
Scikit-Criteria Documentation

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Scikit-Criteria is a collection of Multiple-criteria decision analysis ([MCDA](#)) methods integrated into scientific python stack. Is Open source and commercially usable.

CHAPTER 1

Help & discussion mailing list

Our Google Groups mailing list is [here](#).

You can contact me at: jbc.develop@gmail.com (if you have a support question, try the mailing list first)

CHAPTER 2

Code Repository & Issues

<https://github.com/lelel12/scikit-criteria>

CHAPTER 3

License

Scikit-Criteria is under [The 3-Clause BSD License](#)

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If you use scikit-criteria in a scientific publication, we would appreciate citations to the following paper:

Cabral, Juan B., Nadia Ayelen Luczywo, and José Luis Zanazzi 2016 Scikit-Criteria: Colección de Métodos de Análisis Multi-Criterio Integrado Al Stack Científico de Python. In XLV Jornadas Argentinas de Informática E Investigación Operativa (45JAIIO)-XIV Simposio Argentino de Investigación Operativa (SIO) (Buenos Aires, 2016) Pp. 59-66. <http://45jaiio.sadio.org.ar/sites/default/files/Sio-23.pdf>.

Bibtex entry:

```
@inproceedings{scikit-criteria,
  author={
    Juan B Cabral and Nadia Ayelen Luczywo and Jos\{e\} Luis Zanazzi},
  title={
    Scikit-Criteria: Colecci\{o\}n de m\{e\}todos de an\{a\}lisis
    multi-criterio integrado al stack cient\{i\}fico de {P}ython},
  booktitle = {
    XLV Jornadas Argentinas de Inform\{a\}tica
    e Investigaci\{o\}n Operativa (45JAIIO)-
    XIV Simposio Argentino de Investigaci\{o\}n Operativa (SIO)
    (Buenos Aires, 2016)},
  year={2016},
  pages = {59--66},
  url={http://45jaiio.sadio.org.ar/sites/default/files/Sio-23.pdf}
}
```

Full Publication: <http://sedici.unlp.edu.ar/handle/10915/58577>

5.1 Installing scikit-criteria

The easiest way to install scikit-criteria is using `pip`

```
pip install -U scikit-criteria
```

If you have not installed NumPy or SciPy yet, you can also install these using `conda` or `pip`. When using `pip`, please ensure that *binary wheels* are used, and NumPy and SciPy are not recompiled from source, which can happen when using particular configurations of operating system and hardware (such as Linux on a Raspberry Pi). Building `numpy` and `scipy` from source can be complex (especially on Windows) and requires careful configuration to ensure that they link against an optimized implementation of linear algebra routines. Instead, use a third-party distribution as described below.

5.1.1 Third-party Distributions

If you don't already have a python installation with `numpy` and `scipy`, we recommend to install either via your package manager or via a python bundle. These come with `numpy`, `scipy`, `matplotlib` and many other helpful scientific and data processing libraries.

Available options are:

Canopy and Anaconda for all supported platforms

[Canopy](#) and [Anaconda](#) both ship a recent version of Python, in addition to a large set of scientific python library for Windows, Mac OSX and Linux.

5.2 Tutorial

This section contains a step-by-step by example tutorial of how to use scikit-criteria

Contents:

5.2.1 Quick Start

This tutorial show how to create a scikit-criteria Data structure, and how to feed them inside different multicriteria decisions algorithms.

Conceptual Overview

The multicriteria data are really complex thing; mostly because you need at least 2 totally disconnected vectors to describe your problem: A alternative matrix (`mtx`) and a vector that indicated the optimal sense of every criteria (`criteria`); also maybe you want to add weights to your criteria

The `skcriteria.Data` object need at least the first two to be created and also accepts the weights, the names of the criteria and the names of alternatives as optional parametes.

Your First Data object

First we need to import the Data structure and the MIN, MAX constants from scikit-criteria:

```
[2]: from skcriteria import Data, MIN, MAX
```

Then we need to create the `mtx` and `criteria` vectors.

The `mtx` must be a **2D array-like** where every column is a criteria, and every row is an alternative

```
[3]: # 2 alternatives by 3 criteria
mtx = [
    [1, 2, 3], # alternative 1
    [4, 5, 6], # alternative 2
]
mtx
```

```
[3]: [[1, 2, 3], [4, 5, 6]]
```

The `criteria` vector must be a **1D array-like** with number of elements same as number of columns in the alternative matrix (`mtx`). Every component of the `criteria` vector represent the optimal sense of each criteria.

```
[4]: # let's says the first two alternatives are
# for maximization and the last one for minimization
criteria = [MAX, MAX, MIN]
criteria
```

```
[4]: [1, 1, -1]
```

as you see the MAX and MIN constants are only aliases for the numbers -1 (minimization) and 1 (maximization). As you can see the constants usage makes the code more readable. Also you can use as aliases of minimization and maximization the built-in function `min`, `max`, the numpy function `np.min`, `np.max`, `np.amin`, `np.amax`, `np.nanmin`, `np.nanmax` and the strings `min`, `minimization`, `max` and `maximization`.

Now we can combine this two vectors in our scikit-criteria data.

```
[5]: # we use the built-in function as aliases
data = Data(mtx, [min, max, min])
data
```

```
[5]: ALT./CRIT.    C0 (min)    C1 (max)    C2 (min)
-----
      A0          1          2          3
      A1          4          5          6
```

As you can see the output of the Data structure is much more friendly than the plain python lists.

To change the generic names of the alternatives (A0 and A1) and the criteria (C0, C1 and C2); let's assume that our Data is about cars (*car 0* and *car 1*) and their characteristics of evaluation are *autonomy* (MAX), *comfort* (MAX) and *price* (MIN).

To feed this information to our Data structure we have the params: `anames` that accept the names of alternatives (must be the same number as the rows that `mtx` has), and `cnames` the criteria names (must have same number of elements with the columns that `mtx` has)

```
[6]: data = Data(mtx, criteria,
               anames=["car 0", "car 1"],
               cnames=["autonomy", "comfort", "price"])
data
```

```
[6]: ALT./CRIT.      autonomy (max)      comfort (max)      price (min)
-----
car 0                1                2                3
car 1                4                5                6
```

In our final step let's assume we know in our case, that the importance of the autonomy is the 50%, the comfort only a 5% and the price is 45%. The param to feed this to the structure is called `weights` and must be a vector with the same elements as criterias on your alternative matrix (number of columns)

```
[7]: data = Data(mtx, criteria,
               weights=[.5, .05, .45],
               anames=["car 0", "car 1"],
               cnames=["autonomy", "comfort", "price"])
data
```

```
[7]: ALT./CRIT.      autonomy (max) W.0.5      comfort (max) W.0.05      price (min) W.0.45
-----
car 0                1                2                3
car 1                4                5                6
```

Manipulating the Data

The data object are immutable, if you want to modify it you need create a new one. All the numerical data (`mtx`, `criteria`, and `weights`) are stored as [numpy arrays](#), and the alternative and criteria names as python tuples.

You can acces to the different parts of your data, simply by typing `data.<your-parameter-name>` for example:

```
[8]: data.mtx
```

```
[8]: array([[1, 2, 3],
          [4, 5, 6]])
```

```
[9]: data.criteria
```

```
[9]: array([ 1,  1, -1])
```

```
[10]: data.weights
```

```
[10]: array([0.5 , 0.05, 0.45])
```

```
[11]: data.anames, data.cnames
```

```
[11]: (('car 0', 'car 1'), ('autonomy', 'comfort', 'price'))
```

If you want (for example) change the names of the cars from `car 0` and `car 1`; to `VW` and `Ford` you must copy from your original Data

```
[12]: data = Data(data.mtx, data.criteria,
                weights=data.weights,
                anames=["VW", "Ford"],
                cnames=data.cnames)

data
```

```
[12]: ALT./CRIT.      autonomy (max) W.0.5      comfort (max) W.0.05      price (min) W.0.45
-----
      VW              1              2              3
      Ford            4              5              6
```

Note: A more flexible data manipulation API will be released in future versions.

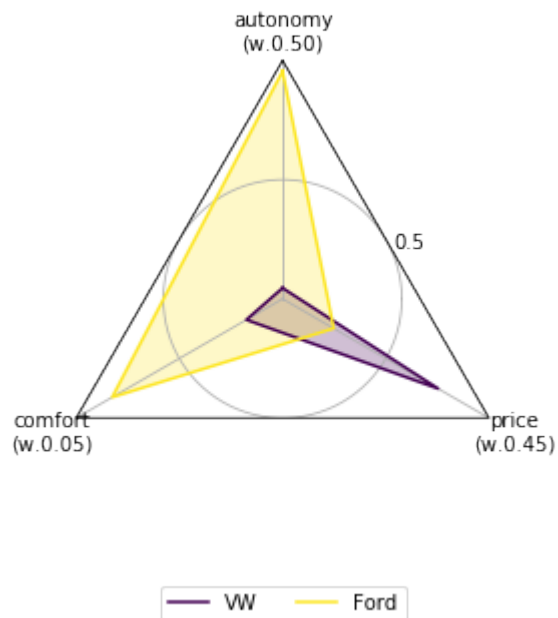
Plotting

The Data structure supports some basic routines for plotting. Actually 5 types of plots are supported:

- [Radar Plot](#) (radar).
- [Histogram](#) (hist).
- [Violin Plot](#) (violin).
- [Box Plot](#) (box).
- [Scatter Matrix](#) (scatter).

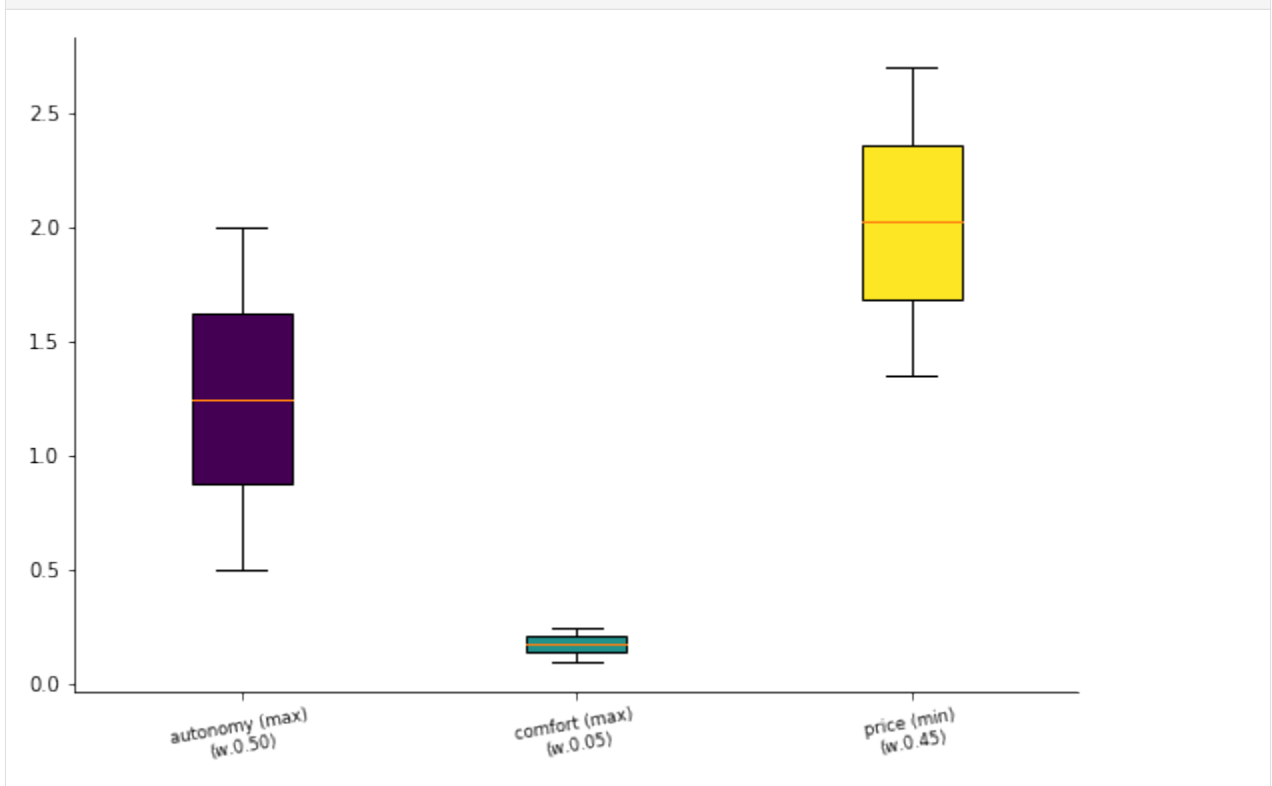
The default scikit criteria uses the Radar Plot to visualize all the data. Take in account that the radar plot by default convert all the minimization criteria to maximization and push all the values to be greater than 1 (obviously all this options can be overriden).

```
[13]: data.plot();
```



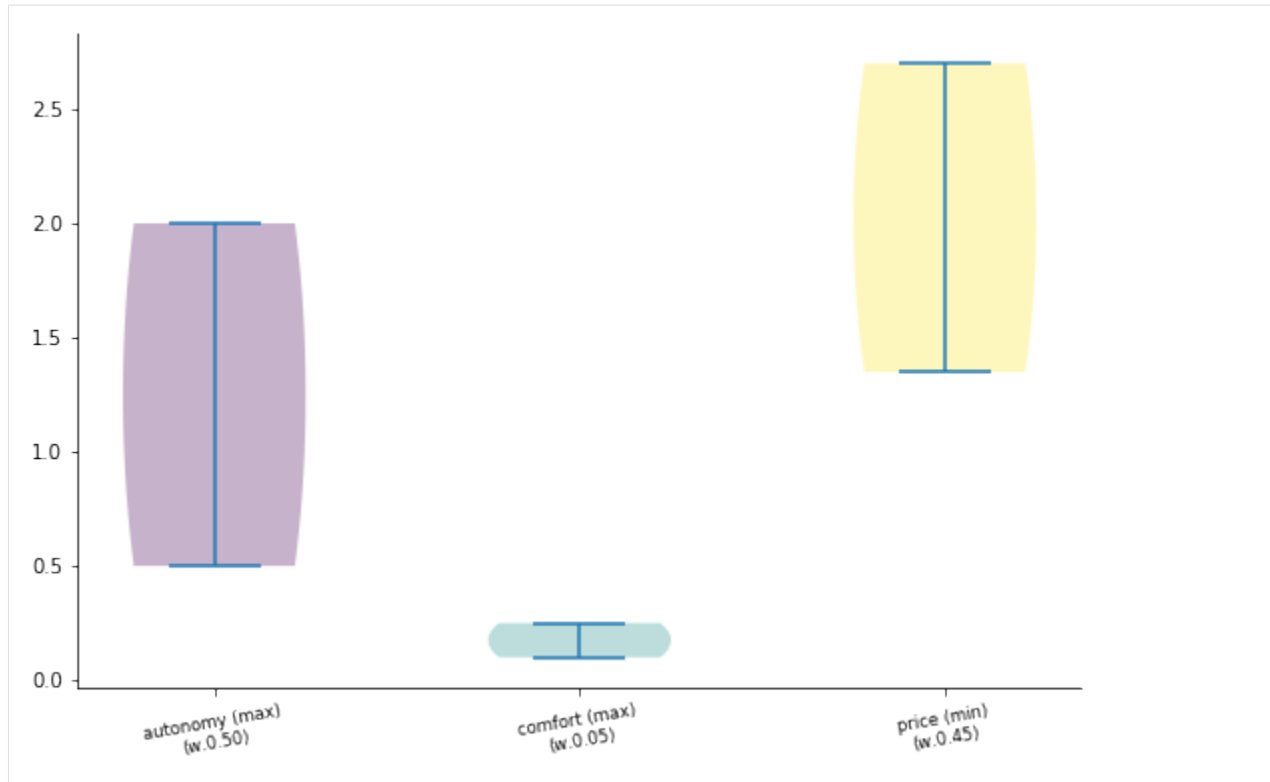
You can access the different plot by passing as first parameter the name of the plot

```
[14]: data.plot("box");
```



or by using the name as method call inside the `plot` attribute

```
[15]: data.plot.violin();
```

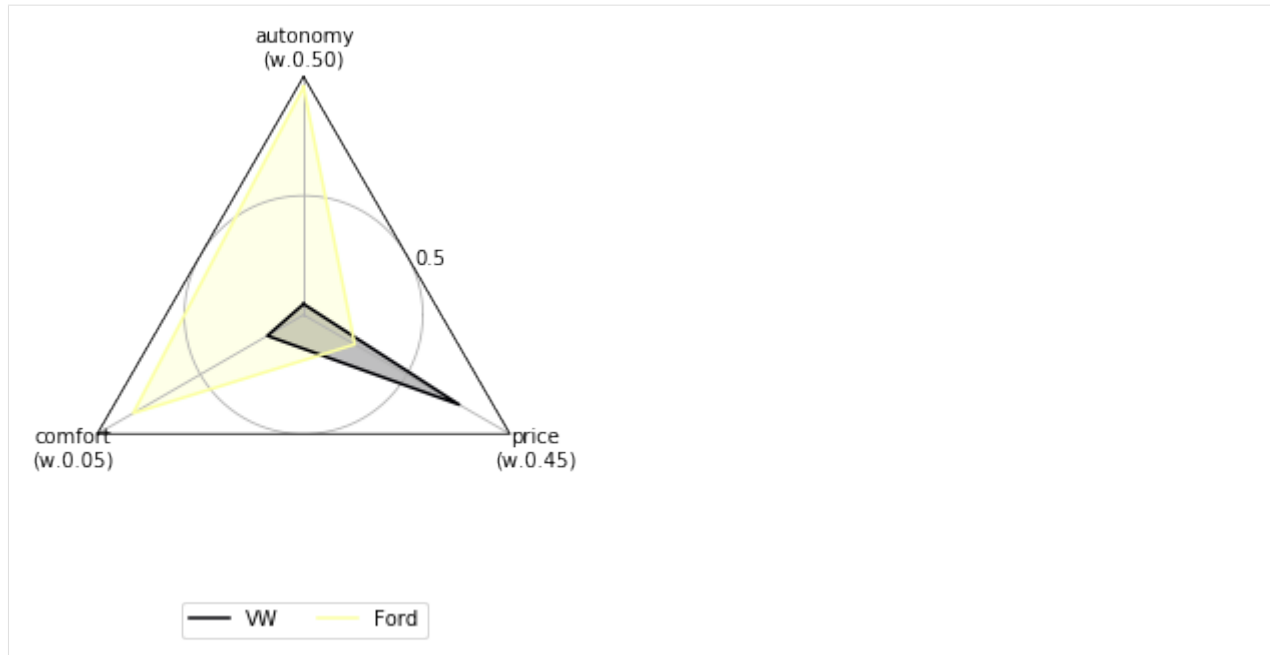


Every plot has their own set of parameters, but at last every one can receive:

- `ax`: The plot axis.
- `cmap`: The color map ([More info](#)).
- `mnorm`: The normalization method for the alternative matrix as string (Default: "none").
- `wnorm`: The normalization method for the criteria array as string (Default: "none").
- `weighted`: If you want to weight the criteria (Default: True).
- `show_criteria`: Show or not the criteria in the plot (Default: True in all except radar).
- `min2max`: Convert the minimization criteria into maximization one (Default: False in all except radar).
- `push_negatives`: If a criteria has values lesser than 0, add the minimum value to all the criteria (Default: False in all except radar).
- `addepsto0`: If a criteria has values equal to 0, add an ϵ value to all the criteria (Default: False in all except radar).

Let's change the colors of the radar plot and show their criteria optimization sense:

```
[16]: data.plot.radar(cmap="inferno", show_criteria=False);
```



Using this data to feed some MCDA methods

Let's rank our dummy data by [Weighted Sum Model](#), [Weighted Product Model](#) and [TOPSIS](#)

```
[17]: from skcriteria.madm import closeness, simple
```

First you need to create the decision maker.

Most of methods accepts hyper parameters (parameters of the to configure the method) as following: 1. the method of normalization of the alternative matrix - in Weighted Sum and Weighted Product we use divided by the sum normalization - in Topsis we can also use the vector normalization 2. the method to normalize the weight array (normally sum); But complex methods has more.

Weighted Sum Model:

```
[18]: # first create the decision maker
# (with the default hiper parameters)
dm = simple.WeightedSum()
dm
```

```
[18]: <WeightedSum (mnorm=sum, wnorm=sum)>
```

```
[19]: # Now lets decide the ranking
dec = dm.decide(data)
dec
```

```
[19]: WeightedSum (mnorm=sum, wnorm=sum) - Solution:
      ALT./CRIT.      autonomy (max) W.0.5      comfort (max) W.0.05      price (min) W.0.45
      ↪Rank
      -----
      ↪-----
      ↪      VW              1              2              3
      ↪1
      ↪      Ford              4              5              6
      ↪2
```

The result says that the **VW** is better than the **FORD**, lets make the maths:

Note: The last criteria is for minimization and because the WeightedSumModel only accepts maximization criteria by default, scikit-criteria invert all the values to convert the criteria to maximization

```
[20]: print("VW:", 0.5 * 1/5. + 0.05 * 2/7. + 0.45 * 1 / (3/9.))
      print("FORD:", 0.5 * 4/5. + 0.05 * 5/7. + 0.45 * 1 / (6/9.))

VW: 1.4642857142857144
FORD: 1.1107142857142858
```

If you want to access this points, the Decision object stores all the particular information of every method in a attribute called `e_`

```
[21]: print(dec.e_)
      dec.e_.points

Extra(points)

[21]: array([1.46428571, 1.11071429])
```

Also you can access the type of the solution

```
[22]: print("Generate a ranking of alternatives?", dec.alpha_solution_)
      print("Generate a kernel of best alternatives?", dec.beta_solution_)
      print("Choose the best alternative?", dec.gamma_solution_)

Generate a ranking of alternatives? True
Generate a kernel of best alternatives? False
Choose the best alternative? True
```

The rank as numpy array (if this decision is a α -solution / alpha solution)

```
[23]: dec.rank_

[23]: array([1, 2])
```

The index of the row of the best alternative (if this decision is a γ -solution / gamma solution)

```
[24]: dec.best_alternative_, data.anames[dec.best_alternative_]

[24]: (0, 'VW')
```

And the kernel of the non supered alternatives (if this decision is a β -solution / beta solution)

```
[25]: # this return None because this
      # decision is not a beta-solution
      print(dec.kernel_)

None
```

Weighted Product Model

```
[26]: dm = simple.WeightedProduct()
      dm

[26]: <WeightedProduct (mnorm=sum, wnorm=sum)>
```

```
[27]: dec = dm.decide(data)
dec
```

```
[27]: WeightedProduct (mnorm=sum, wnorm=sum) - Solution:
      ALT./CRIT.      autonomy (max) W.0.5      comfort (max) W.0.05      price (min) W.0.45
      ↪Rank
      -----
      ↪----
      VW              1              2              3
      ↪2
      Ford            4              5              6
      ↪1
```

As before let's do the math (remember the weights are now exponents)

```
[28]: print("VW:", ((1/5.) ** 0.5) * ((2/7.) ** 0.05) + ((1 / (3/9.)) ** 0.45))
      print("FORD:", ((4/5.) ** 0.5) * ((5/7.) ** 0.05) + ((1 / (6/9.)) ** 0.45))

VW: 2.059534375567646
FORD: 2.07967086650222
```

As we expected the **Ford** are little better than the **VW**. Now lets check the `e_` object

```
[29]: print(dec.e_)
      dec.e_.points

Extra(points)

[29]: array([-0.16198384,  0.02347966])
```

As you note the points are different, this is because internally to avoid [underflows](#) Scikit-Criteria uses a sums of logarithms instead products. So let's check

```
[30]: import numpy as np
      print("VW:", 0.5 * np.log10(1/5.) + 0.05 * np.log10(2/7.) + 0.45 * np.log10(1 / (3/9.
      ↪)))
      print("FORD:", 0.5 * np.log10(4/5.) + 0.05 * np.log10(5/7.) + 0.45 * np.log10(1 / (6/
      ↪9.)))

VW: -0.16198383976167505
FORD: 0.023479658287116456
```

TOPSIS

```
[31]: dm = closeness.TOPSIS()
      dm
```

```
[31]: <TOPSIS (mnorm=vector, wnorm=sum)>
```

```
[32]: dec = dm.decide(data)
      dec
```

```
[32]: TOPSIS (mnorm=vector, wnorm=sum) - Solution:
      ALT./CRIT.      autonomy (max) W.0.5      comfort (max) W.0.05      price (min) W.0.45
      ↪Rank
      -----
      ↪----
      VW              1              2              3
      ↪2
```

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	Ford	4	5	6	
↪1					

The TOPSIS add more information into the decision object.

```
[33]: print(dec.e_)
      print("Ideal:", dec.e_.ideal)
      print("Anti-Ideal:", dec.e_.anti_ideal)
      print("Closeness:", dec.e_.closeness)

Extra(ideal, anti_ideal, closeness)
Ideal: [0.48507125 0.04642383 0.20124612]
Anti-Ideal: [0.12126781 0.01856953 0.40249224]
Closeness: [0.35548671 0.64451329]
```

Where the `ideal` and `anti_ideal` are the normalized sintetic better and worst altenatives created by TOPSIS, and the `closeness` is how far from the *anti-ideal* and how closer to the *ideal* are the real alternatives

Finally we can change the normalization criteria of the alternative matric to `sum` (divide every value by the sum opf their criteria) and check the result:

```
[34]: dm = closeness.TOPSIS(mnorm="sum")
      dm
```

```
[34]: <TOPSIS (mnorm=sum, wnorm=sum)>
```

```
[35]: dm.decide(data)
```

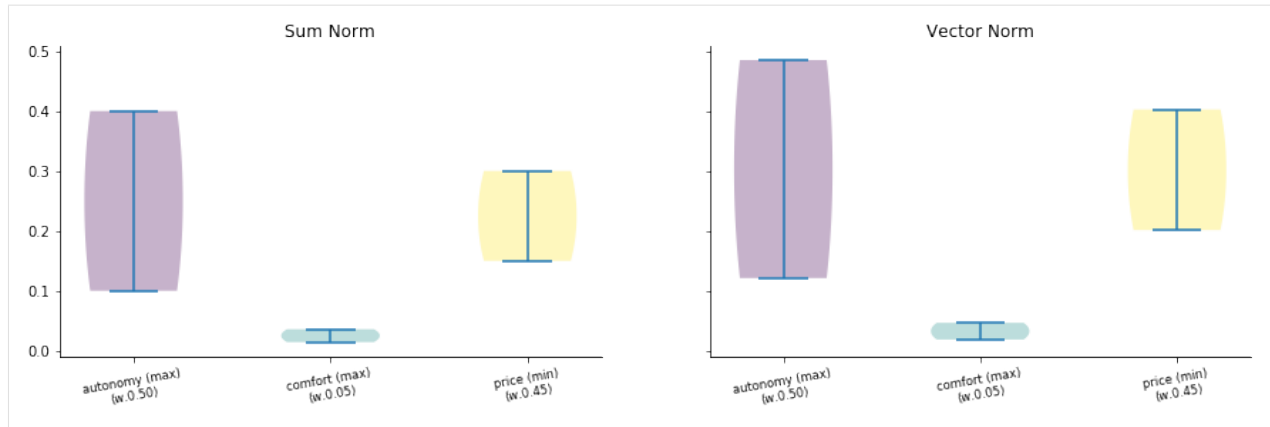
```
[35]: TOPSIS (mnorm=sum, wnorm=sum) - Solution:
      ALT./CRIT.    autonomy (max) W.0.5    comfort (max) W.0.05    price (min) W.0.45
      ↪Rank
      -----
      ↪----
      VW                1                2                3
      ↪2
      Ford              4                5                6
      ↪1
```

The rankin has changed so, we can compare the two normalization by plotting

```
[36]: import matplotlib.pyplot as plt

f, (ax1, ax2) = plt.subplots(1, 2, sharey=True)
ax1.set_title("Sum Norm")
data.plot.violin(mnorm="sum", ax=ax1);

ax2.set_title("Vector Norm")
data.plot.violin(mnorm="vector", ax=ax2);
f.set_figwidth(15)
```

```
[37]: import datetime as dt
import skcriteria
print("Scikit-Criteria version:", skcriteria.VERSION)
print("Running datetime:", dt.datetime.now())
```

```
Scikit-Criteria version: 0.2.10
Running datetime: 2019-08-27 19:49:24.273132
```

5.2.2 The SIMUS tutorial

SIMUS (*Sequential Interactive Model for Urban Systems*)

Is a tool to aid decision-making problems with multiple objectives. The method solves successive scenarios formulated as linear programs. For each scenario, the decision-maker must choose the criterion to be considered objective while the remaining restrictions constitute the constraints system that the projects are subject to. In each case, if there is a feasible solution that is optimum, it is recorded in a matrix of efficient results. Then, from this matrix two rankings allow the decision maker to compare results obtained by different procedures. The first ranking is obtained through a linear weighting of each column by a factor - equivalent of establishing a weight - and that measures the participation of the corresponding project. In the second ranking, the method uses dominance and subordinate relationships between projects, concepts from the French school of MCDM.

The Case: Land rehabilitation

An important port city has been affected by the change in the modality of maritime transport, since the start of containers transport in the mid-20th century. The city was left with 39 hectares of empty docks, warehouses and a railway terminal.

Three projects were developed to decide what to do with this places

- **Project 1:** Corporate towers - Hotels - Navy Base - Small park
- **Project 2:** Habitational towers - Commercial Center in the old Railway terminal.
- **Project 3:** Convention center - Big park and recreational area.

The criteria for the analysis of proposals are:

1. New jobs positions (**jobs**).
 - Green spaces (**green**)
 - Financial feasibility (**fin**)
 - Environmental impact (**env**)

Only for the 2nd criteria a maximum limit of 500 are provided. The decisor has the four criteria as goals, so 4 [Linear Optimizations](#) must be solved.

The data are provided in the next table:

Criteria	Project 1	Project 2	Project 3	Right side value	Optimal Sense
jobs	250	130	350	.	Maximize
green	120	200	340	500	Maximize
fin	20	40	15	.	Maximize
env	800	1000	600	.	Maximize

Data input

We can create a `skcriteria.Data` object with all this information (except the limits):

Note: SIMUS uses the alternatives as columns and the criteria as rows; but in *scikit-criteria* is the opposite, so expect to see the previous table transposed.

```
[1]: # first lets import the DATA class
from skcriteria import Data

data = Data(
    # the alternative matrix
    mtx=[[250, 120, 20, 800],
         [130, 200, 40, 1000],
         [350, 340, 15, 600]],

    # optimal sense
    criteria=[max, max, min, max],

    # names of alternatives and criteria
    anames=["Prj 1", "Prj 2", "Prj 3"],
    cnames=["jobs", "green", "fin", "env"])

# show the data object
data
```

```
[1]: ALT./CRIT.    jobs (max)    green (max)    fin (min)    env (max)
-----
Prj 1           250           120           20           800
Prj 2           130           200           40          1000
Prj 3           350           340           15           600
```

Create the model

```
[2]: # import the class
from skcriteria.madm.simus import SIMUS
```

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```
# create the new simus and
dm = SIMUS()
```

By default the call `SIMUS()` create a solver that internally uses the [PuLP](#) solver to solve the linear programs. Other available solvers are:

- `SIMUS(solver='glpk')` for the [GNU Linear programming toolkit](#)
- `SIMUS(solver='gurobi')` to use [Gurobi Optimizer](#)
- `SIMUS(solver='cplex')` for [IBM ILOG CPLEX Optimization Studio](#)

Note: The check the full list of available optimizers are stored in `skcriteria.utils.lp.SOLVERS`.

Also the `njobs` parameters determines how many cores the user want to use to run the linear programs. For example `SIMUS(njobs=2)` uses up to two cores. (By default all CPUs are used).

Also the last (and most important) parameter is `rank_by` (default is 1): determines which of the two ranks methods executed by `SIMUS` is the one that determines the final ranking. If the experiment is consistent, the two methods *must* determine the *same* ranking (Please check the [paper](#) for more details).

Solve the problem

This is achieved by calling the method `decide()` of the decision maker object (`dm`)

```
[3]: # store the decision inside the dec variable
dec = dm.decide(data, b=[None, 500, None, None])

# let's see the decision
dec
```

```
[3]: SIMUS (mnorm=None, wnorm=None) - Solution:
```

ALT./CRIT.	jobs (max)	green (max)	fin (min)	env (max)	Rank
Prj 1	250	120	20	800	3
Prj 2	130	200	40	1000	2
Prj 3	350	340	15	600	1

If you check the last column the ranking is:

1. Project 3
- Project 2
 - Project 1

Analysis

Most of the “intermediate” data of the `SIMUS` method are stored in the `e_` field of the decision object `dec`.

```
[4]: dec.e_
[4]: Extra(rank_by, solver, stages, stage_results, points1, points2, tita_j_p, tita_j_d,
↪ doms, dom_by_crit)
```

for example the attribute `stages` stores all the Linear programs executed by `SIMUS`:

```
[5]: dec._e.stages
```

```
[5]: [no-name:
      MAXIMIZE
      250*x0 + 130*x1 + 350*x2 + 0
      SUBJECT TO
      _C1: 120 x0 + 200 x1 + 340 x2 <= 500

      _C2: 20 x0 + 40 x1 + 15 x2 >= 15

      _C3: 800 x0 + 1000 x1 + 600 x2 <= 1000

      VARIABLES
      x0 Continuous
      x0 Continuous
      x1 Continuous
      x1 Continuous
      x2 Continuous
      x2 Continuous, no-name:
      MAXIMIZE
      120*x0 + 200*x1 + 340*x2 + 0
      SUBJECT TO
      _C1: 250 x0 + 130 x1 + 350 x2 <= 350

      _C2: 20 x0 + 40 x1 + 15 x2 >= 15

      _C3: 800 x0 + 1000 x1 + 600 x2 <= 1000

      VARIABLES
      x0 Continuous
      x0 Continuous
      x1 Continuous
      x1 Continuous
      x2 Continuous
      x2 Continuous, no-name:
      MINIMIZE
      20*x0 + 40*x1 + 15*x2 + 0
      SUBJECT TO
      _C1: 250 x0 + 130 x1 + 350 x2 <= 350

      _C2: 120 x0 + 200 x1 + 340 x2 <= 500

      _C3: 800 x0 + 1000 x1 + 600 x2 <= 1000

      VARIABLES
      x0 Continuous
      x0 Continuous
      x1 Continuous
      x1 Continuous
      x2 Continuous
      x2 Continuous, no-name:
      MAXIMIZE
      800*x0 + 1000*x1 + 600*x2 + 0
      SUBJECT TO
      _C1: 250 x0 + 130 x1 + 350 x2 <= 350

      _C2: 120 x0 + 200 x1 + 340 x2 <= 500
```

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(continued from previous page)

```

_C3: 20 x0 + 40 x1 + 15 x2 >= 15

VARIABLES
x0 Continuous
x0 Continuous
x1 Continuous
x1 Continuous
x2 Continuous
x2 Continuous]

```

The attribute `stages_results` stores the *eficients restults normalized matrix*

```

[6]: dec.e_.stage_results
[6]: array([[0.125      , 0.        , 0.875      ],
          [0.        , 0.38888889, 0.61111111],
          [0.        , 0.        , 0.        ],
          [0.05681818, 0.94318182, 0.        ]])

```

References

Munier, N., Carignano, C., & Alberto, C. UN MÉTODO DE PROGRAMACIÓN MULTIOBJETIVO. Revista de la Escuela de Perfeccionamiento en Investigación Operativa, 24(39).

```

[7]: import datetime as dt
import skcriteria
print("Scikit-Criteria version:", skcriteria.VERSION)
print("Running datetime:", dt.datetime.now())

Scikit-Criteria version: 0.2.10
Running datetime: 2019-08-27 19:50:11.820481

```

See also:

If you're new to Python, you might want to start by getting an idea of what the language is like. Scikit-criteria is 100% Python, so if you've got minimal comfort with Python you'll probably get a lot more out of our project.

If you're new to programming entirely, you might want to start with this [list of Python resources for non-programmers](#)

If you already know a few other languages and want to get up to speed with Python quickly, we recommend [Dive Into Python](#). If that's not quite your style, there are many other [books about Python](#).

At last if you already know Python but check the [Scipy Lecture Notes](#)

5.3 API

Scikit-Criteria is a collections of algorithms, methods and techniques for multiple-criteria decision analysis.

5.3.1 `skcriteria.base` module

Module containing the basic functionality for the data representation used inside Scikit-Criteria.

```
class skcriteria.base.Data(mtx, criteria, weights=None, anames=None, cnames=None, meta=None)
```

Bases: `object`

Multi-Criteria data representation.

This make easy to manipulate:

- The matrix of alternatives. (`mtx`)
- The array with the sense of optimality of every criteria (`criteria`).
- Optional weights of the criteria (`weights`)
- Optional names of the alternatives (`anames`) and the criteria (`cnames`)
- Optional metadata (`meta`)

Attributes

`anames` Names of the alternatives as tuple of string.

`cnames` Names of the criteria as tuple of string.

`criteria` Sense of optimality of every criteria

`meta` Dict-like metadata

`mtx` Alternative matrix as 2d `numpy.ndarray`.

`weights` Relative importance of the criteria or `None` if all the same

Methods

<code>plot</code>	alias of <code>skcriteria.plot.DataPlotMethods</code>
<code>raw()</code>	Return a (<code>mtx</code> , <code>criteria</code> , <code>weights</code> , <code>anames</code> , <code>cnames</code>) tuple
<code>to_str(**params)</code>	String representation of the Data object.

`anames`

Names of the alternatives as tuple of string.

`cnames`

Names of the criteria as tuple of string.

`criteria`

Sense of optimality of every criteria

`meta`

Dict-like metadata

`mtx`

Alternative matrix as 2d `numpy.ndarray`.

`plot`

alias of `skcriteria.plot.DataPlotMethods`

`raw()`

Return a (`mtx`, `criteria`, `weights`, `anames`, `cnames`) tuple

`to_str(params)`**

String representation of the Data object.

Parameters

`kwargs` : Parameters to configure `tabulate`

Returns

`str` : String representation of the Data object.

weights

Relative importance of the criteria or None if all the same

5.3.2 skcriteria.validate module

This module core functionalities for validate the data used inside scikit criteria.

- Constants that represent minimization and maximization criteria.
- Scikit-Criteria Criteria ndarray creation.
- Scikit-Criteria Data validation.

`skcriteria.validate.MIN = -1`

Int: Minimization criteria

`skcriteria.validate.MAX = 1`

Int: Maximization criteria

exception `skcriteria.validate.DataValidationError`

Bases: `ValueError`

Raised when some part of the multicriteria data (alternative matrix, criteria array or weights array) are not compatible with another part.

`skcriteria.validate.criteriaarr(criteria)`

Validate if the iterable only contains MIN (or any alias) and MAX (or any alias) values. And also always returns an ndarray representation of the iterable.

Parameters

criteria [Array-like] Iterable containing all the values to be validated by the function.

Returns

numpy.ndarray : Criteria array.

Raises

DataValidationError : if some value of the criteria array are not MIN (-1) or MAX (1)

`skcriteria.validate.validate_data(mtx, criteria, weights=None)`

Validate if the main components of the Data in scikit-criteria are compatible.

The function tests:

- The matrix (mtx) must be 2-dimensional.
- The criteria array must be a criteria array (criteriaarr function).
- The number of criteria must be the same number of columns in mtx.
- The weight array must be None or an iterable with the same length of the criteria.

Parameters

mtx [2D array-like] 2D alternative matrix, where every column (axis 0) are a criteria, and every row (axis 1) is an alternative.

criteria [Array-like] The sense of optimality of every criteria. Must has only MIN (-1) and MAX (1) values. Must has the same elements as columns has `mtx`

weights [array like or None] The importance of every criteria. Must has the same elements as columns has `mtx` or None.

Returns

mtx [numpy.ndarray] mtx representations as 2d numpy.ndarray.

criteria [numpy.ndarray] A criteria as numpy.ndarray.

weights [numpy.ndarray or None] A weights as numpy.ndarray or None (if weights is None).

Raises

DataValidationError : If the data are incompatible.

5.3.3 skcriteria.plot package

Plotting utilities

class skcriteria.plot.**DataPlotMethods** (*data*)

Bases: `object`

Data plotting accessor and method

Examples

```
>>> data.plot()
>>> data.plot.hist()
>>> data.plot.scatter('x', 'y')
>>> data.plot.radar()
```

These plotting methods can also be accessed by calling the accessor as a method with the `kind` argument: `data.plot(kind='violin')` is equivalent to `data.plot.violin()`

Methods

<code>__call__([kind])</code>	Make plots of Data using matplotlib.
<code>plot(func[, mnorm, wnorm, anames, cnames, ...])</code>	Preprocess the data and send to the plot function <i>func</i> .
<code>preprocess(data, mnorm, wnorm, anames, ...)</code>	Preprocess the data to be plotted.
<code>radar(**kwargs)</code>	Creates a radar chart, also known as a spider or star chart (http://en.wikipedia.org/wiki/Radar_chart).

bars	
box	
hist	
scatter	
to_str	
violin	

plot (*func*, *mnorm*='none', *wnorm*='none', *anames*=None, *cnames*=None, *cmap*=None, *weighted*=True, *show_criteria*=True, *min2max*=False, *push_negatives*=False, *addepsto0*=False, ***kwargs*)

Preprocess the data and send to the plot function *func*.

Parameters

func [callable] The function that make the plot. The return value of *func* are the return value of this method.

mnorm: string, callable, optional (default="none") Normalization method for the alternative matrix.

wnorm [string, callable, optional (default="none")] Normalization method for the weights array.

anames [list of str or None, optional (default=None)] The list of alternative names to be render in the plot. If is None then the alternative names of data are used.

cnames [list of str or None, optional (default=None)] The list of criteria names to be render in the plot. If is None then the criteria names of data are used.

cmap [string or None, optional (default=None)] Name of the color map to be used (<https://matplotlib.org/users/colormaps.html>)

weighted [bool, optional (default=True)] If the data must be weighted before redering.

show_criteria [bool, optional (default=True)] I the sense of optimality must be rendered in the plot.

min2max [bool, optional (default=False)] If true all the data of the minimization criteria are inverted before render.

push_negatives [bool, optional (default=False)] If True all the criterias with some value < 0 are incremented to be at least 0 in the minimun value.

addepsto0 [bool, optional (default=False)] If true add an small value to all the zeros inside the data.

kwargs : Arguments to send to *func*

Returns

The return value of *func*.

Notes

All the plot methods of Scikit-Criteria returns a matplotlib axis.

preprocess (*data*, *mnorm*, *wnorm*, *anames*, *cnames*, *cmap*, *weighted*, *show_criteria*, *min2max*, *push_negatives*, *addepsto0*)
Preprocess the data to be plotted.

Parameters

data [skcritria.core.Data] The data to be preprocessed.

mnorm: string, callable Normalization method for the alternative matrix.

wnorm [string, callable] Normalization method for the weights array.

anames [list of str or None] The list of alternative names to be render in the plot. If is None then the alternative names of data are used.

cnames [list of str or None] The list of criteria names to be render in the plot. If is None then the criteria names of data are used.

cmap [string or None] Name of the color map to be used (<https://matplotlib.org/users/colormaps.html>)

weighted [bool] If the data must be weighted before redering.

show_criteria [bool] I the sense of optimality must be rendered in the plot.

min2max [bool] If true all the data of the minimization criteria are inverted before render.

push_negatives [bool] If True all the criterias with some value < 0 are incremented to be at least 0 in the minimun value.

addepsto0 [bool] If true add an small value to all the zeros inside the data.

Returns

preprocessed_data [dict] All the data ready to be sent to a plot function

radar (**kwargs)

Creates a radar chart, also known as a spider or star chart (http://en.wikipedia.org/wiki/Radar_chart).

A radar chart is a graphical method of displaying multivariate data in the form of a two-dimensional chart of three or more quantitative variables represented on axes starting from the same point. The relative position and angle of the axes is typically uninformative.

Parameters

frame [{"polygon", "circle"}] Shape of frame surrounding axes.

ax [None or PolarAxes, optional (default=None)] Axis where the radar must be redereed. Is is None a new axis are created.

legendcol [int, optional (default=5)] How many columns must has the legend.

subplots_kwargs [dict or None, optional (default=None)] Argument to send to `matplotlib.pyplot.subplots` if axis is None. If axis is not None, subplots_kwargs are ignored.

Returns

ax [matplotlib.projections.polar.PolarAxes] Axis where the radar are rendered

See also:

[*DataPlotMethods.plot*](#) To check all the available parameters

Notes

All the parameters in `plot()` are supported; but by default this method override some default values:

- `show_criteria=False`
- `min2max=True`
- `push_negatives=True`
- `addepsto0=True`

5.3.4 `skcriteria.madm` package

This package contains several implementations of Multi criteria decision analyssys methods (MADM) methods.

Conflicting criteria are typical in evaluating options: cost or price is usually one of the main criteria, and some measure of quality is typically another criterion, easily in conflict with the cost. In purchasing a car, cost, comfort, safety, and fuel economy may be some of the main criteria we consider – it is unusual that the cheapest car is the most comfortable and the safest one. In portfolio management, we are interested in getting high returns but at the same time reducing our risks, but the stocks that have the potential of bringing high returns typically also carry high risks of losing money. In a service industry, customer satisfaction and the cost of providing service are fundamental conflicting criteria.

Modules:

`skcriteria.madm.simple module`

Simplests method of multi-criteria

```
class skcriteria.madm.simple.WeightedSum (mnorm='sum', wnorm='sum')
    Bases: skcriteria.madm._dmaker.DecisionMaker
```

The weighted sum model (WSM) is the best known and simplest multi-criteria decision analysis for evaluating a number of alternatives in terms of a number of decision criteria. It is very important to state here that it is applicable only when all the data are expressed in exactly the same unit. If this is not the case, then the final result is equivalent to “adding apples and oranges.” To avoid this problem a previous normalization step is necessary.

In general, suppose that a given MCDA problem is defined on m alternatives and n decision criteria. Furthermore, let us assume that all the criteria are benefit criteria, that is, the higher the values are, the better it is. Next suppose that w_j denotes the relative weight of importance of the criterion C_j and a_{ij} is the performance value of alternative A_i when it is evaluated in terms of criterion C_j . Then, the total (i.e., when all the criteria are considered simultaneously) importance of alternative A_i , denoted as $A_i^{WSM-score}$, is defined as follows:

$$A_i^{WSM-score} = \sum_{j=1}^n w_j a_{ij}, \text{ for } i = 1, 2, 3, \dots, m$$

For the maximization case, the best alternative is the one that yields the maximum total performance value.

Parameters

mnorm [string, callable, optional (default="sum")] Normalization method for the alternative matrix.

wnorm [string, callable, optional (default="sum")] Normalization method for the weights array.

Returns

Decision [skcriteria.madm.Decision] With values:

- **kernel_**: None
- **rank_**: A ranking (start at 1) where the i-nth element represent the position of the i-nth alternative.
- **best_alternative_**: The index of the best alternative.
- **alpha_solution_**: True
- **beta_solution_**: False
- **gamma_solution_**: True
- **e_**: Particular data created by this method.
 - **e_.points**: Array where the i-nth element represent the importance of the i-nth alternative.

Notes

If some criteria is for minimization, this implementation calculates the inverse.

References

[1], [2], [3]

Attributes

mnorm Normalization function for the alternative matrix.

wnorm Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata)</code>	Execute the multi-criteria method.

```
doc_inherit = functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma
```

```
solve(ndata)
```

Execute the multi-criteria method.

Parameters

data [`skcriteria.Data`] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

```
class skcriteria.madm.simple.WeightedProduct (mnorm='sum', wnorm='sum')
```

```
Bases: skcriteria.madm._dmaker.DecisionMaker
```

The weighted product model (WPM) is a popular multi-criteria decision analysis method. It is similar to the weighted sum model. The main difference is that instead of addition in the main mathematical operation now there is multiplication.

In general, suppose that a given MCDA problem is defined on m alternatives and n decision criteria. Furthermore, let us assume that all the criteria are benefit criteria, that is, the higher the values are, the better it is. Next suppose that w_j denotes the relative weight of importance of the criterion C_j and a_{ij} is the performance value of alternative A_i when it is evaluated in terms of criterion C_j . Then, the total (i.e., when all the criteria are considered simultaneously) importance of alternative A_i , denoted as $A_i^{WPM-score}$, is defined as follows:

$$A_i^{WPM-score} = \prod_{j=1}^n a_{ij}^{w_j}, \text{ for } i = 1, 2, 3, \dots, m$$

To avoid underflow, instead the multiplication of the values we add the logarithms of the values; so $A_i^{WPM-score}$, is finally defined as:

$$A_i^{WPM-score} = \sum_{j=1}^n w_j \log(a_{ij}), \text{ for } i = 1, 2, 3, \dots, m$$

For the maximization case, the best alternative is the one that yields the maximum total performance value.

Parameters

mnorm [string, callable, optional (default="sum")] Normalization method for the alternative matrix.

wnorm [string, callable, optional (default="sum")] Normalization method for the weights array.

Returns

Decision [`skcriteria.madm.Decision`] With values:

- **kernel_**: None
- **rank_**: A ranking (start at 1) where the i-nth element represent the position of the i-nth alternative.

- **best_alternative_**: The index of the best alternative.
- **alpha_solution_**: True
- **beta_solution_**: False
- **gamma_solution_**: True
- **e_**: Particular data created by this method.
 - **e_.points**: Array where the i-nth element represent the importance of the i-nth alternative.

Notes

The implementation works as follow:

- If we have some values of any criteria < 0 in the alternative-matrix we add the minimum value of this criteria to all the criteria.
- If we have some 0 in some criteria all the criteria is incremented by 1.
- If some criteria is for minimization, this implementation calculates the inverse.
- Instead the multiplication of the values we add the logarithms of the values to avoid underflow.

References

[1], [2], [3]

Attributes

- mnorm** Normalization function for the alternative matrix.
- wnorm** Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata)</code>	Execute the multi-criteria method.

```
doc_inherit = functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma
```

`preprocess (data)`

Normalize the alternative matrix and weight vector.

Creates a new instance of data by aplying the normalization function to the alternative matrix and the weights vector contained inside the given data.

Parameters

data [`skcriteria.Data`] A data to be Preprocessed

Returns

skcriteria.Data A new instance of data with the `mtx` attributes normalized with `mnorm` and `weights` normalized with `wnorm`. `anames` and `cnames` are preseved

solve (*ndata*)

Execute the multi-criteria method.

Parameters

data [`skcriteria.Data`] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

skcriteria.madm.closeness module

Methods based on an aggregating function representing “closeness to the ideal”.

class `skcriteria.madm.closeness.TOPSIS` (*mnorm*='vector', *wnorm*='sum')

Bases: `skcriteria.madm._dmaker.DecisionMaker`

TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the ideal solution and the longest euclidean distance from the worst solution.

An assumption of TOPSIS is that the criteria are monotonically increasing or decreasing, and also allow trade-offs between criteria, where a poor result in one criterion can be negated by a good result in another criterion.

Parameters

mnorm [string, callable, optional (default="vector")] Normalization method for the alternative matrix.

wnorm [string, callable, optional (default="sum")] Normalization method for the weights array.

Returns

Decision [`skcriteria.madm.Decision`] With values:

- **kernel_**: None
- **rank_**: A ranking (start at 1) where the i-nth element represent the position of the i-nth alternative.
- **best_alternative_**: The index of the best alternative.
- **alpha_solution_**: True
- **beta_solution_**: False
- **gamma_solution_**: True
- **e_**: Particular data created by this method.
 - **e_.closeness**: Array where the i-nth element represent the closenees of the i-nth alternative to ideal and worst solution.

References

[1], [2], [3]

Attributes

mnorm Normalization function for the alternative matrix.

wnorm Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata)</code>	Execute the multi-criteria method.

`doc_inherit = functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma`

`solve` (*ndata*)

Execute the multi-criteria method.

Parameters

data [`skcriteria.Data`] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

`skcriteria.madm.moora` module

Implementation of a family of Multi-objective optimization on the basis of ratio analysis (MOORA) methods.

class `skcriteria.madm.moora.RatioMOORA` (*wnorm*='sum')

Bases: `skcriteria.madm._dmaker.DecisionMaker`

The method refers to a matrix of responses of alternatives to objectives, to which ratios are applied.

In MOORA the set of ratios (by default) has the square roots of the sum of squared responses as denominators.

$$\bar{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^m X_{ij}^2}}$$

These ratios, as dimensionless, seem to be the best choice among different ratios. These dimensionless ratios, situated between zero and one, are added in the case of maximization or subtracted in case of minimization:

$$Ny_i = \sum_{i=1}^g Nx_{ij} - \sum_{i=1}^{g+1} Nx_{ij}$$

with: $i = 1, 2, \dots, g$ for the objectives to be maximized, $i = g+1, g+2, \dots, n$ for the objectives to be minimized.

Finally, all alternatives are ranked, according to the obtained ratios.

Parameters

wnorm [string, callable, optional (default="sum")] Normalization method for the weights array.

Returns

Decision [`skcriteria.madm.Decision`] With values:

- **kernel_**: None
- **rank_**: A ranking (start at 1) where the i-nth element represent the position of the i-nth alternative.
- **best_alternative_**: The index of the best alternative.
- **alpha_solution_**: True

- **beta_solution_**: False
- **gamma_solution_**: True
- **e_**: Particular data created by this method.
 - **e_.points**: Array where the i-nth element represent the importance of the i-nth alternative.

References

[1]

Attributes

- mnorm** Normalization function for the alternative matrix.
- wnorm** Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata)</code>	Execute the multi-criteria method.

as_dict()
Create a simply `dict` representation of the object.

Notes

`x.as_dict != dict(x)`

doc_inherit = `functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma`

solve (*ndata*)
Execute the multi-criteria method.

Parameters

data [`skcriteria.Data`] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

class `skcriteria.madm.moora.RefPointMOORA` (*wnorm*='sum')
Bases: `skcriteria.madm._dmaker.DecisionMaker`

Rank the alternatives from a reference point selected with the Min-Max Metric of Tchebycheff.

$$\min_j \{ \max_i |r_i - x_{ij}^*| \}$$

This reference point theory starts from the already normalized ratios as defined in the MOORA method, namely formula:

$$\bar{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^m X_{ij}^2}}$$

Preference is given to a reference point possessing as co-ordinates the dominating co-ordinates per attribute of the candidate alternatives and which is designated as the *Maximal Objective Reference Point*. This approach is called realistic and non-subjective as the co-ordinates, which are selected for the reference point, are realized in one of the candidate alternatives.

Parameters

wnorm [string, callable, optional (default="sum")] Normalization method for the weights array.

Returns

Decision [`skcriteria.madm.Decision`] With values:

- **kernel_**: None
- **rank_**: A ranking (start at 1) where the i-nth element represent the position of the i-nth alternative.
- **best_alternative_**: The index of the best alternative.
- **alpha_solution_**: True
- **beta_solution_**: False
- **gamma_solution_**: True
- **e_**: Particular data created by this method.
- **e_.points**: array where the i-nth element represent the closenees of the i-nth alternative to a reference point based on the *Min-Max Metric of Tchebycheff*.

References

[1], [2]

Attributes

mnorm Normalization function for the alternative matrix.

wnorm Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata)</code>	Execute the multi-criteria method.

`as_dict()`

Create a simply `dict` representation of the object.

Notes

```
x.as_dict != dict(x)
```

```
doc_inherit = functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma
```

`solve(ndata)`

Execute the multi-criteria method.

Parameters

data [skcriteria.Data] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

class skcriteria.madm.moora.FMFMOORA (wnorm='sum')

Bases: skcriteria.madm._dmaker.DecisionMaker

Full Multiplicative Form, a method that is non-linear, non-additive, does not use weights and does not require normalization.

To combine a minimization and maximization of different criteria in the same problem all the method uses the formula:

$$U'_j = \frac{\prod_{g=1}^i x_{gi}}{\prod_{k=i+1}^n x_{kj}}$$

Where j = the number of alternatives; i = the number of objectives to be maximized; ni = the number of objectives to be minimize; and U'_j : the utility of alternative j with objectives to be maximized and objectives to be minimized.

To avoid underflow, instead the multiplication of the values we add the logarithms of the values; so U'_j ;, is finally defined as:

$$U'_j = \sum_{g=1}^i \log(x_{gi}) - \sum_{k=i+1}^n \log(x_{kj})$$

Parameters

wnorm [string, callable, optional (default="sum")] Normalization method for the weights array.

Returns

Decision [skcriteria.madm.Decision] With values:

- **kernel_**: None
- **rank_**: A ranking (start at 1) where the i-nth element represent the position of the i-nth alternative.
- **best_alternative_**: The index of the best alternative.
- **alpha_solution_**: True
- **beta_solution_**: False
- **gamma_solution_**: True
- **e_**: Particular data created by this method.
 - **e_.points**: Array where the i-nth element represent the importance of the i-nth alternative.

Notes

The implementation works as follow:

- Before determine U_j the values are normalized by the ratio sugested by MOORA.

$$\overline{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^m X_{ij}^2}}$$

- If we have some values of any criteria < 0 in the alternative-matrix we add the minimum value of this criteria to all the criteria.
- If we have some 0 in some criteria all the criteria is incremented by 1.
- If some criteria is for minimization, this implementation calculates the inverse.
- Instead the multiplication of the values we add the logarithms of the values to avoid underflow.

References

[1]

Attributes

- mnorm** Normalization function for the alternative matrix.
- wnorm** Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata)</code>	Execute the multi-criteria method.

as_dict()
Create a simply `dict` representation of the object.

Notes

```
x.as_dict != dict(x)
```

```
doc_inherit = functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma
```

preprocess (*data*)
Normalize the alternative matrix and weight vector.

Creates a new instance of data by aplying the normalization function to the alternative matrix and the weights vector contained inside the given data.

Parameters

data [`skcriteria.Data`] A data to be Preprocessed

Returns

skcriteria.Data A new instance of data with the `mtx` attributes normalized with `mnorm` and `weights` normalized with `wnorm`. `anames` and `cnames` are preseved

solve (*ndata*)
Execute the multi-criteria method.

Parameters

data [`skcriteria.Data`] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

class `skcriteria.madm.moora.MultiMOORA`

Bases: `skcriteria.madm._dmaker.DecisionMaker`

MULTIMOORA is composed of the ranking resulting of applying the methods, RatioMOORA, RefPointMOORA and FMFMOORA.

These three methods represent all possible methods with dimensionless measures in multi-objective optimization and one can not argue that one method is better than or is of more importance than the others; so for determining the final ranking the implementation maximizes how many times an alternative i dominates and alternative j .

Returns

Decision [`skcriteria.madm.Decision`] With values:

- **kernel_**: None
- **rank_**: A ranking (start at 1) where the i -nth element represents the position of the i -nth alternative.
- **best_alternative_**: The index of the best alternative.
- **alpha_solution_**: True
- **beta_solution_**: False
- **gamma_solution_**: True
- **e_**: Particular data created by this method.
- **e_.rank_mtx**: 2x3 Array where the first column is the RatioMOORA ranking, the second one the RefPointMOORA ranking and the last the FMFMOORA ranking.

Notes

The implementation works as follows:

- Before determining U_j the values are normalized by the ratio suggested by MOORA.

$$\overline{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^m X_{ij}^2}}$$

- If we have some values of any criteria < 0 in the alternative-matrix we add the minimum value of this criteria to all the criteria.
- If we have some 0 in some criteria all the criteria is incremented by 1.
- If some criteria is for minimization, this implementation calculates the inverse.
- Instead of the multiplication of the values we add the logarithms of the values to avoid underflow.
- For determining the final ranking the implementation maximizes how many times an alternative i dominates and alternative j .

References

[1]

Attributes

- mnorm** Normalization function for the alternative matrix.
- wnorm** Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata)</code>	Execute the multi-criteria method.

as_dict ()
Create a simply `dict` representation of the object.

Notes

```
x.as_dict != dict(x)
```

```
doc_inherit = functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma
```

preprocess (data)
Normalize the alternative matrix and weight vector.

Creates a new instance of data by applying the normalization function to the alternative matrix and the weights vector contained inside the given data.

Parameters

data [`skcriteria.Data`] A data to be Preprocessed

Returns

skcriteria.Data A new instance of data with the `mtx` attributes normalized with `mnorm` and `weights` normalized with `wnorm`. `anames` and `cnames` are preseved

solve (ndata)
Execute the multi-criteria method.

Parameters

data [`skcriteria.Data`] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

skcriteria.madm.electre.py module

ELECTRE is a family of multi-criteria decision analysis methods that originated in Europe in the mid-1960s. The acronym ELECTRE stands for: ELimination Et Choix Traduisant la REalité (ELimination and Choice Expressing REality).

Usually the Electre Methods are used to discard some alternatives to the problem, which are unacceptable. After that we can use another MCDA to select the best one. The Advantage of using the Electre Methods before is that we can apply another MCDA with a restricted set of alternatives saving much time.

```
class skcriteria.madm.electre.ELECTRE1 (p=0.65, q=0.35, mnorm='sum', wnorm='sum',
                                         njobs=None)
    Bases: skcriteria.madm._dmaker.DecisionMaker
```

The ELECTRE I model find the kernel solution in a situation where true criteria and restricted outranking relations are given.

That is, ELECTRE I cannot derive the ranking of alternatives but the kernel set. In ELECTRE I, two indices called the concordance index and the discordance index are used to measure the relations between objects.

Parameters

- p** [float, optional (default=0.65)] Concordance threshold. Threshold of how much one alternative is at least as good as another to be significative.
- q** [float, optional (default=0.35)] Discordance threshold. Threshold of how much the degree one alternative is strictly preferred to another to be significative.
- mnorm** [string, callable, optional (default="sum")] Normalization method for the alternative matrix.
- wnorm** [string, callable, optional (default="sum")] Normalization method for the weights array.
- njobs** [int, default=None] How many cores to use to solve the linear programs and the second method. By default all the availables cores are used.

Returns

Decision [`skcriteria.madm.Decision`] With values:

- **kernel_**: Array with the indexes of the alternatives in the kernel.
- **rank_**: None
- **best_alternative_**: None
- **alpha_solution_**: False
- **beta_solution_**: True
- **gamma_solution_**: False
- **e_**: Particular data created by this method.
 - **e_.outrank**: numpy.ndarray of bool The outranking matrix of superation. If the element[i][j] is True The alternative i outrank the alternative j.
 - **e_.mtx_concordance**: numpy.ndarray The concordance indexes matrix where the element[i][j] measures how much the alternative i is at least as good as j.
 - **e_.mtx_discordance**: numpy.ndarray The discordance indexes matrix where the element[i][j] measures the degree to which the alternative i is strictly preferred to j.
 - **e_.p**: float Concordance index threshold.
 - **e_.q**: float Discordance index threshold.

References

[1], [2], [3]

Attributes

- mnorm** Normalization function for the alternative matrix.
- njobs** How many cores to use to solve the linear programs and the second method.
- p** Concordance threshold.
- q** Discordance threshold.
- wnorm** Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata)</code>	Execute the multi-criteria method.

as_dict ()
Create a simply `dict` representation of the object.

Notes

```
x.as_dict != dict(x)
```

```
doc_inherit = functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma
```

njobs

How many cores to use to solve the linear programs and the second method. By default all the availables cores are used.

p

Concordance threshold. Threshold of how much one alternative is at least as good as another to be significative.

q

Discordance threshold. Threshold of how much the degree one alternative is strictly preferred to another to be significative.

solve (ndata)

Execute the multi-criteria method.

Parameters

data [`skcriteria.Data`] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

skcriteria.madm.simus module

SIMUS (Sequential Interactive Model for Urban Systems) Method

```
class skcriteria.madm.simus.SIMUS (mnorm='none', wnorm='none', rank_by=1, solver='pulp',
                                   njobs=None)
```

Bases: `skcriteria.madm._dmaker.DecisionMaker`

SIMUS (Sequential Interactive Model for Urban Systems) developed by Nolberto Munier (2011) is a tool to aid decision-making problems with multiple objectives. The method solves successive scenarios formulated as linear programs. For each scenario, the decision-maker must choose the criterion to be considered objective while the remaining restrictions constitute the constraints system that the projects are subject to. In each case, if there is a feasible solution that is optimum, it is recorded in a matrix of efficient results. Then, from this matrix two rankings allow the decision maker to compare results obtained by different procedures. The first ranking is obtained through a linear weighting of each column by a factor - equivalent of establishing a weight - and that measures the participation of the corresponding project. In the second ranking, the method uses dominance and subordinate relationships between projects, concepts from the French school of MCDM.

Parameters

mnorm [string, callable, optional (default="none")] Normalization method for the alternative matrix.

wnorm [string, callable, optional (default="none")] Normalization method for the weights array.

rank_by [1 or 2 (default=1)] Wich of the two methods are used to calculate the ranking. The two methods are executed always.

solver [str, default="pulp"] Which solver to use to solve the undelying linear programs. The full list are available in *skcriteria.utils.lp.SOLVERS*

njobs [int, default=None] How many cores to use to solve the linear programs and the second method. By default all the availables cores are used.

Returns

Decision [*skcriteria.madm.Decision*] With values:

- **kernel_**: None
- **rank_**: A ranking (start at 1) where the i-nth element represent the position of the i-nth alternative.
- **best_alternative_**: The index of the best alternative.
- **alpha_solution_**: True
- **beta_solution_**: False
- **gamma_solution_**: True
- **e_**: Particular data created by this method.
 - **rank_by**: 1 or 2. Wich of the two methods are used to calculate the ranking. Esentially if the rank is calculated with *e_.points1* or *e_.points2*
 - **solver**: With solver was used for the underlying linear problems.
 - **stages**: The underlying linear problems.
 - **stage_results**: The values of the variables of the linear problems as a n-dimensional array. When th *n-th* row represent the result values of the variables for the *n-th* stage.
 - **points1**: The points of every alternative obtained by the first method.
 - **points2**: The points of every alternative obtained by the first method.
 - **tita_j_p**: 2nd. method domination.
 - **tita_j_d**: 2nd. method subordination.
 - **doms**: Total dominance matrix of the 2nd. method.
 - **dom_by_crit**: Dominance by criteria of the 2nd method.

References

[1], [2]

Attributes

mnorm Normalization function for the alternative matrix.

njobs How many cores to use to solve the linear programs and the second method.

solver Which solver to use to solve the undelying linear programs.

wnorm Normalization function for the weights vector.

Methods

<code>as_dict()</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.
<code>doc_inherit</code>	
<code>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(data)</code>	Normalize the alternative matrix and weight vector.
<code>solve(ndata, b)</code>	Execute the multi-criteria method.

```
doc_inherit = functools.partial(<function _doc_inherit>, (<class 'skcriteria.madm._dma
```

njobs

How many cores to use to solve the linear programs and the second method. By default all the availables cores are used.

solve(ndata, b)

Execute the multi-criteria method.

Parameters

data [`skcriteria.Data`] Preprocessed Data.

Returns

object object or tuple of objects with the raw result data.

solver

Which solver to use to solve the undelying linear programs. The full list are available in `skcriteria.utils.lp.SOLVERS`

5.3.5 skcriteria.weights package

This package contains utilities to make some treatments to weights

Modules:

skcriteria.weights.equal module

This module contains functions for calculate and compare ranks (ordinal series)

skcriteria.weights.divergence module

Estimate the weights of every criteria bye some kind of divergence index

skcriteria.weights.critic module

This module contains functions for calculate and compare ranks (ordinal series)

5.4 Indices and tables

- `genindex`
- `modindex`
- `search`

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