Documentation of the Sequential Parameter Optimization

• This document describes the Spot features.

Example: spot

```
import numpy as np
from math import inf
from spotPython.fun.objectivefunctions import analytical
from spotPython.spot import spot
from scipy.optimize import shgo
from scipy.optimize import direct
from scipy.optimize import differential_evolution
import matplotlib.pyplot as plt
```

The Objective Function

- The spotPython package provides several classes of objective functions.
- We will use an analytical objective function, i.e., a function that can be described by a (closed) formula:

$$f(x) = x^2$$

```
fun = analytical().fun_sphere
x = np.linspace(-1,1,100).reshape(-1,1)
y = fun(x)
plt.figure()
plt.plot(x,y, "k")
plt.show()
spot_1 = spot.Spot(fun=fun,
                   lower = np.array([-10]),
                   upper = np.array([100]),
                   fun_evals = 7,
                   fun_repeats = 1,
                   max_time = inf,
                   noise = False,
                   tolerance_x = np.sqrt(np.spacing(1)),
                   var_type=["num"],
                   infill_criterion = "y",
```

- spot's __init__ method sets the control parameters. There are two parameter groups:
- 1. external parameters can be specified by the user
- 2. internal parameters, which are handled by spot.

External Parameters

external	-	_		
parameter	type	description	default	mandatory
fun	object	objective		yes
		function		
lower	array	lower bound		yes
upper	array	upper bound		yes
fun_evals	int	number of	15	no
		function		
		evaluations		
fun_evals	int	number of	15	no
		function		
		evaluations		
fun_control	dict	noise etc.	{}	n
max_time	int	max run time	inf	no
		budget		

external				
parameter	$_{\mathrm{type}}$	description	default	mandatory
noise	bool	if repeated evaluations of fun results in different values, then noise should be set to True.	False	no
tolerance_x	float	tolerance for new x solutions. Minimum distance of new solutions, generated by suggest_new_X, to already existing solutions. If zero (which is the default), every new solution is accepted.	0	no
var_type	list	list of type information, can be either "num" or "factor"	["num"]	no
<pre>infill_criter</pre>	ionstring	Can be "y", "s", "ei" (negative expected improvement), or "all"	"у"	no
n_points	int	number of infill points	1	no

external parameter	type	description	default	mandatory
seed	$_{ m int}$	initial seed. If Spot.run() is called twice, different results will be generated. To reproduce results, the seed can be used.	123	no

external	tamo	description	dofe.ul+	mandatar-
parameter	type	description	default	mandatory
log_level	int	log level with	50	no
		the following		
		settings: NOTSET		
		(0), DEBUG (10:		
		Detailed		
		information,		
		typically of		
		interest only		
		when diagnosing		
		problems.),		
		INFO (20:		
		Confirmation		
		that things are		
		working as		
		expected.),		
		WARNING (30:		
		An indication		
		that something		
		unexpected		
		happened, or		
		indicative of		
		some problem in		
		the near future		
		(e.g. 'disk space		
		low'). The		
		software is still		
		working as		
		expected.),		
		ERROR (40: Due		
		to a more		
		serious problem,		
		the software has		
		not been able to		
		perform some		
		function.), and		
		CRITICAL (50:		
		A serious error,		
		indicating that		
		the program		
		itself may be		
		unable to		
		continue		
		running.)		
		ı uınınıg.)		

external	.	J	1-614	
parameter	type	description	default	mandatory
show_models	bool	Plot model.	False	no
		Currently only		
		1-dim functions		
		are supported		
design	object	experimental	None	no
		design		
design_control	dict	control	see below	no
		parameters		
surrogate		surrogate model	kriging	no
surrogate_contr	odlict	control	see below	no
		parameters		
optimizer	object	optimizer	see below	no
optimizer_contr	odlict	control	see below	no
		parameters		

- Besides these single parameters, the following parameter dictionaries can be specified by the user:
 - fun_control
 - design_control
 - surrogate_control
 - optimizer_control

The fun_control Dictionary

external parameter	type	description	default	mandatory
sigma	float	noise: standard deviation seed for rng	0	yes
seed	int		124	yes

The design_control Dictionary

external parameter	type	description	default	mandatory
init_size	int	initial sample size	10	yes

external				
parameter	type	description	default	mandatory
repeats	int	number of repeats of the initial sammples	1	yes

The surrogate_control Dictionary

external					
parameter	type	description	default	mandatory	
noise					
model_optimizer	object	optimizer	${\tt differential_evol} {\color{red} \boldsymbol{u}} {\color{blue} \boldsymbol{t}} {\color{blue} \boldsymbol{ion}}$		
model_fun_evals					
min_theta			-3.		
max_theta			3.		
n_theta			1		
n_p			1		
optim_p			False		
cod_type			"norm"		
var_type					
use_cod_y	bool		False		

The optimizer_control Dictionary

external parameter	type	description	default	mandatory
max_iter	int	max number of iterations. Note: these are the cheap evaluations on the surrogate.	1000	no

Run

```
spot_1.run()
```

Print the Results

```
spot_1.print_results()
```

Show the Progress

```
spot_1.plot_progress()
```

Visualize the Surrogate

- The plot method of the kriging surrogate is used.
- Note: the plot uses the interval defined by the ranges of the natural variables.

```
spot_1.surrogate.plot()
```

1. Init: Build Initial Design

```
print(X)
y = fun(X, fun_control=fun_control)
print(y)
```

Replicability

• Seed

```
gen = spacefilling(2, seed=123)
X0 = gen.scipy_lhd(3)
gen = spacefilling(2, seed=345)
X1 = gen.scipy_lhd(3)
X2 = gen.scipy_lhd(3)
gen = spacefilling(2, seed=123)
X3 = gen.scipy_lhd(3)
X0, X1, X2, X3
```

Surrogates

A Simple Predictor

The code below shows how to use a simple model for prediction.

• Assume that only two (very costly) measurements are available:

```
1. f(0) = 0.5
2. f(2) = 2.5
```

• We are interested in the value at $x_0 = 1$, i.e., $f(x_0 = 1)$, but cannot run an additional, third experiment.

```
from sklearn import linear_model
X = np.array([[0], [2]])
y = np.array([0.5, 2.5])
S_lm = linear_model.LinearRegression()
S_lm = S_lm.fit(X, y)
X0 = np.array([[1]])
y0 = S_lm.predict(X0)
print(y0)
```

- Central Idea:
 - Evaluation of the surrogate model S_{lm} is much cheaper (or / and much faster) than running the real-world experiment f.

Demo/Test: Objective Function Fails

- SPOT expects np.nan values from failed objective function values.
- These are handled.
- Note: SPOT's counter considers only successful executions of the objective function.

```
import numpy as np
from spotPython.fun.objectivefunctions import analytical
from spotPython.spot import spot
import numpy as np
from math import inf
# number of initial points:
ni = 20
# number of points
n = 30
fun = analytical().fun_random_error
lower = np.array([-1])
upper = np.array([1])
design_control={"init_size": ni}
spot_1 = spot.Spot(fun=fun,
            lower = lower,
            upper= upper,
            fun_evals = n,
            show_progress=False,
            design_control=design_control,)
spot_1.run()
# To check whether the run was successfully completed,
# we compare the number of evaluated points to the specified
# number of points.
assert spot_1.y.shape[0] == n
```