

Benchmark Functions for Bayesian Optimization

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0 Benchmark Functions for Bayesian Optimization

- All functions are implemented in <https://github.com/jungtaekkim/bayeso-benchmarks>.
- We refer to [Surjanovic and Bingham, 2013] for specific forms of many benchmark functions, which are described in <https://www.sfu.ca/~ssurjano>.
- The details of **bayeso** [Kim and Choi, 2017] and **bayeso-benchmarks** are introduced in <http://bayeso.org>.
- We will introduce the following benchmark functions in this article.
 1. Ackley
 2. Beale
 3. Bohachevsky
 4. Branin
 5. Cosines
 6. Eggholder
 7. Goldstein-Price
 8. Gramacy & Lee (2012)
 9. Hartmann 6D
 10. Holder Table
 11. Rosenbrock
 12. Six-Hump Camel
 13. Sphere

1 Ackley Function

Given a d -dimensional input, $\mathbf{x} := [x_1, \dots, x_d] \in [-32.768, 32.768]^d$,

$$y = -20 \exp \left(-0.2 \sqrt{\frac{1}{d} \sum_{i=1}^d x_i^2} \right) - \exp \left(\frac{1}{d} \sum_{i=1}^d \cos(2\pi x_i) \right) + 20 + \exp(1). \quad (1)$$

A global optimum is 0, at $\mathbf{x}^* = [0, \dots, 0] \in \mathbb{R}^d$.

2 Beale Function

Given a two-dimensional input, $\mathbf{x} := [x_1, x_2] \in [-4.5, 4.5]^2$,

$$y = (1.5 - x_1 + x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2. \quad (2)$$

A global optimum is 0, at $\mathbf{x}^* = [3.0, 0.5]$.

3 Bohachevsky Function

Given a two-dimensional input, $\mathbf{x} := [x_1, x_2] \in [-100, 100]^2$,

$$y = x_1^2 + 2x_2^2 - 0.3 \cos(3\pi x_1) - 0.4 \cos(4\pi x_2) + 0.7. \quad (3)$$

A global optimum is 0, at $\mathbf{x}^* = [0, 0]$.

4 Branin Function

Given a two-dimensional input, $-5 \leq x_1 \leq 10, 0 \leq x_2 \leq 15$,

$$y = \left(x_2 - \frac{5.1}{4\pi^2} x_1^2 + \frac{5}{\pi} x_1 - 6 \right) + 10 \left(1 - \frac{1}{8\pi} \right) \cos(x_1) + 10. \quad (4)$$

Global optima are 0, at $\mathbf{x}^* = [-\pi, 12.275], [\pi, 2.275]$, and $[9.42478, 2.475]$.

5 Cosines Function

Given a d -dimensional input, $\mathbf{x} := [x_1, \dots, x_d] \in [-2\pi, 2\pi]^d$,

$$y = \sum_{i=1}^d \cos(x_i) \left(\frac{0.1}{2\pi} |x_i| - 1 \right). \quad (5)$$

A global optimum is $-d$, at $\mathbf{x}^* = [0, \dots, 0] \in \mathbb{R}^d$.

6 Eggholder Function

Given a two-dimensional input, $\mathbf{x} := [x_1, x_2] \in [-512, 512]^2$,

$$y = -(x_2 + 47) \sin \left(\sqrt{|x_2 + 0.5x_1 + 47|} \right) - x_1 \sin \left(\sqrt{|x_1 - (x_2 + 47)|} \right). \quad (6)$$

A global optimum is -959.6407 , at $\mathbf{x}^* = [512.0, 404.2319]$.

7 Goldstein-Price Function

Given a two-dimensional input, $\mathbf{x} := [x_1, x_2] \in [-2, 2]^2$,

$$y = \left[1 + A(B - 14x_2 + 6x_1x_2 + 3x_2^2) \right] \left[30 + C(D + 48x_2 - 36x_1x_2 + 27x_2^2) \right], \quad (7)$$

where

$$A = (x_1 + x_2 + 1)^2, \quad (8)$$

$$B = 19 - 14x_1 + 3x_1^2, \quad (9)$$

$$C = (2x_1 - 3x_2)^2, \quad (10)$$

$$D = 18 - 32x_1 + 12x_1^2. \quad (11)$$

A global optimum is 3, at $\mathbf{x}^* = [0, -1]$.

8 Gramacy & Lee (2012) Function

Given a one-dimensional input, $x \in [0.5, 2.5]$,

$$y = \frac{\sin(10\pi x)}{2x} + (x - 1)^4. \quad (12)$$

A global optimum is 0.54856405, at $x^* = -0.86901113$.

9 Hartmann 6D Function

Given a six-dimensional input, $\mathbf{x} := [x_1, \dots, x_6] \in [0, 1]^6$,

$$y = -\sum_{i=1}^4 \alpha_i \exp\left(-\sum_{j=1}^6 A_{ij}(x_j - P_{ij})^2\right), \quad (13)$$

where $\boldsymbol{\alpha} = [1.0, 1.2, 3.0, 3.2]^\top$,

$$\mathbf{A} = \begin{pmatrix} 10 & 3 & 17 & 3.5 & 1.7 & 8 \\ 0.05 & 10 & 17 & 0.1 & 8 & 14 \\ 3 & 3.5 & 1.7 & 10 & 17 & 8 \\ 17 & 8 & 0.05 & 10 & 0.1 & 14 \end{pmatrix}, \quad (14)$$

$$\mathbf{P} = 10^{-4} \begin{pmatrix} 1312 & 1696 & 5569 & 124 & 8283 & 5886 \\ 2329 & 4135 & 8307 & 3736 & 1004 & 9991 \\ 2348 & 1451 & 3522 & 2883 & 3047 & 6650 \\ 4047 & 8828 & 8732 & 5743 & 1091 & 381 \end{pmatrix}. \quad (15)$$

A global optimum is -3.32237 , at $\mathbf{x}^* = [0.20169, 0.150011, 0.476874, 0.275332, 0.311652, 0.6573]$.

10 Holder Table Function

Given a two-dimensional input, $\mathbf{x} := [x_1, x_2] \in [-10, 10]^2$,

$$y = -\left| \sin(x_1) \cos(x_2) \exp\left(\left|1 - \frac{\sqrt{x_1^2 + x_2^2}}{\pi}\right|\right) \right|. \quad (16)$$

Global optima are -19.2085 , at $\mathbf{x}^* = [8.05502, 9.66459], [8.05502, -9.66459], [-8.05502, 9.66459]$, and $[-8.05502, -9.66459]$.

11 Rosenbrock Function

Given a d -dimensional input, $\mathbf{x} := [x_1, \dots, x_d] \in [-2.048, 2.048]^d$,

$$y = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]. \quad (17)$$

A global optimum is 0, at $\mathbf{x}^* = [1, \dots, 1] \in \mathbb{R}^d$.

12 Six-Hump Camel Function

Given a two-dimensional input, $-3 \leq x_1 \leq 3, -2 \leq x_2 \leq 2$,

$$y = \left(4 - 2.1x_1^2 + \frac{x_1^4}{3}\right)x_1^2 + x_1x_2 + (-4 + 4x_2^2)x_2^2. \quad (18)$$

Global optima are -1.0316 , at $\mathbf{x}^* = [0.0898, -0.7126]$ and $[-0.0898, 0.7126]$.

13 Sphere Function

Given a d -dimensional input, $\mathbf{x} := [x_1, \dots, x_d] \in [-5.12, 5.12]^d$,

$$y = \sum_{i=1}^d x_i^2. \quad (19)$$

A global optimum is 0, at $\mathbf{x}^* = [0, \dots, 0] \in \mathbb{R}^d$.

References

- J. Kim and S. Choi. bayeso: A Bayesian optimization framework in Python. <http://bayeso.org>, 2017.
- S. Surjanovic and D. Bingham. Virtual library of simulation experiments: Test functions and datasets. <http://www.sfu.ca/~ssurjano>, 2013.