
Scikit-Criteria Documentation

Release 0.2.1

Juan BC

Aug 26, 2017

Contents

1	Support	3
2	License	5
3	Citation	7
4	Contents	9
4.1	Installing scikit-criteria	9
4.1.1	Third-party Distributions	9
4.2	Tutorial	9
4.2.1	Quick Start	10
4.3	Reference	18
4.3.1	Core Functionalities	19
4.3.2	skcriteria.madm package	19
4.4	Indices and tables	33
	Bibliography	35
	Python Module Index	37

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

Support

- **You can contact me at:** jbc.develop@gmail.com
- **Code Repository & Issues:** <https://github.com/leliel12/scikit-criteria>

CHAPTER 2

License

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

This license allows unlimited redistribution for any purpose as long as its copyright notices and the license's disclaimers of warranty are maintained.

If you are using Scikit-Criteria in your research, please cite:

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>

Installing scikit-criteria

The easiest way to install scikit-learn 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.

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 scikit-learn, in addition to a large set of scientific python library for Windows, Mac OSX and Linux.

Tutorial

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

Contents:

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` contants from `scikit-criteria`:

```
In [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

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

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

The `criteria` vector must be a **1D array-like** whit the same number of elements than columns has the alternative matrix (`mtx`) where every component represent the optimal sense of every criteria.

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

```
Out[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 contantes usage makes the code more readable.

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

```
In [5]: data = Data(mtx, criteria)
        data
```

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

As you can see the output of the `Data` structure is much more friendly as 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), *confort* (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 row the `mtx` has), and `cnames` the criteria names (with the same number of elements as columns has the `mtx`)

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

```
Out [6]: ALT./CRIT.   autonomy (max)   confort (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 confort 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 has your alternative matrix (number of columns)

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

```
Out [7]: ALT./CRIT.   autonomy (max) W.0.5   confort (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 access to the different parts of your data, simply by typing `data.<your-parameter-name>` for example:

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

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

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

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

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

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

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

```
Out [11]: (('car 0', 'car 1'), ('autonomy', 'confort', '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`

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

```

data
      cnames=data.cnames)
Out[12]: ALT./CRIT.      autonomy (max) W.0.5      confort (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.

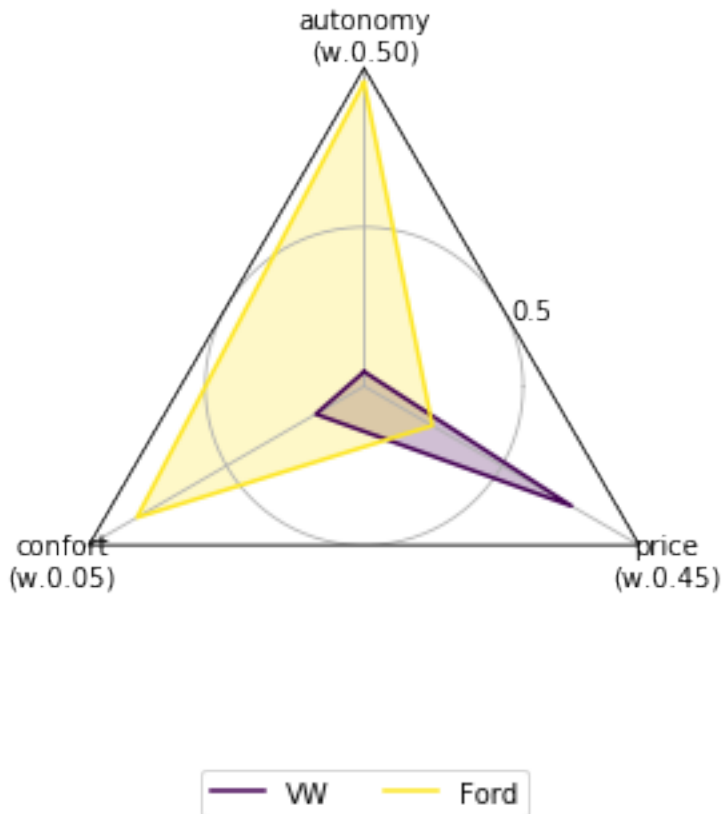
Plotting

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`).

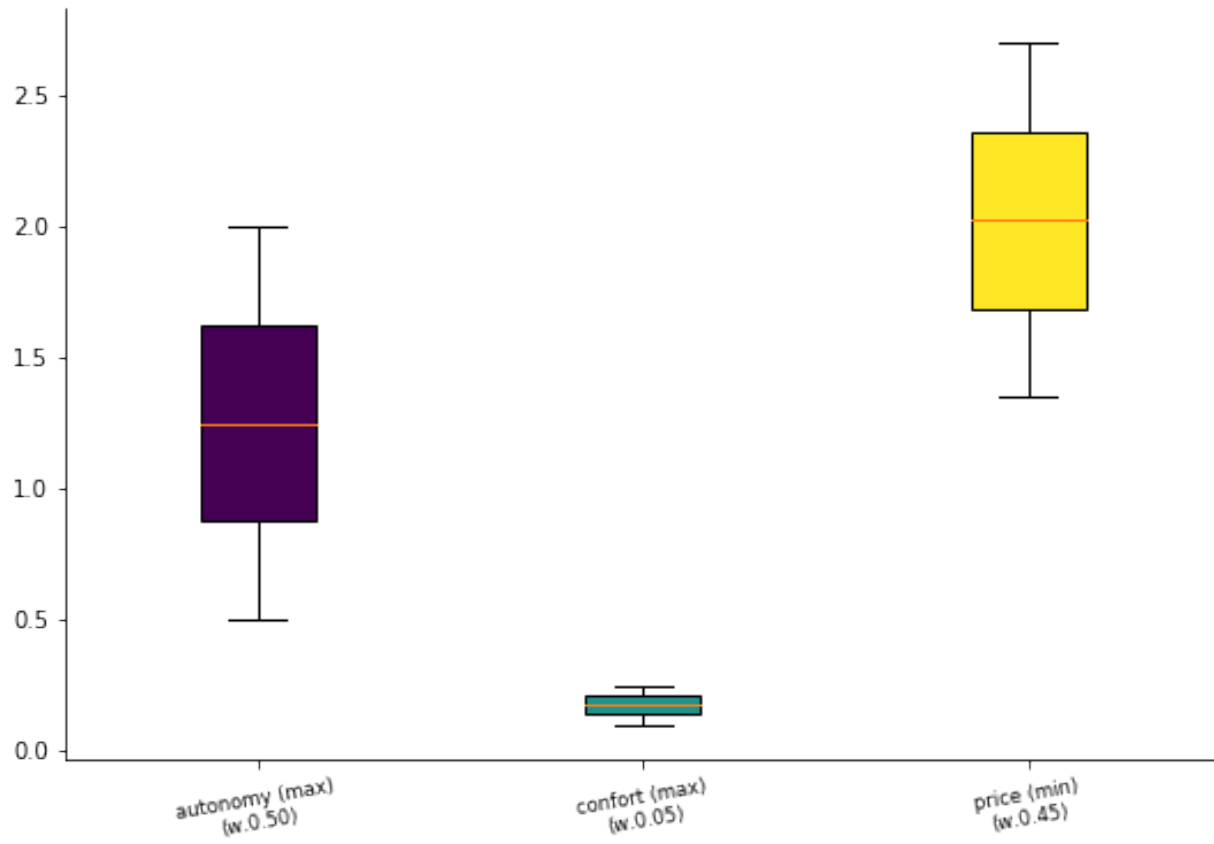
The default scikit criteria uses the Radar Plot to visualize all the data. Take in account that the radar plot by default converts all the minimization criteria to maximization and pushes all the values to be greater than 1 (obviously all these options can be overridden).

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



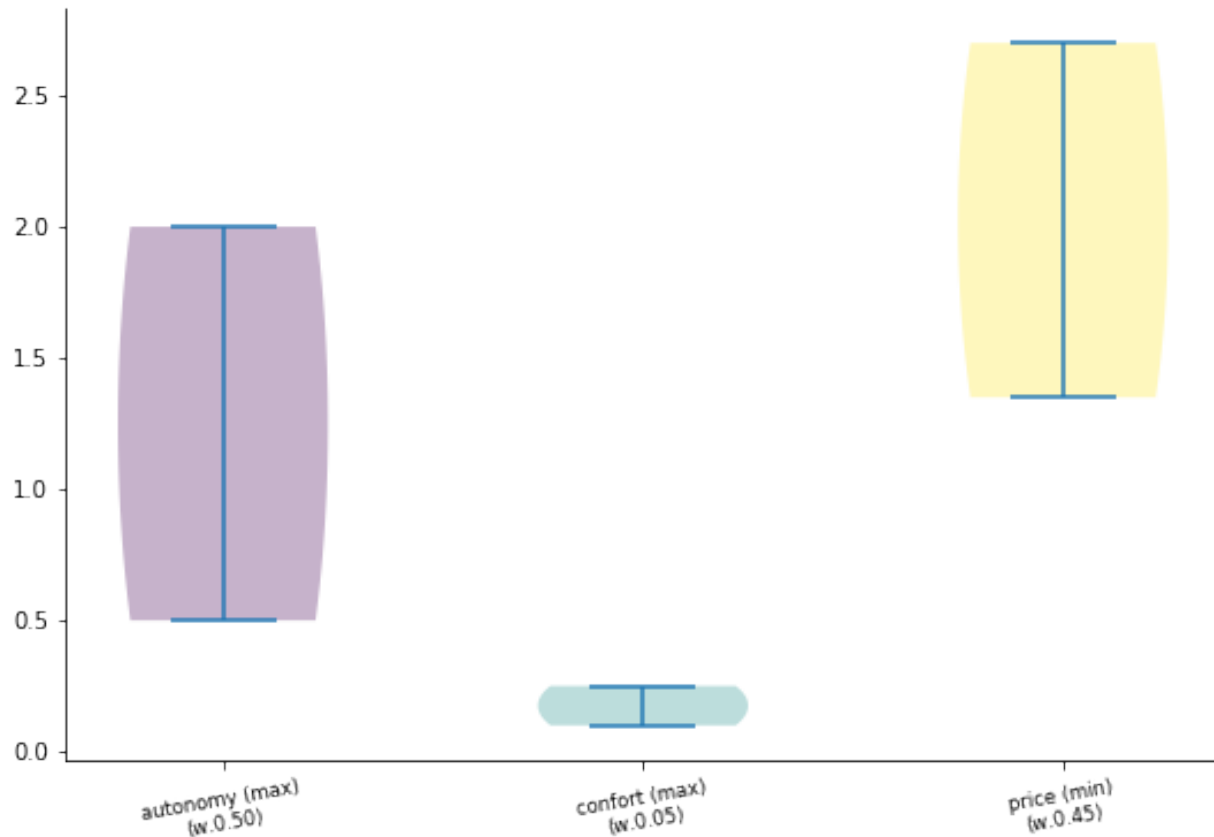
You can accessing the different plot by passing as first parameter the name of the plot

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



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

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

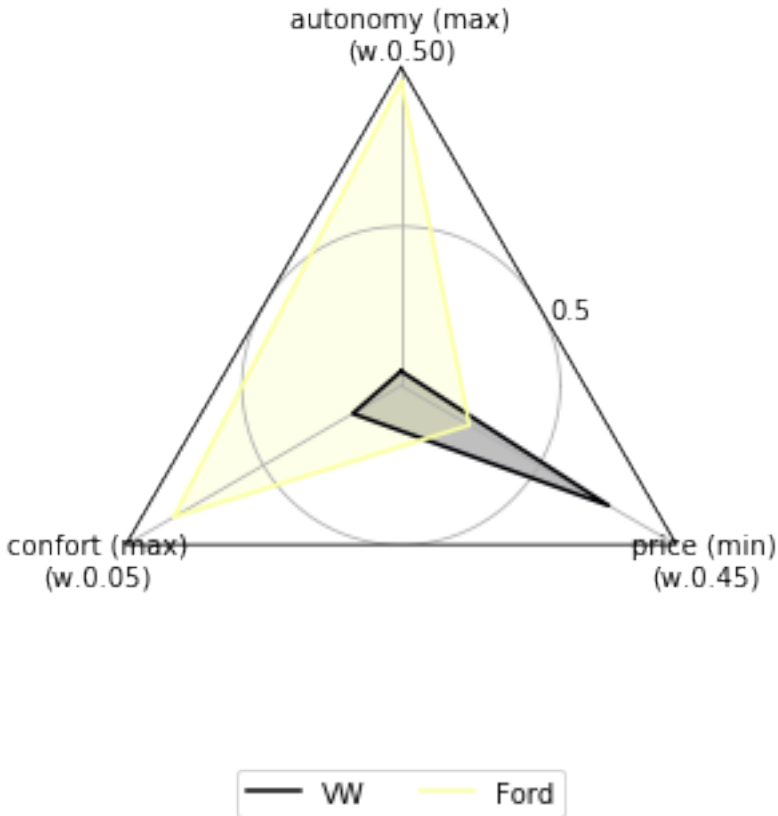


Every plot has their own set of parameters, but at last every one can receive:

- `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:

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



Using this data to feed some MCDA methods

Let's rank our toy data by Weighted Sum Model, Weighted Product Model and TOPSIS

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

First you need to create the decision maker.

Most of methods accepts as hyper parameters (parameters of the to configure the method), the method of normalization of the alternative matrix (divided by the sum in Weighted Sum and Weighted Product, and the `vector` normalization on `Topsis`) and the method to normalize the weight array (normally `sum`); But complex methods has more.

Weighted Sum Model:

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

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

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

```
Out[19]: WeightedSum (mnorm=sum, wnorm=sum) - Solution:
ALT./CRIT.   autonomy (max) W.0.5   confort (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

```
In [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: 1.46428571429
FORD: 1.11071428571
```

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

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

```
Extra(points)
```

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

Also you can access the type of the solution

```
In [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)

```
In [23]: dec.rank_
Out[23]: array([1, 2])
```

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

```
In [24]: dec.best_alternative_, data.anames[dec.best_alternative_]
Out[24]: (0, 'VW')
```

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

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

```
None
```

Weighted Product Model

```
In [26]: dm = simple.WeightedProduct()
         dm
Out[26]: <WeightedProduct (mnorm=sum, wnorm=sum)>
In [27]: dec = dm.decide(data)
         dec
```

```
Out [27]: WeightedProduct (mnorm=sum, wnorm=sum) - Solution:
```

ALT./CRIT.	autonomy (max) W.0.5	confort (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)

```
In [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: 2.05953437557
FORD: 2.0796708665
```

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

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

```
Extra(points)
```

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

As you note the points are different, this is because internally to avoid `undeflows` Scikit-Criteria uses a sums of logarithms instead products. So let's check

```
In [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: -0.161983839762
FORD: 0.0234796582871
```

TOPSIS

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

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

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

```
Out [32]: TOPSIS (mnorm=vector, wnorm=sum) - Solution:
```

ALT./CRIT.	autonomy (max) W.0.5	confort (max) W.0.05	price (min) W.0.45	Rank
VW	1	2	3	2
Ford	4	5	6	1

The TOPSIS add more information into the decision object.

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

```
Extra(anti_ideal, 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 matrix to `sum` (divide every value by the sum of their criteria) and check the result:

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

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

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

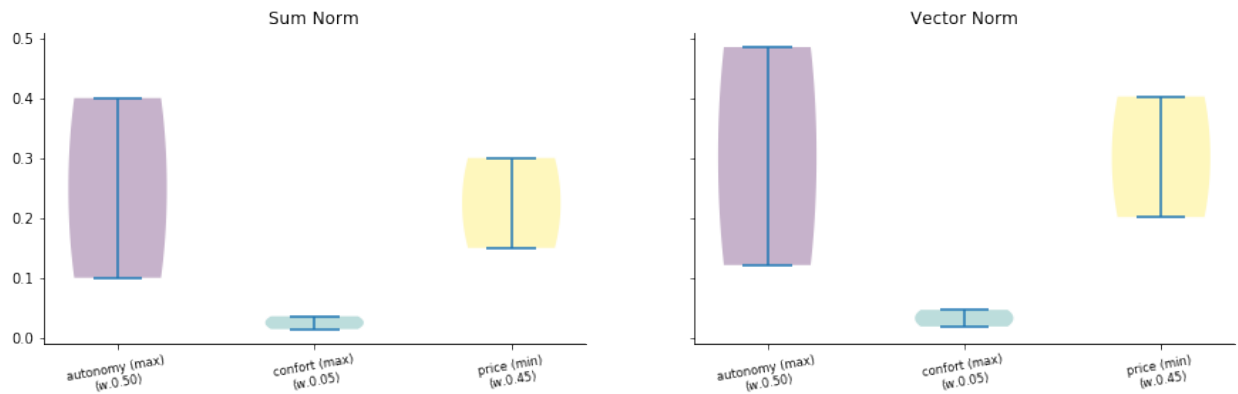
```
Out[35]: TOPSIS (mnorm=sum, wnorm=sum) - Solution:
-----
ALT./CRIT.  autonomy (max) W.0.5  confort (max) W.0.05  price (min) W.0.45  Rank
-----
          VW                1                2                3                2
          Ford                4                5                6      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

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

```
In [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)
```



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](#)

Reference

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

Core Functionalities

Module containing the basic functionality of scikit-criteria including:

- Scikit-Criteria Data representation.
- Scikit-Criteria Criteria representation.
- Scikit-Criteria Data validation.

`skcriteria.core.criteriarr` (*criteria*)

Validate if the iterable only contains MIN (-1) and MAX (1) criteria

`skcriteria.core.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 (*criteriarr* 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.

Returns

- A *mtx* as 2d `numpy.ndarray`.
- A criteria as `numpy.ndarray`.
- A weights as `numpy.ndarray` or None (if weights is None).

`skcriteria.madm` package

This package contains several implementations of Multi criteria decision analysis 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

Simplest method of multi-criteria

class `skcriteria.madm.simple.WeightedSum` (*mnorm='u'sum', wnorm='u'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

[R2328], [R2428], [R2528]

Attributes

<code>mnorm</code>	Normalization function for the alternative matrix.
<code>wnorm</code>	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>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(*args, **kwargs)</code>	Execute the multi-criteria method.

solve (*args, **kwargs)

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=u'sum', wnorm=u'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

[R2631], [R2731], [R2831]

Attributes

<code>mnorm</code>	Normalization function for the alternative matrix.
<code>wnorm</code>	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>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(*args, **kwargs)</code>	Normalize the alternative matrix and weight vector.
<code>solve(*args, **kwargs)</code>	Execute the multi-criteria method.

preprocess (*args, **kwargs)

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 (*args, **kwargs)

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=u'vector', wnorm=u'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

[R13], [R23], [R33]

Attributes

<code>mnorm</code>	Normalization function for the alternative matrix.
<code>wnorm</code>	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>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(*args, **kwargs)</code>	Execute the multi-criteria method.

solve (*args, **kwargs)
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=u'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

[R1317]

Attributes

<code>mnorm</code>	Normalization function for the alternative matrix.
<code>wnorm</code>	Normalization function for the weights vector.

Methods

<code>as_dict(*args, **kwargs)</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>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(*args, **kwargs)</code>	Execute the multi-criteria method.

as_dict (**args, **kwargs*)
Create a simply `dict` representation of the object.

Notes

`x.as_dict != dict(x)`

solve (**args, **kwargs*)
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=u'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

[R1418], [R1518]

Attributes

<code>mnorm</code>	Normalization function for the alternative matrix.
<code>wnorm</code>	Normalization function for the weights vector.

Methods

<code>as_dict(*args, **kwargs)</code>	Create a simply <code>dict</code> representation of the object.
<code>decide(data[, criteria, weights])</code>	Execute the Solver over the given data.

Continued on next page

Table 4.10 – continued from previous page

<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(*args, **kwargs)</code>	Execute the multi-criteria method.

`as_dict(*args, **kwargs)`

Create a simply `dict` representation of the object.

Notes

`x.as_dict != dict(x)`

`solve(*args, **kwargs)`

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=u'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 suggested by MOORA.

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

- 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

[R1620]

Attributes

<code>mnorm</code>	Normalization function for the alternative matrix.
<code>wnorm</code>	Normalization function for the weights vector.

Methods

<code>as_dict(*args, **kwargs)</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>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(*args, **kwargs)</code>	Normalize the alternative matrix and weight vector.
<code>solve(*args, **kwargs)</code>	Execute the multi-criteria method.

`as_dict (*args, **kwargs)`
 Create a simply `dict` representation of the object.

Notes

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

preprocess (*args, **kwargs)

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 (*args, **kwargs)

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.mooraa.MultiMOORA`

Bases: `skcriteria.madm._dmaker.DecisionMaker`

MULTIMOORA is compose the ranking resulting of aplying 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 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_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 follow:

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

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

- 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.
- For determining the final ranking the implementation maximizes how many times an alternative i dominates and alternative j .

References

[R1721]

Attributes

<code>mnorm</code>	Normalization function for the alternative matrix.
<code>wnorm</code>	Normalization function for the weights vector.

Methods

<code>as_dict(*args, **kwargs)</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>make_result(data, kernel, rank, extra)</code>	Create a new <code>skcriteria.madm.Decision</code>
<code>preprocess(*args, **kwargs)</code>	Normalize the alternative matrix and weight vector.
<code>solve(*args, **kwargs)</code>	Execute the multi-criteria method.

`as_dict (*args, **kwargs)`
Create a simply `dict` representation of the object.

Notes

`x.as_dict != dict(x)`

`preprocess (*args, **kwargs)`
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 (**args*, ***kwargs*)

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=u'sum'*, *wnorm=u'sum'*)

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 significantive.

`q` : float, optional (default=0.35)

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

`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_`: Array with the indexes of the alternatives in he kernel.

- **rank_**: None
- **best_alternative_**: None
- **alpha_solution_**: False
- **beta_solution_**: True
- **gamma_solution_**: False
- **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.
 - **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

[R79], [R89], [R99]

Attributes

<code>mnorm</code>	Normalization function for the alternative matrix.
<code>p</code>	Concordance threshold.
<code>q</code>	Discordance threshold.
<code>wnorm</code>	Normalization function for the weights vector.

Methods

<code>as_dict(*args, **kwargs)</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>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(*args, **kwargs)</code>	Execute the multi-criteria method.

as_dict (**args, **kwargs*)
 Create a simply `dict` representation of the object.

Notes

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

p

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

q

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

solve (*args, **kwargs)

Execute the multi-criteria method.

Parameters `data`: `skcriteria.Data`

Preprocessed Data.

Returns `object`

object or tuple of objects with the raw result data.

Indices and tables

- [genindex](#)
- [modindex](#)
- [search](#)

Bibliography

- [R2328] Fishburn, P. C. (1967). Letter to the editor—additive utilities with incomplete product sets: application to priorities and assignments. *Operations Research*, 15(3), 537-542.
- [R2428] Weighted sum model. In Wikipedia, The Free Encyclopedia. Retrieved from https://en.wikipedia.org/wiki/Weighted_sum_model
- [R2528] Tzeng, G. H., & Huang, J. J. (2011). *Multiple attribute decision making: methods and applications*. CRC press.
- [R2631] Bridgman, P.W. (1922). *Dimensional Analysis*. New Haven, CT, U.S.A.: Yale University Press.
- [R2731] Miller, D.W.; M.K. Starr (1969). *Executive Decisions and Operations Research*. Englewood Cliffs, NJ, U.S.A.: Prentice-Hall, Inc.
- [R2831] Wen, Y. (2007, September 16). Using log-transform to avoid underflow problem in computing posterior probabilities. from http://web.mit.edu/wenyang/www/log_transform_for_underflow.pdf
- [R13] Yoon, K., & Hwang, C. L. (1981). *Multiple attribute decision making: methods and applications*. SPRINGER-VERLAG BERLIN AN.
- [R23] TOPSIS. In Wikipedia, The Free Encyclopedia. Retrieved from <https://en.wikipedia.org/wiki/TOPSIS>
- [R33] Tzeng, G. H., & Huang, J. J. (2011). *Multiple attribute decision making: methods and applications*. CRC press.
- [R1317] BRAUERS, W. K.; ZAVADSKAS, Edmundas Kazimieras. The MOORA method and its application to privatization in a transition economy. *Control and Cybernetics*, 2006, vol. 35, p. 445-469.
- [R1418] Brauers, W. K. M., & Zavadskas, E. K. (2012). Robustness of MULTIMOORA: a method for multi-objective optimization. *Informatica*, 23(1), 1-25.
- [R1518] Karlin, S., & Studden, W. J. (1966). *Tchebycheff systems: With applications in analysis and statistics*. New York: Interscience.
- [R1620] Brauers, W. K. M., & Zavadskas, E. K. (2012). Robustness of MULTIMOORA: a method for multi-objective optimization. *Informatica*, 23(1), 1-25.
- [R1721] Brauers, W. K. M., & Zavadskas, E. K. (2012). Robustness of MULTIMOORA: a method for multi-objective optimization. *Informatica*, 23(1), 1-25.
- [R79] Roy, B. (1990). The outranking approach and the foundations of ELECTRE methods. In *Readings in multiple criteria decision aid* (pp.155-183). Springer, Berlin, Heidelberg.

- [R89] Roy, B. (1968). Classement et choix en présence de points de vue multiples. *Revue française d'informatique et de recherche opérationnelle*, 2(8), 57-75.
- [R99] Tzeng, G. H., & Huang, J. J. (2011). *Multiple attribute decision making: methods and applications*. CRC press.

S

skcriteria, 18
skcriteria.core, 19
skcriteria.madm, 19
skcriteria.madm.closeness, 23
skcriteria.madm.electre, 31
skcriteria.madm.moor, 24
skcriteria.madm.simple, 19

A

as_dict() (skcriteria.madm.electre.ELECTRE1 method), 32

as_dict() (skcriteria.madm.mooraa.FMFMOORA method), 28

as_dict() (skcriteria.madm.mooraa.MultiMOORA method), 30

as_dict() (skcriteria.madm.mooraa.RatioMOORA method), 25

as_dict() (skcriteria.madm.mooraa.RefPointMOORA method), 27

C

criteriarr() (in module skcriteria.core), 19

E

ELECTRE1 (class in skcriteria.madm.electre), 31

F

FMFMOORA (class in skcriteria.madm.mooraa), 27

M

MultiMOORA (class in skcriteria.madm.mooraa), 29

P

p (skcriteria.madm.electre.ELECTRE1 attribute), 33

preprocess() (skcriteria.madm.mooraa.FMFMOORA method), 29

preprocess() (skcriteria.madm.mooraa.MultiMOORA method), 30

preprocess() (skcriteria.madm.simple.WeightedProduct method), 22

Q

q (skcriteria.madm.electre.ELECTRE1 attribute), 33

R

RatioMOORA (class in skcriteria.madm.mooraa), 24

RefPointMOORA (class in skcriteria.madm.mooraa), 25

S

skcriteria (module), 18

skcriteria.core (module), 19

skcriteria.madm (module), 19

skcriteria.madm.closeness (module), 23

skcriteria.madm.electre (module), 31

skcriteria.madm.mooraa (module), 24

skcriteria.madm.simple (module), 19

solve() (skcriteria.madm.closeness.TOPSIS method), 24

solve() (skcriteria.madm.electre.ELECTRE1 method), 33

solve() (skcriteria.madm.mooraa.FMFMOORA method), 29

solve() (skcriteria.madm.mooraa.MultiMOORA method), 31

solve() (skcriteria.madm.mooraa.RatioMOORA method), 25

solve() (skcriteria.madm.mooraa.RefPointMOORA method), 27

solve() (skcriteria.madm.simple.WeightedProduct method), 22

solve() (skcriteria.madm.simple.WeightedSum method), 21

T

TOPSIS (class in skcriteria.madm.closeness), 23

V

validate_data() (in module skcriteria.core), 19

W

WeightedProduct (class in skcriteria.madm.simple), 21

WeightedSum (class in skcriteria.madm.simple), 19