swarm Optimization algorithm

Date: 2018

Authors: Lucija Brezočnik, Grega Vrbančič, Iztok Fister Jr. and Klemen Berkovič

License: MIT

Reference paper: Kennedy, J. and Eberhart, R. "Particle Swarm Optimization". Proceedings of IEEE International Conference on Neural Networks. IV. pp. 1942–1948, 1995.

init(*task*)

repair(*x*, *l*, *u*)

runTask(*task*)
Move particles in search space.

setParameters(*NP=25*, *C1=2.0*, *C2=2.0*, *w=0.7*, *vMin=-4*, *vMax=4*, ***ukwargs*)
Set the parameters for the algorith.

Arguments:

NP {integer} – population size

C1 {decimal} – cognitive component

C2 {decimal} – social component

w {decimal} – inertia weight

vMin {decimal} – minimal velocity

vMax {decimal} – maximal velocity

class NiaPy.algorithms.basic.**BareBonesFireworksAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of bare bone fireworks algorithm.

Algorithm: Bare Bones Fireworks Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.sciencedirect.com/science/article/pii/S1568494617306609

Reference paper: Junzhi Li, Ying Tan, The bare bones fireworks algorithm: A minimalist global optimizer, Applied Soft Computing, Volume 62, 2018, Pages 454-462, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2017.10.046.

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*n=10*, *C_a=1.5*, *C_r=0.5*, ***ukwargs*)
Set the arguments of an algorithm.

Arguments:

n {integer} – number of sparks $in [1, infty)$

C_a {real} – amplification coefficient $in [1, infty)$

C_r {real} – reduction coefficient $in (0, 1)$

class NiaPy.algorithms.basic.**CamelAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Camel traveling behavior.

Algorithm: Camel algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.iasj.net/iasj?func=fulltext&aId=118375

Reference paper: Ali, Ramzy. (2016). Novel Optimization Algorithm Inspired by Camel Traveling Behavior. Iraq J. Electrical and Electronic Engineering. 12. 167-177.

lifeCycle(*c*, *fit*, *fitn*, *mu*, *task*)

oasis(*c*, *rn*, *fit*, *fitn*, *alpha*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*NP=50*, *omega=0.25*, *mu=0.5*, *alpha=0.5*, *S_init=10*, *E_init=10*, *T_min=-10*, *T_max=10*, ***ukwargs*)
Set the arguments of an algorithm.

Arguments:

NP {integer} – population size $in [1, infty)$

T_min {real} – minimum temperature, must be true $T_{min} < T_{max}$

T_max {real} – maximum temperature, must be true $T_{min} < T_{max}$

omega {real} – burden factor $in [0, 1]$

mu {real} – dying rate $in [0, 1]$

S_init {real} – initial supply $in (0, infty)$

E_init {real} – initial endurance $in (0, infty)$

walk(*c*, *fit*, *task*, *omega*, *c_best*)

class NiaPy.algorithms.basic.**MonkeyKingEvolutionV1**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of monkey king evolution algorithm version 1.

Algorithm: Monkey King Evolution version 1

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.sciencedirect.com/science/article/pii/S0950705116000198

Reference paper: Zhenyu Meng, Jeng-Shyang Pan, Monkey King Evolution: A new memetic evolutionary algorithm and its application in vehicle fuel consumption optimization, Knowledge-Based Systems, Volume 97, 2016, Pages 144-157, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2016.01.009.

moveMK(*x*, *task*)

moveMokeyKingPartice(*p*, *task*)

moveP(*x*, *x_pb*, *x_b*, *task*)

movePartice(*p*, *p_b*, *task*)

movePopulation(*pop*, *p_b*, *task*)

repair(*x*, *task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters (*NP=40*, *F=0.7*, *R=0.3*, *C=3*, *FC=0.5*, ***ukwargs*)
Set the algorithm parameters.

Arguments:

NP {integer} – Size of population

F {real} – param

R {real} – param

C {real} – param

FC {real} – param

class NiaPy.algorithms.basic.**MonkeyKingEvolutionV2** (***kwargs*)
Bases: NiaPy.algorithms.basic.mke.MonkeyKingEvolutionV1

Implementation of monkey king evolution algorithm version 2.

Algorithm: Monkey King Evolution version 2

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.sciencedirect.com/science/article/pii/S0950705116000198

Reference paper: Zhenyu Meng, Jeng-Shyang Pan, Monkey King Evolution: A new memetic evolutionary algorithm and its application in vehicle fuel consumption optimization, Knowledge-Based Systems, Volume 97, 2016, Pages 144-157, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2016.01.009.

moveMK (*x*, *dx*, *task*)

moveMokeyKingPartice (*p*, *pop*, *task*)

movePopulation (*pop*, *p_b*, *task*)

class NiaPy.algorithms.basic.**MonkeyKingEvolutionV3** (***kwargs*)
Bases: NiaPy.algorithms.basic.mke.MonkeyKingEvolutionV1

Implementation of monkey king evolution algorithm version 3.

Algorithm: Monkey King Evolution version 3

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.sciencedirect.com/science/article/pii/S0950705116000198

Reference paper: Zhenyu Meng, Jeng-Shyang Pan, Monkey King Evolution: A new memetic evolutionary algorithm and its application in vehicle fuel consumption optimization, Knowledge-Based Systems, Volume 97, 2016, Pages 144-157, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2016.01.009.

eval (*X*, *x*, *x_f*, *task*)

neg (*x*)

runTask (*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

class NiaPy.algorithms.basic.**EvolutionStrategy1p1**(***kwargs*)

Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of (1 + 1) evolution strategy algorithm. Uses just one individual.

Algorithm: (1 + 1) Evolution Strategy Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL:

Reference paper:

mutate(*x*, *rho*)

runTask(*task*)

Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*mu=1*, *k=10*, *c_a=1.1*, *c_r=0.5*, *epsilon=1e-20*, ***ukwargs*)

Set the arguments of an algorithm.

Arguments:

mu {integer} –

k {integer} –

c_a {real} –

c_r {real} –

updateRho(*rho*, *k*)

class NiaPy.algorithms.basic.**EvolutionStrategyMp1**(***kwargs*)

Bases: NiaPy.algorithms.basic.es.EvolutionStrategy1p1

Implementation of (mu + 1) evolution strategy algorithm. Algorithm creates mu mutants but into new generation goes only one individual.

Algorithm: (mu + 1) Evolution Strategy Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL:

Reference paper:

setParameters(***kwargs*)
Set the arguments of an algorithm.

Arguments:

mu {integer} –

k {integer} –

c_a {real} –

c_r {real} –

class NiaPy.algorithms.basic.**EvolutionStrategyMpL**(***kwargs*)
Bases: NiaPy.algorithms.basic.es.EvolutionStrategy1p1

Implementation of (mu + lambda) evolution strategy algorithm. Mulation creates lambda individual. Lambda individual compete with mu individuals for survival, so only mu individual go to new generation.

Algorithm: (mu + $lambda$) Evolution Strategy Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL:

Reference paper:

changeCount(*a*, *b*)

mutate(*x*, *rho*)

mutateRepair(*pop*, *task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(***kwargs*)
Set the arguments of an algorithm.

Arguments:

mu {integer} –

k {integer} –

c_a {real} –

c_r {real} –

updateRho(*pop*, *k*)

class NiaPy.algorithms.basic.**EvolutionStrategyML**(***kwargs*)
Bases: NiaPy.algorithms.basic.es.EvolutionStrategyMpL

Implementation of (mu, lambda) evolution strategy algorithm. Algorithm is good for dynamic environments. Mu individual create lambda chields. Only best mu chields go to new generation. Mu parents are discarded.

Algorithm: (mu + $lambda$) Evolution Strategy Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL:

Reference paper:

newPop(*pop*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

class NiaPy.algorithms.basic.**SineCosineAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of sine cosine algorithm.

Algorithm: Sine Cosine Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.sciencedirect.com/science/article/pii/S0950705115005043

Reference paper: Seyedali Mirjalili, SCA: A Sine Cosine Algorithm for solving optimization problems, Knowledge-Based Systems, Volume 96, 2016, Pages 120-133, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2015.12.022.

nextPos(*x*, *x_b*, *r1*, *r2*, *r3*, *r4*, *task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*NP=25*, *a=3*, *Rmin=0*, *Rmax=2*, ***ukwargs*)
Set the arguments of an algorithm.

Arguments:

NP {integer} – number of individual in population

a {real} – parameter for controlon r_1 value

Rmin {integer} – minium value for r_3 value

Rmax {integer} – maximum value for r_3 value

class NiaPy.algorithms.basic.**GlowwormSwarmOptimization**(***kwargs*)

Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of glowwarm swarm optimization.

Algorithm: Glowwarm Swarm Optimization Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.springer.com/gp/book/9783319515946

Reference paper: Kaipa, Krishnanand N., and Debasish Ghose. Glowworm swarm optimization: theory, algorithms, and applications. Vol. 698. Springer, 2017.

calcLuciferin(*L*, *GS_f*)

getBest(*GS*, *GS_f*, *xb*, *xb_f*)

getNeighbors(*i*, *r*, *GS*, *L*)

moveSelect(*pb*, *i*)

probabilityes(*i*, *N*, *L*)

randMove(*i*)

rangeUpdate(*R*, *N*, *rs*)

runTask(*task*)

Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*n=25*, *l0=5*, *nt=5*, *rho=0.4*, *gamma=0.6*, *beta=0.08*, *s=0.03*, ***ukwargs*)

Set the arguments of an algorithm.

Arguments:

n {integer} – number of glowworms in population

l0 {real} – initial luciferin quantity for each glowworm

nt {real} –

rs {real} – maximum sensing range

rho {real} – luciferin decay constant

gamma {real} – luciferin enhancement constant

beta {real} –

s {real} –

class NiaPy.algorithms.basic.**GlowwormSwarmOptimizationV1**(***kwargs*)
Bases: NiaPy.algorithms.basic.gso.GlowwormSwarmOptimization

Implementation of glowwarm swarm optimization.

Algorithm: Glowwarm Swarm Optimization Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.springer.com/gp/book/9783319515946

Reference paper: Kaipa, Krishnanand N., and Debasish Ghose. Glowworm swarm optimization: theory, algorithms, and applications. Vol. 698. Springer, 2017.

calcLuciferin(*L*, *GS_f*)

rangeUpdate(*R*, *N*, *rs*)

setParameters(***kwargs*)
Set the arguments of an algorithm.

Arguments:

n {integer} – number of glowworms in population

l0 {real} – initial luciferin quantity for each glowworm

nt {real} –

rs {real} – maximum sensing range

rho {real} – luciferin decay constant

gamma {real} – luciferin enhancement constant

beta {real} –

s {real} –

class NiaPy.algorithms.basic.**GlowwormSwarmOptimizationV2**(***kwargs*)
Bases: NiaPy.algorithms.basic.gso.GlowwormSwarmOptimization

Implementation of glowwarm swarm optimization.

Algorithm: Glowwarm Swarm Optimization Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.springer.com/gp/book/9783319515946

Reference paper: Kaipa, Krishnanand N., and Debasish Ghose. Glowworm swarm optimization: theory, algorithms, and applications. Vol. 698. Springer, 2017.

rangeUpdate(*P*, *N*, *rs*)

setParameters(***kwargs*)
Set the arguments of an algorithm.

Arguments:

n {integer} – number of glowworms in population

l0 {real} – initial luciferin quantity for each glowworm

nt {real} –

rs {real} – maximum sensing range

rho {real} – luciferin decay constant

gamma {real} – luciferin enhancement constant

beta {real} –

s {real} –

class NiaPy.algorithms.basic.**GlowwormSwarmOptimizationV3**(***kwargs*)
Bases: NiaPy.algorithms.basic.gso.GlowwormSwarmOptimization

Implementation of glowwarm swarm optimization.

Algorithm: Glowwarm Swarm Optimization Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.springer.com/gp/book/9783319515946

Reference paper: Kaipa, Krishnanand N., and Debasish Ghose. Glowworm swarm optimization: theory, algorithms, and applications. Vol. 698. Springer, 2017.

rangeUpdate(*R*, *N*, *rs*)

setParameters(***kwargs*)
Set the arguments of an algorithm.

Arguments:

n {integer} – number of glowworms in population

l0 {real} – initial luciferin quantity for each glowworm

nt {real} –

rs {real} – maximum sensing range

rho {real} – luciferin decay constant

gamma {real} – luciferin enhancement constant

beta {real} –

s {real} –

class NiaPy.algorithms.basic.**HarmonySearch**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of harmony search algorithm.

Algorithm: Harmony Search Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://link.springer.com/chapter/10.1007/978-3-642-00185-7_1

Reference paper: Yang, Xin-She. "Harmony search as a metaheuristic algorithm." Music-inspired harmony search algorithm. Springer, Berlin, Heidelberg, 2009. 1-14.

adjustment(*x*, *task*)

bw(*task*)

improvize(*HM*, *task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*HMS=30*, *r_accept=0.7*, *r_pa=0.35*, *b_range=1.42*, ***ukwargs*)
Set the arguments of the algorithm.

Arguments:

HMS {integer} – Number of harmonys in the memory

r_accept {real} –

r_pa {real} –

b_range {real} –

class NiaPy.algorithms.basic.**HarmonySearchV1**(***kwargs*)
Bases: NiaPy.algorithms.basic.hs.HarmonySearch

Implementation of harmony search algorithm.

Algorithm: Harmony Search Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://link.springer.com/chapter/10.1007/978-3-642-00185-7_1

Reference paper: Yang, Xin-She. "Harmony search as a metaheuristic algorithm." Music-inspired harmony search algorithm. Springer, Berlin, Heidelberg, 2009. 1-14.

bw(*task*)

setParameters(*bw_min=1*, *bw_max=2*, ***kwargs*)
Set the parameters of the algorithm.

Arguments:

bw_min {real} – Minimal bandwidth

bw_max {real} – Maximal bandwidth

class NiaPy.algorithms.basic.**KrillHerdV1**(**kwargs)
Bases: NiaPy.algorithms.basic.kh.KrillHerd

Implementation of krill herd algorithm.

Algorithm: Krill Herd Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: http://www.sciencedirect.com/science/article/pii/S1007570412002171

Reference paper: Amir Hossein Gandomi, Amir Hossein Alavi, Krill herd: A new bio-inspired optimization algorithm, Communications in Nonlinear Science and Numerical Simulation, Volume 17, Issue 12, 2012, Pages 4831-4845, ISSN 1007-5704, https://doi.org/10.1016/j.cnsns.2012.05.010.

crossover(*x*, *xo*, *Cr*)

mutate(*x*, *x_b*, *Mu*)

class NiaPy.algorithms.basic.**KrillHerdV2**(**kwargs)
Bases: NiaPy.algorithms.basic.kh.KrillHerd

Implementation of krill herd algorithm.

Algorithm: Krill Herd Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: http://www.sciencedirect.com/science/article/pii/S1007570412002171

Reference paper: Amir Hossein Gandomi, Amir Hossein Alavi, Krill herd: A new bio-inspired optimization algorithm, Communications in Nonlinear Science and Numerical Simulation, Volume 17, Issue 12, 2012, Pages 4831-4845, ISSN 1007-5704, https://doi.org/10.1016/j.cnsns.2012.05.010.

mutate(*x*, *x_b*, *Mu*)

class NiaPy.algorithms.basic.**KrillHerdV3**(**kwargs)
Bases: NiaPy.algorithms.basic.kh.KrillHerd

Implementation of krill herd algorithm.

Algorithm: Krill Herd Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: http://www.sciencedirect.com/science/article/pii/S1007570412002171

Reference paper: Amir Hossein Gandomi, Amir Hossein Alavi, Krill herd: A new bio-inspired optimization algorithm, Communications in Nonlinear Science and Numerical Simulation, Volume 17, Issue 12, 2012, Pages 4831-4845, ISSN 1007-5704, https://doi.org/10.1016/j.cnsns.2012.05.010.

crossover(*x*, *xo*, *Cr*)

class NiaPy.algorithms.basic.**KrillHerdV4**(**kwargs)
Bases: NiaPy.algorithms.basic.kh.KrillHerd

Implementation of krill herd algorithm.

Algorithm: Krill Herd Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: http://www.sciencedirect.com/science/article/pii/S1007570412002171

Reference paper: Amir Hossein Gandomi, Amir Hossein Alavi, Krill herd: A new bio-inspired optimization algorithm, Communications in Nonlinear Science and Numerical Simulation, Volume 17, Issue 12, 2012, Pages 4831-4845, ISSN 1007-5704, https://doi.org/10.1016/j.cnsns.2012.05.010.

setParameters(*NP=50*, *N_max=0.01*, *V_f=0.02*, *D_max=0.002*, *C_t=0.93*, *W_n=0.42*, *W_f=0.38*, *d_s=2.63*, ***ukwargs*)

Set the arguments of an algorithm.

Arguments:

NP {integer} – Number of krill herds in population

N_max {real} – maximum induced speed

V_f {real} – foraging speed

D_max {real} – maximum diffsion speed

C_t {real} – constant $in [0, 2]$

W_n {real} or {array} – inerta weights of the motion iduced from neighbors $in [0, 1]$

W_f {real} or {array} – inerta weights of the motion iduced from fraging $in [0, 1]$

d_s {real} – maximum euclidean distance for neighbors

nn {integer} – maximu neighbors for neighbors effect

Cr {real} – Crossover rate

Mu {real} – Mutation rate

epsilon {real} – Small numbers for devision

class NiaPy.algorithms.basic.**KrillHerdV11**(***kwargs*)

Bases: NiaPy.algorithms.basic.kh.KrillHerd

Implementation of krill herd algorithm.

Algorithm: Krill Herd Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL:

Reference paper:

Cr(*KH_f*, *KHb_f*, *KHw_f*)

ElitistSelection(*KH*, *KH_f*, *KHo*, *KHo_f*)

Foraging(*KH*, *KH_f*, *KHo*, *KHo_f*, *W_f*, *F*, *KH_wf*, *KH_bf*, *x_food*, *x_food_f*, *task*)

Neighbors(*i*, *KH*, *KH_f*, *iw*, *ib*, *N*, *W_n*, *task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

class NiaPy.algorithms.basic.**FireworksAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of fireworks algorithm.

Algorithm: Fireworks Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://www.springer.com/gp/book/9783662463529

Reference paper: Tan, Ying. "Firework Algorithm: A Novel Swarm Intelligence Optimization Method." (2015).

ExplodeSpark(*x*, *A*, *task*)

ExplosionAmplitude(*x_f*, *xb_f*, *A*, *As*)

GaussianSpark(*x*, *task*)

Mapping(*x*, *task*)

NextGeneration(*FW*, *FW_f*, *FWn*, *task*)

R(*x*, *FW*)

SparsksNo(*x_f*, *xw_f*, *Ss*)

initAmplitude(*task*)

p(*r*, *Rs*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*N=40*, *m=40*, *a=1*, *b=2*, *A=40*, *epsilon=1e-31*, ***ukwargs*)
Set the arguments of an algorithm.

Arguments:

N {integer} – number of Fireworks

m {integer} – number of sparks

a {integer} – limitation of sparks

b {integer} – limitation of sparks

A {real} –

epsilon {real} – Small number for non 0 devision

class NiaPy.algorithms.basic.**EnhancedFireworksAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.basic.fwa.FireworksAlgorithm

Implementation of enganced fireworks algorithm.

Algorithm: Enhanced Fireworks Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://ieeexplore.ieee.org/document/6557813/

Reference paper: S. Zheng, A. Janecek and Y. Tan, "Enhanced Fireworks Algorithm," 2013 IEEE Congress on Evolutionary Computation, Cancun, 2013, pp. 2069-2077. doi: 10.1109/CEC.2013.6557813

ExplosionAmplitude(*x_f*, *xb_f*, *A_min*, *Ah*, *As*, *task*)

GaussianSpark(*x*, *xb*, *task*)

NextGeneration(*FW*, *FW_f*, *FWn*, *task*)

initRanges(*task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*Ainit=20*, *Afinal=5*, ***ukwargs*)
Set the arguments of an algorithm.

Arguments:

N {integer} – number of Fireworks

m {integer} – number of sparks

a {integer} – limitation of sparks

b {integer} – limitation of sparks

A {real} –

epsilon {real} – Small number for non 0 devision

uAmin(*Ainit*, *Afinal*, *task*)

class NiaPy.algorithms.basic.**DynamicFireworksAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.basic.fwa.DynamicFireworksAlgorithmGauss

Implementation of dynamic fireworks algorithm.

Algorithm: Dynamic Fireworks Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6900485&isnumber=6900223

Reference paper: S. Zheng, A. Janecek, J. Li and Y. Tan, "Dynamic search in fireworks algorithm," 2014 IEEE Congress on Evolutionary Computation (CEC), Beijing, 2014, pp. 3222-3229. doi: 10.1109/CEC.2014.6900485

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

class NiaPy.algorithms.basic.**DynamicFireworksAlgorithmGauss**(***kwargs*)
Bases: NiaPy.algorithms.basic.fwa.EnhancedFireworksAlgorithm

Implementation of dynamic fireworks algorithm.

Algorithm: Dynamic Fireworks Algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6900485&isnumber=6900223

Reference paper: S. Zheng, A. Janecek, J. Li and Y. Tan, "Dynamic search in fireworks algorithm," 2014 IEEE Congress on Evolutionary Computation (CEC), Beijing, 2014, pp. 3222-3229. doi: 10.1109/CEC.2014.6900485

ExplosionAmplitude(*x_f*, *xb_f*, *A*, *As*)

Mapping(*x*, *task*)

NextGeneration(*FW*, *FW_f*, *FWn*, *task*)
Elitism Random Selection.

initAmplitude(*task*)

repair(*x*, *d*, *epsilon*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*A_cf=20*, *C_a=1.2*, *C_r=0.9*, *epsilon=1e-08*, ***ukwargs*)
Set the arguments of an algorithm.

Arguments:

N {integer} – number of Fireworks

m {integer} – number of sparks

a {integer} – limitation of sparks

b {integer} – limitation of sparks

A {real} –

epsilon {real} – Small number for non 0 devision

uCF(*xnb*, *xcb*, *xcb_f*, *xb*, *xb_f*, *Acf*, *task*)

class NiaPy.algorithms.basic.**GravitationalSearchAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of gravitational search algorithm.

Algorithm: Gravitational Search Algorithm

Date: 2018

Author: Klemen Berkoivč

License: MIT

Reference URL: https://doi.org/10.1016/j.ins.2009.03.004

Reference paper: Esmat Rashedi, Hossein Nezamabadi-pour, Saeid Saryazdi, GSA: A Gravitational Search Algorithm, Information Sciences, Volume 179, Issue 13, 2009, Pages 2232-2248, ISSN 0020-0255

G(*t*)

d(*x*, *y*, *ln=2*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*NP=40*, *G_0=2.467*, *epsilon=1e-17*, ***ukwargs*)
Set the algorithm parameters.

Arguments:

NP {integer} – number of planets in population

G_0 {real} – starting gravitational constant

8.2.2 NiaPy.algorithms.modified

Implementation of modified nature-inspired algorithms.

class NiaPy.algorithms.modified.**HybridBatAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.basic.ba.BatAlgorithm

Implementation of Hybrid bat algorithm.

Algorithm: Hybrid bat algorithm

Date: 2018

Author: Grega Vrbancic and Klemen Berkovič

License: MIT

Reference paper: Fister Jr., Iztok and Fister, Dusan and Yang, Xin-She. "A Hybrid Bat Algorithm". Elektrotehniski vestnik, 2013. 1-7.

runTask(*task*)
Run algorithm with initialized parameters.

Return:

{decimal} – coordinates of minimal found objective function

{decimal} – minimal value found of objective function

setParameters(***kwargs*)
Set the parameters of the algorithm.

Arguments:

NP {integer} – population size

A {decimal} – loudness

r {decimal} – pulse rate

Qmin {decimal} – minimum frequency

Qmax {decimal} – maximum frequency

class NiaPy.algorithms.modified.**SelfAdaptiveDifferentialEvolutionAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.basic.de.DifferentialEvolutionAlgorithm

Implementation of Self-adaptive differential evolution algorithm.

Algorithm: Self-adaptive differential evolution algorithm

Date: 2018

Author: Uros Mlakar and Klemen Berkvoič

License: MIT

Reference paper: Brest, J., Greiner, S., Boskovic, B., Mernik, M., Zumer, V. Self-adapting control parameters in differential evolution: A comparative study on numerical benchmark problems. IEEE transactions on evolutionary computation, 10(6), 646-657, 2006.

AdaptiveGen(*x*)

runTask(*task*)
Run.

setParameters(*F_l=0.0*, *F_u=2.0*, *Tao1=0.4*, *Tao2=0.6*, ***ukwargs*)
Set the parameters of an algorithm.

Arguments:

F_l {decimal} – scaling factor lower limit

F_u {decimal} – scaling factor upper limit

Tao1 {decimal} – change rate for F parameter update

Tao2 {decimal} – change rate for CR parameter update

class NiaPy.algorithms.modified.**DynNPSelfAdaptiveDifferentialEvolutionAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.modified.jde.SelfAdaptiveDifferentialEvolutionAlgorithm

Implementation of Dynamic population size self-adaptive differential evolution algorithm.

Algorithm: Dynamic population size self-adaptive differential evolution algorithm

Date: 2018

Author: Jan Popič

License: MIT

Reference URL: https://link.springer.com/article/10.1007/s10489-007-0091-x

Reference paper: Brest, Janez, and Mirjam Sepesy Maučec. "Population size reduction for the differential evolution algorithm." Applied Intelligence 29.3 (2008): 228-247.

AdaptiveGen(*x*)

runTask(*task*)
Run.

setParameters(*rp=0*, *pmax=4*, ***ukwargs*)
Set the parameters of an algorithm.

Arguments:

rp {integer} – small non-negative number which is added to value of genp (if it's not divisible)

pmax {integer} – number of population reductions

8.2.3 NiaPy.algorithms.other

Implementation of basic nature-inspired algorithms.

class NiaPy.algorithms.other.**NelderMeadMethod**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Nelder Mead method or downhill simplex method or amoeba method.

Algorithm: Nelder Mead Method

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference URL: https://en.wikipedia.org/wiki/Nelder%E2%80%93Mead_method

init(*task*)

method(*X*, *X_f*, *task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*alpha=1.0*, *gamma=2.0*, *rho=-0.5*, *sigma=0.5*, ***ukwargs*)
Set the arguments of an algorithm.

Arguments:

alpha {real} – Reflection coefficient parameter

gamma {real} – Expansion coefficient parameter

rho {real} – Contraction coefficient parameter

sigma {real} – Shrink coefficient parameter

class NiaPy.algorithms.other.**HillClimbAlgorithm**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of iterative hill climbing algorithm.

Algorithm: Hill Climbing Algorithm

Date: 2018

Authors: Jan Popič

License: MIT

Reference URL:

Reference paper:

Initialize Iterative Hillclimb algorithm class.

See: Algorithm.__init__(self, **kwargs)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*delta=0.5*, *Neighborhood=<function Neighborhood>*, ***ukwargs*)
Set the algorithm parameters/arguments.

See: HillClimbAlgorithm.__setparams(self, delta=0.5, Neighborhood=Neighborhood, **ukwargs)

class NiaPy.algorithms.other.**SimulatedAnnealing**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Simulated Annealing Algorithm.

Algorithm: Simulated Annealing Algorithm

Date: 2018

Authors: Jan Popič

License: MIT

Reference URL:

Reference paper:

Init Simulated Annealing Algorithm.

See: Algorithm.__init__(self, **kwargs)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*delta=0.5*, *T=20*, *deltaT=0.8*, *coolingMethod=<function coolDelta>*, ***ukwargs*)
Set the algorithm parameters/arguments.

See: SimulatedAnnealing.__setparams(self, n=10, c_a=1.5, c_r=0.5, **ukwargs)

class NiaPy.algorithms.other.**MultipleTrajectorySearch**(***kwargs*)
Bases: NiaPy.algorithms.algorithm.Algorithm

BONUS1 = 10
Implementation of Multiple trajectory search.

Algorithm: Multiple trajectory search

Date: 2018

Authors: Klemen Berkovic

License: MIT

Reference URL: https://ieeexplore.ieee.org/document/4631210/

Reference paper: Lin-Yu Tseng and Chun Chen, "Multiple trajectory search for Large Scale Global Optimization," 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence), Hong Kong, 2008, pp. 3052-3059. doi: 10.1109/CEC.2008.4631210

BONUS2 = 1
Implementation of Multiple trajectory search.

Algorithm: Multiple trajectory search

Date: 2018

Authors: Klemen Berkovic

License: MIT

Reference URL: https://ieeexplore.ieee.org/document/4631210/

Reference paper: Lin-Yu Tseng and Chun Chen, "Multiple trajectory search for Large Scale Global Optimization," 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence), Hong Kong, 2008, pp. 3052-3059. doi: 10.1109/CEC.2008.4631210

GradingRun(*x*, *x_f*, *xb*, *xb_f*, *improve*, *SR*, *task*)

LsRun(*k*, *x*, *x_f*, *xb*, *xb_f*, *improve*, *SR*, *g*, *task*)

getBest(*X*, *X_f*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters(*NP=40*, *NoLsTests=5*, *NoLs=5*, *NoLsBest=5*, *NoEnabled=17*, ***ukwargs*)
Set the arguments of the algorithm.

Arguments:

NP, M {integer} – population size

NoLsTests {integer} – number of test runs on local search algorihms

NoLs {integer} – number of local search algoritm runs

NoLsBest {integer} – number of locals search algorithm runs on best solution

NoEnabled {integer} – number of best solution for testing

class NiaPy.algorithms.other.**MultipleTrajectorySearchV1**(***kwargs*)
Bases: NiaPy.algorithms.other.mts.MultipleTrajectorySearch

Implementation of Multiple trajectory search.

Algorithm: Multiple trajectory search

Date: 2018

Authors: Klemen Berkovic

License: MIT

Reference URL: https://ieeexplore.ieee.org/document/4983179/

Reference paper: Tseng, Lin-Yu, and Chun Chen. "Multiple trajectory search for unconstrained/constrained multi-objective optimization." Evolutionary Computation, 2009. CEC'09. IEEE Congress on. IEEE, 2009.

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

NiaPy.algorithms.other.**MTS_LS1**(*Xk*, *Xk_fit*, *Xb*, *Xb_fit*, *improve*, *SR*, *task*, *BONUS1=10*, *BONUS2=1*, *rnd=<module 'numpy.random' from '/home/docs/checkouts/readthedocs.org/user_builds/niapy/envs/stable/lib/python3.6/site-packages/numpy/random/__init__.py'>*)

NiaPy.algorithms.other.**MTS_LS2**(*Xk*, *Xk_fit*, *Xb*, *Xb_fit*, *improve*, *SR*, *task*, *BONUS1=10*, *BONUS2=1*, *rnd=<module 'numpy.random' from '/home/docs/checkouts/readthedocs.org/user_builds/niapy/envs/stable/lib/python3.6/site-packages/numpy/random/__init__.py'>*)

NiaPy.algorithms.other.**MTS_LS3**(*Xk*, *Xk_fit*, *Xb*, *Xb_fit*, *improve*, *SR*, *task*, *BONUS1=10*, *BONUS2=1*, *rnd=<module 'numpy.random' from '/home/docs/checkouts/readthedocs.org/user_builds/niapy/envs/stable/lib/python3.6/site-packages/numpy/random/__init__.py'>*)

NiaPy.algorithms.other.**MTS_LS1v1**(*Xk*, *Xk_fit*, *Xb*, *Xb_fit*, *improve*, *SR*, *task*, *BONUS1=10*, *BONUS2=1*, *rnd=<module 'numpy.random' from '/home/docs/checkouts/readthedocs.org/user_builds/niapy/envs/stable/lib/python3.6/si packages/numpy/random/__init__.py'>*)

NiaPy.algorithms.other.**MTS_LS3v1**(*Xk*, *Xk_fit*, *Xb*, *Xb_fit*, *improve*, *SR*, *task*, *phi=3*, *BONUS1=10*, *BONUS2=1*, *rnd=<module 'numpy.random' from '/home/docs/checkouts/readthedocs.org/user_builds/niapy/envs/stable/lib/python3.6/si packages/numpy/random/__init__.py'>*)

class NiaPy.algorithms.other.**AnarchicSocietyOptimization**(***kwargs*)

Bases: NiaPy.algorithms.algorithm.Algorithm

Implementation of Anarchic Society Optimization algorithm.

Algorithm: Particle Swarm Optimization algorithm

Date: 2018

Authors: Klemen Berkovič

License: MIT

Reference paper: Ahmadi-Javid, Amir. "Anarchic Society Optimization: A human-inspired method." Evolutionary Computation (CEC), 2011 IEEE Congress on. IEEE, 2011.

EI(*x_f*, *xnb_f*, *gamma*)
Get external irregularity index.

FI(*x_f*, *xpb_f*, *xb_f*, *alpha*)
Get fickleness index.

II(*x_f*, *xpb_f*, *theta*)
Get internal irregularity index.

getBestNeighbors(*i*, *X*, *X_f*, *rs*)

init(*task*)

runTask(*task*)
Start the optimization.

Arguments:

task {Task} – Task with bounds and objective function for optimization

Return:

solution {array} – point of best solution

fitness {real} – fitness value of best solution

setParameters (*NP=43, alpha=[1, 0.83], gamma=[1.17, 0.56], theta=[0.932, 0.832], d=<function euclidean>, dn=<function euclidean>, nl=1, F=1.2, CR=0.25, Combination=<function Elitism>, **ukwargs*)

Set the parameters for the algorith.

Arguments:

NP {integer} – population size

alpha {array} – factor for fickleness index function $in [0, 1]$

gamma {array} – factor for external irregularity index function $in [0, infty)$

theta {array} – factor for internal irregularity index function $in [0, infty)$

d {function} – function that takes two arguments that are function values and calcs the distance between them

dn {function} – function that takes two arguments that are points in function landscape and calcs the distance between them

nl {real} – normalized range for neighborhood search $in (0, 1]$

F {real} – mutation parameter

CR {real} – crossover parameter $in [0, 1]$

Combination {function} – Function that combines movment strategies

uBestAndPBest (*X*, *X_f*, *Xpb*, *Xpb_f*)

8.3 NiaPy.benchmarks

Module with implementations of benchmark functions.

class NiaPy.benchmarks.**Rastrigin** (*Lower=-5.12*, *Upper=5.12*)

Bases: object

Implementation of Rastrigin benchmark function.

Date: 2018

Authors: Lucija Brezočnik and Iztok Fister Jr.

License: MIT

Function: **Rastrigin function**

$f(\mathbf{x}) = 10D + \sum_{i=1}^{D} \left(x_i^2 - 10\cos(2\pi x_i)\right)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-5.12, 5.12]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = 10D + sum_{i=1}^D left(x_i^2 -10cos(2pi x_i)right)$

Equation: begin{equation} f(mathbf{x}) = 10D + sum_{i=1}^D left(x_i^2 -10cos(2pi x_i)right) end{equation}

Domain: $-5.12 leq x_i leq 5.12$

Reference: https://www.sfu.ca/~ssurjano/rastr.html

classmethod function()

class NiaPy.benchmarks.**Rosenbrock**(*Lower=-30.0*, *Upper=30.0*)
Bases: object

Implementation of Rosenbrock benchmark function.

Date: 2018

Authors: Iztok Fister Jr. and Lucija Brezočnik

License: MIT

Function: **Rosenbrock function**

$f(\mathbf{x}) = \sum_{i=1}^{D-1} \left(100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\right)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-30, 30]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (1, ..., 1)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^{D-1} (100 (x_{i+1} - x_i^2)^2 + (x_i - 1)^2)$

Equation: begin{equation} f(mathbf{x}) = sum_{i=1}^{D-1} (100 (x_{i+1} - x_i^2)^2 + (x_i - 1)^2) end{equation}

Domain: $-30 leq x_i leq 30$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Griewank**(*Lower=-100.0*, *Upper=100.0*)
Bases: object

Implementation of Griewank function.

Date: 2018

Authors: Iztok Fister Jr. and Lucija Brezočnik

License: MIT

Function: **Griewank function**

$f(\mathbf{x}) = \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos(\frac{x_i}{\sqrt{i}}) + 1$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D frac{x_i^2}{4000} - prod_{i=1}^D cos(frac{x_i}{sqrt{i}}) + 1$

Equation: begin{equation} f(mathbf{x}) = sum_{i=1}^D frac{x_i^2}{4000} - prod_{i=1}^D cos(frac{x_i}{sqrt{i}}) + 1 end{equation}

Domain: $-100 leq x_i leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**ExpandedGriewankPlusRosenbrock**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Implementation of Expanded Griewank's plus Rosenbrock function.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Expanded Griewank's plus Rosenbrock function**

$f(\mathbf{x}) = h(g(x_D, x_1)) + \sum_{i=2}^{D} h(g(x_{i-1}, x_i))$
$g(x, y) = 100(x^2 - y)^2 + (x - 1)^2$
$h(z) = \frac{z^2}{4000} - \cos\left(\frac{z}{\sqrt{1}}\right) + 1$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(\textbf{x}) = h(g(x_D, x_1)) + \sum_{i=2}^{D} h(g(x_{i - 1}, x_i)) \\ g(x, y) = 100 (x^2 - y)^2 + (x - 1)^2 \\ h(z) = \frac{z^2}{4000} - \cos left(\frac{z}{\sqrt{1}} right) + 1$

Equation: \begin{equation} f(\textbf{x}) = h(g(x_D, x_1)) + \sum_{i=2}^{D} h(g(x_{i - 1}, x_i)) \\ g(x, y) = 100 (x^2 - y)^2 + (x - 1)^2 \\ h(z) = \frac{z^2}{4000} - \cos left(\frac{z}{\sqrt{1}} right) + 1 \end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

classmethod function()

class NiaPy.benchmarks.**Sphere**(*Lower=-5.12*, *Upper=5.12*)

Bases: object

Implementation of Sphere functions.

Date: 2018

Authors: Iztok Fister Jr.

License: MIT

Function: **Sphere function**

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

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[0, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D x_i^2$

Equation: begin{equation}f(mathbf{x}) = sum_{i=1}^D x_i^2 end{equation}

Domain: $0 leq x_i leq 10$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Ackley**(*Lower=-32.768*, *Upper=32.768*)

Bases: object

Implementation of Ackley function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Ackley function**

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

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-32.768, 32.768]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(\mathbf{x}^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = -a;expleft(-b sqrt{frac{1}{D} sum_{i=1}^D x_i^2}right) - expleft(frac{1}{D} sum_{i=1}^D cos(c;x_i)right) + a + exp(1)$

Equation: begin{equation}f(mathbf{x}) = -a;expleft(-b sqrt{frac{1}{D} sum_{i=1}^D x_i^2}right) - expleft(frac{1}{D} sum_{i=1}^D cos(c;x_i)right) + a + exp(1) end{equation}

Domain: $-32.768 leq x_i leq 32.768$

Reference: https://www.sfu.ca/~ssurjano/ackley.html

classmethod function()

Return benchmark evaluation function.

class NiaPy.benchmarks.**Schwefel**(*Lower=-500.0*, *Upper=500.0*)

Bases: object

Implementation of Schewel function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Schwefel function**

$f(\mathbf{x}) = 418.9829d - \sum_{i=1}^{D} x_i \sin(\sqrt{|x_i|})$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-500, 500]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(\textbf{x}) = 418.9829d - \sum_{i=1}^{D} x_i \sin(\sqrt{|x_i|})$

Equation: begin{equation} f(textbf{x}) = 418.9829d - sum_{i=1}^{D} x_i sin(sqrt{|x_i|}) end{equation}

Domain: $-500 \leq x_i \leq 500$

Reference: https://www.sfu.ca/~ssurjano/schwef.html

classmethod function()

class NiaPy.benchmarks.**Schwefel221**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Schwefel 2.21 function implementation.

Date: 2018

Author: Grega Vrbančič

Licence: MIT

Function: **Schwefel 2.21 function**

$f(\mathbf{x}) = \max_{i=1,...,D} |x_i|$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(\mathbf{x})=\max_{i=1,\ldots,D}|x_i|$

Equation: begin{equation}f(mathbf{x}) = max_{i=1,...,D}|x_i| end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Schwefel222**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Schwefel 2.22 function implementation.

Date: 2018

Author: Grega Vrbančič

Licence: MIT

Function: **Schwefel 2.22 function**

$f(\mathbf{x}) = \sum_{i=1}^{D} |x_i| + \prod_{i=1}^{D} |x_i|$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x})=sum_{i=1}^{D}|x_i|+prod_{i=1}^{D}|x_i|$

Equation: begin{equation}f(mathbf{x}) = sum_{i=1}^{D}|x_i| + prod_{i=1}^{D}|x_i| end{equation}

Domain: $-100 leq x_i leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**ExpandedScaffer**(*Lower=-100.0*, *Upper=100.0*)
Bases: object

Implementations of High Conditioned Elliptic functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **High Conditioned Elliptic Function**

$f(\mathbf{x}) = g(x_D, x_1) + \sum_{i=2}^{D} g(x_{i-1}, x_i)$

$g(x, y) = 0.5 + \frac{\sin\left(\sqrt{x^2+y^2}\right)^2 - 0.5}{(1+0.001(x^2+y^2))}^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(textbf{x}) = g(x_D, x_1) + sum_{i=2}^D g(x_{i - 1}, x_i) \ g(x, y) = 0.5 + frac{sin left(sqrt{x^2 + y^2} right)^2 - 0.5}{left(1 + 0.001 (x^2 + y^2) right)}^2$

Equation: begin{equation} f(textbf{x}) = g(x_D, x_1) + sum_{i=2}^D g(x_{i - 1}, x_i) \ g(x, y) = 0.5 + frac{sin left(sqrt{x^2 + y^2} right)^2 - 0.5}{left(1 + 0.001 (x^2 + y^2) right)}^2 end{equation}

Domain: $-100 leq x_i leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

classmethod function()

class NiaPy.benchmarks.**ModifiedSchwefel**(*Lower=-100.0*, *Upper=100.0*)
Bases: object

Implementations of Modified Schwefel functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Modified Schwefel Function**

$$f(\mathbf{x}) = 418.9829 \cdot D - \sum_{i=1}^{D} h(x_i)$$
$$h(x) = g(x + 420.9687462275036)$$
$$g(z) = \begin{cases} z \sin\left(|z|^{\frac{1}{2}}\right) & |z| \leq 500 \\ (500 - \mod(z, 500)) \sin\left(\sqrt{|500 - \mod(z, 500)|}\right) - \frac{(z-500)^2}{10000D} & z > 500 \\ (\mod(|z|, 500) - 500) \sin\left(\sqrt{|\mod(|z|, 500) - 500|}\right) + \frac{(z-500)^2}{10000D} & z < -500 \end{cases}$$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(\textbf{x}) = 418.9829 \cdot D - \sum_{i=1}^{D} h(x_i) \\ h(x) = g(x + 420.9687462275036) \\ g(z) = \begin{cases} z \sin\left(|z|^{\frac{1}{2}}\right) & |z| \leq 500 \\ (500 - \mod(z, 500)) \sin\left(\sqrt{|500 - \mod(z, 500)|}\right) - \frac{(z-500)^2}{10000D} & z > 500 \\ (\mod(|z|, 500) - 500) \sin\left(\sqrt{|\mod(|z|, 500) - 500|}\right) + \frac{(z-500)^2}{10000D} & z < -500 \end{cases}$

Equation: \begin{equation} f(\textbf{x}) = 418.9829 \cdot D - \sum_{i=1}^{D} h(x_i) \\ h(x) = g(x + 420.9687462275036) \\ g(z) = \begin{cases} z \sin\left(|z|^{\frac{1}{2}}\right) & |z| \leq 500 \\ (500 - \mod(z, 500)) \sin\left(\sqrt{|500 - \mod(z, 500)|}\right) - \frac{(z-500)^2}{10000D} & z > 500 \\ (\mod(|z|, 500) - 500) \sin\left(\sqrt{|\mod(|z|, 500) - 500|}\right) + \frac{(z-500)^2}{10000D} & z < -500 \end{cases} \end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

classmethod function()

class NiaPy.benchmarks.**Whitley**(*Lower=-10.24*, *Upper=10.24*)

Bases: object

Implementation of Whitley function.

Date: 2018

Authors: Grega Vrbančič and Lucija Brezočnik

License: MIT

Function: **Whitley function**

$$f(\mathbf{x}) = \sum_{i=1}^{D} \sum_{j=1}^{D} \left(\frac{(100(x_i^2 - x_j)^2 + (1 - x_j)^2)^2}{4000} - \cos(100(x_i^2 - x_j)^2 + (1 - x_j)^2) + 1 \right)$$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-10.24, 10.24]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (1, ..., 1)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D sum_{j=1}^D left(frac{(100(x_i^2-x_j)^2 + (1-x_j)^2)^2}{4000} - cos(100(x_i^2-x_j)^2 + (1-x_j)^2)+1right)$

Equation: begin{equation}f(mathbf{x}) = sum_{i=1}^D sum_{j=1}^D left(frac{(100(x_i^2-x_j)^2 + (1-x_j)^2)^2}{4000} - cos(100(x_i^2-x_j)^2 + (1-x_j)^2)+1right) end{equation}

Domain: $-10.24 leq x_i leq 10.24$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Alpine1**(*Lower=-10.0*, *Upper=10.0*)

Bases: object

Implementation of Alpine1 function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Alpine1 function**

$f(\mathbf{x}) = \sum_{i=1}^{D} |x_i \sin(x_i) + 0.1x_i|$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-10, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^{D} left |x_i sin(x_i)+0.1x_i right|$

Equation: begin{equation} f(x) = sum_{i=1}^{D} left|x_i sin(x_i) + 0.1x_i right| end{equation}

Domain: $-10 leq x_i leq 10$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Alpine2**(*Lower=0.0*, *Upper=10.0*)

Bases: object

Implementation of Alpine2 function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Alpine2 function**

$f(\mathbf{x}) = \prod_{i=1}^{D} \sqrt{x_i} \sin(x_i)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[0, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 2.808^D$, at $x^* = (7.917, ..., 7.917)$

LaTeX formats:

Inline: $f(mathbf{x}) = prod_{i=1}^{D} sqrt{x_i} sin(x_i)$

Equation: begin{equation} f(mathbf{x}) = prod_{i=1}^{D} sqrt{x_i} sin(x_i) end{equation}

Domain: $0 leq x_i leq 10$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**HappyCat**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Implementation of Happy cat function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Happy cat function**

$$f(\mathbf{x}) = \left|\sum_{i=1}^{D} x_i{}^2 - D\right|^{1/4} + (0.5\sum_{i=1}^{D} x_i{}^2 + \sum_{i=1}^{D} x_i)/D + 0.5$$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (-1, ..., -1)$

LaTeX formats:

Inline: $f(mathbf{x}) = {left|sum_{i = 1}^D {x_i}^2 - D right|}^{1/4} + (0.5 sum_{i = 1}^D {x_i}^2 + sum_{i = 1}^D x_i) / D + 0.5$

Equation: begin{equation} f(mathbf{x}) = {left| sum_{i = 1}^D {x_i}^2 - D right|}^{1/4} + (0.5 sum_{i = 1}^D {x_i}^2 + sum_{i = 1}^D x_i) / D + 0.5 end{equation}

Domain: $-100 leq x_i leq 100$

Reference: http://bee22.com/manual/tf_images/Liang%20CEC2014.pdf & Beyer, H. G., & Finck, S. (2012). HappyCat - A Simple Function Class Where Well-Known Direct Search Algorithms Do Fail. In International Conference on Parallel Problem Solving from Nature (pp. 367-376). Springer, Berlin, Heidelberg.

classmethod function()

class NiaPy.benchmarks.**Ridge**(*Lower=-64.0*, *Upper=64.0*)

Bases: object

Implementation of Ridge function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Ridge function**

$f(\mathbf{x}) = \sum_{i=1}^{D} (\sum_{j=1}^{i} x_j)^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-64, 64]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(\mathbf{x}) = \sum_{i=1}^{D} (\sum_{j=1}^{i} x_j)^2 $

Equation: begin{equation} f(\mathbf{x}) = \sum_{i=1}^{D} (\sum_{j=1}^{i} x_j)^2 end{equation}

Domain: $-64 \leq x_i \leq 64$

Reference: http://www.cs.unm.edu/~neal.holts/dga/benchmarkFunction/ridge.html

classmethod function()

class NiaPy.benchmarks.**ChungReynolds**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Implementation of Chung Reynolds functions.

Date: 2018

Authors: Lucija Brezočnik

License: MIT

Function: **Chung Reynolds function**

$f(\mathbf{x}) = \left(\sum_{i=1}^{D} x_i^2\right)^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(\mathbf{x}) = \left(\sum_{i=1}^{D} x_i^2\right)^2$

Equation: begin{equation} f(\mathbf{x}) = \left(\sum_{i=1}^{D} x_i^2\right)^2 end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Csendes**(*Lower=-1.0*, *Upper=1.0*)

Bases: object

Implementation of Csendes function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Csendes function**

$f(\mathbf{x}) = \sum_{i=1}^{D} x_i^6 \left(2 + \sin \frac{1}{x_i}\right)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-1, 1]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D x_i^6left(2 + sin frac{1}{x_i}right)$

Equation: begin{equation} f(mathbf{x}) = sum_{i=1}^D x_i^6left(2 + sin frac{1}{x_i}right) end{equation}

Domain: $-1 leq x_i leq 1$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Pinter**(*Lower=-10.0*, *Upper=10.0*)

Bases: object

Implementation of Pintér function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Pintér function**

$f(\mathbf{x}) = \sum_{i=1}^{D} ix_i^2 + \sum_{i=1}^{D} 20i \sin^2 A + \sum_{i=1}^{D} i \log_{10}(1 + iB^2)$; $A = (x_{i-1} \sin(x_i) + \sin(x_{i+1}))$ and $B = (x_{i-1}^2 - 2x_i + 3x_{i+1} - \cos(x_i) + 1)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-10, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D ix_i^2 + sum_{i=1}^D 20i sin^2 A + sum_{i=1}^D i log_{10} (1 + iB^2); A = (x_{i-1}sin(x_i)+sin(x_{i+1}))quad text{and} quad B = (x_{i-1}^2 - 2x_i + 3x_{i+1} - cos(x_i) + 1)$

Equation: begin{equation} f(mathbf{x}) = sum_{i=1}^D ix_i^2 + sum_{i=1}^D 20i sin^2 A + sum_{i=1}^D i log_{10} (1 + iB^2); A = (x_{i-1}sin(x_i)+sin(x_{i+1}))quad text{and} quad B = (x_{i-1}^2 - 2x_i + 3x_{i+1} - cos(x_i) + 1) end{equation}

Domain: $-10 leq x_i leq 10$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Qing**(*Lower=-500.0*, *Upper=500.0*)

Bases: object

Implementation of Qing function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Qing function**

$f(\mathbf{x}) = \sum_{i=1}^{D} \left(x_i^2 - i\right)^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-500, 500]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (\pm i))$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D left (x_i^2 - iright)^2$

Equation: begin{equation} f(mathbf{x}) = sum_{i=1}^D left{(x_i^2 - iright)}^2 end{equation}

Domain: $-500 leq x_i leq 500$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Quintic**(*Lower=-10.0*, *Upper=10.0*)

Bases: object

Implementation of Quintic function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Quintic function**

$f(\mathbf{x}) = \sum_{i=1}^{D} \left|x_i^5 - 3x_i^4 + 4x_i^3 + 2x_i^2 - 10x_i - 4\right|$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-10, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = f(-1 \text{ or } 2)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D left| x_i^5 - 3x_i^4 + 4x_i^3 + 2x_i^2 - 10x_i - 4right|$

Equation: begin{equation} f(mathbf{x}) = sum_{i=1}^D left| x_i^5 - 3x_i^4 + 4x_i^3 + 2x_i^2 - 10x_i - 4right| end{equation}

Domain: $-10 leq x_i leq 10$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Salomon**(*Lower=-100.0*, *Upper=100.0*)
Bases: object

Implementation of Salomon function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Salomon function**

$$f(\mathbf{x}) = 1 - \cos\left(2\pi\sqrt{\sum_{i=1}^{D} x_i^2}\right) + 0.1\sqrt{\sum_{i=1}^{D} x_i^2}$$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = f(0, 0)$

LaTeX formats:

Inline: $f(\mathbf{x}) = 1 - \cos\left(2\pi\sqrt{\sum_{i=1}^{D} x_i^2}\right) + 0.1\sqrt{\sum_{i=1}^{D} x_i^2}$

Equation: \begin{equation} f(\mathbf{x}) = 1 - \cos\left(2\pi\sqrt{\sum_{i=1}^{D} x_i^2}\right) + 0.1\sqrt{\sum_{i=1}^{D} x_i^2} \end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**SchumerSteiglitz**(*Lower=-100.0*, *Upper=100.0*)
Bases: object

Implementation of Schumer Steiglitz function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Schumer Steiglitz function**

$$f(\mathbf{x}) = \sum_{i=1}^{D} x_i^4$$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(\mathbf{x}) = \sum_{i=1}^{D} x_i^4$

Equation: \begin{equation} f(\mathbf{x}) = \sum_{i=1}^{D} x_i^4 \end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Step**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Implementation of Step function.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Step function**

$f(\mathbf{x}) = \sum_{i=1}^{D} (\lfloor |x_i| \rfloor)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(\mathbf{x}) = \sum_{i=1}^D \left(\lfloor \left| x_i \right| \rfloor \right)$

Equation: begin{equation} f(\mathbf{x}) = \sum_{i=1}^D \left(\lfloor \left| x_i \right| \rfloor \right) end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Step2**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Step2 function implementation.

Date: 2018

Author: Lucija Brezočnik

Licence: MIT

Function: **Step2 function**

$f(\mathbf{x}) = \sum_{i=1}^{D} (\lfloor x_i + 0.5 \rfloor)^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

lobal minimum: $f(x^*) = 0$, at $x^* = (-0.5, ..., -0.5)$

LaTeX formats:

Inline: $f(\mathbf{x}) = \sum_{i=1}^D \left(\lfloor x_i + 0.5 \rfloor \right)^2$

Equation: begin{equation}f(mathbf{x}) = sum_{i=1}^D left(lfloor x_i + 0.5 rfloor right)^2 end{equation}

Domain: $-100 leq x_i leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Step3**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Step3 function implementation.

Date: 2018

Author: Lucija Brezočnik

Licence: MIT

Function: **Step3 function**

$f(\mathbf{x}) = \sum_{i=1}^{D} \left(\lfloor x_i^2 \rfloor \right)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D left(lfloor x_i^2 rfloor right)$

Equation: begin{equation}f(mathbf{x}) = sum_{i=1}^D left(lfloor x_i^2 rfloor right)end{equation}

Domain: $-100 leq x_i leq 100$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Stepint**(*Lower=-5.12*, *Upper=5.12*)

Bases: object

Implementation of Stepint functions.

Date: 2018

Author: Lucija Brezočnik

License: MIT

Function: **Stepint function**

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

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-5.12, 5.12]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (-5.12, ..., -5.12)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D x_i^2$

Equation: begin{equation}f(mathbf{x}) = sum_{i=1}^D x_i^2 end{equation}

Domain: $0 leq x_i leq 10$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**SumSquares**(*Lower=-10.0*, *Upper=10.0*)

Bases: object

Implementation of Sum Squares functions.

Date: 2018

Authors: Lucija Brezočnik

License: MIT

Function: **Sum Squares function**

$f(\mathbf{x}) = \sum_{i=1}^{D} ix_i^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-10, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(mathbf{x}) = sum_{i=1}^D i x_i^2$

Equation: begin{equation}f(mathbf{x}) = sum_{i=1}^D i x_i^2 end{equation}

Domain: $0 leq x_i leq 10$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**StyblinskiTang**(*Lower=-5.0*, *Upper=5.0*)

Bases: object

Implementation of Styblinski-Tang functions.

Date: 2018

Authors: Lucija Brezočnik

License: MIT

Function: **Styblinski-Tang function**

$f(\mathbf{x}) = \frac{1}{2} \sum_{i=1}^{D} \left(x_i^4 - 16x_i^2 + 5x_i\right)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-5, 5]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = -78.332$, at $x^* = (-2.903534, ..., -2.903534)$

LaTeX formats:

Inline: $f(mathbf{x}) = frac{1}{2} sum_{i=1}^D left(x_i^4 - 16x_i^2 + 5x_i right) $

Equation: begin{equation}f(mathbf{x}) = frac{1}{2} sum_{i=1}^D left(x_i^4 - 16x_i^2 + 5x_i right) end{equation}

Domain: $-5 leq x_i leq 5$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**BentCigar**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Implementations of Bent Cigar functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Bent Cigar Function**

$f(\mathbf{x}) = x_1^2 + 10^6 \sum_{i=2}^{D} x_i^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(textbf{x}) = x_1^2 + 10^6 sum_{i=2}^D x_i^2$

Equation: begin{equation} f(textbf{x}) = x_1^2 + 10^6 sum_{i=2}^D x_i^2 end{equation}

Domain: $-100 leq x_i leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

classmethod function()

class NiaPy.benchmarks.**Weierstrass**(*Lower=-100.0*, *Upper=100.0*, *a=0.5*, *b=3*, *k_max=20*)

Bases: object

Implementations of Weierstrass functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Weierstass Function**

$f(\mathbf{x}) = \sum_{i=1}^{D} \left(\sum_{k=0}^{k_{max}} a^k \cos\left(2\pi b^k (x_i + 0.5)\right) \right) - D \sum_{k=0}^{k_{max}} a^k \cos\left(2\pi b^k \cdot 0.5\right)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$. Default value of a = 0.5, b = 3 and k_max = 20.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $$f(\textbf{x}) = \sum_{i=1}^D \left(\sum_{k=0}^{k_{max}} a^k \cosleft(2 \pi b^k (x_i + 0.5) \right) \right) - D \sum_{k=0}^{k_{max}} a^k \cos \left(2 \pi b^k \cdot 0.5 \right)$$

Equation: \begin{equation} f(\textbf{x}) = \sum_{i=1}^D \left(\sum_{k=0}^{k_{max}} a^k \cosleft(2 \pi b^k (x_i + 0.5) \right) \right) - D \sum_{k=0}^{k_{max}} a^k \cos \left(2 \pi b^k \cdot 0.5 \right) \end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

a = 0.5

b = 3

classmethod function()

k_max = 20

class NiaPy.benchmarks.**HGBat**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Implementations of HGBat functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **HGBat Function**

:math:“f(\textbf{x}) = \left| \left(\sum_{i=1}^D x_i^2 \right)^2 - \left(\sum_{i=1}^D x_i \right)^2 \right|^{\frac{1}{2}} + \frac{0.5 \sum_{i=1}^D x_i^2 + \sum_{i=1}^D x_i}{D} + 0.5

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $$f(\textbf{x}) = \left| \left(\sum_{i=1}^D x_i^2 \right)^2 - \left(\sum_{i=1}^D x_i \right)^2 \right|^{\frac{1}{2}} + \frac{0.5 \sum_{i=1}^D x_i^2 + \sum_{i=1}^D x_i}{D} + 0.5$$

Equation: \begin{equation} f(\textbf{x}) = \left| \left(\sum_{i=1}^D x_i^2 \right)^2 - \left(\sum_{i=1}^D x_i \right)^2 \right|^{\frac{1}{2}} + \frac{0.5 \sum_{i=1}^D x_i^2 + \sum_{i=1}^D x_i}{D} + 0.5 \end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

classmethod function()

class NiaPy.benchmarks.**Katsuura**(*Lower=-100.0*, *Upper=100.0*, ***kwargs*)

Bases: NiaPy.benchmarks.benchmark.Benchmark

Implementations of Katsuura functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Katsuura Function**

$$f(\mathbf{x}) = \frac{10}{D^2} \prod_{i=1}^{D} \left(1 + i \sum_{j=1}^{32} \frac{|2^j x_i - round(2^j x_i)|}{2^j}\right)^{\frac{10}{D^{1.2}}} - \frac{10}{D^2}$$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(\textbf{x}) = \frac{10}{D^2} \prod_{i=1}^{D} \left(1 + i \sum_{j=1}^{32} \frac{| 2^j x_i - roundleft(2^j x_i right) |}{2^j} right)^\frac{10}{D^{1.2}} - \frac{10}{D^2}$

Equation: \begin{equation} f(\textbf{x}) = \frac{10}{D^2} \prod_{i=1}^{D} \left(1 + i \sum_{j=1}^{32} \frac{| 2^j x_i - roundleft(2^j x_i right) |}{2^j} right)^\frac{10}{D^{1.2}} - \frac{10}{D^2} \end{equation}

Domain: $-100 leq x_i leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

classmethod function()
Get the optimization function.

class NiaPy.benchmarks.**Elliptic**(*Lower=-100.0*, *Upper=100.0*)
Bases: NiaPy.benchmarks.benchmark.Benchmark

Implementations of High Conditioned Elliptic functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **High Conditioned Elliptic Function**

$$f(\mathbf{x}) = \sum_{i=1}^{D} \left(10^6\right)^{\frac{i-1}{D-1}} x_i^2$$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(\textbf{x}) = \sum_{i=1}^{D} \left(10^6 right)^{ frac{i - 1}{D - 1} } x_i^2$

Equation: \begin{equation} f(\textbf{x}) = \sum_{i=1}^{D} \left(10^6 right)^{ frac{i - 1}{D - 1} } x_i^2 \end{equation}

Domain: $-100 leq x_i leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

classmethod function()
Get the optimization function.

class NiaPy.benchmarks.**Discus**(*Lower=-100.0*, *Upper=100.0*)

Bases: object

Implementations of Discus functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Discus Function**

$f(\mathbf{x}) = x_1^2 10^6 + \sum_{i=2}^{D} x_i^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-100, 100]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(\textbf{x}) = x_1^2 10^6 + \sum_{i=2}^D x_i^2$

Equation: \begin{equation} f(\textbf{x}) = x_1^2 10^6 + \sum_{i=2}^D x_i^2 \end{equation}

Domain: $-100 \leq x_i \leq 100$

Reference: http://www5.zzu.edu.cn/__local/A/69/BC/D3B5DFE94CD2574B38AD7CD1D12_C802DAFE_BC0C0.pdf

classmethod function()

class NiaPy.benchmarks.**Michalewicz**(*Lower=0.0*, *Upper=3.141592653589793*, *m=10*)

Bases: object

Implementations of Michalewichz's functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **High Conditioned Elliptic Function**

$f(\mathbf{x}) = \sum_{i=1}^{D} \left(10^6\right)^{\frac{i-1}{D-1}} x_i^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[0, \pi]$, for all $i = 1, 2, ..., D$.

Global minimum: at $d = 2$ $f(\mathbf{x}^*) = -1.8013$ at $\mathbf{x}^* = (2.20, 1.57)$ at $d = 5$ $f(\mathbf{x}^*) = -4.687658$ at $d = 10$ $f(\mathbf{x}^*) = -9.66015$

LaTeX formats:

Inline: $f(\textbf{x}) = - \sum_{i = 1}^{D} \sin(x_i) \sinleft(\frac{ix_i^2}{\pi} \right)^{2m}$

Equation: \begin{equation} f(\textbf{x}) = - \sum_{i = 1}^{D} \sin(x_i) \sinleft(\frac{ix_i^2}{\pi} \right)^{2m} \end{equation}

Domain: $0 \leq x_i \leq \pi$

Reference URL: https://www.sfu.ca/~ssurjano/michal.html

classmethod function()

class NiaPy.benchmarks.**Levy**(*Lower=0.0*, *Upper=3.141592653589793*)

Bases: object

Implementations of Levy functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Levy Function**

$f(\mathbf{x}) = \sin^2(\pi w_1) + \sum_{i=1}^{D-1}(w_i - 1)^2 \left(1 + 10\sin^2(\pi w_i + 1)\right) + (w_d - 1)^2(1 + \sin^2(2\pi w_d))$
$w_i = 1 + \frac{x_i - 1}{4}$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-10, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(\mathbf{x}^*) = 0$ at $\mathbf{x}^* = (1, \cdots, 1)$

LaTeX formats:

Inline: $f(\textbf{x}) = \sin^2 (\pi w_1) + \sum_{i = 1}^{D - 1} (w_i - 1)^2 \left(1 + 10 \sin^2 (\pi w_i + 1) \right) + (w_d - 1)^2 (1 + \sin^2 (2 \pi w_d)) \ w_i = 1 + \frac{x_i - 1}{4}$

Equation: \begin{equation} f(\textbf{x}) = \sin^2 (\pi w_1) + \sum_{i = 1}^{D - 1} (w_i - 1)^2 \left(1 + 10 \sin^2 (\pi w_i + 1) \right) + (w_d - 1)^2 (1 + \sin^2 (2 \pi w_d)) \ w_i = 1 + \frac{x_i - 1}{4} \end{equation}

Domain: $-10 \leq x_i \leq 10$

Reference: https://www.sfu.ca/~ssurjano/levy.html

classmethod function()

class NiaPy.benchmarks.**Sphere**(*Lower=-5.12*, *Upper=5.12*)

Bases: object

Implementation of Sphere functions.

Date: 2018

Authors: Iztok Fister Jr.

License: MIT

Function: **Sphere function**

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

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[0, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(\mathbf{x}) = \sum_{i=1}^{D} x_i^2$

Equation: \begin{equation} f(\mathbf{x}) = \sum_{i=1}^{D} x_i^2 \end{equation}

Domain: $0 \leq x_i \leq 10$

Reference paper: Jamil, M., and Yang, X. S. (2013). A literature survey of benchmark functions for global optimisation problems. International Journal of Mathematical Modelling and Numerical Optimisation, 4(2), 150-194.

classmethod function()

class NiaPy.benchmarks.**Sphere2**(*Lower=-1.0*, *Upper=1.0*)

Bases: object

Implementation of Sphere with different powers function.

Date: 2018

Authors: Klemen Berkovič

License: MIT

Function: **Sun of different powers function**

$f(\mathbf{x}) = \sum_{i=1}^{D} |x_i|^{i+1}$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-1, 1]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(\textbf{x}) = \sum_{i = 1}^D | x_i |^{i + 1}$

Equation: \begin{equation} f(\textbf{x}) = \sum_{i = 1}^D | x_i |^{i + 1} \end{equation}

Domain: $-1 \leq x_i \leq 1$

Reference URL: https://www.sfu.ca/~ssurjano/sumpow.html

classmethod function()

class NiaPy.benchmarks.**Sphere3**(*Lower=-65.536*, *Upper=65.536*)

Bases: object

Implementation of rotated hyper-ellipsoid function.

Date: 2018

Authors: Klemen Berkovič

License: MIT

Function: **Sun of rotated hyper-elliposid function**

$f(\mathbf{x}) = \sum_{i=1}^{D} \sum_{j=1}^{i} x_j^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-65.536, 65.536]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (0, ..., 0)$

LaTeX formats:

Inline: $f(\textbf{x}) = \sum_{i = 1}^D \sum_{j = 1}^i x_j^2$

Equation: \begin{equation} f(\textbf{x}) = \sum_{i = 1}^D \sum_{j = 1}^i x_j^2 \end{equation}

Domain: $-65.536 \leq x_i \leq 65.536$

Reference URL: https://www.sfu.ca/~ssurjano/rothyp.html

classmethod function()

class NiaPy.benchmarks.**Trid**(*D=2*)

Bases: object

Implementations of Trid functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Levy Function**

$f(\mathbf{x}) = \sum_{i=1}^{D} (x_i - 1)^2 - \sum_{i=2}^{D} x_i x_{i-1}$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-D^2, D^2]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(\mathbf{x}^*) = \frac{-D(D+4)(D-1)}{6}$ at $\mathbf{x}^* = (1(D+1-1), \cdots, i(D+1-i), \cdots, D(D+1-D))$

LaTeX formats:

Inline: $f(\textbf{x}) = \sum_{i = 1}^D \left(x_i - 1 \right)^2 - \sum_{i = 2}^D x_i x_{i - 1}$

Equation: \begin{equation} f(\textbf{x}) = \sum_{i = 1}^D \left(x_i - 1 \right)^2 - \sum_{i = 2}^D x_i x_{i - 1} \end{equation}

Domain: $-D^2 \leq x_i \leq D^2$

Reference: https://www.sfu.ca/~ssurjano/trid.html

classmethod function()

class NiaPy.benchmarks.**Perm**(*D=10.0*, *beta=0.5*)

Bases: object

Implementations of Perm functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Arguments: beta {real} – value added to inner sum of funciton

Function: **Perm Function**

$f(\mathbf{x}) = \sum_{i=1}^{D} \left(\sum_{j=1}^{D} (j - \beta) \left(x_j^i - \frac{1}{j^i} \right) \right)^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-D, D]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(\mathbf{x}^*) = 0$ at $\mathbf{x}^* = (1, \frac{1}{2}, \cdots, \frac{1}{i}, \cdots, \frac{1}{D})$

LaTeX formats:

Inline: $f(\textbf{x}) = \sum_{i = 1}^D \left(\sum_{j = 1}^D (j - \beta) \left(x_j^i - \frac{1}{j^i} \right) \right)^2$

Equation: \begin{equation} f(\textbf{x}) = \sum_{i = 1}^D \left(\sum_{j = 1}^D (j - \beta) \left(x_j^i - \frac{1}{j^i} \right) \right)^2 \end{equation}

Domain: $-D leq x_i leq D$

Reference: https://www.sfu.ca/~ssurjano/perm0db.html

classmethod function()

class NiaPy.benchmarks.**Zakharov**(*Lower=-5.0*, *Upper=10.0*)
Bases: object

Implementations of Zakharov functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Levy Function**

$f(\mathbf{x}) = \sum_{i=1}^{D} x_i^2 + \left(\sum_{i=1}^{D} 0.5 i x_i\right)^2 + \left(\sum_{i=1}^{D} 0.5 i x_i\right)^4$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-5, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(\mathbf{x}^*) = 0$ at $\mathbf{x}^* = (0, \cdots, 0)$

LaTeX formats:

Inline: $f(\textbf{x}) = \sum_{i = 1}^D x_i^2 + \left(\sum_{i = 1}^D 0.5 i x_i \right)^2 + \left(\sum_{i = 1}^D 0.5 i x_i \right)^4$

Equation: \begin{equation} f(\textbf{x}) = \sum_{i = 1}^D x_i^2 + \left(\sum_{i = 1}^D 0.5 i x_i \right)^2 + \left(\sum_{i = 1}^D 0.5 i x_i \right)^4 \end{equation}

Domain: $-5 leq x_i leq 10$

Reference: https://www.sfu.ca/~ssurjano/levy.html

classmethod function()

class NiaPy.benchmarks.**DixonPrice**(*Lower=-10.0*, *Upper=10*)
Bases: object

Implementations of Dixon Price function.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Levy Function**

$f(\mathbf{x}) = (x_1 - 1)^2 + \sum_{i=2}^{D} i(2x_i^2 - x_{i-1})^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-10, 10]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(\mathbf{x}^*) = 0$ at $\mathbf{x}^* = (2^{-\frac{2^1-2}{2^1}}, \cdots, 2^{-\frac{2^i-2}{2^i}}, \cdots, 2^{-\frac{2^D-2}{2^D}})$

LaTeX formats:

Inline: $f(\textbf{x}) = (x_1 - 1)^2 + \sum_{i = 2}^D i (2x_i^2 - x_{i - 1})^2$

Equation: begin{equation} f(textbf{x}) = (x_1 - 1)^2 + sum_{i = 2}^D i (2x_i^2 - x_{i - 1})^2 end{equation}

Domain: $-10 leq x_i leq 10$

Reference: https://www.sfu.ca/~ssurjano/dixonpr.html

classmethod function()

class NiaPy.benchmarks.**Powell**(*Lower=-4.0*, *Upper=5.0*)

Bases: object

Implementations of Powell functions.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Levy Function**

$f(\mathbf{x}) = \sum_{i=1}^{D/4} \left((x_{4i-3} + 10x_{4i-2})^2 + 5(x_{4i-1} - x_{4i})^2 + (x_{4i-2} - 2x_{4i-1})^4 + 10(x_{4i-3} - x_{4i})^4\right)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-4, 5]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(\mathbf{x}^*) = 0$ at $\mathbf{x}^* = (0, \cdots, 0)$

LaTeX formats:

Inline: $f(textbf{x}) = sum_{i = 1}^{D / 4} left((x_{4 i - 3} + 10 x_{4 i - 2})^2 + 5 (x_{4 i - 1} - x_{4 i})^2 + (x_{4 i - 2} - 2 x_{4 i - 1})^4 + 10 (x_{4 i - 3} - x_{4 i})^4 right)$

Equation: begin{equation} f(textbf{x}) = sum_{i = 1}^{D / 4} left((x_{4 i - 3} + 10 x_{4 i - 2})^2 + 5 (x_{4 i - 1} - x_{4 i})^2 + (x_{4 i - 2} - 2 x_{4 i - 1})^4 + 10 (x_{4 i - 3} - x_{4 i})^4 right) end{equation}

Domain: $-4 leq x_i leq 5$

Reference: https://www.sfu.ca/~ssurjano/levy.html

classmethod function()

class NiaPy.benchmarks.**CosineMixture**(*Lower=-1.0*, *Upper=1.0*)

Bases: object

Implementations of Cosine mixture function.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Cosine Mixture Function**

$f(\mathbf{x}) = -0.1 \sum_{i=1}^{D} \cos(5\pi x_i) - \sum_{i=1}^{D} x_i^2$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-1, 1]$, for all $i = 1, 2, ..., D$.

Global maximu: $f(x^*) = -0.1D$, at $x^* = (0.0, ..., 0.0)$

LaTeX formats:

Inline: $f(\textbf{x}) = - 0.1 \sum_{i = 1}^D \cos (5 \pi x_i) - \sum_{i = 1}^D x_i^2$

Equation: \begin{equation} f(\textbf{x}) = - 0.1 \sum_{i = 1}^D \cos (5 \pi x_i) - \sum_{i = 1}^D x_i^2 \end{equation}

Domain: $-1 \leq x_i \leq 1$

Reference: http://infinity77.net/global_optimization/test_functions_nd_C.html#go_benchmark.CosineMixture

classmethod function()

class NiaPy.benchmarks.**Infinity**(*Lower=-1.0*, *Upper=1.0*)

Bases: object

Implementations of Infinity function.

Date: 2018

Author: Klemen Berkovič

License: MIT

Function: **Infinity Function**

$f(\mathbf{x}) = \sum_{i=1}^{D} x_i^6 \left(\sin \left(\frac{1}{x_i} \right) + 2 \right)$

Input domain: The function can be defined on any input domain but it is usually evaluated on the hypercube $x_i[-1, 1]$, for all $i = 1, 2, ..., D$.

Global minimum: $f(x^*) = 0$, at $x^* = (420.968746, ..., 420.968746)$

LaTeX formats:

Inline: $f(\textbf{x}) = \sum_{i = 1}^D x_i^6 \left(\sin \left(\frac{1}{x_i} \right) + 2 \right)$

Equation: \begin{equation} f(\textbf{x}) = \sum_{i = 1}^D x_i^6 \left(\sin \left(\frac{1}{x_i} \right) + 2 \right) \end{equation}

Domain: $-1 \leq x_i \leq 1$

Reference: http://infinity77.net/global_optimization/test_functions_nd_I.html#go_benchmark.Infinity

classmethod function()

class NiaPy.benchmarks.**Benchmark**(*Lower*, *Upper*, ***kwargs*)

Bases: object

function()

Get the optimization function.

plot2d()

plot3d(*scale=0.32*)

CHAPTER 9

About

Nature-inspired algorithms are a very popular tool for solving optimization problems. Since the beginning of their era, numerous variants of nature-inspired algorithms were developed. To prove their versatility, those were tested in various domains on various applications, especially when they are hybridized, modified or adapted. However, implementation of nature-inspired algorithms is sometimes difficult, complex and tedious task. In order to break this wall, NiaPy is intended for simple and quick use, without spending a time for implementing algorithms from scratch.

9.1 Mission

Our mission is to build a collection of nature-inspired algorithms and create a simple interface for managing the optimization process along with statistical evaluation. NiaPy will offer:

- numerous benchmark functions implementations,
- use of various nature-inspired algorithms without struggle and effort with a simple interface and
- easy comparison between nature-inspired algorithms

9.2 Licence

This package is distributed under the MIT License.

9.3 Disclaimer

This framework is provided as-is, and there are no guarantees that it fits your purposes or that it is bug-free. Use it at your own risk!

CHAPTER 10

Contributing to NiaPy

First off, thanks for taking the time to contribute!

10.1 Code of Conduct

This project and everyone participating in it is governed by the *Code of Conduct*. By participating, you are expected to uphold this code. Please report unacceptable behavior to niapy.organization@gmail.com.

10.2 How Can I Contribute?

10.2.1 Reporting Bugs

Before creating bug reports, please check existing issues list as you might find out that you don't need to create one. When you are creating a bug report, please include as many details as possible. Fill out the required template, the information it asks for helps us resolve issues faster.

10.2.2 Suggesting Enhancements

- Open new issue
- Write in details what enhancement would you like to see in the future
- If you have technical knowledge, propose solution on how to implement enhancement

10.2.3 Pull requests (PR)

Note: If you are not so familiar with Git or/and GitHub, we suggest you take a look at our *Git Beginners Guide*.

Note: Firstly follow the developers *Installation* guide to install needed software in order to contribute to our source code.

- Fill in the reqired template
- Document new code
- Make sure all the code goes through Pylint without problems (run `make check` command)
- Run tests (run `make test` command)
- Make sure PR builds (Travis and AppVeyor) goes through
- Follow discussion in opened PR for any possible needed changes and/or fixes

CHAPTER 11

Code of Conduct

11.1 Our Pledge

In the interest of fostering an open and welcoming environment, we as contributors and maintainers pledge to making participation in our project and our community a harassment-free experience for everyone, regardless of age, body size, disability, ethnicity, gender identity and expression, level of experience, nationality, personal appearance, race, religion, or sexual identity and orientation.

11.2 Our Standards

Examples of behavior that contributes to creating a positive environment include:

- Using welcoming and inclusive language
- Being respectful of differing viewpoints and experiences
- Gracefully accepting constructive criticism
- Focusing on what is best for the community
- Showing empathy towards other community members

Examples of unacceptable behavior by participants include:

- The use of sexualized language or imagery and unwelcome sexual attention or advances
- Trolling, insulting/derogatory comments, and personal or political attacks
- Public or private harassment
- Publishing others' private information, such as a physical or electronic address, without explicit permission
- Other conduct which could reasonably be considered inappropriate in a professional setting

11.3 Our Responsibilities

Project maintainers are responsible for clarifying the standards of acceptable behavior and are expected to take appropriate and fair corrective action in response to any instances of unacceptable behavior.

Project maintainers have the right and responsibility to remove, edit, or reject comments, commits, code, wiki edits, issues, and other contributions that are not aligned to this Code of Conduct, or to ban temporarily or permanently any contributor for other behaviors that they deem inappropriate, threatening, offensive, or harmful.

11.4 Scope

This Code of Conduct applies both within project spaces and in public spaces when an individual is representing the project or its community. Examples of representing a project or community include using an official project e-mail address, posting via an official social media account, or acting as an appointed representative at an online or offline event. Representation of a project may be further defined and clarified by project maintainers.

11.5 Enforcement

Instances of abusive, harassing, or otherwise unacceptable behavior may be reported by contacting the project team at niapy.organization@gmail.com. The project team will review and investigate all complaints, and will respond in a way that it deems appropriate to the circumstances. The project team is obligated to maintain confidentiality with regard to the reporter of an incident. Further details of specific enforcement policies may be posted separately.

Project maintainers who do not follow or enforce the Code of Conduct in good faith may face temporary or permanent repercussions as determined by other members of the project's leadership.

11.6 Attribution

This Code of Conduct is adapted from the homepage, version 1.4, available at http://contributor-covenant.org/version/1/4 .

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