

# Benchmark Functions for Bayesian Optimization

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## Introduction

In these notes, we cover benchmark functions for Bayesian optimization. Since Bayesian optimization is used to solve a global optimization problem, the benchmark functions described in these notes can be utilized in diverse problems on mathematical optimization.

## 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      | 5. Bukin 6   |
| 2. Beale       | 6. Colville  |
| 3. Bohachevsky | 7. Cosines   |
| 4. Branin      | 8. De Jong 5 |

- 9. Drop-Wave
- 10. Easom
- 11. Eggholder
- 12. Goldstein-Price
- 13. Gramacy & Lee (2012)
- 14. Griewank
- 15. Hartmann 3D
- 16. Hartmann 6D
- 17. Holder Table
- 18. Kim1
- 19. Kim2
- 20. Kim3
- 21. Levy
- 22. Michalewicz
- 23. Rastrigin
- 24. Rosenbrock
- 25. Shubert
- 26. Six-Hump Camel
- 27. Sphere
- 28. Three-Hump Camel
- 29. Zakharov

# 1 Ackley Function

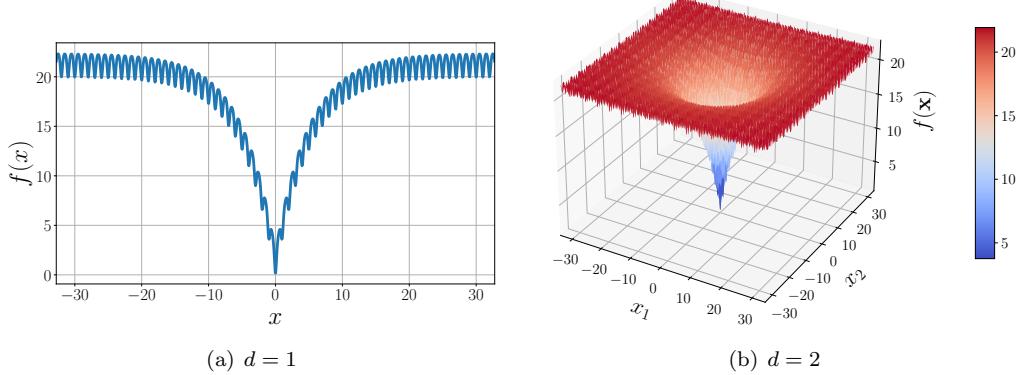


Figure 1: Ackley function.

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

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

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

## 2 Beale Function

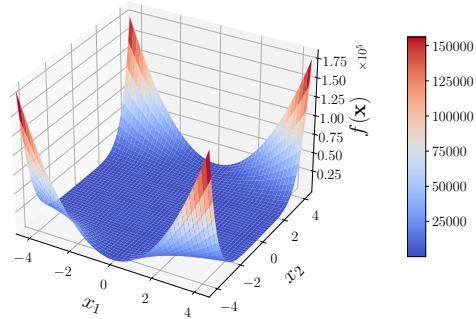


Figure 2: Beale function.

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

$$f(\mathbf{x}) = (1.5 - x_1 + x_1 x_2)^2 + (2.25 - x_1 + x_1 x_2^2)^2 + (2.625 - x_1 + x_1 x_2^3)^2. \quad (2)$$

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

### 3 Bohachevsky Function

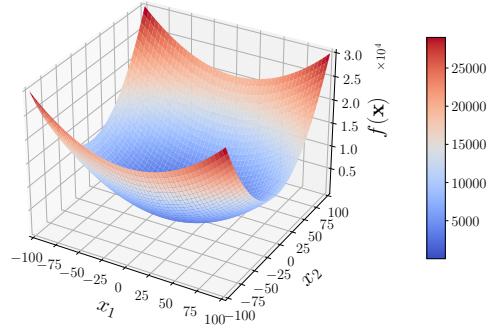


Figure 3: Bohachevsky function.

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

$$f(\mathbf{x}) = x_1^2 + 2x_2^2 - 0.3 \cos(3\pi x_1) - 0.4 \cos(4\pi x_2) + 0.7. \quad (3)$$

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

## 4 Branin Function

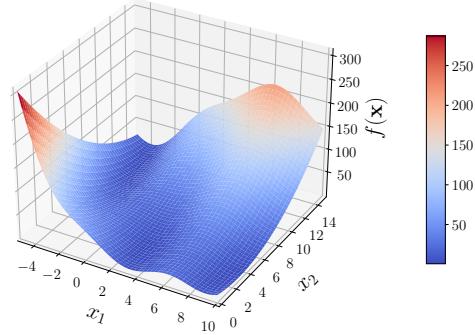


Figure 4: Branin function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2]$  for  $-5 \leq x_1 \leq 10$ ,  $0 \leq x_2 \leq 15$ ,

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

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

## 5 Bukin 6 Function

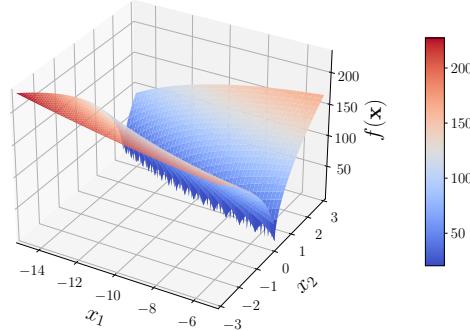


Figure 5: Bukin 6 function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2]$  for  $-15 \leq x_1 \leq -5$ ,  $-3 \leq x_2 \leq 3$ ,

$$f(\mathbf{x}) = 100\sqrt{|x_2 - 0.01x_1^2|} + 0.01|x_1 + 10|. \quad (5)$$

A global optimum is 0, at  $\mathbf{x}^* = [-10, 1]$ .

## 6 Colville Function

Given a four-dimensional input,  $\mathbf{x} := [x_1, x_2, x_3, x_4] \in [-10, 10]^4$ ,

$$\begin{aligned} f(\mathbf{x}) = & 100(x_1^2 - x_2)^2 + (x_1 - 1)^2 + (x_3 - 1)^2 + 90(x_3^2 - x_4)^2 \\ & + 10.1((x_2 - 1)^2 + (x_4 - 1)^2) + 19.8(x_2 - 1)(x_4 - 1). \end{aligned} \quad (6)$$

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

## 7 Cosines Function

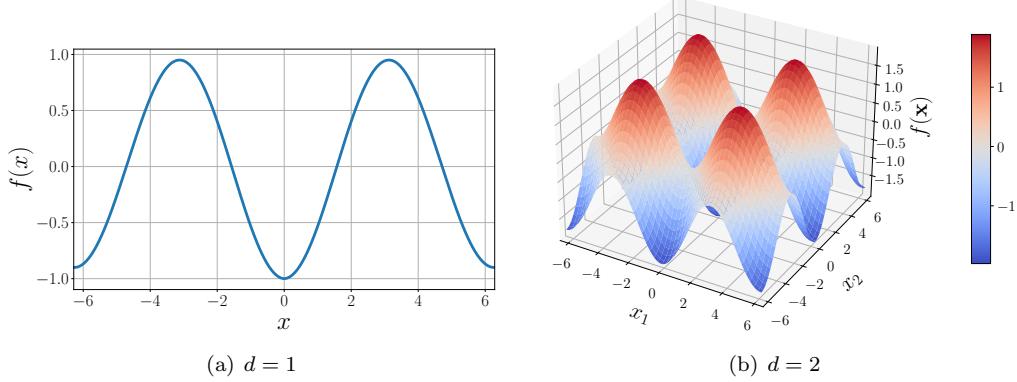


Figure 6: Cosines function.

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

$$f(\mathbf{x}) = \sum_{i=1}^d \cos(x_i) \left( \frac{0.1}{2\pi} |x_i| - 1 \right). \quad (7)$$

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

## 8 De Jong 5 Function

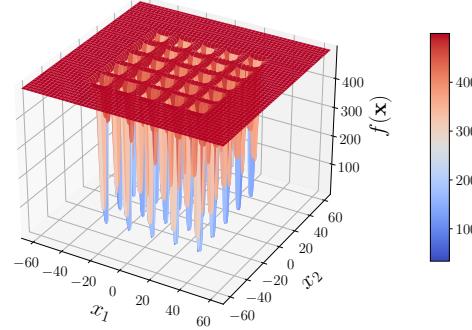


Figure 7: De Jong 5 function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2] \in [-65.536, 65.536]^2$ ,

$$f(\mathbf{x}) = \left( 0.002 + \sum_{i=1}^{25} \frac{1}{i + (x_1 - A_{1i})^6 + (x_2 - A_{2i})^6} \right)^{-1}, \quad (8)$$

where

$$\mathbf{A} = \begin{pmatrix} \mathbf{a} & \mathbf{a} & \mathbf{a} & \mathbf{a} & \mathbf{a} \\ -\mathbf{b} & -0.5\mathbf{b} & 0\mathbf{b} & 0.5\mathbf{b} & \mathbf{b} \end{pmatrix} \in \mathbb{R}^{2 \times 25}, \quad (9)$$

$\mathbf{a} = [-32, -16, 0, 16, 32]$ , and  $\mathbf{b} = [32, 32, 32, 32, 32]$ .

A global optimum is 0.998004, at  $\mathbf{x}^* = [-32.104282, -32.137058]$  or many other points.

## 9 Drop-Wave Function

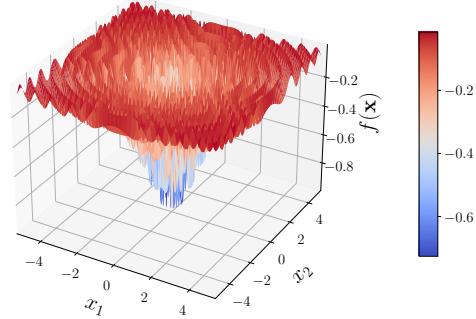


Figure 8: Drop-Wave function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2] \in [-5.12, 5.12]^2$ ,

$$f(\mathbf{x}) = -\frac{1 + \cos(12\sqrt{x_1^2 + x_2^2})}{0.5(x_1^2 + x_2^2) + 2}. \quad (10)$$

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

## 10 Easom Function

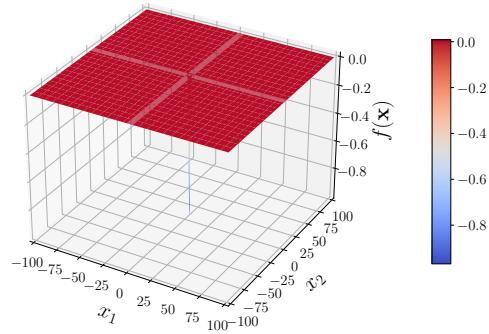


Figure 9: Easom function.

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

$$f(\mathbf{x}) = -\cos(x_1) \cos(x_2) \exp(-(x_1 - \pi)^2 - (x_2 - \pi)^2). \quad (11)$$

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

## 11 Eggholder Function

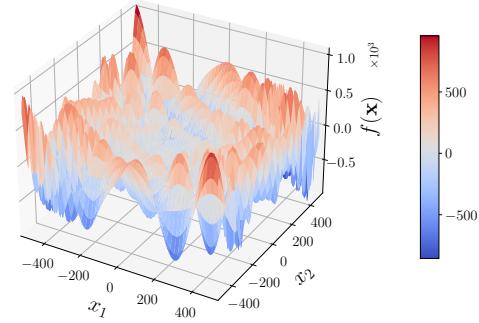


Figure 10: Eggholder function.

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

$$f(\mathbf{x}) = -(x_2 + 47) \sin \left( \sqrt{|x_2 + 0.5x_1 + 47|} \right) - x_1 \sin \left( \sqrt{|x_1 - (x_2 + 47)|} \right). \quad (12)$$

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

## 12 Goldstein-Price Function

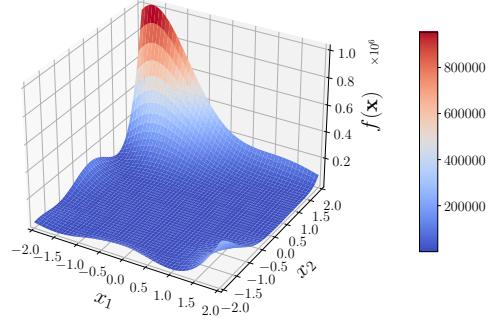


Figure 11: Goldstein-Price function.

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

$$f(\mathbf{x}) = [1 + A(B - 14x_2 + 6x_1x_2 + 3x_2^2)] [30 + C(D + 48x_2 - 36x_1x_2 + 27x_2^2)], \quad (13)$$

where

$$A = (x_1 + x_2 + 1)^2, \quad (14)$$

$$B = 19 - 14x_1 + 3x_1^2, \quad (15)$$

$$C = (2x_1 - 3x_2)^2, \quad (16)$$

$$D = 18 - 32x_1 + 12x_1^2. \quad (17)$$

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

## 13 Gramacy & Lee (2012) Function

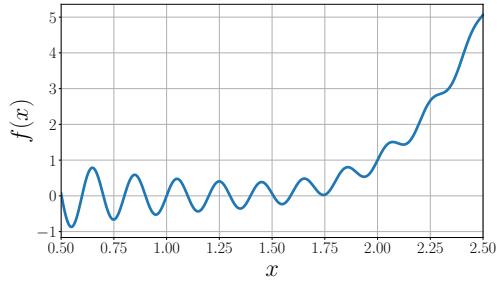


Figure 12: Gramacy & Lee (2012) function.

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

$$f(x) = \frac{\sin(10\pi x)}{2x} + (x - 1)^4. \quad (18)$$

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

## 14 Griewank Function

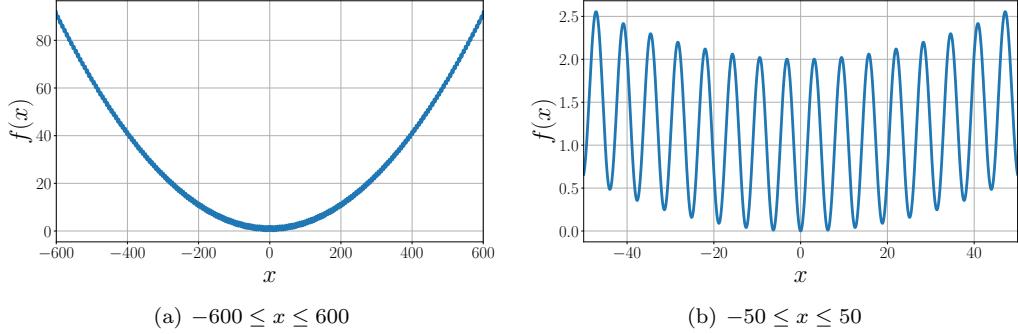


Figure 13: Griewank function ( $d = 1$ ).

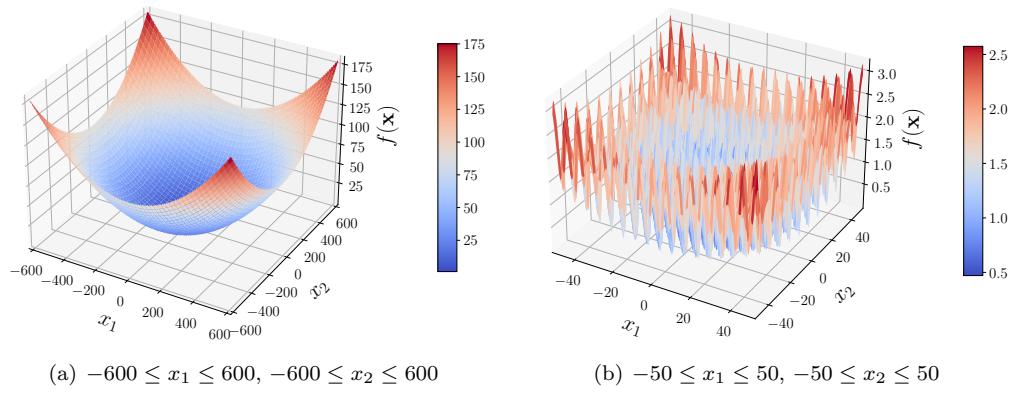


Figure 14: Griewank function ( $d = 2$ ).

Given a  $d$ -dimensional input,  $\mathbf{x} := [x_1, \dots, x_d] \in [-600, 600]^d$ ,

$$f(\mathbf{x}) = \sum_{i=1}^d \frac{x_i^2}{4000} - \prod_{i=1}^d \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1. \quad (19)$$

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

## 15 Hartmann 3D Function

Given a three-dimensional input,  $\mathbf{x} := [x_1, x_2, x_3] \in [0, 1]^3$ ,

$$f(\mathbf{x}) = -\sum_{i=1}^4 \alpha_i \exp \left( -\sum_{j=1}^3 A_{ij}(x_j - P_{ij})^2 \right), \quad (20)$$

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

$$\mathbf{A} = \begin{pmatrix} 3.0 & 10 & 30 \\ 0.1 & 10 & 35 \\ 3.0 & 10 & 30 \\ 0.1 & 10 & 35 \end{pmatrix}, \quad (21)$$

$$\mathbf{P} = 10^{-4} \begin{pmatrix} 3689 & 1170 & 2673 \\ 4699 & 4387 & 7470 \\ 1091 & 8732 & 5547 \\ 381 & 5743 & 8828 \end{pmatrix}. \quad (22)$$

A global optimum is  $-3.86278$ , at  $\mathbf{x}^* = [0.114614, 0.555649, 0.852547]$ .

## 16 Hartmann 6D Function

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

$$f(\mathbf{x}) = -\sum_{i=1}^4 \alpha_i \exp \left( -\sum_{j=1}^6 A_{ij}(x_j - P_{ij})^2 \right), \quad (23)$$

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

$$\mathbf{A} = \begin{pmatrix} 10 & 3 & 17 & 3.5 & 1.7 & 8 \\ 0.05 & 10 & 17 & 0.1 & 8 & 14 \\ 3 & 3.5 & 1.7 & 10 & 17 & 8 \\ 17 & 8 & 0.05 & 10 & 0.1 & 14 \end{pmatrix}, \quad (24)$$

$$\mathbf{P} = 10^{-4} \begin{pmatrix} 1312 & 1696 & 5569 & 124 & 8283 & 5886 \\ 2329 & 4135 & 8307 & 3736 & 1004 & 9991 \\ 2348 & 1451 & 3522 & 2883 & 3047 & 6650 \\ 4047 & 8828 & 8732 & 5743 & 1091 & 381 \end{pmatrix}. \quad (25)$$

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

## 17 Holder Table Function

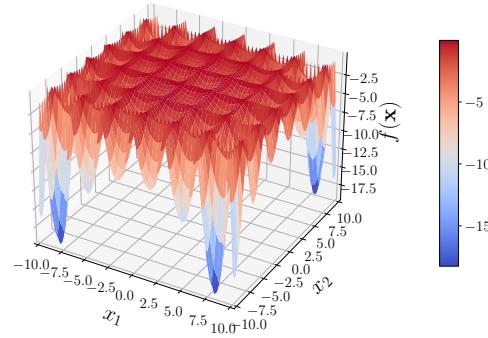


Figure 15: Holder Table function.

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

$$f(\mathbf{x}) = -\left| \sin(x_1) \cos(x_2) \exp\left(\left|1 - \frac{\sqrt{x_1^2 + x_2^2}}{\pi}\right|\right)\right|. \quad (26)$$

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

## 18 Kim1 Function

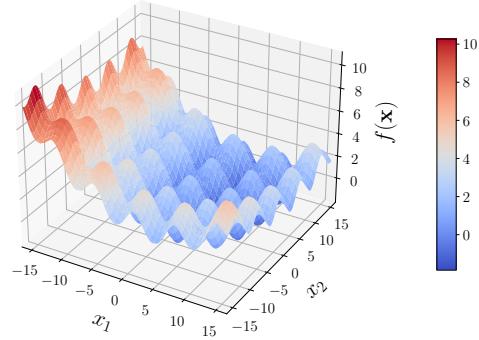


Figure 16: Kim1 function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2] \in [-16, 16]^2$ ,

$$f(\mathbf{x}) = \sin(x_1) + \cos(x_2) + 0.016(x_1 - 5)^2 + 0.008(x_2 - 5)^2. \quad (27)$$

A global optimum is  $-1.97152323$ , at  $\mathbf{x}^* = [4.72130726, 3.17086303]$ .

## 19 Kim2 Function

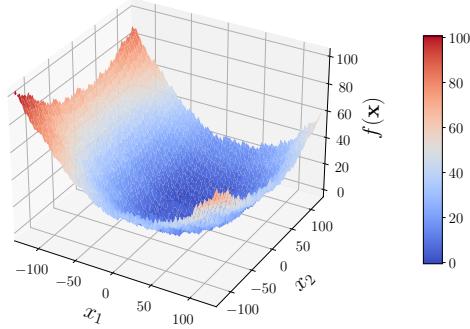


Figure 17: Kim2 function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2] \in [-128, 128]^2$ ,

$$f(\mathbf{x}) = \sum_{i=0}^4 \left( \sin\left(\frac{x_1}{2^i}\right) + \cos\left(\frac{x_2}{2^i}\right) \right) + 0.0032(x_1 - 20)^2 + 0.0016(x_2 - 20)^2. \quad (28)$$

A global optimum is  $-3.45438747$ , at  $\mathbf{x}^* = [-2.10134660, 34.14526252]$ .

## 20 Kim3 Function

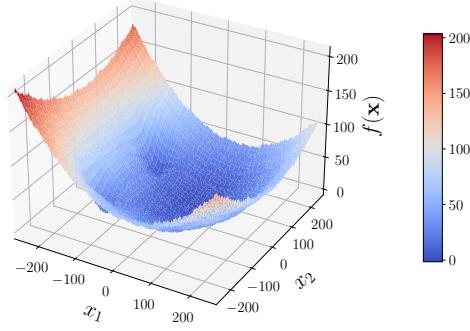


Figure 18: Kim3 function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2] \in [-256, 256]^2$ ,

$$\begin{aligned} f(\mathbf{x}) = & \sum_{i=0}^4 \left( \sin\left(\frac{x_1}{2^i}\right) + \cos\left(\frac{x_2}{2^i}\right) \right) \\ & + 0.0016(x_1 - 40)^2 + 0.0008(x_2 - 40)^2 \\ & - 25600(\phi(\mathbf{x}; \boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1) + \phi(\mathbf{x}; \boldsymbol{\mu}_2, \boldsymbol{\Sigma}_2)), \end{aligned} \quad (29)$$

where  $\phi(\cdot; \boldsymbol{\mu}, \boldsymbol{\Sigma})$  is a probability density function of multivariate Gaussian distribution defined with a mean vector  $\boldsymbol{\mu}$  and a covariance matrix  $\boldsymbol{\Sigma}$ ,  $\boldsymbol{\mu}_1 = [-120, -120]$ ,  $\boldsymbol{\mu}_2 = [-120, 120]$ , and

$$\boldsymbol{\Sigma}_1 = \boldsymbol{\Sigma}_2 = \begin{bmatrix} 1000 & 0 \\ 0 & 1000 \end{bmatrix}. \quad (30)$$

A global optimum is  $-4.94396792$ , at  $\mathbf{x}^* = [48.12477173, 34.19859065]$ .

## 21 Levy Function

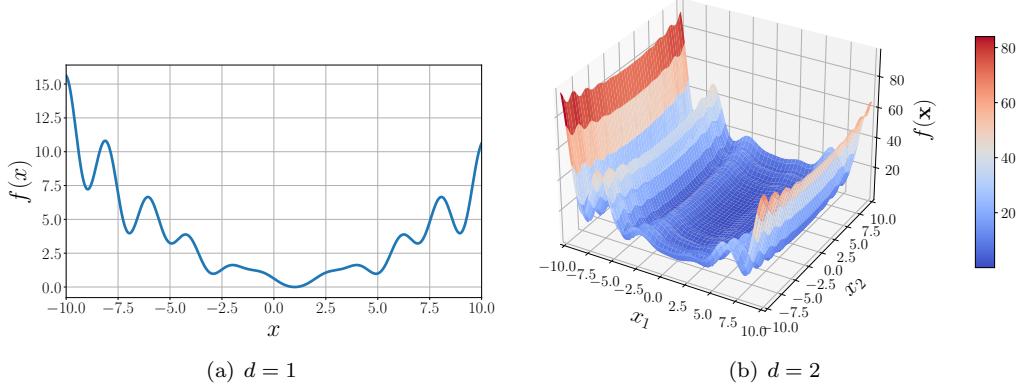


Figure 19: Levy function.

Given a  $d$ -dimensional input,  $\mathbf{x} := [x_1, \dots, x_d] \in [-10, 10]^d$ ,

$$\begin{aligned} f(\mathbf{x}) &= \sin^2\left(\frac{\pi(x_1 + 3)}{4}\right) + \sum_{i=1}^{d-1} \left(\frac{x_i - 1}{4}\right)^2 \left(1 + 10 \sin^2\left(\frac{\pi(x_i + 3)}{4} + 1\right)\right) \\ &\quad + \left(\frac{x_d - 1}{4}\right)^2 \left(1 + \sin^2\left(\frac{\pi(x_d + 3)}{2}\right)\right). \end{aligned} \quad (31)$$

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

## 22 Michalewicz Function

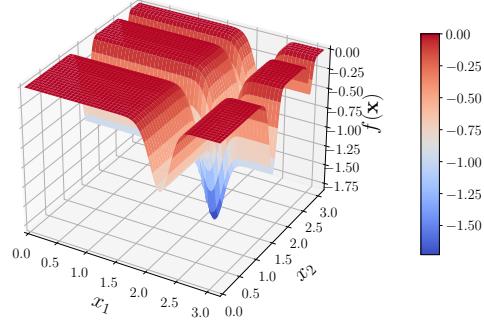


Figure 20: Michalewicz function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2] \in [0, \pi]^2$ ,

$$f(\mathbf{x}) = -\sum_{i=1}^2 \sin(x_i) \sin^{20}\left(\frac{ix_i^2}{\pi}\right). \quad (32)$$

A global optimum is  $-1.801302197$ , at  $\mathbf{x}^* = [2.20279089, 1.57063923]$ .

## 23 Rastrigin Function

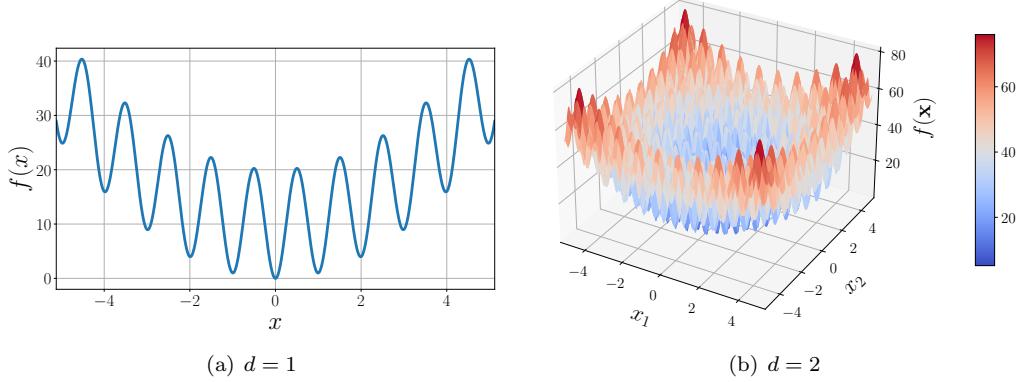


Figure 21: Rastrigin function.

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

$$f(\mathbf{x}) = 10d + \sum_{i=1}^d (x_i^2 - 10 \cos(2\pi x_i)). \quad (33)$$

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

## 24 Rosenbrock Function

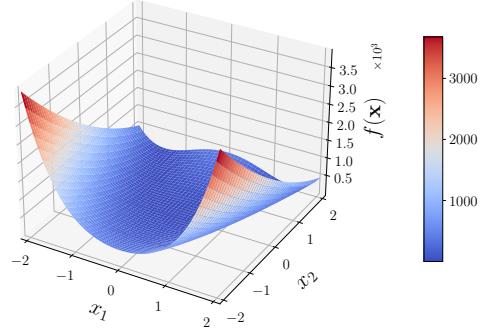


Figure 22: Rosenbrock function ( $d = 2$ ).

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

$$f(\mathbf{x}) = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2], \quad (34)$$

where  $d \geq 2$ . A global optimum is 0, at  $\mathbf{x}^* = [1, \dots, 1] \in \mathbb{R}^d$ .

## 25 Shubert Function

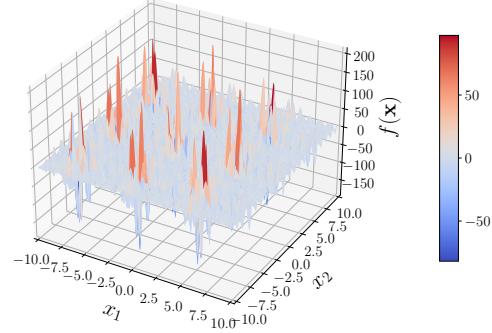


Figure 23: Shubert function.

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

$$f(\mathbf{x}) = \left( \sum_{i=1}^5 i \cos((i+1)x_1 + i) \right) \left( \sum_{i=1}^5 i \cos((i+1)x_2 + i) \right). \quad (35)$$

A global optimum is  $-186.73090883$ , at  $\mathbf{x}^* = [-7.08350641, -7.70831374]$ .

## 26 Six-Hump Camel Function

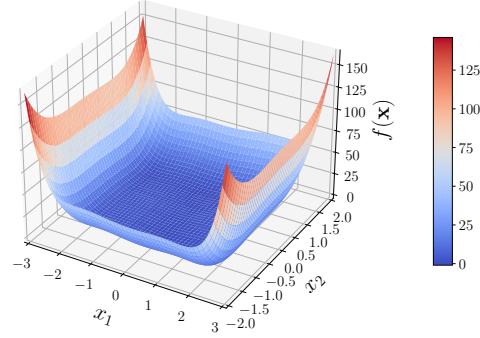


Figure 24: Six-Hump Camel function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2]$  for  $-3 \leq x_1 \leq 3$ ,  $-2 \leq x_2 \leq 2$ ,

$$f(\mathbf{x}) = \left(4 - 2.1x_1^2 + \frac{x_1^4}{3}\right)x_1^2 + x_1x_2 + (-4 + 4x_2^2)x_2^2. \quad (36)$$

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

## 27 Sphere Function

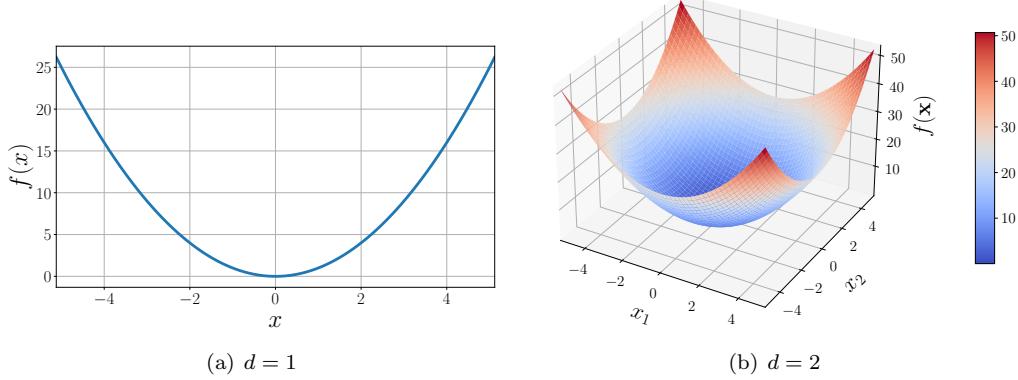


Figure 25: Sphere function.

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

$$f(\mathbf{x}) = \sum_{i=1}^d x_i^2. \quad (37)$$

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

## 28 Three-Hump Camel Function

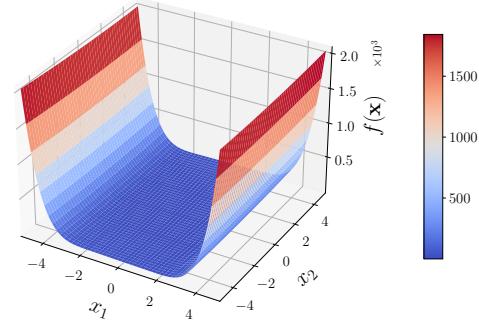


Figure 26: Three-Hump Camel function.

Given a two-dimensional input,  $\mathbf{x} := [x_1, x_2] \in [-5, 5]^2$ ,

$$f(\mathbf{x}) = 2x_1^2 - 1.05x_1^4 + \frac{x_1^6}{6} + x_1x_2 + x_2^2. \quad (38)$$

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

## 29 Zakharov Function

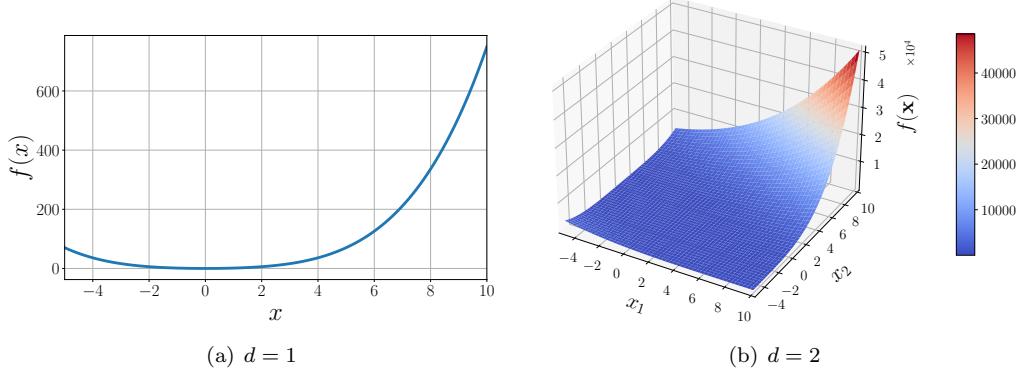


Figure 27: Zakharov function.

Given a  $d$ -dimensional input,  $\mathbf{x} := [x_1, \dots, x_d] \in [-5, 10]^d$ ,

$$f(\mathbf{x}) = \sum_{i=1}^d x_i^2 + \left( \sum_{i=1}^d 0.5ix_i \right)^2 + \left( \sum_{i=1}^d 0.5ix_i \right)^4. \quad (39)$$

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

## References

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