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# **COBYQA Manual**

***Release 1.0.1***

**Tom M. Ragonneau and Zaikun Zhang**

**January 24, 2024**



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## USER GUIDE

This guide explains how to *install* and *use* COBYQA. It also briefly introduce the *framework* of the method. For more details on the Python API of COBYQA, see the *API reference*.

## 1.1 Installation

### 1.1.1 Recommended installation

We highly recommend installing COBYQA via [PyPI](#). This does not need you to download the source code. Install [pip](#) in your system, then execute

```
pip install cobyqa
```

in a command shell (e.g., the terminal in Linux or Mac, or the Command Shell for Windows). If your pip launcher is not `pip`, adapt the command (it may be `pip3` for example). If this command runs successfully, COBYQA is installed. You may verify whether COBYQA is successfully installed by executing

```
python -c "import cobyqa; cobyqa.show_versions()"
```

If your Python launcher is not `python`, adapt the command (it may be `python3` for example).

### 1.1.2 Alternative installation (using source distribution)

Alternatively, although discouraged, COBYQA can be installed from the source code. Download and decompress the [source code package](#). You will obtain a folder containing `pyproject.toml`. In a command shell, change your directory to this folder, and then run

```
pip install .
```

## 1.2 Usage

We provide below basic usage information on how to use COBYQA. For more details on the signature of the *minimize* function, please refer to the *API documentation*.

### 1.2.1 How to use COBYQA

COBYQA provides a `minimize` function. This is the entry point to the solver. It solves unconstrained, bound-constrained, linearly constrained, and nonlinearly constrained optimization problems.

We provide below simple examples on how to use COBYQA.

### 1.2.2 Examples

#### Example of unconstrained optimization

Let us first minimize the Rosenbrock function implemented in `scipy.optimize`, defined as

$$f(x) = \sum_{i=1}^{n-1} 100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2$$

for  $x \in \mathbb{R}^n$ . To solve the problem using COBYQA, run:

```
from cobyqa import minimize
from scipy.optimize import rosen

x0 = [1.3, 0.7, 0.8, 1.9, 1.2]
res = minimize(rosen, x0)
print(res.x)
```

This should display the desired output `[1. 1. 1. 1. 1.]`.

#### Example of linearly constrained optimization

To see how bound and linear constraints are handled using `minimize`, let us solve Example 16.4 of [UU1], defined as

$$\begin{aligned} \min_{x \in \mathbb{R}^2} \quad & (x_1 - 1)^2 + (x_2 - 2.5)^2 \\ \text{s.t.} \quad & -x_1 + 2x_2 \leq 2, \\ & x_1 + 2x_2 \leq 6, \\ & x_1 - 2x_2 \leq 2, \\ & x_1 \geq 0, \\ & x_2 \geq 0. \end{aligned}$$

To solve the problem using COBYQA, run:

```
import numpy as np
from cobyqa import minimize
from scipy.optimize import Bounds, LinearConstraint

def fun(x):
    return (x[0] - 1.0) ** 2.0 + (x[1] - 2.5) ** 2.0

x0 = [2.0, 0.0]
bounds = Bounds([0.0, 0.0], np.inf)
constraints = LinearConstraint([[-1.0, 2.0], [1.0, 2.0], [1.0, -2.0]], -np.inf, [2.0, 6.0, 2.0])
res = minimize(fun, x0, bounds=bounds, constraints=constraints)
print(res.x)
```

This should display the desired output `[1.4 1.7]`.

## Example of nonlinearly constrained optimization

To see how nonlinear constraints are handled, we solve Problem (F) of [UU2], defined as

$$\begin{aligned} \min_{x \in \mathbb{R}^2} \quad & -x_1 - x_2 \\ \text{s.t.} \quad & x_1^2 - x_2 \leq 0, \\ & x_1^2 + x_2^2 \leq 1. \end{aligned}$$

To solve the problem using COBYQA, run:

```
import numpy as np
from cobyqa import minimize
from scipy.optimize import NonlinearConstraint

def fun(x):
    return -x[0] - x[1]

x0 = [1.0, 1.0]
constraints = NonlinearConstraint(lambda x: [
    x[0] ** 2.0 - x[1],
    x[0] ** 2.0 + x[1] ** 2.0,
], -np.inf, [0.0, 1.0])
res = minimize(fun, x0, constraints=constraints)
print(res.x)
```

This should display the desired output `[0.7071 0.7071]`.

## 1.3 Release notes

We provide below release notes for the different versions of COBYQA.

Version	Date	Remarks
1.0.1	2023-01-24	This is a bugfix release. <ol style="list-style-type: none"> <li>1. The documentation has been improved.</li> <li>2. Typos in the examples have been fixed.</li> <li>3. Constants can now be modified by the user.</li> </ol>
1.0.0	2023-01-09	Initial release.

## 1.4 Framework

Work in progress. In the meantime, see Chapter 5 of [UF1].

## 1.5 Subproblem solvers

Work in progress. In the meantime, see Chapter 6 of [US1].

## 1.6 COBYQA license

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## API DOCUMENTATION

### Release

1.0.1

### Date

January 24, 2024

This section references a manual for using COBYQA in Python. Most users will only need to use the [minimize](#) function. An [installation](#) guide and [usage](#) examples are provided in the [user guide](#).

## 2.1 Optimization solver

This module is the entry point of the COBYQA solver. Most users will only need to use the [minimize](#) function.

<a href="#">minimize</a> (fun, x0[, args, bounds, ...])	Minimize a scalar function using the COBYQA method.
<a href="#">show_versions</a> ()	Display useful system and dependencies information.

### 2.1.1 cobyqa.minimize

`cobyqa.minimize`(fun, x0, args=(), bounds=None, constraints=(), callback=None, options=None, \*\*kwargs)

Minimize a scalar function using the COBYQA method.

The Constrained Optimization BY Quadratic Approximations (COBYQA) method is a derivative-free optimization method designed to solve general nonlinear optimization problems. A complete description of COBYQA is given in [3].

#### Parameters

##### fun

[[callable, None]] Objective function to be minimized.

`fun(x, *args) -> float`

where `x` is an array with shape `(n,)` and `args` is a tuple. If `fun` is `None`, the objective function is assumed to be the zero function, resulting in a feasibility problem.

##### x0

[array\_like, shape (n,)] Initial guess.

##### args

[tuple, optional] Extra arguments passed to the objective function.

##### bounds

[[`scipy.optimize.Bounds`, array\_like, shape (n, 2)], optional] Bound constraints of the problem. It can be one of the cases below.

1. An instance of `scipy.optimize.Bounds`. For the time being, the argument `keep_feasible` is disregarded.
2. An array with shape  $(n, 2)$ . The bound constraints for  $x[i]$  are `bounds[i][0] <= x[i] <= bounds[i][1]`. Set `bounds[i][0]` to  $-\infty$  if there is no lower bound, and set `bounds[i][1]` to  $\infty$  if there is no upper bound.

The COBYQA method always respect the bound constraints.

**constraints**

[`scipy.optimize.LinearConstraint`, `scipy.optimize.NonlinearConstraint`, dict, list], optional] General constraints of the problem. It can be one of the cases below.

1. An instance of `scipy.optimize.LinearConstraint`. The argument `keep_feasible` is disregarded.
2. An instance of `scipy.optimize.NonlinearConstraint`. The arguments `jac`, `hess`, `keep_feasible`, `finite_diff_rel_step`, and `finite_diff_jac_sparsity` are disregarded.
3. A dictionary with fields:

**type**

[['eq', 'ineq']] Whether the constraint is an equality `fun(x, *args) == 0` or an inequality `fun(x, *args) >= 0`.

**fun**

[callable] Constraint function.

**args**

[tuple, optional] Extra arguments passed to the constraint function.

4. A list, each of whose elements are described in the cases above.

**callback**

[callable, optional] A callback executed at each objective function evaluation. The method terminates if a `StopIteration` exception is raised by the callback function. Its signature can be one of the following:

`callback(intermediate_result)`

where `intermediate_result` is a keyword parameter that contains an instance of `scipy.optimize.OptimizeResult`, with attributes `x` and `fun`, being the point at which the objective function is evaluated and the value of the objective function, respectively. The name of the parameter must be `intermediate_result` for the callback to be passed an instance of `scipy.optimize.OptimizeResult`.

Alternatively, the callback function can have the signature:

`callback(xk)`

where `xk` is the point at which the objective function is evaluated. Introspection is used to determine which of the signatures to invoke.

**options**

[dict, optional] Options passed to the solver. Accepted keys are:

**disp**

[bool, optional] Whether to print information about the optimization procedure.

**maxfev**

[int, optional] Maximum number of function evaluations.

**maxiter**

[int, optional] Maximum number of iterations.

**target**

[float, optional] Target on the objective function value. The optimization procedure is terminated when the objective function value of a feasible point is less than or equal to this target.

**feasibility\_tol**

[float, optional] Tolerance on the constraint violation. If the maximum constraint violation at a point is less than or equal to this tolerance, the point is considered feasible.

**radius\_init**

[float, optional] Initial trust-region radius. Typically, this value should be in the order of one tenth of the greatest expected change to  $x_0$ .

**radius\_final**

[float, optional] Final trust-region radius. It should indicate the accuracy required in the final values of the variables.

**nb\_points**

[int, optional] Number of interpolation points used to build the quadratic models of the objective and constraint functions.

**scale**

[bool, optional] Whether to scale the variables according to the bounds.

**filter\_size**

[int, optional] Maximum number of points in the filter. The filter is used to select the best point returned by the optimization procedure.

**store\_history**

[bool, optional] Whether to store the history of the function evaluations.

**history\_size**

[int, optional] Maximum number of function evaluations to store in the history.

**debug**

[bool, optional] Whether to perform additional checks during the optimization procedure. This option should be used only for debugging purposes and is highly discouraged to general users.

Other constants (from the keyword arguments) are described below. They are not intended to be changed by general users. They should only be changed by users with a deep understanding of the algorithm, who want to experiment with different settings.

**Returns****scipy.optimize.OptimizeResult**

Result of the optimization procedure, with the following fields:

**message**

[str] Description of the cause of the termination.

**success**

[bool] Whether the optimization procedure terminated successfully.

**status**

[int] Termination status of the optimization procedure.

**x**

[`numpy.ndarray`, shape (n,)] Solution point.

**fun**

[float] Objective function value at the solution point.

**maxcv**

[float] Maximum constraint violation at the solution point.

**nfev**

[int] Number of function evaluations.

**nit**

[int] Number of iterations.

If `store_history` is True, the result also has the following fields:

**fun\_history**

[[numpy.ndarray](#), shape (nfev,)] History of the objective function values.

**maxcv\_history**

[[numpy.ndarray](#), shape (nfev,)] History of the maximum constraint violations.

A description of the termination statuses is given below.

Exit status	Description
0	The lower bound for the trust-region radius has been reached.
1	The target objective function value has been reached.
2	All variables are fixed by the bound constraints.
3	The callback requested to stop the optimization procedure.
4	The feasibility problem received has been solved successfully.
5	The maximum number of function evaluations has been exceeded.
6	The maximum number of iterations has been exceeded.
-1	The bound constraints are infeasible.
-2	A linear algebra error occurred.

**Other Parameters****decrease\_radius\_factor**

[float, optional] Factor by which the trust-region radius is reduced when the reduction ratio is low or negative.

**increase\_radius\_factor**

[float, optional] Factor by which the trust-region radius is increased when the reduction ratio is large.

**increase\_radius\_threshold**

[float, optional] Threshold that controls the increase of the trust-region radius when the reduction ratio is large.

**decrease\_radius\_threshold**

[float, optional] Threshold used to determine whether the trust-region radius should be reduced to the resolution.

**decrease\_resolution\_factor**

[float, optional] Factor by which the resolution is reduced when the current value is far from its final value.

**large\_resolution\_threshold**

[float, optional] Threshold used to determine whether the resolution is far from its final value.

**moderate\_resolution\_threshold**

[float, optional] Threshold used to determine whether the resolution is close to its final value.

**low\_ratio**

[float, optional] Threshold used to determine whether the reduction ratio is low.

**high\_ratio**

[float, optional] Threshold used to determine whether the reduction ratio is high.

**very\_low\_ratio**

[float, optional] Threshold used to determine whether the reduction ratio is very low. This is used to determine whether the models should be reset.

**penalty\_increase\_threshold**

[float, optional] Threshold used to determine whether the penalty parameter should be increased.

**penalty\_increase\_factor**

[float, optional] Factor by which the penalty parameter is increased.

**short\_step\_threshold**

[float, optional] Factor used to determine whether the trial step is too short.

**low\_radius\_factor**

[float, optional] Factor used to determine which interpolation point should be removed from the interpolation set at each iteration.

**standard\_byrd\_omojokun**

[bool, optional] Whether to use the standard Byrd-Omojokun composite-step approach to solve the subproblem or the modified one proposed in [3].

**byrd\_omojokun\_factor**

[float, optional] Factor by which the trust-region radius is reduced for the computations of the normal step in the Byrd-Omojokun composite-step approach.

**threshold\_ratio\_constraints**

[float, optional] Threshold used to determine which constraints should be taken into account when decreasing the penalty parameter.

**large\_shift\_factor**

[float, optional] Factor used to determine whether the point around which the quadratic models are built should be updated.

**large\_gradient\_factor**

[float, optional] Factor used to determine whether the models should be reset.

**resolution\_factor**

[float, optional] Factor by which the resolution is decreased.

**improve\_tcg**

[bool, optional] Whether to improve the steps computed by the truncated conjugate gradient method when the trust-region boundary is reached.

## References

[1], [2], [3]

## Examples

To demonstrate how to use `minimize`, we first minimize the Rosenbrock function implemented in `scipy.optimize` in an unconstrained setting.

```
>>> from cobyqa import minimize
>>> from scipy.optimize import rosen
```

To solve the problem using COBYQA, run:

```
>>> x0 = [1.3, 0.7, 0.8, 1.9, 1.2]
>>> res = minimize(rosen, x0)
>>> res.x
array([1., 1., 1., 1., 1.])
```

To see how bound and constraints are handled using *minimize*, we solve Example 16.4 of [1], defined as

$$\begin{aligned} \min_{x \in \mathbb{R}^2} \quad & (x_1 - 1)^2 + (x_2 - 2.5)^2 \\ \text{s.t.} \quad & -x_1 + 2x_2 \leq 2, \\ & x_1 + 2x_2 \leq 6, \\ & x_1 - 2x_2 \leq 2, \\ & x_1 \geq 0, \\ & x_2 \geq 0. \end{aligned}$$

```
>>> import numpy as np
>>> from scipy.optimize import Bounds, LinearConstraint
```

Its objective function can be implemented as:

```
>>> def fun(x):
...     return (x[0] - 1.0) ** 2.0 + (x[1] - 2.5) ** 2.0
```

This problem can be solved using *minimize* as:

```
>>> x0 = [2.0, 0.0]
>>> bounds = Bounds([0.0, 0.0], np.inf)
>>> constraints = LinearConstraint([[-1.0, 2.0], [1.0, 2.0], [1.0, -2.0]], -np.
    ↳ inf, [2.0, 6.0, 2.0])
>>> res = minimize(fun, x0, bounds=bounds, constraints=constraints)
>>> res.x
array([1.4, 1.7])
```

Finally, to see how nonlinear constraints are handled, we solve Problem (F) of [2], defined as

$$\begin{aligned} \min_{x \in \mathbb{R}^2} \quad & -x_1 - x_2 \\ \text{s.t.} \quad & x_1^2 - x_2 \leq 0, \\ & x_1^2 + x_2^2 \leq 1. \end{aligned}$$

```
>>> from scipy.optimize import NonlinearConstraint
```

Its objective and constraint functions can be implemented as:

```
>>> def fun(x):
...     return -x[0] - x[1]
>>>
>>> def cub(x):
...     return [x[0] ** 2.0 - x[1], x[0] ** 2.0 + x[1] ** 2.0]
```

This problem can be solved using *minimize* as:

```
>>> x0 = [1.0, 1.0]
>>> constraints = NonlinearConstraint(cub, -np.inf, [0.0, 1.0])
>>> res = minimize(fun, x0, constraints=constraints)
>>> res.x
array([0.707, 0.707])
```

### 2.1.2 cobyqa.show\_versions

`cobyqa.show_versions()`

Display useful system and dependencies information.

When reporting issues, please include this information.

The implementation of COBYQA is documented in the *developer guide*. It is completely unnecessary to read the *developer guide* to use COBYQA, and it only provides insights for people interested in the development of derivative-free optimization methods such as COBYQA.





## DEVELOPER GUIDE

This guide does not cover the usage of COBYQA. If you want to use COBYQA in your project, please refer to the [API documentation](#). This guide is intended for developers who want to contribute to the COBYQA solver and to derivative-free optimization solvers in general.

The `cobyqa` module has four submodules, detailed below. Users do not need to import these submodules when using COBYQA.

The `problem` module implements classes for representing optimization problems.

### 3.1 Optimization problem

This module implements classes for representing optimization problems for COBYQA.

<code>ObjectiveFunction</code> (fun, verbose, debug, *args)	Real-valued objective function.
<code>BoundConstraints</code> (bounds)	Bound constraints $x_l \leq x \leq x_u$ .
<code>LinearConstraints</code> (constraints, n, debug)	Linear constraints $a_{ub} @ x \leq b_{ub}$ and $a_{eq} @ x == b_{eq}$ .
<code>NonlinearConstraints</code> (constraints, verbose, debug)	Nonlinear constraints $c_{ub}(x) \leq 0$ and $c_{eq}(x) == b_{eq}$ .
<code>Problem</code> (obj, x0, bounds, linear, nonlinear, ...)	Optimization problem.

#### 3.1.1 `cobyqa.problem.ObjectiveFunction`

**class** `cobyqa.problem.ObjectiveFunction`(fun, verbose, debug, \*args)

Real-valued objective function.

##### Attributes

###### **n\_eval**

Number of function evaluations.

###### **name**

Name of the objective function.

## Methods

<code>__call__(x)</code>	Evaluate the objective function.
--------------------------	----------------------------------

### `cobyqa.problem.ObjectiveFunction.__call__`

`ObjectiveFunction.__call__(x)`

Evaluate the objective function.

#### Parameters

**x**  
[array\_like, shape (n,)] Point at which the objective function is evaluated.

#### Returns

**float**  
Function value at  $x$ .

## 3.1.2 `cobyqa.problem.BoundsConstraints`

**class** `cobyqa.problem.BoundsConstraints(bounds)`

Bound constraints  $x_l \leq x \leq x_u$ .

#### Attributes

**is\_feasible**  
Whether the bound constraints are feasible.

**m**  
Number of bound constraints.

**xl**  
Lower bound.

**xu**  
Upper bound.

## Methods

<code>maxcv(x)</code>	Evaluate the maximum constraint violation.
<code>project(x)</code>	Project a point onto the feasible set.

### `cobyqa.problem.BoundsConstraints.maxcv`

`BoundsConstraints.maxcv(x)`

Evaluate the maximum constraint violation.

#### Parameters

**x**  
[array\_like, shape (n,)] Point at which the maximum constraint violation is evaluated.

#### Returns

**float**  
Maximum constraint violation at  $x$ .

**cobyqa.problem.BoundsConstraints.project****BoundsConstraints.project**(*x*)

Project a point onto the feasible set.

**Parameters****x**  
[array\_like, shape (n,)] Point to be projected.**Returns****numpy.ndarray, shape (n,)**  
Projection of *x* onto the feasible set.**3.1.3 cobyqa.problem.LinearConstraints****class** cobyqa.problem.**LinearConstraints**(*constraints, n, debug*)Linear constraints  $a\_ub @ x \leq b\_ub$  and  $a\_eq @ x == b\_eq$ .**Attributes****a\_eq**  
Left-hand side matrix of the linear equality constraints.**a\_ub**  
Left-hand side matrix of the linear inequality constraints.**b\_eq**  
Right-hand side vector of the linear equality constraints.**b\_ub**  
Right-hand side vector of the linear inequality constraints.**m\_eq**  
Number of linear equality constraints.**m\_ub**  
Number of linear inequality constraints.**Methods**

<b>maxcv</b> ( <i>x</i> )	Evaluate the maximum constraint violation.
---------------------------	--

**cobyqa.problem.LinearConstraints.maxcv****LinearConstraints.maxcv**(*x*)

Evaluate the maximum constraint violation.

**Parameters****x**  
[array\_like, shape (n,)] Point at which the maximum constraint violation is evaluated.**Returns****float**  
Maximum constraint violation at *x*.

### 3.1.4 cobyqa.problem.NonlinearConstraints

**class** cobyqa.problem.**NonlinearConstraints**(*constraints, verbose, debug*)

Nonlinear constraints  $c_{ub}(x) \leq 0$  and  $c_{eq}(x) == b_{eq}$ .

#### Attributes

- m\_eq**  
Number of nonlinear equality constraints.
- m\_ub**  
Number of nonlinear inequality constraints.
- n\_eval**  
Number of function evaluations.

#### Methods

<code>__call__(x)</code>	Evaluate the constraints.
<code>maxcv(x[, cub_val, ceq_val])</code>	Evaluate the maximum constraint violation.

#### cobyqa.problem.NonlinearConstraints.\_\_call\_\_

**NonlinearConstraints.\_\_call\_\_(x)**

Evaluate the constraints.

#### Parameters

- x**  
[array\_like, shape (n,)] Point at which the constraints are evaluated.

#### Returns

- numpy.ndarray, shape (m\_nonlinear\_ub,)**  
Nonlinear inequality constraint function values.
- numpy.ndarray, shape (m\_nonlinear\_eq,)**  
Nonlinear equality constraint function values.

#### cobyqa.problem.NonlinearConstraints.maxcv

**NonlinearConstraints.maxcv(x, cub\_val=None, ceq\_val=None)**

Evaluate the maximum constraint violation.

#### Parameters

- x**  
[array\_like, shape (n,)] Point at which the maximum constraint violation is evaluated.
- cub\_val**  
[array\_like, shape (m\_nonlinear\_ub,), optional] Values of the nonlinear inequality constraints. If not provided, the nonlinear inequality constraints are evaluated at  $x$ .
- ceq\_val**  
[array\_like, shape (m\_nonlinear\_eq,), optional] Values of the nonlinear equality constraints. If not provided, the nonlinear equality constraints are evaluated at  $x$ .

#### Returns

**float**

Maximum constraint violation at  $x$ .

### 3.1.5 cobyqa.problem.Problem

**class** cobyqa.problem.**Problem**(*obj, x0, bounds, linear, nonlinear, callback, feasibility\_tol, scale, store\_history, history\_size, filter\_size, debug*)

Optimization problem.

#### Attributes

**bounds**

Bound constraints.

**fun\_history**

History of objective function evaluations.

**fun\_name**

Name of the objective function.

**is\_feasibility**

Whether the problem is a feasibility problem.

**linear**

Linear constraints.

**m\_bounds**

Number of bound constraints.

**m\_linear\_eq**

Number of linear equality constraints.

**m\_linear\_ub**

Number of linear inequality constraints.

**m\_nonlinear\_eq**

Number of nonlinear equality constraints.

**m\_nonlinear\_ub**

Number of nonlinear inequality constraints.

**maxcv\_history**

History of maximum constraint violations.

**n**

Number of variables.

**n\_eval**

Number of function evaluations.

**n\_orig**

Number of variables in the original problem (with fixed variables).

**type**

Type of the problem.

**x0**

Initial guess.

## Methods

<code>__call__(x)</code>	Evaluate the objective and nonlinear constraint functions.
<code>best_eval(penalty)</code>	Return the best point in the filter and the corresponding objective and nonlinear constraint function evaluations.
<code>build_x(x)</code>	Build the full vector of variables from the reduced vector.
<code>maxcv(x[, cub_val, ceq_val])</code>	Evaluate the maximum constraint violation.

### `cobyqa.problem.Problem.__call__`

`Problem.__call__(x)`

Evaluate the objective and nonlinear constraint functions.

#### Parameters

**x**  
[array\_like, shape (n,)] Point at which the functions are evaluated.

#### Returns

**float**  
Objective function value.

**numpy.ndarray, shape (m\_nonlinear\_ub,)**  
Nonlinear inequality constraint function values.

**numpy.ndarray, shape (m\_nonlinear\_eq,)**  
Nonlinear equality constraint function values.

#### Raises

**`cobyqa.utils.CallbackSuccess`**  
If the callback function raises a `StopIteration`.

### `cobyqa.problem.Problem.best_eval`

`Problem.best_eval(penalty)`

Return the best point in the filter and the corresponding objective and nonlinear constraint function evaluations.

#### Parameters

**penalty**  
[float] Penalty parameter

#### Returns

**numpy.ndarray, shape (n,)**  
Best point.

**float**  
Corresponding objective function value.

**float**  
Corresponding maximum constraint violation.

**cobyqa.problem.Problem.build\_x****Problem.build\_x**(*x*)

Build the full vector of variables from the reduced vector.

**Parameters****x**

[array\_like, shape (n,)] Reduced vector of variables.

**Returns****numpy.ndarray, shape (n\_orig,)**

Full vector of variables.

**cobyqa.problem.Problem.maxcv****Problem.maxcv**(*x*, *cub\_val=None*, *ceq\_val=None*)

Evaluate the maximum constraint violation.

**Parameters****x**

[array\_like, shape (n,)] Point at which the maximum constraint violation is evaluated.

**cub\_val**[array\_like, shape (m\_nonlinear\_ub,), optional] Values of the nonlinear inequality constraints. If not provided, the nonlinear inequality constraints are evaluated at *x*.**ceq\_val**[array\_like, shape (m\_nonlinear\_eq,), optional] Values of the nonlinear equality constraints. If not provided, the nonlinear equality constraints are evaluated at *x*.**Returns****float**Maximum constraint violation at *x*.The *models* module implements the models used by COBYQA.

## 3.2 Quadratic models

This module implements classes for representing the quadratic models used by COBYQA.

<i>Interpolation</i> (pb, options)	Interpolation set.
<i>Quadratic</i> (interpolation, values, debug)	Quadratic model.
<i>Models</i> (pb, options)	Models for a nonlinear optimization problem.

### 3.2.1 cobyqa.models.Interpolation

**class** cobyqa.models.**Interpolation**(*pb, options*)

Interpolation set.

This class stores a base point around which the models are expanded and the interpolation points. The coordinates of the interpolation points are relative to the base point.

#### Attributes

- n**  
Number of variables.
- npt**  
Number of interpolation points.
- x\_base**  
Base point around which the models are expanded.
- xpt**  
Interpolation points.

#### Methods

<code>point(k)</code>	Get the $k$ -th interpolation point.
-----------------------	--------------------------------------

#### cobyqa.models.Interpolation.point

Interpolation.**point**( $k$ )

Get the  $k$ -th interpolation point.

The return point is relative to the origin.

#### Parameters

- k**  
[int] Index of the interpolation point.

#### Returns

**numpy.ndarray, shape (n,)**  
 $k$ -th interpolation point.

### 3.2.2 cobyqa.models.Quadratic

**class** cobyqa.models.**Quadratic**(*interpolation, values, debug*)

Quadratic model.

This class stores the Hessian matrix of the quadratic model using the implicit/explicit representation designed by Powell for NEWUOA [1].



## References

[1]

### Attributes

- n**  
Number of variables.
- npt**  
Number of interpolation points used to define the quadratic model.

### Methods

<code>__call__(x, interpolation)</code>	Evaluate the quadratic model at a given point.
<code>build_system(xpt)</code>	Build the left-hand side matrix of the interpolation system.
<code>curv(v, interpolation)</code>	Evaluate the curvature of the quadratic model along a given direction.
<code>grad(x, interpolation)</code>	Evaluate the gradient of the quadratic model at a given point.
<code>hess(interpolation)</code>	Evaluate the Hessian matrix of the quadratic model.
<code>hess_prod(v, interpolation)</code>	Evaluate the right product of the Hessian matrix of the quadratic model with a given vector.
<code>shift_x_base(interpolation, new_x_base)</code>	Shift the point around which the quadratic model is defined.
<code>solve_system(interpolation, rhs)</code>	Solve the interpolation system.
<code>update(interpolation, k_new, dir_old, ...)</code>	Update the quadratic model.

### `cobyqa.models.Quadratic.__call__`

`Quadratic.__call__(x, interpolation)`

Evaluate the quadratic model at a given point.

#### Parameters

- x**  
[`numpy.ndarray`, shape (n,)] Point at which the quadratic model is evaluated.
- interpolation**  
[`cobyqa.models.Interpolation`] Interpolation set.

#### Returns

- float**  
Value of the quadratic model at  $x$ .

### `cobyqa.models.Quadratic.build_system`

`static Quadratic.build_system(xpt)`

Build the left-hand side matrix of the interpolation system.

#### Parameters

- xpt**  
[`numpy.ndarray`, shape (n, npt)] Interpolation points.

#### Returns

`numpy.ndarray`, shape  $(npt + n + 1, npt + n + 1)$   
Left-hand side matrix of the interpolation system.

### `cobyqa.models.Quadratic.curv`

`Quadratic.curv(v, interpolation)`

Evaluate the curvature of the quadratic model along a given direction.

#### Parameters

**v**  
`[numpy.ndarray, shape (n,)]` Direction along which the curvature of the quadratic model is evaluated.

#### **interpolation**

`[cobyqa.models.Interpolation]` Interpolation set.

#### Returns

**float**  
Curvature of the quadratic model along *v*.

### `cobyqa.models.Quadratic.grad`

`Quadratic.grad(x, interpolation)`

Evaluate the gradient of the quadratic model at a given point.

#### Parameters

**x**  
`[numpy.ndarray, shape (n,)]` Point at which the gradient of the quadratic model is evaluated.

#### **interpolation**

`[cobyqa.models.Interpolation]` Interpolation set.

#### Returns

`numpy.ndarray`, shape  $(n,)$   
Gradient of the quadratic model at *x*.

### `cobyqa.models.Quadratic.hess`

`Quadratic.hess(interpolation)`

Evaluate the Hessian matrix of the quadratic model.

#### Parameters

#### **interpolation**

`[cobyqa.models.Interpolation]` Interpolation set.

#### Returns

`numpy.ndarray`, shape  $(n, n)$   
Hessian matrix of the quadratic model.

**cobyqa.models.Quadratic.hess\_prod****Quadratic.hess\_prod**(*v*, *interpolation*)

Evaluate the right product of the Hessian matrix of the quadratic model with a given vector.

**Parameters****v**`[numpy.ndarray, shape (n,)]` Vector with which the Hessian matrix of the quadratic model is multiplied from the right.**interpolation**`[cobyqa.models.Interpolation]` Interpolation set.**Returns**`numpy.ndarray, shape (n,)`Right product of the Hessian matrix of the quadratic model with *v*.**cobyqa.models.Quadratic.shift\_x\_base****Quadratic.shift\_x\_base**(*interpolation*, *new\_x\_base*)

Shift the point around which the quadratic model is defined.

**Parameters****interpolation**`[cobyqa.models.Interpolation]` Previous interpolation set.**new\_x\_base**`[numpy.ndarray, shape (n,)]` Point that will replace `interpolation.x_base`.**cobyqa.models.Quadratic.solve\_system****static Quadratic.solve\_system**(*interpolation*, *rhs*)

Solve the interpolation system.

**Parameters****interpolation**`[cobyqa.models.Interpolation]` Interpolation set.**rhs**`[numpy.ndarray, shape (npt + n + 1,)]` Right-hand side vector of the interpolation system.**Returns**`numpy.ndarray, shape (npt + n + 1,)`

Solution of the interpolation system.

**bool**

Whether the interpolation system is ill-conditioned.

**Raises**`numpy.linalg.LinAlgError`

If the interpolation system is ill-defined.

### cobyqa.models.Quadratic.update

`Quadratic.update(interpolation, k_new, dir_old, values_diff)`

Update the quadratic model.

This method applies the derivative-free symmetric Broyden update to the quadratic model. The *knew*-th interpolation point must be updated before calling this method.

#### Parameters

##### **interpolation**

[[cobyqa.models.Interpolation](#)] Updated interpolation set.

##### **k\_new**

[int] Index of the updated interpolation point.

##### **dir\_old**

[[numpy.ndarray](#), shape (n,)] Value of `interpolation.xpt[:, k_new]` before the update.

##### **values\_diff**

[[numpy.ndarray](#), shape (npt,)] Differences between the values of the interpolated nonlinear function and the previous quadratic model at the updated interpolation points.

#### Raises

##### **[numpy.linalg.LinAlgError](#)**

If the interpolation system is ill-defined.

## 3.2.3 `cobyqa.models.Models`

**class** `cobyqa.models.Models(pb, options)`

Models for a nonlinear optimization problem.

#### Attributes

##### **ceq\_val**

Values of the nonlinear equality constraint functions at the interpolation points.

##### **cub\_val**

Values of the nonlinear inequality constraint functions at the interpolation points.

##### **fun\_val**

Values of the objective function at the interpolation points.

##### **interpolation**

Interpolation set.

##### **m\_nonlinear\_eq**

Number of nonlinear equality constraints.

##### **m\_nonlinear\_ub**

Number of nonlinear inequality constraints.

##### **n**

Dimension of the problem.

##### **npt**

Number of interpolation points.

## Methods

<i>ceq</i> (x[, mask])	Evaluate the quadratic models of the nonlinear equality functions at a given point.
<i>ceq_curv</i> (v[, mask])	Evaluate the curvature of the quadratic models of the nonlinear equality functions along a given direction.
<i>ceq_grad</i> (x[, mask])	Evaluate the gradients of the quadratic models of the nonlinear equality functions at a given point.
<i>ceq_hess</i> ([mask])	Evaluate the Hessian matrices of the quadratic models of the nonlinear equality functions.
<i>ceq_hess_prod</i> (v[, mask])	Evaluate the right product of the Hessian matrices of the quadratic models of the nonlinear equality functions with a given vector.
<i>cub</i> (x[, mask])	Evaluate the quadratic models of the nonlinear inequality functions at a given point.
<i>cub_curv</i> (v[, mask])	Evaluate the curvature of the quadratic models of the nonlinear inequality functions along a given direction.
<i>cub_grad</i> (x[, mask])	Evaluate the gradients of the quadratic models of the nonlinear inequality functions at a given point.
<i>cub_hess</i> ([mask])	Evaluate the Hessian matrices of the quadratic models of the nonlinear inequality functions.
<i>cub_hess_prod</i> (v[, mask])	Evaluate the right product of the Hessian matrices of the quadratic models of the nonlinear inequality functions with a given vector.
<i>determinants</i> (x_new[, k_new])	Compute the normalized determinants of the new interpolation systems.
<i>fun</i> (x)	Evaluate the quadratic model of the objective function at a given point.
<i>fun_alt_grad</i> (x)	Evaluate the gradient of the alternative quadratic model of the objective function at a given point.
<i>fun_curv</i> (v)	Evaluate the curvature of the quadratic model of the objective function along a given direction.
<i>fun_grad</i> (x)	Evaluate the gradient of the quadratic model of the objective function at a given point.
<i>fun_hess</i> ()	Evaluate the Hessian matrix of the quadratic model of the objective function.
<i>fun_hess_prod</i> (v)	Evaluate the right product of the Hessian matrix of the quadratic model of the objective function with a given vector.
<i>reset_models</i> ()	Set the quadratic models of the objective function, nonlinear inequality constraints, and nonlinear equality constraints to the alternative quadratic models.
<i>shift_x_base</i> (new_x_base, options)	Shift the base point without changing the interpolation set.
<i>update_interpolation</i> (k_new, x_new, fun_val, ...)	Update the interpolation set.

**cobyqa.models.Models.ceq****Models.ceq**(*x*, *mask=None*)

Evaluate the quadratic models of the nonlinear equality functions at a given point.

**Parameters****x**`[numpy.ndarray, shape (n,)]` Point at which to evaluate the quadratic models of the nonlinear equality functions.**mask**`[numpy.ndarray, shape (m_nonlinear_eq,), optional]` Mask of the quadratic models to consider.**Returns**`numpy.ndarray`

Values of the quadratic model of the nonlinear equality functions.

**cobyqa.models.Models.ceq\_curv****Models.ceq\_curv**(*v*, *mask=None*)

Evaluate the curvature of the quadratic models of the nonlinear equality functions along a given direction.

**Parameters****v**`[numpy.ndarray, shape (n,)]` Direction along which the curvature of the quadratic models of the nonlinear equality functions is evaluated.**mask**`[numpy.ndarray, shape (m_nonlinear_eq,), optional]` Mask of the quadratic models to consider.**Returns**`numpy.ndarray`Curvature of the quadratic models of the nonlinear equality functions along *v*.**cobyqa.models.Models.ceq\_grad****Models.ceq\_grad**(*x*, *mask=None*)

Evaluate the gradients of the quadratic models of the nonlinear equality functions at a given point.

**Parameters****x**`[numpy.ndarray, shape (n,)]` Point at which to evaluate the gradients of the quadratic models of the nonlinear equality functions.**mask**`[numpy.ndarray, shape (m_nonlinear_eq,), optional]` Mask of the quadratic models to consider.**Returns**`numpy.ndarray`

Gradients of the quadratic model of the nonlinear equality functions.

**cobyqa.models.Models.ceq\_hess****Models.ceq\_hess**(*mask=None*)

Evaluate the Hessian matrices of the quadratic models of the nonlinear equality functions.

**Parameters****mask**[[numpy.ndarray](#), shape (m\_nonlinear\_eq,)] optional] Mask of the quadratic models to consider.**Returns**[numpy.ndarray](#)

Hessian matrices of the quadratic models of the nonlinear equality functions.

**cobyqa.models.Models.ceq\_hess\_prod****Models.ceq\_hess\_prod**(*v, mask=None*)

Evaluate the right product of the Hessian matrices of the quadratic models of the nonlinear equality functions with a given vector.

**Parameters****v**[[numpy.ndarray](#), shape (n,)] Vector with which the Hessian matrices of the quadratic models of the nonlinear equality functions are multiplied from the right.**mask**[[numpy.ndarray](#), shape (m\_nonlinear\_eq,)] optional] Mask of the quadratic models to consider.**Returns**[numpy.ndarray](#)Right products of the Hessian matrices of the quadratic models of the nonlinear equality functions with *v*.**cobyqa.models.Models.cub****Models.cub**(*x, mask=None*)

Evaluate the quadratic models of the nonlinear inequality functions at a given point.

**Parameters****x**[[numpy.ndarray](#), shape (n,)] Point at which to evaluate the quadratic models of the nonlinear inequality functions.**mask**[[numpy.ndarray](#), shape (m\_nonlinear\_ub,)] optional] Mask of the quadratic models to consider.**Returns**[numpy.ndarray](#)

Values of the quadratic model of the nonlinear inequality functions.

**cobyqa.models.Models.cub\_curv****Models.cub\_curv**(*v*, *mask=None*)

Evaluate the curvature of the quadratic models of the nonlinear inequality functions along a given direction.

**Parameters****v**

[[numpy.ndarray](#), shape (n,)] Direction along which the curvature of the quadratic models of the nonlinear inequality functions is evaluated.

**mask**

[[numpy.ndarray](#), shape (m\_nonlinear\_ub,), optional] Mask of the quadratic models to consider.

**Returns**[numpy.ndarray](#)

Curvature of the quadratic models of the nonlinear inequality functions along *v*.

**cobyqa.models.Models.cub\_grad****Models.cub\_grad**(*x*, *mask=None*)

Evaluate the gradients of the quadratic models of the nonlinear inequality functions at a given point.

**Parameters****x**

[[numpy.ndarray](#), shape (n,)] Point at which to evaluate the gradients of the quadratic models of the nonlinear inequality functions.

**mask**

[[numpy.ndarray](#), shape (m\_nonlinear\_eq,), optional] Mask of the quadratic models to consider.

**Returns**[numpy.ndarray](#)

Gradients of the quadratic model of the nonlinear inequality functions.

**cobyqa.models.Models.cub\_hess****Models.cub\_hess**(*mask=None*)

Evaluate the Hessian matrices of the quadratic models of the nonlinear inequality functions.

**Parameters****mask**

[[numpy.ndarray](#), shape (m\_nonlinear\_ub,), optional] Mask of the quadratic models to consider.

**Returns**[numpy.ndarray](#)

Hessian matrices of the quadratic models of the nonlinear inequality functions.



**cobyqa.models.Models.cub\_hess\_prod****Models.cub\_hess\_prod**(*v*, *mask=None*)

Evaluate the right product of the Hessian matrices of the quadratic models of the nonlinear inequality functions with a given vector.

**Parameters****v**

[[numpy.ndarray](#), shape (n,)] Vector with which the Hessian matrices of the quadratic models of the nonlinear inequality functions are multiplied from the right.

**mask**

[[numpy.ndarray](#), shape (m\_nonlinear\_ub,), optional] Mask of the quadratic models to consider.

**Returns**[numpy.ndarray](#)

Right products of the Hessian matrices of the quadratic models of the nonlinear inequality functions with *v*.

**cobyqa.models.Models.determinants****Models.determinants**(*x\_new*, *k\_new=None*)

Compute the normalized determinants of the new interpolation systems.

**Parameters****x\_new**

[[numpy.ndarray](#), shape (n,)] New interpolation point. Its value is interpreted as relative to the origin, not the base point.

**k\_new**

[int, optional] Index of the updated interpolation point. If *k\_new* is not specified, all the possible determinants are computed.

**Returns**{float, [numpy.ndarray](#), shape (npt,)}

Determinant(s) of the new interpolation system.

**Raises**[numpy.linalg.LinAlgError](#)

If the interpolation system is ill-defined.

**Notes**

The determinants are normalized by the determinant of the current interpolation system. For stability reasons, the calculations are done using the formula (2.12) in [1].

## References

[1]

### `cobyqa.models.Models.fun`

`Models.fun(x)`

Evaluate the quadratic model of the objective function at a given point.

#### Parameters

**x**

[`numpy.ndarray`, shape (n,)] Point at which to evaluate the quadratic model of the objective function.

#### Returns

**float**

Value of the quadratic model of the objective function at  $x$ .

### `cobyqa.models.Models.fun_alt_grad`

`Models.fun_alt_grad(x)`

Evaluate the gradient of the alternative quadratic model of the objective function at a given point.

#### Parameters

**x**

[`numpy.ndarray`, shape (n,)] Point at which to evaluate the gradient of the alternative quadratic model of the objective function.

#### Returns

`numpy.ndarray`, shape (n,)

Gradient of the alternative quadratic model of the objective function at  $x$ .

#### Raises

`numpy.linalg.LinAlgError`

If the interpolation system is ill-defined.

### `cobyqa.models.Models.fun_curv`

`Models.fun_curv(v)`

Evaluate the curvature of the quadratic model of the objective function along a given direction.

#### Parameters

**v**

[`numpy.ndarray`, shape (n,)] Direction along which the curvature of the quadratic model of the objective function is evaluated.

#### Returns

**float**

Curvature of the quadratic model of the objective function along  $v$ .

**cobyqa.models.Models.fun\_grad****Models.fun\_grad( $x$ )**

Evaluate the gradient of the quadratic model of the objective function at a given point.

**Parameters**

**$x$**   
[`numpy.ndarray`, shape (n,)] Point at which to evaluate the gradient of the quadratic model of the objective function.

**Returns**

`numpy.ndarray`, shape (n,)  
Gradient of the quadratic model of the objective function at  $x$ .

**cobyqa.models.Models.fun\_hess****Models.fun\_hess()**

Evaluate the Hessian matrix of the quadratic model of the objective function.

**Returns**

`numpy.ndarray`, shape (n, n)  
Hessian matrix of the quadratic model of the objective function.

**cobyqa.models.Models.fun\_hess\_prod****Models.fun\_hess\_prod( $v$ )**

Evaluate the right product of the Hessian matrix of the quadratic model of the objective function with a given vector.

**Parameters**

**$v$**   
[`numpy.ndarray`, shape (n,)] Vector with which the Hessian matrix of the quadratic model of the objective function is multiplied from the right.

**Returns**

`numpy.ndarray`, shape (n,)  
Right product of the Hessian matrix of the quadratic model of the objective function with  $v$ .

**cobyqa.models.Models.reset\_models****Models.reset\_models()**

Set the quadratic models of the objective function, nonlinear inequality constraints, and nonlinear equality constraints to the alternative quadratic models.

**Raises**

`numpy.linalg.LinAlgError`  
If the interpolation system is ill-defined.

**cobyqa.models.Models.shift\_x\_base****Models.shift\_x\_base**(*new\_x\_base*, *options*)

Shift the base point without changing the interpolation set.

**Parameters****new\_x\_base**[`numpy.ndarray`, shape (n,)] New base point.**options**

[dict] Options of the solver.

**cobyqa.models.Models.update\_interpolation****Models.update\_interpolation**(*k\_new*, *x\_new*, *fun\_val*, *cub\_val*, *ceq\_val*)

Update the interpolation set.

This method updates the interpolation set by replacing the *knew*-th interpolation point with *xnew*. It also updates the function values and the quadratic models.

**Parameters****k\_new**

[int] Index of the updated interpolation point.

**x\_new**[`numpy.ndarray`, shape (n,)] New interpolation point. Its value is interpreted as relative to the origin, not the base point.**fun\_val**[float] Value of the objective function at *x\_new*. Objective function value at *x\_new*.**cub\_val**[`numpy.ndarray`, shape (m\_nonlinear\_ub,)] Values of the nonlinear inequality constraints at *x\_new*.**ceq\_val**[`numpy.ndarray`, shape (m\_nonlinear\_eq,)] Values of the nonlinear equality constraints at *x\_new*.**Raises**`numpy.linalg.LinAlgError`

If the interpolation system is ill-defined.

The *framework* module implements the trust-region framework used by COBYQA.

## 3.3 Trust-region framework

This module implements classes for representing the trust-region framework used by COBYQA.

<code>TrustRegion</code> (pb, options, constants)	Trust-region framework.
---	-------------------------

### 3.3.1 cobyqa.framework.TrustRegion

**class** cobyqa.framework.TrustRegion(*pb, options, constants*)

Trust-region framework.

#### Attributes

**best\_index**

Index of the best interpolation point.

**ceq\_best**

Values of the nonlinear equality constraints at **x\_best**.

**cub\_best**

Values of the nonlinear inequality constraints at **x\_best**.

**fun\_best**

Value of the objective function at **x\_best**.

**m\_linear\_eq**

Number of linear equality constraints.

**m\_linear\_ub**

Number of linear inequality constraints.

**m\_nonlinear\_eq**

Number of nonlinear equality constraints.

**m\_nonlinear\_ub**

Number of nonlinear inequality constraints.

**models**

Models of the objective function and constraints.

**n**

Number of variables.

**penalty**

Penalty parameter.

**radius**

Trust-region radius.

**resolution**

Resolution of the trust-region framework.

**x\_best**

Best interpolation point.

## Methods

<code>decrease_penalty()</code>	Decrease the penalty parameter.
<code>get_constraint_linearizations(x)</code>	Get the linearizations of the constraints at a given point.
<code>get_geometry_step(k_new, options)</code>	Get the geometry-improving step.
<code>get_index_to_remove([x_new])</code>	Get the index of the interpolation point to remove.
<code>get_reduction_ratio(step, fun_val, cub_val, ...)</code>	Get the reduction ratio.
<code>get_second_order_correction_step(step, options)</code>	Get the second-order correction step.
<code>get_trust_region_step(options)</code>	Get the trust-region step.
<code>increase_penalty(step)</code>	Increase the penalty parameter.
<code>lag_model(x)</code>	Evaluate the Lagrangian model at a given point.
<code>lag_model_curv(v)</code>	Evaluate the curvature of the Lagrangian model along a given direction.
<code>lag_model_grad(x)</code>	Evaluate the gradient of the Lagrangian model at a given point.
<code>lag_model_hess()</code>	Evaluate the Hessian matrix of the Lagrangian model at a given point.
<code>lag_model_hess_prod(v)</code>	Evaluate the right product of the Hessian matrix of the Lagrangian model with a given vector.
<code>merit(x[, fun_val, cub_val, ceq_val])</code>	Evaluate the merit function at a given point.
<code>reduce_resolution(options)</code>	Reduce the resolution of the trust-region framework.
<code>set_best_index()</code>	Set the index of the best point.
<code>set_multipliers(x)</code>	Set the Lagrange multipliers.
<code>shift_x_base(options)</code>	Shift the base point to <code>x_best</code> .
<code>sqp_ceq(step)</code>	Evaluate the linearization of the nonlinear equality constraints.
<code>sqp_cub(step)</code>	Evaluate the linearization of the nonlinear inequality constraints.
<code>sqp_fun(step)</code>	Evaluate the objective function of the SQP sub-problem.
<code>update_radius(step, ratio)</code>	Update the trust-region radius.

### **cobyqa.framework.TrustRegion.decrease\_penalty**

**TrustRegion.decrease\_penalty()**

Decrease the penalty parameter.

### **cobyqa.framework.TrustRegion.get\_constraint\_linearizations**

**TrustRegion.get\_constraint\_linearizations(x)**

Get the linearizations of the constraints at a given point.

#### **Parameters**

**x**  
[`numpy.ndarray`, shape (n,)] Point at which the linearizations of the constraints are evaluated.

#### **Returns**

`numpy.ndarray`, shape (m\_linear\_ub + m\_nonlinear\_ub, n)  
Left-hand side matrix of the linearized inequality constraints.

`numpy.ndarray`, shape (m\_linear\_ub + m\_nonlinear\_ub,)
   
Right-hand side vector of the linearized inequality constraints.

`numpy.ndarray`, shape (m\_linear\_eq + m\_nonlinear\_eq, n)
   
Left-hand side matrix of the linearized equality constraints.

`numpy.ndarray`, shape (m\_linear\_eq + m\_nonlinear\_eq,)
   
Right-hand side vector of the linearized equality constraints.

### `cobyqa.framework.TrustRegion.get_geometry_step`

`TrustRegion.get_geometry_step(k_new, options)`

Get the geometry-improving step.

Three different geometry-improving steps are computed and the best one is returned. For more details, see Section 5.2.7 of [1].

#### Parameters

**k\_new**  
[int] Index of the interpolation point to be modified.

**options**  
[dict] Options of the solver.

#### Returns

`numpy.ndarray`, shape (n,)
   
Geometry-improving step.

#### Raises

`numpy.linalg.LinAlgError`
  
If the computation of a determinant fails.

#### References

[1]

### `cobyqa.framework.TrustRegion.get_index_to_remove`

`TrustRegion.get_index_to_remove(x_new=None)`

Get the index of the interpolation point to remove.

If  $x_{new}$  is not provided, the index returned should be used during the geometry-improvement phase. Otherwise, the index returned is the best index for included  $x_{new}$  in the interpolation set.

#### Parameters

**x\_new**  
[`numpy.ndarray`, shape (n,), optional] New point to be included in the interpolation set.

#### Returns

**int**  
Index of the interpolation point to remove.

**float**  
Distance between `x_best` and the removed point.

#### Raises

`numpy.linalg.LinAlgError`
  
If the computation of a determinant fails.

**cobyqa.framework.TrustRegion.get\_reduction\_ratio****TrustRegion.get\_reduction\_ratio**(*step, fun\_val, cub\_val, ceq\_val*)

Get the reduction ratio.

**Parameters****step**[`numpy.ndarray`, shape (n,)] Trust-region step.**fun\_val**

[float] Objective function value at the trial point.

**cub\_val**[`numpy.ndarray`, shape (m\_nonlinear\_ub,)] Nonlinear inequality constraint values at the trial point.**ceq\_val**[`numpy.ndarray`, shape (m\_nonlinear\_eq,)] Nonlinear equality constraint values at the trial point.**Returns****float**

Reduction ratio.

**cobyqa.framework.TrustRegion.get\_second\_order\_correction\_step****TrustRegion.get\_second\_order\_correction\_step**(*step, options*)

Get the second-order correction step.

**Parameters****step**[`numpy.ndarray`, shape (n,)] Trust-region step.**options**

[dict] Options of the solver.

**Returns**`numpy.ndarray`, shape (n,)

Second-order correction step.

**cobyqa.framework.TrustRegion.get\_trust\_region\_step****TrustRegion.get\_trust\_region\_step**(*options*)

Get the trust-region step.

The trust-region step is computed by solving the derivative-free trust-region SQP subproblem using a Byrd-Omojokun composite-step approach. For more details, see Section 5.2.3 of [1].

**Parameters****options**

[dict] Options of the solver.

**Returns**`numpy.ndarray`, shape (n,)

Normal step.

`numpy.ndarray`, shape (n,)

Tangential step.



## References

[1]

### `cobyqa.framework.TrustRegion.increase_penalty`

`TrustRegion.increase_penalty(step)`

Increase the penalty parameter.

#### Parameters

**step**

[`numpy.ndarray`, shape (n,)] Trust-region step.

### `cobyqa.framework.TrustRegion.lag_model`

`TrustRegion.lag_model(x)`

Evaluate the Lagrangian model at a given point.

#### Parameters

**x**

[`numpy.ndarray`, shape (n,)] Point at which the Lagrangian model is evaluated.

#### Returns

**float**

Value of the Lagrangian model at  $x$ .

### `cobyqa.framework.TrustRegion.lag_model_curv`

`TrustRegion.lag_model_curv(v)`

Evaluate the curvature of the Lagrangian model along a given direction.

#### Parameters

**v**

[`numpy.ndarray`, shape (n,)] Direction along which the curvature of the Lagrangian model is evaluated.

#### Returns

**float**

Curvature of the Lagrangian model along  $v$ .

### `cobyqa.framework.TrustRegion.lag_model_grad`

`TrustRegion.lag_model_grad(x)`

Evaluate the gradient of the Lagrangian model at a given point.

#### Parameters

**x**

[`numpy.ndarray`, shape (n,)] Point at which the gradient of the Lagrangian model is evaluated.

#### Returns

`numpy.ndarray`, shape (n,)

Gradient of the Lagrangian model at  $x$ .

**cobyqa.framework.TrustRegion.lag\_model\_hess****TrustRegion.lag\_model\_hess()**

Evaluate the Hessian matrix of the Lagrangian model at a given point.

**Returns****numpy.ndarray, shape (n, n)**Hessian matrix of the Lagrangian model at  $x$ .**cobyqa.framework.TrustRegion.lag\_model\_hess\_prod****TrustRegion.lag\_model\_hess\_prod(v)**

Evaluate the right product of the Hessian matrix of the Lagrangian model with a given vector.

**Parameters****v****[numpy.ndarray, shape (n,)]** Vector with which the Hessian matrix of the Lagrangian model is multiplied from the right.**Returns****numpy.ndarray, shape (n,)**Right product of the Hessian matrix of the Lagrangian model with  $v$ .**cobyqa.framework.TrustRegion.merit****TrustRegion.merit(x, fun\_val=None, cub\_val=None, ceq\_val=None)**

Evaluate the merit function at a given point.

**Parameters****x****[numpy.ndarray, shape (n,)]** Point at which the merit function is evaluated.**fun\_val****[float, optional]** Value of the objective function at  $x$ . If not provided, the objective function is evaluated at  $x$ .**cub\_val****[numpy.ndarray, shape (m\_nonlinear\_ub,), optional]** Values of the nonlinear inequality constraints. If not provided, the nonlinear inequality constraints are evaluated at  $x$ .**ceq\_val****[numpy.ndarray, shape (m\_nonlinear\_eq,), optional]** Values of the nonlinear equality constraints. If not provided, the nonlinear equality constraints are evaluated at  $x$ .**Returns****float**Value of the merit function at  $x$ .

**cobyqa.framework.TrustRegion.reduce\_resolution****TrustRegion.reduce\_resolution**(*options*)

Reduce the resolution of the trust-region framework.

**Parameters****options**

[dict] Options of the solver.

**cobyqa.framework.TrustRegion.set\_best\_index****TrustRegion.set\_best\_index**()

Set the index of the best point.

**cobyqa.framework.TrustRegion.set\_multipliers****TrustRegion.set\_multipliers**(*x*)

Set the Lagrange multipliers.

This method computes and set the Lagrange multipliers of the linear and nonlinear constraints to be the QP multipliers.

**Parameters****x**[[numpy.ndarray](#), shape (n,)] Point at which the Lagrange multipliers are computed.**cobyqa.framework.TrustRegion.shift\_x\_base****TrustRegion.shift\_x\_base**(*options*)Shift the base point to *x*\_best.**Parameters****options**

[dict] Options of the solver.

**cobyqa.framework.TrustRegion.sqp\_ceq****TrustRegion.sqp\_ceq**(*step*)

Evaluate the linearization of the nonlinear equality constraints.

**Parameters****step**[[numpy.ndarray](#), shape (n,)] Step along which the linearization of the nonlinear equality constraints is evaluated.**Returns**[numpy.ndarray](#), shape (m\_nonlinear\_ub,)Value of the linearization of the nonlinear equality constraints along *step*.

**cobyqa.framework.TrustRegion.sqp\_cub****TrustRegion.sqp\_cub**(*step*)

Evaluate the linearization of the nonlinear inequality constraints.

**Parameters****step**[[numpy.ndarray](#), shape (n,)] Step along which the linearization of the nonlinear inequality constraints is evaluated.**Returns**[numpy.ndarray](#), shape (m\_nonlinear\_ub,)Value of the linearization of the nonlinear inequality constraints along *step*.**cobyqa.framework.TrustRegion.sqp\_fun****TrustRegion.sqp\_fun**(*step*)

Evaluate the objective function of the SQP subproblem.

**Parameters****step**[[numpy.ndarray](#), shape (n,)] Step along which the objective function of the SQP subproblem is evaluated.**Returns****float**Value of the objective function of the SQP subproblem along *step*.**cobyqa.framework.TrustRegion.update\_radius****TrustRegion.update\_radius**(*step*, *ratio*)

Update the trust-region radius.

**Parameters****step**[[numpy.ndarray](#), shape (n,)] Trust-region step.**ratio**

[float] Reduction ratio.

The [subsolvers](#) module implements the subproblem solvers used by COBYQA.

## 3.4 Subproblem solvers

This module implements the subproblem solvers of COBYQA.

The trust-region subproblems, i.e., the normal and tangential Byrd-Omojokun subproblems, are solved approximately using variations of the truncated conjugate gradient method. The function below implements these methods.

<a href="#">normal_byrd_omojokun</a> (aub, bub, aeq, beq, xl, ...)	Minimize approximately a linear constraint violation subject to bound constraints in a trust region.
<a href="#">tangential_byrd_omojokun</a> (grad, hess_prod, ...)	Minimize approximately a quadratic function subject to bound constraints in a trust region.
<a href="#">constrained_tangential_byrd_omojokun</a> (grad, ...)	Minimize approximately a quadratic function subject to bound and linear constraints in a trust region.

### 3.4.1 cobyqa.subsolvers.normal\_byrd\_omojokun

`cobyqa.subsolvers.normal_byrd_omojokun(aub, bub, aeq, beq, xl, xu, delta, debug, **kwargs)`

Minimize approximately a linear constraint violation subject to bound constraints in a trust region.

This function solves approximately

$$\min_{s \in \mathbb{R}^n} \frac{1}{2} (\|\max\{A_x s - b_x, 0\}\|^2 + \|A_\varepsilon s - b_\varepsilon\|^2) \quad \text{s.t.} \quad \begin{cases} l \leq s \leq u, \\ \|s\| \leq \Delta, \end{cases}$$

using a variation of the truncated conjugate gradient method.

#### Parameters

##### **aub**

[`numpy.ndarray`, shape (m\_linear\_ub, n)] Matrix  $A_x$  as shown above.

##### **bub**

[`numpy.ndarray`, shape (m\_linear\_ub,)] Vector  $b_x$  as shown above.

##### **aeq**

[`numpy.ndarray`, shape (m\_linear\_eq, n)] Matrix  $A_\varepsilon$  as shown above.

##### **beq**

[`numpy.ndarray`, shape (m\_linear\_eq,)] Vector  $b_\varepsilon$  as shown above.

##### **xl**

[`numpy.ndarray`, shape (n,)] Lower bounds  $l$  as shown above.

##### **xu**

[`numpy.ndarray`, shape (n,)] Upper bounds  $u$  as shown above.

##### **delta**

[float] Trust-region radius  $\Delta$  as shown above.

##### **debug**

[bool] Whether to make debugging tests during the execution.

#### Returns

[`numpy.ndarray`, shape (n,)]

Approximate solution  $s$ .

#### Other Parameters

##### **improve\_tcg**

[bool, optional] If True, a solution generated by the truncated conjugate gradient method that is on the boundary of the trust region is improved by moving around the trust-region boundary on the two-dimensional space spanned by the solution and the gradient of the quadratic function at the solution (default is True).

#### Notes

This function implements Algorithm 6.4 of [1]. It is assumed that the origin is feasible with respect to the bound constraints and that *delta* is finite and positive.

## References

[1]

### 3.4.2 cobyqa.subsolvers.tangential\_byrd\_omojokun

`cobyqa.subsolvers.tangential_byrd_omojokun(grad, hess_prod, xl, xu, delta, debug, **kwargs)`

Minimize approximately a quadratic function subject to bound constraints in a trust region.

This function solves approximately

$$\min_{s \in \mathbb{R}^n} g^\top s + \frac{1}{2} s^\top H s \quad \text{s.t.} \quad \begin{cases} l \leq s \leq u, \\ \|s\| \leq \Delta, \end{cases}$$

using an active-set variation of the truncated conjugate gradient method.

#### Parameters

##### **grad**

[`numpy.ndarray`, shape (n,)] Gradient  $g$  as shown above.

##### **hess\_prod**

[callable] Product of the Hessian matrix  $H$  with any vector.

`hess_prod(s) -> `numpy.ndarray`, shape (n,)`

returns the product  $Hz$ .

##### **xl**

[`numpy.ndarray`, shape (n,)] Lower bounds  $l$  as shown above.

##### **xu**

[`numpy.ndarray`, shape (n,)] Upper bounds  $u$  as shown above.

##### **delta**

[float] Trust-region radius  $\Delta$  as shown above.

##### **debug**

[bool] Whether to make debugging tests during the execution.

#### Returns

`numpy.ndarray`, shape (n,)

Approximate solution  $s$ .

#### Other Parameters

##### **improve\_tcg**

[bool, optional] If True, a solution generated by the truncated conjugate gradient method that is on the boundary of the trust region is improved by moving around the trust-region boundary on the two-dimensional space spanned by the solution and the gradient of the quadratic function at the solution (default is True).

## Notes

This function implements Algorithm 6.2 of [1]. It is assumed that the origin is feasible with respect to the bound constraints and that  $\delta$  is finite and positive.

## References

[1]

### 3.4.3 cobyqa.subsolvers.constrained\_tangential\_byrd\_omojokun

`cobyqa.subsolvers.constrained_tangential_byrd_omojokun`(*grad, hess\_prod, xl, xu, aub, bub, aeq, delta, debug, \*\*kwargs*)

Minimize approximately a quadratic function subject to bound and linear constraints in a trust region.

This function solves approximately

$$\min_{s \in \mathbb{R}^n} g^T s + \frac{1}{2} s^T H s \quad \text{s.t.} \quad \begin{cases} l \leq s \leq u, \\ A_{\mathcal{I}} s \leq b_{\mathcal{I}}, \quad A_{\mathcal{E}} s = 0, \\ \|s\| \leq \Delta, \end{cases}$$

using an active-set variation of the truncated conjugate gradient method.

#### Parameters

##### **grad**

[`numpy.ndarray`, shape (n,)] Gradient  $g$  as shown above.

##### **hess\_prod**

[callable] Product of the Hessian matrix  $H$  with any vector.

`hess_prod(s) -> `numpy.ndarray`, shape (n,)`

returns the product  $Hs$ .

##### **xl**

[`numpy.ndarray`, shape (n,)] Lower bounds  $l$  as shown above.

##### **xu**

[`numpy.ndarray`, shape (n,)] Upper bounds  $u$  as shown above.

##### **aub**

[`numpy.ndarray`, shape (m\_linear\_ub, n)] Coefficient matrix  $A_{\mathcal{I}}$  as shown above.

##### **bub**

[`numpy.ndarray`, shape (m\_linear\_ub,)] Right-hand side  $b_{\mathcal{I}}$  as shown above.

##### **aeq**

[`numpy.ndarray`, shape (m\_linear\_eq, n)] Coefficient matrix  $A_{\mathcal{E}}$  as shown above.

##### **delta**

[float] Trust-region radius  $\Delta$  as shown above.

##### **debug**

[bool] Whether to make debugging tests during the execution.

#### Returns

`numpy.ndarray`, shape (n,)

Approximate solution  $s$ .

#### Other Parameters

##### **improve\_tcg**

[bool, optional] If True, a solution generated by the truncated conjugate gradient method that is on the boundary of the trust region is improved by moving around the trust-region boundary on the two-dimensional space spanned by the solution and the gradient of the quadratic function at the solution (default is True).

## Notes

This function implements Algorithm 6.3 of [1]. It is assumed that the origin is feasible with respect to the bound and linear constraints, and that *delta* is finite and positive.

## References

[1]

The geometry-improving subproblems are solved approximately using techniques developed by Powell for his solver BOBYQA [DS1]. The functions below implement these techniques.

<code>cauchy_geometry(const, grad, curv, xl, xu, ...)</code>	Maximize approximately the absolute value of a quadratic function subject to bound constraints in a trust region.
<code>spider_geometry(const, grad, curv, xpt, xl, ...)</code>	Maximize approximately the absolute value of a quadratic function subject to bound constraints in a trust region.

### 3.4.4 cobyqa.subsolvers.cauchy\_geometry

`cobyqa.subsolvers.cauchy_geometry(const, grad, curv, xl, xu, delta, debug)`

Maximize approximately the absolute value of a quadratic function subject to bound constraints in a trust region.

This function solves approximately

$$\max_{s \in \mathbb{R}^n} \left| c + g^T s + \frac{1}{2} s^T H s \right| \quad \text{s.t.} \quad \begin{cases} l \leq s \leq u, \\ \|s\| \leq \Delta, \end{cases}$$

by maximizing the objective function along the constrained Cauchy direction.

#### Parameters

##### **const**

[float] Constant  $c$  as shown above.

##### **grad**

[`numpy.ndarray`, shape (n,)] Gradient  $g$  as shown above.

##### **curv**

[callable] Curvature of  $H$  along any vector.

`curv(s) -> float`

returns  $s^T H s$ .

##### **xl**

[`numpy.ndarray`, shape (n,)] Lower bounds  $l$  as shown above.

##### **xu**

[`numpy.ndarray`, shape (n,)] Upper bounds  $u$  as shown above.

##### **delta**

[float] Trust-region radius  $\Delta$  as shown above.

##### **debug**

[bool] Whether to make debugging tests during the execution.

#### Returns

[`numpy.ndarray`, shape (n,)]

Approximate solution  $s$ .



## Notes

This function is described as the first alternative in Section 6.5 of [1]. It is assumed that the origin is feasible with respect to the bound constraints and that *delta* is finite and positive.

## References

[1]

### 3.4.5 cobyqa.subsolvers.spider\_geometry

`cobyqa.subsolvers.spider_geometry(const, grad, curv, xpt, xl, xu, delta, debug)`

Maximize approximately the absolute value of a quadratic function subject to bound constraints in a trust region.

This function solves approximately

$$\max_{s \in \mathbb{R}^n} \left| c + g^T s + \frac{1}{2} s^T H s \right| \quad \text{s.t.} \quad \begin{cases} l \leq s \leq u, \\ \|s\| \leq \Delta, \end{cases}$$

by maximizing the objective function along given straight lines.

#### Parameters

##### **const**

[float] Constant  $c$  as shown above.

##### **grad**

[`numpy.ndarray`, shape (n,)] Gradient  $g$  as shown above.

##### **curv**

[callable] Curvature of  $H$  along any vector.

`curv(s) -> float`

returns  $s^T H s$ .

##### **xpt**

[`numpy.ndarray`, shape (n, npt)] Points defining the straight lines. The straight lines considered are the ones passing through the origin and the points in *xpt*.

##### **xl**

[`numpy.ndarray`, shape (n,)] Lower bounds  $l$  as shown above.

##### **xu**

[`numpy.ndarray`, shape (n,)] Upper bounds  $u$  as shown above.

##### **delta**

[float] Trust-region radius  $\Delta$  as shown above.

##### **debug**

[bool] Whether to make debugging tests during the execution.

#### Returns

[`numpy.ndarray`, shape (n,)]

Approximate solution  $s$ .

## Notes

This function is described as the second alternative in Section 6.5 of [1]. It is assumed that the origin is feasible with respect to the bound constraints and that *delta* is finite and positive.

## References

[1]

The *utils* module implements the utilities for COBYQA.

## 3.5 Utilities

This module implements utilities for COBYQA.

<i>MaxEvalError</i>	Exception raised when the maximum number of evaluations is reached.
<i>TargetSuccess</i>	Exception raised when the target value is reached.
<i>CallbackSuccess</i>	Exception raised when the callback function raises a <i>StopIteration</i> .
<i>FeasibleSuccess</i>	Exception raised when a feasible point of a feasible problem is found.
<i>get_arrays_tol</i> (*arrays)	Get a relative tolerance for a set of arrays.
<i>exact_1d_array</i> (x, message)	Preprocess a 1-dimensional array.
<i>show_versions</i> ()	Display useful system and dependencies information.

### 3.5.1 *cobyqa.utils.MaxEvalError*

**exception** *cobyqa.utils.MaxEvalError*

Exception raised when the maximum number of evaluations is reached.

### 3.5.2 *cobyqa.utils.TargetSuccess*

**exception** *cobyqa.utils.TargetSuccess*

Exception raised when the target value is reached.

### 3.5.3 *cobyqa.utils.CallbackSuccess*

**exception** *cobyqa.utils.CallbackSuccess*

Exception raised when the callback function raises a *StopIteration*.

### 3.5.4 cobyqa.utils.FeasibleSuccess

**exception** `cobyqa.utils.FeasibleSuccess`

Exception raised when a feasible point of a feasible problem is found.

### 3.5.5 cobyqa.utils.get\_arrays\_tol

`cobyqa.utils.get_arrays_tol(*arrays)`

Get a relative tolerance for a set of arrays.

#### Parameters

**\*arrays: tuple**

Set of *arrays* to get the tolerance for.

#### Returns

**float**

Relative tolerance for the set of arrays.

### 3.5.6 cobyqa.utils.exact\_1d\_array

`cobyqa.utils.exact_1d_array(x, message)`

Preprocess a 1-dimensional array.

#### Parameters

**x**

[array\_like] Array to be preprocessed.

**message**

[str] Error message if *x* cannot be interpreter as a 1-dimensional array.

#### Returns

**numpy.ndarray**

Preprocessed array.

### 3.5.7 cobyqa.utils.show\_versions

`cobyqa.utils.show_versions()`

Display useful system and dependencies information.

When reporting issues, please include this information.

#### Version

1.0

#### Useful links

[Issue tracker](#) | [Mailing list](#)

#### Authors

[Tom M. Ragonneau](#) | [Zaikun Zhang](#)

COBYQA is a derivative-free optimization solver designed to supersede [COBYLA](#). Using only functions values, and no derivatives, it aims at solving problems of the form

$$\min_{x \in \mathcal{X}} f(x) \quad \text{s.t.} \quad \begin{cases} A_{\mathcal{I}}x \leq b_{\mathcal{I}}, & A_{\mathcal{E}}x = b_{\mathcal{E}}, \\ c_{\mathcal{I}}(x) \leq 0, & c_{\mathcal{E}}(x) = 0, \end{cases}$$

where  $\mathcal{X} = \{x \in \mathbb{R}^n : l \leq x \leq u\}$ . COBYQA always respect the bound constraints throughout the optimization process. Hence, the nonlinear functions  $f$ ,  $c_{\mathcal{I}}$ , and  $c_{\mathcal{E}}$  do not need to be well-defined outside  $\mathcal{X}$ . In essence, COBYQA is a derivative-free trust-region SQP method based on quadratic models obtained by underdetermined interpolation. For a more detailed description of the algorithm, see the [framework description](#).

To install COBYQA, run in your terminal

```
pip install cobyqa
```

For more details on the installation and the usage of COBYQA, see the [user guide](#).

## CITING COBYQA

If you would like to acknowledge the significance of COBYQA in your research, we suggest citing the project as follows.

- T. M. Ragonneau. “Model-Based Derivative-Free Optimization Methods and Software.” PhD thesis. Hong Kong, China: Department of Applied Mathematics, The Hong Kong Polytechnic University, 2022. URL: <https://theses.lib.polyu.edu.hk/handle/200/12294>.
- T. M. Ragonneau and Z. Zhang. COBYQA Version 1.0.1. 2024. URL: <https://www.cobyqa.com>.

The corresponding BibTeX entries are given hereunder.

```
@phdthesis{rago_thesis,  
  title      = {Model-Based Derivative-Free Optimization Methods and Software},  
  author     = {Ragonneau, T. M.},  
  school     = {Department of Applied Mathematics, The Hong Kong Polytechnic  
↪University},  
  address    = {Hong Kong, China},  
  year       = 2022,  
  url        = {https://theses.lib.polyu.edu.hk/handle/200/12294},  
}  
  
@misc{razh_cobyqa,  
  author     = {Ragonneau, T. M. and Zhang, Z.},  
  title      = {{COBYQA} {V}ersion 1.0.1},  
  year       = 2024,  
  url        = {https://www.cobyqa.com},  
}
```



## STATISTICS

As of January 24, 2024, COBYQA has been downloaded 2,506 times, including

- 0 times on [GitHub](#), and
- 2,506 times on [PyPI](#) ([mirror downloads](#) excluded).





## ACKNOWLEDGMENTS

This work was partially supported by the [Research Grants Council](#) of Hong Kong under Grants PF18-24698, PolyU 253012/17P, PolyU 153054/20P, PolyU 153066/21P, and [The Hong Kong Polytechnic University](#).



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